MARKET TIMING WITH THE ANALYTICAL NETWORK PROCESS

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ABSTRACT

In this paper we develop a stock market timing model based on expert judgments and observable market valuation and sentiment indicators. We apply it to the US stock market. We use the model for monthly, weekly and daily timing decisions over the period from 1994 to 2008. Two different strategies are used: switching between holding the market index and holding cash as well as holding the index and going short. In the case of monthly timing, a buy and hold strategy would have delivered a return of 4.5%, the best ANP timing model on a monthly basis delivered a return of 8.4% (long-cash) and 8.5% (long-short); on a weekly basis 8.1% (long-cash) and 6.5% (long-short); on a daily basis 14.4% (long-cash) and 19.2% (long-short). In the daily case we apply White's Reality Check for data snooping and Hansen's test for superior predictive ability (SPA) and for the case of long-cash we find genuine outperformance even while adjusting for data snooping.

Keywords: Market Timing, Financial Crisis Probability, Data Snooping

1 Introduction

It has long been the goal of many investors to find methods and models for timing the stock market. The strategy is intuitive and appealing: invest in the stock market when the market is expected to go up and hold cash or go short, when the market is expected to fall. Shilling (1992) found that invetors could have boosted their returns from 11.2% to 19.0% per annum during the period from 1946 to 1991, just by avoiding exposure to the 50 worst months.

If markets were efficient the task of market timing would surely be useless and it would be impossible to beat a buy-and-hold strategy. For this reason, market timing rules usually build on empirical findings rather than theoretical models. In this area, it is common to use well-known indicators, such as the price-earnings ratio (Campbell and Shiller, 1988b and 2000) or the dividend yield (Shiller, 1984), (Fama and French, 1988) and various other indicators. From a methodological point of view, OLS regression is usually the tool of choice to generate predictions.

By now there is a large body of literature that investigates the profitability of market timing rules. Fisher and Statman (2006a and 2006b) investigate the profitability of timing strategies derived from financial indicators. Shen (2003) finds that the difference between the price-earnings ratio and various interest rates

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is useful for market timing. The potential of interest rates alone is investigated by Breen, Lawrence and Jagannath (1989) and Prather and Bertin (1997 and 1998). Copeland and Copeland (1999) analyse the use of an implied volatility index for market timing decision. All of these studies usually use one or two indicators for deriving a timing signal. In this paper, we take a different approach and build a market timing model based on the Analytical Network Process (ANP). In order to derive market timing decisions, we use expert knowledge as well as observable financial indicators, many of which have been applied in isolation. In the awareness of possible data snooping biases, we use White's Reality Check (White, 2000) and Hansen's test for superior predictive ability (Hansen, 2005).

The remainder of the paper is organized as follows: Section 2 provides a short introduction to the analytical network process, Section 3 describes the ANP timing model, i.e. the indicators that are employed as well as the mapping from observed values to 1-9 scores. In Section 4 we present the empirical results of our backtests and conclude with suggestions for further research in Section 5.

2 The Analytical Network Process

Developing our market timing strategy is based on the enhanced method of the Analytic Hierarchy Process (AHP), containing feedback and inner dependencies, namely the Analytic Network Process (ANP). A process relating to expert judgment that is able to reflect statistically immeasurable connections. In a system of n components with feedback and dependencies, every component can interact with other components or even influence itself. The system of components $\{C_a,...,C_n\}$ and the linkage $L = \{(C_a, C_a), (C_a, C_b),...,(C_n, C_n)\}$ between them forms the network structure, c.f. Niemira and Saaty (2004). This network is essential to obtain reliable weights for each component in the network, the basic idea of the ANP multicriteria decision making model.

The derivation of the weights for all n components C_n is based on expert judgments regarding the dependencies in relevance to an overall criterion. In our case, of financial market analysis this criteria is the contribution to a financial crisis. These judgments value pairwise comparison of linked components by using the $1-9$ scale (Table 1) from Saaty (1977). Detailed observations of scale performance and comparisons to various types of scales can be found in Saaty (1980), which affirmed that the $1-9$ scale is ideal for the ANP. For more detailed inspection of the scale performance see Harker and Vargas (1987).

Table 1: Scale of Relative Importance

Intensity of Importance	Definition	Explanation
1	Equal importance	Two activities contribute equally to the objective
2	Weak or slight	
3	Moderate importance	Experience and judgment slightly favor one activity over another
4	Moderate plus	
5	Strong importance	Experience and judgment strongly favor one activity over another
6	Strong plus	
7	Very strong or demonstrated importance	An activity is favored very strongly over another; its dominance demonstrated in practice
8	Very, very strong	
9	Extreme importance	The evidence favoring one activity over another is of the highest possible order or affirmation

In order to justify the scale and derive weights, it is necessary to rely on basic axioms:

1. Weights belong to the closed interval $[0,1]$

2. Every ratio for $\{C_a, C_b\}$ assigned by an expert's judgment enforces a reciprocal value for $\{C_b, C_a\}$

3. Homogeneity exists to allow computations of the priorities after the expert judgments

The mathematical combination of the network structure and expert's pairwise comparisons is done by using a matrix approach, which delivers the Supermatrix $\mathbf{W}$. To create the Supermatrix for a network system, it is assumed that there are N clusters, denoted by C_h, $h = 1,...,N$. Each cluster C_h has n_h elements: $e_{h_1}, e_{h_2}, ..., e_{h_{n_h}}$.

It is a complete system of clusters $\{C_a,...,C_N\}$ and their weights W_{ij}.

$$\mathbf{W} = \begin{array}{c} \mathrm{C}_1 \\ \mathrm{C}_2 \\ \vdots \\ \mathrm{C}_\mathrm{N} \end{array} \begin{pmatrix} \mathbf{W}_{11} & \mathbf{W}_{12} & \cdots & \mathbf{W}_{1\mathrm{N}} \\ \mathbf{W}_{21} & \mathbf{W}_{22} & \cdots & \mathbf{W}_{2\mathrm{N}} \\ & \vdots & \ddots & \\ \mathbf{W}_{\mathrm{N}1} & \mathbf{W}_{\mathrm{N}2} & & \mathbf{W}_{\mathrm{NN}} \end{pmatrix}$$

The entry $\mathbf{W_{ij}}$ is called a block of the Supermatrix, with the form:

$$\mathrm{W}_{\mathrm{ij}} = \begin{pmatrix} \mathrm{W}_{\mathrm{i1}}^{(\mathrm{j}_1)} & \mathrm{W}_{\mathrm{i1}}^{(\mathrm{j}_2)} & & \mathrm{W}_{\mathrm{i1}}^{(\mathrm{j}_{\mathrm{n}_\mathrm{j}})} \\ \mathrm{W}_{\mathrm{i2}}^{(\mathrm{j}_1)} & \mathrm{W}_{\mathrm{i2}}^{(\mathrm{j}_2)} & \cdots & \mathrm{W}_{\mathrm{i2}}^{(\mathrm{j}_{\mathrm{n}_\mathrm{j}})} \\ & \vdots & & \\ \mathrm{W}_{\mathrm{in}_\mathrm{i}}^{(\mathrm{j}_1)} & \mathrm{W}_{\mathrm{in}_\mathrm{i}}^{(\mathrm{j}_2)} & & \mathrm{W}_{\mathrm{in}_\mathrm{i}}^{(\mathrm{j}_{\mathrm{n}_\mathrm{j}})} \end{pmatrix}$$

The columns of these $\mathbf{W_{ij}}$ are principal eigenvectors of the influence of the elements in the i-th component on the elements in the j-th component.

From pairwise comparisons a priority vector is obtained that represents the impact of a given set of elements on another element or component in the network. In the case of no connection between elements or components a value of zero is assigned to their comparison like suggested by Saaty (2004). The basic intention of employing the Supermatrix was to develop a way in which these derived vectors are combined to one system. By containing influences of elements on themselves or components influences on other components, Saaty and Vargas (2006) show that the Supermatrix represents all connections of the network in one system. To develop a priority vector for the complete network system by using the Supermatrix demand further computation. Each column of the Supermatrix includes several priority vectors with different priority elements. Synthesizing these various priority vectors is necessary to receive an overall priority vector for the complete Supermatrix. This is done by normalizing the matrix and multiplying it by itself to obtain the limit of the Supermatrix. Normalizing the Supermatrix means to create a stochastic matrix. The multiplication of a matrix with itself is also known as raising the matrix to powers.

$$\lim_{k \to \infty} \mathbf{W}^k$$

This delivers the global priority vector which can be used to gain the weights of all components and elements.

3 The ANP Timing Model and Inference

To develop a market timing strategy based on financial crisis probability, it is necessary build a predictive model of financial crises. Since the *ANP* creates static results, variation over time needs special implementation. Historical data analysis is used to build a time varying model that reflects changes in value of basic market indicators. These indicators will be merged into a network system to use the *ANP*. Combined with results of data analysis, financial crisis probability that will serve as threshold for market timing strategies is computed.

3.1 Indicators

For obtaining useful indicators for construction of a timing model based on the ANP we resort to the financial literature. The financial literature offers a large number of papers about indicators that have been employed for market timing. In the following sections we will shortly describe the indicators employed in our network model.

3.1.1 Price-Earnings Ratio

The price-earnings ratio (PER) is one of the most widely used ratios in the financial literature. Like many other financial ratios, it is motivated by the idea that stock prices do not wander away too much from their fundamental values, thus the PER has a tendency to be mean reverting. Among others Campbell and Shiller (1988a, 1998b and 2001) and Fama and French (1988 and 1989) argue that the PER has predictive power for future returns. Thus in our timing model a high PER will increase the probability of a sharp decline, whereas a low PER will lower the probability of a sharp decline.

3.1.2 Put-Call Ratio

The put-call ratio also measures investor sentiment. It is defined as the trading volume of puts relative to the trading volume of calls. When the ratio is high, i.e. the number of puts traded is significantly higher than the number of calls, the market is said to be pessimistic and vice versa. Fisher and Statman (2000) do not use the put-call ratio directly, but stress the importance of sentiment indicators for investment strategies.

3.1.3 Credit Spread

The credit spread measures investors' trust in the future profitability of companies. Fama and French (1989) document that the difference in yields between BAA-rated and a AAA-rated corporate bonds has valuable information for predicting future returns. An increase in the credit spread indicates high risk aversion and thus increases the probability of a sharp decline of the market.

3.1.4 Term Spread

In our case the term spread is calculated as the difference between the yield of a 10-year government bond and a 3-month Treausury Bill. In general, the term structure of interest rates may contain useful information about future economic activity and expected inflation e.g. Mishkin (1990). In the context of financial markets, the term spread has shown to be useful to predict future returns, c.f. Campbell (1987) and Fama and French (1989).

3.1.5 Implied Volatility

Volatility and its implications for investment decisions have been investigated very closely in the financial literature. Since the theoretical work of Merton (1980) and an empirical investigation of French and Schwert (1987) there has been a large number of essays that investigated the value of volatility for investment decision. We will only refer to the theoretical discussion of Christoffersen and Diebold (2006) and to the applied work of Copeland and Copeland (1999) and the numerous reference therein.

3.1.6 Trade Volume

The trading volume is also an indicator for the current condition of the market. If the volume is high the market is usually very nervous and a sharp decline is more likely than in the times of low volume. Naturally the volume increases with higher prices and also over time as the stock market became more and more popular.

3.1.7 Commodity Prices

The impact of commodity prices on future returns in the stock market is not always clear. High prices of some natural resources may help some companies. A high oil price might, for example, help some oil exploration companies whose means of exploration might be too expensive for a low oil price. On the contrary a high oil price will undoubtedly be counterproductive to most automobile manufacturers. In general, there is a tendency for high commodity prices to increase the probability of a decline in the stock market.

3.2 Network Model

The structure of feedback and dependencies for the financial crisis model was developed by experts of financial markets. These experts from ATACAMA Capital GmbH[1] built a network model by considering any possible linkage. Figure 1 shows the final linkage. To create the network, it is necessary to merge the previous mentioned factors into homogeneous clusters. The connections between the clusters and elements lead to a set of pairwise comparisons, which were carried out by expert judges.

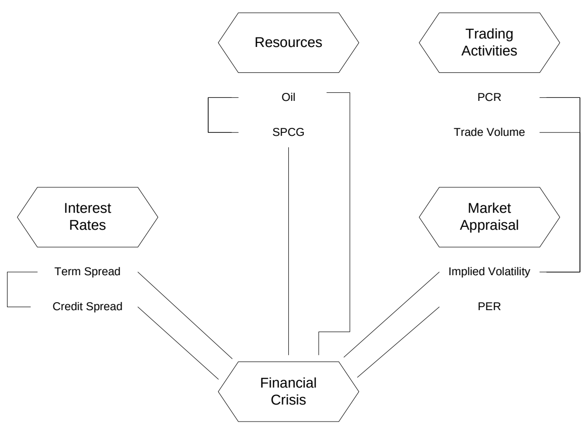

Figure 1: Connection between Market Indicators in the Financial Crisis Network

3.3 Expert Opinions

Expert knowledge of economics and stock markets are essential to compare the market indicators of the financial crisis network. According to the network structure, pairwise comparisons are needed for all connections to develop the Supermatrix. These comparisons, based on judgments of experts from ATACAMA Capital, are used to derive the Supermatrix. The Supermatrix can be found in the Appendix.

The Supermatrices computed by the judgments of experts can be seen in Tables 9, 10 and 11 in the Appendix. The first table contains the unweighted Supermatrix, the second table shows the weighted Supermatrix and finally the limit Supermatrix can be found in the third table. This limit Supermatrix derives a priority vector which includes the overall limiting and can be transformed to display cluster priorities. In this approach where a financial crisis is the relevant cluster, a normalization of the limiting priorities without crisis is needed to interpret the influence of the market indicators.

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[1] www.atacap.com, an asset management company focused on innovative strategies based on financial research and market analysis

This vector of market indicator weights, displayed in Table 1, is used in the next chapter to compute the probability of upcoming financial crisis.

Table 2: Market indicator weights

Indicator	Weight
Credit Spread	0.34
Implied Volatility	0.14
Oil	0.05
Price-Earnings Ratio	0.34
Put-Call Ratio	0.02
SPGSCI	0.02
Term Spread	0.03
Trade Volume	0.06

Table 3: Scoring Rule for Quantiles

Score	Threshold for Lower Tail of Distribution
1	less 75%
3	greater* 75% but less 80%
5	greater* 80% but less 85%
7	greater* 85% but less 90%
8	greater* 90% but less 95%
9	greater* 95%

* or equal

3.4 Deriving Timing Decisions

Combining static weights gained by expert judgments with market indicator time series is used to build a finacial crisis prediction model, which will be used to determine a market timing strategy. The basic idea is to rely on certain thresholds of the computed financial crisis probability to decide whether investing in the market index is profitable or not.

3.4.1 Financial Crisis Probability

Historical data sets for all market indicators are analyzed and individual quantiles for every indicator are computed. Allocation of single values to different quantiles is necessary to receive comparable and interpretable evaluations over time. The cumulative distribution of every market indicator is divided into 20 quantiles. Market indicators are supposed to increase financial crisis chances when their value is extraordinary (Section 3.1), that induces that focusing on high value quantiles is necessary.

These quantiles imply a score for the market indicator by using the rule from Table 3, which Niemira and Saaty (2004) call the signaling technique for evaluating incoming information on the scale 1-9. The original idea of the signaling technique was introduced as an alternative to regression, where the signal approach should provide diagnostic and predictive content, see Goldstein, Kaminsky and Reinhart (2000).

After every point in time t ($t = 1,...,T$) is assigned with the derived score for the corresponding market indicator value, the weighted overall score in $s_{total,t}$ is computed by using the weights w_i derived by the ANP model and the scores $s_{i,t}$ of the indicators i.

$$s_{total,t} = \sum_i w_i s_{i,t}, \quad i = 1,...,8 \tag{1}$$

where i is an index for the eight market indicators.

The maximum of $s_{total,t}$ equals 9, since the weights sum up to 1 and the maximal score is 9 for every indicator. In order to receive an interpretable probability value it is necessary to divide (1) by nine.

$$p_t = \frac{s_{total,t}}{max(Scorevalue)} = \frac{\sum_i w_i s_{i,t}}{9} \tag{2}$$

These probabilities for all T observed points in time deliver a time series where on the one hand absolute values of financial crisis probability p_t are of note and on the other hand changes $\delta_t = p_t - p_{t-1}$ from $t-1$ to t are of interest to interpret the crisis probability.

3.4.1 Thresholds

It is incidental to define thresholds for the absolute value and the gain of the financial crisis probability p_t to derive rules for the market timing strategy. These thresholds define whether switching to cash or short position is necessary. Different thresholds and their combinations define different scenarios of market timing. After inspecting the data, thresholds of financial crisis probability and its changes from one period to another are determined:

- probability p_t of 25% to 70% in steps of 5%, i.e. 10 different thresholds
- increase of probability δ_t of 5% to 20% in steps of 2,5%, i.e. 7 different thresholds

The combination of different thresholds delivers 70 different scenarios to create 70 rules for our market timing strategies. That means, every strategy is based on a unique combination of (a) financial crisis probability and (b) financial crisis probability change thresholds, which induce switching to other investments.

3.5 Inference

Dangers of data snooping have long been recognized as serious problem of empirical studies in finance cf. for instance Lo and MacKinlay (1990), Brock, Lakonishok and LeBaron (1992) and Ferson, Sarkissian and Simin (2003). As we are investigating a total of 70 timing rules, a robust methodology to avoid spurious statistical inference due to data snooping is needed. Thus we employ the "Reality Check" (RC) by White (2000) and the test for superior predictive ability (SPA) introduced by Hansen (2005). Both procedures allow for intensive search for models while ensuring that the obtained results are robust and not a result of mere chance. Both procedures build on the work of Diebold and Mariano (1995) and West (1996) and will briefly be outlined in this section. We refer the reader to the articles of White (2000) and Hansen (2005) for a rigorous derivation of the procedures described below.

The RC tests the null hypothesis that the best model does not have superior predictive ability over the benchmark, while taking into account the full set of models, against the alternative that the best model has superior predictive ability. The test is based on the $l \times 1$ performance statistic:

$$\bar{\mathbf{f}} = \frac{1}{n}\sum_{t=R}^{T} \hat{\mathbf{f}}_{t+1} \tag{3}$$

where l is the number of timing rules, n is the number of prediction periods indexed from R through T so that $T = R + n - 1$. $\hat{\mathbf{f}}_{t+1} = f(\mathbf{Z}_t, \hat{\boldsymbol{\beta}}_t)$ is the performance measure, where $\mathbf{Z}_t$ is a matrix, which contains a vector of dependent variables and a vector of predictor variables. $\hat{\boldsymbol{\beta}}_t$ is a vector of estimated parameters.

It is assumed that these parameters satisfy the conditions of Diebold and Mariano (1995) and West (1996), so that parameter uncertainty vanishes asymptotically. In our case there are no estimated parameters, so that we do not have to verify, that the conditions for asymptotic irrelevance are met.

We use the returns generated from the l timing rules as a performance measure. In the full sample from 1994-2008 $n = 5479$ and $l = 70$. For a timing rule k, we choose the following form for $f_{k,t+1}$:

$$f_{k,t+1} = \ln\left[1+\left(\frac{S_{t+1}-S_t}{S_t}X_k(\mathbf{Z}_t,\boldsymbol{\beta}_k)-\frac{S_{t+1}-S_t}{S_t}X_0(\mathbf{Z}_t,\boldsymbol{\beta}_0)\right)\right], \quad k=1,...,l \tag{4}$$

where $\mathbf{Z}_t$ consists of the predictor variables as described in Section 3.1, S_t is the price of the S&P index at time t and X_k and X_0 are "timing functions", which take on the value 1 for "invest in the stock market" and 0 for "hold cash" or -1 for "go short". With the performance statistic, we will test whether there exists a timing rule that delivers superior performance over a simple buy-and-hold strategy. Formally, the null states as,

$$H_0 : \max_{k=1,...,l}\{E(f_k)\} \le 0. \tag{5}$$

If the null can be rejected, it has been established that there exists a timing rule that leads to superior performance over a simple buy-and-hold strategy. It has been shown by White (2000) that under weak assumptions about the stationarity, dependence structure and moments of $\hat{\mathbf{f}}_t$ the distribution of the test statistic can be obtained by application of the stationary bootstrap of Politis and Romano (1994) as follows. In step 1, we generate a resample of $\{f_{k,t}\}_{t=R}^{t=T}$ for each timing rule $k=1,...,l$ by drawing (geometrically distributed) blocks from the observed return series, with mean block length $1/q$. We shall denote the resampled series by $f^*_{k,t,j}$, where the subscript j indicates the j-th repetition of the bootstrap. We will repeat the process J times. In step 2, we compute the mean of the bootstrapped return series, $\bar{f}^*_{k,j} = n^{-1}\sum_{t=R}^{T} f^*_{k,t,j}, \forall\, k=1,...,l$. In step 3, we compute the following statistics

$$V_{RC} = \max_{k=1,...,l}\{\sqrt{n}\,\bar{f}_k\}, \tag{6}$$

$$V^*_{RC,j} = \max_{k=1,...,l}\{\sqrt{n}(\bar{f}^*_{k,j} - \bar{f}_k)\}, \quad j=1,..,J \tag{7}$$

We then compare V_{RC} with the quantiles of $V^*_{RC,j}$. Thus, a p-value of the RC is given by

$$p_{RC} = \sum_{j=1}^{J}\frac{1_{V^*_{RC,j}>V_{RC}}}{J}, \tag{8}$$

where $1_{\{\cdot\}}$ denotes the indicator function. In our empirical analysis we set $J=1000$ and choose a smoothing parameter of $q=0.5$. (Hansen, 2005) proposes some refinements of the RC that lead to more power in most cases. The SPA is very similar to the RC, yet it includes some refinements that can improve power in many conditions. The SPA makes use of the following studentized test statistic

$$V_{SPA} = \max\left[\max_{k=1,..,l}\frac{\sqrt{n}\,\bar{f}_k}{\hat{\sigma}_k},0\right] \tag{9}$$

where $\hat{\sigma}^2_k$ is a consistent estimate of $\sigma^2_k = var(\sqrt{n}\,\bar{f}_k)$. We will employ the estimator given in (Hansen, 2005). He also suggests to invoke a different null distribution, which is based on $N(\hat{\boldsymbol{\mu}},\hat{\boldsymbol{\Omega}})$, where $\hat{\boldsymbol{\Omega}}$ denotes a consistent estimate of the asymptotic covariance matrix of $\bar{\mathbf{f}}$ and $\hat{\boldsymbol{\mu}}$ is an estimate for $E(\mathbf{f}_t)$. (Hansen, 2005) advocates the use of the following estimator

$$\hat{\mu}_k = \bar{f}_k 1_{\{\sqrt{n}(\bar{f}_k/\hat{\sigma}_k) \le -\sqrt{2\ln\ln n}\}}. \tag{10}$$

(Hansen, 2005) shows by choosing this estimator, the irrelevant models do not influence the distribution of the test statistic asymptotically. This is done by applying the law of the iterated logarithm, which ensures that $\frac{\sqrt{n}\,\bar{f}_k - \mu_k}{\sigma_k}$ stays within certain bounds with probability 1 asymptotically. The implementation of the SPA is also very similar to the implementation of the RC. In step 1, we generate a resample of $\{f_{k,t}\}_{t=R}^{t=T}$ for each timing rule $k = 1,...,l$ by drawing (geometrically distributed) blocks from the observed return series. We shall denote the resampled series $\{f^*_{k,t,j}\}$, where the subscript j indicates the j-the repetition of the bootstrap. We will repeat the process J times. In step 2, we compute $Z^*_{k,t,j} = f^*_{k,t,j} - \bar{f}_k 1_{\{\sqrt{n}(\bar{f}_k/\hat{\sigma}_k) \le -\sqrt{2\ln\ln n}\}} \; \forall k = 1,...,l, t = R,...,T$. In step 3, we compute the following statistics

$$V_{SPA} = \max\left[\max_{k=1,..,l} \frac{\sqrt{n}\,\bar{f}_k}{\hat{\sigma}_k}, 0\right] \tag{11}$$

$$V^*_{SPA,j} = \max\left[\max_{k=1,..,l} \frac{\sqrt{n}\bar{Z}^*_{k,j}}{\hat{\sigma}_k}, 0\right], \quad j = 1,.., J \tag{12}$$

where $\bar{Z}^*_{k,j} = n^{-1}\sum_{t=R}^{T} Z_{k,t,j}$. We then compare V_{SPA} with the quantiles of $V^*_{SPA,j}$. Thus, a p-value of the SPA is given by

$$p_{SPA} = \sum_{j=1}^{J} \frac{1_{V^*_{SPA,j} > V_{SPA}}}{J}. \tag{13}$$

4 Empirical Results

The timing model described in Section 3.4 is used to determine rules for switching to an alternative investment rather than holding the S&P 500, which will be called Long in this article. Consider two alternatives, annual interest of 4% called cash and entering a short position called short.

In times of fast market changes and financial instability, we focus on timing decision derived from daily observations. We focus on daily timing decision as this seems appropriate for the market dynamics today. Additionally, we present the results for weekly and monthly timing decisions.

Historical data analysis of market indicators is done from 1994 to 2008. After combining the results of this analysis with the weights from expert judgment we received the financial crisis probability, described in Section 3.4.1 for every day during these 15 years. Using the thresholds from Section 3.4.2 to create timing strategies lead to remarkable results, either in long-cash and long-short investments.

4.1 Long-Cash

Switching from stock index investments to cash during unstable times is less risky than entering a short position to avoid swings and receive a constant return. In order to keep the model simple, a fixed annual interest of 4% is used during the whole period of observation.

Table 4 contains an overview of the general performance of the ANP based market timing strategies. The results of daily strategies are notably, since 76% gain higher return than the basic buy and hold strategy investing in the S&P 500. On average, even with the few underperforming rules, the annual return is 4.08% higher during all the time from the beginning of 1994 till the end of 2008.

Table 4: Overview Long-Cash Timing Strategies

Summary Statistics	Day	Week	Month
Rules with good performance *	57	49	61
Rules with poor performance *	13	16	9
Average advantage per rule *	4.08%	0.87%	1.32%

* compared to Buy and Hold

The best market timing strategy is inspected more precisely in Table 5. In case of daily timing decisions, the best strategy uses thresholds of 30% for financial crisis probability and 17.5% or 20% for its change, where both models performed equal (weekly 25% and 10%, monthly 35% and 10%). Compared to a buy and hold strategy with an annual return of 4.50% we receive 14.40% when using this best daily model. Figure 2 shows the time series of buy and hold an the best timing strategy. Computing the ratio of cash positions, the strategy lead to an investment in interest in nearly 60% of the time. The interest investments outperformed in 60% of the time compared to the buy and hold return. On average a period of cash investment takes about 8 days with an average winning of 0.04% per day compared to the buy and hold strategy, that means after deciding to switch the investment from long to cash, the model stays in cash for 8 days on average with an average advantage of 0.32% during one cash period. Since switching from one investment to another causes transaction fees, we take care of this issue in 4.3. Additionally weekly and monthly results are also displayed, but not discussed here since we focus on daily strategies.

Table 5: Summary Long-Cash Timing Strategies

Summary Statistics	Best Rule Day	Best Rule Week	Best Rule Month	Buy and Hold
Annualized average return	14.40%	8.10%	8.36%	4.50%
P-value	0.031			
Total number of long or cash positions	5479	783	181	
Total number of cash positions	3266	699	132	
Number of winning cash positions *	1949	339	64	
Number of loosing cash positions *	1317	360	68	
Average number of periods in cash position	7.97	11.85	4.55	
Average difference per cash position *	0.04%	0.05%	0.34%	

* compared to long

4.2 Long-Short

If a market timing model has good predictive ability, it should be possible to increase the returns by going short and not just holding cash. This strategy bears more risk but also more potential gains compared to the long-cash strategy. Table 6 summarizes the results of the long-short strategies for daily, weekly and monthly data.

In this case, our focus is on daily strategies also, for which 76% gain higher values than a buy and hold strategy. On average timing strategies produce an outperformance of 5.57% in terms annual return during the observed period from 1994 to 2008.

Table 6: Overview Long-Short Timing Strategies

Summary Statistics	Day	Week	Month
Rules with good performance *	57	35	41
Rules with poor performance *	13	31	29
Average advantage per rule *	5.57%	-0.28%	0.36%

* compared to Buy and Hold

In Table 7 we display, the best rule in daily market timing uses thresholds of 30% for financial crisis probability and 17.5% (or 20%, with equal results) for its change (weekly 35% and 17.5% or 20%, monthly 35% and 12.5%). An annualized average return of 19.24% is almost 15% higher than the buy and hold strategy. This means during the observed 15 years an outcome of 1400% instead of less than 200% can be created, Figure 2 illustrated these results. The timing strategy suggests short investments in 48% of the time, where 51% are effective. This leads to an average difference per short position of 0.07% which seems rather small, but in case of daily investments this creates a large effect. A period of short investments is about four days long on average. Accounting for transaction costs does not qualitatively change the results, we refer to section 4.3 for further computation.

Table 7: Summary Long-Short Timing Strategies

Summary Statistics	Best Rule	Best Rule	Best Rule	Buy and Hold
	Day	Week	Month	
Annualized average return	19.24%	6.51%	8.47%	4.50%
P-value	0.068			
Total number of long or short positions	5479	783	181	
Total number of short positions	2650	670	134	
Number of winning short positions *	1350	312	61	
Number of loosing short positions *	1300	358	73	
Average number of periods in short position	3.81	8.70	5.15	
Average difference per short position *	0.07%	0.04%	0.41%	

* compared to long

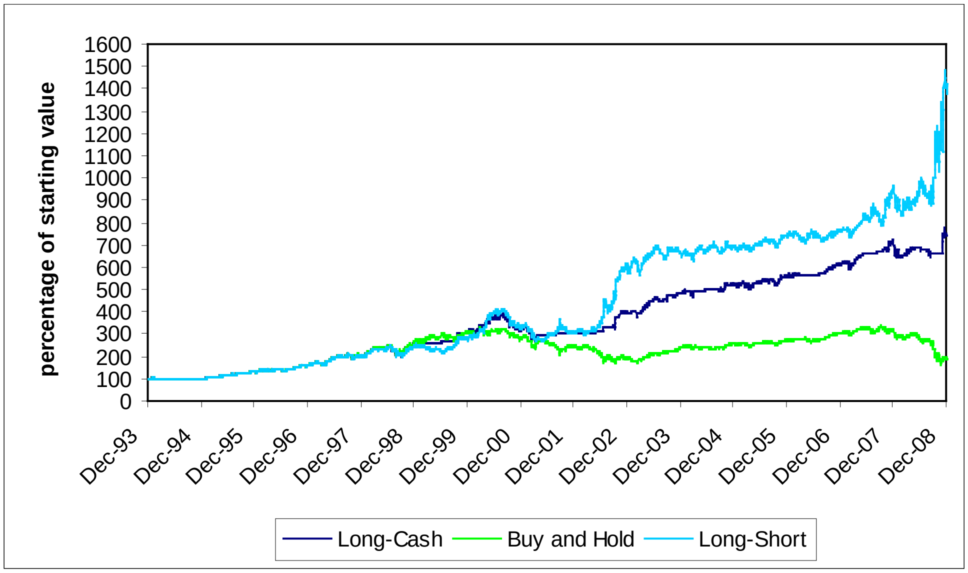

Figure 2: Buy and Hold vs. Best Timing Strategy

4.3 Transaction Fees

Transaction fees are common in financial markets investments. To calculate the results of the market timing strategy with respect to these fees, we assume a fee of 0.05% per transaction taken from Fama and Blume (1966). The results for the best daily strategy of section 4 are nevertheless respectable.

The long-cash strategy gained an annualized average net return of 11.3% and the long-short strategy received 13.8%, compared to the buy and hold strategy with 4.5% even the net performance of the timing strategy is remarkable.

5 Conclusion

In this paper we develop a stock market timing model based on the Analytical Hierarchy Process and apply it to the US stock market. Through application of the model, one could have obtained higher returns than through a buy and hold strategy in the backtested period. The proposed model may serve as a first step for asset managers and banks to put their timing decision in a structured framework.

In comparison with a regression model, our model has the advantage that it does not require vast amounts of data to yield reliable estimates.The expert judgments for the backtest of our model were obtained in June 2008, which may induce a possible bias in our backtest as these judgment are most likely to be time-varying also, we therefore suggest to use our model with these judgment for prediction in the near future. In order to increase robustness we should ask experts of financial markets periodically and then update the judgments and use these new judgments for further predictions until the judgments are updated again.

Another issue that should be addressed in future research is the integration of market indicators that are observed at different frequencies. A feasible solution to this problem could provide a bridge to include macro indicators which are usually observed at lower frequencies and also have a tendency to have a more inert effect on the objective.

APPENDIX

1.1 Expert Judgments

Table 8: Judgment Matrices

Financial Crisis	Interest Rates	Market Appraisal	Resources	Sentiment
Interest Rates	1	1/3	4	4
Market Appraisal	3	1	4	2
Resources	1/4	1/4	1	1/2
Sentiment	1/4	1/2	2	1

Resources	Financial Crisis	Resources
Financial Crisis	1	9
Resources	1/9	1

Market Appraisal	Interest Rates	Trading Activities
Interest Rates	1	3
Trading Activities	1/3	1

Crisis	Credit Spread	Term Spread
Credit Spread	1	6
Term Spread	1/6	1

Crisis	SPGSCI	Oil
SPGSCI	1	1/3
Oil	3	1

Crisis	PER	Implied Volatility
PER	1	6
Implied Volatility	1/6	1

Implied Volatility	PCR	Trade Volume
PCR	1	1/4
Trade Volume	4	1

1.2 Supermatrices

Table 9: Unweighted Supermatrix

	Crisis	No Crisis	Credit Spread	Term Spread	Implied Volatility	PER	SPGSCI	Oil	PCR	Trade Volume
Crisis	0	0	0.9	0.9	0.9	0.9	0.9	0.9	0	0

No Crisis	0	0	0.1	0.1	0.1	0.1	0.1	0.1	0	0
Credit Spread	0.86	0.86	0	1	0	1	0	0	0	0
Term Spread	0.14	0.14	0	0	0	0	0	0	0	0
Implied Volatility	0.14	0.14	0	0	0	0	0	0	1	1
PER	0.86	0.86	0	0	0	0	0	0	0	0
SPGSCI	0.25	0.25	0	0	0	0	0	1	0	0
Oil	0.75	0.75	0	0	0	0	1	0	0	0
PCR	0.5	0.5	0	0	0.2	0	0	0	0	0
Trade Volume	0.5	0.5	0	0	0.8	0	0	0	0	0

Table 10: Weighted Supermatrix

	Crisis	No Crisis	Credit Spread	Term Spread	Implied Volatility	PER	SPGSCI	Oil	PCR	Trade Volume
Crisis	0	0	0.9	0.45	0.45	0.45	0.81	0.81	0	0
No Crisis	0	0	0.1	0.05	0.05	0.05	0.09	0.09	0	0
Credit Spread	0.24	0.24	0	0.5	0	0.5	0	0	0	0
Term Spread	0.04	0.04	0	0	0	0	0	0	0	0
Implied Volatility	0.08	0.08	0	0	0	0	0	0	1	1
PER	0.51	0.51	0	0	0	0	0	0	0	0
SPGSCI	0.03	0.03	0	0	0	0	0	0.1	0	0
Oil	0.08	0.08	0	0	0	0	0.1	0	0	0
PCR	0.01	0.01	0	0	0.1	0	0	0	0	0
Trade Volume	0.01	0.01	0	0	0.4	0	0	0	0	0

Table 11: Limit Supermatrix

	Crisis	No Crisis	Credit Spread	Term Spread	Implied Volatility	PER	SPGSCI	Oil	PCR	Trade Volume
Crisis	0.36	0.36	0.36	0.36	0.36	0.36	0.36	0.36	0.36	0.36
No Crisis	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04
Credit Spread	0.21	0.21	0.21	0.21	0.21	0.21	0.21	0.21	0.21	0.21
Term Spread	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
Implied Volatility	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08
PER	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2
SPGSCI	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
Oil	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03
PCR	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
Trade Volume	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04

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