International Stock Return Predictability: What is the Role of the United States?

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ABSTRACT

We investigate lead-lag relationships among monthly country stock returns and identify a leading role for the United States: lagged U.S. returns significantly predict returns in numerous non-U.S. industrialized countries, while lagged non-U.S. returns display limited predictive ability with respect to U.S. returns. We estimate a news-diffusion model, and the results indicate that return shocks emanating in the United States are only fully reflected in equity prices outside of the United States with a lag, consistent with a gradual information diffusion explanation of the predictive power of lagged U.S. returns.

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Although some controversy remains, stock return predictability in the United States and other industrialized countries appears well established. For example, Fama and Schwert (1977), Campbell (1987), Breen, Glosten, and Jagannathan (1989), Fama and French (1988, 1989), Ferson and Harvey (1991), Lettau and Ludvigson (2001), Cochrane (2008), and Pástor and Stambaugh (2009) provide evidence for the United States; Cutler, Poterba, and Summers (1991), Harvey (1991), Bekaert and Hodrick (1992), Ferson and Harvey (1993), Solnik (1993), Ang and Bekaert (2007), and Hjalmarsson (2010) provide international evidence. In light of this evidence, return predictability is now incorporated into leading asset pricing models (e.g., Campbell and Cochrane (1999), Bansal and Yaron (2004)).

This paper uncovers a powerful new predictor of monthly stock returns in industrialized countries: lagged U.S. market returns. Indeed, we show that lagged U.S. returns predict returns in numerous non-U.S. industrialized countries substantially better than countries' own economic variables, including lagged nominal interest rates and dividend yields. We identify lagged U.S. returns as a powerful return predictor in the context of an investigation of lead-lag relationships among country stock returns, a previously unexamined aspect of international return predictability.[1] We also find that lagged returns of non-U.S. countries have limited predictive ability for U.S. returns. Together, these results point to a leading role for the United States in the international equity market.

Our analysis of lead-lag relationships in international returns proceeds in four steps. First, as a benchmark, we estimate conventional predictive regression models for eleven industrialized countries using monthly data for 1980 to 2010,[2] where each predictive regression relates a country's excess return to its lagged interest rate and dividend yield. The interest rate and dividend yield are the two most prominent economic predictors that enter directly into asset pricing models and are used by Ang and Bekaert (2007) in their international return predictability study. A key econometric issue is the Stambaugh (1999) bias, and we control for this bias via a multivariate wild bootstrap procedure. Not only is the bootstrap procedure robust to the Stambaugh (1999) bias for hypothesis testing, but it allows for conditional heteroskedasticity in stock returns. In line with Ang and Bekaert (2007) and Hjalmarsson (2010), we find that interest rates generally exhibit stronger predictive ability across countries than dividend yields.

Second, we perform pairwise Granger causality tests, which are the standard tool for studying lead-lag relationships in portfolios of U.S. stocks (e.g., Brennan, Jegadeesh, and Swaminathan (1993), Chordia and Swaminathan (2000), Hou (2007)). We test for Granger causality using augmented predictive regressions, where each predictive regression now includes a country's own lagged return and another country's lagged return as additional regressors. By controlling for a country's own lagged return, we guard against spurious evidence of lead-lag relationships. Furthermore, in our international context, we adjust lagged country returns to account for any differences in closing times across national equity markets.[3] Basing inferences on the wild bootstrap, pairwise Granger causality test results demonstrate the predictive power of lagged U.S. returns: U.S. returns significantly Granger cause returns in nine of the ten non-U.S. countries, and lagged U.S. returns have a quantitatively important impact on non-U.S. returns.[4]

To further assess the importance of U.S. returns, we perform Granger causality tests for model specifications that include lagged returns for multiple countries jointly as predictors. Lagged U.S. returns continue to display significant predictive power in numerous countries, and the quantitative influence of lagged U.S. returns supersedes that of other countries. Lagged returns for non-U.S. countries also continue to have only a limited impact on U.S. returns.

Third, to better understand lead-lag relationships in international returns, we specify and estimate an empirical news-diffusion model. While this model is purely econometric, it allows us to empirically examine how return shocks emanating in one country affect returns in another country, where the extent of contemporaneous adjustment across countries is governed by a diffusion parameter. We estimate the model's structural parameters via generalized method of moments (GMM), and the results indicate that U.S. return shocks have statistically and economically significant effects on non-U.S. returns. Moreover, the diffusion parameter estimates show that

U.S. shocks are only fully reflected in non-U.S. equity prices with a lag. We also compare the magnitudes of the estimated coefficients on lagged U.S. returns in the Granger causality tests to the magnitudes implied by the estimated structural parameters in the news-diffusion model. The results suggest that information frictions explain a substantial portion, but not all, of the predictive power of lagged U.S. returns.

Fourth, to address concerns relating to the potential fragility of in-sample results (Goyal and Welch (2008)), we examine the out-of-sample predictive power of lagged U.S. returns. We find that lagged U.S. returns deliver statistically significant and economically sizable out-of-sample gains for numerous non-U.S. countries. The out-of-sample gains tend to be concentrated during NBER-dated business-cycle recessions and are particulary large during the recent Global Financial Crisis and concomitant Great Recession.

Why does the United States lead much of the world? Rizova (2010) appears to provide the closest economic story, arguing that a two-country, Lucas-tree framework with gradual information diffusion (e.g., Hong and Stein (1999), Hong, Torous, and Valkanov (2007)) can cause returns in one country to predict returns in a trading-partner country. In our context, the United States is a large trading partner for many countries. In addition, since the U.S. equity market is the world's largest, investors likely focus more intently on this market, so that information on macroeconomic fundamentals relevant for equity markets worldwide diffuses gradually from the U.S. market to other countries' markets. This parallels the gradual information diffusion explanation of the lead-lag relationships in portfolios of U.S. stocks (e.g., Lo and MacKinlay (1990), Brennan, Jegadeesh, and Swaminathan (1993), Chordia and Swaminathan (2000), Hou (2007), Cohen and Frazinni (2008), Menzly and Ozbas (2010)). In particular, Lo and MacKinlay (1990) find that returns on large-cap U.S. stocks lead returns on small-cap U.S. stocks. Hence, in its leading role, the United States in an international setting resembles portfolios of large-cap stocks in a U.S. domestic setting.[5]

In sum, our results show that lead-lag relationships are an important feature of international stock return predictability, with the United States generally playing a leading role. The predictive ability of lagged U.S. returns is not only an interesting empirical fact with implications for international hedging and investing. It also has important implications for asset pricing models. Specifically, one cannot simply apply an analogous version of a U.S. asset pricing model based on economic variables to another country; instead, our results call for an international asset pricing model that explicitly incorporates the leading role of the United States.

The rest of the paper is organized as follows. Section I reports estimation results for benchmark predictive regressions for eleven industrialized countries. Section II augments the benchmark predictive regressions with lagged excess returns to analyze lead-lag relationships among the eleven country returns. Section III reports estimation results for the news-diffusion model. Section IV provides out-of-sample evidence on the predictive ability of lagged U.S. returns. Section V concludes.

I. Benchmark Predictive Regressions

A predictive regression model, which relates excess returns to a set of lagged instruments, is the standard framework for analyzing stock return predictability. Following Ang and Bekaert (2007), we use a country's nominal interest rate and dividend yield as the two instruments in the benchmark predictive regression model,

$$r_{i,t+1} = \beta_{i,0} + \beta_{i,b} bill_{i,t} + \beta_{i,d} dy_{i,t} + \varepsilon_{i,t+1}, \tag{1}$$

where $r_{i,t+1}$ is the return on a broad stock market index in excess of the risk-free rate from the end of month t to the end of month $t+1$ for country i ($i = 1, \ldots, N$), $bill_{i,t}$ ($dy_{i,t}$) is the nominal interest rate (log dividend yield) at the end of month t, and $\varepsilon_{i,t+1}$ is a zero-mean disturbance term. Observe that, following Solnik (1993), Ang and Bekaert (2007), and Hjalmarsson (2010), among others, excess returns are measured in the national currency. As noted by Solnik (1993), the national currency excess return is approximately equal to the currency-hedged excess return for investors from any country due to interest rate parity, where the forward premium equals the difference in risk-free interest rates.[6]

We estimate (1) for eleven industrialized countries: Australia, Canada, France, Germany, Italy, Japan, the Netherlands, Sweden, Switzerland, the United Kingdom, and the United States. Our sample spans 1980:02 to 2010:12; all data are from *Global Financial Data*. Stock returns are derived from the "Total Return Indices—Stocks" series in *Global Financial Data*'s Total Return Database, and excess returns are computed relative to each country's three-month Treasury bill rate. The three-month Treasury bill rate also serves as $bill_{i,t}$ in (1). Following convention, a smoothed dividend series (an average of dividends from month $t-11$ through month t) is used to compute the dividend yield. The selection of countries and sample period is dictated by data availability and our desire to analyze return predictability for a relatively large number of countries. In particular, when we analyze the predictive ability of lagged country returns in Section II, we require daily data to adjust lagged monthly returns for differences in closing times across national equity markets, and daily data for all eleven countries are available beginning in 1980.

All of the return indices are value weighted (according to market capitalization) and cover the broad market. More information on the *Global Financial Data* return indices is provided in Table AI of the Internet Appendix that accompanies this paper. (All table numbers with an "A" prefix appear in the Internet Appendix.) The stocks comprising the indices trade on well-known exchanges that have been in existence for a century or longer.[7] Table I reports summary statistics for monthly excess returns (in percent) for the eleven countries. The average monthly excess returns range from 0.22% (Japan) to 1.03% (Sweden). The standard deviations and maximum/minimum values clearly indicate the high volatility of excess returns for each country, with Italy displaying the greatest volatility over the sample. The Netherlands, Sweden, Switzerland, the United Kingdom, and the United States all have monthly Sharpe ratios above 0.10, while Japan has the lowest Sharpe

Table I about here

ratio (0.04). Some countries exhibit fairly sizable positive autocorrelations in their returns, ranging from 0.11 to 0.18; Australia, the United Kingdom, and the United States display the smallest autocorrelations (0.05, 0.02, and 0.06, respectively).[8]

Ordinary least squares (OLS) estimates of $\beta_{i,b}$ ($\beta_{i,d}$) in the benchmark predictive regression, (1), are reported in the second and sixth (third and seventh) columns of Table II. The t-statistics given in parentheses below the OLS estimates are based on heteroskedasticity-robust standard errors (White (1980)). To increase the robustness of our statistical inferences, we compute empirical p-values using a variant of the wild bootstrap procedures in Gonçalves and Kilian (2004) and Cavaliere, Rahbek, and Taylor (2010). This bootstrap procedure preserves the contemporaneous correlations across all variables in the data, allows for general forms of conditional heteroskedasticity, and guards against the well-known Stambaugh (1999) bias and concomitant nominal size distortions that potentially plague predictive regressions. The wild bootstrap procedure is described in detail in the Internet Appendix.

Table II about here

With the exception of Japan (Italy), all of the $\hat{\beta}_{i,b}$ ($\hat{\beta}_{i,d}$) estimates are negative (positive) in Table II, in line with the extant literature.[9] For more powerful tests of predictability, following the recommendation of Inoue and Kilian (2004), the p-values are for one-sided alternative hypotheses ($\beta_{i,b} < 0$ and $\beta_{i,d} > 0$, respectively). For brevity, we put coefficient estimates and R^2 statistics that are significant at the 10% level in bold in Table II; the wild bootstrapped p-values themselves are reported in Table AIII. The nominal interest rate is a significant return predictor for Canada, Germany, the Netherlands, and the United Kingdom at the 10% level, while the dividend yield is a significant predictor for the United Kingdom. The more extensive evidence of predictive ability for nominal interest rates compared to dividend yields is consistent with the recent findings of Ang and Bekaert (2007) and Hjalmarsson (2010).

Due to the large unpredictable component inherent in monthly stock returns, the R^2 statistics are relatively small in the fourth and eighth columns of Table II; nevertheless, even monthly R^2 statistics near 0.5% can signal economically significant predictability (e.g., Kandel and Stambaugh (1996), Campbell and Thompson (2008)). Canada, Germany, the Netherlands, the United Kingdom, and the United States all have R^2 statistics above 1%. The parentheses under the R^2 statistics in Table II report χ^2-statistics for testing the null hypothesis of no return predictability for country i:

$$H_0: \ \beta_{i,b} = \beta_{i,d} = 0. \tag{2}$$

We reject this null for Canada, the Netherlands, and the United Kingdom based on the wild bootstrapped p-values.

Following Ang and Bekaert (2007) and Hjalmarsson (2010), we also estimate a pooled version of (1) that imposes $\beta_{i,b} = \bar{\beta}_b$ and $\beta_{i,d} = \bar{\beta}_d$ for all i (allowing for country-specific constants). The t-statistics for the $\hat{\bar{\beta}}_b$ and $\hat{\bar{\beta}}_d$ estimates are based on standards errors computed from a GMM procedure that accounts for heteroskedasticity and the contemporaneous correlations among country returns (e.g., Ang and Bekaert (2007)). Neither the $\hat{\bar{\beta}}_b$ nor $\hat{\bar{\beta}}_d$ estimate is significant at conventional levels. For a pooled version of (1) based on $i =$ FRA, DEU, GBR, and USA, the group of four countries used by Ang and Bekaert (2007), the $\hat{\bar{\beta}}_b$ and $\hat{\bar{\beta}}_d$ estimates (-0.14 and 1.54, respectively) are both significant according to the wild bootstrapped p-values, in line with their findings.

We also estimate benchmark predictive regressions for excess returns computed from the *Morgan Stanley Capital International* country indices. The results, reported in Table AIV, are similar to those in Table II. Furthermore, we estimate predictive regressions for each of the non-U.S. countries with the lagged U.S. nominal interest rate and dividend yield replacing a country's own interest rate and dividend yield as regressors. As shown in Table AV, the evidence for return predictability in the non-U.S. countries is generally weaker using the U.S. interest rate and dividend yield in place of the non-U.S. countries' own interest rates and dividend yields.

To check that the wild bootstrap adequately accounts for the Stambaugh (1999) bias when making inferences, we also estimate (1) using the multipredictor augmented regression method (mARM) of Amihud, Hurvich, and Wang (2009). The mARM employs reduced-bias coefficient estimates for hypothesis testing in multiple predictive regression models, such as (1).[10] Since mARM is explicitly designed to account for the Stambaugh (1999) bias, we can get a sense of the wild bootstrap's ability to account for the Stambaugh (1999) bias when making inferences. The key concern is that the Stambaugh (1999) bias leads to inflated t-statistics (in absolute value) for the OLS slope coefficient estimates and thus over-rejection of the null hypothesis of no predictive ability. If the wild bootstrap fails to adequately adjust for the Stambaugh (1999) bias, we would thus expect the wild bootstrapped p-values to be systematically smaller than the mARM p-values and lead to more frequent rejections. Comparing the p-values across Tables AIII and AVI, the wild bootstrapped p-values actually produce fewer rejections relative to the mARM p-values, indicating that the wild bootstrap satisfactorily controls for the Stambaugh (1999) bias when making inferences. A possible explanation for the greater number of rejections for the mARM vis-á-vis wild bootstrapped p-values is that, while both account for the Stambaugh (1999) bias, the mARM p-values do not account for conditional heteroskedasticity. We continue to rely on the wild bootstrap to make inferences in Section II, where we include lagged country excess returns as additional predictors in (1).

II. Predictive Power of Lagged International Returns

The previous section provided evidence of international stock return predictability based on national interest rates and dividend yields. In this section, we investigate lead-lag relationships in international returns by estimating augmented predictive regressions.

A. Pairwise Granger Causality Tests

The augmented prediction regression takes the form,

$$r_{i,t+1} = \beta_{i,0} + \beta_{i,i} r_{i,t} + \beta_{i,j} r_{j,t} + \beta_{i,b} bill_{i,t} + \beta_{i,d} dy_{i,t} + \varepsilon_{i,t+1}, \ i \neq j, \tag{3}$$

where we continue to measure $r_{i,t}$ and $r_{j,t}$ in their respective national currencies. This specification allows us to analyze the predictive power of lagged country-j returns with respect to country-i returns, which is tantamount to testing whether country-j returns Granger cause country-i returns. Pairwise Granger causality tests are widely used in studies of lead-lag relationships among portfolios of U.S. stocks, and (3) extends such tests to an international setting. It is important to include $r_{i,t}$ as an explanatory variable in (3), since return autocorrelation in conjunction with contemporaneously correlated returns can generate spurious evidence of lead-lag relationships (e.g., Boudoukh, Richardson, and Whitelaw (1994), Hameed (1997), Chordia and Swaminathan (2000)).[11] Furthermore, the inclusion of $bill_{i,t}$ and $dy_{i,t}$ as explanatory variables in (3) controls for the predictive ability of the national economic variables emphasized in the return predictability literature.

When analyzing lead-lag relationships among country returns, we need to account for differences in closing times across some national equity markets. The complete set of market opening and closing times for the countries in our sample are reported in Table AI. The Australian and Japanese markets close at 1:00a Eastern Standard Time, before any of the European or North American markets open. The European markets open at 3:00a, while the Canadian and U.S. markets open at 9:30a. The European markets subsequently close at 11:30a (with the exceptions of Switzerland and Germany, which close at 11:20a and 2:00p, respectively), followed by the close of the Canadian and U.S. markets at 4:00p. Given these differences in market closing times, with respect to monthly returns, all of the information released on the last day of the month cannot be incorporated into all equity markets in the same month. Specifically, for markets that are closed when information is initially released in another country on the last day of month t, equity prices cannot adjust to the news until the first day of month $t+1$, potentially giving rise to spurious evidence of lead-lag relationships among monthly country returns. To avoid this problem, we adjust $r_{j,t}$ in (3) to reflect any differences in closing times between markets in countries i and j. In particular, if the close of the equity market in country i occurs prior to the market close in country j, then we exclude the last trading day of month t when computing $r_{j,t}$ in (3).[12]

Table III reports OLS estimates of $\beta_{i,j}$ in (3) for each i, along with heteroskedasticity-robust t-statistics, and we assess the statistical significance of the t-statistics using wild bootstrapped p-values. For brevity, we put significant $\hat{\beta}_{i,j}$ estimates in bold in Table III; the wild bootstrapped p-values themselves and R^2 statistics for all of the augmented predictive regressions are reported in Table AVIII. Following Chordia and Swaminathan (2000), the p-values are for a test of H_0: $\beta_{i,j} = 0$ against $H_A : \beta_{i,j} > 0$.[13] In line with the literature on lead-lag relationships in portfolios of U.S. stocks, a positive $\beta_{i,j}$ in (3) can be interpreted as adjustment delays in country-i equity prices to information relevant for country i contained in country-j equity price movements. Following Ang and Bekaert (2007) and Hjalmarsson (2010) in the context of conventional predictive regressions, the last row of Table III reports estimation results for a pooled version of (3) that imposes the following slope homogeneity restrictions (allowing for country-specific constants): $\beta_{i,i} = \bar{\beta}_i$, $\beta_{i,j} = \bar{\beta}_j$, $\beta_{i,b} = \bar{\beta}_b$, and $\beta_{i,d} = \bar{\beta}_d$ for all $i \neq j$. As emphasized by Hjalmarsson (2010), even if the slope homogeneity restrictions do not hold exactly, pooled estimates can meaningfully measure average relationships in the data.

Table III about here

Of the 110 $\hat{\beta}_{i,j}$ estimates in Table III, 98 are positive; 48 of these are significant at conventional levels. While there is reasonably widespread evidence of predictive ability for lagged country returns in Table III, lagged U.S. returns clearly display the strongest predictive power. Nine of the $\hat{\beta}_{i,\text{USA}}$ estimates are significant, and six are equal to or greater than 0.20 (for $i =$ AUS, CAN, DEU, NLD, SWE, GBR). The pooled $\hat{\bar{\beta}}_{\text{USA}}$ estimate is also significant and sizable (0.17). Furthermore, the $\hat{\beta}_{i,\text{USA}}$ estimates in the last column of Table III are larger than nearly all of the corresponding estimates in the second through eleventh columns. This is reflected in the average of the $\hat{\beta}_{i,\text{USA}}$ estimates across countries, 0.19, which is larger than any of the other corresponding averages. In contrast, the United States row in Table III shows that lagged non-U.S. returns have limited predictive ability for U.S. returns: only two of the ten $\hat{\beta}_{\text{USA},j}$ estimates are significant (for $j =$ ITA, SWE), and both of these estimates are below 0.10. Overall, the relatively large $\hat{\beta}_{i,\text{USA}}$ and small $\hat{\beta}_{\mathrm{USA},j}$ estimates in Table III indicate a leading role for the United States in the international equity market.

Although lagged U.S. returns exhibit the strongest overall predictive ability in Table III, lagged Swedish and Swiss returns also display substantial predictive ability, especially for other European countries. Lagged Swedish returns significantly predict returns for nine of the ten non-Swedish countries at conventional levels, and the $\hat{\beta}_{i,\mathrm{SWE}}$ estimates are equal to or greater than 0.15 for $i =$ CAN and NLD. Lagged Swiss returns are significant return predictors for seven of the non-Swiss countries. The $\hat{\beta}_{i,\mathrm{CHE}}$ estimates are particulary sizable for four European countries: France (0.16), Germany (0.26), Italy (0.21), and the Netherlands (0.34). The pooled $\hat{\beta}_{i,\mathrm{SWE}}$ and $\hat{\beta}_{i,\mathrm{CHE}}$ estimates in the last row of Table III are also significant and fairly sizable (0.11 and 0.13, respectively).

To understand the predictive ability of lagged U.S. returns, consider lead-lag relationships among portfolio returns in the U.S. domestic context. Such relationships, including the well-known finding that large-cap returns lead small-cap returns (Lo and MacKinlay (1990)), have been interpreted as evidence of information frictions resulting from limited attention and limited information-processing capabilities on the part of investors. These limitations cause share prices in certain market segments to underact to information relevant for broader economic conditions (e.g., Hong and Stein (1999), Hong, Torous, and Valkanov (2007)), thereby generating cross-segment predictive ability for lagged returns. As argued by Hong, Torous, and Valkanov (2007), in the presence of limits to arbitrage (Shleifer and Vishny (1997)), predictive ability for lagged segment returns can exist in equilibrium, even when there are traders who are aware of the information frictions and attempt to profit from them. Now, in our international context, since the U.S. economy is the world's largest in terms of GDP and an important trading partner for many countries, shocks to the U.S. economy have important implications for economic conditions in other industrialized countries.[14] Since the U.S. equity market is also the world's largest in terms of market capitalization, the U.S. market likely receives the most attention from investors, so that information on global macroeconomic fundamentals diffuses gradually from the U.S. equity market to other countries' markets. This result is consistent with Rizova's (2010) Lucas-tree model with gradual cross-country information diffusion.

Since the Swedish and Swiss equity markets are substantially smaller than the U.S. market, the predictive ability of lagged Swedish and Swiss returns in Table III is caused by different factors than those for the United States. Market concentration and institutional ownership are two plausible factors. Both the Swedish and Swiss equity markets are among the most highly concentrated for the industrialized countries in our sample. According to data from the World Federation of Exchanges, the largest ten firms comprised 52% and 68% of total market capitalization for Sweden and Switzerland, respectively, on average for 2002 to 2004.[15] In the context of information frictions, shocks to macroeconomic fundamentals are likely to be more quickly impounded into broad stock price indices for markets that are comprised of a relatively small number of large firms, since more information is typically available for large firms.

Institutional ownership also appears to play an important role, especially for Sweden. Henrekson and Jakobsson (2003) observe that Swedish ownership policies from 1945 to 1985 were designed to stimulate institutional ownership and favored large companies, and, indeed, the household ownership share of Swedish stocks decreased steadily during this period and remained relatively low thereafter. Furthermore, extending an earlier study by Dahlquist and Robertsson (2001), Aggarwal, Erel, Ferreira, and Matos (2011) recently report that institutional ownership in Sweden is among the highest in the world. Many studies, such as Grinblatt and Titman (1989), Chordia, Roll, and Subrahmanyam (2005), and Boehmer and Kelley (2009), find that markets with more institutional investors exhibit greater pricing efficiency, due to the enhanced capacity of institutional investors to gather and process information and conduct research. Swedish share prices should thus react more quickly to shocks relative to many European counterparts.[16]

To examine the robustness of the results in Table III, we estimate (3) using returns from *Global Financial Data* and *Morgan Stanley Capital International* that are not adjusted for differences in market closing times. The results, reported in Tables AX and AXI, respectively, are very similar to those in Table III. Furthermore, since the literature considers additional national economic variables as return predictors, we test the predictive power of lagged country returns when controlling for five additional national economic variables for which monthly data are available for most of the countries: the term spread, inflation rate, real exchange rate growth, real oil price growth, and industrial production growth.[17] To accommodate a relatively large number of national economic variables, we proceed along the lines of Ludvigson and Ng (2007) and estimate (3) with $z_{i,t}$ replacing $(bill_{i,t}, dy_{i,t})'$, where $z_{i,t}$ is a vector containing the first two principal components from the 7×1 vector containing the seven economic variables for country i. The results are reported in Table AXII and are again very similar to those in Table III.[18]

B. General Model Specification

Equation (3) provides a framework for pairwise Granger causality tests. A more general specification for testing the predictive power of lagged country returns is given by:[19]

$$r_{i,t+1} = \beta_{i,0} + \beta_{i,i} r_{i,t} + \sum_{j \neq i} \beta_{i,j} r_{j,t} + \beta_{i,b} bill_{i,t} + \beta_{i,d} dy_{i,t} + \varepsilon_{i,t+1}. \tag{4}$$

Equation (4) is a single equation from an augmented VAR(1) model for all eleven country returns, where, in addition to lagged returns from all eleven countries, we include country i's national economic variables as regressors. This general specification simultaneously controls for all other lagged country returns when testing for Granger causality. OLS estimation of (4), however, is plagued by a plethora of correlated regressors, resulting in imprecise parameter estimates and weak statistical tests. Here, we use two approaches for improving estimation and testing.

Our first approach is a pooled version of (4), again in the spirit of Ang and Bekaert (2007) and Hjalmarsson (2010). To apply this approach, we impose the following slope homogeneity restrictions: $\beta_{i,i} = \bar{\beta}_i$, $\beta_{i,j} = \bar{\beta}_j$, $\beta_{i,b} = \bar{\beta}_b$, and $\beta_{i,d} = \bar{\beta}_d$ for $i = 1, \ldots, N$. In the context of the bias-efficiency tradeoff, pooling potentially introduces biases, but it increases estimation efficiency; as such, pooling can improve estimation by reducing mean squared error. Furthermore, as previously indicated, pooled estimates measure average relationships in the data. Table IV reports pooled OLS estimates of $\bar{\beta}_j$, along with bias-corrected wild bootstrapped 90% confidence intervals. (The construction of the bootstrapped confidence intervals is described in detail in the Internet Appendix.) The pooled estimation results in Table IV largely agree with the pairwise Granger causality test results in Table III. Lagged Swedish and U.S. returns remain significantly positive predictors in Table IV. Furthermore, lagged U.S. returns continue to display the strongest quantitative effects; indeed, the $\hat{\bar{\beta}}_{\text{USA}}$ estimate of 0.17 in Table IV matches the corresponding pooled estimate in the last row of Table III. The main difference between the results in Tables III and IV involves the Netherlands. Lagged Dutch returns, which are typically statistically insignificant in Table III, have a significantly negative effect in Table IV ($\hat{\bar{\beta}}_{\text{NLD}} = -0.12$). But the predictive ability of lagged Dutch returns does not appear robust, as we discuss below.

Table IV about here

Our second approach draws on important recent advances in the statistical learning literature. Tibshirani's (1996) seminal least absolute shrinkage and selection operator ("LASSO") performs both parameter shrinkage and variable selection, thereby generating more stable and interpretable estimates in models with a large number of regressors. Similar to ridge regression, the LASSO minimizes the sum of squared residuals subject to a penalty term. However, ridge regression shrinks parameter estimates based on an ℓ_2 penalty, which precludes shrinkage to zero; in contrast, the LASSO allows continuous shrinkage to zero—and thus variable selection—by employing an ℓ_1 penalty. A drawback to the LASSO is that it tends to arbitrarily select a single predictor from a group of correlated predictors, making it less informative in settings with many correlated regressors, such as ours. The elastic net of Zou and Hastie (2005) avoids this problem by including both ℓ_1 (LASSO) and ℓ_2 (ridge) terms in the penalty. We estimate (4) via the adaptive elastic net (Zou and Zhang (2009), Ghosh (2011)), which is a weighted version of the elastic net that achieves optimal large-sample performance in terms of variable selection and parameter estimation.[20] The adaptive elastic net is described in detail in the Internet Appendix.

Adaptive elastic net estimates of $\beta_{i,j}$ in (4) and bias-corrected wild bootstrapped 90% confidence intervals are reported in Table V. The results are again similar to those for the pairwise Granger causality tests in Table III, with lagged U.S. returns demonstrating the strongest overall predictive power in Table V. Lagged U.S. returns are selected as return predictors by the adaptive elastic net for nine of the ten non-U.S. countries. Seven of the $\hat{\beta}^*_{i,\text{USA}}$ estimates are greater than or equal to 0.10, and seven are significant according to the confidence intervals (despite the relatively large number of regressors in many cases). The average of the $\hat{\beta}^*_{i,\text{USA}}$ estimates across the ten non-U.S. countries is 0.14, which is larger in magnitude than any of the other averages in the last row of Table V. Lagged Swedish and Swiss returns also appear as important predictors in a number of cases in Table V, with lagged Swiss returns exhibiting particularly strong predictive ability for Italian and Dutch returns (where the $\hat{\beta}^*_{i,\text{CHE}}$ estimates are above 0.20). Lagged Dutch returns are selected as return predictors for six countries. The $\hat{\beta}^*_{i,\text{NLD}}$ estimates for these countries are all negative, in contrast to the generally small and positive $\hat{\beta}_{i,\text{NLD}}$ estimates in Table III. However, only two of the $\hat{\beta}^*_{i,\text{NLD}}$ estimates in Table V are significant (for $i = \text{ITA, SWE}$), and the $\hat{\beta}^*_{i,\text{NLD}}$ estimate for $i = \text{ITA}$ is much larger in magnitude than the others. Since lagged Dutch returns do not exhibit consistent predictive ability across many countries in Table V and typically demonstrate limited predictive ability in Table III (including for Italy), the predictive ability of lagged Dutch returns does not appear robust. In contrast, the predominant predictive power of lagged U.S. returns is quite robust across Tables III–V.[21]

Table V about here

III. News-Diffusion Model

As discussed in Section II, the predictive ability of lagged U.S. returns is consistent with information frictions across national equity markets. To analyze international information frictions more formally, we specify the following empirical news-diffusion model:

$$r_{i,t+1} = \mu_{i,t} + u_{i,t+1} + \theta_{i,j}\lambda_{i,j}u_{j,t+1} + (1-\theta_{i,j})\lambda_{i,j}u_{j,t}, \quad (5)$$

$$r_{j,t+1} = \mu_{j,t} + \theta_{j,i}\lambda_{j,i}u_{i,t+1} + (1-\theta_{j,i})\lambda_{j,i}u_{i,t} + u_{j,t+1}, \quad (6)$$

where

$$\mu_{i,t} = \beta_{i,0} + \beta_{i,b}bill_{i,t} + \beta_{i,d}dy_{i,t}, \quad (7)$$

$$\mu_{j,t} = \beta_{j,0} + \beta_{j,b}bill_{j,t} + \beta_{j,d}dy_{j,t} \quad (8)$$

are the expected return components corresponding to national economic variables in countries i and j, respectively; $u_{i,t+1}$ and $u_{j,t+1}$ are serially and contemporaneously uncorrelated return shocks emanating in countries i and j, respectively; $\lambda_{i,j}$ measures the total impact of a unit country-j return shock on country-i returns; and $\theta_{i,j}$ is a diffusion parameter that measures the proportion of the total impact of a country-j return shock contemporaneously incorporated into country-i returns. The news-diffusion model allows for a return shock emanating in one country to be fully incorporated into another country with a lag, thereby permitting cross-country information frictions.[22]

Solving (6) for $u_{j,t+1}$, lagging one month, and substituting into (5), we have

$$r_{i,t+1} = \mu_{i,t} - (1-\theta_{i,j})\lambda_{i,j}\mu_{j,t-1} + (1-\theta_{i,j})\lambda_{i,j}r_{j,t} + e_{i,t+1}, \quad (9)$$

where

$$e_{i,t+1} = u_{i,t+1} + \theta_{i,j}\lambda_{i,j}u_{j,t+1} - (1-\theta_{i,j})\lambda_{i,j}[\theta_{j,i}\lambda_{j,i}u_{i,t} + (1-\theta_{j,i})\lambda_{j,i}u_{i,t-1}]. \quad (10)$$

The coefficient on $r_{j,t}$ in (9) establishes the conditions under which lagged country-j returns predict country-i returns in the context of the news-diffusion model:

$$\lambda_{i,j} \neq 0, \tag{11}$$

$$\theta_{i,j} \neq 1. \tag{12}$$

These conditions are intuitive. Equation (11) requires country-j return shocks to affect returns in country i; if country-j shocks are irrelevant for country i, then lagged country-j returns will not predict returns in country i. If $\lambda_{i,j} \neq 0$, (12) indicates that lagged country-j returns affect country-i returns if it takes more than one month for a country-j return shock to be fully reflected in country-i equity prices, as would result from international information frictions.

Section II documents the predictive power of lagged U.S. returns for non-U.S. returns. We can interpret this in the context of (9), where i represents a non-U.S. country and j the United States. Assuming that $\theta_{\mathrm{USA},i} = 1$, so that lagged non-U.S. returns do not predict U.S. returns, generally consistent with the results in Section II, (9) becomes

$$r_{i,t+1} = \mu_{i,t} - (1-\theta_{i,\mathrm{USA}})\lambda_{i,\mathrm{USA}}\mu_{\mathrm{USA},t-1} + (1-\theta_{i,\mathrm{USA}})\lambda_{i,\mathrm{USA}}r_{\mathrm{USA},t} + e_{i,t+1}, \tag{13}$$

where

$$e_{i,t+1} = u_{i,t+1} + \theta_{i,\mathrm{USA}}\lambda_{i,\mathrm{USA}}u_{\mathrm{USA},t+1} - (1-\theta_{i,\mathrm{USA}})\lambda_{i,\mathrm{USA}}\lambda_{\mathrm{USA},i}u_{i,t}. \tag{14}$$

The coefficient on $r_{\mathrm{USA},t}$ in (13) identifies the factors that strengthen the predictive ability of lagged U.S. returns for non-U.S. countries. The larger the total impact of a U.S. return shock on country i—embodied by a larger $\lambda_{i,\mathrm{USA}}$—the greater the predictive ability of lagged U.S. returns; stronger economic links with the United States correspond to a larger $\lambda_{i,\mathrm{USA}}$. Furthermore, greater information frictions—in the form of a smaller $\theta_{i,\mathrm{USA}}$—promote greater predictive power for lagged U.S. returns; as $\theta_{i,\mathrm{USA}}$ decreases, investors focus more intently on the United States vis-á-vis country i, so that a larger portion of a shock emanating in the United States is reflected outside the

United States with a delay.

When U.S. return shocks are important for non-U.S. countries and information frictions exist, (13) indicates that a conventional predictive regression based on national economic variables alone will be insufficient for modeling return predictability for non-U.S. countries; instead, the predictive regression should be augmented with lagged U.S. returns. Strictly speaking, (13) also indicates that U.S. economic variables from month $t-1$ (due to the presence of $\mu_{\text{USA},t-1}$) should be included in the predictive regression. These U.S. economic variables should have limited relevance for predicting $r_{i,t+1}$ compared to $r_{\text{USA},t}$, however, since fluctuations in expected U.S. returns ($\mu_{\text{USA},t-1}$) are only a small component of actual U.S. returns. Furthermore, (14) indicates that the error term in the predictive regression will be autocorrelated. Again, this is likely to be of only limited relevance in practice, since the coefficient on $u_{i,t}$ in (14) will likely be "close" to zero; indeed, if country i is small relative to the United States, $\lambda_{\text{USA},i} = 0$, and the autocorrelation vanishes.

To glean further insight into international information frictions, we estimate the structural parameters of the news-diffusion model. To identify the structural parameters, we assume that the non-U.S. countries are small, so that return shocks emanating in these countries do not affect U.S. returns ($\lambda_{\text{USA},i} = 0$). While this assumption is unlikely to exactly hold, given the sheer size of the U.S. economy and the relatively limited GDP share of U.S. exports, this appears to be a reasonably "safe" identifying assumption for the purpose of estimating the news-diffusion model's structural parameters. Then, the news-diffusion model can be simplified to:

$$r_{\text{USA},t+1} = x'_{\text{USA},t}\beta_{\text{USA}} + u_{\text{USA},t+1}, \tag{15}$$

$$r_{i,t+1} = x'_{i,t}\beta_i + \theta_{i,\text{USA}}\lambda_{i,\text{USA}}u_{\text{USA},t+1} + (1-\theta_{i,\text{USA}})\lambda_{i,\text{USA}}u_{\text{USA},t} + u_{i,t+1}, \tag{16}$$

for $i = \text{AUS},\ldots,\text{GBR}$, where $x_{i,t} = (1, bill_{i,t}, dy_{i,t})'$ and $\beta_i = (\beta_{i,0}, \beta_{i,b}, \beta_{i,d})'$. Collecting the 53 parameters in (15)–(16) in the following vector,

$$\phi = (\beta'_{\text{USA}}, \beta'_{i,\text{AUS}}, \theta_{\text{AUS,USA}}, \lambda_{\text{AUS,USA}}, \ldots, \beta'_{i,\text{GBR}}, \theta_{\text{GBR,USA}}, \lambda_{\text{GBR,USA}})', \tag{17}$$

we estimate ϕ using two-step GMM based on the following 73 moment conditions:

$$E[x_{\text{USA},t} u_{\text{USA},t+1}(\phi)] = 0, \tag{18}$$

$$E[(bill_{i,t}, dy_{i,t})' u_{\text{USA},t+1}(\phi)] = 0, \quad i = \text{AUS}, \ldots, \text{GBR}, \tag{19}$$

$$E[(x'_{i,t}, u_{\text{USA},t+1}(\phi), u_{\text{USA},t}(\phi))' u_{i,t+1}(\phi)] = 0, \quad i = \text{AUS}, \ldots, \text{GBR}. \tag{20}$$

These moment conditions represent a set of orthogonality conditions implied by the news-diffusion model and make GMM estimation tractable.

GMM estimates of the parameters in (15)–(16) are reported in Table VI. We concentrate on the estimates of $\theta_{i,\text{USA}}$ and $\lambda_{i,\text{USA}}$, the key structural parameters in the news-diffusion model. To account for differences in closing times across national equity markets, we exclude the last trading day of the month when computing $r_{\text{USA},t+1}$ in (15), so that $u_{\text{USA},t+1}$ contains information available to investors in all markets. The $\tilde{\lambda}_{i,\text{USA}}$ estimates in the fifth and eleventh columns of Table VI range from 0.65 (Japan) to 1.08 (Sweden). The t-statistics for the $\tilde{\lambda}_{i,\text{USA}}$ estimates are for testing H_0: $\lambda_{i,\text{USA}} = 0$ against H_A: $\lambda_{i,\text{USA}} > 0$, and they all indicate significance at the 1% level. These results point to statistically and economically significant links between each country's equity market and the U.S. market. The $\tilde{\theta}_{i,\text{USA}}$ estimates are reported in the fourth and tenth columns of Table VI; the t-statistics below the estimates are for a test of H_0: $\theta_{i,\text{USA}} = 1$ against H_A: $\theta_{i,\text{USA}} < 1$. Consistent with international information frictions, all of the $\tilde{\theta}_{i,\text{USA}}$ estimates are significantly less than one.[23]

Table VI about here

Table VI also reports pooled estimates of the news-diffusion model parameters based on the following homogeneity restrictions: $\beta_{i,b} = \bar{\beta}_b$, $\beta_{i,d} = \bar{\beta}_d$ for all i; $\theta_{i,\text{USA}} = \bar{\theta}_{\text{USA}}$, $\lambda_{i,\text{USA}} = \bar{\lambda}_{\text{USA}}$ for all $i \neq \text{USA}$. The GMM estimate of $\bar{\theta}_{\text{USA}}$ ($\bar{\lambda}_{\text{USA}}$) is 0.86 (0.90), which is significantly less than one (greater than zero). Overall, there is extensive evidence in Table VI that non-U.S. returns underreact to U.S. return shocks, consistent with information frictions in international equity markets. This underreaction generates predictive power for lagged U.S. returns outside of the United States.

Of course, we do not claim that information frictions are solely responsible for the predictive ability of lagged U.S. returns. We can gauge the relative importance of information frictions by comparing the coefficients on $r_{\mathrm{USA},t}$ in (13) implied by the GMM estimates of $\theta_{i,\mathrm{USA}}$ and $\lambda_{i,\mathrm{USA}}$ in Table VI with the $\hat{\beta}_{i,\mathrm{USA}}$ estimates in the last column of Table III. To facilitate the comparisons, the sixth and twelfth columns of Table VI report $\tilde{\beta}_{i,\mathrm{USA}} = (1-\tilde{\theta}_{i,\mathrm{USA}})\tilde{\lambda}_{i,\mathrm{USA}}$, where the t-statistics in parentheses below the $\tilde{\beta}_{i,\mathrm{USA}}$ estimates are for testing H_0: $\beta_{i,\mathrm{USA}} = 0$ against H_A: $\beta_{i,\mathrm{USA}} > 0$ and the standard errors used to compute the t-statistics are calculated via the delta method. We reject $\tilde{\beta}_{i,\mathrm{USA}} = 0$ at conventional significance levels for all countries, implying that information frictions give rise to predictive power for lagged U.S. returns. Comparing the $\tilde{\beta}_{i,\mathrm{USA}}$ estimates in Table VI to the corresponding $\hat{\beta}_{i,\mathrm{USA}}$ estimates in Table III, we see that the former are generally smaller than the latter, indicating that information frictions do not account for all of the predictive ability of lagged U.S. returns. Nevertheless, the $\tilde{\beta}_{i,\mathrm{USA}}$ estimates in Table VI are over half the size of the corresponding $\hat{\beta}_{i,\mathrm{USA}}$ estimates in Table III for Canada, France, Germany, Italy, Japan, the Netherlands, Sweden, and Switzerland. Furthermore, the $\tilde{\beta}_{i,\mathrm{USA}}$ estimates fully account for the $\hat{\beta}_{i,\mathrm{USA}}$ estimates for France, Sweden, and Switzerland. The pooled estimate of $\bar{\beta}_{\mathrm{USA}}$ in Table VI is 0.12, which is approximately 70% of the corresponding pooled estimate of 0.17 in Table III. Overall, the news-diffusion model estimates suggest that information frictions are a key, but not the only, source of the predictive power of lagged U.S. returns.

IV. Out-of-Sample Evidence

Goyal and Welch (2008) recently show that, despite significant in-sample evidence of return predictability, excess return forecasts from predictive regressions based on a variety of popular economic variables often fail to outperform the naïve historical average forecast in out-of-sample tests. This points to the potential fragility of in-sample evidence of return predictability. In light of Goyal and Welch (2008), we test whether forecasting models that utilize lagged U.S. returns can outperform historical average baseline forecasts of country excess returns.

The historical average forecast corresponds to the constant expected excess return model,

$$r_{i,t+1} = \beta_{i,0} + \varepsilon_{i,t+1}, \tag{21}$$

which is tantamount to a no predictability baseline model. The historical average forecast of the month-$(t+1)$ excess return for country i is simply the average country-i excess return from the beginning of the available sample through month t. For each of the ten non-U.S. countries, we compare the historical average forecast to a forecast generated from a competing predictive regression model that includes lagged U.S. returns as a regressor:

$$r_{i,t+1} = \beta_{i,0} + \beta_{i,\mathrm{USA}} r_{\mathrm{USA},t} + \varepsilon_{i,t+1}. \tag{22}$$

When forming month-$(t+1)$ excess return forecasts based on (22), we estimate the parameters in (22) using OLS and data through month t and then plug $r_{\mathrm{USA},t}$ into the fitted predictive regression. Forming forecasts in this manner simulates the situation of an investor in real time.

To compare the historical average forecasts against the competing predictive regression forecasts, we employ the Campbell and Thompson (2008) out-of-sample R^2 statistic, R^2_{OS}. The R^2_{OS} statistic measures the proportional reduction in mean squared forecast error (MSFE) for the forecasting model that includes lagged U.S. returns relative to the historical average forecast. We also compute the Clark and West (2007) *MSFE-adjusted* statistic to test the null of equal MSFE ($R^2_{OS} = 0$) against the alternative that the competing model has a lower MSFE than the baseline model ($R^2_{OS} > 0$).[24]

The second and fifth columns of Table VII report R^2_{OS} statistics comparing the historical average and predictive regression forecasts for the 1985:01 to 2010:10 forecast evaluation period, so that data for 1980:02 to 1984:12 are used to estimate the model parameters for the initial out-of-sample forecasts. The selection of 1985:01 to 2010:10 as the forecast evaluation period strikes a balance between having enough observations available to compute reasonably accurate parameter estimates when generating the initial forecasts and having a relatively large number of forecasts available for evaluation. The R^2_{OS} statistics in the second and fifth columns are positive for nine of the ten non-U.S. countries (Australia is the exception). For these countries, the predictive regression model, which utilizes the information in lagged U.S. returns, has a lower MSFE than the constant expected excess return model, which ignores the information in lagged U.S. returns. Seven of the R^2_{OS} statistics are above 1%, and thus economically sizable, and nine are statistically significant at conventional levels according to the *MSFE-adjusted* statistic.[25]

Table VII about here

In the spirit of White (2000), Inoue and Kilian (2004), Rapach and Wohar (2006), and Clark and McCracken (2012), we employ a wild bootstrap procedure to compute data-mining-robust critical values for the *MSFE-adjusted* statistics that account for the fact that we are analyzing multiple, correlated country return forecasts. The bootstrap generates a pseudo sample of excess return data under a constant expected excess return process for each return series, where we preserve the contemporaneous correlations among country returns in the data. For the pseudo sample, we generate historical average and predictive regression forecasts, as well as the *MSFE-adjusted* statistic, for each country. We then store the maximum *MSFE-adjusted* statistic. Repeating this process, we build up a empirical distribution of maximum *MSFE-adjusted* statistics under the null hypothesis of no return predictability for any country. The 1% bootstrapped critical value for the maximum *MSFE-adjusted* statistic is 2.49. The maximum statistic of 3.81 (for the Netherlands) in the second and fifth columns of Table VII thus appears robust to data mining across countries.

Figure 1 plots differences in cumulative squared forecast errors for the historical average vis-á-vis predictive regression forecasts. Goyal and Welch (2004, 2008) recommend this graphical

Figure I about here

device for assessing the consistency of out-of-sample forecasting gains. In particular, we can conveniently determine whether the competing model outperforms the baseline model for any out-of-sample period by comparing the height of the curve at the beginning and end of the period (where a curve that is higher at the end of the period represents a lower MSFE for the competing model during the out-of-sample period). The differences in cumulative squared forecast errors in Figure 1 indicate that lagged U.S. returns provide out-of-sample forecasting gains on a reasonably consistent basis over time for most countries. Nevertheless, there is a tendency for the gains to be concentrated in NBER-dated U.S. business-cycle recessions (delineated by the vertical bars in Figure 1). For example, the curves are positively and relatively steeply sloped for most countries during the recession of the early 1990s corresponding to the first Gulf War and oil price spike. Moreover, forecasts based on lagged U.S. returns generate very substantial out-of-sample gains relative to the historical average starting in the fall of 2008 during the height of the Global Financial Crisis and concomitant Great Recession.

The fact that some of the strongest out-of-sample gains occur during U.S. recessions in Figure 1 is perhaps not surprising, since recessions are periods of "large" shocks representing rapidly changing macroeconomic fundamentals, which can lead to substantial revisions in expected cash flows. Given the importance of the United States in the world economy, these return shocks also substantially affect expected cash flows outside the United States. Combined with information frictions, the out-of-sample predictive ability of lagged U.S. returns for non-U.S. returns will then be especially evident during U.S. recessions.

The third and sixth columns of Table VII report R^2_{OS} statistics for a pooled version of (22) that imposes a set of slope homogeneity restrictions, $\beta_{i,\mathrm{USA}} = \bar{\beta}_{\mathrm{USA}}$ for all $i \neq \mathrm{USA}$, on the competing forecasting models. In terms of the bias-efficiency tradeoff, pooling restrictions can improve forecasting performance by reducing the variability of parameter estimates (Hjalmarsson (2010)), and, indeed, the R^2_{OS} statistics are typically larger for the forecasts based on pooled estimation of (22). All of the R^2_{OS} statistics in the third and sixth columns of Table VII are positive and significant according to the *MSFE-adjusted* statistics, providing further evidence that excess return forecasts based on lagged U.S. returns outperform naïve historical average baseline forecasts.

We further analyze out-of-sample return predictability for two alternative baseline forecasting models: (i) a first-order autoregressive model and (ii) the benchmark predictive regression based on a country's own lagged nominal interest rate and log dividend yield. For each alternative baseline, the competing forecasting model includes lagged U.S. returns as an additional regressor. The results, reported in Table AXVII, show that forecasting models that include lagged U.S. returns generally continue to provide significant out-of-sample gains relative to models that ignore lagged U.S. returns.

V. Conclusion

We analyze lead-lag relationships among industrialized country stock returns, a previously unexplored aspect of international return predictability. Our investigation points to a leading role for the United States with respect to monthly international excess return predictability: lagged U.S. returns have substantial predictive power for many non-U.S. returns, even after controlling for two key national economic variables (interest rates and dividend yields) and countries' own lagged returns; in contrast, lagged non-U.S. returns have limited predictive ability for U.S. returns. We present both in-sample and out-of-sample evidence of the predictive power of lagged U.S. returns, thereby increasing the reliability of our empirical findings.

Information frictions provide a ready explanation for the leading role of the United States. Applying concepts from Hong and Stein (1999) and Hong, Torous, and Valkanov (2007) to an international context, and in line with the economic insight of Rizova (2010), we posit that many investors focus more intently on the U.S. market, which, in the presence of information-processing limitations, creates a gradual diffusion of relevant information on macroeconomic fundamentals across countries, thereby generating predictive power for lagged U.S. returns. We specify an empirical news-diffusion model to highlight the role of information frictions. GMM estimation of the model's structural parameters indicates that return shocks emanating in the U.S. market are only fully incorporated outside of the U.S. with a lag, supporting the relevance of information frictions. We recognize that alternative explanations of the predictive power of lagged U.S. returns, including risk-based explanations, are also possible. In any event, our results indicate that conventional predictive regressions based on national economic variables alone are inadequate for many non-U.S. countries and need to be augmented with lagged U.S. returns to capture an important source of international return predictability.

Footnotes

[1]A number of studies examine contemporaneous relationships among country stock returns (e.g., Bekaert, Hodrick, and Zhang (2009)), while lead-lag relationships appear largely ignored in the context of international return predictability. King and Wadhwani (1990) investigate the cross-country effects of market openings and announcements on very high-frequency (hourly) returns for Japan, the United Kingdom, and the United States around the time of the October 1987 stock market crash; in contrast, we analyze lead-lag relationships at a lower monthly data frequency, thereby permitting the inclusion of macroeconomic variables and squarely situating our study in the stock return predictability literature.

[2]The 1980 starting date is dictated by data availability for a relatively large number of countries. Our conclusions are not altered, however, by using a longer sample for fewer countries.

[3]Similar results obtain without this adjustment.

[4]Ahn, Boudoukh, Richardson, and Whitelaw (2002) test the importance of stale pricing in illiquid markets by comparing autocorrelations for daily returns. In the Internet Appendix, we examine the relevance of stale pricing for monthly return predictability and find that it plays a minimal role.

[5]Interestingly, in independent and subsequent studies, Bollerslev, Marrone, Xu, and Zhou (2011) find that the United States also plays a leading role in terms of variance premia (i.e., the U.S. variance premium predicts returns in non-U.S. countries better than non-U.S. countries' own variance premia), while Dahlquist and Hasseltoft (2011) find that the United States plays a special role in the global bond market.

[6]The approximation becomes more accurate for shorter time periods (monthly returns in our

case). Solnik (1993) also points out that working with national currency returns obviates the need to develop a risk premium model for exchange rates, allowing us to focus on time-varying expected returns in equity markets.

[7]Drawing on Jorion and Goetzmann (1999) and their own calculations, Dimson, Marsh, and Staunton (2002) give the following founding dates for exchanges within countries: Australia, 1871; Canada, 1861; France, 1724; Germany, 1685; Italy, 1808; Japan, 1878; the Netherlands, 1611; Sweden, 1901; Switzerland, 1850; the United Kingdom, 1698; the United States, 1792.

[8]We also compute summary statistics for monthly excess returns based on *Morgan Stanley Capital International* country total return indices. The summary statistics are reported in Table AII and are very similar to those in Table I. We focus on excess returns based on the *Global Financial Data* country indices, since daily data for country indices from *Morgan Stanley Capital International* begin relatively recently, while, as previously indicated, daily data from *Global Financial Data* begin in 1980 for the eleven countries.

[9]Observe that $\hat{\beta}_{i,d}$ is substantially larger for the United Kingdom than any other country, including the United States. This agrees with Kellard, Nankervis, and Papadimitriou (2010), who find that the dividend yield exhibits greater predictive power in the United Kingdom vis-á-vis the United States. They attribute this to a weaker "disappearing dividends" effect (Fama and French (2001)) in the United Kingdom relative to the United States.

[10]Amihud and Hurvich (2004), Lewellen (2004), and Campbell and Yogo (2006) develop testing procedures that explicitly account for the Stambaugh (1999) bias for predictive regressions with a single predictor. Amihud, Hurvich, and Wang (2009) is a multipredictor extension of Amihud and Hurvich (2004).

[11]See, e.g., Poterba and Summers (1988) and Patro and Wu (2004) for evidence of autocorrela-

tion in international stock returns.

[12]The complete set of adjustments are reported in Table AVII. Note that the Swiss market closes at 11:20a, while the other non-German European markets close at 11:30a. We treat the Swiss market as closing at the same time as the non-German European markets; our results are not sensitive to this assumption. For France, Sweden, Switzerland, and the United States, daily data for total stock return indices are not available going back to 1980. When testing the predictive ability of lagged French, Swedish, Swiss, and U.S. returns for Australian and Japanese returns (and the predictive ability of lagged U.S. returns for European returns), we compute French, Swedish, Swiss, and U.S. monthly returns excluding the last trading day of the month using daily data for composite stock price indices. Excluding dividends is unlikely to be important, since monthly return fluctuations are dominated by price changes.

[13]The conventional Granger causality test is based on H_0: $\beta_{i,j} = 0$ against H_A: $\beta_{i,j} \neq 0$. As Chordia and Swaminathan (2000) observe, by testing for the existence of predictability and its sign, the $\beta_{i,j} > 0$ alternative is a more stringent test.

[14]Supporting the relevance of U.S. economic conditions for the rest of the world, Table AIX shows that U.S. industrial production growth Granger causes industrial production growth for the seven non-U.S. countries in our sample for which monthly industrial production data are available (Canada, France, Germany, Japan, the Netherlands, Sweden, and the United Kingdom).

[15]The data are available at http://www.world-exchanges.org/. We are very grateful to an anonymous referee for pointing out the equity market concentration idea, among his/her numerous insightful and very helpful comments.

[16]This is also consistent with Griffin, Hirschey, and Kelly (2011), who find that the Swedish market, along with the U.S. and U.K. markets, consistently ranks among the top markets in reacting

to financial news according to a variety of measures.

[17]As indicated in footnote 14, monthly industrial production data are not available for Australia, Italy, and Switzerland; monthly data are available for each country for all of the other national economic variables.

[18]For reasons previously discussed, we measure excess returns in national currencies. Nevertheless, we also estimate (3) with all excess returns measured in U.S. dollars, and the results are reported in Table AXIII. In this case, lagged U.S. returns are statistically and economically significant return predictors for Canada, Japan, the Netherlands, Sweden, and the United Kingdom. (The pooled estimate of the coefficient on lagged U.S. returns is also significant.) As implied in footnote 6, the less extensive evidence of predictive ability for lagged U.S. returns is likely due to challenges in predicting exchange rates. While beyond the scope of the present paper, it would be interesting in future research to explore international stock return predictability measured in U.S. dollars by combining models of exchange rate and stock return predictability, along the lines of Bekaert and Hodrick (1992).

[19]We are grateful to the same referee for raising this interesting issue.

[20]The LASSO and elastic net are more robust than alternative approaches to variable selection and parameter estimation, e.g., backward or forward stepwise regressions. See Bai and Ng (2008) for a survey of variable selection and parameter estimation with many potential predictors, as well as applications of the LASSO and elastic net to macroeconomic forecasting. Our paper appears to be the first to apply the adaptive elastic net to stock returns.

[21]Following the suggestion of the Acting Editor, we also conduct a series of predictive "horse races" pitting lagged U.S. returns against lagged returns for each of the other countries in turn (controlling for each county's own lagged return and economic variables) in pooled regressions. As

shown in Table AXVI, lagged U.S. returns are statistically and economically significant predictors of non-U.S. returns when matched against lagged returns for any other country, and the coefficient on lagged U.S. returns is at least twice the size of the coefficient on the competing country's lagged returns in all cases.

[22]The news-diffusion model allows for either underreaction ($\theta_{i,j} < 1$) or overreaction ($\theta_{i,j} > 1$) in country i to a country-j return shock; information frictions imply $\theta_{i,j} < 1$.

[23]The significance of the t-statistics in Table VI is based on asymptotic GMM p-values. Because of the high computational costs, we do not generate wild bootstrapped p-values for the news-diffusion model, so that the results should be interpreted with this caveat in mind. The test of the overidentifying restrictions used to estimate the news-diffusion model has a J-statistic of 26.02 and corresponding p-value of 0.17, so that we fail to reject the overidentifying restrictions at conventional significance levels.

[24]The Diebold and Mariano (1995) and West (1996) statistic is widely used to test for differences in MSFE between competing models. Clark and McCracken (2001) and McCracken (2007), however, show that the Diebold and Mariano (1995) and West (1996) statistic has a non-standard asymptotic distribution when comparing forecasts from nested models, as is the case for our applications. Clark and West (2007) modify the Diebold and Mariano (1995) and West (1996) statistic so that it approximately has a standard asymptotic distribution when comparing forecasts from nested models.

[25]Observe that we reject $R^2_{OS} = 0$ in favor of $R^2_{OS} > 0$ for Australia based on the *MSFE-adjusted* statistic, despite the negative R^2_{OS} statistic for Australia. This results from the comparison of nested forecasts, as discussed in footnote 24.

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Table I

Summary statistics, monthly country excess stock returns, 1980:02–2010:12

The table reports summary statistics for monthly national currency excess returns (in percent) for eleven industrialized countries. The excess return is the return on a broad market index in excess of the three-month Treasury bill rate. Sharpe ratio is the mean of the excess return divided by its standard deviation. Data are from *Global Financial Data*.

(1)	(2)	(3)	(4)	(5)	(6)	(7)
Country	Mean	Standard deviation	Minimum	Maximum	Autocorrelation	Sharpe ratio
Australia	0.35	5.07	−43.06	14.99	0.05	0.07
Canada	0.30	4.72	−23.31	13.42	0.13	0.06
France	0.50	5.73	−22.49	21.58	0.13	0.09
Germany	0.51	5.71	−24.09	19.84	0.09	0.09
Italy	0.42	6.98	−20.66	28.78	0.09	0.06
Japan	0.22	5.39	−21.68	17.51	0.12	0.04
Netherlands	0.68	5.38	−23.69	15.78	0.11	0.13
Sweden	1.03	6.73	−22.61	33.90	0.15	0.15
Switzerland	0.55	4.63	−24.88	12.22	0.18	0.12
United Kingdom	0.50	4.68	−27.33	12.90	0.02	0.11
United States	0.55	4.50	−22.09	12.96	0.06	0.12

Table II

Benchmark predictive regression model estimation results, 1980:02–2010:12

The table reports OLS estimates of $\beta_{i,b}$ and $\beta_{i,d}$ (denoted by $\hat{\beta}_{i,b}$ and $\hat{\beta}_{i,d}$, respectively) and the R^2 statistic for the predictive regression model,

$$r_{i,t+1} = \beta_{i,0} + \beta_{i,b} bill_{i,t} + \beta_{i,d} dy_{i,t} + \varepsilon_{i,t+1},$$

where $r_{i,t+1}$ is the monthly national currency excess return and $bill_{i,t}$ ($dy_{i,t}$) is the three-month Treasury bill rate (log dividend yield) for country i. Heteroskedasticity-robust t-statistics are reported in parentheses in the second, third, sixth, and seventh columns; t-statistics for $\hat{\beta}_{i,b}$ ($\hat{\beta}_{i,d}$) are for testing H_0: $\beta_{i,b} = 0$ against H_A: $\beta_{i,b} < 0$ (H_0: $\beta_{i,d} = 0$ against H_A: $\beta_{i,d} > 0$). Parentheses below the R^2 statistics in the fourth and eighth columns report heteroskedasticity-robust χ^2 statistics for testing H_0: $\beta_{i,b} = \beta_{i,d} = 0$. "Pooled" estimates impose the restrictions that $\beta_{i,b} = \bar{\beta}_b$ and $\beta_{i,d} = \bar{\beta}_d$ for all i. Bold indicates significance at the 10% level according to wild bootstrapped p-values.

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
i	$\hat{\beta}_{i,b}$	$\hat{\beta}_{i,d}$	R^2	i	$\hat{\beta}_{i,b}$	$\hat{\beta}_{i,d}$	R^2
Australia	−0.05	0.68	0.13%	Netherlands	**−0.32**	1.82	**1.72%**
	(−0.49)	(0.29)	(0.26)		(−2.54)	(1.81)	(6.48)
Canada	**−0.23**	1.44	**2.58%**	Sweden	−0.01	1.18	0.45%
	(−2.42)	(1.22)	(6.47)		(−0.19)	(1.24)	(1.54)
France	−0.09	0.92	0.31%	Switzerland	−0.15	0.23	0.55%
	(−1.00)	(0.86)	(1.09)		(−1.32)	(0.25)	(2.01)
Germany	**−0.33**	1.68	1.24%	United Kingdom	**−0.16**	**3.71**	**2.60%**
	(−1.86)	(1.24)	(3.78)		(−1.67)	(2.90)	(8.75)
Italy	−0.01	−0.69	0.14%	United States	−0.19	1.61	1.51%
	(−0.08)	(−0.59)	(0.37)		(−1.66)	(2.03)	(4.15)
Japan	0.04	0.41	0.10%	Pooled	−0.06	0.53	0.35%
	(0.32)	(0.68)	(0.59)		(−1.06)	(1.20)	(2.06)

Table III

Pairwise Granger causality test results, 1980:02–2010:12

The table reports OLS estimates of $\beta_{i,j}$ (denoted by $\hat{\beta}_{i,j}$) for the predictive regression model,

$$r_{i,t+1} = \beta_{i,0} + \beta_{i,i} r_{i,t} + \beta_{i,j} r_{j,t} + \beta_{i,b} bill_{i,t} + \beta_{i,d} dy_{i,t} + \varepsilon_{i,t+1},\ i \neq j,$$

where $r_{i,t+1}$ is the monthly national currency excess return and $bill_{i,t}$ ($dy_{i,t}$) is the three-month Treasury bill rate (log dividend yield) for country i. Heteroskedasticity-robust t-statistics are reported in parentheses; t-statistics are for testing H_0: $\beta_{i,j} = 0$ against H_A: $\beta_{i,j} > 0$. Bold indicates significance at the 10% level according to wild bootstrapped p-values. "Average" is the column average of the $\beta_{i,j}$ estimates. "Pooled" estimates impose the restrictions that $\beta_{i,j} = \bar{\beta}_j$ for all $i \neq j$.

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
i	$\hat{\beta}_{i,\mathrm{AUS}}$	$\hat{\beta}_{i,\mathrm{CAN}}$	$\hat{\beta}_{i,\mathrm{FRA}}$	$\hat{\beta}_{i,\mathrm{DEU}}$	$\hat{\beta}_{i,\mathrm{ITA}}$	$\hat{\beta}_{i,\mathrm{JPN}}$	$\hat{\beta}_{i,\mathrm{NLD}}$	$\hat{\beta}_{i,\mathrm{SWE}}$	$\hat{\beta}_{i,\mathrm{CHE}}$	$\hat{\beta}_{i,\mathrm{GBR}}$	$\hat{\beta}_{i,\mathrm{USA}}$
AUS		**0.11**	**0.12**	**0.13**	**0.08**	**0.10**	**0.13**	**0.08**	**0.11**	0.07	**0.20**
		(1.35)	(1.96)	(2.06)	(2.24)	(1.91)	(1.77)	(1.91)	(1.67)	(0.94)	(2.34)
CAN	0.05		0.06	0.06	**0.06**	0.06	0.06	**0.15**	0.08	0.07	**0.21**
	(0.84)		(1.21)	(1.24)	(1.53)	(1.26)	(0.79)	(3.73)	(1.00)	(0.99)	(2.19)
FRA	0.01	−0.01		−0.03	−0.05	0.04	0.002	**0.14**	**0.16**	0.03	0.12
	(0.15)	(−0.15)		(−0.31)	(−0.91)	(0.53)	(0.02)	(2.27)	(1.47)	(0.26)	(1.28)
DEU	0.03	0.09	**0.13**		0.06	**0.09**	0.06	**0.14**	**0.26**	0.07	**0.22**
	(0.37)	(1.11)	(1.49)		(1.29)	(1.42)	(0.55)	(2.49)	(2.26)	(0.77)	(2.33)
ITA	−0.01	0.06	**0.16**	0.11		0.05	−0.06	0.06	**0.21**	**0.15**	**0.15**
	(−0.07)	(0.66)	(1.63)	(1.21)		(0.72)	(−0.59)	(0.99)	(1.84)	(1.48)	(1.59)
JPN	0.04	**0.12**	**0.11**	0.02	0.03		0.07	**0.09**	**0.11**	**0.11**	**0.11**
	(0.70)	(1.70)	(2.07)	(0.44)	(0.78)		(1.17)	(1.77)	(1.61)	(1.71)	(1.48)
NLD	**0.10**	**0.15**	**0.15**	**0.15**	0.05	**0.11**		**0.16**	**0.33**	0.11	**0.32**
	(1.46)	(1.95)	(2.20)	(1.79)	(1.05)	(2.12)		(2.76)	(3.28)	(1.11)	(3.69)
SWE	−0.03	**0.16**	0.05	0.08	0.08	0.06	0.01		0.12	0.10	**0.23**
	(−0.31)	(1.75)	(0.58)	(0.88)	(1.09)	(0.76)	(0.13)		(1.23)	(0.90)	(2.22)
CHE	0.03	0.03	0.005	−0.02	−0.003	0.02	−0.01	**0.13**		0.02	**0.14**
	(0.50)	(0.41)	(0.07)	(−0.20)	(−0.08)	(0.51)	(−0.08)	(3.14)		(0.32)	(1.67)
GBR	**0.11**	0.08	0.08	0.02	0.01	**0.09**	−0.02	**0.09**	**0.11**		**0.23**
	(1.74)	(1.02)	(1.17)	(0.26)	(0.24)	(1.85)	(−0.18)	(2.03)	(1.42)		(2.26)
USA	0.06	0.03	0.01	−0.01	**0.06**	−0.0003	0.01	**0.09**	0.04	0.02	
	(1.00)	(0.27)	(0.20)	(−0.20)	(1.52)	(−0.01)	(0.18)	(2.31)	(0.48)	(0.22)	
Average	0.04	0.08	0.09	0.05	0.04	0.06	0.03	0.11	0.15	0.08	0.19
Pooled	0.03	**0.07**	**0.08**	0.05	**0.04**	**0.06**	0.02	**0.11**	**0.13**	**0.08**	**0.17**
	(0.65)	(1.34)	(2.02)	(1.08)	(1.32)	(1.52)	(0.42)	(3.56)	(2.22)	(1.45)	(2.98)

Table IV

Estimation results for the pooled general model specification, 1980:02–2010:12

The table reports pooled OLS estimates of $\bar{\beta}_{i,j}$ (denoted by $\hat{\bar{\beta}}_j$) for the predictive regression model,

$$r_{i,t+1} = \beta_{i,0} + \bar{\beta}_i r_{i,t} + \sum_{j \neq i} \bar{\beta}_j r_{j,t} + \bar{\beta}_b bill_{i,t} + \bar{\beta}_d dy_{i,t} + \varepsilon_{i,t+1},\ i = 1, \ldots, N,$$

where $r_{i,t+1}$ is the monthly national currency excess return and $bill_{i,t}$ ($dy_{i,t}$) is the three-month Treasury bill rate (log dividend yield) for country i. Bias-corrected wild bootstrapped 90% confidence intervals are reported in brackets. Bold indicates significance at the 10% level.

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
$\hat{\bar{\beta}}_{\text{AUS}}$	$\hat{\bar{\beta}}_{\text{CAN}}$	$\hat{\bar{\beta}}_{\text{FRA}}$	$\hat{\bar{\beta}}_{i,\text{DEU}}$	$\hat{\bar{\beta}}_{i,\text{ITA}}$	$\hat{\bar{\beta}}_{\text{JPN}}$	$\hat{\bar{\beta}}_{\text{NLD}}$	$\hat{\bar{\beta}}_{\text{SWE}}$	$\hat{\bar{\beta}}_{\text{CHE}}$	$\hat{\bar{\beta}}_{\text{GBR}}$	$\hat{\bar{\beta}}_{\text{USA}}$
−0.03	−0.01	0.03	−0.03	0.01	0.02	**−0.12**	**0.08**	0.08	0.004	**0.17**
[−0.12, 0.06]	[−0.12, 0.09]	[−0.06, 0.11]	[−0.12, 0.06]	[−0.04, 0.06]	[−0.04, 0.09]	[−0.23, −0.01]	[0.03, 0.14]	[−0.05, 0.21]	[−0.11, 0.12]	[0.05, 0.29]

Table V

Adaptive elastic net estimation results for the general model specification, 1980:02–2010:12

The table reports adaptive elastic net estimates of $\beta_{i,j}$ (denoted by $\hat{\beta}^{*}_{i,j}$) for the predictive regression model,

$$r_{i,t+1} = \beta_{i,0} + \beta_{i,i} r_{i,t} + \sum_{j \neq i} \beta_{i,j} r_{j,t} + \beta_{i,b} bill_{i,t} + \beta_{i,d} dy_{i,t} + \varepsilon_{i,t+1},$$

where $r_{i,t+1}$ is the monthly national currency excess return and $bill_{i,t}$ ($dy_{i,t}$) is the three-month Treasury bill rate (log dividend yield) for country i. Bias-corrected wild bootstrapped 90% confidence intervals are reported in brackets. Bold indicates significance at the 10% level. "Average" is the column average of the $\hat{\beta}^{*}_{i,j}$ estimates.

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
i	$\hat{\beta}^{*}_{i,\text{AUS}}$	$\hat{\beta}^{*}_{i,\text{CAN}}$	$\hat{\beta}^{*}_{i,\text{FRA}}$	$\hat{\beta}^{*}_{i,\text{DEU}}$	$\hat{\beta}^{*}_{i,\text{ITA}}$	$\hat{\beta}^{*}_{i,\text{JPN}}$	$\hat{\beta}^{*}_{i,\text{NLD}}$	$\hat{\beta}^{*}_{i,\text{SWE}}$	$\hat{\beta}^{*}_{i,\text{CHE}}$	$\hat{\beta}^{*}_{i,\text{GBR}}$	$\hat{\beta}^{*}_{i,\text{USA}}$
AUS		0	0	0	0.01	0	0	0	0	0	**0.12**
					[−0.01, 0.03]						[0.05, 0.25]
CAN	0		0	0	0	0	−0.06	**0.13**	0	0	**0.10**
							[−0.18, 0.01]	[0.08, 0.21]			[0.02, 0.23]
FRA	0	−0.09		−0.11	−0.05	0	−0.07	**0.16**	0.17	−0.01	0.12
		[−0.25, 0.03]		[−0.29, 0.03]	[−0.15, 0.02]		[−0.25, 0.09]	[0.07, 0.28]	[−0.01, 0.39]	[−0.17, 0.13]	[−0.04, 0.32]
DEU	−0.06	−0.02	0.04		−0.02	0.03	−0.13	**0.10**	**0.19**	−0.09	**0.22**
	[−0.20, 0.08]	[−0.19, 0.13]	[−0.10, 0.19]		[−0.05, 0.10]	[−0.07, 0.13]	[−0.32, 0.06]	[0.01, 0.21]	[0.002, 0.40]	[−0.27, 0.07]	[0.04, 0.44]
ITA	−0.07	0	**0.15**	0.05		0	**−0.41**	0	**0.27**	**0.17**	0.07
	[−0.22, 0.01]		[0.01, 0.34]	[−0.05, 0.19]			[−0.71, −0.29]		[0.08, 0.51]	[0.02, 0.41]	[−0.05, 0.23]
JPN	0	0.04	**0.04**	0	0		0	0.04	0	−0.003	0
		[−0.01, 0.11]	[0.01, 0.12]					[−0.002, 0.10]		[−0.04, 0.04]	
NLD	0	0	0.01	0	0	0.04		**0.09**	**0.21**	−0.07	**0.22**
			[−0.07, 0.09]			[−0.03, 0.12]		[0.01, 0.19]	[0.04, 0.41]	[−0.24, 0.07]	[0.08, 0.40]
SWE	**−0.13**	0.07	0	0	0.07	0	−0.13		0.01	0	**0.30**
	[−0.31, −0.003]	[−0.04, 0.23]			[−0.03, 0.19]		[−0.37, 0.01]		[−0.11, 0.12]		[0.13, 0.55]
CHE	0	0	0	0	0	0	0	**0.10**		0	**0.08**
								[0.06, 0.17]			[0.01, 0.18]

Table V (continued)

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
i	$\hat{\beta}^*_{i,\mathrm{AUS}}$	$\hat{\beta}^*_{i,\mathrm{CAN}}$	$\hat{\beta}^*_{i,\mathrm{FRA}}$	$\hat{\beta}^*_{i,\mathrm{DEU}}$	$\hat{\beta}^*_{i,\mathrm{ITA}}$	$\hat{\beta}^*_{i,\mathrm{JPN}}$	$\hat{\beta}^*_{i,\mathrm{NLD}}$	$\hat{\beta}^*_{i,\mathrm{SWE}}$	$\hat{\beta}^*_{i,\mathrm{CHE}}$	$\hat{\beta}^*_{i,\mathrm{GBR}}$	$\hat{\beta}^*_{i,\mathrm{USA}}$
GBR	0	0	0	0	0	0.002 $[-0.02, 0.03]$	$-$**0.11** $[-0.25, -0.06]$	**0.04** $[0.02, 0.12]$	0		**0.19** $[0.09, 0.38]$
USA	0	0	0	-0.03 $[-0.11, 0.01]$	0.02 $[-0.01, 0.06]$	0	0	**0.08** $[0.04, 0.16]$	0	0	
Average	-0.01	-0.001	0.02	-0.01	0.01	0.01	-0.09	0.08	0.08	-1×10^{-8}	0.14

Table VI

News-diffusion model parameter estimates, 1980:02–2010:12

The table reports two-step GMM parameters estimates for the news-diffusion model,

$$\begin{aligned} r_{\text{USA},t+1} &= x'_{\text{USA},t}\beta_{\text{USA}} + u_{\text{USA},t+1}, \\ r_{i,t+1} &= x'_{i,t}\beta_i + \theta_{i,\text{USA}}\lambda_{i,\text{USA}}u_{\text{USA},t+1} + (1-\theta_{i,\text{USA}})\lambda_{i,\text{USA}}u_{\text{USA},t} + u_{i,t+1}, \end{aligned}$$

where $r_{i,t+1}$ is the monthly national currency excess return, $x_{i,t} = (1, bill_{i,t}, dy_{i,t})'$, $\beta_i = (\beta_{i,0}, \beta_{i,b}, \beta_{i,d})'$, and $bill_{i,t}$ ($dy_{i,t}$) is the three-month Treasury bill rate (log dividend yield) for country i. GMM estimation is based on 73 moment conditions representing a set of orthogonality conditions implied by the news-diffusion model. Heteroskedasticity-robust t-statistics are reported in parentheses. The t-statistics for $\tilde{\beta}_{i,b}$ ($\tilde{\beta}_{i,d}$) are for testing H_0: $\beta_{i,b} = 0$ against H_A: $\beta_{i,b} < 0$ (H_0: $\beta_{i,d} = 0$ against H_A: $\beta_{i,d} > 0$). The t-statistics for $\tilde{\theta}_{i,\text{USA}}$ ($\tilde{\lambda}_{i,\text{USA}}$) are for testing H_0: $\theta_{i,\text{USA}} = 1$ against H_A: $\theta_{i,\text{USA}} < 1$ (H_0: $\lambda_{i,\text{USA}} = 0$ against H_A: $\lambda_{i,\text{USA}} > 0$). The $\tilde{\beta}_{i,\text{USA}}$ estimates are computed as $\tilde{\beta}_{i,\text{USA}} = (1-\tilde{\theta}_{i,\text{USA}})\tilde{\lambda}_{i,\text{USA}}$. The t-statistics for $\tilde{\beta}_{i,\text{USA}}$ are for testing H_0: $\beta_{i,\text{USA}} = 0$ against H_A: $\beta_{i,\text{USA}} > 0$. Bold indicates significance at the 10% level. "Pooled" estimates impose the following homogeneity restrictions: $\beta_{i,b} = \bar{\beta}_b$, $\beta_{i,d} = \bar{\beta}_d$ for all i; $\theta_{i,\text{USA}} = \bar{\theta}_{\text{USA}}$, $\lambda_{i,\text{USA}} = \bar{\lambda}_{\text{USA}}$ for all $i \neq \text{USA}$.

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
i	$\tilde{\beta}_{i,b}$	$\tilde{\beta}_{i,d}$	$\tilde{\theta}_{i,\text{USA}}$	$\tilde{\lambda}_{i,\text{USA}}$	$\tilde{\beta}_{i,\text{USA}}$		$\tilde{\beta}_{i,b}$	$\tilde{\beta}_{i,d}$	$\tilde{\theta}_{i,\text{USA}}$	$\tilde{\lambda}_{i,\text{USA}}$	$\tilde{\beta}_{i,\text{USA}}$
AUS	0.01	−0.70	**0.88**	**0.70**	**0.09**	NLD	**−0.20**	**2.35**	**0.82**	**1.02**	**0.18**
	(0.17)	(−0.51)	(−1.95)	(9.45)	(1.74)		(−1.90)	(2.50)	(−3.77)	(14.98)	(3.26)
CAN	**−0.22**	**1.71**	**0.88**	**0.91**	**0.11**	SWE	−0.04	**2.43**	**0.76**	**1.08**	**0.26**
	(−2.61)	(1.55)	(−3.23)	(16.60)	(2.82)		(−0.54)	(2.64)	(−3.90)	(10.80)	(3.20)
FRA	−0.08	**1.19**	**0.86**	**0.96**	**0.13**	CHE	**−0.13**	**1.35**	**0.82**	**0.90**	**0.16**
	(−1.04)	(1.30)	(−2.96)	(13.94)	(2.61)		(−1.54)	(1.64)	(−3.82)	(14.24)	(3.27)
DEU	**−0.31**	**2.26**	**0.84**	**0.96**	**0.16**	GBR	**−0.16**	**3.78**	**0.91**	**0.80**	**0.07**
	(−2.03)	(1.86)	(−2.84)	(11.15)	(2.50)		(−2.17)	(3.63)	(−1.83)	(13.50)	(1.66)
ITA	0.04	0.56	**0.85**	**0.83**	**0.12**	USA	**−0.20**	**1.43**			
	(0.49)	(0.50)	(−1.97)	(7.43)	(1.67)		(−2.02)	(2.02)			
JPN	0.07	**0.98**	**0.85**	**0.65**	**0.10**	Pooled	**−0.08**	**0.37**	**0.86**	**0.90**	**0.12**
	(0.55)	(1.86)	(−1.78)	(7.65)	(1.53)		(−2.02)	(1.31)	(−6.65)	(27.52)	(5.83)

Table VII

Out-of-sample predictive ability of lagged U.S. returns, 1985:01–2010:12

The table reports the Campbell and Thompson (2008) out-of-sample R^2 statistic, R^2_{OS} (in percent), which measures the reduction in mean squared forecast error for the constant expected excess excess return model relative to a competing model that utilizes lagged U.S. returns. The constant expected return (competing) model is given by $r_{i,t+1} = \beta_{i,0} + \varepsilon_{i,t+1}$ ($r_{i,t+1} = \beta_{i,0} + \beta_{i,\mathrm{USA}} r_{\mathrm{USA},t} + \varepsilon_{i,t+1}$), where $r_{i,t+1}$ is the monthly national currency excess return for country i. The third and sixth columns report results when the pooling restrictions, $\beta_{i,\mathrm{USA}} = \bar{\beta}_{\mathrm{USA}}$ for all $i \neq$ USA, are imposed on the competing model. The simulated out-of-sample forecasts are based on models estimated recursively using OLS and data available through the month of forecast formation. Parentheses below the R^2_{OS} statistic report the Clark and West (2007) *MSFE-adjusted* statistic for testing H_0: $R^2_{OS} = 0$ against H_A: $R^2_{OS} > 0$. Bold indicates significance at the 10% level. "Average" is the average of the R^2_{OS} statistics across the ten countries.

(1)	(2)	(3)	(4)	(5)	(6)
i	R^2_{OS}	R^2_{OS}, pooled	i	R^2_{OS}	R^2_{OS}, pooled
Australia	−**0.69**%	**0.50**%	Netherlands	**3.81**%	**3.88**%
	(1.49)	(1.60)		(2.62)	(2.58)
Canada	**1.30**%	**1.86**%	Sweden	**2.90**%	**2.76**%
	(2.36)	(2.18)		(2.25)	(2.31)
France	**1.52**%	**1.90**%	Switzerland	**2.64**%	**2.95**%
	(1.90)	(2.12)		(2.45)	(2.40)
Germany	**1.57**%	**1.98**%	United Kingdom	0.28	**0.43**%
	(1.78)	(1.91)		(0.97)	(1.34)
Italy	**0.92**%	**1.54**%	Average	1.51%	1.91%
	(1.54)	(2.05)			
Japan	**2.82**%	**1.30**%			
	(1.33)	(1.65)			

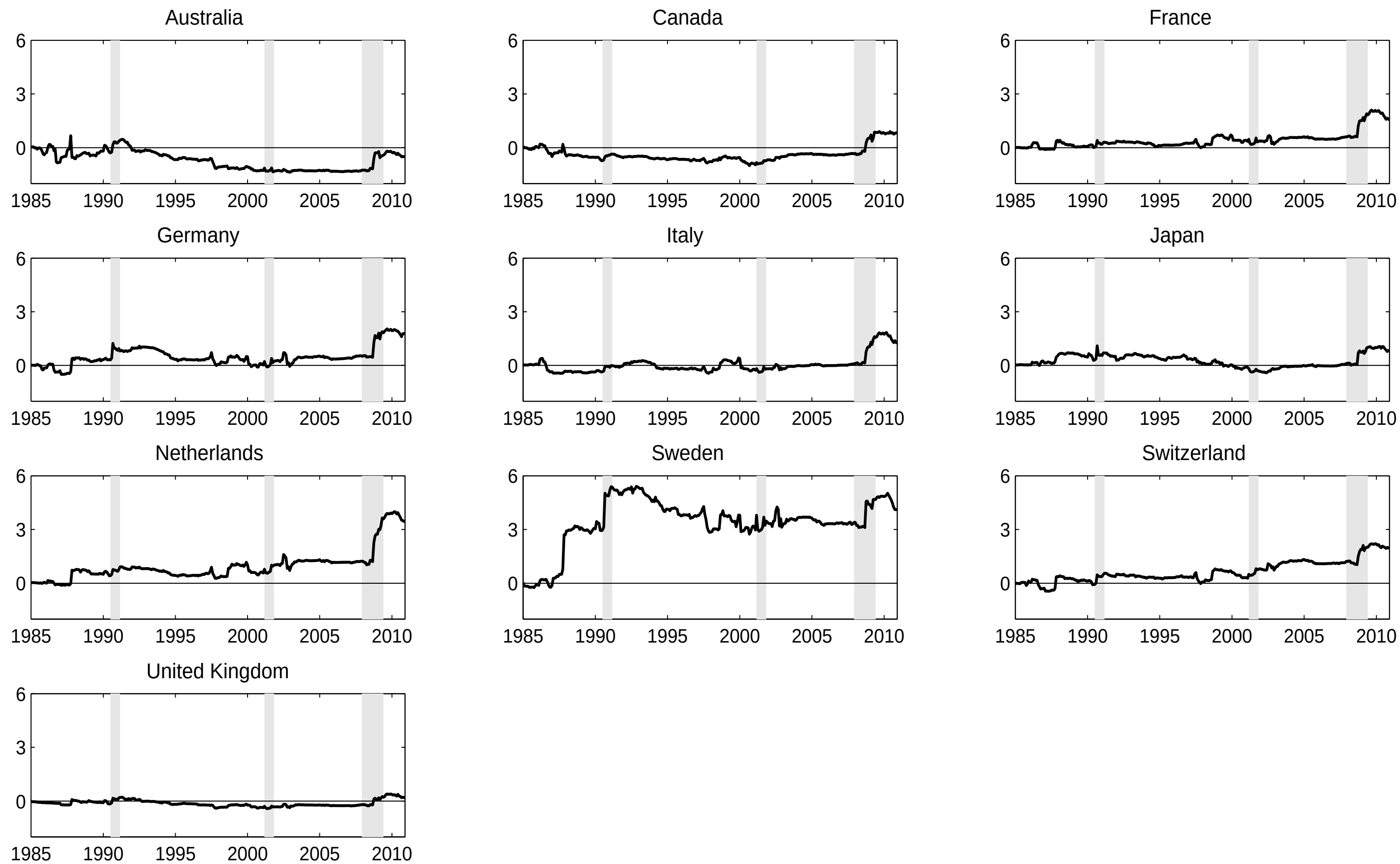

Figure 1. Out-of-sample results, forecasts based on lagged U.S. returns vs. historical average forecasts, 1985:01–2010:12. The figure depicts differences in cumulative squared forecast errors for monthly excess return forecasts based on the constant expected excess return model and a competing model that utilizes lagged U.S. excess returns. The simulated out-of-sample forecasts are based on models estimated recursively using OLS and data available through the month of forecast formation. The constant expected excess return baseline model (corresponding to the historical average forecast) is given by $r_{i,t+1} = \beta_{i,0} + \varepsilon_{i,t+1}$, where $r_{i,t+1}$ is the monthly national currency excess return for country i; the competing model includes $r_{USA,t}$ as an additional regressor. Vertical bars depict NBER-dated U.S. business-cycle recessions.