Return Predictability and Contrarian Profits of International Index Futures

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Using futures markets, we find significant lead-lag relationships among 11 industrialized countries. Lagged monthly returns for several countries have return predictability comparable to those in the United States for the 1988-2016 period, complementing the results of Rapach, Strauss, and Zhou (2013). The international futures markets are more correlated in market downturns, while the lead-lag relationships are more significant in market upturns. Consistent with these asymmetric relationships, a contrarian strategy (in particular, by buying the losers) offers significant profits in an up market but not in a down market. The contrarian profits are negatively correlated with the momentum profits and are not captured by a factor model using global equity factors and momentum profits.

Keywords: asymmetric relationships, contrarian profits, international index futures, return predictability

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1. INTRODUCTION

Stock return predictability is an important and controversial issue for investors. In a seminar paper, Lo and McKinlay (1990a) find that returns on large US stocks lead returns on small stocks. Rapach et al. (2013; hereafter, RSZ) examine predictability in an international setting. They show that lagged US monthly index returns significantly predict returns in non-US industrialized countries during the period 1980–2010. They point out that such lead-lag relationships, including the Lo and McKinlay findings, can be interpreted as evidence of information friction resulting from limited attention and investors' limited information-processing capabilities.

In particular, investors focus more on the US market, "which, in the presence of information-processing limitations, creates a gradual diffusion of relevant information on macroeconomic fundamentals across countries, thereby generating predictive power for lagged US returns" (RSZ, p. 1658). See Hong and Stein (1999), Hong et al. (2007), and RSZ for theoretical models of this gradual diffusion process.

In this paper, we extend the results of RSZ in several important areas. First, we use futures data with the same 11 sample countries as RSZ and a more recent period, 1988–2016. Futures contracts with lower transaction costs, no short-sale constraints, and electronic trading facilitate an examination of the lead-lag relationship and trading strategies. Unlike futures, stock indexes used in prior research are not practically tradable. The active futures contracts in electronic exchanges also minimize the illiquidity problem and other market imperfections, such as the bid-ask spread and stale price bias for some inactive stocks in an index. Second, we follow the approach of McQueen et al. (1996) in investigating directional asymmetry. McQueen et al. find that the predictive power of US large stocks is asymmetric in up (i.e., good) and down (i.e., bad) markets, with a slow response by small stocks to good news. Third, as documented by Lo and MacKinlay (1990a), if returns on some stocks systematically lead or lag those of others, a trading strategy that sells "winners" and buys "losers" can yield excess returns. We use a similar contrarian strategy, that of Jegadeesh (1990) and Lehmann (1990), to capture this arbitrage profit. RSZ do not examine the asymmetric relationships and the trading strategy.

We confirm the predictive power of US lagged returns for other countries, although US dominance is weaker than reported in RSZ. Some countries have influence on others comparable to that of the US. In particular, lagged Swedish returns can predict US returns both in-sample and out-of-sample. We find that all international futures returns are highly correlated with one another, while the markets are more correlated during market downturns. Consistent with McQueen et al. (1996), the contemporaneous relationships are more significant in down markets, and the lead-lag relationships are more significant in up markets. These results indicate that investors sell all international stocks quickly when the aggregate market is down, and it takes longer to determine which country portfolio to buy when the market is up.

The significant lead-lag relationships among country futures suggest that potential profits can be gained from using a contrarian strategy. We show that the strategy of taking a short position on the winner (the futures with the largest returns last month) and a long position on the loser (the futures with the smallest returns last month) offers arbitrage profit of 0.66% (t = 2.31) per month. Further analysis of up and down markets reveals that profit comes primarily from the up market and the long position, 0.95% (t = 2.83). The alphas given by a model using the market and other global factors are similar. Including returns from the popular Jegadeesh and Titman (1993) momentum strategy in the model does not change the alphas qualitatively. These results obtained using a simple strategy are important to investors in tactical asset allocation.

We review the literature in Section 2 and describe the data and preliminary results in Section 3. Section 4 reports the results of symmetric return predictability. Section 5 investigates the asymmetric return predictability. Section 6 examines the contrarian profits suggested by the lead-lag relationships. We conclude the paper in Section 7.

2. LITERATURE REVIEW

Lo and McKinlay (1990a) write one of the most influential and earliest papers in the literature on return predictability. They show that large stocks lead small stocks in the United States. Boudoukh et al. (1994) and others find that this lead-lag relationship can be explained by the significant autocorrelation of the small stock portfolio. The lagged returns on large firms is simply represented by the lagged returns on small firms. However, Lo and McKinlay (1990b) refute this explanation unless one assumes an unreasonable level of nontrading for small stocks.

McQueen et al. (1996) show that the relationship between US large and small firms is asymmetric in up and down markets. Large and small stocks are more contemporaneously related in a down market, but the large stock portfolio leads the small stock portfolio only in an up market. McQueen et al. explain that both large and small stocks react quickly (within a month) to negative macroeconomic news, but small stocks adjust to positive news with a delay (more than a month). They state that "investors attempt to sell all stocks quickly when news of the economy is bad. When the news is good, the market participants quickly buy large, easy to price stocks but take their time and 'shop around' before buying smaller, more volatile stocks" (p. 917). This delay is consistent with the herding behavior by institutional investors examined in Sias and Starks (1997) and Wermers (1999). Chang et al. (2000) investigate investor behavior within different international markets. They find that the rate of increase in return dispersion as a function of the market return is higher in market upturns, consistent with the directional asymmetry of McQueen et al.

Examining international stock return predictability among 11 industrialized countries using stock indexes, RSZ document the dominant role of the United States in leading other countries. RSZ provide both in-sample and out-of-sample evidence of US return predictability. Put another way, in an international environment, the United States is similar to a large stock portfolio in a US domestic environment. RSZ explain their results in the context of the gradual information diffusion model of Hong and Stein (1999), in which investors can process only a portion of public information because either they have limited information-processing capability or it is too costly for them to research all information.[1] The authors describe the United States as a large trading partner for most countries and the US stock market as the largest worldwide. Investors pay more attention to the US market; consequently, information on the macroeconomy that is relevant to international equity markets diffuses gradually from the US market to other countries. RSZ further develop a novel news-diffusion model to show that US returns shocks are only fully reflected in other countries with a lag.

RSZ report that Swedish and Swiss returns also demonstrate evident in-sample predictability. Notably, both the United States and Sweden can predict returns in nine (out of ten) foreign countries with significant bidirectional Granger causality between the United States and Sweden. RSZ point out that Sweden has higher institutional ownership than other countries and institutional investors are more capable of collecting and processing information, which contribute to the Swedish market's higher pricing efficiency.

[1] Hong et al. (2007) show that industry returns that are informative about the economy can predict the overall market because information diffuses only gradually across markets. However, using more recent data, Tse (2015) shows that the results of Hong et al. are less significant.

The results of RSZ are important for international portfolio managers, and it is worthwhile to examine their results in different settings. We use international futures contracts (with no short-sale constraints and lower transaction costs than the underlying indexes) and consider different market conditions, such as McQueen et al. (1996). In the US stock market, Jegadeesh and Titman (1995) show overreaction to firm-specific news and a delayed reaction to macroeconomic news, although most of the predictability is attributable to the former. In the current study, we use international futures prices, which are likely to be driven by macroeconomic news. Thus, the contribution of a delayed reaction to contrarian profits will be greater.

Lo and MacKinlay (1990a) show that lead-lag relationships among markets generate contrarian profits, although RSZ do not pursue this practical issue. A contrarian strategy of selling winners and buying losers in the next period has been extensively examined by Jegadeesh (1990) and Lehmann (1990) for US stocks. One popular explanation of this short-term returns reversal is that the price concession reflects compensation for liquidity providers. Avramov et al. (2006) show that contrarian profits derive primarily from small and illiquid stocks. Another explanation is related to investors' overreaction to information or fads.

Da et al. (2014) find that liquidity shocks and investor sentiment play different roles in monthly returns reversals. Liquidity provision explains the reversal on losers because fire sales are more likely than fire purchases. Therefore, contrarian profits are attributable to liquidity shocks on the long side in down markets, while the short side of profits is driven by investor sentiment. Hameed and Mian (2015) report that intra-industry reversals are the main reason for contrarian profits and intra-industry reversals are stronger following market downturns. These results based on US stocks encourage us to examine contrarian profits in up and down markets using international futures markets, in which the problem of illiquidity is less important than it is in stock markets.

3. DATA AND PRELIMINARY RESULTS

We collect daily settlement prices for 11 index futures from Commodity Systems, Inc. (CSI), from January 1988 (or the first full month that the contract is traded) to December 2016. The 11 industrialized countries are the same ones that RSZ study, which use cash indexes: Australia, Canada, France, Germany, Italy, Japan, the Netherlands (NLD), Sweden, Switzerland (CHE), the United Kingdom (UK), and the United States. It is important to reexamine the results of RSZ which suggest that the markets are not informationally efficient using different data and periods. The three-month Treasury bill rates or money market rates for each country are collected from the Organization for Economic Cooperation and Development (OECD) database. Dividend yields are obtained from Datastream and Bloomberg.

Table 1 provides information on the futures exchanges and underlying indexes that represent the broad stock markets. Australia, Japan, the UK, and the United States start at the beginning of the period, and Canada starts the latest, in October 1999.[2] We begin the sample in 1988 because few countries have earlier futures trading and so that our results will not be biased by the market crash in October 1987. Several papers, for example, Hamao et al. (1990), show the change in the relationships among international stock markets caused by the crash. All the futures

[2]We use the Nikkei index futures traded on the Singapore Exchange (SGX), instead of Japan's Osaka Stock Exchange (OSE), because OSE contracts started trading later, in October 1988, and the SGX and OSE futures prices are closely related. For simplicity, we call the SGX contract the Japanese futures market.

contracts are traded on electronic platforms.[3] In an electronic market, which have no exogenous/designated liquidity suppliers, liquidity is generated endogenously. Electronic exchanges provide greater liquidity and price discovery than floor trading as well as attracting more informed traders (Bloomfield et al., 2005).

Daily futures returns are computed as percentage changes using active nearby contracts and then roll over to the next contracts within the delivery month. Monthly returns are calculated by compounding the daily returns, as in Bessembinder (1992). Using the same approach, Moskowitz et al. (2012, p. 247) point out that, in financial futures with little storage costs or convenience yield, the roll return is almost zero. Focusing on liquid futures instead of individual stocks and indexes and looking at monthly data mitigate many issues related to market imperfection, such as the bid-ask spread, stale prices, short-sale constraints, and transaction costs. Applying futures contracts to a trading strategy is much more practical than doing so in stocks and nontradable indexes.[4]

Table 1 shows the summary statistics for monthly returns. All the mean returns are positive, with a range from 0.12% in Japan to 0.96% in Sweden. The mean returns are also significant at the 10% level, except in Italy and Japan. These two countries also have the highest volatility (6.48% and 6.23%, respectively), resulting in the lowest Sharpe ratios (0.05 and 0.02, respectively). The first-order autocorrelations, presented in the last column, show that the futures have low autocorrelations (less than 0.10 and 0.04 in the United States), except in Canada (0.22)

[3]More precisely, futures contracts in Japan, the UK, and the United States switched from floor trading to electronic trading in the 1990s. The other nine countries have been using electronic trading since the beginning of the contracts.
[4]Chan et al. (2000) use 23 stock indexes of developed and emerging markets to examine momentum strategies. As they mention, investors may not be able to implement their strategies because short selling is restricted and stock index futures are not available in some countries. They also show that more momentum profits come from emerging markets.

and Switzerland (0.13). Although our sample period is different from that of RSZ, these summary statistics are generally comparable to theirs.[5]

<Table 1>

RSZ use excess returns calculated by the returns on a market index in excess of the risk-free rate. As shown in Koijen et al. (2016) and Moskowitz et al. (2012), futures returns are the same as excess returns based on a fully collateralized position.[6]

Panel A of Table 2 presents the correlations among the 11 countries. Not surprisingly, all the correlations are highly correlated (more than 0.5), with a few exceptions that are still above 0.4. We examine the correlations by partitioning the months into up and down markets. In an up market, the aggregate market offers positive returns, and a down market offers negative (and zero) returns. The aggregate market is represented by the global equity portfolio (in excess of the Treasury bill rate) obtained from the AQR data library. The global portfolio consists of 24 countries, including all 11 sample countries. AQR also provides the global equity factors of firm size (small-minus-big, *GSMB*) and value (high-minus-low, *GHML*) for calculating alphas in Section 6.

<Table 2>

Panels B and C of Table 2 report the correlations during market upturns and downturns. We observe that, for each of the 55 pairs, the correlation is considerably higher when the market is down. Consider the correlations between the United States and other countries. When we condition on months when the market rises (drops), the correlation with Australia is 0.30 (0.56),

[5]In RSZ, the average monthly excess returns range from 0.22% (Japan) to 1.03% (Sweden). Italy has the highest volatility (6.98%), and Japan has the lowest Sharpe ratio (0.04).
[6]See detailed derivations in Koijen et al. (2016). Moskowitz et al. (2012, p. 231) highlight that, for the equity indexes, the futures return series are almost perfectly correlated with the corresponding returns of the underlying cash indexes in excess of the Treasury bill rate.

Canada 0.47 (0.69), France 0.44 (0.67), Germany 0.48 (0.67), Italy 0.34 (0.55), Japan 0.07 (0.38), the Netherlands 0.46 (0.70), Sweden 0.32 (0.66), Switzerland 0.39 (0.67), and the UK 0.39 (0.71). These asymmetric correlations are reported by Longin and Solnik (2001) and others. These preliminary results give first evidence that investors sell stocks across the globe within a month or a short time during market downturn, while taking longer to buy international stocks.

4. PREDICTIVE REGRESSIONS

4.1. Benchmark predictive regression

Following Ang and Bekaert (2007) and RSZ, we start with the following benchmark predictive regression model for country *i*:

$$r_{it} = \omega_{i,0} + \omega_{i,b}\, TB_{i,t-1} + \omega_{i,d}\, DY_{i,t-1} + e_{i,t} \tag{1}$$

where r_{it} is the monthly futures returns, $TB_{i,t-1}$ is the lagged interest rate, and $DY_{i,t-1}$ is the lagged (log) dividend yield. Like Hong et al. (2007, 2014), we estimate Eq. (1) and the following regressions using ordinary least squares (OLS) with Newey-West heteroskedasticity and serial correlation correction.[7]

As shown in Table 3, $\omega_{i,b}$ are negative for ten countries, and $\omega_{i,d}$ are positive for seven countries, consistent with prior research. However, only two $\omega_{i,b}$ (France and the UK) and two $\omega_{i,d}$ (the UK and the United States) are significant based on the 10% significance level. The last column of the table reports the *p*-value of the joint hypothesis of no return predictability:

[7]We report the *t*-statistics using 12 lags in the Newey-West estimation, while the results are almost the same for three lags.

$$H_o: \omega_{i,b} = \omega_{i,d} = 0 \qquad (2)$$

The joint hypothesis is rejected for only one country (the UK). Therefore, the interest rate and dividend yield generally have no predictive power for country index returns. We have replicated all the results of the predictive regressions throughout the paper without using the interest rates and dividend yields, and the results are similar.

<Table 3>

For robustness checks, we obtain the empirical p-values using the same wild bootstrap procedures as in RSZ. The wild bootstrap considers the contemporaneous correlations across markets, allows for heteroskedasticity by conditioning on the residuals, and reduces the Stambaugh (1999) bias.[8] We report the wild bootstrapped p-values of the predictive regressions in an appendix. The overall results do not change qualitatively.[9] RSZ provide the detailed bootstrap procedures modified from Gonçalves and Kilian (2004) and Cavaliere et al. (2010) and program codes in their internet appendix.

4.2. Pairwise Granger causality

We estimate the following pairwise regressions for the 11 monthly futures returns, r_{it}:

$$r_{it} = \beta_{ij,0} + \beta_{ij}\, r_{i,t-1} + \theta_{ij}\, r_{j,t-1} + \beta_{ij,b}\, TB_{i,t-1} + \beta_{ij,d}\, DY_{i,t-1} + e_{ij,t}\ ,\ \ i \neq j \qquad (3)$$

[8] In predictive regressions with small samples, Stambaugh (1999) shows that the predictive coefficients are baised if the regressors are highly persistent and their innovations are correlated with returns.
[9] According to the bootstrapped p-values, the UK is still the only country that rejects the joint hypothesis of (2).

where $r_{i,t-1}$ and $r_{j,t-1}$ are the one-month lagged returns for countries i and j, respectively. The coefficient θ_{ij} describes the cross-market Granger causality from country j to country i. The coefficient β_{ij} controls the influence of its own market-lagged returns. On a given trading day, the Asia-Pacific markets (Australia and Japan) open first, then the European markets, and the North American markets (Canada and the United States) last. Like RSZ, we need to account for these different trading time zones, ensuring that the information released on the last day of the month in a given time zone is not incorporated into the monthly return in earlier time zones. For example, if r_{it} is the Asia-Pacific monthly return and r_{jt} is the European or North American monthly return in Eq. (3), we exclude the last trading day of month t when calculating r_{jt}. Similarly, if r_{it} is the European returns and r_{jt} is the North American returns, we exclude the last trading day of month t for r_{jt}. Nevertheless, the results are similar without this adjustment.

The cross-market causality coefficients θ_{ij} and t-statistics in parentheses of the pairwise regressions from country j (in columns) to country i (in rows) are presented in Panel A of Table 4. In Panel B, we report the panel data results for each country j. The panel data analysis imposes the same coefficients, particularly θ_j, for all markets i ($i \neq j$) in Eq. (3):

$$r_{it} = \omega_i + \beta_i r_{i,t-1} + \theta_j r_{j,t-1} + \beta_{b,i} TB_{i,t-1} + \beta_{d,i} DY_{i,t-1} + e_{it} , \tag{4}$$

We estimate panel data model (4) using the Arellano–Bover/Blundell–Bond estimation. As shown by Baltagi (2013) and other advanced texts on econometrics, use of lagged dependent variables on the right-hand side of the model (namely, a dynamic panel data model) will induce unobserved panel-level effects, fixed or random, making standard estimators inconsistent. Arellano and Bover

(1995) and Blundell and Bond (1998) develop a consistent generalized method of moments (GMM) estimator for this model.

<Table 4>

Consider the results of individual pairwise Granger causality (3) from country *j* to country *i* represented by θ_{ij} . Among the 110 cross-market causalities, 100 are positive (with the same direction of the lead-lag relationship) and 33 are significant at the 10% level. None of the 10 negative causalities are significant. The US market has significant predictive power for four countries (Australia, Germany, Italy, and the Netherlands), although RSZ show that the United States can predict returns for nine countries. We note that all other countries, except Japan, also Granger cause or lead at least one country. In particular, Sweden, France, and Switzerland lead eight, six, and five countries, respectively. Sweden is also the only country that can predict returns in the United States, $\theta_{ij} = 0.14$ ($t = 2.59$). RSZ attribute Sweden's predictive power to the country's high institutional stock ownership.

Based on panel data analysis (4), all countries (except Japan and the Netherlands) can significantly predict other markets in the aggregate. Although the United States lead only four countries in individual predictive regressions, Sweden and the United States have almost the same predictive power for other countries based on the panel model with a coefficient $\theta_j = 0.158$ and 0.156, respectively, followed by France, 0.149, and Switzerland, 0.142, all with *t*-statistics of more than 6. For reference only, we find that the results using the usual fixed-effect model are similar: The same nine countries give significant results with the same order of θ_j, Sweden, the United States, France, and Switzerland. The corresponding results (in the descending order of θ_j) in RSZ are the United States, 0.17; Switzerland, 0.13; Sweden, 0.11; and France, 0.08.

We also replicate the results beginning in November 1992, with the first monthly return from Sweden. The results are almost the same. In particular, the United States leads the same four countries in the individual predictive regressions and the coefficient of predictability in the United States, θ_j, in the panel data model is 0.151 (t = 5.47). Although the role of the United States in international stock return predictability may not be as dominant as shown by RSZ, the overall results are consistent. Most important, we find that the lagged returns of the United States and the other 10 industrialized countries can be a powerful predictor of the current returns in other countries using futures contracts.

4.3. Out-of-sample forecasts

We follow an approach similar to RSZ to examine the out-of-sample predictability of each country j by comparing the mean squared forecast errors (MSFEs) of the null and alternative models. RSZ only study the out-of-sample predictive ability of the United States. The parsimonious (restricted) model used in the null hypothesis for country i is the naïve historical average forecast, μ_i, as in RSZ and Goyal and Welch (2008). The alternative (unrestricted) model includes the lagged return of country j.

The null and alternative models are represented by Eq. (5) and (6), respectively.

$$r_{it} = \mu_i + e_{it} \tag{5}$$

$$r_{it} = \mu_{ij} + \phi_{ij} r_{j,t-1} + e_{ij,t} \tag{6}$$

The first 10 years are used as the initial estimation sample. The simulated forecasts for month t are calculated recursively using OLS and data available through month $t-1$; therefore, the sample size increases by one as we make successive forecasts.

Table 5 reports the out-of-sample R_{OS}^2 statistic, which measures the percentage reduction in mean-squared forecast error (MSFE) for the alternative model (6) relative to the null model (5). The last row of the table presents the average values of R_{OS}^2 of each country j. The MSFE calculated for the alternative model is adjusted for the sampling error induced by the nested alternative model. As Clark and West (2007) show, the alternative model introduces sampling error into the forecasting process that will inflate its MSFE.[10] The *MSFE-adjusted* t-statistic (or *ENC-t* as discussed in Clark and McCracken, 2001) in parentheses tests the difference between the MSFEs of the null and alternative models. Note that the test is one-sided for testing H_o: $R_{OS}^2 = 0$ against H_a: $R_{OS}^2 > 0$. If country j has out-of-sample forecast ability for country i, the null will be rejected with a positive statistic. The distribution of the *MSFE-adjusted* test statistic is not asymptotically normal. Critical values provided in the table are generated by 5,000 Monte Carlo simulations, as in Clark and West.

<Table 5>

Table 5 shows that the United States has significant out-of-sample forecast ability for five countries and the average (median) reduction in MSFE is 2.28% (1.58%). However, Sweden can forecast nine countries and the average (median) reduction in MSFE is the highest, 3.83% (3.74%).

[10] Clark and McCracken (2001) and Clark and West (2007) find that the t-statistic used in the popular Diebold and Mariano (1995) model (or the *MSFE-normal* statistic in Clark and West) is seriously undersized. Diebold and Mariano use unadjusted MSFE of the alternative model. In their forecasts of stock returns and GDP growth, Clark and West show that the *MSFE-adjusted* statistic is positive, while the *MSFE-normal* statistic (and, accordingly, the unadjusted R_{OS}^2) is negative. We also use the forecast encompassing statistic, *ENC-F*, examined in Clark and McCracken (2001), which has higher power than the Diebold and Mariano (1995) statistic. The results using the Clark-Cracken statistic are similar to those reported in Table 5.

Sweden is also the only country that can significantly out-of-sample forecast the United States, while the United States cannot forecast Sweden. France also offers an average and a median reduction in MSFE larger than 1%.

We further consider two different null models: a first-order autoregressive (AR) model and the AR model with a country's own lagged interest rate and dividend yield. The alternative model of each case includes lagged US returns as an additional independent variable. The results do not change qualitatively.[11] In sum, both the in-sample and out-of-sample results show that the United States and other countries (particularly Sweden) have cross-market return predictability.

5. ASYMETRIC PREDICTABILITY

These Granger-causality tests assume symmetric predictability: lagged positive and negative returns have the same power to predict cross-market returns. We have shown that international futures markets are more correlated in a market downturn, suggesting that the markets exhibit lead-lag relationships in a market upturn. We examine this directional asymmetry—immediate reaction to good news and delayed reaction to bad news—in the following model, similar to one in McQueen et al. (1996):

$$\begin{aligned} r_{it} = \omega_i + \beta_i\, r_{i,t-1} + \delta_j^{UP} MKTUP_t \times r_{j,t} + \delta_j^{DN} MKTDN_t \times r_{j,t} \\ + \theta_j^{UP} MKTUP_{t-1} \times r_{j,t-1} + \theta_j^{DN} MKTDN_{t-1} \times r_{j,t-1} + e_{it}\,,\ \ i \neq j \end{aligned} \tag{7}$$

[11] Consider, e.g., the forecast ability of Sweden for the United States. The *MSFE-adjusted t*-statistics of the AR model and the AR model with interest rate and dividend yield are 1.86 and 1.83, respectively, while the United States indicates no forecast ability for Sweden.

where $MKTUP_t$ ($MKTDN_t$) is a dummy variable equal to 1 if the aggregate market return is positive (negative) and 0 otherwise in month t. δ_j^{UP} describes the contemporaneous relationship between country i and country j in market upturns and δ_j^{DN} in market downturns. Similarly, θ_j^{UP} and θ_j^{DN} represent the lead-lag relationships from country j to country i in market upturns and downturns, respectively.

Corresponding to the causality from US large stocks to small stocks, McQueen et al. (1996) call δ_j^{UP} and δ_j^{DN} concurrent betas and θ_j^{UP} and θ_j^{DN} lagged betas. The authors emphasize the importance of considering concurrent and lagged betas (i.e., contemporaneous and lead-lag relationships) in the same equations. For simplicity, we only report the results of these four coefficients in panel data model (7) in Table 6. We also test the hypothesis of equality between the up and down market coefficients:

$$H_o: \delta_j^{UP} = \delta_j^{DN} \tag{8}$$

$$H_o: \theta_j^{UP} = \theta_j^{DN} \tag{9}$$

<Table 6>

Consider the concurrent coefficients, δ_j^{UP} and δ_j^{DN}. Both coefficients are highly significant for all 11 countries. δ_j^{UP} is smaller than δ_j^{DN} in all cases, and the difference is significant in eight cases, as shown by the rejection of the hypothesis of coefficient equality. The average values of δ_j^{UP} and δ_j^{DN} are 0.64 and 0.78, respectively, and the corresponding median values are 0.69 and 0.80. In contrast, the lagged coefficients show that θ_j^{UP} is larger than θ_j^{DN} for seven countries, and five of them (Australia, France, Italy, Switzerland, and the United States) are significantly different.[12] The average values of θ_j^{UP} and θ_j^{DN} are 0.081 and 0.046, respectively, and the median values are 0.089 and 0.052.

The overall results suggest that, on a monthly basis, international stock markets react to bad macroeconomic news simultaneously but react to good macroeconomic news with a delay. Following the discussions of McQueen et al. (1996), international investors sell stocks across the globe in down markets. However, in up markets, investors take longer to follow trends in other countries. Although we can employ more complicated models by including other variables, the asymmetric predictive model provides a simple approach that can enhance our understanding of the relationships in international stock markets.[13]

6. CONTRARIAN PROFITS

Lo and McKinlay (1990a) show that "if returns on some stocks systematically lead or lag those of others, a portfolio strategy that sell 'winners' and buys 'loser' can produce positive expected returns." We explore the lead-lag relationships among international futures markets by using the popular contrarian strategy of Jegadeesh (1990) and Lehmann (1990). We rank the futures markets based on their previous-month returns and form a self-financing investment strategy by taking a long position on the loser (the market with the lowest return) and a short position on the winner (the market with the highest return) for the next month. This strategy creates a situation for investors in real time.

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[12]Japan is the only counterexample showing that the lagged market downturn coefficient is significantly larger than that in a market upturn. The reason is beyond the scope of the current study. However, offering no conclusive explanations, previous studies—e.g., Asness (2011) and Fama and French (2012)—have shown that Japan is also the only major stock market in which the momentum strategy of Jagadeesh and Titman (1993) does not work.

[13]For instance, Han et al. (2017) get better stock return predictability by incorporating options trading motives into their model.

A loser is not necessarily a market with negative returns. Consider an up market in month $t-1$. All markets offered positive returns. However, market *i* may have reflected good news more slowly than market *j* and other markets, leading to Granger causality from market *j* to market *i*. Thus, buying the loser (i.e., market *i*) gives contrarian profits in month *t*, even if selling the winner (market *j*) may not offer any profits.

In Table 7, we report the profits on the long-short contrarian portfolios, as well as the separate long and short positions. Panel A shows that the contrarian strategy offers an average monthly profit of 0.66% (t = 2.31). Dividing profit between the long and short positions, we find that long-side profit is 0.90% (t = 2.81), while short-side profit is 0.25% (t = 0.93).

<Table 7>

In Panels B and C, we consider the contrarian profits in up and down markets, respectively. The profit in market upturns is 0.95 (t = 2.83), with profits on the long and short sides being 1.20% (t = 3.23) and 0.24% (t = 0.67), respectively. The profit in market downturns is 0.25 (t = 0.51), and the profits on both sides are insignificant. The contrarian strategy works in market upturns, but not in market downturns. These results are consistent with the significant contemporaneous relationship in a down market and lead-lag relationship in an up market. More specifically, buying losers (that lagged other countries in the previous month) in market upturns yields excess returns. As discussed in the literature review, the contrarian profits cannot be explained by liquidity provision because the profits are obtained in market upturns.

In Table 8, we estimate alphas (or excess profits) by using the following global factor model with the Newey-West estimation:

$$r_{contrarian,t} = \alpha + \lambda_1 GLMKT_t + \lambda_2 GLSML_t + \lambda_3 GLHML_t + \varepsilon_t \tag{10}$$

where $r_{contrarian,t}$ are contrarian returns, and *GLMKT, GLSML,* and *GLHML* are the global factors of excess market returns, small-minus-large size and high-minus-low value. We find $\alpha = 0.54\%$ ($t = 2.07$). Using the US factors from the Fama-French data library does not change the results.

<Table 8>

We further control the contrarian profits by including the momentum profits, $r_{momentum,t}$, derived from the Jegadeesh-Titman momentum strategy in Eq. (10).

$$r_{contrarian,t} = \alpha + \lambda_1 GLMKT_t + \lambda_2 GLSML_t + \lambda_3 GLHML_t + \lambda_4 r_{momentum,t} + \varepsilon_t \tag{11}$$

The momentum profits are calculated as follows. Consistent with Daniel and Moskowitz (2016), Fama and French (1996), and Jegadeesh and Titman (1993), we first rank the futures markets based on their cumulative returns from the past 12 months (skipping the nearest month). We then buy the winner and sell the loser and hold the portfolio for a month. In Eq. (11), January 1989 is the first month of the contrarian and momentum profits. The alpha remains almost the same, 0.58% ($t = 2.02$). We note that $\lambda_4 = -0.11$ ($t = -1.92$). The coefficient of correlation between the contrarian returns and momentum returns is −0.144 (p-value = 0.008). Therefore, the contrarian strategy offers excess returns that are incremental to and negatively correlated with those of the momentum strategy.

For comparison purposes, the Sharpe ratios of the contrarian returns and momentum returns are 0.12 and 0.04, respectively. The average profit in the momentum strategy is 0.27%, and the alphas with the three-factor global factor model and the four-factor model (with the contrarian return being the fourth factor) are 0.39% and 0.47%. Therefore, the contrarian strategy outperforms that momentum strategy.

Nevertheless, we are not conducting a comprehensive analysis between the two strategies; in particular, the momentum strategy has been improved by recent research, for example, Barroso and Santa-Clara (2015) and Daniel and Moskowitz (2016).[14] Instead, we show that the significant lead-lag relationships induce contrarian profits that are not captured by a momentum strategy.

7. CONCLUSIONS

We examine international stock return predictability and contrarian profits using monthly futures returns in 11 industrialized countries during the period 1988-2016. RSZ use monthly returns of stock indexes for the same sample countries during an earlier period, 1980-2010. Liquid futures contracts (with no short-sale constraints, lower transaction costs, and other smaller market imperfections) are better than indexes and individual stocks in investigating the relationships and trading strategies in international stock markets. Our results extend those of RSZ in several important areas.

While RSZ report the dominant role of the United States in predicting other countries, we show that Sweden, France, and Switzerland provide in-sample predictability comparable to that in the United States. Swedish returns have higher average out-of-sample predictability than US returns. We also find significant lead-lag relationships among markets.

RSZ focus on symmetric lead-lag relationships. However, we show asymmetric contemporaneous and lead-lag relationships among markets. The market returns are more contemporaneously correlated in market downturns, while the lead-lag relationships are more significant in market upturns. These results indicate that investors react more quickly to bad news than to good news. When one national market is down, investors in other countries will sell their

[14] Moreover, Kang and Kwon (2017) show that momentum in international commodity futures can predict business cycles.

own domestic stocks (or the same investors who hold different international stocks will sell other countries' stocks) in the same month. In contrast, when one market is up, investors will take longer to consider buying stocks of other countries.

Exploring these asymmetric lead-lag relationships, we find that a simple contrarian strategy—buying losers and selling winners—offers significant profits. Contrarian profits are obtained in market upturns, and cannot be explained by global equity factors. Contrarian and momentum profits are also negatively correlated. An examination of combining these two strategies warrants future research. The overall results are important for portfolio managers in international investment.

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Table 1. Summary statistics of monthly futures returns

Daily futures returns are computed as percentage changes using the active nearby contracts and then roll over to the next contracts within the delivery month. Monthly returns are calculated by compounding the daily returns, as in Bessembinder (1992) and Moskowitz et al. (2012). Data are obtained from CSI, Inc. The sample ends in December 2016.

Country	Exchange	Index	Start	Mean	*t*-stat	Std	Max	Min	Auto-corr.
Australia	SFE	ASX SPI 200	Jan-88	0.394	1.85	3.98	11.16	-13.85	0.003
Canada	MEF	SP Canada 60	Oct-99	0.479	1.65	4.18	12.02	-16.52	0.216
France	EURONEXT	CAC 40	Sep-88	0.489	1.66	5.45	13.42	-18.21	0.067
Germany	EUREX	DAX 30	Dec-90	0.607	1.80	5.96	20.20	-24.78	0.053
Italy	MIF	FTSE MIB	Dec-94	0.350	0.88	6.48	21.31	-17.40	0.009
Japan	SGX	Nikkei 225	Jan-88	0.123	0.37	6.23	21.43	-25.04	0.036
Netherlands	EOE	AEX	Nov-92	0.660	2.02	5.58	16.25	-20.93	0.056
Sweden	OMX	OMX 300	Nov-92	0.959	2.68	6.10	28.43	-18.61	0.058
Switzerland	EUREX	Swiss Market	Dec-90	0.732	2.88	4.50	13.52	-19.63	0.130
UK	EURONEXT	FTSE 100	Jan-88	0.380	1.70	4.17	13.72	-13.01	0.006
US	CME	SP 500	Jan-88	0.598	2.71	4.12	10.95	-17.25	0.036

Table 2. Correlations

Panel A presents the correlations of monthly futures returns between countries for the full sample. Panels B and C report the correlations during the market upturns and downturns, respectively. The up market means the aggregate market offers positive returns and the down market offers negative (and zero) returns. The aggregate market is represented by the global equity portfolio (in excess of the Treasury bill rate) obtained from the AQR data library.

Panel A: Whole sample

	Australia	Canada	France	Germany	Italy	Japan	NLD	Sweden	CHE	UK	US
Australia	1.000	0.663	0.608	0.618	0.587	0.489	0.649	0.585	0.581	0.663	0.649
Canada	0.663	1.000	0.693	0.641	0.615	0.553	0.687	0.633	0.576	0.711	0.781
France	0.608	0.693	1.000	0.868	0.835	0.504	0.867	0.761	0.735	0.767	0.718
Germany	0.618	0.641	0.868	1.000	0.766	0.478	0.858	0.778	0.705	0.736	0.734
Italy	0.587	0.615	0.835	0.766	1.000	0.494	0.770	0.694	0.638	0.697	0.642
Japan	0.489	0.553	0.504	0.478	0.494	1.000	0.515	0.518	0.425	0.463	0.520
Netherlands	0.649	0.687	0.867	0.858	0.770	0.515	1.000	0.764	0.770	0.814	0.750
Sweden	0.585	0.633	0.761	0.778	0.694	0.518	0.764	1.000	0.633	0.699	0.673
Switzerland	0.581	0.576	0.735	0.705	0.638	0.425	0.770	0.633	1.000	0.707	0.680
UK	0.663	0.711	0.767	0.736	0.697	0.463	0.814	0.699	0.707	1.000	0.784
US	0.649	0.781	0.718	0.734	0.642	0.520	0.750	0.673	0.680	0.784	1.000

Panel B: Up market

	Australia	Canada	France	Germany	Italy	Japan	NLD	Sweden	CHE	UK	US
Australia	1.000	0.318	0.342	0.351	0.366	0.044	0.337	0.249	0.318	0.422	0.297
Canada	0.318	1.000	0.361	0.330	0.314	0.123	0.378	0.261	0.211	0.355	0.474
France	0.342	0.361	1.000	0.754	0.735	0.143	0.741	0.585	0.552	0.604	0.442
Germany	0.351	0.330	0.754	1.000	0.592	0.087	0.754	0.650	0.494	0.578	0.484
Italy	0.366	0.314	0.735	0.592	1.000	0.131	0.621	0.544	0.425	0.491	0.340
Japan	0.044	0.123	0.143	0.087	0.131	1.000	0.149	0.172	0.082	0.084	0.068
NLD	0.337	0.378	0.741	0.754	0.621	0.149	1.000	0.615	0.612	0.621	0.455
Sweden	0.249	0.261	0.585	0.650	0.544	0.172	0.615	1.000	0.409	0.464	0.319
CHE	0.318	0.211	0.552	0.494	0.425	0.082	0.612	0.409	1.000	0.518	0.390
UK	0.422	0.355	0.604	0.578	0.491	0.084	0.621	0.464	0.518	1.000	0.622
US	0.297	0.474	0.442	0.484	0.340	0.068	0.455	0.319	0.390	0.622	1.000

Panel C: Down market

	Australia	Canada	France	Germany	Italy	Japan	NLD	Sweden	CHE	UK	US
Australia	1.000	0.508	0.484	0.479	0.428	0.392	0.535	0.501	0.480	0.571	0.545
Canada	0.508	1.000	0.548	0.465	0.445	0.407	0.557	0.573	0.376	0.617	0.693
France	0.484	0.548	1.000	0.863	0.790	0.397	0.855	0.720	0.725	0.719	0.670
Germany	0.479	0.465	0.863	1.000	0.749	0.374	0.815	0.709	0.689	0.647	0.667
Italy	0.428	0.445	0.790	0.749	1.000	0.470	0.732	0.601	0.583	0.629	0.549
Japan	0.392	0.407	0.397	0.374	0.470	1.000	0.412	0.473	0.316	0.333	0.376
NLD	0.535	0.557	0.855	0.815	0.732	0.412	1.000	0.704	0.725	0.787	0.695
Sweden	0.501	0.573	0.720	0.709	0.601	0.473	0.704	1.000	0.579	0.649	0.658
CHE	0.480	0.376	0.725	0.689	0.583	0.316	0.725	0.579	1.000	0.665	0.672
UK	0.571	0.617	0.719	0.647	0.629	0.333	0.787	0.649	0.665	1.000	0.713
US	0.545	0.693	0.670	0.667	0.549	0.376	0.695	0.658	0.672	0.713	1.000

Table 3. Benchmark model

The benchmark model of the predictive regression of monthly returns, r_{it}, includes the country's lagged interest rate, $TB_{i,t-1}$, and the lagged (log) dividend yield, $DY_{i,t-1}$, as the dependent variables. The *t*-statistics with Newey-West heteroskedasticity and serial correlation correction are in parentheses.

	$TB_{i,t-1}$ $\omega_{i,b}$	$DY_{i,t-1}$ $\omega_{i,d}$	*p*-value, H_0: $\omega_{i,b}=\omega_{i,d}=0$
Australia	-0.081	1.093	0.339
	(-1.25)	(0.85)	
Canada	-0.306	-0.729	0.709
	(-0.79)	(-0.36)	
France	-0.125	0.204	0.158
	(-1.69)	(0.13)	
Germany	-0.194	0.219	0.128
	(-1.63)	(0.16)	
Italy	-0.179	-1.459	0.581
	(-0.97)	(-0.95)	
Japan	-0.132	0.952	0.190
	(-0.77)	(1.03)	
Netherlands	-0.240	0.294	0.374
	(-1.00)	(0.18)	
Sweden	-0.100	-0.277	0.815
	(-0.50)	(-0.15)	
Switzerland	0.006	-0.197	0.930
	(0.11)	(-0.17)	
UK	-0.088	2.781	0.014
	(-1.78)	(2.85)	
US	-0.067	1.377	0.240
	(-0.93)	(1.67)	

Table 4. Pairwise Granger-causality

Panel A reports the cross-market causality coefficients θ_{ij} and Newey-West *t*-statistics in parentheses of the pairwise regressions from country *j* (in columns) to country *i* (in rows). In Panel B, the panel data analysis imposes the same coefficient, θ_j, for all markets *i* ($i \neq j$) of causality from market *j*. We estimate the panel data model using the Arellano–Bover/Blundell–Bond estimation. Results of the fixed-effects model are also reported for reference. *t*-statistics are in parentheses. Significant coefficients at the 10% significance level are in boldface.

Panel A: Cross-market causality coefficients θ_{ij} in individual predictive regressions

$i \setminus j$	Australia	Canada	France	Germany	Italy	Japan	NLD	Sweden	CHE	UK	US
Australia		**0.137**	**0.129**	0.052	0.032	0.061	0.053	**0.101**	0.060	**0.152**	**0.130**
		(2.15)	(2.35)	(1.17)	(0.69)	(1.27)	(0.905)	(2.37)	(0.81)	(2.52)	(1.83)
Canada	0.086		**0.188**	**0.137**	**0.137**	0.065	**0.102**	**0.258**	**0.125**	0.069	0.049
	(0.90)		(3.17)	(3.32)	(2.92)	(0.93)	(1.79)	(4.35)	(1.72)	(0.70)	(0.33)
France	0.009	0.037		-0.026	-0.126	-0.034	-0.061	**0.175**	**0.191**	-0.059	0.131
	(0.07)	(0.36)		(-0.28)	(-1.63)	(-0.63)	(-0.53)	(2.05)	(1.94)	(-0.52)	(1.07)
Germany	0.208	0.113	**0.237**		0.050	0.023	-0.097	0.172	**0.201**	0.075	**0.233**
	(1.57)	(1.20)	(2.00)		(0.58)	(0.30)	(-0.73)	(1.41)	(1.73)	(0.67)	(1.95)
Italy	**0.397**	0.124	**0.455**	**0.187**		0.101	**0.190**	**0.334**	**0.316**	0.253	**0.317**
	(2.58)	(1.10)	(4.25)	(1.96)		(1.30)	(1.92)	(3.81)	(2.46)	(1.48)	(2.10)
Japan	0.074	0.162	**0.168**	0.087	0.020		0.075	0.052	0.116	**0.135**	0.075
	(0.91)	(1.20)	(2.42)	(1.35)	(0.29)		(0.92)	(0.70)	(1.56)	(1.78)	(0.71)
Netherlands	**0.284**	0.112	**0.344**	0.188	0.036	0.096		**0.250**	**0.407**	0.239	**0.308**
	(2.12)	(0.91)	(3.33)	(1.62)	(0.50)	(1.23)		(2.66)	(3.30)	(1.51)	(2.01)
Sweden	0.072	0.089	0.086	0.020	-0.085	0.055	-0.047		0.043	0.008	0.074
	(0.68)	(0.70)	(0.81)	(0.18)	(-1.03)	(0.88)	(-0.40)		(0.40)	(0.06)	(0.63)
Switzerland	0.124	0.024	0.025	0.009	-0.049	0.030	-0.076	**0.135**		0.088	0.107
	(1.53)	(0.35)	(0.35)	(0.13)	(-0.84)	(0.56)	(-0.96)	(2.48)		(1.16)	(1.00)
UK	0.053	0.030	0.127	0.029	0.001	0.037	-0.034	**0.111**	0.117		0.088
	(0.67)	(0.42)	(2.01)	(0.58)	(0.00)	(0.80)	(-0.47)	(2.02)	(1.62)		(0.88)
US	0.022	0.066	0.099	0.029	0.042	0.029	0.002	**0.139**	0.030	0.044	
	(0.30)	(0.50)	(1.63)	(0.42)	(0.78)	(0.63)	(0.03)	(2.59)	(0.34)	(0.76)	

Panel B: Panel data analysis

GMM dynamic panel estimator											
θ_j	**0.109**	**0.102**	**0.149**	**0.051**	-0.007	**0.035**	0.003	**0.158**	**0.142**	**0.102**	**0.156**
	(4.24)	(3.68)	(6.60)	(2.65)	(-0.37)	(2.40)	(0.14)	(8.45)	(6.05)	(3.75)	(6.00)
Fixed-effects model											
θ_j	**0.120**	**0.092**	**0.149**	**0.063**	0.006	**0.042**	0.021	**0.153**	**0.140**	**0.100**	**0.149**
	(3.23)	(5.34)	(5.16)	(3.27)	(0.32)	(3.25)	(0.81)	(5.02)	(3.98)	(3.87)	(4.78)

Table 5. Out-of-sample forecast

The table reports the out-of-sample R_{OS}^2statistic, which measures the percentage reduction in mean-squared forecast error (MSFE). The null model used in the null hypothesis for country *i* is the naïve historical average forecast. The alternative model includes the lagged returns of country *j* as the independent variable. The first 10 years are used as the initial estimation sample and the simulated forecasts for month *t* are calculated recursively using data available through month *t*−1. The MSFE calculated for the alternative model is adjusted for the sampling error induced by the nested alternative model as in Clark and West (2007). The *MSFE-adjusted t*-statistic in parentheses tests the difference between the MSFEs of the null and alternative models. If country *j* has out-of-sample forecast ability for country *i*, the null will be rejected with a positive statistic. Note that the test is one-sided and critical values are generated by 5,000 simulations. The average critical values at the 10%, 5%, and 1% levels of significance are 0.92, 1.30, and 2.03, respectively. Significant reductions in MSFEs are in boldface.

i \ *j*	Australia	Canada	France	Germany	Italy	Japan	NLD	Sweden	CHE	UK	US
Australia		-0.74	**1.49**	-1.51	-1.42	0.78	-2.34	**1.43**	-2.04	**1.50**	1.02
		(-0.26)	(0.94)	(-1.38)	(-1.74)	(0.80)	(-1.50)	(1.31)	(-1.56)	(1.05)	(0.72)
Canada	-2.05		1.67	5.85	**5.40**	1.37	1.25	**9.03**	-0.51	0.27	1.31
	(-1.26)		(0.14)	(0.52)	(1.75)	(0.15)	(0.16)	(1.22)	(-0.07)	(0.04)	(0.20)
France	-1.39	-1.66		-0.53	-1.11	-1.36	-0.89	**3.20**	**2.39**	-0.70	**1.86**
	(-1.21)	(-0.61)		(-0.61)	(-1.60)	(-1.66)	(-1.28)	(1.78)	(1.43)	(-1.19)	(1.09)
Germany	**2.05**	-0.06	1.35		**0.94**	-0.29	-1.02	**1.84**	**1.72**	0.01	**2.23**
	(1.59)	(-0.02)	(0.90)		(0.95)	(-0.48)	(-1.45)	(1.67)	(1.42)	(0.02)	(1.47)
Italy	**6.71**	-0.73	**3.32**	**1.38**		1.06	0.97	**5.32**	**3.72**	1.50	**4.67**
	(1.77)	(-0.33)	(1.58)	(0.99)		(0.66)	(0.87)	(2.21)	(1.39)	(0.64)	(1.46)
Japan	-0.11	2.31	**2.51**	0.79	-0.19		0.77	0.63	0.35	**1.16**	-0.18
	(-0.24)	(0.88)	(1.77)	(0.78)	(-0.34)		(0.57)	(0.90)	(0.35)	(1.15)	(-0.25)
Netherlands	**5.71**	-1.31	**3.52**	**2.47**	1.00	**2.51**		**4.27**	**6.36**	**2.49**	**5.89**
	(2.11)	(-0.38)	(1.53)	(1.64)	(0.74)	(1.28)		(1.79)	(2.11)	(1.16)	(1.85)
Sweden	0.72	0.40	0.93	0.46	-0.24	-0.01	-0.97		0.64	0.01	1.19
	(0.67	(0.10)	(0.55)	(0.43)	(-0.52)	(-0.01)	(-1.68)		(0.75)	(0.01)	(0.63)
Switzerland	**5.17**	0.25	**2.50**	**2.00**	0.49	**1.00**	0.64	**6.42**		**4.64**	**5.76**
	(2.43)	(0.10)	(1.76)	(1.47)	(0.68)	(1.01)	(0.63)	(2.00)		(1.87)	(2.14)
UK	-1.21	-1.07	0.03	-1.57	-1.14	-0.11	-2.03	**1.22**	0.27		-0.95
	(-1.60)	(-1.08)	(0.03)	(-1.53)	(-1.74)	(-0.25)	(-1.30)	(1.10)	(0.32)		(-1.30)
US	-0.64	-2.52	0.51	-1.58	0.61	-0.14	-1.18	**4.93**	-1.34	-0.58	
	(-0.72)	(-0.85)	(0.48)	(-1.45)	(0.42)	(-0.23)	(-1.06)	(2.11)	(-1.37)	(-0.84)	
Average	1.50	-0.51	1.78	0.78	0.43	0.48	-0.48	3.83	1.16	1.03	2.28
Median	0.31	-0.73	1.58	0.62	0.15	0.38	-0.92	3.74	0.49	0.71	1.58

Table 6. Asymmetric predictive regressions: Panel data results

The table reports the results of directional asymmetry–immediate reaction to good news and delayed reaction to bad news–similar to McQueen et al. (1996). δ_j^{UP} describes the contemporaneous relationship between country *i* and country *j* in market upturns and δ_j^{DN} in market downturns. Similarly, θ_j^{UP} and θ_j^{DN} represent the lead-lag relationships from country *j* (in columns) to other countries *i* in market upturns and downturns, respectively. *t*-statistics are in parentheses.

Country *j*	Concurrent coefficients			Lagged coefficients		
	δ_j^{UP}	δ_j^{DN}	*p*-value of H_0: $\delta_j^{UP} = \delta_j^{DN}$	θ_j^{UP}	θ_j^{DN}	*p*-value of H_0: $\theta_j^{UP} = \theta_j^{DN}$
Australia	0.799	0.856	0.172	0.177	0.105	0.080
	(28.30)	(34.74)		(5.72)	(3.87)	
Canada	0.782	0.843	0.150	-0.017	-0.031	0.753
	(26.86)	(33.86)		(-0.53)	(-1.10)	
France	0.653	0.799	0.000	0.122	0.069	0.030
	(41.56)	(51.20)		(6.42)	(3.40)	
Germany	0.593	0.651	0.009	0.055	0.073	0.421
	(40.22)	(46.88)		(3.13)	(4.25)	
Italy	0.418	0.726	0.000	0.074	0.001	0.002
	(30.53)	(46.89)		(4.67)	(0.06)	
Japan	0.270	0.564	0.000	-0.026	0.052	0.003
	(15.76)	(33.63)		(-1.46)	(2.81)	
Netherlands	0.691	0.706	0.513	0.051	0.047	0.855
	(41.75)	(48.47)		(2.57)	(2.49)	
Sweden	0.530	0.694	0.000	0.089	0.124	0.132
	(36.38)	(43.37)		(5.29)	(6.41)	
Switzerland	0.734	0.821	0.006	0.111	-0.044	0.000
	(34.07)	(39.20)		(4.55)	(-1.45)	
UK	0.861	0.945	0.015	0.139	0.096	0.207
	(36.51)	(45.02)		(5.13)	(3.82)	
US	0.686	1.019	0.000	0.122	0.016	0.000
	(29.04)	(44.14)		(4.69)	(0.57)	
Average	0.638	0.784		0.081	0.046	
Median	0.686	0.799		0.089	0.052	

Table 7. Contrarian Profits

This table reports the profits on the long-short contrarian portfolios, as well as the separate long and short positions. Panel A uses the full sample, Panels B and C consider the contrarian profits in up and down markets, respectively.

	N	Mean	*t* Value	Std
Panel A: Full sample				
Long	347	0.904	2.81	6.00
Short	347	0.248	0.93	4.97
$r_{contrarian}$	347	0.656	2.31	5.29
Panel B: Up market				
Long	200	1.198	3.23	5.24
Short	200	0.243	0.67	5.18
$r_{contrarian}$	200	0.954	2.83	4.76
Panel C: Down market				
Long	147	0.506	0.89	6.90
Short	147	0.255	0.66	4.70
$r_{contrarian}$	147	0.251	0.51	5.92

Table 8. Factor models of contrarian profits

We estimate alphas or excess profits by using a global factor model with the Newey-West estimation. The global factors obtained from AQR data are excess global market returns (*GLMKT*), small-minus-large size (*GLSML*), and high-minus-low value (*GLHML*). Using the US factors does not change the results. This table reports the results on the long-short contrarian portfolios, $r_{contrarian}$, as well as the separate long and short positions. Panel A uses the full sample, and Panels B and C consider the contrarian profits in up and down markets, respectively. The last two rows of each panel include the Jegadeesh-Titman momentum profits, $r_{momentum,t}$, in the factor model. *t*-statistics are in parentheses.

	alpha	*GLMKT*	*GLSML*	*GLHML*	$r_{momentum}$
Panel A: Full sample					
Long	0.484	0.999	-0.045	0.013	
	(2.26)	(15.35)	(-0.28)	(0.13)	
Short	-0.052	0.779	-0.109	-0.043	
	(-0.29)	(16.66)	(-0.96)	(-0.45)	
$r_{contrarian}$	0.537	0.219	0.064	0.056	
	(2.07)	(3.02)	(0.46)	(0.45)	
$r_{contrarian}$	0.578	0.206	0.087	0.042	-0.105
	(2.02)	(2.85)	(0.61)	(0.26)	(-1.92)
Panel B: Up market					
Long	0.953	0.939	-0.205	0.038	
	(2.79)	(10.80)	(-1.16)	(0.31)	
Short	0.125	0.939	-0.189	-0.188	
	(0.61)	(11.85)	(-1.25)	(-1.46)	
$r_{contrarian}$	0.828	0.001	-0.016	0.226	
	(2.14)	(0.01)	(-0.11)	(1.25)	
$r_{contrarian}$	0.832	0.021	0.030	0.278	0.049
	(1.97)	(0.20)	(0.16)	(1.52)	(0.57)

Panel C: Down market					
Long	-0.042	1.045	-0.001	-0.049	
	(-0.12)	(16.45)	(-0.00)	(-0.26)	
Short	-0.092	0.659	0.020	0.089	
	(-0.33)	(10.66)	(0.12)	(0.72)	
$r_{contrarian}$	0.050	0.387	-0.021	-0.138	
	(0.13)	(3.79)	(-0.07)	(-0.63)	
$r_{contrarian}$	-0.055	0.320	0.138	-0.196	-0.332
	(-0.14)	(3.74)	(0.54)	(-1.04)	(-4.06)

APPENDIX

Tables 3A and Table 4A reports the results of Tables 3 and 4, respectively, using *p*-values generated by wild bootstrapping. The resampling process is repeated 2,000 times.

Table 3A. Benchmark model

The benchmark model of the predictive regression of monthly returns, r_{it}, includes the country's lagged interest rate, $TB_{i,t-1}$, and the lagged (log) dividend yield, $DY_{i,t-1}$, as the dependent variables. The *t*-statistics with Newey-West heteroskedasticity and serial correlation correction are in parentheses. The *p*-values generated by the wild bootstrap are in brackets.

	$TB_{i,t-1}$ $\omega_{i,b}$	$DY_{i,t-1}$ $\omega_{i,d}$	*p*-value, H_0: $\omega_{i,b} = \omega_{i,d} = 0$
Australia	-0.081	1.093	[0.612]
	(-1.25)	(0.85)	
	[0.43]	[0.35]	
Canada	-0.306	-0.729	[0.778]
	(-0.74)	(-0.37)	
	[0.25]	[0.92]	
France	-0.125	0.204	[0.486]
	(-1.69)	(0.13)	
	[0.27]	[0.68]	
Germany	-0.194	0.219	[0.301]
	(-1.63)	(0.16)	
	[0.18]	[0.75]	
Italy	-0.179	-1.459	[0.725]
	(-0.97)	(-0.95)	
	[0.31]	[0.95]	
Japan	-0.132	0.952	[0.426]
	(-0.77)	(1.03)	
	[0.44]	[0.50]	
Netherlands	-0.240	0.294	[0.408]
	(-1.00)	(0.18)	
	[0.23]	[0.67]	
Sweden	-0.100	-0.277	[0.837]
	(-0.50)	(-0.15)	
	[0.35]	[0.81]	

Switzerland	0.006	-0.197	[0.959]
	(0.11)	(-0.17)	
	[0.71]	[0.85]	
UK	-0.088	2.781	[0.069]
	(-1.78)	(2.85)	
	[0.29]	[0.04]	
US	-0.067	1.377	[0.452]
	(-0.93)	(1.67)	
	[0.37]	[0.28]	

Table 4A. Pairwise Granger-causality

Panel A reports the cross-market causality coefficients θ_{ij} and Newey-West *t*-statistics in parentheses of the pairwise regressions from country *j* (in columns) to country *i* (in rows). In Panel B, the panel data analysis imposes the same coefficient, θ_j, for all markets *i* ($i \neq j$) of causality from market *j*. The *p*-values generated by the wild bootstrap are in brackets. Significant coefficients at the one-sided 10% level according to the bootstrapped *p*-values are in boldface.

Panel A: Cross-market causality coefficients θ_{ij} in individual predictive regressions

$i \setminus j$	Australia	Canada	France	Germany	Italy	Japan	NLD	Sweden	CHE	UK	US
Australia		**0.137**	**0.129**	0.052	0.032	**0.061**	0.053	**0.105**	0.060	**0.152**	**0.130**
		(2.15)	(2.35)	(1.17)	(0.69)	(1.27)	(0.95)	(2.37)	(0.81)	(2.52)	(1.83)
		[0.07]	[0.01]	[0.18]	[0.24]	[0.06]	[0.20]	[0.01]	[0.18]	[0.02]	[0.05]
Canada	0.086		**0.188**	**0.137**	**0.137**	0.065	0.102	**0.258**	**0.125**	0.069	0.049
	(0.90)		(3.17)	(3.32)	(2.92)	(0.93)	(1.79)	(4.35)	(1.72)	(0.70)	(0.33)
	[0.24]		[0.02]	[0.02]	[0.02]	[0.14]	[0.11]	[0.00]	[0.08]	[0.31]	[0.37]
France	0.009	0.037		-0.026	-0.126	-0.034	-0.061	**0.175**	**0.191**	-0.059	0.131
	(0.07)	(0.36)		(-0.28)	(-1.63)	(-0.63)	(-0.53)	(2.05)	(1.94)	(-0.52)	(1.07)
	[0.47]	[0.39]		[0.59]	[0.92]	[0.72]	[0.65]	[0.01]	[0.06]	[0.71]	[0.13]
Germany	**0.208**	0.113	**0.237**		0.050	0.023	-0.097	**0.172**	**0.201**	0.075	**0.233**
	(1.57)	(1.20)	(2.00)		(0.58)	(0.30)	(-0.73)	(1.41)	(1.73)	(0.67)	(1.95)
	[0.05]	[0.23]	[0.06]		[0.30]	[0.39]	[0.71]	[0.05]	[0.05]	[0.32]	[0.03]
Italy	**0.397**	0.124	**0.455**	**0.187**		0.101	0.190	**0.334**	**0.316**	**0.253**	**0.317**
	(2.58)	(1.10)	(4.25)	(1.96)		(1.30)	(1.92)	(3.81)	(2.46)	(1.48)	(2.10)
	[0.00]	[0.18]	[0.00]	[0.05]		[0.13]	[0.11]	[0.00]	[0.01]	[0.08]	[0.01]
Japan	0.074	0.162	**0.168**	0.087	0.020		0.075	0.053	0.116	**0.135**	0.075
	(0.91)	(1.20)	(2.42)	(1.35)	(0.29)		(0.92)	(0.70)	(1.56)	(1.78)	(0.71)
	[0.26]	[0.15]	[0.01]	[0.11]	[0.40]		[0.24]	[0.27]	[0.11]	[0.09]	[0.26]
Netherlands	**0.284**	0.112	**0.344**	0.188	0.036	**0.096**		**0.250**	**0.407**	0.239	**0.308**
	(2.12)	(0.91)	(3.33)	(1.62)	(0.50)	(1.23)		(2.66)	(3.30)	(1.51)	(2.01)
	[0.01]	[0.21]	[0.01]	[0.11]	[0.35]	[0.10]		[0.00]	[0.00]	[0.10]	[0.01]
Sweden	0.072	0.089	0.086	0.020	-0.085	0.055	-0.047		0.043	0.008	0.074
	(0.68)	(0.70)	(0.81)	(0.18)	(-1.03)	(0.88)	(-0.40)		(0.40)	(0.06)	(0.63)
	[0.32]	[0.28]	[0.22]	[0.43]	[0.89]	[0.23]	[0.63]		[0.37]	[0.51]	[0.31]
Switzerland	**0.124**	0.024	0.025	0.009	-0.049	0.030	-0.076	**0.135**		0.088	0.107
	(1.53)	(0.35)	(0.35)	(0.13)	(-0.84)	(0.56)	(-0.96)	(2.48)		(1.16)	(1.00)
	[0.09]	[0.38]	[0.40]	[0.46]	[0.79]	[0.28]	[0.81]	[0.03]		[0.20]	[0.21]
UK	0.053	0.030	**0.127**	0.029	0.001	0.037	-0.034	**0.111**	**0.117**		0.088
	(0.67)	(0.42)	(2.01)	(0.58)	(0.00)	(0.80)	(-0.47)	(2.02)	(1.62)		(0.88)
	[0.24]	[0.38]	[0.06]	[0.33]	[0.51]	[0.20]	[0.66]	[0.03]	[0.09]		[0.18]
US	0.022	0.066	**0.099**	0.029	0.042	0.029	0.002	**0.139**	0.030	0.044	
	(0.30)	(0.50)	(1.63)	(0.42)	(0.78)	(0.63)	(0.03)	(2.59)	(0.34)	(0.76)	
	[0.39]	[0.35]	[0.08]	[0.36]	[0.27]	[0.24]	[0.51]	[0.02]	[0.37]	[0.35]	

Panel B: Panel data analysis

Fixed-effects model

θ_j	**0.120**	**0.092**	**0.149**	**0.063**	0.006	**0.042**	0.021	**0.153**	**0.140**	**0.100**	**0.149**
	(3.23)	(5.34)	(5.16)	(3.27)	(0.32)	(3.25)	(0.81)	(5.02)	(3.98)	(3.87)	(4.78)
	[0.00]	[0.00]	[0.00]	[0.00]	[0.75]	[0.00]	[0.41]	[0.00]	[0.00]	[0.00]	[0.00]