The Baltic Dry Index as a Predictor of Global Stock Returns, Commodity Returns, and Global Economic Activity*

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Abstract

The goal of this paper is to show that the growth rate of the Baltic Dry Index (BDI) has predictive ability for a range of stock markets, which is demonstrated through in-sample tests and out-of-sample statistics. The documented stock return predictability is also of economic significance, as seen by examining the certainty equivalent returns and Sharpe ratios of portfolio strategies that exploit the BDI growth rate. In addition, the BDI growth rate predicts the returns of commodity indexes, and we find some evidence for joint predictability of stock and commodity returns in a system of predictive regressions. Finally, the BDI growth rate predicts the growth in global economic activity, establishing further BDI's role in revealing a link between the real and financial sectors.

KEY WORDS: Baltic Dry Index; global stock markets; commodity returns; global real economic activity; predictive regressions; out-of-sample statistic; economic significance.

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1. Introduction

The idea of this paper is to propose a predictor for global stock markets, commodities, and global economic activity. We show that the three-month growth rate of the Baltic Dry Index (hereafter, BDI) predicts the returns of a number of stock markets, when in-sample inference is based on the conservative Hodrick (1992) covariance estimator under the null hypothesis of no predictability. This new predictor consistently outperforms the historical average return benchmark, as revealed by the out-of-sample R^2 statistic of Campbell and Thompson (2008), and the significance of the adjusted mean-squared prediction error statistic of Clark and West (2007). Substantiating economic significance, portfolio strategies designed to exploit the predictive ability of the BDI growth rate provide higher certainty equivalent returns and Sharpe ratios than those of the no-predictability counterpart that assumes i.i.d. returns (e.g., Pesaran and Timmermann (1995) and Kandel and Stambaugh (1996)). We also show that the BDI growth rate predicts returns of commodity indexes and the growth in real economic activity across a range of developed and emerging market economies. Finally, we provide some supportive evidence for joint predictability in a system of predictive regressions.

Our interest in the BDI stems from observations made within the investment community, which often suggest that the BDI is a leading indicator of economic activity reflecting global demand for raw materials. One example epitomizing this viewpoint is a quote from the *Wall Street Journal* (July 9, 2010):

> *Sure, the index—an indication of the daily rate for a ship carrying dry bulk goods such as grain, coal and iron ore—has collapsed. Through Friday, it has fallen 30 straight days. And since its recent May 26 peak of 4,209, the index has dropped by nearly 55% to 1,902 Friday. So, are the prices in the shipping markets signalling a hard-landing, or worse, a double dip recession?*

The importance attached to the BDI as a gauge of the state of the economy is seen by the repeated attention in the *Wall Street Journal* (also, for example, June 23 and July 13, 2010), and elsewhere in the financial media. At the same time, there are detractors who doubt that the BDI is a barometer of global economic activity, since its fluctuation is driven by factors other than demand ("Baltic Index Faces Questions," *Wall Street Journal*, March 2, 2010). Such opposite views prompt us to evaluate the predictive power of the BDI within a rigorous econometric framework, and across the real and the financial sectors.

Our evidence on the predictive content of the BDI growth rate is gathered from four MSCI regional stock market indexes, as well as the individual stock markets in the G-7 countries, 12 other developed and

12 emerging market economies, and we use US dollar-denominated returns. Transcending the stock market universe, we also employ a sample of commodity indexes, and industrial production data collected from 20 countries.

Our empirical questions are five-fold: First, does the BDI growth rate constitute a common predictor of stock returns across the world in an in-sample analysis? Second, does the BDI growth rate maintain its predictive ability when appraised in an out-of-sample framework? Third, what evidence can one bring to bear on the economic significance of stock return predictability based on the BDI growth rate? Fourth, how does the BDI growth rate perform in the presence of alternative predictors of stock returns? Finally, how strong is the predictive power of the BDI growth rate outside the stock markets, particularly for the returns of commodity indexes, and for the growth of real economic activity across countries? Throughout, we stress the evidence from a cross-section of countries and, hence, we adhere to a growing body of studies that rely on international evidence to establish the robustness of the investigated relations.[1]

In an in-sample regression of stock returns on the lagged three-month BDI growth rate, we find that the slope coefficient estimate on the BDI growth rate is positive, with Hodrick (1992) p-values below 0.05 for a number of markets. Confirming the conclusions drawn from our in-sample inferences, the out-of-sample R^2 statistic, calculated both with expanding and rolling windows, is typically higher than those reported in Campbell and Thompson (2008), Goyal and Welch (2008), Rapach, Strauss, and Zhou (2010), and Henkel, Martin, and Nardari (2010). The evidence is reinforced by the low p-values for the null hypothesis that the BDI growth rate does not significantly improve on a forecast based on the historical average return (e.g., Clark and West (2007)). Our results with the BDI growth rate as a predictor, thus, contrast the unsatisfactory out-of-sample performance of an array of predictors, as in Goyal and Welch (2008).

Along another key dimension, we elaborate on the economic significance of predictability by showing that the certainty equivalent returns and Sharpe ratios associated with the BDI-based portfolio strategy outweigh those obtained with a strategy that assumes i.i.d. returns. Pointing to its practical usefulness, the BDI-based strategy can often generate twice the Sharpe ratio of the i.i.d.-based strategy.

In agreement with our results from stock markets, a higher BDI growth rate is positively associated with subsequent commodity returns and industrial production growth, and the latter effect is significant for

[1] In this sense, our work is related to, among others, Korajczyk and Viallet (1989), Cutler, Poterba, and Summers (1991), Harvey (1991, 1995), Bekaert and Hodrick (1992), Campbell and Hamao (1992), Ferson and Harvey (1993), Heston and Rowenhorst (1994), Bekaert and Harvey (1995), Dumas and Solnik (1995), De Santis and Gerard (1997), Fama and French (1998), Griffin and Karolyi (1998), Rowenhorst (1998), Bossaerts and Hillion (1999), Jorion and Goetzmann (1999), Rangvid (2006), Guidolin and Timmermann (2008), Bekaert, Hodrick, and Zhang (2009), Pakthuanthong and Roll (2009), Rapach, Strauss, and Zhou (2009), Hjalmarsson (2010), and Henkel, Martin, and Nardari (2010).

most of the countries in our sample.

Predictors of global stock returns have been identified previously, for example, by Harvey (1991, 1995) (the lagged world stock market return), and Rapach, Strauss, and Zhou (2009) (the lagged US stock market return). Conducting in-sample inference with two predictors, we find that, while accounting for the lagged world (US) return, the BDI growth rate still firmly predicts global stock returns in our sample. The same finding is corroborated by out-of-sample statistics and the economic significance of portfolio strategies that exploit stock return predictability, when a model including both the BDI growth rate and the lagged world (US) return is viewed as nesting the models that feature each predictor separately.

Overall, the importance of the BDI growth rate as a predictor stems from two findings. First, the BDI growth rate exhibits a positive and statistically significant relation to subsequent global stock returns, commodity returns, and industrial production growth. Second, the predictability is corroborated in statistical terms, in-sample and out-of-sample, as well as through metrics of economic significance, and in the presence of some alternative predictors. Movements in the BDI growth rate, thus, capture variation across the real and financial sectors, and the association appears stable across a multitude of economies.[2]

The paper proceeds as follows. Section 2 describes the BDI, articulates its relation to global economic activity, and elaborates on the time series properties of the BDI growth rate. Section 3 is devoted to the in-sample evidence on predictability of global stock markets. Section 4 presents evidence on the out-of-sample statistical significance and economic significance of stock return predictability. Section 5 examines the predictability of commodity index returns, while Section 6 explores whether industrial production growth can be predicted via the BDI growth rate. Section 7 provides further evidence and interpretation of the pattern of predictability. Conclusions are offered in Section 8.

2. The BDI and its relation to global economies and markets

The BDI has been published daily by the Baltic Exchange in London since May 1985. Based on daily quotes for booking vessels of various sizes and across multiple maritime routes, the BDI is an indicator of

[2] Keim and Stambaugh (1986) and Campbell (1987, 1991) show return predictability by term structure variables, whereas Kothari and Shanken (1997) and Pontiff and Schall (1998) provide evidence on book-to-market as a return predictor. Contributions that shed light on the predictive ability of the dividend yield include Lewellen (2004), Lettau and Ludvigson (2005), Campbell and Yogo (2006), Ang and Bekaert (2007), Boudoukh, Richardson, and Whitelaw (2008), Cochrane (2008), Lettau and Nieuwerburgh (2008), Pástor and Stambaugh (2009), and Binsbergen and Koijen (2010). Besides, Baker and Wurgler (2000) explore the role of corporate variables, Polk, Thompson, and Vuolteenaho (2006) examine relative valuations in predicting returns, Hong, Torous, and Valkanov (2007) employ industry portfolio returns, and Bakshi, Panayotov, and Skoulakis (2010) investigate the predictability of real economic activity, bond returns, and stock returns by option-implied forward variances.

transportation costs for raw materials shipped by sea. More specifically, the BDI is calculated as a weighted average of the Baltic Exchange's indexes for the shipping costs of the four largest dry-vessel classes.

Based on the premise that the supply structure of the shipping industry is generally predictable and relatively inflexible, changes in shipping costs have been seen largely as due to changes in the worldwide demand for raw materials (Stopford (2009) provides an in-depth analysis of the shipping industry). This link to global demand has prompted interest in the BDI as a leading indicator of economic activity.

Besides, the BDI exhibits other advantages as a predictor. Specifically, it is never revised ex-post, unlike some other economic indicators, and is largely devoid of speculative content. On the other hand, certain specifics of the shipping industry can be viewed as diminishing the index's predictive potential. For example, highly inelastic supply may generate excessive volatility in shipping costs, causing the index to deviate from the fundamentals of global trade and real economic activity. The relevance of the BDI for predicting variables beyond economic growth, and in particular for predicting asset returns, has not been examined yet, which provides a motivation for undertaking our study.

To set the stage for the subsequent analysis, we consider some features characterizing the dynamics of the BDI. To do so, we calculate log changes in the BDI index over the preceding one month and three months, and define the corresponding BDI growth rate as

$$g_{[t-j\to t]} \;\equiv\; \ln(\mathrm{BDI}_t/\mathrm{BDI}_{t-j}), \qquad \text{for } j = 1,3. \tag{1}$$

The log changes over three months are equivalent to moving sums of monthly log changes, and akin to the twelve-month moving sums of aggregate dividends or earnings that have been adopted in predictive studies of stock returns. The sample is from May 1985 to September 2010 (305 observations), and Panel A of Table Appendix-I reports the descriptive statistics for the $g_{[t-1\to t]}$ and $g_{[t-3\to t]}$ time series, including autocorrelations ρ_j for lags $j = 1,\ldots,6$, and the p-value for the Ljung-Box test statistic for six lags.

A crucial feature of the monthly BDI growth rate series, $g_{[t-1\to t]}$, is its high volatility when compared, for example, to financial asset returns over the same time period, as evidenced by the annualized standard deviation of 191.1%. In contrast, the moving sum series, $g_{[t-3\to t]}$, is substantially less volatile with an annualized standard deviation of 127.4%. Given the advantages of using predictors with low variability, as argued by Campbell and Shiller (1988) and Fama and French (1988b), among others, we employ the $g_{[t-3\to t]}$ as the predictive variable in our analysis to smooth out short-term noise. In addition, this choice may also help allay concerns about potential seasonality in the $g_{[t-1\to t]}$ series. The predictive ability of

$g_{[t-3 \to t]}$ will be substantiated through a number of metrics.

Another important aspect of the data is that the autocorrelations of $g_{[t-3 \to t]}$ do not exceed 0.74. In the context of our predictive exercises to come, this feature indicates that using the BDI growth rate is not subject to inference issues that afflict other predictors, such as the aggregate dividend yield, that may exhibit near-unit-root dynamics (e.g., Cavanagh, Elliott, and Stock (1995), Stambaugh (1999), Valkanov (2003), Ferson, Sarkissian, and Simin (2003), Lewellen (2004), and Campbell and Yogo (2006)).

To examine more concretely the nature of the persistence in the BDI growth rate series, we fit all MA(q)-GARCH(1,1) models with $q \leq 6$ and ARMA(p,q)-GARCH(1,1) models with $p \leq 3$ and $q \leq 3$, with disturbances distributed Normal or t. Panel B of Table Appendix-I shows that MA(3)-IGARCH(1,1) with t distributed disturbances is the best model for $g_{[t-3 \to t]}$ according to the Bayesian information criterion (BIC), consistent with the selection of the MA(1)-IGARCH(1,1) model with t distributed disturbances as the best for $g_{[t-1 \to t]}$.

Our findings from the model selection impart two implications. First, we need not worry about the presence of a unit root in the BDI growth rate dynamics. Second, given the persistence in the BDI growth rates, we compute throughout p-values following the procedures in Hodrick (1992) and Newey and West (1994), which have been shown to be robust to the presence of persistent shocks (see also, Ang and Bekaert (2007) and Wei and Wright (2009)).

The goal of this paper is to investigate the predictive content of the BDI growth rate for global stock markets and global real economic activity. The link between economic activity and financial markets has been stressed in both empirical and theoretical studies, including those by Fama (1990), Cochrane (1991, 1996), Restoy and Rockinger (1994), Boldrin, Christiano, and Fisher (2001), Vassalou (2003), Balvers and Huang (2007), Cooper and Priestley (2009), Ou-Yang, Wei, and Zhang (2009), Moller and Rangvid (2009). and Belo (2010).

3. A common predictor of global stock returns: In-sample evidence

To investigate the relationship between the BDI growth rate and stock markets, we use returns of four regional stock market indexes, together with returns of the individual G-7, 12 additional developed, and 12 emerging stock markets. Having a broad sample of returns from stock markets is essential for establishing the pervasiveness of the results. The predicted variable throughout is the log excess return of a Morgan

Stanley Capital International (MSCI) total return index, denominated in US dollars. Thus, our empirical analysis is conducted from the viewpoint of US-based investors (e.g., Harvey (1991), De Santis and Gerard (1997), Guidolin and Timmermann (2008), Bekaert, Hodrick, and Zhang (2009), and Pakthuanthong and Roll (2009)).

We employ the following MSCI regional indexes: World, G-7, EAFE (developed markets excluding the US and Canada), and Emerging Markets. Further, we consider individual markets that are currently included in the MSCI World index. Our choice of developed markets (beyond G-7) and emerging markets is partly based on considerations of data availability, since, in particular for our out-of-sample tests, the length of the return time series is of concern (see Appendix A for data description, and Table 1 for the list of markets).

To evaluate the predictive content of the BDI growth rate, we initially focus on in-sample inference. Specifically, we examine the ability of the BDI growth rate to predict stock returns both at the one-month horizon and multi-month horizons using overlapping returns. Next, we consider a setting with two predictors and examine the predictive ability of the BDI growth rate in the presence of alternative predictors, for example, the lagged world return or the lagged US return.

3.1. Predictability of monthly stock returns

Table 1 presents the predictive regression results for monthly returns of the stock markets in our sample. The regression specification is

$$r_{[t\to t+1]} = \alpha + \beta g_{[t-3\to t]} + \varepsilon_{t+1}, \tag{2}$$

where $r_{[t\to t+1]}$ is the log excess return of a stock market for month $t+1$ and $g_{[t-3\to t]} = \ln(\mathrm{BDI}_t/\mathrm{BDI}_{t-3})$. We show the estimates of the slope coefficients β, and the corresponding two-sided p-values H[p] and NW[p], based (i) on the Hodrick (1992) 1B covariance matrix estimator under the null of no predictability, and (ii) on the heteroscedasticity and autocorrelation consistent (HAC) covariance matrix estimator from Newey and West (1987), with optimal lag selected as in Newey and West (1994), respectively.

Four major conclusions follow from the reported results for regional indexes and G-7 markets. First, the slope coefficient estimates are uniformly positive, implying that an increase in the BDI growth rate is associated with higher future stock returns. Further, the magnitudes of β are similar, ranging between 0.015 and 0.042.

Second, and importantly, the slope coefficient estimates are significant at the 5% level for eight out of the 11 regional indexes and G-7 markets, with most Hodrick p-values below 0.05. These low p-values are obtained across a range of markets, and specifically under the stringent Hodrick (1992) method of computing standard errors. The Newey and West (1987) p-values are even lower. Overall, there is strong evidence for the relevance of $g_{[t-3\to t]}$ as a common predictor of stock returns in our sample.

Third, the adjusted R^2's range, with one exception, between 1.9% and 3.8% for $g_{[t-3\to t]}$. The adjusted R^2's for $g_{[t-3\to t]}$ are relatively high, compared to those typically reported for predictive regressions with other predictors of stock returns (e.g., Campbell and Thompson (2008) and Goyal and Welch (2008)).

The exception is the Japanese stock market, which is relatively insensitive to movements in the BDI, with adjusted R^2's that are the lowest within our sample of G-7 markets. We observe the same feature based on out-of-sample yardsticks (see Table 4), where, for instance, the out-of-sample R^2's for Japan are the only negative ones among those for the G-7 markets.

To reinforce the common predictor conclusion, we next comment on the in-sample predictive regression results for the remaining developed and emerging markets. While the slope coefficient estimates are in a similar range (0.021–0.054) for the developed markets, a greater variation is observed for emerging markets. Furthermore, speaking to the strength of the evidence favoring predictability, there are 9 (16) out of the 24 markets where the Hodrick p-values are below 0.05 (0.10). The Newey and West p-values on β are again sizeably lower than their Hodrick counterparts, with a large fraction being below 0.05. Finally, the adjusted R^2's are in the range 0.3%–4.6%, with Argentina being the only market with a negative adjusted R^2.

To summarize, there appears to be consistency in the positive signs and magnitudes of the slope coefficient estimates in Table 1. The common thread is that the three-month BDI growth rate, $g_{[t-3\to t]}$, appears to be a robust predictor of global stock returns, with statistically significant β estimates, according to the Hodrick (1992) p-values, for most of the regional indexes and stock markets.

3.2. Predictability at longer horizons and joint p-values

Motivated by the extensive literature discussing short- versus long-horizon stock return predictability, we next ask the question: Does the BDI growth rate have predictive ability for stock returns over horizons longer than a month?

Besides helping to establish the robustness of the BDI growth rate as a predictor, this question also relates to an ongoing debate in the predictability literature.[3] Underlying our interest is, in particular, the fact that the BDI growth rate tends to be less persistent than some traditional predictors, whereas it has been recognized that it is often the predictor's persistence that accounts for enhanced predictability over longer horizons (e.g., Campbell (2001)).

For each market in our sample, we run the following predictive regressions with overlapping return observations:

$$r_{[t\to t+k]} = \alpha + \beta g_{[t-3\to t]} + \varepsilon_{t+k}, \qquad \text{for } k=3 \text{ and } k=6, \tag{3}$$

where $r_{[t\to t+k]}$, for $k=3$ ($k=6$) denotes cumulative log excess return over the three (six) months following month t, respectively, and $g_{[t-3\to t]} = \ln(\mathrm{BDI}_t/\mathrm{BDI}_{t-3})$, as previously. We report p-values for the slope coefficients β, relying on the approach in Hodrick (1992), under the null of no predictability.

Table 2 reveals a contrast between the predictability of three- and six-month stock returns. On one hand, three-month returns are still consistently predictable by the BDI growth rate, with β estimates significant at the 5% level for all regional indexes, five G-7, nine additional developed, and six emerging markets. For instance, the highest p-value for β is 0.020 for the regional indexes. Furthermore, the adjusted R^2's are uniformly higher than those for one-month returns, and are typically in the 3%–7% range.

On the other hand, the evidence for predictability disappears when six-month returns are considered. First, no slope coefficient estimate remains significant, even at the 10% level, and second, all R^2's drop and become negative for many markets.

The above pattern in the R^2's obtained with one-month up to six-month returns reveals a distinguishing trait of the BDI growth rate, when adopted as a predictor. For other predictors, for example, the dividend yield, it has been documented that adjusted R^2's typically first increase with the horizon and decrease only at multi-year horizons (e.g., Campbell, Lo, and MacKinlay (2003, Ch. 7)). This behavior has been justified under the assumption of a persistent predictor with autoregressive dynamics which loses informativeness only for the distant future. In contrast, the information content of the BDI growth rate seems to disappear over a few months.

Finally, we follow the approach outlined in Ang and Bekaert (2007, Appendix B, equation (B7)) and investigate the hypothesis of joint predictability across one-, three-, and six-month horizons. Based on

[3] Although longer-horizon returns have been shown to be more predictable (e.g., Fama and French (1988b), Menzly, Santos, and Veronesi (2004), and Lettau and Ludvigson (2005)), predictive inference issues with longer-horizon returns have also been identified (e.g., Richardson and Stock (1989), Stambaugh (1999), and Boudoukh, Richardson, and Whitelaw (2008)).

the covariance matrix estimator of Hodrick (1992) and the accompanying χ^2 test statistics, the p-values reported in the last two columns of Table 2 indicate that joint predictability cannot be statistically rejected across the one- and three-month horizons (one-, three-, and six-month horizons), with p-values below 0.05 for 16 (11) indexes and markets, respectively. Thus, our evidence points to joint return predictability at multiple horizons with the BDI growth rate.

3.3. Role of alternative predictors

Another question to ask at this point is: How does the BDI growth rate fare in the presence of alternative predictors? Addressing it, we first contemplate as alternatives the lagged MSCI World index return and the lagged US stock return.

The MSCI World index return has been previously examined as a predictor of global stock returns by Harvey (1991, 1995). Although we recognize that the US return exhibits sizable correlation with the World index return (0.87 in our sample), we include it in our analysis, motivated by Rapach, Strauss, and Zhou (2009), who have shown that it outperforms competing predictors for 12 developed markets, when the excess returns for these markets are denominated in the local currency.

In our setting with dollar-denominated returns, we employ regressions of the form:

$$r_{[t\to t+1]} = \alpha + \beta g_{[t-3\to t]} + \delta x_{[t-1\to t]} + \varepsilon_{t+1}, \tag{4}$$

where $r_{[t\to t+1]}$ denotes the log excess return of a market for month $t+1$, and $x_{[t-1\to t]}$ denotes the log excess return for month t, either for the World or the US stock market. The empirical question is whether the β estimate on $g_{[t-3\to t]}$ is statistically significant in the presence of $x_{[t-1\to t]}$.

Speaking to the merit of the BDI growth rate as a global predictor, Table 3 first shows that the β estimates slightly decrease in magnitude, compared to Table 1, but remain close to the 0.03–0.05 range. Further, the reported Hodrick (1992) p-values for the β estimates reaffirm the predictive ability of the BDI growth rate when either of the two alternative predictors is employed. Specifically, in the presence of the lagged US return, β is significant at 5% (10%) for 3 (4) of the regional indexes, 3 (6) of the G-7 markets, 2 (7) among the 12 other developed markets, and 3 (6) among the emerging markets.

Table 3 also shows that the statistical significance of the δ estimates is similar across the two alternative predictors. For instance, when the lagged US return is used, δ is significant at 5% (10%) for none of the regional indexes, 1 (2) of the G-7 markets, 1 (4) among the 12 other developed markets, and 2 (3) among the emerging markets. In sum, the evidence implies that the BDI growth rate favorably compares to these two lagged returns as a global predictor.

Relying on the Hodrick (1992) covariance matrix, we also calculate the joint *p*-values for the null hypothesis $\beta = \delta = 0$. There are 18 (17) markets out of 35 for which the joint *p*-values are below 0.10 when the lagged world (US) return is combined with the BDI growth rate, suggesting that the two predictors complement each other in predicting global stock returns, even when one of the predictors is insignificant.

Guided by the studies of Harvey (1991, 1995), Jones and Kaul (1996), Ang and Bekaert (2007), Guidolin and Timmermann (2008), Hjalmarsson (2010), and Hong and Yogo (2010), we have also explored the performance of the BDI growth rate in conjunction with other candidate predictors: (i) US term premium, (ii) US default spreads, (iii) log change in a commodity index (CRB, Moody's, or Reuters), and (iv) log change in the price of crude oil. Although not reported, the gist of those exercises is that the positive link between the BDI growth rate and future stock returns remains robust over our sample period, even after incorporating other predictors.

Appendix B examines the regression specification (4) in subsamples. It is shown that our conclusions about the predictability of stock returns with the BDI growth rate also hold in subsamples. For example, in the presence of an alternative predictor, the β estimates that are statistically significant in the full sample, when using Hodrick standard errors, typically remain significant in the majority of the subsamples. The β estimates are also positive in every subsample.

The basic message from the in-sample predictive regression results, presented in Tables 1 through 3, is that the BDI growth rate is a common variable that helps predict stock market returns and survives the addition of alternative predictors. Identifying the three-month BDI growth rate as a common predictor of dollar-denominated stock returns is an innovation of this paper, and differentiates our work from the extant literature.

4. Out-of-sample assessment of stock return predictability

Yet another perspective on the predictive ability of the BDI growth rate can be garnered by assessing statistical and economic significance in an out-of-sample setting. We consider both statistical out-of-sample tests (e.g., Campbell and Thompson (2008), Goyal and Welch (2008), and Clark and West (2007)) and present evidence on the economic significance of return predictability (e.g., Pesaran and Timmermann (1995) and Kandel and Stambaugh (1996)), where our attention is centered on certainty equivalent returns and Sharpe ratios of portfolio strategies. Out-of-sample tests can be viewed as imposing higher hurdles to demonstrating return predictability.

4.1. Statistical significance of predictability

The out-of-sample predictive ability of the BDI growth rate is evaluated using two metrics: (i) the out-of-sample R^2, as suggested in Campbell and Thompson (2008), and (ii) the adjusted mean-squared prediction error statistic, as developed in Clark and West (2007). The latter can be a useful device for comparing the predictions from nested models.

4.1.1. Evidence from the out-of-sample R^2 statistic

The out-of-sample R^2 statistic, denoted hereafter by R^2_{OS}, is defined as

$$R^2_{OS} \;=\; 1 \;-\; \frac{\sum_{t=0}^{T-1}(r_{[t\to t+1]} - \widehat{r}_{t+1})^2}{\sum_{t=0}^{T-1}(r_{[t\to t+1]} - \overline{r}_{t+1})^2}, \tag{5}$$

where $\widehat{r}_{t+1}$ is the prediction for month $t+1$ from a BDI-based predictive regression and $\overline{r}_{t+1}$ is the historical average return, both estimated using data up to and including month t. The viability of a predictor is demonstrated through a positive R^2_{OS}, which indicates a lower mean-squared prediction error from a predictive regression model, relative to that from a prediction based on the historical average return.

It is customary to calculate R^2_{OS} either with an expanding window, where $\widehat{r}_{t+1}$ and $\overline{r}_{t+1}$ are estimated using all data available up to and including month t, or with a rolling window of size τ, where only data from the τ months up to and including month t are used. While the expanding window has the advantage of fully utilizing the available data, the choice of a rolling window has also been justified, since it may better account for potential time variation in model parameters, or may keep constant the effect of estimation uncertainty on forecast performance (see Giacomini and White (2006)).

Table 4 presents the results on the out-of-sample R^2 statistic, based on an expanding window with initial length of 120 or 180 months, as well as a rolling window with a fixed length of 120 or 180 months. The R^2_{OS}'s for the regional indexes are consistently positive, and among the highest across our sample. Besides, R^2_{OS}'s are positive for six G-7 markets, conveying the out-of-sample predictive ability of the BDI growth rate. The big picture is largely preserved across the developed (emerging) markets, where the R^2_{OS}'s are positive in 32 (22) out of 48 (46) instances.

The results appear aligned across expanding and rolling windows, and it is seldom that the R^2_{OS}'s are smaller for the longer 180-month window. In particular, using an expanding window with initial length of 180 months, the R^2_{OS}'s are above 3.7% for all four regional indexes, above 2.4% for six G-7 markets, above 2.1% for six out of 12 developed markets, and above 2% for three out of 12 emerging markets. In contrast, the R^2_{OS}'s are negative for one G-7 market, three developed markets, and six emerging markets. Any lack of out-of-sample predictability appears to be tilted towards emerging markets, which also exhibit a large dispersion in R^2_{OS}'s.

When positive, the R^2_{OS}'s average 4.8%, 4.6%, 2.8%, and 3.3% for the regional indexes, G-7, developed, and emerging markets, respectively. The R^2_{OS}'s for the US returns range between 3.9% and 6.5%. In contrast, Goyal and Welch (2008) find that a host of variables that predict US stock returns in-sample, in fact relinquish their predictive superiority over the historical average return, when subjected to out-of-sample tests.

One question worth clarifying is: How do the R^2_{OS}'s obtained for the BDI growth rate compare to those reported for other predictors? For example, Campbell and Thompson (2008, Table 2) show R^2_{OS} below 1% at the monthly frequency for 11 predictors of US stock returns, while Rapach, Strauss, and Zhou (2009, Table III) show R^2_{OS}'s that range between -0.28% and 3.07%, when the lagged US return is used as a predictor, for their sample of monthly returns of developed markets. Our results from the R^2_{OS} statistic suggest that the BDI growth rate performs better than some alternative predictors of stock index returns.

4.1.2. Evidence from the mean-squared prediction error

We further examine the relevance of the BDI growth rate as a predictor from the perspective of statistical significance in an out-of-sample context. Specifically, we investigate whether it significantly improves on a forecast based solely on the historical average return, in parallel to the exercise conducted for the out-of-sample R^2, and we additionally evaluate its incremental predictive ability in the presence of the lagged world (US) return.

To this end, we consider a benchmark model as well as a model obtained by incorporating an additional predictor. We refer to the former as the nested model and the latter as the full model. In what follows, we first take the model with no predictors (i.i.d.) as the benchmark model, and the BDI-based predictive regression model as the full model. Second, we take the predictive regression model based on the BDI growth rate or the lagged world (US) return as the benchmark model, and the predictive regression model based on the combination of the BDI growth rate and the lagged world (US) return as the full model.

Our empirical exercise relies on a formal test of the null hypothesis that the full model does not significantly improve on the forecast from the nested model. We follow Clark and West (2007), who develop an adjusted mean-squared prediction error (MSPE) statistic for evaluating forecasting models, by defining:

$$f_{t+1} = (r_{[t\to t+1]} - \widehat{r}_{t+1,\text{nested}})^2 - [(r_{[t\to t+1]} - \widehat{r}_{t+1,\text{full}})^2 - (\widehat{r}_{t+1,\text{nested}} - \widehat{r}_{t+1,\text{full}})^2], \tag{6}$$

where $\widehat{r}_{t+1,\text{full}}$ is the predicted return for month $t+1$ from the full model and $\widehat{r}_{t+1,\text{nested}}$ is the predicted return for month $t+1$, both obtained using data up to and including month t. The t-statistic from the regression of f_{t+1} on a constant is the MSPE-adjusted statistic.

We apply the above test to compare the predictive regression model with the BDI growth rate to the i.i.d. model with the historical average return as predictor. Presented in Table 4 are the one-sided p-values for the MSPE-adjusted statistic, obtained based on an expanding window with initial length of 120 (180) months as well as a rolling window of 120 (180) months. As we explain below, these results are consistent with the reported R^2_{OS}'s from two perspectives, and attest to the out-of-sample predictive ability of the BDI growth rate.

First, the p-values for the regional indexes do not exceed 0.03. Strengthening the evidence, out of the 28 reported p-values for the G-7 markets, 16 are below 0.05 and eight are between 0.05 and 0.10. As delineated before, the exception is Japan, with all four p-values exceeding 0.10. Among the developed markets, 16 (34) out of 48 p-values are below 0.05 (0.10). The predictive ability of the BDI growth rate appears to weaken when moving to emerging markets with 16 (25) out of 48 p-values below 0.05 (0.10).

Second, stock markets that do not show evidence for significant predictive power of the BDI growth rate based on the MSPE-adjusted p-values also display negative R^2_{OS}. Furthermore, the p-values are consistent across both the expanding and rolling windows, and the different window lengths, speaking to the stability of the results.

An additional insight, in terms of incremental predictive ability, can be gleaned from the reported MSPE-adjusted p-values in Table 5, where we consider nested models with the BDI growth rate or the lagged world (US) return as the sole predictor, whereby in both cases the full model incorporates both the BDI growth rate and the lagged world (US) return. A low p-value for the MSPE-adjusted statistic when the nested model includes a lagged return would indicate that adding the BDI growth rate as a predictor improves on a prediction based only on the respective lagged return.

Quantifying the importance of the BDI growth rate as a predictor in the presence of alternative predictors, the results of Table 5 indicate that when the nested model is based exclusively on the lagged US return, the MSPE-adjusted statistic is significant at the 5% (10%) level for 3 (4) of the regional indexes, 3 (4) of the G-7 markets, 1 (6) of the developed markets, and 1 (4) of the emerging markets. In turn, the corresponding occasions of significance at the 5% (10%) level are 0 (0), 0 (1), 1 (3), and 1 (2), respectively, when the BDI growth rate is the sole predictor in the nested model. Therefore, the results generally confirm the BDI growth rate's predictive ability, whereas the evidence from the emerging markets appears weaker.

In summary, we can draw two key conclusions from the out-of-sample statistical results. For one, the accumulation of evidence demonstrates the predictive power of the BDI growth rate for the majority of regional indexes and markets. For another, they agree with and reinforce the results from in-sample predictive regressions, and consolidate the relevance of the BDI growth rate as a predictor of global stock market returns.

4.2. Economic significance of predictability

With the intent to establish the economic significance of predictability via the BDI growth rate, we further elaborate on the BDI-based predictive regression model and the no-predictability i.i.d. model, and examine the out-of-sample performance of portfolio strategies associated with these two models. We consider an investor with an investment opportunity set consisting of a stock index and a risk-free bond. The investor's portfolio gross return is $R^P_{t+1} = (1-\omega_t)R^f_{t+1} + \omega_t R_{t+1}$, where is ω_t is the portfolio weight on the stock index determined in month t, R^f_{t+1} is the gross return of the risk-free bond over month $t+1$, and the gross stock index return is $R_{t+1} \equiv R^f_{t+1} e^{r_{[t\to t+1]}}$. We assume that the investor's preferences are described by a CRRA utility function with coefficient of relative risk aversion denoted by γ, and impose no borrowing and no short-selling constraints on the portfolio positions.

The investor's portfolio allocation at time t is, thus, determined by solving the following optimization problem:

$$\max_{\omega_t \in [0,1]} \mathbb{E}_t \left(U\left[(1-\omega_t) R^f_{t+1} + \omega_t R_{t+1} \right] \right), \qquad \text{with} \qquad U[x] = \frac{x^{1-\gamma}}{1-\gamma}, \tag{7}$$

where $\mathbb{E}_t(\cdot)$ is the expectation operator characterized by the conditional distribution of $r_{[t\to t+1]}$, which is assumed to be Normal.

Each predictive model gives rise to different estimates of conditional means and standard deviations and, in turn, to different conditional distributions. The models are reestimated sequentially, and the new estimates are used to obtain the updated conditional distribution of the log excess return $r_{[t \to t+1]}$. More specifically, we use an initial sample of length equal to 120 months, and, subsequently, reestimate both models using an expanding as well as a rolling window of length equal to 120 months.

Guided by Kandel and Stambaugh (1996), among others, we adopt two metrics for gauging the economic significance of predictability associated with the BDI growth rate. First, for both strategies, we compute the certainty equivalent return (CER) defined as

$$\text{CER} \; = \; U^{-1}\left[\frac{1}{T}\sum_{t=0}^{T-1} U\left[(1-\omega_t^*)\, R_{t+1}^f + \omega_t^* R_{t+1}\right]\right] \; - \; 1, \tag{8}$$

where T is the number of out-of-sample months, and ω_t^* is the optimal allocation in the stock index according to each strategy in month t. Second, we report the Sharpe ratios (SR) for both strategies.

Table 6 displays CER and SR, in annualized terms, for $\gamma = 3$. An important observation that arises is that the in-sample and out-of-sample statistical evidence, that we documented previously, is corroborated by favorable economic significance results. For example, the CER for the BDI-based strategy exceeds its counterpart for the i.i.d. strategy in 33 (35) out of 35 markets when using an expanding (rolling) window.

With an expanding window, the average improvement in CER is 374 (234) basis points for the regional (G-7) stock indexes. For the developed markets, the CER associated with the BDI-based model ranges between 286 and 1,236 basis points, with an average improvement of 314 basis points. For the emerging markets, the BDI-based portfolio strategy delivers substantial utility gains, with an average improvement over the i.i.d. strategy of 499 basis points. There is sizable variation in the CER across markets, whereby the i.i.d.-based strategy surpasses the BDI-based counterpart for two countries. The results based on the rolling estimation window qualitatively mirror those generated based on the expanding window.

The Sharpe ratio results uncover an analogous overall ranking between the two portfolio strategies, with the BDI-based strategy often generating twice the Sharpe ratio of the i.i.d. strategy. For example, with the expanding window, the SR of the i.i.d. strategy for the regional indexes ranges between 0.12 and 0.19, while it ranges between 0.31 and 0.60 for the BDI-based strategy. For the G-7 markets, the SR ranges between −0.30 and 0.37 (0.01 and 0.54) for the the i.i.d. (BDI-based) strategy. The ranking obtained with the expanding window concurs with the one obtained from the rolling window.

Our results on economic significance should be viewed as conservative compared to, for instance, those in Campbell and Thompson (2008), who allow leverage up to 50%. The results with $\gamma = 6$ impart a similar message and are omitted.

What is the incremental improvement, in terms of CER and Sharpe ratio, when the BDI growth rate is augmented by the lagged world (US) return in a bivariate predictor framework? Table 7 presents five sets of results obtained when the set of predictors consists of (i) the BDI growth rate, (ii) the lagged world return, (iii) the lagged US return, (iv) the BDI growth rate plus the lagged world return, and (v) the BDI growth rate plus the lagged US return.

We note that the BDI-based strategy dominates the strategy based on the lagged world return. This is seen from the incremental CER generated in three regional indexes, four G-7 markets, seven developed markets, and nine emerging markets. The BDI-based strategy fares slightly better against the lagged US return-based strategy, generating incremental CER for four regional indexes, five G-7 markets, eight developed markets, and nine emerging markets. At the same time, we observe that the lagged world returns provide superior economic significance compared to lagged US returns. Conforming with the aforementioned results, the BDI-based strategy also tends to produce a rise in Sharpe ratios, affirming the broader relevance of the BDI growth rate, even when one deviates from the customary i.i.d. model benchmark of no-predictability.

The main takeaway from the results in Tables 6 and 7 is that they support the economic significance of the BDI growth rate as a predictor across global stock markets. When comparing strategies within a market, there are material gains to incorporating BDI growth rate as a predictor in the asset allocation decision. This economic dimension is generally aligned with the preceding statistical evidence favoring predictability, with utility gains outweighing the counterparts established in the context of traditional predictors (see, among others, Campbell and Thompson (2008), Goyal and Welch (2008), Rapach, Strauss, and Zhou (2010), and Moller and Rangvid (2009)).

5. Predicting commodity returns and evidence on joint predictability

One may argue that changes in the BDI are linked to changes in the prices of commodities, given the notion that the BDI is sensitive to developments in the demand for raw materials and global trade. This argument can be considered in conjunction with the previous finding that the behavior of commodity prices varies over the business cycle (Fama and French (1988a)), and also with the strand of research that explores the time variation in expected commodity returns (e.g., Bessembinder and Chan (1992), Gorton, Hayashi, and Rouwenhorst (2008), and Hong and Yogo (2010)).

An outstanding question then is whether the BDI growth rate has predictive power for commodity returns, and we contribute by examining such a relation, both in-sample and out-of-sample. Given our findings in Section 3, we also address the question whether commodity indexes and stock markets exhibit joint return predictability.

We examine commodity return predictability using established commodity indexes and subindexes, and we focus first on the Moody's Commodity Index, the Reuters Commodity Index, and the CRB Spot Index (see Appendix A for details). The indexes represent the commodity universe from different perspectives, as manifested, for example, in the average correlation of 0.67 between their monthly returns.[4] Table 8 presents in-sample results from predictive regressions with $g_{[t-3\to t]}$ (Panel A), and the corresponding out-of-sample statistics (Panel B).

The slope coefficient estimates on the BDI growth rate are positive, mirroring our results from stock markets, reported in Table 1. Besides, the β estimates are strongly significant, with a maximum Hodrick (Newey and West) p-value of 0.045 (0.031), and the adjusted-R^2's range between 5.7% and 11.1%. Turning to the out-of-sample evidence, we observe that R^2_{OS}'s are predominantly positive, and can be as high as 12%. In addition, the p-values for the MSPE-adjusted statistic are below 0.05 in 11 out of 12 counts. Collectively, the results in Table 8 bolster our evidence on the predictive ability of the BDI growth rate.

Next we consider two CRB subindexes: Foodstuffs and Raw Industrials (details are in Appendix A). It is seen that all slope coefficient estimates remain positive (Panel A), but statistical significance, both in-sample and out-of-sample, vanishes for the Foodstuffs subindex. The differential predictive ability for the two subindexes, thus, lends some credence to the view that the predictive power of the BDI growth rate may be connected to the relation between the BDI and the global demand for industrial raw materials.

Returning to our theme of the BDI's merit as a common predictor across markets, we appeal to a statistical test of the joint predictability of commodity returns and stock returns. We employ a system of equations of the type: $\mathbf{r}_{[t\to t+1]} = \mathbf{a} + \mathbf{b}\, g_{[t-3\to t]} + \mathbf{e}_{t+1}$, where $\mathbf{b}$ is an $L \times 1$ vector of regression slope coefficients, and L is the number of equations. We take L to be either two, three, or four, and combine each stock market and possible pair or triple of stock markets with each of the commodity indexes. Then, we

[4] The use of various indexes is justified by the potentially large differences between the respective construction methodologies. In particular, commodity indexes may vary with respect to the identity of the individual commodity components, the weighting scheme, and the accounting for possible extreme concentrations. These differences may bring divergence between the indexes' dynamics, necessitating the examination of predictability from the perspective of multiple indexes.

use the Hodrick (1992) procedure to test whether $\mathbf{b} = \mathbf{0}_{L\times 1}$, and the p-values are based on the χ^2 statistic with L degrees of freedom. Boudoukh, Richardson, and Whitelaw (2008) and Cochrane (2008), among others, have emphasized the importance of testing for joint significance of a common predictor in a system of predictive regressions.

We report below the number of cases where the respective Hodrick joint p-value is below 0.05, or between 0.05 and 0.10, when each of the commodity indexes is used in the joint test.

		Moody's Index		Reuters Index		CRB Index	
	total	< 0.05	$[0.05, 0.10]$	< 0.05	$[0.05, 0.10]$	< 0.05	$[0.05, 0.10]$
1 stock + 1 commodity	35	35	0	33	2	3	16
2 stocks + 1 commodity	465	213	252	268	190	7	90
3 stocks + 1 commodity	4495	773	1857	1000	2448	27	400

For example, with the Moody's commodity index and three stock indexes, there are 2630 instances out of 4495 in which the joint p-value is below 0.10, broadly indicating joint predictability across stock and commodity returns. The evidence for joint predictability is stronger (weaker) for the Reuters (CRB) index, with 3448 (427) p-values below 0.10. The unifying picture that emerges is that $g_{[t-3\to t]}$ is useful in predicting commodity and stock returns, both within a system of regressions, as well as in single regressions.

6. Predictability of global real economic activity

Finally, we examine the predictive power of the BDI growth rate for real economic activity across a broad spectrum of countries, while striving to maintain an overlap with the set of countries considered in Section 3. Investigating potential ties of the BDI growth rate to real economic activity may help clarify interlinkages between stock markets, commodity markets, and the real sector.

Our measure of real economic activity is industrial production (see also, Stock and Watson (1989, 2003), Croushore and Stark (2003), Clements and Galvao (2008), and Aruoba, Diebold, and Scotti (2009)), and we concentrate on the monthly growth rate of the seasonally adjusted production of total industry (excluding construction). We obtain data on industrial production for 20 OECD countries that are also in our sample from Table 1. Denote the industrial production growth rate by $z_{[t-1\to t]} \equiv \ln(\mathrm{IP}_t/\mathrm{IP}_{t-1})$, where IP_t is the level of industrial production in month t for a country.

Econometric concerns arise when examining the predictability of $z_{[t\to t+1]}$, as its own past values may contain predictive information (see, e.g., Stock and Watson (2003), Kilian (2009), and references therein). In particular, including lags of the industrial production growth rate on the right-hand side of a linear predictive regression invalidates the assumptions underlying least squares inference.

The relevant question to research is whether the BDI growth rate $g_{[t-3\to t]}$ has predictive content for $z_{[t\to t+1]}$ *beyond* the industrial production growth rate's own past values. To account for the time-series dependence in industrial production growth rate, we follow a two-step procedure. First, we estimate via maximum likelihood for each country a number of time-series models for $z_{[t\to t+1]}$ that incorporate (i) an ARMA(p,q) structure, with and without GARCH(1,1) dependence, and (ii) the BDI growth rate. Second, we select the best of these models by using the Bayesian information criterion, and employ this model to assess the incremental predictive ability of the BDI growth rate.

More concretely, we examine ARMAX models of the type:

$$z_{[t\to t+1]} \;=\; \alpha \;+\; \beta\, g_{[t-3\to t]} \;+\; \sum_{i=1}^{p} \psi_i\, z_{[t-i\to t-i+1]} + \sum_{j=1}^{q} \xi_j\, \varepsilon_{t-j+1} + \varepsilon_{t+1}, \tag{9}$$

for $p \leq 2$ and $q \leq 2$, and where ε_{t+1} can follow a GARCH(1,1) specification (thus, we estimate for each country a total of 16 models). Our object of interest is the slope coefficient β on the BDI growth rate $g_{[t-3\to t]}$ and its statistical significance. The rationale for using the specification (9) is to explicitly take into account the dependence structure of the industrial production growth rate.

Table 9 reports, for each country, the respective coefficient estimates and their two-sided p-values. We note that (i) the autoregressive conditional heteroskedasticity is present in 12 (out of 20) countries, implying the importance of including such a feature, and (ii) the MA(1) component, when present, is typically negative, while the AR(1) component can be of either sign. For instance, the dynamics of the US industrial production growth rate is found to be best described by an ARMA(1,2) specification, with a statistically significant ARCH, but not GARCH, effect.

Turning to the predictive power of the BDI growth rate in our ARMAX setting, we find that out of the 20 reported β estimates, 15 are positive and statistically significant at the 5% confidence level. For example, the β estimate for the US is 0.003, with a p-value of 0.000. Note also that the β estimate for Japan is 0.003, with a p-value of 0.059, while the returns of the Japanese stock market appear detached from variations in the BDI growth rate, as we document in Sections 3 and 4.

The BDI growth rate is positively related to the subsequent growth rate of industrial production, and the effect is statistically significant for most developed and emerging market countries. These results complement the evidence for the predictive links between the real economy and the financial sector (e.g., Fama (1990), Cochrane (1991), Vassalou and Liew (2000), Vassalou (2003), Rangvid (2006), and Belo (2010)), testifying to the possible validity of such links on a more global scale than previously documented.

7. Discussion of the pattern of predictability

The cornerstone of our findings is that increases in the BDI growth rate could predict increases in economic growth, concurring with strengthening commodity prices and rising stock markets. What could be a possible channel for this predictability?

Note that stock return predictability has often been attributed to the fact that the respective predictor reflects expected business conditions (e.g., Fama and French (1989) and Ferson and Harvey (1991)). In our context, such an argument agrees with the intuition that the BDI's predictive ability stems from its sensitivity to developments in the real sector.

The above intuition may also be consistent with a gradual diffusion of information framework, for example, as in Hong, Torous, and Valkanov (2007) who examine, in the context of several developed countries, the ability of the respective country's industry portfolio returns to predict aggregate stock market returns up to two months ahead. They show this ability to be correlated with the propensity of industry portfolio returns to also predict market fundamentals, such as industrial production growth in the respective country, whereby the slope coefficient estimates in the predictive regressions for market returns and industrial production growth, respectively, are of the same sign. It may be worth stressing the analogy between the industry portfolio returns as predictors and the BDI growth rate, which (i) is able to predict stock returns *and* industrial production growth, and (ii) exhibits a positive sign in all respective slope coefficient estimates, across a number of countries. The documented return predictability up to three months with the BDI growth rate (our Table 2) speaks to the plausibility of a framework that incorporates gradual absorption of information across markets.

Moving on, note that the positive slope coefficients on the BDI growth rate for stock returns and industrial growth do not follow a priori from the relation of a predictor to business conditions and fundamentals.[5]

[5] For example, Campbell and Diebold (2009) examine the Livingston six-month growth forecast and find that it is significantly and negatively associated with future stock returns at the annual horizon, which may be attributed to the persistence in business conditions at short horizons or may reflect the relation between expected business conditions and expected stock market risk, as measured by return volatility. Besides, Charoenrook (2005) reports that the Consumer Sentiment Index negatively predicts market returns at the monthly horizon.

In this regard, we surmise that the BDI growth rate may be reflecting a specific type of information, namely about future cash flows (Campbell (1991) and Campbell and Shiller (1988)). Exploring this contention, we provide evidence from two perspectives.

First, we perform predictive regressions of US Treasury bond returns on the BDI growth rate. The motivation here is that a predictor that predominantly captures time-variation in discount rates is likely to display predictive ability for Treasury bond returns, as their cash flows are fixed (see Chen and Zhao (2009), but also Campbell, Polk, and Vuolteenaho (2010) for the possible effect of bond index construction). We consider the regression $r^{\text{Treas}}_{[t\to t+1]} = \alpha + \beta g_{[t-3\to t]} + \varepsilon_{t+1}$, where $r^{\text{Treas}}_{[t\to t+1]}$ is the return of a US Treasury bond index (from Ibbotson), in excess of the one-month risk-free rate, and obtain,

	β	H[p]	DW	$\overline{R}^2$
Intermediate US Treasury bonds	−0.005	0.186	1.76	1.1
Long-term US Treasury bonds	−0.011	0.446	2.00	1.1

The lack of predictability of bond returns, as suggested by the high Hodrick p-values, may point to a cash flow channel for the BDI's predictive ability.

Second, we exploit an observation made in Cochrane (2008, equation (19)) that if a predictor helps to forecast either the next-period stock return, or dividend yield, or dividend growth, which is the cash flow proxy, then this predictor *must* also help forecast at least one of the other two variables. The reasoning relies on the relation $d_t - p_t = E[r_{t+1}|\Omega_t] - E[\Delta d_{t+1}|\Omega_t] + \rho E[d_{t+1} - p_{t+1}|\Omega_t]$, where d and p are log dividend and log stock price, respectively, r is stock return, Δ denotes growth, ρ is a positive constant, and Ω_t is the information set at time t which, in our context, includes the BDI growth rate in addition to the dividend yield. To examine this implication, we employ US data on dividends and dividend yields (from the web site of Michael Roberts, May 1985 to December 2008). The dividend variables are adjusted for net equity issues following Boudoukh, Michaely, Richardson, and Roberts (2007). Our findings from the predictive regressions with the BDI growth rate and the dividend yield as predictors are presented below:

Predicted variable	Predictors					
	BDI growth rate		Dividend yield			
	β	H[p]	θ	H[p]	DW	$\overline{R}^2$
Excess Return	0.027	0.043	0.015	0.218	1.93	3.1
Dividend growth	0.030	0.056	−0.014	0.614	2.20	1.6
Dividend yield	0.003	0.951	0.984	0.000	2.23	97.2

Given the small and insignificant slope estimate on the BDI growth rate for the regression with the dividend yield as the predicted variable, the positive and statistically significant slope estimates on the BDI growth rate in the regressions with the market return and dividend growth are mutually consistent. In other words, under the conjectured cash flow channel *and* with a positive relation between the BDI growth rate and future dividend growth, a positive slope coefficient on the BDI growth rate when predicting market returns could be expected. Therefore, these predictive regressions add to the evidence in support of a cash flow link for interpreting BDI's predictive ability.

8. Conclusions

This paper examines the evidence for predictability of global stock market returns, commodity index returns, and growth in global real economic activity, using the three-month growth rate of the Baltic Dry Index (BDI) as predictor.

We establish several empirical findings. First, the slope coefficients in predictive regressions of stock market returns on the BDI growth rate are overwhelmingly positive and statistically significant for a number of markets, in an in-sample analysis. Second, the out-of-sample R^2 statistic is at par or higher than those reported in the extant literature. In addition, we obtain low p-values for the null hypothesis that the BDI growth rate does not significantly improve on a forecast based on the historical average return. Third, we establish the economic significance of predictability by showing that the certainty equivalent returns and Sharpe ratios associated with a BDI-based portfolio strategy exceed those obtained with a portfolio strategy, based on the assumption of i.i.d. stock returns. Fourth, a higher BDI growth rate has a positive and statistically significant impact on commodity returns. Fifth, the BDI growth rate is positively related to the subsequent growth rate of industrial production, and this effect is statistically significant for the majority of the countries in our sample, both developed and emerging market economies.

Collectively, both statistical and economic significance tests provide evidence for the BDI growth rate's predictive ability, which is also robust to the presence of alternative predictors. The results reported in this paper, thus, help demonstrate the relevance of the BDI as a predictor that captures variation across the real and financial sectors of a multitude of economies around the world. Furthermore, our line of research can be extended to examine the possible role of the BDI growth rate as a pricing factor in explaining variations in the cross section of expected stock returns.

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Appendix A: Description of data on global stock markets, commodities, and industrial production

Stock Markets: We use MSCI total return stock indexes, denominated in US dollars and available at Datastream. We calculate log excess returns, where the risk-free rate series is taken from the data library of Kenneth French. To match the first available observation for the Baltic Dry Index, our return sample starts, when possible, in May 1985 and ends in September 2010.

The markets included in our sample exhibit stylized return properties with respect to the mean, standard deviation, and autocorrelations that are comparable, for example, to those in Bekaert and Harvey (1995, Table I). Our sample of global stock markets is comprehensive, similar to those in Bekaert, Hodrick, and Zhang (2009), Bossaerts and Hillion (1999), Hjalmarsson (2010), and Jorion and Goetzmann (1999). Detailed summary statistics for our sample of stock market returns are available upon request.

We consider four regional MSCI stock indexes: World, G-7, EAFE, and Emerging markets. Among the individual markets, we include those in G-7, together with another 12 developed markets in the MSCI World index. Further, we include 12 emerging market countries, which are in the MSCI World index and among those with the largest stock market capitalization. For the emerging markets, the sample starts typically in December 1987.

Three of the regional indexes have 305 monthly observations, except for the Emerging markets index (274 observations; sample starts in December 1987). Moreover, the G-7 and other developed markets have full sample with 305 observations, except for Portugal (274 observations; sample starts in December 1987). Eight emerging markets have 274 monthly observations, except for China, India, Poland, and South Africa (214 observations; sample starts in December 1992), and Russia (190 observations; sample starts in December 1994).

Commodities: We consider three prominent spot commodity indexes: the Moody's Commodity Index, the Reuters Commodity Index, and the CRB Spot Index. Each series starts in May 1985 and contains 305 observations. The data source is Datastream. We calculate commodity index returns as monthly changes in the log of the respective index level, in excess of the risk-free rate.

To give some background on the composition of the indexes, we note that the Moody's Commodity Index is made up of 15 commodities (cocoa, coffee, cotton, copper, hides, hogs, lead, maize, silver, silk, steel scrap, sugar, rubber, wheat, and wool), weighted by the level of US production or consumption. The Reuters index of staple commodity prices is a geometric average of 17 commodities (wheat, cotton, coffee, wool, copper, sugar, rubber, maize, rice, beef, soyabeans, cocoa, tin, groundnuts, copra, zinc, and lead), weighted by their importance in international trade. The CRB Spot Index is an unweighted geometric average of 22 commodities, with two major CRB subindexes: Raw Industrials (burlap, copper scrap, cotton, hides, lead scrap, print cloth, rosin, rubber, steel scrap, tallow, tin, wool tops, and zinc), and Foodstuffs (butter, cocoa beans, corn, cottonseed oil, hogs, lard, steers, sugar, and wheat).

Commodity indexes may be based not only on spot prices, but also on futures prices. When futures prices are used, the indexes reflect the selection of futures contacts to be used, and the roll-over scheme. Such considerations are more specifically related to the design of a trading strategy and not to the dynamics of the underlying commodity prices, which is our concern. For this reason, we omit futures-based commodity indexes in our empirical analysis.

Industrial Production: Our measure of real economic activity is industrial production, as, for instance, in Stock and Watson (1989) and Aruoba, Diebold, and Scotti (2009). We obtain from Datastream data on the seasonally adjusted production of total industry (excluding construction). Included in our sample are 20 OECD countries that are also represented in Table 1.

Comparable data on industrial production at the monthly frequency was unavailable for some countries, making our set smaller than that for stock returns. Most of our time series on industrial production starts in May 1985, except for India (starting in April 1994), Korea (starting in January 1990), and Russia (starting in January 1993). Countries that are missing in our sample either did not have an industrial production series at the monthly frequency, or, if available, it was not seasonally adjusted.

Appendix B: Gauging the predictive power of the BDI growth rate in subsamples

Here we assess the reliability of the BDI growth rate as a predictor of stock returns across subsamples, and ask: How pervasive is the positive slope coefficient on the BDI growth rate in subsamples, both in univariate- and bivariate-predictor settings? Is the slope coefficient on the BDI growth rate statistically significant according to the Hodrick p-values in subsamples?[6]

We address these questions using rolling subsamples with a length of 20 years (240 observations), whereby the first subsample starts in May 1985, and the subsequent ones start at six-month intervals. This procedure yields 11 subsamples over May 1985 to September 2010. The length of the subsamples is chosen

[6]This line of inquiry is in the vein of, among others, Nelson and Kim (1993), Kothari and Shanken (1997), and Ferson, Sarkissian, and Simin (2003), and aims at studying the stability of the relation between the BDI growth rate and future stock returns.

to allow a sufficiently long time series to detect predictability in an in-sample exercise, and yet to assess robustness over diverse business conditions.

In each subsample, we estimate $r_{[t\to t+1]} = \alpha + \beta g_{[t-3\to t]} + \delta r^{\text{world}}_{[t-1\to t]} + \varepsilon_{t+1}$ (as in equation (4)), as well as the restricted specifications with $\beta = 0$ and $\delta = 0$. Table Appendix-II provides evidence across the 21 markets with full sample of stock returns (305 observations). Replacing the lagged world return with the lagged US return provides similar results.

Several conclusions are noteworthy in the context of our subsample analysis. First, as in the predictive regressions reported in Tables 1 and 3, the slope coefficient β on the BDI growth rate is positive in each market and subsample, both in univariate- and bivariate-predictor settings. Second, the predictive power of the BDI growth rate does not diminish in the presence of the lagged world return. For most of the markets with significant β estimates in Table 3, the β estimates are still statistically significant in the majority of the subsamples. In contrast, the δ estimate is not significant even once for 18 out of 21 markets (in the unrestricted estimation (4)).

Finally, the average adjusted R^2 is typically higher with the BDI growth rate as a single predictor, as opposed to when the BDI growth rate is combined with the lagged world return. Thus, the lagged world return does not appear to enhance joint explanatory power beyond the BDI growth rate.

It is worth emphasizing that the positive β estimates in conjunction with their statistical significance over a number of subsamples and markets suggest that the predictability pattern discussed in this paper is not an artifact of a particular subsample. The results obtained over subsamples could be relevant for understanding the source of the predictability with the BDI growth rate and, in particular, the possible cash flow link, as explored in Section 7.

Out-of-sample tests, analogous to those reported in Tables 4 and 6, and based on a 10-year estimation window and a 10-year evaluation window, provide similar conclusions about predictability with the BDI growth rate in subsamples. Complete tabulations are available from the authors.

Table 1
Baltic Dry Index and the predictability of stock returns

The forecasting variable is the three-month BDI growth rate, defined as $g_{[t-3\to t]} = \ln(\mathrm{BDI}_t/\mathrm{BDI}_{t-3})$. Results are presented for the predictive regressions $r_{[t\to t+1]} = \alpha + \beta g_{[t-3\to t]} + \varepsilon_{t+1}$, where $r_{[t\to t+1]}$ denotes the log excess return of a stock market for month $t+1$, denominated in US dollars. Reported are the β estimates, as well as two-sided p-values for the null hypothesis $\beta = 0$, denoted by H[p] and NW[p], based on the Hodrick (1992) covariance estimator, and the procedure in Newey and West (1987) with optimal lag selected as in Newey and West (1994), respectively. The Durbin-Watson statistic and the adjusted R^2 (in %) are denoted by DW and $\overline{R}^2$. The number of observations is denoted by NOBS. To save space, we do not report the intercept in the regressions. All data series ends in September 2010. The data are described in Appendix A.

	β	H[p]	NW[p]	DW	$\overline{R}^2$	NOBS
Regional indexes						
World	0.029	0.020	0.011	1.83	3.8	305
G-7	0.029	0.018	0.009	1.85	3.7	305
EAFE	0.028	0.038	0.035	1.79	2.6	305
Emerging	0.042	0.023	0.010	1.71	3.4	274
G-7 markets						
US	0.029	0.017	0.001	1.93	3.7	305
Japan	0.015	0.202	0.120	1.78	0.2	305
UK	0.031	0.014	0.003	1.90	3.3	305
Canada	0.037	0.019	0.002	1.86	3.8	305
Germany	0.039	0.051	0.014	2.01	2.9	305
France	0.031	0.061	0.007	1.89	2.1	305
Italy	0.034	0.044	0.005	1.94	1.9	305

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Table 1 – continued

	β	H[p]	NW[p]	DW	$\bar{R}^2$	NOBS
Developed markets						
Australia	0.035	0.057	0.018	1.99	2.1	305
Austria	0.054	0.034	0.023	1.76	4.6	305
Belgium	0.034	0.126	0.096	1.56	2.4	305
Denmark	0.036	0.019	0.021	2.07	3.5	305
Hong Kong	0.021	0.136	0.136	1.88	0.3	305
Netherlands	0.031	0.061	0.042	1.96	2.6	305
Norway	0.041	0.076	0.085	1.77	2.3	305
Portugal	0.025	0.113	0.154	1.78	1.2	305
Singapore	0.037	0.039	0.062	1.90	1.8	305
Spain	0.028	0.137	0.137	1.79	1.2	305
Sweden	0.040	0.027	0.002	1.82	2.5	305
Switzerland	0.028	0.054	0.016	1.86	2.5	305
Emerging markets						
Argentina	0.021	0.409	0.441	1.89	-0.1	274
Brazil	0.056	0.016	0.001	2.23	1.0	274
Chile	0.025	0.111	0.153	1.67	0.9	274
China	0.027	0.167	0.224	1.81	0.4	214
India	0.046	0.040	0.062	1.83	3.0	214
Korea	0.051	0.062	0.045	1.92	2.0	274
Malaysia	0.026	0.041	0.030	1.68	0.7	274
Mexico	0.034	0.092	0.051	1.81	1.1	274
Poland	0.057	0.056	0.011	1.87	2.0	214
Russia	0.086	0.009	0.001	1.71	3.2	190
South Africa	0.031	0.130	0.045	1.99	1.4	214
Taiwan	0.047	0.014	0.007	1.80	1.8	274

Table 2

Baltic Dry Index and the predictability of stock returns at longer horizons

The forecasting variable is the three-month BDI growth rate, defined as $g_{[t-3\to t]} = \ln(\mathrm{BDI}_t/\mathrm{BDI}_{t-3})$. Results are presented for the predictive regressions $r_{[t\to t+k]} = \alpha + \beta g_{[t-3\to t]} + \varepsilon_{t+k}$, where $r_{[t\to t+k]}$, for $k=3$ ($k=6$) denotes the cumulative log excess return of a stock market over the three (six) months following month t, denominated in US dollars. Reported are the β estimates, as well as two-sided p-values for the null hypothesis $\beta=0$, denoted by H[p] and based on the Hodrick (1992) covariance estimator. The adjusted R^2 (in %) is denoted by $\overline{R}^2$. To save space, we do not report the intercepts in the regressions. The last two columns show p-values for the null hypothesis that the β coefficients in predicting one- and three-month returns, or one-, three-, and six-month returns, respectively, are jointly equal to zero, following Ang and Bekaert (2007, Appendix B, equation (B7)).

	Three-month horizon			Six-month horizon			Joint p-value	
	β	H[p]	$\overline{R}^2$	β	H[p]	$\overline{R}^2$	1,3 m	1,3,6 m
Regional indexes								
World	0.080	0.014	8.5	0.058	0.231	1.7	0.029	0.058
G-7	0.078	0.013	8.3	0.057	0.225	1.8	0.025	0.054
EAFE	0.084	0.020	7.1	0.057	0.277	1.2	0.070	0.108
Emerging	0.102	0.012	5.2	0.040	0.485	0.0	0.014	0.021
G-7 markets								
US	0.076	0.013	8.1	0.062	0.185	2.3	0.024	0.057
Japan	0.061	0.069	2.2	0.048	0.364	0.3	0.304	0.343
UK	0.086	0.005	7.8	0.063	0.140	1.7	0.011	0.026
Canada	0.095	0.006	7.2	0.052	0.273	0.7	0.005	0.009
Germany	0.108	0.052	7.7	0.064	0.418	1.0	0.119	0.126
France	0.091	0.050	6.2	0.056	0.384	0.8	0.123	0.158
Italy	0.102	0.033	6.2	0.059	0.408	0.6	0.095	0.096

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Table 2 – continued

	Three-month horizon			Six-month horizon			Joint p-value	
	β	H[p]	$\bar{R}^2$	β	H[p]	$\bar{R}^2$	1,3 m	1,3,6 m
Developed markets								
Australia	0.100	0.021	6.1	0.069	0.283	1.2	0.098	0.140
Austria	0.147	0.010	8.9	0.079	0.349	0.8	0.022	0.037
Belgium	0.071	0.110	2.6	0.016	0.750	-0.3	0.034	0.080
Denmark	0.098	0.003	8.9	0.071	0.129	1.8	0.005	0.013
Hong Kong	0.050	0.113	0.8	-0.003	0.953	-0.3	0.106	0.085
Netherlands	0.086	0.035	6.8	0.062	0.279	1.4	0.094	0.186
Norway	0.091	0.045	3.2	0.058	0.290	0.4	0.016	0.036
Portugal	0.075	0.045	3.5	0.041	0.399	0.1	0.159	0.265
Singapore	0.096	0.021	3.8	0.039	0.512	0.0	0.032	0.027
Spain	0.101	0.053	5.7	0.075	0.293	1.3	0.238	0.318
Sweden	0.098	0.025	4.5	0.063	0.312	0.6	0.030	0.063
Switzerland	0.082	0.044	7.5	0.064	0.280	2.1	0.101	0.168
Emerging markets								
Argentina	0.086	0.127	0.8	0.177	0.019	2.0	0.563	0.280
Brazil	0.120	0.014	2.0	0.058	0.394	-0.1	0.003	0.010
Chile	0.050	0.165	1.0	0.023	0.591	-0.2	0.029	0.070
China	0.059	0.201	0.6	0.003	0.963	-0.5	0.279	0.288
India	0.121	0.020	5.9	0.015	0.823	-0.4	0.045	0.034
Korea	0.095	0.121	2.2	0.002	0.983	-0.4	0.073	0.088
Malaysia	0.089	0.002	2.5	0.062	0.144	0.2	0.081	0.110
Mexico	0.095	0.071	2.8	0.061	0.421	0.2	0.172	0.226
Poland	0.183	0.036	6.7	0.154	0.231	1.9	0.106	0.195
Russia	0.168	0.021	3.5	0.068	0.483	-0.2	0.005	0.012
South Africa	0.080	0.124	3.6	0.018	0.809	-0.4	0.213	0.144
Taiwan	0.115	0.013	3.1	0.034	0.619	-0.2	0.025	0.017

Table 3
Predicting stock returns with the BDI growth rate and the lagged world (US) return

The predicted variable $r_{[t\to t+1]}$ is the log excess return of a stock market for month $t+1$, denominated in US dollars. Results are presented for the predictive regressions $r_{[t\to t+1]} = \alpha + \beta g_{[t-3\to t]} + \delta x_{[t-1\to t]} + \varepsilon_{t+1}$, where $g_{[t-3\to t]}$ is the three-month BDI growth rate, and $x_{[t-1\to t]}$ is the lagged world return ($r^{\text{world}}_{[t-1\to t]}$) or the lagged US return ($r^{\text{us}}_{[t-1\to t]}$). Reported are the estimates of β and δ, and the corresponding Hodrick (1992) two-sided p-values, denoted by H[p]. The adjusted R^2 (in %) is denoted by $\overline{R}^2$. We also present the p-values for the null hypothesis $\beta = \delta = 0$, relying on the Hodrick (1992) estimator, denoted by Joint H[p]. To save space, we do not report the intercept in the regressions.

	$g_{[t-3\to t]}$		$r^{\text{world}}_{[t-1\to t]}$			Joint	$g_{[t-3\to t]}$		$r^{\text{us}}_{[t-1\to t]}$			Joint
	β	H[p]	δ	H[p]	$\overline{R}^2$	H[p]	β	H[p]	δ	H[p]	$\overline{R}^2$	H[p]
Regional indexes												
World	0.026	0.031	0.087	0.235	4.2	0.056	0.027	0.029	0.075	0.264	4.0	0.055
G-7	0.026	0.028	0.083	0.252	4.0	0.052	0.026	0.026	0.071	0.286	3.9	0.052
EAFE	0.024	0.069	0.123	0.144	3.4	0.071	0.025	0.063	0.114	0.126	3.3	0.062
Emerging	0.036	0.041	0.171	0.131	4.1	0.057	0.037	0.038	0.155	0.166	3.9	0.058
G-7 markets												
US	0.027	0.022	0.051	0.505	3.6	0.053	0.028	0.020	0.033	0.668	3.5	0.054
Japan	0.009	0.477	0.177	0.074	1.3	0.098	0.009	0.434	0.173	0.049	1.3	0.066
UK	0.027	0.025	0.119	0.136	3.9	0.036	0.029	0.020	0.085	0.261	3.5	0.041
Canada	0.031	0.036	0.179	0.037	5.3	0.033	0.033	0.030	0.136	0.083	4.6	0.040
Germany	0.037	0.062	0.051	0.647	2.6	0.143	0.036	0.066	0.083	0.445	2.8	0.130
France	0.030	0.073	0.048	0.617	1.9	0.167	0.029	0.074	0.058	0.511	2.0	0.161
Italy	0.030	0.067	0.104	0.317	2.0	0.108	0.032	0.058	0.080	0.388	1.9	0.116

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Table 3 – continued

	$g_{[t-3\to t]}$		$r^{\text{world}}_{[t-1\to t]}$			Joint	$g_{[t-3\to t]}$		$r^{\text{us}}_{[t-1\to t]}$			Joint
	β	H[p]	δ	H[p]	$\overline{R}^2$	H[p]	β	H[p]	δ	H[p]	$\overline{R}^2$	H[p]
Developed markets												
Australia	0.030	0.097	0.124	0.250	2.3	0.103	0.033	0.071	0.048	0.645	1.8	0.151
Austria	0.044	0.072	0.297	0.044	7.1	0.041	0.046	0.063	0.253	0.050	6.4	0.037
Belgium	0.028	0.167	0.174	0.108	3.5	0.212	0.029	0.165	0.157	0.096	3.3	0.179
Denmark	0.034	0.015	0.051	0.572	3.3	0.049	0.035	0.015	0.025	0.767	3.2	0.048
Hong Kong	0.018	0.189	0.088	0.411	0.2	0.297	0.019	0.169	0.061	0.562	0.1	0.313
Netherlands	0.027	0.089	0.110	0.237	3.1	0.138	0.028	0.086	0.103	0.260	3.0	0.133
Norway	0.032	0.134	0.257	0.047	4.0	0.088	0.035	0.119	0.209	0.107	3.4	0.114
Portugal	0.019	0.214	0.176	0.114	2.1	0.159	0.019	0.226	0.200	0.072	2.4	0.107
Singapore	0.033	0.049	0.094	0.435	1.7	0.117	0.035	0.044	0.062	0.593	1.5	0.117
Spain	0.023	0.218	0.135	0.217	1.6	0.185	0.024	0.197	0.119	0.238	1.5	0.201
Sweden	0.033	0.061	0.200	0.119	3.5	0.050	0.033	0.062	0.218	0.085	3.8	0.037
Switzerland	0.025	0.080	0.072	0.378	2.6	0.121	0.025	0.082	0.091	0.263	2.8	0.103
Emerging markets												
Argentina	0.006	0.818	0.410	0.063	0.9	0.172	0.005	0.834	0.469	0.027	1.3	0.078
Brazil	0.043	0.059	0.333	0.188	1.5	0.040	0.052	0.022	0.099	0.639	0.7	0.052
Chile	0.019	0.177	0.148	0.128	1.4	0.194	0.019	0.181	0.158	0.091	1.4	0.152
China	0.029	0.147	-0.048	0.816	-0.1	0.344	0.029	0.143	-0.061	0.762	0.0	0.339
India	0.033	0.100	0.344	0.039	5.2	0.053	0.038	0.073	0.251	0.106	4.0	0.080
Korea	0.041	0.127	0.250	0.151	2.6	0.086	0.045	0.098	0.182	0.294	2.1	0.126
Malaysia	0.018	0.167	0.222	0.060	1.6	0.038	0.020	0.120	0.190	0.118	1.2	0.062
Mexico	0.032	0.110	0.057	0.714	0.8	0.238	0.030	0.132	0.116	0.433	1.0	0.210
Poland	0.048	0.110	0.259	0.259	2.2	0.111	0.058	0.058	-0.015	0.942	1.5	0.156
Russia	0.061	0.047	0.641	0.047	5.4	0.015	0.063	0.046	0.641	0.042	5.6	0.012
South Africa	0.032	0.118	-0.018	0.906	0.9	0.291	0.030	0.137	0.022	0.883	0.9	0.314
Taiwan	0.046	0.021	0.046	0.794	1.4	0.047	0.043	0.031	0.137	0.420	1.7	0.038

Table 4
Out-of-sample assessment of stock return predictability

The forecasting variable is the three-month BDI growth rate, defined as $g_{[t-3\to t]} = \ln(\text{BDI}_t/\text{BDI}_{t-3})$, and the predicted variable is the log excess return $r_{[t\to t+1]}$ of a stock market for month $t+1$. The table presents the out-of-sample R^2 statistic (in %) of Campbell and Thompson (2008), defined as $R^2_{OS} = 1 - \frac{\sum_{t=0}^{T-1}(r_{[t\to t+1]}-\widehat{r}_{t+1})^2}{\sum_{t=0}^{T-1}(r_{[t\to t+1]}-\overline{r}_{t+1})^2}$, where $\widehat{r}_{t+1}$ is the prediction for month $t+1$, obtained from the BDI-based predictive regression estimated from data up to and including month t, and $\overline{r}_{t+1}$ is the average return observed up to and including month t. Shown also are one-sided p-values for the MSPE-adjusted statistic, developed in Clark and West (2007), for the null hypothesis that using the BDI growth rate does not significantly improve on a forecast based solely on the historical average return. Results are based on both an expanding window with initial length of 120 (180) months, and a rolling window with length of 120 (180) months.

	Panel A: Out-of-sample R^2				*Panel B: MSPE-adjusted p-value*			
	Expanding		Rolling		Expanding		Rolling	
	120 m	180 m	120 m	180 m	120 m	180 m	120 m	180 m
Regional indexes								
World	4.2	5.7	3.0	5.2	0.021	0.019	0.021	0.017
G-7	4.3	5.9	3.2	5.5	0.018	0.017	0.018	0.014
EAFE	2.7	3.7	0.9	3.6	0.043	0.039	0.039	0.027
Emerging	2.6	3.7	0.9	2.3	0.024	0.035	0.033	0.045
G-7 markets								
US	4.5	6.5	3.9	5.7	0.017	0.015	0.014	0.015
Japan	-0.8	-0.7	-2.6	-0.6	0.315	0.246	0.260	0.118
UK	5.7	7.2	4.7	6.3	0.010	0.008	0.012	0.012
Canada	3.5	4.9	2.6	3.8	0.012	0.011	0.011	0.011
Germany	2.3	3.1	0.7	2.3	0.073	0.069	0.056	0.060
France	1.4	2.4	-0.1	1.9	0.085	0.069	0.048	0.053
Italy	1.1	3.2	0.7	3.7	0.076	0.044	0.025	0.017

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Table 4 – continued

	Panel A: Out-of-sample R^2				*Panel B: MSPE-adjusted p-value*			
	Expanding		Rolling		Expanding		Rolling	
	120 m	180 m	120 m	180 m	120 m	180 m	120 m	180 m
Developed markets								
Australia	2.3	3.2	1.8	2.8	0.068	0.063	0.053	0.061
Austria	4.7	5.8	3.6	5.3	0.036	0.034	0.036	0.033
Belgium	0.1	0.2	-2.5	-0.7	0.149	0.146	0.150	0.141
Denmark	3.1	3.4	1.4	2.4	0.017	0.022	0.020	0.021
Hong Kong	-0.4	-0.2	-1.9	-1.8	0.180	0.133	0.151	0.167
Netherlands	1.2	1.7	-1.0	0.7	0.082	0.077	0.071	0.073
Norway	1.5	1.8	-0.4	1.2	0.071	0.076	0.077	0.071
Portugal	-0.8	-0.9	-3.8	-2.8	0.126	0.113	0.095	0.109
Singapore	1.1	2.1	0.4	0.2	0.040	0.041	0.020	0.037
Spain	-0.8	-0.3	-2.3	-0.2	0.240	0.198	0.117	0.095
Sweden	2.0	2.4	0.2	1.7	0.021	0.024	0.030	0.022
Switzerland	2.6	4.7	1.4	3.4	0.077	0.069	0.057	0.071
Emerging markets								
Argentina	-6.6	-5.4	-4.4	-4.0	0.937	0.852	0.407	0.300
Brazil	1.2	-3.5	0.0	-1.4	0.008	0.041	0.020	0.047
Chile	-1.9	-8.1	-2.2	-9.4	0.068	0.194	0.067	0.208
China	-3.1	-9.0	-5.6	-10.6	0.200	0.408	0.184	0.400
India	2.7	1.1	1.6	0.7	0.053	0.106	0.049	0.103
Korea	0.5	0.5	0.3	0.5	0.087	0.118	0.108	0.133
Malaysia	-0.4	-6.7	-0.5	-8.7	0.025	0.075	0.015	0.098
Mexico	-1.5	2.0	-3.0	0.8	0.351	0.055	0.186	0.074
Poland	5.0	8.3	4.2	6.8	0.042	0.035	0.044	0.048
Russia	6.1	n.a.	4.2	n.a.	0.034	n.a.	0.046	n.a.
South Africa	-3.8	-3.6	-5.0	-3.6	0.196	0.237	0.246	0.252
Taiwan	1.3	4.6	1.1	5.6	0.025	0.019	0.051	0.013

Table 5

Predicting stock returns out-of-sample using the BDI growth rate and the lagged world (US) return

The predicted variable is the log excess return $r_{[t \to t+1]}$ of a stock market for month $t+1$. We consider two models: a nested benchmark model and a full model obtained by incorporating an additional predictor. The nested model is the predictive regression model based on the BDI growth rate or the lagged world (US) return. The full model is the predictive regression model based on the combination of the BDI growth rate and the lagged world (US) return. Shown also are one-sided p-values for the MSPE-adjusted statistic, developed in Clark and West (2007), for the null hypothesis that using the full model does not significantly improve on a forecast based on the nested model. Results are based on an expanding window with initial length of 120 months.

	MSPE-adjusted p-values			
Full model	$g_{[t-3\to t]} + r^{\text{world}}_{[t-1\to t]}$		$g_{[t-3\to t]} + r^{\text{us}}_{[t-1\to t]}$	
Nested model	$g_{[t-3\to t]}$	$r^{\text{world}}_{[t-1\to t]}$	$g_{[t-3\to t]}$	$r^{\text{us}}_{[t-1\to t]}$
Regional indexes				
World	0.236	0.032	0.365	0.030
G-7	0.245	0.027	0.391	0.025
EAFE	0.110	0.086	0.171	0.078
Emerging	0.143	0.053	0.227	0.049
G-7 markets				
US	0.668	0.021	0.879	0.020
Japan	0.021	0.745	0.054	0.677
UK	0.056	0.011	0.172	0.010
Canada	0.078	0.025	0.148	0.018
Germany	0.804	0.089	0.532	0.097
France	0.872	0.111	0.658	0.115
Italy	0.350	0.134	0.524	0.114

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Table 5 – continued

	MSPE-adjusted p-values			
Full model	$g_{[t-3\to t]}+r^{\text{world}}_{[t-1\to t]}$		$g_{[t-3\to t]}+r^{\text{us}}_{[t-1\to t]}$	
Nested model	$g_{[t-3\to t]}$	$r^{\text{world}}_{[t-1\to t]}$	$g_{[t-3\to t]}$	$r^{\text{us}}_{[t-1\to t]}$
Developed markets				
Australia	0.527	0.131	0.798	0.089
Austria	0.048	0.071	0.086	0.063
Belgium	0.057	0.227	0.086	0.220
Denmark	0.855	0.018	0.895	0.018
Hong Kong	0.666	0.313	0.824	0.261
Netherlands	0.271	0.133	0.324	0.126
Norway	0.021	0.104	0.041	0.097
Portugal	0.130	0.304	0.094	0.331
Singapore	0.604	0.071	0.716	0.059
Spain	0.377	0.454	0.411	0.404
Sweden	0.337	0.083	0.324	0.081
Switzerland	0.441	0.106	0.307	0.112
Emerging markets				
Argentina	0.018	0.946	0.027	0.938
Brazil	0.518	0.025	0.881	0.010
Chile	0.143	0.135	0.113	0.145
China	0.927	0.220	0.828	0.210
India	0.057	0.155	0.111	0.107
Korea	0.140	0.167	0.342	0.134
Malaysia	0.023	0.167	0.115	0.114
Mexico	0.777	0.484	0.678	0.584
Poland	0.247	0.108	0.950	0.051
Russia	0.032	0.098	0.051	0.084
South Africa	0.976	0.237	0.945	0.270
Taiwan	0.837	0.034	0.716	0.054

Table 6
Economic significance of predictability with the BDI growth rate: Certainty equivalent return and Sharpe ratio

This table presents evidence on the out-of-sample performance of two portfolio strategies involving a stock and a risk-free bond. The strategies are based on two different models for stock log excess returns: (i) an i.i.d. model and (ii) a predictive regression model employing the BDI growth rate as the predictor. Each model is used to sequentially solve a series of one-period-ahead static problems for an investor with CRRA preferences and a coefficient of relative risk aversion equal to 3. We impose no borrowing and no short-selling constraints. The conditional distribution of stock log excess return is assumed to be Normal under both models. Shown are the certainty equivalent return (CER) in percent, as well as the Sharpe ratio (SR), for each strategy, both in annualized terms. We report results based on an expanding window with initial length of 120 months, and a rolling window with length of 120 months.

	Expanding window				Rolling window			
	CER i.i.d.	CER BDI	SR i.i.d.	SR BDI	CER i.i.d.	CER BDI	SR i.i.d.	SR BDI
Regional indexes								
World	2.68	5.40	0.19	0.36	2.49	6.00	0.10	0.40
G-7	2.49	5.19	0.17	0.34	2.42	5.56	0.09	0.37
EAFE	2.06	4.83	0.12	0.31	0.62	5.97	-0.26	0.40
Emerging	3.45	10.23	0.27	0.60	-1.58	8.98	-0.12	0.54
G-7 markets								
US	3.57	5.97	0.27	0.40	5.10	6.22	0.34	0.42
Japan	1.08	2.49	-0.30	0.01	1.99	2.90	-0.53	0.04
UK	3.66	6.20	0.24	0.41	4.60	6.01	0.28	0.40
Canada	5.20	8.34	0.37	0.54	3.32	8.77	0.29	0.57
Germany	2.84	6.80	0.19	0.45	2.50	9.29	0.12	0.59
France	3.60	5.34	0.29	0.37	3.47	7.83	0.22	0.51
Italy	3.34	4.56	0.17	0.30	3.16	7.02	0.11	0.46

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Table 6 – continued

	Expanding window				Rolling window			
	CER i.i.d.	CER BDI	SR i.i.d.	SR BDI	CER i.i.d.	CER BDI	SR i.i.d.	SR BDI
Developed markets								
Australia	5.68	6.64	0.38	0.44	4.02	6.55	0.30	0.43
Austria	1.99	5.85	0.10	0.39	-1.66	5.81	-0.07	0.38
Belgium	-0.71	2.86	0.17	0.27	3.65	5.78	0.24	0.40
Denmark	7.06	12.36	0.50	0.77	7.45	13.69	0.51	0.87
Hong Kong	3.10	3.88	0.22	0.30	0.32	3.05	-0.02	0.23
Netherlands	1.63	4.34	0.26	0.35	2.74	7.10	0.19	0.47
Norway	3.87	8.81	0.27	0.56	0.55	7.32	0.12	0.48
Portugal	3.09	7.04	-0.08	0.44	3.48	7.30	0.09	0.45
Singapore	2.34	6.50	0.06	0.42	-1.77	8.29	-0.31	0.53
Spain	6.04	7.09	0.45	0.49	6.46	8.33	0.44	0.55
Sweden	4.40	9.01	0.40	0.57	4.12	9.51	0.31	0.58
Switzerland	5.19	7.00	0.37	0.47	5.29	7.10	0.36	0.47
Emerging markets								
Argentina	3.95	-4.35	0.22	-0.06	2.19	2.43	0.00	0.15
Brazil	7.39	15.07	0.47	0.86	5.64	13.56	0.34	0.74
Chile	5.81	11.05	0.46	0.64	1.07	12.22	0.17	0.72
China	4.22	11.26	-0.04	0.74	3.46	12.01	-0.03	0.69
India	9.43	21.27	0.57	0.97	6.91	21.36	0.42	0.96
Korea	5.31	14.18	0.34	0.78	1.59	9.62	-0.06	0.56
Malaysia	5.52	12.09	0.38	0.82	2.95	9.07	0.03	0.63
Mexico	5.33	2.98	0.38	0.32	0.77	1.21	0.14	0.20
Poland	8.44	13.96	0.50	0.72	3.71	10.25	0.13	0.54
Russia	7.45	14.59	0.36	0.69	2.24	12.72	0.12	0.60
South Africa	10.39	16.62	0.62	0.88	5.88	14.17	0.33	0.78
Taiwan	3.20	7.58	0.00	0.45	1.43	5.79	-0.65	0.33

Table 7
Economic significance of predictability with the BDI growth rate in the presence of lagged world (US) return: Certainty equivalent return and Sharpe ratio

This table presents evidence on the out-of-sample performance of five portfolio strategies involving a stock and a risk-free bond. The strategies are based on five different predictive regression models for stock log excess returns using the following predictors: (i) the BDI growth rate, (ii) the lagged world return, (iii) the lagged US return, (iv) the BDI growth rate plus the lagged world return, and (v) the BDI growth rate plus the lagged US return. Each model is used to sequentially solve a series of one-period-ahead static problems for an investor with CRRA preferences and a coefficient of relative risk aversion equal to 3. We impose no borrowing and no short-selling constraints. The conditional distribution of stock log excess return is assumed to be Normal under both models. Shown are the certainty equivalent return in percent, as well as the Sharpe ratio, for each strategy, both in annualized terms. We report results based on an expanding window with initial length of 120 months.

	Panel A: Certainty equivalent return					*Panel B: Sharpe ratio*				
	BDI	r^{world}	r^{us}	r^{world}+BDI	r^{us}+BDI	BDI	r^{world}	r^{us}	r^{world}+BDI	r^{us}+BDI
Regional indexes										
World	5.40	4.51	4.38	5.96	5.78	0.36	0.30	0.29	0.40	0.38
G7	5.19	4.30	4.03	5.66	5.39	0.34	0.28	0.26	0.37	0.35
EAFE	4.83	5.08	4.60	6.51	6.63	0.31	0.33	0.29	0.44	0.44
Emerging	10.23	8.84	8.76	12.37	12.68	0.60	0.54	0.53	0.71	0.73
G-7 markets										
US	5.97	4.46	4.02	5.79	5.62	0.40	0.31	0.28	0.39	0.38
Japan	2.49	3.47	2.80	3.61	3.35	0.01	0.14	0.08	0.16	0.15
UK	6.20	6.33	5.30	6.83	6.19	0.41	0.42	0.35	0.46	0.41
Canada	8.34	10.40	8.64	10.62	9.30	0.54	0.66	0.56	0.67	0.59
Germany	6.80	2.80	4.51	6.52	7.43	0.45	0.20	0.30	0.44	0.49
France	5.34	3.54	4.07	5.29	5.08	0.37	0.28	0.30	0.37	0.35
Italy	4.56	4.32	4.19	5.02	4.58	0.30	0.26	0.25	0.33	0.30

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Table 7 – continued

	Panel A: Certainty equivalent return					Panel B: Sharpe ratio				
	BDI	r^{world}	r^{us}	r^{world}+BDI	r^{us}+BDI	BDI	r^{world}	r^{us}	r^{world}+BDI	r^{us}+BDI
Developed markets										
Australia	6.64	6.87	6.02	6.82	6.18	0.44	0.47	0.40	0.45	0.41
Austria	5.85	8.60	6.91	9.62	9.24	0.39	0.55	0.46	0.62	0.58
Belgium	2.86	3.59	3.58	3.83	3.63	0.27	0.32	0.32	0.32	0.31
Denmark	12.36	6.23	5.70	10.88	10.86	0.77	0.46	0.43	0.69	0.69
Hong Kong	3.88	2.70	2.46	2.36	2.50	0.30	0.23	0.21	0.24	0.24
Netherlands	4.34	3.62	4.15	5.03	5.52	0.35	0.32	0.34	0.38	0.39
Norway	8.81	9.65	7.99	11.43	10.92	0.56	0.63	0.53	0.71	0.67
Portugal	7.04	6.00	8.09	6.36	8.33	0.44	0.36	0.52	0.38	0.52
Singapore	6.50	3.26	2.39	6.15	5.83	0.42	0.17	0.11	0.40	0.38
Spain	7.09	7.48	6.94	7.40	7.69	0.49	0.50	0.47	0.50	0.51
Sweden	9.01	6.78	6.28	8.69	9.14	0.57	0.46	0.44	0.55	0.57
Switzerland	7.00	6.28	6.81	7.32	8.03	0.47	0.43	0.46	0.48	0.53
Emerging markets										
Argentina	-4.35	8.81	10.18	1.23	1.91	-0.06	0.53	0.60	0.19	0.21
Brazil	15.07	9.56	7.48	13.65	14.62	0.86	0.58	0.47	0.76	0.83
Chile	11.05	7.77	8.32	11.04	11.04	0.64	0.52	0.54	0.64	0.64
China	11.26	3.61	3.83	11.24	11.15	0.74	-0.32	-0.26	0.73	0.72
India	21.27	19.00	16.37	21.71	21.67	0.97	0.91	0.80	0.99	0.99
Korea	14.18	10.21	8.19	15.08	14.89	0.78	0.75	0.61	0.85	0.84
Malaysia	12.09	10.34	9.12	13.56	13.04	0.82	0.83	0.70	0.89	0.86
Mexico	2.98	4.67	7.08	2.66	2.89	0.32	0.36	0.45	0.31	0.30
Poland	13.96	12.29	6.56	15.88	12.41	0.72	0.73	0.38	0.83	0.64
Russia	14.59	16.30	15.53	16.13	14.72	0.69	0.76	0.73	0.75	0.69
South Africa	16.62	5.89	10.78	15.55	16.48	0.88	0.36	0.64	0.83	0.87
Taiwan	7.58	3.45	4.40	7.25	7.34	0.45	0.06	0.20	0.43	0.44

Table 8

BDI growth rate and the predictability of commodity index returns

This table reports both in-sample and out-of-sample results. The forecasting variable is the three-month BDI growth rate, defined as $g_{[t-3\to t]} = \ln(\mathrm{BDI}_t/\mathrm{BDI}_{t-3})$. Results are presented for the predictive regressions $r_{[t\to t+1]} = \alpha + \beta g_{[t-3\to t]} + \varepsilon_{t+1}$, where $r_{[t\to t+1]}$ denotes the log excess return on a commodity index for month $t+1$. We use three spot indexes (the Moody's Commodity Index, the Reuters Commodity Index, and the CRB Spot Index), and the two major CRB subindexes (Foodstuffs and Raw Industrials). Panel A focuses on in-sample results and reports the β estimates, as well as the corresponding two-sided p-values, denoted by H[p] and NW[p], based on the Hodrick (1992) covariance estimator, and the procedure in Newey and West (1987) with optimal lag selected as in Newey and West (1994), respectively. The Durbin-Watson statistic and the adjusted R^2 (in %) are denoted by DW and $\overline{R}^2$. To save space, we do not report the intercept in the regressions. Panel B presents the out-of-sample R^2 statistic (in %) of Campbell and Thompson (2008), defined as $R^2_{OS} = 1 - \frac{\sum_{t=0}^{T-1}(r_{[t\to t+1]}-\widehat{r}_{t+1})^2}{\sum_{t=0}^{T-1}(r_{[t\to t+1]}-\overline{r}_{t+1})^2}$, where $\widehat{r}_{t+1}$ is the prediction for month $t+1$, based on a predictive regression estimated from data up to and including month t, and $\overline{r}_{t+1}$ is the historical average return observed up to and including month t. Shown also are one-sided p-values for the MSPE-adjusted statistic, developed in Clark and West (2007), for the null hypothesis that using the BDI does not significantly improve on a forecast based solely on the historical average return. Results are presented using both an expanding window with initial length of 120 (180) months, and a rolling window with length of 120 (180) months.

	Panel A: In-sample results					*Panel B: Out-of-sample results*							
	β	H[p]	NW[p]	DW	$\overline{R}^2$	Out-of-sample R^2				MSPE-adjusted, p-value			
						Expanding		Rolling		Expanding		Rolling	
						120 m	180 m	120 m	180 m	120 m	180 m	120 m	180 m
Commodity indexes													
Moody's	0.028	0.006	0.005	1.73	7.3	5.9	5.5	4.6	5.1	0.006	0.010	0.006	0.011
Reuters	0.045	0.016	0.001	1.65	11.1	11.5	12.1	10.0	11.6	0.018	0.022	0.021	0.025
CRB	0.021	0.045	0.031	1.58	5.7	2.2	2.3	-0.3	1.6	0.037	0.044	0.046	0.052
Commodity subindexes													
CRB, Foodstuffs	0.017	0.086	0.026	1.82	2.0	0.0	0.0	-1.0	-0.1	0.075	0.086	0.114	0.102
CRB, Raw Industrials	0.024	0.044	0.004	1.50	6.3	2.8	2.9	-0.6	1.7	0.033	0.038	0.039	0.046

Table 9
Predicting the growth rate of industrial production with the BDI growth rate

The predicted variable is the industrial production growth rate over month $t+1$, denoted by $z_{[t \to t+1]}$. Results are presented for the ARMAX specification $z_{[t \to t+1]} = \alpha + \beta g_{[t-3 \to t]} + \sum_{i=1}^{p} \psi_i z_{[t-i \to t-i+1]} + \sum_{j=1}^{q} \xi_j \varepsilon_{t-j+1} + \varepsilon_{t+1}$, where $g_{[t-3 \to t]}$ is the BDI growth rate, defined as $g_{[t-3 \to t]} = \ln(\mathrm{BDI}_t / \mathrm{BDI}_{t-3})$, and ε_{t+1} is normally distributed with possible GARCH(1,1) effects. We use maximum likelihood to fit all ARMAX models with $p \leq 2$ and $q \leq 2$, with or without a GARCH(1,1) component, and show results for the best model, selected according to the Bayesian information criterion. Reported are the coefficient estimates and their two-sided p-values (in square brackets). To save space, we do not report the constants in either the ARMA or GARCH specification.

	$g_{[t-3 \to t]}$	AR(1)	AR(2)	MA(1)	MA(2)	ARCH	GARCH
G-7 economies							
US	0.003	0.810		-0.821	0.253	0.486	-0.063
	[0.000]	[0.000]		[0.000]	[0.000]	[0.000]	[0.236]
Japan	0.003	0.589		-0.889	0.394	0.430	0.213
	[0.059]	[0.000]		[0.000]	[0.000]	[0.000]	[0.127]
UK	0.005	-0.304					
	[0.000]	[0.000]					
Canada	0.004	0.774		-0.832	0.248		
	[0.015]	[0.000]		[0.000]	[0.000]		
Germany	0.001			-0.363		0.521	-0.025
	[0.560]			[0.000]		[0.000]	[0.824]
France	0.009	0.826		-1.297	0.515		
	[0.000]	[0.000]		[0.000]	[0.000]		
Italy	0.006	-0.317				0.301	-0.031
	[0.078]	[0.000]				[0.000]	[0.884]

Continued on the next page

Table 9 – continued

	$g_{[t-3\rightarrow t]}$	AR(1)	AR(2)	MA(1)	MA(2)	ARCH	GARCH
Developed economies							
Austria	0.007	-0.478	-0.285				
	[0.001]	[0.000]	[0.000]				
Belgium	0.010			-0.456			
	[0.000]			[0.000]			
Denmark	0.002	0.449		-0.736		0.108	0.830
	[0.205]	[0.000]		[0.000]		[0.004]	[0.000]
Netherlands	0.006			-0.629		0.145	0.480
	[0.019]			[0.000]		[0.067]	[0.038]
Norway	0.001	1.330	-0.353	-1.811	0.829	0.599	0.130
	[0.002]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.228]
Portugal	0.008	-0.527					
	[0.002]	[0.000]					
Spain	0.003	0.729		-1.278	0.564	0.510	0.109
	[0.001]	[0.000]		[0.000]	[0.000]	[0.000]	[0.282]
Sweden	0.014			-0.194			
	[0.000]			[0.000]			
Emerging economies							
Brazil	0.003	0.590	0.178	-0.943		0.895	0.000
	[0.012]	[0.000]	[0.002]	[0.000]		[0.000]	[0.000]
India	0.003	-0.504					
	[0.058]	[0.000]					
Korea	0.028	-0.129					
	[0.000]	[0.051]					
Poland	0.012	-0.266				0.424	0.361
	[0.001]	[0.000]				[0.000]	[0.004]
Russia	0.019			0.018		0.438	0.448
	[0.000]			[0.000]		[0.001]	[0.000]

Table Appendix-I
Features of the Baltic Dry Index dynamics

The one-month and three-month BDI growth rates are defined as $g_{[t-j\to t]} = \ln(\mathrm{BDI}_t/\mathrm{BDI}_{t-j})$, for $j=1$ and $j=3$. For each of the series $g_{[t-1\to t]}$ and $g_{[t-3\to t]}$, Panel A displays the annualized mean, annualized standard deviation, skewness, kurtosis, autocorrelations ρ_j for lags $j=1,\ldots,6$, and the p-value for the Ljung-Box test statistic for six lags, denoted by $p\text{-}LB_6$. Panel B displays the maximum likelihood parameter estimates of the best model, selected according to the BIC criterion, among all MA(q)-GARCH(1,1) models with $q \leq 6$ and ARMA(p, q)-GARCH(1,1) models with $p \leq 3$ and $q \leq 3$ when disturbances are distributed Normal or t. For both series, the selected model involves an IGARCH volatility structure and t distributed disturbances. The degrees of freedom estimate, denoted by df, of the t distribution is also reported, with standard errors in parentheses. All p-values are shown in square brackets. The sample period is May 1985 to September 2010 (305 observations). Time aggregation of the MA(1)-IGARCH(1,1) model for $g_{[t-1\to t]}$ yields MA(3)-IGARCH(1,1) model for $g_{[t-3\to t]}$ with the same IGARCH parameters, as reflected in the estimates.

Panel A: Descriptive statistics

	Mean	Std.	Skewness	Kurtosis	ρ_1	ρ_2	ρ_3	ρ_4	ρ_5	ρ_6	$p\text{-}LB_6$
$g_{[t-1\to t]}$	0.038	1.911	-1.90	21.63	0.27	-0.04	-0.05	-0.11	-0.03	-0.01	[0.000]
$g_{[t-3\to t]}$	0.041	1.274	-2.64	21.06	0.74	0.30	-0.06	-0.14	-0.15	-0.19	[0.000]

Panel B: Estimation of ARMA-GARCH(1,1) models

	Const.	MA(1)	MA(2)	MA(3)	ARCH	GARCH	Dist.	df	BIC
$g_{[t-1\to t]}$	0.004	0.135			0.051	0.949	t	6.251	-1.359
	[0.427]	[0.012]			[0.001]	[0.000]		(1.538)	
$g_{[t-3\to t]}$	0.014	1.133	1.130	0.150	0.051	0.949	t	5.910	-1.333
	[0.416]	[0.000]	[0.000]	[0.005]	[0.002]	[0.000]		(1.387)	

Table Appendix-II
Evidence from subsamples

Rolling subsamples with a length of 20 years (240 observations) are constructed, whereby the first subsample starts in May 1985, and the remaining ones start at six-month intervals, for a total of 11 subsamples over May 1985 to September 2010 for each of the 21 markets with full sample of stock returns (305 observations). In each subsample we estimate $r_{[t\to t+1]} = \alpha + \beta g_{[t-3\to t]} + \delta r^{\text{world}}_{[t-1\to t]} + \varepsilon_{t+1}$ (as in equation (4)), as well as the restricted specifications with $\beta = 0$ and $\delta = 0$. $r_{[t\to t+1]}$ is the log excess return of a stock market for month $t+1$, $g_{[t-3\to t]}$ is the three-month BDI growth rate, and $r^{\text{world}}_{[t-1\to t]}$ is the lagged world return. Reported are (i) the number (denoted by #) of $\beta > 0$ and/or $\delta > 0$, (ii) the number of $\text{H}[p] < 0.10$, respectively for the β and δ estimates, and (iii) the average adjusted R^2.

	BDI growth rate			Lagged world return			BDI and lagged world return				
	# $\beta > 0$	# $\text{H}[p]$ <0.10	Avg. $\overline{R}^2$	# $\delta > 0$	# $\text{H}[p]$ < 0.10	Avg. $\overline{R}^2$	# $\beta > 0$	# $\text{H}[p]$ <0.10	# $\delta > 0$	# $\text{H}[p]$ <0.10	Avg. $\overline{R}^2$
World	11	11	2.9	10	0	0.2	11	9	8	0	2.6
G-7	11	10	2.8	9	0	0.1	11	9	7	0	2.5
EAFE	11	9	2.2	11	0	0.3	11	9	10	0	2.0
US	11	8	2.9	7	0	0.1	11	7	6	0	2.6
Japan	11	2	0.3	11	0	0.2	11	1	11	0	0.3
UK	11	4	2.0	11	2	0.5	11	4	9	0	1.9
Canada	11	4	2.2	11	10	1.9	11	4	11	8	3.1
Germany	11	9	2.3	8	0	-0.1	11	9	6	0	1.9
France	11	6	1.8	5	0	-0.1	11	7	4	0	1.5
Italy	11	9	1.9	10	0	0.1	11	9	7	0	1.7
Australia	11	4	1.7	11	0	0.2	11	3	11	0	1.5
Austria	11	4	2.8	11	8	3.3	11	3	11	7	4.7
Belgium	11	7	1.8	11	3	0.9	11	6	11	0	2.0
Denmark	11	11	2.5	5	3	0.6	11	11	4	0	2.6
Hong Kong	11	3	0.1	7	0	-0.3	11	3	6	0	-0.3
Netherlands	11	9	2.0	10	0	0.2	11	8	9	0	1.8
Norway	11	3	1.5	11	5	1.5	11	1	11	3	2.2
Singapore	11	10	1.6	11	0	0.2	11	9	11	0	1.4
Spain	11	7	1.4	11	0	0.2	11	6	11	0	1.2
Sweden	11	10	1.8	11	0	0.8	11	9	11	0	2.0
Switzerland	11	9	1.8	11	0	0.3	11	5	11	0	1.6