INDUSTRIAL PRODUCTION AND STOCK RETURNS

by

Peter Young

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Name: **Peter YOUNG**

Degree: **Master of Business Administration**

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Supervisory Committee:

____

Dr. Peter Klein
Associate Professor of Finance

____

Dr. Robert Grauer
Endowed Professor of Finance

Date Approved: May 4/06

ABSTRACT

This project extends the work of Schwert (1990) titled "Stock Returns and Real Activity: A Century of Evidence" which looks at the relationship between real activity, as measured by industrial production, and stock returns. The intent is to see if the relationship between stock returns and industrial production continues to hold with the addition of the years 1989 to 2004 with the hope the relationship still exists. It is expected that the relationship between Industrial Production and Stock Returns will be broken due to the transformation of the US economy from a manufacturing to a service oriented economy in the latter part of the 20^{th} century however the findings indicate that the relationship continues to exist and appears to have strengthen in the sample period.

DEDICATION

This paper is dedicated to the following professors:

Dr. Andrey Pavlov, who made the subject of econometrics and statistics fun, especially in describing in an understandable way how hypothesis testing is actually interpreted, "...your worst nightmare comes true!"

Dr. Robert Grauer, who showed me how the different side of academic finance and especially how interpreting statistical numbers can depend very much on what you wish to prove to disprove.

Dr. Peter Klein, who showed me how banks determine all their clients should be in a balanced portfolio, and then shows how portfolio allocation process is very much dependant on the inputs involved which includes risk tolerances, expected returns and the variance co-variance matrix.

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GLOSSARY

Div	Dividend Yield
P_b	Babson Industrial Production, seasonally adjusted industrial production output index.
P_{mr}	Miron – Romer Industrial Production, a non-seasonally adjusted industrial production output index.
R	CRSP Value Weighted Stock Returns
DEF	Default Spread defined as the difference between Moody's seasoned Aaa and Baa yields as reported on the Federal Reserve website, www.federalreserve.gov
Term	Term Spread defined as the difference between Moody's seasoned Aaa and the Federal Funds Rate as reported on the Federal Reserve website, www.federalreserve.gov

1 INTRODUCTION

This paper will attempt to answer the question of whether industrial production can predict stock returns, but more importantly the intent is to see if industrial production numbers as produced by the Federal Reserve still holds relevance especially since significant manufacturing capacity has been off-shored starting in the late 1980s. In order to answer this question I have referred to Schwert (1990) which looked at the relationship between industrial production and stock returns. I have reasoned if the industrial production index is still relevant to the 21st century that is if it is still able to predict stock returns, I will find that the results should not be much different from Schwert (1990). However due to the recent off-shoring of manufacturing capabilities, the question of whether industrial production can still predict returns is in question. Due to this, I would expect that the results for the years 1989 to 2004 will show that industrial production is not statistically significant.

In the following sections I have set out a short literature review of predictability studies published in the past using various methods and variables. Section 3 of this project describes the data and the methodology I have used in order to answer the above stated question regarding the relationship between industrial production and stock returns. This is then followed by the conclusion which will summarize my findings.

2 LITERATURE REVIEW

In 1970 Eugene Fama (1970) introduced Efficient Markets Hypothesis where he categorized the market as either Weak Form, Semi-Strong Form or Strong Form efficient, in 1991 he revisited the issue and renamed the above 3 categories Return Predictability, Event Studies and Private Information (Fama 1991). The importance of return predictability is based on the idea that if returns are predictable then by carefully reviewing the variables that influence stock price and returns, one should be able to generate substantial profits. In short if returns are predictable, then a "crystal ball" exists, in the form of a regression equation or a trading rule, where an investor is able to exploit the relationship between excess returns and certain lagged variable or variables. As can be seen from the late 1990's prices and returns are not predictable with vast numbers of individuals loosing most if not all their savings, either that or if someone has indeed found variables that actually predict returns, then they are keeping it a tightly held secret which leaves the rest of us in the rain. In reviewing the literature I hope to be able to get a sense of what the literature says about predictability and whether my dream of being able to generate substantial returns by looking at some select variables isn't fuelled by some hotdog fuelled hallucination.

In most articles it is well established that return are predictable but mostly in the long term thus bringing up the possibility of mean reversion of stock prices. The question then arises is what is the cause of return predictability, is it due to investors adjusting their spending patterns to adjust for economic conditions or is it the result of investor behaviour and sentiment. However a number of studies have also made findings that dispute idea of long term predictability indicating that long-term predictability is not present but short-term predictability is present. As well there are a number of papers that appear to question the methodology used in finding predictability and the statistical tests used in measuring predictability models.

In the following sections I will first review the literature showing that long-term predictability exists and what variables are used in the models. The next section reviews the articles that argue short-term predictability is more prevalent and what variables are used in those studies. The following section will present some alternative theories as to why return predictability is or is not present, and finally a section will be presented on the statistical and methodological problems that exist in most studies of return predictability.

2.1 Long-term Predictability

The most intuitive variable that can be used in predicting stock prices and thus returns is the dividend yield, as it has been observed that the value of a company should be the discounted present value of all dividend payments into the future. The reasoning behind this is an investor will look to the potential cash generation power of a company, as represented by its dividends, for valuation purposes, this is established in equity valuation books as the Dividend Discount model and its derivatives. Thus it is not surprising that the dividend yield is used as a forecasting variable in most studies of return predictability.

Long-term predictability of returns appears to be accepted in most studies of Efficient Markets. Fama and French (1988) looked at dividend yields to forecast stock returns over the time period of 1927 to1956 and found that the variances of unexpected returns decline over time. Their findings indicate that Dividend Yields are negatively auto-correlated to the return horizon and explain only a small portion of stock returns in the short term, which they define as monthly or quarterly returns; however 25% of the variance of returns over a three- to five-year period is explained by the dividend yield.[1] The authors offer 2 explanations for their findings, which are:

1. High autocorrelations causes the variance of expected returns to grow faster than the return horizon
2. The growth of the variance of unexpected returns with the return horizon is attenuated by a discount rate effect – shock to the expected returns generate opposite shocks to current prices.[2]

In other words, rational investors expect returns to increase over time, or the famous "hockey stick" graph, and as expected returns grow are tempered by an increase in the discount rate used to discount future dividends to the present to arrive at a price for the security. As well they state that the negative auto-correlation may be evidence of mean reversion over the long-term, however they also admit that the auto-correlation may be the result sample bias. In calculating the correlation between divided yields and returns, Fama and French indicate that the above mentioned sample bias may have caused the R^2 to be overstated and for the out of sample R^2 to be

[1] Fama, Eugene F. and Kenneth R. French, "Dividend Yields and Expected Stock Returns", *Journal of Financial Economics*, 1988, pg. 24
[2] Ibid, pg. 3

understated.[3] While their study appears to provide proof that stock returns are predictable, the sample bias they indicate puts the findings into doubt.

Campbell and Shiller (1988) use dividends to predict stock prices, but they use accounting data to predict earnings and thus dividends with the reasoning that a stock's price is the present value of its future dividends with data from S & P Composite Stock Price Index for the period 1871 to 1987. In recognition of the fact that earnings are noisy, in the sense that earnings can be negative in certain years while value cannot be negative, they use a moving average of earnings to avoid this problem citing that use of average earnings is common in calculating the price to earnings ratios.[4] Using the Vector Auto-Regression approach they show that stock prices are predictable by showing that the variance between the predicted stock value and the actual stock value declines over a long horizon, defined as over 2 to 4 years. Their results show that 20 ~ 30% of variances can be explained by lagged multi-year stock returns or dividend ratios however the authors also note that the use of moving averages in earning makes the stock prices and returns very volatile over the long term thus raising questions in regards to the usefulness of the model.[5]

Bekaert and Hodrick (1992) studied the predictable components of both the excess returns on equities and the foreign exchange market in an attempt to answer whether markets are inefficient or the result of changes in risk premiums over time. In their study they use the traditional measure of return predictability, dividend yields, short-term interest rates, default spreads, and yields in the term structure of interest rates for the equity markets (they also use the forward premium to predict returns on the foreign exchange markets.[6]) In their study they use data for four countries, the US, Japan, the UK and Germany from Morgan Stanley Capital International, Ibbotson Associates, Financial Times Actuaries, the Monthly Report of the Deutsche Bundesbank and Citicorp Database Services to see if the predictability components are the same in all markets. Performing a Vector Auto-Regressions the study surprisingly finds that the forward premium used to predict returns on the foreign exchange market might also be used to forecast excess returns on the equity markets. As well the study finds that mean reversion is present in the long horizon for both the US and the UK but does not appear to be present in either Japan or Germany. The study also looks at the effect of changes in the dividend yield to the long-horizon expected returns; they find that for a 1% increase in dividend yields, there is a 2 – 4%

[3] Ibid. pg. 18
[4] Campbell, John Y. and Robert J. Shiller, "Stock Prices, Earnings, and Expected Dividends", *The Journal of Finance*, Vol. 43, No. 3, pg. 664
[5] Ibid, pg. 662
[6] Bekaert, Geert and Robert J. Hodrick, "Characterizing Predictable Components in Excess Returns on Equity and Foreign Exchange Markets", *The Journal of Finance*, Vol. 47, No. 2 (June 1992), pg.467

increase in expected returns for the following 48 months.[7] In their final analysis they are able to show that returns are predictable but unable to show that the predictability of returns is the result of either market inefficiency or due to changes in risk premium over time. While the study proves that return predictability exists, it also states that for the US market a mean reversion effect is present that is stock prices tend to move back to a long term average price however they do not present how this long term average price is calculated. The lack of mean reversion in both the Japanese and German markets, while at first sounds intriguing, it should be noted that the study measures the returns in these 2 markets in US dollars, indicating that the exchange rate mechanisms are possibly masking the mean reversion of returns in both Japan and Germany. It should also be noted that the sample period the authors use is the period from January 1981 to December 1989, meaning that the sample used in the study could very well be biased.

Related to the dividends yield is the earnings numbers that company's report on an annual basis, in fact dividends are often paid out of annual earnings. By extension it may be possible to predict excess stock returns based on the earnings outlook for securities. Lamont (1998) studies the potential predictive ability of earning for stock returns using data from 1947 to 1994. He specifically looks at the dividend payout ratio as well as earnings for the period to see if there is any predictive power, his reasoning for selecting the dividend payout ratio is that the ratio can be seen as a "permanent component of stock prices"[8], or in other words dividends are known to be "sticky" that is they tend to move up but very rarely move down, investors thus value stocks based on a permanent component then add on a potential growth and risk premium to the basic price. His reasoning for selecting earnings as a predictive variable is that "the level of earnings is a good measure of current business conditions", finding that stock premiums are negatively correlated to economic activity.[9] He notes that his findings are in direct contradiction to the established literature stating that earnings are poor variables to use due to a "noise" factor, meaning that earnings can be negative while stock valuations remain positive. Lamont claims that the noises seen by most researchers is actually short term information that is useful in predicting expected returns, but due to the noise earnings variables together with dividends are better at predicting short-term excess returns, but not long-term returns. This is surprising as most studies using dividends often find that returns are predictable only in the long term.

Menzly, Santos, and Veronesi (2004) observed that while a positive relationship between dividend yield and expected returns exists over time, there is a also a negative relationship over

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[7] Ibid, pg. 506
[8] Lamont, Owen, "Earnings and Expected Returns", *The Journal of Finance*, Vol. 53, No. 5, October 1998, pg.1564
[9] Ibid, pg. 1564

the same time period between the growth in dividend yields and expected returns as investors would require a higher premium due to cash flows being deferred further into the future.[10] The result is that the effects essentially cancel each other out and leads to the question of whether the dividend yield can effectively forecast expected returns. The authors' link the dividend yields to investors' risk tolerances and show that due to changes in risk preferences the dividend yield by itself may be a poor predictor of future expected returns. To correct for the effects of changes in risk preferences, the authors propose to divide the dividend yield by a price/ consumption ratio to control for changes in risk preferences.[11] The authors use simulations to predict growth in dividends and expected returns for a cross section of industries and then try to isolate the where returns predictability originates from.

Aside from the traditional variables used to predict returns, there have been studies that have attempted to predict returns using other factors, Haugen and Baker (1996) used the APT approach to return predictability and found that their model is accurate in predicting expected returns even after correcting for sample bias that have been noted in previous studies. Their model uses several factors including risk factors, liquidity factors, and factors indicating price levels, factors indicating growth potential, technical factors, and sector variables, in all they use about 12 factors to predict expected returns.[12] The model is initially applied to the US market as represented by the Russell 1000 index and then they apply it internationally to France, Japan, Germany and the UK. The model appear to be able to predict returns in all five countries allowing the authors to prove that there are common factors that determine expected returns in different markets. Of all the studies presented this one showed the most promise due to its use of variables that are the most understandable. Although this approach appears to be enticing the reality of such a complex model, 12 factor variables, may be hard to put into practice, and the question of the potential profits that can be generated from the Haugen and Baker model. Hanna and Ready (2003) looked at the issue of profitability when they reviewed portfolio strategies when transaction costs were included, they found that although the Haugen and Baker model produced stronger predictability before transaction costs were factored in, the transaction costs does appear to eliminate any potential profits that can be generated from the model. They also

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[10] Menzly, Lior, Tano Santos, and Pietro Veronesi, "Understanding Predictability", *Journal of Political Economy*, 2004, Vol. 112, pg. 37

[11] Ibid, pg. 3

[12] Haugen, Robert A. and Nardin L. Baker, "Commonality in the determinants of expected stock returns", *The Journal of Financial Economics*, Vol. 41, 1996, pg.436 ~ 437

bring up the issue that the predictability in the Haugen and Baker model could be the result of increased risk.[13]

Another approach to predicting returns that seems more natural is the use of variables that measure economic activity, as security prices should reflect the current economic potential of the companies as represented by their securities. Most of the studies that used variables measuring economic activity date from September 1990. Fama (1990) looked at real GDP, industrial production and investment as these factors determine the cash flows to firms.[14] He noted that previous studies appeared to show that large fractions of stock return variances (more than 50%) were attributed to the above variables. However he finds that there is a measurement problem when using industrial production number in the short term as it is also includes growth rates for future periods, that is when using the current industrial production growth rate it will have included in it the effects of previous periods, Fama thus advocates the use of long term industrial production numbers. In short Fama questions the ability of GDP, industrial production and investment variables to predict expected returns noting that the variables chosen were selected based on "goodness of fit rather than the directives of a well developed theory" although his regressions find that the explanatory power of the variables is very high, about 0.85.[15]

Schwert (1990) like Fama (1990) looks at the relationship between returns and economic activity but uses 65 years of additional data (Fama (1990) uses data from 1953 to 1987), from 1884 to 1988 using 2 different measures of industrial production, the Miron-Romer index and the Babson index both of which he has included with industrial production numbers from the Federal Reserve Board Index up to 1941. The Miron-Romer index is a value weighted average of 13 industrial product indices that is not seasonally adjusted while the Babson index is a seasonally adjusted index of physical production that includes the effects of imports and exports. Schwert however confirms earlier studies that find that current stock prices and future industrial production growth rates are highly correlated and offers 3 explanations as to why this relationship exists:

1. Information about future real activity may be reflected in stock prices well before it occurs

[13] Hanna, J. Douglas and Mark J. Ready, "Profitable Predictability in the Cross-Section of Stock Returns", *Unpublished Manuscript*, July 28, 2003, pg. 29
[14] Fama, Eugene F., Stock Returns, Expected Returns, and Real Activity", *The Journal of Finance*, Vol. 45, No. 4, September 1990, pg. 1089
[15] Ibid, pg. 1107

2. Changes in discount rates may affect stock prices and real investment similarly, but the output from real investment doesn't appear for some time after it is made
3. Changes in stock prices are changes in wealth, and this can affect the demand for consumption and investment good[16]

At the same time, Balvers, Cosimano and MacDonald (1990) studied the theory that stock returns can be predicted based on forecasts of industrial output using data from 1947 to 1987, they do not use data before 1947 due to data contamination, principally due to major historical events and the economic policies initiated to address those events. Their reasoning for using lagged industrial production to predict stock returns is based on how the rational consumer would react to economic events. As an example if the investor in question is aware that economic conditions in the near future would turn for the worse, they would defer current spending into the future through savings and investments thus accepting a lower rate of return, however if they feel that future economic condition is improving they would defer saving and spend a larger percentage of their current income. As a result they present 3 testable propositions:

1. Stock returns are predictable
2. Stock returns depend negatively on current output
3. Stock returns incorporate the information embodied in current output in a manner consistent with the theoretical model[17]

In order to test to see if their model works in general and not just for the US, they apply their model to Canada, Japan and the UK. Their results show that using lagged industrial output, their model appears to be able to predict stock returns for the sample period and the prediction increases in strength the longer the measurement period with the industrial output variables predicting more than 20% of the stock returns. Their results do not only hold for the US but also for Canada, Japan and the UK, thus showing that in general industrial output in the current period can predict stock returns for subsequent periods. Their study also shows that the relationship between industrial output and stock returns is stronger than the relationship between dividends and stock returns. An interesting question to be raised is how industrial production in one nation affects stock prices of another seeing as two of the countries in question, Canada and Japan,

[16] Schwert, G. William, "Stock Returns and Real Activity: A Century of Evidence", *The Journal of Finance*, Vol. 45, No. 4, September 1990, pg. 1242
[17] Balvers, Ronald J., Thomas F. Cosimano, and Bill MacDonalc, "Predicting Stock Returns in an Efficient Market", *The Journal of Finance*, Vol. 45, No. 4, September 1990, pg. 1110

export most if not all of their industrial output to the US. Thus the question that can be raised is for integrated economies, how does the industrial output of one larger economy affect the stock prices of the other economy?

2.2 Short Horizon

As the above studies show, long-term return predictability is well established using the dividend yield as the primary predictor. However as the Bekaert and Hodrick study also shows that other variables appear to be able to forecast returns, theses are the short-term rates, the term structure of interest rates and default spread. Recently there have been studies that challenge the view that returns are predictable in the long term, principally using short-term interest rates like the T-bill rates. The Breen, Glosten and Jagannathan (1989) study used one-month interest rate as the forecasting variable for excess stock returns. The reasoning for using interest rates to predict excess market returns is the relationship between inflation and excess market returns where excess market returns appears to be negatively related to interest rates as seen in the reaction of financial indices to changes in the central bank rate. Their study uses one-month T-bills rates to predict excess returns on both a value weighted and equal weighed index on the NYSE for the period April 1954 to December 1986. They note that in previous studies the variations in predictive models is high and this may be due to the fact that the relationship between excess returns and interest rates is non-linear.[18] The results of their study show that the short term interest rate is negatively related to excess returns and concludes that the T-bill rate do predict excess returns, however they also show that this predictive power applies only to the value weighted index and not for the equal weighted index of the NYSE. Their explanation for this strange outcome is possible leptokurtosis and January seasonal distribution of the equal weighted index excess returns.[19] The use of interest rates leads one to then question whether interest rates themselves are predictable, thus raising the issue of whether the Expectations Hypothesis for interest rates holds that is long term interest rates is equivalent to the average short term rates over the same long term period. Most studies reject the pure expectations hypothesis however in a recent study by Francis A. Longstaff (2000); he shows that using the premium on weekly and monthly rates it is possible to predict interest rates in the very short term, less than one month. The study uses the closing overnight, one-week, two-week, three-week, one-month, two-month,

[18] Breen, William, Lawrence R. Glosten and Ravi Jagannathan, "Economic Significance of Predictable Variations of Stock Index Returns", *The Journal of Finance*, Vol. 44, No. 5, Dec 1989, pg. 1179
[19] Ibid, pg. 1189

and three-month general collateral government repo rate for the periods May 21 1991 up to October 15, 1999.

The Longstaff study could only prove that the Expectations Hypothesis could not be rejected over the very short term, less than one-month; however for longer terms most studies appear to reject the expectations hypothesis. The rejection of the hypothesis should be a problem for stock returns predictability as Breen, Glosten and Jagannathan used one-month rates to forecast excess returns. A study by Bekaert and Hodrick (2001) however brings this into doubt as they show that the traditional tests for Expectations Hypothesis often over reject. The study does not conclusively prove that the Expectation Hypothesis holds but they do note that the poor results for testing the hypothesis can be due to the requirement in the theory that the risk premiums for long term rates are held constant, which can be reasoned is often not the case. Changes in risk premium over time would make testing for Expectations Hypothesis much more difficult to prove.

A study by Ang and Bekaert (2001) appears to support the view that stock predictability is only possible in the short term and only with short-term rates, thus supporting the Breen, Glosten and Jagannathan study. Instead of using just the short-term interest rate, Ang and Bekaert use the short-term rate, the dividend yield and the earnings yield to predict returns not only for the US but also for France, Germany, Japan and the UK. The reasoning here is that the variables for predicting excess returns should be the same around the globe and should not be particular to just one country. The results of their findings were that short term rates appears to be the only variable that is robust across countries, that is local short term rates appear to be the only variable that common for all five nations and only in the short term. As further proof they also regress the variables across nations and find that the US short-term rates appears to be strong predictors of foreign equity returns, but that local short term rates do not predict US returns. This is intuitive as the countries in the study are closely tied to that of the US, thus when the US encounters economic difficulties it can be assumed that the 4 countries in the study also encounter economic difficulties. In light of this fact it is not hard to see that US short-term interest rates have a large impact on non-US equity returns.

Aside from the above variables of dividend yield and short term rates, there have been other variables used to predict excess returns; some of these variables are macro-economic in nature while others use accounting data or more intriguing other classes of stocks.

2.3 The Behavioral Approach

It has been noted above that the topic of return predictability is now divided into 2 views, one seeing expected returns are contingent of the business cycles where consumption is smoothed over time, the alternative view is that excess returns vary over time and thus cannot be accurately predicted.[20] The latter view is congruent with the behavioral finance where the general view is that investor beliefs regarding stock valuations often are not accurate resulting in over valuations in some cases and under valuations in others, over time investors arrive at the conclusion that an over valuation situation has occurred resulting in a massive correction to the over valued stocks. A study by Kenneth West (1988) attempts to explain stock price volatility by reviewing studies on the subject and finds that there does not seem to be an explanation for price volatility. In this absence he puts forward the idea of "fads" as an explanation, by fads he means that the market is made up of uninformed investors and informed investors. The uninformed investors can be seen as those investors who tune into CNBC every morning and invest in the next big thing that is advertised, an example is the "dot com" boom of the late 1990's, and the informed investors are the professional money managers. In this scenario the uninformed investors (West calls them naïve investors) regularly chase the next "sure" bet pushing prices up and then over react to bad news driving prices lower than necessary, thus indirectly stating that returns are not predictable over any period. It should be noted that the author states that most of the evidence for fads is indirect with little or no formal evidence.[21] A similar paper by Avanidhar Subrahmanyam (2003) looked at price reversals over a short period using transaction data from the Institute for Studies of Securities Markets and the NYSE Trades and Automated Quotations databases for 1988 to 1992 and 1993 to 1998 respectively. The thesis of the paper is that price reversals are due to the effects of market makers filling up inventory and the effect of reversal of investor beliefs. The finds indicate that price reversals are mostly the result of belief reversals of investors. This findings suggest that returns are not predictable as stock prices and thus returns are based the beliefs of the investors who buy and sell the stock, or the "animal spirits". Venkat and Reinganum (2004) also study this phenomenon using "glamour" stocks and value stocks to test stock return predictability using data over the period 1957 to 1997. Their finding show that glamour stocks have a negative relationship to market returns[22], however the relationship is lagged by 36months, that is the past 36 month return of glamour stocks can predict the stock

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[20] Eleswarapu, Venkat R. and Marc R. Reinganum, "The Predictability of Aggregate Stock Market Returns: Evidence Based on Glamour Stocks", *The Journal of Business*, April 2004, pg. 275

[21] West, Kenneth D., "Bubbles, Fads and the Stock Price Volatility Tests: A Partial Evaluation", *The Journal of Finance*, Vol. 43, No. 3, pg.654

[22] Ibid, pg. 283

return for the next 12 months. As well their study shows that value stock cannot predict future stock returns, or at best do not add any value to their regressions during the sample period. The reason for this could be that investors may begin to look at the glamour stocks more closely when they "feel" that an over valuation situation is occurring. This is quite intuitive especially in light of the technology bubble situation in the late 1990's where Internet companies with no positive earning or for that matter no earning history what so ever commanding astronomical valuations only to have their valuations reduce to zero overnight although their financial information hadn't changed.

2.4 Issues to Statistical Tests

Fama (1990) raised in his review of the relationship between output and stock returns the issue of selecting variables more for their goodness of fit over sound theory. This problem is further heightened with the numerous studies of stock return predictability using the same dataset repeatedly, a problem the statistician evidently call "model over fit" or more undiplomatically "data snooping" or "data torturing", where false relationships can be found by repeatedly applying tests to the same datasets. This issue has been dealt with in several papers and they offer both solutions and raises questions as to the validity of the above tests for return predictability.

Bossaerts and Hillion (1999) offer solutions to the overuse of the same datasets, these are:

1. Collect new data covering different time periods and/ or markets
2. Use standardized test to adjust for over fitting tendencies, based on either theoretical approximations like the Bonferroni bounds or bootstrapping stationary time series[23]

The authors note that in the statistical literature there are other methods that can be used to guard against "model over fit" principally using model selection criteria. Although the authors find several studies that confirm return predictability they note that none were based on a formal model selection criteria, and then proceed to create a return predictability model that both solves the issue of "model over fit" and allows for good out of sample predictability. The results of their efforts was a model that was able to prove return predictability in sample but unable to do so out of sample. They explain two sources for this lack of out of sample predictability that the true

[23] Bossaerts, Peter and Pierre Hillion, "Implementing Statistical Criteria to Select Return Forecasting Models: What Do We Learn?", *The Review of Financial Studies*, Vol. 12, No. 2, Summer 1999, pg. 406

prediction model is most likely non-linear while the model they selected was liner in nature, and that returns appear to be non-stationary, the cause then being attributed to market participants going through a learning process, or rather a "Bayesian learning" process.[24]

Of greater concern is the statistical tests used to prove return predictability raising questions as to the appropriateness of tests used. Torous, Valkanov, and Yan (2004) show that the most common variables used to prove return predictability, namely dividend yield, short term rates, default spreads, term spread and more recently book to market ratios may follow a random walk, that is the variables are random in nature. This randomness of the variables they argue is closely integrated with the randomness of stock returns, indeed they note that the debate on whether stock returns follow a random walk is very established, however it is uncertain how integrated the variables used are. The authors argue that the most common tests used in finance literature, the augmented Dickey-Fuller test may not be appropriate in light of the uncertain integration of the above variables as they argue that the test itself has a lower power to reject the null hypothesis.[25] The study proposes to use alternative tests to account for the uncertainty surrounding integration of variables especially in calculating the confidence intervals for the variables used in return prediction. In calculating the confidence intervals using both the traditional measures and using the Bonferroni confidence intervals for the slope coefficients, they find that the traditional long-term predictability does not materialize. In fact the Bonferroni confidence intervals they calculate indicate that intervals are much larger than the traditional confidence intervals. They interpret the widen spread in the adjusted confidence intervals as lack of proof for long term return predictability, however they surprising also show that the confidence intervals for the short term, of 1 to 3 months, are very smaller than the long term. In short they state that long-term predictability of returns is based on the use of inappropriate tests and short-term predictability is possible. They back this thesis up by using the monthly data for traditional variables for the period December 1926 to December 1994. The tests involve both regressions for the whole period and for sub-period samples of pre- 1952 and post 1952, and show that the results are robust for the entire sample as well and for the 2 sub-samples. This study seems to support the finding of Breen, Glosten and Jagannathan (1989) and addresses some of the previously mentioned problems with studies in return predictability especially in regards to the assumptions imposed on the data, as well as appearing to make a well thought out case for using the traditional variables to predict returns in the short term. In their tables they show that the variable with the largest impact on returns predictability is dividend yield and book to market

[24] Ibid, pg.408
[25] Torous, Walter, Rossen Valkanov, and Shu Yan, "On Predicting Stock Returns with Nearly Integrated Explanatory Variables", *The Journal of Business*, October 2004, Vol. 77, No. 4, pg. 939

ratios. However this study like others does not address if the model and the tests work outside of the sample period and issue brought up by Bossaerts and Hillion (1999).

2.5 Summary of Literature Review

In reviewing the literature regarding returns predictability, the vast majority of the work is based primarily on predicting returns using the lagged dividend yield, default spread, short term rates, term spread and the recent book to market ratios. While the majority of the literature point to the fact that predictability is possible only in the long-term, there have been studies that attempt to disprove this, but the remaining consensus is still that it is the long term that returns are predictable. Bossaerts and Hillion (1999) raise the issue that most studies use the same data sets repeatedly broaching the issue of "data snooping", "data mining", "data torturing", or more statistically correct term of model over fit. They attempt to correct for this through the use of model selection criteria in hopes of avoiding model over fit and in generating a model that actual works out of sample. While the results of their study shows that return predictability is present, it is present only in sample and when the model is applied out of sample it appears to do a very poor job of predicting returns using the traditional variables. Of all the studies I have looked at the most compelling and approach appeared to be using industrial output numbers as a predictive variable for return predictability. The reason I find this approach to be sounder is fact that stock prices should reflect the cash generation power of the company it represents, and cash generation power is linked to a large extent on the economic conditions in general as represented by industrial output or GDP numbers. Although Fama (1990) raised doubts as to the theoretical soundness of the regressions, noting that the variables were select for goodness of fit rather than the directives of a well developed theory"[26], he did find that the explanatory power was quite high at 0.85, and that over 50% variances of returns on the NYSE exchange was accounted for by

[26] Fama, Eugene F., Stock Returns, Expected Returns, and Real Activity", *The Journal of Finance*, Vol. 45, No. 4, September 1990, pg. 1107

changes in industrial output. Unfortunately this line of study appeared to have fallen by the wayside after 1990 as most recent literature on return predictability again focused on dividend yields, short term rates, term spreads, default spreads, and more recently on book to market. Overall the evidence appears that returns are predictable but there is a debate as to which variables actually can predict returns and more importantly concerns regarding "data mining" by researchers in the subject matter.

3 METHODOLOGY AND RESULTS

This project is based on a study by Prof. G. William Schwert titled "Stock Returns and Real Activity: A Century of Evidence" first published in September 1990 in the *Journal of Finance* utilizing data encompassing the period 1889 to 1988. I have used this article as the basis of my project using data for the period 1954 to 2000 with a sub-period from 1988 to 2000 for 2 reasons, first to see if the results still hold more recent data and primarily to determine if recent changes in the US economy from manufacturing oriented to services oriented has any affect on using industrial production to predict stock returns. As a result of increased outsourcing of production to low cost countries like China, India, Indonesia, Malaysia and Vietnam in the 1990's it would thus be interesting to see if the industrial production indexes still have the strong predictive qualities first seen in Prof. Schwert's study and whether the Federal Reserves' industrial output indexes have any more relevance for the US economy of the 21st century especially in regards to forecasting stock returns. It should be noted that in response to the changes in the US economy, the Federal Reserve has periodically updated the industrial production indexes through discontinuing and introducing new industrial series reflecting new categories of production like computer chip production.

The intent of this project is to look at whether industrial production can forecast stock returns into the future with the rationale that industrial production should lead stock returns. Increased production is often associated with increased spending on capital equipment by industries, prompting further production increases to replenish inventories, resulting in increased profits. The increased cash flow or rather earnings from increased production would be recognized by investors who will then reassess stock valuations and begin to price them higher resulting in higher returns.

Industrial Production numbers, both seasonally and non-seasonally adjusted, Moody's seasoned Aaa and Baa corporate bond yields and the Federal Funds Rate was obtained from the Federal Reserve website, www.federalreserve.gov , while the CRSP value weighted common stock portfolio returns and dividend yield were kindly provided by Prof. R. Grauer. I have used the Federal Funds Rate in lieu of the Treasury Bill Rate largely based on the belief that most corporations do not have access to the latter rate but are able to obtain funds at a rate close to the Federal Funds Rate; the data ranges from July 1954 to the present.

Schwert (1990) used the Babson and the new Miron – Romer Industrial Production index for his original study; however he has noted that both the above mentioned indexes are similar to the seasonally and non-seasonally adjusted industrial production indices released by the Federal Reserve.[27] I have thus used both indices from the Federal Reserve websites to proxy for the Babson and Miron – Romer Industrial Production indices. In addition Schwert (1990) used data dating back to 1889 to 1988, however I am interested in determining if changes in the US economy in the 1990's, especially from outsourcing manufacturing, has affected the value of using Industrial Production as a predictive variable. Treasury Bill Rates for the period prior 1938 can be found in Frederick R. Macaulay's book "The Movements of Interest Rates, Bond Yields and Stock Prices in the United States since 1856" published in 1938 of which I am still awaiting the results of my search from the library.

I have arranged the data from July 1954 to December 2000 using only monthly returns, lagging both the returns and industrial production variables where appropriate.

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[27] Schwert, G. William, "Stock Returns and Real Activity: A Century of Evidence", *The Journal of Finance*, Vol. 45, No. 4, September 1990, pg. 1239

RESULTS

The data used for this paper is primarily taken from the Federal Reserve website, www.federalreserve.gov, and provided by Prof. R. Grauer who was kind enough to share with me his CRSP index returns and dividend yield data for the period 1926 to 2005. I have elected to use the data set from July 1954 onwards due to the limitation I found regarding Federal Funds Rate data going back only to July 1954. I used the Federal Funds Rate as a proxy for the risk free rate reasoning that most if not all corporations will in most instances be unable to borrow at the Treasury Bill yield. Schwert (1990) observed the primary difference between the Babson Industrial Production index and the Miron Romer Industrial Production index appeared to be only that the former was seasonally adjusted while the latter was not seasonally adjusted. Thus I have used the seasonally adjusted and non-seasonally adjusted data from the Federal Reserve website, with the data starting from 1919 and stretches to the present. The Default spread was calculated through taking the difference between the average yield on Moody's seasoned Aaa and Baa as found on the Federal Reserve website. The Term spread was calculated through taking the difference between the average yields on Moody's seasoned Aaa bonds and the Federal Funds Rate. While it may be shorter than the original length of time it does extend the data slightly up to 2000, and thus it would be interesting to see if the relationship still holds.

As per the original paper I have used the following regression models to determine if there is a relationship between the industrial production indices, both seasonally adjusted and non-seasonally adjusted, and stock returns with the dependant variable is lagged 3, 6, 9, and 12 months. In the first set of regression index returns against have been regressed against industrial production with the appropriate lags, in the second regression industrial production has been regressed against index returns.

As well I have grouped the regressions into sub-periods, the first is 1954 to 1988 to replicate Schwert (1990) results for this time period and the second sub-period is 1989 to 2004 to determine if the results still hold especially since the reported changes in the structure of the US economy during this time from a manufacturing to a services based economy.

Table I presents the summary statistics for monthly industrial production rates for both the seasonally adjusted and the non-seasonally adjusted industrial production, and similar to the original study while the means for both series are close the standard deviation for the non-seasonally adjusted industrial production index is higher. However the autocorrelations appear to show that while the seasonally adjusted industrial production numbers decline after the third lag, for the non-seasonally adjusted data, autocorrelation appears to increase after the third lag. This can potentially be due to the data set used as it only covers the period from July 1954 to December 2000 or from the fact the data set covers the "Tech Asset Bubble" years of the 1990's.

Relationship between Stock Returns and Industrial Production

Table 2 presents the summary statistics for the following regression:

$$P(t) = \alpha + \sum_{k=1}^{4} b_k R(t+k) + e(t+k)$$

Where P (t) is the logarithmic production growth for the seasonally adjusted and non-seasonally adjusted industrial production index. Similar to the original paper the results of the regression show that the seasonally adjusted industrial production index, or the Babson index, is statistically more significant than the Miron – Romer index as represented by the non-seasonally adjusted industrial production index. This is especially so for the returns lagged 12 months with t-statistics larger than 3 at the 95% confidence level for the Babson series with the Miron – Romer series showing that it is not statistically significant. The R^2 for the Babson series is 0.0329 as opposed to 0.0045 for the Miron – Romer index indicating that the Babson series more correlated to stock returns for the period 1954 to 2000. However the coefficients and the t-stats for the period 1954 to 1988 do not match the original findings of Schwert (1990) which showed statistically significant results for lags of 6, 9, and 12 months. Instead my results show only a statistically significant result for a lag of 12 months with a negative relationship between returns and industrial production. This divergent finding could be the result of the data set used; while Schwert (1990) did not describe how the Babson or the Miron – Romer Industrial Production Indexes are constructed he did indicate that they were both similar to the seasonally and non-seasonally adjusted industrial production indexes found on the Federal Reserve websites.[28] The results for the sub - period 1988 to 2004 are substantially different with the R^2 falling to 0.0386 and with all the lagged variables statistically insignificant. The Miron – Romer series shows a slight improvement in the sub-period with R^2 increasing to 0.0181 but again all the variables are not significant as in the previous regression for the entire sample size and the 1954 to 1988 sub-periods. The fact that the constant is statistically significant in both overall sample and the sub-period indicates that some other variable exists to explain stock returns over the period studied.

Relationship between Industrial Production and Stock Return

Table 3 presents the summary statistics for the following regression:

$$R(t) = \alpha + \sum_{k=1}^{4} b_k P(t+k) + e(t+k)$$

Where P(t+k) is the logarithmic growth rate of the seasonally adjusted and non-seasonally adjusted industrial production index lagged 3, 6, 9 and 12 months. The results here while different from the original paper with the 1954 to 1988 period from Schwert (1990) indicating a statistically significant positive relationship for the periods with a 3 month lag, however my

[28] Ibid.,

results for this period indicates a statistically significant positive relationship with a 6 month lag. This discrepancy again is potentially due to the data series I have used which may be different from that of Schwert (1990). However the Babson series, as represented by the seasonally adjusted industrial production index, with an R^2 of 0.0348 is more highly correlated than the Miron – Romer series with an R^2 of 0.0134 to stock returns. However the lagged variable that is statistically significant is both the variables lagged 6 months and to a certain degree lagged 3 months, again as in the previous regressions the Miron – Romer series variables are not statistically significant. The results for the sub-period 1988 to 2000 however are surprising with R^2 for the Babson index improving to 0.04 and with one lagged variable, lagged 3 months, still indicating it is statistically significant at the 90% level, again the Miron – Romer series variables do not show any statistical significance at any level, however the R^2 has improved during the sub-period to 0.0291 from 0.0134. As with the previous regression the constant while small is still statistically significant indicating again other factors influencing stock returns which is most likely due to the alluded "Tech Bubble" of the late 1990's mention in the preceding paragraphs.

It should be noted that while the results do not conclusively show that industrial production, specifically the seasonally adjusted data of the Babson series as opposed to the non-seasonally adjusted data of the Miron – Romer series, is related to or predicts stock returns it does show that there is a relationship. The results may be the result of the sample period selected with the period from 1990 to 1999 witnessing the growth of and the puncturing of the technology asset bubble during this period which may explain why the constant is statistically significant for both the sample period and the sub-period.

4 CONCLUSIONS

I find that the seasonally adjusted data is more relevant than the non-seasonally adjusted data in predicting stock returns, with lags of 3, 6, and 12 months appearing to be more statistically significant. However this result applies only to seasonally adjusted data and not to the non-seasonally adjusted data indicating that potential problems may exist in the data I have collected, specifically it could be related to the sample period selected especially the data for the period 1990 to 1999.

The results show that while stock returns appear to display a statistically significant relationship after a lag, the seasonally adjusted index seems to show a stronger relationship especially with a 3, 6 and 9 months lag. The potential explanation is increased industrial production leads to increase in economic activity resulting in higher earnings for companies. The potential higher earnings should result in an increase in stock valuations resulting in stock gains. The results for the non-seasonally adjusted data indicate a relationship between returns and industrial production does not exist at all as seen by the low R^2 and statistically insignificance of the lagged variables.

The results for the sub-period of 1988 to 2000 also seem to indicate that the industrial production index can no longer predict stock returns. A potential explanation for this is the transformation of the US economy from a manufacturing based to a services based economy as evidenced by the significant off-shoring of production facilities to low cost countries in the developing world accompanied by an increase in professional services exports. As a future project it would be interesting to study the relationship between industrial production growth in developing counties and stock returns in the U.S.

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Table 1 **Summary Statistics for Stock Returns, Divided Yield, Default and Term Spreads and Monthly Industrial Production Growth, 1954 to 2000**

Summary statistics presenting the mean, standard deviation and autocorrelations lagged 1 through 6, 12, 24, 36, and 48 months. R(t) is the monthly real returns on a value weighted portfolio of common stocks from CRSP and D(t)/V(t) is the monthly dividend yield. The DEF (t) is the difference between Moody's seasoned Aaa and Baa corporate bond yields as found on the Federal Reserve website. TERM(t) is the difference between Moody's Aaa corporate bond yield and the Federal Funds Rate. $P^b(t)$ and $P^{mr}(t)$ are the monthly logarithmic growth rates for the Babson seasonally adjusted and the Miron – Romer non-seasonally adjusted industrial output indices.

Variable	Sample Size	Mean	Standard Deviation	Autocorrelations for Monthly Lags 1	2	3	4	5	6	12	24	36	48
						1954 – 2000							
R(t,t+1)	558	0.01	0.04	0.05	-0.33	-0.01	0.00	0.06	-0.05	0.04	-0.01	-0.02	-0.02
D(t)/V(t)	558	0.03	0.01	0.99	0.97	0.96	0.94	0.92	0.90	0.81	0.73	0.68	0.61
DEF(t)	558	-0.95	0.43	0.97	0.94	0.91	0.89	0.86	0.93	0.68	0.49	0.35	0.38
TERM(t)	558	1.45	1.76	0.95	0.88	0.81	0.75	0.71	0.67	0.41	-0.02	-0.15	-0.10
$P^b(t)$	558	-0.00	0.00	0.41	0.23	0.16	0.08	-0.01	0.01	-0.16	-0.19	-0.02	-0.00
$P^{mr}(t)$	558	-0.00	0.01	-0.20	-0.13	-0.06	0.04	0.06	0.04	0.80	0.78	0.80	0.80

Table 2 **Regression of Monthly Production Growth Rates on lagged Monthly Returns on Market Portfolio of Common Stocks,**

1954 to 2004

P(t) is the monthly logarithmic growth rate of industrial production. The seasonally adjusted and non seasonally adjusted monthly industrial production data is used as a proxy for the Babson and Miron – Romer industrial production data respectively, the data covers the years 1954 to 2004. R(t) is the monthly returns for the stock market portfolio lagged every quarter up to 1 year.

$$P(t) = \alpha + \sum_{k=1}^{4} b_k R(t+k) + e(t+k)$$

	Babson Monthly		Miron – Romer Monthly	
	1954 - 2004			
	b	t(b)	b	t(b)
Constant	0.0008	6.8265	0.0007	2.5586
R(t+3)	-0.0022	-0.9195	0.0074	1.1972
R(t+6)	-0.0020	-0.8152	-0.0004	-0.0611
R(t+9)	0.0005	0.1991	-0.0033	-0.5309
R(t+12)	0.0000	0.0520	0.0000	0.0430
R^2	0.0027		0.0030	
Sample Size	607		607	

	Babson Monthly		Miron - Romer Monthly	
	1954 – 1988			
	B	t(b)	B	t(b)
Constant	0.0011	6.8489	0.0011	2.9149
R(t+3)	-0.0024	-0.7381	-0.0105	-1.2946
R(t+6)	-0.0042	-1.2729	-0.0111	-1.3669
R(t+9)	-0.0046	-1.3984	0.0024	0.2999
R(t+12)	-0.0135	-4.1150	-0.0046	-0.5674
R^2	0.0476		0.0095	
Sample Size	416		416	

	Babson Monthly		Miron - Romer Monthly	
	1989 - 2004			
	b	T(b)	B	t(b)
Constant	0.0004	4.7115	0.0005	1.1976
R(t+3)	-0.0006	-0.3001	-0.0086	-1.0221
R(t+6)	0.0017	0.8171	0.0087	1.0355
R(t+9)	0.0048	2.3064	0.0040	0.4736
R(t+12)	0.0000	0.9377	0.0000	0.8946
R^2	0.0386		0.0181	
Sample Size	191		191	

Table 3 **Regression of Monthly Returns on Market Portfolio of Common Stocks on lagged Monthly Production Growth Rates, 1954 to 2004.**

R(t) is the monthly returns for the stock market portfolio. The seasonally adjusted and non seasonally adjusted monthly industrial production data is used as a proxy for the Babson and Miron – Romer industrial production data respectively, the data covers the years 1954 to 2000 and is lagged every quarter up to 1 year.

$$R(t) = \alpha + \sum_{k=1}^{4} b_k P(t-k) + e(t-T)$$

	Babson Monthly		Miron - Romer Monthly	
	1954 - 2004			
	b	t(b)	B	t(b)
Constant	0.0066	3.3627	0.0086	4.7223
P(t+3)	1.8213	2.5806	0.2175	0.7866
P(t+6)	1.1859	1.6466	0.3299	1.2073
P(t+9)	1.4026	1.9526	0.7171	2.6234
P(t+12)	0.0679	0.0952	0.4614	1.6489
R^2	0.0270		0.0194	
Sample Size	596		596	

	Babson Monthly		Miron - Romer Monthly	
	1954 – 1988			
	b	t(b)	b	t(b)
Constant	0.0060	2.5585	0.0091	4.1400
P(t+3)	1.3472	1.8535	0.1284	0.4229
P(t+6)	1.9166	2.5986	0.5197	1.7217
P(t+9)	1.3698	1.8380	0.4452	1.4719
P(t+12)	0.1414	0.1911	-0.2958	-0.9753
R^2	0.0405		0.0146	
Sample Size	416		416	

	Babson Monthly		Miron - Romer Monthly	
	1988 - 2004			
	b	t(b)	b	t(b)
Constant	0.0027	0.6833	0.0093	2.8049
P(t+3)	8.9515	3.2946	1.1788	1.7340
P(t+6)	2.0378	0.7213	-0.2971	-0.4265
P(t+9)	-2.0209	-0.7245	-0.1307	-0.1875
P(t+12)	5.0627	1.8846	0.6987	1.0252
R^2	0.0909		0.0226	
Sample Size	191		191	