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Global Wealth Maximization Using Neuroeconomic Behavioral Drivers and Continuous Automated Trading

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GLOBAL WEALTH MAXIMIZATION USING

NEUROECONOMIC BEHAVIORAL DRIVERS AND

CONTINUOUS AUTOMATED TRADING

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ABSTRACT

Digital technologies are ushering in an era of global market access for equity traders. Global markets, 24/7 access and an unprecedented trading opportunities have coalesced to further a need for automated trading. This paper presents a theory of stochastic price formation which is modeled by twin neural networks to simulate the psychology of high-frequency equity trading across global markets. The ex-post efficiency of the WINKS automated trading framework is calibrated by estimating quasi-elasticity coefficients. We document the relative importance of firm fundamental factors in the cognitive control of automated trading compared to the simple and less profitable buy-and-hold strategy.

Keywords: Neuroeconomics, Automated Trading, Artificial Neural Networks; and, Cognitive Science.

1 INTRODUCTION

How wonderful it would be to predict a future stock price without error. In such a world, a world that would be characteristic of certain outcomes, the individual who is seeking to maximize wealth would only need to choose an appropriate risk level. Well, informed investors know all too well that world does not and cannot exist. In fact, both informed and un-informed investors realize that there are a myriad of different factors which typically come together to bedevil the utopian ideal of certainty. As a consequence, from the casual to the active intra-day pattern observer, traders continue to seek methodologies that offer risk-mitigated paths for wealth maximization in both stable and volatile markets. Increasingly, the more promising evolutionary trends in trading 24/7 global markets rely on quantitative modeling and computational science to forecast volatility and directional price patterns over shorter and shorter investment horizons. But, forecast modeling based in technical market components alone has also proven to have its own limitations. Contemporary model builders have come to understand that opportunities associated with trading in global markets brings with it a need to extend quantitative models to expressly incorporate local cultural idiosyncrasies (for a discussion of volatility and liquidity impacts in emerging markets, see Al-Khouri and Al-Ghazawi (2008)). While model builders explore various avenues by which to capture these unique components of cultural diversity, an emerging approach is to impute behavioral consequences into the "learning algorithms" that produce an artificial intelligence (AI) of the data it models – domestic or international.

The purpose of this paper is to integrate cognitive science, or behavioral decision theory (BDT), with an artificial intelligence (AI) based multiple criteria decision aiding model (MCDA) to explain how individuals trade equity securities in their attempt to maximize wealth while mitigating perceived risks to the wealth accumulating process. To achieve this objective, we present a BDT information system that is engaged in the continuous receipt and evaluation of new information. More directly, the system presented in this paper implements an MCDA artificial intelligence-based automated trading system that includes a nested decision subsystem.

Automated trading of equity securities is a complex system that continuously integrates various cognitive and algorithmic processes that receive and interpret new market data in order to update the individual's share allocation decision under the precept of wealth maximization. The efficient automated trading system depends on its ability to use a set of mathematical models and market rules to algorithmically derive optimal market decisions. These decisions include choices of whether to open, sell short, hold or close a specific equity position within the framework of the continuous trading environment. To evaluate one such automated trading information system, this paper introduces the **Wi**nORS$_{e\text{-}AI}$ **N**euroeconomic **K**nowledge-based market trading **S**ystem (WINKS). The WINKS system is a dual radial basis function (RBF) artificial neural network (ANN) stock price (return) forecasting framework that combines end-of-day (EOD) forecasts with intra-day forecasts to determine the quantities for intra-day and EOD transaction decisions.

The paper proceeds as follows. Section 2 introduces the stochastic integral model as a theory of trading an equity security for profitability. Section 3 presents the WINKS algorithm followed by a statistical review of automated trading results. Section 4 provides a nonparametric analysis of how firm fundamental variables contribute to the production of profitable trades within the context of the WINKS high-frequency trading system. Section 5 provides a summary and conclusion.

2 THE STOCHASTIC INTEGRAL AS A MODEL OF EQUITY TRADING PROFITS

Stochastic calculus has rapidly become the language of financial modeling (see Brock et. al. (1992), for a discussion). In this section we present a characterization of the Shreve (2004) framework for use of the stochastic integral to characterize uncertain stock trading. The methodology is developed in a manner that is designed to support the WINKS framework.

Consider X_t to be the random variable of a stock's market price at time t. As in prior research, we assume that the price process X follows a geometric Brownian motion with a constant drift and volatility (Tsay (2005) provides an in depth discussion). Next we define a trading strategy θ that determines the quantity $\theta_t(\omega)$ of each security held in each state $\omega \in \Omega$ and at each time t. The trading system envisioned by this approach assumes a market that is not characterized by the no-risk unlimited profit arbitrage effects of trading on advanced knowledge. That is, θ is adapted and corresponds to the necessary restriction that the trading strategy can only make use of the available information at any time t. This prevents the possibility of unlimited gains through high frequency trading or flash-crash trading (For description of May 6th, 2010 flash crash see: http://en.wikipedia.org/wiki/May_6,_2010_flash_crash) . The condition that θ is adapted implies that the stochastic integral will not diverge when calculated as a limit of Riemann sums. Hence, given a price process X and a trading strategy θ that satisfies the no arbitrage conditions, the total financial gain $\int_s^t \theta_u dX_u$ between any times $s, t \geq 0$ is defined by Ito's stochastic integral. Since this is a continuous-time stochastic process, it is assumed that there is an underlying filtered probability space $(\Omega, V, (V_t)_{t\geq 0}, P)$. The increasing sequence of σ-algebra of $V, \{V_t : t \in [0, \infty]\}$, determines the relevant timing of information. That is, V_t represents the information available up until time t, and is loosely viewed as the set of events whose outcomes are certain to be revealed to investors as true or false by, or at, time t. Finally, the trading strategy θ is adapted if $\theta_t(\omega)$ is V_t measurable.

2.1 Buy and Hold

The buy-hold (BH) strategy is a short-horizon element of the WINKS trading strategy captured by θ. Under the BH strategy an investor initiates a position immediately after some stopping time T and closes it at some later stopping time *U*. For a position size $\theta_t\ (\omega)$ that is V_t measurable, the trading strategy θ is defined by $\theta_t = 1_{(T<t\leq U)}\theta_t(\omega)$. By definition, the gain from the BH trade strategy is the position size multiplied by the interim price change, or $\int_0^U \theta_t dX_t = \theta_t(X_U - X_T)$.

2.2 The N-Dimensional Trading Strategy

A typical financial model allows for *n* different securities, with price process $X_1, \ldots, X_n$. The investor can choose an associated *N*-dimensional trading strategy $\theta = (\theta_1, \ldots, \theta_n)$ for which the total gain from the equity trading process is: $\int \theta_t dX_t \equiv \sum_{i=1}^{n} \int \theta_{it}\, dX_{it}$. The technical restrictions that define the stochastic integrals can be augmented for the allowable set θ to include budget limits, credit constraints, short-sales restrictions or various other managerially imposed investment constraints.

3 AUTOMATED TRADING SYSTEM AND THE PRODUCTION OF PROFITABILITY

The prediction and mapping capabilities of ANNs in general, and the RBF topology specifically, has resulted in an extraordinary amount of interest in applying various ANN algorithmic topologies to stock market prediction and forecast behavior (for example, see Refenes, P., et.al. (1996)). The usefulness of RBF ANNs continues to be exploited in complex financial optimization and mapping studies to describe chaotic appearing data patterns (Dash and Kajiji (2008)) as well as intraday stock prices that exhibit skewed patterns defined by the sign of a trade (Tay and Ting (2006)) . The objectives for this section of the paper are twofold. The first objective is to specify the K4-RBF ANN that provides both EOD and 20-minute ahead forecasts for individual securities is described. The second objective for this section is to define the WINKS decision algorithm system in pseudo detail. Like many auto trading systems WINKS relies upon the prediction of price at time period *t+1* given a price observation at time t with a known information set, θ. Within WINKS the functional form of all prediction models (both the EOD and 20-minute ahead forecasts) is as follows:

$$x_{t+1} = f_\theta\left(x_t, P_{1,t}, P_{2,t}, \ldots, P_{k,t} \,\middle|\, \theta\right) \tag{1}$$

Where x_t is the price of the target security at time *t* and $P_i, \ldots, P_k$ captures the set of *k* exogenous predictor variables.

3.1 High-Frequency Neuroeconomics for Stock Price Forecasting

The automated trading algorithm employed by WINKS is based upon Kajiji's (2001) K4-RBF ANN. WINKS employs this ANN to produce an analytic approximation for the next period stock return by mapping the noisy exogenous data stream which may be described as follows,

$$\{[x(k), y_i : [\mathbb{R}^n, \mathbb{R}]\}_{k=1}^{m} \tag{2}$$

where $x(k)$ is the input vector for predictor k, y_i is the output for stock i, and n is the dimension of the input space, and m is the number of basis functions. The data is drawn from the noisy set:

$$\{[y_i = f[x(k) + \epsilon]\}_{k=1}^{m} \tag{3}$$

As shown in figure 1, the RBF ANN topology is defined by three layers: the input layer, the hidden layer (linear layer) and the output layer.

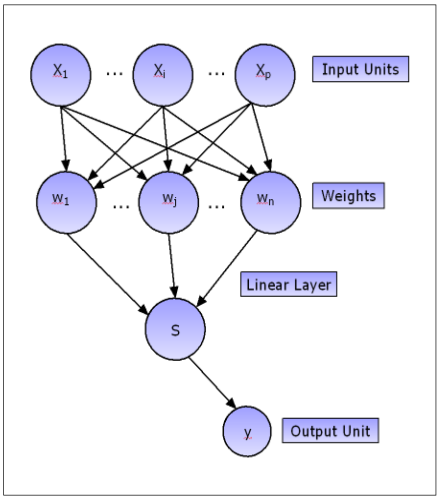

Figure 1: The RBF ANN Topology

The input layer has no particular calculating power; its primary function is to distribute the information to the hidden layer of the RBF network. The hidden, or middle, layer embraces computing units, or hidden nodes. Each hidden node is defined by a center. The center, $c(k)$, is a parameter vector of the same dimension as the input data vector, $x(k)$, and calculates the Euclidean distance between the center and the network input vector x defined by $\|x(k) - c(k)\|$. The results are passed through a nonlinear activation function, $\emptyset(k)$, to produce output from the hidden nodes. The Gaussian basis function shown in eq. 4 is a widely used approach to establish the activation function.

$$\emptyset(k) = exp\left(\frac{\|x(k) - c(k)\|^2}{\sigma_j^2}\right), \quad j = 1 \ldots m \tag{4}$$

where σ_j is a positive scalar and is referred to as the width of the center. The output layer is a linear combiner with the ith output of the network model being a weighted sum of the hidden nodes:

$$\hat{y}_i = \sum_{j=1}^{m} \emptyset(k)\, w_j, \quad i = 1 \ldots p \tag{5}$$

where p is the number of outputs (generally p = 1), w represents output layer weights, and $\hat{y}$ is the network output to estimate the target y. For generalizations see Haykin (1994). For additional discussion on the foundations of RBF ANNs, see D.S. Broomhead and D. Lowe (1988), H. Lohinger (1993), Parthasarathy and Narendra (1991) as well as Sanner and Slotine (1992).

The Kajiji (2001) extension to the traditional RBF ANN specification introduced multiple objectives within a Bayesian RBF ANN framework. By adding a weight penalty term to the SSE optimization objective, the modified SSE is restated as the following cost function:

$$C = \sum_{i=1}^{p}(\hat{y}_i - f(x_i))^2 + \sum_{j=1}^{m} v_j w_j^2 \tag{6}$$

where: v_j are regularization parameters or weight decay parameters. Under this specification the function to be minimized is stated as:

$$C = \frac{argmin}{v}\left(\zeta \sum_{i=1}^{p}(y_i - f(x_i|\bar{v}))^2 + \sum_{j=1}^{m} v_j w_j^2\right) \tag{7}$$

In early implementations of the RBF topology, iterative techniques were commonly employed to compute the weight decay vector $\bar{v}$. With the introduction of weight decay methods by Hoerl and Kennard (1970) and Hemmerle (1975) iterative techniques were decried as they lacked specificity and added to the computational burden [see, Orr (1996; 1997)]. The K4-RBF algorithm eliminated this latter inefficiency by the incorporation of a globally optimized regularization parameter based on Crouse's (1995) Bayesian enhancement to optimal ridge regression. The extensions embraced by the K4-RBF ANN allow the dual-objective, multiple criteria decision analytic (MCDA) algorithm to directly attack the twin evils that deter efficient ANN modeling: the "*curse of dimensionality*" (multicollinearity or over-parameterization) and inflated residual sum of squares (inefficient weight decay). The benefit to WINKS is straightforward. First, the excellent mapping capabilities of the RBF topology are applied to the generalized- volatility forecasting problem inherent in all price forecasting systems. Second, the algorithmic speed generated by K4-RBF ANN enhancements permit the computational algorithm to operate in a high-frequency forecasting environment for thousands of securities.

3.2 The WINKS Automated Trading Algorithm

The inherited computational commonality among decision theory, the cognitive sciences, artificial intelligence and operations research has been well established in the literature (see, Zimmerman (1991) for a review). The flow chart presented in figure 2 provides the detail pseudo-algorithm of WINKS. The design goal for the WINKS automated trading algorithm was to create an *N*-dimensional high frequency cognitive decision making engine that generates probability judgment(s) about trading decisions when presented with new trading-relevant data. For the 2,225 securities tracked by the global database, WINKS executes one RBF ANN to produce a 20-minute BH investment decision which is immediately compared to the daily EOD forecast that was generated by a separate RBF ANN model executed during a market's overnight hours. Data input to WINKS is restricted to the global exchanges supported by *Yahoo!* Finance (see Appendix A for detail).

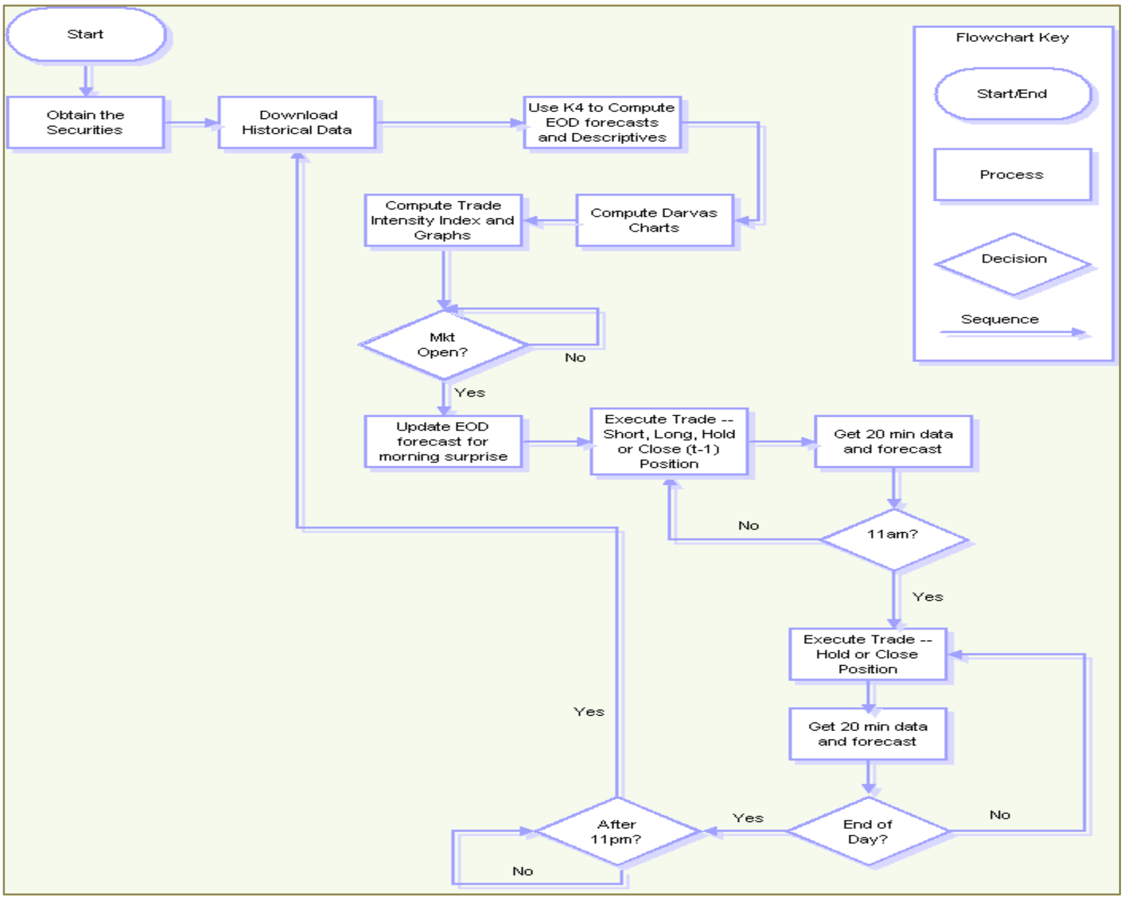

Figure 2: WINKS Flow Chart

3.3 WINKS Performance

The high frequency trading exercise for the 2,225 securities entered into the WinORS$_{e\text{-}AI}$ database by over 600 independent portfolio builders was executed during U.S. trading hours (9:30 EST to 4 p.m. EST) beginning on 01-June-2009 through 19-March-2009, inclusive.   The trading process was initiated by investing US$1,000 into each security. This formed the base for buy-and-hold results and the initial starting point for daily trade activity as determined by WINKS. Table 1 presents a comparison of the results produced by BH and WINKS. We note that trading efficiency is defined as: ((WINKS trade profit – BH trade profit) / Initial $ Investment). Positive and negative trades are indicated by +ve / -ve, respectively.

Although the results are illustrative, it is clear that over the test period WINKS was able to produce annualized rates of return that far exceed those of the simple BH strategy. The most impressive results were recorded by trading TVL with an annualized return of 172% compared to the BH similar result of 140%.   On the low end, ticker symbol CMED generated a negative rate of return compared to the 62% rate of return obtained by trading. The impact of being able to trade both long and short is obvious in this result.

Table 1: Comparison of Buy-Hold v/s Trading: June 01, 2009 to March 19, 2010

Equity Ticker	BH Profit	BH Annualized RoR	WINKS Trading Profit	WINKS Annualized RoR	WINK S+ve Trades	WINK S-ve Trades	WINKS Trading Efficiency
TVL	$1925	140%	$2402	172%	45	14	48%
WLL	$700	55%	$912	71%	40	17	22%
PLCE	$229	18%	$850	66%	26	16	63%
CMED	$(339)	-29%	$806	62%	41	21	116%
ILMN	$24	2%	$632	49%	26	16	61%

4 FUNDAMENTAL FACTORS TO PRODUCE KNOWLEDGEABLE TRADING

In this section of the research we investigate the relationship between firm fundamental characteristics and PPT. Over the past 40 years, a large body of research has evolved to identify firm-specific factors that efficiently explain the variability of excess average market returns. To achieve this outcome the extant literature reports a reliance on the classic efficient markets approach founded by Fama and French (1993) that introduced the well-known three-factor model. In addition to the common market factor, the Fama-French model established a firm-specific contribution by including a factor for size and value. Specifically, the former factor is often referred to as SMB, or small cap minus big. The value factor, HML, was captured by calculating high book/price stocks minus low. Carhart (1997) extended the model to include a fourth factor to encapsulate market risk (the momentum effect). Both domestic (U.S.) and international version of the Carhart formulation have been subject to extensive investigation and support (for example, see Lam, Li and So, (2009) for significant findings on the global applicability of the four-factor model).

Unlike current econometric studies that focus on portfolio and equilibrium theoretic implications of market pricing, this paper expands traditional micro-economic production theory to include a turbulent boundary area – the theory of production knowledge. In an unpublished essay, Sidney Winter (2002) reintroduced his earlier essay on the need for the academy to expand its definition of production theory. Winter made the observation that the seemingly ambiguous scope of productive knowledge, a theory without sharp boundaries, was enough to convince many economists that the concept lacked practical value. However, Winter went on to argue that, at a fundamental level, evolutionary change can only come about when theorists display a willingness to reconsider the conceptual structure that is appropriate to encapsulate the importance of modern-day advances in the role of knowledge as an input-output transformation for goods that may not be traditional consumption items. Similar questions about the nature of evolving economic theory have been raised by Thorstein Veblen (1998).

Our intention here is to extend the foundation of production sets to encompass the production of knowledge – trading knowledge for risk mitigation and wealth maximization. Knowledge production is an extension to classical approaches that applies cognitive learning from a pattern of firm-level inputs to produce efficient time-weighted trading profitability. This approach to expanding the production set model involves a specification of the RBF-ANN, BDT and proxies for Carhart's four factor market behavior model. The research introduces a nonparametric methodology to achieve the calibration of quasi-elasticity estimates to measure the scale and relative contribution provided by firm fundamental variables in the process of "learning" how to produce profitable trading patterns.

4.1 Production Elasticity

Production elasticity is a unit-less tool for measuring the responsiveness of a function to changes in its parameters (factors). The derivative is commonly used to compute the responsiveness as a percentage rate of change. Stated differently, it is well known that for the function $y = f(x)$, the unit free average elasticity, $\mathrm{E}_{\mathrm{y/x}}$, of the variable *y* with respect to the variable *x* is given by the ratio: $\mathrm{E}_{\mathrm{y/x}} = \frac{\%\Delta\mathrm{y}}{\%\Delta\mathrm{x}}$. For estimation purposes we implement (8):

$$\ln(y) = \ln A + \sum_{i=1}^{n} \beta_i \ln(x_i)\,,\ for\ \beta_i > 0\,. \tag{8}$$

In a manner that is consistent with the properties stated above, all inputs are interchangeable and each input must be used in strictly positive amounts to obtain a positive output. This is a straight forward estimation by OLS techniques when provided with a log-linear estimation equation. However, there are some systems for which the assumption of a functional form is not advisable. The production of PPT is one such system. For that reason alone, we propose a distribution free estimation procedure – the learning RBF ANN.

4.2 Nonparametric Estimation of Fundamental Trading Predictors

For the primary analysis, we begin with a time series of 20-minute price observations for 2,225 securities from all U.S. trading dates from June 01, 2009 to March 19, 2010 inclusive. To eliminate structural biases in the econometric analysis of trading performance we eliminate all non-equity stocks and those equities that do not have *Yahoo!* calculated or reported fundamental characteristics. Upon completing data reduction procedures a full-sample size of 1,765 is produced. For efficient cross-sectional modeling we sample from within the full content population. The data sampling is guided by the use of the target variable of the study – *percent positive trades* (PPT):

$$\% \text{ Positive Trades} = \text{Round}\left(\frac{\#\text{ positive trades}}{\text{total }\#\text{ trades}} \text{ x } 100\right) \tag{9}$$

The scatter plot of percent positive trades is shown in figure 3. Immediately obvious is the implied lower/upper bands at approximately 30% and 80%, respectively.

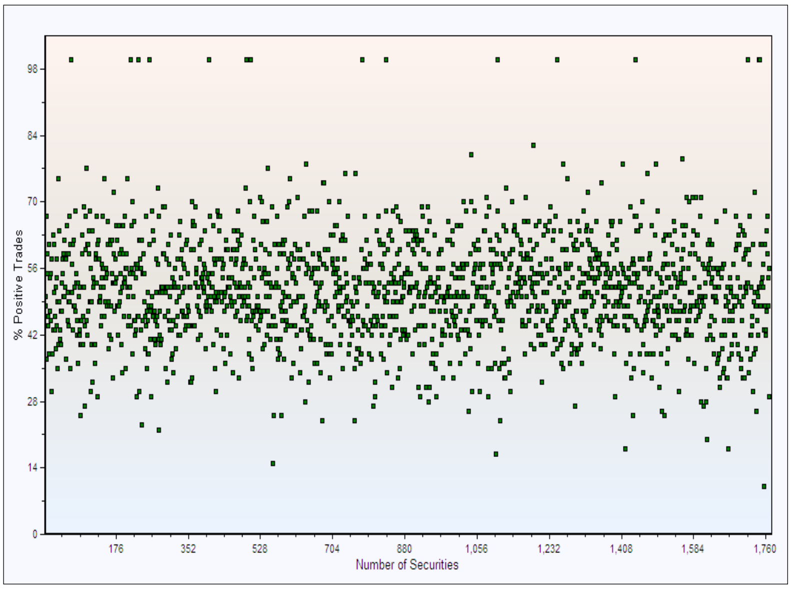

Figure 3: Percent Positive Trades by Security on March 19, 2010

4.2.1 Neural Network Modeling and Cognitive Decision Theory

As reported by Patterson (1996) ANNs are complex computational algorithms that trace their roots to modeling low-level structures of the human brain. Recent research authored by Lewicki, Hill, and Czyzewska (1992) in the cognitive science of non-conscious information processing has demonstrated the efficiency of the human brain to learn simple input-output co-variations from extremely complex stimuli.

To create a training sample from the cross-sectional observations on 19-March-2010, the full sample of 1,765 securities is separated into four strata (h) based on the value of the target variable. These strata are: 1- to 25-precent; over 25- to 50-percent; over 50- to 75-percent; and, over 75- to 100-percent. After strata creation, we compute a total econometric sample size by setting a minimum error rate (E) of 0.75 by use of the following equation:

$$n_h = \left(\frac{N_h}{N}\right) x\ n$$

A simple random sample of size n_h is drawn from each stratum. This process results in the selection of 793 securities for the training set. After attaching an identifier to each of the 793 securities, the full sample data base is sorted to place the 793 securities at the top of the observation list.

4.2.2 Nonparametric Quasi-Elasticity Estimation

Nonparametric regression relaxes the usual assumption of linearity and thereby enables a more robust data exploration that typically uncovers economic structure that might otherwise be overlooked. However, it is also well-known that the modeling performance of many forms of nonparametric regression dissipates as the number of independent variables increases. The problem is one of increasing variance dimensionality or, as discussed above, "*the curse of dimensionality*." As developed in section 3.1 of this paper, this problem is not material to the current application as the production theoretic model is estimated by the variance-reducing K4-RBF ANN. Specifically, we state a functional form RBF-ANN model with one "output" target variable and a "production" set which consists of four predictor (factor input) variables. As in all production theoretic models, the factors of production are used to create value – value that accounts for economic performance (or, PPT in this case). Because there is no a priori reason to assume a functional form for the production of PPT, the estimation model, eq. (10), equates value producing PPT to a set of firm-specific factors:

$$lnPPT_i = w_1 lnP_1 + w_2 lnP_2 + w_3 lnP_3 + w_4 lnP_4 \tag{10}$$

where for each *ith* security PPT is as previously defined. P_1 is the Bayesian estimated *Vasicek adjusted beta* (see Young, et.al, (1991) for a comparative forecasting efficiency of alternate beta calculations)*;* P_2 is *book/price ratio* computed from annualized book value and the most recent observed trade price; P_3 is the security's *current market capitalization*; and, P_4 is the *% change from 50 day MA (moving average)* as obtained from *Yahoo!* Finance. In the next section we describe the results of applying the K4-RBF ANN as a nonparametric regression system.

4.3 Firm Fundamentals and the Production of Profitable Market Trades

4.3.1 Fundamental Data

As reported above, the equity securities subjected to the WINKS automated trading system totaled 1,765 unique ticker symbols. On a daily basis, high-frequency trading characteristics are recorded every 20-minutes for each security. These characteristics include: bid, ask, last trade price, Vasicek beta and volume. In addition to market characteristics, periodically the *Yahoo!* Finance database is interrogated for firm fundamental data. For this study, the focus is on three fundamental variables returned by *Yahoo!:* book / price ratio, market capitalization and the percent change from the 50-day moving average. Table 2 presents descriptive statistics for the 1,765 securities as extracted from the *Yahoo!* database.

Table 2: Descriptive Statistics

Description	***PPT***	***Absolute (Vasicek Beta)***	***Book / Price***	***Market Cap (x '000)***	***% Δ from 50 Day MA***
Mean	51.364	1.231	0.829	\$8,500,868	2.874
Deviation	10.770	0.811	5.315	\$24,074,418	4.794
Mode	50.000	1.060	0.453	\$200,900	0.045
Min Value	10.000	0.000	0.000	\$1.58	0.002
Max Value	100.000	10.110	195.342	\$316,500,000	112.658
Q1	45.000	0.660	0.303	\$374,650	0.621
Q2	51.000	1.100	0.522	\$1,440,000	1.685
Q3	57.000	1.670	0.826	\$5,888,499	3.552

4.3.2 Nonparametric Model Estimation

Achieving an efficient solution to the nonparametric ANN model compels one to join the science of research with the art of the procedure. The algorithmic rules for solving the K4-RBF ANN are straightforward. Preparing the data before application of an ANN is not. One critical step for efficiency is to rescale the data. Choosing a method by which to remap the input data requires application by simulation. To that end, this research presents findings based on three alternate data transformation mappings. The decision of selecting a data transformation that produces a dominant solution is as simple as comparing model fitness errors. Table 3 presents the ANOVA characteristics associated with the supervised learning of the K4-RBF ANN after alternate data transformations.

Table 3: K4-RBF ANN ANOVA with Softmax Transfer Function.

Description	***Norm:2***	***Norm:1***	***STD:1*** [a]
Validation Error	5.77E-04	8.00E-03	1.20E-04
Fitness Error	6.88E-04	9.07E-03	9.93E-05
R-Square	99.29%	91.75%	99.90%
AIC	-12842	-8291	-16260
Schwarz	-12820	-8269	-16238

a: Selected data scaling

In this table, three different MSE error metrics are reported. In each case the MSE expresses the difference between actual and predicted PPT. The specific errors include the training error which is the MSE for PPT values in the data range reserved for supervised learning. The validation error is the calculated MSE for that part of the data set that is treated as "out-of-sample." Lastly, the fitness error reports the MSE over the entire data set. It is this latter error measure that is used for comparative model selection. R-square, AIC and Schwarz are well known in the literature (see Wikipedia for definitions and summary characteristics). Of the three data transformations tested method *STD:1* is deemed to be the most efficient solution based on its low metrics for validation error, AIC and Schwarz. The extreme fit of this model renders any analysis of the residual terms unnecessary.

Figure 3 displays the predictive ability, or quality of fit, achieved by the selected model. As with any predictive ability chart, the goal here is to observe a closeness of fit between the actual and predicted data. The observed results clearly demonstrate a near perfect fit; a finding that is confirms the ANOVA analysis as presented above.

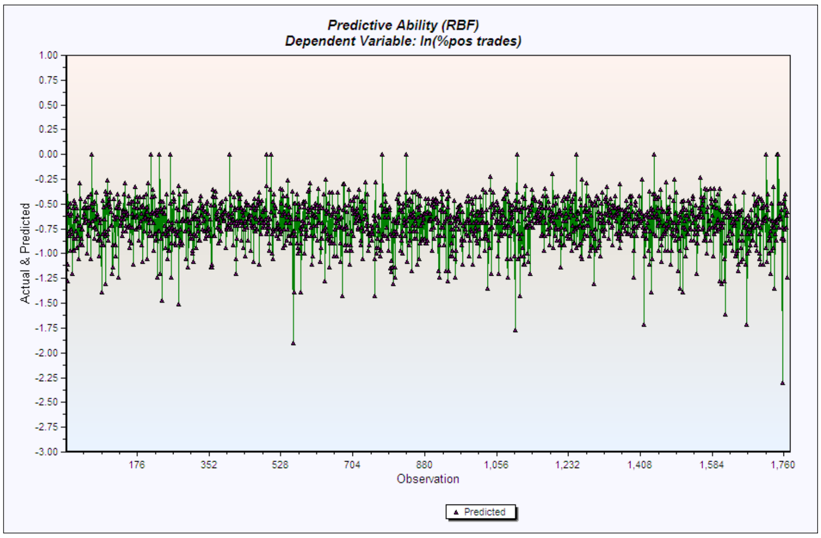

Figure 3: Predictive Ability Chart

4.3.3 Policy Implications

Table 4 presents the K4-RBF weights calibrated under the three alternate data transformations: Norm:2, Norm:1 and STD:1. RBF weights represent the AI counterpart to comparative nonlinear regression coefficients. Thus, in the terms of the production-theoretic empirical experiment these weights are quasi-elasticity estimates of the production function's input factors.

Table 4: Estimated K4-ANN Weights (w_i) By Transformation Type

Estimated Weights	***Norm:2***	***Norm:1***	***STD:1****
Ln(Abs(Vasicek's Beta))	0.124	0.208	-1.529
Ln(Abs(Book To Last Trade Price))	0.051	0.194	-1.520
Ln(Market Capitalization / 10000)	0.265	0.227	1.206
Ln(% Change From 50 Day MA)	0.138	0.199	-0.124

***Selected Model**

Based on the selected model, the PPT knowledge production function exhibits diminishing returns to scale (-1.966). In traditional production theory, decreasing returns to scale is associated with problems of management of large, multi-unit firms. This strict interpretation is misleading when evaluating the overall performance of the PPT knowledge production system. To the classical theorists, one would interpret this to mean that for a proportionate and simultaneous increase in all of the input factors, the percentage change in PPT would decline by a greater proportion. However, this is not a complete view of the knowledge function's behavior. To expand our interpretation it is important to interrogate the elasticity of each factor to understand how change in the individual factor inputs is expected to influence change in the target variable (PPT).

The Vasicek beta is a Bayesian market risk factor that adjusts both high- and low- beta stocks towards the market average (1.0). The reported level for this weight is -1.529. Hence, for each 1-percent change in this adjusted measure of market risk (deviation away from the benchmark of 1.0), the PPT of the WINKS trading platform declines by approximately 1.5%. Of course, over time, high beta stocks tend to fall while low beta stocks tend to rise. This result implies that PPT tends to increase as the market risk of individual securities approaches the market's aggregate level of risk. Stated differently, one way to stabilize automated trading performance is to choose neither very high, nor very low beta stocks for WINKS management.

In the Fama-French model, it is reasonable to argue that when an estimated coefficient attached to SMB is around one (1.0), this is indicative of a small cap portfolio. Conversely, an estimated model coefficient for the SMB factor that is not significantly different from zero would warrant just the opposite interpretation (large cap). In similar fashion, a coefficient near one for the book/price ratio would indicate a portfolio with an overall high book/price ratio. The usual interpretation of the Fama and French measurement of risk through these measures is not always consistent with conventional wisdom. For example, if high returns are associated with high risk, then stocks with a high book/price ratio must be more risky than the market as a whole. This perception of risk would suggest that stocks can only be cheap because they are risky.

To the BDT trader, whether operating under the WINKS platform or not, it is possible that a high book/price ratio is indicative of a buying opportunity. The quasi-elasticity of book/trade price reported by solving the K4-RBF ANN is -1.520. This is a result that suggests for a 1 percent increase (decrease) in the book/price ratio the stock's PPT will decline (increase) by approximately 1.5%. We can infer that as a value stock reduces its measure of perceived risk through the book/price ratio, the WINKS platform is able to increase the profitable experience of trading this particular stock.

The elasticity measure for firm size (capitalization) is 1.206. This reflects the penance of the WINKS trading platform for larger sized firms. For each 1 percent increase in firm size, the PPT is expected to increase by approximately 1.2 percent. Ozenbas, et. al. (2010) has provided a congruent view with results obtained from a different research objective. He reported accentuated intraday stock price volatility and lower trading efficiency at both market open and close. This effect was particularly evident for large-cap stocks. These authors also report that large-cap stocks lead smaller-cap stocks in finding new equilibrium values. By extrapolation, this finding suggests that as large-cap stocks seek their new intraday equilibrium value, the WINKS platform is able to trade the early day price inefficiencies effectively.

The proxy for the Carhart momentum factor was implemented by including the difference between the stock price and its 50-day moving average. The stock price moving average is not necessarily a stock price prediction indicator but, rather, a method by which to describe the current direction of the price series with an identifiable lag. A common interpretation of the price moving average is based on a comparison of the moving average to the dynamics of the underlying stock price. Traditional trading logic suggests that whenever the instrument price rises (falls) above (below) its moving average, a buy (sell) signal is generated. The K4-RBF elasticity weight for this factor is reported as -0.124. This indicates that for a 10 percent stock price deviation above (below) the 50-day moving average, the expected trading profitability under WINKS decreases (increases) by 1.2 percent. Earlier evidence for some part of this price-profitability behavior was reported by Schnusenberg (2006). He found little stock price momentum associated with abnormal returns subsequent to new market highs. The results also found some evidence that the variance of abnormal returns in the windows surrounding new high days is significantly larger than the variance over the same window on non-high days. Schnusenberg concluded that new highs in a stock market index present a psychological barrier for investors. These findings are consistent with the view that as a stock price rises above its moving average to reach a new high, the trading opportunities for this stock are impacted by increasing variability -- a condition that can dampen the ability of the WINKS system to increase the PPT of stocks that meet this condition.

5 SUMMARY AND CONCLUSION

This research had dual objectives. The first was to introduce a new approach to automated trading based upon a stochastic learning machine that explicitly incorporated a BDT framework. Within this context, the paper developed the WINKS dual RBF ANN automated trading platform. In addition to trade management rules, WINKS was enumerated within a stochastic behavioral base. The algorithmic foundation of WINKS coupled a dual implementation of the K4 optimized RBF ANN to produce a foundation for a directional high-frequency price forecasting system. The second objective of the paper postulated an extension to traditional production economics. The purpose of this extension was to estimate quasi-elasticity coefficients through AI mapping of a knowledge production function. More directly, the model phase was designed to examine the effectiveness of a four-factor firm-level pricing equation to explain knowledge output (PPT) as generated by the WINKS automated trading framework. The approach permitted the direct observation of the relative contribution of firm fundamentals to the process of producing profitable high-frequency automated stock trading.

In practical trading terms, the execution of WINKS over the defined test period resulted in cost-adjusted trading profits that exceeded those reported by the simple buy-and-hold strategy. In addition to summary results for the entire sample of securities, the research exemplified individual stock trading results by focusing on five securities. The trading efficiency of the WINKS platform ranged from 22-percent to 116-percent across these five instruments. Similarly, the annualized rate of return was reported to range from 49-percent to 172-percent.

Upon reviewing the performance of WINKS it is obvious that an important question remains unanswered: how does one identify which stocks WINKS can trade profitably? The first step in providing an answer to this question evolved from the dual objectives of this research. WINKS performance, as measured by PPT, was modeled by a non-parametric ANN production-theoretic model. For parsimony with the current state of finance research, the model was constructed as a firm-level approach using proxies for the four-factor Carhart equilibrium system. The elasticity estimates for the four factors yielded results that corroborate and extend contemporary findings. We feel the production-theoretic approach preferred in this research added to the ongoing quest for improved trading efficiency in global markets by providing a metric (elasticity) to signal direction, magnitude and relevance in the production of PPT.

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Appendix A: Global Exchanges

Country	Exchange
United States of America	American Stock Exchange
United States of America	BATS Exchange
United States of America	Chicago Board of Trade
United States of America	Chicago Mercantile Exchange
United States of America	Dow Jones Indexes
United States of America	NASDAQ Stock Exchange
United States of America	New York Board of Trade
United States of America	New York Commodities Exchange
United States of America	New York Mercantile Exchange
United States of America	New York Stock Exchange
United States of America	OTC Bulletin Board Market
United States of America	Pink Sheets
United States of America	S & P Indices
Argentina	Buenos Aires Stock Exchange
Austria	Vienna Stock Exchange
Australia	Australian Stock Exchange
Brazil	BOVESPA - Sao Paolo Stock Exchange
Canada	Toronto Stock Exchange
Canada	TSX Venture Exchange
Chile	Santiago Stock Exchange
China	Shanghai Stock Exchange
China	Shenzhen Stock Exchange
Denmark	Copenhagen Stock Exchange
France	Euronext
France	Paris Stock Exchange
Germany	Berlin Stock Exchange
Germany	Bremen Stock Exchange
Germany	Dusseldorf Stock Exchange
Germany	Frankfurt Stock Exchange
Germany	Hamburg Stock Exchange
Germany	Hanover Stock Exchange
Germany	Munich Stock Exchange
Germany	Stuttgart Stock Exchange
Germany	XETRA Stock Exchange
Hong Kong	Hong Kong Stock Exchange
India	Bombay Stock Exchange
India	National Stock Exchange of India
Indonesia	Jakarta Stock Exchange
Israel	Tel Aviv Stock Exchange
Italy	Milan Stock Exchange
Japan	Nikkei Indices
Mexico	Mexico Stock Exchange
Netherlands	Amsterdam Stock Exchange
New Zealand	New Zealand Stock Exchange

Appendix A: Global Exchanges (continued)

Country	Exchange
Norway	Oslo Stock Exchange
Singapore	Singapore Stock Exchange
South Korea	Korea Stock Exchange
South Korea	KOSDAQ
Spain	Barcelona Stock Exchange
Spain	Bilbao Stock Exchange
Spain	Madrid Fixed Income Market
Spain	Madrid SE C.A.T.S.
Spain	Madrid Stock Exchange
Sweden	Stockholm Stock Exchange
Switzerland	Swiss Exchange
Taiwan	Taiwan OTC Exchange
Taiwan	Taiwan Stock Exchange
United Kingdom	FTSE Indices
United Kingdom	London Stock Exchange

Founded in 1892, the University of Rhode Island is one of eight land, urban, and sea grant universities in the United States. The 1,200-acre rural campus is less than ten miles from Narragansett Bay and highlights its traditions of natural resource, marine and urban related research. There are over 14,000 undergraduate and graduate students enrolled in seven degree-granting colleges representing 48 states and the District of Columbia. More than 500 international students represent 59 different countries. Eighteen percent of the freshman class graduated in the top ten percent of their high school classes. The teaching and research faculty numbers over 600 and the University offers 101 undergraduate programs and 86 advanced degree programs. URI students have received Rhodes, Fulbright, Truman, Goldwater, and Udall scholarships. There are over 80,000 active alumnae.

The University of Rhode Island started to offer undergraduate business administration courses in 1923. In 1962, the MBA program was introduced and the PhD program began in the mid 1980s. The College of Business Administration is accredited by The AACSB International - The Association to Advance Collegiate Schools of Business in 1969. The College of Business enrolls over 1400 undergraduate students and more than 300 graduate students.

Mission

Our responsibility is to provide strong academic programs that instill excellence, confidence and strong leadership skills in our graduates. Our aim is to (1) promote critical and independent thinking, (2) foster personal responsibility and (3) develop students whose performance and commitment mark them as leaders contributing to the business community and society. The College will serve as a center for business scholarship, creative research and outreach activities to the citizens and institutions of the State of Rhode Island as well as the regional, national and international communities.

The creation of this working paper series has been funded by an endowment established by William A. Orme, URI College of Business Administration, Class of 1949 and former head of the General Electric Foundation. This working paper series is intended to permit faculty members to obtain feedback on research activities before the research is submitted to academic and professional journals and professional associations for presentations.

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