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Support Vector Machines and Artificial Neural Networks: Assessing the Validity of Using Technical Features for Security Forecasting

James DiPadua

A dissertation submitted in partial fulfilment of the requirements of
Dublin Institute of Technology for the degree of
M.Sc. in Computing (Data Analytics)

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DECLARATION

I certify that this dissertation which I now submit for examination for the award of MSc in Computing (Data Analytics), is entirely my own work and has not been taken from the work of others save and to the extent that such work has been cited and acknowledged within the test of my work.

This dissertation was prepared according to the regulations for postgraduate study of the Dublin Institute of Technology and has not been submitted in whole or part for an award in any other Institute or University. The work reported on in this dissertation conforms to the principles and requirements of the Institute's guidelines for ethics in research.

I hold no positions, short or long, in any of the firms included in this study, nor was the work sponsored by any third-party entity. Further, this research is not intended to be construed as providing or implying investment advice.

Signed: ______________________________

James DiPadua

Date: **30 August, 2016**

Abstract

Stock forecasting is an enticing and well-studied problem in both finance and machine learning literature with linear-based models such as ARIMA and ARCH to non-linear Artificial Neural Networks (ANN) and Support Vector Machines (SVM). However, these forecasting techniques also use very different input features, some of which are seen by economists as irrational and theoretically unjustified. In this comparative study using ANNs and SVMs for 12 publicly traded companies, derivative price "technicals" are evaluated against macro- and microeconomic fundamentals to evaluate the efficacy of model performance. Despite the efficient market hypothesis positing the ill-suitability of technicals as model inputs, this study finds technical indicators to be nearly as performant as fundamentals at forecasting the future prices of a security. Additionally, all model predictions were fed into an automated trading machine and evaluated against a simple Buy-and-Hold, finding model performance at par with the passive Buy-and-Hold investment strategy.

Key Words: *Stock Forecasting, Feature Selection, Support Vector Machine, Artificial Neural Networks*

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List of Acronyms

ANN - Artificial Neural Networks

ARMA / ARIMA - Autoregressive Moving Average, Autoregressive Interval-

ARCH / GARCH - Autoregressive

BAH - Buy-and-Hold

CCI - Commodity Channel Index

DJIA - Dow Jones Industrial Average

EMH - Efficient Market Hypothesis

FF-NN / BP-NN - Forward Feed Neural Network, Backpropagation-

MA / SMA/ WMA - Moving Average, Simple-, Weighted-

MACD - Moving Average Convergence/Divergence

MSE / RMSE - Mean Squared Error, Root-

MAE - Mean Absolute Error

NYSE - New York Stock Exchange

RSI - Relative Strength Indicator

S&P500 - Standard & Poor's 500

1. Introduction

Financial security exchange markets, "stock markets," are large, volatile and seemingly chaotic (Huang, Nakamori and Wang, 2005; Wang, Wang, Zhang and Guo, 2011; Vui, Soon, On, and Alfred, 2013). The allure of identifying inflection points, being able to time the market, and to reduce risk yet maintain or increase profitability through participation in stock markets has generated immense interest among investors and researchers alike. The presence of the financial markets can be felt in nearly every sector of the economy, in nearly every corner of the world, attracting researchers from finance and economic interests and also from statistics and machine learning practitioners. The event-horizon-like nature of the financial markets, pulling all economic and social actors into its gravitational force is even examined in social justice and ecology research (Galaz, Gars, Moberg, Nykvist and Repinski, 2015). In 2013, according to Galaz, Gars, Moberg, Nykvist and Repinski (2015), the total wealth under professional management (investment firms, sovereign wealth funds, hedge funds, mutual funds, etc) reached 68.7 trillion USD, or approximately 18 times the national GDP of Germany for 2015 and approximately three *times* the total 2014 GDP for the *entire* EuroZone (CIA; TradingEconomics).

Indeed, the financial markets permeate every facet of contemporary life, and as a consequence of this pervasiveness, *locating the opportunities for entering and exiting a position using advanced statistical and machine learning techniques has garnered much research and investment attention.* While this paper does not seek to provide a specific answer to whether stock markets might be predicted or to evaluate every facet through which a security might be valued, the research intent is to provide a single answer to a simple question: do historical prices conveyed through technical factors such as moving averages allow a machine-based algorithm to accurately forecast stock prices?

1.1. Project Background

There are markets around the world where securities are exchanged daily between investors. The primary goal with these exchanges is to extract a profit, often through price arbitrage, a process of seeking a price differential between what one investor is willing to pay and what another perceives as the intrinsic value of the security (Refenes, Zapranis and Francis, 1994). However, determining the intrinsic value of a security is non-trivial, subject to extensive research and heated debate (Fama, 1965; Fama and French, 1988; Shleifer and Summers, 1990; Mankiw, Romer and Shapiro, 1991). Because of the complex, time-variant, non-trivial nature of security price forecasting, as well as the profit motive, security price forecasting is extensively present in machine learning literature (Atsalakis and Valavanis, 2009). Security forecasting is an alluring problem space for multiple reasons, mostly notably the promise for investment profit with reduced risk exposure. From a research perspective, security price forecasting is also an exciting area due to its inherent complexity--to accurately predict the movement of a stock or commodity is to not just “see the future” but to instill a structure to what frequently manifests itself as an erratic maelstrom of randomness.

As explored in more detail in the Literature Review many models rely extensively upon the use of historically derivative technical features--that is, model input features extrapolated from past security closing prices. Examples of these derivative features are frequently classified as Moving Averages. These, among other derivative technical features, are explained in more detail in chapter three, 'Design/Methodology.' In brief, however, it is worth noting that this class of features, from the perspective of economic theory, is “non-rational” because stock prices show a non-time dependency, or a "Random Walk" (Fama, 1965; Fama and French, 1988). It is from this perspective that the research question is posed.

The following research will seek to forecast the closing price of publicly traded companies by creating contrasted models of feature inputs:

1. One model will rely *exclusively* upon technical features derived from historical closing prices;
2. Another will utilize micro- and macroeconomic data to forecast the closing price;
3. Finally, a third model will use a combination of the two previous models’ features to ascertain whether a combination of fundamental and technical features predicts future closing with reduced error than the previous “pure” models.

The desired goal for the three input feature types is to assess the validity and the predictive power of the so-called "irrational" technical factors while also assessing additive fundamental features.

For each of the three models, the forecasted prices are fed to a lightweight trading machine which makes buy, hold and sell decisions. This layer is included in the experiment for two purposes: 1) recent soft computing research attempts to operationalize machine learning by stepping beyond theoretical evaluations of model efficacy using traditional statistical tools such as Root Mean Square Error (RMSE) by mimicking the decision to buy, sell or hold in conditions of uncertainty (Thawornwong, Enke and Dagli, 2003; Kara, Boyacioglu and Baykan, 2011; Teixeira, Inácio de Oliveira, 2010); 2) by inducing a trading machine to make purchase and sell decisions based on the forecast, the models are easily contrasted to the more traditional investment strategy of "buy and hold," which seeks to make investment profits over a long period by avoiding "market timing." Investment giant Warren Buffett is one example of a vocal proponent of buy and hold, having once wrote that "our favorite holding period is forever" (Buffett, 1989). In other words, if machine learning algorithms have the potential to identify the pattern within the highly volatile, time-variant, noise-riddled security exchanges then market timing is of less concern and investors equipped with sufficient models can enter and exit positions as conditions indicate by their models.

1.2. Research Aims and Objectives

Succinctly, the aim of this research is to evaluate the validity of using technical features as an input to algorithmic forecasting and, subsequently, making trading decisions. In this regard, and in light of the existing literature explored below (Chapter 2), **the effective *Null Hypothesis is that technical features*, on the basis of being reflections of past information disclosure only, *provide no predictive power* for future security prices**.

A myriad of studies in security price forecasting use technical indicators as the primary inputs to the learning problem (Thawornwong, Enke and Dagli, 2003; Teixeira and Inácio de Oliveira, 2010; Wen, Yang, Song, and Jia, 2010; Kara, Boyacioglu and Baykan, 2011; Chang, Fan and Lin, 2011; Ni, Ni and Gao, 2011; Ticknor, 2013); however, the economic theory for their use is hotly debated (Fama and French, 1988; Shleifer and Summers, 1990; DeLong, Shleifer, Summers and Waldmann, 1990; Verma, Baklaci and Soydemir, 2008). Indeed, much research into the use of technical features concerns itself with confirmation bias (Sullivan, Timmermann and White, 2001)--that is, it is presumed that because an investor's or data mining researcher's choices were validated by the market (or the data analysis), either by a price increase or decrease, the investor continues to use and laud the efficacy of technical features. This experiment will effectively treat the indicators as a black box, not looking for chart-based trends such as "head and shoulders"[1] or "double-tops"[2] (Gifford, 1995; Murphy, 1999; Schulmeister, 2009; Friesen, Weller and Dunham, 2009; Bako and Sechel, 2013). All that is available to the algorithm are the inputs, from which a next-day forecast is derived and a trading decision determined.

However, rather than simply stop at an evaluation of the technical features as "rational model inputs," it seems prudent to understand both the micro- and macroeconomic factors at play in investment decisions -- that is, by assuming that investors are at least marginally rational and use the changes in economic conditions as additional inputs to their models, one can then evaluate whether a combination of economic features ("fundamentals") provides a more accurate depiction of security prices than a purely technical model based upon moving averages and historical "patterns".

1.3. Research Methods

This experiment consists of secondary, empirical research and seeks to provide an inductive basis for future work by comparing three non-dependent models. As with most secondary research, the data were obtained from external sources (Google and Yahoo! Finance sites and the Federal Reserve Bank, St Louis). The research is empirical because it is direct and measureable. The use of empirical evaluation techniques establishes an inductive basis for understanding and selecting feature inputs for future security forecasting problems.

[1] *Historical price pattern consisting of three maxima reminiscent of a bust used for directional forecasting*

[2] *Another price pattern used to signal a developing contraction period*

1.4. Scope and Limitations

To scope the experiment, 12 companies were selected for inclusion. Each of the companies is contained within the Standard & Poor's 500 index ("S&P500"), an internationally recognized index tracking the largest 500 companies on US exchanges. To qualify for the study, each company needed to be listed as part of the S&P500 for the duration of the experiment period.

The research uses nine years of daily trade data, beginning January 2006, ending December 2015. Model training data spans the first eight years of this 9-year period (2006 - 2014), with 2015 reserved for security forecasting. Generally, the data for each company is a matrix of 38 features by a total of 2450 observations (range 2407 to 2485, mean 2454).

To further constrain the experiment's scope and limit confounds, the companies could have no share splits or entered into major mergers with other companies during the 9-year period. Further, careful attention also was paid in company selection in an attempt to pull from a variety of economic sectors.

A full list of the companies, their sector and ticker symbol are available in Chapter 3, "Design / Methodology". The full qualification criteria are also outlined in Chapter 3, "Selection Criteria."

1.5. Organization of Dissertation

The remainder of this dissertation is organized as follows:

- **Chapter 2 ("Literature Review")** is dedicated to an exploration of the previous research in security forecasting, inclusive of perspectives in finance, econometrics and machine learning. There is special attention paid to the motivation of this study's principal examination of technical indicators as inputs to security forecasting with machine learning. There is also an outline of similar studies utilizing the forecasted price as inputs to simple trading machines, which this researcher finds compelling as a model validation method.
- **Chapter 3 ("Design / Methodology")** will explore the selection of the participating companies in more detail. The section titled "Data Preparation" will provide details on the data transformation necessary to create valid inputs.

Subsequent sections in chapter 3 will clarify the models for both the neural network, the support vector machine and the trading algorithm used in the final evaluation phase.

- **Chapter 4 ("Implementation / Results")** provides a run-down of the three experimental phases applied to each of the participating company share prices. To help with data exploration, a visual guide is provided in chapter 4, section 2. Model development and model tuning are outlined in detail in Chapter 4 as well. Chapter 4 concludes with a sample of visualizations of the experiments' results. The first section in chapter 4 ("Software") provides a detailed overview of the program developed to support the experiment and its evaluation.
- Evaluation of the experiments is reserved for **Chapter 5 ("Evaluation / Analysis")**. In addition to a digest of the three-phased experiments' results, observations of the experiment are provided. The limitations of this research, both of model inclusion and in rational extrapolation, are expanded in detailed in 5.3.
- **Chapter 6 ("Conclusions and Future Work")** provides a summary of the entire research project, clarifies the contribution to the general body of research within security forecasting research as well as points to areas for further investigation.

2. Literature Review

The following literature review, organized into two parts ("Finance & Econometrics" and "Machine Learning & Forecasting") acts as a guide through a portion of the existing research into the expansive and complex field of security forecasting. There are two main topics of prior research evaluated, with Figure 1 outlining each branch:

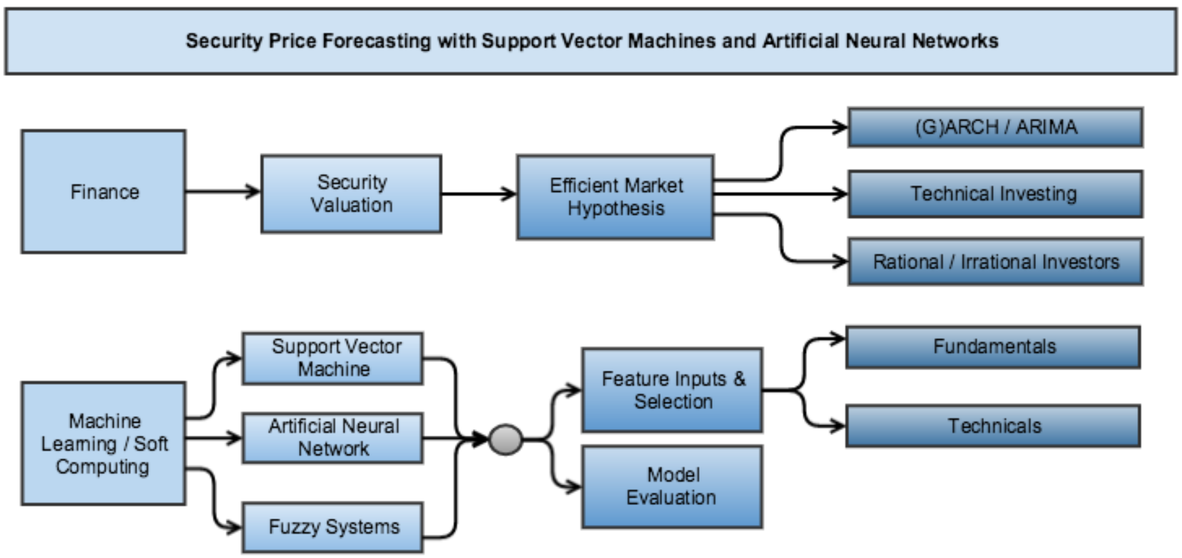


Figure 2.1 provides a hierarchy of existing research used to guide the overall research question regarding the use of historical prices, and their derivatives, as valid inputs ("features") for machine learning based security price forecasting.

First, the overarching research question is focused on exploring the validity and "rationality" of using historic prices for security forecasting and is therefore heavily influenced by previous researchers in economics, finance and behavioral psychology.

Second, the project is deeply rooted in machine learning and as such will examine previous research conducted using machine learning algorithms for security price forecasting. In particular, the Support Vector Machine (SVM) and Artificial

Neural Network (ANN) are evaluated as the primary tools for regression forecasting.

While every effort will be made to expose the historical research of each topic separately, where appropriate or unavoidable, references will be made from one topic branch to another. Perhaps somewhat outside the scope of this particular research experiment, tangentially related subtopics of research such as feature selection techniques in security forecasting will be provided to help contextualize the experiment within its general vicinity to these pre-existing soft computing applications.

As a guiding assumption, it is assumed the reader has a full understanding of the mechanics and underlying algorithmic design of SVMs and ANNs and no space in this literature review is devoted to explaining their origins or presenting their mathematical properties. An excellent primer on SVMs and ANNs is Vapnik's *The Nature of Statistical Learning Theory,* Second Edition (Vapnik, 1999). In a similar manner, the forecasting of security prices is an inherently time series-based analysis. While this literature review touches upon the expansive amount of research on time series data mining techniques, a survey of best practices are available in Fu (2011) and Cao (2003).

Note on the lexicon:

In the literature, there is a varying mix of terminology for the Artificial Neural Network (ANN). Some researchers simply use the ANN while others use Multi-layer Perceptron (MLP). As far as this researcher can see, the two terms are interchangeable with some bias toward one over another, depending on application field. For the purpose of this research, ANN is used. In a similar manner, one will see a divergence in language used to describe model inputs: computer science and machine learning literature frequently use "feature" to be synonymous with "expert" whereas economics refer to "states" or "factors" and statisticians use "components". This paper uses features to denote the numerical inputs to all models. Last in this regard is a mix use of machine learning and statistical learning, which are synonymous, with differences in use typically stemming from a researcher's background in statistics (statistical learning) or computer science (machine learning). This article opts to use machine learning.

2.1. Financial Security Forecasting

As a quick reminder, **this research seeks to understand what feature inputs are important and empirically *legitimate* for forecasting security prices**. To begin to address this gap in existing computer science literature, an examination of finance and economics was in order.

2.1.1. Origins of Financial Forecasting

With such tantalizing upside, there is a considerable body of research into security price forecasting, exhibiting a wide range of creative approaches, perspectives and motivations for security exchange. Much of this research, as one might imagine, originates in finance departments, typified by efforts to seek out fundamental justification for security prices, with monikers such as arbitrage pricing theory (APT), efficient market hypothesis (EMH) and asset pricing models (Fama, 1965, 1976; Refenes, Zapranis and Francis, 1994; Ron and Ross, 1980). One might also look to game theory, in particular bargaining games, to being understanding the forces at work in the exchange of securities (Nash, 1950). Indeed, research in security forecasting also extends to evolutionary game theory (Parke and Waters, 2007). Beyond these pure economic models, there is the hotly debated method of "technical analysis" or "charting" which seeks to find patterns in historical price changes in order to ascertain future prices and market movement (Gifford, 1995; Murphy, 1999).

2.1.2. Security Valuation -- An Economist Perspective

Investigation into the economic theory of security forecasting began for this researcher with an examination of the efficient market hypothesis (EMH) due to a high-frequency of citing the EMH's primary author Eugene Fama in machine learning literature (Fama, 1965; Fama, 1976). The EMH appeared to be one of a short list of economic models dominating the finance landscape for decades. However, despite the research of economists such as Fama showing "conclusively" that future security prices were uncoupled ("independent") from historical prices, a school of "chartist" forecasters developed, citing Charles Dow as the principal founder due to his observation of a cyclical nature in security prices (Gifford, 1995; Bako and Sechel, 2013). Within the pursuit of identifying patterns which the cognizant investor might exploit, additional research into the seasonality--or the predictable timing factor based on the month of the year, day of the week, etc--have also been examined. For example, Sullivan, Timmermann and White (2001) show a moderate seasonal effect. Their conclusion and evaluation of corporate need -- ie having to sell to make profits or write down losses--is compelling but they researchers clearly communicate the seasonality effects are moderate *at best*, further buttressing the notion that security pricing is more akin to a Random Walk (Fama, 1965; Fama and French, 1988).

Debate surrounding the validity of using charts to forecast security prices heated into the 1990s between Fama and an opposing set of economists such as DeLong, Shleifer, Summers, and Waldmann (DeLong, Shleifer, Summers, and Waldmann, 1990; Shleifer and Summers, 1990). This second group found that while “noise traders”--another pejorative name given to the investors relying upon “irrational” chart reading—may not economically possess a strong foundation, the effects of the “irrationality” on the market can be protracted, due to interaction effects with arbitrage-based investors (DeLong, Shleifer, Summers and Waldmann, 1990). Verma, Baklaci, and Soydemir (2008) even sought to understand the degree to which investor sentiment (i.e. “irrational noise”) influences stock prices. Mankiw, Romer and Shapiro (1991) cite earlier work by Shapiro showing that market volatility is indeed too high--so high, in fact, that the valuations cannot be based upon fundamental values *at all.*

2.1.3. Efficient Market Hypothesis and the Random Walk

To help resolve this debate, at least in the hopes of seeing justifiable input features for a security forecasting experiment, the following section examines the EMH and Random Walk in more detail.

The EMH consists of three forms: weak, semi-strong, and strong (Fama, 1970; Tsai and Hsiao, 2010). The weak form of the EMH simply examines whether future prices are a mere reflection of past prices, and in regard fall within the examination of the random walk (Fama, 1965; Fama, 1970; Tsai and Hsiao, 2010; Vui, Soon, On and Alfred, 2013). The semi-strong form of EMH posits that markets adjust rationally to publically available information such as splits, earnings announcements and adjustments to interest rates, whereas the strong form is an examination into potential monopolistic access to information on the part of select investors or groups of investors (Fama, 1970). Despite some researchers concluding the EMH is an inaccurate depection of market behavior (Cao, Leggio and Schniederjans, 2005) or that the price movements of securities perceived to be random (in the sense of a "temporily independent random walk") is instead a noisy, non-linear process (Huang, Nakamori and Wang, 2005; Lee, 2009), machine-based security forecasting researchers frequently cite Fama's EMH (Thawornwong, Enke and Dagli, 2003; Enke and Thawornwong, 2005; Huang, Nakamori and Wang, 2005; Schulmeister, 2009; Verma, Baklaci and Soydemir, 2008; Teixeira and Inácio de Oliveira, 2010; Tsai, Hsiao, 2010; Vui, Soon, On and Alfred, 2013). This is important because under a semi-strong efficient market hypothesis, as a liberal democracy with a functionally free media and securities oversight regulatory board (such as the Securities Exchange Commission), *the past prices will effectively reflect all information pertinent to the valuation of a security in the past but not in the future.* Yet, many of those same researchers previously cited use historical prices to forecast future prices.

However, under the EMH, the primary inputs could be economic in nature--in a semi-strong EMH, historical prices would merely reflect all historically available information, relying upon new information to alter the base valuations. And, as such, it was here that the researcher identified one set of configurations for input features: micro- and macroeconomic factors.

2.1.4. Econometric Forecasting: (G)ARCH

Almost as a response to the EMH and its primacy as a model for security pricing, researchers began examining the evidence of what appeared to be autocorrelated events in security prices: that is, that specific patterns of price movement were followed by similar patterns, though the magnitude (positive or negative) were unknown. It was here that the Autoregressive conditional heteroscedasticity (ARCH) model, and derivatives such as generalized autoregressive conditional heteroscedasticity model (GARCH), was developed (Engle, 1982; Bollerslev, Chou, and Kroner, 1992). The ARCH model developed by Engle (1982) was proposed to forecast inflation rates in the UK and, pertinent to the EMH, depended upon past prices to arrive at the future forecast. The ARCH model was developed to help explain the clustering behavior of securities--that large (or small) price changes will likely be followed by similarly large (or small) price changes but of an unknown sign (i.e. positive or negative) (Bollerslev, Chou, and Kroner, 1992).

The novelty of the (G)ARCH-models is that it uses a non-stationary variance--a variance in prices that changes depending on the time period evaluated within the time-series--and as such acts as a strong counter-argument to Fama's EMH which used a (single) stable variance throughout the time-series. Because of the clustering and repetitive nature of the ARCH model, this may be a pattern intuited by technical "chartists," though that is speculation as there was no specific literature reviewed by this researcher to indicate that intuited behavior on the part of technical investors. As illustrated in the survey of ARCH and GARCH research, contemporary finance assumes that time series are continuous stochastic equations but data are typically in discrete intervals (Bollerslev, Chou and Kroner, 1992). However, this seeming gap appears to be negligible when the time series is of small enough intervals. Another appeal of ARCH-models is the ability to examine the interaction effects of various markets, macroeconomic indicators and/or securities on other markets and securities and if so to what extent because it is an inherently linear model (Bauwens, Laurent, Rombouts, 2006).

Another counter-model to the EMH, is the Autoregressive and Moving Average (ARMA) model: autoregressive (AR) and moving average (MA) (Mondal, Shit and Goswami, 2014). Autoregressive Integrated Moving Average (ARIMA) is based on ARMA Model, in which ARIMA converts non-stationary data to stationary data (*ibid).*

Though considerable research is conducted using the machine learning algorithms covered thus far in an effort to examine their potential improvements over (G)ARCH and ARIMA models, this is not to imply that econometric research has ceased using the aforementioned models as recent studies have shown the continued efficacy of ARIMA to forecast security prices (Mondal, Shit and Goswami, 2014; Rounaghi, Zadeh, 2016). Zhang and Frey (2015) used a combination ARMA-GARCH model for high-frequency data, though the model itself pushes the limit of linear statistical models as it uses a hidden markov to control regime switching (between ARMA and GARCH)

Despite the strong appeal of ARCH (and derivatives such as GARCH and EGARCH), the general models developed are linear in nature. The appeal of the SVM and ANN is the ability to capture *nonlinear* relationships. Morefore, the process is simplified in that there is no longer a need to model variance over time. Rather than creating ever-increasing complexity to linear models, the SVM and ANN might simply skip to more elegant nonlinear models that capture the same relationships (past prices containing pertinent t+1 information) while being more comprehensible.

The important take-away for the research into (G)ARCH and ARIMA pricing models is that they *do* rely upon past prices as inputs, and it is here that one finds the justification for a second experimental model using historically derivative “technical” inputs to the forecasting model.

2.1.5. Investment Decisions -- A Human Behavioral Constraint

As a short primer on the behavioral economics of security forecasting, particularly in context of selecting legitimate, justifiable and rational model inputs, one must consider an examination of De Bondt and Thaler (1985) whose work in human psychological tendencies engaging in economic decision making evaluate the response of investors to information. In addition to pointing to prior work by Kahneman and Tversky work in 1982 in which they (Kahneman and Tversky) concluded that Bayes' rule is not an entirely accurate model for characterizing individual's response to the acquisition of new information, De Bondt and Thaler show that *individuals tend to overweight recent information and undervalue prior, "base rate," data.* In the realm of securities, this means that there is too great a discount of dividends and that stock price movements are closely tied to the changes in prior year earnings. One is left to ask, as De Bondt and Thaler do, how is it that the over-reaction to new information is a reflection of price arbitrage?

The De Bondt and Thaler research fits in nicely with a vein of research into the rationality of markets with a notable mention to work conducted by Verma, Baklaci and Soydemir (2008) in which the researchers found that short-term responses are swift and severe, particularly to bad news and that the reaction extends beyond what would be rationally justified by pre-existing models. One can likely understand this intuitively but it is also backed by behavioral research conducted by Loewenstein (2000) where he states that visceral factors, those emotional states controlling preferences such as hunger, sexual drive, etc, can change rapidly because these visceral factors are themselves affected by the changes in bodily and *external* stimuli. Loewenstein further concludes that it is the myriad of ever-shifting visceral states within the human which cause people who would otherwise appear "normal" to engage in extreme discounting of the future. So far as investment decisions, a discounting of the future would be an irrational mistake. For example, a "stumble" one quarter where growth was slower than expected or a merger was blocked by antitrust regulators may cause investors to "flee" irrationally, causing an unjustifiable drop in a security. This statement is also backed by Loewenstein's (2000) investigation into decision making where he concludes that though visceral factors are transient, they can cause individuals to take extreme action and that important decisions such as investments induce powerful emotions, and as such many of life's inflection points are heavily influenced by intense visceral states.

Friesen, Weller, and Dunham's 2009 work plays an important role in the further investigation of trading rules as well as the role of confirmation bias, particularly in light of bias, autocorrelation and the justification for interpreting the past to posit the future. Friesen, Weller, and Dunham find there is indeed indication of momentum in stock prices over the short-term, which provides the evidence to support trading rules designed to detect these short-term trends. Aligning well again with the work from Verma et al. (2008), the researchers point to large, infrequent signals (market news including economic changes) as rationally interpreted while shorter-term, higher-frequency signals (war, supply constraints) may be interpreted in a biased manner.

While economists frequently characterize the actors within the economy as rational, with investors lauded as a special class within the general body of economic actors, this may be an oversimplification. Fama himself stated that his finance models assumed actors assessed the universe of alternatives but that, "[it is] completely unrealistic to presume that when market prices are determined, they result from a conscious assessment...by all or even most or even many investors" (Fama, 1976).

So, when one uses machine learning to forecast prices, the machine algorithms base their learning in historical reactions (by individuals) to new market stimuli. It is for this purpose, the third set of experimental inputs consists of a blend of purely technical and purely fundamental inputs is formed. In a sense, it becomes a question of whether the machine algorithms effectively "learn" *how individuals might respond* to both historical patterns (technicals) and the change in economic conditions (fundamentals).

2.2. Machine Learning and Forecasting

The forecasting problem, due to the constant variability of prices and the differing motivations of the actors prompting these exchanges, constitutes non-trivial knowledge discovery (Fayyad, Piatetsky-Shapiro and Smyth, 1996). As such, the data mining and machine learning research communities were quick to pick up the mantel of examining the nonlinear problem of price changes with over two decades of research into a variety of nuanced approaches (Atsalakis and Valavanis, 2009; Vui et al., 2013). Beyond simply security prices, machine learning has been applied to other nonlinear problems, including wind forecasting, sunspot location, bankruptcy candidates and corporate (financial) distress (Liu, Tian, and Li, 2012; Cao, 2003; Tsai, 2009; Li, Wang, and Chen,2015).

2.2.1. Artificial Neural Networks

Beginning in the early 1990s, researchers focused on comparisons of neural networks with traditional statistical approaches, allured by the ability to provide better forecasting under non-parametric conditions (Wang, Wang, Zhang, and Guo, 2011). As one might expect, researchers began by trying to show the power of advanced algorithms such as the Artificial Neural Network (ANN) to outperform generally established forecasting benchmarks such as [Generalized] Autoregressive Conditional Heteroskedasticity ([G]ARCH) (Refenes, Zapranis and Francis, 1994; Guresen, Kayakutlu, and Daim, 2011).
After a flurry of research with ANN designs ranging from Multi-Layer Perceptron (MLP) with general forward feed (FF-NN) (Refenes, Zapranis and Francis, 1994; Atsalakis and Valavanis, 2009) and slightly more complex backpropagation (BP-NN) (Wang, Wang, Zhang, and Guo, 2011), the field saw further innovation and advancement with a myriad of different flavors of backpropagation error-regulating algorithms ranging from Bayesian regulators (Ticknor, 2013) to artificial bee colonies (Hsieha, Hsiao, and Yeh, 2011) to genetic algorithm (GA) (Wang et al., 2012). Results with ANN have been consistently promising but the improved forecasting with advanced machine algorithms such as ANN and GA should not be used to conclude the models do not rely upon the assumption of

linear correlations as previous statistical models do (Wang et al., 2012). According to the survey work conducted by Vui, Soon, On and Alfred (2013), the forward feed neural network (FF-NN) is most common and outperforms probabilistic ANN (though not conclusively), with strong evidence also pointing to the viability of genetic algorithms for the backpropagation (BP) portion of a BP-NN.

2.2.2. Support Vector Machines

In tandem to the work with ANN, data mining and machine learning researchers began applying other algorithms to the nonlinear problem, including Support Vector Machines (SVM), now a mainstay in contemporary machine algorithm research (Tay and Cao, 2001; Huang, Nakamori and Wang, 2005; Li, Wang and Chen, 2015). The primary difference between the SVM and the ANN is the optimization strategy. Whereas the ANN seeks to minimize the (empirical) error rate and find a global minimum, the SVM seeks to reduce structural risk, minimizing an upper bound of generalization and so is, by its nature, less prone to being "stuck" in a local minimum (Cao, 2003; Tay and Cao, 2005; Lee, 2009; Wen, Yang, Song, and Jia, 2010; Chai, Du, Lai, and Lee, 2015; Li, Wang and Chen, 2015).

Researchers have also lauded the simplicity of the algorithm itself, which has fewer parameters to concern researchers, unlike an ANN which worries about depth and breadth of architecture as well as learning rates and penalty weights (Refenes, Zapranis and Francis, 1994; Cao, 2003; Kara, Boyacioglu and Baykan, 2011; Vui, Soon, On and Alfred, 2013).

2.2.3. Fuzzy Logic

While some research may be mired in an attempt to forecast the market *exactly*, a fuzzy logic approach seeks to simplify the problem. Some researchers simply choose to forecast the *direction* of the market (Kim, 2003; Lee, 2009; Huang, Nakamori, and Wang, 2005; Kara, Boyacioglu and Baykan, 2011) while others have created simple algorithmic rules for buying and selling securities (Kim and Han, 2001; Thawornwong, Enke, and Dagli, 2003; Enke, Thawornwong, 2005; Teixeira and Inácio de Oliveira, 2010; Chang, Fan and Lin, 2011).

Despite the depth of literature available for the evaluation of ANNs applied to forecasting, one should not conclude the ANN is the out-right best model. Indeed, the SVM model constructed by Ni, Ni and Gao (2011) was provacoative while the trading system constructed by Teixeira, L.A. and Inácio de Oliveira (2010) relied upon the Nearest Neighbor algorithm and performed well, relative to general literature benchmarks which used profit comparisions to "buy and hold" strategies. Further, the fuzzy rule model proposed by Kim and Han (2001) did not rely on any advanced algorithms for making trading decisions, instead constructed simple buy-, sell-, and hold-conditions (i.e. simple "if-then-else" clauses) and also showed promising results.

There is a strong affinity between "fuzzy" logic and security forecasting because of the volatile and imprecise nature of security prices. By generalizing away from the specifics of an *exact price* and focusing model development on general trends (such as gain or loss), researchers are better equipped to make significant progress without burdening themselves with the need to find the "single true model," *which may not exist for all securities*.

To provide a concrete example, the researchers Enke and Thawornwong (2005) constructed a novel trading algorithm for purchasing the S&P500 or 10-year Treasury Bills. The inputs to the system relied upon fundamental variables and fed into an ANN. They found the trading system was able to outperform against simple Buy-and-Hold strategies. Nonetheless, the authors were also careful to point out that better performance does not necessarily equate to being more profitable as asset allocation is of paramount importance with investment decisions.

The paradigm of using fuzzy logic rules or fuzzy models plays a large role in the design of the overall experiment, in particular the development of a buy-sell machine to make comparisons to "buy-and-hold" strategies. For this researcher, the use of fuzzy systems to operationalize the forecasts of a precise machine algorithm, be that ANN or SVM, is exceptionally compelling because the fuzzy system is able to step outside traditional statistical metrics for something more tangible: profit or loss.

2.2.4. Feature Selection and Inputs for Machine Algorithms

When approaching a machine learning problem, an important decision to make is what feature inputs are relevant to solving the problem--as the saying goes, "garbage in, garbage out." In fact, *the very motivation of the research question herein is to locate legitimate, rational and justifiable model inputs.*

In the literature there is an expansive set of inputs employed. Atsalakis and Valavanis (2009) summarize the results showing a huge diversity of inputs, not just with a simple dichotomy of "technical versus fundamental indicators" but with a large diversity within those selections, too. For security forecasting, understanding the difference and role of fundamental and technical indicators appears to be a key issue.

Whereas fundamental factors are the macro- and microeconomic restrictions to a business (interest rates, cash flow, product margins, dividends, and general costs of doing business), technical indicators are values derived from historical trade information, such as Open and Close prices and total volume of securities exchanged (Fama, 1976; Shleifer and Summers, 1990; Gifford, 1995; Murphy, 1999; Tsai and Hsiao, 2010). Of note is that many of the features described as "fundamentals" might equally be classified as technicals--volume is an interesting example, frequently cited as a fundamental under the justification of it representing one of the economic conditions under which a security is traded (Ticknor, 2013). Volume, as a proxy indicator for the Efficient Market Hypothesis, appears to be a stretch of the definition. For the purposes of our evaluation, we will make a clear delineation between economic factors such as interest rates, currency exchanges and natural gas prices as fundamentals and volume and price or price derivatives (Moving Average, Relative Strength Indicator) as technical features.

One method to resolve the input problem by researchers is simply to aggregate a large set of feature inputs, ranging from variously derived technical values to a selection of economic fundamentals, and then to implement feature reduction. Stepwise Regression Analysis is one such technique, as implemented by Chang, Fan, and Lin (2011). Principal Component Analysis (PCA) is another common selection (Tsai, and Hsiao, 2010).

Tsai and Hsiao (2010) took a creative approach of applying a pseudo-ensemble of three feature reduction techniques, PCA, GA and Classification and Regression Trees (CART), and applying them as single model evaluations, "joins" and "intersects" of selected features, ultimately concluding that an intersection of selected features between PCA and GA as inputs to a BP-ANN provided the best results while GA was the most effective of the individual feature reduction techniques in their model.

The literature appears to be predominantly comprised of technical input variables, particularly derivatives values such as Simple Moving Average (and variations), Commodity Channel Index and Moving Average Convergence Divergence (MACD), to name but a few. It's unclear if this is a conscious choice over the selection of fundamentals as the motivation for selecting one set of inputs over another is not frequently explored in detail, if at all. Notable exceptions to this are Thawornwong, Enke and Dagli (2003) and Enke and Thawornwong (2005) who in the two studies, exclusively examined the role of technicals and fundamentals (respectively) on price forecasting. Nonetheless, the choice of technicals almost implies the "noise trader" approach as a bias, since technicals use historical price data to establish a pattern. That is, the technical variables themselves are derivatives of the price movements over time, establishing to some degree a picture of momentum--Momentum and Moving Average being two commonly used technical indicators. Table 2.1 provides a *small* example of the technical variables used as inputs into both traditional statistical and machine algorithm based models.

Indicator Name	**Abbreviation**	**Description**
Moving Average	MA	Shows the average price of a security over a specified time period, such as 5, 30 or 100 days
Relative Strength Indicator	RSI	Provides an indication of the strength of a security's average of gains over the average losses, as a comparison of closing prices above (or below) previous closes
Commodity Channel Index	CCI	A measurement of a security's price from its statistical mean based on historical price metrics
Moving Average Convergence/Divergence	MACD	Makes a comparison of (exponential) moving averages to a "signal line" to provide insight into whether a market is moving in the same or divergent direction to the previous periods

Table 2.1 provides a small example of historically derivative metrics used both by investment practitioners and machine learning researchers as feature inputs to their models.

While much of the existing literature reviewed here focuses on the use of technical indicators as proxies for available information -- that is, as a method of expressing the Efficient Market Hypothesis -- there are no reviewed models relying upon the daily news as a component of feature inputs. Indeed, with the findings from Verma et al. (2008) indicating the at-times voraciously salient impact of sentiment on security prices, one would expect a set of sentiment analyses to be more routine. One interesting model which does make use of text mining techniques (of company management's "discussions" within quarterly and annual reports) as an input to security forecast is presented by Wang, Huang and Wang (2012). Their text mining approaches improved the predictive efficacy of a traditional Autoregressive Interval Moving Average (ARIMA) model.

2.2.5. The "What" of Security Forecasting

When evaluating the securities forecasting literature, it becomes evident that many researchers chose, rather than specific company share prices, to forecast stock indicies such as the Dow Jones Industrial Average (DJIA) (Wang, Wang, Zhang and Guo, 2011), the S&P 500 (S&P), the London FTSE 100 (Hsieh, Hsiao and Yeh, 2011) and emerging market indices including the Sao Palo Stock Exchange (SPSE) (Teixeira and Inácio de Oliveira, 2010) and the Istanbul Stock Exchange (ISE) (Kara, Boyacioglu and Baykan, 2011). Perhaps it is simply precedent as much of the early research was done in this regard. However, there are some researchers who focused on specific shares for their forecasting (Thawornwong, Enke and Dagli, 2003). Others yet, create a basket of shares in order to approximate indices (Guresen, Kayakutlu and Daim, 2011), the index itself or even significantly large portions of the index component shares (Huang, Nakamori and Wang, 2005; Wen, Yang, Song and Jia, 2010).

When reading research on the forecasting of an index, one has to wonder why the index was chosen--this reason and motivation for the selection of an index goes frequently unstated, leaving one only to speculate: perhaps the index has a smoothing effect, allowing the researchers to more easily apply a model in a pre-generalized method with a built-in bias for momentum where the aggregate "herd" of stocks moves cohesively, thereby lending itself well to the machine learning algorithms. Moreover, the studies forecasting the index often seek to forecast the *direction* of the index (Kim, 2003) and so are able to report significantly higher accuracy rates, even though the base rate for a boolean is *essentially* 50% (under "random" conditions).

In this manner, one is left to suspect some form bias, perhaps even unconscious, but nonetheless providing ground for Keogh and Kasetty's (2003) call for better benchmarking in data mining: choosing test candidates that will create more impactful model results than if applied to a more complex scenario. To balance the last statement, one should note the challenges of forecasting a **specific value** for a single time observation when the ratio of signal-to-noise is low and so directional prediction is an arguably valid simplification mechanism. Others have sought to forecast the probability distributions of an index-at-close as another simplification process (Weigend and Shi, 2000).

2.2.6. Data Pre-Processing

Not to be confused with the somewhat pejorative moniker "noise trader," an emerging body of research now takes to applying wavelet algorithms to the price inputs in an attempt to "denoise" the variable inputs. An early example of pre-training data transformation is Tay and Cao (2001) in which they transformed the prices into a relative difference in percentage of price, which makes the data more symmetrical. After this transformation, the authors went a step further by replacing all values that were more than two standard deviations with the next closest value. The goal with the replacements was to remove the major shocks in the learning algorithm's training set, under the presumption that those events were rare and simply added to the overall noise in the system. This transformation was unique to the reviewed literature but might be considered a precursor, in some ways, to future wavelet transformations which sought to reduce noise and variance by applying smoothing functions.

Hsieh, Hsiao and Yeh (2011), for example, applied the Haar wavelet transform to decompose the price feature before conducting stepwise regression analysis for feature selection--their model ultimately fed into an artificial bee colony-driven BP-ANN. Another compelling example of wavelet transforms applied to price inputs was conducted by Wang, Wang, Zhang and Guo (2011) in which a threefold Discrete Fourier Transform (DFT) was applied, in an attempt at separating the noise from the signal. In this study, Wang et al. found two passes with the DFT into a ANN outperformed the third transformation pass, in which too much signal flattening had occurred.

Another common pre-processing step is to *normalize* the feature values so that they range from 0 to 1 or -1 to 1 (Lee, 2009; Wen, Yang, Song, and Jia, 2010). This is done so that none of the features carry too large a weight. That is, if a feature input such as Volume is used, it may be measured in millions of units but another input feature such as a moving average may only be measured in tens (or hundreds) or dollars.

2.2.7. Ensembles: Multiple Predictors are Greater than One

A theme noteworthy within the literature is the inclusion of ensembles. An ensemble is the combination of multiple prediction models or model pipelines combined, often through a weighting or 'voting' mechanism, that through the blending of the forecasts, is able to make better predictions. (Dietterich, 2000) The rational thought exercise leading to an ensemble technique is that if there is a complex task for which a learning expertise is required to perform, then multiple experts will perform better than one. (Huang, Nakamori and Wang, 2005) Bagging, an ensembling technique, takes different samples from the overall training set (with replacement for each removed sample) and uses these subsets as inputs to the learning algorithm. The outputs are then blended to arrive at a final model prediction. (West, Dellana and Qian, 2005) Another ensembling technique Adaptive Boosting (or 'AdaBoosting' or, simply, 'Boosting) is an iterative, resampling technique in which the misclassified classes are given a higher distribution in the new sample, and correctly classified are given a lower distribution. (West, Dellana and Qian, 2005) After the resample is complete, the algorithms are retrained and new forecasts provided. This process may be completed multiple times.

While there is some evidence of ensemble in the literature, ensembling does not appear as a standard technique, rather a single "best model" is still the frequent reporting tool. This may not necessarily be due to researcher bias but simply the result of a complex field still seeking to homogenize around general single-model best practices. It was the reliance upon a single model which motivated West, Dellana and Qian (2005) to evaluate cross-validation, bagging and boosting as possible ensemble techniques--ultimately concluding that an ensemble of ANN models outperformed the single best model.

Examples of ensembles in security forecasting literature include Huang, Nakamori, and Wang (2005), Tsai and Hsiao (2010), Wang, Wang, Zhang, and Guo (2012), Wang, Wang, Zhang, and Guo (2011), and Wu, Luo and Li (2015).

When implementing ensembling techniques, experimenters should be wary of the findings from Zhou, Wu and Tang (2002) who found that ensembling some (or many) of the predicted models may perform better than an across-the-board aggregation of all models, particularly when measuring for a generalized model.

2.2.8. Model Evaluation

The last major research area pertinent to this experiment is the method of model evaluation. As Keogh and Kasetty (2003) illustrate, there is a need for creating a rigorous method of evaluating a model's efficacy, an area according to Keogh and Kasetty (ibid) the data mining community has been prone to positing exaggerated results. Despite a lack of clear-cut benchmarks, the literature for model evaluation is as diverse as the predictive models.

In terms of statistical measures, many researchers chose to use measures such as root mean square error (RMSE) (Kara, Boyacioglu and Baykan, 2011), mean absolute percent error (MAPE) (Ticknor, 2013), mean squared error (MSE) (Wen, Yang, Song, and Jia, 2010) and normalized mean square error (Tay and Cao, 2002). As stated previously, some researchers elected to forecast the *direction* of the market--for example whether the next day movement of the market will be higher or lower than the previous day. In these instances, the researchers chose classification metrics such as F1 scores (Lee, 2009). Others yet chose to compare their models based on profitabilty (Kim and Han, 2001; Thawornwong, Enke and Dagli, 2003; Teixeira and Inácio de Oliveira, 2010; Wen, Yang, Song and Jia, 2010) and in some cases developing trading algorithms for comparision with the less active investement strategy of "buying and holding" (Kim and Han, 2001; Thawornwong, Enke and Dagli, 2003; Enke and Thawornwong, 2005). From a the 100-plus survey conducted by Atsalakis and Valavanis (2009), it is clear that researchers use varying evaluation techniques for their models. However, the standard statistical measures are used, namely root mean square error (RMSE), mean absolute error (MAE) and mean squared error (MSE), with perhaps a skew toward using RMSE. One advantage of RMSE is that the results are reported in the same form as the predicted variable--for example "dollars" for a stock price.

As one might expect, there is a mixed set of results regarding the comparison of various algorithmic approaches to security forecasting, with some researchers claiming outperformance with SVMs while others illustrate "conclusively" the superior efficacy of ANNs (Huang, Nakamori and Wang, 2005; Kara, Boyacioglu, and Baykan, 2011). Moverover, the detailed meta-study of over 100 research studies, many of which included internal comparisons themselves, conducted by Atsalakis and Valavanis (2009) did not conclude with a single-best model archetype, but the rather conservative notion that ANN and neuro-fuzzy models are *appropriate* soft computing techniques for stock forecasting.

2.3. Summary

2.3.1. Summary of Literature

A common thread in security forecasting model inputs is a citation of Fama's Efficient Market Hypothesis (EMH), which effectively states that an efficient market is one in which information freely disseminates and is therefore fully reflected in a security price (Fama, 1965; Fama, 1970; Cao, Leggio and Schniederjans, 2005). That is, security prices fully reflect all public information pertinent to a security, with no information "advantage" that some arbitrage investors have over others. The market is informationally efficient and so security prices fully reflect all information. As such, **the use of historical prices to forecast future prices is invalid because it is only new information not reflected in security prices (new innovations, new market growth, new profitability, etc) that will impact future prices. Nonetheless, there are dozens and dozens of studies which rely upon technical indicators to forecast the future—and claims of successfully doing so while citing the Efficient Market Hypothesis as relevant.**

2.3.2. Gaps in Literature and Open Problems

So perhaps ironically, these researchers cite the EMH from an act of precedent in prior influential work but then use tools which would seemingly contradict the EMH. In any case, one is left to ask, "*are technical values reliably useful as inputs to a security* *forecasting model?"* and if so, to "what extent do they impact a model in contrast with traditional fundamental values?" As far as this author is aware, aside from work completed by Thawornwong, Enke and Dagli (2003) little research has been conducted that is focused exclusively on the *validity* of using technical variables as inputs to security forecasting.

The machine learning literature focused on financial security forecasting relies extensively on historic price derivatives. These same studies frequently cite Fama's Efficient Market Hypothesis as a basis for the use of historical information to reflect the intrinsic value of a security. However, a careful reading of Fama's work, including his seminal work "The Behavior of Stock-Market Prices" (1965), would indicate that Fama himself sees the market response to information as swift—and so there is very little information in historic prices to indicate the direction of future stock prices.

It is by no means intended to position this research question as entirely novel, as other researchers have also noted the tension between academia's reluctance toward the use of technical features. Zhu and Zhou (2009), for example, see the skepticism around technical analysis as originating from research methods which use technical analysis as "all or nothing," which in their opinion is too simplistic to adequately represent the actual use of technicals within industry. Their take, and research, is compelling in that allowing for an asset allocation mechanism which is more fluid allows for general models to leverage the value of technicals as an a variance approximator since the "True Model" is unknown. This in many ways fits in nicely with the work by DeLong, Shleifer, Summers and Waldmann (1990) who found that a market may experience protracted, irrational valuations from noise traders until the effects of arbitrage are able to rebalance security valuation. Thier research also maps well to the subsequent work by Verma, Baklaci and Soydemir (2008) as well as the psychological or "behavioral economic" basis for understanding the interplay between market participants and visceral factors (De Bondt, and Thaler, 1985; Loewenstein, 2000).

2.3.3. The Research Question

It was through a review of the conflicting notions of legitimate model inputs used in literature, of which were too frequently left unjustified outside a few notable examples

(Thawornwong,Enke and Dagli, 2003) that the primary impetus for the research at hand was generated: ***are technical indicators a valid input for machine learning algorithms and do they perform at or near the level of fundamentals-only models?***

3. Design / Methodology

3.1. Introduction

The following chapter will explore the data required to satisfy the research and experimentation indicated by the overriding research question:

1. **Are technical indicators a valid input for machine learning security forecasting** and whether a) fundamental economic indicators perform better than the technical model or b) does a blend of technical and fundamental indicators prove more effectual for the learning algorithms.
2. In addition to an overview of the input data for the experiment and the selection criteria for the included companies, **this chapter clarifies the nuances of data treatment** -- this is an important consideration because, for example, some fundamental data is released at different regularities than daily values such as High, Low, and Close.
3. This **chapter concludes with an explanation of the model development**, the tools implemented to evaluate model performance and the limitations and strengths of the design.

Figure 3.1 provides an overview of the following sections, each outlining the design, methodologies, and considerations pertinent to the execution of this research endeavour.

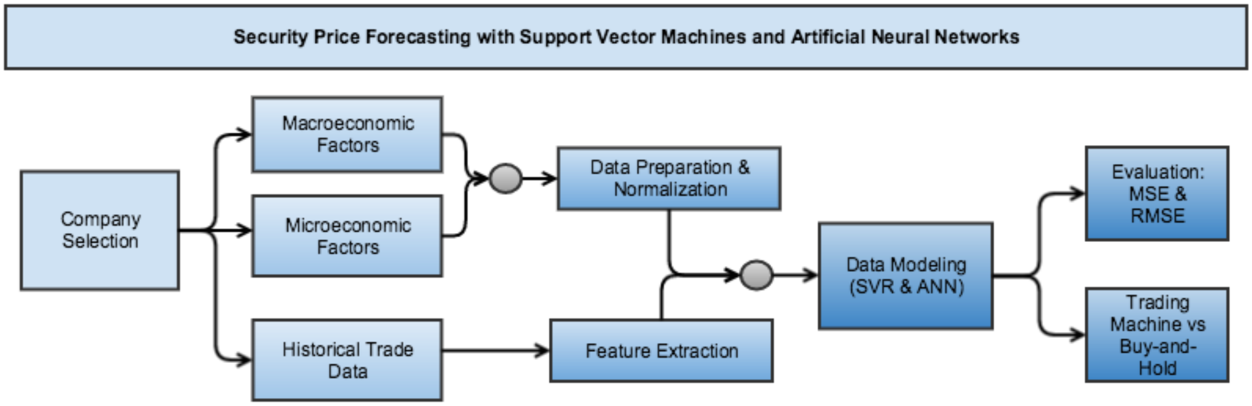


Figure 3.1 provides an overview of the design architecture for evaluating the efficacy of technical indicators used in Support Vector Machines and Artificial Neural Networks. In addition to addressing the company selection process, the macro- and microeconomic indicators and the process for deriving technical features, data modeling and trading machine algorithms are addressed in detail.

3.2. Studied Companies

From a larger body of 50 securities, an initial candidate list of 22 were identified. This group was then pair-down again to 12 companies traded on the S&P 500, listed in Table 3.1. To arrive at this final group, the company was required to meet a number of selection criteria outlined in the following section.

Company	Ticker	Exchange	Industry	Market Capitalization, Billions USD†
AT&T Inc.	T	NYSE	Telecommunication Services	269.23
Boeing Co	BA	NYSE	Industrials, Aviation	82.50
Capital One Financial Corp.	COF	NYSE	Financials, Consumer Credit	31.96
Chevron Corporation	CVX	NYSE	Oil & Gas Refining	195.02
Ford Motor Company	F	NYSE	Automotive	51.14
General Electric Company	GE	NYSE	Industrials, Industrial Conglomerates	289.66
McDonald's Corporation	MCD	NYSE	Consumer Goods and Services	105.75
Microsoft Corporation	MSFT	Nasdaq	Technology, Software	402.06
Oracle Corporation	ORCL	NYSE	Technology, Enterprise Software	168.17
Target Corporation	TGT	NYSE	Consumer Goods and Services	41.41
Wal-Mart Stores, Inc.	WMT	NYSE	Consumer Goods and Services	226.27
ExxonMobil Corporation	XOM	NYSE	Oil & Gas Refining	389.53

Table 3.1 provides a summary of the studied companies, along with the exchange ticker symbol. Due to the designed-in restrictiveness of the study, only one company (Microsoft) from the Nasdaq was able to meet all study-inclusion requirements. †Values as of July 1, 2016, obtained from Google Finance.

3.2.1. Selection Criteria

3.2.1.a. US Exchange

In order to be included in the study, each company must be listed on a US exchange (i.e. New York Stock Exchange, "NYSE," or Nasdaq) as a normal, non-ADR (American Depositary Receipt). This criteria were implemented in order to normalize currency exchange rates -- that is, all company shares are valued in the same currency (USD) thereby eliminating concern for currency arbitrage reflected in the security prices. Further, the securities were exchanged in the same time zone (EST, GMT+4), allowing for any major news to equally affect all shares. Moreover, "crises" as experienced by the US circa 2008 - 2009 ("the Great Recession") were equally present in the studied securities as they were all US-based while effectively normalizing for non-US crises such as the Eurozone's "Grexit" (2015).

3.2.1.b. Capitalization, Liquidity, and Visibility

Each company must be listed on the S&P500 for the duration of the study. The S&P500 is an index of the largest 500 companies listed on either the NYSE or Nasdaq managed by Standard & Poor's Financial Services LLC ("S&P"), a division of McGraw Hill Financial. The purpose of this constraint was to limit the range of possible companies in the experiment.

Because companies in the S&P500 constitute the largest companies on US exchanges, the experiment attempts to reduce volatility restricted to smaller firms which may be less established than larger, more stable companies in the S&P500. Moreover, the largest companies are also actively traded, often with large volume of shares exchanged daily. This is important because smaller company shares may experience high-volatility due to a lack of liquidity in the underlying shares--that is, if a company share is not traded frequently, the market exchange of a share may inflect a high rate of change from previous trades. By limiting the study to companies to the S&P500, this low-volume trade risk can be minimized.

Finally, **the S&P500 companies will be exposed to a high degree of scrutiny by the investment community and so, in light of Fama's Efficient Market Hypothesis, should be good candidates for evaluating the validity of information availability as**

reflected in historical prices. That is to say, because the companies are tracked not just by a myriad of third-party investment advisors but also by innumerable individual investors and investment firms, technical indicators should, according to Fama's EMH, carry no worthwhile information and only new changes in company performance should impact shares (Fama, 1965; Fama and French, 1988).

This is a nuanced point of the study so a moment of attention is worthwhile here: **the rationality of technical indicators is called into question because the purpose of a technical indicator is to provide a historical price pattern from which investors might extrapolate trade inflection points in the future but the Random Walk would indicate there is no temporal dependency of future prices on historical prices (Fama, 1965). However, if technical indicators are able to provide a rubric for price forecasting, as illustrated by a low mean squared error (MSE) or root mean squared error (RMSE), then contrary to economic theory, derivative technical indicators *are* valid inputs to security forecasts.**

3.2.1.c. Security Stability -- Splits and Mergers

Stock splits (and reverse splits) are another possible confound this study attempted to control for. A stock split is when a share is divided from a single unit into multiple units.

For example, in June of 2014, Apple Corporation's shares were split 7-to-1. This means that for every share an investor possesses, the share was divided into 7 equal allotments. The new exchange price is then reflected by this further dilution as a directly divisible portion of the pre-split price. Following the example of Apple's 7-to-1 split, the new price was it's pre-split price divided by 7 ($700 / 7 = $70 per post-split share).

There are numerous reasons a firm may enter a split, though often it is to provide a higher degree of liquidity to the underlying security. A reverse split occurs when two or more shares of a company are "combined" into a new single share. While the study could have attempted to account for splits by tracking an "adjusted share price," it was determined early that this would simply constitute another confound to the study itself. This constraint, for example, excludes Apple, Google and Coca-Cola from the study.

3.2.1.d. Sector Variance

It was intuited that some company shares may be more easily modeled than others--for example shares of an oil and gas extraction company such as Exxon due to the tangibility of its underlying commodity (oil and gas). As such, the study's included companies attempted to pull from a variety of sectors. It is worth noting, particularly in the context of the experiment's goal to operationalize the forecasted security prices, that the purpose of diversifying the included securities by sector also creates a semi-realistic investor portfolio without being too general, as with previous work forecasting a major *index* itself (Kim, 2003; Enke and Thawornwong, 2005; Huang, Nakamori and Wang, 2005; Kara, Boyacioglu and Baykan, 2011).

3.2.1.e. Data Availability

The last major constraint was availability of data. Because much of the included data goes beyond simply open/close prices, it was important that specific information be available. Larger companies with a longer track record of presence on the exchanges increased the odds that the desired data could be gathered. Data availability notwithstanding, the data were gathered from a variety of disparate sources, often requiring multiple sources to complete a single company profile.

3.3. Data

Daily exchange data span a 9-year period. The first eight years were reserved for training and the final ninth year used as the test year--the "forecast period." For each company, there consists approximately 2500 daily observations over the 9-year period. The period selected was purposefully intended to capture the 2007 - 2009 market collapse in the US equities market. Due to slight variance in available data on each company and an implementation of complete cases only, the total data vary slightly by company. There is a mean daily observations of 2454, corresponding with approximately 272 trading days per year (range 2407 to 2485). In total the companies have up to 38 input features, depending on experiment type (Technicals, Fundamentals, Blended).

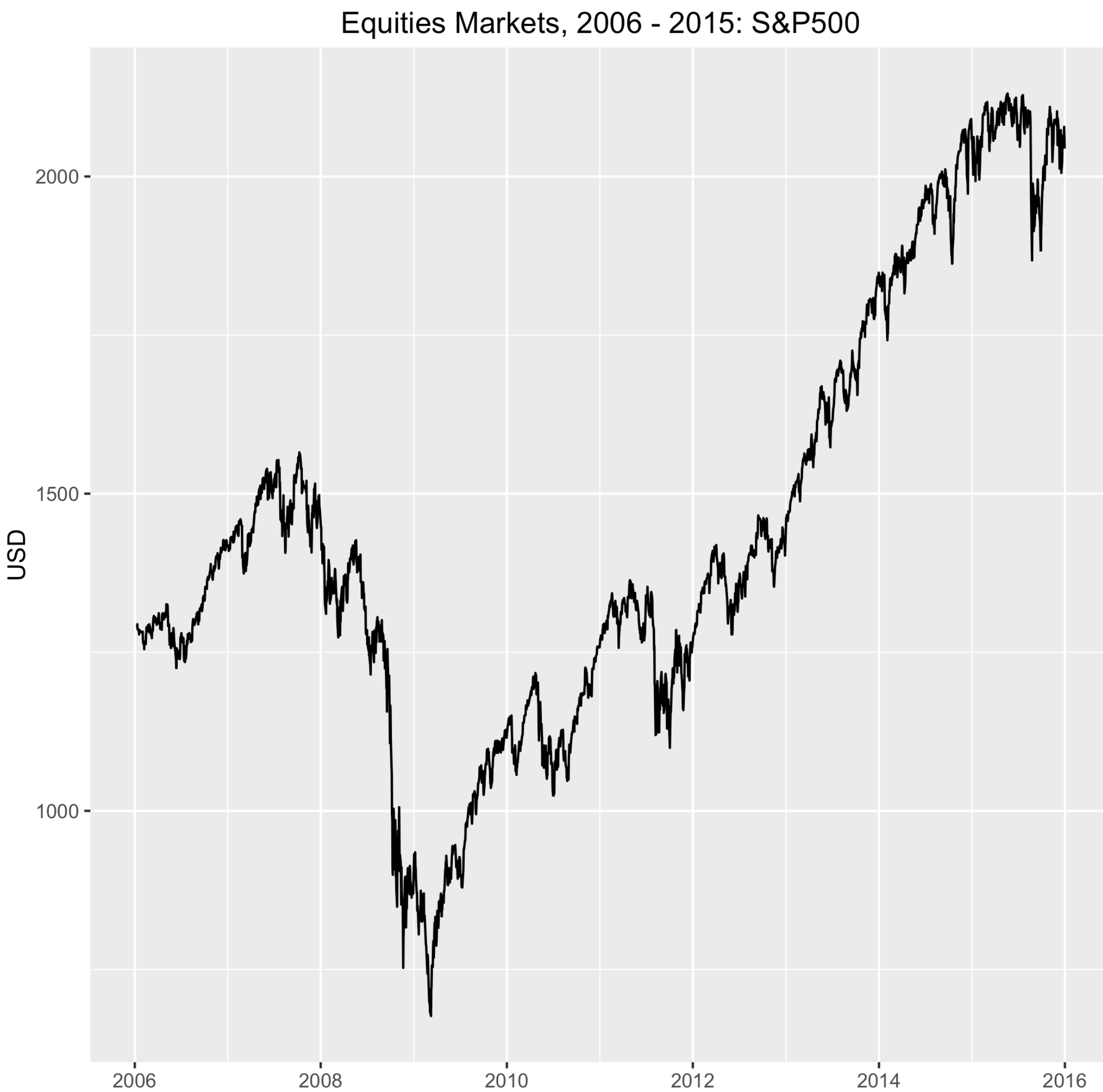


Figure 3.2 provides a historical view of the S&P500, a frequently used index for conceptualizing the growth or diminishment of the US economy as represented by the increase or decrease in the valuation of its largest corporate entities. Data span from 2006 to 2016 and include the sharp decline in the S&P500 which began at the end of 2007 and accelerated its decline into 2008, finally reaching its lowest point in the first quarter of 2009.

3.3.1. Daily Values

For each security in the study, the daily Open, High, Low and Close price were gathered. The transactional data was sourced from Yahoo! Finance, a frequently used source for security data. The raw data included the Volume of shares exchanged as well as an Adjusted Close. These two latter values were excluded from the study, the former because most prior research makes little use of Volume--likely because high volume can indicate both positive and negative news and so constitutes needless noise. The last value (Adjusted Close) was excluded because, as outlined within the "Selection Criteria," any security which would carry an adjusted close (due to splits) for the experiment's examination window (2006-2015) were excluded from the study.

For the derivative technical features, please referenced Chapter 3 "Data Preparation / Feature Extraction" below.

3.3.2. Fundamentals

In order to model the economic factors impacting a business, two general sets of data were gathered: Macro- and Microeconomic Indicators.

1. The **Macroeconomic Indicators** *are defined herein as values external to the enterprise itself***.** That is, economic changes outside the direct control of the company itself. Examples include currency exchange rates, unemployment and new housing construction starts.
2. In contrast to the macroeconomic indicators, this study includes a number of **microeconomic indicators**, *those features more directly within the control of the company itself*. These include free cash flow, net profit (or loss) and gross margins. These features are included within the study to make each trained model company-specific.

So whereas the macroeconomic features provide a generalized environment in which a company is operating--and provide a general context in which investors are presumably evaluating a company's underlying stock value--the microeconomic indicators provide company-specific constraints used in the formulation of a company's value.

3.3.2.1. Fundamentals - Macroeconomic Indicators

These fundamentals are meant to act as proxies for the general health of the economy. As conducted by Huang, Nakamori, and Wang (2005), the S&P500's closing price was used as a proxy ("indirect") feature to represent a market assessment of the economy as a whole as well as to capture potential information not directly represented within the macro-economic feature set. Explained succinctly in the Huang et al. study (2005), the S&P500 is a collection of the 500 largest US traded companies, effectively spanning every industry and as such can be used as a proxy-feature representing a general litmus for the economy at large. This same study also provides an excellent example of relevant macroeconomic inputs such as industrial production, interest rates and gross domestic product (GDP).

Macroeconomic data were gathered from the United States Federal Reserve Economic Data, St Louis Fed ("FRED"). Ininial "proof of concept" data were gathered in the fall of 2015. Finalized data were gathered in the Spring of 2016. All data from FRED were updated at this time as noticeable revisions of the economic data were present. While there was concern that these revised figures were not representative of data available to investors at the time of reporting--because they investors were operating on non-revised data--Pierdzioch, Döpke and Hartmann (2008) showed that investment outcomes showed little change when accounting for revised figures. In all instances, the revisions were less than 1% change from previously gathered values.

Indicator	Abbrev.	Definition	Frequency
Civilian Labor Force Participation Rate	CIVPART	Percentage of individuals 16+ employed or seeking employment	Monthly
Civilian Unemployment Rate	UNRATE	Jobless individuals as percentage of total workforce	Monthly
Consumer Price Index, All Urban Consumers, All Items	CPIAUCSL	A measurement of changes in average price for a basket goods and services, restricted to urban residents, approx. 88% of US population†	Monthly
Federal Debt to GDP	GFDEGDQ188S	A ratio between Federal Gross Debt and Gross Domestic Product	Annually
Initial Jobless Claims, 4-Week Moving Average	IC4WSA	A moving average of all new jobless claims	Weekly
London Interbank Offered Rate (LIBOR)	USD1MTD156N	An average interest rate banks borrow funds from other banks, acting as a reference rate for short term interest rates	Daily
New Housing Starts	HOUSTNSA	The total of new home construction projects started in US	Monthly
Personal Consumption Expenditures	PCE	A measure accounting for approx two-thirds of final US household expenditures	Monthly
Personal Savings Rate	PSAVERT	A percentage of household saving to disposable personal income	Monthly
% Change Real Gross Domestic Product	A191RL1Q225SBEA	Measure in the percentage change in economic output adjusted for inflation	Quarterly
S&P500 Closing	spClose	An index of the 500 largest companies traded on US exchanges	Daily
USD / Euro Exchange	DEXUSEU	The exchange rate between a US Dollar and the Eurozone Euro	Daily
USD per Barrel Oil (Brent Crude)	DCOILBRENTEU	A crude produced in the North Sea, used as a reference price for other crude types	Daily
10-year Treasury, Constant Maturity	DFII10	A yield on US-backed treasury bonds, frequently used as a benchmark for other interest rates such as mortgages or as a “signal” for investor confidence	Daily

Table 3.2 provides a summary of each macroeconomic indicator included in the study and a short explanation for its inclusion and, if available, a citation of prior work using a similar feature.

3.3.2.2. Fundamentals - Microeconomic Indicators

Microeconomic indicators are included, as mentioned above, to provide company-specific context for the learning algorithms. These features include the free cash flow, net profit, margins and earnings per share. These data were largely gathered from YCharts, a subscription-based data repository for company financials. Data were gathered during a free seven-day trial, so no monetary value was exchanged for the study's data. Table 3.3 summarizes the included micro-economic indicators and includes a justification for the metric.

Indicator	Abbrev.	Definition	Frequency
Total Revenue	total_revenue	The gross receipts received by company, before interest, taxes, depreciation and amortization	Quarterly
Net Income	net_income	Total revenue after expenses	Quarterly
Earnings per Share, Annual	EPS	The net income divided by the total outstanding shares ("float") aggregated as the prior 4 quarters	Annual-to-Date
Total Assets	total_assets	Total cash / cash-equivalents and receivables presented on balance sheet	Quarterly
Total Liabilities	total_liabilities	Total debt and financial obligations owed to individuals or businesses	Quarterly
Free Cash Flow	free_cash_flow	Net change in cash for a period minus cash outlays for expenditures and dividends	Quarterly
Profit Margin	profit_margin	Cash available after accounting for expenditures as a percentage of total gross revenue	Quarterly
Price per Earnings	PE	The ratio between a stock price and the company's earnings per share	Daily

Table 3.3 shows the microeconomic features used for training on each company-specific model. If available, prior work using the same indicators is also provided.

3.4. Data Preparation / Feature Extraction

3.4.1. Derivative Technicals

Due to the nature of technical features, their values are all derivative of past price changes and, for the most part, may be summarized as variations of moving averages. The following section will provide an explanation for each of the technical values included in the study and the motivation for its inclusion.

3.4.1.1. Moving Averages

The study included two main types of Moving Average: Simple and Weighted. The simple moving average is a strict mean price over a given period, whereas the weighted moving average gives more impact to the near-term periods within the overall averaged period. For example, "yesterday" would carry more influence to the average than a close price from "last Thursday." The study included four moving averages of each type. The intent was to capture different pricing trends while also representing what appear to be commonly used moving averages by both prior researchers and technical trading practitioners (Gifford, 1995; Thawornwong, Enke and Dagli, 2003; Teixeira and Inácio de Oliveira, 2010; Kara, Boyacioglu and Baykan, 2011; Chang, Fan and Lin, 2011; Ticknor, 2013). The simple moving average spanned from the previous 5 trading days to a maximum of 200 days. The weighted moving average spanned the previous 10 days to a maximum of 200 trading days. Note that for both SMA and WMA, the security's closing price was used for the calculation.

3.4.1.2. Relative Strength Indicator

The relative strength indicator (RSI) is largely to buttress "trading rules" which, according to technical traders, illustrates inflection points and market "signals" for when a security is “Overbought” or “Oversold” by tracking the magnitude of gains over the magnitude of declines in a security over an examination period, such as 10 days (Gifford, 1995; Murphy, 1999; Thawornwong, Enke and Dagli, 2003). The motivation for the RSI feature was to provide an indicator frequently used both in machine learning literature and by technical practitioners (Thawornwong, Enke and Dagli, 2003; Teixeira and Inácio de Oliveira, 2010; Wen, Yang, Song, and Jia, 2010; Kara, Boyacioglu and Baykan, 2011; Ni, Ni and Gao, 2011; Chang, Fan and Lin, 2011; Ticknor, 2013).

3.4.1.3. Commodity Channel Index

Originally proposed by Donald Lambert in 1980 to track the cyclical valuations of tangible industrial commodities such as copper, the CCI has been applied by investors and traders across a number of security types (Harrington, 2005). The CCI value typically ranges from -100 to 100 with market entry signals initiated when the CCI cross zero. In addition to being a strong metric used by technical trading practitioners, the CCI is used in a number of existing research configurations such as Kim and Han (2001) and Kara, Boyacioglu and Baykan (2011).

Variable Name	Frequency	Definition	
Open	Daily	The price of the first exchange when markets open	
High	Daily	The highest exchanged price on a given day	
Low	Daily	The lowest exchanged price on a given day	
Close	Daily	The price of the security for the last exchange before markets close	
Volume	Daily	The total number of shares exchanged on the market	
Simple Moving Average (SMA)	Daily	An average of all observations over a number of periods. Here, 8 previous Closing prices	$= \sum_{i=1}^{t} C_i / t$
Weighted Moving Average (WMA)	Daily	Similar to SMA but weighting oldest periods less than most recent. Here uses 12 previous Closing prices	$= (\sum_{i=1}^{t} W_i * C_i) / \sum_{i=1}^{t} W_t$
Relative Strength Indicator	Daily	Compares magnitudes of gains and losses, resulting in range from 0 to 100	$= 100 - 100/(1 + RS)$ $RS = AvgGain / AvgLoss$ $AvgGain = (\sum_{i=1}^{t} Gains) / t$ $AvgLoss = (\sum_{i=1}^{t} Losses) / t$
Commodity Channel Index	Daily	A measurement of a security's price from its statistical mean based on historical price metrics	$= (TP - SMA_{20}) / (.015 * MD)$ $TP = \sum_{i=1}^{t} (P_{i-high} + P_{i-low} + P_{close}) / 3$

Table 3.4 defines the type of technical feature used in this study as well as the formulas for calculating the feature itself. In the formulas, C is the closing price, W is a weight for a specific period†, P is a price, denoted as "close" or "high" (at time period i). RS is "relative strength," TP is "typical price" and is calculated for each period over a measured timeframe (20 used here). For the purpose of this study, Secondary variables have been excluded. We include them here in order to provide transparency. †As a weight, one has flexibility in this adjustment parameter, allocating variable weights per period or a constant decrement for each period prior to time t, such that, for example, time t-1 might carry half as much weight as time t; time t-2 would carry half again the weight of time t-1, etc.

3.4.1.4. Non-daily Data

Worth mention is the treatment of Earnings Dates and underlying quarterly (or annually) reported data.

While a company's fiscal quarter (or annual operation) will cease on specific dates (e.g. December 31st), the actual results for that quarter or year are not known for a number of weeks afterward. As such, there is an offset of time, specific to each company, delineating the actual end of the quarter and the pragmatic end of a quarter. In other words, while the fiscal quarter may have ended on December 31st or September 31st of each year, the investors do not have access to actual performance until afterward and as such are operating on "old information." For example, the reporting date for most company prior-year data occurs in late January. This means investors are unaware of the actual fiscal performance for holdings they possess. If a company experienced lower (or higher) than expected performance, investors as a class are unaware of this performance until after the "earnings release date" (and earnings call). This experiment attempts to account for the information black-out period by propagating prior-quarter's data forward up until the new quarterly (or annual) data is made available. This is a subtle point in the data and constitutes an assumption. If one were to simply pull the raw financial data, one might mistakenly attribute that data as publicly available at the quarter-end date. Financial release data were gathered based on the earnings call dates, as collated by both ConferenceCall.org and verified on Etrade.com.

As is likely evident, the quarterly (and annual) data are reported as single values for a specified period. As such, for both company microeconomic indicators as well as general macroeconomic indicators, the factors are treated as constants for the duration of the reporting period. In other words, if the four-week unemployment new claims data reported 300,000 new claimants for the prior four-week period, that 300,000 is generated as a daily value of 300,000 until the next new claimant data are released. The same process is followed for all micro- and macro-economic data. A research justification for this decision was based upon Pierdzioch, Döpke and Hartmann (2008) who found that despite any noise present in the real-time data, investors can use current macroeconomic information and achieve the same average utility. That is, even if the macroeconomic data were subsequently corrected, the investment decisions used to determine the overall market volatility based upon (somewhat) incorrect figures resulted in nearly the same overall results as using the actual (subsequently corrected) macroeconomic data. This resulted in the final two assumptions to non-daily values: 1) to propagate macro-economic figures as constants for an entire period and 2) to use the currently available macroeconomic figures and effectively ignore that some data might have been updated since their original release. Indeed from the time data gathering began in the Fall of 2015 until mid-Spring 2016, there were updates and slight modifications to macroeconomic figures.

3.5. Data Modeling

3.5.1. Model Evaluation

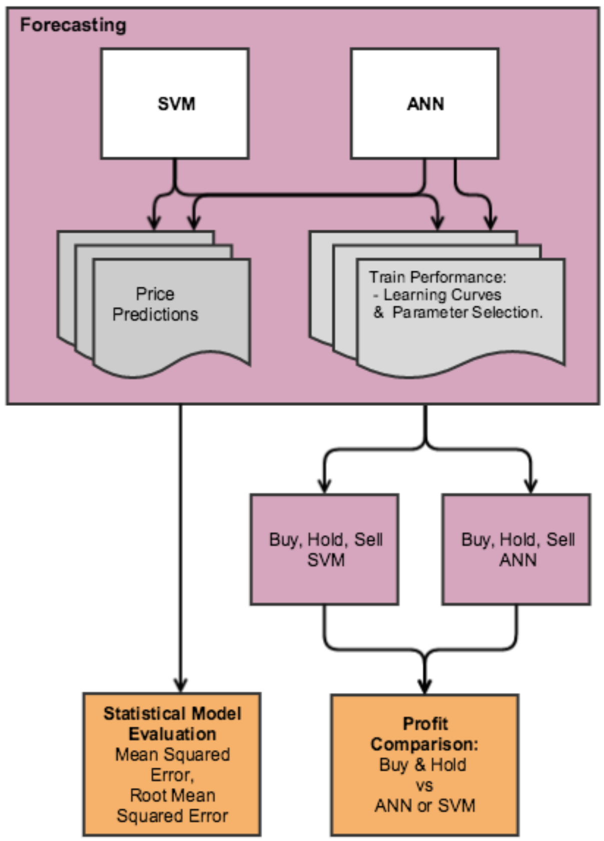


Figure 3.3 illustrates the model pipeline for training, testing and evaluating model performance.

Depicted by **Figure 3.3** (left), this experiment uses two methods to evaluate the performance of the input indicators and the predictive algorithms:

The first method relies upon the 100-plus survey conducted by Atsalakis and Valavanis (2009) which illustrates that researchers use varying evaluation techniques for their models. However, the standard statistical measures used are root mean square error (RMSE), mean absolute error (MAE) and mean squared error (MSE). RMSE and MSE are also used by Refenes Zapranis and Francis (1994); Enke and Thawornwong (2005); Hsieha, Hsiao and Yeh (2011); and Ticknor (2013).

The second method uses the operationalized trading machine which makes a comparison of the profit generated by the model itself, also mimicking prior work (Thawornwong, Enke and Dagli, 2003; Enke and Thawornwong, 2005; Wen, Yang, Song, and Jia, 2010; Chang, Fan and Lin, 2011; Ticknor, 2013). Though the former statistical evaluation is likely adequate from a theory-based research perspective, the later is able to bridge the gulf between theory and praxis by operationalizing the regression. From this researcher's perspective, rather than reporting a theoretical regression error, the trading machine is able to simulate what a trader utilizing the models might have experienced. Further, it is a seemingly trivial matter to compare the profit of a machine-based algorithmic buying scheme to buy-and-hold and this marginal increase in labor dramatically improves the compelling nature of the overall research project.

3.5.2. Trading Machine

The price-based trading machine (PBTM) is intentionally simple by design. For example, the PBTM is only able to take long positions (buy) and not make shorts or speculate with option purchases. The PBTM is intended to be a simple contrast to the 'buy-and-hold' strategy (BAHS) which will make a single purchase in a company and hold the [long] position until a future date.

For the purposes of the experimental comparison, both the PBTM and the BAHS must completely exit their positions at the end of trading 2015. For each company, both the PBTM and BAHS models are provided $1000 for investment (Wen, Yang, Song, and Jia, 2010). The BAHS will simply make a $1000 purchase at the beginning of the period (January 2015). The PBTM, on the other hand, will make purchase and sell decisions based upon the input model's forecasted prices: if the forecasted price is higher than the previous close *and* there is not already an open position, then the PBTM will make a stock purchase, using the entire $1000 for investment. Similar to Teixeira and Inácio de Oliveira (2010), the PBTM position is exited if there is a gain of more than 10% (stopgain) or a loss greater than 3% (stoploss) or if the experiment period ends prior to exiting the open position(December 2015). The purchase and sell prices for both PBTM and BAHS is the mean of the next day's Open, Low, High, and Close prices, as an emulation of a realistic execution price. This configuration is loosely based upon the models presented by Enke and Thawornwong (2005); Teixeira and Inácio de Oliveira (2010); Wen, Yang, Song, and Jia (2010); and Ticknor (2013).

3.6. Strengths and Weaknesses of Designed Solution

3.6.1. Strengths

The primary strength of the experiment is that all features are treated as a black-box. Whereas some prior research into the use of technicals often implements specific trading rules (Kim and Han, 2001; Friesen, Weller and Dunham,2009; Chang, Fan and Lin, 2011), the models treated all inputs as generic features of the same depth and shape. This is particularly important with regards to the *null hypothesis* that due to the EMH *technicals are an invalid learning machine input for stock price regressions.*

Following the explicit absence of trading rules, the learning algorithms in the technicals model are able to "learn" *if* there are any patterns in the historical prices, as purported by technical "chartists". The trading machine then makes purchase decisions based upon those learned patterns. This effectively, though to a limited capacity, allows the experiment to mimic how a technical, chart-based investor *might* make decisions.

Another strength of this design is that he experiment seeks to use a moderately wide range of companies to help eliminate industry bias. Rather than focus on two or three companies or upon a specific industry type (pharmaceuticals, oil & gas, etc) or on an *index* of companies (such as the S&P500), the experiment looks at a moderate range of companies spanning multiple industry segments. This is important because an index is a somewhat abstract notion and the direct applicability of testing the relationship of the EMH to an index is unclear. Moreover, the disparate industry inclusion allows the experiment to test the EMH and technical indicators in a variety of settings, some of which may be more susceptible to forecasting (based on technicals) than others.

Worth noting is that this experiment continues a recent need to make model comparisons between ANN and SVR and establish benchmarks across a number of companies. The setup and data are both reproducible making a "template" from which more companies could be fed into the same experimental process and a broader evaluation made. That is, there is nothing inherent in the experiment to stop the evaluation at 12 companies (other than time).

3.6.2. Weaknesses

The first major weakness in the experiments, meant to train and forecast price movements, is that each model type (technicals, fundamentals, blended) pull from a limited set of features. For the technicals-only experiment, there may be much better derivative features to include. For example, a number of previous researchers have used William's %R, Stochastic Oscillator (%K and %D) and MACD as learning inputs while other studies use weighted averages and Open, High, Low and Close as inputs (Kim and Han, 2001; Kim, 2003; Thawornwong, Enke and Dagli, 2003; Teixeira and Inácio de Oliveira, 2010; Hsieh, Hsiao and Yeh, 2011; Kara, Boyacioglu and Baykan, 2011; Ticknor, 2013). However, the selection and *limitation* of used features was essentially arbitrary. Increasing the range of feature options or deriving different magnitudes of weighted averages (different time windows) could yield very different results.

Another major weakness is that all three models are treated exactly the same. For example, if the fundamentals are released quarterly, it may be more apt to generate models specific to earnings release dates which seek to forecast 1-week or 1-month out dates, rather than daily values. On the opposite end of the spectrum is to train and test the technicals-only model on intraday data (hourly, etc) and to experiment with the inclusion of Volume or conducting wavelet transformations prior to training and testing. In other words, each forecasting perspective (technicals, fundamentals, blended) are effectively very different types of inputs and so models might be better suited to be custom to the input type, rather than generic.

A tangentially related weakness is that the purchase and sell prices might not reflect a realistic execution price. The price was calculated as a mean of the day's Open, High, Low and Close prices in an attempt to estimate a semi-realistic market rate. However, a careful investor with the prior-decision to make a buy or sell decision, might very well execute the trade at a better-than-mean price.

Another weakness of the experiment is that the trade decisions are made on a daily basis. It may be more effectual if the models would make intraday forecasts and to enter and exit positions on a daily basis. That is, rather than forecasting the Close price exclusively, the models could be used to forecast the Open, High, Low *and* Close, and then to make purchase decisions based on the four price points while subsequently attempting to make buy and sell decisions within the single day timeframe. Such a process might limit the risks of maintaining open positions for prolonged periods, as well as focus more on market timing--the main advantage proposed by a machine learning application.

The experiment and models could be expanded to include a range of feature tests or feature-limiting (PCA, SVD) to examine which features help (or erode) model efficacy. A specific focus on feature selection and feature-inclusion rules could also help elucidate the effects of propagating quarterly or monthly data as constants (for the Fundamentals and Blended models).

4. Implementation / Results

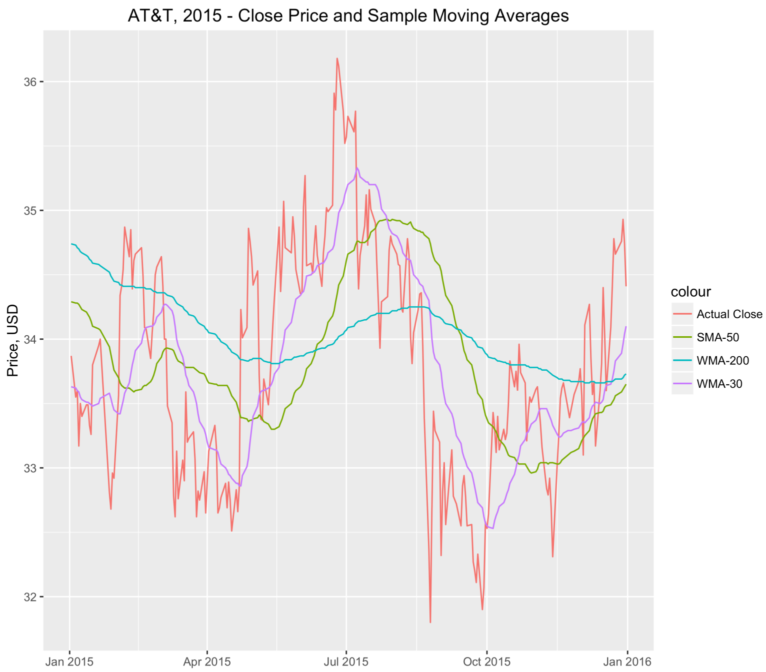
4.1. Software

The experiment was conducted using Python scripts. In particular, the project relies heavily upon Numpy, Pandas and Scikit Learn, three very commonly used open source libraries intended for machine learning and data analysis. The Artificial Neural Network used Keras, another open source library for Python built as an extension to Theano. Some post-experiment analysis and data visualization utilized R, another open source software package designed for statistical analysis. Ggplot2, an R package, was utilized in particular for the post-experiment data visualizations.

4.2. Data Exploration

The following section will outline the features used in the three experiment phases. The initial experiment consisted of training and testing models using derived technical features and, as such, are covered first. Following the technical features, the fundamental economic features are provided. Those fundamentals are subdivided into microeconomic (specific to the company) and macroeconomic (economy at large).

4.2.1. Technical Indicators



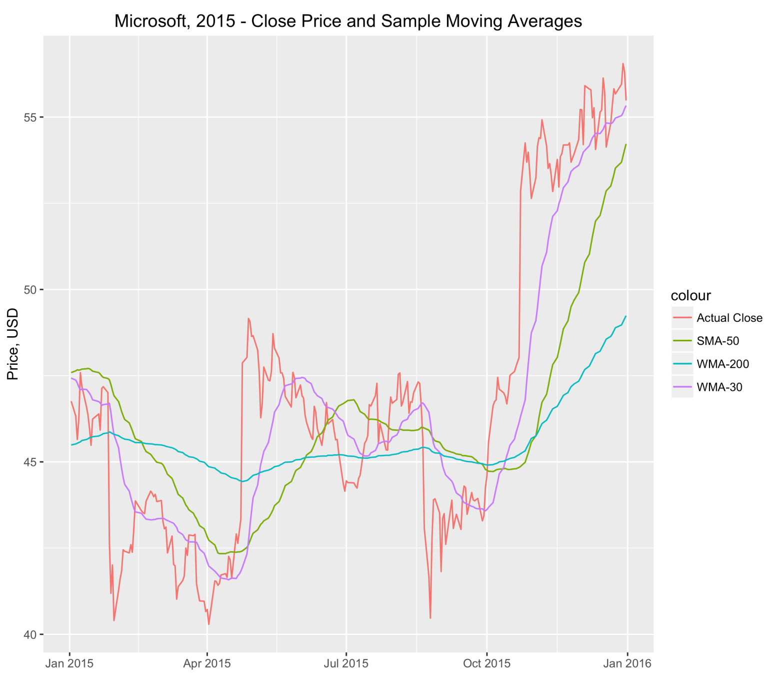


Figure 4.1 (left) shows two of the 12 companies' close prices ("Actual Close") with a sample of the 10 moving averages provided to the SVR and ANN for training. All companies exhibit high volatility on a day-to-day basis for 2015 with rapid changes from year-to-date highs and year-to-date-lows, which is common across the 12 companies in the study group. The moving averages provide a smoothing to the daily fluctuations and are used by traders to find inflection points--changes in direction--for making purchase and sell decisions.

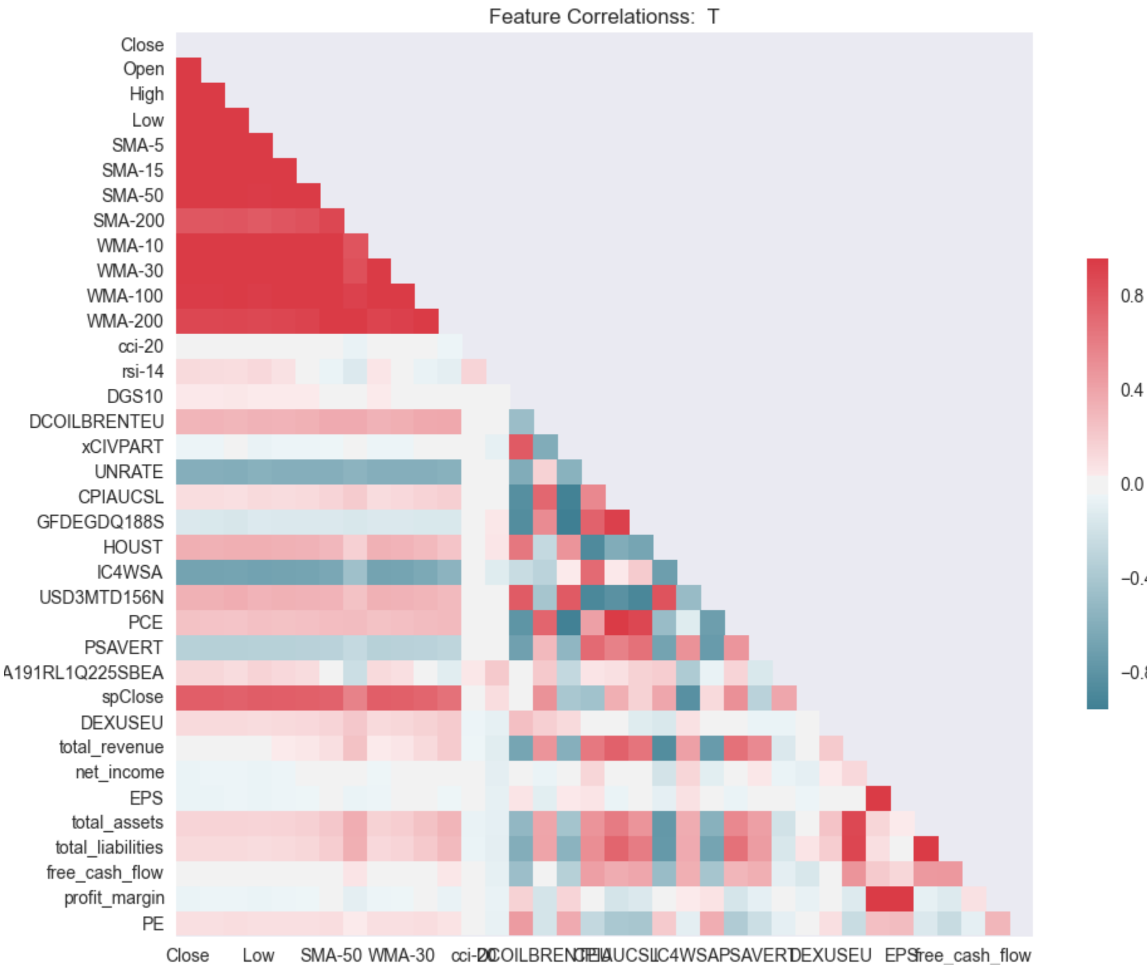


Figure 4.2, showing AT&T, is a correlation-based heat map for all features used in the experiment. As one might expect, there is a very strong correlation between the historical moving prices and the actual Close price, since Close is used for calculating the moving average itself. There is only a moderate to negligible correlation between other technical features such as the CCI and RSI. This is common across all securities in the study.

Figure 4.2 provides a heatmap (for AT&T) illustrating the correlation between the various features and the security's underlying Close price. *A priori* one would expect the Moving Averages (SMA-5, 15, etc) to have a high correlation with the closing price of the security since they are strictly derivative. From a hypothesis perspective, this does not provide significant information for developing new features. In terms of correlations with fundamental factors, intuition is again useful. For example, there *should* be a positive correlation between a security within the S&P500 and the index closing price itself. So far as company-specific factors, there is a variance among companies more closely tied to the price of oil (Chevron and Exxon) and those more decoupled (Oracle and Microsoft).

What is striking across the class of included securities is the CCI and RSI which appear to have no correlation whatsoever. The full set of heatmaps for all companies is available in Appendix A.

4.2.2. MicroEconomic Indicators

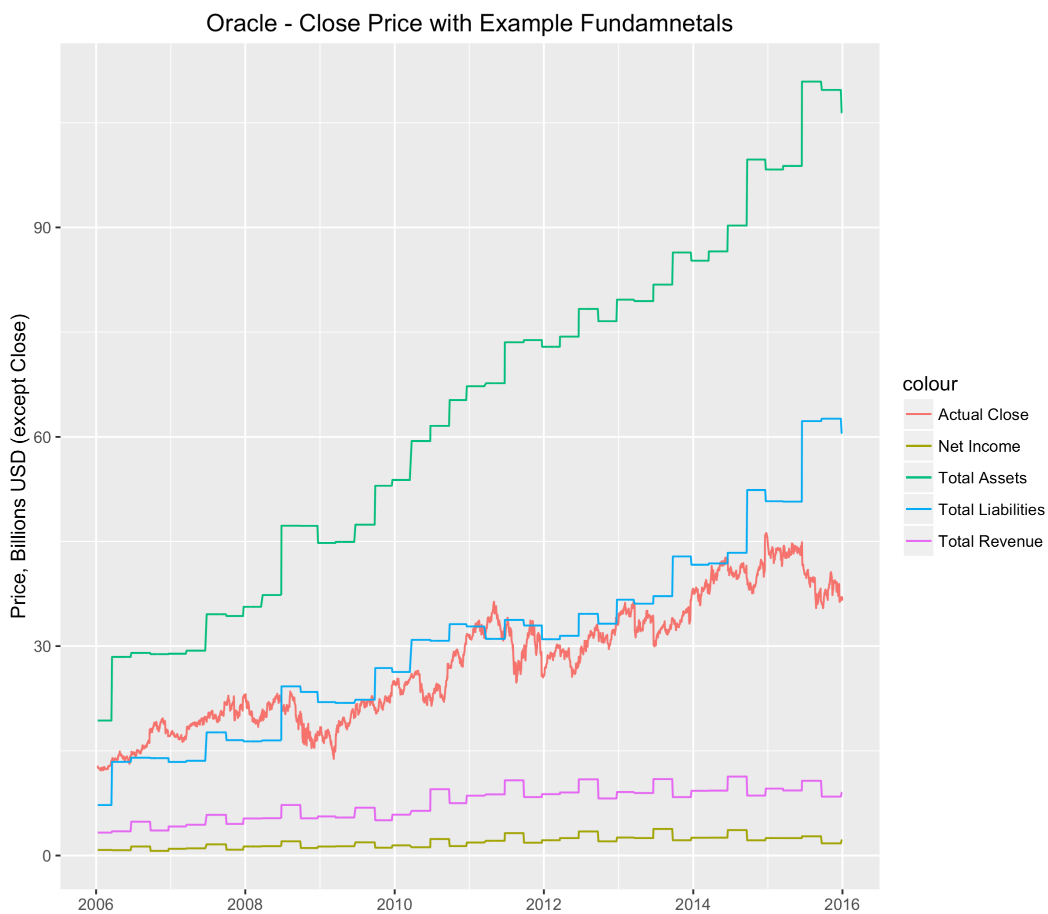
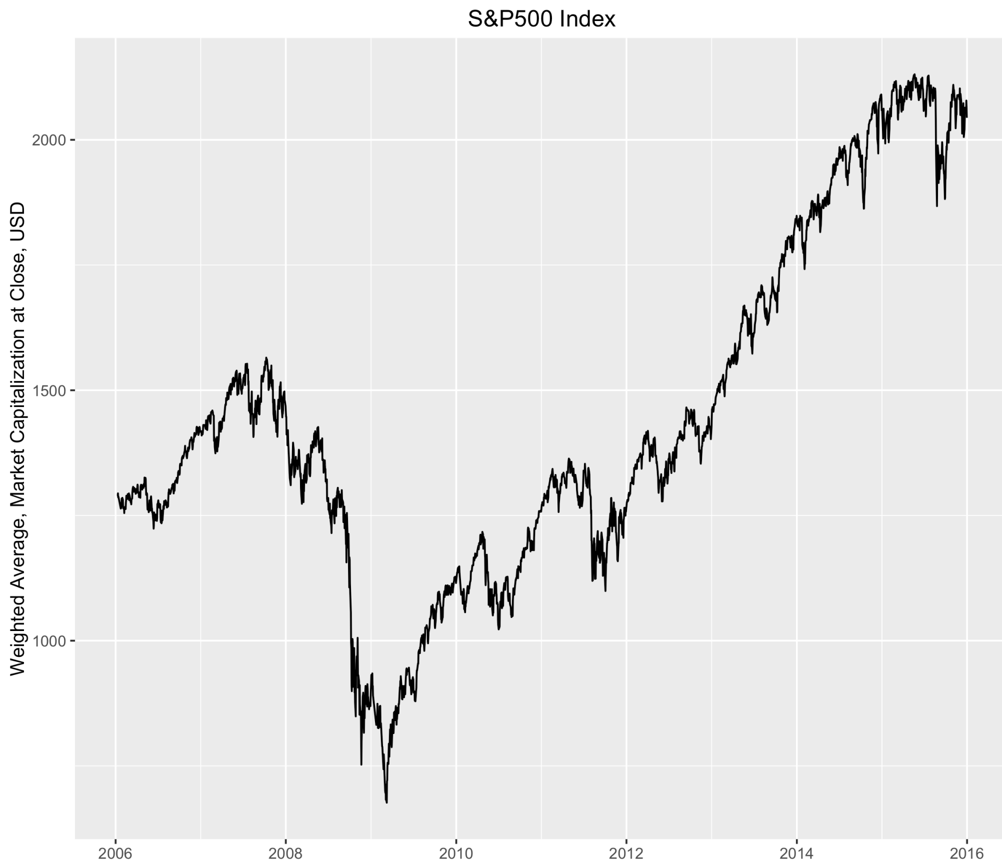


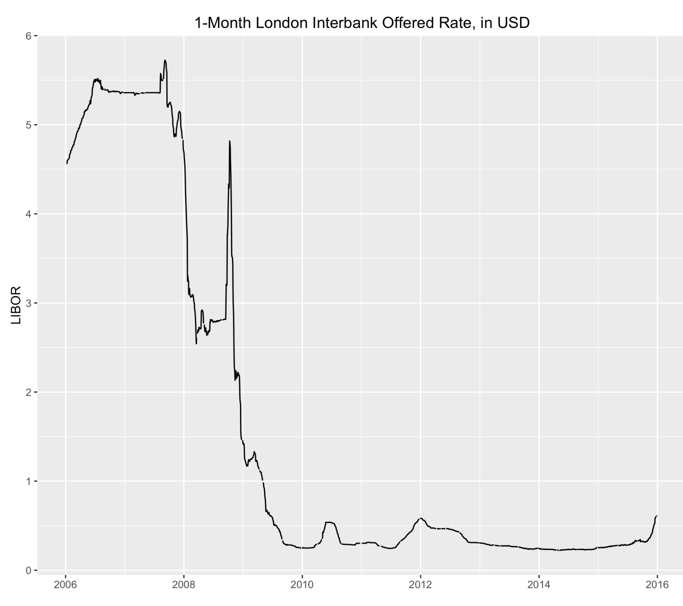
Figure 4.3 shows a the price of Oracle over time in relation to the changing microeconomic fundamentals. As one would expect, the security price (red) increases as net income increases, showing that indeed a security is rationally justified by the performance of the business.

Figure 4.3, typical of the included securities, illustrates a real connection between the fundamentals of a company (Net Income, Total Liabilities, etc) and its market value ("Closing price"). This connection is a good indication for the contrasting hypotheses in that if the fundamentals made *no impact* on the underlying security, then there would be little comparative power to the purely technical model. A more expansive set of Fundamentals-to-Closing price figures are provided in Appendix B.

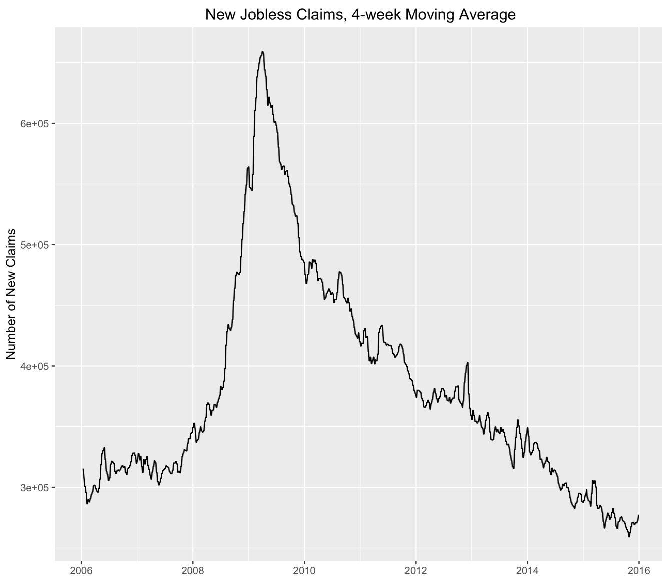
4.2.3. MacroEconomic Indicators

Below are a set of figures outlining specific economic factors from the period 2006 through 2015. One can see, for example, the swift and immediate impact of the 2007 / 2008 financial meltdown reflected in exchange rates, GDP and new jobless claims. Following the 9-year graphs of economic indicators are a set of figures intended to provide insight into the volatility and ranges for those same economic indicators on a year-by-year basis. The figures, in both cases, are a small selection of the full set available in Appendix C.

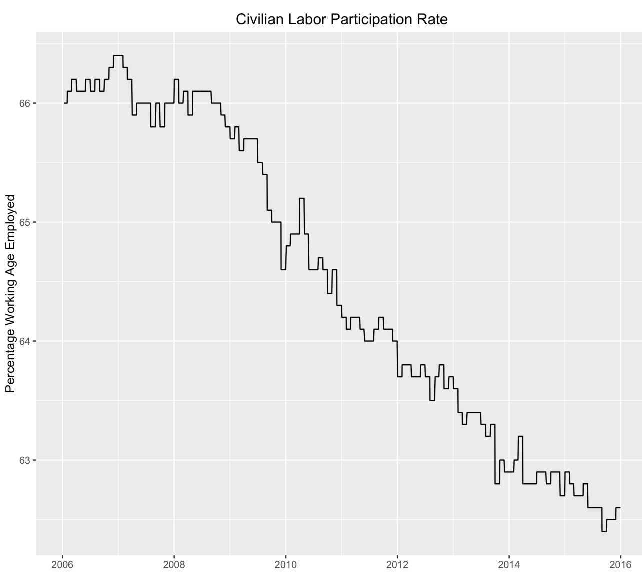




The data (figures 4.4 - 4.7, above and left) imply that while there has been a steady recovery in the broader S&P500 index since its 2008/2009 collapse, other tertiary indicators such as LIBOR (left) and Labor Participation (below) have *not* recovered in the same manner. This is nonobvious because *unemployment claims indeed drop; however, total labor*



participation does not increase markedly in the period of 2009 through 2016. This is interesting as it pertains to the study itself because the learning algorithms will be posed with a non-direct relationship, underlying the nonlinearity of the securities market while also underscoring the importance of including a broad range of economic factors into the learning equation.



4.3. Data Preparation

Due to the disparate sources for the data on each company as well as the micro- and macroeconomic features, much of the data preparation work was restricted to merging the data or expanding annual, quarterly and monthly reported figures into daily values. As outlined in Chapter 3, "Non-daily Data," the micro- and macroeconomic features which were reported in non-daily values (quarterly, annual, etc) were expanded as constants for the entire reporting period.

Due to the interaction of international markets with US markets, there may be instances where a LIBOR or USD-Euro exchange value is reported. However, if the market was closed in the US due to a US holiday (such as July 4th), the observation was excluded from the study. Similarly, if a value was not reported due to an international market closure (such as with LIBOR), the entire observation for the US market event was excluded. In other words, the data is complete data only. No partial observations were included in this study.

Another major step in the data preparation phase was to shift the closing price to be the predictor value while also maintaining it as a feature for subsequent inputs. That is, the close for *today* is based upon the features from *yesterday*: the dependent variable predicted by the SVR and ANN uses the prior day features (High, Close, S&P500, USD/Euro, etc) as the independent variables. However, the predictor's *true value* becomes an input for the next day's regression.

Finally, before features were fed into either the SVR or the ANN, all features were scaled from 0 to 1 (Kim, 2003; Lee, 2009). The purpose of this was to eliminate any possible "overweighting" by the models by larger values, which was a factor because some features were percentages (reported as decimal values) and others ranged in the hundreds of thousands (Initial Jobless Claims, 4-week Average).

4.4. Data Modeling

For purposes of cross-validation and shuffling, the experiment resisted the urge to randomly sample from the entire data set because the intent of the experiment is to evaluate, strictly, whether past stock prices and the derivative technical indicators used by traders worldwide would yield valid, profitable results when fed into a machine learning algorithm. As such, the hold-out data set is the final 10% of the data, comprising 2015 trades. Previous work, such as Enke and Thawornwong (2005), use this same process of using the tail end of the data for the test.

To help alleviate potential for the ANN and SVR to overfit the training data (2006 - 2014), the experiment workflow does make use of a holdout set (a cross-validation set) that is used for a) parameter tuning and b) selecting the "best model" based on the performance of the train model on the cross-validation set. For the SVR, the workflow uses a 2-fold grid search which allows the system to train on a range of parameters (generally a total of 36 different combinations gamma and C, the weight of each training sample and the curve-fit of the SVR respectively). Chai, Du, Lai and Lee (2015) found that a grid search parameter tuning scheme performed better than genetic algorithm while also being computationally less expensive. Each combination is trained and tested against the cross-validation set (holdout) and then the best combination of the C and gamma are selected. Gamma and C were typically one of $1.5e^{-4}$ to $1.0e^{-5}$ and 1000 to 1584, respectively. The full range of gamma included six equidistant steps from $1e^{-5}$ and 1.0 while C included equidistant steps from 1.0 to $1e^{4}$. The primary kernel for the SVM was the radial basis function (RBF) which in the literature is frequently used as the SVM kernel (Tay and Cao, 2002; Lee, 2009; Wen, Yang, Song, and Jia, 2010). Other options include the standard linear or polynomial kernel. The RBF kernel appears to be more favored by researchers as it does not rely upon linear relationships in the data, as is the intrinsic nature of security prices (ibid).

The backpropagation ANN architecture was determined and tuned using a holdout set early in the experimental process. Rather than expend too much time looking for the exact, 100% perfect architecture and internal parameters (learning rate, decay, and momentum), a generally acceptable architecture was established and applied to each company. This differs slightly from the SVR because the grid search used in the SVR allowed each trained "best model" to be company-specific (within a range of initial parameters), whereas the ANN was unfortunately applied as a single, rigid template to all companies. Allowing for more customization or tuning on a company-level is certainly a space for future research. Nonetheless, the ANN architecture is summarized as a three-layer ANN with a single input layer using a hyperbolic tangent function ("tahn") to a 50-unit hidden-layer which itself possesses a 10-unit output that consolidates to a single linear output layer. Each of the layers also possesses a 10% dropout which was found to have better performance than when excluded.

One might ask why an additional pre-processing step such as Principle Component Analysis or Singular Value Decomposition weren't used to simply select the most impactful features. Said simply, it was beyond the scope of the experiment to determine which of the technical values proved more useful for the machine learning algorithms as this particular experiment was more concerned with the validity and rationality of using derivative technical features for security price forecasting when there existed a large body of literature indicating the irrationality and invalidity of such values. This constitutes, certainly, an area for future research.

In terms of technical-only models, one might also examine whether moving averages applied to fundamentals such as crude prices and exchange prices, as a blend between technical and fundamental inputs, might further improve the efficacy of a blended model.

4.5. Model Validation

4.5.1. SVR Model

Company	MSE	RMSE (USD)	Profit (Loss): Model, in USD	Profit (Loss): Buy & Hold, in USD
AT&T Inc.	25.091	5.009	(73.51)	42.45
Boeing Co	2984.521	54.631	0	133.24
Capital One Financial Corp.	855.921	29.256	(126.33)	(41.99)
Chevron Corporation	1162.150	34.090	(94.12)	(183.91)
Ford Motor Company	41.959	6.478	(56.73)	(73.59)
General Electric Company	63.501	7.969	50.4	253.80
McDonald's Corporation	995.192	31.547	18.63	281.65
Microsoft Corporation	244.978	15.652	0	332.16
Oracle Corporation	277.367	16.654	0	(98.87)
Target Corporation	83.238	9.123	0	107.40
Wal-Mart Stores, Inc.	768.468	27.721	0	(234.71)
ExxonMobil Corporation	408.297	20.206	(71.00)	(158.23)

Table 4.3 provides the experiment results for the SVRs profitability (or loss) using technical features versus the buy-and-hold strategy.

Company	MSE	RMSE (USD)	Profit (Loss): Model, in USD	Profit (Loss): Buy & Hold, in USD
AT&T Inc.	25.691	5.069	(113.1)	42.45
Boeing Co	2969.359	54.492	0	133.24
Capital One Financial Corp.	859.160	29.311	(96.08)	(41.99)
Chevron Corporation	1140.809	10.715	(57.73)	(183.91)
Ford Motor Company	41.061	6.408	(50.02)	(73.59)
General Electric Company	55.850	7.473	83.52	253.80
McDonald's Corporation	959.124	30.970	0.68	281.65
Microsoft Corporation	245.284	15.661	0	332.16
Oracle Corporation	275.933	16.611	0	(98.87)
Target Corporation	83.873	9.158	0	107.40
Wal-Mart Stores, Inc.	494.712	22.242	0	(234.71)
ExxonMobil Corporation	402.490	20.062	(121.95)	(158.23)

Table 4.2 provides the experiment results for the SVRs profitability (or loss) using fundamental features versus the buy-and-hold strategy.

Company	MSE	RMSE (USD)	Profit (Loss): Model, in USD	Profit (Loss): Buy & Hold, in USD
AT&T Inc.	24.939	4.9939	(91.06)	42.45
Boeing Co	2929.963	54.129	0	133.24
Capital One Financial Corp.	842.723	29.030	(107.03)	(41.99)
Chevron Corporation	1140.510	33.771	(110.47)	(183.91)
Ford Motor Company	41.145	6.414	(50.02)	(73.59)
General Electric Company	54.688	7.395	83.52	253.80
McDonald's Corporation	941.482	30.684	6.92	281.65
Microsoft Corporation	245.237	15.660	0	332.16
Oracle Corporation	276.428	16.626	0	(98.87)
Target Corporation	83.519	9.1390	0	107.40
Wal-Mart Stores, Inc.	487.328	22.075	0	(234.71)
ExxonMobil Corporation	402.933	20.073	(104.55)	(158.23)

Table 4.3 provides the experiment results for the SVRs profitability (or loss) in the blended-model versus the buy-and-hold strategy.

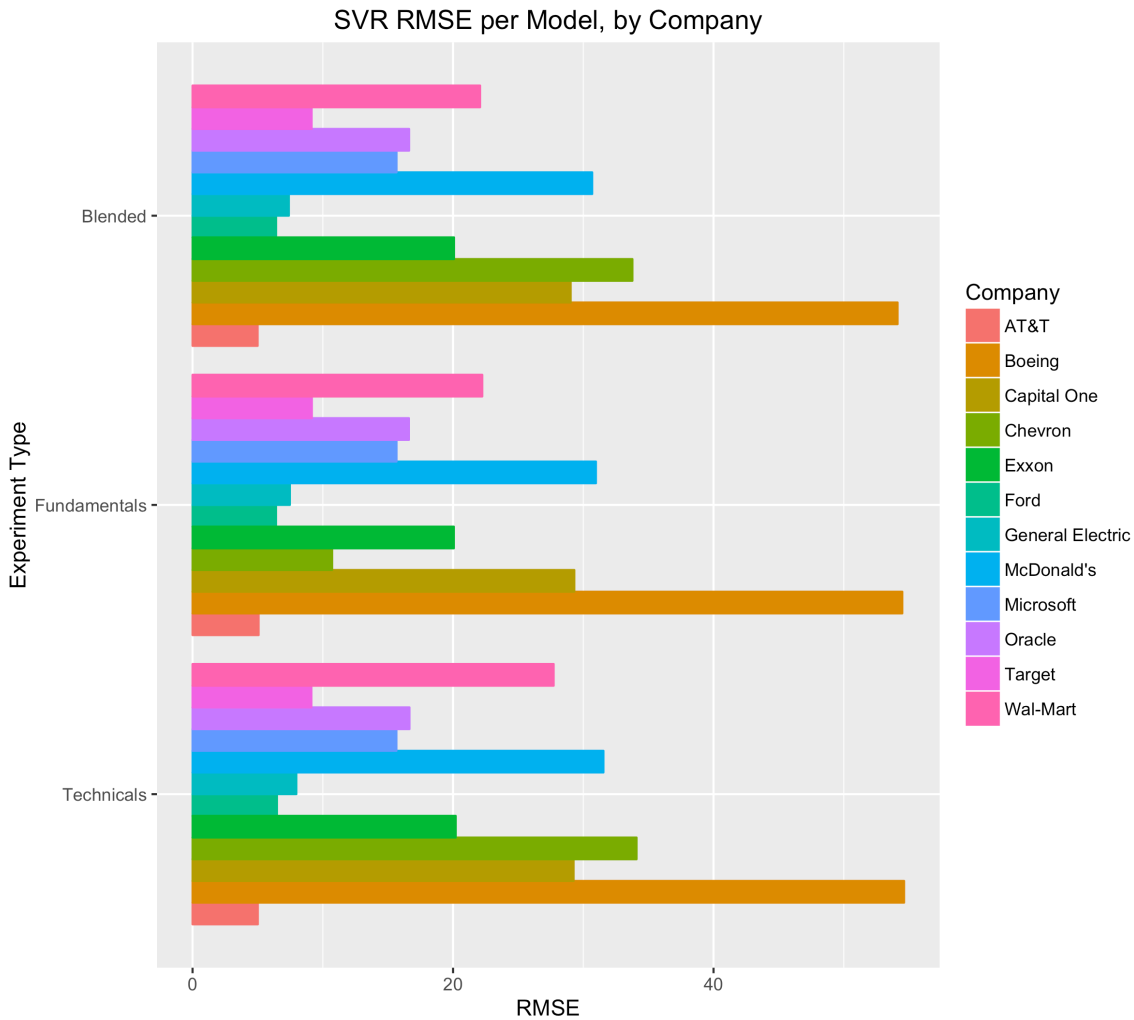


Figure 4.8 illustrates the RMSE for each of the three experimental SVR models for each company included in the study.

4.5.2. ANN Model

Company	MSE	RMSE (USD)	Profit (Loss): Model, in USD	Profit (Loss): Buy & Hold, in USD
AT&T Inc.	18.370	4.286	(72.06)	42.45
Boeing Co	3177.961	56.373	0	133.24
Capital One Financial Corp.	832.084	28.846	0	(41.99)
Chevron Corporation	1046.523	32.350	(96.92)	(183.91)
Ford Motor Company	35.136	5.928	(22.01)	(73.59)
General Electric Company	65.165	8.072	40.54	253.80
McDonald's Corporation	1325.642	36.409	0	281.65
Microsoft Corporation	246.894	15.713	0	332.16
Oracle Corporation	301.686	17.369	0	(98.87)
Target Corporation	106.895	10.339	0	107.40
Wal-Mart Stores, Inc.	415.461	20.383	0	(234.71)
ExxonMobil Corporation	527.649	22.971	(77.00)	(158.23)

Table 4.4 provides the experiment results for the ANNs profitability (or loss) in the technicals-only model versus the buy-and-hold strategy.

Company	MSE	RMSE (USD)	Profit (Loss): Model, in USD	Profit (Loss): Buy & Hold, in USD
AT&T Inc.	27.245	5.220	(61.05)	42.45
Boeing Co	3197.286	56.545	0	133.24
Capital One Financial Corp.	924.724	30.409	0	(41.99)
Chevron Corporation	4124.168	64.220	(82.90)	(183.91)
Ford Motor Company	47.632	6.902	0	(73.59)
General Electric Company	168.968	12.999	(20.88)	253.80
McDonald's Corporation	1362.377	36.910	0	281.65
Microsoft Corporation	801.198	28.305	0	332.16
Oracle Corporation	387.177	19.677	0	(98.87)
Target Corporation	182.565	13.512	0	107.40
Wal-Mart Stores, Inc.	531.725	23.059	0	(234.71)
ExxonMobil Corporation	525.087	22.915	(76.09)	(158.23)

Table 4.5 provides the experiment results for each model's profitability (or loss) using fundamental features versus the buy-and-hold strategy.

Company	MSE	RMSE (USD)	Profit (Loss): Model, in USD	Profit (Loss): Buy & Hold, in USD
AT&T Inc.	55.706	7.464	(95.12)	42.45
Boeing Co	3091.925	55.605	0	133.24
Capital One Financial Corp.	1029.205	32.081	0	(41.99)
Chevron Corporation	2398.477	48.974	(86.00)	(183.91)
Ford Motor Company	40.152	6.336	0	(73.59)
General Electric Company	73.153	8.553	18.12	253.80
McDonald's Corporation	1361.035	36.892	0	281.65
Microsoft Corporation	1024.945	32.015	0	332.16
Oracle Corporation	520.480	22.814	0	(98.87)
Target Corporation	145.606	12.067	0	107.40
Wal-Mart Stores, Inc.	586.253	24.213	0	(234.71)
ExxonMobil Corporation	1053.166	32.453	(122.79)	(158.23)

Table 4.6 provides the experiment results for the ANNs blended-model profitability (or loss) versus the buy-and-hold strategy.

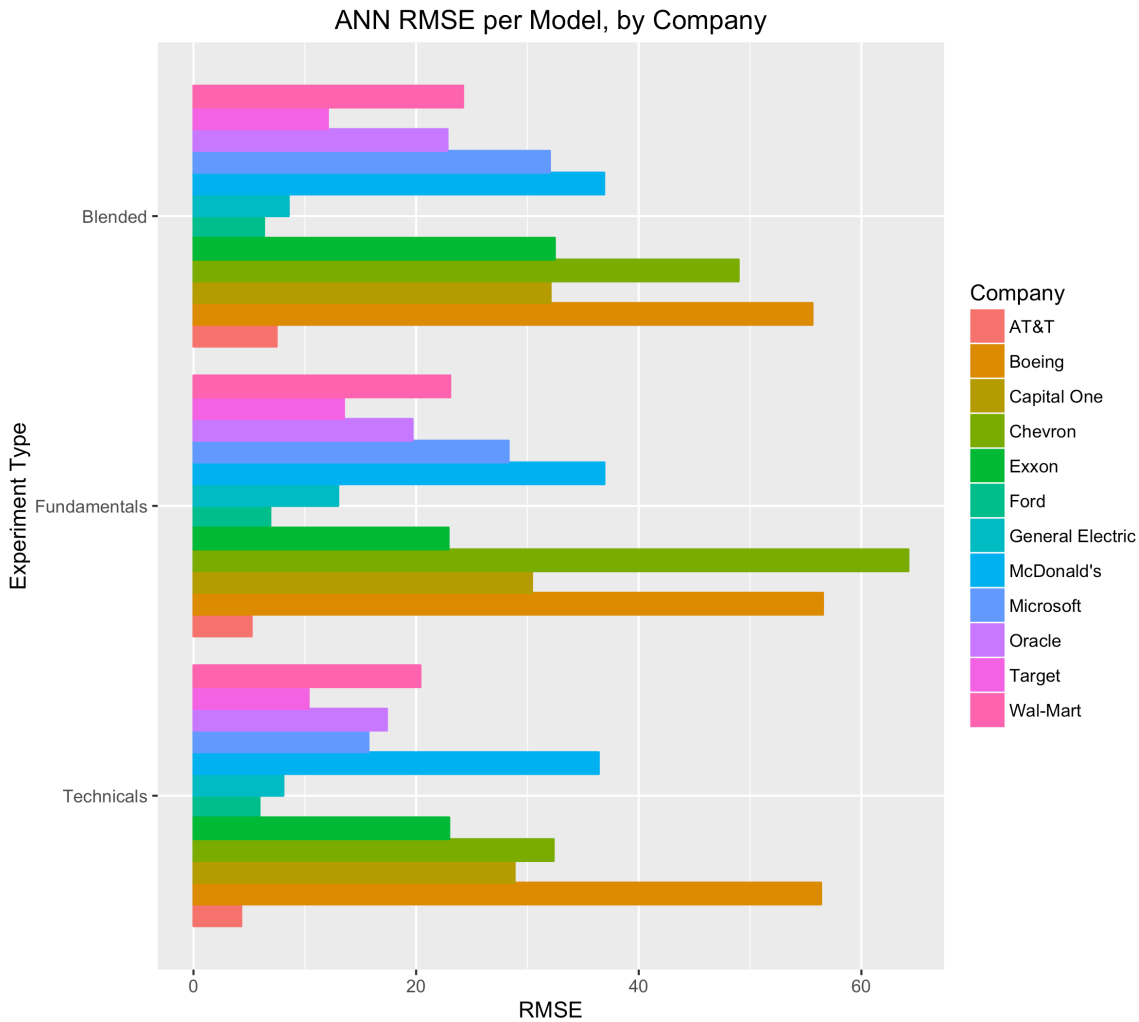
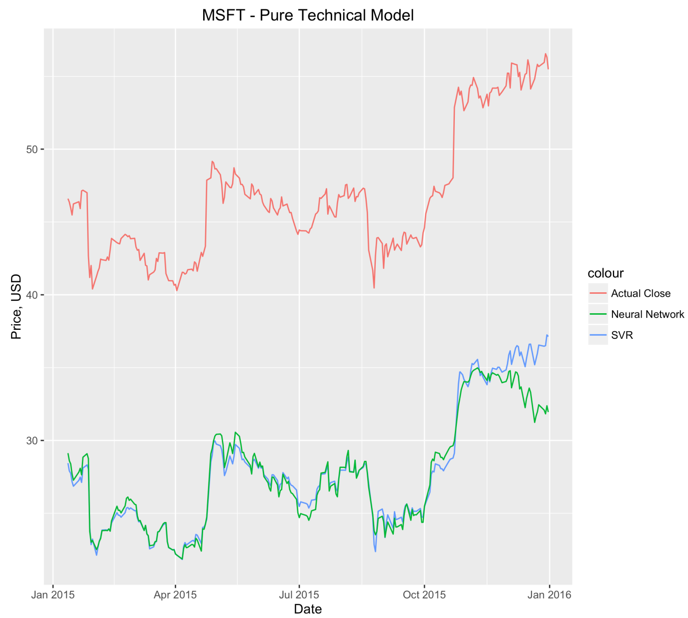


Figure 4.9 illustrates the RSMEs generated by the ANN experimental models and each company included in the study.

4.6. Model Prediction & Visualization



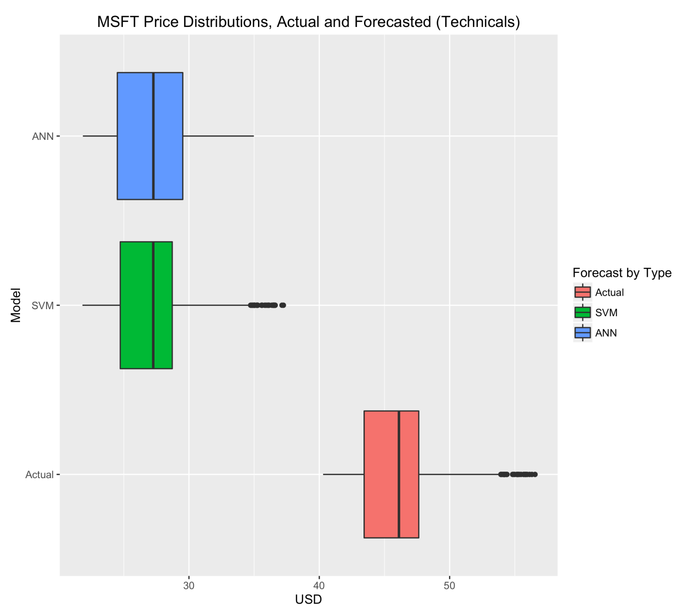
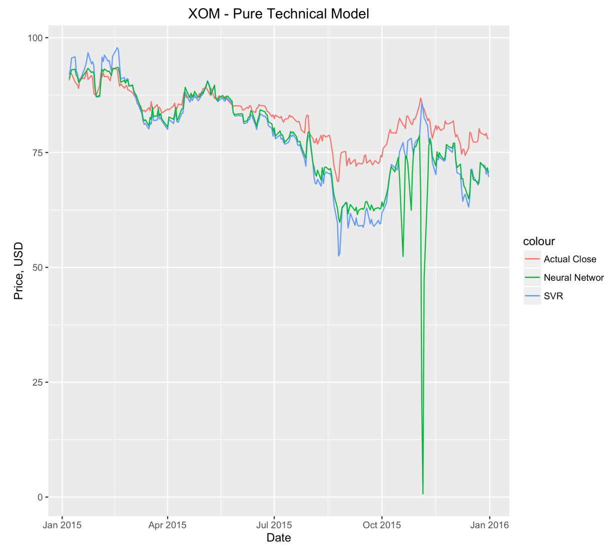


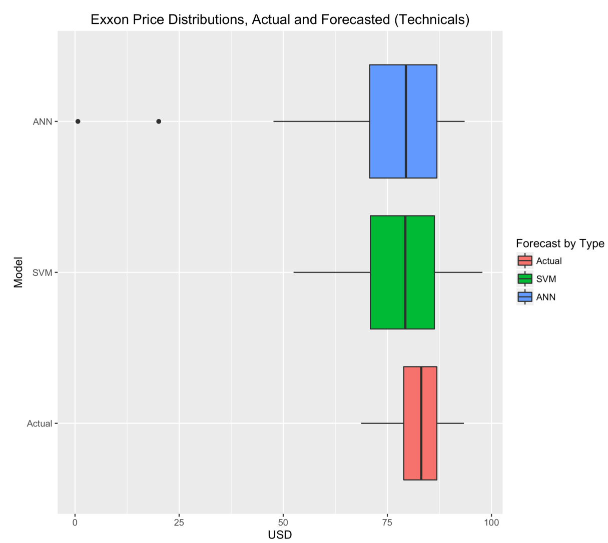
Figure 4.10.a Depicts the actual closing price (Red) for Microsoft's stock price for the 2015 period. The SVR (blue) and ANN (green), using the Technical features only, are also presented. *While the error is clearly high, what is striking about the image is the* ***directional consistency*** *with the actual price.*

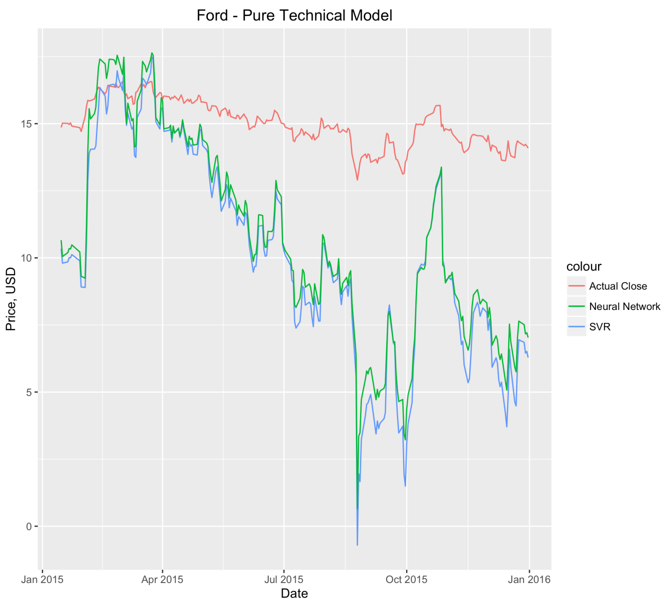
Figure 4.10.b shows the distribution of prices for each model type. Again, while the forecasted prices are clearly off, the relative variance is a close approximation for the actual.

Figure 4.11.a depicts the actual closing price (Red) for Exxon, 2015. The SVR (blue) and ANN (green), using the Technical features only, are also presented. The sharp drop in the prediction with the ANN (circa November, 2015) is a common occurrence across many of the ANN experiments, buttressing the notion that more tuning, on a per-company, per-model basis, may yield more consistent results. Despite this outlier, both the SVR and ANN show remarkable consistency with the actual price. As with Microsoft (Figure 4.10.a), the directional forecast is also consistent with the closing price.

Figure 4.11.b shows the distribution of prices for each model type.







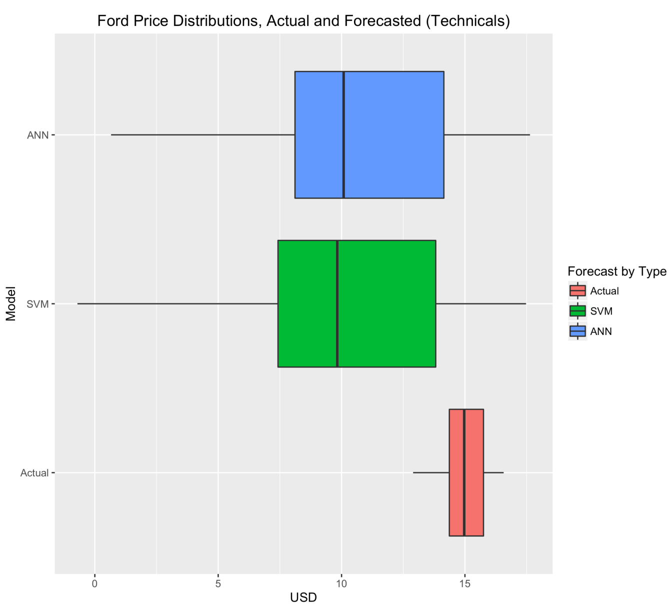
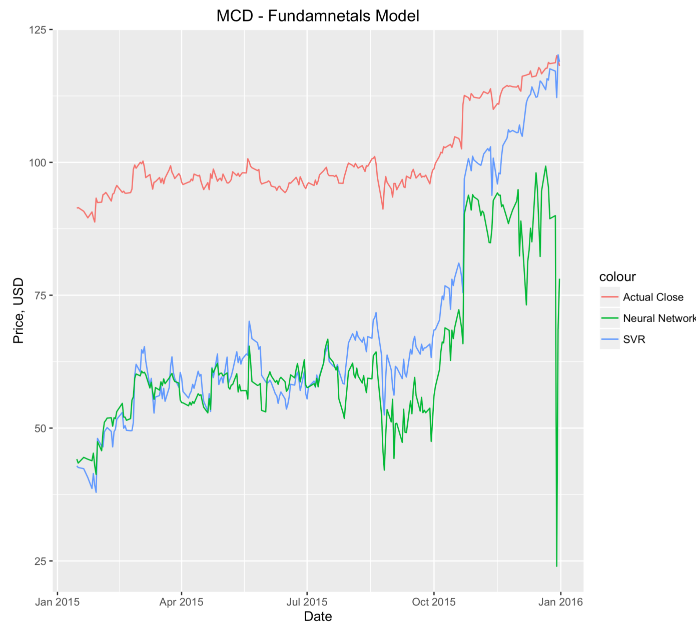


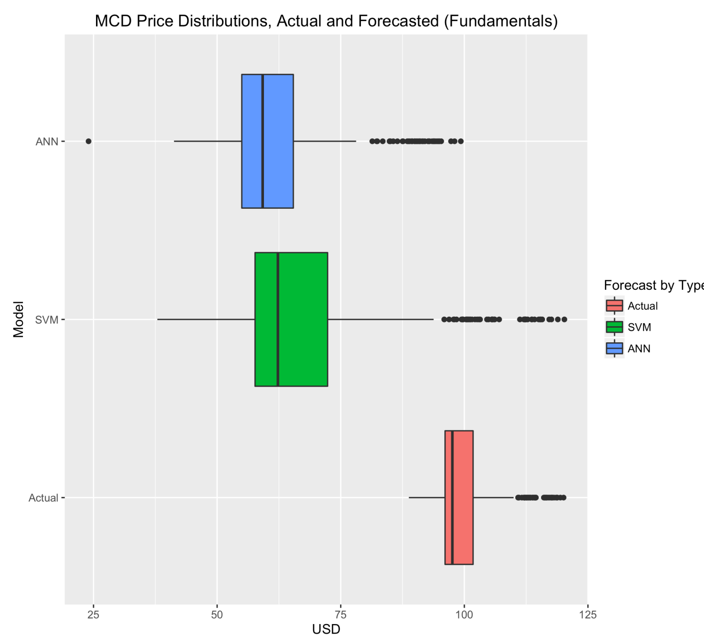
Figure 4.12.a is provided to show an example of a security (Ford) which exhibited a relatively stable security with a minor decline for the 2015 period yet *the SVR and ANN both forecasted steep declines in price. In this regard, the two models followed almost the exact same pattern, implying that perhaps there were important fundamental properties reflected in the (relative) price stability which remained unaccounted for in the technicals-only model.*

Figure 4.12.b shows a much higher distribution of forecasted prices than the actual narrow band Ford traded within.

Figure 4.13.a, showing the forecasts for *McDonald's, exhibits many of the characteristics already see but combined in a single security: the general direction of the forecasts follows the actual closing price and there is a large outlier forecast with the ANN model (end of 2015). While the magnitude of the gain was exaggerated within the SVR model, the SVR model did correctly forecast the consistent gain in closing price exhibited in the last quarter of 2015.*

Figure 4.13.b reinforces the error offset of the two predictive models against the actual. Unlike the previous figures, the McDonald's stock exhibited a rapid change (outliers) in security price in which the models perform acceptably in forecasting the outliers.





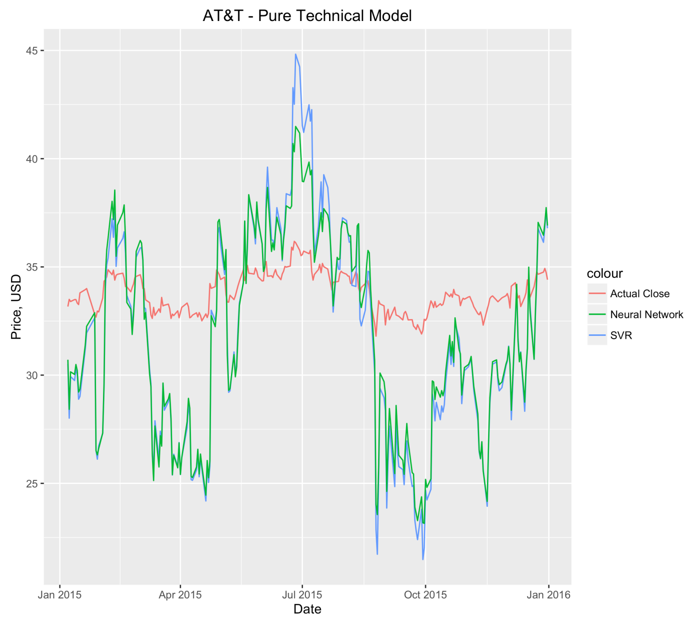


Figure 4.14.a is provided to show a weaker model. The general shape of AT&T's security price is followed but *both the SVR and ANN exhibit a tendency to greatly inflate the expected security price, implying an oversensitivity to the provided features.*

Figure 4.14.b reinforces the high volatility of the security compared with the generally tight band that AT&T traded within for 2015.

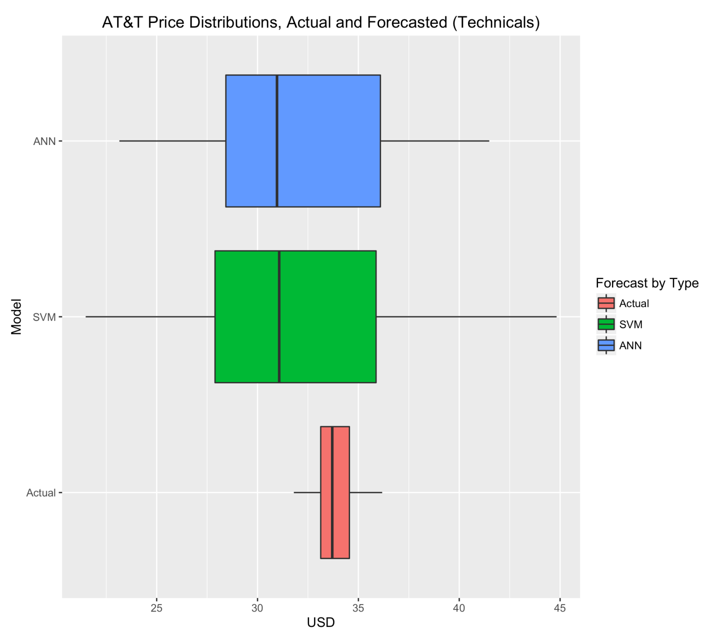
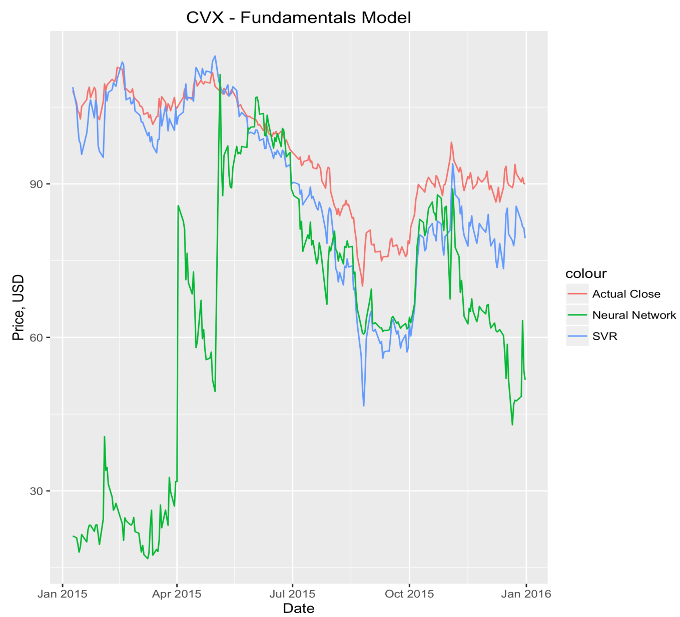


Figure 4.15.a shows Chevron's actual

and two forecasted closing prices (SVR-Blue; ANN-Green). *The SVR shows particular potential with a tight following to the actual close price. While the steep falloff in price for the SVR was indeed greater than the actual, the SVR model does show a highly consistent model, tracking well with actual decreases and increases in the security price. The ANN appears to have a poor fit with a much greater error.*

Figure 4.15.b provides insight into the price distribution for 2015. The SVR and ANN both show a greater distribution of prices than the actual, though the SVR range is encouragingly close to the actual.



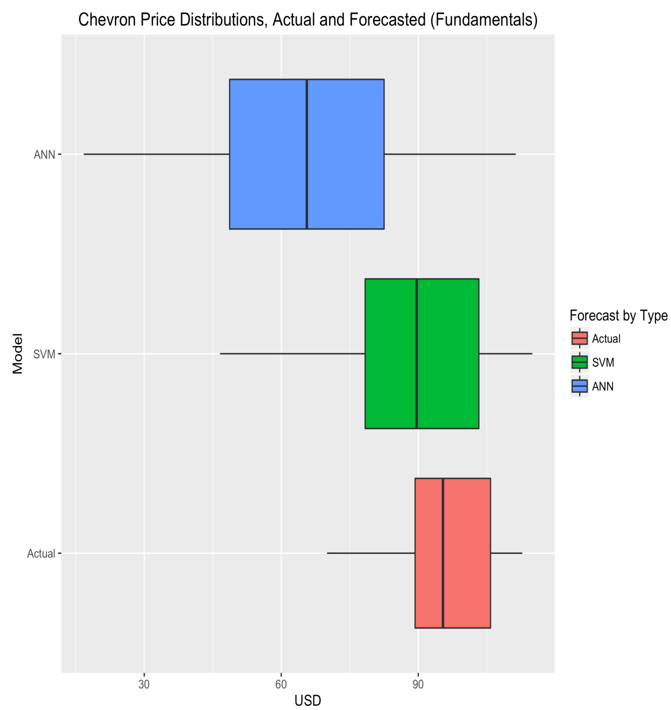
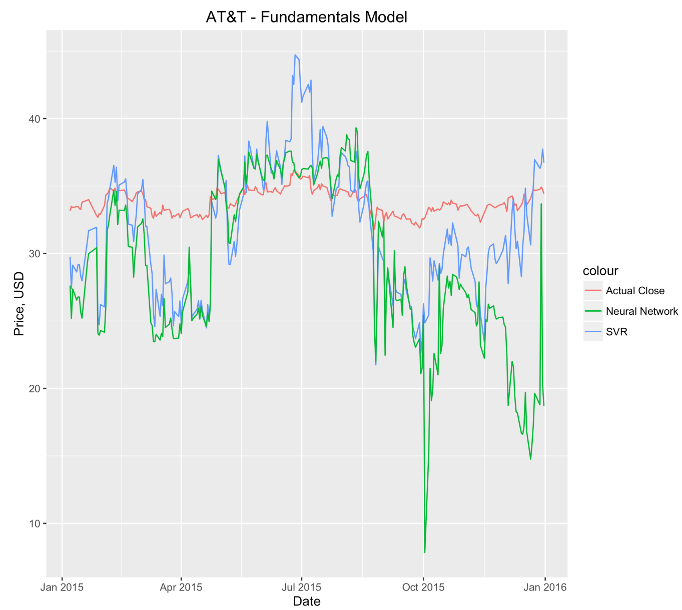
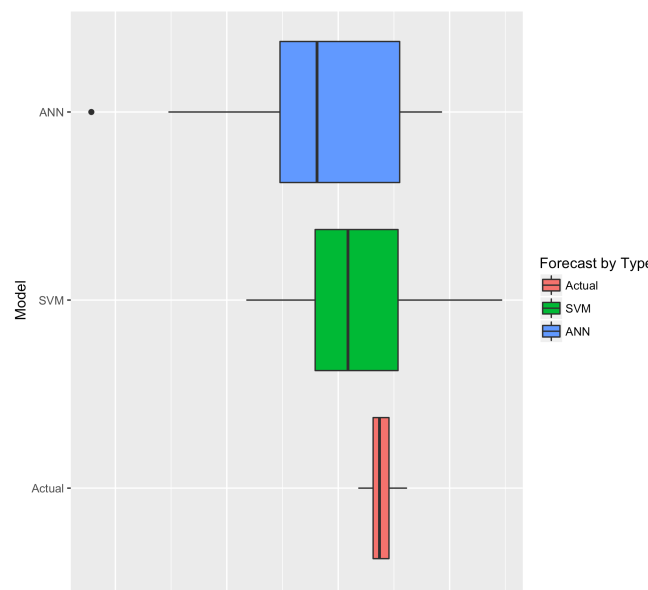


Figure 4.16.a provides the fundamentals model for AT&T. The

primary similarity with the technicals driven model (Figure 4.14.a,b) is the much greater range in total prices. While the models roughly followed the general shape of AT&T's price over 2015, the magnitude of changes were much greater in the ANN and SVR models. *Figure 4.16.b is again similar to the AT&T-technicals model, implying there are likely important valuation considerations not captured by either the technicals or the provided fundamentals.*





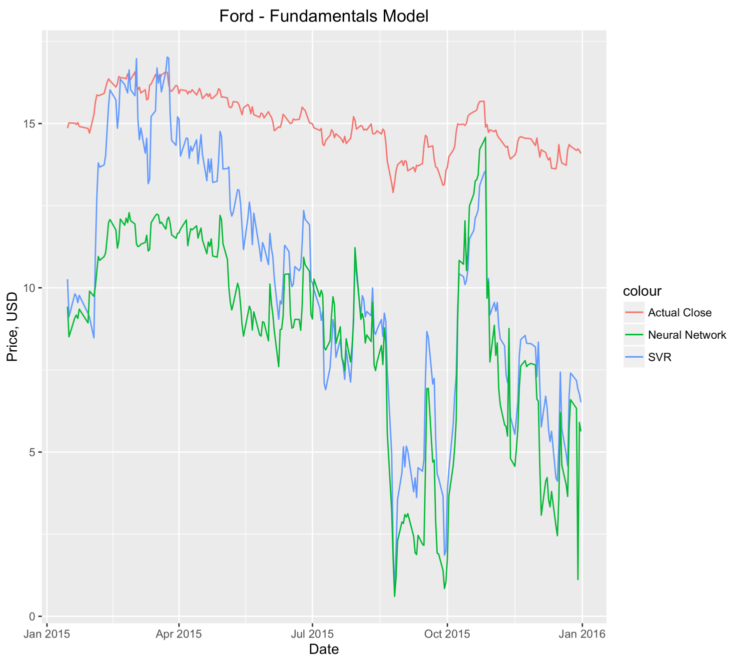
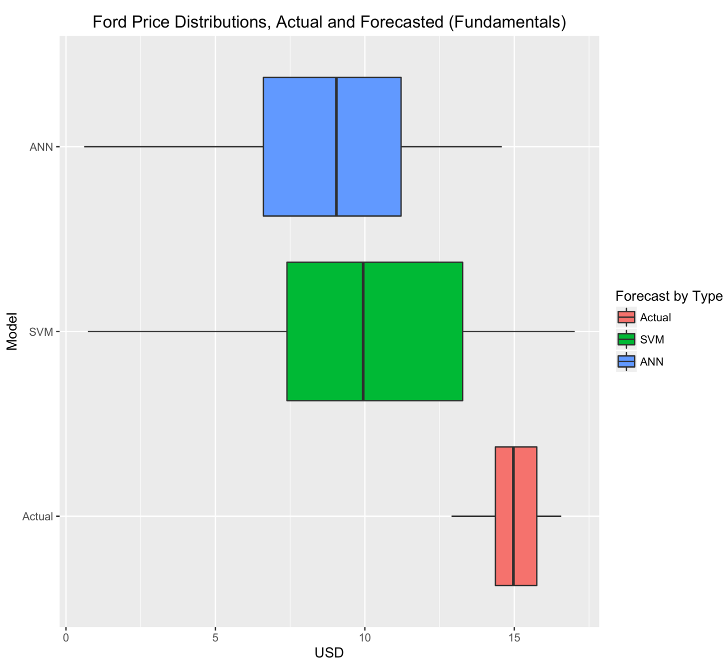


Figure 4.17.a Provides the fundamental model for Ford Motors. The forecasted prices look remarkably similar to those in the technicals-only model (Figure 4.12a, b) in both the much greater-than-actual price as well as the range in price variance. The SVR and ANN both trade within the general trend (decline) of the Actual; however, the variance in prices is nearly 4 fold those present in the actual.



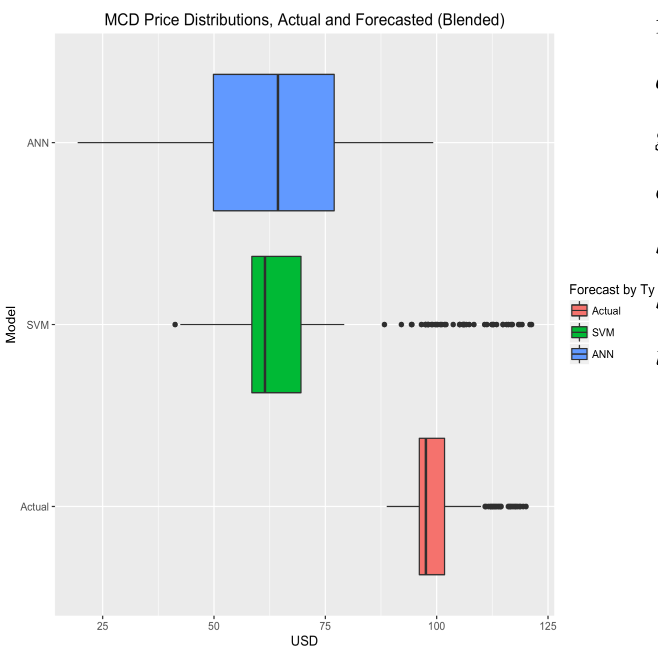
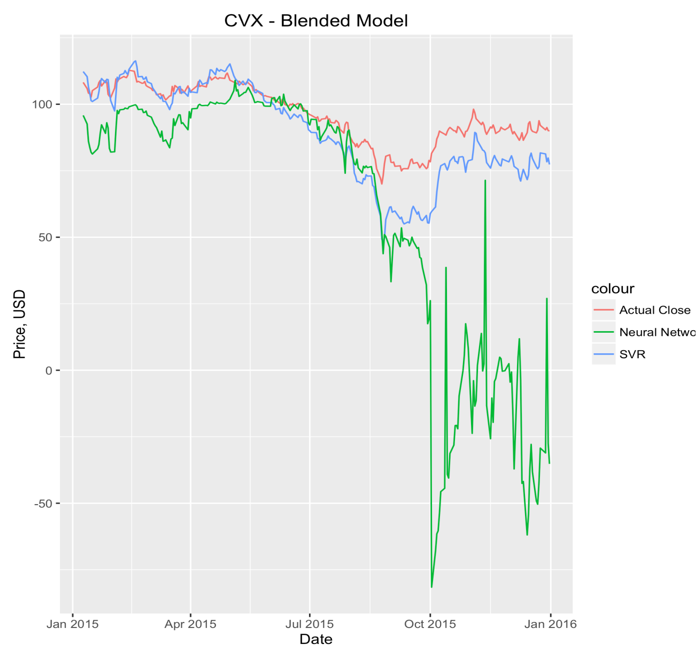
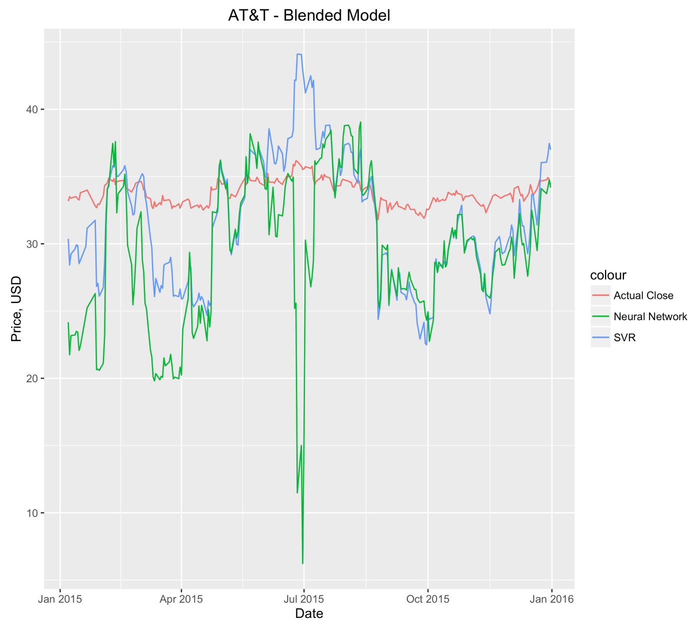


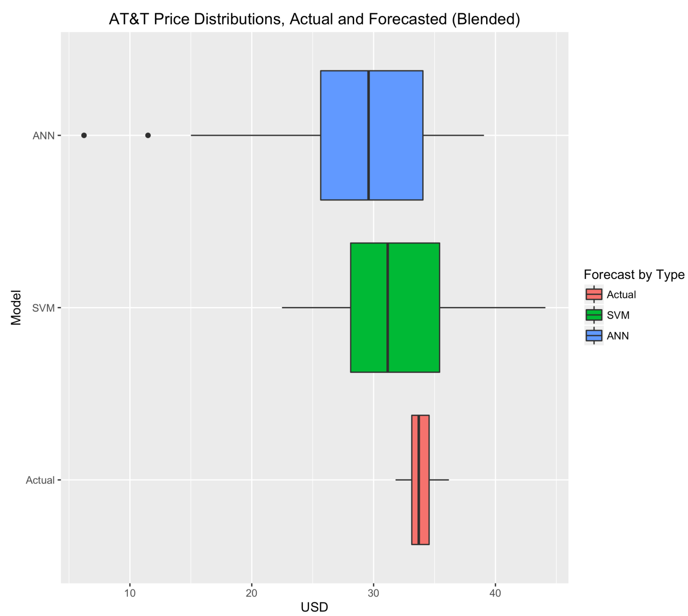
Figure 4.18.a provides an example of a blended model, using McDonald's. The model performs similarly to the prior technicals only model. The drastic outlier and high variance previously shown in the same technicals-only model is balanced for the ANN model. In the blended model, the rapid increase in security price was forecasted by both models, though as before, the total *magnitude* of the increase was much greater than the actual.

Figure 4.18.b provides an insight into the variance of prices. *The SVR again appears to provide the best guidance for the actual value with an even tighter range of prices than before, matching both the narrow band the actual traded in as well as the rapid increases (outliers).*

The blended model for Exxon (Figure 4.19.a,b) was particularly predictive in the case of the SVR, which tracked closely with the actual closing price throughout the duration of 2015, as well as in its overall range of prices. The ANN appears to be fairly underfit, with some strong tracking in the early portion of 2015, but a drastic variance in prices for the later half of 2015. This was somewhat surprising as the technicals-only model (Figure 4.11.a,b) was much more stable for the ANN. Figure 20b. provides the same graph, showing the same high-variance pricing for Chevron, again surprising considering the stability of the fundamentals-only model.



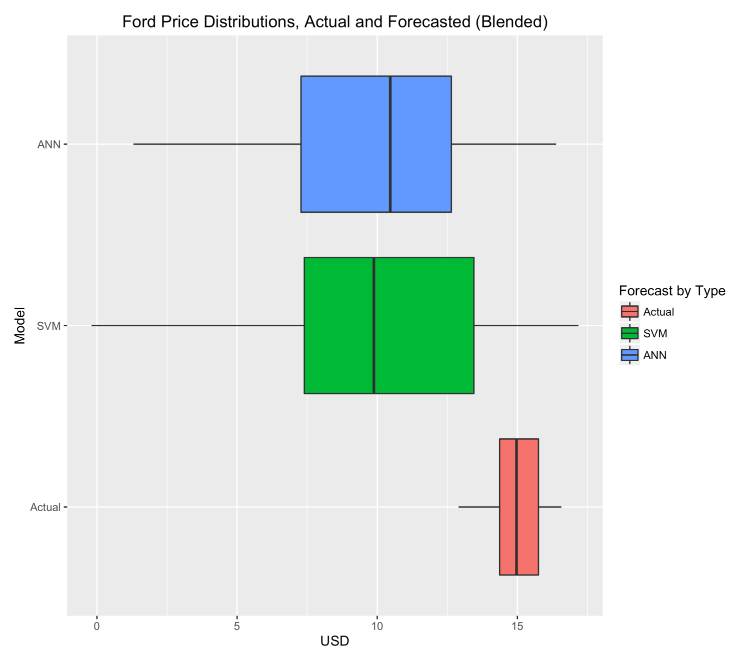




The blended model for AT&T (Figure 4.20.a,b) did not perform noticeably better than either the Technicals (Figure 4.14.a,b) or Fundamentals (Figure 4.16.a,b) models. The distribution of prices was still consistently higher with a poor predictive power for the SVR and ANN.

This furthers the implications drawn from the previous models that important features used to forecast the security's prices are missing from the models, which were unable to find strong connections between the provided technical and fundamental factors.

The blended technicals and fundamentals model for Ford (Figure 4.21a, b) do not show an improvement over the previous models. *Ford is not atypical in this regard and provides a good example across all three experimental paradigms* (Technicals: Figures 4.12a, b and Fundamentals: Figures 4.17.a, b): *acceptable performance in the independent technical and fundamental models, with good directional forecasting (gain / loss in closing price) but with large base-line offsets in price and often a much greater (2x) magnitude in price range.*



5. Evaluation / Analysis

5.1. Evaluation of Results

While, the MSE (and RMSE) across many companies dropped with the blend of Fundamentals and Technicals for the SVR model, those drops were modest and may simply be the result of undertuning. The average performance for the ANN models was significantly better (as measured by average MSE across all companies) for the Technicals-only model. However, this may also be the result of underfitting the data in the subsequent experiment models. As illustrated by Figures 4.17.b and 4.18.b, there is significant variance in the prices forecasted by the ANN versus the Actual and the SVR forecasts, though this variance was reduced in some fundamental models (figures 4.13.b & 4.15.b) and blended models (figure 4.18.b). Conversely, the SVRs performed consistently well, matching the general shape, direction and distribution of actual prices better, and it is for this reason that the SVR (and SVMs in general) are often cited as being easier to work with: parameter tuning is significantly easier than architecting a well-rounded ANN model (Tay and Cao, 2002; Kim, 2003; Yeh, Huang and Lee, 2011).

So far as the underlying research question regarding the predictive power of a technicals-only model, the conclusion is that technicals ***are a valid input, performing at nearly the same level as fundamentals-based models***. Indeed, the difference in mean RMSE between the Technicals- and Fundamentals-only models is only $2.51 for the SVR and $5.14 for the ANN. For a factor classified as irrational (Technicals), the *a priori* intuition would be that the technicals-based model would be effectively "random" but **the technical models tracked security price changes with an acceptable degree of accurately to convince this researcher that even if economic theory may classify historical prices as irrational justifications for security purchasing decisions, they are *ipso facto* rational so far as justifying their inclusion in future forecasting research.**

5.2. Observations from the Results

The first clear signal from all three experiments is that some participant company shares are much more closely tied to the fundamentals of the market -- and that they are more "easily" forecasted using both the SVR and the ANN. Examples include the oil and gas companies Exxon (XOM) and Chevron (CVX). Another good example of a model that performed well once coupled with fundamentals is McDonald's.

In all three cases, one can intuit that the business models are indeed more closely tied to the underlying economic conditions (included in this study) than alternative businesses such as Oracle or Microsoft. For example, the price of oil will closely map to the total earnings of CVX and XOM: as the price of oil goes up (as valued in USD), the total earnings for the period will see a corresponding increase, assuming costs are essentially fixed. In a similar manner, MCD which operates globally, earnings can be greatly impacted by general consumer-oriented fundamentals such as unemployment. For all three companies, as global players, the exchange rate of the USD to the EURO will also likely play an influencing role.

It was beyond the scope of this project to investigate the specific features which improved (or diminished) the performance of the models; however, this would certainly constitute a fertile landscape for future investigations.

So far as the profitability of the trading machine, it should be noted that simply because a "Buy-and-Hold" resulted in a greater loss than the algorithmic trading machine, does not mean that the trading machine proved more accurate at predicting market prices. That is, **in some cases, the trading machine simply never generated a buy signal, resulting in *no trades* for the entire period**. In highly volatile markets in which prices swing rapidly from positive to negative, this may be an acceptable behavior but it *does not prove anything*. As noted below, the automated trading machine's configuration was indeed a limitation of the experiment and worth additional attention in the future.

5.3. Strengths of the Results

The **primary strength of the results is the establishment of a justification for feature selection in future work** and to address an often overlooked explanation for researchers' use of features, frequently in the context of the EMH. With a simple contrast between Technical-only and Fundamental-only models, the EMH is called into question. The experiments show that technical features *are able* to forecast the direction, if not the exact price, for a class of securities.

A **secondary strength is that the models are lightweight and the pipeline is sufficiently extensible to easily accommodate more test companies and additional model options** because the models avoid hyper-tuning on a per-company basis. Moreover, train and test time are short enough (approx 30 min) to act as a prototype for actual day-to-day operations in an investment setting.

Another strength is the results reinforce previous findings that SVMs are easier to tune and can achieve relatively better performance on smaller training sets than ANN. While there is a small gridsearch enabled on the SVR, its selected range was typically only one of four value combinations (between gamma and C). The ANN was itself a single hard-coded structure and converged within a couple of minutes but it was clear to this researcher that hours could be spent on tuning each company for each experiment.

A final strength of the findings is the consistently high "base error" in the forecasted prices but the exceptionally accurate directional movement in all forecasted models. Securities forecasted in this experiment, particularly with the SVR, maintained a consistent price error but tracked direction well. Retooling to examining directional movement seems to be among the most promising areas for future examination.

5.4. Limitations of the Results

The primary limitation of the results is one of model development. Not only are there likely great economic candidate features that were unexplored (Real Median Household Income, Federal interest rates, and gold prices, to name but a few), there are also softer features contained within current events. For example, including an investor sentiment as it relates to the 2015 "GreExit" crisis, in which Greece was on the brink of a major capital default, could yield important indicators for the closing prices of securities. Another important aspect limiting the research were the non-US fundamentals: China and the EU play large roles in global exchange markets and yet, aside from USD-to-Euro exchanges, these important macroeconomic indicators were excluded completely from the study.

Beyond fundamentals, **there are a plethora of technical features that were not engineered**, such as Moving Average Convergence Divergence (MACD), Stochastic %K and Stochastic %D. While the prior literature frequently uses moving averages as used in this study, MACD (among others) are also used by technical chart-based evaluations and could provide important signals, particularly in the case of the pure technical models.

An important secondary limitation of the results is of model tuning. Due to the scope of time allocated to this research, the models may be under-tuned. There is reason to suspect that the Artificial Neural Network, for example, could be tuned on a per-security basis. Because of the tools and time available, only a single ANN architecture was used for all companies across all experimental phases. However, as was found with the SVR, each security used slightly parameters to achieve the "best model," implying a single ANN architecture for not just every security but every configuration of input feature (technical, fundamental, technical + fundamental) may not achieve the best results, despite model convergence. In addition to general model tuning on a company-level basis, alternative ANN models might include convolutional neural networks or applying wavelet transformations to de-noise the inputs to the ANN.

While the research indicates that technical inputs are able to capture some price movement, **the evaluated securities were only a small portion of all available securities.** 12 of the thousands of publicly traded companies represents only the smallest margin of statistical significance and so a better study would approach 30 to 50 companies. Further, while the research attempted to include a range of companies representing the various segments of the economy (Gas & Oil, Consumer Goods, Finance, Automotive, Software and Technology, Telecommunications), more attention to expanding the represented companies for each segment may yield more confidence to research results.

Another limitation of the research is the range of investment options available to the trading machine. To follow prior research, stop losses and stop gains were used. A stop loss is a maximum percentage loss on a holding that once met, a position is exited. Stop gains are the opposite: after a threshold of gain is reached (10%), the position is exited even if the position might yield better results. This is an obvious limitation because profits and losses are capped but position entry and close subjects the experiment to market timing: exiting a position prematurely could result in significant losses. Moreover, many advanced trading strategies include shorting a security -- that is, taking a contrarian position which seeks to profit from a security's decline in price, versus the traditional profit-through-gain.

Another notable area of limitation is the range of feature inputs. Finding that technical features perform at or near-par with fundamentals may be further buttressed by using other technical notions such as “bear or bull” or length of time (in bear/bull conditions), days of consecutive price increase or decrease, or even gathering moving averages for the indirect fundamentals such as the price of oil or the S&P500 itself.

The last major limitation of the research is that the models’ susceptibility to black swan events were not tested--events such as the financial crisis of 2008 (Taleb, 2007; Lewis, 2010). Would the models appropriately detect fast changes in market conditions and would the trading machine appropriately exit the exposed positions?

6. Conclusions and Future Work

6.1. Summary

By examining 12 companies within the S&P500 using technical features as inputs to the machine learning algorithms, **this research implies that technical indicators are an *adequate* input set for machine learning-based security price forecasting and that the EMH can be called into question**. However, in the case of the SVR, the fundamentals-based model did perform at a lower overall RMSE than the technicals-model and so should likely be included in most models seeking to forecasting security prices. While there *is* a pattern to historical prices which calls the EMH into question, at least so far as the investment community “predictably reacts” to new conditions, **the efficient market hypothesis is to *some degree* reaffirmed in that *new information* contain pertinent, important information for updating security valuation not represented by historical prices and patterns**. In other words, it might be counter-argued that the rapid change in underlying security price due to significant changes in earnings incorrectly forecasted by the SVR and ANN is a reaffirmation that new information strongly influenced security prices relative to near-term technical indicators. Yet it might also be noted again, the market can overreact to this new information (De Bondt and Thaler, 1985; Verma, Baklaci and Soydemir, 2008).

6.2. Contribution and Impact

This research sought to examine the debate surrounding the rationality of technical features into forecasting strategies implemented within machine learning literature. **The general conclusion is that technical features are able to forecast the next-day price of a security at an approximate parity with fundamentals-based models. While economic theory may indicate these inputs are "irrational" and based upon "noise," the models were *ipso facto* capable of generating acceptable forecasts by learning the pattern in previous exchanges.**

As with other previous researchers, this researcher can also conclude that SVMs are, in all likelihood, more pragmatically better suited toward use in forecasting due to the ease of model tuning.

6.3. Future Work

This research shows that for 12 of 500 S&P500 companies, technical indicators were a legitimate input for machine learning algorithms in 2015. The research implies that future studies might seek to replicate the results by expanding the number of years tested--rather than simply testing the hypotheses for 2015, models might train and test for other time periods, of course requiring larger training sets.

Future work might better explore the fundamental input features by broadening the included factors as the generic macroeconomic factors and the company-specific microeconomic factors may also be too limited in scope. In this regard, another area worth examining is to understand if an assumption of how the fundamentals were propagated forward as constants altered the forecasts.

It is worth noting that because all features were treated as a blackbox with no feature reduction process such as SVD or PCA, this experiment setup cannot identify which features impeded or improved the performance of the models--this may be particularly important for the blended model which performed worse for the SVM (slight improvement in ANN) than either the technical or fundamentals-only models.

Expanding the number of technical inputs to included notions of "bear or bull" market -- or number of consecutive days of increase--might also be illuminating: for example, *is there* a legitimate notion of "overbought" and "oversold" as often claimed by practitioners of the Relative Strength Indicator (RSI) or is that merely a case of selective confirmation bias? Could analyst earnings estimates or assessments ("buy", "market perform", "hold", etc) be included in the models? Perhaps the days to earnings could also be an important feature. Another interesting area to examine is the inclusion of After- and Pre-Market prices because most earnings release data come after market hours and so the new information made available in the earnings release is *not* reflected in the end-of-market Close price used as a major component of the next-day forecasts. If After- and Pre-Market prices could be included, the models may better capture what the actual close price will be.

Researchers might seek to evaluate hourly or sub-hour data: do technical indicators perform even more accurately (or less) when the timeframe for evaluation is much smaller?

Alluded to previously, there might be fertile ground to integrate sentiment: not only to examine how analysts rate a security but to integrate traditional and social media into models (Dondio & Longo, 2011; Longo, Dondio, & Barrett, 2010). In this case, it would be important to build robust trust mechanisms, an example of which might include an integration of an Information Foraging scheme to evaluate various channels such as online / social media (Longo, Barrett, & Dondio, 2009; Longo et al., 2010) before integrating the sentiment scores with the technical and fundamental feature mining. This thesis has presented an inductive, data-driven approach for prediction. Because of the dynamism of the features involved in such a prediction, this study could be tackled from a different perspective by, for instance, employing deductive reasoning techniques for inference. Examples include (Longo, 2015; Longo & Dondio, 2014; Longo & Hederman, 2013; Longo, Kane, & Hederman, 2012; Rizzo, Dondio, Delany, & Longo, 2016).

As also seems clear from an examination of the price forecast vs actual close charts (example figures 4.10.a, 4.11.a, 4.13a, .15.a, 4.18.a, 4.19.a, 4.19.b), ***it may be more prudent for the trading machines to simply make decisions based on previous forecast regardless of the actual close and simply seek to make directional purchase decisions***.

That is, these same experiments might be run again and, rather than use a Forecast vs Previous Close comparison for making purchase (or sell) decisions, the trading machine simply makes a comparison *to its own prior forecasts*. If the forecast is higher than the previous, then a purchase is made. If lower, then a sell or a hold. As previous experimenters have done to forecast the direction, the models might be re-evaluated on a binary (up/down) basis rather than a regression basis.

The trading machine could expand to include shorts. The current trading machine is only able to take long positions--buying the security to obtain profit from increases in price after purchase. But the forecasts also detect downward movement and so could, hypothetically, take short positions and seek profit from a lower market price.

With a clear baseline justification for feature inputs, the study could be used for doctoral work by expanding company inclusion range and depth of features.

7. Bibliography

Andrade, E.B., and Ariely, D. (2009). The enduring impact of transient emotions on decision making. *Organizational Behavior and Human Decision Processes*. Vol 109. 1-8

Atsalakis, G., and Valavanis, K. (2009). Surveying stock market forecasting techniques - Part II: Soft computing methods. *Expert Systems with Applications*. 36. 5932–5941.

Bako, E.D., and Sechel, IC (2013). Technical and Fundamental Anomalies. Paradoxes of Modern Stock Exchange Markets. *Annals of the University of Oradea, Economic Science Series*. 22 (1). 37 - 43

Board of Governors of the Federal Reserve System (US). 10-Year Treasury Inflation-Indexed Security, Constant Maturity [DFII10]. retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/DFII10. January 21, 2016.

Board of Governors of the Federal Reserve System (US). U.S. / Euro Foreign Exchange Rate [DEXUSEU]. retrieved from FRED, Federal Reserve Bank of St. Louis. https://fred.stlouisfed.org/series/DEXUSEU. January 21, 2016.

Bollerslev, T., Chou, R. and Kroner, K. (1992). ARCH modeling in finance, A review of the theory and empirical evidence. Journal of Econometrics. 52. 5-59.

Buffett, W. (1989). Letter to Shareholders. BERKSHIRE HATHAWAY INC. Retrieved from http://www.berkshirehathaway.com/letters/1988.html on May 23, 2016

Chai, J., Du, J. Lai, K.K., and Lee, Y.P. (2015). A Hybrid Least Square Support Vector Machine Model with Parameters Optimization for Stock Forecasting. *Mathematical Problems in Engineering.* 2015. 7 pages. DOI: http://dx.doi.org/10.1155/2015/231394

CIA. *World Fact Book*. Retrieved from https://www.cia.gov/library/publications/the-world-factbook/geos/gm.html on May 23, 2016

Cao, L.J. (2003). Support vector machines experts for time series forecasting. *Neurocomputing*. 51. 321–339.

Cao, Q., Leggio, K. B., and Schniederjans, M. J. (2005). A comparison between Fama and French's model and artificial neural networks in predicting the Chinese stock market. *Computers & Operations Research*. 32. 2499–2512

Chang, P.C., Fan, C.Y., and Lin J.L. (2011). Trend discovery in financial time series data using a case based fuzzy decision tree. *Expert Systems with Applications*. 38. 6070–6080.

Dietterich, T. (2000). Ensemble Methods in Machine Learning. Lecture Notes in Computer Science. 1857. 1-15.

De Bondt, W., and Thaler, R. (1985). Does the Stock Market Overreact?. *The Journal of Finance*. 40(3). 793-805

DeLong, J., Shleifer, A., Summers, H., and Waldmann, R. (1990). Noise trader risk in financial markets. *Journal of Political Economy*. 98. 703-738.

Dondio, P., & Longo, L. (2011). Trust-Based Techniques for Collective Intelligence in Social Search Systems. In *Next Generation Data Technologies for Collective Computational Intelligence* (pp. 113–135). Springer.

Longo, L. (2015). A defeasible reasoning framework for human mental workload representation and assessment. *Behaviour and Information Technology*, *34*(8), 758–786.

Longo, L., Barrett, S., & Dondio, P. (2009). Information Foraging Theory as a Form of Collective Intelligence for Social Search. In *Computational Collective Intelligence. Semantic Web, Social Networks and Multiagent Systems, First International Conference, ICCCI, Wroclaw, Poland, October 5-7* (pp. 63–74).

Longo, L., & Dondio, P. (2014). Defeasible reasoning and argument-based medical systems: an informal overview. In *27th International Symposium on Computer-Based Medical Systems, New York, USA* (pp. 376–381). IEEE.

Longo, L., Dondio, P., & Barrett, S. (2010). Enhancing Social Search: A Computational Collective Intelligence Model of Behavioural Traits, Trust and Time. *Transactions on Computational Collective Intelligence*, *2*, 46–69.

Longo, L., & Hederman, L. (2013). Argumentation Theory for Decision Support in Health-Care: A Comparison with Machine Learning. In *Brain and Health Informatics - International Conference, BHI 2013, Maebashi, Japan, October 29-31* (pp. 168–180).

Longo, L., Kane, B., & Hederman, L. (2012). Argumentation Theory in Health Care. In *Proceedings of CBMS 2012, The 25th IEEE International Symposium on Computer-Based Medical Systems, June 20-22, Rome, Italy* (pp. 1–6).

Rizzo, L., Dondio, P., Delany, S. J., & Longo, L. (2016). Modeling Mental Workload Via Rule-Based Expert System: A Comparison with NASA-TLX and Workload Profile. In L. Iliadis & I. Maglogiannis (Eds.), *Artificial Intelligence Applications and Innovations: 12th IFIP WG 12.5 International Conference and Workshops, AIAI 2016, Thessaloniki, Greece, September 16-18, 2016, Proceedings* (pp. 215–229). Cham: Springer International Publishing. Retrieved from http://dx.doi.org/10.1007/978-3-319-44944-9_19

Roll, R., and Ross, S. (1980) An empirical investigation of the arbitrage pricing theory. *Journal of Finance*. 35(5). 1073-1103

Sharpe, W. (1964). Capital Asset Prices: A Theory of Market Equilibrium under Conditions of Risk. *The Journal of Finance*. 19(3). 425-442

Shleifer, A., and Summers, L. (1990). The noise trader approach to finance. *Journal of Economic Perspectives*. 4. 19-33.

Schulmeister, S. (2009). Profitability of technical stock trading: Has it moved from daily to intraday data?. *Review of Financial Economics*. 18. 190–201.

Scholer, K. (June, 2015). A Look at Apple One Year After Its ‘Unusual’ 7-for-1 Stock Split. *WallStreet Journal*. Retrieved from http://blogs.wsj.com/moneybeat/2015/06/09/a-look-at-apple-one-year-after-its-unusual-7-for-1-stock-split/ on May 23, 2016

Sullivan, R., Timmermann, A., and White, H. (2001). Dangers of data mining: The case of calendar effects in stock returns. Journal of Econometrics. 105. 249–286.

S&P Dow Jones Indices LLC. S&P 500© [SP500]. retrieved from FRED, Federal Reserve Bank of St. Louis. https://fred.stlouisfed.org/series/SP500. January 21, 2016.

Taleb, N. (2007). *Black Swan*. London: Penguin Books

Tay, F., and Cao, L.J. (2001). Application of support vector machines in financial time series forecasting. *Omega*. 29. 309–317.

Tay, F., and Cao, L.J. (2002). Modified support vector machines in financial time series forecasting. *Neurocomputing*. 48. 847–861.

Teixeira, L.A., and Inácio de Oliveira, A.L. (2010). A method for automatic stock trading combining technical analysis and nearest neighbor classification. *Expert Systems with Applications*. 37. 6885–6890.

Thawornwong, S., Enke, D., and Dagli, C.H. (2003). Neural Networks as a Decision Maker for Stock Trading: A Technical Analysis Approach. *International Journal of Smart Engineering System Design*. 5. 313–325.

Ticknor, J. (2013). A Bayesian regularized artificial neural network for stock market forecasting. *Expert Systems with Applications*. 40. 5501–5506.

TradingEconomics. European Union GDP. Retrieved from http://www.tradingeconomics.com/european-union/gdp on May 23, 2016

Tsai, C.F. (2009). Feature selection in bankruptcy prediction. *Knowledge-Based Systems*. 22. 120–127.

Tsai, C.F., and Hsiao, Y.C. (2010). Combining multiple feature selection methods for stock prediction: Union, intersection, and multi-intersection approaches. *Decision Support Systems*. 50. 258–269.

US. Bureau of the Census. Housing Starts: Total: New Privately Owned Housing Units Started [HOUST]. retrieved from FRED, Federal Reserve Bank of St. Louis. https://fred.stlouisfed.org/series/HOUST. May 2, 2016.

US. Bureau of the Census. Real Median Household Income in the United States [MEHOINUSA672N]. retrieved from FRED, Federal Reserve Bank of St. Louis. https://fred.stlouisfed.org/series/MEHOINUSA672N. January 21, 2016.

US. Bureau of Economic Analysis. Personal Consumption Expenditures [PCE]. retrieved from FRED. Federal Reserve Bank of St. Louis. https://fred.stlouisfed.org/series/PCE. May 1, 2016.

US. Bureau of Economic Analysis. Personal Saving Rate [PSAVERT]. retrieved from FRED. Federal Reserve Bank of St. Louis. https://fred.stlouisfed.org/series/PSAVERT. May 1, 2016.

US. Bureau of Economic Analysis. Real Gross Domestic Product [A191RL1Q225SBEA]. retrieved from FRED. Federal Reserve Bank of St. Louis. https://fred.stlouisfed.org/series/A191RL1Q225SBEA. May 1, 2016.

US. Bureau of Labor Statistics. Consumer Price Index for All Urban Consumers: All Items [CPIAUCNS]. retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/CPIAUCNS. May 1, 2016.

US. Bureau of Labor Statistics. Civilian Labor Force Participation Rate [CIVPART]. retrieved from FRED, Federal Reserve Bank of St. Louis. https://fred.stlouisfed.org/series/CIVPART. January 21, 2016.

US. Bureau of Labor Statistics. Civilian Unemployment Rate [UNRATE]. retrieved from FRED, Federal Reserve Bank of St. Louis. https://fred.stlouisfed.org/series/UNRATE. January 21, 2016.

US. Bureau of Labor Statistics. Understanding the CPI: Frequently Asked Questions. retrieved from http://stats.bls.gov:80/cpi/cpifaq.htm. May 1, 2016.

US. Employment and Training Administration. 4-Week Moving Average of Initial Claims [IC4WSA]. retrieved from FRED. Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/IC4WSA. January 21, 2016.

US. Energy Information Administration. Crude Oil Prices: Brent - Europe [DCOILBRENTEU]. retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/DCOILBRENTEU. January 21, 2016.

Vapnik, V. N. (1999). *The Nature of Statistical Learning Theory, Second Edition*. New York, NY: Springer-Verlag.

Verma, R., Baklaci, H., and Soydemir, G. (2008). The impact of rational and irrational sentiments of individual and institutional investors on DJIA and S&P500 index returns. *Applied Financial Economics*. 18. 1303-1317.

Vui, C.S., Soon, G.K., On, C.K., and Alfred, R. (2013). A Review of Stock Market Prediction with Artificial Neural Network (ANN). 2013 IEEE International

Conference on Control System: Computing and Engineering, 29 Nov. - 1 Dec. 2013: Penang, Malaysia, IEEE: Piscataway, 477-482.

Wang, B.H., Huang, H.J., and Wang, X.L. (2012). A novel text mining approach to financial time series forecasting. *Neurocomputing*. 83. 136–145.

Wang, J.Z., Wang, J.J., Zhang, Z.G., and Guo, S.P. (2011). Forecasting stock indices with back propagation neural network. *Expert Systems with Applications*. 38. 14346–14355.

Wang, J.J., Wang, J.Z., Zhang, Z.G., and Guo, S.P. (2012). Stock index forecasting based on a hybrid model. *Omega*. 40. 758–766.

West, D., Dellana, S., and Qian, J.X. (2005). Neural network ensemble strategies for financial decision applications. *Computers & Operations Research*. 32. 2543–2559.

Weigend, A., and Shi, S. (2000). Predicting Daily Probability Distributions of S&P500 Returns. *Journal of Forecasting*. Vol. 19. 375 - 392

Wen, Q., Yang, Z., Song, Y., and Jia, P. (2010). Automatic stock decision support system based on box theory and SVM algorithm. Expert Systems with Applications. 37. 1015–1022.

West, D., Dellan, S., and Qian, J. (2005). Neural network ensemble strategies for financial decision applications. *Computers & Operations Research*. 32. 2543–2559.

Wu, L. Luo, P., and Li, Y.L. (2015). Stock Price Forecasting: Hybrid Model of Artificial Intelligent Methods. *Inzinerine Ekonomika-Engineering Economics.* 26(1). 40-48.

YCharts. (2016). Various. [Data file]. Retrieved from https://ycharts.com/, May 27, 2016

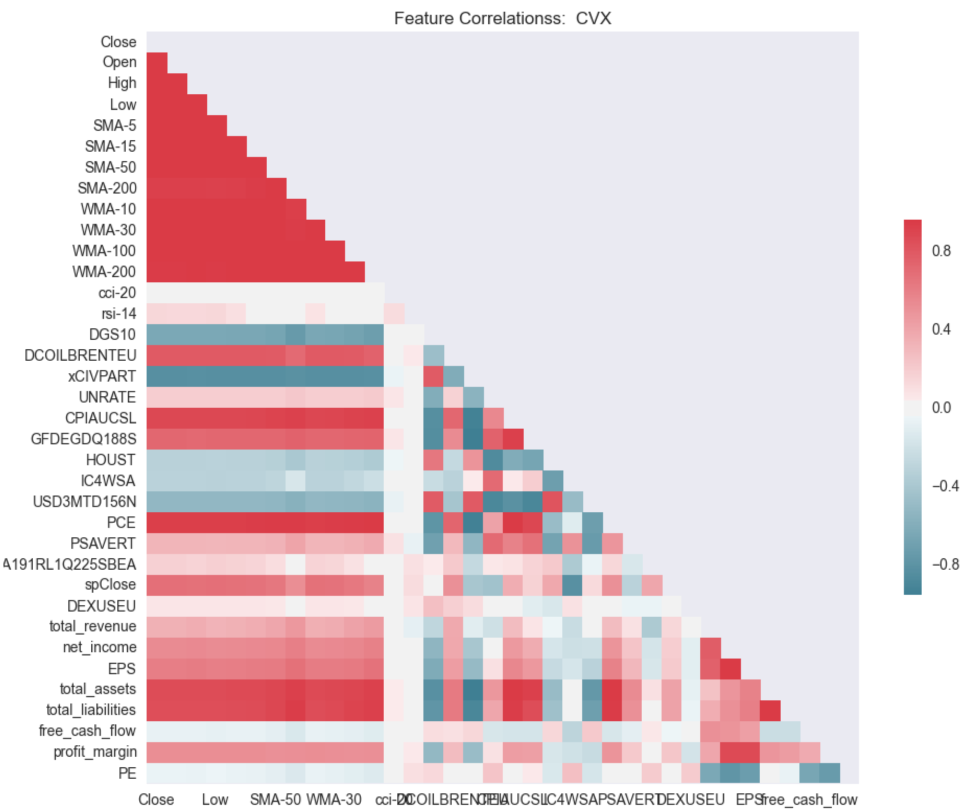
Yeh, C.Y., Huang, C.W., and Lee, S.J. (2011). A multiple-kernel support vector regression approach for stock market price forecasting. *Expert Systems with Applications*. 38. 2177–2186.

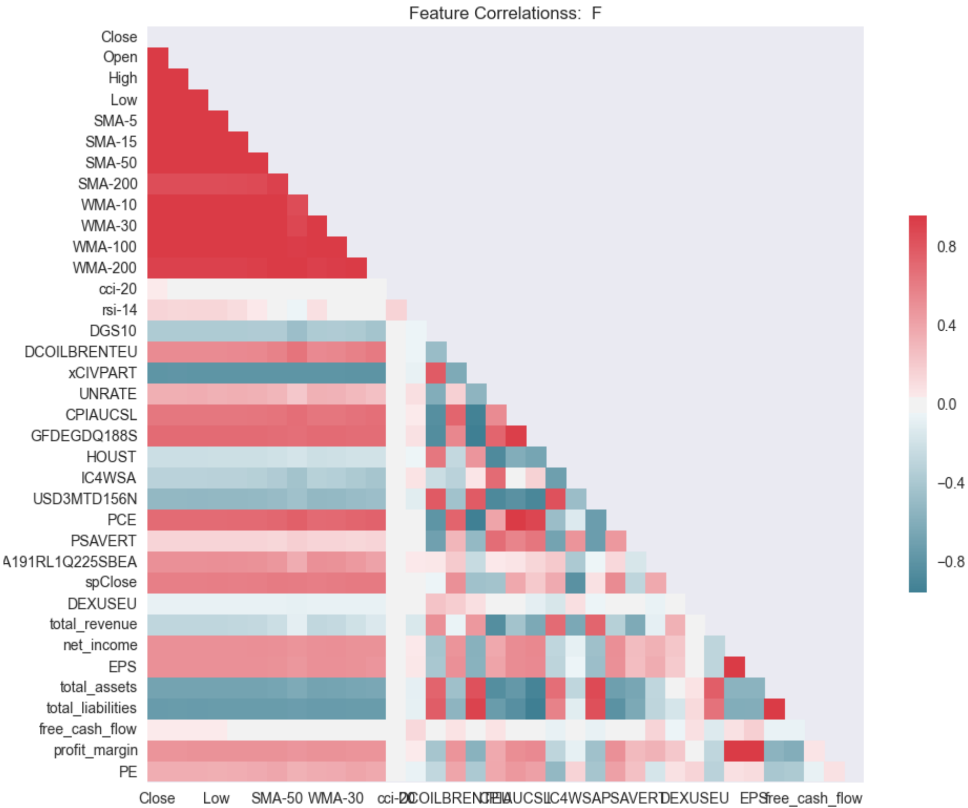
Zhou, Z.H., Wu, J.X.and Tang, W. (2002). Ensembling neural networks: Many could be better than all. *Artificial Intelligence*. 137. 239–263.

Zhu, Y., and Zhou, G. (2009). Technical analysis: An asset allocation perspective on the use of moving averages. *Journal of Financial Economics*. 92. 519–544

8. Appendix A: Feature Correlation Heatmaps

The following figures provide heatmaps for the correlations of the features' values with the Close price. Because experiment 3, 'Blended', uses the full set of features shared across the experiments, only a single heatmap has been produced for each company. Further, because the figures are predictably "consistent," only a sample of the most typical have been included here.

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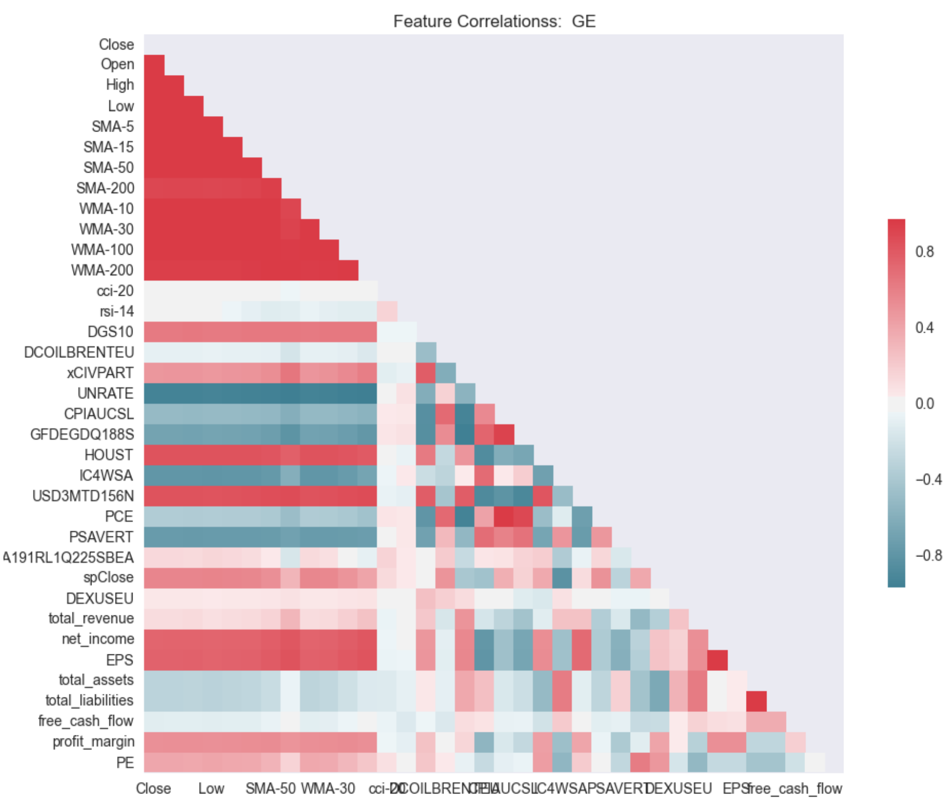
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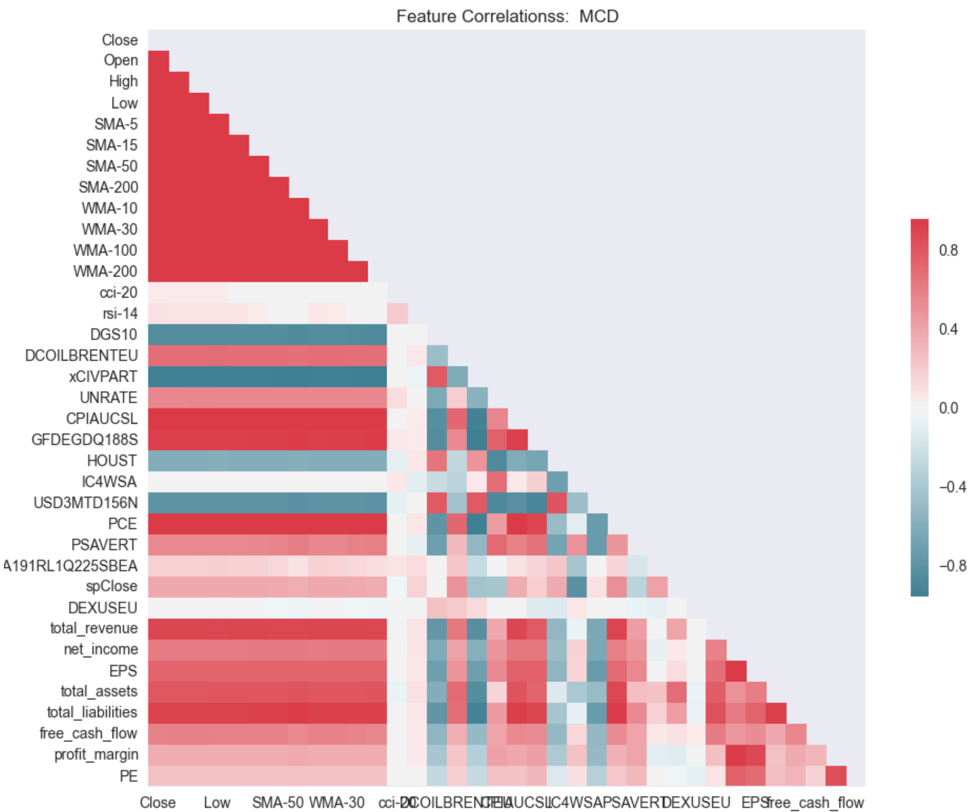
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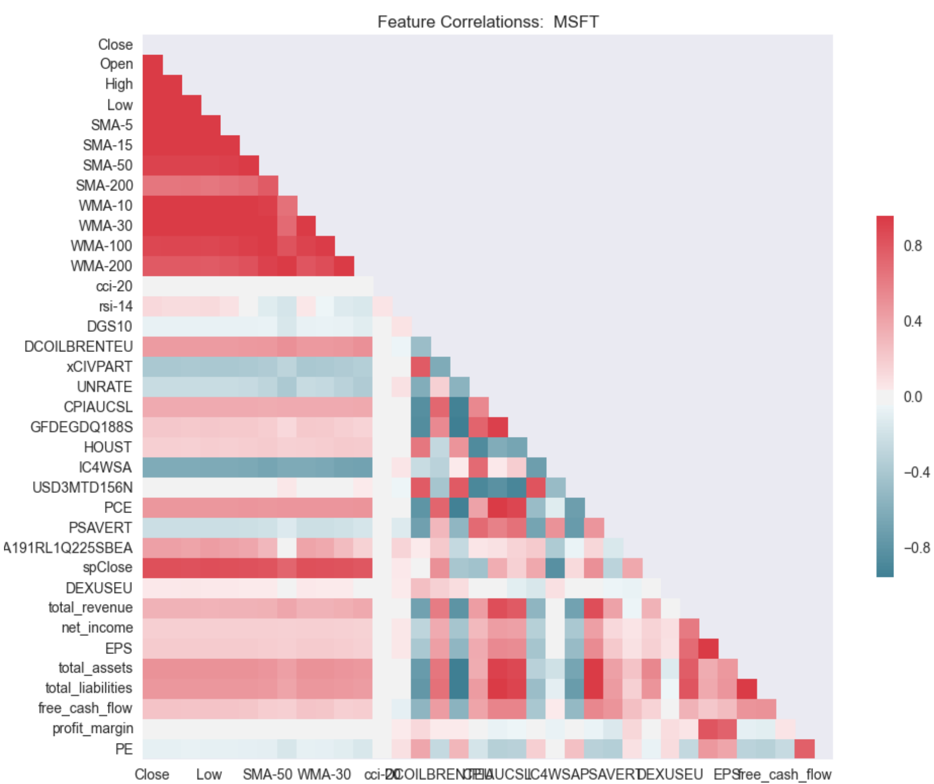
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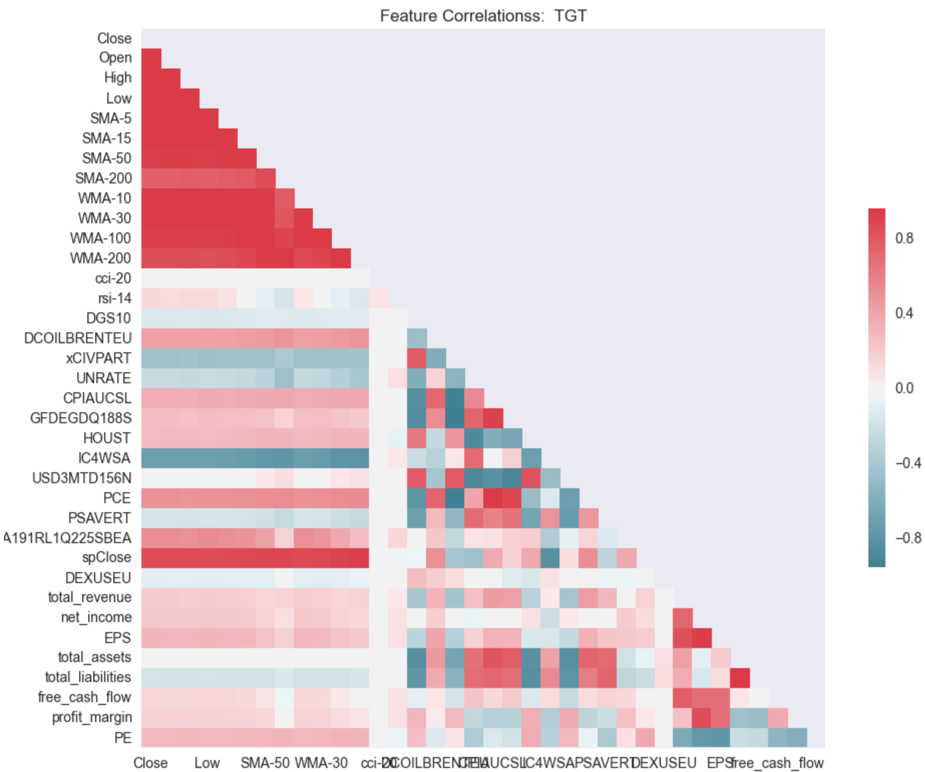
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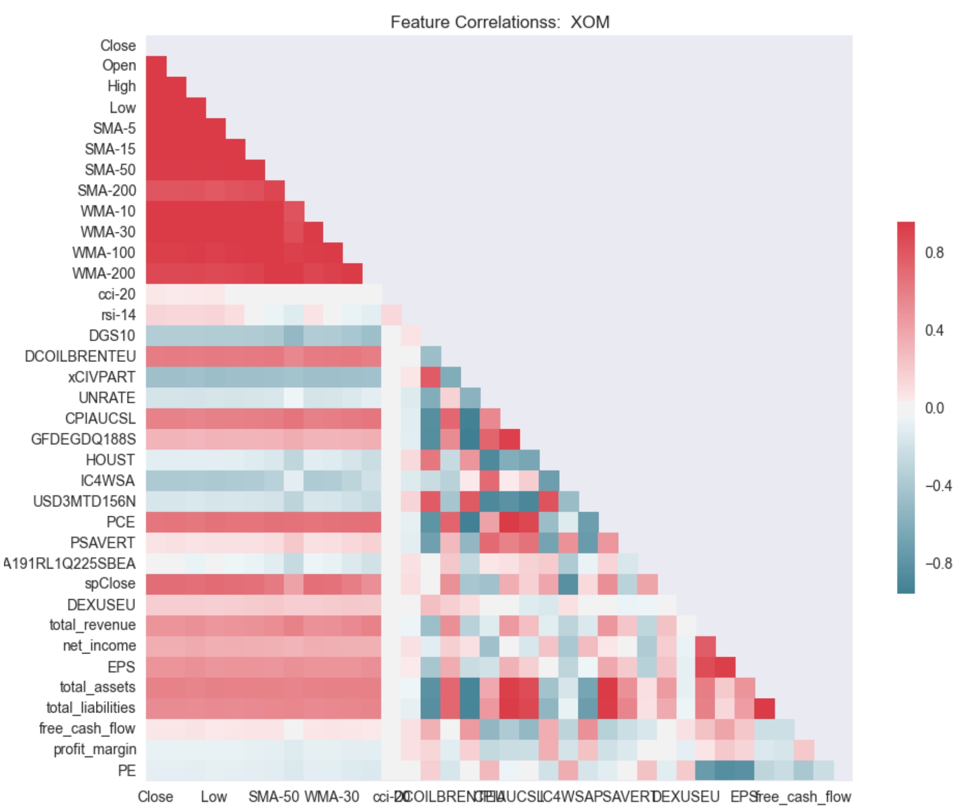
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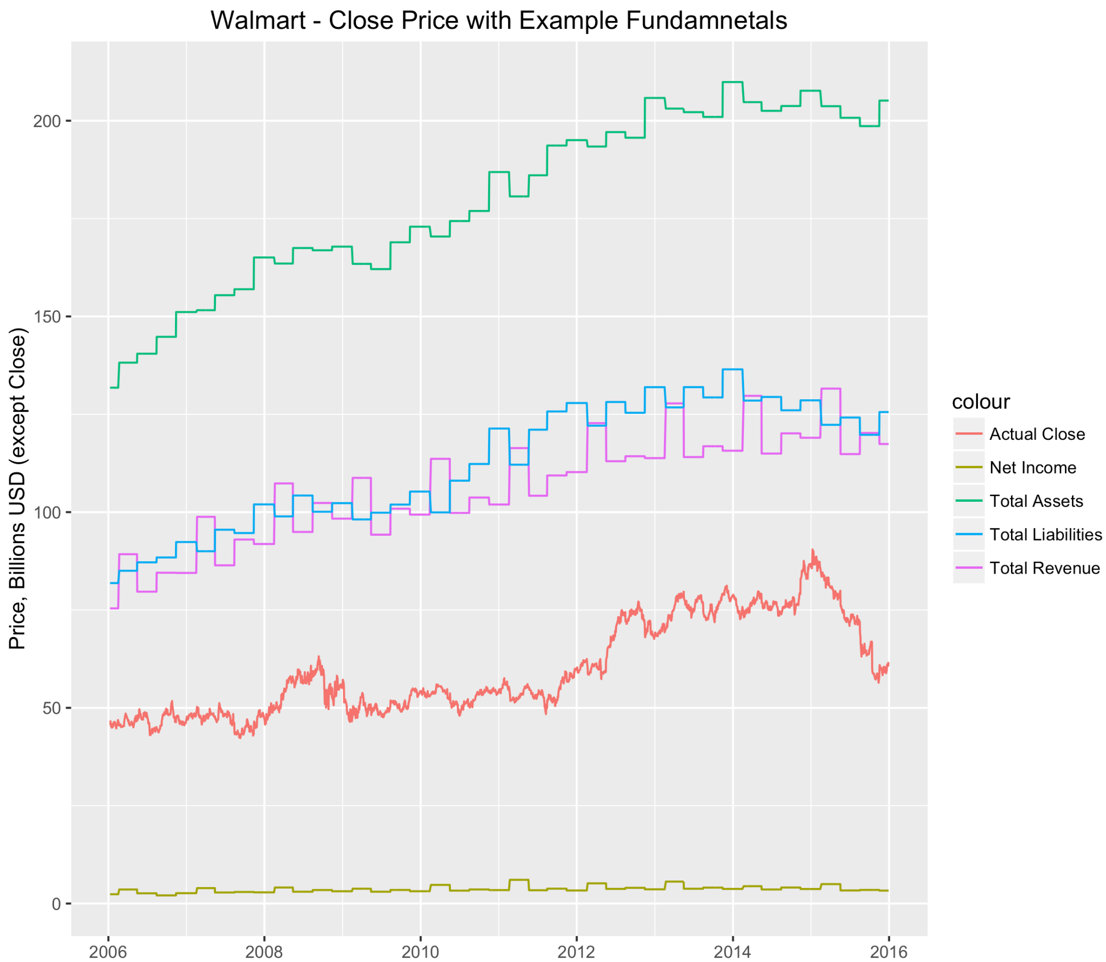
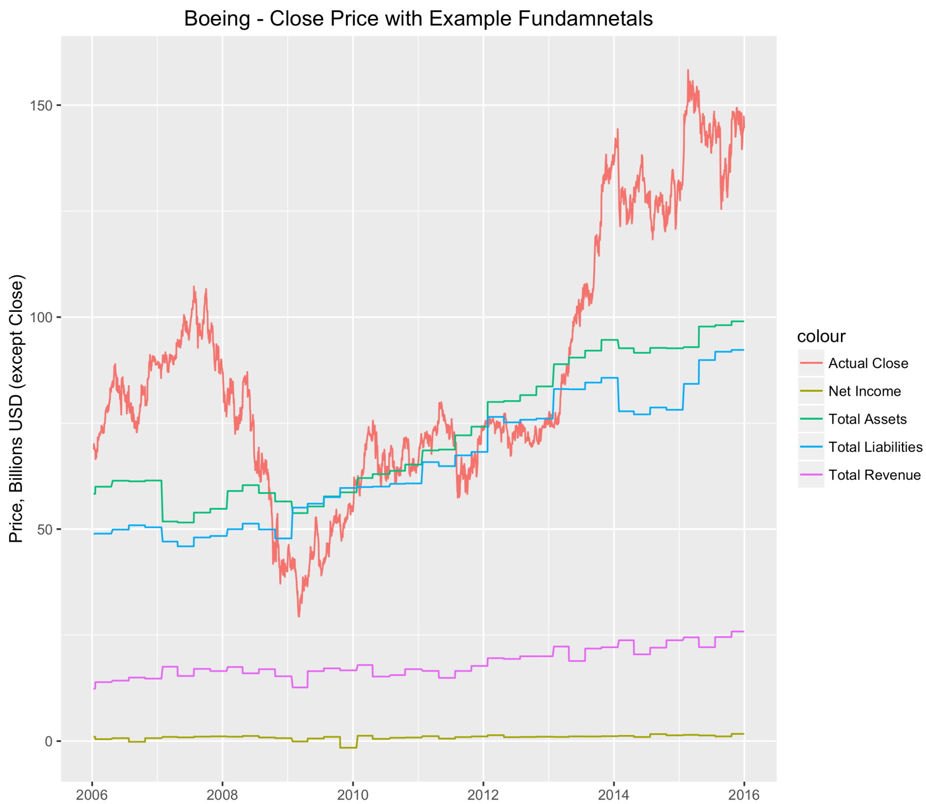
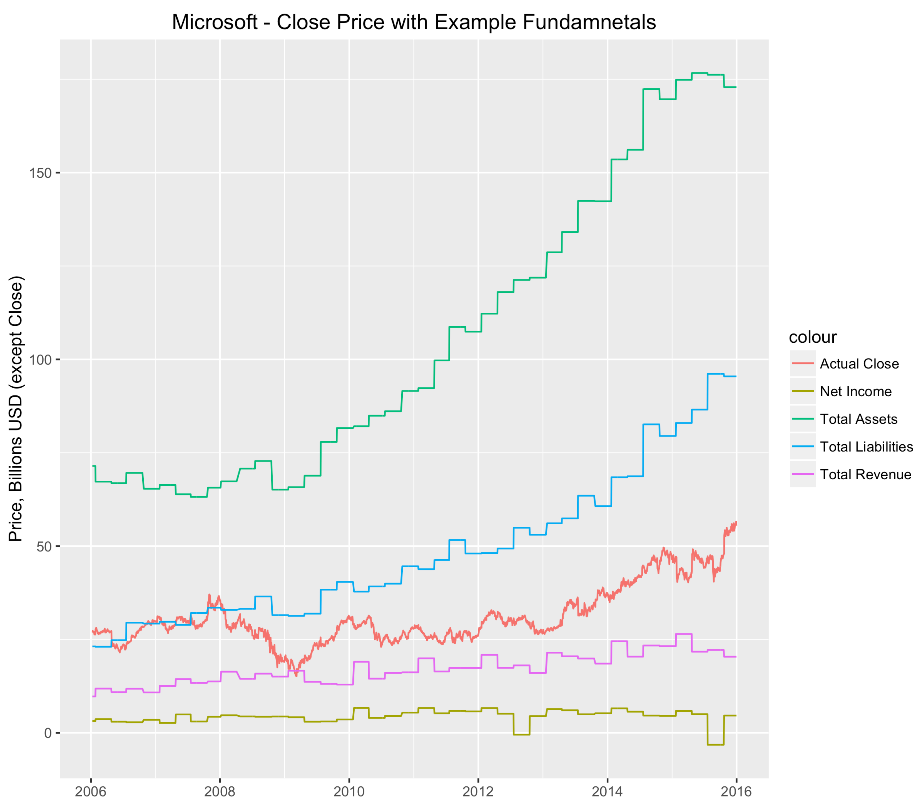
9. Appendix B: Visualizing Price and Economic Indicators

To see that there is indeed a relationship (if not loose, pseudo-dependency) between the Close and other economic indicators, the following figures were produced to illustrate the change in security price as a response to changes in economic conditions. Because the story is generally consistent across all firms (improvements in earnings result in increased security prices and decrements in profitability or margin result in a lowered price), a sample of the companies is included here.

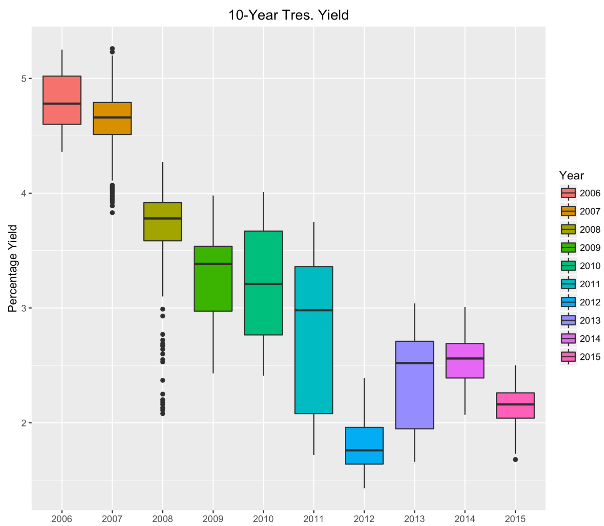


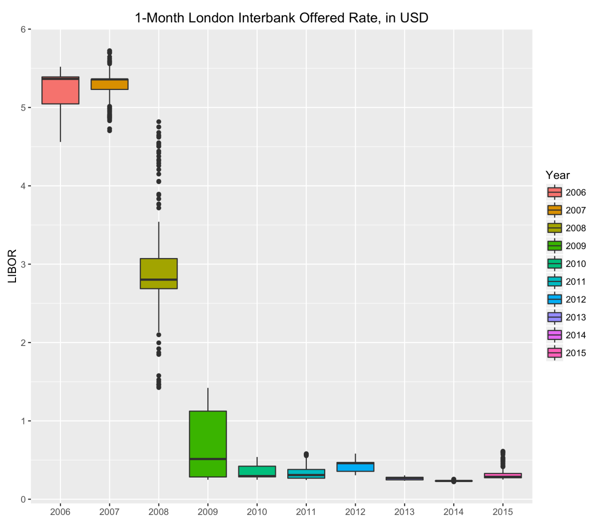
Equities Markets: S&P500, XOM and Brent Crude
USD Price
120
90
60
30
2006
2008
2010
2012
2014
2016
colour
Brent Crude
Exxon Closing

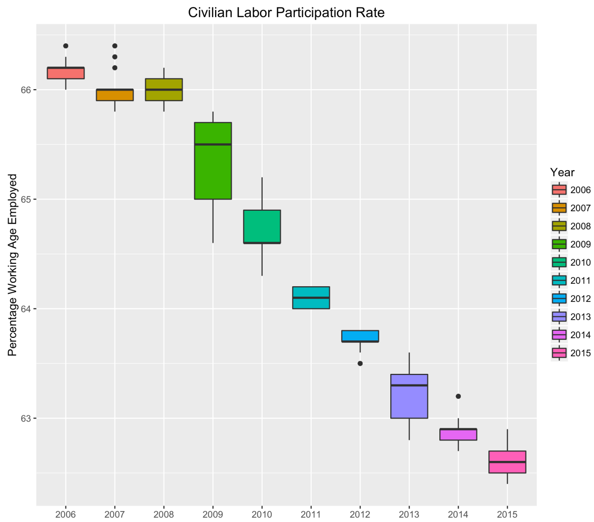

Boeing - Close Price with Example Fundamnetals
Price, Billions USD (except Close)
0
50
100
150
2006
2008
2010
2012
2014
2016
colour
Actual Close
Net Income
Total Assets
Total Liabilities
Total Revenue

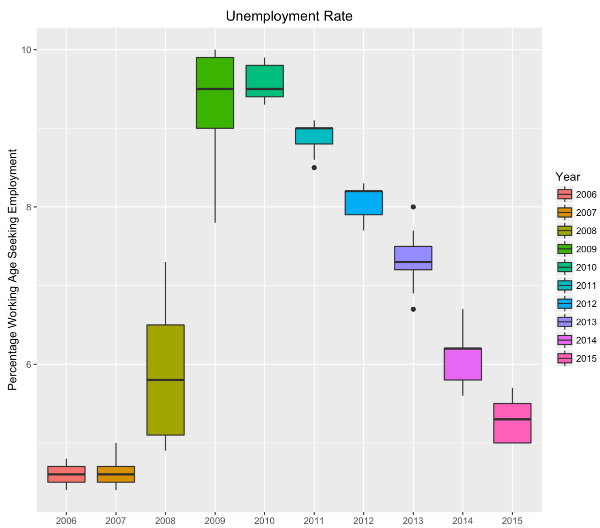

Microsoft - Close Price with Example Fundamnetals
Price, Billions USD (except Close)
0
50
100
150
2006
2008
2010
2012
2014
2016
colour
Actual Close
Net Income
Total Assets
Total Liabilities
Total Revenue

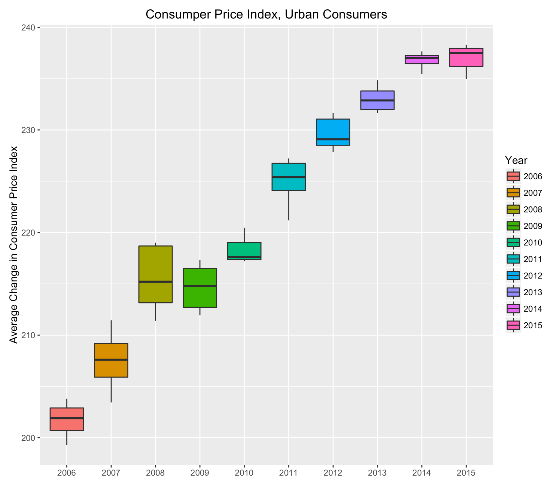
10. Appendix C: Distribution of Feature Input Indicators by Year



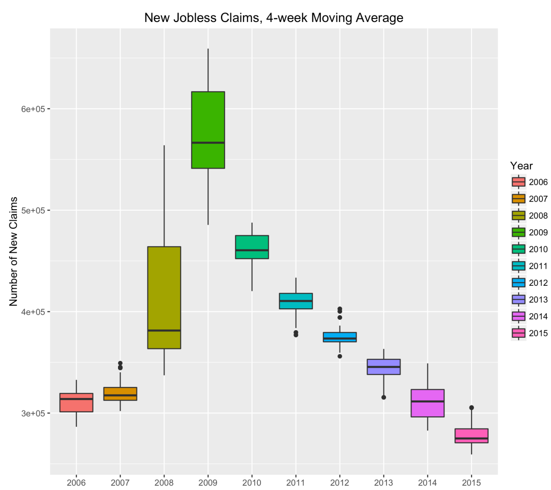


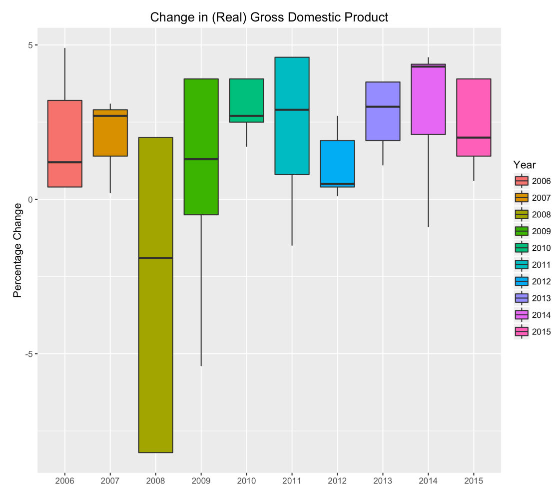

Civilian Labor Participation Rate
Percentage Working Age Employed
66
65
64
63
2006
2007
2008
2009
2010
2011
2012
2013
2014
2015
Year
2006
2007
2008
2009
2010
2011
2012
2013
2014
2015

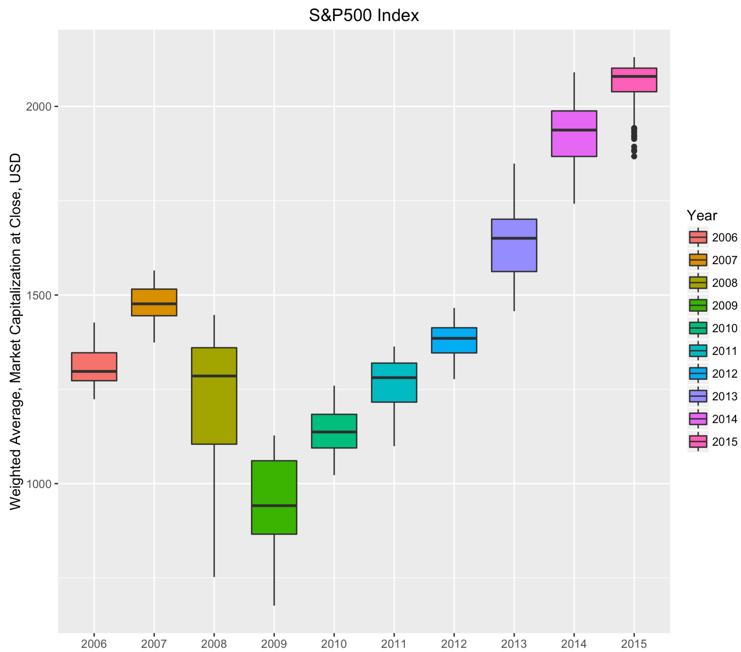

Unemployment Rate
Percentage Working Age Seeking Employment
10
8
6
2006
2007
2008
2009
2010
2011
2012
2013
2014
2015
Year
2006
2007
2008
2009
2010
2011
2012
2013
2014
2015

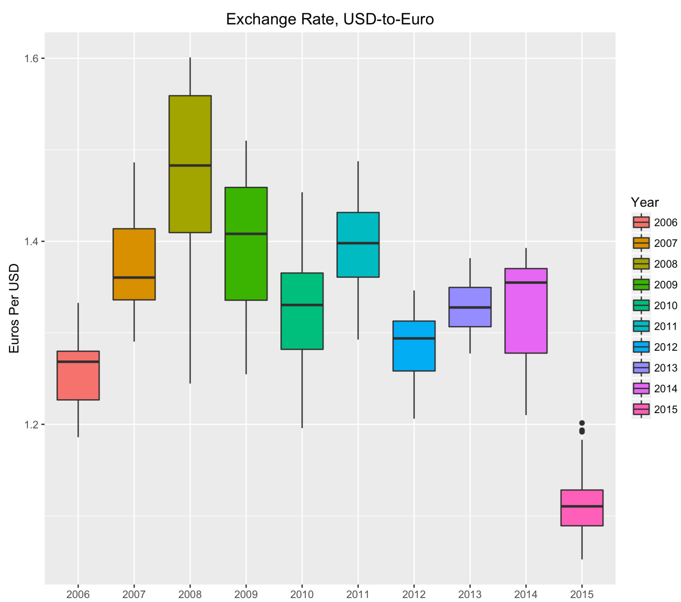

Consumper Price Index, Urban Consumers
Average Change in Consumer Price Index
200
210
220
230
240
2006
2007
2008
2009
2010
2011
2012
2013
2014
2015
Year


Ratio of Federal Debt to (Real) GDP
Percentage, Federal Debt to GDP
60
70
80
90
100
2006
2007
2008
2009
2010
2011
2012
2013
2014
2015
Year


New Jobless Claims, 4-week Moving Average
Number of New Claims
3e+05
4e+05
5e+05
6e+05
2006
2007
2008
2009
2010
2011
2012
2013
2014
2015
Year


Change in (Real) Gross Domestic Product
Percentage Change
-5
0
5
2006
2007
2008
2009
2010
2011
2012
2013
2014
2015
Year


S&P500 Index
Weighted Average, Market Capitalization at Close, USD
2000
1500
1000
2006
2007
2008
2009
2010
2011
2012
2013
2014
2015
Year
2006
2007
2008
2009
2010
2011
2012
2013
2014
2015


Exchange Rate, USD-to-Euro
Euros Per USD
1.6
1.4
1.2
2006
2007
2008
2009
2010
2011
2012
2013
2014
2015
Year
2006
2007
2008
2009
2010
2011
2012
2013
2014
2015