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A Recursive Modelling Strategy for Market Timing of the TSE 300 Index

by

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ABSTRACT

Daily macroeconomic variables are used to forecast movements in the Toronto Stock Exchange 300 Total Return Index using a recursive modelling strategy. The time frame analyzed is from January 1989 to May 1999. A market timing strategy is used whereby the forecaster invests a portfolio in either the TSE 300 Total Return Index or 30-day Government of Canada Treasury Bills, depending on which asset is predicted to have a higher return that day. The strategies used emulate those in a paper by Pesaran and Timmermann (1995). The results indicate that if the forecaster faces transaction costs up to and including 0.25 percent, then this trading strategy delivers higher average returns than the TSE 300 Total Return Index for the sample time period. If, however, transaction costs are greater than 0.25 percent then the market timing strategy does not deliver higher average returns than the TSE 300 Total Return Index.

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On a more personal note, I thank my wife, Tannis, and my parents, John and Edna, for their support and encouragement.

DEDICATION

To my wife, Tannis, and my son, Wade.

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LIST OF ABBREVIATIONS

ADF Test	Augmented Dickey-Fuller Test
AIC	Akaike Information Criteria
ASE	Alberta Stock Exchange
BIC	Bayesian Information Criteria
CAPM	Capital Asset Pricing Model
CPI	Consumer Price Index
DJIA 30	Dow Jones Industrial Average Index of 30 companies
Fed (The)	The US Federal Reserve
GDP	Gross Domestic Product
HQC	Hannan-Quinn Criteria
NYSE	New York Stock Exchange
RBS	Adjusted R^2
S&P 500	The Standard and Poor Index of 500 companies
SIC	Schwarz Information Criteria
T-bill	Treasury Bill
TSE 300	Toronto Stock Exchange Index of 300 companies
VSE	Vancouver Stock Exchange

Chapter 1

INTRODUCTION

It is often theorized that, in the absence of risk considerations, it is not possible to outperform a market index such as the TSE 300 (^TSE) or the S&P 500 (^SPX) by switching one's portfolio between the market index and a safe asset such as government treasury bills. Countless studies have supported this notion, including Pesaran and Timmermann (1995), Davidson & Froyen (1982), Sorensen (1982), and Pearce (1987). Other analysts have found that short-term market returns *are* predictable using publicly available information. Examples include Keim & Stambaugh (1986), Campbell (1987), and Fama & French (1988). One way to explore the possibility of outperforming a market would be to evaluate whether it would be possible to use publicly available information to outperform one of the aforementioned stock market indices by switching a portfolio between the market index and a safe asset, such as government issued treasury bills. A study such as this could be accomplished by simulating an investor's actions in real time using publicly available information thought to contain information useful for predicting stock returns. Presumably, the investor predicts how this information will affect the returns of the stock market index.

This thesis examines the ability of an "informed" investor to outperform an investment in the TSE 300 Total Return Index using the strategy just described. If an investor uses a strategy of "buying and holding" the TSE 300 index, then each period this investor simply earns the rate of return yielded on the TSE 300 index. The objective of

this thesis is to determine whether it would have been possible to exploit a historical correlation of stock market index returns and macroeconomic variables to beat this buy-and-hold strategy in terms of average return.

This thesis generates recursive forecasts for the excess rate of return on the TSE 300 Total Return Index over the 30-day Canadian treasury bill rate based on a set of daily macroeconomic variables. Using these forecasts, it then simulates in "real time" the strategy of a hypothetical investor who switches his or her portfolio between the index and treasury bills according to which asset has the higher predicted return.

Stock market forecasting is generally categorized as one of two types: microforecasting or macroforecasting. Microforecasting, also known as "security analysis" (Henriksson & Merton, 1981), involves setting up a series of predictions for various individual stocks for the following trading period. These stocks are then determined to be either "under-valued" or "over-valued". In an effort to earn returns greater than the average market return, the forecaster trades into the "under-valued" stocks and trades out of the "over-valued" stocks. Examples of microforecasting in the literature include Ang & Chua (1991), Treynor & Black (1973), and Lintner (1965). The techniques used by these authors yielded limited success, however. For example, Ang & Chua (1991) found that they could outperform a market portfolio in the absence of transaction costs, but even if very small transaction costs were implemented, the returns earned by their strategy failed to outperform a strategy of buy-and-hold the market portfolio.

Macroforecasting, also known as *market-timing* (Henriksson & Merton, 1981), involves determining whether an entire market index is over- or under-valued relative to a risk-free rate of return (Merton, 1981).

An approach often taken in macroforecasting is to take the forecasted return for the stock market index and compare it to a risk-free asset. If, at time t, the predicted return on the index at time $t+1$ is *greater* than the predicted return on the risk-free asset at time $t+1$, then the market index is held. If the predicted return on the index at time $t+1$ is *less* than the predicted return on the risk-free asset at time $t+1$, then the forecaster trades out of the market index and into the risk-free asset. This strategy is continued for a number of periods. If the forecast for the excess rate of return on the index over the safe asset is correct frequently enough, then it is possible for the investor to earn returns greater than those earned simply by investing in the stock market index and holding his or her portfolio in the index over the entire sample time period.

In most of the literature, macroforecasting involves the use of monthly data or quarterly data. This is due to the fact that data for many macroeconomic variables are only generated monthly or even less frequently. For example, inflation and money supply data are typically only available monthly. Macroeconomic variables which measure a country's economic performance, such as Gross Domestic Product (GDP), are available only quarterly for most developed countries.

In this paper however, the technique of macroforecasting is applied using *daily* data to generate forecasts for the excess rate of return on the TSE 300 Total Return Index. This strategy has an advantage in that it allows for higher frequency shifts in portfolios.

The disadvantage is that the information set upon which forecasts are made is restricted to data available only on a daily basis. This latter characteristic will restrict the number of variables available for use in making forecasts.

Despite this limitation, the results from this strategy of market-timing based on daily macro-economic variables indicate that it is possible to earn returns significantly greater than the returns earned by the market portfolio. However, there are two caveats. The first is that even though a portfolio may yield a higher return on average, it *may* also carry greater risk. Investing in the stock market is often perceived as a risky endeavor in the first place, and a strategy of frequently moving in and out of the market may be riskier than buying and holding an asset in the stock market. For this reason, the investor may not prefer the higher return portfolio. The second caveat to consider is transaction costs. A day-to-day trading strategy such as the one used for this thesis potentially involves a large number of trades, bearing in mind that trading in financial assets generally incurs costs on a per-trade basis. These transaction costs must be considered when determining which portfolio earns a greater return since transaction costs will reduce the net return from the trading strategy.

Despite these caveats, the outcomes are quite promising. The results indicate that this strategy yields returns with a lower standard deviation than the buy-and-hold portfolio. In other words, this strategy appears to generate *higher returns* and be *less risky* than a buy-and-hold strategy of the TSE 300 Total Return Index.

In the absence of transaction costs, average returns using this recursive modelling strategy are approximately three times greater than returns earned by the TSE 300 Total

Return Index over the same time period. Transaction costs up to and including 0.25 percent still yield returns greater than the market portfolio. Returns diminish as transaction costs increase, however. A trading strategy with 0.25 percent transaction costs yields average returns of about 10 percent[1]. This still compares favourably with the annual returns earned from the TSE 300 Total Return Index over the sample period of 7.86 percent. Under transaction costs of 0.5 percent the switching portfolio yields returns less than those earned by the market portfolio. These results indicate that it would be unlikely for an individual investor to profit from this strategy because transaction costs this low likely could not be obtained by a common investor. However an institutional investor, such as a mutual fund manager, could potentially face transaction costs this low since floor traders pay a transaction cost of only 0.1% (Ang & Chua, 1991).

[1] This transaction cost covers both selling the original asset and buying the new asset.

Chapter 2

LITERATURE REVIEW

This chapter discusses previous efforts at forecasting individual stocks and stock markets. The chapter will be broken down into three general sections: macroforecasting, microforecasting, and Canadian studies. Examples in the literature of macroforecasting include Poterba & Summers (1986), Schwert (1989), Balvers, Cosimano & McDonald (1990), and Pesaran & Timmermann (1995). Attempts at microforecasting include Merton (1981), Fama & French (1988), Fama & French (1989), and Ang & Chua (1991). Examples of Canadian studies include Darrat (1990) and Serletis & Sondergard (1996).

2.1 Macroforecasting

Poterba and Summers (1986) analyzed the relationship between stock markets and volatility. There is a wide range of literature indicating that changes in risk resulting from stock market volatility may be responsible for a significant portion of the variation in stock prices. Authors who have explored this proposition include Malkiel (1979) and Pindyck (1984). These studies stem from other authors' findings indicating that it is difficult to attribute stock market fluctuations to future dividends, expected cash flows or real interest rates. Conventional financial theory would suggest that these variables should have explanatory power for fluctuations in stock markets.

The sample period analyzed by Poterba and Summers (1986) was from 1928 to 1984. When testing the relationship between stock market volatility and market returns for the Standard and Poor Composite Index from 1946 and later (i.e. post World War II),

the authors found that the effects of shocks from volatility decay quickly, and therefore affect returns for only short periods of time. After only three months, the level of volatility as a result of a shock was very small. When the entire sample was considered, i.e. 1928 to 1984, the results were more robust because volatility shocks had stronger effects on stock prices. Poterba and Summers attributed this finding to the fact that the Great Depression years were included in the sample[2]. When only the postwar years were considered, then the effects of volatility on the stock market were much smaller.

Poterba and Summers used an alternative technique to test the effect of volatility on stocks by analyzing the persistence of changes in *ex ante* market volatilities which are inferred from option prices, similar to the Merton (1981) paper, which is discussed in section 2.2. This methodology was used to analyze volatility expectations, under the assumption that as the price for an option rises, the higher is the anticipated volatility, and vice versa. The results of this technique were quite similar to those of the previous methodology. This reinforced the previous evidence which indicated that volatility is not a great determinant of stock price changes. However, this finding may not hold up if ARCH/GARCH models were used to test the same hypothesis[3]. The Poterba and Summers (1986) study pre-dates the development of these techniques.

Schwert (1989), like Poterba & Summers (1986), analyzed the relationship between stock market volatility and returns[4]. Officer (1973) suggested that the volatility

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[2] The Great Depression, 1929-1939, had a much higher level of stock market volatility than any decade since (Poterba & Summers, 1986; Schwert, 1989).

[3] ARCH/GARCH models (Autoregressive Conditional Heteroscedasticity and Generalized Autoregressive Conditional Heteroscedasticity) are relatively new methods of incorporating volatility into a model.

[4] Aside from the Great Depression mentioned earlier, other periods of high stock market volatility include the American Civil War (1861-1865) and the OPEC Oil Crisis (1973-1974).

of macroeconomic variables is related to stock market volatility while Black (1976) and Christie (1982) argued that financial leveraging offers a better explanation for stock market volatility. Poterba & Summers (1986) and Pindyck (1984) suggested that stock market volatility is related to expected stock market returns while Masarco & Meltzer (1983) and Lauterbach (1989) argued that macroeconomic volatility and interest rates are correlated.

For Schwert's study, the time period from 1857 to 1987 was analyzed using monthly data. For the period from 1885 to 1927 the Dow Jones Composite Index was used, while from 1928 to 1987 the Standard & Poor's Composite Index was used. Schwert analyzed stock market volatility and its relationship with real and nominal macroeconomic volatility, economic activity, financial leverage, and stock trading activity. He noted that stock market volatility is an important policy issue because changes in the volatility of stock markets have negative effects on risk-averse investors. Increased market volatility further affects investment, consumption, and other business cycle components.

The findings indicated that while financial leverage is significantly correlated with stock market volatility, it explains only a small portion of the variation in stock returns. Additionally, Schwert found that macroeconomic activity, inflation, interest rates and corporate bond return volatility are all related to stock return volatility. A further finding indicated that there is an increase in stock market volatility during economic recessions. However, all of the above factors have only weak effects on the level of stock market volatility.

When Schwert analyzed the effects of trading volumes on volatility, there was surprisingly little correlation evident between the two variables. The author noted that while high levels of trading activity and stock market volatility seem to occur simultaneously, Schwert was unable to determine whether this phenomenon was attributable to "trading noise" or to "information flow" to the stock market[5].

Balvers, Cosimano, and McDonald (1990) related financial asset returns to movements in aggregate output, or GDP. The theory behind their model was that changes in aggregate output lead to attempts by investors to smooth consumption, thereby changing the required rate of return on financial assets held by the investors.

Three time series were used in this paper: industrial production, the NYSE value-weighted return series and, in order to convert nominal returns into real terms, inflation rates. The theoretical core underlying this paper was the existence of a representative firm and a representative investor. A general equilibrium model was then solved. The firm's objective was to determine its level of investment each period in order to maximize shareholder wealth. The consumer's objective was to maximize the present value of utility from consumption. This was accomplished through *consumption-smoothing*. The consumer then maximized the discounted present value of utility subject to a budget constraint.

Three testable propositions were presented: (1) stock returns are predictable, (2) stock returns are negatively related to current output, and (3) stock returns incorporate the information implied by current output. The three propositions were tested with data from

[5] Trading noise occurs when investors have heterogeneous beliefs. New information causes price changes and trading. Alternatively, information flow happens when investors use price movements as information in

1947 to 1987 with results indicating that current output could predict over 20 percent of the variation in financial assets.

Further findings indicated that output has a negative effect on stock returns. This last result supports the theory that when dividends at the end of the holding period are expected to be higher than current dividends, investors require a higher rate of return on their current period savings. Higher anticipated dividends at the end of the holding period imply that the consumer's future wealth will be higher than current wealth. Investors therefore require a higher rate of return in order to transfer purchasing power from the current period (low wealth) to the end of the holding period (high wealth). Increasing savings during periods of low wealth causes consumers to follow an undesirable, lumpy consumption pattern. This phenomenon creates some predictability of future stock price movements. An investor will not be better off by taking advantage of these higher returns because it will cause consumption that is less smooth and thereby reduce the investor's utility. This suggests that the performance of a portfolio should not be judged purely on mean return, but also return variability. Thus, a market may be efficient even if profits can be made from forecasting the market return, given publicly available information.

Pesaran and Timmermann (1995) used a recursive modelling strategy in order to attempt to outperform a market portfolio using macroforecasting. The authors used this methodology to forecast the excess rate of return of the S&P 500 index over short term treasury bills. They assumed that the investor has beliefs over the set of variables that could affect future stock returns but does not know the true model. The investor merely believes that some base set of variables may be correlated with future returns.

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order to make trading decisions.

In each period, Pesaran and Timmerman regressed the excess rate of return of the S&P 500 index against all possible combinations of variables from this base set. An optimal model was then selected and used to forecast next period's excess return. The optimal model was chosen using various model selection criteria, such as the Akaike Information Criteria (AIC) and the Schwarz Information Criteria (SIC). The investor's portfolio is then placed in either the S&P 500 index or treasury bills, depending on whether the forecast for the excess rate of return on the S&P 500 index is positive or negative.

This process continued for each time period in the sample. Pesaran and Timmerman found that for selected time periods it was possible to outperform the S&P 500. In particular, they found that the predictability of stock returns is related to the volatility of the stock market, much like the findings of Poterba & Summers (1986) and Schwert (1989). During periods of relatively low stock market volatility such as the 1960s and 1980s, it was comparatively difficult to forecast the S&P 500 index accurately. However during the 1970s, which was a period of high stock market volatility, forecasting accuracy was much higher. Pesaran and Timmermann suggested that this contrast may be a result of incomplete learning in the face of macroeconomic shocks, such as the oil price shock of 1973 or the US Federal Reserve (the Fed) switching to a regime of interest rate targeting in the 1970s. The conditional success of market timing is not unlike the findings of Fama & French (1988), Fama & French (1989), Darrat (1990), and Ang & Chua (1991).

2.2 Microforecasting

Merton (1981) evaluated the performance of investment managers and calculated equilibrium prices for the market timer's forecasts. Since the main goal of investment managers is to outperform the market, it is an interesting experiment to determine whether these managers have superior forecasting skills.

Merton claims that the forecasting techniques of investment managers are of two varieties: microforecasting and macroforecasting, as described in chapter 1. Microforecasting often involves the implementation of the Capital Asset Pricing Model (CAPM)[6]. Macroforecasting, on the other hand, tries to identify when assets in general are under- or over-valued relative to the risk-free rate of return.

Merton's model is very simple and is similar to the strategies later employed by Pesaran & Timmermann (1995), and Ang & Chua (1991). The forecaster predicts that either stocks will earn a higher return than bonds, or that bonds will perform at least as well as stocks. Merton developed an unusual technique whereby a strategy in the options market was used to determine "under-valued" options. Under-valued options are defined as option values which are priced less than the market would otherwise determine. Investment managers would then buy these "under-valued" options and theoretically earn returns superior to a market portfolio.

Merton assumed that markets are frictionless in the sense that there are no taxes, no transaction costs and that the investment managers are heterogeneous. The assumption of heterogeneous managers means that each manager has different beliefs, information

[6] The Capital Asset Pricing Model expresses the relationship among security prices when the securities are chosen by investors on the basis of expected return and expected variance.

and forecasting abilities. Merton concluded that if the market timer's forecasts were based solely on publicly available information, then the value of the forecast was zero.

In their widely cited article, Fama and French (1988) found that a slow mean-reverting process induces a negative autocorrelation in stock returns[7]. Their results were robust over the long term but were not as strong for the short term. Predictable price variation due to mean reversion accounted for 40 percent of the variance of stock prices over a three to five year time horizon when analyzing small firms. When considering only large firms, about 25 percent of price variation was due to mean reversion. Over all, about 35 percent of stock price variation was a result of mean reversion. Alternatively, when a short-run analysis was performed, predictable variation made up only three percent of the total variation in returns.

In this model, stock prices were assumed to have both a random walk and a stationary component. Mean reversion is hypothesized to be slow so it can easily be missed in near-term horizons, explaining why the results are not very robust for short-term analyses. Conversely, these slow mean reversions should be more evident when longer-term horizons are used.

Data used for this paper was simply the one-month returns on all of the New York Stock Exchange stocks from 1926 to 1985 and the Consumer Price Index (CPI). The CPI was necessary in order to transform the nominal returns into real returns. Fama and French also analyzed whether this negative autocorrelation was attributable to firm-specific, or common factors. If the autocorrelation was due to firm-specific factors, then

[7] Simply put, mean reversion hypothesizes that a given price change tends to be reversed over time by a predictable change in the opposite direction (Serletis and Sondergard, 1996).

it would seem unlikely that returns would be forecastable using macroeconomic variables. However, Fama and French's findings do support the theory that the negative autocorrelation is due to common factors. This suggests that macroeconomic variables could be used to predict stock returns.

Fama and French (1989) analyzed the relationship between business conditions and the expected return on stocks and bonds. The authors addressed two specific questions. Do expected returns on stocks and bonds move together, or similarly do the same variables forecast bond and stock returns? Secondly, is the variance of expected stock and bond returns partially explainable by business conditions?

Data used for this paper included the equal- and value-weighted portfolios of the New York Stock Exchange (NYSE). The equal-weighted portfolio is affected more by small company stocks while the value-weighted portfolio is affected more by the stocks of large companies. Other authors who attempted to market-time the NYSE include Fama & French (1988) and Balvers, Cosimano & McDonald (1990). Corporate bond data was drawn from a sample of 100 bonds. The one-month treasury bill was used in order to calculate excess returns on the NYSE portfolio. As discussed in this section 2.1, Pesaran and Timmermann (1995) developed the same determination for excess returns. Dividend yields were obtained by summing monthly dividends on the portfolio for the year and dividing by the value of the portfolio. The term (maturity) premium was obtained by subtracting the one-month treasury bill rate from the Aaa bond portfolio. The default (risk) spread was simply the difference between the return on the portfolio of the 100 corporate bonds and the return on the Aaa bond.

The findings of Fama & French (1989) indicated that expected excess returns on bonds and stocks moved together while dividend yields were able to forecast both stock and bond returns. The authors found that expected returns contained a term premium that was related to the business-cycle. Expected returns also had a risk-premium which was related to long-term aspects of business conditions. These long-term effects could last through several business cycles. The variation in the risk premium was more robust for low-grade bonds than for high-grade bonds while at the same time more robust for stocks than for bonds. The overall findings of Fama and French (1989) were that expected returns are lower during strong economic periods while expected returns are higher during economic slowdowns.

Ang and Chua (1991) used microforecasting to market-time in their paper as well. Ang & Chua's methodology was a seven-step process. The first step was to select a sample of common stocks and to choose a time period[8]. The second step was to form clusters of stocks from the sample previously selected. Next, locally optimal forecasting models were constructed. The globally optimal models for each security were then selected. The specification of the optimal models were chosen based on the Akaike Information Criteria. One-step-ahead forecasts were then made with the optimal forecasting models. The one-step-ahead forecasts were then used to simulate a trading strategy. Finally, the performance of this trading strategy was evaluated against a buy-and-hold strategy of a market index, the Dow Jones Industrial Average 30 (DJIA 30).

[8] Common stocks are shares whose owner has last claim on the corporation's assets, but has voting rights in the company (Ebert et al, 1997).

One limitation of this study is that transaction costs were not considered in the primary trading results due to the level of complexity involved with such a process. The authors address this limitation by assuming that the investor ignores all transaction costs when making trades. The effects of the transaction costs were only determined after trades are made. This is a limitation of the model because a rational investor would not behave this way, rather he or she would make trades only if the expected gain was greater than the transaction cost. A set of myopic trading strategies which take transaction costs into account were then included, so that trades were only made if the following period's return after the trade was expected to exceed the transaction cost plus the return from holding the current asset in the investor's portfolio. The trading strategy is similar to the Pesaran and Timmermann (1995) strategy in that the investor has the option of holding either treasury bills or common stock.

The authors find that with no transaction costs, there are frequent trades and that the strategy outperforms a buy-and-hold strategy in the DJIA 30. However, when transaction costs are considered in the model, the strategy under-performs the DJIA 30. Even transaction costs of 0.1 percent, which is what floor traders pay, imply that their switching strategy is unable to generate a return greater than the DJIA 30.

2.3 Canadian Studies

Darrat (1990) analyzed the effects of monetary and fiscal policy on the Toronto Stock Exchange, noting that this had been done extensively for the United States but rarely for other countries, including Canada. Examples of forecasting US markets using

monetary and government fiscal variables include Sorensen (1982) and Davidson & Froyen (1982). Darrat's model used the change in the log of the TSE 300 index as the dependent variable. The independent variables for the model were the three-month Government of Canada treasury bill rate and its standard deviation, the industrial production index, long term government bond yields, government budget deficits, inflation, changes in money supply, and the Canada/U.S. exchange rate. Darrat used both current and lagged values for these variables.

Darrat's findings suggest that Canadian stock prices completely reflect monetary policy. In other words, monetary policy contains no useful information for predicting the TSE 300 index. However, fiscal policy does appear to have a lagged effect on stock prices in Canada. These findings suggest that market timing of the TSE 300 index is possible using publicly available information, such as Canadian fiscal policy.

Serletis and Sondergard (1996) evaluated the permanent and temporary components of Canadian stock prices. In this paper, they investigated the efficient market hypothesis by applying unit root tests, variance ratio tests, univariate long-horizon regressions, mean reversion tests, non-linearity tests, and chaos tests on the TSE 300 Total Return Index[9]. Their findings indicate that the Toronto Stock Exchange is an efficient market. Just as in Darrat's (1990) paper, data used for the Serletis and Sondergard paper was the TSE 300 Total Return Index. The hypothesis tested is that tomorrow's asset prices are expected to be the same as today's asset prices. This is called a *martingale* and is expressed by

[9] In its semi-strong form, market efficiency implies that asset prices fully reflect all publicly available information.

(2.3.1) $E_t(x_{t+1} \mid \Omega_t) = x_t$

where

x_t = the asset price at time t.

x_{t+1} = the asset price at time $t+1$.

Ω_t = the information set at time t.

Using Unit Root Tests and the TSE 300 Index in raw data form did not support a martingale hypothesis. In other words, it can not be expected that tomorrow's price will be the same as today's price. However, if logged price changes (i.e. returns) were used instead, then the martingale hypothesis holds and tomorrow's return is expected to be today's return and random error.

Similar to the tests performed by Fama and French (1988), Serletis and Sondergard tested for mean-reversion in stock returns. To test for mean-reversion, they use two techniques: Variance Ratio Tests and regression-based tests. The Variance Ratio Test suggested that short-horizon returns (daily or weekly) are mean-reverting, while longer-horizon returns (bi-weekly) follow a random walk. Using a regression-based test, the authors found that the TSE 300 index is not mean-reverting. Recently, tests of efficient market hypotheses have been based on non-linear or chaotic tests. *White chaos* is based on the theory that fluctuations and irregularities in the stock market are explainable endogenously and can be traced to the non-linear structure in the time series

of returns or other variables. Using the *BDS Nonparametric Test for Whiteness*, Serletis and Sondergard found support for the efficient market hypothesis.

Chapter 3

METHODOLOGY

In chapter 2, a summary was presented outlining some previous papers on the subject of stock market forecasting. Macroforecasting, microforecasting and Canadian studies were the three main themes. Chapter 3 describes the model used in this thesis for forecasting and market-timing the TSE 300 index in an attempt to outperform the returns earned on the TSE 300 index. Chapter 4 summarizes the results of the model and tests the accuracy of the forecasts.

Chapter 3 is comprised of four sections. The first section outlines the potential explanatory variables in each model. Section 3.2 describes the model being used while section 3.3 describes the strategy that would theoretically be implemented by an investor trying to outperform the TSE 300 index. The final section of chapter 3 tests the data for stationarity and provides summary statistics for the data.

Following the methodology used by Pesaran and Timmerman (1995), this thesis employs a recursive modelling strategy in order to forecast the excess rate of return of the TSE 300 Total Return Index over short term treasury bills[10].

3.1 Explanatory Variables Potentially in each Model

In this section, the rationale for using various independent variables in the models will be outlined. The process begins by considering a base set of variables which might

[10] Excess rate of return is defined as the daily return on the market index *minus* the daily return on 30-day treasury bills.

be potentially useful in explaining one step ahead excess returns (ρ_{t+1}) for the TSE 300 Total Return Index. Excess returns, (ρ_t), are defined as the daily rate of return on the stock market index (r_t) minus the daily treasury bill rate (r_t^f), or

$$(3.1.1) \qquad \rho_t = r_t - r_t^f.$$

where ρ_t is the excess return on the TSE 300 Index at time t.

There will be a constant base set of regressors, X_t, which may be in the model used to forecast ρ_{t+1}. An optimal subset, X_t^*, is then selected at each point in time from this base set of regressors. This optimal subset will vary over time.

This thesis will use the daily return on the Toronto Stock Exchange 300 Total Return Index minus the daily rate of return on thirty-day Government of Canada treasury bills as the dependent variable, ρ_t. The base set of variables that contain information potentially useful for forecasting the following day's excess return, ρ_{t+1}, is given by

$$(3.1.2) \qquad X_t = \{\rho_t, XSP_t, dCNTB_t, dUSTB_t, dXR_t, USSP_t, CNSP_t\}$$

where ρ_t is the current excess return of the Toronto Stock Exchange 300 Total Return Index, XSP_t is the current excess return of the S&P 500 index over 30-day US treasury bills, $dCNTB_t$ is the first difference of the log of the Canadian 90-day treasury bill rate, $dUSTB_t$ is the first difference of the log of the US 90-day treasury bill rate, $CNSP_t$ is the spread between the 12 month Canadian government bond rate and the 30-day Canadian treasury bill rate, $USSP_t$ is the spread between the 12 month US government bond rate

and the 30-day US treasury bill rate, and dXR_t is the first difference of the logged Canada-US exchange rate.

No decision needs to be made regarding which variables to include and which variables to exclude for each point in time as variable inclusion is time dependent. All independent variables have the potential to be included in the model used to forecast excess returns on the TSE 300 index, but are not *necessarily* included in that model at each point in time. Variable inclusion becomes time dependent as the investor learns which variables are best able to predict the TSE 300 index excess returns.

There are two necessary criteria for selecting which variables can be potential regressors in this model. First, all data that is included in the model must be available at a daily frequency. The second criterion is that the variable must have a potentially significant relationship with Canadian stock returns.

The S&P 500 index is fairly well accepted as one of the best indicators of overall stock performance in the United States. Canada has an open economy by international standards, as approximately one-third of Canada's GDP is exported and a similar amount of Canada's consumption is from imports. About 80 percent of Canada's trade is with the United States (Chandler, 2000). Therefore movements in the United States economy, which are represented by the S&P 500 index, should have a significant effect on the TSE 300 Total Return Index. More specifically, the TSE 300 index and the S&P 500 index should be positively correlated since a strong US economy translates into stronger markets for Canadian exporting companies.

Because of this positive relationship between the US and Canadian economies, the Canada-US exchange rate should also have an effect on the TSE 300 index. The exchange rate is defined in this paper as the ratio of the Canadian dollar to the US dollar. As Canada's dollar appreciates relative to the United States dollar, Canada's exports will become more expensive to Americans and will negatively impact Canada's exporting industries. Conversely, a depreciation of the Canadian dollar relative to the US dollar lowers the cost of Canadian exports to the US and should benefit the Canadian export industry. The Toronto Stock Exchange should reflect this. Therefore, there should also be a positive relationship between the Canada-US exchange rate and the TSE 300 index.

The ninety-day treasury bill rate is a proxy for monetary policy. Market analysts frequently talk about how the US Federal Reserve, or the Bank of Canada, may try to prevent inflation by "cooling off" the economy through the raising of short-term interest rates. The ninety-day treasury bill rate should reflect this. There are a few explanations as to why a change in the ninety-day treasury bill rate should affect an economy. The first explanation is that as interest rates rise, the cost of borrowing increases. This increases a firm's debt costs, reduces profits and slows down the economy. Since the value of a firm is simply the net present value of future profits, a reduction in profits reduces the market value of a firm on the stock market by lowering share prices. This in turn puts downward pressure on the TSE 300 index. A corollary to this theory is that, if short term interest rates are increased, consumers will likely reduce their purchases of durable goods, such as appliances and automobiles, because the cost of credit will have increased.

A second explanation as to why higher interest rates reduce the value of stocks is because when interest rates go up, the opportunity cost of money goes up. In an era of high interest rates, an investor can put his money into bonds which now earn a higher rate of return. Higher interest rates thus make stocks a less attractive asset, thereby pushing down stock prices. In other words, the return on TSE 300 Total Return Index and the ninety-day treasury bill rate should be negatively related.

The same argument follows for the 90-day US treasury bill rate. When the United States Federal Reserve raises interest rates, the US economy theoretically slows down likely leading to weaker foreign demand for Canadian goods. In addition, Canada is in direct competition with the US for foreign capital. Canada's interest rates must be tied to the US rates, otherwise foreign capital will leave Canada in favour of higher returns earned in the United States. For this reason, movements in US interest rates may be partially reflected in Canadian interest rates. Therefore it is likely that the US 90-day treasury bill rate and the return on the TSE 300 index have an inverse relationship as well.

The spread between the yields on government bonds of different maturities and the short term treasury bill rate is widely cited as having a strong relationship with real income (Friedman and Kuttner, 1992) and as a gauge of inflationary expectations. The difference between assets that are the same in all aspects except their term to maturity is also known as a *term- premium,* or *maturity-premium*, as discussed by Fama and French (1989). The Toronto Stock Exchange can be taken as a reasonable proxy for real income in Canada and so there is reason to believe that the spread between 12 month and one

month government securities should have explanatory power for the TSE 300 Total Return Index. The terms of these variables were chosen to represent the term spread because these were also the variables used by Pesaran and Timmermann (1994) to define the term spread in their model.

3.2 Model Selection

Having now defined the base set of potential explanatory variables in section 3.1, the model can be constructed. As noted in section 3.1, not all of the independent variables were included in each model at each point in time. Various selection criteria were implemented in order to do a search across all possible independent variables to determine the optimal subset for each time period in the sample. Let model m_i be written as:

(3.2.1) $Y_t = \alpha_i + \beta_i X_{it-1} + e_{it}$

where:

X_{it-1} = a subset of X_t in model m_i.

e_{it} = a random error, which is normally distributed with mean 0 and variance σ^2.

α_i = a constant in model i.

Model i can be described by a 7 x 1 vector of binary code k_i. Element j of k_i is 1 when variable j is included in model i and is zero if j is not included. All of the possible models were then estimated for each time period in the sample. Since there are seven

possible independent variables to explain excess returns on the TSE 300 index, there are 128 (2^7) possible models to forecast the excess return on the TSE 300 index at each point in time. Once each of the 128 possible models was estimated, a preferred model was chosen using one of four different model selection criteria. The four different criteria considered were *adjusted* R^2 (RBS), *Bayesian Information Criterion* (BIC), *Akaike Information Criterion* (AIC) and *Hannan-Quinn Criterion* (HQC). Each of these selection criteria present a different trade-off between parsimony and fit. The measurement of fit is done by maximizing the value of the log-likelihood function while parsimony is measured by the number of freely estimated coefficients.

The log-likelihood is given by:

(3.2.2) $$\hat{L}L_{t,i} = \frac{-t}{2}\left[1 + \log\left(2\pi\hat{\sigma}^2_{t,i}\right)\right]$$

(3.2.3) $$\hat{\sigma}^2_{t,i} = \frac{\sum_{\tau=0}^{t-1}\left(\rho_{\tau+1} - X'_{\tau,i}\hat{\beta}_{t,i}\right)^2}{t}$$

The various model selection criteria include this measure of fit (log-likelihood) minus a penalty term for the number of freely estimated parameters,

(3.2.4) $$\mathrm{K} = \sum_{j=1}^{7} k_i$$

The Akaike Information Criteria is defined by

(3.2.5) $$AIC_{t,i} = \hat{L}L_{t,i} - (K+1)$$

The Bayesian Information Criteria is defined by

(3.2.6) $BIC_{t,i} = \hat{L}L_{t,i} - \frac{1}{2}(K+1)\log(t)$

The Hannan-Quinn Criteria is defined by

(3.2.7) $HQC_{t,i} = \hat{L}L_{t,i} - \ln(\ln(t))K$

Finally, the adjusted R^2 is defined by[11]

(3.2.8) $\overline{R}^2_{t,i} = 1 - \frac{\hat{\sigma}^2_{t,i}}{S^2_{\rho,t}}$

where $\tilde{\sigma}^2_{t,i}$ is the unbiased estimator of σ^2 given by

(3.2.9) $\tilde{\sigma}^2_{t,i} = \sum_{\tau=0}^{t-1}\left(\rho_{\tau+1} - X'_{\tau,i}\hat{\beta}_{t,i}\right)^2 / (t - k_i - 1)$

the sample variance for the first t observations on ρ,

(3.2.10) $S^2_{\rho,t} = \sum_{\tau=1}^{t}(\rho_t - \overline{\rho}_t)^2 / (t-1)$, and

(3.2.11) $\overline{\rho}_t = t^{-1}\sum_{\tau=1}^{t}\rho_t$.

[11] Adjusted R^2 can also be expressed in terms of the trade-off between parsimony and fit: It can be shown that adjusted R^2 and $TC_{t,i}$ are equivalent in the narrow sense that they select the exact same models, where

$$TC_{t,i} = \hat{L}L_{t,i} - \frac{1}{2}\log\left(\frac{t}{t-K-1}\right)$$

All four model selection criteria are affected positively by the log-likelihood and negatively by the number of explanatory variables in the model, with the punishment for over-specification being more or less severe for each criteria.

Adjusted R^2 punishes over-specification the least and therefore will tend to select models with the largest number of explanatory variables while Akaike Information Criteria is the second most forgiving of over-specification. The Hannan-Quinn criteria is the second harshest penalizer of over-specification while the Bayesian Information Criteria penalizes over-specification the most. BIC tends to select models with the fewest variables relative to the other three criteria as a result of this characteristic. Table 3.2.1 ranks the four selection criteria in terms of their relative levels of parsimony and fit with BIC being the most parsimonious and RBS providing the best fit.

Table 3.2.1: Parsimony vs. Fit of Selection Criteria

Selection Criteri	Parsimony	Fit
BIC	1	4
HQC	2	3
AIC	3	2
RBS	4	1

3.3 Investor Strategy

Using the now selected optimal model, forecasts were made for the next period. Since the forecasts are for excess returns of the TSE 300 Total Return Index over treasury bills, a simple selection process was used to determine whether to place the investor's portfolio in the TSE 300 index or in thirty-day treasury bills. If the forecast for the excess

return on the TSE 300 index was negative, then the portfolio was placed into treasury bills because the forecast implies that TSE 300 index predicted return will be less than the return on treasury bills. Alternatively, if the forecast for the excess return on TSE 300 index was positive, then the portfolio was placed in the TSE 300 index.

This methodology operates under the assumption of zero transaction costs. However, in the presence of transaction costs the investor must consider whether the expected gain from switching the portfolio between assets outweighs the transaction cost that will be incurred from the trade. For example, if the portfolio was in treasury bills at time t, then the investor will trade out of treasury bills and into the TSE 300 index only if the expected gain at $t+1$ outweighs the transaction cost. Otherwise, even if the forecast of the excess return was positive but smaller than the transaction cost, the investor stays in treasury bills. Likewise, if the portfolio was in the TSE 300 index at time t, then the investor stays in the TSE 300 index unless the forecast for the excess rate of return on the TSE 300 index at time $t+1$ was negative *and* its absolute value was greater than the transaction cost. Much like the previous case, even if the forecast was negative but the absolute value was smaller than the transaction cost, the portfolio stays in the TSE 300 index.

A variable c is used to represent the transaction costs involved in this switching strategy. This variable c captures the cost of both buying and selling of assets so that c is only paid once per trade. The alternative would be to pay c twice per trade, i.e. once when the original asset is sold and once again when the new asset is bought. Allowing c to incorporate both the buying and selling of assets simplifies the model somewhat

because the transaction cost faced when selling equities is typically much greater than the transaction cost faced when buying government securities. Using this assumption a different value for c is not necessary for both of the trading scenarios.

Using this information, the evolution of wealth from this switching portfolio can be traced over time. If the portfolio was in the TSE 300 index at time t and the investor did not trade at the end of time t, then the value of the portfolio at the end of time $t+1$ becomes:

(3.3.1) $W_{t+1} = W_t(1 + r_{t+1})$

where

W_{t+1} is the value of the portfolio at the end of time $t+1$.

W_t is the value of the portfolio at the end of time t.

c is the transaction cost expressed as a percentage of the portfolio. c captures both transaction costs incurred from selling and buying.

r_t is the actual daily rate of return on the TSE 300 Total Return index at time t, and

r_t^f is the actual daily rate of return on treasury bills at time t.

If the portfolio was in the TSE 300 index at time t and was switched to T-Bills at the end of period t, then the value of the portfolio at time $t+1$ becomes:

(3.3.2) $W_{t+1} = W_t(1 - c)(1 + r_{t+1}^f)$

If the portfolio was in T-Bills at time t and did not trade at the end of time t, then the value of the portfolio at time $t+1$ becomes:

(3.3.3) $W_{t+1} = W_t(1 + r_{t+1}^f)$

If the portfolio was in T-Bills at time t and was switched to the TSE 300 index at the end of time t, then the value of the portfolio at time $t+1$ becomes:

(3.3.4) $W_{t+1} = W_t(1 - c)(1 + r_{t+1})$

This procedure was repeated for each period until the end of the sample. That is, for each period the investor estimated all 128 models, picked the optimal model, generated forecasts from that model, and then chose between treasury bills and the TSE 300 index based on the sign and the level of the forecast.

As benchmarks, the wealth obtained from a buy-and-hold strategy of both the TSE 300 index and 30-day government of Canada treasury bills were also determined. These results were compared to the results of the trading strategies under each of the selection criterion, *AIC*, *BIC*, *RBS*, and *HQC*. The findings are reported in sections 4.4 and 4.5.

3.4 Data Sources

The data set used for this thesis is daily and begins January 3, 1989 and ends May 28, 1999, covering approximately ten-and-a-half years. For simplicity, the first period to be forecast was January 2, 1990 while the period from January 3, 1989 to December 31, 1989 was used strictly for model estimation and variable selection. In collecting data for the TSE 300 Total Return Index, the closing price was used. All of the data came from the Standard and Poor (2000) DRI Basic Economics Database.

As discussed in section 3.1, data from both Canada and the US was used. One limitation of running regressions using daily data from different countries is that many statutory holidays from different countries are non-coinciding. Holidays such as President's Day, Martin Luther King Jr. Day, and American Thanksgiving in the United States are not recognized in Canada, while in Canada we have Victoria Day, Canada Day, and Remembrance Day which are not celebrated in the United States. Data was collected for every day that the Toronto Stock Exchange was open over the sample period. However, there are several days throughout the year when the American stock markets are closed while the Toronto Stock Exchange is open. Therefore, the day after an American holiday there is no new American information for the investor on which to base his or her forecasts. In these situations, the previous day's data is used as proxy for the day in which there is no observation available. For example, on the 4th of July the hypothetical investor uses data for the S&P 500, the US term spread, and American treasury bills from the 3rd of July to forecast the excess return on TSE 300 index on the 5th of July, so long as July 3rd does not fall on a weekend.

Chapter 4

RESULTS

In chapter 3, the methodology used for this thesis was presented. Chapter 4 will discuss the results of the model, in which there are five sections. The first section summarizes the data and shows the results of Augmented Dickey Fuller Tests for stationarity of the data. The second section of chapter 4 discusses the frequency at which the variables were included in each optimal model at each point in time. Section 4.3 performs a test of the accuracy of the signs of the forecasts, while the fourth section outlines the performance of a $1000 investment in the trading strategies under zero transaction costs. Section 4.5 discusses the implications of different transaction cost scenarios while section 4.6 compares the riskiness of the trading strategies against the riskiness of the TSE 300 index itself.

4.1 Summary Statistics

The data used for this paper begins January 1989 and covered most of the 1990s. To avoid the problem of spurious regressions, the data was tested for stationarity. In order to test for stationarity, the *Augmented Dickey-Fuller Test (ADF Test)* was used (Dickey & Fuller, 1976). The *ADF Test* takes the following form:

$$\Delta Y_t = \alpha + \rho Y_{t-1} + \sum_{j=1}^{p} \lambda_j \Delta Y_{t-j} + \varepsilon_t \qquad (4.1.1)$$

The ADF Test determines whether the variance is non-stationary, $\rho=0$, or stationary, $\rho<1$. The lagged term ΔY_{t-j} is included in equation in order to account for serial correlation in the error term.

Table 4.1.1 shows the mean, standard deviation, maximum, minimum, and Augmented Dickey Fuller statistic for the excess return on the TSE 300 index and the explanatory variables. The summary statistics for the TSE 300 Total Return Index and 30-day treasury bills are also shown. In each case the null hypothesis of non-stationarity is rejected using the 95% confidence level of 2.86.

Table 4.1.1 – Summary Statistics

Variable	Mean	Std. Dev.	Maximum	Minimum	ADF
TSE 300 Total Return	0.000376	0.006964	0.046842	-0.063711	
TSE 300 Excess Return	0.000200	0.006967	0.046736	-0.063799	-13.03
Canadian 1 Month T Bill	0.000176	0.000081	0.000353	0.000066	
Canadian Yield Spread	0.000013	0.000018	0.000080	-0.000037	-3.23
Change in Can 3 M T Bill	-0.000334	0.017503	0.427899	-0.196860	-19.35
S&P 500 Excess Return	0.000564	0.008835	0.049753	-0.071254	-15.00
US Yield Spread	0.000016	0.000011	0.000092	-0.000021	-4.61
Change in US 3 M T Bill	-0.000228	0.009792	0.047701	-0.100747	-14.63
Growth Rate ($Can/$US)	0.000081	0.002998	0.015470	-0.016905	-16.07

The graphs on the following three pages plot the daily growth rates of the TSE 300 Total Return Index, the daily rate of return on 30-day Government of Canada treasury bills, and excess rate of return on the TSE 300 Total Return Index.

Figure 4.1.1: TSE 300 Total Return Index - Daily Returns

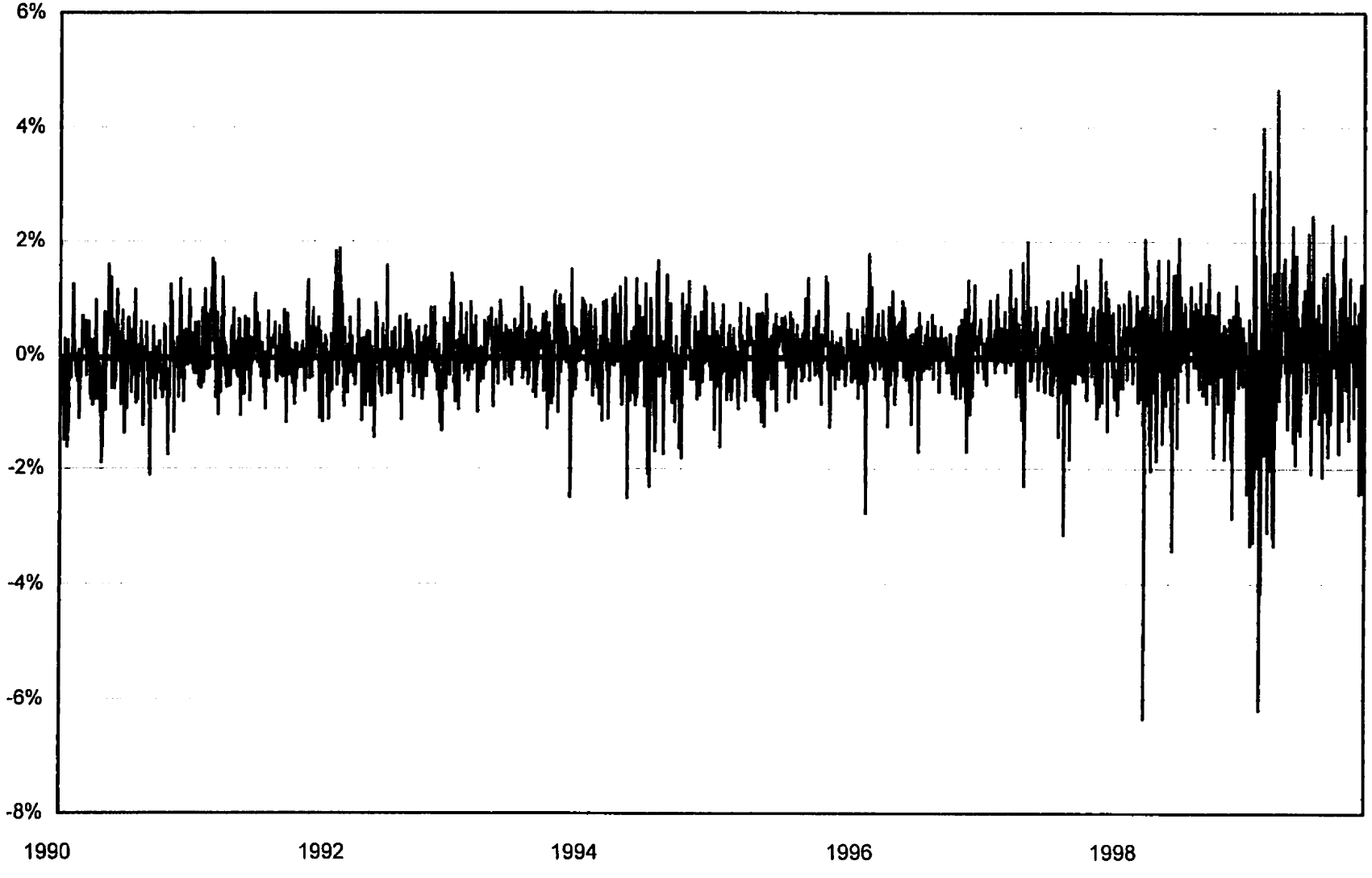


Figure 4.1.2: 30-Day Bank of Canada Treasury Bill - Daily Returns

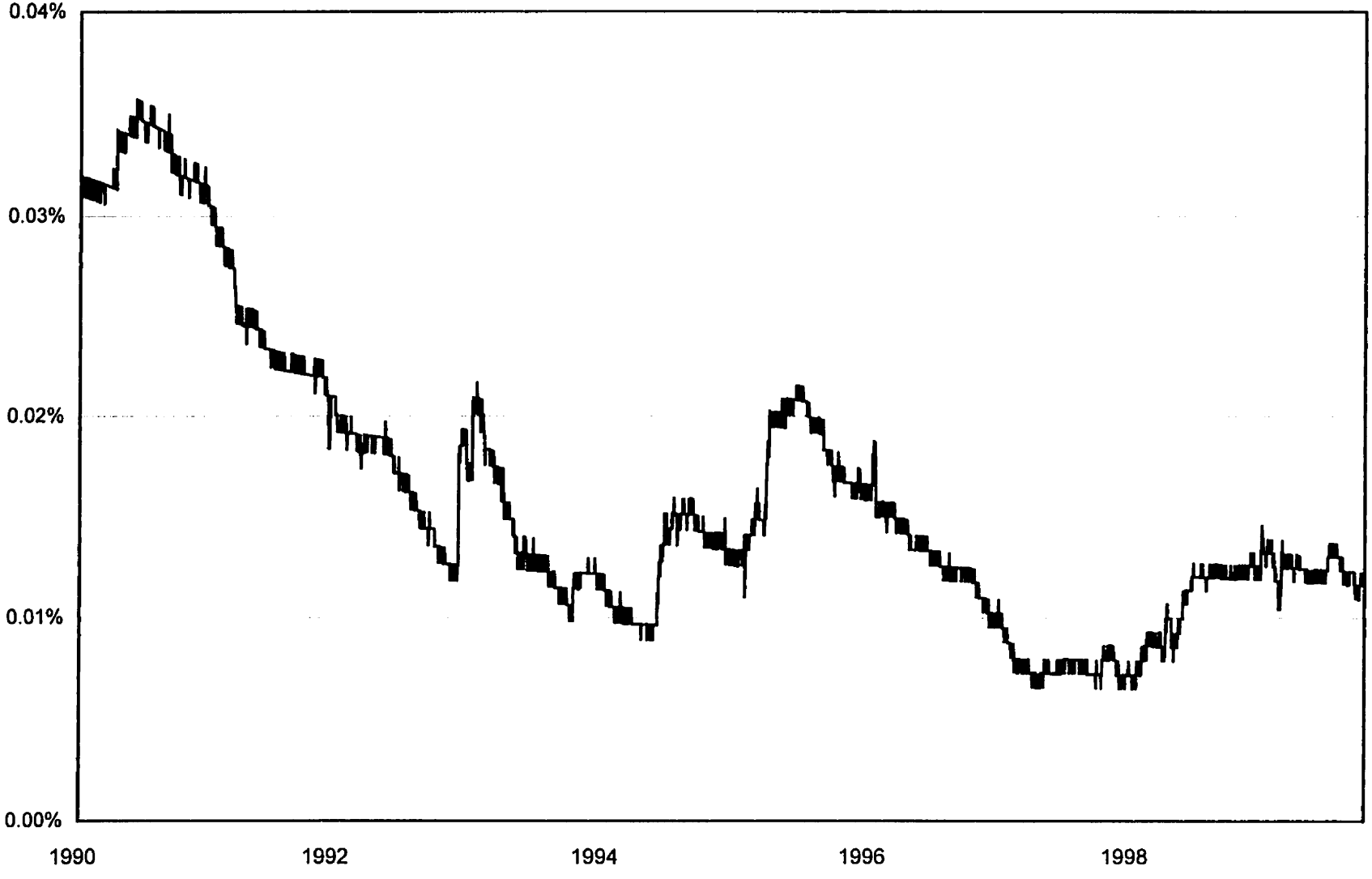
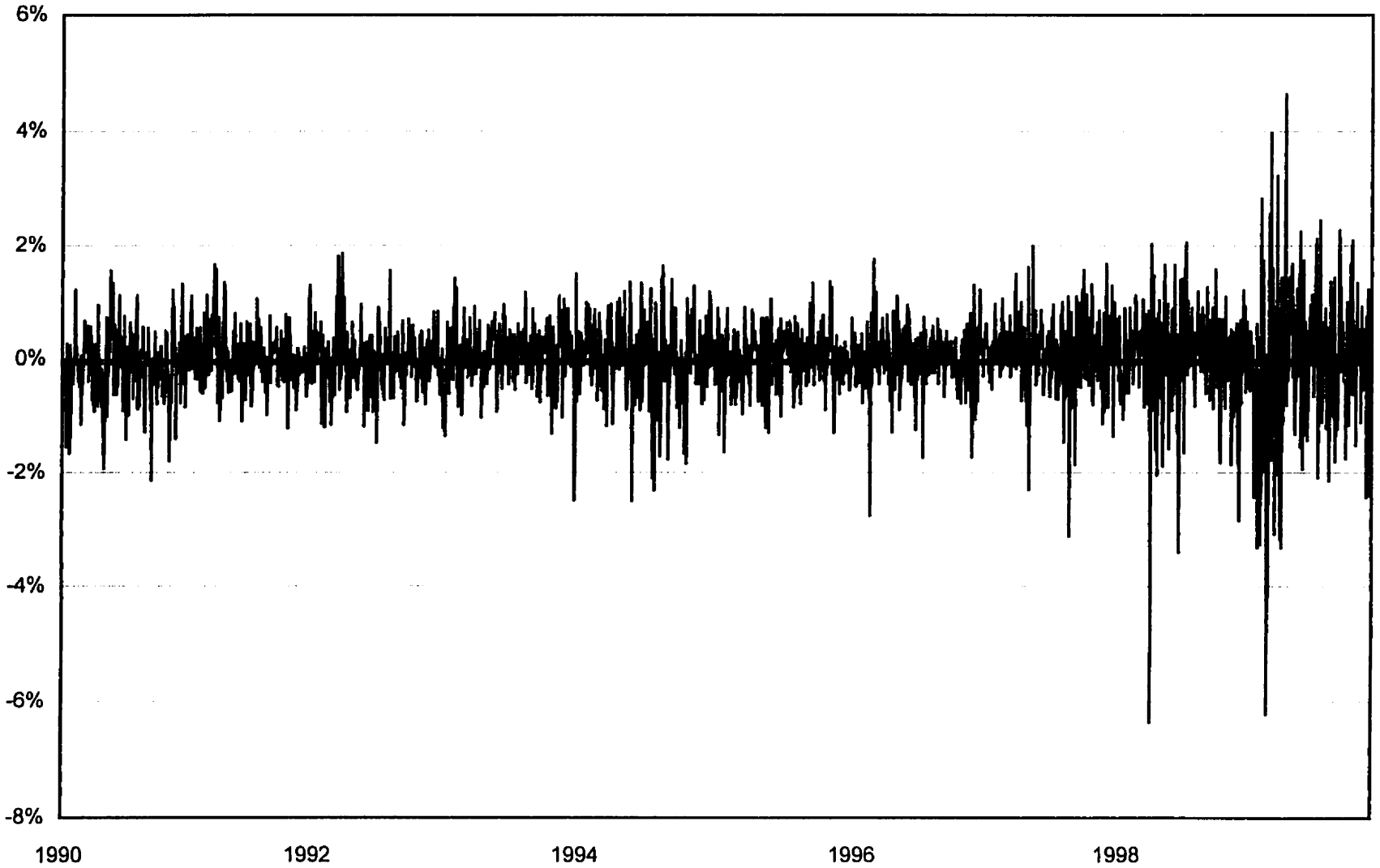


Figure 4.1.3: TSE 300 Total Return Index - Daily Excess Returns



4.2 Variable Inclusion Rates

Using the four model selection criterion of *Akaike Information Criteria*, *adjusted R^2*, *Bayesian Information Criteria* and *Hannan-Quinn Criteria*, the base set of variables were either included in or excluded from the optimal model over time as follows. Unsurprisingly, the adjusted R^2 criteria yielded models with the highest number of variables included. As shown in table 4.2.1 when adjusted R^2 is used as the model selection criteria the one day lag of the TSE 300 index excess returns was included almost every time, at 99.7 percent of the time. The first difference of the Canadian ninety-day treasury bill was included in the optimal model at each point in time 29.8 percent of the time while the US ninety-day treasury bill rate was included 47.7 percent of the time. The daily excess returns on the S&P 500 and the first difference of the logged Canada-US exchange rate were included 36.3 and 7.9 percent of the time, respectively, while the Canadian and US interest rate spreads were included 27.4 and 50.2 percent of the time.

Table 4.2.1: Optimal Subsets of Variables as Chosen by Model Selection Criteria

	RBS	AIC	HQC	BIC
% Times ρ_{t-1} Included:	99.7	97.3	96.8	96.8
% Times XSP_{t-1} Included:	36.3	20.5	1.5	0.0
% Times $dCNTB_{t-1}$ Included:	29.8	7.2	0.0	0.0
% Times $dUSTB_{t-1}$ Included:	47.7	34.0	16.2	1.3
% Times dXR_{t-1} Included:	7.9	5.6	0.0	0.0
% Times $USSP_{t-1}$ Included:	50.2	41.8	0.4	0.0
% Times $CNSP_{t-1}$ Included:	27.4	15.4	0.0	0.0

Using the Akaike Information Criteria to select the optimal model, the lagged excess rate of return on the TSE 300 index was included in 97.3 percent of the models. The change in the Canadian ninety-day treasury bill rate was included in 7.2 percent of the periods while the US ninety-day treasury bill rate was included in 34.0 percent of the periods. The daily excess return on the S&P 500 and the first difference of the logged Canada-US exchange rate were included 20.5 percent and 5.6 percent of the time, respectively. The spread between Canadian long and short term interest rates were included 15.4 while the spread between US long and short term interest rates were included in the optimal model 41.8 percent of the time.

Using the Hannan-Quinn criteria to determine the optimal model, the daily excess return on the lagged TSE 300 index was included 96.8 percent of the time while the change in US ninety-day treasury bill rate was included 16.2 percent of the time. The US interest rate spread was included 0.4 percent of the time while the daily excess return on the S&P 500 index was included 1.5 percent of the time. The change in the Canadian treasury bill rate, the Canadian interest rate spread and the first difference of the logged Canada-US exchange rate were never included in any of the models selected by the Hannan-Quinn criteria.

Using the Bayesian information criteria penalized the inclusion of more variables the most harshly and thus most of the explanatory variables were included quite infrequently in comparison to the other three selection criteria. The daily excess return on the lagged TSE 300 index was still included 96.8 percent of the time however the US ninety-day treasury bill rate was included in the optimal model only 1.3 percent of the

time. None of the other variables were included in any of the optimal models at any point in time when Bayesian Information Criteria was used for model selection.

The overall results suggest that the base set of explanatory variables contain information useful for explaining excess returns on the TSE 300 index since the model selection criteria include the variables in question at least some of the time.

4.3 Forecast Performance

This section determines whether the optimally selected models have predictive ability for one-step ahead excess returns on the TSE 300 index. In order to examine the predictive power of the forecasts made using the recursive modelling strategy, a non-parametric test of predictive performance, designed by Pesaran and Timmerman (1992), was used. Rather than test for the accuracy of the *magnitude* of the forecasts, the Pesaran and Timmerman test simply analyzes the frequency of the accuracy of the *sign* of the forecasts, in this case whether they are positive or negative. This methodology is particularly useful for the purposes of this thesis because the trades made in this market-timing procedure are based not so much on magnitude, but more importantly on the sign of the forecasts. The attributes of this test make it particularly useful for this analysis.

This test analyzes the statistical significance of the correlation between forecasted values and the actual values of excess returns on stocks or stock market indices. The non-parametric test of predictive performance for a forecast x_t of variable y_t is based on the standardized statistic.

Let x_t be the forecast of y_t.

N is the number of observations.

$\hat{P}$ = the estimated probability that the sign of the forecast is correct.

$\hat{P}_y$ = the estimated probability that the sign of the actual value is positive.

$\hat{P}_x$ = the estimated probability that the sign of the forecast is positive.

(4.3.1) $S_N = \dfrac{\hat{P} - \hat{P}_*}{\left\{\hat{V}(\hat{P}) - \hat{V}(\hat{P}_*)\right\}^{\frac{1}{2}}}$ which is distributed N(0,1),

where

(4.3.2) $\hat{V}(\hat{P}) = N^{-1}\hat{P}_*(1-\hat{P}_*)$,

and

(4.3.3) $\hat{V}(\hat{P}_*) = N^{-1}(2\hat{P}_y - 1)^2\hat{P}_x(1-\hat{P}_x) + N^{-1}(2\hat{P}_x - 1)^2\hat{P}_y(1-\hat{P}_y) + 4N^{-2}\hat{P}_y\hat{P}_x(1-\hat{P}_y)(1-\hat{P}_x)$

(4.3.4) $\hat{P}_* = \hat{P}_y\hat{P}_x + (1-\hat{P}_y)(1-\hat{P}_x)$

and P_x and P_y are estimated by using their respective sample proportions.

The methodology used by Pesaran and Timmerman is called the "Predictive Failure Test" and is based on the proportion of times that the sign of the forecasted variable is forecasted correctly. A forecaster who predicts that the excess return will be positive every time will be right more than half the time, however this strategy would score zero on Pesaran and Timmermann's test, even though the forecast is correct more than fifty percent of the time[12]. This aspect of the test makes it particularly useful because it "weeds out" erroneous forecasting strategies such as the one just described.

[12] This result occurs because the TSE 300 Total Return Index grew by a positive amount 55.2% of the time, as discussed later in this section.

Quantitative information on the forecasted variable is unnecessary as only the signs of the actual and the forecast values are required.

The null hypothesis is that the forecasting technique has *no* power to forecast the sign of the one-day ahead excess return on the TSE 300 index. Thus, the alternative hypothesis is that the forecasting technique used in this thesis *does* have ability to predict the sign of the one-day ahead excess return on the TSE 300 index.

The excess return on the TSE 300 index was positive 1446 times, or 55.2 percent of the time over the sample of 2621 observations while the excess return was negative 1174 times, or 44.8 percent of the time. On one occasion the excess return was zero. Using Akaike Information Criteria to select the optimal models, the TSE 300 index was correctly forecasted positive 797 times and correctly predicted negative 593 times, or 58.7 percent correct in total[13]. Using Bayesian Information Criteria, the TSE 300 index was correctly forecasted positive 798 times and correctly predicted negative 594 times, which translates in a forecast accuracy of 58.8 percent. The adjusted R^2 model selection criteria yielded a correct positive forecast 791 times and a correct negative forecast 600 times for a forecast accuracy of 58.7 percent. Under Hannan-Quinn criteria, the positive values of the TSE 300 index were correctly predicted 792 times while the negative values were accurately forecasted 588 times for a correct sign forecast rate of 58.2 percent.

These figures reveal an important aspect of the model's results in that they suggest that the recursive modelling forecasts do better than a naïve forecast of always positive. Since the excess return on the TSE 300 index is positive on 55.2 percent of days, a forecaster who simply predicts that the excess return is positive every time will

forecast accurately 55.2 percent of the time. If the recursive modelling strategy could not forecast better than 55.2 percent of the time, the forecasts would be no better than simply predicting that the TSE 300 Total Return Index increases in value every period.

Table 4.3.1: Test Statistics for Forecast Accuracy

Selection Criteria	Test Statistic
AIC	8.27
BIC	8.35
RBS	8.34
HQC	7.84

Table 4.3.1 shows that the test statistics for the forecasting ability of the model using all four model selection criterion lie between 7.8 and 8.4, all of which are statistically significant. Recall that the test statistic is normally distributed and so the 95% confidence level is 2.86. Therefore the null hypothesis can be rejected meaning the results show that the forecasts contain useful information for predicting the sign of the one-day-ahead excess return on the TSE 300 Total Return Index.

4.4 Portfolio Growth

Results were obtained using the four selection criteria to find out what return would have been earned if the investor had earmarked $1,000 using these strategies on January 2, 1990 and continued until May 28, 1999. For a simple comparison, if an

[13] The results of the Pesaran and Timmermann test are shown in Appendix A.

investor had placed a $1,000 portfolio in thirty-day Government of Canada Treasury Bills on January 2, 1990 and rolled the investment over until May 28th 1999, the $1,000 would have grown to $1,468.22 by May 28, 1999. This translates into an average annual rate of return of 4.17 percent. On the other hand, if $1,000 were invested in the Toronto Stock Exchange 300 Total Return Index on January 2, 1990, the same $1000 portfolio would be worth $2,038.02 by May 28, 1999. This translates into an average annual rate of return of 7.86 percent.

In the absence of transaction costs, the trading strategies developed in this paper yield surprisingly large returns when compared to the returns earned on the TSE 300 Total Return Index or on 30-day treasury bills. Using Akaike Information Criteria as the model selection criteria in the recursive modelling strategy, $1,000 invested on January 2, 1990 becomes $9,317.42 by May 28, 1999, a high annual rate of return of 26.8 percent. This is a far better return than would have been be earned from a simple investment in the TSE 300 index or in 30-day treasury bills. Results for the other three model selection criteria are similarly strong. Using adjusted R^2 as the model selection criteria, the model indicates the same $1,000 invested on January 2, 1990 to be worth $9,419.31 by May 28, 1999, which translates into an annual rate of return of 26.9 percent. Similarly, using the Hannan-Quinn Criteria to select the optimal models yields $9,326.18 over those same years, or a rate of return of 26.8 percent. Bayesian Information Criteria yields $9,649.87, which works out to an annual rate of return of 27.3 percent. These results are summarized in table 4.4.1.

Table 4.4.1: Summary Statistics of Portfolios under Zero Transaction Costs

Zero Transaction Costs	RBS	AIC	HQC	BIC	Buy & Hold
Final Wealth	$9419.31	$9317.42	$9326.18	$9649.87	$2038.02
Mean Annual Return	26.9%	26.8%	26.8%	27.3%	7.86%
Mean Daily Return	0.0947%	0.0942%	0.0942%	0.0957%	0.0376%
Std. Dev of Returns	0.004949	0.004932	0.004886	0.004876	0.006964
Proportion in Stocks	54.8%	55.4%	55.4%	55.4%	100%
Number of Switches	941	917	931	911	0

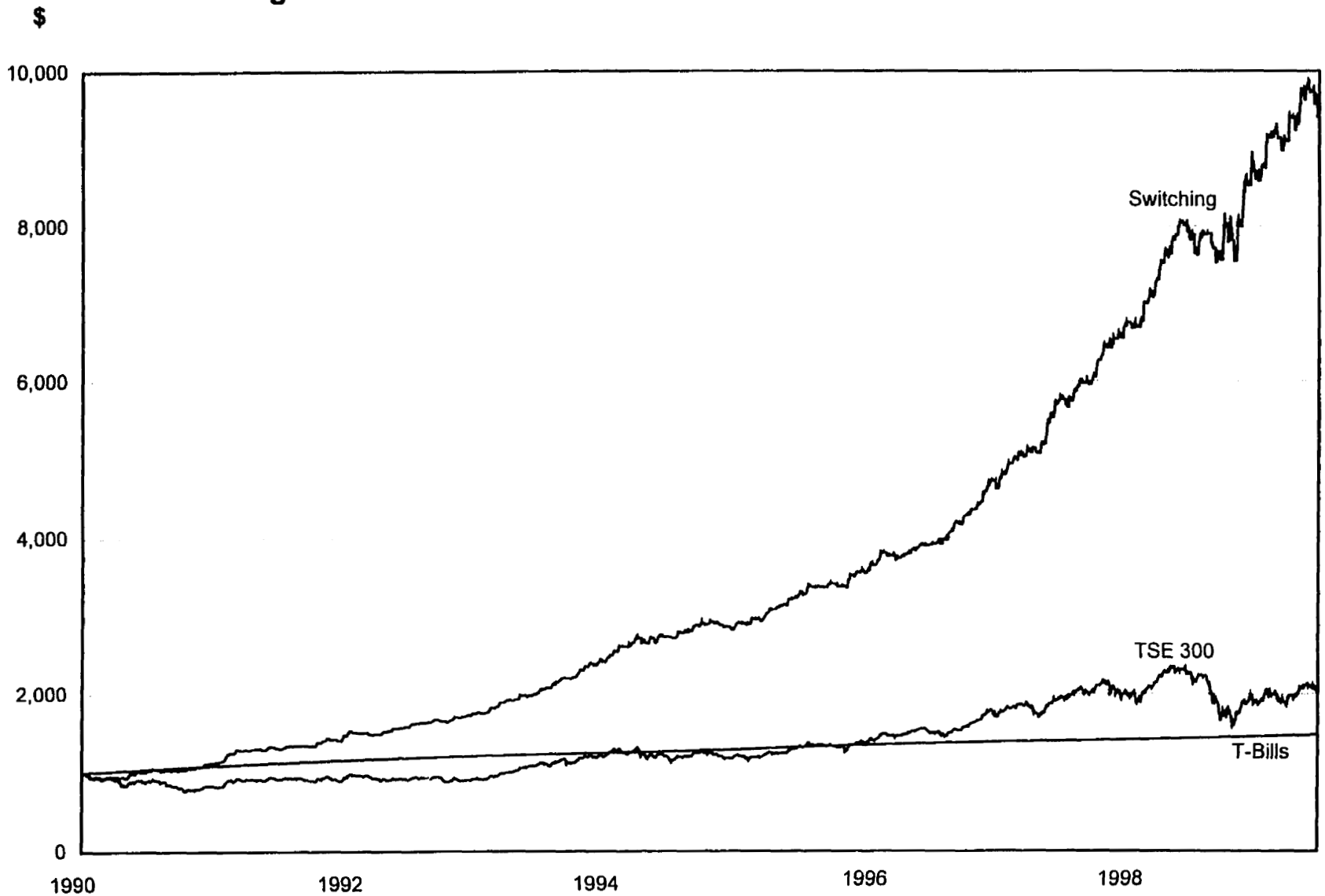
Figure 4.4.1 plots the time path of a $1,000 investment in the trading strategy if adjusted R^2 was used for the model selection criteria. The growth patterns for investments in the trading strategy using the other selection criteria, i.e. Akaike Information Criteria, Bayesian Information Criteria, and Hannan-Quinn Criteria yield similar results. As a benchmark, the portfolio growth patterns are also shown for buy-and-hold strategies in the TSE 300 Total Return Index and 30-day Government of Canada treasury bills.

The time path of the switching portfolio under zero transaction costs begins by following the TSE 300 index for several months, which initially shrinks the investment to less than the original $1,000. Eventually some beneficial trades are made and by the middle of 1993 the switching portfolio doubles to over $2,000. At this same point the buy-and-hold strategy actually underperforms an investment in 30-day treasury bills. By the middle of 1996 the switching portfolio doubles again to $4,000 while the buy-and-hold strategy finally outperforms treasury bills. By 1998 the switching portfolio doubles again to $8,000, however it becomes quite volatile at this point due to the TSE 300 index itself increasing in volatility. The switching portfolio in fact does not break $8,000 permanently until late in 1998. The TSE 300 index experiences a market correction and

drops substantially at this point. This period late in 1998 is perhaps the most interesting because although the TSE 300 index is falling, the switching strategy grows quite rapidly, clearly making some timely forecasts and trades. The switching strategy peaks just under $10,000 near the end of the sample before it falls off to its value on May 28, 1999 of $9,419.31. This large increase in the switching strategy during 1998 suggests that increased market volatility may improve the performance of the switching strategy.

Portfolio switches between the TSE 300 index and treasury bills are quite frequent under the zero transaction cost scenario. As indicated in table 4.4.1, 911 trades are made under the BIC trading strategy, 917 switches are made using the AIC trading strategy, 931 trades are made using the HQC switching strategy, and 941 trades are made under the RBS switching strategy. This suggests that, on average, a portfolio switch is made about every three days if there are no transaction costs.

Figure 4.4.1: Value of Portfolio over Time - Zero Tansaction Costs



4.5 Implementation of Transaction Costs

Transaction costs are absent for the returns above. As would be expected, returns are not as high in the presence of transaction costs because the forecasts require a large number of trades, potentially as frequently as one per day. As mentioned in section 3.3, trades are made only when the expected gain is sufficiently large to cover the transaction cost. A range of transaction costs were used in order to check the sensitivity of the performance of the trading strategies as the transaction costs changed. Tables 4.5.1 to 4.5.3 present the findings when transaction costs are implemented.

Table 4.5.1: Summary Statistics of Portfolios under 0.1% Transaction Costs

Transaction Costs = 0.1%	Adjusted R^2	AIC	HQC	BIC
Final Wealth	$4342.15	$3943.89	$3471.08	$3323.39
Mean Annual Return	16.9%	15.7%	14.1%	13.6%
Mean Daily Return	0.0620%	0.0579%	0.0525%	0.0507%
Std. Deviation of Returns	0.005113	0.005164	0.005088	0.005081
Proportion in Stocks	56.9%	58.6%	57.1%	57.6%
Number of Switches	407	397	409	407

Table 4.5.2: Summary Statistics of Portfolios under 0.25% Transaction Costs

Transaction Costs = 0.25%	Adjusted R^2	AIC	HQC	BIC
Final Wealth	$2452.80	$2504.09	$2593.88	$2628.03
Mean Annual Return	10.0%	10.3%	10.7%	10.8%
Mean Daily Return	0.0378%	0.0387%	0.0402%	0.0407%
Std. Deviation of Returns	0.005170	0.005045	0.005150	0.005045
Proportion in Stocks	58.8%	58.0%	59.1%	54.4%
Number of Switches	115	111	109	109

Table 4.5.3: Summary Statistics of Portfolios under 0.5% Transaction Costs

Transaction Costs = 0.5%	Adjusted R^2	AIC	HQC	BIC
Final Wealth	$1174.78	$1079.18	$1133.94	$1234.39
Mean Annual Return	1.7%	0.8%	1.3%	2.3%
Mean Daily Return	0.0067%	0.0032%	0.0053%	0.0088%
Std. Deviation of Returns	0.004798	0.005040	0.005097	0.004858
Proportion in Stocks	49.6%	51.7%	51.8%	49.7%
Number of Switches	10	12	12	10

In the case of the Akaike Information Criteria, excess profits above a buy-and-hold strategy of the TSE 300 index can potentially be earned with certain transaction costs. In other words, greater returns can be earned from the switching strategy than can be gained from the TSE 300 index when transaction costs are low, but not when transaction costs are large. As shown in tables 4.5.1, 4.5.2, and 4.5.3, average returns of 15.7 percent can be made if the transaction cost is 0.1 percent. If the transaction cost is 0.25 percent then returns of 10.3 percent can be earned and if the transaction cost is 0.5

percent then returns of 0.8 percent can be obtained. Transaction costs of 0.25 percent and less outperform an investment in the TSE 300 index which earned a rate of return of 7.86 percent over the same time period. However, beyond a transaction cost of 0.25 percent, returns using this switching strategy under-perform the TSE 300 index.

The results for the other three model selection strategies are remarkably similar. For the adjusted R^2, rates of return earned when the transaction costs are 0.1 percent, 0.25 percent, and 0.5 percent are 16.9 percent, 10.0 percent, and 1.7 percent, respectively. Using the Bayesian information criteria for model selection, the rates of return earned with transaction costs of 0.1 percent, 0.25 percent, and 0.5 percent are 13.6 percent, 10.8 percent, and 2.3 percent, respectively. Using the Hannan-Quinn criteria to select the optimal model, annual yields earned with transaction costs of 0.1 percent, 0.25 percent, and 0.5 percent are 14.1 percent, 10.7 percent and 1.3 percent respectively. These results reflect the logical intuition that the higher the transaction costs, the lower the returns earned when using the trading strategy.

Figures 4.5.1 to 4.5.3 plot the paths of $1,000 investments in the trading strategy over the sample period if adjusted R^2 was used for the model selection criteria under the three transaction cost scenarios. Figure 4.5.1 plots the portfolio growth pattern with 0.1 percent transaction costs, figure 4.5.2 shows the results under 0.25 percent transaction costs, and figure 4.5.3 plots the growth pattern under 0.5 percent transaction costs. The growth patterns for investments in the trading strategy using the other selection criteria, i.e. Akaike Information Criteria, Bayesian Information Criteria, and Hannan-Quinn Criteria yield similar results although graphs of these are not presented. As a benchmark,

the portfolio growth patterns are shown for buy-and-hold strategies in the TSE 300 Total Return Index and thirty-day Government of Canada treasury bills.

The switching strategy under all three transaction scenarios struggle early in the sample period as they all underperform treasury bills until at least early in 1991. Under 0.1 percent transaction costs, the strategy outperforms the TSE 300 index early in the sample and by 1995 doubles to $2,000 while the TSE 300 index is doing no better than treasury bills at the same point. Although the switching strategy outperforms the TSE 300 index for most of the sample period, the two strategies diverge even more strongly in the middle of 1998, which is when the TSE 300 index experienced a significant correction. This time period is also when the level of volatility of the TSE 300 index markedly increases. Some accurate forecasts and timely trades were made around this time which enabled the switching portfolio to decline only modestly while the TSE 300 index was declining rapidly. The switching strategy doubles again to $4,000 late in 1998 while the TSE 300 index is only then doubling for the first time to $2,000. Interestingly, during the last few months of the sample the TSE 300 index experiences a minor decline while the switching strategy appears to magnify this decline as the switching portfolio performs worse than the TSE 300 index for this short period of time.

Under 0.25 percent transaction costs the switching portfolio takes much longer to double as both the strategy and the TSE 300 index do not double until 1997. As was the case in zero and 0.1 percent transaction cost scenarios, during the market correction of 1998, the switching strategy under 0.25 percent transaction costs made some timely trades and forecasts to avoid being hit quite as hard as the TSE 300 index. It becomes

quite clear in the case of 0.25 percent transaction costs that not nearly as many trades are being made, indicating that the forecasts are frequently smaller in magnitude than the transaction cost. Frequent long, flat stretches in the graph indicate that treasury bills are being held for extended periods of time. The switching portfolio ends up with a value of $2,425.80, still better than the buy-and-hold portfolio.

Under 0.5% transaction costs, very few trades are made. The switching portfolio starts in the TSE 300 index and stays there until late 1993, when the first trade is made, moving from the TSE 300 index into treasury bills. The switching portfolio stays in treasury bills for an extended period, until 1997 when the portfolio is switched back into the TSE 300 index for a short period before it is switched back to treasury bills. Late in 1998 there are more frequent trades which, not surprisingly, coincides with increasing volatility in the TSE 300 itself. Overall, the trading strategy under 0.5% transaction costs performs very poorly, even worse than a buy-and-hold strategy of treasury bills. The final portfolio is worth $1,174.78, an annual rate of return of only 1.7 percent.

An interesting, but predictable finding is that as transaction costs increase, the number of trades decreases. This result is due to the fact that a trade is only made when the magnitude of the forecast is greater than the transaction cost. As the transaction cost increases, it will be less likely that the forecast will be greater than the transaction cost. Under zero transaction costs, 941 trades are made, or once every two to three days. Under 0.1% transaction costs, 407 trades are made, or one every six or seven days. Under 0.25% transaction costs 115 trades are made, while under 0.5% transaction costs only 10 trades are made.

Figure 4.5.1: Value of Portfolio over Time - 0.1% Tansaction Costs

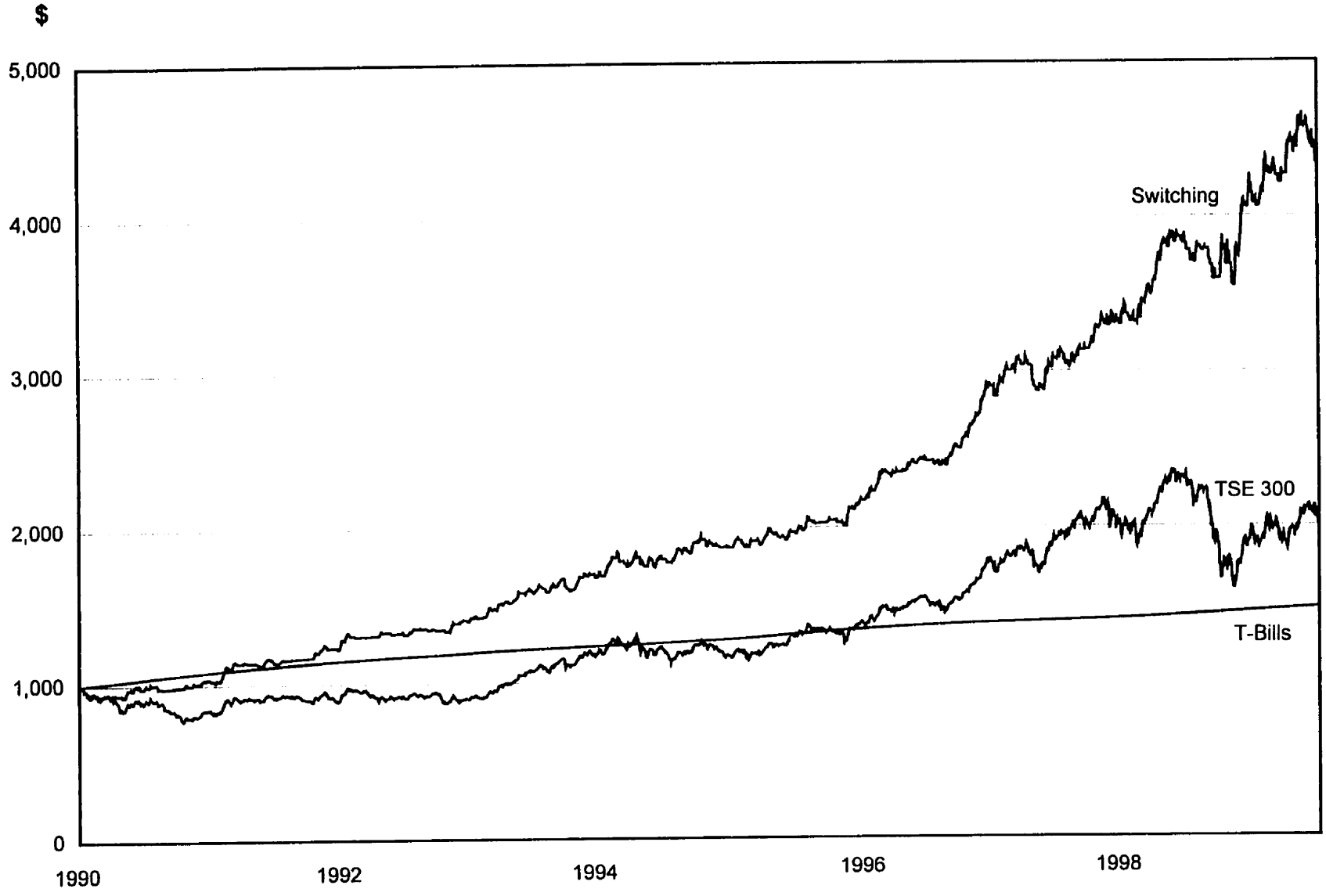


Figure 4.5.2: Value of Portfolio over Time - 0.25% Tansaction Costs

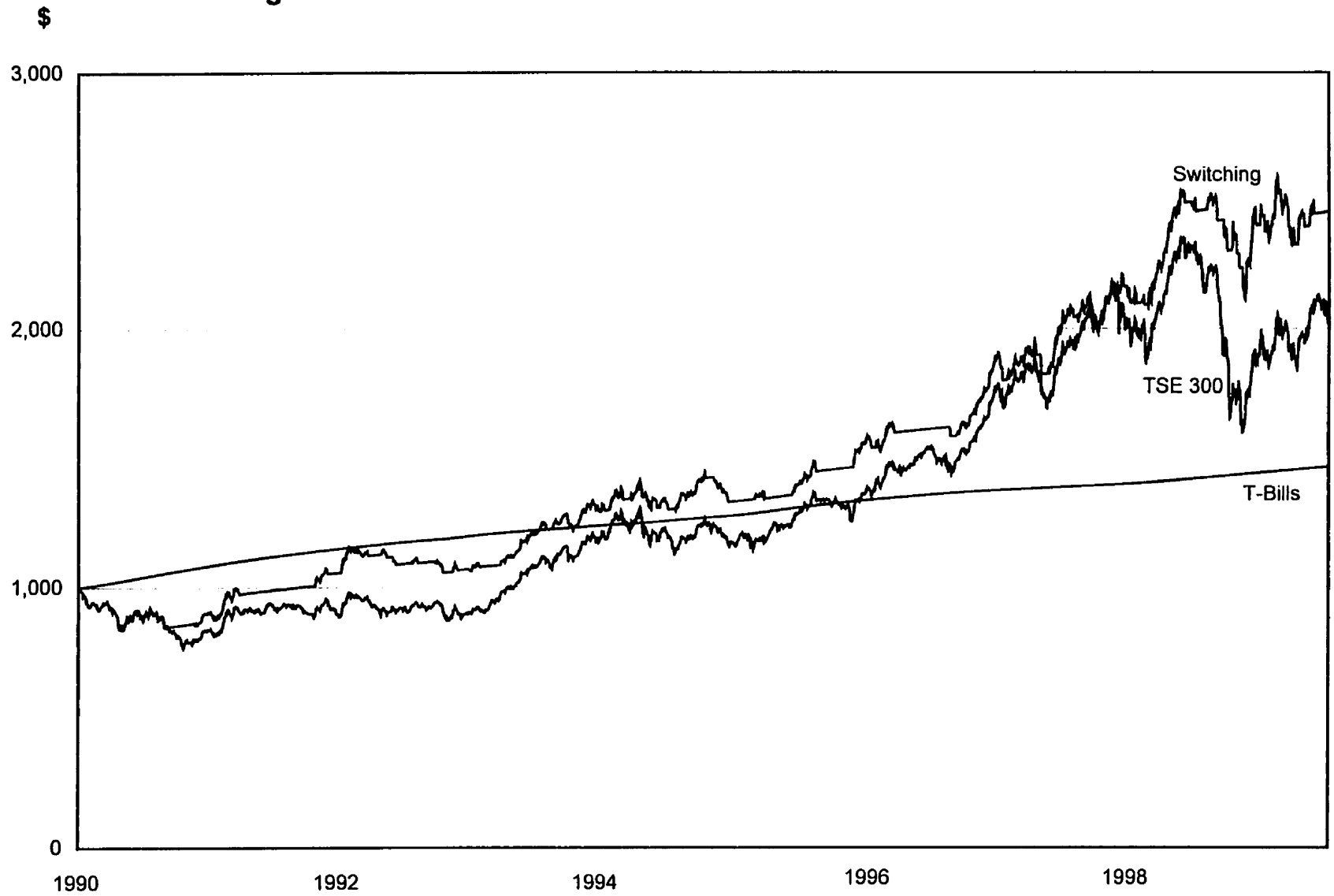
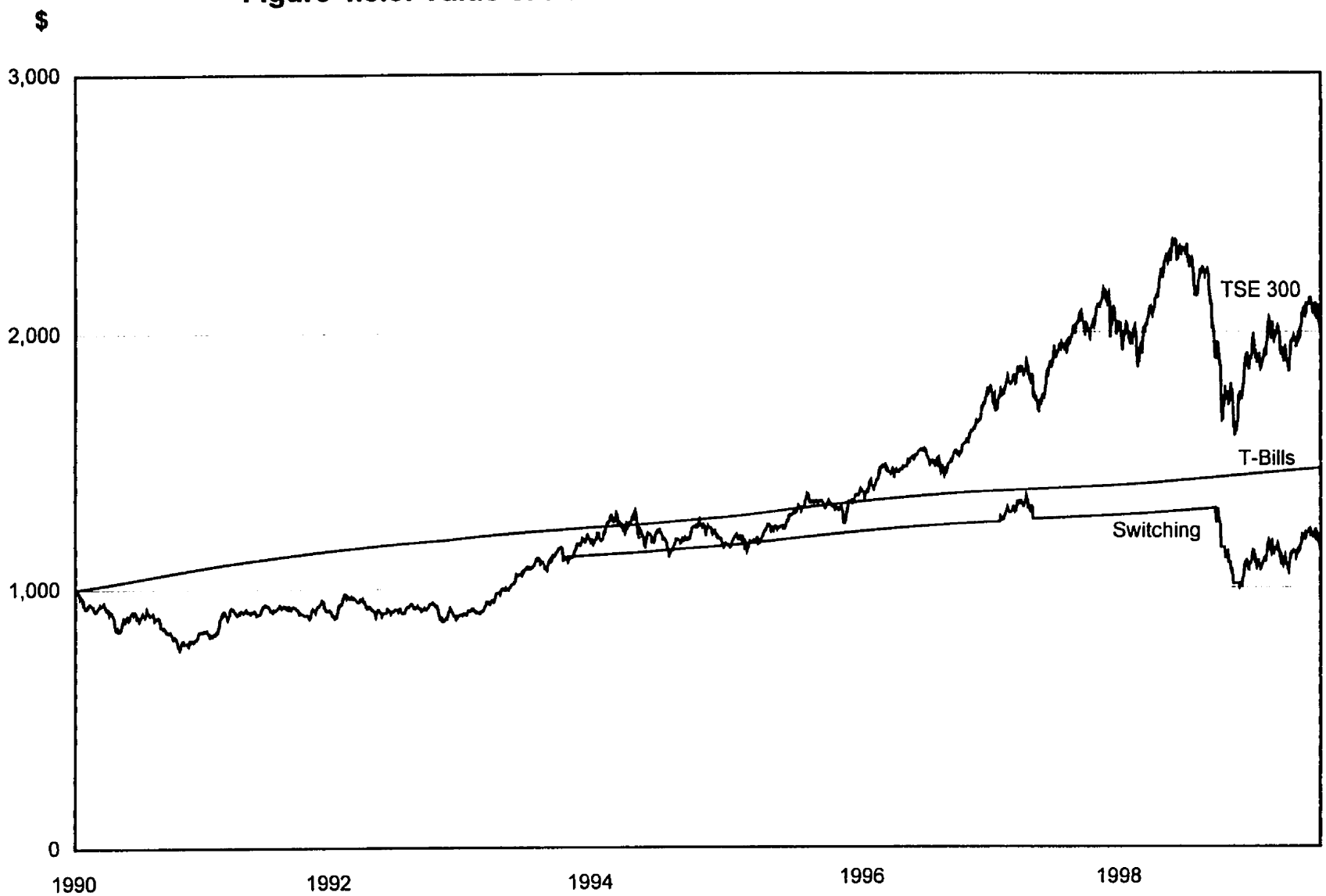


Figure 4.5.3: Value of Portfolio over Time - 0.5% Tansaction Costs



4.6 The Riskiness of the Trading Strategies

In terms of average return, the results indicate that if transaction costs are low enough then the trading strategies outlined in chapter 3 outperform the returns realized by the TSE 300 Total Return Index. Therefore, a risk-neutral investor would certainly prefer to invest in the trading strategy since it outperforms the market portfolio. However, few investors are risk-neutral: most investors, in fact, would consider themselves risk-averse. Therefore the amount of risk associated with different portfolio strategies must be considered in order to determine whether an investment in the trading strategy would actually be preferred by a typical risk-averse individual, even with superior returns.

Referring to table 4.4.1, in the absence of transaction costs the standard deviations of returns from the trading strategies discussed lie between 0.004876 for Bayesian Information Criteria and 0.004949 for adjusted R^2. At the same time the standard deviation of the TSE 300 Total Return Index is 0.006964. These statistics suggest that the volatility of the return on the TSE 300 index is significantly greater than the volatility of any of the trading strategies under zero transaction cost scenarios. This finding is not surprising since the portfolios were in the TSE 300 Index 54% of the time and in treasury bills 46% of the time, as shown in table 4.4.1.

Implementing transaction costs appears to increase the risk of the trading strategies, but only marginally. Under a transaction cost of 0.1%, the standard deviations range from 0.005081 for Bayesian Information Criteria to 0.005164 for Akaike Information Criteria. If the transaction cost is 0.25%, the standard deviations are in the range of 0.005045 for Akaike Information Criteria and Bayesian Information Criteria to

0.005170 for adjusted R^2. This is also expected because the portfolios are in treasury bills less frequently than in the zero transaction cost scenario, as indicated in tables 4.5.1 and 4.5.2. If the transaction cost is 0.5%, then the standard deviations are even lower at 0.004798 for adjusted R^2 and 0.005097 for the Hannan-Quinn Criteria. In the 0.5% transaction cost scenario, the portfolio was in treasury bills about 50% of the time, as shown in table 4.5.3. Thus, it is not surprising that the 0.5% transaction cost scenario had the lowest standard deviation.

All of the standard deviations of the trading strategies are significantly less than the standard deviation of the TSE 300 Total Return Index. This suggests that the trading strategies imply *less* risk than the TSE 300 Total Return Index when using models such as the CAPM. However, this conclusion may not result with different classes of utility functions. For instance, using measures of risk such as skewness or kurtosis may suggest different levels of risk associated with the trading strategies. However, under a CAPM framework the switching strategies would be a superior investment strategy than the TSE 300 Total Return Index, yielding higher returns and lower risk as long as transaction costs are 0.25% or less.

Chapter 5

CONCLUDING REMARKS

This thesis used seven daily macroeconomic variables to forecast movements in the Toronto Stock Exchange 300 Total Return Index using a recursive modelling strategy. A trading strategy based on these forecasts was simulated whereby an investor made daily trades of a portfolio between the TSE 300 index and Government of Canada treasury bills, depending on which asset had the higher forecast return.

There were four possible scenarios. If the portfolio was already in treasury bills and the forecast for the excess return on the TSE 300 index was positive and greater than the transaction cost, then the investor traded into the TSE 300 index. If the forecast was less than the transaction cost, then the investor held treasury bills. If the portfolio was already in the TSE 300 index, then the investor traded into treasury bills only if the forecast for the excess return on the TSE 300 index was negative and the absolute value of the forecast was greater than the transaction cost. Otherwise the investor kept the portfolio in the TSE 300 index.

The seven daily variables were examined for their predictive ability on the excess return of the Toronto Stock Exchange 300 Total Return Index. These variables included the one-day lag of the excess return on the TSE 300 index itself, the change in the Government of Canada ninety-day treasury bill rate, the change in the ninety-day US treasury bill rate, the excess return of the Standard and Poor 500 index, the spread between Canadian one-year bonds and 30-day Canadian treasury bills, the spread

between US one-year bonds and 30-day US treasury bills, and the Canada-US exchange rate. By far the most frequently used variable to explain the excess return of the TSE 300 index was the one-day lag of the excess return of the TSE 300 index, as it was included in at least 96 percent of the models. The next most frequently included variables were the US ninety-day treasury bill rate and the US term spread. Canadian treasury bills, the excess rate of return on the S&P 500, and the Canadian term spread were included somewhat less frequently. Least frequently included was the Canada-US exchange rate.

Using a test for analyzing the performance of the models, the forecasts generated from this model contain information useful for market timing, according to the Pesaran and Timmermann (1992) test of predictive performance. This is confirmed by examining the portfolios implied by the recursive modelling strategy.

It is apparent from the results of this paper that using the models described previously, and in the absence of transaction costs, it is possible to earn a rate of return on substantially greater than the rate of return earned from a simple buy-and-hold strategy of the TSE 300 index. Using any of the four selection criteria identified, average annual rates of return yielded, in the absence of transaction costs, 26 to 27 percent under the trading strategies.

The introduction of transaction costs reduced these high rates of return significantly. However, in a low transaction cost scenario it was still possible to earn returns greater than the return earned by holding the TSE 300 Total Return Index. Using all four model selection criteria, returns of around 13 to 15 percent could be earned in the presence of a transaction cost of 0.1 percent, which is still a substantial improvement over

the 7.86 percent earned by the TSE 300 Total Return Index over the sample period in question. When the transaction costs were increased to 0.25 percent, the rates of return were about 10 percent. If the transaction costs were further increased to 0.5 percent, then this strategy yielded returns just slightly above zero. So long as the transaction costs are 0.25% or lower, the returns earned from this strategy are still above the return earned on the TSE 300 Total Return Index.

Although the trading strategies perform better than a buy-and-hold strategy of the TSE 300 index under low transaction costs, the value of the trading strategies can only be determined when the overall risk of the strategies are compared. When the standard deviations of the two investment strategies are stacked against each other, a buy-and-hold strategy in the TSE 300 Total Return Index actually has greater risk under a CAPM framework than the trading strategies under any of the transaction cost scenarios analyzed. This result indicates that with transaction costs of 0.25% or less, the trading strategies earn *greater* returns and have *less* risk, when using a CAPM framework, than the TSE 300 Total Return Index.

The crucial conclusion to arrive at is the fact that floor traders face a transaction cost of 0.1 percent (Ang & Chua, 1991) when they make trades through the stock exchange in which they are operating. Thus, it was possible for stock brokers to have exploited publicly available information during the 1990s in order to earn returns greater than the TSE 300 index. This is an indication that market timing may be possible for the TSE 300 index. However, since it is only stock brokers and institutional investors such as mutual fund managers that can trade at such a low cost, it would be a stretch to say that

anyone could have used publicly available information to earn returns greater than the market using the strategies developed in this thesis. The transaction costs faced by the public during the time period analyzed are likely much greater than 0.1 percent. Institutional investors, such as mutual fund managers, may have been able to use transaction costs this low however, and so may have indirectly allowed access by average investors to these low transaction costs.

Although inappropriate for use in this thesis, an interesting future extension would be to evaluate the market timing opportunities available since internet trading companies have emerged, such as E-Trade™, Ameritrade™ and others. These internet companies charge a flat rate per trade, rather than a percentage of the amount being traded. Therefore the larger the volume being moved, the lower the percentage transaction fee. Internet trading was not available over the majority of the time period studied in this paper. Therefore it would not be a legitimate exercise to determine whether profitable trading strategies using internet trading would have been available during the 1990s using the market-timing strategy in this study. Performing a study such as this would likely prove to be interesting once enough historical data becomes available on stock market trading using internet brokers.

A second possible extension of this thesis would be increasing the number of possible lags of the explanatory variables. The model used in this thesis regressed the growth rate of the excess rate of return of the TSE 300 index against the one-day lags of seven macroeconomic variables. Increasing the number of lags to include more than a one-day lag may increase the explanatory power of the model, however the level of

complexity would increase exponentially by adding more lags. The model as described in this thesis contains seven explanatory variables each lagged one day, making 128 (2^7) possible models at each point in time. If each explanatory variable was expanded to include two lagged terms instead of just one, there would then be 16,384 (2^{14}) possible models to estimate each day. It is quite evident that increasing the number of lagged variables makes the complexity of the model increase very rapidly.

A third possible extension to this thesis could be to apply the same forecasting and switching strategies to other stock markets, specifically other Canadian stock markets. In addition to forecasting the Toronto Stock Exchange, a forecaster could attempt to forecast the Alberta Stock Exchange (ASE) or the Vancouver Stock Exchange (VSE) to determine whether a switching strategy between these stock markets and treasury bills would yield comparable results to those obtained for the TSE 300[14]. Theoretically, many of the same explanatory variables used to explain the Toronto Stock Exchange could be used to forecast the ASE or the VSE. Daily economic indicators of the specific province's industrial focus could also be used as explanatory variables. For example, the one day lag of the daily prices of crude oil and natural gas, or the TSE oil and gas index, would likely be useful in explaining the Alberta economy since the oil and gas sector is large in that province. In British Columbia, daily commodity prices such as forest and mining products or a commodities index could potentially be useful in explaining the Vancouver Stock Exchange since natural resources are a dominant component of the British Columbia economy.

[14] The Alberta Stock Exchange and the Vancouver Stock Exchange recently merged to form the Canadian Venture Exchange (^CDNX).

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Appendix A:

CONTINGENCY TABLES

The following tables are contingency tables comparing the signs of the forecast values against the signs of the actual values, as discussed in Section 4.3. Values in the top left corner of the tables indicate a correct positive forecast, while values in the bottom right corner of the tables indicate a correct negative forecast. Values in the bottom left of the tables indicate an incorrect positive forecast while values in the top right indicate an incorrect negative forecast. Therefore values along the top left/bottom right diagonal indicate correct forecasts.

Table A.1: Contingency Tables using Adjusted R^2

	Forecast Positive	Forecast Negative
Actual Positive	791	470
Actual Negative	508	600

Table A.2: Contingency Tables using Akaike Information Criteria

	Forecast Positive	Forecast Negative
Actual Positive	797	464
Actual Negative	515	593

Table A.3: Contingency Tables using Hannan-Quinn Criteria

	Forecast Positive	Forecast Negative
Actual Positive	792	469
Actual Negative	520	588

Table A.4: Contingency Tables using Bayesian Information Criteria

	Forecast Positive	Forecast Negative
Actual Positive	798	463
Actual Negative	514	594