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Abstract

In this paper we look into the lead-lag relationships between different stock markets. For this we investigate the effect that the lagged excess returns of one country has on the excess returns of another country using different model specifications. First we follow Rapach et al. (2013) and we find similar results, namely that Sweden shows a leading role in-sample, whereas the U.S. shows a leading role both in-sample and out-of-sample. Furthermore, we extend this research by looking more in-depth into Europe. For this we add seven European countries into the analysis. We find that the lagged excess returns of the U.S. have a predictive ability in the Pairwise Granger causality tests, where we only include the lagged excess returns of the country itself. However, U.S.' lagged excess returns have no predictive ability in the general model specification, where we include the lagged excess returns of all countries. So it seems that the U.S. lost its leading role. Besides that, we find that Finland shows a leading role both in-sample in all the specifications and out-of-sample. However, we find that the U.S. has better out-of-sample predictive performance than Finland. This, in combination with the result that the U.S. does show a predictive ability in the Pairwise Granger tests, indicates that the U.S. still has a leading role in the international stock market.

1 Introduction

Nowadays, a lot of financial assets exist, and to predict the returns of these assets has been of interest for a lot of years for both researchers and financial practitioners. Evidence have been found that asset returns are predictable to some extent. For example, Fama and Schwert (1977) find that the inflation rate has a negative effect on stock returns, whereas Campbell (1987) shows that the excess returns on stocks and on (corporate and government) bonds can be predicted using variables that describe the term structure of interest rates. Breen et al. (1989) conclude that predictions of the excess stock return based on nominal interest rates are economically significant, indicating that a profit can be made using a trading strategy based on their forecasts. Finally, Ang and Bekaert (2007) find the results that dividend yields significantly predict excess stock returns, especially in combination with the short term interest rate and at a short horizon.

So a lot of research has been conducted about stock return predictability, giving rise to many significant predictors of excess stock returns. However, little research exists about the potential predictive power of the excess stock returns of one country on that of other countries. Rapach et al. (2013) find significant predictive power of United States' excess returns on that of other countries, both in-sample and out-of-sample. They conclude that lead-lag relationships exist between the excess returns of the U.S. and that of other countries, which might be due to the gradual information spill from the U.S. to those countries.

In this research we further investigate these lead-lag relationships between the excess returns of different countries. We look more in-depth into the European area. For this we incorporate more European countries into our research and see if we can find more countries that have a leading role on the excess returns of other countries. In Rapach et al. (2013) they already find that some European countries seem to exhibit this leading role, since these countries have significant effects on other countries' excess returns in-sample. However, they do not investigate whether these results also hold out-of-sample.

By doing this, we investigate whether lead-lag relationships between the excess returns of different countries exist and whether we can use this to predict the excess returns on stocks. So in this way the research adds to the scarce literature on the stock predictability using the excess returns of other countries. This research can then be used by other researchers, because it indicates whether information gradually spills to other countries and if this can be used to explain and forecast the movement in excess stock returns. Furthermore, this research is also interesting from a practical perspective. Financial practitioners, such as investors and hedge fund managers, can use the results of this research to make profitable trading strategies or to hedge themselves against certain risks.

When following the research of Rapach et al. (2013) we find similar results, namely that Sweden shows a predictive ability in-sample and the U.S. shows a predictive ability both in-sample and out-of-sample. However, when we extend this research by including additional European countries, we find that the lagged excess returns of the U.S. have no predictive ability in all the models. This might indicate that the U.S. lost its leading role. Finland is the only country that exhibits a leading role in-sample across all the models. However, the news-diffusion model indicates that this is not the result of information frictions that might be present between the stock markets. Furthermore, we find that the lagged excess returns of Finland have a predictive ability out-of-sample. Nevertheless, the lagged excess returns of the U.S. show a predictive ability out-of-sample in more cases than the lagged excess returns of Finland. We also find that the lagged excess returns of the U.S. have a predictive ability when we only control for the effect of the lagged excess returns of the country itself. So these results indicate that the U.S. still exhibits a leading role.

We structure the rest of the paper as follows. In section 2 we discuss the data that we use in the research. In section 3 we describe the methods that we use throughout the research. We represent the results of this research in section 4. Finally, we conclude the paper in section 5.

2 Data

The data that we use in this research consist of the (excess) stock return, nominal interest rate and dividend yield. For the stock return we use a broad stock market index that is available for that country and that describes the whole stock market. In this research we use the excess stock return, which is the stock return in excess to the risk-free interest rate, where the return is taken over the end of period t until the end of the next period $t+1$. We do this by taking the closing price of the stock index on the last day of month $t+1$ and on the last day of month t. Subsequently, we calculate the simple return using these two prices and we use this as the monthly stock return. For the risk-free rate we take the same variable as for the nominal interest rate (discussed hereafter).

The excess returns are measured in the national currency, so that we don't have to account for exchange rate risk premiums. Furthermore, they are adjusted for differences in closing times between the national stock markets, so that the lagged monthly returns don't include information of the next month when investigating the predictive ability of lagged returns on that of another country. If, for example, we have Australia and the U.S., where the stock markets close at 1:00am and 4:00pm Eastern Standard Time respectively, then the stock market of Australia closes before that of the U.S.. Then the information that comes available after the closing of the Australian stock market is still being incorporated in the American stock market index. On the other hand, the Australian stock index can only react to this information the next day. So if we want to investigate the predictive ability of the lagged excess returns of the U.S. on the excess returns of Australia, we would incorporate (some) information into the lagged excess returns of the U.S. that is only available for Australia in the next month. We solve this issue by using the closing prices of the stock index on the second last day for both month t and $t+1$ instead of the closing prices on the last days when calculating the returns. We do this for every case where the stock market of the predictor country closes after that of the country whose excess returns we want to predict.

For the nominal interest rate we use the three-month Treasury bill rate. For the dividend yield we take a smoothed dividend series, where we take the average dividend over the last twelve months (months $t-11$ up to and including t). As Ang and Bekaert (2007) reason, the monthly dividend yields have a strong seasonal component. By taking a smoothed dividend series we adjust for the seasonal component. For the dividend yield series we mostly use the logarithm of this series.

The countries that we include into the analysis are the following eleven countries: Australia, Canada, France, Germany, Italy, Japan, the Netherlands, Sweden, Switzerland, the United Kingdom, and the United States (U.S.). The sample period is 1980:02 to 2010:12. The data originate from Global Financial Data, but it is also available from the author's website[1]. In table 13 in the appendix we show the summary statistics of the country's excess stock returns. Comparing these results with the results in table 1 of Rapach et al. (2013), we see that our summary statistics are exactly the same as the summary statistics that they report.

For the extension we look more in-depth into Europe. For this we add Austria, Belgium, Denmark, Finland, Ireland, Norway and Spain into our analysis and we exclude the non-European countries except the U.S.. We still use a broad stock index of a country to compute the stock returns. For the data of the stock indices we use the data of the Wall Street Journal[2], with the exceptions being the stock indices of Austria[3] and Sweden. For these we use the data of Yahoo finance[4], because this data is not included in the Wall Street Journal data. For the nominal interest rate[5] we use the short term interest rates of the OECD database[6]. The dividend yield is not available to us and instead we use the inflation rate as the second economic variable. As discussed in the introduction, Fama and Schwert (1977) find that the inflation rate has a negative effect on stock returns, so it can be useful to use this as a controlling variable. For the inflation rate we use the annual growth rate of the Consumer

[1] http://sites.slu.edu/rapachde/home/research

[2] http://markets.wsj.com/

[3] The data of Austria's stock index contained some null values. These were deleted from the dataset. This shouldn't have a large consequence, since we calculate the stock returns with the prices at the end of two consecutive months. We can still do this, but the last day we use might differ a bit from the actual last trading day of a month.

[4] https://finance.yahoo.com/

[5] The value of 2001:11 of Sweden is missing. This value is replaced by the average of 2001:10 and 2001:12.

[6] https://data.oecd.org/

Price Index (CPI), which is available at the OECD database. For the analysis we use the sample period 1998:02 to 2016:12. In tables 14 through 17 in the appendix we show information about the country codes and the stock indices we use, and we indicate when to exclude the last trading day when computing the stock returns, for the replication and extension respectively. The information in tables 14 and 15 originate from the Internet appendix of Rapach et al. (2013).

In table 18 in the appendix we show the summary statistics of the excess stock returns for the extension. These differ a lot from the values reported in table 13, but that can be the consequence of different data and a different sample period. We see that Denmark, Finland and Italy have the highest mean excess returns, with values above the 0.5. The standard deviations are mostly between 4 and 7, but the standard deviation for Italy is 12.11, which is relatively much higher than that of the rest. The minimums are all quite close to each other, with values ranging from -0.15 to -0.30 for most countries. However, that of Sweden is much lower, namely -75.05. Italy has by far the highest maximum of 154.95%, with 30.5% the second highest value. The excess returns of all countries show a small and positive autocorrelation of below 0.20, aside from those of Austria, Belgium and Denmark. The Sharp Ratio's are all between the 0 and 0.10, with the exception being the United-Kingdom, which has a negative Sharpe Ratio because of a negative mean excess return.

3 Methodology

Here we discuss the econometric methods that we use in the research, both for the replication and for the extension.

3.1 Benchmark Predictive Regression Model

First of all we run benchmark predictive regressions, where we use the nominal interest rate and the dividend yield to predict the excess stock return. This is given by

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

where $r_{i,t+1}$ is the excess return of the stock index of country i at time $t+1$, $bill_{i,t}$ is the three-month Treasury bill rate and $dy_{i,t}$ is the log dividend yield for country i at time t, and $\epsilon_{i,t+1}$ is the error term. We run this regression for all eleven countries using ordinary least squares (OLS) and we use White heteroskedasticity consistent standard-errors for the t-tests. We test whether these two variables exhibit significant predictability on the excess returns, both individually and jointly. For this we perform t-tests for the null-hypothesis H_0: $\beta_{i,b} = 0$ against the alternative hypothesis H_A: $\beta_{i,b} < 0$ and for the null-hypothesis H_0: $\beta_{i,d} = 0$ against the alternative hypothesis H_A: $\beta_{i,d} > 0$. For the joint test we perform an F-test for the null-hypothesis H_0: $\beta_{i,b} = \beta_{i,d} = 0$. For this test we report the $\chi^2(2)$-statistic, since the F-statistic is asymptotically $\chi^2(\nu)/\nu$ distributed, where ν is the degrees of freedom. In this case $\nu = 2$, so we compare the χ^2-statistic with the critical value of the $\chi^2(2)$-distribution. We construct the p-values using a wild-bootstrap procedure based on the procedures of Gonçalves and Kilian (2004) and Cavaliere et al. (2010). This is done to account for the Stambaugh (1999) bias, which leads to higher t-statistics in absolute value. This approach is followed throughout the whole research. We also use a pooled estimate where we force the slope coefficients to be the same across the regressions, so that $\beta_{i,b} = \bar{\beta}_b$ and $\beta_{i,d} = \bar{\beta}_d$. The standard errors that we use to perform the t-tests on these coefficients are based on a generalized method of moments (GMM) procedure.

Besides that, we also run these regressions but using the U.S.' interest rate and dividend yield as regressors, to see whether the U.S.' variants of these variables also have significant predictability on the excess returns of non-U.S. countries. This is given by

$$r_{i,t+1} = \beta_{i,0} + \beta_{i,b} bill_{USA,t} + \beta_{i,d} dy_{USA,t} + \epsilon_{i,t+1} \tag{2}$$

where the same notation is used as in equation 1. With these regressions we can see whether it might be more informative to use the U.S.' economic variables instead of the economic variables of the country itself. If so, this might be an indication that information in the form of these economic variables spills over to other countries and that it might be a good idea to use the lagged excess returns of the U.S. to predict the excess returns of other countries.

3.2 Pairwise Granger Causality Tests

Next we perform pairwise Granger causality tests, where we run the augmented prediction regressions. These regressions are given by

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

where $r_{i,t}$ is the lagged excess return of the country itself and $r_{j,t}$ is the lagged excess return of another country. The same notation is applied as in equation 1 and we run these regressions using OLS. With these regressions we analyze whether the lagged excess returns of one country can significantly predict those of another country. This means that we investigate the presence of Granger causality between the excess returns of country j and those of country i. We add the country's own lagged returns to avoid spurious evidence of Granger causation, because the excess returns might be correlated, and we add the economic variables to control for the predictive power that these variables have. We test the predictive ability of the lagged excess returns using a t-test. This test is given by $H_0 : \beta_{i,j} = 0$ against $H_A : \beta_{i,j} > 0$ and we use White standard errors to perform this test. We use this one sided test, because a $\beta_{i,j} > 0$ can be interpreted as a reaction of the excess returns of country j on information contained in the lagged excess returns of country i. We also use pooled estimates where we impose a slope homogeneity restriction on $\beta_{i,j}$, given by $\beta_{i,j} = \bar{\beta}_j$, as well as on the other slope parameters, given by $\beta_{i,i} = \bar{\beta}_{AR}$, $\beta_{i,b} = \bar{\beta}_b$ and $\beta_{i,d} = \bar{\beta}_d$.

We also run these regressions where we control for the effect of multiple economic variables. For this we use the Treasury bill rate and the dividend yield, but we also use the industrial production growth, inflation rate, real oil price growth, real exchange rate growth and the term spread. If we add all these variables into the regressions we would have seven extra regressors and seven extra parameters. To avoid adding too much regressors to our model, we try to achieve dimension reduction by using principal component analysis (PCA). We perform PCA using the seven economic variables described above and we try to extract the common factors of these variables. For this we take the first two principal components and we use these two factors as economic variables in our model. This model is given by

$$r_{i,t+1} = \beta_{i,0} + \beta_{i,i} r_{i,t} + \beta_{i,j} r_{j,t} + \beta_{i,f1} \hat{f}_{1,it} + \beta_{i,f2} \hat{f}_{2,it} + \epsilon_{i,t+1}, \quad i \neq j \tag{4}$$

3.3 General Model Specification

Furthermore, we use a more general framework for testing the predictive power of lagged excess returns on the excess returns of other countries. This framework is given by

$$r_{i,t+1} = \beta_{i,0} + \beta_{i,i} r_{i,t} + \sum_{j \neq i} \beta_{i,j} r_{j,t} + \beta_{i,b} bill_{i,t} + \beta_{i,d} dy_{i,t} + \epsilon_{i,t+1} \tag{5}$$

where the same notation is used as in equation 3. The only difference is that here we include the lagged excess returns of all eleven countries, so that we also control for the effect that the lagged excess returns of other countries have when investigating for the presence of Granger causality. However, we now include a large amount of regressors that are most likely correlated with each other, which results in inaccurate OLS parameter estimates that can't be used for statistical inferences. This is reasoned by Rapach et al. (2013) and they consider two approaches to deal with this problem. First of all, they consider pooled estimates where they impose slope homogeneity restrictions on all slope parameters in equation 5. These restrictions are given by $\beta_{i,i} = \bar{\beta}_{AR}$, $\beta_{i,j} = \bar{\beta}_j \; j \neq i$, $\beta_{i,b} = \bar{\beta}_b$ and $\beta_{i,d} = \bar{\beta}_d$. The model is now given by

$$r_{i,t+1} = \beta_{i,0} + \bar{\beta}_{AR} r_{i,t} + \sum_{j \neq i} \bar{\beta}_j r_{j,t} + \bar{\beta}_b bill_{i,t} + \bar{\beta}_d dy_{i,t} + \epsilon_{i,t+1} \tag{6}$$

We perform these regressions using OLS. Using the pooled estimates may result in a bias in the parameter estimates, but it often comes with an increase in efficiency. So we are dealing with a bias-efficiency trade-off in this case. By using this we also try to improve our estimation accuracy so that we avoid getting inaccurate parameter estimates, because of the many correlated regressors that we add into our regression. We also construct 90% confidence intervals that are based on a wild-bootstrap procedure. This approach is used throughout the rest of the research when constructing the confidence intervals.

The second approach is the adaptive elastic net estimation procedure (Zou and Zhang (2009)), which is a weighted adaption of the elastic net. The elastic net combines two shrinkage methods, namely ridge regression and least absolute shrinkage and selection operator (LASSO). Both these methods are subject to drawbacks. Ridge regression prevents the parameters to be shrunk to zero, so that is does not apply variable selection. On the other hand, in situations with multiple correlated regressors, LASSO chooses one predictor randomly. So it does not provide us with useful information in our setting, where we indeed have multiple correlated regressors. So by combining these two methods, the elastic net utilizes the strength of both methods.

For the adaptive elastic net we estimate the parameters in equation 5 by minimizing the sum of squared residuals, but subject to two different penalty terms. This minimization is given by

$$\min_{\beta_i} \left[\sum_{t=0}^{T-1} (r_{i,t+1} - x_t'\beta_i)^2 + \lambda_1 \sum_{k=1}^{K} \omega_k |\beta_{i,k}| + \lambda_2 \sum_{k=1}^{K} \beta_{i,k}^2 \right] \tag{7}$$

where $x_t' = (1, r_{i,t}, r_{i,t}, ..., r_{i-1,t}, r_{i+1,t}, ..., r_{11,t}, bill_{i,t}, dy_{i,t})$, $r_{i,t+1}$ is the excess return of country i, λ_1 is the parameter associated with the penalty term of LASSO, ω_k are the weights that we assign to the LASSO penalty term and λ_2 is the parameter associated with the penalty term of ridge regression. By using the adaptive elastic net we perform both variable selection and parameter shrinkage. In this way we try to deal with the inaccurate parameter estimates as a consequence of the correlated regressors. For the weights we use $\omega_k = |\hat{\beta}_{i,k}|^{-\gamma}$ for $\gamma > 0$. We use five-fold cross validation to obtain the values for the parameters λ_1, λ_2 and γ.

We also apply the general model specification with pooled estimates, but then we only control for the lagged excess returns of one other country. This is given by

$$r_{i,t+1} = \beta_{i,0} + \bar{\beta}_{AR} r_{i,t} + \bar{\beta}_{USA} r_{USA,t} + \bar{\beta}_j r_{j,t} + \bar{\beta}_b bill_{i,t} + \bar{\beta}_d dy_{i,t} + \epsilon_{i,t+1} \tag{8}$$

where the same notation is used as before. We use these regressions to see whether lagged U.S. returns have a significant predictive ability on the excess returns of other countries, when we control for the effect of the lagged excess returns of one non-U.S. country. This in contrary to equation 6 where we control for the effect of the lagged excess returns of all other countries.

3.4 News-Diffusion Model

Besides that, we use a news-diffusion model to study the information frictions across the different stock markets. The news-diffusion model we use is given by

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

$$r_{j,t+1} = \mu_{j,t} + u_{j,t+1} + \theta_{j,i}\lambda_{j,i}u_{i,t+1} + (1-\theta_{j,i})\lambda_{j,i}u_{i,t} \tag{10}$$

where $r_{i,t+1}$ is the excess return of country i at time $t+1$ and $u_{i,t+1}$ is a return shock occurring in country i at time $t+1$. These return shocks are uncorrelated between countries and they also don't possess autocorrelation. For $\mu_{i,t+1}$ and $\mu_{j,t+1}$ we use the estimated excess return based on the benchmark predictive regression model (equation 1). This is given by

$$\mu_{i,t} = \beta_{i,0} + \beta_{i,b} bill_{i,t} + \beta_{i,d} dy_{i,t} \tag{11}$$

$$\mu_{j,t} = \beta_{j,0} + \beta_{j,b} bill_{j,t} + \beta_{j,d} dy_{j,t} \tag{12}$$

where we use the same notation as before. The parameter $\lambda_{i,j}$ indicates the total effect of the return shock of country j on the excess return of country i. The parameter $\theta_{i,j}$ indicates what portion of this total effect is incorporated in the current excess return (thus the return at time $t+1$). This model also permits the shock to be reflected in the excess return of the other country with a lag. In this way we can investigate the presence of information frictions.

Next we write equation 10 in terms of $u_{j,t+1}$ and substitute this in equation 9. This gives

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

The last term consists of different shocks and is given by

$$e_{i,t+1} = u_{i,t+1} + \theta_{i,j}\lambda_{i,j}u_{j,t+1} - (1-\theta_{i,j})\lambda_{i,j}[\theta_{j,i}\lambda_{j,i}u_{i,t} + (1-\theta_{j,i})\lambda_{j,i}u_{i,t-1}] \tag{14}$$

With equations 13 and 14 we can see under which conditions the lagged excess returns of country j have a significant predictive ability on the excess returns of country i. The first condition is that $\lambda_{i,j} \neq 0$, which indicates that the excess returns of country i are affected by the excess returns of country j. If this is not the case, then the lagged excess returns of country j have no predictive ability on the excess returns of country i. The second condition is given by $\theta_{i,j} \neq 1$, which indicates that it takes time before a return shock of country j is reflected in the excess returns of country i. So given that the first condition is met, this condition indicates that the lagged excess returns of country j have predictive ability on the excess returns of country i.

Next we assume that lagged returns of non-U.S. countries don't have a predictive ability on the returns of the U.S., which corresponds with $\theta_{USA,i} = 1$. Using this we can rewrite equation 13 as

$$r_{i,t+1} = \mu_{i,t} - (1-\theta_{i,USA})\lambda_{i,USA}\mu_{USA,t-1} + (1-\theta_{i,USA})\lambda_{i,USA}r_{USA,t} + e_{i,t+1}. \tag{15}$$

Here the last term consists again of different shock terms and it is given by

$$e_{i,t+1} = u_{i,t+1} + \theta_{i,USA}\lambda_{i,USA}u_{USA,t+1} - (1-\theta_{i,USA})\lambda_{i,USA}\lambda_{USA,i}u_{i,t} \tag{16}$$

Here we focus on the information frictions between the U.S. and non-U.S. countries, so in equations 15 and 16 we replace index j with USA. Since the economy of the U.S. is relatively much larger than that of the other countries, we assume that return shocks of non-U.S. countries have no effect on the excess returns of the U.S., which corresponds with $\lambda_{USA,i} = 0$. Using this we can rewrite the news-diffusion model as

$$r_{USA,t+1} = x'_{USA,t}\beta_{USA} + u_{USA,t+1} \tag{17}$$

$$r_{i,t+1} = x'_{i,t}\beta_i + \theta_{i,USA}\lambda_{i,USA}u_{USA,t+1} + (1-\theta_{i,USA})\lambda_{i,USA}u_{USA,t} + u_{i,t+1} \tag{18}$$

where $x_{i,t} = (1, bill_{i,t}, dy_{i,t})'$, $\beta_i = (\beta_{i,0}, \beta_{i,b}, \beta_{i,d})'$ and i includes all the countries except the U.S., so $i = AUS, ..., GBR$. Next we put all the parameters in the parameter vector ϕ given by

$$\phi = (\beta'_{USA}, \beta'_{AUS}, \theta_{AUS,USA}, \lambda_{AUS,USA}, ..., \beta'_{GBR}, \theta_{GBR,USA}, \lambda_{GBR,USA})' \tag{19}$$

We use GMM to estimate the 53 parameters in this vector. For this we define a total of 73 moment conditions, which are given by

$$E[x_{USA,t}u_{USA,t+1(\phi)}] = 0 \tag{20}$$

$$E[(bill_{i,t}, dy_{i,t})'u_{USA,t+1}(\phi)] = 0 \quad i = AUS, ..., GBR \tag{21}$$

$$E[(x'_{i,t}, u_{USA,t+1}(\phi), u_{USA,t}(\phi))'u_{i,t+1}(\phi)] = 0 \quad i = AUS, ..., GBR \tag{22}$$

Furthermore, we perform t-tests on the coefficients $\lambda_{i,USA}$ and $\theta_{i,USA}$. These tests are given by $H_0 : \lambda_{i,USA} = 0$ against $H_A : \lambda_{i,USA} > 0$ and $H_0 : \theta_{i,USA} = 1$ against $H_A : \theta_{i,USA} < 1$. A positive $\lambda_{i,USA}$ indicates that return shocks of the U.S. affect the excess returns of country i, whereas a $\theta_{i,USA}$ of smaller than one indicates that the lagged excess returns of the U.S. have a predictive ability on the excess returns of country i. Besides that, we also use pooled estimates where we impose slope homogeneity restrictions on the slope parameters, given by $\beta_{i,b} = \bar{\beta}_b$ and $\beta_{i,d} = \bar{\beta}_d$ for all i, and $\theta_{i,USA} = \bar{\theta}_{USA}$ and $\lambda_{i,USA} = \bar{\lambda}_{USA}$ for all $i \neq USA$.

Finally, we also test the coefficient of $r_{USA,t}$ in equation 15, given by $\beta_{i,USA} = (1-\theta_{i,USA})\lambda_{i,USA}$. This test is given by $H_0 : \beta_{i,USA} = 0$ against $H_A : \beta_{i,USA} > 0$. The standard errors that we use for this test are based on the delta method (see appendix section 6.1). The coefficient $\beta_{i,USA}$ represents the effect of lagged U.S. returns on the returns of country i resulting from information frictions. With this test we investigate whether the information frictions lead to a significant predictive ability of U.S.' lagged returns on the returns of country i.

3.5 Out-of-sample predictive ability tests

Finally, we investigate the out-of-sample predictive ability of lagged excess returns. For this we compare the forecasts of models that include lagged excess returns as a predictor with the forecasts of different baseline models. For the comparison we use the out-of-sample R^2, which is given by

$$R^2_{OS} = 1 - \frac{\sum_{t=1}^{T}(r_{i,t} - \hat{r}_{i,t})^2}{\sum_{t=1}^{T}(r_{i,t} - \bar{r}_{i,t})^2} \tag{23}$$

where $r_{i,t}$ is the excess return of country i at time t, $\hat{r}_{i,t}$ is the one-step ahead forecast based on the forecasting model and $\bar{r}_{i,t}$ is the one-step ahead forecast based on the baseline model. The R^2_{OS} computes the relative difference in the mean squared forecast error (MSFE) between the forecasts of the forecasting model and the forecasts of the baseline model. We make the forecasts based on a recursively out-of-sample setting. For this we take the data until time t and we use this data to estimate the model parameters. Then we use these parameters to construct the one-step ahead forecast. Subsequently, we add the next data point and then we repeat the same steps. We use 1985:01 to 2010:10 as our forecasting period, so the first forecast we construct is on 1985:01. Besides that, we use 1980:02 to 1984:12 as our initial estimation sample. For our analysis we use three different baseline models. First we use a baseline model that is based on the historical average of the excess returns. This is given by

$$r_{i,t+1} = \beta_{i,0} + \epsilon_{i,t+1} \tag{24}$$

The second baseline model is based on a first-order autoregressive process. This model is given by

$$r_{i,t+1} = \beta_{i,0} + \beta_{i,i} r_{i,t} + \epsilon_{i,t+1} \tag{25}$$

The third and final baseline model is based on the benchmark predictive regression model described in section 3.1. This is given by

$$r_{i,t+1} = \beta_{i,0} + \beta_{i,b} bill_{i,t} + \beta_{i,d} dy_{i,t} + \epsilon_{i,t+1} \tag{26}$$

Our forecasting models are the same as the baseline models described above, but adding the lagged excess return of the U.S. as an extra predictor. So this is given by the models above, but then we add the term $\beta_{i,USA} r_{USA,t}$.

Besides that we also look at forecasts based on a forecasting model with pooled estimates. For this we impose the following slope homogeneity restrictions: $\beta_{i,USA} = \bar{\beta}_{USA}$, $\beta_{i,i} = \bar{\beta}_{AR}$, $\beta_{i,b} = \bar{\beta}_b$ and $\beta_{i,d} = \bar{\beta}_d$. For the baseline models we use the same models, so here we don't impose the pooling restrictions. Using this we can see whether forecasts that are based on models that use the average effects of the regressors can still produce significantly better forecasts than the baseline models. Finally, we use the Clark and West (2007) MSFE-adjusted statistic to test whether our forecasting models produce significantly better forecasts than the baseline models. This test is given by $H_0 : R^2_{OS} = 0$ against $H_A : R^2_{OS} > 0$.

3.6 Extension

For the extension we apply the same methods as described above, but now we apply them to a different dataset, which is discussed in section 2. The only difference is that we use the inflation rate instead of the dividend yield as a second economic variable in all the models. We denote the coefficient of this variable with $\beta_{i,inf}$. Furthermore, we perform the t-test of the coefficient of inflation against the alternative hypothesis $H_A : \beta_{i,inf} < 0$, since we expect that the inflation rate has a negative effect on the excess stock returns. We apply the news-diffusion model and the out-of-sample analysis with Finland as the leading country, since Finland is the only country that shows a predictive ability consistently across the results of the different models. Finally, we also apply the out-of-sample analysis with the U.S. as leading country to see whether this country shows a significant out-of-sample predictive ability, as Rapach et al. (2013) find in their research. Besides that, we compare these results with the results where Finland is the leading country, so we can see whether Finland shows a larger predictive ability than the U.S.

4 Results

In this section we report the results of our research. We first report the results of the replication part. After that, we report the results of the extension.

4.1 Benchmark Predictive Regression Model

Table 1: Results of the Benchmark Predictive Regression Model

country	$\hat{\beta}_{i,b}$	$\hat{\beta}_{i,d}$	R^2	country	$\hat{\beta}_{i,b}$	$\hat{\beta}_{i,d}$	R^2
AUS	-0.05	0.68	0.13%	NLD	-0.32*	1.82	1.72%*
	(-0.49)	(0.29)	(0.26)		(-2.54)	(1.81)	(6.48)
	[0.28]	[0.60]	[0.91]		[0.02]	[0.10]	[0.07]
CAN	-0.23*	1.44	2.58%*	SWE	-0.02	1.18	0.45%
	(-2.42)	(1.22)	(6.47)		(-0.19)	(1.24)	(1.54)
	[0.02]	[0.35]	[0.08]		[0.46]	[0.25]	[0.53]
FRA	-0.09	0.92	0.31%	CHE	-0.15	0.23	0.55%
	(-1.00)	(0.86)	(1.09)		(-1.32)	(0.25)	(2.01)
	[0.23]	[0.45]	[0.67]		[0.11]	[0.65]	[0.46]
DEU	-0.33*	1.68	1.24%	GBR	-0.16*	3.71*	2.60%*
	(-1.86)	(1.24)	(3.78)		(-1.67)	(2.90)	(8.75)
	[0.10]	[0.22]	[0.20]		[0.06]	[0.01]	[0.02]
ITA	-0.01	-0.69	0.14%	USA	-0.19	1.61	1.51%
	(-0.08)	(-0.59)	(0.37)		(-1.66)	(2.03)	(4.15)
	[0.45]	[0.88]	[0.86]		[0.12]	[0.11]	[0.23]
JPN	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)
	[0.61]	[0.51]	[0.81]		[0.14]	[0.19]	[0.32]

This table shows the parameter estimates of the benchmark predictive regressions as well as the R^2 of these regressions. The numbers in parentheses represent the heteroskedasticity-robust t-statistics in the columns for $\hat{\beta}_{i,b}$ and $\hat{\beta}_{i,d}$, and heteroskedasticity-robust χ^2-statistics in the columns for the R^2. The numbers in brackets represent the p-values based on the wild-bootstrap procedure. The pooled estimates are obtained by imposing slope homogeneity restrictions on $\hat{\beta}_{i,b}$ and $\hat{\beta}_{i,d}$. Significant coefficients at a 10% significance level are indicated with a *.

In table 1 we show the results of the benchmark predictive regression model. We see that both economic variables display very little predictive ability on the excess stock returns. Especially the dividend yield shows almost no predictive ability, having a significant effect in only one of the eleven cases. The Treasury bill rate shows a bit more predictive ability, but still it has a significant effect in only four of the eleven cases. The two variables together also show little predictive ability, where the two variables have a jointly significant effect on the excess returns for only three of the eleven countries. The only country where both variables have a significant effect, both individually and jointly, is the United-Kingdom, indicating that the excess returns of this country can be predicted with these economic variables. Furthermore, we see that the coefficient of the Treasury bill rate (dividend yield) is negative (positive) for ten of the eleven countries. We expect that the Treasury bill rate (dividend yield) has indeed a negative (positive) effect on the country's excess returns. The R^2 values are all relatively low, but since stock returns contain a large stochastic part that is not predictable, even low R^2 values of 1% can indicate a high predictive ability. Finally, the pooled estimates (which can be seen as the average effects) are also not significant, indicating that on average these variables have no predictive ability on the excess returns. Comparing these results with the results of table IA.III of Rapach et al. (2013), we see that they report a coefficient of -0.01 for $\hat{\beta}_{SWE,b}$ and we have a coefficient of -0.02. The coefficient is -0.015 so we expect this to be a rounding error (either on our side or their side). The authors report a R^2 of 1.35% for the pooled regression and we report a R^2 of 0.35%. We think that the 1 is a typo on the authors' side. Furthermore, the p-values are slightly different in some cases, but we expect this since the bootstrapped p-values are based on random draws (which aren't seeded). Although the p-values are not exactly the same, we report the same significant coefficients as the authors, indicating that these differences are not significant and are due to randomness.

In table 19 in the appendix we show the results of the benchmark predictive regression model where we use the U.S. economic variables as the predictors. Both economic variables show very little predictive ability, with the Treasury bill rate having a significant effect in only two cases and the dividend yield in only one case. The two variables together have a jointly significant effect in only two cases. Comparing these results with those of table 1, we see that the U.S.' economic variables don't have a larger predictive ability than the national economic variables, so it's not better to use the economic variables of the U.S. as the predictors. Comparing the results with table IA.V of Rapach et al. (2013), we see that they report a t-statistic of 1.15 for the joint test of France, where we report a value of 0.15. We think that this is a typo on the side of the authors. Besides that, only the p-values are slightly different. However, we report the same significant coefficients as the authors, indicating that these differences are based on randomness. So we find the same results reported in Rapach et al. (2013), namely that the national and U.S.' economic variables show little predictive ability on the excess stock returns.

4.2 Pairwise Granger Causality Tests

In table 2 we show the results of the pairwise Granger causality tests. The lagged excess returns of most countries show a significant predictive ability in less than half the cases (5 out of 10). The exceptions are Sweden, Switzerland and the U.S., which have a significant effect in 9, 7 and 9 cases respectively. So lagged excess returns of these countries show a predictive ability on the excess returns of other countries. The average value of the coefficients are 0.11, 0.15 and 0.19 for Sweden, Switzerland and the U.S. respectively, whereas the average value for the other countries is below the 0.10. So the average effects of these three countries are also higher than those of the other countries. Furthermore, we see that eight of the eleven pooled estimates are significant, indicating that the lagged excess returns have a significant effect on average on the excess returns of other countries. Besides that, we see that the lagged excess returns of only two non-U.S. countries show a significant predictive ability on the excess returns of the U.S., namely Italy and Sweden. This supports the idea that the excess returns of the U.S. exhibit a leading role. Comparing the results with table IA.8 of Rapach et al. (2013), we see that they report a coefficient and t-statistic of 0.003 and 0.08 respectively for $\hat{\beta}_{CHE,ITA}$, whereas we report values of -0.003 and -0.08. Since all the other results are comparable, we expect this to be a typo on the side of the authors. Even though the p-values are slightly different, we report the same significant results as the authors, indicating that these differences are based on randomness.

In table 20 in the appendix we show the results of the pairwise Granger causality tests, but controlling for multiple economic variables instead of only the Treasury bill rate and the dividend yield. Controlling for these extra variables doesn't have much impact on the results. The lagged excess returns of most countries still have a significant effect in less than half the cases. The only exceptions are again Sweden, Switzerland and the U.S., which show a significant effect in 9, 6 and 8 of the cases respectively. The pooled estimates are also significant for most countries (7 out of 11 cases). Comparing these results with those of table IA.XII of Rapach et al. (2013), we see that they report a R^2 of 1.63% whereas we report a value of 1.64%. The value is 1.635, so we expect this to be a rounding error. Besides that, they report R^2 values of 2.49% and 2.77% in the first two columns for Germany, while we report values of 1.39% and 1.77%. Since all the other results are the same, we think that these are typos made by the authors. Furthermore, we see that the authors report significant results for $\hat{\beta}_{i,CAN}$ for Australia, $\hat{\beta}_{i,DEU}$ for Italy and $\hat{\beta}_{i,USA}$ for Italy, while we don't have significant results there. The p-values are all close to 0.10, so these differences are probably caused by the randomness of the wild-bootstrap procedure. So, although they report significance in these cases, it's questionable if this is actually true, since different random draws in the bootstrap procedure will produce different results.

With the pairwise Granger causality tests we see that the lagged excess returns of Switzerland, Sweden and the U.S. show predictive ability on the excess returns of other countries. This is also the case when we control for the effect of multiple economic variables. Furthermore, the lagged excess returns of non-U.S. countries show no predictive ability on the excess returns of the U.S..

Table 2: Results of the Pairwise Granger Causality Tests

Country	$\hat{\beta}_{i,AUS}$	$\hat{\beta}_{i,CAN}$	$\hat{\beta}_{i,FRA}$	$\hat{\beta}_{i,DEU}$	$\hat{\beta}_{i,ITA}$	$\hat{\beta}_{i,JPN}$	$\hat{\beta}_{i,NLD}$	$\hat{\beta}_{i,SWE}$	$\hat{\beta}_{i,CHE}$	$\hat{\beta}_{i,GBR}$	$\hat{\beta}_{i,USA}$
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)
		[0.09]	[0.03]	[0.02]	[0.01]	[0.03]	[0.06]	[0.03]	[0.06]	[0.19]	[0.01]
		0.95%	1.70%	1.84%	1.48%	1.27%	1.59%	1.12%	1.08%	0.67%	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)
	[0.22]		[0.13]	[0.13]	[0.07]	[0.11]	[0.24]	[0.00]	[0.20]	[0.19]	[0.02]
	4.13%		4.37%	4.34%	4.59%	4.35%	4.20%	7.24%	4.35%	4.27%	5.58%
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)
	[0.45]	[0.55]		[0.63]	[0.81]	[0.32]	[0.50]	[0.01]	[0.08]	[0.39]	[0.11]
	2.14%	2.14%		2.17%	2.36%	2.24%	2.13%	3.92%	2.94%	2.17%	2.64%
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)	(1.43)	(0.55)	(2.49)	(2.26)	(0.77)	(2.33)
	[0.34]	[0.13]	[0.07]		[0.11]	[0.08]	[0.30]	[0.00]	[0.01]	[0.23]	[0.01]
	2.20%	2.50%	2.84%		2.47%	2.73%	2.25%	3.78%	3.99%	2.35%	3.86%
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)
	[0.52]	[0.28]	[0.06]	[0.14]		[0.26]	[0.73]	[0.17]	[0.05]	[0.09]	[0.06]
	0.77%	0.89%	1.91%	1.32%		0.91%	0.91%	1.02%	2.15%	1.50%	1.46%
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)
	[0.26]	[0.04]	[0.02]	[0.35]	[0.21]		[0.13]	[0.04]	[0.05]	[0.05]	[0.08]
	1.75%	2.51%	2.65%	1.68%	1.78%		2.02%	2.55%	2.34%	2.43%	2.28%
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)	(3.70)
	[0.09]	[0.03]	[0.01]	[0.05]	[0.17]	[0.01]		[0.00]	[0.00]	[0.15]	[0.00]
	3.46%	3.88%	3.94%	3.77%	3.03%	3.78%		4.99%	6.16%	3.21%	6.09%
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)
	[0.59]	[0.05]	[0.28]	[0.20]	[0.16]	[0.25]	[0.46]		[0.13]	[0.20]	[0.02]
	3.02%	3.91%	3.08%	3.21%	3.46%	3.15%	2.99%		3.43%	3.27%	4.54%
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)
	[0.31]	[0.34]	[0.49]	[0.58]	[0.55]	[0.32]	[0.53]	[0.00]		[0.36]	[0.06]
	3.70%	3.69%	3.63%	3.64%	3.63%	3.69%	3.63%	5.75%		3.66%	4.54%
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)
	[0.05]	[0.16]	[0.15]	[0.41]	[0.43]	[0.04]	[0.57]	[0.02]	[0.09]		[0.02]
	3.51%	3.00%	3.15%	2.66%	2.65%	3.49%	2.65%	3.72%	3.24%		4.82%
USA	0.06	0.03	0.01	-0.01	0.06*	0.00	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)	
	[0.17]	[0.39]	[0.44]	[0.60]	[0.08]	[0.52]	[0.45]	[0.01]	[0.34]	[0.43]	
	2.24%	1.97%	1.95%	1.95%	2.55%	1.93%	1.95%	3.28%	2.01%	1.95%	
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)
	[0.23]	[0.07]	[0.01]	[0.15]	[0.10]	[0.06]	[0.32]	[0.00]	[0.02]	[0.07]	[0.00]
	1.69%	1.70%	1.87%	1.69%	2.01%	1.80%	1.49%	2.59%	2.12%	1.88%	2.72%

This table shows the parameter estimates of $\beta_{i,j}$ in the regressions for the Pairwise Granger Causality Tests as well as the R^2 of these regressions. The numbers in parentheses represent the heteroskedasticity-robust t-statistics. The numbers in brackets represent the p-values based on the wild-bootstrap procedure. The fourth row for every country, the value below the p-values, denotes the R^2 values for the regressions. The row average denotes the average of the $\hat{\beta}_{i,j}$ values for a specific j, so it's the average of the $\hat{\beta}_{i,j}$ values in that column. The pooled estimates are obtained by imposing a slope homogeneity restriction on $\hat{\beta}_{i,j}$, as well as on the other slope parameters. Significant coefficients at a 10% significance level are indicated with a *.

4.3 General Model Specification

Table 3: Results of the General Model Specification with pooled estimates

Country	$\hat{\bar{\beta}}_j$	Conf. int.	Country	$\hat{\bar{\beta}}_j$	Conf. int.
AUS	-0.03	[-0.12, 0.06]	NLD	-0.12*	[-0.23, -0.01]
CAN	-0.01	[-0.12, 0.09]	SWE	0.08*	[0.03, 0.14]
FRA	0.03	[-0.06, 0.11]	CHE	0.08	[-0.05, 0.21]
DEU	-0.03	[-0.12, 0.07]	GBR	0.004	[-0.10, 0.11]
ITA	0.01	[-0.04, 0.06]	USA	0.17*	[0.05, 0.29]
JPN	0.02	[-0.04, 0.09]			

This table shows the parameter estimates of $\bar{\beta}_j$, the pooled estimate of $\beta_{i,j}$, for the general model specification. We impose slope homogeneity restrictions on all the slope parameters in the model, and for every country we report the slope parameter of the lagged excess returns of that country, given by $\hat{\bar{\beta}}_j$. The values in brackets represent the 90% confidence interval based on the wild-bootstrap procedure. Significant coefficients at a 10% significance level are indicated with a *.

In table 3 we show the results of the general model specification, where we use pooled estimates to deal with the problem of multiple correlated regressors. We see similar results as in tables 2 and 20, namely that the lagged excess returns of Sweden and the U.S. show predictive ability on the excess returns of other countries. However, we see that the lagged excess returns of Switzerland have no significant predictive ability, although in tables 2 and 20 they do have a significant predictive ability in more than half the cases. Finally, we see the remarkable result that the lagged excess returns of the Netherlands have a significant predictive ability, which is not supported by the results of tables 2 and 20. Comparing the results with table 4 in Rapach et al. (2013) we see that all the results are the same, except for the confidence intervals of $\hat{\bar{\beta}}_{DEU}$ and $\hat{\bar{\beta}}_{GBR}$. These confidence intervals are based on the wild-bootstrap procedure which uses random draws. The differences in the confidence intervals are probably caused by this randomness, since these differences are not larger than 0.01.

Table 4: Results of the General Model Specification based on the Adaptive Elastic Net estimation procedure

Country	$\hat{\beta}^*_{i,AUS}$	$\hat{\beta}^*_{i,CAN}$	$\hat{\beta}^*_{i,FRA}$	$\hat{\beta}^*_{i,DEU}$	$\hat{\beta}^*_{i,ITA}$	$\hat{\beta}^*_{i,JPN}$	$\hat{\beta}^*_{i,NLD}$	$\hat{\beta}^*_{i,SWE}$	$\hat{\beta}^*_{i,CHE}$	$\hat{\beta}^*_{i,GBR}$	$\hat{\beta}^*_{i,USA}$
AUS		0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.12*
		[0.00, 0.00]	[0.00, 0.00]	[0.00, 0.00]	[0.00, 0.00]	[0.00, 0.00]	[0.00, 0.00]	[0.00, 0.00]	[0.00, 0.00]	[0.00, 0.00]	[0.06, 0.25]
CAN	0.00		0.00	0.00	0.01	0.00	-0.07	0.14*	0.00	0.00	0.11*
	[0.00, 0.00]		[0.00, 0.00]	[0.00, 0.00]	[-0.03, 0.05]	[0.00, 0.00]	[-0.20, 0.01]	[0.08, 0.21]	[0.00, 0.00]	[0.00, 0.00]	[0.02, 0.24]
FRA	0.00	0.00		0.00	0.00	0.00	0.00	0.10*	0.05	0.00	0.01
	[0.00, 0.00]	[0.00, 0.00]		[0.00, 0.00]	[0.00, 0.00]	[0.00, 0.00]	[0.00, 0.00]	[0.07, 0.19]	[-0.01, 0.14]	[0.00, 0.00]	[-0.05, 0.04]
DEU	0.00	0.00	0.00		0.00	0.00	-0.07*	0.07*	0.09	0.00	0.12*
	[0.00, 0.00]	[0.00, 0.00]	[0.00, 0.00]		[0.00, 0.00]	[0.00, 0.00]	[-0.21, -0.03]	[0.01, 0.17]	[0.00, 0.25]	[0.00, 0.00]	[0.01, 0.28]
ITA	-0.06	0.00	0.15	0.04		0.00	-0.39*	0.00	0.26*	0.16*	0.06
	[-0.20, 0.01]	[0.00, 0.00]	[-0.01, 0.35]	[-0.06, 0.18]		[0.00, 0.00]	[-0.71, -0.27]	[0.00, 0.00]	[0.08, 0.54]	[0.02, 0.39]	[-0.06, 0.22]
JPN	0.00	0.04	0.05*	0.00	0.00		0.00	0.04*	0.00	0.00	0.00
	[0.00, 0.00]	[-0.01, 0.11]	[0.01, 0.13]	[0.00, 0.00]	[0.00, 0.00]		[0.00, 0.00]	[0.00, 0.10]	[0.00, 0.00]	[0.00, 0.00]	[0.00, 0.00]
NLD	0.00	0.00	0.01	0.00	0.00	0.04		0.09*	0.21*	-0.07	0.22*
	[0.00, 0.00]	[0.00, 0.00]	[-0.07, 0.10]	[0.00, 0.00]	[0.00, 0.00]	[-0.03, 0.12]		[0.01, 0.19]	[0.04, 0.40]	[-0.24, 0.07]	[0.07, 0.40]
SWE	-0.13*	0.07	0.00	0.00	0.07	0.00	-0.14		0.00	0.00	0.32*
	[-0.31, 0.00]	[-0.04, 0.22]	[0.00, 0.00]	[0.00, 0.00]	[-0.03, 0.20]	[0.00, 0.00]	[-0.37, 0.00]		[0.00, 0.00]	[0.00, 0.00]	[0.12, 0.57]
CHE	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.11*		0.00	0.08*
	[0.00, 0.00]	[0.00, 0.00]	[0.00, 0.00]	[0.00, 0.00]	[0.00, 0.00]	[0.00, 0.00]	[0.00, 0.00]	[0.06, 0.19]		[0.00, 0.00]	[0.00, 0.19]
GBR	0.05	-0.03	0.04	-0.05	-0.002	0.05	-0.13*	0.06*	0.05		0.19*
	[-0.03, 0.16]	[-0.15, 0.05]	[-0.04, 0.15]	[-0.16, 0.03]	[-0.05, 0.05]	[-0.02, 0.12]	[-0.29, -0.04]	[0.01, 0.14]	[-0.07, 0.18]		[0.08, 0.39]
USA	0.01	0.00	0.00	-0.06*	0.03	-0.001	0.00	0.09*	0.00	0.00	
	[-0.05, 0.09]	[0.00, 0.00]	[0.00, 0.00]	[-0.16, 0.00]	[-0.01, 0.09]	[-0.04, 0.04]	[0.00, 0.00]	[0.05, 0.17]	[0.00, 0.00]	[0.00, 0.00]	
AVG	-0.01	0.01	0.02	-0.01	0.01	0.01	-0.07	0.06	0.06	0.01	0.11

This table shows the parameter estimates of $\beta_{i,j}$ in the general model specification based on the adaptive elastic net estimation procedure. These estimates are denoted by $\hat{\beta}^*_{i,j}$. The row AVG shows the average of the estimates for a specific j. The values in brackets represent the 90% confidence interval based on the wild-bootstrap procedure. Significant coefficients at a 10% significance level are indicated with a *.

In table 4 we show the results of the general model specification, where we use the Adaptive Elastic net estimation procedure to deal with the correlated regressors. We see that most countries don't get selected in more than half the cases. The exceptions are the Netherlands, Sweden and the U.S., which are selected 6, 8 and 9 times respectively. Besides that, we see that the lagged excess returns of Sweden (the U.S.) have a significant coefficient in 8 (7) of the 10 cases, which is consistent with our earlier findings that the lagged excess returns of these two countries show a significant predictive ability. Although the lagged excess returns of the Netherlands are selected in 6 of the cases, in only 3 of the cases they have a significant coefficient, which shows that the lagged excess returns of the Netherlands have little predictive ability. Comparing these results with table V of Rapach et al. (2013), we see that a lot of results are different. This can be explained by the fact that the Adaptive Elastic Net, as well as the wild bootstrap procedure used to construct the confidence intervals, are both dependent on random draws which aren't seeded. We see for example that we don't select Italy in the regression for Australia, but in Rapach et al. (2013) they do select this country. On the other hand, we select Australia in the regression for the United-Kingdom, but Rapach et al. (2013) don't select this country. The differences in our significant results in comparison to their significant results are the following: $\hat{\beta}^*_{i,FRA}$ is not significant for Italy, $\hat{\beta}^*_{i,DEU}$ is significant for the U.S., $\hat{\beta}^*_{i,NLD}$ is significant for Germany, $\hat{\beta}^*_{i,SWE}$ is significant for Japan and $\hat{\beta}^*_{i,CHE}$ is not significant for Germany. Nevertheless, this does not alter our main findings that the lagged excess returns of Sweden and the U.S. display predictive ability in most cases, whereas this is not the case for the lagged excess returns of other countries.

In table 21 in the appendix we show the results of the general model specification, where we only add the lagged excess returns of the U.S. and that of one non-U.S. country. In this scenario, the lagged excess returns of the U.S. still show a predictive ability on the excess returns of other countries. The coefficient $\hat{\hat{\beta}}_{USA}$ is significant in all cases and $\hat{\hat{\beta}}_{SWE}$ is the only other coefficient that is significant. So only the Swedish lagged excess returns show a predictive ability besides those of the U.S.. Comparing these results with table IA.XVI in Rapach et al. (2013), we see that they report a value of 0.19 for $\hat{\hat{\beta}}_{USA}$ in the first row, whereas we report a value of 0.18. The coefficient is 0.180, so we think that this is a typo on the side of the authors. Besides that, some of the confidence intervals are slightly different, but these differences are not larger than 0.01, so this is caused by the randomness of the wild-bootstrap procedure. Finally, we report exactly the same significant results as the authors.

With the general model specification we find results that are consistent with those of the pairwise Granger causality tests, namely that the lagged excess returns of Sweden and the U.S. show predictive ability on the excess returns of other countries. However, here we see less evidence that the lagged excess returns of Switzerland have a predictive ability. The lagged excess returns of non-U.S. countries still show little predictive ability on the excess returns of the U.S..

4.4 News-Diffusion Model

Table 5: Results of the News-Diffusion Model

Country	$\hat{\beta}_{i,b}$	$\hat{\beta}_{i,d}$	$\hat{\theta}_{i,USA}$	$\hat{\lambda}_{i,USA}$	$\hat{\beta}_{i,USA}$	Country	$\hat{\beta}_{i,b}$	$\hat{\beta}_{i,d}$	$\hat{\theta}_{i,USA}$	$\hat{\lambda}_{i,USA}$	$\hat{\beta}_{i,USA}$
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)	(-3.14)	(16.59)	(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)	(27.53)	(5.83)

This table shows the parameter estimates of the news-diffusion model based on the two step GMM estimation procedure. The numbers in parentheses represent the heteroskedasticity-robust t-statistics. The row Pooled contains the pooled parameter estimates where we impose slope homogeneity restrictions on all four slope parameters, namely $\hat{\beta}_{i,b}$, $\hat{\beta}_{i,d}$, $\hat{\theta}_{i,USA}$ and $\hat{\lambda}_{i,USA}$. A * indicates significant coefficients at a 10% significance level.

In table 5 we show the results of the news-diffusion model. First of all, the assumption we make that the lagged excess returns of non-U.S. countries have little predictive ability on the returns of the U.S., is supported by the results of tables 2, 20, 3, 4 and 21. We focus on the parameters λ and θ. We test if the parameter λ is equal to 0, which indicates that the excess returns of the U.S. do not predict the excess returns of another country. We also test if the parameter θ is equal to 1, which indicates that it doesn't take time before the excess return of a country responds to a shock of the excess returns of the U.S.. We see that for every country the estimates for λ and θ are significantly different from 0 and 1 respectively. This indicates that the excess returns of the U.S. have a predictive ability on the excess returns of all other countries. Furthermore, it also indicates that information frictions exist between the stock market of the U.S. and the stock market of another country. Finally, the parameter $\hat{\beta}_{i,USA}$ indicates whether the lagged excess returns of the U.S. have a predictive ability because of the presence of information frictions. For every country the $\hat{\beta}_{i,USA}$ is significantly different from zero, which indicates that the lagged excess returns of the U.S. have a predictive ability on the excess returns of every other country, because of the presence of information frictions between the stock markets of both countries. For the pooled estimates we also see that the $\hat{\beta}_{i,USA}$ is significant, indicating that on average the lagged excess returns of the U.S. can significantly predict the returns of other countries because of the presence of information frictions. Comparing these results with table VI of Rapach et al. (2013), we see that the only differences are the t-statistic of $\hat{\lambda}_{i,USA}$ for Canada and the t-statistic of $\hat{\lambda}_{i,USA}$ for the pooled setting. They report values of 16.60 and 27.52 and we report values of 16.59 and 27.53 respectively. The values are 16.594 and 27.526 respectively, so we think that these are typos made by the authors. All the other results in this table are exactly the same as those reported in Rapach et al. (2013). So we find evidence that the lagged excess returns of the U.S. have a predictive ability on the returns of other countries as a consequence of the presence of information frictions.

4.5 Out-of-sample predictive ability tests

Table 6: Out-of-sample forecasting power of lagged U.S. returns

	Baseline: historical average		Baseline: AR		Baseline: BM predictive	
Country	R^2_{OS}	R^2_{OS}, pooled	R^2_{OS}	R^2_{OS}, pooled	R^2_{OS}	R^2_{OS}, pooled
AUS	-0.69%*	0.50%*	-0.27%*	0.71%*	-0.58%*	0.18%
	(1.49)	(1.60)	(1.42)	(3.58)	(1.46)	(0.77)
CAN	1.30%*	1.86%*	-1.94%	0.34%*	2.48%*	5.43%*
	(2.36)	(2.18)	(0.85)	(1.99)	(2.60)	(2.78)
FRA	1.52%*	1.91%*	0.09%	1.28%*	1.56%*	4.36%*
	(1.90)	(2.12)	(0.54)	(1.96)	(1.91)	(2.76)
DEU	1.57%*	1.98%*	0.99%*	2.23%*	1.59%*	3.37%*
	(1.78)	(1.91)	(1.58)	(1.84)	(1.80)	(2.35)
ITA	0.92%*	1.54%*	0.36%	1.76%*	0.81%*	3.26%*
	(1.54)	(2.05)	(1.00)	(4.33)	(1.47)	(1.62)
JPN	0.82%*	1.30%*	0.14%	1.65%*	0.95%*	3.68%*
	(1.33)	(1.65)	(0.90)	(2.74)	(1.40)	(1.41)
NLD	3.81%*	3.88%*	3.52%*	3.66%*	3.54%*	6.72%*
	(2.62)	(2.58)	(3.35)	(2.35)	(2.58)	(3.52)
SWE	2.90%*	2.76%*	1.09%*	1.83%*	3.35%*	4.59%*
	(2.25)	(2.31)	(1.59)	(2.79)	(2.38)	(3.35)
CHE	2.64%*	2.95%*	0.14%	1.69%*	2.68%*	4.66%*
	(2.45)	(2.40)	(0.94)	(2.90)	(2.53)	(2.77)
GBR	0.28%	0.43%*	0.74%*	3.24%*	0.47%	1.22%*
	(0.97)	(1.34)	(1.29)	(1.31)	(1.12)	(2.53)
AVG	1.51%	1.91%	0.49%	1.84%	1.68%	3.75%

This table shows the out-of-sample R^2, denoted by R^2_{OS}, of our forecasting models against three different baseline models. For the forecasting model we add the lagged U.S. returns to the baseline model. The columns with "pooled" report the R^2_{OS} value, where we impose a slope homogeneity restriction on the parameter of the lagged U.S. returns in the forecasting model, that is $\beta_{i,USA} = \bar{\beta}_{USA}$. The numbers in parentheses represent the MSFE-adjusted statistics. The row AVG represents the average of the R^2_{OS} values for a specific forecasting model. Significant results at a 10% significance level are indicated with a *. AR is a first-order autoregressive model and BM predictive is the benchmark predictive regression model.

In table 6 we show the results of the out-of-sample test statistics. We see that our forecasting models systematically outperform the different baseline models. Especially for the historical average model and the benchmark predictive regression model, where we see that our model outperforms the baseline model in 9 out of 10 cases, with the exception being the United-Kingdom. Our model outperforms the AR baseline less often, but still in 5 out of 10 cases our model performs better. If we look at the columns with the pooled statistics, we see that our models outperform all the baseline models in all cases, with the only exception being the benchmark predictive regression baseline for Australia. This indicates that using the average effect of the lagged excess returns of the U.S. on the excess returns of other countries gives significantly better forecasts than the baseline models. Comparing these results with tables VII and IA.XVII in Rapach et al. (2013), we see that they report a MSFE-adjusted statistic of 3.57 for the pooled model against the AR baseline for Australia, while we report a value of 3.58. The value is 3.575, so we think that this is a rounding error. Besides that, they report a R^2_{OS} of 2.34% in the same column for the United-Kingdom and we report a value of 3.24%. Furthermore, they report a MSFE-adjusted statistic of 1.56 for the benchmark predictive regression baseline for Australia and we report a value of 1.46. All other values are exactly the same, so we think that these last two differences are typos made by the authors. So in the out-of-sample setting we also find evidence that the lagged excess returns of the U.S. have a predictive ability on the excess returns of other countries.

4.6 Extension

4.6.1 Benchmark Predictive Regression Model

Table 7: Results of the Benchmark Predictive Regression Model

country	$\hat{\beta}_{i,b}$	$\hat{\beta}_{i,inf}$	R^2	country	$\hat{\beta}_{i,b}$	$\hat{\beta}_{i,inf}$	R^2
AUT	-0.43*	-1.24*	6.07*	NLD	-0.50*	-0.80*	5.96*
	(-1.72)	(-2.17)	(8.38)		(-2.05)	(-1.95)	(12.47)
	[0.05]	[0.01]	[0.02]		[0.02]	[0.03]	[0.00]
BEL	-0.47*	-0.80*	8.75*	NOR	-0.45*	-0.62*	2.69*
	(-2.43)	(-2.30)	(13.43)		(-2.03)	(-1.35)	(6.48)
	[0.01]	[0.01]	[0.00]		[0.01]	[0.09]	[0.04]
DNK	-0.50*	-0.29	3.94*	ESP	-0.21	-0.33	1.76
	(-2.00)	(-0.53)	(7.68)		(-0.59)	(-1.00)	(4.73)
	[0.02]	[0.30]	[0.02]		[0.30]	[0.18]	[0.10]
FIN	-0.27	-1.33*	8.66*	SWE	-0.84*	-0.45	4.80*
	(-0.88)	(-3.69)	(23.79)		(-1.48)	(-0.75)	(14.17)
	[0.22]	[0.00]	[0.00]		[0.07]	[0.25]	[0.00]
FRA	-0.35	-0.94*	4.99*	CHE	-0.44	-0.27	2.79*
	(-1.42)	(-1.91)	(11.52)		(-1.23)	(-0.56)	(6.91)
	[0.11]	[0.03]	[0.00]		[0.18]	[0.29]	[0.03]
DEU	-0.51*	-0.81	3.89*	GBR	-0.27*	-0.21	2.63*
	(-1.83)	(-1.30)	(9.72)		(-2.39)	(-0.76)	(5.82)
	[0.05]	[0.11]	[0.01]		[0.01]	[0.21]	[0.06]
IRL	-0.84*	0.002	6.23*	USA	-0.06	-0.73*	5.19*
	(-2.41)	(0.01)	(12.25)		(-0.38)	(-2.44)	(10.13)
	[0.01]	[0.49]	[0.00]		[0.39]	[0.01]	[0.01]
ITA	-0.48	0.001	0.45	Pooled	-0.42*	-0.49*	3.23*
	(-0.95)	(0.001)	(2.90)		(-2.74)	(-2.84)	(16.71)
	[0.17]	[0.52]	[0.23]		[0.01]	[0.01]	[0.01]

This table shows the parameter estimates of the benchmark predictive regressions as well as the R^2 of these regressions. The numbers in parentheses represent the heteroskedasticity-robust t-statistics in the columns for $\hat{\beta}_{i,b}$ and $\hat{\beta}_{i,inf}$, and heteroskedasticity-robust χ^2-statistics in the columns for the R^2. The numbers in brackets represent the p-values based on the wild-bootstrap procedure. The pooled estimates are obtained by imposing slope homogeneity restrictions on $\hat{\beta}_{i,b}$ and $\hat{\beta}_{i,inf}$. Significant coefficients at a 10% significance level are indicated with a *.

In table 7 we show the results of the benchmark predictive regression model for the extension. We see that both the Treasury bill rate and the inflation rate show some predictive ability, since these variables have a significant effect in 9 and 7 cases respectively. Furthermore, these variables have a jointly significant effect in 13 out of 15 cases, with the exceptions being Italy and Spain. The most remarkable result is that we get R^2 values of above 5% in 6 out of 15 cases, which is relatively high when working with stock returns. In table 1 we see that in the replication part, the economic variables have far less predictive ability. Furthermore, the R^2 values are below 2% in most cases. This indicates that the economic variables have a larger predictive ability in the extended analysis.

Table 8: Results of the Pairwise Granger Causality Tests

country	$\hat{\beta}_{i,AUT}$	$\hat{\beta}_{i,BEL}$	$\hat{\beta}_{i,DNK}$	$\hat{\beta}_{i,FIN}$	$\hat{\beta}_{i,FRA}$	$\hat{\beta}_{i,DEU}$	$\hat{\beta}_{i,IRL}$	$\hat{\beta}_{i,ITA}$	$\hat{\beta}_{i,NLD}$	$\hat{\beta}_{i,NOR}$	$\hat{\beta}_{i,ESP}$	$\hat{\beta}_{i,SWE}$	$\hat{\beta}_{i,CHE}$	$\hat{\beta}_{i,GBR}$	$\hat{\beta}_{i,USA}$
AUT		-0.01	0.03	0.08	0.11	0.06	0.18*	0.02	-0.03	0.14*	0.12*	0.08*	0.01	0.08	0.14
		(-0.06)	(0.41)	(1.08)	(1.25)	(0.83)	(2.32)	(1.02)	(-0.33)	(3.89)	(1.47)	(1.35)	(0.08)	(0.66)	(1.23)
		[0.52]	[0.37]	[0.16]	[0.11]	[0.24]	[0.01]	[0.18]	[0.64]	[0.02]	[0.09]	[0.09]	[0.47]	[0.29]	[0.13]
		9.73%	9.79%	10.23%	10.28%	9.98%	11.60%	9.82%	9.76%	11.91%	10.68%	10.59%	9.73%	9.87%	10.28%
BEL	0.05		0.03	0.01	0.05	0.07	0.11*	0.01	-0.02	0.06	0.06	0.03	0.20*	0.08	0.21*
	(0.58)		(0.35)	(0.11)	(0.49)	(0.84)	(1.49)	(0.34)	(-0.22)	(1.62)	(0.93)	(0.42)	(1.82)	(0.64)	(2.15)
	[0.29]		[0.38]	[0.45]	[0.33]	[0.23]	[0.08]	[0.42]	[0.60]	[0.11]	[0.22]	[0.38]	[0.05]	[0.31]	[0.02]
	11.15%		11.04%	10.99%	11.09%	11.34%	11.86%	11.00%	11.01%	11.67%	11.31%	11.11%	12.37%	11.14%	12.71%
DNK	0.14*	0.21*		0.24*	0.30*	0.25*	0.23*	0.02	0.22*	0.12*	0.15*	0.13*	0.37*	0.22*	0.41*
	(1.75)	(1.74)		(3.37)	(3.38)	(3.16)	(2.47)	(1.07)	(2.36)	(2.62)	(2.06)	(1.48)	(3.42)	(1.85)	(3.61)
	[0.06]	[0.05]		[0.00]	[0.00]	[0.00]	[0.01]	[0.11]	[0.01]	[0.03]	[0.03]	[0.08]	[0.00]	[0.05]	[0.00]
	6.18%	6.23%		9.21%	8.82%	8.72%	7.80%	4.74%	7.01%	6.45%	6.35%	6.71%	9.59%	6.10%	10.59%
FIN	-0.04	-0.17	-0.30		-0.04	-0.09	-0.14	-0.04	-0.24	-0.02	0.02	0.01	0.01	-0.17	-0.08
	(-0.42)	(-1.34)	(-2.43)		(-0.23)	(-0.71)	(-1.35)	(-1.65)	(-1.75)	(-0.20)	(0.21)	(0.31)	(0.04)	(-1.02)	(-0.49)
	[0.64]	[0.90]	[0.99]		[0.61]	[0.76]	[0.89]	[0.92]	[0.96]	[0.56]	[0.44]	[0.43]	[0.50]	[0.86]	[0.68]
	11.83%	12.59%	14.94%		11.78%	12.05%	12.69%	12.12%	13.35%	11.78%	11.78%	11.77%	11.75%	12.21%	11.88%
FRA	0.07	-0.13	-0.10	0.19*		-0.01	0.02	0.00	-0.22	0.03	0.07	0.01	0.21	-0.09	0.04
	(1.00)	(-0.96)	(-1.01)	(1.78)		(-0.07)	(0.27)	(0.23)	(-1.16)	(0.68)	(0.62)	(0.26)	(1.30)	(-0.53)	(0.25)
	[0.16]	[0.81]	[0.81]	[0.04]		[0.52]	[0.40]	[0.46]	[0.88]	[0.28]	[0.30]	[0.43]	[0.13]	[0.71]	[0.43]
	5.98%	6.03%	6.13%	7.37%		5.59%	5.62%	5.59%	6.55%	5.71%	5.79%	5.61%	6.64%	5.72%	5.62%
DEU	0.10	-0.09	-0.10	0.29*	0.30*		0.05	0.02	-0.17	0.06*	0.16*	0.03	0.19	0.03	0.21*
	(1.27)	(-0.67)	(-0.87)	(2.54)	(1.45)		(0.59)	(1.57)	(-0.93)	(1.53)	(1.47)	(0.32)	(1.21)	(0.19)	(1.37)
	[0.10]	[0.71]	[0.78]	[0.01]	[0.08]		[0.28]	[0.18]	[0.82]	[0.09]	[0.08]	[0.41]	[0.13]	[0.45]	[0.10]
	4.79%	4.39%	4.55%	7.55%	5.22%		4.31%	4.33%	4.72%	4.62%	5.12%	4.23%	4.93%	4.18%	5.03%
IRL	0.11	0.05	0.01	0.10	0.18*	0.09		0.04*	0.01	0.02	0.14*	0.12*	0.14	0.13	0.22*
	(1.26)	(0.38)	(0.13)	(1.27)	(1.73)	(1.05)		(2.16)	(0.11)	(0.43)	(1.66)	(1.97)	(1.22)	(1.04)	(1.88)
	[0.11]	[0.37]	[0.45]	[0.11]	[0.05]	[0.16]		[0.07]	[0.47]	[0.35]	[0.06]	[0.02]	[0.14]	[0.17]	[0.04]
	8.63%	7.89%	7.82%	8.46%	9.23%	8.36%		8.37%	7.82%	7.85%	9.02%	9.73%	8.46%	8.26%	9.11%
ITA	0.24*	0.27*	0.20	0.37*	0.42*	0.31*	0.29*		0.28*	0.21*	0.28*	0.18	0.35*	0.33*	0.32*
	(2.22)	(1.34)	(0.98)	(2.05)	(1.81)	(1.59)	(2.06)		(1.36)	(1.33)	(1.79)	(1.15)	(2.16)	(1.29)	(1.81)
	[0.01]	[0.09]	[0.19]	[0.01]	[0.03]	[0.05]	[0.02]		[0.09]	[0.08]	[0.03]	[0.15]	[0.02]	[0.10]	[0.03]
	1.77%	1.48%	1.23%	4.00%	3.15%	2.53%	2.30%		1.92%	2.29%	2.08%	1.72%	1.89%	1.50%	1.64%
NLD	0.10	0.02	-0.03	0.25*	0.46*	0.22*	0.18*	0.01		0.11*	0.22*	0.04	0.42*	0.25	0.32*
	(1.10)	(0.17)	(-0.34)	(2.32)	(2.39)	(1.71)	(2.11)	(0.80)		(2.47)	(1.91)	(0.39)	(2.55)	(1.36)	(2.41)
	[0.15]	[0.42]	[0.60]	[0.02]	[0.01]	[0.05]	[0.02]	[0.22]		[0.04]	[0.04]	[0.41]	[0.01]	[0.11]	[0.02]
	6.73%	6.12%	6.15%	9.57%	9.62%	7.95%	7.85%	6.14%		7.62%	8.40%	6.27%	10.08%	7.02%	8.47%
NOR	0.20*	0.10	0.08	0.13*	0.12	0.19*	0.16*	0.04*	0.07		0.17*	0.14*	0.07	0.16	0.31*
	(1.97)	(0.86)	(0.73)	(1.58)	(1.15)	(2.13)	(1.71)	(1.75)	(0.68)		(1.92)	(2.87)	(0.53)	(1.23)	(2.14)
	[0.02]	[0.21]	[0.26]	[0.07]	[0.15]	[0.02]	[0.05]	[0.07]	[0.29]		[0.03]	[0.03]	[0.30]	[0.14]	[0.02]
	4.59%	3.24%	3.22%	3.86%	3.39%	4.38%	3.95%	3.35%	3.16%		4.18%	4.42%	3.10%	3.43%	4.93%
ESP	0.07	-0.14	-0.13	0.14*	0.04	0.01	0.03	0.01	-0.11	0.04		0.05	0.03	-0.05	0.06
	(0.88)	(-1.01)	(-1.17)	(1.54)	(0.24)	(0.07)	(0.28)	(0.41)	(-0.80)	(0.78)		(0.95)	(0.21)	(-0.27)	(0.38)
	[0.20]	[0.80]	[0.85]	[0.06]	[0.38]	[0.46]	[0.38]	[0.42]	[0.77]	[0.24]		[0.16]	[0.42]	[0.60]	[0.35]
	2.30%	2.52%	2.74%	3.17%	1.98%	1.94%	1.98%	1.99%	2.41%	2.11%		2.19%	1.97%	1.99%	2.03%
SWE	-0.08	-0.27	-0.28	0.18*	-0.11	-0.04	0.00	-0.03	-0.09	0.03	-0.08		-0.04	-0.04	-0.02
	(-0.93)	(-1.57)	(-1.54)	(2.44)	(-0.52)	(-0.45)	(0.01)	(-0.53)	(-0.82)	(0.45)	(-0.54)		(-0.24)	(-0.31)	(-0.14)
	[0.79]	[0.93]	[0.93]	[0.01]	[0.65]	[0.65]	[0.48]	[0.66]	[0.78]	[0.37]	[0.66]		[0.59]	[0.62]	[0.56]
	5.21%	6.99%	7.44%	6.54%	5.16%	4.92%	4.84%	5.07%	5.13%	4.92%	5.14%		4.87%	4.88%	4.85%
CHE	0.01	-0.05	-0.05	0.05	0.05	-0.02	0.05	0.01	-0.09	0.05	0.10*	0.01		-0.01	0.04
	(0.21)	(-0.47)	(-0.74)	(0.68)	(0.44)	(-0.21)	(0.73)	(0.62)	(-0.99)	(1.58)	(1.74)	(0.20)		(-0.06)	(0.31)
	[0.40]	[0.66]	[0.75]	[0.27]	[0.35]	[0.58]	[0.25]	[0.33]	[0.82]	[0.12]	[0.05]	[0.44]		[0.54]	[0.41]
	5.34%	5.44%	5.56%	5.63%	5.45%	5.35%	5.58%	5.37%	5.92%	5.95%	6.42%	5.35%		5.33%	5.40%
GBR	0.02	-0.03	-0.02	0.11	0.18*	0.07	0.05	0.02*	-0.02	0.04	0.13*	0.08*	0.21*		0.17*
	(0.27)	(-0.41)	(-0.32)	(1.36)	(1.78)	(0.99)	(0.79)	(1.84)	(-0.19)	(1.31)	(1.98)	(1.50)	(2.00)		(1.65)
	[0.37]	[0.63]	[0.62]	[0.10]	[0.05]	[0.18]	[0.21]	[0.09]	[0.58]	[0.16]	[0.03]	[0.04]	[0.03]		[0.06]
	2.68%	2.71%	2.70%	4.07%	4.37%	3.14%	2.91%	2.90%	2.67%	3.05%	4.57%	4.22%	4.85%		3.75%
USA	0.00	-0.02	0.00	0.09	0.12	0.04	0.04	0.03*	0.00	0.01	0.07	0.10*	0.05	0.07	
	(0.05)	(-0.17)	(-0.01)	(1.19)	(1.01)	(0.56)	(0.48)	(2.10)	(0.02)	(0.35)	(0.88)	(2.02)	(0.44)	(0.51)	
	[0.46]	[0.56]	[0.51]	[0.15]	[0.21]	[0.33]	[0.31]	[0.10]	[0.50]	[0.37]	[0.23]	[0.05]	[0.36]	[0.34]	
	5.48%	5.49%	5.48%	6.32%	6.19%	5.64%	5.61%	5.97%	5.48%	5.52%	5.94%	7.46%	5.62%	5.61%	
Average	0.07	-0.02	-0.05	0.16	0.16	0.08	0.09	0.01	-0.03	0.06	0.12	0.07	0.16	0.07	0.17
Pooled	0.08*	0.01	-0.02	0.15*	0.14*	0.09*	0.09*	0.01	0.02	0.07*	0.11*	0.08*	0.15*	0.10	0.17*
	(1.41)	(0.14)	(-0.25)	(2.55)	(2.09)	(1.69)	(1.56)	(0.99)	(0.31)	(1.96)	(2.10)	(1.31)	(1.69)	(0.96)	(1.98)
	[0.10]	[0.49]	[0.60]	[0.01]	[0.03]	[0.08]	[0.08]	[0.22]	[0.43]	[0.07]	[0.03]	[0.09]	[0.07]	[0.20]	[0.04]
	3.94%	3.53%	3.73%	4.87%	4.38%	4.22%	4.20%	4.89%	3.69%	4.41%	4.65%	4.44%	4.32%	4.04%	4.53%

This table shows the parameter estimates of $\beta_{i,j}$ in the regressions for the pairwise Granger causality tests as well as the R^2 of these regressions. The numbers in parentheses represent the heteroskedasticity-robust t-statistics. The numbers in brackets represent the p-values based on the wild-bootstrap procedure. The fourth row for every country, the value below the p-values, denotes the R^2 values for the regressions. The row average denotes the average of the $\hat{\beta}_{i,j}$ values for a specific j, so it's the average of the $\hat{\beta}_{i,j}$ values in that column. The pooled estimates are obtained by imposing a slope homogeneity restriction on $\hat{\beta}_{i,j}$, as well as on the other slope parameters. Significant coefficients at a 10% significance level are indicated with a *.

4.6.2 Pairwise Granger Causality Tests

In table 8 we show the results of the pairwise Granger causality tests. We see that the lagged excess returns of most countries do not show a predictive ability on the excess returns of other countries. The lagged excess returns of most countries have a significant effect in less than half the cases (7 out of 14 cases). The exceptions are Finland, Spain and the U.S., where the lagged excess returns have a significant effect in 8, 9 and 8 cases respectively. Besides that, we see that the average of the coefficients of the lagged excess returns is 0.16, 0.12 and 0.17 for Finland, Spain and the U.S. respectively, which is relatively higher than for most countries. The pooled coefficients of these countries are also significant and they are larger than for most other countries. This indicates that the average effect of the lagged excess returns of these countries can be used to predict the excess returns of other countries. The pooled coefficients of France and Switzerland are also significant and relatively high. So the lagged excess returns of these countries have a relatively large effect in some cases, but in most cases they don't have a significant effect at all. Furthermore, we see that the lagged excess returns of other countries have very little predictive ability on the excess returns of these three countries. The excess returns of Finland, Spain and the U.S. can be significantly predicted in 0, 1 and 2 cases respectively. These results might indicate that these three countries have a leading role in the international stock market.

4.6.3 General Model Specification

Table 9: Results of the General Model Specification with pooled estimates

Country	$\hat{\bar{\beta}}_j$	Confidence interval	Country	$\hat{\bar{\beta}}_j$	Confidence interval
AUT	0.05	[-0.06, 0.16]	NLD	-0.19*	[-0.38, -0.01]
BEL	-0.11	[-0.27, 0.05]	NOR	0.05*	[0.01, 0.10]
DNK	-0.16*	[-0.30, -0.02]	ESP	0.06	[-0.07, 0.19]
FIN	0.13*	[0.01, 0.26]	SWE	0.06	[-0.02, 0.13]
FRA	0.07	[-0.11, 0.26]	CHE	0.12	[-0.08, 0.32]
DEU	-0.01	[-0.15, 0.14]	GBR	-0.09	[-0.29, 0.11]
IRL	0.07	[-0.03, 0.18]	USA	0.09	[-0.11, 0.28]
ITA	-0.01	[-0.04, 0.02]			

This table shows the parameter estimates of $\bar{\beta}_j$, the pooled estimate of $\beta_{i,j}$, for the general model specification. We impose slope homogeneity restrictions on all the slope parameters in the model, and for every country we report the slope parameter of the lagged excess returns of that country, given by $\hat{\bar{\beta}}_j$. The values in brackets represent the 90% confidence interval based on the wild-bootstrap procedure. Significant coefficients at a 10% significance level are indicated with a *.

In table 9 we show the results of the general model specification, where we use pooled estimates to solve the problem of multiple correlated regressors. We see that the pooled coefficients of Denmark, Finland, the Netherlands and Norway are significant. This indicates that the lagged excess returns of these countries have predictive ability on the excess returns of other countries after controlling for the effect of the lagged excess returns of all other countries. Furthermore, we see that the lagged excess returns of Spain and the U.S. have no predictive ability in this case, whereas it was the case in the pairwise Granger causality tests.

Table 10: Results of the General Model Specification based on the Adaptive Elastic Net estimation procedure

Country	$\hat{\beta}^*_{i,AUT}$	$\hat{\beta}^*_{i,BEL}$	$\hat{\beta}^*_{i,DNK}$	$\hat{\beta}^*_{i,FIN}$	$\hat{\beta}^*_{i,FRA}$	$\hat{\beta}^*_{i,DEU}$	$\hat{\beta}^*_{i,IRL}$	$\hat{\beta}^*_{i,ITA}$	$\hat{\beta}^*_{i,NLD}$	$\hat{\beta}^*_{i,NOR}$	$\hat{\beta}^*_{i,ESP}$	$\hat{\beta}^*_{i,SWE}$	$\hat{\beta}^*_{i,CHE}$	$\hat{\beta}^*_{i,GBR}$	$\hat{\beta}^*_{i,USA}$
AUT	0.00	0.00	-0.02	0.00	0.05	0.00	0.13*	0.00	-0.15*	0.09*	0.05	0.04*	-0.02	0.00	0.02
	[0.00,0.00]	[0.00,0.00]	[-0.11,0.03]	[0.00,0.00]	[-0.03,0.18]	[0.00,0.00]	[0.09,0.27]	[0.00,0.00]	[-0.38,-0.15]	[0.07,0.17]	[0.00,0.14]	[0.02,0.10]	[-0.12,0.05]	[0.00,0.00]	[-0.05,0.09]
BEL	0.002	0.00	0.00	0.00	0.00	0.00	0.02	0.00	-0.04	0.02	0.00	0.00	0.10*	0.00	0.13
	[-0.02,0.02]	[0.00,0.00]	[0.00,0.00]	[0.00,0.00]	[0.00,0.00]	[0.00,0.00]	[-0.01,0.07]	[0.00,0.00]	[-0.20,0.01]	[-0.01,0.06]	[0.00,0.00]	[0.00,0.00]	[0.04,0.23]	[0.00,0.00]	[0.07,0.28]
DNK	0.00	0.00	0.00	0.08*	0.00	0.00	0.01	0.00	0.00	0.01	0.00	0.00	0.14*	-0.12*	0.25*
	[0.00,0.00]	[0.00,0.00]	[0.00,0.00]	[0.04,0.19]	[0.00,0.00]	[0.00,0.00]	[-0.03,0.06]	[0.00,0.00]	[0.00,0.00]	[-0.03,0.04]	[0.00,0.00]	[0.00,0.00]	[0.05,0.33]	[-0.41,-0.08]	[0.15,0.52]
FIN	0.02	0.00	-0.24*	0.00	0.14*	0.00	0.00	-0.02	-0.18*	0.002	0.03	0.04*	0.10*	-0.003	0.00
	[-0.04,0.11]	[0.00,0.00]	[-0.49,-0.14]	[0.00,0.00]	[0.02,0.38]	[0.00,0.00]	[0.00,0.00]	[-0.05,-0.02]	[-0.47,-0.12]	[-0.05,0.06]	[-0.04,0.10]	[0.03,0.10]	[0.01,0.29]	[-0.13,0.09]	[0.00,0.00]
FRA	0.07*	-0.04	-0.11	0.21*	0.00	0.00	0.00	0.00	-0.21*	0.002	0.00	0.00	0.26*	-0.07	0.00
	[0.00,0.20]	[-0.17,0.06]	[-0.28,0.00]	[0.10,0.39]	[0.00,0.00]	[0.00,0.00]	[0.00,0.00]	[0.00,0.00]	[-0.48,-0.05]	[-0.04,0.04]	[0.00,0.00]	[0.00,0.00]	[0.08,0.56]	[-0.28,0.06]	[0.00,0.00]
DEU	0.07	-0.08	-0.14*	0.26*	0.12	0.00	0.00	0.00	-0.33*	0.04*	0.06	0.00	0.18*	-0.12	0.11
	[-0.02,0.21]	[-0.26,0.02]	[-0.33,-0.04]	[0.16,0.47]	[-0.03,0.41]	[0.00,0.00]	[0.00,0.00]	[0.00,0.00]	[-0.67,-0.17]	[0.01,0.10]	[-0.02,0.19]	[0.00,0.00]	[0.05,0.45]	[-0.41,0.01]	[-0.02,0.33]
IRL	0.07	0.00	0.00	0.00	0.27*	0.00	0.00	0.00	-0.30*	0.00	0.00	0.09*	0.00	0.00	0.11
	[-0.02,0.19]	[0.00,0.00]	[0.00,0.00]	[0.00,0.00]	[0.11,0.59]	[0.00,0.00]	[0.00,0.00]	[0.00,0.00]	[-0.66,-0.20]	[0.00,0.00]	[0.00,0.00]	[0.03,0.18]	[0.00,0.00]	[0.00,0.00]	[-0.02,0.30]
ITA	0.00	0.00	0.00	0.26*	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	[0.00,0.00]	[0.00,0.00]	[0.00,0.00]	[0.14,0.56]	[-0.18,0.11]	[0.00,0.00]	[0.00,0.00]	[0.00,0.00]	[0.00,0.00]	[0.00,0.00]	[0.00,0.00]	[0.00,0.00]	[0.00,0.00]	[0.00,0.00]	[0.00,0.00]
NLD	0.00	-0.07	-0.14*	0.17*	0.01	0.00	0.08*	0.00	0.00	0.06*	0.05	0.00	0.33*	0.00	0.00
	[0.00,0.00]	[-0.24,0.05]	[-0.32,-0.05]	[0.04,0.35]	[-0.15,0.16]	[0.00,0.00]	[0.02,0.21]	[0.00,0.00]	[0.00,0.00]	[0.03,0.14]	[-0.02,0.17]	[0.00,0.00]	[0.13,0.63]	[0.00,0.00]	[0.00,0.00]
NOR	0.09*	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-0.17*	0.00	0.03	0.08*	0.00	0.00	0.25*
	[0.01,0.24]	[0.00,0.00]	[0.00,0.00]	[0.00,0.00]	[0.00,0.00]	[0.00,0.00]	[0.00,0.00]	[0.00,0.00]	[-0.47,-0.10]	[0.00,0.00]	[-0.05,0.15]	[0.02,0.19]	[0.00,0.00]	[0.00,0.00]	[0.05,0.55]
ESP	0.07*	0.00	-0.14*	0.20*	0.00	0.00	0.00	0.00	-0.14*	0.00	0.00	0.03*	0.00	0.00	0.00
	[0.03,0.20]	[0.00,0.00]	[-0.34,-0.07]	[0.12,0.41]	[0.00,0.00]	[0.00,0.00]	[0.00,0.00]	[0.00,0.00]	[-0.39,-0.07]	[0.00,0.00]	[0.00,0.00]	[0.03,0.08]	[0.00,0.00]	[0.00,0.00]	[0.00,0.00]
SWE	0.00	-0.30*	-0.36*	0.49*	-0.21	0.00	0.04	0.00	0.00	0.05*	0.00	0.00	0.10	0.00	0.00
	[0.00,0.00]	[-0.63,-0.14]	[-0.72,-0.11]	[0.16,0.89]	[-0.77,0.25]	[0.00,0.00]	[-0.03,0.15]	[0.00,0.00]	[0.00,0.00]	[0.02,0.14]	[0.00,0.00]	[0.00,0.00]	[-0.02,0.36]	[0.00,0.00]	[0.00,0.00]
CHE	0.00	0.00	-0.03	0.04	0.01	0.00	0.03	0.00	-0.16*	0.04*	0.11*	0.00	0.00	0.00	0.00
	[0.00,0.00]	[0.00,0.00]	[-0.11,0.01]	[-0.02,0.12]	[-0.08,0.09]	[0.00,0.00]	[-0.01,0.11]	[0.00,0.00]	[-0.37,-0.12]	[0.02,0.09]	[0.05,0.23]	[0.00,0.00]	[0.00,0.00]	[0.00,0.00]	[0.00,0.00]
GBR	0.00	0.00	-0.02	0.03	0.04*	0.00	0.00	0.00	-0.12*	0.00	0.02	0.03*	0.12*	0.00	0.00
	[0.00,0.00]	[0.00,0.00]	[-0.10,0.02]	[0.00,0.12]	[0.00,0.14]	[0.00,0.00]	[0.00,0.00]	[0.00,0.00]	[-0.31,-0.09]	[0.00,0.00]	[0.00,0.08]	[0.03,0.08]	[0.07,0.31]	[0.00,0.00]	[0.00,0.00]
USA	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.06*	0.00	0.00	0.00
	[0.00,0.00]	[0.00,0.00]	[0.00,0.00]	[0.00,0.00]	[0.00,0.00]	[0.00,0.00]	[0.00,0.00]	[0.00,0.00]	[0.00,0.00]	[0.00,0.00]	[0.00,0.00]	[0.03,0.13]	[0.00,0.00]	[0.00,0.00]	[0.00,0.00]
AVG	0.03	-0.03	-0.08	0.12	0.03	0.00	0.02	0.00	-0.12	0.02	0.02	0.02	0.09	-0.02	0.06

This table shows the parameter estimates of $\beta_{i,j}$ in the general model specification based on the adaptive elastic net estimation procedure. These estimates are denoted by $\hat{\beta}^*_{i,j}$. The row AVG shows the average of the estimates for a specific j. The values in brackets represent the 90% confidence interval based on the wild-bootstrap procedure. Significant coefficients at a 10% significance level are indicated with a *.

In table 10 we show the results of the general model specification based on the Adaptive Elastic Net estimation procedure. We see that the lagged excess returns of Denmark, Finland, France, The Netherlands, Norway and Switzerland are selected the most, namely 10 times for the Netherlands and 9 times for the other countries. However, the lagged excess returns of Denmark, France and Norway have a significant effect in only 5, 3 and 5 cases respectively. The lagged excess returns of Finland, the Netherlands and Switzerland are not only selected the most, they also have a significant effect in most cases, namely 7, 9 and 7 times respectively. The lagged excess returns of Sweden also have a significant effect 7 times, even though they are only selected in 7 out of 14 cases. Furthermore, the average effects of Finland and the Netherlands are the largest, with values of 0.12 and -0.12 respectively, which are the only values above the 0.10 in absolute value. This means that on average the lagged excess returns of these countries have the largest effect on the excess returns of other countries. Finally, we see that the lagged excess returns of the Netherlands show a predictive ability in both table 9 and table 10. So the Dutch lagged excess returns show a significant effect when controlling for the effect of the lagged excess returns of all other countries. However, it fails to have a significant effect when it is the only predictor besides the economic variables.

The results in tables 8, 9 and 10 consistently indicate that the lagged excess returns of Finland have a predictive ability on the excess returns of other countries. Besides that, in table 8 we also see that the excess returns of Finland cannot be significantly predicted. These results indicate that Finland might have a leading role in the international stock market.

4.6.4 News-Diffusion Model

Table 11: Results of the News-Diffusion Model with Finland as leading country

Country	$\hat{\beta}_{i,b}$	$\hat{\beta}_{i,inf}$	$\hat{\theta}_{i,FIN}$	$\hat{\lambda}_{i,FIN}$	$\hat{\beta}_{i,FIN}$	Country	$\hat{\beta}_{i,b}$	$\hat{\beta}_{i,inf}$	$\hat{\theta}_{i,FIN}$	$\hat{\lambda}_{i,FIN}$	$\hat{\beta}_{i,FIN}$
AUT	-0.26	-1.15*	0.92	0.59*	0.05	NLD	-0.25	-0.82*	1.03	0.64*	-0.02
	(-0.92)	(-1.91)	(-0.64)	(6.08)	(0.60)		(-0.95)	(-2.15)	(0.32)	(9.44)	(-0.32)
BEL	-0.41*	-0.60*	1.08	0.44*	-0.03	NOR	-0.20	-0.44	0.96	0.73*	0.03
	(-1.87)	(-1.93)	(0.39)	(5.18)	(-0.42)		(-0.80)	(-1.10)	(-0.33)	(8.20)	(0.32)
DNK	-0.25	-0.56	0.89*	0.63*	0.07	ESP	-0.14	-0.42*	1.09	0.54*	-0.05
	(-0.89)	(-1.02)	(-1.39)	(9.77)	(1.28)		(-0.37)	(-1.30)	(0.69)	(6.98)	(-0.75)
FIN	-0.04	-1.43*				SWE	-0.37	-0.54*	1.02	0.66*	-0.02
	(-0.12)	(-3.50)					(-1.27)	(-1.59)	(0.28)	(10.73)	(-0.29)
FRA	-0.26	-0.72*	1.06	0.61*	-0.04	CHE	-0.30	-0.29	1.06	0.39*	-0.02
	(-1.03)	(-1.69)	(0.76)	(12.03)	(-0.80)		(-0.87)	(-0.67)	(0.37)	(6.36)	(-0.39)
DEU	-0.33	-0.96*	0.98	0.77*	0.02	GBR	-0.23*	-0.29	1.11	0.40*	-0.05
	(-1.08)	(-1.64)	(-0.37)	(12.86)	(0.36)		(-1.79)	(-1.16)	(0.77)	(6.96)	(-0.85)
IRL	-0.98*	0.07	0.95	0.60*	0.03	USA	-0.18	-0.58*	1.00	0.45*	0.00
	(-3.08)	(0.26)	(-0.48)	(7.72)	(0.46)		(-1.16)	(-2.08)	(-0.02)	(7.83)	(0.02)
ITA	-0.41	-0.04	0.86	0.78*	0.11	Pooled	-0.93*	-0.60*	0.98	0.64*	0.02
	(-0.73)	(-0.03)	(-0.85)	(5.84)	(0.75)		(-7.59)	(-5.81)	(-0.58)	(20.42)	(0.57)

This table shows the parameter estimates of the news-diffusion model based on the two step GMM estimation procedure, where Finland is the leading country. The numbers in parentheses represent the heteroskedasticity-robust t-statistics. The row Pooled contains the pooled parameter estimates where we impose slope homogeneity restrictions on all four slope parameters, namely $\hat{\beta}_{i,b}$, $\hat{\beta}_{i,inf}$, $\hat{\theta}_{i,FIN}$ and $\hat{\lambda}_{i,FIN}$. Significant coefficients at a 10% significance level are indicated with a *.

In table 11 we show the results of the news-diffusion model with Finland as the leading country. We see that the coefficient $\lambda_{i,FIN}$ is significant in all cases, which indicates that the excess returns of all countries are affected by the lagged excess returns of Finland. However, the coefficient $\theta_{i,FIN}$ is only significant for Denmark, which means that return shocks of Finland do not take a month to be reflected in the excess returns of other countries. This indicates that the current excess returns are more informative than the lagged excess returns of Finland when predicting the excess returns of other countries. Furthermore, we see that the coefficient $\beta_{i,FIN}$ is never significant, indicating that the lagged excess returns of Finland have no predictive ability as a consequence of information frictions between the stock markets. These results are in contrast to the results in table 5 of the replication part, where we find that the presence of information frictions give rise to a predictive ability of U.S.' lagged excess returns.

4.6.5 Out-of-sample predictive ability tests

Table 12: Out-of-sample forecasting power of lagged returns of Finland

	Baseline: historical average		Baseline: AR		Baseline: BM predictive	
Country	R^2_{OS}	R^2_{OS}, pooled	R^2_{OS}	R^2_{OS}, pooled	R^2_{OS}	R^2_{OS}, pooled
AUT	4.82%*	4.50%*	0.55%	-1.95%	1.94%*	5.37%*
	(2.06)	(1.91)	(0.89)	(0.43)	(1.66)	(3.29)
BEL	3.11%*	5.07%*	-0.19%	-1.93%	0.58%	6.51%*
	(2.05)	(2.17)	(-0.69)	(0.76)	(0.85)	(3.43)
DNK	3.92%*	4.16% *	1.78%*	3.60%*	1.96%*	8.41%*
	(2.18)	(2.23)	(1.89)	(1.69)	(1.82)	(4.07)
FRA	1.57%*	2.02%*	0.01%	1.02%*	0.77%	6.10%*
	(1.47)	(1.70)	(0.86)	(1.79)	(1.08)	(2.87)
DEU	1.19%*	2.25%*	-2.88%	1.35%	-0.10%	3.35%*
	(1.38)	(1.90)	(0.35)	(1.13)	(0.72)	(3.31)
IRL	3.46%*	4.31%*	0.10%	0.14%*	1.90%*	0.54% *
	(2.19)	(2.27)	(0.47)	(2.25)	(1.71)	(2.86)
ITA	1.88%*	1.59%*	-4.81%*	3.75%*	1.90%*	5.85%*
	(1.91)	(1.74)	(1.28)	(3.25)	(2.13)	(1.79)
NLD	2.09%*	1.68%*	-0.88%	1.04%	1.06%	3.75%*
	(1.46)	(1.42)	(0.67)	(0.77)	(1.15)	(2.73)
NOR	0.71%	1.50%*	-0.94%	1.11%	-0.12%	2.81%*
	(0.97)	(1.36)	(0.00)	(1.17)	(0.42)	(1.43)
ESP	0.89%	1.19%	0.66%	1.55%*	0.75%	1.86%*
	(1.01)	(1.28)	(0.92)	(2.92)	(0.87)	(1.87)
SWE	-3.59%	-1.79%	-3.89%	-1.30%	1.22%*	22.06%*
	(0.43)	(0.65)	(0.19)	(0.20)	(1.32)	(2.48)
CHE	2.28%*	0.61%*	-0.49%	-4.50%*	0.59%	3.04%*
	(1.79)	(1.77)	(-0.24)	(1.49)	(0.92)	(2.98)
GBR	0.09%	-0.74%	1.43%*	0.70%*	0.26%	0.48%*
	(0.47)	(1.26)	(1.79)	(3.03)	(0.61)	(2.10)
USA	1.72%	3.04%*	-0.09%	2.43%*	0.98%	-3.17%*
	(1.18)	(1.67)	(0.39)	(3.62)	(0.97)	(3.01)
AVG	1.72%	2.10%	-0.69%	0.50%	0.98%	4.78%

This table shows the out-of-sample R^2, denoted by R^2_{OS}, of our forecasting models against three different baseline models. For the forecasting model we add the lagged returns of Finland to the baseline model. The columns with "pooled" report the R^2_{OS} value, where we impose a slope homogeneity restriction on the parameter of the lagged returns of Finland in the forecasting model, that is $\beta_{i,FIN} = \bar{\beta}_{FIN}$. The numbers in parentheses represent the MSFE-adjusted statistics. The row AVG represents the average of the R^2_{OS} values for a specific forecasting model. Significant results at a 10% significance level are indicated with a *. AR is a first-order autoregressive model and BM predictive is the benchmark predictive regression model.

In table 12 we show the results of the out-of-sample analysis, where we use Finland as the leading country. We see that our forecasting model outperforms the historical baseline model, where our forecasts are significantly better in 9 out of 14 times. However, for the AR baseline and the benchmark predictive regression baseline our model produces significantly better forecasts in only 3 and 5 cases respectively. For the AR baseline only 2 of the 3 significant results have a positive R^2_{OS}, so in one case we don't get a reduction in the MSFE. Furthermore, we see that the models based on pooled estimates outperform all the baseline models in most cases, namely 11, 8 and 14 times respectively for the historical, AR and benchmark predictive regression baselines. The R^2_{OS} is positive in 11, 7 and 13 of the significant cases respectively. The average R^2_{OS} values for the pooled models are also higher than the average values for the models where we don't use pooled estimates. This indicates that the average effect of the lagged excess returns of Finland can be used to produce significantly better forecasts.

In table 22 in the appendix we show the results of the out-of-sample analysis, where the U.S. is the leading country. The lagged returns of the U.S. have a significant predictive power in 11, 4 and 9 cases for the historical, AR and benchmark predictive regression baselines respectively. Both the R^2_{OS}

is positive and the lagged returns of the U.S. have a significant forecasting power in 10, 9 and 12 cases for the historical, AR and benchmark predictive regression baselines respectively. When we compare these results with the results where Finland is the leading country, we see that the significant results are quite similar. The only remarkable difference is that the lagged excess returns of the U.S. have a significant predictive power in 9 cases against the benchmark predictive regression baseline, whereas the lagged excess returns of Finland have a significant predictive ability in only 5 cases against the same baseline. This indicates that the lagged excess returns of Finland don't outperform the lagged excess returns of the U.S. in the out-of-sample setting. Furthermore, the lagged excess returns of the U.S. show a more robust predictive power, because they perform better against the benchmark predictive baseline than Finland does. So in order to produce forecasts of the excess returns of various countries, it is better to use the lagged excess returns of the U.S as a predictor than the lagged excess returns of Finland.

5 Conclusion

In this research we investigate the potential lead-lag relationships between the equity markets of different countries. First we follow the research of Rapach et al. (2013) and we use the same methods and the same data as they use. With this dataset we find similar results as the results that they report. We find that the lagged excess returns of Sweden and the U.S. have a significant predictive ability on the excess returns of other countries across the different models. Furthermore, the news-diffusion model shows that the presence of information frictions between the stock markets gives rise to a predictive ability of the lagged excess returns of the U.S.. Finally, we find that the predictive ability of U.S.' excess returns is also present in the out-of-sample analysis. So the U.S. exhibits a leading role in the international stock market both in-sample and out-of-sample.

Besides that, we also look more in-depth into Europe when investigating the existence of these lead-lag relationships. For this we use a different dataset, where we include additional European countries and where we use a different sample period. Here we see that the predictive ability of the lagged excess returns of the U.S. is not consistent across the different models, so it seems that the U.S. lost its leading role in-sample. On the other hand, the lagged excess returns of Finland show a significant predictive ability consistently across the models, indicating that Finland exhibits a leading role in-sample. However, the results of the news-diffusion model indicate that this predictive ability is not caused by information frictions that could be present between the stock markets of Finland and that of other countries. Finally, we find that the lagged excess returns of Finland can significantly predict the excess returns of other countries out-of-sample, especially when we use the average effect that the lagged excess returns of Finland have on the excess returns of other countries. Nevertheless, when we apply the out-of-sample predictive tests with the U.S. as leading country, we see that the lagged excess returns of the U.S. can significantly predict the excess returns of other countries more often than was the case for Finland. So the lagged excess returns of Finland do not outperform those of the U.S. out-of-sample. Furthermore, we find that the lagged excess returns of the U.S. show a predictive ability in most cases for the pairwise Granger causality tests. These results, in combination with the out-of-sample results, indicate that the U.S. still has a leading role if we only control for the effect that the lagged excess returns of the country itself have. However, when we control for the effect of the lagged excess returns of all countries, this leading role seems to be no longer present.

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6 Appendix

6.1 Delta method

With the delta method we compute the standard error of a function of the parameters. Assume that the parameters are given by θ and we want to compute the standard error of g(θ), a function of the parameters. The variance of this function is then given by

$$var(g(\theta)) = \frac{\partial g(\theta)}{\partial \theta'} \Sigma \frac{\partial g(\theta)}{\partial \theta} \tag{27}$$

where $\frac{\partial g(\theta)}{\partial \theta}$ is the gradient of g(θ) and Σ is the covariance matrix of θ. To calculate the standard error of g(θ) we take the square root of the variance.

In our case the parameters are given by $\phi = (\beta'_{USA}, \beta'_{AUS}, \theta_{AUS,USA}, \lambda_{AUS,USA}, ...,$ $\beta'_{GBR}, \theta_{GBR,USA}, \lambda_{GBR,USA})'$ and the function of the parameters is given by $g(\phi) = (1 - \theta_{i,USA})\lambda_{i,USA}$. Then the gradient of the function g(ϕ) is given by

$$\frac{\partial g(\phi)}{\partial \theta} = (0, 0, ..., -\lambda_{i,USA}, 1 - \theta_{i,USA}, ..., 0, 0)' \tag{28}$$

and Σ is the covariance matrix of the GMM parameters.

6.2 Tables

Table 13: Summary statistics of the excess stock returns

Country	Mean (%)	Stand Dev (%)	Minimum (%)	Maximum (%)	Autocorrelation	Sharpe Ratio
AUS	0.35	5.07	-43.06	14.99	0.05	0.07
CAN	0.30	4.72	-23.31	13.42	0.13	0.06
FRA	0.50	5.73	-22.49	21.58	0.13	0.09
DEU	0.51	5.71	-24.09	19.84	0.09	0.09
ITA	0.42	6.98	-20.66	28.78	0.09	0.06
JPN	0.22	5.39	-21.68	17.51	0.12	0.04
NLD	0.68	5.38	-23.69	15.78	0.11	0.13
SWE	1.03	6.73	-22.61	33.90	0.15	0.15
CHE	0.55	4.63	-24.88	12.22	0.18	0.12
GBR	0.50	4.68	-27.33	12.90	0.02	0.11
USA	0.55	4.50	-22.09	12.96	0.06	0.12

This table shows the summary statistics of the monthly excess stock returns of a stock market index for that country. Stand Dev denotes the standard deviation of the excess stock returns. The Sharpe Ratio is calculated by dividing the mean of the excess returns by the standard deviation of the excess returns.

Table 14: Information on the stock indices used in the replication part and the opening and closing times of the stock markets

Country	Country code	Global Financial Data series name	Opening Times	Closing times
Australia	AUS	ASX Accumulation Index—All Ordinaries	7:00pm	1:00am
Canada	CAN	Canada S&P/TSX-300 Total Return Index	9:30am	4:00pm
France	FRA	CAC All-Tradable Total Return Index	3:00am	11:30am
Germany	DEU	CDAX Total Return Index	3:00am	2:00pm
Italy	ITA	BCI Global Return Index	3:00am	11:30am
Japan	JPN	Nikko Securities Composite Total Return	7:00pm	1:00am
Netherlands	NLD	All-Share Return Index	3:00am	11:30am
Sweden	SWE	OMX Stockholm Benchmark Gross Index	3:00am	11:30am
Switzerland	CHE	Swiss Performance Index	3:00am	11:20am
United Kingdom	GBR	FTSE All-Share Return Index	3:00am	11:30am
United States	USA	S&P 500 Total Return Index	9:30am	4:00pm

This table shows the country codes that are used for each country in the second column. The third column shows the data series name of the stock return indices from Global Financial data. The fourth and fifth column show the opening and closing times of the stock markets that are reported by Rapach et al. (2013) respectively. The times are expressed in the Eastern Standard Time.

Table 15: Information on excluding the last trading day for the replication part

	AUS	CAN	FRA	DEU	ITA	JPN	NLD	SWE	CHE	GBR	USA
AUS		1	1	1	1	0	1	1	1	1	1
CAN	0		0	0	0	0	0	0	0	0	0
FRA	0	1		1	0	0	0	0	0	0	1
DEU	0	1	0		0	0	0	0	0	0	1
ITA	0	1	0	1		0	0	0	0	0	1
JPN	0	1	1	1	1		1	1	1	1	1
NLD	0	1	0	1	0	0		0	0	0	1
SWE	0	1	0	1	0	0	0		0	0	1
CHE	0	1	0	1	0	0	0	0		0	1
GBR	0	1	0	1	0	0	0	0	0		1
USA	0	0	0	0	0	0	0	0	0	0	

This table shows when we exclude the last trading day when computing the stock return. The rows indicate the country whose excess returns are used as a dependent variable. The columns indicate the country whose lagged excess returns are used as a predictor. A 1 indicates that we exclude the last trading day and a 0 indicates that we include the last trading day when computing the stock returns.

Table 16: Information on the stock indices used in the extension and the opening and closing times of the stock markets

Country	Country code	Stock index	Opening times	Closing times
Austria	AUT	ATX	6:55	15:35
Belgium	BEL	BEL-20 Index	7:00	15:30
Denmark	DNK	OMX Copenhagen 20 Index	7:00	15:00
Finland	FIN	OMX Helsinki 25 Index	7:00	15:30
France	FRA	CAC 40 Index	7:00	15:30
Germany	DEU	DAX	6:00	18:00
Ireland	IRL	ISEQ (Irish Stock Exchange) Overall Index	7:00	15:30
Italy	ITA	FTSE MIB Index	7:00	15:30
Netherlands	NLD	Amsterdam AEX Index	7:00	15:30
Norway	NOR	Oslo Stock Exchange Equity Index	7:00	15:30
Spain	ESP	IBEX 35 Index	7:00	15:30
Sweden	SWE	OMX Stockholm 30 Index	7:00	15:30
Switzerland	CHE	Swiss Market Index SMI Index	7:00	15:30
United Kingdom	GBR	FTSE 100 Index GBP	7:00	15:30
United States	USA	S&P 500 Index	13:30	20:00

This table shows the country codes that are used for each country in the second column. The third column shows the stock index that we use for that country. The fourth and fifth column show the opening and closing times of the stock markets. The times are expressed in the Greenwich Mean Time. The stock index data are from http://markets.wsj.com/, with the exceptions being those of Austria and Sweden, where the data are from https://finance.yahoo.com/. We use the opening and closing times that are reported on https://www.stockmarketclock.com/exchanges, with the exceptions being the stock markets of Belgium and the Netherlands, where we use the times reported on https://www.beurstijden.nl/openingstijden-aandelenbeurzen/.

Table 17: Information on excluding the last trading day for the extension

	AUT	BEL	DNK	FIN	FRA	DEU	IRL	ITA	NLD	NOR	ESP	SWE	CHE	GBR	USA
AUT		0	0	0	0	1	0	0	0	0	0	0	0	0	1
BEL	1		0	0	0	1	0	0	0	0	0	0	0	0	1
DNK	1	1		1	1	1	1	1	1	1	1	1	1	1	1
FIN	1	0	0		0	1	0	0	0	0	0	0	0	0	1
FRA	1	0	0	0		1	0	0	0	0	0	0	0	0	1
DEU	0	0	0	0	0		0	0	0	0	0	0	0	0	1
IRL	1	0	0	0	0	1		0	0	0	0	0	0	0	1
ITA	1	0	0	0	0	1	0		0	0	0	0	0	0	1
NLD	1	0	0	0	0	1	0	0		0	0	0	0	0	1
NOR	1	0	0	0	0	1	0	0	0		0	0	0	0	1
ESP	1	0	0	0	0	1	0	0	0	0		0	0	0	1
SWE	1	0	0	0	0	1	0	0	0	0	0		0	0	1
CHE	1	0	0	0	0	1	0	0	0	0	0	0		0	1
GBR	1	0	0	0	0	1	0	0	0	0	0	0	0		1
USA	0	0	0	0	0	0	0	0	0	0	0	0	0	0	

This table shows when we exclude the last trading day when computing the stock return. The rows indicate the country whose excess returns are used as a dependent variable. The columns indicate the country whose lagged excess returns are used as a predictor. A 1 indicates that we exclude the last trading day and a 0 indicates that we include the last trading day when computing the stock returns.

Table 18: Summary statistics of the excess stock returns with additional European countries

Country	Mean (%)	Stand Dev (%)	Minimum (%)	Maximum (%)	Autocorrelation	Sharpe Ratio
AUT	0.31	6.10	-28.23	14.35	0.24	0.05
BEL	0.09	4.92	-21.82	14.26	0.23	0.02
DNK	0.57	5.46	-19.24	20.06	0.11	0.10
FIN	0.53	6.72	-21.22	30.52	0.25	0.08
FRA	0.15	5.41	-17.77	13.14	0.12	0.03
DEU	0.44	6.34	-25.70	21.17	0.08	0.07
IRL	0.17	6.01	-21.83	19.38	0.18	0.03
ITA	0.52	12.11	-17.01	154.95	0.03	0.04
NLD	0.03	5.74	-20.52	15.41	0.09	0.01
NOR	0.14	8.16	-74.47	16.99	0.09	0.02
ESP	0.08	6.14	-21.60	16.57	0.06	0.01
SWE	0.05	7.70	-75.05	17.15	0.03	0.01
CHE	0.12	4.37	-19.10	13.59	0.18	0.03
GBR	-0.08	4.05	-13.50	8.36	0.01	-0.02
USA	0.26	4.42	-17.24	10.74	0.10	0.06

This table shows the summary statistics of the monthly excess stock returns of a stock market index for that country, including the additional European countries. Stand Dev denotes the standard deviation of the excess stock returns. The Sharpe Ratio is calculated by dividing the mean of the excess returns by the standard deviation of the excess returns.

Table 19: Results of the Benchmark Predictive Regression Model with U.S. variables as predictors

country	$\hat{\beta}_{i,b}$	$\hat{\beta}_{i,d}$	R^2	country	$\hat{\beta}_{i,b}$	$\hat{\beta}_{i,d}$	R^2
AUS	-0.20*	0.79	0.95%	NLD	-0.03	0.88	0.38%
	(-1.83)	(1.19)	(3.38)		(-0.22)	(1.03)	(1.53)
	[0.05]	[0.26]	[0.23]		[0.56]	[0.36]	[0.56]
CAN	-0.29*	0.99	2.42%*	SWE	-0.05	1.41	0.60%
	(-2.39)	(1.13)	(6.22)		(-0.36)	(1.22)	(2.12)
	[0.02]	[0.36]	[0.09]		[0.47]	[0.24]	[0.40]
FRA	-0.05	0.33	0.04%	CHE	-0.08	0.57	0.22%
	(-0.34)	(0.36)	(0.15)		(-0.87)	(0.78)	(0.79)
	[0.47]	[0.58]	[0.95]		[0.32]	[0.47]	[0.76]
DEU	-0.05	0.66	0.15%	GBR	-0.16	1.72*	1.49%*
	(-0.39)	(0.67)	(0.50)		(-1.45)	(2.51)	(6.38)
	[0.48]	[0.48]	[0.83]		[0.15]	[0.03]	[0.07]
ITA	0.06	0.02	0.07%	USA	-0.19	1.61	1.51%
	(0.30)	(0.02)	(0.18)		(-1.66)	(2.03)	(4.15)
	[0.72]	[0.63]	[0.93]		[0.12]	[0.12]	[0.25]
JPN	-0.03	0.68	0.21%	Pooled	-0.10	0.88	0.44%
	(-0.26)	(0.80)	(0.93)		(-0.97)	(1.25)	(1.57)
	[0.51]	[0.33]	[0.65]		[0.30]	[0.31]	[0.58]

This table shows the parameter estimates of the benchmark predictive regressions as well as the R^2 of these regressions, but with using the U.S. variables as predictors. So $bill_{i,t}$ and $dy_{i,t}$ are $bill_{USA,t}$ and $dy_{USA,t}$ respectively for all countries. The numbers in parentheses represent the heteroskedasticity-robust t-statistics in the columns for $\hat{\beta}_{i,b}$ and $\hat{\beta}_{i,d}$, and heteroskedasticity-robust χ^2-statistics in the columns for the R^2. The numbers in brackets represent the p-values based on the wild-bootstrap procedure. The pooled estimates are obtained by imposing slope homogeneity restrictions on $\hat{\beta}_{i,b}$ and $\hat{\beta}_{i,d}$. Significant coefficients at a 10% significance level are indicated with a *.

Table 20: Results of the Pairwise Granger Causality Tests in combination with Principal Component Analysis

Country	$\hat{\beta}_{i,AUS}$	$\hat{\beta}_{i,CAN}$	$\hat{\beta}_{i,FRA}$	$\hat{\beta}_{i,DEU}$	$\hat{\beta}_{i,ITA}$	$\hat{\beta}_{i,JPN}$	$\hat{\beta}_{i,NLD}$	$\hat{\beta}_{i,SWE}$	$\hat{\beta}_{i,CHE}$	$\hat{\beta}_{i,GBR}$	$\hat{\beta}_{i,USA}$
AUS		0.10	0.12*	0.13*	0.08*	0.09*	0.13*	0.08*	0.11*	0.07	0.20*
		(1.29)	(1.88)	(1.99)	(2.26)	(1.88)	(1.74)	(1.86)	(1.57)	(0.89)	(2.24)
		[0.11]	[0.03]	[0.02]	[0.01]	[0.03]	[0.04]	[0.04]	[0.06]	[0.19]	[0.01]
		0.96%	1.58%	1.77%	1.49%	1.21%	1.62%	1.09%	1.02%	0.66%	2.26%
CAN	0.04		0.05	0.05	0.05	0.05	0.04	0.15*	0.07	0.07	0.21*
	(0.69)		(1.06)	(1.09)	(1.25)	(1.08)	(0.62)	(3.68)	(0.89)	(0.99)	(2.14)
	[0.25]		[0.15]	[0.14]	[0.11]	[0.14]	[0.27]	[0.00]	[0.19]	[0.17]	[0.01]
	2.89%		3.08%	3.07%	3.23%	3.05%	2.92%	6.03%	3.08%	3.07%	4.31%
FRA	0.01	0.002		-0.02	-0.04	0.04	0.02	0.15*	0.16*	0.04	0.12
	(0.18)	(0.02)		(-0.20)	(-0.78)	(0.61)	(0.17)	(2.50)	(1.56)	(0.32)	(1.28)
	[0.44]	[0.50]		[0.58]	[0.76]	[0.29]	[0.42]	[0.01]	[0.07]	[0.37]	[0.13]
	1.79%	1.78%		1.79%	1.94%	1.91%	1.79%	3.92%	2.67%	1.83%	2.29%
DEU	0.03	0.10	0.12*		0.06*	0.10*	0.08	0.16*	0.25*	0.09	0.22*
	(0.45)	(1.25)	(1.40)		(1.38)	(1.58)	(0.77)	(2.73)	(2.23)	(0.96)	(2.29)
	[0.35]	[0.12]	[0.09]		[0.10]	[0.06]	[0.25]	[0.00]	[0.02]	[0.18]	[0.01]
	1.39%	1.77%	1.91%		1.69%	2.08%	1.51%	3.39%	3.10%	1.63%	3.00%
ITA	-0.001	0.06	0.16*	0.12		0.05	-0.03	0.07	0.22*	0.15*	0.13
	(-0.01)	(0.66)	(1.58)	(1.31)		(0.69)	(-0.27)	(1.07)	(1.98)	(1.45)	(1.36)
	[0.52]	[0.28]	[0.08]	[0.12]		[0.27]	[0.60]	[0.15]	[0.03]	[0.08]	[0.10]
	2.30%	2.43%	3.34%	2.89%		2.43%	2.33%	2.60%	3.81%	3.03%	2.80%
JPN	0.04	0.12*	0.11*	0.03	0.03		0.08	0.09*	0.11*	0.12*	0.11*
	(0.70)	(1.72)	(2.03)	(0.52)	(0.83)		(1.31)	(1.80)	(1.61)	(1.77)	(1.47)
	[0.26]	[0.05]	[0.03]	[0.33]	[0.21]		[0.10]	[0.04]	[0.06]	[0.05]	[0.08]
	1.90%	2.68%	2.78%	1.85%	1.95%		2.27%	2.75%	2.50%	2.63%	2.42%
NLD	0.10	0.15*	0.14*	0.15*	0.04	0.12*		0.17*	0.32*	0.12	0.33*
	(1.38)	(1.88)	(2.00)	(1.68)	(0.97)	(2.38)		(2.96)	(3.04)	(1.19)	(3.46)
	[0.11]	[0.04]	[0.02]	[0.05]	[0.18]	[0.01]		[0.00]	[0.00]	[0.13]	[0.00]
	2.53%	2.98%	2.83%	2.77%	2.09%	3.09%		4.42%	5.00%	2.36%	5.01%
SWE	-0.04	0.15*	0.03	0.06	0.08	0.05	-0.005		0.10	0.09	0.23*
	(-0.42)	(1.65)	(0.40)	(0.73)	(1.03)	(0.69)	(-0.05)		(1.01)	(0.86)	(2.15)
	[0.67]	[0.06]	[0.35]	[0.27]	[0.21]	[0.28]	[0.52]		[0.17]	[0.23]	[0.02]
	2.47%	3.26%	2.44%	2.56%	2.84%	2.53%	2.40%		2.69%	2.67%	3.88%
CHE	0.03	0.03	0.003	-0.004	0.005	0.03	0.02	0.13*		0.03	0.13*
	(0.53)	(0.43)	(0.04)	(-0.05)	(0.13)	(0.63)	(0.33)	(3.32)		(0.44)	(1.48)
	[0.33]	[0.37]	[0.48]	[0.54]	[0.45]	[0.28]	[0.39]	[0.00]		[0.35]	[0.08]
	4.39%	4.38%	4.31%	4.31%	4.32%	4.41%	4.34%	6.70%		4.36%	5.04%
GBR	0.09	0.06	0.05	-0.001	-0.003	0.08*	-0.03	0.09*	0.09		0.22*
	(1.26)	(0.81)	(0.74)	(-0.01)	(-0.09)	(1.58)	(-0.37)	(2.07)	(1.19)		(2.04)
	[0.13]	[0.24]	[0.25]	[0.50]	[0.54]	[0.07]	[0.63]	[0.02]	[0.13]		[0.03]
	0.72%	0.43%	0.39%	0.18%	0.18%	0.80%	0.24%	1.32%	0.59%		2.02%
USA	0.06	0.04	0.002	-0.02	0.05*	-0.001	0.01	0.09*	0.03	0.02	
	(1.06)	(0.39)	(0.04)	(-0.31)	(1.41)	(-0.02)	(0.15)	(2.27)	(0.35)	(0.23)	
	[0.18]	[0.34]	[0.47]	[0.60]	[0.09]	[0.50]	[0.43]	[0.01]	[0.36]	[0.42]	
	1.21%	0.94%	0.87%	0.90%	1.41%	0.87%	0.88%	2.18%	0.92%	0.89%	
Average	0.04	0.08	0.08	0.05	0.04	0.06	0.03	0.12	0.15	0.08	0.19
Pooled	0.03	0.07*	0.08*	0.05	0.03	0.06*	0.02	0.11*	0.13*	0.08*	0.17*
	(0.63)	(1.32)	(1.88)	(1.02)	(1.22)	(1.51)	(0.36)	(3.50)	(2.18)	(1.45)	(2.93)
	[0.28]	[0.10]	[0.03]	[0.17]	[0.13]	[0.07]	[0.35]	[0.00]	[0.02]	[0.09]	[0.00]
	1.45%	1.50%	1.64%	1.47%	1.55%	1.52%	1.28%	2.42%	1.87%	1.72%	2.55%

This table shows the parameter estimates of $\beta_{i,j}$ in the regressions for the pairwise Granger causality tests as well as the R^2 of these regressions. Here we use multiple economic variables and we use principal component analysis to extract the first two factors of those variables. Subsequently, we use these factors instead of $bill_{i,t}$ and $dy_{i,t}$ in the regressions. The numbers in parentheses represent the heteroskedasticity-robust t-statistics. The numbers in brackets represent the p-values based on the wild-bootstrap procedure. The fourth row for every country, the value below the p-values, denotes the R^2 values for the regressions. The row average denotes the average of the $\hat{\beta}_{i,j}$ values for a specific j, so it's the average of the $\hat{\beta}_{i,j}$ values in that column. The pooled estimates are obtained by imposing a slope homogeneity restriction on $\hat{\beta}_{i,j}$, as well as on the other slope parameters. Significant coefficients at a 10% significance level are indicated with a *.

Table 21: Results for the General Model Specification with pooled estimates for U.S. returns and the returns of one non-U.S. country

Country	$\hat{\bar{\beta}}_{USA}$	Conf. int.	$\hat{\bar{\beta}}_j$	Conf. int.	Country	$\hat{\bar{\beta}}_{USA}$	Conf. int.	$\hat{\bar{\beta}}_j$	Conf. int.
AUS	0.18*	[0.07, 0.28]	-0.02	[-0.10, 0.07]	JPN	0.16*	[0.07, 0.25]	0.03	[-0.03, 0.10]
CAN	0.19*	[0.08, 0.29]	-0.02	[-0.12, 0.08]	NLD	0.20*	[0.11, 0.29]	-0.06	[-0.14, 0.03]
FRA	0.16*	[0.06, 0.26]	0.03	[-0.04, 0.09]	SWE	0.14*	[0.04, 0.23]	0.07*	[0.03, 0.12]
DEU	0.17*	[0.07, 0.27]	0.001	[-0.07, 0.07]	CHE	0.15*	[0.04, 0.25]	0.06	[-0.04, 0.16]
ITA	0.17*	[0.07, 0.26]	0.02	[-0.03, 0.06]	GBR	0.17*	[0.06, 0.28]	0.005	[-0.10, 0.11]

This table shows the pooled parameter estimates of U.S. returns and of the returns of one non-U.S. country, denoted by $\hat{\bar{\beta}}_{USA}$ and $\hat{\bar{\beta}}_j$ respectively. We run this regression for every non-U.S. country separately. The numbers in brackets represent the 90% confidence interval based on the wild-bootstrap procedure. Significant coefficients at a 10% significance level are indicated with a *.

Table 22: Out-of-sample forecasting power of lagged returns of the U.S.

	Baseline: historical average		Baseline: AR		Baseline: BM predictive	
Country	R^2_{OS}	R^2_{OS}, pooled	R^2_{OS}	R^2_{OS}, pooled	R^2_{OS}	R^2_{OS}, pooled
AUT	3.53%*	4.16%*	-0.98%	-1.43%	0.81%	6.21%*
	(1.62)	(1.67)	(0.38)	(0.67)	(1.15)	(3.35)
BEL	6.54%*	6.22%*	0.30%	0.13%*	2.59%*	7.55%*
	(2.27)	(2.18)	(1.09)	(1.59)	(1.84)	(3.45)
DNK	8.27%*	8.22%*	6.61%*	8.11%*	5.51%*	11.28%*
	(3.09)	(3.05)	(2.68)	(3.12)	(2.92)	(4.49)
FIN	3.87%*	4.11%*	-4.00%	1.52%*	1.40%*	6.94%*
	(2.30)	(2.33)	(-2.02)	(1.41)	(1.61)	(4.15)
FRA	1.14%*	0.06%*	-0.79%	-0.83%*	0.24%	3.53%*
	(1.34)	(1.32)	(0.06)	(2.12)	(0.82)	(2.68)
DEU	2.52%*	2.80%*	1.54%*	2.35%*	1.18%*	3.82%*
	(1.97)	(2.07)	(1.45)	(1.83)	(1.53)	(3.40)
IRL	5.36%*	6.57%*	1.47%*	3.18%*	3.45%*	2.92%*
	(2.27)	(2.45)	(1.68)	(2.86)	(2.10)	(3.10)
ITA	0.52%*	1.00%*	2.09%	3.56%*	0.46%*	5.49%*
	(1.71)	(1.59)	(1.28)	(2.51)	(1.68)	(1.75)
NLD	2.79%*	2.78%*	1.01%*	2.86%*	1.49%*	4.74%*
	(1.89)	(1.81)	(1.53)	(1.56)	(1.61)	(2.98)
NOR	2.53%*	2.50%*	-2.19%	2.67%*	1.54%*	2.75%*
	(2.01)	(1.97)	(0.98)	(1.91)	(1.67)	(1.86)
ESP	-0.31%	-1.61%	-0.80%	-1.32%*	-0.38%	-1.77%*
	(0.59)	(0.66)	(0.10)	(3.03)	(0.12)	(1.70)
SWE	-1.57%	-2.92%	-0.81%	-2.19%	-1.87%	21.91%*
	(-1.13)	(0.62)	(-0.55)	(0.73)	(-1.92)	(2.54)
CHE	1.92%*	-0.27%*	-1.03%	-4.72%*	0.70%*	1.41%*
	(1.84)	(1.70)	(0.10)	(1.74)	(1.34)	(3.18)
GBR	-0.44%	-3.60%	1.20%	-2.09%*	-0.34%	-7.26%*
	(0.37)	(0.95)	(1.28)	(3.54)	(0.19)	(2.01)
AVG	2.62%	2.14%	0.26%	0.84%	1.20%	4.97%

This table shows the out-of-sample R^2, denoted by R^2_{OS}, of our forecasting models against three different baseline models. For the forecasting model we add the lagged returns of the U.S. to the baseline model. The columns with "pooled" report the R^2_{OS} value, where we impose a slope homogeneity restriction on the parameter of the lagged returns of the U.S. in the forecasting model, that is $\beta_{i,USA} = \bar{\beta}_{USA}$. The numbers in parentheses represent the MSFE-adjusted statistics. The row AVG represents the average of the R^2_{OS} values for a specific forecasting model. Significant results at a 10% significance level are indicated with a *. AR is a first-order autoregressive model and BM predictive is the benchmark predictive regression model.