A Stock Market Trading System
Based on Foreign and Domestic Information.

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ABSTRACT

This paper investigates whether a particular magnitude and direction of inter-regional return signal transmission dominates the performance of domestic trading in American, European and Australasian stock markets. A trading system design, based on fuzzy logic rules, combines direct and indirect channels of foreign information transmission, modelled by stochastic parameter regressions, with domestic momentum information to generate stock market trading signals. Filters that control for magnitude and direction of trading signals are then used to investigate incremental impact on economic performance of the proposed investment system. The results indicate that at reasonable levels of transaction costs very profitable trades that are fewer in number do not increase investment performance as much as trades based on foreign information of a specific low-to-medium daily return magnitude of 0.5% to 0.75%. These information-based strategies are profitable on risk-adjusted bases and relative to a market, but performance declines considerably when traded instruments are used.

Keywords: Stock market trading; Information transmission; Fuzzy system rules; Stock trading system design; System testing and performance evaluation; Stock market forecasting.

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1. Introduction

The design of many stock market trading systems based on synthesis of fuzzy logic and the rule-base evidential reasoning methods of Dempster (1968) and Shafer (1976) has produced ample evidence of predictability in price movements (see, e.g., Chang and Liu (2008), Dymova, Sevastianov and Bartosiewicz (2010), Boyacioglu and Avci (2010), Dymova, Sevastianov and Kaczmarek (2012), Escobar, Moreno and Múnera (2013), Chourmouziadis and Chatzoglou (2016), Chang, Wu and Lin (2016) or Rubell and Jessy (2016), among others). The empirical results on the performance of this type of stock trading expert systems suggests that financial markets function consistently with the Adaptive Markets Hypothesis (AMH) proposed by Lo (2004 and 2005), according to which the market efficiency phenomenon tends to evolve over time, and the predictability of stock prices can arise periodically depending on evolving market conditions and agent behaviour (see, e.g., Urquhart and McGroarty (2014 and 2016) or Manahov and Hudson (2014), among others).

Amongst the studies that are based on the fuzzy logic systems, many rely on the 'IF–THEN' decision rule in underlying pattern-recognition technical analysis methods. Some of these systems are more dynamic than others. For example, Cervelló-Royo, Guijarro and Michniuk (2015) introduce a new definition of the weight grid of the charting heuristic flag pattern that includes the two parameters used by Teixeira and De Oliveira (2010), namely: stop loss and take profit. These allow the dynamic modelling of the 'closing operations' and limit both their losses and profits. The authors report performance that 'beats the market,' which reinforces similar positive results of the flag pattern reported in previous studies such as Leigh, Paz and Purvis (2002) and Leigh et al. (2002). Lee and Jo (1999) develop a candlestick chart analysis (chart interpreter) based on the IF–AND/OR–THEN–EXPLANATION rule to detect simple and composite patterns, where the EXPLANATION part provides information about what the pattern really means. They present results of high profitability when applied to the

Korean stock market. Interestingly, they apply priority values when patterns are in conflict. Some other studies also exploit dynamic techniques that include the IF-THEN rule as well as other heuristics. Leigh, Purvis and Ragusa (2002), for example, investigate, over a rolling window (reoptimization), a price-volume pattern recognizer, a feedforward neural network with backpropagation learning and a genetic algorithm configuration search, and a cross-validation experiment containing the first two techniques. Arévalo et al. (2017) use a dynamic window scheme to update the stop loss and take profit rules implemented by Cervelló-Royo, Guijarro and Michniuk (2015) in the flag pattern recognizer. Tsinaslanidis (2018) proposes the dynamic time warping (DTW) algorithm and two modifications: subsequence DTW and derivative DTW. They present evidence that this method captures common characteristics of the entire family of technical analysis patterns and is free of technical descriptions or guidelines for the identification of specific patterns. All these studies, as well as others, report superior performance of their techniques over the most recent prior. However, they rely solely on pattern detection in the price history of the same asset or, more rarely, in contemporaneous correlations between assets of the same market. In this paper, we apply an elaborate IF-THEN rule in an entirely different dynamic sequential setup that harvests evolving patterns within and between international and domestic price information rather than within domestic price information only.

In the context of a sequential information transmission mechanism, this study examines stock market predictability by designing and evaluating a trading system that is conceptually close to fuzzy logic systems based on the 'IF–THEN' rule. More specifically, we investigate the degree to which foreign and domestic stock market return signals of different magnitude and direction help predict domestic stock market returns. The reasoning is that if overnight foreign information is relevant to the direction and magnitude of next day's domestic market returns, then one ought to expect foreign signals of different strengths to have different impact.

Is there a particular magnitude, or a specific range of strength, of signal that is dominantly transmitted? Is the distribution of the impact of different strength signals uniform? Do the prevailing conditions of the domestic market matter when foreign information of different magnitude is transmitted? Can any of these predictabilities, if they exist, 'beat' the market after considering risk, transaction costs and practical trading viability? These questions motivate the design of the system and the analyses in this paper.

The focus in this paper is on the design, construction and performance evaluation of a stock market trading system based on the processes described above. Our approach and the forecasting tool we propose are conceptually similar to a stock trading fuzzy expert system, such as the ones proposed by the literature reviewed above. Ours perhaps shares similarities with the rule system used by Rubell and Jessy (2016) for formulating daily trading decisions for stocks listed on the NASDAQ trading platform. The trading strategy presented in Rubell and Jessy (2016) performed better than the popular technical analysis indicators (such as the Moving Average Convergence/Divergence (MACD), Relative Strength Index (RSI), Stochastic Oscillator (SO) and Chaikin Oscillator (CO)). The authors also report an over-performance of this strategy relative to an alternative benchmark model, similar to the conclusions reached by all the papers reviewed above as well as others in the field. However, our approach differs in the type of information and method used in pattern detection. We also rigorously assess the performance and possible limitations of the trading strategy we propose to demonstrate its usefulness in practical stock trading activities.

Our starting point are the ideas presented, and the empirical findings reported, in the seminal paper by Engle et al. (1990), which documents spill-overs of volatility from one market to another, dubbed 'meteor showers', and persistence in volatility over time within the same market, dubbed 'heat waves'. These spillovers and persistence in volatility have been studied by Baillie and Bollerselv (1990), Ito et al. (1992), Melvin and Hogan (1994) and Melvin and

Peiers Melvin (2003), amongst others. The equivalent in returns has been analysed by Eun and Shim (1989), Hamao et al. (1990), Lin et al. (1994), Longin and Solnik (2001) and Bekaert et al. (2005), amongst others. In particular, Ibrahim and Brzeszczyński (2009) document time variation in the return equivalent of the heat wave and meteor showers and provide evidence from eight international stock market indices of both direct and indirect channels of information transmission. The direct channel of transmission between a pair of markets (say, A and B) refers to the transmission of return signals from one to the other (say from A to B), and the indirect channel refers to the impact on this relationship from a third market (say C) that operates in intermediate time between the first two markets (A and B). Thus, foreign information is transmitted directly from one market to another and indirectly through other markets.

When foreign information arrives through the direct or indirect channels at the investor's domestic market, it either corroborates or contradicts the prevailing domestic market momentum. This conditioning gives rise to an 'IF–THEN.' type of a trading rule: IF the foreign information coincides in direction with the domestic market momentum, THEN the combined signal to invest domestically is strengthened, otherwise it is weakened. Beside direction, there is also the size or magnitude of information from the two streams to consider. The foreign signal could be stronger or larger in magnitude and, hence, more significant than domestic momentum. Signals of different magnitude may have different intensity of impact. This adds another layer to the 'IF–THEN' rule. Thus, combinations of direction and magnitude of foreign and domestic signals could have varying degrees of economic benefit to domestic investors. This paper designs and assesses the performance of a trading system based on the strength, type and direction of foreign information by using the conditional time-varying (dynamic) FIT model of Ibrahim and Brzeszczyński (2009) and by measuring domestic market momentum with the Relative Strength Index (*RSI*) as a popular technical analysis indicator.

Do all return signals that arrive from foreign markets matter to domestic market traders, or only those of a specific magnitude and direction? It is logical to rationalise that during certain times the prevailing state of the domestic market could dominate some weak incoming foreign signals, while during other times the reverse could be true and foreign signals of a certain magnitude are more significant. It is also logical to rationalise that if an incoming foreign signal coincides in direction with domestic market momentum then the signal strengthens convictions about the future direction of domestic market returns. Taking Engle et al.'s (1990) meteor showers metaphor into more detail, a larger meteoroid (large foreign information) is more likely to survive the passage through the Earth's atmosphere (domestic market condition), and the energy release upon impact (intensity of impact) is directly related to its size. Also, the Earth's atmosphere acts as a dampener and a filter by slowing down and burning off smaller meteoroids. Could domestic market momentum be acting as a dampener to large incoming foreign signals and a filter to smaller ones? This obviously depends on velocity and approach. The alignment of the Earth in its orbit relative to that of the meteoroid determines the angle and speed of impact. Similarly, when the direction of prevailing domestic market momentum is in alignment to that of incoming foreign signals, the effect of the foreign impact could be enhanced; otherwise, it is dampened.

In this paper, we simulate a trading system based on concepts similar to fuzzy logic rules and fuzzy sets, where foreign signals and domestic signals act as the input data (or input variables) to define a signal to trade (buy, sell, or do nothing). We also use filters to fine-tune the signals input to the system. This is similar in principle to a fuzzy inference system (FIS), known also as fuzzy expert system in providing signals to investors in the form of 'buy', 'sell' or 'hold' decisions. Our system, however, is designed differently. We use other rules and consider different multiple antecedents (premises) as inputs based on foreign as well as domestic stock market information (while Rubell and Jessy, 2016, and most of the literature reviewed above, consider direct domestic stock information and no transmission channels). Further, the economic benefit of knowledge about the dynamically-changing strength and direction of foreign and domestic stock market signals on domestic market trading is measured. Specifically, the incremental impact on investment performance is dissected by introducing two filters (or two rules), one on the signalling market and the other on the domestic market.

The filter that is applied to the foreign signal operates as a gate of varying width that allows foreign return signals of only a specific magnitude to pass through and affect a trader's conviction about their likely impact on domestic returns. Similarly, different bands are applied to the *RSI* domestic momentum indicator as a domestic gate that restricts the quality of the incoming foreign information signal. The narrower the *RSI* band the more selective the trader is of which foreign signal to consider depending on whether or not its direction coincides with that of domestic market momentum. Varying the width of these gates provides a rich combination of restrictions, or rules, that allow the measurement of economic relevance of the strength of foreign and domestic return signals on domestic trading. They also allow the identification of the range of magnitude of foreign information signals that is economically dominant, since the strength of smaller signals of particular direction may not be as economically significant as larger signals of different direction. Economic benefit is measured by the performance of trading strategies constructed on the basis of different combinations of the magnitude and direction of foreign and domestic market information controlled by filters. These effects are analysed in nine indices that represent the largest stock markets in the U.S., Europe and Australasia. Results indicate that a foreign signal in the range of 0.5% to 0.75% is most economically relevant in spot markets (i.e., in markets where buying or selling leads to immediate delivery of the asset or product being traded), while a higher range seems more relevant in futures markets (i.e., markets of deferred delivery of asset or product being traded), especially when domestic information interference is restricted. To guard against claims of data snooping we run White’s (2002) reality check and test robustness over sub-periods, across different specifications, and by using futures as traded instruments.

These results have implications on the size and sign of international dependence of stock markets and market efficiency. Regulatory organisations are interested in guards against systemic risk and international contagion, and credit rating models may incorporate measures of equity market interdependence. The analysis of persistence in the impact of foreign signals, the interaction with domestic market momentum and the degree to which domestic markets are affected by international and global information transmission channels are relevant endeavours. For example, market integration is sometimes defined as the degree to which returns of a market depend on international market shocks, and market efficiency by the speed by which relevant information is incorporated into prices, which implies the absence of correlation in returns if markets are fully efficient. A more realistic definition of efficiency is the absence of persistent arbitrage opportunities based on prior domestic or foreign information. Thus, evidence of economically beneficial trading systems based on sequential foreign and domestic information would either constitute a violation of market efficiency or further support for pricing models that factor in sequential information transmission. This paper contributes to the literature by designing an appropriate trading system that provides such evidence on risk-adjusted and dynamic bases (where it is updated daily).

The contribution of this paper is two-fold. First, it designs and tests a dynamic trading system that incorporates domestic and foreign information from international stock markets. It presents evidence that in spot stock indices there exists a specific low-to-medium magnitude sequential foreign information signal that penetrates domestic market momentum conditions with higher frequency. It is mostly trades with this magnitude of return, rather than those that are less frequent but of larger return, that have a dominant economic impact on trading strategies based on a combination of foreign and domestic market information. Second, tests based on the Capital Asset Pricing Model (CAPM) and its international version (ICAPM) show that trading systems or strategies using spot stock indices based on such signals earn positive excess returns on risk adjusted and net of transaction cost bases. However, these excess returns largely disappear when such strategies are implemented using stock index futures as tradable stock index proxies (although see Dymova, Sevastianov and Bartosiewicz, 2010).

The remainder of the paper is organised as follows. Section 2 describes econometric methodology, Section 3 presents the design of the trading system and the resulting investment strategy rules that are based on Fuzzy logic, Section 4 discusses the data used in the empirical analyses, Section 5 presents empirical results and robustness checks using spot index data, Section 6 provides a discussion of the viability of trading strategies using futures contracts, and Section 7 concludes.

2. Methodology

2.1. Foreign information transmission

Sequential incorporation of foreign information into domestic stock market prices is modelled by the Foreign Information Transmission (FIT) model of Ibrahim and Brzeszczyński (2009). This model describes the impact of information of foreign market *x* on the returns of domestic market *y* by the following stochastic parameter regression:

$$y_t = \alpha_t + \beta_t x_t + w_t, \tag{1}$$

where y_t and x_t are open-to-close day-*t* continuously compound returns; α_t and β_t are the intercept and slope coefficients and w_t is an error term. The change over time in the coefficients is further assumed to depend on the returns of another market, *z*, that operates in the interim between the operating hours of markets *x* and *y*, according to the following equations:

$$(\alpha_{t+1} - \bar{\alpha}) = [a + b(z_t - \bar{z})](\alpha_t - \bar{\alpha}) + \nu_{\alpha,t+1}, \tag{2}$$

$$\left(\beta_{t+1}-\bar{\beta}\right)=[c+d(z_t-\bar{z})]\left(\beta_t-\bar{\beta}\right)+\nu_{\beta,t+1}, \tag{3}$$

where a, b, c and d are constant coefficients; $\bar{z}$, $\bar{\alpha}$ and $\bar{\beta}$ are long-run average values (also called 'steady states') of the variable z and the time-varying coefficients α_t and β_t; and $\nu_{\alpha,t+1}$ and $\nu_{\beta,t+1}$ are associated error terms. Conditional on x_t and data observed through t-1, gathered in the vector $\boldsymbol{Y}_{t-1}$, it is assumed that the vector of error terms $(\upsilon_{t+1}\ w_t)'$ has a Gaussian distribution, viz.,

$$\begin{bmatrix}\boldsymbol{\nu}_{t+1}\\ w_t\end{bmatrix}|x_t,\boldsymbol{Y}_{t-1}\Bigg]\sim N\left(\begin{bmatrix}\mathbf{0}\\ 0\end{bmatrix},\begin{bmatrix}\boldsymbol{Q} & \mathbf{0}\\ \mathbf{0}' & \sigma_w^2\end{bmatrix}\right), \tag{4}$$

where $\boldsymbol{\nu}_{t+1}=(\nu_{\alpha,t+1}\ \nu_{\beta,t+1})'$, and $\boldsymbol{Q}$ is a diagonal matrix. Stationarity is ensured by requiring the eigenvalues of the matrix

$$\boldsymbol{F}(z_t)=\begin{pmatrix}a+b(z_t-\bar{z}) & 0\\ 0 & c+d(z_t-\bar{z})\end{pmatrix} \tag{5}$$

to be inside the unit circle for all t = 1, …, T. The additional assumption that $\boldsymbol{\xi}_t|\boldsymbol{Y}_{t-1}\sim N(\hat{\boldsymbol{\xi}}_{t|t-1},\boldsymbol{P}_{t|t-1})$, where $\boldsymbol{\xi}_t=\left(\alpha_t-\bar{\alpha}\ \ \beta_t-\bar{\beta}\right)'$, allows the distribution of $\boldsymbol{\xi}_t$ conditional on y_t, x_t and $\boldsymbol{Y}_{t-1}$ to also be Gaussian with mean $\hat{\boldsymbol{\xi}}_{t|t}$ and variance $\boldsymbol{P}_{t|t}$ that can be updated by the Kalman filter. Note that the system is dynamic in that Equations (1), (2) and (3) are sequential and the Kalman filter updates projections on a daily basis. A one-period-ahead forecast for y_t and its mean squared error are then calculated iteratively and used to evaluate the sample log-likelihood function. This is then maximized iteratively to obtain estimates of the free parameters and their standard errors.[1]

[1] The state-space representation of the model is programmed using the mathematical and statistical system GAUSS v.3.2.28. GAUSS' Maximum Likelihood (ML) add-on module is used for optimizing the sample log likelihood function (c.f., Hamilton (1994), Section 13.8). For each call to the subroutine that calculates the Log-likelihood function for a given set of parameter values, the Kalman Filter (KF) iterations (equations 13.8.6 to 13.8.9 of Hamilton (1994)) are started with $\hat{\xi}_{1|0}$ taken from random draws of $N(0, P_{1|0})$ where $P_{1|0}$ is given by $[I-F\otimes F]^{-1}.vec(Q)$, I is a conforming identity matrix, $\otimes$ denotes the Kronecker product, and *vec* is the vector operator (c.f., Hamilton (1994), p. 378). There are as many KF iterations as observations for every maximum likelihood recursion. Starting values for $\bar{\alpha}$, $\bar{\beta}$, Q and the variance of w are taken from parameter estimates, their covariance matrix and variance of residuals estimates of an OLS regression of y on x. The parameters a, b, c and d are initialized at 0. Optimization is carried out using a combination of the Polak-Ribiere Conjugate Gradient

The model describes two distinct sequential information transmission effects of foreign markets on domestic markets. The first is a direct 'meteor shower' from foreign market *x* to domestic market *y*, where information embedded in the returns of market *x* during trading hours that immediately precede those of market *y* spill over, transfer or transmit, at least partially, to returns of domestic market *y* when it opens next. The coefficients α_t and β_t measure the 'level' and 'intensity' of this transmission relationship at time *t*, while $\bar{\alpha}$ and $\bar{\beta}$ are the respective long-run average, or steady state, values. The second effect is an indirect 'meteor shower' to domestic market *y* through another foreign market *z* that operates in the interim between market *x* and market *y*. The coefficients *b* and *d* capture the impact of news in *z*, measured by the deviation of *z* from its steady state, $(z_t - \bar{z})$, on the changes over time in the level and intensity of the direct relationship between *x* and *y*. Accordingly, information signals are transmitted directly from market *x* to market *y* and indirectly through market *z*. FIT models these two effects simultaneously.

The model can also be used to produce dynamic forecasts of intensity (beta) deviations for the next day, $(\beta_{t+1} - \bar{\beta})$. This feature provides a day trader with useful information about the 'strength' of the expected impact of both the direct and indirect channels of foreign information transmission on the direction and magnitude of next-day domestic returns. If the forecasted deviation is large a day trader can act on the consequential increase in conviction about the direction and magnitude of next day returns by raising his stakes and multiplying his trades by applying high leverage.[2] In this manner, foreign stock market information is modelled sequentially to forecast future domestic returns (*i.e.*, direction and magnitude of price changes)

(PRCG) and the Broyden, Fletcher, Goldfarb and Shanno (BFGS) algorithms (standard errors at convergence are calculated using BFGS) with the 'Half' iterative steplength method for updating parameter estimates. The convergence criterion applied is such that all elements of the relative gradient vector are less than or equal to 10^{-6}.

[2] This will be discussed further below in Section 3.2.

and to inform traders about which trade multiples they should apply (*i.e.*, strength of conviction about direction and magnitude of future price changes).[3]

2.2. Domestic market momentum

The prevailing state of the domestic market at the time of foreign information arrival is measured by the Relative Strength Index (*RSI*) as a popular momentum indicator developed by Wilder (1978) and used by Irwin and Uhriq (1984), Isakov and Hollistein (1999), Wong et al. (2003) and Newsome and Turner (2007), amongst others. The version used to gauge local market conditions is

$$RSI_t \equiv 100 - \left(100 \Big/ \left(1 + \sum_{j=1}^{10} | y_{t-j}^{+} | \Big/ \sum_{j=1}^{10} | y_{t-j}^{-} | \right)\right), \tag{6}$$

where, y denotes open-to-close continuously compounded day returns of domestic market y; $y_{t-j}^{+} = y_{t-j}$ if $y_{t\text{-}j} > 0$, and 0 otherwise; and $y_{t-j}^{-} = y_{t-j}$ if $y_{t\text{-}j} < 0$, and 0 otherwise. The *RSI* index values range from 0 to 100. Values above (below) 50 would result if the ten days that precede day t are dominated by positive (negative) returns and, consequently, reflect overbought (oversold) domestic market conditions. A 'neutral zone' is often specified symmetrically around 50 when the *RSI* signal is considered as too weak to be decisive about the exact state of the domestic market. The 'benchmark' lower (*RSIL*) and upper (*RSIU*) bounds of the neutral zone used here as a base case, i.e., the initial thresholds, are 20 and 80, respectively, but varying these bounds is used as a tool for analysing the effect of foreign signal direction more closely. This is explained next.

[3] Note that with respect to the popular concept of 'smart beta' amongst financial industry practitioners (see, for example, The Economist, 2013) the dynamics of 'beta' assumed in Equation (3) is 'smart' in the sense that it is updated daily with relevant information from its past history (β_t) and with sequential foreign information from market *z*. This updating also allows construction of trading strategies that benefit from market movements in any direction (see Section 3.1 below).

3. Application of the fuzzy logic concept to the design of the stock market trading system and the development of investment strategy rules

The trading system we propose and describe in this section is based on input estimates from the FIT model and the *RSI*. Our stock market trading strategy is conceptually close to a fuzzy inference system (FIS), known also as fuzzy expert system; an example of which is recently discussed by Rubell and Jessy (2016).

We consider a domestic investor in each of the major financial centres in the main geographical regions and time zones of the U.S., Europe and Australasia. Analysing the inter-regional transmission of return signals (meteor showers) across the largest markets in these regions would set a benchmark for smaller markets, since the latter are likely to exhibit stronger meteor showers from the former. Accordingly, the stock indices of the largest markets in the three geographical regions are chosen. The U.S. region is represented by the Dow Jones Industrial Average, the Standard and Poor's 500, and the NASDAQ Composite, the European region by the Financial Times Stock Exchange 100 index of the London Stock Exchange (LSE), the pan European Euro STOXX 50 index, and the DAX of Germany, and the Australasian region by the NIKKEI 225 of the Tokyo Stock Exchange (TSE), the ASX of the Australian Stock Exchange and the Hang Seng of Hong Kong. These will henceforth be referred to as DJIA, S&P, NQ, FTSE, STOXX, DAX, NIKKEI, ASX and HS, respectively. The chronological trading sequence in GMT allowing for daylight savings is as follows. Australasian markets open around 00:00 or 01:00 GMT and close at 06:00 or 07:00, European markets open around 08:00 or 9:00 and close around 16:30 or 17:30 and U.S. markets open around 13:30 or 14:30 and close at 21:00 or 22:00. The domestic investor in each region is assumed to be a day trader who follows a simple strategy of either buying or selling the main domestic stock index (y) at domestic market open and unwinding at domestic market close. Thus, the output is a decision to either 'Buy' or 'Sell' at market open. This decision is based on a signal extracted from a combination of two sources: domestic momentum and foreign information.

The first is domestic momentum information measured by *RSI* that sets the domestic market conditions. These conditions are decided by the following 'IF–THEN' rules:

IF: *RSI* is less than or equal to *RSIL*,
THEN: the domestic market is *oversold*;

IF; *RSI* is greater than or equal to *RSIU*,
THEN: the domestic market is *overbought*;

IF: *RSI* is in between *RSIL* and *RSIU*,
THEN: the domestic market condition is *undecided*.

The second is foreign information transmitted overnight from stock markets *x* and *z* modelled by FIT, which describes foreign information transmission in the chronological sequence in which the *x*, *y* and *z* markets trade. In the case of *y* being the European market, for example, a domestic U.K. investor would buy or sell a domestic index (e.g., FTSE 100) at market open and unwind at market close, depending on previous day's domestic momentum information of the U.S. market (measured by *RSI*) and overnight foreign information from Australasia, represented by returns of, say, NIKKEI (market *x*) on day *t* (measured by FIT). The indirect information channel, which is the Australasian interpretation of the U.S. signal, captured by returns of the Australasian index (e.g., NIKKEI) on day *t* (market *z*), is used to inform the trade multiple or leverage. We do not analyse sequences in which markets *y* and *x*, or *y* and *z*, overlap in trading hours, which we call a 'major overlap', but initially we allow those where an overlap between *x* and *z* exists, which we call a 'minor overlap'. Thus, only non-overlapping direct channels of information transmission are considered. Specifically, we analyse four relationships or sequences. In the order *y*, *x* and *z*, these are: $FTSE_t$, $DJIA_{t-1}$ and $NIKKEI_t$ (dubbed the FTSE model); $NIKKEI_t$, $FTSE_{t-1}$ and $DJIA_{t-1}$ (NIKKEI model); $STOXX_t$, NQ_{t-1} and HS_{t-1} (STOXX model); and ASX_t, DAX_{t-1} and $S\&P_{t-1}$ (ASX model).

Trading is, therefore, guided by domestic momentum information and sequential foreign information transmission that follow chronological sequences meaningful to each domestic trader. The exact manner in which domestic and foreign information (the inputs) are combined to generate trading signals (the outputs) is presented in the next section.

3.1. Information trading

Domestic momentum information (*RSI*) is combined with foreign information (FIT) to filter or refine the signal to trade in a domestic market. There are three possible outcomes of such interaction in any given day. The first occurs when the domestic momentum signal (oversold or overbought) coincides in direction to the foreign information signal (positive or negative). This arises when FIT forecasts positive (negative) returns for the next day and *RSI* indicates an oversold (overbought) domestic market conditions. In these cases the decision rule is to trade according to the combined signal by instigating a buy (sell) trade in oversold (overbought) domestic markets at domestic market open and unwinding the trade at domestic market close. The second possible outcome occurs when the two signals contradict each other. This arises when FIT forecasts negative (positive) returns for the next day while *RSI* indicates an oversold (overbought) domestic condition. In these cases the decision rule is to refrain from trading. The third possible outcome occurs when the signals from *RSI* and FIT neither coincide nor contradict each other. This arises when *RSI* is in a neutral state (between *RSIL* and *RSIU*, initially set at 20 and 80). In these cases the decision rule is to trade based solely on the foreign signal from the FIT model (*i.e.*, buy/sell if FIT forecasts positive/negative returns).

The resulting trading rule is therefore:

IF: FIT forecast is positive and *RSI* indicates neutral or oversold domestic market conditions
THEN: buy at next market open and unwind at market close

IF: FIT forecast is negative and *RSI* indicates overbought or neutral domestic market conditions

THEN: sell at next market open and unwind at market close

IF: FIT forecast is positive and *RSI* indicates overbought domestic market conditions, or
FIT forecast is negative and *RSI* indicates oversold domestic market conditions
THEN: do not trade at next market open

IF: FIT forecast is positive and *RSI* indicates neutral conditions
THEN: buy at next market open and unwind at market close

Two sets of information are therefore combined in a manner meaningful to a domestic day trader. In effect, the set that describes domestic market conditions is used to filter the second set of incoming foreign information. Thus, the current state of the domestic market weeds out incoming foreign information signals and rationally winnows the useful (coinciding) from the confusing (contradicting) in a manner similar to how the direction and speed (*i.e.*, velocity) of Earth in its orbit allows it to 'pick' or 'miss' incoming meteoroids of a specific direction and speed (velocity).

3.2 Leverage allocation

The above trading rules are also applied in a 'leveraged' version that allocates higher multiples to certain trade signals in specific cases. In these 'leveraged' trades *RSI* trade signals (when *RSI* is above *RSIU* or below *RSIL*) are multiplied by 2. FIT trade signals are multiplied by 1, 2 or 3 depending on the size of the intensity deviation forecast for the next day, $(\beta_{t+1} - \bar{\beta})$. If the forecast lies in the outermost quintiles of in-sample intensity deviations, then it is considered as large and a leverage multiple of 3 is applied; if the forecast lies in the next two inner quintiles of in-sample deviations, then it is considered as medium and a leverage multiple of 2 is applied, and if the forecast lies in the innermost quintile of in-sample deviations then it is considered as small and a multiple of 1 is applied (*i.e.*, no leverage).

These multiples are combined in the following manner. In cases when both foreign (FIT) and domestic (*RSI*) signals coincide in direction then a combined leverage of 6 (2 (*RSI*)

× 3 (FIT)) is applied to trades instigated when FIT intensity deviation forecasts are large; a leverage multiple of 4 (2 (*RSI*) × 2 (FIT)) is applied when FIT intensity deviation forecasts are medium and a leverage multiple of 2 (2 (*RSI*) × 1 (FIT)) is applied when FIT intensity deviation forecasts are small. In cases when *RSI* is neutral then leverage multiples of 1, 2, or 3 are applied depending solely on the size of the FIT intensity deviation forecast. Finally, no trade is instigated (*i.e.*, a leverage of 0 is applied) when domestic and foreign signals contradict in direction.

These rules are summarised as follows:

IF:	FIT and *RSI* signals coincide in direction and *RSI is not neutral* and FIT intensity deviation forecasts are *large*, *medium* or *small*
THEN:	trade and apply a leverage multiple of *6*, *4* or *2*, respectively.
IF:	FIT and *RSI* signals coincide in direction and *RSI is neutral* and FIT intensity deviation forecasts are *large*, *medium* or *small*
THEN:	trade and apply a leverage multiple of *3*, *2* or *1*, respectively, depending solely on FIT.
IF:	FIT and *RSI* signals do *not* coincide in direction
THEN:	do not trade

3.3. Signal strength and direction filters

In order to analyse more carefully the interaction of the strength and direction of foreign and domestic return signals, we further enhance the trading system by proposing a mechanism where two additional filters are overlaid. The first controls the magnitude or strength of incoming foreign information. Foreign return signals smaller than the pre-set filter value, which is allowed to vary between 0% and 5%, are considered as of insufficient size to affect the outlook for next day returns in the domestic market and, consequently are not acted upon in trading. A value of 2%, for example, implies that foreign market returns of 2% or lower are considered as too weak to affect forecasts of domestic returns, and hence are ignored. The filter, therefore, restricts incoming foreign return signals of a certain size from being considered in trading decisions, similar to how the Earth's atmosphere filters incoming meteor showers by burning off smaller meteoroids. Accordingly, this filter is applied in order to clarify whether a specific size of incoming foreign information dominates the 'meteor shower' phenomena (*i.e.*, has a greater economic impact for the domestic trader). Consequently, information of a larger magnitude is expected to thread itself through to impact domestic returns. However, there may not be many such signals to have a dominant economic impact on investment, and a larger number of smaller signals may dominate instead. The filter, therefore, acts as a search tool for the range of signal strength which dominates the economic benefits that foreign information transmission provides.

The second filter controls the number of foreign signals that are restricted to coincide in direction to domestic momentum signals. This filter is the width of the *RSI* neutral zone. At one extreme, applying lower and upper bounds *RSIL* and *RSIU* (also called the *RSI* 'bands') of 0/100 for this neutral zone implies that trading in the domestic market is solely dependent on foreign information (FIT) signals (*i.e.*, *RSI* is made redundant and, consequently, domestic momentum does not play a part in filtering incoming foreign signals according to coincidence in direction with domestic momentum). At the other extreme, applying lower and upper bounds of 50/50 for this neutral zone implies that trading in the domestic market is solely dependent on foreign (FIT) signals that coincide in direction with domestic (*RSI*) signals (*i.e.*, *RSI* is made fully operational in filtering out all foreign information that do not coincide in direction with domestic momentum). Other bands in between these two extremes, such as 10/90, 20/80, 30/70 and 40/60, allow for varying degrees of direction filtering. Accordingly, this is a signal direction filter and is similar to the Earth's orbit in acting as a 'velocity' sifter of incoming meteoroids of different orbits (angle of incidence and direction of approach). At one extreme orbits intersect head on, while at the other extreme orbits coincide and, depending on relative velocity, may never intersect. This allows us to test the degree of economic importance of foreign signal direction, and whether a specific degree of direction control is economically dominant.

In this manner, therefore, the characteristics of incoming foreign information are dissected into strength and direction, and the economic significance of various combinations of these dissections is tested.

The trading strategy designed, constructed and tested in our study, relies on the fuzzy logic concept because of the application of the fuzzy logic rule. Although the variables in our system do not all necessarily have to always be constrained between 0 and 1 (e.g. *RSI* indicator, which by definition is (0,1)), they can be normalised within such interval (if needed).

In summary, our trading system relies on the fuzzy system rule, which can be generally described verbally as follows:

IF: the foreign buy signal is [VERY STRONG / STRONG / WEAK etc.] and
the domestic momentum signal is [VERY STRONG / STRONG / WEAK etc.],
i.e. the domestic market is [VERY STRONGLY / STRONGLY / WEAKLY etc.] oversold,

THEN: the system generates a [VERY STRONG / STRONG / WEAK etc.] buy signal

A similar rule applies to the formulation of the sell signal.

3.4 Transaction costs

As direct trading in stock indices requires trading in individual stocks, and these have different transaction costs (e.g., bid-ask spreads), the effect of the above filters on the performance of trading strategies is investigated at different levels of transaction costs ranging from 0% to 0.25%, with 0.1% considered as the 'normal' rate for a round trip trading of stocks (*i.e.*, buying (selling) at domestic market open and unwinding by selling (buying) at domestic market close).

Some wholesale trading platforms offer transaction rates lower than 0.1%, and larger trades are negotiable.[4]

4. Data and estimation

Daily open and close levels of the spot indices covering the period from 1 June 1998 to 31 May 2011 are obtained from Datastream. We also construct a database of futures contracts on these indices collected from a different data provider (Portara Capital Ltd), the analysis of which is deferred to Section 6. This section and Section 5 present analysis using spot indices. Continuously compounded open-to-close daily returns during the initial ten-year period from 1 June 1998 to 31 May 2008 are calculated and used for FIT in-sample estimation. Coefficient estimates are then used to forecast index returns as well as level and intensity deviations on a daily basis throughout the out-of-sample period from 1 June 2008 to 31 May 2011 (782 observations). Throughout this period the sign of the forecasted daily returns is used to determine the trade type (*i.e.*, whether a buy or a sell), and FIT forecasts of beta deviations are used to determine trade multiples (*i.e.*, the level of leverage) for FIT leveraged trades. *RSI* is then used as a gate that allows through foreign signals that are aligned in direction to that of

[4] These platforms mainly offer index proxy products. In countries where Contracts for Difference (CFDs) are available, the typical spread on CFD stock index trading ranges from 0.01% to 0.15% with initial margin and variation margin requirements of around 7% and 2%, respectively (see, for example, http://www.plus500.co.uk). The indices used in this study are amongst the most heavily traded and, consequently, have the least spreads (e.g., during trading hours, the FTSE100 typically had a spread of 1 index unit at a time when the index was around 6500 units). Futures are the main index instruments used by professionals while CFDs are more geared for private investors. CFD related trades account of a sizable proportion of trading in some European and Asian markets, and although are prohibited by the SEC in the US, many brokers have European or Asian trading arms. Obviously, one need not reside in a particular country to be able to trade CFDs. Although, many proprietary platform providers use their own models to price indices, Direct Market Access (DMA) CFD providers guarantee matching each CFD trade with a physical trade in the underlying market to alleviate concerns that their prices do not match those of the underlying instruments. See, for example, http://www.londonstockexchange.com/prices-and-markets/stocks/tools-and-services/direct-market-access/direct-market-access.htm. DMA providers (such as iDealing.com) usually charge a flat commission fee of GBP 5 per contract and 50 pence for one-way settlement. For FTSE 100 futures at an index level of 6500, for example, these costs, together with around 5 index points of bid-ask spread (a very high estimate), translate to only around 0.0009% of contract value for a round trip. Thus, our 'normal' level of transaction costs of 0.1% is very much on the conservative side, especially for institutional traders.

domestic momentum. The strength and direction filters discussed in Section 3.3 are subsequently overlaid.

Table 1 presents descriptive statistics of the in-sample continuously compound returns of all the indices used. Returns range from -9.4% to 14.9% with a mean and a mode that are either zero or near zero, standard deviations range from 0.08% to 1.58%, skewness values are negative (except for NQ and HS) and excess kurtosis ranges from 2.7 to 6.07, which indicates a degree of clustering. The Ljung-Box $Q(10)$ statistics for the level provides initial indication that serial correlation in returns is significant for NIKKEI, FTSE, STOXX, HS and DAX, but not for DJIA, S&P, ASX and NQ. The $Q(10)$ statistics for squared returns, however, confirms clustering and significant heteroskedasticity of the auto-correlated form in the returns of all indices. If the structural features of FIT do not incorporate this heteroskedasticity fully, then the significance of parameter estimates would be affected. Accordingly, and in order to eliminate this problem from the outset, FIT is estimated using return series adjusted for heteroskedasticity by dividing each return series by estimates of its conditional standard deviations obtained by fitting an appropriate GARCH(p,q) specification. This is a procedure similar to the standard Generalised Least Squares (GLS) technique. It has the advantages of preserving the sign of returns (*i.e.*, the direction of information signals) which drives our trading strategies, eliminating heteroskedasticity from the outset, and simplifying the Kalman Filter estimation of FIT. Q(10) statistics, reported in Table 2, confirm the adequacy of this procedure in eliminating both serial correlation and heteroskedasticity.

Table 2 presents the estimation results of the FIT model using heteroskedasticity adjusted returns for the FTSE, STOXX, NIKKEI and ASX models. A general to specific estimation procedure is adopted whereby insignificant parameters from an initial fully parameterised version, as in equations (1)–(3), are dropped one at a time, and the Likelihood Ratio (LR) test is used at each step to confirm this pruning. The table reports estimates of these final specifications that have only the remaining significant parameters. Estimates of the steady-state level, $\bar{\alpha}$, of the meteor shower relationship for all four (y) indices are insignificant, while those of the steady-state intensity, $\bar{\beta}$, are positive and statistically significant. This indicates a clear meteor shower from markets x to markets y, where return signals are transmitted overnight directly, and in the same direction, from international to domestic stock markets. Thus, on average, a positive (negative) return signal emanating in an international market overnight impacts next day returns in domestic markets positively (negatively) with intensities of 0.3078 on FTSE, 0.2861 on STOXX, 0.1475 on NIKKEI, and 0.3900 on ASX. The sign and magnitude of these intensities are consistent with OLS estimates (Table 2) and similar 'betas' estimated in prior studies (e.g., Aggarwal and Park, 1994, between S&P and NIKKEI over the period 4/1987–3/1991). Significant negative estimates of parameter a throughout, indicate a negative serial correlation in daily level deviations, and significant positive estimates of parameter b for NIKKEI reveal that foreign overnight information from third markets, z, that operate in intermediate time between x and y, significantly affects changes over time in the level deviations.[5] Significant estimates of the parameters c and d throughout further confirm that the intensity deviations are time varying, serially correlated and co-vary with foreign information from markets z. Thus, both the direct and indirect channels of foreign information operate in these markets. The Ljung-Box at ten lags, $Q(10)$, for the levels and the squares are all insignificant, which confirms the absence of any serial correlation or heteroskedasticity left in the residuals following the adjustment procedure and the modelling of expected returns by FIT.

[5] Note that significant estimates of the a parameter confirm that level deviations are time varying even though the steady state value of the level is insignificantly different from zero. In other words, alphas change over time around a zero average. Moreover, these changes are significantly affected by overnight foreign information from markets z for NIKKEI since the estimate of the b parameter is significant for this index. These dynamics operate on a daily basis.

5. Results of trading strategies

In this section we present results of the trading strategy of a day domestic trader in each of the four indices. Discussion focusses on the overall performance measured by total returns throughout the entire out-of-sample period as well as on the average returns per trade, which depend on the level of filters on the foreign signals and the *RSI* bands. Stricter filters imply fewer transactions. Robustness is discussed in Section 5.4 and risk-adjusted performance in Section 5.5. For additional robustness, and to show the effects of compounding, we use compound returns in the discussion of Sections 5.1 to 5.3, but we use cumulative returns in the discussion of Section 5.5. All results are available from the authors.

5.1 Foreign information magnitude

Figure 1 shows total compound returns and average return per trade for the FTSE, STOXX, NIKKEI and ASX models without leverage (*RSI* bands fixed at 20/80) against different levels of transaction costs and different levels of the strength filter that operates on the size of foreign information. It illustrates a non-linear relationship between total return and the level of the strength filter, but an almost linear relationship between total return and transaction costs. The strategies benefit from increasing the strength filter from 0% to a specific range of about 0.5%–0.75%, while for higher filter levels the performance declines. The low performance at lower filter levels of 0%–0.5% and high rates of transaction costs is mainly due to the fact that these filter levels allow trades based on weak foreign signals. The low performance at higher filter levels, and the decrease in sensitivity of this performance to different rates of transaction costs, is mainly due to the fact that there are fewer trades at these filter levels, and the number of trades decreases with higher filter levels. The profitability per trade increases, however. This proves expectations that more restrictive filter levels lead to more profitable transactions, but this is true only when the underlying meteor shower relationship is tenable. Accordingly, this confirms that the meteor shower is both statistically and economically significant, since the strength or magnitude of foreign signals affects domestic strategy performance. The implication is that the strength of foreign market return signals are indeed relevant to domestic market investments.

In particular, Figure 1 reveals that there is a specific size of foreign information that is dominant in terms of economic impact on domestic investments. At reasonable to low rates of transaction costs, very profitable trades (those that are singled out by higher levels of the strength filter) do not increase investment performance as much as trades based on foreign information of return strength between 0.5% and 0.75%. Although trades based on large incoming foreign information are highly profitable (Figure 1, right panels) they are, however, fewer in number. It seems, therefore, that a particular size of foreign information is capable of penetrating domestic market conditions with larger numbers, and these, rather than the highly profitable but fewer trades, dominate the economic performance of domestic investment strategies. Thus, it seems that in stock markets denser meteor showers of relatively smaller meteoroids have greater impact than lighter meteor showers of relatively larger meteoroids.

Next we turn our attention to the analysis of interaction between the filter on the foreign signal and the *RSI* bands.

5.2. Domestic information direction

Figure 2 shows total compound returns and average return per trade for the four models without leverage against different *RSI* bands and different levels of the strength filter that operates on the size of foreign information. Transaction costs are fixed at the ‘normal’ level of 0.1%. The figure shows the non-linear relationship between performance and filter level as well as highest performance at filter values of 0.5%–0.75% exhibited in Figure 1 across all *RSI* bands. In addition, the increase in average return per trade with increasing filter values is also consistent across all *RSI* bands. These results confirm that the conclusions reached above in Section 5.1 are robust to the degree by which foreign information is restricted to coincide in direction with domestic information (which is what *RSI* does at different bands).

As explained in Section 3, *RSI* bands act as gates (filters) that control which foreign signals are acted upon depending on whether or not they coincide in direction with domestic momentum. The tighter the bands the narrower the gate. At 50/50 all foreign signals are filtered by coinciding direction and only those that coincide in direction are acted upon (*i.e.*, instigate trades), while at 0/100 none are filtered and all incoming foreign signals are acted upon. Focussing on strategy performance across *RSI* bands would reveal the effect of direction filtering on economic performance. Figure 2 shows that the performance across *RSI* bands varies more at lower than at higher levels of the strength filter. In particular, the highest performance occurs at wide *RSI* bands of 30/70 or wider (*i.e.*, towards 0/100). Thus, in general wider *RSI* bands lead to better performance. This means that some domestic investment strategies slightly favour foreign information that coincides with their own domestic market momentum (e.g., FTSE and STOXX), while others benefit from foreign information of any direction (e.g., NIKKEI and ASX).

5.3. Leverage

Figure 3 shows leveraged strategy performance by filter and transaction costs (*i.e.*, leveraged version of Figure 1). The shape of the graphs remains roughly the same. This means that the leverage imposed according to beta deviations forecasted by the FIT model mainly magnifies the profits while leaving unaltered the overall patterns of profitability.

Figure 4 shows the leveraged equivalent of Figure 2. It reflects a similar picture. High performance is exhibited at wide *RSI* bands of 30/70 or wider (NIKKEI shows some high performance at narrow *RSI* bands), but variation in performance across *RSI* bands is magnified.

Performance peaks emerge at low levels of the strength filter. In general, performance of strategies is magnified to phenomenal levels and the emerging variations, though quite substantial, operate at very high levels of profitability.

Overall, the findings from these models indicate a very clear effect of the strength filter on foreign information, decreases in which always increase strategy performance. However the results for the impact of the *RSI* bands can be market specific, and when leverage is applied different bands can lead to different performance, albeit a high performance nonetheless.

5.4. Robustness checks

Prior to investigating risk-adjusted performance in sub-section 5.5 below, we run two robustness checks. The first is a test of the hypothesis that the above investigated strategies built on the information-based fuzzy logic system together with sequential foreign information (FIT) and domestic momentum (RSI) do indeed perform better than a benchmark buy and hold index strategy. We do this by calculating White's (2000) Reality Check *p*-value. The second is a simple time-series validation check of strategy performance over non-overlapping forecast sub-periods.

To conduct the first check, note that the prior treatment of the time series data of index log returns described in Section 4 imply that the underlying treated series are stationary strong mixing sequences satisfying the basic assumption on the row data upon which White's measure is built. We proceed by applying White's Reality Check across spot index strategies assuming, using White's notation, q=b=τ=1, i.e., the smoothing parameter (q), the random resampling block length (b), and the forecast horizon (τ) are 1 (daily); the prediction period count n = 781 (the number of our total out-of-sample days), and the performance measure of interest is the per-period (daily) return difference between a strategy model k =1*,…I* and the buy-and-hold strategy of the relevant benchmark index. In our context, the vector of I models over which the recursive calculations are conducted contains combination specifications of strength filter values {0.1%–1% incremented by 0.1%, and 2%, 3%, and 5%} and *RSI* values {0/100, 10/90, 20/80, 30/70, 40/60, 50/50} for each index strategy. We restrict the search to non-levered strategies only, as leverage is shown to primarily have a magnifying rather than a pattern changing effect, and the hypothesis of whether a strategy beats the market index should not be dependent on leverage but on the inherent merit of the fuzzy-logic system's use of foreign and domestic information.

Conducting these recursive calculations reveals that the best specification/model is Nikkei [0.5%, 20/80] with average return difference from benchmark of $\bar{f} = 0.2389\%$ (and an associated Reality Check p-value of 0.005642.[6] Accordingly, at least the best information-based strategy model/specification provides statistically higher returns than the underlying buy-and-hold benchmark strategy (i.e., it beats the market). This generally confirms the statistical significance of the performance of the information-based fuzzy logic trading system over a buy-and-hold strategy. In Section 6 we further test whether this profitability actually materialises in practice (i.e., economically significant) when tradable instruments are used as proxies for non-tradable spot indices.

The second check divides the total out-of-sample prediction period (06.2008–05.2011) into three non-overlapping sub-periods (06.2008–05.2009; 06.2009–05.2010; 06.2010–05.2011) and performance is calculated for the best non-leveraged strategies of the four index models. Table A2 in the Appendix presents the number of trades and the cumulative raw returns for these best non-leveraged variants. The performance is strongly positive in all periods, except for the STOXX strategy during the last sub-period of 06.2010–05.2011, where relatively small negative cumulative return is observed (though still better than that of the index). The

[6] For the first model 1, the sample value $V_1 = n^{1/2}\bar{f}_1$ is compared to the percentiles of $\bar{V}^*_{1,i} = n^{1/2}(\bar{f}^*_{1,i} - \bar{f}_1)$, where i=1,…N, and $\bar{f}^*_{1,i}$ are $N = 100$ averages over random stationary bootstrapped samples of length n=781. For the k^{th} model $\bar{V}_k = \max\{n^{1/2}\bar{f}_k, V_{k-1}\}$ is compared to the percentiles of $\bar{V}^*_{k,i} = mas\{n^{1/2}(\bar{f}^*_{k,i} - \bar{f}_k), \bar{V}^*_{k-1,i}\}$.

performance of all strategies decreases, however, over the three non-overlapping sub-periods, which reflects the generally decreasing number of trades.

5.5. Risk adjusted performance

We now investigate whether the strategies' performance holds on a risk adjusted basis. The number of strategies graphed in Figures 1–4 is too large to consider displaying risk-adjusted performance measures for all. Accordingly, a selection is made and the results are tabulated instead of graphed. The selected strategies are those that attained the highest total return amongst the information-based strategies, together with a simple buy-and-hold benchmark for each index.[7] Table 3 reports the number of round-trip trades, raw cumulative returns, the Modified Sharpe Ratio (MSR) and certainty equivalent (CEQ) returns (at different levels of risk aversion, γ) for this selection. First, the poor performance of the indices throughout the out-of-sample period is evident in the negative raw returns and the low MSR and CEQ returns of the benchmark buy-and-hold strategies. The benchmark strategies yielded raw cumulative returns that range from -32.41% to -1.05%, MSR values that range from -0.0842 to 0.0019 and CEQ returns that range from -0.0668% to -0.0102 (for the normal level of risk aversion of γ=1). In contrast, all tabulated information based strategies yielded raw returns ranging from 84% to 455.49%, MSR values ranging from 0.0770 to 0.2633 and CEQ returns (at γ=1) ranging from 0.0991% to 0.5057%. They all also yielded positive CEQ returns at risk aversion parameter values of 2 or less (1 being the 'normal' level) and some yielded positive CEQ returns at risk aversion parameter value of even 10. In fact, all non-leveraged strategies yielded positive CEQ

[7] Specifically, four strategies are reported for each index (this section reports results for all four indices). The first two are the best performing leveraged and non-leveraged strategies across the range of filter values while keeping fixed the RSI bands at 20/80 and transaction costs at 0.1%. The second two are the best leveraged and unleveraged strategies across both ranges of RSI bands and filter values while keeping transactions costs fixed at 0.1%.

returns at all levels of risk aversion.[8] Consequently, these results confirm robustness on risk-adjusted basis and at different levels of risk aversion.

We also investigate the extent of these strategies' risk-adjusted performance relative to a market. We report Jensen's alpha estimates obtained by estimating excess return regressions of four different versions of CAPM models.[9] These regressions are:

(1) Excess returns in domestic currency of the strategy on excess returns of a broad domestic market index. The broad market indices used are: FTSE All Share for the UK, S&P Eurozone for Europe, NIKKEI All Stocks for Japan, and ASX All Ordinaries for Australia.

(2) Excess returns in domestic currency of the strategy on excess returns of the MSCI World index (both in local currency).

(3) Currency-adjusted (to USD) excess returns of the strategy on the excess returns of the MSCI World index (in USD).

(4) In a version of the International CAPM (ICAPM), the excess returns in domestic currency of the strategy are regressed on the excess returns of the MSCI World index in in local currency and excess returns of a relevant Effective Exchange Rate index, which measures the value of a currency relative to a basket of international currencies.[10]

Excess returns are calculated using a relevant country specific local risk-free rate. To conserve reporting space on the large number of resulting combinations, these regressions are carried

[8] As expected, at extremely high levels of risk aversion some strategies tabulated in Table 3 yield negative CEQ returns. At sufficiently high levels of risk aversion any trading strategy whose performance varies over time will return negative CEQ returns. A risk aversion parameter of 10 is ten times the normal level.

[9] Versions of the CAPM and the International CAPM (ICAPM) are used instead of empirical versions of the APT model for the following reasons. First, a multi-factor model can be argued to be a less objective tool for comparison, while the CAPM is more often used in the literature as a commonly accepted benchmark. Second, there is a lack of consensus on the nature and the number of the factors in the APT, where significance of certain factors may differ across markets and vary over time. Factor identification is, therefore, debatable, and any analysis using APT models may very well be more subjective than an application of the commonly accepted versions of the CAPM or ICAPM. Third, APT regressions with macro-economic factors may suffer from multi-collinearity unless orthogonalisation is carried out first (which may further obscure factor identification and interpretation).

[10] The Effective Exchange Rate Indices (ERIs) of the Bank of England are used. These indices are a weighted average of the movements in cross-exchange rates against a basket of other currencies, with the weights reflecting the relative importance of the other currencies, as measured by trade flows between the relevant countries. See http://www.bankofengland.co.uk/statistics/Pages/iadb/notesiadb/effective_exc.aspx.

out on only a selection of strategies for each index, namely, the best four and worst four performing strategies amongst the entire set of strategies considered for that index at the normal 0.1% level of transaction costs. This is the set that contains all leveraged and non-leveraged combinations of the full range of filter and *RSI* values considered above.[11] As the results of all four versions of the CAPM are qualitatively similar, we conserve space by reporting in Table 4 ('Spot indices' left panel) the alpha estimates for only the first version of the CAPM. All results are available from the authors. Note that unlike Table 3, which reports risk-adjusted performance of only the best performing strategies, Table 4 reports alpha estimates of the worst as well as the best performing strategies.

Most alpha estimates for the best performing variants are positive and statistically significant at 1% or 5%. Alpha estimates of the worst performing variants are either positive and statistically significant (e.g., NIKKEI), or positive or negative and statistically insignificant. There are no significant negative estimates. These results represent a very strong and persistent level of evidence on positive risk-adjusted performance. At best all these strategies beat the market, and at worst they perform no less well than the market, be it a domestic or an international market. In addition, currency adjustments do not have a qualitative effect on these results.

6. The trading system in practice

The evidence on inter-regional transmission effects presented in Section 5 is based on data on the most popular stock market indices reported by the stock exchanges and the media and are the most frequently watched by fund managers. Thus, the analysis is relevant from the practical point of view in the sense that it is what most investors will perceive as emanating return signals

[11] Specifically, eight strategies are reported for each index: four best and four worst. The selection of the four best is described in Footnote 6. The selection of the four worst is equivalent, but at the negative end of the distribution.

given the visible spot index levels reported in the media. To measure the degree of this 'misperception' and its implications on market efficiency we have to recognise that investors cannot implement trading strategies on these indices directly, but require tradable instruments that 'proxy' for these indices. Accordingly, we use high frequency data on the main futures contracts that trade on these indices in the stock or derivative markets in their respective countries. The data, obtained from Portara Capital Ltd, constitutes the recorded prices of the opening and closing trades of the legacy (traditional) day trading sessions in the respective markets.[12] These sessions coincide with the opening and closing times of the underlying stock markets. Specifically, the contracts used are: the FTSE index futures (symbol QFA) traded on the Euronext LIFFE Equities and Index Derivatives (EUREID) in London (trading session in exchange time: 08:00–16:30), Euro STOXX 50 (symbol DSX) futures traded on EUREX in Germany (exchange time: 08:00 – 16.30), NIKKEI 225 OSE futures (symbol JNK) traded on the Osaka Securities Exchange (exchange time: 09:00–15:15), and the Australian 200 financial futures (symbol AP) traded on the Sydney Futures Exchange (exchange time: 09:50–16:30). The obtained prices are those of the first trade and the last trade at opening and closing of these sessions, respectively. It is important to note, however, that most of these futures contracts trade for longer periods (e.g., QFA trading hours are 01:00–21:00) even though the trading volume per minute outside the legacy session times is far lower and is increasingly sporadic overnight. Continuous non-back-adjusted price series are constructed using volume rollover over the sequence of the most heavily traded set of maturities (cycle) traditionally used by futures traders.[13]

[12] Portara Capital Ltd is a historical data, software and support provider for professional hedge funds and corporate trading entities. Its business partner is CQG Inc. and Portara's data is based on CQG's millisecond databank (see http://www.portara.org/history.php and http://www.cqg.com).

[13] The rollover rule is that the next nearest contract is rolled to if either 100% of the daily volume in this contract is greater than the two-day average of the maturing contract or two days remain to the maturity of the maturing contract, whichever occurs first. The maturity cycle used for rollover is HMUZ, which stands for March, June, September and December delivery months. Prices are unadjusted to reflect actual trade prices.

We apply our trading system and conduct trading strategies using these actual trade prices of the futures contracts that constitute the main instruments used in practice by institutions for trading these indices. For conformity and comparison purposes we carry out these strategies based on the same signals extracted from spot-index data and used in Section 5 for spot index strategies, as these are the main signals 'observed' and perceived by investors. The futures strategies are carried out for the four models. The FTSE and STOXX models do not have an overlap, while the NIKKEI and ASX models have a minor overlap between markets x and z only. As transaction costs for futures trading are much lower than for trading stocks we use the realistic level of 0.001% costs (see footnote 4), but we discuss the effects of varying it. Figure 5 presents the results for non-leveraged strategies by *RSI* bands and size filter for these models. In general, we observe a much lower performance than that observed earlier for spot index strategies. Specifically, FTSE and STOXX strategies yield negative total return across most of *RSI* bands and filter values, and ASX strategies yield negative total return across all *RSI* bands and filter values. Only NIKKEI strategies yield positive performance over a sizable range of *RSI* bands and filter values. When observed, positive performance of the FTSE, STOXX and ASX futures strategies tends to concentrate at *RSI* bands of 50/50 or slightly lower and filter values of 4.5% or higher. NIKKEI's best performance tends to concentrate on low filter values of 1.5% or lower, and at these levels, performance increases as *RSI* becomes increasingly operationalised (i.e., *RSI* bands towards 50/50). The highest average return per trade is concentrated on high filter values and the 50/50 *RSI* band. Overall, the 0.5%–0.75% signal that is dominant in spot indices is visible in futures in NIKKEI and ASX strategies, but only at the *RSI* band of 50/50. For FTSE and STOXX strategies, the dominant magnitude signal tends to be much larger (4.5% or 5%), and also at *RSI* band of 50/50. The prominence of the 50/50 *RSI* band, almost throughout, implies that futures strategies benefit if all foreign information signals are filtered by domestic momentum. Figure 6 presents the leveraged equivalent of Figure 5. Leverage accentuates the profitability of strategies and for the two relationships that have no overlap (FTSE and STOXX) higher filter values and *RSI* bands of near 50/50 (or 45/55) and 20/80 (or 25/75) produce positive performance. The performance of leveraged NIKKEI strategies can be very high, especially for lower filter values and *RSI* bands from 30/70 to 50/50. ASX leveraged strategies are highly loss making, and the few that are positive are again concentrated at high filter levels and *RSI* bands from 0/100 to 20/80. Overall, the results show that the meteor shower effect, although present and profitable in some cases, is far weaker in futures than in spot indices, and that futures, most likely due to their longer trading hours, incorporate much of foreign information. Filtering incoming foreign information by size also seems relevant, since high filter values can produce profitable strategies, especially for non-overlapping relationships. Amongst the two relationship models that exhibit a minor overlap NIKKEI strategies are, in general, profitable and more so at lower filter values, while ASX strategies are loss-making and more so at lower filter values.

We further analyse performance of these futures strategies on a risk-adjusted basis. We look at the two best performing leveraged and non-leveraged strategies across the range of filter values while keeping fixed the *RSI* bands at 20/80 (for comparison with spot indices) and transaction costs at 0.001% and the two best performing leveraged and unleveraged strategies across both ranges of *RSI* bands and filter values while keeping transactions costs fixed at 0.001%. Table 5 reports the number of round-trip trades, raw cumulative returns, the Modified Sharpe Ratio (MSR) and certainty equivalent (CEQ) returns (at different levels of risk aversion: γ) for this selection. In a marked contrast with corresponding results for spot index strategies (Table 3), the raw returns (cumulative) of the best futures strategies are far lower. One FTSE strategy and all ASX strategies yield negative raw returns, but the other three FTSE strategies and all STOXX and NIKKEI strategies yield large positive raw returns. However, raw returns of all reported futures strategies are higher than those reported in Table 3 for spot index benchmark buy and hold strategies. This indicates that some futures strategies, namely the best variants reported, are on average more profitable than passive buy-and-hold investments in the underlying indices.[14] Both the MSR and CEQ results reported in Table 4 further confirm the generally low magnitude of this performance on risk-adjusted basis. Most of the three profitable FTSE strategies and all of STOXX and NIKKEI strategies show positive risk-adjusted performance to risk aversion level of 2, and some at 5.

For completeness, we also assess the risk-adjusted performance of these four best performing, as well as the four worst performing, strategies relative to an index, in the same manner as conducted in Section 5.4 and reported in Table 4 for spot index strategies. Table 4 ('Futures' right panel) reports the alpha estimates of the first CAPM model for this selection of strategies. Results of the other CAPM and ICAPM models, show similar results, and are reported in Table A1 in the Appendix. In general, and in contrast with the 'Spot indices' left panel, estimates of alpha for futures strategies are not significant, except for one NIKKEI best-variant strategy, which is marginally significantly positive, and three FTSE worst-variant strategies, which are significantly negative at the 5% level. Despite this lower performance relative to an index, alpha estimates of all STOXX and NIKKEI futures best strategies, two of ASX's best variants, and three of NIKKEI's worst variants are positive, even if not significant. Thus, although some strategies are profitable on risk-adjusted basis, most of these best performing futures strategies struggle to beat the market.

7. Conclusions

This paper proposes a trading strategy based on the fuzzy logic rules to investigate whether a particular magnitude or direction of signals in the form of the inter-regional transmission

[14] Most of these positive raw return strategies also yield positive, though much reduced, raw returns if transaction costs were kept at the same 0.1% level as that assumed for spot index strategies (results available from the authors).

effects in returns dominates the performance of domestic trades in the six major stock markets in the U.S., Europe and Australasia. Direct and indirect channels of foreign information transmission are modelled by the FIT model of Ibrahim and Brzeszczyński (2009). Domestic momentum is measured by the Relative Strength Index (*RSI*). A trading system that depends on both the foreign and domestic information signals is then constructed. Two types of filters are subsequently overlaid to dissect the strength and direction of foreign information in order to enable the measurement of its incremental effects.

The results using spot index data indicate that a foreign signal in the range of 0.5% to 0.75% is most relevant, especially when domestic information interference is restricted. At reasonable to low rates of transaction costs very profitable trades do not increase investment performance as much as trades based on foreign information of return strength between 0.5% and 0.75%. Although trades relying on large incoming foreign information are highly profitable, they are, however, fewer in number. Accordingly, it seems that a particular size of foreign information is capable of penetrating domestic market conditions with higher frequency, and these, rather than the highly profitable but relatively infrequent trades, dominate the performance of domestic investment strategies. This effect is persistent across the investigated markets. The performance of foreign information based spot index strategies is quite substantial on a net of transaction costs, as well as on risk-adjusted, basis. They also generate statistically significant positive alphas in simple CAPM and in the International CAPM regressions.

However, given that investors need a tradable proxy to implement such strategies, we also used the same information signals perceived by investors from spot index data to simulate similar trades on index futures contracts. Although some strategies are profitable at the lower transaction rates applicable to futures, the best performing futures strategies struggle to beat the market and, apart from one NIKKEI strategy, have insignificant positive and negative alphas. The inter-regional transmission of stock market signals is weak in futures and these contracts seem to incorporate foreign information (most likely due to their longer trading hours). Thus, what appears to be profitable predictability in the reported spot index data does not necessarily translate to market inefficiency when trading strategies are implemented in practice using tradable instruments.

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Declarations of interest

None.

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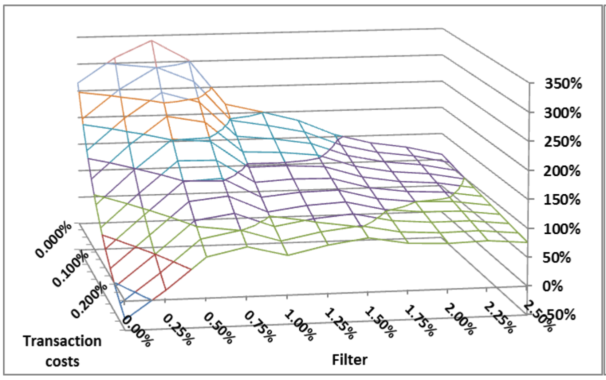
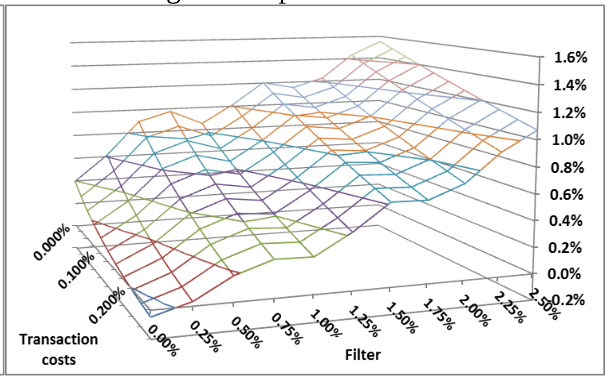
Figure 1. FTSE, STOXX, NIKKEI and ASX spot index strategy performance without leverage by filter and transaction costs.

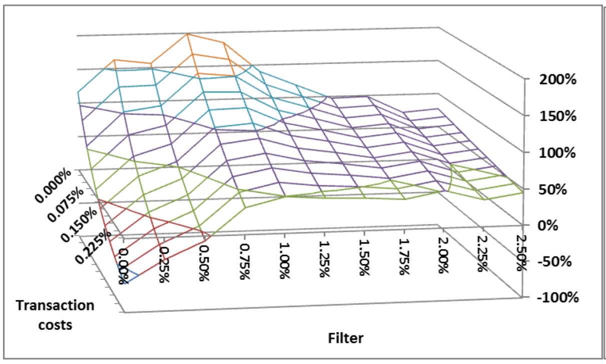
FTSE: Total return



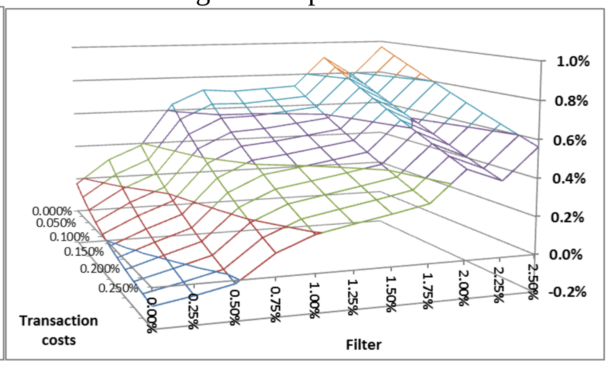
FTSE: Average return per trade



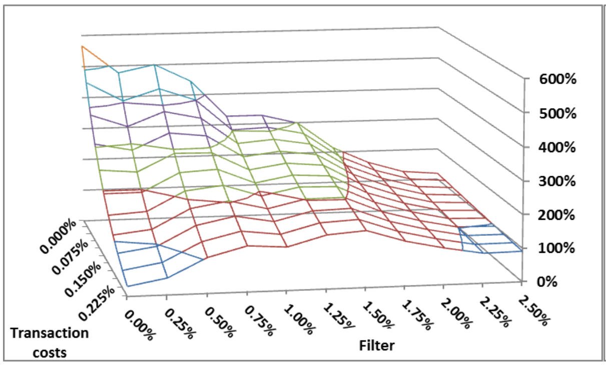
STOXX: Total return



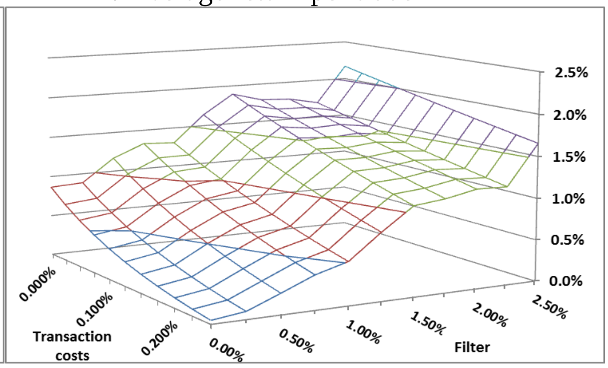
STOXX: Average return per trade



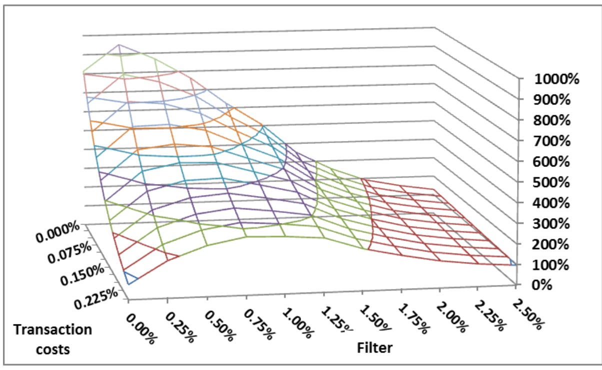
NIKKEI: Total return



NIKKEI: Average return per trade



ASX: Total return



ASX: Average return per trade

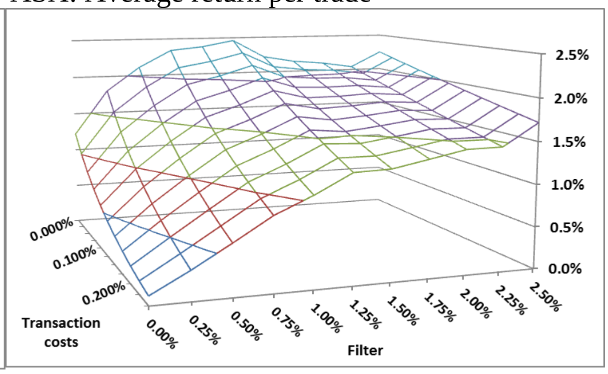
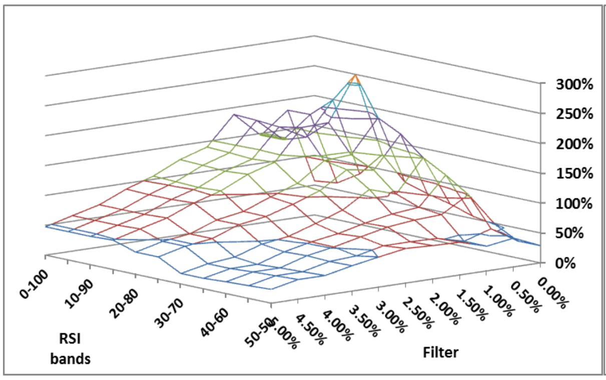


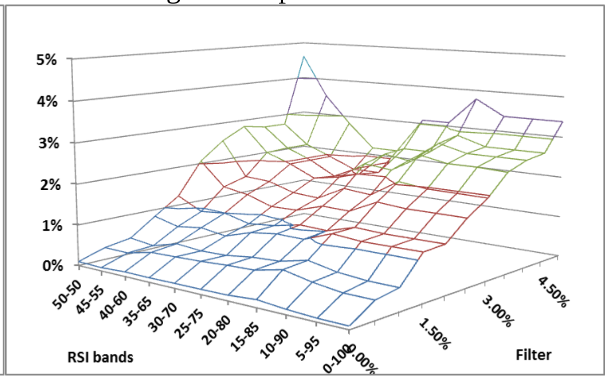
Figure 1 shows total compound return and average compound return per trade at different levels of foreign filter and RSI bands for FTSE, STOXX, NIKKEI and ASX spot index strategies without leverage. *RSI* bands are fixed at 20/80.

Figure 2. FTSE, STOXX, NIKKEI and ASX spot index strategy performance without leverage by filter and *RSI* bands.

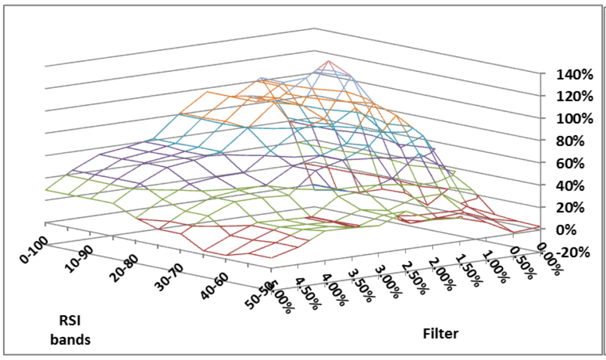
FTSE: Total return



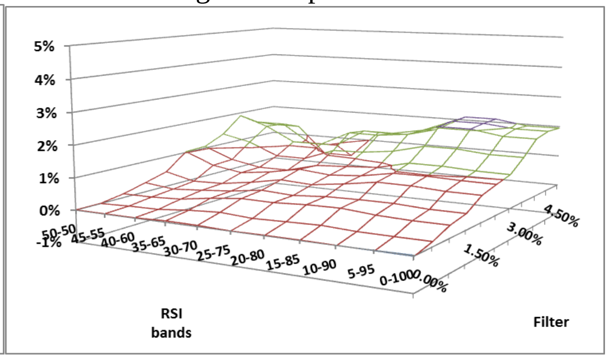
FTSE: Average return per trade



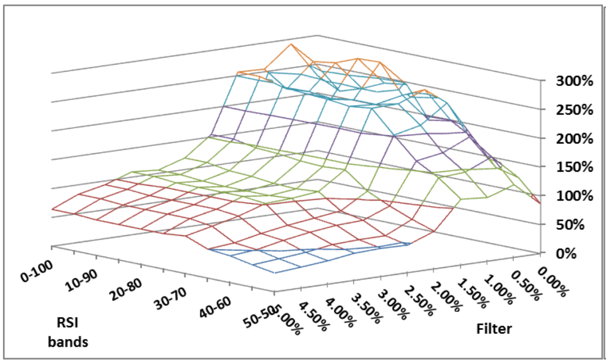
STOXX: Total return



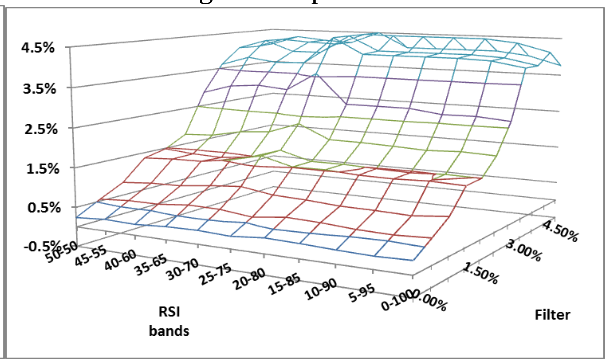
STOXX: Average return per trade



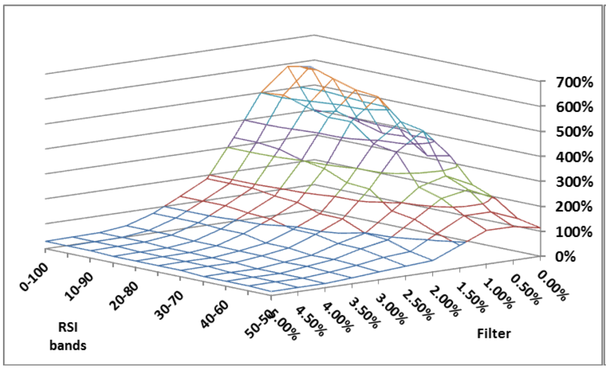
NIKKEI: Total return



NIKKEI: Average return per trade



ASX: Total return



ASX: Average return per trade

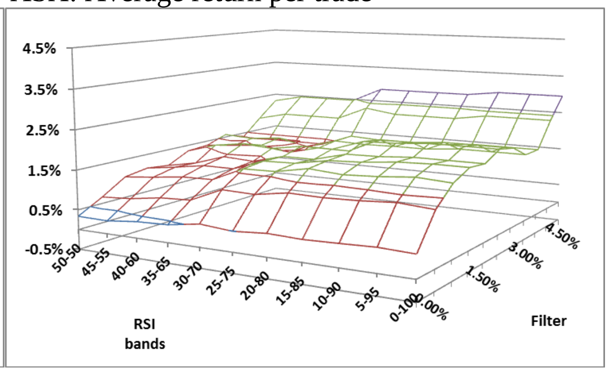


Figure 2 shows total compound return and average compound return per trade at different levels of foreign filter and *RSI* bands for FTSE, STOXX, NIKKEI and ASX spot index strategies without leverage. Transaction costs are fixed at 0.1%.

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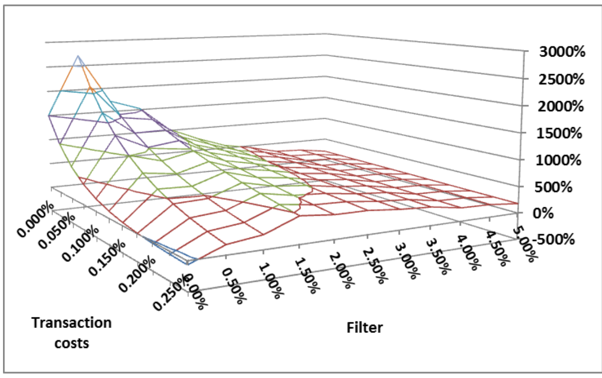
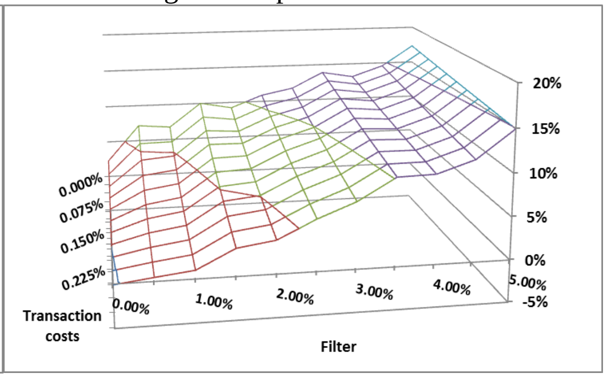
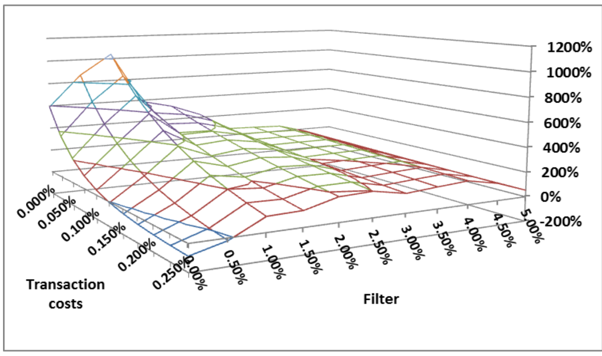
FTSE: Total return



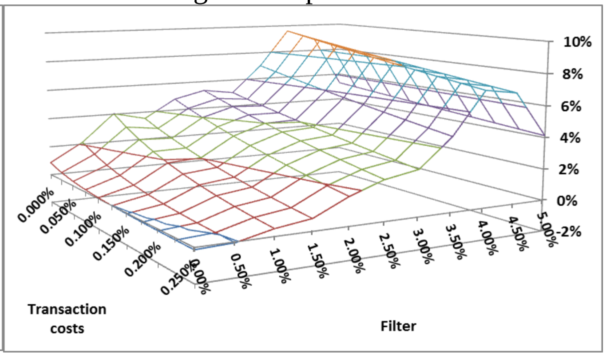
FTSE: Average return per trade



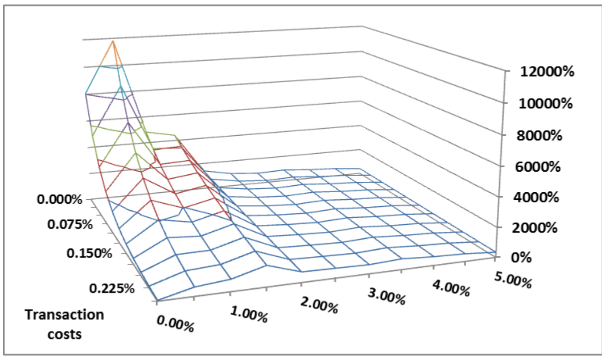
STOXX: Total return



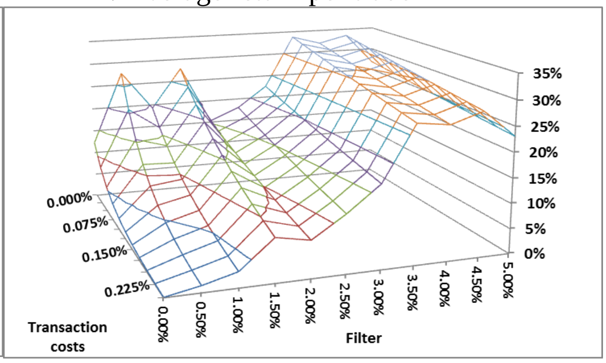
STOXX: Average return per trade



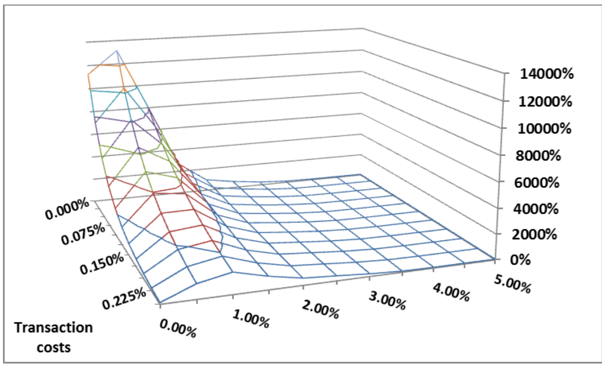
NIKKEI: Total return



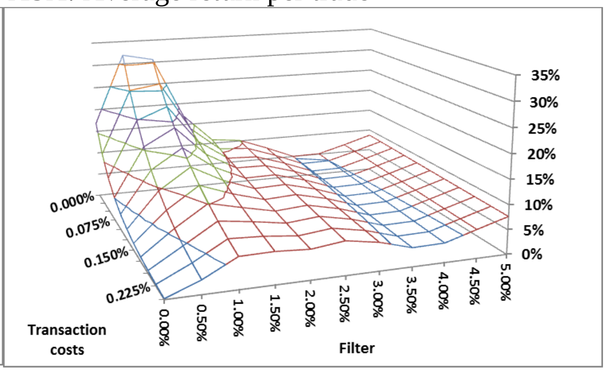
NIKKEI: Average return per trade



ASX: Total return



ASX: Average return per trade



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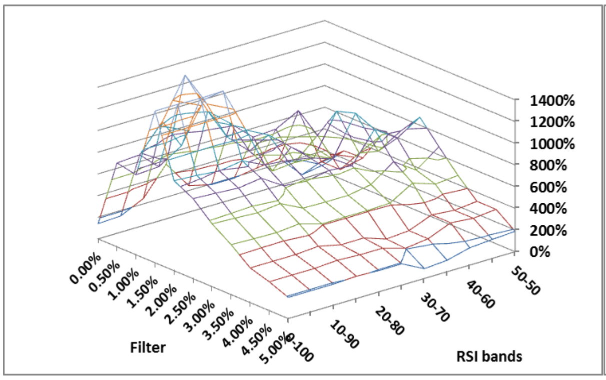
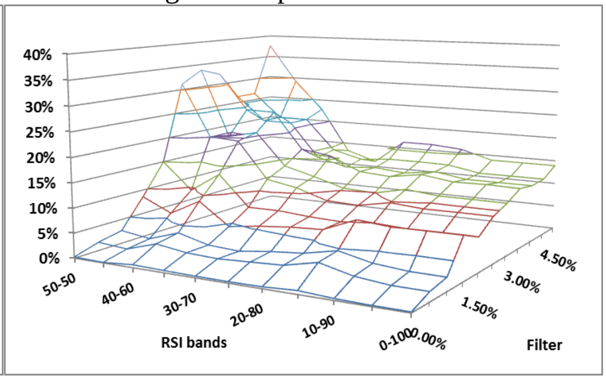
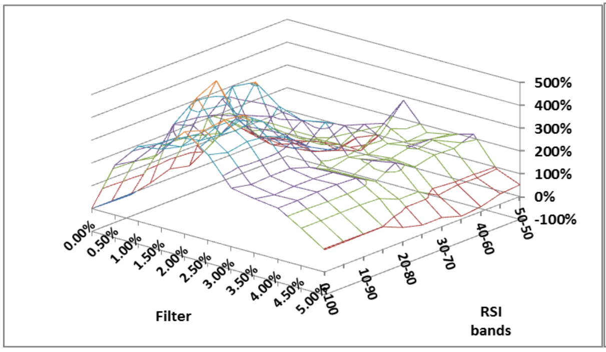


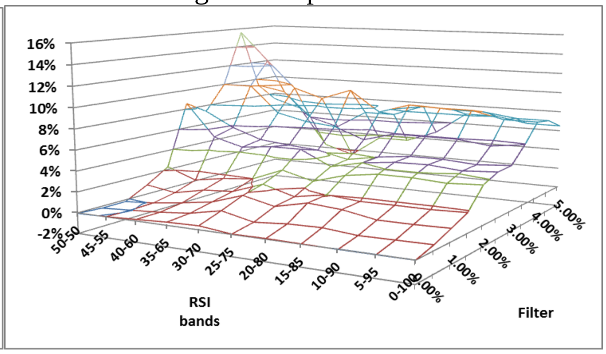
FTSE: Average return per trade



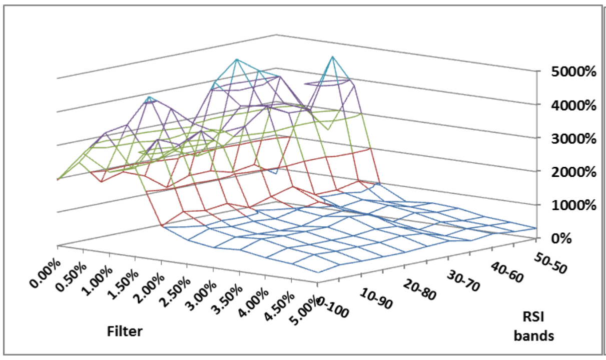
STOXX: Total return



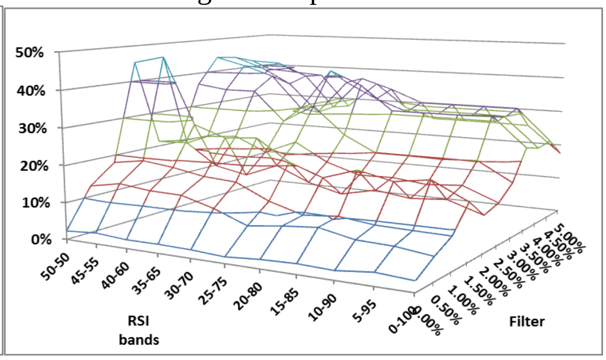
STOXX: Average return per trade



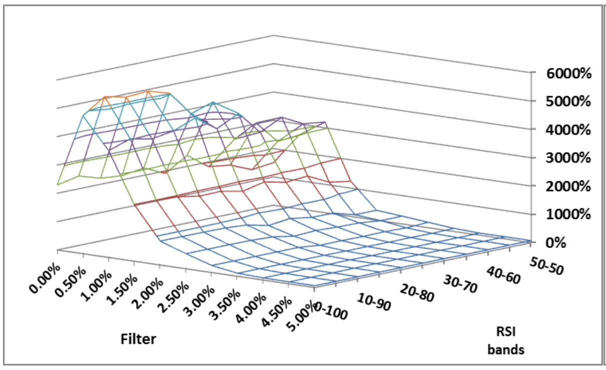
NIKKEI: Total return



NIKKEI: Average return per trade



ASX: Total return



ASX: Average return per trade

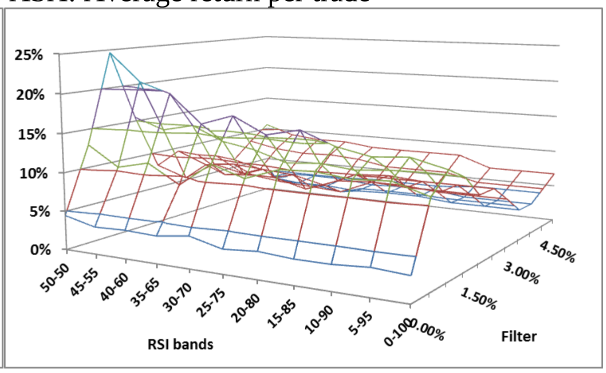


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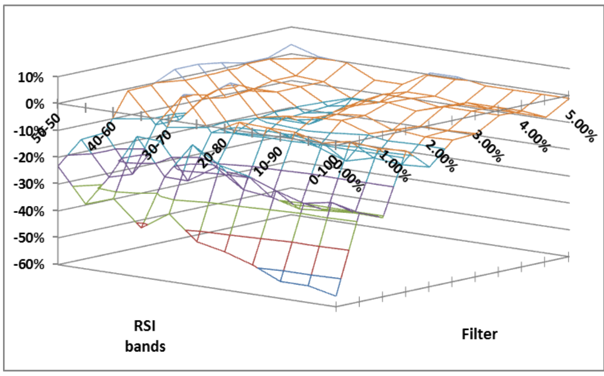
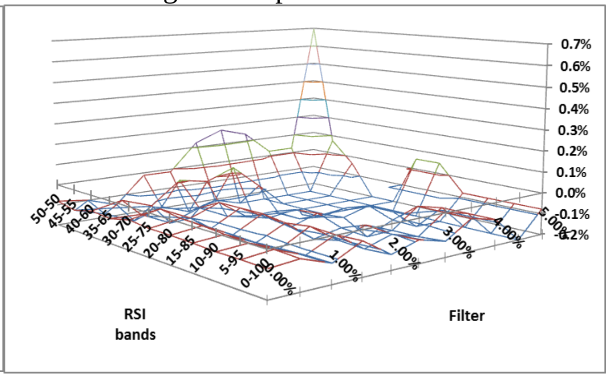
Figure 5. FTSE, STOXX, NIKKEI and ASX futures strategy performance without leverage by filter and *RSI* bands.

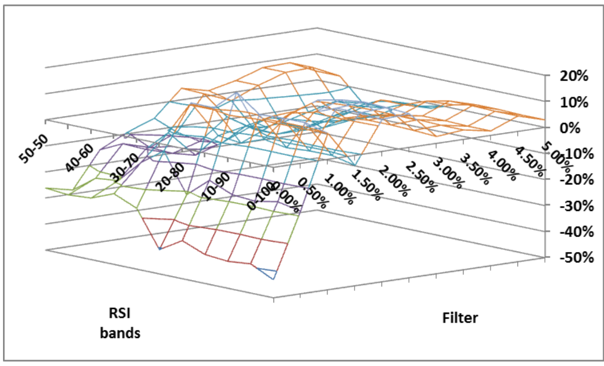
FTSE: Total return



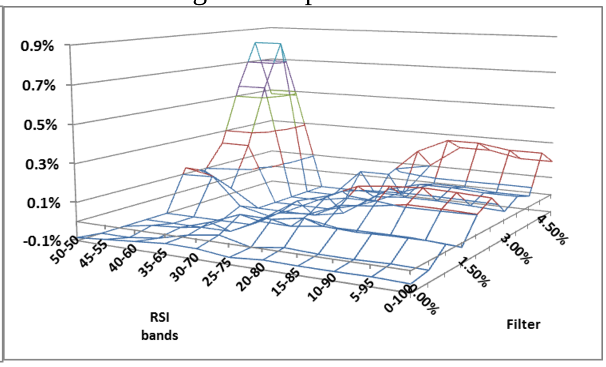
FTSE: Average return per trade



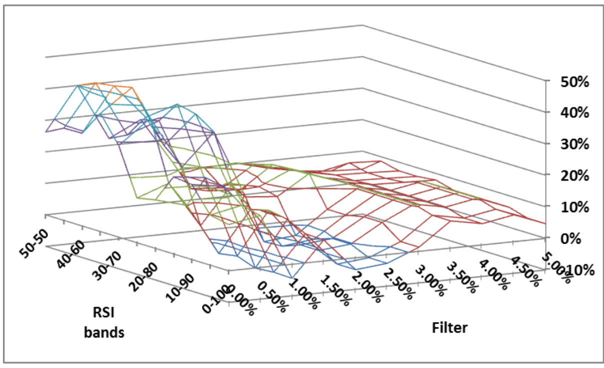
STOXX: Total return



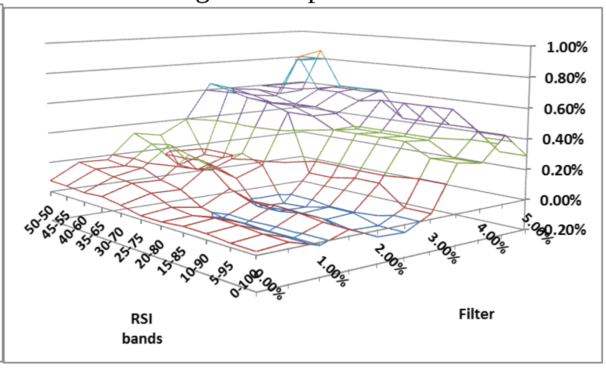
STOXX: Average return per trade



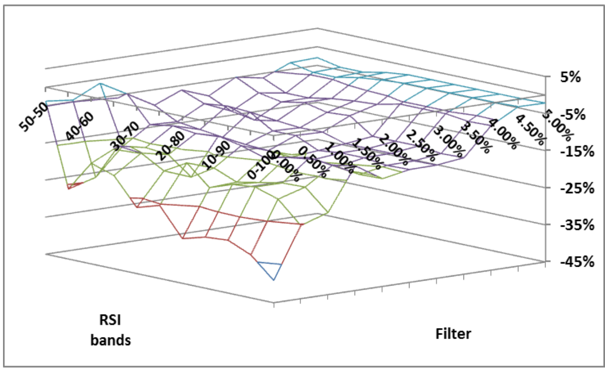
NIKKEI: Total return



NIKKEI: Average return per trade



ASX: Total return



ASX: Average return per trade

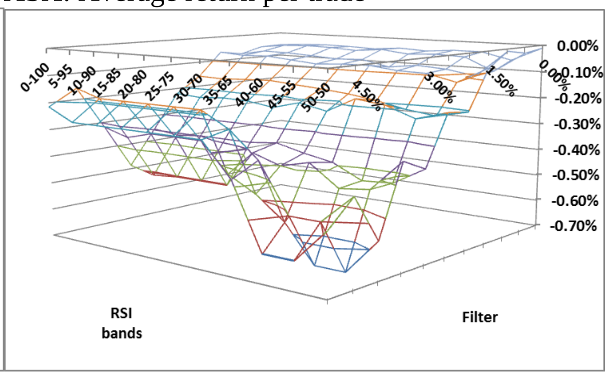
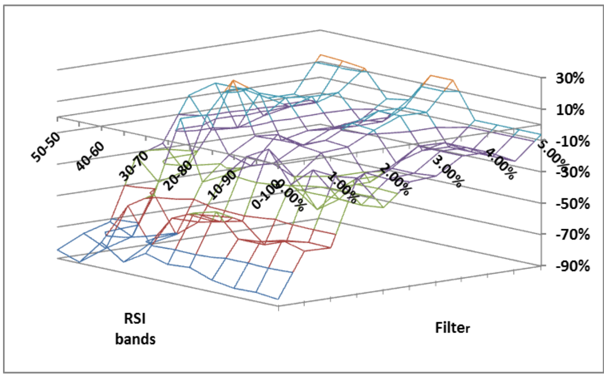


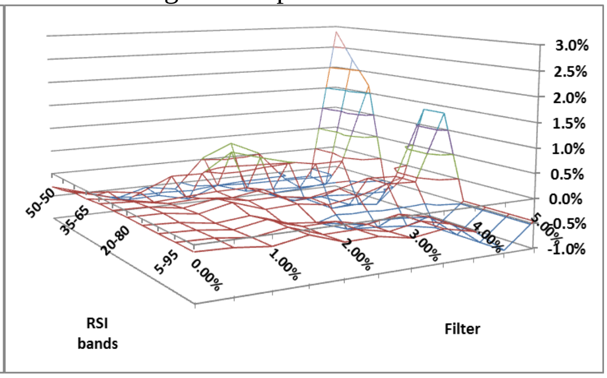
Figure 5 shows total compound return and average compound return per trade at different levels of foreign filter and *RSI* bands for FTSE, STOXX, NIKKEI and ASX futures strategies without leverage. Transaction costs are fixed at 0.001%.

Figure 6. FTSE, STOXX, NIKKEI and ASX futures strategy performance with leverage by filter and *RSI* bands.

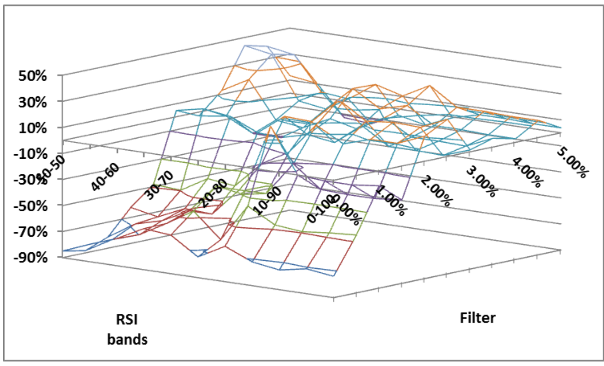
FTSE: Total return



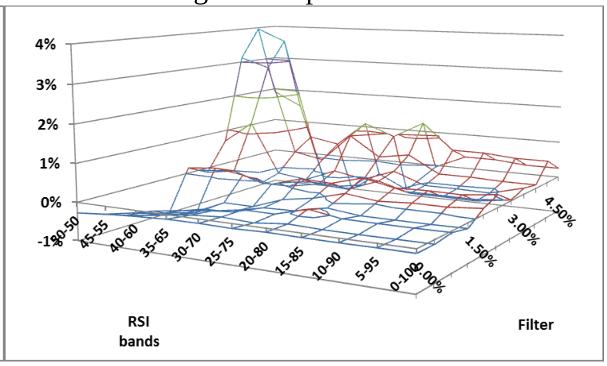
FTSE: Average return per trade



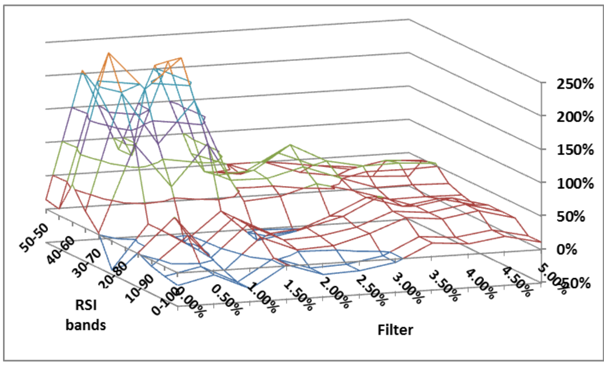
STOXX: Total return



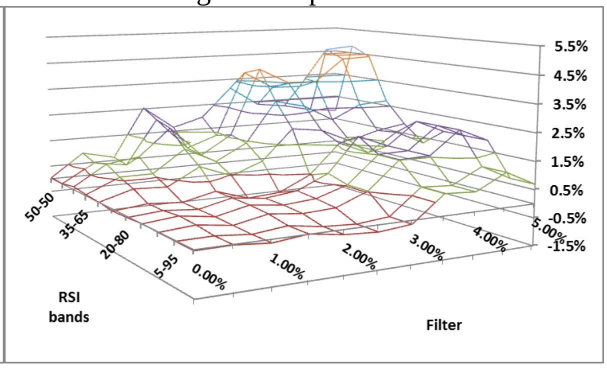
STOXX: Average return per trade



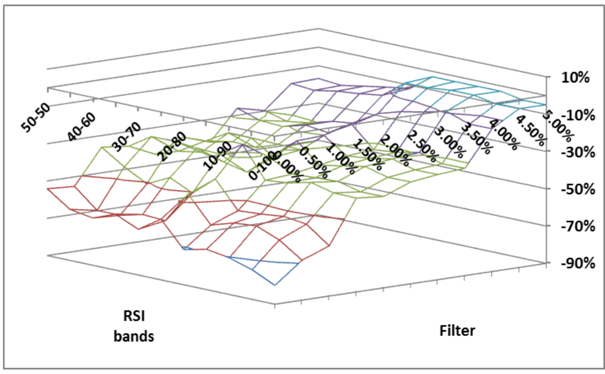
NIKKEI: Total return



NIKKEI: Average return per trade



ASX: Total return



ASX: Average return per trade

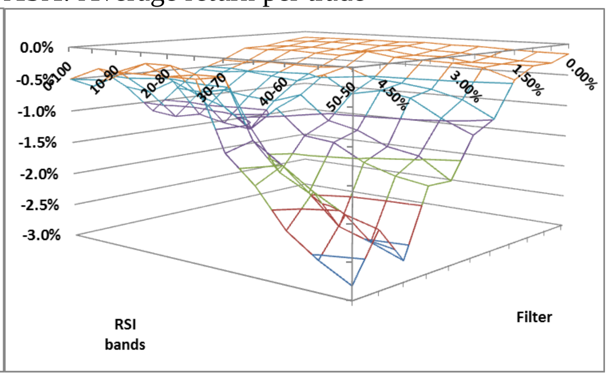


Figure 6 shows total compound return and average compound return per trade at different levels of foreign filter and *RSI* bands for FTSE, STOXX, NIKKEI and ASX futures strategies with leverage. Transaction costs are fixed at 0.001%.

Table 1. Descriptive statistics of spot index returns.

	DJIA	NIKKEI	FTSE	S&P	STOXX	ASX	NQ	HS	DAX
Minimum	-0.071337	-0.067770	-0.058857	-0.070438	-0.074238	-0.061409	-0.093839	-0.050748	-0.091029
Maximum	0.062051	0.072763	0.059038	0.055720	0.070653	0.044233	0.148955	0.082970	0.073988
Mean	0.000198	-0.000385	0.000022	0.000077	-0.000051	0.000190	-0.000591	-0.000108	-0.000220
Mode	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
Stdev	0.010743	0.011469	0.011637	0.011110	0.013920	0.007904	0.015839	0.011313	0.014676
Skewness	-0.1462	-0.0514	-0.1760	-0.0160	-0.1106	-0.4412	0.1412	0.1131	-0.1906
Kurtosis	3.6559	2.7292	2.7430	2.8819	3.3988	4.7856	6.0790	3.3185	3.5816
Q(10) Level	10.01	21.36*	48.71***	13.56	29.27***	9.93	13.63	19.04**	17.24**
Q(10) Square	228.61***	194.18***	230.97***	676.12***	1574.29***	630.02***	717.99***	589.70***	1773.84***

Table 1 presents descriptive statistics on the continuously compound returns of the DJIA, NIKKEI, FTSE, S&P, STOXX, ASX, NQ, HS, and DAX stock market indices throughout the in-sample estimation period of 1 June 1998 through 31 May 2008 (2610 observations). ***, **, * denote significance at 1%, 5% and 10%, respectively.

Table 2. FIT and OLS estimation results using spot index data.

	FTSE model	STOXX model	NIKKEI model	ASX model
	Estimate	Estimate	Estimate	Estimate
$\bar{\beta}$	0.3078***	0.2861***	0.1475***	0.3900***
$Stdev(v_{\alpha})$	0.8701***	0.5517***	0.5004***	-0.5993***
$Stdev(v_{\beta})$	0.1232**	0.0450**	0.3114***	0.2570***
$Stdev(w)$	0.3816***	0.7768***	0.7762***	0.6237***
$\hat{a}$	-0.1891***	-0.2521**	-0.2541***	-0.1647***
$\hat{b}$	-	-	0.1471***	-
$\hat{c}$	-0.2192***	-0.4748***	0.1406***	-0.4043**
$\hat{d}$	0.968**	0.6046***	-0.1491***	0.3093***
Max.Lik.	-1.3786	-1.3806	-1.3984	-1.3262
Q(10) Level	16.2404	9.0829	7.5024	8.0213
Q(10) Square	13.7841	11.7581	14.3262	5.8216
OLS β	0.2414***	0.2601***	0.1427***	0.3845***

Table 2 presents FIT estimation results using heteroskedasticity (GARCH(*p*, *q*)) adjusted continuously compounded open-to-close spot index daily returns throughout the period 1 June 1998 through 31 May 2008 (2610 observations). The 'FTSE model' is the FIT relationship where markets *y*, *x* and *z* are $FTSE_t$, $DJIA_{t-1}$ and $NIKKEI_t$, respectively. In the STOXX model they are $STOXX_t$, NQ_{t-1} and HS_{t-1}. In the 'NIKKEI model' they are $NIKKEI_t$, $FTSE_{t-1}$ and $DJIA_{t-1}$, respectively. In the ASX model they are ASX_t, DAX_{t-1} and $S\&P_{t-1}$. Max.Lik. is the optimised Maximum Log-likelihood value. ***, **, * denote significance at 1%, 5% and 10%, respectively. '-' denotes dropped insignificant parameter. The last raw presents estimates of the OLS beta of market *y* on market *x*.

Table 3. Spot index trading strategy out-of-sample performance: number of trades, raw return and risk-adjusted measures.

Strategy or benchmark index	Number of trades	Raw return	Modified Sharpe ratio	Certainty Equivalent (CEQ) measure				
				$\gamma = 0.5$	$\gamma = 1$	$\gamma = 2$	$\gamma = 5$	$\gamma = 10$
Benchmark index (simple buy-and-hold strategy)								
FTSE 100 index	2 x 1 = 2	-32.41%	0.0019	-0.0035%	-0.0102%	-0.0235%	-0.0635%	-0.1301%
NIKKEI 225 index	2 x 1 = 2	-1.05%	-0.0842	-0.0609%	-0.0668%	-0.0785%	-0.1136%	-0.1721%
EURO STOXX 50 index	2 x 1 = 2	-24.20%	-0.0358	-0.0339%	-0.0374%	-0.0443%	-0.0650%	-0.0995%
ASX index	2 x 1 = 2	-16.99%	-0.0739	-0.0509%	-0.0580%	-0.0723%	-0.1150%	-0.1862%
FTSE model								
Filter = 0.50%, *RSI* = [20,80], NL	2 x 380 = 760	116.73%	0.1156	0.1425%	0.1385%	0.1305%	0.1064%	0.0662%
Filter = 0.50%, *RSI* = [20,80], L	2 x 380 = 760	299.20%	0.0942	0.3383%	0.2980%	0.2172%	-0.0251%	-0.4289%
Filter = 0.50%, *RSI* = [15,85], NL	2 x 395 = 790	136.76%	0.1293	0.1677%	0.1632%	0.1544%	0.1278%	0.0836%
Filter = 0.50%, *RSI* = [15,85], L	2 x 395 = 790	338.74%	0.1147	0.3942%	0.3592%	0.2891%	0.0790%	-0.2712%
STOXX model								
Filter = 1.00% *RSI* = [20,80], NL	2 x 257 = 514	84.00%	0.0935	0.1023%	0.0991%	0.0928%	0.0737%	0.0418%
Filter = 1.00%, *RSI* = [20,80], L	2 x 257 = 514	228.17%	0.0770	0.2537%	0.2186%	0.1483%	-0.0627%	-0.4144%
Filter = 1.00%, *RSI* = [15,85], NL	2 x 536 = 1072	88.70%	0.0951	0.1080%	0.1046%	0.0977%	0.0771%	0.0427%
Filter = 1.00%, *RSI* = [20,80], L	2 x 257 = 514	228.17%	0.0770	0.2537%	0.2186%	0.1483%	-0.0627%	-0.4144%
NIKKEI model								
Filter = 0.50%, *RSI* = [20,80], NL	2 x 429 = 858	143.25%	0.1400	0.1784%	0.1741%	0.1656%	0.1401%	0.0976%
Filter = 0.50%, *RSI* = [20,80], L	2 x 429 = 858	437.86%	0.1219	0.5050%	0.4528%	0.3484%	0.0350%	-0.4872%
Filter = 0.50%, *RSI* = [0,100], NL	2 x 470 = 940	143.86%	0.1351	0.1788%	0.1742%	0.1649%	0.1373%	0.0913%
Filter = 1.50%, *RSI* = [45,55], L	2 x 102 = 204	455.49%	0.1300	0.5294%	0.4798%	0.3806%	0.0831%	-0.4129%
ASX model								
Filter = 0.5%, *RSI* = [20,80], NL	2 x 412 = 824	189.60%	0.2623	0.2334%	0.2314%	0.2273%	0.2152%	0.1951%
Filter = 0.5%, *RSI* = [20,80], L	2 x 412 = 824	414.14%	0.2383	0.5093%	0.4973%	0.4734%	0.4016%	0.2821%
Filter = 0.5%, *RSI* = [5,95], NL	2 x 442 = 884	199.74%	0.2633	0.2457%	0.2434%	0.2390%	0.2257%	0.2036%
Filter = 0.5%, *RSI* = [5,95], L	2 x 442 = 884	419.61%	0.2507	0.5168%	0.5057%	0.4835%	0.4170%	0.3062%

Table 3 presents the out-of-sample performance of trading strategies using spot index data. The number of trades takes into account round-trip transactions (for opening and closing the position); transaction costs are set at 0.1%; the raw return for the benchmark indices is a simple holding period return and for the strategies is a cumulative return based on daily trades; L and NL refer to leveraged and non-leveraged strategies, respectively. The table presents the best performing variants of the strategies.

Table 4. Alpha estimates of daily CAPM model: Spot indices and futures.

Spot indices		**Futures**	
FTSE models (best variants)		FTSE models (best variants)	
Filter = 0.50%, *RSI* = [20,80], NL	0.000584**	Filter = 2.25%, *RSI* = [20,80], NL	-0.000057
Filter = 0.50%, *RSI* = [20,80], L	0.003756**	Filter = 5.00%, *RSI* = [20,80], L	0.000336
Filter = 0.50%, *RSI* = [15,85], NL	0.000586**	Filter = 3.00%, *RSI* = [50,50], NL	-0.000016
Filter = 0.50%, *RSI* = [15,85], L	0.004310***	Filter = 2.50%, *RSI* = [40,60], L	0.000434
FTSE models (worst variants)		FTSE models (worst variants)	
Filter = 0%, *RSI* = [20,80], NL	0.000034	Filter = 0%, *RSI* = [20,80], NL	-0.000704
Filter = 5.00%, *RSI* = [20,80], L	0.001570	Filter = 0%, *RSI* = [20,80], L	-0.001702**
Filter = 5.00%, *RSI* = [35,65], NL	0.000190	Filter = 0%, *RSI* = [0,100], NL	-0.001022**
Filter = 0%, *RSI* = [45,55], L	-0.000373	Filter = 0%, *RSI* = [45,55], L	-0.002405**
STOXX model (best variants)		STOXX model (best variants)	
Filter = 1.00% *RSI* = [20,80], NL	0.000673**	Filter = 1.00%, *RSI* = [20,80], NL	0.000268
Filter = 1.00%, *RSI* = [20,80], L	0.000979***	Filter = 2.50%, *RSI* = [20,80], L	0.000540
Filter = 1.00%, *RSI* = [15,85], NL	0.000862***	Filter = 1.00%, *RSI* = [20,80], NL	0.000268
Filter = 1.00%, *RSI* = [20,80], L	0.000979***	Filter = 4.00%, *RSI* = [50,50], L	0.000631
STOXX model (worst variants)		STOXX model (worst variants)	
Filter = 0%, *RSI* = [20,80], NL	-0.000362	Filter = 0%, *RSI* = [20,80], NL	-0.000479
Filter = 0%, *RSI* = [20,80], L	0.000511	Filter = 0%, *RSI* = [20,80], L	-0.000573
Filter = 0%, *RSI* = [0,100], NL	-0.000634	Filter = 0%, *RSI* = [0,100], NL	-0.000642
Filter = 0.50% *RSI* = [50,50], L	-0.000665	Filter = 0.50%, *RSI* = [50,50], L	-0.001572
NIKKEI model (best variants)		NIKKEI model (best variants)	
Filter = 0.50%, *RSI* = [20,80], NL	0.001209***	Filter = 0.00%, *RSI* = [20,80], NL	0.000309
Filter = 0.50%, *RSI* = [20,80], L	0.005616**	Filter = 3.50%, *RSI* = [20,80], L	0.000836
Filter = 0.50%, *RSI* = [0,100], NL	0.001145***	Filter = 0.50%, *RSI* = [35,65], NL	0.000519
Filter = 1.50%, *RSI* = [45,55], L	0.006106**	Filter = 0.50%, *RSI* = [40,60], L	0.002319 *
NIKKEI model (worst variants)		NIKKEI model (worst variants)	
Filter = 2.50%, *RSI* = [20,80], NL	0.001012	Filter = 2.25%, *RSI* = [20,80], NL	-0.000063
Filter = 5.00%, *RSI* = [20,80], L	0.002538*	Filter = 0%, *RSI* = [20,80], L	0.000675
Filter = 5.00%, *RSI* = [50,50], NL	0.000403	Filter = 1.00%, *RSI* = [10,90], NL	0.000026
Filter = 5.00%, *RSI* = [0,100], L	0.001998*	Filter = 0%, *RSI* = [25,75], L	0.000408
ASX model (best variants)		ASX model (best variants)	
Filter = 0.5%, *RSI* = [20,80], NL	0.001652***	Filter = 2.50%, *RSI* = [20,80], NL	0.000081
Filter = 0.5%, *RSI* = [20,80], L	0.003694***	Filter = 5.00%, *RSI* = [20,80], L	-0.000477
Filter = 0.5%, *RSI* = [5,95], NL	0.001666***	Filter = 1.00%, *RSI* = [50,50], NL	0.000536
Filter = 0.5%, *RSI* = [5,95], L	0.003570***	Filter = 4.50%, *RSI* = [10,90], L	-0.000271
ASX model (worst variants)		ASX model (worst variants)	
Filter = 2.50%, *RSI* = [20,80], NL	0.000672***	Filter = 0%, *RSI* = [20,80], NL	-0.000242
Filter = 5.00%, *RSI* = [20,80], L	0.000167	Filter = 0%, *RSI* = [20,80], L	-0.000535
Filter = 5.00%, *RSI* = [50,50], NL	-0.000011	Filter = 0%, *RSI* = [0,100], NL	-0.000289
Filter = 4.00%, *RSI* = [40,60], L	0.000384	Filter = 0%, *RSI* = [0,100], L	-0.000780

Table 4 presents Jensen's alpha estimates by a daily CAPM model in which excess returns of strategy is regressed against a domestic broad market index (FTSE All Share for the UK, NIKKEI All Stocks for Japan, S&P Eurozone for Europe, and ASX All Ordinaries for Australia). A domestic risk-free rate is used for the relevant market. The two non-leveraged best variants for the STOXX spot index model have the same parameters and the same investment strategy. Thus, their alpha estimates are the same. Cells in grey indicate positive alpha estimates; ***, **, and * denote significance at 1%, 5% and 10% levels, respectively; transaction costs are set at 0.1% for spot indices and 0.001% for futures; L and NL denote leveraged and unleveraged strategies.

Table 5. Futures trading strategy out-of-sample performance: number of trades, raw return and risk-adjusted measures.

Strategy or benchmark index	# of trades	Raw return	Modified Sharpe Ratio	Certainty Equivalent (CEQ) measure				
				γ = 0.5	γ = 1	γ = 2	γ = 5	γ = 10
FTSE model – Futures								
Filter = 2.25%, *RSI* = [20,80], NL	2 x 85 = 170	-4.82%	-0.0042	-0.0080%	-0.0089%	-0.0107%	-0.0160%	-0.0249%
Filter = 5.00%, *RSI* = [20,80], L	2 x 12 = 24	24.64%	0.0183	0.0240%	0.0168%	0.0022%	-0.0415%	-0.1143%
Filter = 3.00%, *RSI* = [50,50], NL	2 x 20 = 40	3.92%	0.0137	0.0045%	0.0042%	0.0036%	0.0017%	-0.0013%
Filter = 2.50%, *RSI* = [40,60], L	2 x 44 = 88	30.82%	0.0186	0.0279%	0.0170%	-0.0050%	-0.0709%	-0.1806%
STOXX model – Futures								
Filter = 1.00%, *RSI* = [20,80], NL	2 x 255 = 510	20.69%	0.0251	0.0223%	0.0198%	0.0150%	0.0004%	-0.0238%
Filter = 2.50%, *RSI* = [20,80], L	2 x 80 = 160	49.17%	0.0251	0.0468%	0.0315%	0.0008%	-0.0912%	-0.2444%
Filter = 1.00%, *RSI* = [20,80], NL	2 x 255 = 510	20.69%	0.0251	0.0223%	0.0198%	0.0150%	0.0004%	-0.0238%
Filter = 4.00%, *RSI* = [50,50], L	2 x 14 = 28	48.16%	0.0325	0.0525%	0.0435%	0.0256%	-0.0280%	-0.1175%
NIKKEI model – Futures								
Filter = 0.00%, *RSI* = [20,80], NL	2 x 628 = 1256	19.82%	0.0210	0.0214%	0.0179%	0.0109%	-0.0102%	-0.0453%
Filter = 3.50%, *RSI* = [20,80], L	2 x 26 = 52	51.30%	0.0406	0.0590%	0.0525%	0.0395%	0.0004%	-0.0648%
Filter = 0.50%, *RSI* = [35,65], NL	2 x 348 = 696	40.41%	0.0549	0.0492%	0.0470%	0.0426%	0.0295%	0.0075%
Filter = 0.50%, *RSI* = [40,60], L	2 x 313 = 626	179.74%	0.0639	0.1973%	0.1651%	0.1005%	-0.0930%	-0.4156%
ASX model – Futures								
Filter = 2.50%, *RSI* = [20,80], NL	2 x 62 = 124	-15.10%	-0.0092	-0.0209%	-0.0214%	-0.0224%	-0.0254%	-0.0305%
Filter = 5.00%, *RSI* = [20,80], L	2 x 9 = 18	-2.10%	-0.0013	-0.0034%	-0.0039%	-0.0050%	-0.0082%	-0.0135%
Filter = 1.00%, *RSI* = [50,50], NL	2 x 132 = 264	-0.21%	-0.0012	-0.0030%	-0.0036%	-0.0047%	-0.0080%	-0.0136%
Filter = 4.50%, *RSI* = [10,90], L	2 x 12 = 24	-1.93%	-0.0013	-0.0033%	-0.0038%	-0.0049%	-0.0081%	-0.0136%

Table 5 presents the out-of-sample performance of trading strategies using futures data. The number of trades takes into account round-trip transactions (for opening and closing the position); transaction costs are set at 0.001%; the raw return for the benchmark indices is the strategies' cumulative return based on daily trades; L and NL refer to leveraged and non-leveraged strategies, respectively. The table presents the best performing variants of the four strategies with no overlap (FTSE and STOXX) or minor overlap (NIKKEI and ASX).

Appendix

Table A1. Alpha estimates: daily CAPM and ICAPM models (futures)

Types of CAPM / ICAPM models:	(1)	(2)	(3)	(4)
FTSE model – Futures (best variants)				
Filter = 2.25%, *RSI* = [20,80], NL	-0.000057	-0.000050	-0.000034	-0.000049
Filter = 5.00%, *RSI* = [20,80], L	0.000336	0.000553	0.000317	0.000213
Filter = 3.00%, *RSI* = [50,50], NL	-0.000016	0.000067	0.000051	0.000041
Filter = 2.50%, *RSI* = [40,60], L	0.000434	0.000265	0.000552	0.000297
STOXX model – Futures (best variants)				
Filter = 1.00%, *RSI* = [20,80], NL	0.000268	0.000203	0.000253	0.000214
Filter = 2.50%, *RSI* = [20,80], L	0.000540	0.000423	0.000619	0.000450
Filter = 1.00%, *RSI* = [20,80], NL	0.000268	0.000203	0.000253	0.000214
Filter = 4.00%, *RSI* = [50,50], L	0.000631	0.000431	0.000573	0.000358
NIKKEI model – Futures (best variants)				
Filter = 0.00%, *RSI* = [20,80], NL	0.000309	0.000285	0.000698	0.000309
Filter = 3.50%, *RSI* = [20,80], L	0.000836	0.000725	0.000614	0.000653
Filter = 0.50%, *RSI* = [35,65], NL	0.000519	0.000481	0.000849	0.000551
Filter = 0.50%, *RSI* = [40,60], L	0.002319 *	0.002335 *	0.002562 *	0.002403 *
ASX model – Futures (best variants)				
Filter = 2.50%, *RSI* = [20,80], NL	0.000081	-0.000121	-0.000009	-0.000177
Filter = 5.00%, *RSI* = [20,80], L	-0.000477	0.000029	0.000027	-0.000060
Filter = 1.00%, *RSI* = [50,50], NL	0.000536	-0.000025	-0.000034	-0.000026
Filter = 4.50%, *RSI* = [10,90], L	-0.000271	-0.000045	0.000029	-0.000028

Table A1 presents Jensen's alpha estimates by four types of daily CAPM model: (1) returns of strategy against the domestic broad market index (FTSE All Share for the UK, S&P Eurozone for Europe, NIKKEI All Stocks for Japan, and ASX All Ordinaries for Australia) in local currency, (2) returns of strategy against the world MSCI index both in local currency, (3) currency-adjusted returns (in USD) against the world MSCI index (in USD), (4) International CAPM (ICAPM) same as (2) but with return of local currency against basket of international currency added. The two non-leveraged best variants for the STOXX model have the same parameters, and the same investment strategy. Thus, their alpha estimates are the same. Model (1) is the same as the one reported in Table 5 in the main text of the paper (results from model (1) are repeated here for the purpose of comparison with other variants of the CAPM / ICAPM models). Cells in grey indicate positive alpha estimates; * denote significance at 1%, all other values are insignificant at 10%; transaction costs are set at 0.001%; L and NL denote leveraged and unleveraged strategies.

Table A2. Sub-period out-of-sample performance of the best non-leveraged spot index strategies

Strategy	Number of trades	Raw return	Number of trades	Raw return	Number of trades	Raw return	Number of trades	Raw return
FTSE model								
Sample:	06.2008 – 05.2011		06.2008 – 05.2009		06.2009 – 05.2010		06.2010 – 05.2011	
Filter = 0.50%, *RSI* = [20,80], NL	2 x 380 = 760	116.73%	2 x 176 = 352	95.60%	2 x 107 = 214	14.25%	2 x 97 = 194	6.87%
Filter = 0.50%, *RSI* = [15,85], NL	2 x 395 = 790	136.76%	2 x 182 = 364	112.17%	2 x 114 = 228	17.41%	2 x 98 = 198	7.19%
STOXX model								
Sample:	06.2008 – 05.2011		06.2008 – 05.2009		06.2009 – 05.2010		06.2010 – 05.2011	
Filter = 1.00% *RSI* = [20,80], NL	2 x 257 = 514	84.00%	2 x 138 = 276	76.81%	2 x 71 = 142	9.80%	2 x 48 = 96	-2.61%
Filter = 1.00%, *RSI* = [15,85], NL	2 x 268 = 536	88.70%	2 x 142 = 284	78.18%	2 x 77 = 154	12.33%	2 x 49 = 98	-1.81%
NIKKEI model								
Sample:	06.2008 – 05.2011		06.2008 – 05.2009		06.2009 – 05.2010		06.2010 – 05.2011	
Filter = 0.50%, *RSI* = [20,80], NL	2 x 429 = 858	143.25%	2 x 167 = 334	109.42%	2 x 141 = 282	21.06%	2 x 121 = 242	12.77%
Filter = 0.50%, *RSI* = [0,100], NL	2 x 470 = 940	143.86%	2 x 183 = 366	116.26%	2 x 159 = 318	21.44%	2 x 128 = 256	6.17%
ASX model								
Sample:	06.2008 – 05.2011		06.2008 – 05.2009		06.2009 – 05.2010		06.2010 – 05.2011	
Filter = 0.5%, *RSI* = [20,80], NL	2 x 412 = 824	189.60%	2 x 168 = 336	100.77%	2 x 131 = 262	51.40%	2 x 113 = 226	37.43%
Filter = 0.5%, *RSI* = [5,95], NL	2 x 442 = 884	199.74%	2 x 185 = 370	103.33%	2 x 142 = 284	58.95%	2 x 115 = 230	37.46%

Table A2 presents the out-of-sample overall and sub-period performance of non-levered trading strategies using spot index data (corresponds to Table 3). The number of trades takes into account round-trip transactions (for opening and closing the position); transaction costs are set at 0.1%; the raw return for the benchmark indices is a simple holding period return and for the strategies is a cumulative return based on daily trades; NL refers to non-leveraged strategies. The table presents the best performing variants of the strategies