Near High Frequency Production Economics for Global Wealth Creation: Automated Trading, Neuroeconomics and Trading Fundamentals

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ABSTRACT

Unlike the markets of twenty years ago, today's financial markets are dominated by analysts and traders who rely upon quantitative analytics and computational algorithms that bear interdisciplinary orientations. Prior to the wide-scale adoption of normative methods from fields like applied mathematics, computer science and neuroscience, the pedagogy of stock return predictability was guided by normative theories of rational choice. Across Academia the race to incorporate contemporary asset pricing theory and active experiential learning in the classroom setting has helped to evolve and define an academically generic approach to the study and management of the student managed investment fund (SMIF). The traditional SMIF was designed to assist students in "learning by doing" during their exposure to the knowledge-base in asset valuation, portfolio management, accounting, and economics. As the theory of investment valuation expanded to include the latent cognitive factors that may actually influence investor trading activity, the creation of new knowledge through active and participatory learning transformations in the SMIF classroom did not follow suit. Constructed on a neuroeconomics foundation, this research extends the pedagogy available to the active learning SMIF classroom by introducing a risk-mitigated near high-frequency trading (NHFT) system. Unlike the more widely discussed high-frequency paradigm, the NHFT model relies more on state-of-art forecasting of interval market values than on the raw processing speed applied to millisecond data flows. Additionally, by recasting the use of the neuro-inspired learning algorithm the research estimates quasi-elasticity metrics for a four-factor production-theoretic model to explain algorithmic trading profitability.

Keywords: Automated Trading, Neuroeconomics, Technical Indicators and Production Economics

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1 INTRODUCTION

Individuals rely on efficient trading of financial securities to obtain returns within a risk mitigated strategy. With the onset of digital technologies and the emergence of 24/7 access to traded markets, the traditional buy-and-hold (BH) approach to trading and portfolio management found new strategic competition from professionals who advocate and practice active trading strategies. High frequency trading (HFT) is an extremum form of active trading. Further, at the extremum there is both an aggressive and passive type of HFT. Aggressive HFT occurs when only market orders are executed. Passive HFT is defined as placing only limit orders – orders that are not immediately marketable and serve only to provide liquidity to the market (see, Kearns, et. al. (2010) for discussion). In this study we focus solely on aggressive HFT.

Absent direct human intervention, HFT relies solely on proprietary formula-driven trading algorithms to execute low latency trades in as little as milliseconds. Proponents of HFT argue that its merits are measured by increased market liquidity, broader trader transparency, and increased risk mitigation (for a robust review, see Biais, Foucault et al. (2012), Angel, Harris et al. (2011), Goldstein, Kumar et al. (2014)). Owing to HFT's commitment to quantitative and computational methods as professionals seek to promote excellence in the use of HFT tools argue that it is the responsibility of Academia to promote a supporting pedagogy. Today, an important operational tool in financial education is the student managed investment fund, or SMIF. Typically, the SMIF is a classroom or club activity that applies what is taught in various investments related classes to the management of "real dollar" portfolios (Melton and Mackey (2010) discuss SMIF organizational strategies; see McCarthy, et.al (2010) for a discussion on the role of experiential learning). Despite a long list of potential benefits associated with hosting a SMIF, a cursory search for evidence on the use of breakthrough HFT strategies yields insignificant results. Instead, it is more likely that within the academic community HFT is more likely an academic topic covered by classroom review rather than an experiential tool that is used in the actual practice of fund management (for example see the class syllabus from Steven's Institute, NJ[1]).

Why is this so? There are at least two important deterrents that stall the adoption of an operational HFT platform in academia. One is the general unavailability of a cost-effective commercial platform that can be widely adopted across both private and public institutions. The other is an ideological concern. The uncertainty introduced by regulators who question

[1] http://www.stevens.edu/business/sites/business/files/QF%20427_428%5b1%5d.pdf

the predatory nature of HFT raises concerns about regulatory intervention in a system that has a transitory management team. Globally, and for a myriad of different reasons, sovereign regulators continue to discuss *"Clamping Down on Rapid Trades in the Stock Market"* (2011). But, within the academic community it is truly fair to say that when one door closes, another opens. That is, it is only logical that Academia would investigate the impact of slowing HF automated trades from milliseconds to, say, minutes. In a timescale measured by minutes instead of milliseconds, automated and algorithmic trading would be 'near' high-frequency. To the point, near high frequency trading (NHFT) is an algorithmic method that relies on the use of near-continuous market data and corresponding news and, unlike an efficient HFT system, the NHFT approach does not require co-located computer servers with low-latency digital data flow.

Absent low-latency millisecond order flow data, the algorithmic models that drive a NHFT system are obligated to consider commodity price formation characteristics such as long memory, non-stationary, regime shifts and other time-series effects. But, to Academia these statistical characteristics set the stage to redefine the study of NHFT as a pedagogy that intersects nonlinear financial data mapping and the theory of chaotic prediction. Academic inquiry has already produced an extant literature that crosses interdisciplinary boundaries; boundaries that include the disciplines of computational finance, behavioral finance, artificial intelligence and high frequency prediction (for example, see Andersen, et. al (2008) for a comprehensive review and Al-Khouri and Ghazawi (2008) for assessment of volatility and liquidity impacts in emerging markets). For convenience, we group the latter three disciplines under the heading of computational neuroscience.

For decades computational finance and computational neuroscience have undoubtedly been active research areas. The last decade has witnessed an especially transformative change in both fields as for at least two reasons. First, and foremost, there is (computer) hardware advancement. The ability to store and process large amounts of tick-level order flow financial data locally and in 'cloud-ready' environments make it possible to invoke new machine-learning methods to train state-of-the-art learning algorithms. The second major contribution has come in the form of software applications that dynamically align with recent advances in both economic theory and newly configured computational hardware.

The interdisciplinary scope of the investigation proposed by this research leads to twin objectives. The initial objective is to develop an automated neuroeconomics based NHFT system. Known from this point forward as The Web Intraday Neuro-Knowledge Automated Trader System (WINKS), the NHFT is designed to engage multiple radial basis function artificial neural networks (RANNs) to predict next period price for two types of financial instruments: a futures contract and domestically traded equity instruments. A practical application of WINKS is accomplished by examination of simulated performance for two generically defined SMIFs. Additionally, to overcome the domestic investment bias of U.S. domiciled SMIFs (Jennings and Jennings (2006)), WINKS is also applied to an investment portfolio comprised of traded instruments from BRIC countries.

The second objective is to uncover the production (quasi-) elasticity metrics that explain the allocative efficiency of trading of equity instruments profitably under WINKS management. This objective requires using the selected RANN as a nonlinear regression to map the neuro responses of technical and fundamental capital market variables onto the profitability production frontier.

The paper is organized as follows. The next section introduces the stochastic integral to establish the conditions of capital market price formation and portfolio trading strategies in a near continuous market. Section three defines WINKS and introduces the role of the RANN. Section four describes the risk-adjusted performance of SMIFs managed by WINKS. Section five presents the estimation of production-theoretic elastic metrics to explain profitable trades under WINKS. The research ends with a summary and conclusions in section 6.

2 THE STOCHASTIC INTEGRAL: RELATIONSHIP TO EQUITY TRADING

Stochastic calculus has rapidly become the language of financial modeling (Brock (1992)). To illuminate the descriptive behavior of NHFT in the absence of arbitrage opportunities we rely upon the contribution of the stochastic integral as characterized by Shreve (2004) with additional definition from (Ait-Sahalia and Jacod (2014)). In the one dimensional case 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 (see Tsay (2005) for discussion). Next, we define a predictable trading strategy, θ, which determines the quantity $\theta_t(\omega)$ of the security to hold in each state $\omega \epsilon \Omega$ and at each time *t*. As stated earlier, 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 (Ederington (1979)). 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 either high frequency trading or flash-crash trading. Further, 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 defined by the integral $\int_r^s \theta_u dX_u$ between any times r, $s \geq 0$ is explained by Ito's stochastic integral. Since this is a continuous-time stochastic process, it is assumed that there is an underlying filtered probability space (Ω, 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 no later than at time t. Lastly, the trading strategy θ is adapted if $\theta_t(\omega)$ is V_t measurable. Under the assumption of Brownian motion, the simple stochastic integral is extensible to a larger class of integrands as long as the integrand is predictable. We observe the predictable and locally bounded process θ with the following properties: a) $|\theta(\omega)| \leq n$ for all $0 < t \leq T_n(\omega)$ and b) T_n is a sequence of stopping times increasing to ∞.

2.1 Buy and Hold

The buy-and-hold (BH) strategy is a fixed term trading diversification strategy captured by θ. Under the BH strategy an investor transaction times, t_i, are fixed. Immediately after reaching stopping time t_i the BH portfolio is subject to rebalancing before reaching stopping time T_{i+1}. The BH strategy closes with portfolio dissolution at some later stopping time U. For a position size $\theta_t(\omega)$ that is V_t measurable, the trading strategy θ is defined as $\theta_t = 1_{(t<t+1\leq U)}\theta_t(\omega)$. By definition, the gain from the BH trade strategy is caused by the position size and 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 UNDER WINKS

The stochastic integral offers two immediate advantages when describing the price formation process in relation to the use of HFT (and, NHFT) methods. First, the theory can be applied systematically across all traded market instruments and; secondly, the theory is scalable across various timescale representations. Facing the aforementioned price formation process, WINKS operation is configured to efficiently consider the following trading attributes: a) real-time data verification; b) machine driven order flow, c) real-time monitoring of positions; and d) regulatory compliance. Upon the receipt of financial data and related market information, WINKS applies its algorithmic trading logic. It is at this stage where a major component of operational risk surfaces – algorithmic, or model risk.

Model non-performance is traceable to at least two operating characteristics. One is model topology risk. A second is model parametrization risk. To mitigate performance failures from these sources of operational risk, WINKS engages an enhanced optimizing RANN. The prediction and mapping performance of artificial neural networks (ANNs) applied to stock market prediction and forecast behavior is well chronicled in the literature (see, for example, Refenes (1996), Kajiji (2001), Dash, et. al. (2002), and Tsay (2005)). Academic studies have also examined how well automated trading systems perform when such systems combine computational commonality from decision theory, the cognitive sciences, artificial intelligence and operations research (see, Zimmerman (1991) for a discussion and review). To achieve prediction of a derivative's price for hedge evaluation and profitable trading for equities, WINKS introduces a RANN topology that optimizes the parameterization step. Not to lose focus, the output from WINKS is not just statistical. Simply stated, the output is a traditional trade signal (buy, sell, or hold) with quantity attached for both the derivative hedging contract and all managed equity securities.

3.1 Advances in Neuroeconomics and the Predictability of Market Price

Mapping the period-to-period return of price changes is a nonlinear modeling problem. The apparent chaotic signals in a returns time series results from a deterministic system showing aperiodic, long-term behavior with sensitive dependence on initial conditions (Gomez-Gil, et. al., (2011)). Advances in machine learning algorithms from operations research coupled with an overall increase in computational power have produced a body of findings to show that learning algorithms are more and more capable of tackling these highly nonlinear and complex problems (Casdagli (1989)). The topologies that define learning networks are quite diverse; however, in this study we limit our focus to the RANN which first emerged in the neural network literature in the late 1980's.

A primary source of complexity in stock market forecasting is found within the complex interactions among market-influencing factors, random process like unexpected news and the well establish risk and return relationship of the underlying instrument. Compared to parametric forecasting methods, ANNs do not make any assumptions about the distribution of the underlying data. For this reason, ANN applications have been widely used in a variety of financial market studies (see, for example, Ludwig, et.al. (2005) and Kansas (2003)). Table one provides an alignment of neural network jargon and statistical jargon as a way to highlight the kindred relationship among generalized linear models, maximum redundancy analysis, projection pursuit, and cluster analysis (Sarle (1994)).

Table 1: Terminology

Parametric Statistics	**Nonparametric ANNs**
Estimation	Learning
Regression	Supervised Learning
Parameters	Weights
Independent variables	Inputs
Dependent variable(s)	Output(s)

In the section 3.1.1 we provide a theoretical underpinning for the two intended uses of the RANN topology in this paper. The first use is as an econometric mapping and forecast tool. The second use takes advantage of the RANN's ability to perform a nonlinear regression with output in the form of linear-additive weights. We begin by examining the specifics of how an optimized learning RANN is used to generate a next period forecast of stock return (price). This is followed by a discussion on why it is important to transform input data to better facilitate optimize learning to take place. The section continues with a review covering the importance of network parameterization. Section 3 closes with a pseudo algorithm that describes WINKS as a behavioral stock trading platform.

3.1.1 RANN Learning in WINKS

Provided with an information set, θ_t, WINKS is a trading system that is designed to predict the price of a traded instrument at time period *t+1*. The information contains exogenous and possibly noisy prices over *q* historical periods (*t*, *t-1*, *t-2,…, T-q*). To accomplish its appointed task in addition to θ_t WINKS formulates various fundamental and technical rules to control for unique, but observed, volatility risk not captured in θ_t. Like any automated system, there are safeguards in place. Two such examples are: a) WINKS restricts short sales of low-priced stocks (i.e., <= $1.00/share) and b) stocks with zero or very low returns volatility (not RANN suitable) are trade prohibited. Equation (1) states the presumptive predictive behavioral model used by WINKS,

$$y_{t+1} = f_\theta\left(y_t, x_{1,t}, x_{2,t}, \dots, x_{k,t} \,\middle|\, \theta_t\right) \tag{1}$$

where y_t is the price/return of the target security at time t and $x_{i,t}$,…, $x_{k,t}$ captures the set of k exogenous predictor variables at time t. The actual learning model(s) utilize an enhanced multiple objective univariate RANN.

The enhanced RANN is a Bayesian enhanced RANN with a closed form derivation of the RANN regularization parameter (see the pioneering work of Kajiji (2001)). Equation (2) states the foundations of the network design that achieves both mapping- and computational-efficiency,

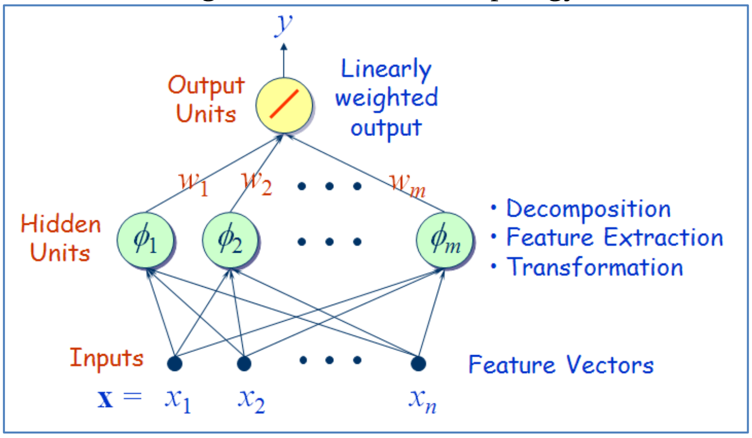
$$\{[x(k), y(i) : [\mathbb{R}^{\mathrm{n}}, \mathbb{R}]\}_{\mathrm{k=1}}^{\mathrm{m}} , \quad (2)$$

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

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

Figure 1 depicts a typical RANN topology across its three layers: the input layer (which is process free), the layer of weights (middle or hidden layer), and the output layer. In the broadest terms, the input layer is described by the predictor variables that are used to form a prediction of the output variable in time period $t+1$. In this paper the output unit is the actual period return forecast for the traded instrument.

Figure 1: The RANN Topology



The middle (or hidden) layer embraces computing units (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 $x(k)$ defined by $\|x(k) - c(k)\|$. As is evidenced by figure 1 all inputs play a role in determining the best weights to generate the output required. This is the “learning” portion of the network. The results are passed through a nonlinear activation function, $\emptyset(k)$, to produce output from the hidden nodes. The primary method of activation used in this research uses the widely known Gaussian transfer function which is described as

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

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 *i*th output of the network model being a weighted sum of the hidden nodes:

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

where p is the number of outputs (in the univariate case p = 1), w represents the linear and additive output layer weights, and $\hat{y}$ is the network output estimate of the target y (for additional discussion see Haykin (1994), Broomhead and Lowe (1988), Lohinger (1993), Parthasarathy and Narendra (1991) and Sanner and Slotine (1992)). A common problem faced by the traditional implementation of RANN topology is its propensity to learn slowly and, when confounded by a large bias, to produce non-optimal weights. To address this issue the Tikhonov regularization parameter (v) (lambda or weight penalty) is often added to the cost function as shown in equation 6.

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

Here v_j expresses the regularization, or weight decay, parameters. Under this specification the function to be minimized is restated as:

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

Early implementations of the RANN topology relied exclusively on iterative techniques to compute the weight decay vector $\bar{v}$. With the computational advances in parametric weight decay methods by Hoerl and Kennard (1970) and Hemmerle (1975) non-specific and computationally burdensome iterative techniques faded in popularity [see, Orr (1996, 1997)]. Kajiji (2001) added two significant extensions to the traditional RANN. First, she developed a closed-form solution to estimate specifically the regularization parameter. Second, based on Crouse's (1995, 2012) Bayesian enhancement to ridge regression she invoked *A priori* information to further reduce network learning error (SSE). This optimizing dual objective version of RANN is well known as the K4-RANN. Stated differently, the K4-RANN is a dual-objective, multiple criteria decision analytic (MCDA) algorithm that directly attacks the twin evils that befuddle traditional ANN modeling: (a) the "*curse of dimensionality*" (multicollinearity or over-parameterization) and (b) an inflated residual sum of squares (inefficient weight decay). Owing to these extensions, the K4-RANN is particularly well-suited for the stated objectives of the algorithmically driven WINKS.

3.1.2 RANN Data Transformation Alternatives

In general, RANNs are invoked after the input data set has been statistically transformed. The process of data transformation modifies the distribution of the variables to match the inputs (Shi (2000)). The K4-RANN method supports the following transformation methods: standardization (zero mean and unit variance); normalization over the range [0,1], (Norm-1); and, normalization over the range [-1,1], (Norm-2). Both Norm-1 and Norm-2 fall in the class of min-max normalizations (Jiawei, Kamber et al. (2012) provide a more detailed and generalized discussion).

3.1.3 RANN Parameterization

The process of parameterization involves choosing: a) a transfer (radial) function and b) a rule for minimizing the error signal in mapping the target variable. The selection of a radial function is what makes the RBF method unique when compared to alternative learning methods such as back-propagation, self-organizing maps, and general purpose feed-forward networks. Radial functions decrease (increase) monotonically from a central point. In addition to a Gaussian transfer function (equation 4) the K4-RANN technique supports four other well-known transfer functions (e.g., Cauchy, Softmax, multiquadric (MQ), and inverse MQ, or, MQ^{-1}. Network information flow does not occur without some error. The K4-RANN algorithm supports several error minimization rules of which the GVC (generalized cross-validation method) tends to be the primary choice when the transfer function is Gaussian. Alternative choices include: UEV (unbiased estimate of variance); FPE (final prediction error); and, BIC (Bayesian information criterion).

3.2 WINKS Trading: A Pseudo-Algorithm for K4-RANN Mapping

A pseudo algorithm description of WINKS, version 1.1.4 is presented in figure 2 below. This version of the WINKS automated trader was executed on a Microsoft Windows 2008 server with dual quad-core AMD CPUs with 32 gigabytes of RAM, and a two (2) two-terabyte hard drives. Besides normal maintenance, the combined hardware and software system is designed to operate 24/7 with minimal user-intervention. In the next section we present the results of applying WINKS to three alternative portfolios. Two portfolios represent generalized SMIFs. The third portfolio introduces international investment vehicles from BRIC countries.

Figure 2: WINKS Pseudo-Code

1. Initial setup: establish a database of securities based upon all managed portfolios.
2. Daily at 11 p.m. begin/update algorithmic procedures:
   a. Update the historical open, high, low, close, and volume data for every security in the WINKS database from Yahoo! Finance with the current day-end information.
   b. Compute the security's descriptive statistics – expected return, standard deviation of returns, skewness, and kurtosis and update the historical data base.
   c. Compute the Trade Intensity (TI) index and compare against:
      i. Equity candle sticks, volume, and
      ii. The current EOD predicted value for all securities.
3. Compute the 3day, and 5day trend for every security
4. Compute the Darvas upper/lower hinges for every security.
5. Every 20 minute from 9:40 a.m. to 11a.m.
   a. Obtain next actual trade price
   b. Compute log-returns for 100, 20-minute data points.
      i. Update the K4-RANN EOD forecast
      ii. Update the K4-RANN 20-minute ahead price forecast
   c. Trade – integrate TI and Darvas hinge to execute NHF trade: Short, Long, Hold, or Close Open position.
      i. Short open only if current trade price > $1.00
      ii. Close any open position for which the actual rate-of-return ≥ -2.00%
6. From 11:20 a.m. and for every 20 minute time interval until market close (4.00 p.m.)
   a. Obtain next actual trade price
   b. Compute log-returns for 100, 20-minute data points
      i. Update the K4-RANN EOD forecast
      ii. Update the K4-RANN 20-minute ahead price forecast
   c. Trade – execute a restricted Hold or Close NHF trade
7. At 11:00 pm, go to Step 2 and repeat

Note: WINKS follows the SIFMA trade calendar

4 SMIF PERFOMANCE UNDER WINKS

By and large, the student managed investment fund (SMIF) is a vehicle created by academic institutions – namely colleges and schools of business – to provide real-world portfolio management and security analysis experience to enrolled students. A recent survey by Peng, et. al. (2009) solidifies the opinion that the typical SMIF, whether supported by a stand-alone trading room or not, serves as a vehicle by which the host institution can gain significant external visibility – an outcome that can enhance student recruitment and fundraising activities. SMIFs are generally associated with an academic course of study that teaches value investing and passive investment management. A review of excerpts from web pages hosted by various SMIFs overwhelmingly supports this view:

- "The SMIF actively manages an all-cap value portfolio with approximately $351,000 in assets under management."
- "The Student Managed Portfolio invests in large-cap domestic securities within the S&P 500 and Russell Value 1000 Indices...using "bottom-up" fundamental analysis... We look primarily at stocks with relatively low Price/Earnings and Price/Book ratios, strong dividend yield, superior relationship of total return to Price/Earnings paid, solid financial statements, and strong long term growth prospects among other factors."

- The SMIF seeks to "…earn a rate of return, calculated on the entirety of the fund, that is superior to the market benchmark, defined as the S&P Index, in each one-year, three-year, and five-year period"…and…"to manage the fund in the context of portfolio management rather than a collection of individual stocks."
- "The long-term goal of the Student Managed Investment Fund is to manage a balanced fund that provides the income and capital gains… Our primary strategy for investment decisions is to find undervalued securities and hold those securities until their value is fully realized by the market… risk management is critical and should be measured and controlled through proper monitoring of active exposures relative to the stated benchmark."

This paper does not seek to provide a survey of SMIFs and their unique investment objectives. Instead, we generalize the behavior of the SMIF universe by selecting two internet hosted SMIF portfolios (*c.* December, 2014 - January, 2015). For comparative purposes we label these funds SMIF-01 and SMIF-02, respectively. We also observe a portfolio size of approximately 10 to 25 securities for the SMIF offered on a traditional semester (or quarter) basis. Each of the sample SMIFs selected for this research fall into this range. Post Internet review, it is also evident that any portfolio diversification decisions are likely to be made on a security-by-security basis rather than by a principle of optimal diversification. This section continues with an identification of inputs, expected outputs and fundamental factors needed to fully engage WINKS to manage a generalized SMIF as well as a BRIC alternative portfolio.

4.1 Inputs for Neuroeconomic modelling

The neuroeconomic approach to econometric modeling is ideally suited to learn how the complex latent relationships among explanatory variables explain the behavior of the target (dependent) variable.

4.1.1 Equity-Based K4-RANN Modelling

To predict equity prices (returns), WINKS relies upon the one-period lagged interaction among the five factors and the target variable. Two factors are ETF portfolios: ticker VXX (the S&P 500 VIX short-term futures ETN) and ticker PLW (a 1-30 year maturity laddered treasury ETF). In addition to the two ETN/ETF factors, the equity-based K4-RANN incorporates three supporting firm size factors that account for small-, medium- and large-cap stocks. The ETF tickers for these factors are: IWM, MDY and SPY, respectively.

4.1.2 Futures-based K4-RANN Modelling

Prediction of the near-term E-mini S&P futures contract (ticker ES) is produced by relating the futures index value (or, its return) to the one-period lagged value (return) of two input factors. These factors are the VXX (as previously defined) and the other is the Trend Intensity Index (TRI, of the Thomson Reuters Corporation). TRI is a technical indicator that captures the strength of a trend in stock price behavior using enhancements to the relative strength index (RSI) and Average Directional Index (ADX) indicator (for more information, see: http://www.marketvolume.com/technicalanalysis/trendintensityindex.asp).

4.2 K4-RANN Modelling of Traded Period-to-Period Chaotic Returns

The design objective for WINKS is to create a multivariate *N*-dimensional K4-RANN to map financial returns data to support a NHFT decision system. Before initiating network training WINKS invokes equation (8) to compute market returns through the *i-th* variable,

$$r_{i,t} = 1 + (lnP_t - lnP_{t-1}) \; . \tag{8}$$

Subsequently, returns data is transformed to standardized variables with a zero mean and unit variance. Additional system modelling characteristics and assumptions include: a) the trade transaction fee is set at $0.004 to follow the Interactive Brokers (IB) bundled fee structure for U.S. based trades[2]; b) the K4-RANN, WINKS can exactly predict the EOD price of the ES near-term futures contract; c) in addition to an exact quantity, the WINKS predicted trade indicator signals a defined market decision to buy / sell / hold; d) the K4-RANN prediction is valid for a discrete and fixed holding period of 20-minutes; and, e) an individual trader's actions do not influence the market or create adverse price movement.

In section 4.2.1 we provide a detailed description of the K4-RANN stock price prediction system. Section 4.2.2 mirrors section 4.2.1 but for the near-term S&P 500 futures contract (ticker ES). The ES contract forms the basis upon which a standard short-hedge is implemented.

4.2.1 The WINKS Equity Stock Price Prediction System

Inside WINKS the K4-RANN econometric forecasting model is executed continuously and simultaneously over the course of the exchange trading day. The notation used to describe the NHFT model is as follows. The time unit is stated in minutes per day based on a 20-minute timescale between trade evaluations. Next period (*t+1*) price predictions are obtained from solving the K4-RANN econometric model on a security-by-security basis. At time (*t+1*) equations 9 and 10 work together to produce both a return and price prediction for the *i-th* security. Network training utilized the most recent 100 log-return observations across all variables up to market close. For all securities, the specified K4-RANN econometric

[2] IB has changed its fee structure to $0.05 bps of trade value instead of the $0.004 per trade as reported in this research http://www.interactivebrokers.com/.

parameter settings employ a Gaussian transfer function with a radius of 1.0 using a GCV error minimization rule.

$$(r_{i,t}) = \beta_1(r_{VXX,t-1}) + \beta_2(r_{PLW,t-1}) + \beta_3(r_{IWN,t-1}) + \beta_4(r_{MDY,t-1}) + \beta_5(r_{SPY,t-1}) + \varepsilon_t \tag{9}$$

$$P_{i,t+1} = (P_{i,t}) + \left(1 + e^{(r_{i,t})}\right) \tag{10}$$

4.2.2 The WINKS Futures Contract Prediction System

Rebalancing an investment portfolio to replicate index performance can lead to increased trading costs and an inability to forestall wealth depreciation (Cai and Houge, 2007). As an alternative to portfolio rebalancing investors can turn to index hedging as a way to incorporate market index wealth performance targets. The index hedging approach to risk mitigation requires the analyst to predict the future price of the target index (or, its futures contract derivative). In this study, to produce a new EOD futures (*F*) index prediction, the K4-RANN is applied to equation (11). Equation (12) converts the return prediction to an index value. In this system, K4-RANN parameterization uses a Gaussian transfer function with a radius of 1.0 along with a GVC error minimization rule. Data transformation is performed by creating standardized variables with zero mean and unit variance.

$$(r_{F,t}) = \beta_1(r_{VXX,t-1}) + \beta_2(r_{TRI,t-1}) + \varepsilon_t \tag{11}$$

$$F_{t+1} = (F_t) + (1 + e^{(r_{F,t})}) \tag{12}$$

4.2.3 The WINKS Stock Index Hedging System

The objective of hedging underlying portfolios with the ES is to offset the expected systematic loss of wealth due to a bearish-price prediction for the market index. Because the minimum effective time of any open hedge is one trading day, this study defaults to the non-stochastic minimum variance hedge ratio (MVHR) of Johnson (1960) and Ederington (1979). For this hedge ratio when the measured relationship is such that $\hat{f}_{t+1} \leq f_t$, the MVHR is obtained and an optimal hedge position is opened by

$$N_f = -\beta_P\left(\frac{S_P}{f_t}\right),$$

where S_P is the current market value of the portfolio (p), f_t is the current price of the ES near-term futures contract and β_P is the market beta of the portfolio. Conversely, whenever an opened hedge position is subject to an expected reversal in the price of ES such that $\hat{f}_{t+1} > f_t$, the hedged position is closed by offset. It is important to note that the forecasted value of the derivative contract is what triggers the decision to hedge; however, actual MVHR values are based on actual market prices.

4.3 The Hedged Performance of SMIFs under WINKS

The comparative NHFT experiment examines three portfolios – two are representative of typical SMIFs and the other is a portfolio that is comprised of BRIC country ETFs. All investable components trade across two U.S. security exchanges – the NYSE and NASDAQ exchanges. Both exchanges trade continuously during the regular market hours from 9:30 a.m. EST to 4:00 p.m. Pre-market and after-market trades are not considered. The trading experiment was run from 02-January-2015 through July 31-2015. All instrument trades over the simulation period were under the sole control of the WINKS algorithmic procedures. Portfolio simulations were initiated with a dollar trade amount of US$2,500 per equity instrument. Hence, the initial traded shares for any equity are calculated by a divisor equal to the trade price. Upon the generation of subsequent trade signals the number of shares traded is determined by dividing the current balance available for instrument trade (i.e., $2,500 adjusted for prior trade profitability).

For each of the three investment portfolios and their constituent securities the following alternative investment strategies were simulated. First, there is the traditional buy-and-hold strategy (also referred to as the unmanaged portfolio, *U*). Second, is the risk-mitigated and hedged portfolio (*M*). Portfolio *M* is portfolio *U* modified by the dynamic application of the MVHR where the decision to hedge is obtained from K4-RANN EOD predicted futures price. Lastly, there is portfolio *T*; the investment plan managed solely by the WINKS system. In this study we evaluate portfolio performance comparatively based on the following metrics: annualized return; the Sharpe ratio; the Modigliani and Miller risk-adjusted-return performance measure (M^2); and, *VaR* (value-at-risk).

4.3.1 Comparative Portfolio Holdings

Table 2 presents a comparative view of the tickers held across SMIF-01 and SMIF-02 (source: Yahoo Financial). For clarity we note that only ticker SHLD (Sears Holdings Corp) appears on both lists. We also note that reported market capitalization values are time dependent real-time quotes. Published *Yahoo Financial* definitions differentiate a large cap fund from a mid-cap fund based on the market values of the companies held in the portfolio. Large-cap designation requires a firm to have a market value greater than $8 billion while a mid-cap company is one whose market capitalization is in the $1 billion to $8 billion range.

The average market capitalization of the firms in portfolios SMIF-01 and SMIF-02 is $5.32B and $17.73B, respectively. By prior definition, SMIF-01 is a small cap fund and SMIF-02 is a mid- and large-cap fund. The BRIC fund is comprised of 40 small- and mid-cap funds and 3 ETFs (a listing is provided in appendix A).

Table 2: The SMIF Approved Investment List

SMIF-01			**SMIF-02**		
	Beta	Market Cap (B$)		Beta	Market Cap (B$)
CLB	2.04	$4.70	AMWD	1.18	$1.06
CPK	1.02	$0.78	AWH	0.75	$3.92
DSX	1.18	$0.59	BIG	1.29	$2.23
GALT	1.20	$0.05	DE	0.68	$31.50
HUM	1.25	$28.09	EBAY	0.88	$34.43
IJJ	1.07	n/a	GGG	1.83	$4.16
IJS	1.12	n/a	GLW	1.61	$22.02
PEZ	0.94	n/a	LH	0.40	$12.48
PLPC	1.00	$0.18	MCO	1.42	$22.20
PWR	1.09	$4.97	MO	1.01	$109.40
SFG	1.17	$4.81	SHLD	3.13	$2.68
SHLD	3.13	$2.71	SODA	0.50	$0.34
STZ	0.86	n/a	TEL	0.99	$25.16
SWX	0.90	$2.65	TEN	1.20	$3.08
TOWN	0.82	$0.96	TISI	0.39	$0.93
UAL	0.58	$22.61	VRSN	1.60	$8.07
WPP	0.77	$0.44	VTI	1.01	n/a
XRAY	1.21	$7.94			
Average		$5.32	Average		$17.73

The next section reviews the trading characteristics generated by WINKS control of the three sample portfolios. This section provides a clear view of the NHF engine and its implied efficiency.

4.3.2 WINKS NHF Trading Results

Table 3 presents comparative analytics of WINKS trading across the three investigatory portfolios. As previously identified the two SMIFs differ by capitalization emphasis. At the start of the WINKS simulation period each stock was initialized with an investment rounded to approximately US$2,500 based on trade price of that day. Allowing for whole share trades the beginning value of each SMIF is between $42,000 and $45,000. Performance metrics for the simulation period are presented in table 3. The presentation includes the number of automated trades executed by WINKS over the period.

Table 3: Characteristic WINKS Performance

Trade Descriptor	**SMIF-01**	**SMIF-02**	**BRIC**
Capitalization	Small Cap	Large Cap	International
Number of Instruments	18	17	43
Beginning Value ($)	44,351	42,015	$107,106
Buy Hold Profit / Loss ($)	$258	$905	($18,081)
Buy Hold Profit / Loss %	0.58%	2.15%	(16.88%)
Net Trading Profit / Loss ($)	$5,664	$2,154	($7,791)
Net Trading Profit / Loss (%)	12.77%	5.13%	(7.27%)
Number of Trades	1,563	1,477	2,968

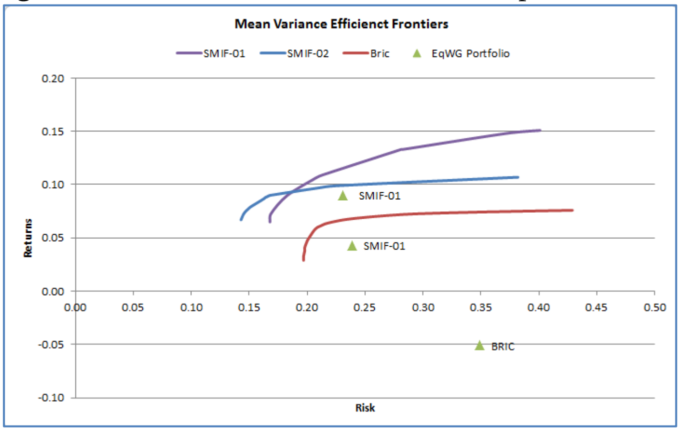
The role of the "(firm) size" premium in the production of investment returns is often challenged for a number of reasons. Recent evidence from Asness, et. al. (2015) finds the "size" premium's interaction with "value" and "momentum" factors is significant and stable when a portfolio's constituent investments control for quality versus junk. By extension, we can assume that the study SMIFs have, through the due diligence of value analysis, controlled for quality in the selection of portfolio investment vehicles. Hence, it is not surprising to find that the auto-traded small cap portfolio outperforms the similarly managed large-cap portfolio. Lastly, the results show that the BRIC fund did not perform profitably under WINKS control. This is directly attributable to model risk. Specifically, the domestic-oriented K4-RANN econometric equation (eq. 11) is not capable of learning the volatility pattern of the BRIC international securities.

4.3.3 Comparative Mean-Variance Efficient Sets

The mean-variance (MV) efficient frontier sets provide additional insights on the relative performance of the three portfolios. Figure 3 presents the three efficient sets – one for each of the sample portfolios.

The efficient set for small-cap SMIF-01 exhibits breadth and it clearly dominates the efficient sets associated with the other two funds. A closer examination reveals that among the three, the SMIF-01 efficient set has the highest potential return (maximum rate of return portfolio) and it also has a minimum variance portfolio (MVP) that, while matching the expected return of the large-cap SMIF-02, dominates in the risk plane. The efficient set for the BRIC portfolio is dominated at all expected return levels by efficient sets produced for the two SMIFs.

Figure 3: MV Efficient Frontiers for Sample Portfolios



4.3.4 Futures Contract: Predictive Performance

Figure 4a displays the results of fitting equation 11, the one-period ahead returns prediction for ticker ES. Over the simulation period 01-Jan-2015 to 31-Jul-2015 there were 152 prediction points. The importance of risk-mitigation hedging requires an emphasis on correct forecast direction. We find that 55.63% of the predictions for EOD ES price evidenced a correct directional prediction. The forecast MAPE is 11.69%; a value which implies that, on average, the absolute dollar-level of the prediction has an error of just under 12%.

Figure 4: Returns and Price Prediction for Futures Index

a) Actual and Predicted Returns b) Actual and Predicted Price

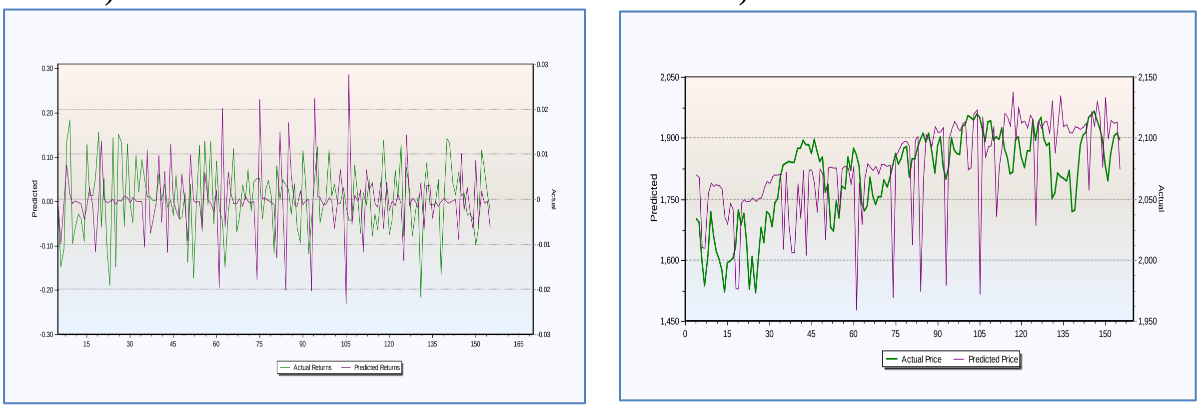


Figure 4b displays the estimated price of ES as derived from equation 12 plotted against the actual futures contract price. Knowing that the only 55-percent of the predictions are in the right direction leaves open for ongoing discussion what level of model risk actually characterizes the futures prediction system.

4.3.5 Comparative Risk-Adjusted Hedged Performance

Lawrence (2008) was one of the first to note that SMIFs do not robustly use financial derivatives as a risk-mitigation technique. Coincidently, Saunders (2008, 2015) argued that

SMIFs should add risk mitigation to portfolio management in the form of covered calls. In the automated trading arena where long and short positions are equally available, the consequences of adding risk-mitigation to the algorithmically controlled trades can be quite substantial. This section examines the effect of applying the predicted MVHR hedge ratio to the implicit BH diversification of the three study portfolios.

For each study portfolio we compare three alternative investment scenarios. Within each fund we define the managed portfolio (*M*) as the start-of-period BH portfolio hedged on a daily basis using ES. Portfolio (*U*) is the unmanaged/unmodified BH diversification plan. Lastly, portfolio (*T*) is the unhedged WINKS managed investment plan. Table 4 provides the comparative risk-adjusted performance measures for the *M*, *U*, and *T* portfolios. The table also provides the average daily return and the standard deviation of this return. The Sharpe (*reward-to-variability*), ratio is presented for ranking purposes. The Modigliani-Miller ranking alternative (M^2) is provided as a complement. Although M^2 is derived from the Sharpe ratio it has the advantage of being in units of percent return. Although it is not without controversy, *Value-at-risk* (*VaR*) remains a current standard in firm-wide risk measurement. *VaR* captures the maximum probable loss on an investment over a specific period of time at a given confidence level (*p=0.05*).

Table 4: Select Performance Measures

	SMIF-01			SMIF-02			BRIC		
	M	*U*	*T*	*M*	*U*	*T*	*M*	*U*	*T*
Average Daily Return	0.06%	-0.02%	0.03%	0.11%	0.02%	0.01%	-0.04%	-0.08%	0.06%
Std Dev of Return	1.03%	0.99%	0.60%	1.06%	0.84%	0.30%	1.12%	1.22%	0.88%
***VaR* (%)**	1.96%	1.96%	1.13%	1.97%	1.62%	0.59%	2.24%	2.48%	1.66%
***VaR* ($)**	$43.49	$38.69	$24.41	$47.30	$34.26	$12.19	$43.08	$44.68	$37.35
Sharpe	20.11	-9.02	20.49	37.97	10.10	7.80	-13.24	-25.12	26.12
M^2	15.56%	-6.87%	15.86%	29.32%	7.86%	6.09%	-10.11%	-19.26%	20.19%

The futures-based MVHR hedge strategy is set to initiate coincidently with the start of the WINKS trading simulation. The performance of the MVHR hedge ratio is dependent on the correlated structure of underlying asset returns. We are able to report a statistically significant correlation between the returns of both portfolios and the market index. The correlation (ρ) and *p-value (p)* combination for SMIF-01 (small-cap) and SMIF-02 (large-cap) is ρ=0.282 with a *p*=0.00026 and ρ=0.729 with a *p*=0.00001, respectively. Over the simulation period, the result of this exercise is expressed in the results of portfolio *M*. We find that the hedged small-cap SMIF-01 recorded markedly different performance versus the un-hedged BH counterpart (*U*). For example, the *VaR* is identical for fund *M* and *U* (1.96%).

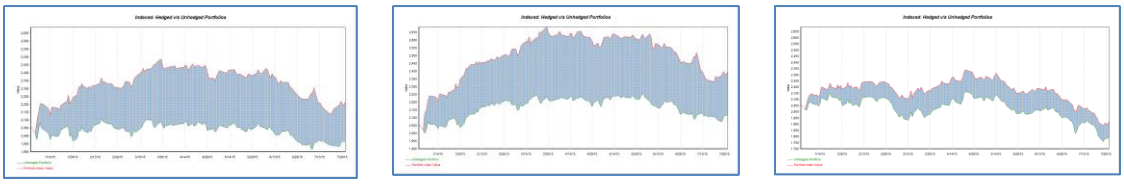
But hedging activity produces (as it should) a comparatively higher expected daily return (0.06% vs -0.02%). The ranked results of these two portfolios corroborate the performance observations. The fact that a hedged BH portfolio outperforms the equivalent unhedged fund is expected. However, the more interesting inquiry involves a risk-adjusted comparison of the hedged fund and the WINKS managed fund. Interestingly, the comparative M^2 metrics are nearly identical for *M* and *T* (15.56% vs 15.86%); but, the *VaR* level is noticeably less (1.96% vs 1.13%). This observation immediately suggests that NHFT using the algorithmic features of WINKS produces less tail risk while generating greater fund returns (0.06% vs 0.11%).

The BRIC portfolio is a poor performer under all trading alternatives. All trade management alternatives produced negative returns even though the *VaR* metric across all portfolios is more uniform in value. Clearly, BRIC domiciled investment instruments are not suitable for WINKS administration. This observation is not surprising given the insignificant returns correlation between the BRIC portfolio and the S&P 500 (ρ = -0.007; *p-value* = 0.92729).

Figure 5 provides a chart view of applying an index MVHR to each of the sample portfolios over the simulation period. The top most line of the area chart is the value of the hedged SMIF (BH with index hedge attached) and the bottom line displays the value of the market index. The range of the area between the two lines is a clear indicator of hedge profitability.

Figure 5: Profit from a MVHR Application for Sample Portfolios

SMIF-01 SMIF-02 BRIC



The BRIC results show that while the MVHR is effective, it is not sufficient to cover the poor BH performance of the uncorrelated BRIC fund.

5 BEHAVIORAL FACTORS AND THE PRODUCTION OF WEALTH

Factor models are routinely invoked to better measure efficient returns. Extant reasoning begins with the classic Fama and French (1993) three factor model. In addition to the common market factor, the Fama-French model introduced additional factors to account for size and another for value. Carhart (1997) was one of the first to extended the three-factor model by including a momentum effect. Domestic and international versions of the Carhart formulation proposition have been subjected to extensive investigation (for applicability of the four-factor model, see Lam, Li and So, (2009)). In the following section we introduce a variant of a factor model; it is a variant suitable for the investigation of either security or portfolio returns. With a focus on NHFT this research is primarily concerned with the profitability evaluation of the individual investment instruments held across the three sample portfolios. Specifically, we seek to understand if four fundamental factors can explain the target variable "*percent profitable trades.*"

5.1 Behavioral Calibration of the Complex Production Functions

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, under a nonparametric approach to regression it is also well-known that modeling performance declines as the number of independent variables increases. The problem is one of increasing variance dimensionality or, what was described earlier as "*the curse of dimensionality*." Fortunately, owing to the theoretical underpinnings of the K4-RANN, the dimensionality problem is not material to formulation of the production theoretic model proposed in this section (see Kajiji and Dash (2012)) on behavioral extensions to production economics using the K4-RANN).

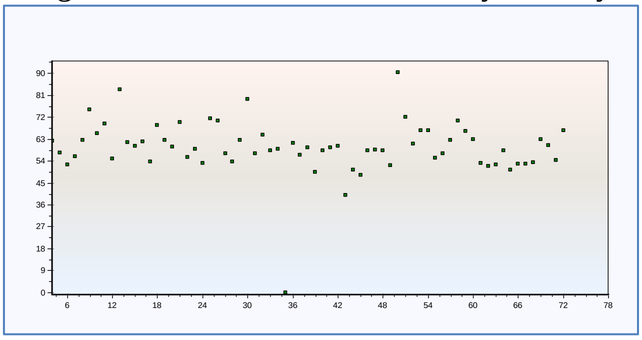
5.1.1 The Target Variable: PPT

In this section we provide a more complete definition of *PPT* (equation 14),

$$\text{Percent Positive Trades} = PPT = \text{ Round}\left(\frac{\text{\# positive trades}}{\text{total \# trades}} \text{ x } 100\right). \tag{14}$$

The spread of the 77 PPT target variables is depicted graphically in figure 6 as shown below.

Figure 6: Percent Positive Trades by Security



From figure 6 one is able to observe that WINKS produces *PPT* that lies with the lower/upper range of 30- to 80-percent, respectively. Between these two observed bounds the *PPT* plot shows a remarkable level of symmetry in PPT spread. Still, the empirical research question remains – is it possible to explain the production of *PPT* with fundamental factors?

5.1.2 The K4-RANN Production-Theoretic Model

The functional form of the K4-RANN is a multiplicative production-theoretic model with one target variable and five factor variables. Continuing with the reasoning provided by Kajiji and Dash (2012), the mapping exercise purposes to convert the multiplicative interaction among production factors by a logarithm transformation. This mapping relationship of equation 13 expresses the *PPT* production function from a cross section of firm-specific fundamental production factors:

$$ln(PPT) \quad = ln(\alpha) + \sum_{i=1}^{5} w_i(lnF_i) \tag{13}$$

Here α is the equation constant; F_1 is instrument's beta*;* F_2 is *book/price ratio* computed from annualized book value and the most recently observed trade price; F_3 is the security's *current market capitalization*; and, F_4 is the technical indicator *percent-change from 50 day the moving average*; and, F_5 is the instrument's PEG ratio (price-to-earnings ratio divided by the growth rate of earnings).

5.2 The Data

Preparation for the empirical estimation of the K4-RANN production model is based on a averaging of time-series fundamental data for 77 tickers in the current study. On July 31, 2015 a cross-section of trade and fundamental variables for each investment instrument was thus tabulated in preparation for the econometric analysis[3]. We also computed the values for the percent profitable trade value for each of the 77 tickers on July 31, 2015. Structural bias in the econometric analysis of trading performance was eliminated by excluding all non-equity stocks. Also excluded were equity stocks that do not have *Yahoo! Finance* reported fundamental data on the estimation date. After all adjustments, the number of tickers for the K4-RANNeconometric estimation is reduced to 69 tickers.

5.3 Behavioral Networks and the Double-Log Production Function

Achieving an efficient solution to the nonparametric RANN model compels one to join the science of RANN optimization and parameterization with the art crafting an intuitive decision-model. To this end, this research presents alternative model formulations that represent this combined approach. Along the way the alternate models clearly provide evidence of the importance attached to data transformation methods and review of alternate

[3] Every attempt was made to capture and process the fundamental information for all securities on close of business July 31, 2015

model parameterization (see: Dash and Kajiji (2008) for details on the data transformation methods). We select a dominant decision-making solution by comparing 'Fitness Error' across the three models in Table 5.

Table 5: K4-RANN ANOVA: Alternate Parametrization

Description	*Model 1*	***Model 2***	*Model 3**
Data Transform	STD-1	STD-1	STD-1
Validation Error	2.23E-02	2.30E-02	1.54E-02
Fitness Error	1.81E-01	4.42E-02	1.65E-02
R-Square	94.67%	98.79%	99.87%
AIC	-105.854	-203.196	-270.926
Schwarz	-92.449	-189.792	-257.522
Error Minimization	UEV	GCV	GCV
Transfer Function	MQ	MQ^{-1}	Gaussian

**Selected model*

The error measures reported in this table are traditionally computed mean-squared error (MSE) metrics. The MSE measures are divided into two sub-domains. Validation error reports the MSE for fitted function on data that is not used to train the network. It is the MSE for the *out-of-sample* data used in the training of the network. Fitness error is the MSE over the entire data set. We use the Fitness Error metric for comparative model evaluation. As supportive and adjunct evaluation metrics, R-squared, AIC (Akaike information criterion) and the Schwarz Bayesian information criterion are well known in the literature.[4] Based on the low validation error metric and the comparatively high negative values for AIC and Schwarz, model 3 is the most efficient solution for the stated research objectives.

5.4 Quasi-Elasticity Policy Implications

The K4-RANN learning weights are presented in table 6. In the terms of the production-theoretic decision model these weights serve as quasi-elasticity estimates of the production function's input factors. A policy review of each follows.

Table 6: Estimated K4-RANN Weights (w_i) By Transformation Type

Estimated Weights	*Model 1*	*Model 2*	*Model 3**
Constant	0.095	-0.138	-0.026
***Ln*(Abs(*Yahoo Beta*))**	0.087	0.111	0.121
***Ln*(Abs(*Book / Price Ratio*))**	0.043	0.024	0.034
***Ln*(*Market Capitalization / 10000*)**	-0.262	-0.237	0.011
Ln(% Change from 50 Day MA)	-0.114	0.234	0.021
Ln(PEG Ratio)	0.169	0.162	0.009
Returns-to-Scale	-0.018	0.156	0.170

**Selected Model*

[4] For discussion, examples, and computational issues see: http://en.wikipedia.org/wiki/R-square , http://en.wikipedia.org/wiki/AIC_(statistics) , and http://en.wikipedia.org/wiki/Schwarz_criterion

For the dominant model 3, the production of *PPT* is characterized by diminishing returns to scale (0.170). This finding implies that, over the long-run, changes to *PPT* would be less than proportional to the simultaneous change in all fundamental factor inputs. Diminishing marginal returns infers that it is not possible to increase *PPT* within WINKS by uniformly and continuously increasing all input factors. A closer look at the factor quasi-elasticity metrics yields a more intuitive understanding of how WINKS actually works to produce profitable trades on a security-by-security basis.

5.4.1 The Market Risk Factor

The K4-RANN weight for the beta coefficient is 0.121. For a 1% change in market beta level the WINKS trading platform increases *PPT* by 1.21%. From an operational point of view, one could argue that as the WINKS platform expands to include additional high-beta stocks the system's trading profitability will show a positive response. A practical implementation plan would be to increase the number of small- to mid-cap stocks in the SMIF.

5.4.2 The Impact of the Multi-Dimensional Book/Trade Price Factor

The estimated quasi-elasticity metric for the book/trade price factor is 0.034. In this case a 1% increase (decrease) in the book/price ratio for a WINKS traded stock will cause the stock's *PPT* to increase (decrease) by approximately 3.4%. Firms with strong historical accounting profitability relative to trade price are efficiently traded by WINKS.

5.4.3 Firm Capitalization

The quasi-elasticity metric for firm size (market capitalization) is 0.011. The size of this weight demonstrates a lack of bias for large-cap firms. That is, for each 1% increase in firm size (capitalization), *PPT* is expected to increase by a modest 1.1%. Ozenbas, et. al. (2010) have provided a congruent view in their report on intraday stock volatility. The authors find that large-cap stocks lead smaller-cap stocks in finding new equilibrium values.

5.4.4 Price Change Momentum

The technical indicator "*Difference Between the Stock Price and its 50-day Moving Average*" provides a proxy for the momentum effect. Traditional trading logic suggests that whenever the instrument price rises (falls) above (below) its moving average, a buy (sell) signal is generated. The K4-RANN quasi-elasticity weight for this factor is reported as 0.021. This reported finding indicates that for a small deviation in stock price, say 1%, above (below) the 50-day moving average, the expected trading profitability under WINKS increases (decreases) by 2.1%. Prior evidence provided by Schnusenberg (2006) on the momentum effect is consistent with this elasticity metric. In the 2006 study, Schnusenberg found little stock price momentum was associated with abnormal returns after a stock achieved new market highs.

5.4.5 PEG Ratio

The price/earnings to growth (PEG) ratio is used to determine a stock's value relative to its current earnings growth. The PEG ratio provides a more complete investment picture than that offered by the unadjusted P/E ratio. By way of example, the lower the PEG ratio, the more undervalued the investment opportunity given its current earnings performance. In this model, the K4-RANN weight for the PEG ratio is 0.009. A 10-percent increase (decrease) in this ratio would be expected to increase *PPT* by just less than 1%.

5.4.6 Constant Term

The weight associated with the constant term is used to determine the value of the WINKS NHFT system when all input factors taken together fail to explain traded profitability. To the trader, this is similar to a scenario where she decides to ignore all input variables (i.e., assume their current levels all equal zero), the trader would expect the loss on traded funds managed by WINKS to approximate (2.6) percent.

6 OBSERVATIONS AND CONCLUSION

This research embraced two objectives. The first was to develop a supporting theory and application protocol to support a behavioral approach to the near high-frequency trading of market securities. Within this context, the research evolved an automated dual RANN NHFT platform – WINKS. With an applied focus on the role of pedagogy to support HFT, the research introduced an empirical test of the WINKS platform with contextual support of the generalized SMIF. The findings generated from the WINKS simulation applied to both a small- and a large-cap SMIF produced comparative results that reinforced current finding of fact. Post simulation risk metrics were consistent with extant findings on performance differences between small- and large-cap funds. For example, there was a clear indication that WINKS management produced greater after-cost risk-adjusted returns for the small-cap SMIF than it did for the large-cap student fund.

The small-cap fund, SMIF-01, also exhibited a significant response to MVHR hedging. Although the VaR metric was identical for fund *M* and fund *U* (1.96%), the hedged version of the portfolio earned a substantially higher expected daily return (0.06% vs -0.02%). Focusing on the comparison between the WINKS traded portfolio, *T*, and portfolio *M* we find some previously undiscovered results. The comparative M^2 metrics were virtually identical for *M* and *T* (15.56% vs 15.86%), but the *VaR* metric for portfolio *T* was noticeably smaller (1.13% vs 1.96%). This finding allows us to conclude that NHFT under WINKS management produces less tail risk while generating greater overall fund returns (0.06% vs 0.11%). Similar findings were presented for the large-cap fund, SMIF-02. While the small-cap fund experienced a greater number of trades, the large-cap fund exhibited the potential for smaller catastrophic risk (with lesser return opportunities). Lastly, we noted that the BRIC portfolio had no measureable returns correlation with the domestic S&P 500 index. Not surprisingly, the simulation results for this portfolio led us to conclude that the portfolio is not suitable for either WINKS management or MVHR hedging.

The second objective of the research postulated an extension to the empirical estimation of a double-log production function to estimate the allocative efficiency of firm fundamental variables in the production of profitable automated market trades. To this end, quasi-elasticity coefficients were estimated by K4-RANN mapping. The estimated elasticity coefficients confirmed diminishing returns-to-scale om the production of profitable trades by over reliance on firm fundamental factors to drive profitable NHFT under WINKS management.

The aggregate review of WINKS performance leaves at least two important questions unanswered. First, it is logical to ponder if there is a specific method that analysts should rely upon to evaluate algorithmic model risk. Models are known to evolve over time. With that said, this research does not address the time frame of algorithmic model review nor does the research attempt to determine how operational risk should be managed within the context of 24/7 global trading. Model performance on both domestic and international securities is a clear research issue in version 1.1.4 of WINKS. A second unanswered question is directed at the process by which one can identify trading instruments that have a high probability of profitable trades under WINKS control. A partial resolution of this question evolved as the research addressed the manuscript’s second primary objective. During the process of developing a behavioral learning equation to map profitable trading performance, the elasticity estimates of the five production factors provided insight on how to construct a fundamental variable stock screener. The stock screener would help identify securities with a high propensity to trade profitably within WINKS. For example, the role of market beta was found to be of greater importance than, say, a firm’s PEG ratio.

Other important operational questions remain for future research. For example, knowing that WINKS (and automated trade algorithms in general) produce unprofitable trades, it is imperative that we investigate a philosophy for trading loss mitigation. For example, questions like, “Just how long the automated system should remain invested in a losing trade?” Overall, this paper provided new evidence that academic pedagogy can and should introduce HFT (and NHFT) tools and active fund hedging as a part of the SMIF experience. With the promising results obtained by executing the behaviorally based prediction systems that underlie the WINKS NHFT approach, a compelling argument exists to expand allied research efforts and experiential opportunities.

APPENDIX A: BRIC PORTFOLIO

BRIC-Part 1			**BRIC – Part 2**		
	Beta	Market Cap (B$)		Beta	Market Cap (B$)
BAK	2.09	$2.92	ITUB	1.76	$44.84
BBD	1.92	$33.97	MBT	1.50	$7.69
BORN	3.20	$0.03	MTL	-0.25	$0.34
BRFS	0.62	$16.96	ONP	0.09	$0.04
BSPM	3.76	$0.01	PBR	2.22	$36.79
CBD	1.95	$4.90	RDY	0.72	$11.32
CGA	0.30	$0.06	REDF	1.89	$0.04
CIG	1.41	$3.22	SBS	3.02	$2.99
CPL	1.35	$4.82	SEED	-0.59	$0.03
CTCM	3.86	$0.27	SID	1.67	$1.17
ELP	1.70	$2.46	SIFY	1.65	$0.18
EPI	1.08	n/a	SPU	-0.60	$0.03
ERJ	0.65	$4.86	SEED	-0.59	$6.30
FBR	0.44	$7.97	SID	1.67	$17.07
GFA	2.25	$0.23	SIFY	1.65	$9.98
GGB	0.86	$2.63	SPU	-0.60	$24.99
GOL	2.16	$0.35	TSU	0.77	$19.69
HDB	1.05	$307.85	TTM	1.85	$30.73
IBN	1.92	$28.24	UGP	1.28	$1.61
IFN	1.14	$0.77	VALE	0.93	$44.84
IGC	2.66	$0.00	VIV	0.62	$7.69
IIF	1.07	n/a	WIT	1.18	$0.34
INFY	1.72	$41.51	WNS	0.54	$0.04
INP	0.96	n/a	**Average**		**$17.00**

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