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How beneficial is international stock market information in domestic stock market trading?

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This paper uses the foreign information transmission (FIT) model of Ibrahim and Brzeszczynski [Inter-regional and region-specific transmission of international stock market returns: The role of foreign information. *Journal of International Money and Finance* 28, no. 2: 322–43] to quantify the incremental benefits of foreign overnight international stock market information over domestic market momentum information. The main objective is to answer the question: how much more (or less) returns will a day trader earn by using various combinations of different interpretations of foreign news signals and domestic market momentum than the latter alone? Trading strategies are constructed with added features that take advantage of better modelling of changes over time in the return equivalent of the meteor shower of Engle, Ito, and Lin [Meteor showers or heat waves? Heteroscedastic intra-daily volatility in the foreign exchange market. *Econometrica* 58, no. 3: 525–42]. The results show that overnight international information is more economically beneficial than previous-day's domestic information. Moreover, better modelling of the time variation in the impact of this overnight information has substantial benefits to stock market investors.

Keywords: meteor shower; information transmission; Kalman filter; FIT

1. Introduction

This paper aims to empirically quantify the difference in economic benefit between foreign and domestic stock market information using new methodological developments. Economic benefit is measured by the performance of trading strategies constructed on the basis of different combinations of domestic and foreign market information. The aim is to answer the question: how much more (or less) returns will a day trader earn by using various combinations of different interpretations of foreign news signals and domestic market momentum than the latter alone? This paper assesses the degree to which foreign information might be important to traders who formulate trading strategies based on the strength and direction of the relationships that exist between their domestic market and other foreign markets.

When an information signal is transmitted from one international stock market to another it arrives with a particular intensity of impact. This 'meteor shower' has been documented in volatility by Engle, Ito, and Lin (1990) and in returns by Hamao, Masulis, and Ng (1990), amongst others.[1] More recently, Ibrahim and Brzeszczynski (2009) provide evidence that the intensity of meteor showers in returns between pairs of international stock markets changes over time, and that these changes are affected by information (return) signals from yet other international stock markets that operate in intermediate time. Information is, therefore, transmitted directly from one market to another and indirectly through other markets. This transmission is reflected in the direction (sign) and magnitude of returns. More importantly, Ibrahim and Brzeszczynski (2009) develop a conditional time-varying foreign information transmission (FIT) methodology that captures these direct and indirect effects in a better way than traditional static techniques. This methodology allows traders to forecast the impact of foreign information on the level and intensity of meteor showers, i.e. the effect of information (sign and magnitude of returns) from some international markets on the alphas and betas that describe the return relationships that exist between pairs of other markets. For example, the New York Stock Exchange (NYSE) opens after the Tokyo Stock Exchange (TSE) closes, and traders of NYSE indices will have reviewed the performance of the TSE overnight and may trade on the basis of this 'news'. However, the London Stock Exchange (LSE) operates in the interim. It opens after TSE closes but before NYSE starts trading for the day. Asian news may, therefore, have been digested in Europe and implemented in security prices and, hence, reflected in returns there prior to the open of USA markets. This 'European interpretation' of the Asian news signal may, therefore, strengthen or weaken a USA day trader's conviction about it. If the European interpretation strengthens the USA trader's conviction, then the trader might want to increase his trade multiples (leverage). If it weakens the conviction, then the trader might want to decrease the trade multiples (leverage), or not trade at all. This process can be viewed in terms of the probability that the trader assigns to day-to-day return forecasts being realised in the correct direction. If the trader thinks that the probability is higher, then he will be more confident to increase the leverage.

In addition to previous-day's, or overnight, 'news' from abroad, there are domestic market conditions to consider. If favourable foreign news arrives at a time when domestic markets have been gathering momentum, and are now in a state regarded as oversold, then the combined signal can be interpreted as a definite buy. If overseas news arrives at a time when domestic markets have lost previous momentum and have gained momentum in the opposite direction, however, and are now overbought, then the conflicting signals weaken the trader's resolution to buy. Similarly, when foreign news that arrives overnight is unfavourable and domestic markets are overbought, then the combined signal can be interpreted as a strong sell, but if the domestic market is oversold, then the foreign selling signal is weakened.

The remainder of the paper is organised as follows. Section 2 reviews the FIT model used to describe the effect of foreign information. Section 3 presents a discussion of the construction of trading strategies. Section 4 presents a description of the data used, and a discussion of the performance results of trading strategies. Section 5 presents results of robustness analysis, and Section 6 concludes.

2. FIT methodology

The central methodology we use to describe the changing impact of foreign news on local markets is the FIT model, introduced by Ibrahim and Brzeszczynski (2009). FIT is a conditional time-varying methodology that describes the effect some variables have on the relationships that exist between other variables. In its simplest form, it is depicted as the following regression of y on x with time-varying coefficients α_t and β_t and an error term w_t:

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

The change over time in the coefficients is further assumed to depend on another, exogenous, variable, z, according to equations such as

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

and

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

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 $\mathbf{Y}_{t-1}$, it is assumed that the vector of error terms $(\boldsymbol{\nu}_{t+1}\ w_t)'$ has a Gaussian distribution, viz.

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

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

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

to be inside the unit circle for all $t = 1, \ldots, T$. Full technical description and details of the estimation procedure are provided by Ibrahim and Brzeszczynski (2009). Three central features of particular relevance, however, will be re-iterated here.

The terms $(\alpha_t - \bar{\alpha})$, $(\beta_t - \bar{\beta})$ and $(z_t - \bar{z})$ are time-t (or day t) deviations of alpha, beta and the variable z from their long-run averages or steady states. These deviations, therefore, represent 'news' or 'signals'. The first two represent 'news' about the level (alpha) and intensity (beta) of the relationship between the variables (or returns of stock markets) y and x. The third represents news about the variable (or return of stock market) z. Equations (2) and (3), therefore, describe how the level and intensity of the relationship between two markets change over time, and how these changes are affected by signals, or news, from a third stock market, z. In particular, the coefficients b and d measure the impact of news that arise in the z market on changes over time in the relationship between the y and x markets. In other words, they measure the effect of intermediate foreign, z, information on the meteor shower between two markets. This represents the main incremental information that the FIT model provides over linear (ordinary least squares, OLS) regressions of y on x. In particular, if d is significantly positive (negative), then favourable foreign news signals from market z (positive z deviation) have an increasing (decreasing) effect on the intensity of the meteor shower from market x to market y.

An econometric advantage of this innovative methodology is that it incorporates the phenomenon of volatility clustering that is often modelled by ARCH and stochastic volatility specifications. However, it does so through its formulation of the deterministic structure of the system (i.e. expected returns) rather than injecting heteroskedasticity through innovations or residuals (unexpected returns). Specifically, the term $\beta_t x_t$ of Equation (1) is a product of an AR(1) process for β_t with a random variable, x_t, and this is a type of specification shown by Granger and Machina (2002) to generate volatility drift or clustering. Thus, conditional heteroskedasticity is structurally inherent. Any remaining 'excess' heteroskedasticity, however, will have to be taken into account by other means such as incorporating ARCH terms in Equations (1)–(3), considering heteroskedasticity consistent residuals or prior transformation of the data in a manner equivalent to the standard generalised least squares (GLS) technique.

In a more practical setting, the model can generate a conditional forecast, y_{t+1}, the sign of which can be used to determine whether a trader should buy or sell the domestic market index y on day

$t+1$. The model can also generate a forecast of beta deviation, $(\beta_{t+1} - \bar{\beta})$, which can be used to gauge the direction and size of the change in the intensity of meteor shower for the next time period (day) $t+1$. A trader can then use this information to buy (or sell) more or less of the local market index (y) at market open on day $t+1$. In other words, the forecast of intensity deviation can be used to inform a trader about the trade multiple or leverage that could be applied to the trade on day $t+1$. If the forecast is large, then a large trading multiple will be applied, and if small then a smaller multiple. Increased or decreased leverage applied in this manner, therefore, is taken as the trader's response to his increased or decreased confidence that the probability of the forecast being realised in the right direction is higher or lower.

3. Trading strategies

We consider a domestic investor in each of the three major financial centres in the main geographical regions and time zones of the USA, Europe and Asia. Analysing the meteor showers across the largest markets in these regions would set a benchmark for smaller markets, since smaller markets are likely to exhibit stronger meteor showers from the larger ones. Accordingly, the indices of the largest markets in the three geographical regions are chosen. The USA region is represented by the Dow Jones Industrial Average (DJIA) index of the NYSE, the European region by the Financial Times Stock Exchange 100 (henceforth, FTSE) index of the LSE and the Asian region by the NIKKEI 225 (henceforth, NIKKEI) index of the TSE. The chronological trading sequence in GMT allowing for daylight savings is as follows. TSE opens around 00:00 or 01:00 GMT and closes at 06:00 or 07:00, LSE opens around 08:00 or 9:00 and closes around 16:30 or 17:30 and NYSE opens around 13:30 or 14:30 and closes 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. The trader's decision to buy or sell is based on a signal extracted from either, or a combination, of two sources. The first is domestic momentum information which we measure by a popular momentum indicator – the Relative Strength Index (RSI), developed by Wilder (1978) and used by Irwin and Uhriq (1984), Isakov and Hollistein (1999), Wong, Manzur, and Chew (2003) and Newsome and Turner (2007), amongst others. The second is foreign information transmitted overnight from stock market x, which is modelled by either a simple linear (OLS) regression of the returns of stock market y on those of stock market x or by the novel time-varying FIT methodology. FIT also incorporates the effect of information of a third market, z, which operates in intermediate time between markets y and x. In the case of y being the USA market, for example, a domestic USA investor would buy or sell the DJIA at NYSE market open and unwind at market close, depending on domestic momentum information of the USA market and/or overnight foreign information from Asia, represented by returns of NIKKEI (market x) on day t. The FIT model will also incorporate an indirect information channel – the European interpretation of the Asian signal as captured by returns of the FTSE on day t (market z). European investors trade the FTSE 100 on day t (market y) depending on domestic information or foreign information from DJIA on day $t-1$ (market x), and FIT trades would incorporate the returns of NIKKEI on day t (market z) as the Japanese interpretation of the USA signal. Asian investors trade the NIKKEI on day t (market y) depending on domestic information or foreign information from FTSE on day $t-1$ (market x), and FIT trades would incorporate the returns of DJIA on day $t-1$ (market z) as the American interpretation of the European signal. Thus, domestic traders implement strategies that follow chronological sequences meaningful to them. We present in more detail the trading strategies next.[2]

3.1 *RSI trades*

RSI is an index that measures domestic momentum. The version we use to gauge local market conditions is

$$\mathrm{RSI}_t \equiv 100 - \frac{100}{1 + RS_t}, \tag{6}$$

$$\mathrm{RS}_t = \frac{\sum_{j=1}^{10} |r_{t-j}|}{\sum_{j=1}^{10} |r^*_{t-j}|}, \tag{7}$$

where

$$r_{t-j} = \begin{cases} r_{t-j} & \text{if } r_{t-j} > 0, \\ 0 & \text{otherwise,} \end{cases} \tag{8}$$

$$r^*_{t-j} = \begin{cases} r_{t-j} & \text{if } r_{t-j} < 0, \\ 0 & \text{otherwise,} \end{cases} \tag{9}$$

and r denotes continuously compounded day returns. In words, RS_t is the ratio of the sum of positive to the sum of negative daily returns during the 10 days that precede day t. The RSI index has values ranging from 0 to 100. Values above 50 would indicate overbought domestic market conditions and values below 50 would indicate 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. Usually, 30 and 70 are taken as the lower and upper bounds of this neutral zone, but we use 20 and 80 because these provide more conservative estimates for comparison purposes.[3] In leveraged trades that are based solely on domestic momentum, we apply an arbitrary multiple of 2 to trades that are prompted by an RSI signal above or below the bounds. In non-leveraged versions of such trades, the multiple applied is 1 (i.e. no leverage). No trades are initiated when RSI lies within the bounds. All leveraged trades, whether RSI or otherwise, will be denoted by a superscript (L).

3.2 *OLS trades*

These are trades conducted based on a relationship described by an equation similar to (1), but with constant coefficients (i.e. a simple linear (OLS) regression of returns of market y on x). If the beta of this regression is positive, then a positive news signal from the signalling market, x, is estimated to increase the expected return of the domestic market, y, in which the investor trades. In this case, when the return of the index representing market x on a particular day is positive (negative), a buy (sell) trade in the index of market y is initiated at next open and wound up at market close. If the beta of the regression is negative, then the opposite type of trade is conducted. This is done with no leverage (i.e. a trade multiple of one is applied), since the static linear OLS regression model provides no information about changes in the intensity of the meteor shower from x to y. The trader cannot trade or refrain from trading, if either market y is closed for the day or the signalling market x was closed during the immediately preceding trading session.

3.3 *FIT trades*

The FIT model provides daily return forecasts of market y, the sign of which can be used to determine whether the index representing the market, the DJIA for the USA, the FTSE for Europe or NIKKEI for Asia, should be bought or sold for the day. A positive (negative) return forecast can, therefore, be taken as a buy (sell) signal. This signal may differ from that generated by OLS, however. Accordingly, and in order to facilitate comparison on equal grounds between models of foreign information (OLS and FIT), the same foreign signal, as generated by OLS, is used in both models. Thus, a positive (negative) return from the signalling market, x, is taken as a buying (selling) signal for the domestic market, y.[4]

FIT also provides information about changes in the intensity of meteor showers, which can be used to indicate the degree of leverage, or multiple, that ought to be applied to leveraged trades on a particular day. If the intensity deviation, $(\beta_{t+1} - \bar{\beta})$, is forecasted to be high for day $t + 1$, then trades will be conducted with high leverage, and if low, then with low leverage. This is applied in the following manner. The range of in-sample daily intensity deviations is divided into quintiles. A multiple for the trade on a particular day is then decided by gauging in which quintile does the forecast intensity deviation for the day falls. If the forecast intensity deviation belongs to the two outermost quintiles (that contain the largest deviations in magnitude), then leveraged trades are conducted with an arbitrarily chosen high multiple of 3; if it belongs to the next two inner quintiles then leveraged trades are conducted with an arbitrarily chosen medium multiple of 2 and if it belongs to the innermost quintile then leveraged trades are conducted with a multiple of 1 (i.e. no leverage). Non-leveraged trades will simply apply a multiple of 1 to all signals for trading. The trader refrains from trading if either market y is closed for the day or the signalling market x was closed during the immediately preceding trading session.

3.4 *Combination trades*

Domestic information can also be combined with foreign information to filter or refine the signal to trade. If the arriving foreign signal (from OLS or FIT) coincides with the domestic market momentum signal (from RSI), then a multiple of 1 is applied to non-leveraged trades, and the leverage multiples described above are combined for leveraged trades. If the two signals contradict, however, then no trade is initiated. In cases when one of the signals is neutral, then the other, non-neutral, signal is used to signal for a trade. If this trade is non-leveraged, then a trade multiple of 1 is applied. If the trade is leveraged, instead, then the relevant leverage multiple described above is applied.[5]

Table 1 provides a summary of the multiples that will apply to trades under the various possible combinations of domestic (RSI) and foreign (FIT) conditions. Negative values reported in the table indicate a negative foreign signal and positive values indicate a positive foreign signal. When the arriving foreign signal is strongest, and coincides in direction with the momentum of the domestic market, then the multiple applied to trades is 6 (3 (FIT) $\times$ 2 (RSI)); when the strength of the foreign signal is medium, then the multiple applied is 4 (2 (FIT) $\times$ 2 (RSI)); and when it is weak, then the multiple applied is 2 (1 (FIT) $\times$ 2 (RSI)). If RSI indicates neutral domestic market conditions, then the trader acts solely according to the strength of the foreign signal, and domestic conditions do not, therefore, amplify the foreign signal. Finally, the trader refrains from trading in only two conditions: when the domestic market is closed for the day, or when the foreign signal and the domestic conditions do not coincide (i.e. the foreign signal indicates a buy (sell), while the domestic market is overbought (oversold)).

Table 1. Leverage multiples applied to FIT and RSI trades.

				FIT (foreign signal)						
				Leverage						
	States	RSI range	Leverage	+3	+2	+1	0	−1	−2	−3
RSI (domestic market condition)	Overbought	[80–100]	+2	0	0	0	0	−2	−4	−6
	Neutral	(20–80)	+1	+3	+2	+1	0	−1	−2	−3
	Oversold	[0–20]	+2	+6	+4	+2	0	0	0	0

Notes: The choice of leverage values and grades of +1 and +2 for RSI and ±1, ±2 and ±3 for FIT are, on the main, arbitrary and other values and grades can be applied just as well. The practical constraint, however, is the increased possibility of losing 100% or more of capital in one day if higher leverage multiples are chosen. For instance, our maximum trade multiple of 6 implies that it would require the domestic market index to decrease by 16.67% in one day (effectively crash) in order to lose 100% of starting capital. Higher trade multiples would imply a possibility of losing 100% of capital with single-day decreases lower than 16.67%.

3.5 *Transaction costs and trading*

The normal level of 0.1% of contract value is applied as transaction costs for a round trip. This is the normal marginal cost for trading indices online in futures format, but can be a lesser amount if large trades are conducted over the counter. Some 'wholesale' trading platforms also offer flexible means for implementing the above strategies since trading can occur near, if not at, the actual opening and closing levels of market indices.

4. Data and results

4.1 *Data*

Daily open and close levels of the DJIA, NIKKEI and FTSE indices covering the period from 1 June 1998 to 31 May 2011 are obtained from Datastream. The starting date of 1 June is chosen arbitrarily, and the end date is chosen as the most recent to the date of starting the analyses in this paper. Open and close index levels are then used to calculate holding period day returns for each index. Data during the initial 10-year period from 1 June 1998 to 31 May 2008 are used for OLS and 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. 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.

4.2 *Estimation results of underlying relationships*

Initial tests reveal heteroskedasticity of auto-correlated conditional form in the day returns of the three markets.[6] Since this would have a direct effect on the significance of coefficient estimates, we opt to account for heteroskedasticity by transforming the return series in a manner equivalent to the standard GLS technique. Each return series is divided by the series of its conditional standard deviations estimated by an appropriate GARCH(p, q) model. The resulting 'standardised' series are then used in the estimation of all relationships. This procedure has the compound benefit of preserving the direction of information signals (i.e. the sign of returns), simplifying the Kalman

Table 2. OLS and FIT estimation results.

	DJIA model		FTSE model		NIKKEI model	
	Estimate	t-Stat	Estimate	t-Stat	Estimate	t-Stat
OLS						
α	0.0201	1.03	−0.0033	−0.17	−0.0405	−2.09
β	0.1103	5.66	0.2414	12.70	0.1427	7.36
R^2	0.0122		0.0583		0.0204	
Multiple R	0.1102		0.2415		0.1427	
FIT						
$\bar{\beta}$	0.1117	5.44	0.3078	14.55	0.1475	7.70
Stdev (ν_α)	−0.1258	−3.47	0.8701	24.32	0.5004	30.45
Stdev (ν_β)	0.0320	1.80	0.1232	−1.83	0.3114	7.92
Stdev (w)	0.9634	48.42	0.3816	5.36	0.7762	42.66
a	−0.6958	−7.34	−0.1891	−7.71	−0.2541	−10.64
b	0.4102	5.15	–	–	0.1471	5.04
c	−0.1440	−2.74	−0.2192	−2.71	0.1406	6.66
d	−1.0613	−10.20	0.968	2.05	−0.1491	−6.00
Max. lik.	−1.4076		−1.3786		−1.3984	
Engle LM (10)	11.0597 (0.3529)		13.7948 (0.1826)		13.5754 (0.1935)	
F-test (10,2588)	1.106 (0.353)		1.381 (0.183)		1.359 (0.193)	
	Level	Square	Level	Square	Level	Square
Ljung–Box Q(10)	8.3294	11.1838	16.2404	13.7841	7.5024	14.3262
	(0.5013)	(0.2633)	(0.0620)	(0.1302)	(0.5747)	(0.1112)

Notes: Tabulated are OLS and FIT estimation results using heteroskedasticity-adjusted data. The FIT relationship dubbed the 'DJIA model' has markets y, x and z being DJIA(t), NIKKEI(t) and FTSE 100(t), respectively, where t denotes day t. For the 'FTSE model' they are FTSE 100(t), DJIA($t-1$) and NIKKEI 225(t), respectively. For the 'NIKKEI model', they are NIKKEI 225(t), FTSE 100($t-1$) and DJIA($t-1$), respectively. OLS versions of these models are corresponding static relationships between y and x only.

filter modelling, and eliminating heteroskedasticity from the outset.[7] A battery of tests, reported in Table 2, confirms no heteroskedasticity left in the residuals.

Table 2 lists unconditional OLS in-sample estimation results of regressing index y 'standardised' returns on index x 'standardised' returns. The estimated values of alpha and beta determine the basic linear relationship that exists between these two indices. Estimated alphas are insignificantly different from zero for DJIA and FTSE, but significantly negative for NIKKEI. Estimated betas, however, are significantly positive, indicating that when market x transmits a positive (negative) signal (return) then DJIA, FTSE and NIKKEI respond in the same direction with 11.03%, 24.14% and 14.27% sensitivity, respectively. Note, that this relationship, as is common with most return regressions of equilibrium models (such as the CAPM), is not particularly strong statistically, since R^2 ranges from 1.22% to 5.83% and multiple R from 11.02% to 24.15%.[8]

The table also lists parameter estimates of the FIT model of Equations (1)–(3) for these three relationships. Note that this model includes the additional information from a third market, z. A general to specific estimation procedure is adopted, whereby insignificant parameters from an initial full specification are dropped one at a time, and the likelihood ratio test is used at each step to confirm this pruning. The table reports estimates of these final specifications that have only the significant parameters.

The table reports that the steady-state estimates of alpha, $\bar{\alpha}$, are insignificantly different from zero for the three relationships, and of beta, $\bar{\beta}$, are 0.1117 for DJIA, 0.3078 for FTSE and 0.1475 for

NIKKEI. The sign of beta estimates coincides with that of OLS estimates and indicates a positive relationship between domestic markets and the signalling markets. Significant estimates of the parameters a and c indicate that alpha and beta deviations are correlated over time. In addition, significant estimates of the parameter b for DJIA and FTSE indicate that alpha deviations over time depend on information signals from market z, which are the FTSE and NIKEEI 225, respectively. Significant estimates of the parameter d for all three relationships indicate that beta deviations over time depend on information signals from the respective third market, z. Thus, FTSE(t) signals are important in determining changes over time in the intensity of the impact of NIKKEI(t) on DJIA(t); NIKKEI(t) signals are important in determining changes over time in the intensity of the impact of DJIA($t-1$) on FTSE(t) and DJIA($t-1$) signals are important in determining changes over time in the intensity of the impact of FTSE($t-1$) on NIKKEI(t). Specifically, a positive news signal from FTSE on day t, defined as $(z_t - \bar{z})$, of one unit in magnitude would cause tomorrow's beta deviations between DJIA and NIKKEI to be reduced by a factor of 1.0613 relative to today's deviations. Similarly, a positive news signal from NIKKEI on day t of one unit in magnitude would cause tomorrow's deviations between FTSE and DJIA to be equal to today's deviations multiplied by a factor of 0.968. Finally, a positive news signal from DJIA on day $t-1$ of one unit in magnitude would cause tomorrow's deviations between NIKKEI and FTSE to be equal to today's deviations multiplied by a factor of -0.1491.

Table 2 also reports, for FIT models, the maximum likelihood function value, Engle's LM test of hetersokedasticiy at 10 lags ($T \times R^2$), an F-test on ARCH (10) and Ljung–Box Q-statistics (10) on the level and square of residuals. All tests confirm the absence of both serial correlation and heteroskedasticity in the residuals.

4.3 *Performance results of trading strategies*

All results relate to daily trading strategies on the DJIA, FTSE and NIKKEI indices throughout the out-of-sample (forecast) period from market open on 1 June 2008 to market close on 31 May 2011. Daily trades follow the rules described above. Leveraged strategies are denoted by a superscript (L). Twelve funds that start with a hypothetical investment of \$1 m just prior to open of trading on 1 June 2008 are constructed for each domestic index. Three of these funds are based solely on domestic information: a fund that passively tracks the index and earns the domestic index return on a daily basis, an RSI fund that follows the RSI-based investment rules described above and a leveraged version denoted by $\mathrm{RSI}^{\mathrm{L}}$ that applies the leverage multiples described in Table 1. Three more funds are constructed based solely on international information: OLS, FIT and a leveraged version of the latter, denoted by $\mathrm{FIT}^{\mathrm{L}}$. The final six funds that we construct are based on a combination of information types, viz. OLS + RSI, OLS + $\mathrm{RSI}^{\mathrm{L}}$, FIT + RSI, FIT + $\mathrm{RSI}^{\mathrm{L}}$, $\mathrm{FIT}^{\mathrm{L}}$ + RSI and $\mathrm{FIT}^{\mathrm{L}}$ + $\mathrm{RSI}^{\mathrm{L}}$. Table 3 lists all 12 funds with a brief description of each.

Fund performance is measured by its return, reported in Table 4, certainty equivalent (CEQ) returns, reported in Table 6 and Sharpe ratio, reported in Table 7. The quality and robustness of performance over time are assessed by the time series behaviour of fund value throughout the out-of-sample period, plotted in Figure 1, and during subdivisions of the out-of-sample period, reported in Table 10.

In order to conserve space, and to ease viewing, a selection of four primary funds is plotted in Figure 1 for each index. The graphs show that the general trend of fund value increases during a period when the underlying indices passed through a dramatic initial period of a bear market followed by a prolonged period of recovery. None of the funds that are based on information-related trading performs as bad as the passive buy-and-hold index funds; not even those based

Table 3. Fund notation and description.

Fund notation	Description
DJIA/FTSE/NIKKEI	Passive tracking fund. Earns day returns of the index
RSI	RSI fund. Earns returns on day trades signalled by RSI
RSI^L	Same as RSI but trades are multiplied by 2
OLS	OLS fund. Earns returns on day trades signalled by OLS
OLS + RSI	Fund earns returns on trades jointly signalled by OLS and RSI
$OLS + RSI^L$	Same as OLS+RSI but RSI signalled trades are multiplied by 2
FIT	FIT fund. Earns returns on trades signalled by FIT
FIT + RSI	Fund earns returns on trades jointly signalled by FIT and RSI
$FIT + RSI^L$	Same as FIT+RSI but RSI signalled trades are multiplied by 2
FIT^L	Same as FIT but high intensity trades are multiplied by 3, medium intensity trades by 2 and low intensity by 1
$FIT^L + RSI$	Fund earns returns on trades jointly signalled by FIT^L and RSI
$FIT^L + RSI^L$	Same as FIT^L+RSI but RSI signalled trades are multiplied by 2

Note: The table lists the notation used for the 12 funds constructed for each index together with a brief description of their strategies.

on leveraged strategies. In fact, starting with an arbitrary fund value of $1 m, the minimum value reached is $0.5467 m by RSI^L on 10 October 2008, from which it recovered to $0.7940 m in two days. The minimum reached by other information-based strategies ranges from $0.6382 m to $0.9932 m. Accordingly, even during such an initial bear-market period of high volatility, none of the constructed funds would have been at risk of bankruptcy.[9]

Table 4 presents the results of the trading strategies. Panels A and B report cumulative returns, gross and net of transaction costs, respectively, and Panels C and D report gross and net continuously compounded returns. As cumulative gross returns are unaffected by compounding and transaction costs, their comparison across strategies would reveal underlying patterns of relative fund performance. Hence, the ensuing descriptive coverage will first focus on Panel A. Comparison across panels and the effects of transaction costs and compounding will be subsequently discussed.

Panel A reports RSI strategy total returns of 23.63%, 9.25% and 5.18% for DJIA, FTSE and NIKKEI, respectively, and corresponding OLS/FIT strategy total returns of 109.83%, 128.96% and 199.46%. Accordingly, OLS and FIT outperform RSI by a factor of 4.6 for DJIA (calculated as 109.83%/23.63%), 13.9 for FTSE and 38.5 for NIKKEI. Moreover, adding RSI to OLS/FIT increases returns for DJIA, FTSE and NIKKEI by −2.23% (calculated as 107.6–109.83%), 8.95% and −1.42%, respectively. However, adding OLS/FIT to RSI increases returns for DJIA, FTSE and NIKKEI by 83.97% (107.6–23.63%), 128.66% and 192.86%, respectively. These are striking results that show the magnitude of the incremental benefit of using more recent foreign information over prior domestic momentum information. Even when domestic information about momentum is beneficial in trading, the meteor shower effect of foreign information is much more so. Similar qualitative results are found in returns net of transaction costs (Panel B), and in compound returns (Panels C and D). Detailed discussions of the effects of transaction costs and compounding, however, are deferred to later parts of this section.

Comparing the performance of funds in the FIT^L columns with corresponding values in the OLS/FIT columns of Panel A would reveal the incremental benefit of using the information that the third market, z, provides.[10] For DJIA, the total return values reported in the FIT^L column are 128.66%, 127.94% and 134.75% higher than the corresponding values reported in the OLS/FIT

Table 4. Trading strategies average per trade and total returns.

	DJIA model			FTSE model			NIKKEI model		
	RSI	OLS/FIT	FIT^L	RSI	OLS/FIT	FIT^L	RSI	OLS/FIT	FIT^L
Panel A. Cumulative gross returns									
		0.16%	0.34%		0.18%	0.44%		0.28%	0.74%
	–	(708)	(708)	–	(737)	(737)	–	(711)	(711)
		109.83%	238.49%		128.96%	321.05%		199.46%	528.59%
RSI	0.19%	0.17%	0.36%	0.09%	0.21%	0.51%	0.05%	0.30%	0.78%
	(124)	(646)	(646)	(102)	(667)	(667)	(114)	(656)	(656)
	23.63%	107.6%	235.54%	9.25%	137.91%	337.07%	5.18%	198.04%	514.53%
RSI^L	0.38%	0.18%	0.39%	0.18%	0.21%	0.52%	0.09%	0.31%	0.82%
	(124)	(646)	(646)	(102)	(667)	(667)	(114)	(656)	(656)
	47.26%	119.42%	254.17%	18.51%	139.74%	347.55%	10.36%	205.42%	538.52%
Panel B. Cumulative returns net of transaction costs (at 0.1%)									
		0.06%	0.12%		0.08%	0.22%		0.18%	0.52%
	–	(708)	(708)	–	(737)	(737)	–	(711)	(711)
		39.03%	81.69%		55.26%	158.75%		128.36%	369.19%
RSI	0.09%	0.07%	0.14%	−0.01%	0.11%	0.28%	−0.05%	0.20%	0.56%
	(124)	(646)	(646)	(102)	(667)	(667)	(114)	(656)	(656)
	11.23%	43.00%	91.64%	−0.95%	71.21%	189.37%	−6.12%	132.44%	367.13%
RSI^L	0.18%	0.08%	0.16%	−0.02%	0.10%	0.29%	−0.11%	0.21%	0.58%
	(124)	(646)	(646)	(102)	(667)	(667)	(114)	(656)	(656)
	22.46%	49.82%	101.37%	−1.89%	69.84%	193.95%	−12.24%	134.52%	379.72%
Panel C. Continuous compound gross returns									
		0.24%	0.64%		0.31%	1.52%		0.80%	14.12%
	–	(708)	(708)	–	(737)	(737)	—	(711)	(711)
		172.54%	455.21%		228.28%	1117.03%		572.18%	10041.61%
RSI	0.20%	0.26%	0.71%	0.07%	0.40%	2.28%	0.03%	0.86%	13.82%
	(124)	(646)	(646)	(102)	(667)	(667)	(114)	(656)	(656)
	24.89%	167.77%	456.21%	7.28%	264.55%	1523.63%	3.12%	566.62%	9068.04%
RSI^L	0.42%	0.31%	0.83%	0.10%	0.40%	2.25%	0.02%	0.90%	12.25%
	(124)	(646)	(646)	(102)	(667)	(667)	(114)	(656)	(656)
	51.89%	198.32%	534.78%	10.15%	264.46%	1503.95%	1.97%	587.56%	8035.19%
Panel D. Continuous compound returns net of transaction costs (at 0.1%)									
		0.05%	0.02%		0.08%	0.19%		0.32%	2.75%
	–	(708)	(708)	–	(737)	(737)	–	(711)	(711)
		34.24%	15.63%		57.07%	139.89%		230.09%	1957.84%
RSI	−0.27%	0.06%	0.05%	−0.02%	0.13%	0.41%	−0.06%	0.37%	3.05%
	(124)	(646)	(646)	(102)	(667)	(667)	(114)	(656)	(656)
	−32.87%	40.33%	31.80%	−1.61%	87.07%	270.37%	−6.37%	245.87%	1997.63%
RSI^L	−0.45%	0.08%	0.06%	−0.07%	0.12%	0.37%	−0.14%	0.36%	2.38%
	(124)	(646)	(646)	(102)	(667)	(667)	(114)	(656)	(656)
	−56.18%	48.70%	37.59%	−7.36%	81.13%	244.89%	−15.94%	238.30%	1560.42%

Notes: The table reports three values, vertically stacked, for each strategy or combination of strategies: average profit per trade, the number of trades (in parenthesis) and total returns. Panels A and B report cumulative returns and panels C and D report continuously compounded returns. Gross returns (Panels A and C) assume nil transaction costs. Simple buy-and-hold passive strategies for DJIA, FTSE and NIKKEI yielded cumulative gross returns of −0.54%, −1.05% and −32.41%, cumulative net returns of −0.64%, −1.15% and −32.50%, compound gross returns of 12.10%, −4.67% and −40.45% and compound net returns of −47.37%, −55.29% and −71.37%, respectively. Cumulative returns of buy-and-hold strategies with and without transaction costs are nearly similar because trading costs are deducted only once at the beginning and once at the end of the investment holding period.

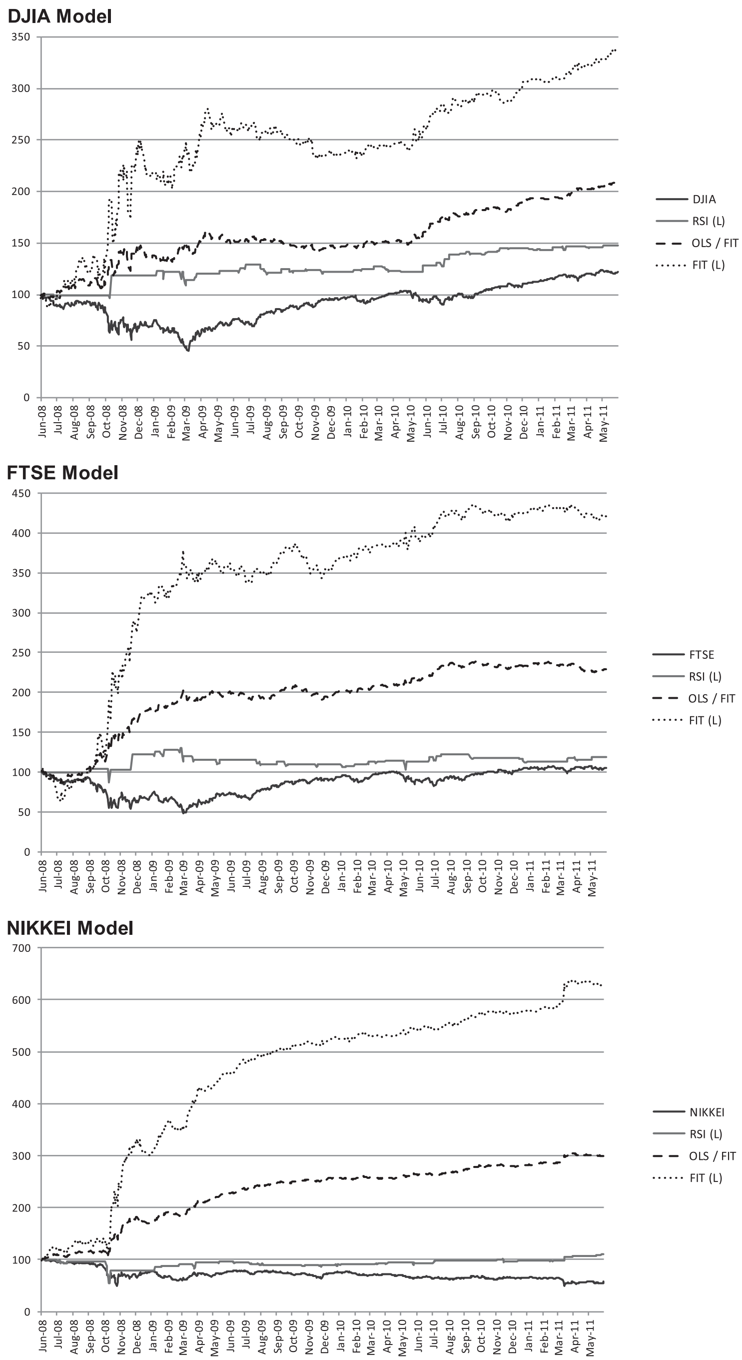

Figure 1. Funds performance: DJIA, FTSE and NIKKEI.

Notes: Graphed are cumulative gross returns for a selection of funds for ease of viewing. Graphs of other strategies are available from the authors. The funds graphed are the buy-and-hold index fund, RSI^L, OLS/FIT and FIT^L. Other funds exhibit line graphs very close to related graphed ones. The line graph of RSI, for example, is very close to RSI^L. Those of OLS/FIT+RSI and OLS/FIT+RSI^L are very close to that of OLS/FIT, and those of FIT^L+RSI and FIT^L+RSI^L are very close to that of FIT^L.

column. For FTSE, these differences are 192.09%, 199.16% and 207.81%, and for NIKKEI they are 329.13%, 316.49% and 331.1%, respectively. These are substantial incremental improvements to performance. Thus, the z market's interpretation of the x market's signal is very useful in revising the conviction about (level of intensity of) the relationship that exists between the domestic market, y, and the foreign market, x. This revision is much more valuable than domestic market momentum alone and substantially enhances the performance of strategies based on the direct foreign information from markets x (i.e. OLS/FIT strategies). This is a clear evidence of the potential size of the incremental economic benefits of modelling daily changes in the intensity of meteor showers, and the impact of intermediate foreign information.

Note that the incremental usefulness of foreign information is evident even though it explains little variation over time in domestic returns. When described by a static OLS regression it exhibits a low R^2 of 1.2% for DJIA, 5.8% for FTSE and 2% for NIKKEI, as reported in Table 2. This meagre explanatory power, however, does not necessarily reflect the enhanced ability of foreign information to predict the direction of domestic returns and, as the results show, it is this latter ability that is responsible for more than quintupling the performance of trading strategies (for NIKKEI, the multiplication factor is 38.5, as reported above). This is true because the performance of these trades is based primarily on the ability to predict return direction rather than the ability to explain return variation over time, which is what R^2 captures.

In general, applying higher leverage magnifies returns. Higher leverage applied to RSI trades increases returns (in Panel A) from 23.63% to 47.26% for DJIA, from 9.25% to 18.51% for FTSE and from 5.18% to 10.36% for NIKKEI. Similarly, higher leverage applied to OLS/FIT trades increases their returns, but in a much pronounced manner: from 109.83% to 238.49% for DJIA, from 128.96% to 321.05% for FTSE and from 199.46% to 528.59% for NIKKEI. Combination strategies also yield magnified returns with leverage. These results confirm the fact that the rules governing the strategies underlying the funds are, on average, successful in choosing profitable trades (i.e. in predicting the direction of returns). Leverage magnifies the benefits that this ability brings about. Prediction ability will be discussed in more detail below.

Comparing the performance of strategies under the FIT^{L} column with the corresponding OLS/FIT strategies in Panel A reveals substantial enhancements in returns from leverage. The magnification factor is around 2.2 for DJIA, 2.4 for FTSE and 2.6 for NIKKEI. Even higher magnification factors are exhibited in cumulative returns net of transaction costs (Panel B). This may potentially seem to be a rather surprising result, since the largest leverage multiple of three is applied to only 40% of FIT trades.[11] Moreover, the high factors are not driven by compounding effects, since the figures just reported are for cumulative returns. (The corresponding magnification factors in compound returns of Panels C and D are much higher, as expected. The exception is DJIA in Panel D, which is highly affected by negative observations that occur early on during the investment period.) Thus, the profitability of extreme intensity (beta) quintile trades is, therefore, much higher than that of other trades. This result is mainly due to the ability of the model to forecast the direction of trades combined with the volatility of the indices. This means that the grading of signals by their forecast intensity deviations, and the consequential leverage allocation, is very useful indeed. Forecasting intensity deviations is a central feature of FIT. Accordingly, FIT does not only exceed RSI's ability to forecast the direction of returns, but also exceeds that of OLS, because the additional daily information it provides about future intensity deviations in meteor showers is economically profitable, and hence adds value.[12] This point is investigated further below in Section 4.5.

The above results are also reflected in average per trade figures. For example, as reported in Panel A, RSI signals trigger 124 trades for DJIA, 102 for FTSE and 114 for NIKKEI, with average per trade figures of 0.19%, 0.09% and 0.05%, respectively. OLS/FIT trade rules sig-nal for 708 trades for DJIA, 737 trades for FTSE and 711 trades for NIKKEI, with average per trade figures of 0.16%, 0.18% and 0.28%, respectively. Thus, the use of foreign infor-mation allows for 5.7 (708/124) to 6.3 (711/114) times more trades than the use of domestic information and, on the main, generates higher profitability. The leverage ability of FIT further increases per trade profitability to 0.34% for DJIA, 0.44% for FTSE and 0.74% for NIKKEI. Thus, foreign information generates more profitable trades, and the indirect channel of foreign information from third markets, *z*, can generate even higher profitability by appropriate allocation of leverage.

The effect of compounding is substantial. Comparing corresponding values in Panels A and C reveals the extent of magnification in performance from compounding. The average per trade figures of OLS/FIT, for example, increase from 0.16% (cumulative) to 0.24% (compounded) for DJIA, from 0.18% to 0.31% for FTSE and from 0.28% to 0.80% for NIKKEI. The effect for FIT^{L} strategies is phenomenal, where values increase from 0.34% to 0.64% for DJIA, from 0.44% to 1.52% for FTSE and from 0.74% to 14.12% for NIKKEI. In contrast, the compounding effect is not as large for RSI trades. Average per trade figures for RSI strategies increase from 0.19%(cumulative) to 0.20% (compounded) for DJIA, but decrease from 0.09% to 0.07% for FTSE and from 0.05% to 0.03% for NIKKEI. Obviously, not only the magnitude of trade returns affects compounded values, but also their incidence over the out-of-sample period.

Transaction costs are a central factor in determining the profitability of trading strategies. Com-paring corresponding values in Panel A and Panel B reflects their detrimental effects on cumulative returns. The total cumulative returns of RSI strategies are reduced by more than half for DJIA (from 23.63% to 11.23%) and from positive to negative values for FTSE (9.25% to −0.95%) and again, from positive to negative values for NIKKEI (from 5.18% to −6.12%). Other strategies' performance is also affected but, unlike RSI, is not rendered negative for FTSE and NIKKEI, mainly because these strategies are highly profitable before transactions costs are applied. Com-paring results for compound returns in Panels C and D shows the magnified detrimental effect of transaction costs due to compounding. RSI trades for DJIA, FTSE and NIKKEI yield −32.87%,
−1.61% and −6.37% percent, respectively, while other trades remain profitable. The incidence of negative trades earlier on during the out-of-sample period is apparent in the substantially reduced performance of FIT^{L} trades, but this is no surprise since leverage and compounding act in unison in magnifying the reductions in returns caused by transactions costs.

Fund cumulative returns net of different levels of transaction costs ranging from 0% to 0.5% are reported in Table 5. The normal level of transaction costs applied to index trades is around 0.1%, and is often smaller for 'wholesale' orders of large volumes. The values in the first two columns, entitled 0% and 0.1% transaction costs, are the same as those reported in Table 4, and are discussed above. At 0.2% transaction costs, all funds for DJIA are loss making, only three funds for FTSE (OLS/FIT + RSI, FIT^{L} + RSI and FIT^{L} + RSI^{L}) are profit making, and only RSI and RSI^{L} for NIKKEI are loss making. At 0.3% transaction costs, all funds for the three indices are loss making except funds based on FIT^{L} for NIKKEI. At levels of transaction costs of 0.4% or higher all funds are loss making. Thus, some funds based on foreign information remain profitable at two or three times the normal level of transaction costs, but funds based on domes-tic information can be loss making even at normal levels of transaction costs. The resilience of foreign information-based strategies to the depleting effects of transaction costs is particu-larly notable for NIKKEI. Furthermore, the patterns discussed above of relative performance of RSI, OLS/FIT and FIT^{L} strategies are preserved at different levels of transaction costs. Direct channels of foreign information are therefore much more beneficial than domestic information,

Table 5. Fund cumulative return net of transaction costs.

	Transaction costs					
	0%	0.1%	0.2%	0.3%	0.4%	0.5%
DJIA model						
RSI	23.63%	11.23%	−1.17%	−13.57%	−25.97%	−38.37%
RSI^L	47.26%	22.46%	−2.34%	−27.14%	−51.94%	−76.74%
OLS/FIT	109.83%	39.03%	−31.77%	−102.57%	−173.37%	−244.17%
OLS/FIT + RSI	107.60%	43.00%	−21.06%	−86.20%	−150.80%	−215.40%
OLS/FIT + RSI^L	119.42%	49.82%	−19.78%	−89.38%	−158.98%	−228.58%
FIT^L	238.49%	81.69%	−75.11%	−231.91%	−388.71%	−545.51%
FIT^L + RSI	235.54%	91.64%	−52.26%	−196.16%	−340.06%	−483.96%
FIT^L + RSI^L	254.17%	101.37%	−51.43%	−204.23%	−357.03%	−509.83%
FTSE model						
RSI	9.25%	−0.95%	−11.15%	−21.35%	−31.55%	−41.75%
RSI^L	18.51%	−1.89%	−22.29%	−42.69%	−63.09%	−83.49%
OLS/FIT	128.96%	55.26%	−18.44%	−92.14%	−165.84%	−239.54%
OLS/FIT + RSI	137.91%	71.21%	4.51%	−62.19%	−128.89%	−195.59%
OLS/FIT + RSI^L	139.74%	69.84%	−0.06%	−69.96%	−139.86%	−209.76%
FIT^L	321.05%	158.75%	−3.55%	−165.85%	−328.15%	−490.45%
FIT^L + RSI	337.07%	189.37%	41.67%	−106.03%	−253.73%	−401.43%
FIT^L + RSI^L	347.55%	193.95%	40.35%	−113.25%	−266.85%	−420.45%
NIKKEI model						
RSI	5.18%	−6.12%	−17.42%	−28.72%	−40.02%	−51.32%
RSI^L	10.36%	−12.24%	−34.84%	−57.44%	−80.04%	−102.64%
OLS/FIT	199.46%	128.36%	57.26%	−13.84%	−84.94%	−156.04%
OLS/FIT + RSI	198.04%	132.44%	66.84%	1.24%	−64.36%	−129.96%
OLS/FIT + RSI^L	205.42%	134.52%	63.62%	−7.28%	−78.18%	−149.08%
FIT^L	528.59%	369.19%	209.79%	50.39%	−109.01%	−268.41%
FIT^L + RSI	514.53%	367.13%	219.73%	72.33%	−75.07%	−222.47%
FIT^L + RSI^L	538.52%	379.72%	220.92%	62.16%	−96.68%	−255.48%

Note: Tabulated are cumulative fund returns, net of different levels of transaction costs, for the entire out-of-sample period from 1 June 2008 through 31 May 2011.

and the indirect channels of foreign information through third markets, z, are incrementally valuable.

At the usual 20/80 bounds that is used to define the neutral zone within which no trades are signalled, RSI generates 124, 102 and 114 trades for DJIA, FTSE and NIKKEI, respectively. A 10/90 set of bounds would lead RSI to generate 41, 33 and 32 trades for DJIA, FTSE and NIKKEI, with a total cumulative gross return of 10.31%, 10.91% and 7.78%, respectively. Bounds of 30/70, 40/60, and 50/50 would lead RSI to generate 275, 494 and 747 trades for DJIA (the last being one trade per NYSE working day) with total cumulative gross returns of 5.9%, 13.34% and 26.67%, respectively. The same bounds would lead RSI to generate 235, 495 and 747 trades for FTSE, with total cumulative gross returns of 9.63%, 13.66% and −8.03%, respectively. For NIKKEI 266, 478 and 747 trades would be generated with total cumulative gross returns of −0.72%, −3.34% and 3.46%, respectively. The 20/80 bounds have, therefore, been chosen mainly because they are more restrictive than the usual bounds used by traders and, in this study, strategies at these bounds achieve highest returns across indices. Therefore, at these bounds RSI would act as the most conservative benchmark (across bounds) for comparison purposes. Basic non-adjusted RSI is used for simplicity and, therefore, we edge on the side of caution by choosing the set of bounds (20/80) at which this version of RSI performs best. Outperformance of FIT or OLS would not then be dependent on a weakly specified RSI.[13]

The 10-day lag length used to calculate RSI is the normal lag length adopted by practitioners. A shorter lag length would weigh recent domestic information more heavily, while a longer lag length would dilute the effect of more recent information. At a lag length of five days, the RSI strategy for DJIA yields 14.72% cumulative gross returns and −12.68% cumulative net returns. These values represent a worse performance than the 23.63% and 11.23% figures reported in Table 4 and calculated for RSI with a 10-day lag length. The OLS + RSI strategy for DJIA with a five-day lag length yields 93.12% and 36.22% cumulative gross and net returns, respectively, while the version with 10-day lag length, reported in Table 4, yields higher values of 107.6% and 43%, respectively. The same pattern repeats across other strategies where RSI with a 10-day lag length performs better than the version with 5-day lag length, which weighs recent information more heavily. Thus, the incremental benefits documented above for strategies based on foreign information are not due to a weakly specified RSI with respect to the amount and relevance of the prior domestic information it incorporates.[14]

As far as volatility is concerned, fund daily values fluctuate with positive gains and negative losses made from correct and incorrect predictions of return direction. Both gains and losses are also magnified by leverage when it is applied. For example, the time series of the values of DJIA, FTSE and NIKKEI passive funds have standard deviations over the out-of-sample period of 17.59%, 14.74% and 10.14%, respectively. In contrast, RSI fund values have standard deviations of 7.06%, 3.46%, and 3.42% for DJIA, FTSE and NIKKEI, respectively, and FIT^{L} + RSI^{L} funds values have standard deviations of 63.99%, 109.06% and 157.33% for DJIA, FTSE and NIKKEI, respectively. Other combinations of strategies and leverage have standard deviations that range between these values. Accordingly, higher fund performance is accompanied by increased riskiness and, it would, therefore, be necessary to compare the funds on a risk-adjusted basis. This is carried out next.

4.4 *Risk-adjusted performance*

Risk-adjusted performance is measured by CEQ returns, reported in Table 6, and the Sharpe ratio, reported in Table 7.[15] Table 6 reports CEQ returns over a range of values of the risk aversion parameter, γ. Focussing first on the reported values at the 'normal' level of risk aversion of $\gamma = 1$, FIT^{L} strategies exhibit values that range from 0.2167 for FIT^{L} of DJIA to 0.5884 for FIT^{L} of NIKKEI; OLS/FIT strategies exhibit values that range from 0.1251 for OLS/FIT+RSI of DJIA to 0.2458 for OLS/FIT+RSI^{L} of NIKKEI and RSI values range from 0.0018 for RSI^{L} of NIKKEI to 0.0522 for RSI^{L} of DJIA. The difference in magnitude of CEQ returns between these groups of strategies is substantial. Roughly, FIT^{L} strategies yield about double the CEQ returns of OLS/FIT strategies, which in turn yield about seven times the CEQ returns of RSI strategies. Accordingly, foreign information is far more valuable on risk-adjusted basis than domestic information, which is still useful and yields positive, albeit very small, CEQ returns. Moreover, the indirect channel of foreign information that operates through third markets, z, is incrementally beneficial, since FIT^{L} strategies yield higher CEQ returns than OLS/FIT strategies. These observations are supportive of the conclusions reported above, in Section 4.3, in discussions of cumulative and compound return results.

Higher values of the risk aversion parameter reduce CEQ returns, especially when fund mean returns are low and/or their riskiness (volatility) is high. RSI and RSI^{L} strategies of FTSE and

Table 6. CEQ returns.

Gamma	Passive Fund	RSI	RSI^L	OLS/FIT	OLS/FIT+RSI	OLS/FIT+RSI^L	FIT^L	FIT^L+RSI	FIT^L+RSI^L
DJIA model									
0.5	0.0206%	0.0284%	0.0559%	0.1335%	0.1309%	0.1454%	0.2604%	0.2586%	0.2790%
1	0.0137%	0.0275%	0.0522%	0.1273%	0.1251%	0.1389%	0.2167%	0.2169%	0.2338%
2	−0.0001%	0.0257%	0.0449%	0.1151%	0.1134%	0.1259%	0.1292%	0.1334%	0.1435%
3	−0.0138%	0.0238%	0.0375%	0.1028%	0.1017%	0.1130%	0.0418%	0.0500%	0.0532%
4	−0.0276%	0.0220%	0.0302%	0.0905%	0.0901%	0.1000%	−0.0457%	−0.0335%	−0.0372%
5	−0.0413%	0.0202%	0.0228%	0.0783%	0.0784%	0.0870%	−0.1332%	−0.1169%	−0.1275%
10	−0.1101%	0.0110%	−0.0139%	0.0170%	0.0201%	0.0222%	−0.5704%	−0.5342%	−0.5791%
FTSE model									
0.5	−0.0036%	0.0063%	0.0138%	0.1543%	0.1668%	0.1678%	0.3598%	0.3884%	0.3919%
1	−0.0103%	0.0048%	0.0080%	0.1479%	0.1613%	0.1610%	0.3132%	0.3499%	0.3434%
2	−0.0236%	0.0020%	−0.0035%	0.1350%	0.1504%	0.1475%	0.2200%	0.2729%	0.2465%
3	−0.0369%	−0.0009%	−0.0150%	0.1220%	0.1394%	0.1339%	0.1268%	0.1959%	0.1497%
4	−0.0502%	−0.0038%	−0.0265%	0.1091%	0.1285%	0.1204%	0.0336%	0.1189%	0.0528%
5	−0.0635%	−0.0067%	−0.0380%	0.0962%	0.1175%	0.1068%	−0.0596%	0.0419%	−0.0441%
10	−0.1302%	−0.0210%	−0.0955%	0.0316%	0.0628%	0.0391%	−0.5256%	−0.3431%	−0.5286%
NIKKEI model									
0.5	−0.0609%	0.0047%	0.0072%	0.2489%	0.2474%	0.2540%	0.6319%	0.6167%	0.6230%
1	−0.0668%	0.0033%	0.0018%	0.2432%	0.2422%	0.2458%	0.5884%	0.5759%	0.5578%
2	−0.0785%	0.0006%	−0.0092%	0.2319%	0.2317%	0.2295%	0.5014%	0.4944%	0.4276%
3	−0.0902%	−0.0021%	−0.0201%	0.2206%	0.2211%	0.2132%	0.4144%	0.4129%	0.2973%
4	−0.1019%	−0.0049%	−0.0310%	0.2093%	0.2106%	0.1969%	0.3274%	0.3314%	0.1671%
5	−0.1136%	−0.0076%	−0.0420%	0.1980%	0.2001%	0.1806%	0.2404%	0.2499%	0.0369%
10	−0.1722%	−0.0213%	−0.0966%	0.1415%	0.1475%	0.0991%	−0.1945%	−0.1576%	−0.6144%

Notes: Tabulated are values of CEQ returns defined as $\hat{\mu}_k - (\gamma/2)\hat{\sigma}_k^2$, where $\hat{\mu}_k$ and $\hat{\sigma}_k^2$ are the mean and variance of excess returns of strategy/fund k, and γ is the risk aversion parameter. This formulation assumes a multi-period investor with quadratic utility. The 'normal' level of risk aversion is 1, higher (lower) values indicate higher (lower) levels of risk aversion.

Table 7. Trading strategies Sharpe ratios.

	RSI	OLS/FIT	FIT^L
DJIA model			
	–	2.49/–14.85/16.64/1.12	2.03/–13.11/13.77/1.05
RSI	1.35/–4.99/5.23/1.05	2.50/–13.63/16.06/1.18	2.06/–12.16/13.26/1.09
RSI^L	1.37/–4.95/5.23/1.06	2.64/–13.69/16.05/1.17	2.13/–12.13/13.40/1.11
FTSE model			
	–	2.80/–16.90/17.66/1.05	2.63/–14.08/14.29/1.02
RSI	0.28/–4.73/4.99/1.06	3.26/–15.79/17.46/1.11	3.04/–13.70/14.08/1.03
RSI^L	0.36/–4.61/4.99/1.08	2.97/–15.65/15.14/0.97	2.80/–13.65/12.19/0.89
NIKKEI model			
	–	4.74/–13.07/16.00/1.22	4.53/–10.90/13.42/1.23
RSI	0.23/–4.15/4.64/1.12	4.87/–11.78/15.80/1.34	4.55/–9.94/13.24/1.33
RSI^L	0.24/–4.14/4.64/1.12	4.06/–10.22/13.09/1.28	3.77/–8.58/11.00/1.28

Notes: Tabulated values are in the format SR/SRs($-$)/SRs($+$)/IR, where SR is the Sharpe ratio, SRs($-$) is the Sharpe ratio calculated using only negative returns, SRs($+$) is the Sharpe ratio calculated using only positive returns and IR is an index ratio calculated as SRs($+$)/|SRs($-$)| (which aims to show any asymmetry between days when model forecast is correct and days when it is incorrect). The corresponding numbers for the DJIA, FTSE and NIKKEI indices (i.e. for a simple buy-and-hold strategies) are 0.46/–16.00/16.29/1.02 for DJIA, 0.05/–17.32/17.86/1.03 for FTSE and –1.01/–14.60/14.94/1.02 for NIKKEI.

NIKKEI, for example, show negative CEQ returns at levels of risk aversion of 2 or higher. This is mainly due to the small mean return that these strategies yield relative to their volatility. In contrast, OLS/FIT strategies exhibit positive CEQ returns at all tabulated levels of risk aversion. FIT^L strategies, however, show negative CEQ returns at levels of risk aversion of 4 or more, even though their CEQ returns is higher than all other strategies at low levels of risk aversion. Thus, the spread across different levels of risk aversion of CEQ returns for FIT^L strategies is greater than that of other strategies. This is evidence of the high volatility that these strategies have relative to their (high) mean returns. Accordingly, these strategies are more susceptible to variations in risk aversion. Note that the corresponding CEQ returns of the passive index funds, DJIA, FTSE and NIKKEI, are negative at all levels of risk aversion, except DJIA at $\gamma = 0.5$ and $\gamma = 1$.

Table 7 reports four values separated by slashes for each strategy or combination of strategies. The first, denoted by SR, is the standard Sharpe ratio calculated by dividing the series of fund excess returns (excess of the domestic risk-free rate) by its standard deviation. First, all SR are positive for all strategies, which is evidence of the usefulness on risk-adjusted basis of both domestic and foreign information. Second, values of this ratio for RSI strategies range from 0.23 for NIKKEI to 1.37 for RSI^L of DJIA. The ratio for RSI^L strategies is slightly higher than that for RSI strategies for all three index models. Values of the ratio for OLS/FIT strategies range from 2.49 for DJIA to 4.87 for OLS/FIT+RSI for NIKKEI, representing roughly 1.9–19.5 times those of RSI. (Ratios for FIT^L are closer, but lower in magnitude, to those of OLS/FIT than RSI, and this will be discussed in more detail below.) Thus, adding OLS/FIT to RSI strategies increases risk-adjusted performance by 1.9–19.5 times, but adding RSI to OLS/FIT strategies increases performance only marginally, from 2.49 to 2.5 for DJIA, 2.80 to 3.26 for FTSE and 4.74 to 4.87 for NIKKEI. These results confirm the substantial incremental benefit of foreign information over domestic information on risk-adjusted basis. Accordingly, the incremental higher profitability of strategies that are based on foreign, rather than domestic, information does not come about with disproportionately increased riskiness. This is in line with the CEQ return results presented in the previous paragraphs.

The next two ratios presented in Table 7 for each strategy are dissections of the Sharpe ratio of each fund. The first, denoted by SRs(−), is the Sharpe ratio calculated using fund negative returns only (i.e. losing trades), and the second, denoted by SRs(+), is the Sharpe ratio calculated using fund positive returns only (i.e. winning trades). The reason for presenting these ratios is to gauge the relative risk-adjusted performance of losing trades, when the model(s) generate(s) incorrect predictions of return direction, which is captured by SRs(−), over that of successful trades, when the model(s) generate(s) correct predictions of return direction, which is captured by SRs(+). The higher values of SRs(+) relative to those of SRs(−) for most funds confirm the positive Sharpe ratio, SR, and reflect the fact that risk-adjusted performance of winning trades is higher in magnitude than that of losing trades. Two exceptions are OLS/FIT+RSI^{L} and FIT^{L}+RSI^{L} of FTSE, where SR(+) is lower in magnitude than SR(−). The fact that these two funds have a positive Sharpe ratio, SR, however, indicates that strategy losses during days when the models produce incorrect predictions of return direction have a slightly lower variance than that of the returns of all trades.

Finally, Table 7 lists values of an index, which we denote by IR, constructed to capture the profitability of incremental forecast accuracy. This, fourth value for each strategy, is calculated by dividing the Sharpe ratio of positive, or profitable, trades by the absolute value of the Sharpe ratio of negative or losing, trades. IR values greater than 1 would, therefore, indicate successful forecasting ability. The increment beyond a value of 1 for this index reflects the percentage difference in risk-adjusted performance between profitable and losing trades. A value of 1.20, for instance, would indicate that the risk-adjusted profit of profitable trades is 20% greater than the risk-adjusted losses of losing trades.

A few conclusions are warranted. First, the tabulated values of this index are almost all greater than 1, confirming the profitability of strategies over the out-of-sample period. In general, this is evidence for the benefits of using domestic momentum as well as foreign overnight information, especially since the DJIA, FTSE and NIKKEI indices returned a loss of −0.54%, −1.05% and −32.41%, respectively.[16] Second, in each market the IR ratios for FIT/OLS strategies are higher than those of RSI strategies, except, again for OLS/FIT + RSI^{L} of FTSE. For DJIA, adding OLS/FIT to RSI and RSI^{L} increases the index from 1.05 to 1.18 and from 1.06 to 1.17, respectively; representing 13% and 11% improvement in risk-adjusted returns. For NIKKEI, the respective improvements are 22% and 16%. In contrast, adding domestic momentum information through RSI, does not improve this percentage by much. This is supportive of previous results.

A peculiar result in Table 7, however, are the lower values of the Sharpe ratio (in the three indices), and values of the IR index (in DJIA and FTSE), for FIT^{L} strategies relative to those of OLS/FIT strategies. On face value, this may indicate detrimental risk-adjusted contribution of the indirect channel of foreign information from third markets, z, and is contradictory to conclusions reached from discussion of returns in Section 4.3. A closer inspection, however, of the relative values of SRs(+) and SRs(−) between FIT^{L} and FIT/OLS strategies shows that the volatility of profitable trades is higher in FIT^{L} strategies than in corresponding FIT/OLS strategies. For example, under DJIA the ratio of SRs(+) of OLS/FIT to that of FIT^{L} is around 1.21 (16.64/13.77 or 160.06/13.26), while the ratio of SRs(−) between these two strategies is around 1.13 (−14.85/−13.11 or −13.63/−12.16). The same strategies in FTSE show ratios of around 1.23 for SRs(+) and around 1.15 for SRs(−). For NIKKEI, they are 1.19 for both SRs(+) and SRs(−). However, for NIKKEI the IR values are roughly the same for both OLS/FIT and FIT^{L}. Accordingly, there is an asymmetry between positive and negative Sharpe ratios across OLS/FIT and FIT^L strategies. For symmetric risk, all utility functions behave like the quadratic, and in this symmetry Sharpe ratio is known to have a direct correspondence with utility maximisation. With asymmetric risk, or ‘skewed’ returns, however, this correspondence is affected. Indeed, the skewness of fund returns is slightly different across corresponding OLS/FIT and FIT^L strategies. FIT^L funds for DJIA have return skewness that ranges from 1.00 (for $FIT^L + RSI^L$) to 1.10 (for $FIT^L + RSI$), while the values for corresponding OLS/FIT funds are 0.69 and 0.74. The same ranges for FTSE are 1.27–3.67 for FIT^L funds and 0.84–2.59 for OLS/FIT funds. In NIKKEI, the same ranges are 1.84–3.33 for FIT^L funds and 1.37–2.59 for OLS/FIT funds. Thus, FIT^L fund returns are clearly more skewed than the corresponding OLS/FIT funds. This affects the Sharpe ratio. The Sharpe ratio is also affected by high kurtosis (cf., Cuthbertson and Nitzsche 2005, 174), and by virtue of leverage, which averages to about 2.2 times, FIT^L strategies exhibit higher kurtosis. FIT^L funds for DJIA have excess kurtosis ranging from 11.03 to 11.36, while corresponding OLS/FIT funds have lower kurtosis ranging from 7.00 to 7.86. The pattern of lower kurtosis for OL/FIT funds than that of FIT^L repeats for FTSE and NIKKEI indices. Moreover, the fact that values of SRs(+) and SRs(−) are lower for FIT^L funds than corresponding values of OLS/FIT funds also confirms a higher variance. Thus, FIT^L fund returns exhibit higher variance, skewness and kurtosis. Accordingly, patterns found in values of the Sharpe ratio correspond to patterns of CEQ returns at high levels of risk aversion, as reported in Table 6, but deviate at lower levels of risk aversion mainly because of skewness and kurtosis. The indirect channel of foreign information through third markets is, therefore, useful at lower levels of risk aversion, but can be associated with disproportionately higher risk at higher levels of risk aversion. The incremental benefit of this channel of information, therefore, seems to be more investor specific than the direct channel of foreign information, since it is sensitive to levels of risk aversion. Overall, these results document the incremental value of meteor-shower-type foreign information over momentum-type domestic information.

4.5 *Relative prediction and leverage allocation ability*

Table 8 lists values of two direction quality measures of prediction ability: the first, denoted by Q, is the proportion of number of trades for which return direction is correctly predicted, and the second is the Pesaran and Timmermann (1992) measure, denoted by S_n, which ranges from −0.5 for zero accuracy in predicting return direction to 0.5 for perfect prediction accuracy. These measures are the same for leveraged and unleveraged strategies and, in order to avoid repetition, values are reported once for both leveraged and unleveraged strategies. Moreover, the patterns across strategies are the same for both measures and, hence, the discussion will focus on values of the Q measure, but conclusions apply equally to both measures. Table 8 shows that RSI is correct only 25%, 27.45% and 41.59% of the time during the out-of-sample period for DJIA, FTSE and NIKKEI, respectively. Hence, only 31 trades produced positive returns out of the total 124 that it signalled for DJIA; only 28 trades produced positive returns out of the 102 trades that it signalled for FTSE and only 47 trades produced positive returns out of the 114 trades that it signalled for NIKKEI. At Q values of 45.34% for DJIA, 54.27% for FTSE and 51.05% for NIKKEI, the foreign information-based models of OLS/FIT far outperform the domestic information-based model of RSI. Adding foreign information to domestic information, i.e. OLS/FIT to RSI, increases return direction prediction accuracy by 18.03% (from 25% to 43.03%) for DJIA, 25.47% (from 27.45% to 52.92%) for FTSE and 9.17% (from 41.59% to 50.76%) for NIKKEI. In contrast, adding domestic information to foreign information, i.e. RSI to OLS/FIT, marginally reduces prediction accuracy by 2.31% (from 45.34% to 43.03%) for DJIA, 1.35% for FTSE and 0.29% for NIKKEI. These

Table 8. Signal and model direction quality.

	RSI	OLS/FIT/FIT^{L}
DJIA model		
	–	45.34% / –0.0488
RSI/RSI^{L}	25.00% / –0.2497	43.03% / –0.0725
FTSE model		
	–	54.27% / 0.0423
RSI/RSI^{L}	27.45% / –0.2238	52.92% / 0.0284
NIKKEI model		
	–	51.05% / 0.0170
RSI/RSI^{L}	41.59% / –0.0827	50.76% / 0.0150

Notes: The table reports two direction quality measures separated by a slash for each strategy. The first is $Q = N\{r_t r_t^* > 0\}/N\{r_t r_t^* \neq 0\}$, where r_t^* is the return forecast of a strategy, the numerator, $N\{r_t r_t^* > 0\}$, is the number of trades for which the directions of the forecast and the actual return are the same (i.e. profitable trades) and the denominator, $N\{r_t r_t^* \neq 0\}$, is the total number of observations in the sample (excluding the zero-return observations). The second is the Pesaran and Timmermann (1992) measure $S_n = \sum_{i=1}^{m} (\hat{P}_{ii} - \hat{P}_{io}\hat{P}_{oi})$ where in an $m \times m$ contingency table of return categories ($+$, $-$ and 0), n is the total number of observations, n_{io} is the ith row total, n_{oj} is the jth column total, $\hat{P}_{ii} = n_{ii}/n$, $\hat{P}_{io} = n_{io}/n$, and $\hat{P}_{oi} = n_{oi}/n$. S_n ranges from -0.5 for zero accuracy in predicting direction of returns to 0.5 for perfect prediction accuracy, and a value of 0 would indicate 50% prediction accuracy.

results show clearly that foreign information provides substantial improvements to predictive ability of domestic returns than domestic information embedded in the prior 10-day history of domestic returns, which is what RSI incorporates.

We next comment on a specific feature of FIT not shared with OLS, which is its ability to identify trades to which high leverage should be applied. Table 9 lists performance values of three primary-leverage FIT^{L} strategies. Panel A reports the performance of these strategies without leverage multiplies applied, while Panel B reports the same with multiples applied. These strategies are not listed in Table 4, and are constructed here for the sole purpose of gauging the incremental value of leverage.

The first column of Panel A (entitled FIT (1,0,0)) shows that 286 DJIA trades, signalled by FIT to receive the highest leverage of three, yielded a total cumulative return of 52.17% (or 0.18% per trade). The corresponding 294 trades for FTSE yielded 74.99% (or 0.26% per trade) and the 298 of NIKKEI yielded 139.01% (or 0.18% of trade). The second column (entitled FIT (0,1,0)) shows that 288 DJIA trades, signalled by FIT to receive the middle leverage of two, yielded a total cumulative return of 24.31% (or 0.08% per trade). The corresponding 298 FTSE trades yielded 42.12% (or 0.14% per trade) and the 287 of NIKKEI yielded 51.11% (or 0.18% per trade). Finally, the third column (entitled FIT (0,0,1)) shows that 134 DJIA trades, signalled by FIT to receive the lowest leverage of 1, yielded a total cumulative return of 33.35% (or 0.25% per trade). The corresponding 145 FTSE trades yielded 11.85% (or 0.08% per trade) and the 126 NIKKEI trades yielded 9.34% (or 0.07% per trade). Accordingly, FIT seems to allocate its highest leverage to the most profitable trades, middle leverage to the slightly less profitable trades and lowest leverage to the least profitable trades. This pattern is clearest for FTSE and NIKKEI, but largely shared by DJIA. The tabulated corresponding Sharpe ratios and CEQ returns confirm that the relative

Table 9. Performance of primary leverage FIT strategies.

	DJIA model			FTSE model			NIKKEI model		
	FIT (1, 0, 0)	FIT (0, 1, 0)	FIT (0, 0, 1)	FIT (1, 0, 0)	FIT (0, 1, 0)	FIT (0, 0, 1)	FIT (1, 0, 0)	FIT (0, 1, 0)	FIT (0, 0, 1)
Panel A									
Return per trade	0.18%	0.08%	0.25%	0.26%	0.14%	0.08%	0.47%	0.18%	0.07%
Number of trades	(286)	(288)	(134)	(294)	(298)	(145)	(298)	(287)	(126)
Cumulative return	52.17%	24.31%	33.35%	74.99%	42.12%	11.85%	139.01%	51.11%	9.34%
Compounded return	57.95%	24.71%	38.36%	97.48%	48.92%	11.62%	275.01%	64.04%	9.27%
Sharpe ratio	1.42	1.12	2.46	1.92	1.82	0.66	3.74	2.83	0.91
CEQ (for $\gamma = 1$)	0.0575%	0.0274%	0.0407%	0.0828%	0.0468%	0.0099%	0.1684%	0.0627%	0.0108%
	DJIA model			FTSE model			NIKKEI model		
	FIT (3, 0, 0)	FIT (0, 2, 0)	FIT (0, 0, 1)	FIT (3, 0, 0)	FIT (0, 2, 0)	FIT (0, 0, 1)	FIT (3, 0, 0)	FIT (0, 2, 0)	FIT (0, 0, 1)
Panel B									
Return per trade	0.55%	0.17%	0.25%	0.77%	0.28%	0.08%	1.40%	0.36%	0.07%
Number of trades	(286)	(288)	(134)	(294)	(298)	(145)	(298)	(287)	(126)
Cumulative return	156.52%	48.61%	33.35%	224.96%	84.24%	11.85%	417.02%	102.22%	9.34%
Compounded return	169.78%	48.74%	38.36%	414.66%	111.85%	11.62%	3461.95%	160.57	9.27%
Sharpe ratio	1.17	1.14	2.46	1.97	1.89	0.66	3.75	2.84	0.91
CEQ (for $\gamma = 1$)	0.1241%	0.0499%	0.0407%	0.2028%	0.0919%	0.0099%	0.4538%	0.1219%	0.0108%

Notes: FIT^{L} leverage parameters (c, b, a) are based on the following quintiles of 'in-sample' intensity (beta) deviations: $c = $ 1st and 5th quintile, $b = $ 2nd and 4th quintile and $a = $ middle 3rd quintile. Each panel lists the average cumulative return per trade, the number of trades, the total cumulative return, the compound return (gross of transaction costs), the Sharpe ratio and the CEQ return when risk aversion is 1 (i.e. $\gamma = 1$). Panel A presents results without applying leverage multiplies to trades and Panel B presents results with leverage multiples applied. The average leverage multiple applied across trades in Panel B is 2.2.

ranking of these groups is preserved when performance is adjusted for risk. The pattern is also repeated in Panel B when leverage multiples are applied. The relatively higher scale of the FIT (1, 0, 0) trades is apparent. Accordingly, most of the superior performance of FIT^L reported in Tables 4 and 6 is due to trades that were identified (correctly) by FIT to be worthy of being allocated the higher leverage multiples of two and three. This is also apparent from the relative scale of the returns of the respective leverage strategies plotted in Figure 2. It is, therefore, clear that FIT's capability of allocating leverage is credible, and the incremental information it provides about the changing intensity of meteor showers is economically valuable. The numbers reported in Table 9 are quantifications of these incremental benefits.

Finally, it is interesting to note from the average return per trade plots of Figures 3–5 that profits from FIT^L trades tend to be non-linearly related to leverage, particularly the *b* or *c* leverage, which are the leverages applied to the outermost (highest) and middle (medium) intensity quintile trades, but roughly linearly related to the *a* leverage, which is the one applied to the innermost (lowest) intensity quintile trades. This indicates a need to pre-calibrate the degree of leverage that ought to be applied, particularly to trades identified with the outermost intensity quintiles. In this application with DJIA, FTSE and NIKKEI, and period of study, it seems that (2, 1, 10), (3, 2, 1) and (8, 7, 1), in order of (*c*, *b*, *a*) would have been optimal multiples to apply for DJIA, FTSE and NIKKEI trades, respectively. Note, however, that in many cases the considerable scale of profitability provided by the FIT (1, 0, 0) high-intensity trades, especially in NIKKEI, lend ample room for error or manoeuvre in this pre-calibration. For instance, in the NIKKEI case any value within the range 0–10 for any of the three leverage multiples would yield profits. In the case of the most restrictive DJIA, profits could be earned, with leverages *c*, *b* and *a* being within the ranges 1–4, 1–3 and 1–10, respectively.

5. Robustness

The above results are reported over a 3-year out-of-sample period of an initial 9-month bear-market period followed by a 27-month slowly rising market period. During these two consecutive periods, the DJIA decreased by 48% and rebounded to the same level, the FTSE decreased by 50% and gained back only 32% and the NIKKEI decreased by 42% and rebounded to about the same level. Accordingly, sub-periods may show different fund performance than those reported in Table 4 and discussed above for the entire 3-year out-of-sample period. The graphs of Figure 1, however, exhibit the day-to-day performance, and hence reveal the relative performance of funds on a daily basis throughout the out-of-sample period. This is, therefore, an already robust means of comparison across models over time. Nonetheless, we run a further check on whether the superior performance of FIT reported above is particular to the length of the out-of-sample period. This is carried out by investigating performance over non-overlapping sub-periods of the total out-of-sample duration. The 3-year out-of-sample period from 1 June 2008 to 31 May 2011 is divided into 3, 4 and 10 equal and non-overlapping sub-periods. Table 10 reports the cumulative gross returns that FIT, as a sample of foreign information funds, together with the passive index tracking funds, would have earned over these non-overlapping periods. First, the table reports substantial positive fund performance during bear-market periods, such as periods 1 and 4 in the 4 sub-samples division and periods 1, 2, 3, and 7 in the 10 sub-samples division. This may indicate that the frequency and magnitude of common international foreign information dominate domestic information more when news is bad than good. However, this is not always the case since the FIT funds outperform the indices during some bull-market periods, such as periods 2 and 3 in the three sub-samples division for NIKKEI and DJIA, respectively.

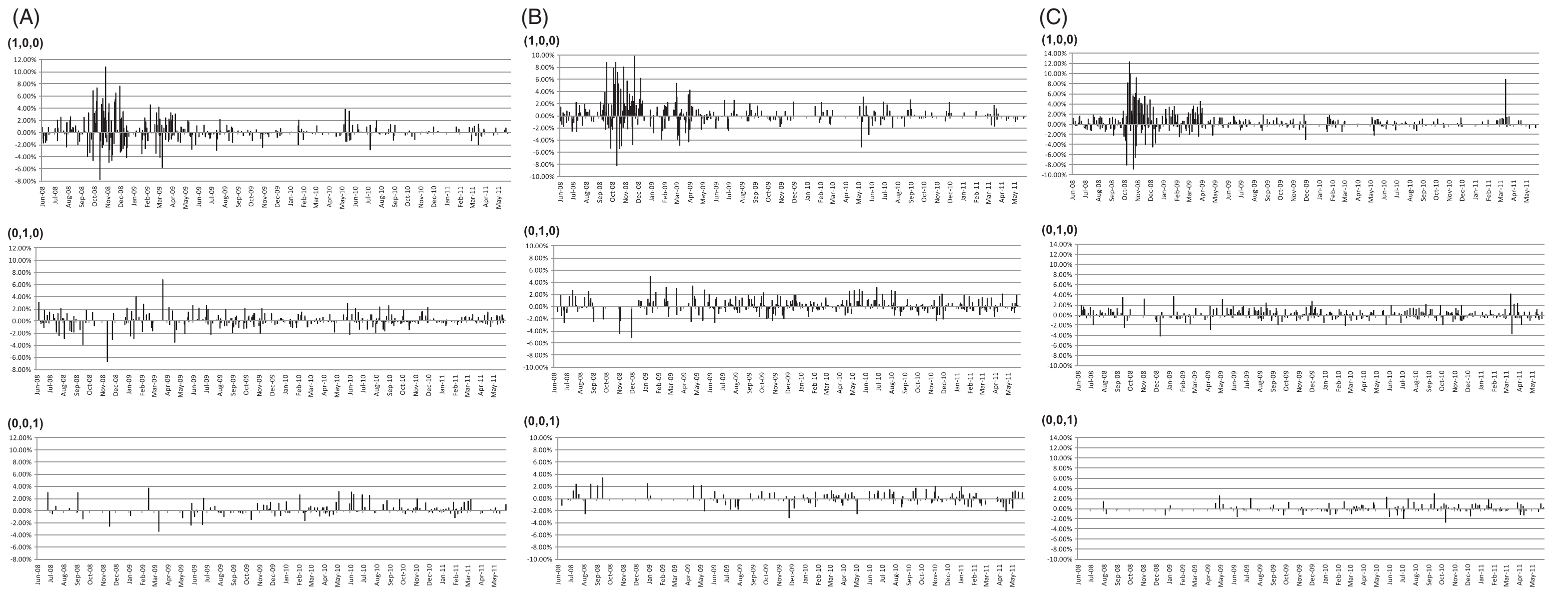

Figure 2. FIT primary leverage strategy returns: (A) DJIA model, (B) FTSE model. and (C) NIKKEI model.
Note: FIT leverage parameters (c, b, a) are based on the following quintiles of 'in-sample' beta deviation: c = 1st and 5th quintile, b = 2nd and 4th quintile and a = middle 3rd quintile.

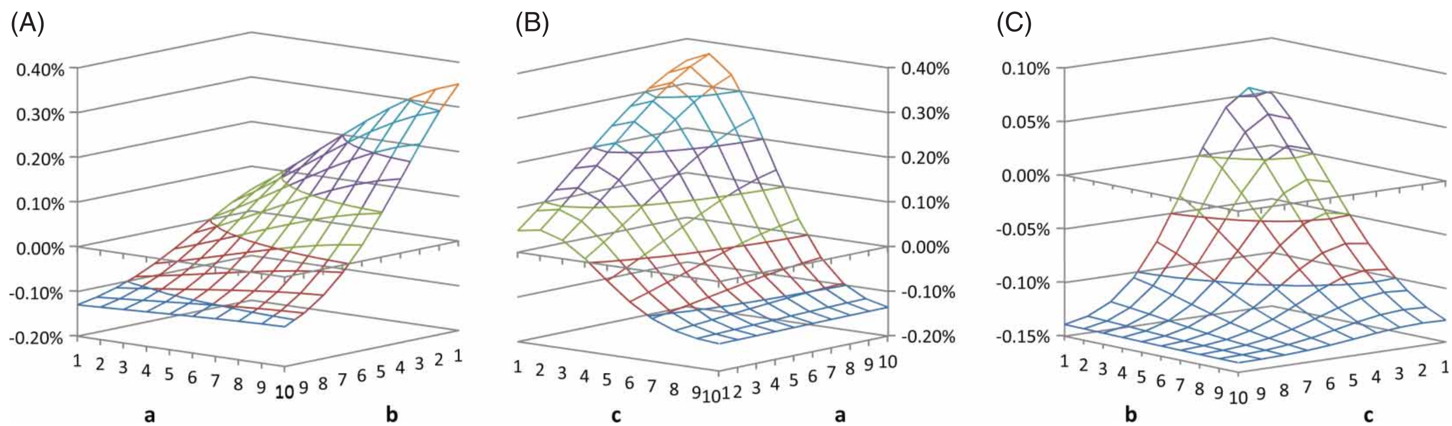

Figure 3. FIT^L average return per trade at leverage levels (c, b, a): DJIA model. (A) Average returns per trade for leverage levels a and b keeping c constant $= 1$. (B) Average returns per trade for leverage levels a and c keeping b constant $= 1$. (C) Average returns per trade for leverage levels b and c keeping a constant $= 1$. Notes: FIT^L leverage parameters (c, b, a) are based on the following quintiles of 'in-sample' intensity (beta) deviations: $c = $ 1st and 5th quintile, $b = $ 2nd and 4th quintile and $a = $ middle 3rd quintile. Average per trade returns are negative at some combinations of leverage, since most strategy returns relate to outermost intensity quintile trades, and conducting those with high leverage when mis-forecasted can cause large losses or even fund bankruptcy.

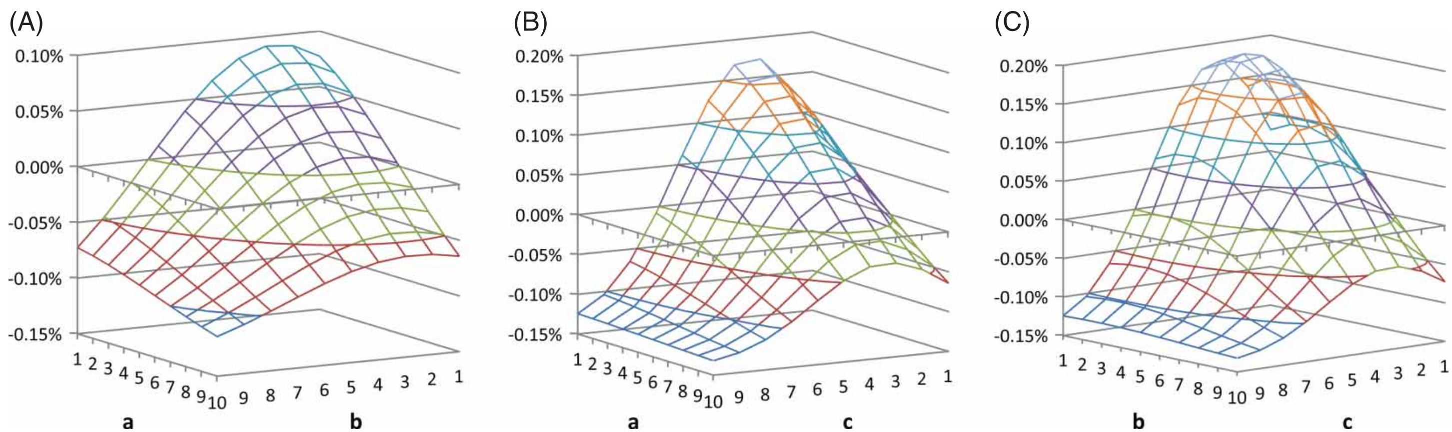

Figure 4. FIT^{L} average return per trade at leverage levels (c, b, a): FTSE model. (A) Average returns per trade for leverage levels a and b keeping c constant $= 1$. (B) Average returns per trade for leverage levels a and c keeping b constant $= 1$. (C) Average returns per trade for leverage levels b and c keeping a constant $= 1$.

Notes: FIT^{L} leverage parameters (c, b, a) are based on the following quintiles of 'in-sample' intensity (beta) deviations: $c = $ 1st and 5th quintile, $b = $ 2nd and 4th quintile and $a = $ middle 3rd quintile. Average per trade returns are negative at some combinations of leverage, since most strategy returns relate to outermost intensity quintile trades, and conducting those with high leverage when mis-forecasted can cause large losses or even fund bankruptcy.

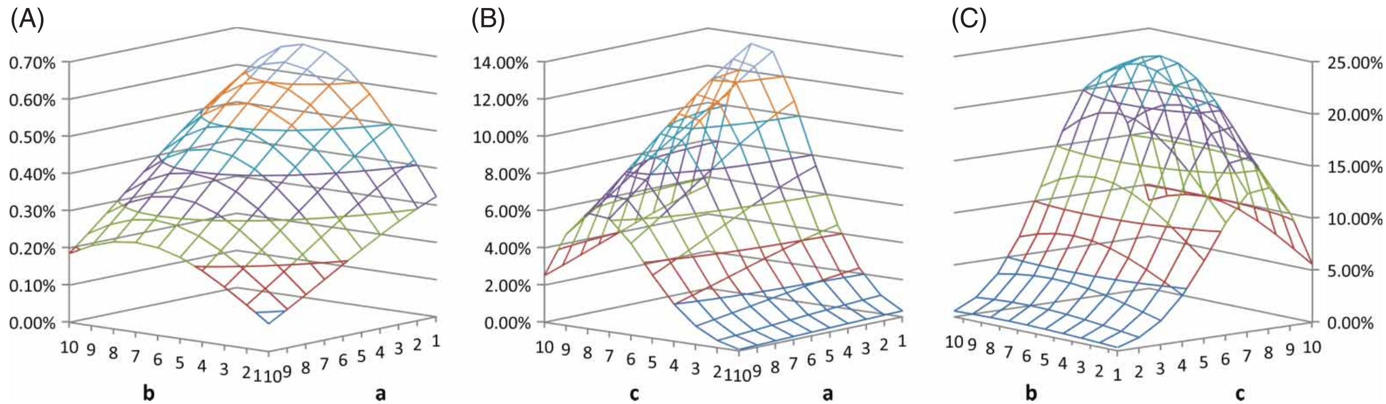

Figure 5. FIT[L] average return per trade at leverage levels (*c*, *b*, *a*): NIKKEI model. (A) Average returns per trade for leverage levels *a* and *b* keeping *c* constant = 1. (B) Average returns per trade for leverage levels *a* and *c* keeping *b* constant = 1. (C) Average returns per trade for leverage levels *b* and *c* keeping *a* constant = 1.

Notes: FIT[L] leverage parameters (*c*, *b*, *a*) are based on the following quintiles of 'in-sample' intensity (beta) deviations: *c* = 1st and 5th quintile, *b* = 2nd and 4th quintile and *a* = middle 3rd quintile. Average per trade returns are negative at some combinations of leverage, since most strategy returns relate to outermost intensity quintile trades, and conducting those with high leverage when mis-forecasted can cause large losses or even fund bankruptcy.

Table 10. Fund cumulative returns: different out-of-sample periods.

	Period	Model			Simple buy-and-hold strategy		
		DJIA	FTSE	NIKKEI	DJIA index	FTSE index	NIKKEI index
Three sub-samples							
1	02/06/2008–29/05/2009	50.71%	99.13%	127.13%	−32.74%	−27.02%	−33.61%
2	01/06/2009–31/05/2010	7.70%	13.83%	35.90%	19.23%	17.44%	2.64%
3	01/06/2010–31/05/2011	48.84%	14.00%	34.75%	24.04%	15.45%	−0.55%
Four sub-samples							
1	02/06/2008–02/03/2009	48.65%	99.22%	87.94%	−46.48%	−40.10%	−49.24%
2	03/03/2009–30/11/2009	−1.66%	−7.27%	65.96%	52.92%	43.16%	30.20%
3	01/12/2009–30/08/2010	31.67%	39.92%	17.68%	−3.23%	0.21%	−1.43%
4	31/08/2010–31/05/2011	31.17%	−2.91%	27.88%	25.62%	15.16%	7.72%
Ten sub-samples							
1	02/06/2008–18/09/2008	6.50%	13.60%	18.56%	−12.80%	−19.39%	−19.90%
2	19/09/2008–06/01/2009	29.91%	65.02%	52.69%	−18.25%	−4.94%	−21.93%
3	07/01/2009–24/04/2009	18.07%	21.04%	44.44%	−10.23%	−10.41%	−4.66%
4	27/04/2009–12/08/2009	−3.01%	−8.20%	26.84%	15.95%	13.49%	18.80%
5	13/08/2009–30/11/2009	−4.48%	0.50%	11.37%	10.49%	10.05%	−11.06%
6	01/12/2009–18/03/2010	4.31%	16.78%	2.64%	4.21%	8.71%	15.75%
7	19/03/2010–06/07/2010	24.32%	17.01%	5.51%	−9.61%	−12.01%	−13.42%
8	07/07/2010–22/10/2010	4.90%	8.57%	18.69%	14.33%	15.64%	1.12%
9	25/10/2010–09/02/2011	12.77%	3.50%	4.82%	9.94%	5.42%	12.66%
10	10/02/2011–31/05/2011	16.54%	−8.85%	13.90%	2.70%	−1.03%	−8.33%

Notes: Tabulated are cumulative returns for FIT models (without leverage) and buy-and-hold index strategies. The out-of-sample investment period of 783 days from 1 June 2008 through 31 May 2011 is divided into 3, 4 and 10 sub-samples.

In general, the table shows that most returns are positive, and often substantial, in all sub-periods except one or two in which the negative return is relatively very small in magnitude. Thus, funds more than make up for the relatively small losses when they occur. This, and the graphs of Figure 1, which, in effect, are breakdowns of the out-of-sample period to daily sub-periods, clearly show that though the general trend of performance is positive, leverage funds are particularly advantaged during the first 9 months. This is expected, since forecast performance of most models deteriorates with the duration of out-of-sample forecast period, which in our case is rather long.

6. Conclusion

The aim of this paper is to answer the question: how much more (or less) returns will a day trader earn by using various combinations of different interpretations of foreign news signals and domestic market momentum than the latter alone?

Foreign information of previous-day or overnight trading in international stock markets is very useful. In domestic day trading, these meteor showers can be responsible for more than quintupling the performance of strategies that are based on domestic momentum information alone. The way this foreign information is interpreted by other international markets that operate in intermediate time also seems to offer incremental risk-adjusted economic benefits. These benefits are further enhanced by taking into account (i.e. modelling, as by FIT) the daily changes in the effect this intermediate overnight interpretations have on the intensity of meteor showers.

The paper also presents clear evidence that the grading of foreign information signals by their forecasted intensity deviations provided by FIT, and the consequential ability to allocate leverage, is very useful indeed.

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Notes

1. Other relevant papers about signal transmission effects include: Ito, Engle, and Lin (1992), Lin, Engle, and Ito (1994), Longin and Solnik (2001), Bekaert, Harvey, and Ng (2005), Masih and Masih (2001), Climent and Meneu (2003), Eun and Shim (1989), Bekaert and Harvey (1997, 2000), Pagan and Schwert (1990), King and Wadhwani (1990), Bollerslev, Chou, and Kroner (1992), Adjaoute, Bruand, and Gibson-Asner (1998), Baillie and Bollerslev (1991), Melvin and Hogan (1994) and Melvin and Melvin (2003).
2. Thus, DJIA is taken as the y variable, NIKKEI as the x variable and FTSE as the z variable in the FIT model of Equations (1)–(3). The chronological sequence of trading in these markets is preserved in the empirical application. Accordingly, signals (returns) from NIKKEI trades occur prior to NYSE open on the same day, and FTSE signals, which are from a market that is intermediate in time (up to 2 or 3 pm GMT), affect the relationship between DJIA and NIKKEI.
3. We investigate effects of relaxing this assumption later on in the text. For the same reason, we have chosen the above version of RSI over a more traditional version where RS is defined in terms of only numbers of positive or negative price changes (i.e. a version that ignores relative return magnitude).
4. The rule is simplified to the cases when the steady-state values of alpha i.e. $\bar{\alpha}$ are either zero or positive and those of beta, $\bar{\beta}$ are positive. Estimation results of the relationships considered, reported in Table 2, show that all estimates of $\bar{\alpha}$ are zero and those of $\bar{\beta}$ are positive. Thus, predicted, expected, or forecast returns of market y are directly proportional to returns from the signalling market, x.
5. Note that this construction, by and large, uses one set of information (the domestic set) to filter the other set (the foreign set) with the aim of strengthening or weakening the conviction of the domestic investor about the direction of the day-ahead returns. An investor with only foreign information is in possession of a smaller set of information but would perhaps trade more frequently. This is because the additional set of domestic information effectively reduces the number of trades by forcing the investor to be more selective of which trades to initiate (and with what leverage).
6. DJIA day returns series exhibit significant alpha and beta GARCH(1,1) coefficients of 0.0664 (9.93) and 0.9262 (130.60), where values in parenthesis are z-statistics. The same coefficient estimates for NIKKEI are 0.0800 (11.03) and 0.9097 (117.36), and for FTSE are 0.1024 (10.70) and 0.8903 (89.83). The sum of alpha and beta is less than 1 for all three relationships, which shows stationarity. A battery of tests on heteroskedasticity and autocorrelations, reported in Table 2, further confirm the adequacy of a GARCH(1,1) lag structure.
7. Although estimations of the relationships are carried out using 'standardised' returns, the trading strategies are obviously carried out on non-standardised returns to reflect actual trading gains or losses.
8. In general, the value that R^2 takes on tends to be low when the magnitude of returns expected or forecasted by a model is small relative to that of actual observed returns. This is true despite the fact that the model may form perfectly correct expectations or forecasts of the *direction* of returns. Direction quality measures such as those we present in Table 6 are more reflective of a model's ability to forecast return direction, which is a feature that is central to the profitability of the trading strategies considered.
9. Conceptually, such risk would arise mainly from conducting highly leveraged trades based on wrong forecasts during volatile days. Technically, the DJIA needs to crash by 16.67% for one who applies our highest level of leverage (a multiple of 6) to lose all fund capital in one single day. Obviously, a series of high leveraged trades based on wrong forecasts can lead to the same demise over an extended period.
10. This benefit is cumulative with the FIT model's ability at allocating leverage based on categories of intensity deviations. Section 4.5 investigates FIT's ability at allocating leverage by isolating its performance.
11. The largest leverage of 3 is applied to approximately 40% of FIT trades – these are trades initiated as a result of forecast intensity (beta) deviations that belong to the two outermost quintiles (first and fifth quintiles) of beta deviations. In

other words, these are trades carried out during days when the intensity impact of foreign information is forecast to be strongest. Another 40% of trades get allocated a leverage of 2 (second and fourth quintiles), and 20% of trades a leverage of 1 (middle quintile).

12. The ability to predict return direction is analysed in detail in Section 4.5 by using direction quality measures.
13. Bounds for RSI strategies will obviously need to be pre-specified before trading. This can be done using in-sample data.
14. Other momentum measures would probably show similar performance to RSI, since such measures are based on the same principle of relative moving averages. For example, a moving average convergence divergence (MACD) of 10/30 (−3%, 3%), where 10/30 are the respective short and long moving average lengths and the (−3%, 3%) are the filter bounds, gives identical direction signals to those given by the RSI (10 lags with 20/80 bounds used in this study) during days when they both give a signal. An MACD of 10/30 (0%, 0%) gives signals that coincide 73% of the time with those given by RSI (10 lags with 50/50 bounds).
15. Many of the Treynor betas, especially for funds based on DJIA and FTSE, are either statistically insignificantly different from zero or negative during the out-of-sample period. Average excess returns, however, are positive for all funds. For cases of zero betas, this is evidence of a risk adjustment not explaining away the performance of corresponding strategies. We thank an anonymous referee for this observation. Nonetheless, it is well known that the Treynor measure is hard or impossible to interpret when betas are negative, and cannot be calculated when betas are zero. Accordingly, the Treynor measure is not reported, but relevant calculations are available from the authors upon request.
16. These are cumulative gross returns (holding period returns). These values are noted in the caption of Table 4.

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