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An Anatomy of the Predictability of International Stock Returns*

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Abstract

This paper gives a better understanding of the lead-lag relationships in the international stock return market. Firstly, we reproduce the outcomes of Rapach et al. (2013) and also conclude that there is a significant predictive ability between countries. Similar to Rapach et al. (2013), we find that the most dominant predictors for international excess returns are the United States' excess returns. Secondly, we further investigate the predictive ability, by examining the predictive ability of positive and negative lagged excess returns, lagged excess returns in months of high and low volatility, and the predictive ability of lagged excess returns during U.S. recession or U.S. economic growth. We conclude that the general predictive ability of positive and negative lagged excess returns is equal, but differs for specific countries. When making a distinction between the predictive ability of lagged excess returns in months of high and low volatility, we conclude that the months with high volatility have more predictive ability. Furthermore, we see that the lagged United States' excess returns in times of U.S. Recessions have more predictive ability than the lagged excess returns during American economic growth.

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1 Introduction

Stock return predictability is a widely researched topic. Rapach et al. (2013) investigate the predictive power of other countries lagged excess returns and conclude that there is a lead-lag relationship in the international stock return markets. Before international stock excess returns were considered as predictors for excess returns, national economic variables were used as predictors. Ang and Bekaert (2007) describe how the nominal interest rate and the dividend yield are two important variables for predicting returns. Stambaugh (1999) examines the method of regressing returns on lagged stochastic regressors, and discovers a bias, which is important to control for. Eventually, Ang and Bekaert (2007) and Hjalmarsson (2010) conclude that the predictive ability across countries is larger than the predictive ability of these national economic variables. Therefore, we investigate the international stock return model as mentioned by Rapach et al. (2013), because it incorporates these across countries components. In order to evaluate both in-sample and out-of-sample performance, Welch and Goyal (2008) provide a framework to determine the usefulness of the models for predicting excess stock returns. This paper mainly discusses the in-sample evaluation, and focuses on the lead-lag relationships in the international stock return markets.

Rapach et al. (2013) conclude that the lagged international excess returns, with lagged United States' excess returns in particular, have predictive ability. Based on this finding we further examine this lead-lag relationship. Firstly, we make a distinction between the predictive ability of lagged positive and negative excess returns of a specific country for forecasting another country's excess returns. In general we conclude that the predictive ability is equally strong for positive and negative excess returns, as the number of significant estimates overall is similar. Nonetheless, the predictive ability of positive and lagged excess returns differs for specific countries, with Canada amongst others having a large predictive ability when using lagged negative excess returns and no predictive ability of the lagged positive excess returns. Secondly, we estimate the predictive ability of the returns of a specific country by distinguishing the excess returns in months of high and low volatility, to find if the predictive ability is different. We conclude that lagged excess returns in months of high volatility have larger predictive ability than excess returns in months with low volatility. For the United Kingdom and the United States, this effect is particularly strong. Lastly, as Rapach et al. (2013) conclude that lagged U.S. monthly excess returns have a substantial predictive ability, we examine the predictive ability during U.S. recessions and times of a growing U.S. economy. The results show that the lagged U.S. excess returns in times of U.S. recessions have more predictive ability than in times of a growing U.S. economy. The above mentioned results give a better understanding of the lead-lag relationships in the international stock markets, and contribute to existing scientific literature on the subject and should be of interest to the investor community.

2 Data

In order to investigate the lead-lag relationships in the international stock markets, we use data[1] for the following countries: Australia (AUS), Canada (CAN), France (FRA), Germany (DEU), Italy (ITA), Japan (JPN), The Netherlands (NLD), Sweden (SWE), Switzerland (CHE), United Kingdom (GBR) and the United States (USA).

[1]The data used is from the Global Financial Data.

When regressing country i's monthly[2] excess returns on country j's lagged monthly excess returns, we adjust for the fact that that markets around the world have different closing times[3]. This is crucial because released information at the last trading day of the month in an open market cannot be incorporated into the price of the closed markets until the first day of the next month. We solve this by excluding the last trading day of the month of a country j if the closing time of country i's market is before the closing time of country j's market and calculating the monthly returns without this last trading day. This adjustment is done for all of the following models. We compute the monthly returns from daily closing prices which are available from 1980 for all eleven countries. The returns for every country are computed using the national currency. We choose the same sample as Rapach et al. (2013), from February 1980 (1980:02) up to and including December 2010 (2010:12). The excess returns are computed by subtracting the risk free rate of the monthly returns. The risk free rate is the three month Treasury bill rate at the end of the specific month. Moreover, we use dividend yield data which we incorporate in the regressions.

Table 1: Summary Statistics

The table shows summary statistics of the countries' excess returns, calculated by the difference between the return and the three-month Treasury bill rate. Column two up to and including column five are reported in percentages. The Sharpe ratio is computed by dividing the mean excess return of a country by its standard deviation.

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

The summary statistics are reported in Table 1. Firstly, one sees that the average monthly excess returns in the sample for the different countries range between 0.22% in Japan and 1.03% in Sweden. Secondly, the largest standard deviation occurs for Sweden, with a value of 6.73%. Furthermore, the U.S. has the smallest standard deviation, namely 4.5%. Thirdly, Australia, with an average excess return of 0.35%, has the largest negative excess return in the sample, being -43.06%, while Sweden has the largest positive excess return (33.90%). Besides having the highest positive excess return, Sweden seems to have relatively high returns overall, with a minimum of -22.61%. Fourthly, the autocorrelations are ranging from 0.02 for the UK, to 0.18 for Switzerland. Lastly, the Sharpe ratios are all relatively small, which is due to the fact that this ratio is calculated by dividing the mean of the excess returns, which is close to zero, by the standard deviation. The highest ratio of 0.15 is for Sweden, which shows that Sweden on average has the highest risk adjusted return.

[2]Throughout the paper, we use monthly excess returns, but for simplicity we write excess returns.

[3]The specific closing times are mentioned in Appendix A.

3 Methodology

In the methodology, we discuss all relevant methods that are used throughout the paper. Firstly, we reproduce some of the methods of Rapach et al. (2013). Secondly, our own extensions for the international stock excess return prediction model are discussed.

3.1 Replication

In the Replication part, we thus describe the methods introduced by Rapach et al. (2013). Firstly, the Benchmark Regression is covered. Secondly, we discuss the Pairwise Granger Causality model, which will be fundamental for our extensions. Thirdly, the General Model Specification of Rapach et al. (2013) is explained, and lastly, the Out-of-Sample Evaluation is mentioned.

3.1.1 Benchmark Predictive Regressions

As stated by Ang and Bekaert (2007), two important predictors for stock prices are the nominal interest rate and the dividend yield. In order to recreate the benchmark model of Rapach et al. (2013) for predicting excess returns, we only use these two variables and a constant in the following regression:

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

where $r_{i,t+1}$ is the excess return during the period from month t until month $t+1$ of country i, $bill_{i,t}$ is the three-month Treasury bill rate at the end of month t of country i, and $dy_{i,t}$ is the natural logarithm of the dividend yield at the end of month t of country i. The coefficients $\beta_{i,0}, \beta_{i,b}$, and $\beta_{i,d}$ correspond to the constant, the coefficient of the nominal interest rate variable, and the coefficient of the log dividend yield variable respectively. The error term $\epsilon_{i,t+1}$ has a mean equal to zero.

Because this implies a regression of returns on to a stochastic lagged regressor (dividend yield), we compute empirical p-values (next to heteroskedasticity robust t-statistics) with a variant of the wild bootstrap procedure. This covers the bias discovered in Stambaugh (1999). The variant of the wild bootstrap procedure[4] is explained in detail in the Internet Appendix of Rapach et al. (2013). The t-statistics and wild bootstrapped p-values are following from testing $H_0 : \beta_{i,b} = 0$ and $H_0 : \beta_{i,d} = 0$ against $H_a : \beta_{i,b} < 0$ and $H_a : \beta_{i,d} > 0$ repsectively. Furthermore, we test for no predictability at all by means of a χ^2 statistic, testing $H_0 : \beta_{i,b} = \beta_{i,d} = 0$

3.1.2 Pairwise Granger Causality for Full Sample

In order to extend the benchmark model, Rapach et al. (2013) add lagged excess returns of the country corresponding to the dependent variable (country i) and lagged excess returns of a different country (country j) to (1). The extended model is as follows:

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

where $r_{i,t}$ and $r_{j,t}$ are excess returns for the period from the end of month $t-1$ up to and including month t for countries i and j respectively and $\beta_{i,i}$ and $\beta_{i,j}$ are the coefficients for these lagged excess returns respectively.

[4] Throughout the rest of the paper, this method will be called wild bootstrap procedure.

The other factors have similar interpretation as in subsubsection 3.1.1. We perform a test for Granger Causality by testing if the lagged excess returns of country j Granger cause the excess returns of country i. This is done by testing the significance of $\beta_{i,j}$ in equation (2).

Apart from including the effect of $r_{j,t}$ on $r_{i,t+1}$, the addition of country i's own excess returns $r_{i,t}$ and the country i's national variables $bill_{i,t}$ and $dy_{i,t}$ is of importance, in order to control for the part that is predicted by these national economic variables. Because we include lagged excess returns from country j as a predictor for country i's excess return, we adjust for differences in the closing times for the different markets as described in section 2.

Furthermore, a pooled estimation is performed with the restrictions that $\beta_{i,i} = \bar{\beta}_{AR}, \beta_{i,j} = \bar{\beta}_j, \beta_{i,b} = \bar{\beta}_b$ and $\beta_{i,d} = \bar{\beta}_d$ for $i = 1 \ldots N$, to obtain an idea about the average relationship for the used data. Again, the significance of the $\beta_{i,j}$ estimates is based on the empirical bias corrected p-values, according to the wild bootstrap procedure. Also, heteroskedasticity robust t-statistics are computed. Both methods for assigning significance follow from testing $H_0 : \beta_{i,j} = 0$ against $H_a : \beta_{i,j} > 0$[5].

3.1.3 General Model Specification

The general model for assessing the predictive ability of different countries on the excess returns of a specific country i is a VAR(1) model for all of the countries, with the country i's economic variables as additional regressors. The regression specification as mentioned by Rapach et al. (2013) is as follows:

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

The interpretation of the $\beta_{i,j}$ coefficients is similar to the interpretation in subsubsection 3.1.2, but now, the lagged excess returns of all countries are included in the regression. The seminal least absolute shrinkage and selection operator (LASSO), introduced by Tibshirani (1996), is a method for parameter shrinkage and variable selection. Due to some complications, the improvement of this model resulted in the adaptive elastic net (Zou and Zhang (2009), Ghosh (2011)). The estimates of the $\beta_{i,j}$ are obtained by using this adaptive elastic net, as explained in detail in the Internet Appendix of Rapach et al. (2013). In order to evaluate the parameter estimates, we construct a 90% confidence interval with the bias-corrected wild bootstrap method. We furthermore perform a pooled version of (3), which consists of the homogeneity restrictions: $\beta_{i,i} = \bar{\beta}_{AR}, \beta_{i,j} = \bar{\beta}_j, \beta_{i,b} = \bar{\beta}_b$, and $\beta_{i,d} = \bar{\beta}_d$, for i = 1, ..., N.

3.1.4 Out-of-Sample evaluation

Although in-sample evaluation can show a significant indication of international stock return predictability, Welch and Goyal (2008) show that the out-of-sample forecasts of these models often fail to outperform the baseline model, using the historical average as predictor. The historical average forecast is performed as follows:

$$r_{i,t+1} = \beta_{i,0} + \epsilon_{i,t+1} \tag{4}$$

where $\beta_{i,0}$ is the average of the excess returns from the start of the sample period up to and including the last observation at time t. This model is compared to the following model which incorporates lagged U.S. excess

[5] For the replications, both t-statistics and bootstrapped p-values follow from testing this hypothesis.

returns as dependend variable:

$$r_{i,t+1} = \beta_{i,0} + \beta_{i,USA} r_{USA,t} + \epsilon_{i,t+1} \qquad i \neq USA \tag{5}$$

Following this specification, the prediction of the excess return of time $t+1$ is computed by estimating the coefficients of the regression with data up to and including time t. The forecasting period is from January 1985 to October 2010. In order to compare the models as stated in equation (4) and (5), the out-of-sample R^2_{OS}, as mentioned in Campbell and Thompson (2008), and the adjusted mean squared forecast error (MSFE) mentioned by Clark and West (2007) are used. The above mentioned out-of-sample evaluation follows from Rapach et al. (2013).

For the extensions, the out-of-sample evaluation is not needed, because the data is transformed. Due to these transformations, there is no continuous time line to predict, thus an out-of-sample evaluation is irrelevant. Furthermore, the focus of the extensions is not to make a good prediction model, but to understand the predictive ability of different type of returns.

3.2 Extensions

In this section, we discuss our extensions on the Pairwise Granger Causality model introduced by Rapach et al. (2013). Firstly, we examine the predictive power of lagged positive and negative excess returns. Secondly, we investigate the predictive power of lagged excess returns in months of high and low volatility, and lastly, we analyse the predictive ability of lagged U.S. excess returns in times of U.S. Recessions and economic growth.

3.2.1 Impact of Positive and Negative Returns

Because Rapach et al. (2013) conclude that international lagged excess returns have a significant impact on country i's excess returns, we further investigate this lead-lag relationship. In this section, we assess the difference in the predictive ability of the positive and negative international lagged excess returns. We do so by performing the following regressions:

$$r_{i,t+1} = \beta_{i,0} + (\beta_{i,i} r_{i,t} + \beta_{i,j} r_{j,t} + \beta_{i,b} bill_{i,t} + \beta_{i,d} dy_{i,t}) I(r_{j,t} \geq 0) + \epsilon_{i,t+1} \qquad i \neq j \tag{6}$$

$$r_{i,t+1} = \beta_{i,0} + (\beta_{i,i} r_{i,t} + \beta_{i,j} r_{j,t} + \beta_{i,b} bill_{i,t} + \beta_{i,d} dy_{i,t})(1 - I(r_{j,t} < 0)) + \epsilon_{i,t+1} \qquad i \neq j \tag{7}$$

where $I(r_{j,t} \geq 0)$ is an indicator function having value 1 if $r_{j,t}$, the lagged excess return of country j, is larger or equal to zero and 0 if it is negative. The coefficients $\beta_{i,0}$,$\beta_{i,i}$, $\beta_{i,j}$, $\beta_{i,b}$, and $\beta_{i,d}$ in regression (6) have a similar interpretation as in equation (2), but are computed when only using the observations matching to the positive lagged excess returns of country j. The same holds for the coefficients in regression (7), using the observations matching the negative lagged excess returns of country j. The moving block bootstrapped p-values (and heteroskedasticity robust t-statistics) of the coefficient estimates are based on a moving block bootstrap procedure when testing $H_0 : \beta_{i,j} = 0$ against $H_a : \beta_{i,j} > 0$[6]. A wild bootstrap is not necessary because the data is divided into parts according to positive or negative lagged excess returns of country j[7]. Still, we use a

[6] For all $\beta_{i,j}$ in the extensions, this hypothesis for testing significance holds.

[7] For further extensions, the same argument for the moving block bootstrapped p-values holds.

moving block bootstrap because the observations have the characteristics of a time series. The moving block bootstrap procedure is explained in detail in subsubsection 3.2.4.

It is of great importance to be cautious when selecting the corresponding observations with the positive or negative lagged excess returns of country j. For every of the 110 regressions the selection of the observations for the lagged excess returns of country i, the Treasury bill and log dividend of country i has to match the periods where the lagged excess returns of country j is either positive or negative. If the closing time of country j is after the closing time of country i, it is important to choose the data matching the positive or negative lagged monthly excess returns of country j computed excluding the last trading day in the month. This implies that not all regressions when looking at positive or negative returns will contain the same number of observations.

If for example we look at if negative Japanese lagged excess returns Granger cause French excess returns and if negative Canadian lagged excess returns Granger cause French excess returns, the number of negative Japanese lagged excess returns can be different from the number of negative lagged Canadian excess returns. Additionally, for Canada, the number of lagged negative excess returns are based on the excess returns excluding last trading day, and for Japan, the regular negative lagged excess returns are used. The number of observations used for all of the variables in (7) will most likely be different for the above explained two cases.

3.2.2 Predictability of High and Lower Volatility Regimes

Apart from making a distinction in positive and negative returns, a distinction among periods of relative high and low volatility is also rather interesting to evaluate. Therefore, we specify the following regressions:

$$r_{i,t+1} = \beta_{i,0} + (\beta_{i,i} r_{i,t} + \beta_{i,j} r_{j,t} + \beta_{i,b} bill_{i,t} + \beta_{i,d} dy_{i,t}) I(vix_{j,t} \geq x_j) + \epsilon_{i,t+1} \qquad i \neq j \tag{8}$$

$$r_{i,t+1} = \beta_{i,0} + (\beta_{i,i} r_{i,t} + \beta_{i,j} r_{j,t} + \beta_{i,b} bill_{i,t} + \beta_{i,d} dy_{i,t})(1 - I(vix_{j,t} \geq x_j)) + \epsilon_{i,t+1} \qquad i \neq j \tag{9}$$

where $I(vix_{j,t} \geq x_j)$ is an indicator function with value 1 if the volatility index (vix) of country j is larger than or equal to x_j and 0 if the value is below x_j. For every month, we compute the monthly volatility with the daily closing prices by taking the standard deviation of the daily returns. The average monthly volatility of country j is used as the bound x_j.

The coefficients $\beta_{i,0}$, $\beta_{i,i}$, $\beta_{i,j}$, $\beta_{i,b}$, and $\beta_{i,d}$ in regression (8) have similar interpretations as explained for the previous regressions. However, in this regression only the observations matching to the lagged excess returns of country j corresponding to months with the volatility being higher than x_j are taken into account. The same holds for the coefficients in (9), when using observations matching to lagged excess returns of country j corresponding to months with volatility below x_j. The significance of the coefficient estimates is based on the moving block bootstrapped p-values.

Again, it is important to compute the regressors precisely. For all regressions, the data for the lagged variables is used depending on the volatility of the returns in the lagged month of country j. This again implies that the number of observations are all based on the characteristics of the information of country j, as previously described in subsubsection 3.2.1.

3.2.3 Predictability in Times of U.S. Recessions

Since Rapach et al. (2013) conclude that the predictive ability of the lagged U.S. excess returns is the greatest of all examined countries, we further research the U.S. predictive ability in more detail. Lagged excess returns in times of U.S. recession could have different impact on international excess returns than in times of a growing US economy. Equation (10) and (11) contain data of periods of U.S. recession and U.S. economic growth respectively.

$$r_{i,t+1} = \beta_{i,0} + (\beta_{i,i} r_{i,t} + \beta_{USA,1} r_{USA,t} + \beta_{i,b} bill_{i,t} + \beta_{i,d} dy_{i,t}) I_t(x) + \epsilon_{i,t+1} \qquad i \neq USA \tag{10}$$

$$r_{i,t+1} = \beta_{i,0} + (\beta_{i,i} r_{i,t} + \beta_{USA,0} r_{USA,t} + \beta_{i,b} bill_{i,t} + \beta_{i,d} dy_{i,t})(1 - I_t(x)) + \epsilon_{i,t+1} \quad i \neq USA \tag{11}$$

where $I_t(x)$ is an indicator function that has value 1 if it is stated that the US has been in an economic recession in month t and 0 if the US had an economic growth in the corresponding month t. In equation (10), only lagged observations are used for the months where the US has a recession, and in equation (11) the lagged observations during economic growth are used. Again, the significance of the coefficient estimates is based on the moving block bootstrapped p-values.

Furthermore, because Rapach et al. (2013) show that some of the national economic variables, such as the Treasury bill rate and or log dividend yield, have a significant influence on country i's excess returns, we will assess the predictive ability of these variables when using the observations in times of a U.S. recession and in times of U.S. economic growth. The following two regressions are performed:

$$r_{i,t+1} = \beta_{i,0} + (\beta_{i,b} bill_{i,t} + \beta_{i,d} dy_{i,t}) I_t(x) + \epsilon_{i,t+1} \tag{12}$$

$$r_{i,t+1} = \beta_{i,0} + (\beta_{i,b} bill_{i,t} + \beta_{i,d} dy_{i,t})(1 - I_t(x)) + \epsilon_{i,t+1} \tag{13}$$

where the coefficients have similar interpretations as before, but equation (12) and (13) use the observations in times of U.S. recession and U.S. economic growth respectively. The significance for the $\beta_{i,b}$ and $\beta_{i,d}$ is according to the moving block bootstrapped p-values when testing $H_0 : \beta_{i,b} = 0$ and $H_0 : \beta_{i,d} = 0$ against $H_a : \beta_{i,b} < 0$ and $H_a : \beta_{i,d} > 0$ respectively. In order to test no predictability at all, we compute the χ^2 statistic for testing $H_0 : \beta_{i,b} = \beta_{i,d} = 0$

3.2.4 Moving Block Bootstrap

In order to test for significant coefficient estimates, we compute moving block bootstrapped p-values for testing $H_0 : \beta_{x,y} = 0$ against $H_a : \beta_{x,y} > 0$. The p-values are computed as follows:

First, a regression under the null hypothesis $H_0 : \beta_{x,y} = 0$ is performed. For example, if we want to check the significance with the moving block bootstrap of the $\hat{\beta}_{i,j}$ in regression (6), we first evaluate the model under H_0, which means estimating the following regression:

$$r_{i,t+1} = \beta_{i,0} + (\beta_{i,i} r_{i,t} + \beta_{i,b} bill_{i,t} + \beta_{i,d} dy_{i,t}) I(r_{j,t} \geq 0) + \epsilon_{i,t+1} \qquad i \neq j \tag{14}$$

From this regression, we obtain the estimates $\hat{\beta}_{i,0}$, $\hat{\beta}_{i,i}$, $\hat{\beta}_{i,b}$ and $\hat{\beta}_{i,d}$ as well as the corresponding errors $\hat{e}_{t+1}$, for $t = 1, ..., T$.

Next, we start the bootstrapping process by defining a new dependent variable $\tilde{y}_{i,t+1}$, using the fixed regressors in (14), the estimated coefficients in this regression and the mutated errors $\tilde{e}_{i,t+1}$ which are computed as follows. First, the estimated errors $\hat{e}_{t+1}$, obtained from the regression (14) are divided into $T - L + 1$ blocks of size L. The first block contains observations $1, .., L$ of $\hat{e}_{t+1}$, the second block observations $2, ..., (L+1)$ all the way up to the last block, containing observations $(T - L + 1), ..., T$ of $\hat{e}_{t+1}$. From all of the $T - L + 1$ blocks, T/L blocks are randomly chosen (replication is allowed). With these chosen blocks, the new errors $\tilde{e}_{i,t+1}$ are created. If the division T/L is not an integer value, the value is rounded down on integers. Next, an extra block from the moving blocks is selected, and the remaining values for the error term $\tilde{e}_{i,t+1}$ are filled up by the values from the last randomly chosen block. The new dependent variable is computed as following:

$$\tilde{y}_{i,t+1} = \hat{\beta}_{i,0} + (\hat{\beta}_{i,i} r_{i,t} + \hat{\beta}_{i,b} bill_{i,t} + \hat{\beta}_{i,d} dy_{i,t}) I(r_{j,t} \geq 0) + \tilde{e}_{i,t+1} \qquad i \neq j \tag{15}$$

using the estimates of the regression in (14), the fixed regressors and the bootstrapped errors $\tilde{e}_{i,t+1}$.

Using $\tilde{y}_{i,t+1}$, a regression as in equation (6) is performed, but now with the bootstrapped $\tilde{y}_{i,t+1}$ as dependent variable:

$$\tilde{y}_{i,t+1} = \beta^*_{i,0} + (\beta^*_{i,i} r_{i,t} + \beta^*_{i,j} r_{j,t} + \beta^*_{i,b} bill_{i,t} + \beta^*_{i,d} dy_{i,t}) I(r_{j,t} \geq 0) + \epsilon_{i,t+1} \qquad i \neq j \tag{16}$$

As we now use a new dependent variable, a new $\hat{\beta}_{i,j}$ estimate is obtained.

When repeating this bootstrapping process 2000 times, we obtain 2000 $\hat{\beta}^*_{i,j}$ estimates for the 2000 regressions as stated in (16), which are all different due to the random nature of block selecting which leads to randomly selected $\tilde{e}_{i,t+1}$, and $\tilde{y}_{i,t+1}$. In order to compute the bootstrapped p-values for the $\beta_{i,j}$ estimate in (6), we calculate the proportion of the 2000 bootstrapped estimates of $\beta^*_{i,j}$ in (16) that is larger than the $\beta_{i,j}$ estimate.

With respect to the block size, there is a substantial trade off between the amount of samples we obtain and the amount correlation that we preserve. There, we perform a sensitivity analysis with block sizes of three, five, and ten. For every extension, we use a moving block bootstrap to calculate the p-values for the $\beta_{i,j}$ coefficient estimate which assigned the significance of the estimate. We investigate whether changing the block size gives different results. The results that are reported throughout the paper are based on a block size of five, which is the benchmark for the block sizes. Per extension, for block sizes of three and ten, we look at the percentage of estimates that lead to the same conclusion for significance as when using the benchmark block size of five. For the extensions in subsubsection 3.2.1 and subsubsection 3.2.2, we count the number of times the different block size (three or ten) gives equal significance to the $\beta_{i,j}$ estimates and divide this by the total number of regressions. For the extension in subsubsection 3.2.3, only ten regressions are performed for the United States, thus the proportion of equally assigned significance of these ten regressions is calculated.

4 Results

In this section, the results of the discussed models are reported and analysed. The results of the replications are mentioned first, after which the findings of the extensions are reported.

4.1 Replication

The results of the Benchmark Regression, the Pairwise Granger Causality model, the General Model Specification and the Out-of-Sample Evaluation are discussed in this section and are similar to the findings by Rapach et al. (2013).

4.1.1 Benchmark Regression

Table 2 reports the results of the benchmark regression as stated in equation (1). We can see that all $\beta_{i,b}$ estimates are negative except for Japan, and that except for Italy, all $\beta_{i,d}$ estimates are positive. The expectation of the effect of the Treasury bill rate and log dividend yield being negative and positive respectively thus holds. For the countries Canada, Germany, The Netherlands and the United Kingdom, the nominal interest rate is a significant predictor. However, the log dividend yield is only found to be a significant excess return predictor for the United Kingdom. Since in general returns are known to be highly unpredictable, low R^2 statistics occur. For the countries with a significant $\beta_{i,b}$ or $\beta_{i,d}$ estimate, the R^2 is higher than 1%.

Table 2: Benchmark Regression

This table shows estimates of the benchmark regression as described in equation (1). The second and sixth column contain the estimates for the coefficient of the Treasury bill rate with the heteroskedasticity-robust t-statistic, testing $H_0 : \beta_{i,b} = 0$ against $H_a : \beta_{i,b} < 0$, in the parentheses below and the third and seventh columns show the estimates for the coefficient of the log dividend yield with again the t-statistics, testing $H_0 : \beta_{i,d} = 0$ against $H_a : \beta_{i,d} > 0$, in the parentheses below. In the fourth and eighth column, the R^2 statistic for every regression is shown. In the parenthesis below these R^2 statistics, the χ^2 statistic for testing $H_0 : \beta_{i,b} = \beta_{i,d} = 0$ are stated. Furthermore, the pooled estimates are shown, which impose the restriction that $\beta_{i,b} = \bar{\beta}_b$ and $\beta_{i,d} = \bar{\beta}_d$. The asterisk indicates significance on 10% or better, based on wild bootstrapped p-values.

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

4.1.2 Granger Causality for Full Sample

In order to conclude if we can predict a country i's excess returns with lagged country j's excess returns, we test the significance of the estimate of $\beta_{i,j}$ in regression (2). The estimates of the $\beta_{i,j}$ coefficients are given in Table 3. We see that the estimates often are positive. For 98 out of the 110 regressions, the estimates are positive. Furthermore, 47 estimates are significant, which indicates a significant lead-lag relationship in the international stock market. The U.S. has the strongest predictive ability, with nine out of ten estimates being significant and most of the estimates being greater than 0.20. Sweden and Switzerland also seem to have high predictive ability, with nine and seven significant estimates respectively. Furthermore, it is interesting to see that the lagged excess returns of eight out of the ten countries Granger cause the excess returns of The Netherlands, with most of the $\beta_{NLD,j}$ estimates being larger or equal to 0.15. When testing the significant impact on U.S. excess returns, only two out of the ten non U.S. lagged excess return have significant predictability. When looking at the pooled results, which indicate the average relationships, eight out of the eleven estimates are significant, with the pooled $\hat{\bar{\beta}}_{USA}$ having the largest value of 0.17. The leading predictive ability of the U.S. is confirmed by the pooled results.

Table 3: Granger Causality

The table reports the $\beta_{i,j}$ estimates of regression (2). In the parenthesis below the coefficient estimates, heteroskedasticity-robust t-statistic are shown for testing $H_0 : \beta_{i,j} = 0$ against $H_a : \beta_{i,j} > 0$. Furthermore, the asterisk indicates significance at a 10% significance level according to wild bootstrapped p-values.

1	2	3	4	5	6	7	8	9	10	11	12
i	$\hat{\beta}_{i,AUS}$	$\hat{\beta}_{i,CAN}$	$\hat{\beta}_{i,FRA}$	$\hat{\beta}_{i,DEU}$	$\hat{\beta}_{i,ITA}$	$\hat{\beta}_{i,JPN}$	$\hat{\beta}_{i,NLD}$	$\hat{\beta}_{i,SWE}$	$\hat{\beta}_{i,CHE}$	$\hat{\beta}_{i,GBR}$	$\hat{\beta}_{i,USA}$
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)
CAN	0.05		0.06	0.06	0.06*	0.06	0.06	0.15*	0.08	0.07	0.21*
	(0.84)		(1.21)	(1.24)	(1.53)	(1.26)	(0.79)	(3.73)	(1.00)	(0.99)	(2.19)
FRA	0.01	−0.01		−0.03	−0.05	0.04	0.002	0.14*	0.16*	0.03	0.12
	(0.15)	(−0.15)		(−0.31)	(−0.91)	(0.53)	(0.02)	(2.27)	(1.47)	(0.26)	(1.28)
DEU	0.03	0.09	0.13*		0.06	0.09*	0.06	0.14*	0.26*	0.07	0.22*
	(0.37)	(1.11)	(1.49)		(1.29)	(1.42)	(0.55)	(2.49)	(2.26)	(0.77)	(2.33)
ITA	−0.01	0.06	0.16*	0.11		0.05	−0.06	0.06	0.21*	0.15*	0.15*
	(−0.07)	(0.66)	(1.63)	(1.21)		(0.72)	(−0.59)	(0.99)	(1.84)	(1.48)	(1.59)
JPN	0.04	0.12*	0.11*	0.02	0.03		0.07	0.09*	0.11*	0.11*	0.11*
	(0.70)	(1.70)	(2.07)	(0.44)	(0.78)		(1.17)	(1.77)	(1.61)	(1.71)	(1.48)
NLD	0.10*	0.15*	0.15*	0.15*	0.05	0.11*		0.16*	0.33*	0.11	0.32*
	(1.46)	(1.95)	(2.20)	(1.79)	(1.05)	(2.12)		(2.76)	(3.28)	(1.11)	(3.69)
SWE	−0.03	0.16*	0.05	0.08	0.08	0.06	0.01		0.12	0.10	0.23*
	(−0.31)	(1.75)	(0.58)	(0.88)	(1.09)	(0.76)	(0.13)		(1.23)	(0.90)	(2.22)
CHE	0.03	0.03	−0.0003	−0.02	0.00	0.02	−0.01	0.13*		0.02	0.14*
	(0.50)	(0.41)	(0.07)	(−0.20)	(−0.08)	(0.51)	(−0.08)	(3.14)		(0.32)	(1.67)
GBR	0.11*	0.08	0.08	0.02	0.01	0.09*	−0.02	0.09*	0.11*		0.23*
	(1.74)	(1.02)	(1.17)	(0.26)	(0.24)	(1.85)	(−0.18)	(2.03)	(1.42)		(2.26)
USA	0.06	0.03	0.01	−0.01	0.06*	−0.0003	0.01	0.09*	0.04	0.02	
	(1.00)	(0.27)	(0.20)	(−0.20)	(1.52)	(−0.01)	(0.18)	(2.31)	(0.48)	(0.22)	
Average	0.04	0.08	0.09	0.05	0.04	0.06	0.03	0.11	0.15	0.08	0.19
Pooled	0.03	0.07*	0.08*	0.05	0.04*	0.06*	0.02	0.11*	0.13*	0.08*	0.17*
	(0.65)	(1.34)	(2.02)	(1.08)	(1.32)	(1.52)	(0.42)	(3.56)	(2.22)	(1.45)	(2.98)

The leading role of the United States could be explained by the findings of Lo and MacKinlay (1990). They conclude that large-cap returns lead small-cap returns. Since the U.S. has the world's largest equity market, when classifying this on the market capitalization, the market as itself can be seen as a large-cap return and the other countries' markets as small-cap returns.

4.1.3 Pooled General Model

The general model, as specified in equation (3), is first performed by setting the homogeneity restrictions: $\beta_{i,i} = \bar{\beta}_{AR}, \beta_{i,j} = \bar{\beta}_j, \beta_{i,b} = \bar{\beta}_b$, and $\beta_{i,d} = \bar{\beta}_d$, for i = 1, . . . , N. The pooled estimates are given in Table 4. The pooled estimates for the U.S., Sweden, and The Netherlands are significant. The strong predictive ability for the U.S., and Sweden became clear in subsubsection 3.1.2, but the significance for The Netherlands is relatively unexpected. The pooled estimate of $\bar{\beta}_{USA}$ of the general model, being 0.17, corresponds to the value in Table 3 ($\hat{\bar{\beta}}_{USA} = 0.17$) and is again the largest value. The Swedish pooled estimate of 0.08 is also in compliance with the estimate in Table 3 ($\hat{\bar{\beta}}_{SWE} = 0.11$). However, the pooled estimate of The Netherlands has a negative value of -0.12, which is different from the value in Table 3 ($\hat{\bar{\beta}}_{NLD} = 0.02$). Analysing at the Dutch results in Table 5, we see that the Dutch estimates are not robust, which will be discussed later.

Table 4: Pooled Estimates for General Model

This table shows estimates for $\bar{\beta}_{i,j}$ in regression (3) when using the pooled restrictions $\beta_{i,i} = \bar{\beta}_{AR}, \beta_{i,j} = \bar{\beta}_j, \beta_{i,b} = \bar{\beta}_b$, and $\beta_{i,d} = \bar{\beta}_d$, for i = 1. In the brackets below the coefficient estimates, the bias-corrected wild bootstrapped 90% confidence interval are reported. The asterisk shows significance at 10% or better.

1 $\hat{\bar{\beta}}_{AUS}$	2 $\hat{\bar{\beta}}_{CAN}$	3 $\hat{\bar{\beta}}_{FRA}$	4 $\hat{\bar{\beta}}_{DEU}$	5 $\hat{\bar{\beta}}_{ITA}$	6 $\hat{\bar{\beta}}_{JPN}$
-0.03 [-0.12,0.06]	-0.01 [-0.12,0.09]	0.03 [-0.06,0.11]	-0.03 [-0.12,0.07]	0.01 [-0.04,0.06]	0.02 [-0.04,
7 $\hat{\bar{\beta}}_{NLD}$	**8** $\hat{\bar{\beta}}_{SWE}$	**9** $\hat{\bar{\beta}}_{CHE}$	**10** $\hat{\bar{\beta}}_{GBR}$	**11** $\hat{\bar{\beta}}_{USA}$	
-0.12* [-0.23,-0.01]	0.08* [0.03,0.14]	0.08 [-0.05,0.21]	0.004 [-0.10,0.11]	0.17* [0.05,0.29]	

Table 5: Adaptive Elastic Net Estimates for General Model

The table contains the estimates of $\beta_{i,j}$ in the regression as described in equation (3). Only the estimates chosen by the adaptive elastic net are reported and are named $\hat{\beta}^*_{i,j}$. In the brackets below the estimates, the bias-corrected wild bootstrapped 90% confidence intervals can be found. The asterisk shows significance of the estimates at 10% or better.

1 i	2 $\hat{\beta}^*_{i,AUS}$	3 $\hat{\beta}^*_{i,CAN}$	4 $\hat{\beta}^*_{i,FRA}$	5 $\hat{\beta}^*_{i,DEU}$	6 $\hat{\beta}^*_{i,ITA}$	7 $\hat{\beta}^*_{i,JPN}$	8 $\hat{\beta}^*_{i,NLD}$	9 $\hat{\beta}^*_{i,SWE}$	10 $\hat{\beta}^*_{i,CHE}$	11 $\hat{\beta}^*_{i,GBR}$	12 $\hat{\beta}^*_{i,USA}$
AUS		0	0	0	0.01	0	0	0	0	0	0.12*
					[-0.01,0.03]						[0.05,0.25]
CAN	0		0	0	0	0	-0.06	0.13*	0	0	0.10*
							[-0.18,0.01]	[0.08,0.21]			[0.02,0.23]
FRA	0	-0.09		-0.11	-0.05	0	-0.07	0.16*	0.17	-0.01	0.12
		[-0.25,0.04]		[-0.29,0.03]	[-0.15,0.02]		[-0.25,0.09]	[0.07,0.28]	[-0.01,0.39]	[-0.17,0.13]	[-0.04,0.32]
DEU	-0.06	-0.02	0.04		-0.02	0.03	-0.13	0.10*	0.19*	-0.09	0.22*
	[-0.20,0.08]	[-0.19,0.13]	[-0.10,0.19]		[-0.05,0.10]	[-0.07,0.13]	[-0.32,0.06]	[0.01,0.21]	[0.002,0.40]	[-0.27,0.07]	[0.04,0.44]
ITA	-0.07	0	0.15*	0.05		0	-0.41*	0	0.27*	0.17*	0.07
	[-0.22,0.01]		[0.01,0.34]	[-0.05,0.19]			[-0.71,-0.29]		[0.08,0.51]	[0.02,0.41]	[-0.05,0.23]
JPN	0	0.04	0.04*	0	0		0	0.04	0	0.003	0
		[-0.01,0.11]	[0.02,0.12]					[-0.002,0.10]		[-0.04,0.04]	
NLD	0		0.01	0	0	0.04		0.09*	0.21*	-0.07	0.22*
			[-0.07,0.09]			[-0.03,0.12]		[0.01,0.19]	[0.04,0.41]	[-0.24,0.07]	[0.08,0.41]
SWE	-0.13*	0.07	0	0	0.07	0	-0.13		0.01	0	0.30*
	[-0.31,-0.003]	[-0.04,0.23]			[-0.03,0.19]		[-0.37,0.01]		[-0.11,0.12]		[0.13,0.55]
CHE	0	0	0	0	0	0	0	0.10*		0	0.08*
								[0.06,0.17]			[0.01,0.18]
GBR	0	0	0	0	0	0.002	-0.11*	0.04*	0		0.19*
						[-0.02,0.03]	[-0.25,-0.06]	[0.02,0.12]			[0.09,0.38]
USA	0	0	0	-0.03	0.02	0	0	0.08*	0	0	
				[-0.11,0.01]	[-0.01,0.06]			[0.04,0.16]			
Average	-0.03	-0.001	0.02	-0.01	0.01	0.01	-0.09	0.08	0.08	1.0×10^{-8}	0.14

The results for the non-pooled general model are stated in Table 5[8]. The adaptive elastic net method selects

[8]The confidence intervals computed by the wild bootstrap procedure sometimes slightly differ from Rapach et al. (2013), which is due to the randomness of the bootstrap procedure.

the lagged U.S. excess returns as good predictors for nine out of ten times, which again confirms that the lagged U.S. excess returns are the most dominant predictors. Most of the $\hat{\beta}^{*}_{i,USA}$ values are higher than 0.10. Furthermore, the Swedish and Dutch lagged returns are selected eight and six times respectively. The Swedish estimates are often significant, with values around 0.10. However, the Dutch estimates all are negative, which is remarkable in the table. Moreover, only two Dutch estimates are significant, which shows that the robustness of the Dutch predictive ability is relatively low.

4.1.4 Out-of-Sample Evaluation

In this section, we discuss the out-of-sample performance. Table 6 contains the R^2_{OS} statistics, from testing the out-of-sample performance of equation (5) against the performance of the historical average, discussed in (4). As we can see from the results, all of the normal R^2_{OS} for the non-U.S. countries are positive, except for Australia. This means that the mean squared forecast error (MSFE) of the model in equation (5) is lower than the historical average model for almost all countries. The significance of this R^2_{OS} statistic also shows that the prediction of the model with lagged U.S. excess returns outperforms the baseline model, using the historical average as predictor. This is the case for all countries except the United Kingdom. However, for the pooled results, all of the non-U.S. countries have a significant R^2_{OS}.

Table 6: Out-of-Sample Evaluation

The second and fifth column show the out of sample R^2 statistic (R^2_{OS}) for testing the forecasts, computed by the estimates from the regression as stated in equation (5), against the forecasts following from the historical average as mentioned in equation (4). The third and sixth column show this statistic, but now for a pooled version of (5), that is with the restriction that $\beta_{i,USA} = \hat{\beta}_{USA}$ for all $i \neq$ USA.

1 2,i	2 R^2_{OS}	3 $R^2_{OS,pooled}$	4 i	5 R^2_{OS}	6 $R^2_{OS,pooled}$
Australia	-0.69^* (1.49)	0.50^* (1.60)	Netherlands	3.81^* (2.62)	3.88^* (2.58)
Canada	1.30^* (2.36)	1.86^* (2.18)	Sweden	2.90^* (2.25)	2.76^* (2.31)
France	1.52^* (1.90)	1.91^* (2.12)	Switzerland	2.64^* (2.45)	2.95^* (2.40)
Germany	1.57^* (1.78)	1.98^* (1.91)	United Kingdom	0.28 (0.97)	0.43^* (1.34)
Italy	0.92^* (1.54)	1.54^* (2.05)	Average	1.51	1.91
Japan	0.82^* (1.33)	1.30^* (1.65)			

4.2 Extensions

In this subsection, we discuss the results of our extensions. Firstly, the predictive power of lagged positive and negative excess returns is reported. Secondly, the results of the significance of lagged excess returns in months of high and low volatility are shown, and lastly, the predictive ability of lagged U.S. excess returns in times of U.S. recessions and economic growth becomes clear.

4.2.1 Impact of Positive and Negative Returns

Table 7 contains the $\beta_{i,j}$ estimates and indicates whether a particular country j Granger causes country i when we only use the lagged variables if the corresponding lagged excess return of country j is positive. We see that 89 of the 110 $\beta_{i,j}$ estimates prove to be positive of which 32 estimates are significant. Compared to the results shown in Table 3, less estimates are significant, namely 32 versus 47 significant estimates. The reduction in significance could partly be caused by the different computation of the p-values. Nevertheless, the results still indicate a predictive ability for the international stock markets.

Table 7: Impact of Positive Lagged Excess Returns

The table reports the $\beta_{i,j}$ estimates of regression (6), so only when using positive lagged country j's excess returns (and the corresponding data). In the parenthesis below the coefficient estimates, heteroskedasticity-robust t-statistic are shown for testing $H_0 : \beta_{i,j} = 0$ against $H_a : \beta_{i,j} > 0$. Furthermore, the asterisk indicates significance at a 10% significance level according to the moving block bootstrapped p-values.

1	2	3	4	5	6	7	8	9	10	11	12
i	$\hat{\beta}_{i,AUS}$	$\hat{\beta}_{i,CAN}$	$\hat{\beta}_{i,FRA}$	$\hat{\beta}_{i,DEU}$	$\hat{\beta}_{i,ITA}$	$\hat{\beta}_{i,JPN}$	$\hat{\beta}_{i,NLD}$	$\hat{\beta}_{i,SWE}$	$\hat{\beta}_{i,CHE}$	$\hat{\beta}_{i,GBR}$	$\hat{\beta}_{i,USA}$
AUS		−0.02	0.13	0.22*	0.01	0.07	0.25*	0.07	0.09	−0.04	0.13
		(−0.18)	(1.05)	(2.05)	(0.23)	(0.93)	(1.94)	(0.93)	(0.75)	(−0.26)	(1.09)
CAN	0.14		0.13	0.22*	0.12	0.09	0.21*	0.25*	0.08	−0.02	0.32*
	1.30)		(1.68)	(2.52)	(1.98)	(1.26)	(2.00)	(3.32)	(0.70)	(−0.20)	(2.90)
FRA	0.18*	−0.17		−0.002	0.01	0.06	0.10	0.18*	0.25*	−0.26	0.23*
	1.32)	(−1.07)		(−0.01)	(0.14)	(0.48)	(0.62)	(1.87)	(1.58)	(−1.44)	(1.56)
DEU	0.02	−0.07	0.12		0.03	0.03	0.14	0.16	0.24*	−0.14	0.23*
	0.16)	(−0.47)	(0.82)		(0.45)	(0.34)	(0.99)	(1.71)	(1.57)	(−0.98)	(1.48)
ITA	0.18*	−0.06	0.23*	−0.05		−0.23	−0.13	0.13	0.50*	0.08	0.24*
	0.94)	(−0.29)	(1.44)	(−0.33)		(−1.64)	(−0.68)	(1.19)	(2.47)	(0.38)	(1.25)
JPN	0.14*	−0.05	0.04	0.04	0.02		0.10	0.07	0.18*	0.05	0.11
	0.99)	(−0.37)	(0.34)	(0.44)	(0.25)		(0.83)	(0.82)	(1.09)	(0.35)	(0.71)
NLD	0.19*	0.01	0.24*	0.06	0.14	0.11		0.24*	0.35*	−0.04	0.28*
	1.74)	(0.08)	(2.15)	(0.47)	(2.00)	(1.27)		(2.48)	(2.42)	(−0.29)	(2.03)
SWE	−0.03	0.04	0.25*	0.20*	0.26*	0.16*	0.17*		0.20*	0.11*	0.29*
	−0.14)	(0.20)	(2.06)	(1.62)	(1.99)	(1.18)	(1.04)		(1.15)	(0.66)	(1.52)
CHE	0.04	−0.09	0.00	−0.19	0.03	0.05	0.03	0.12		−0.13	0.10
	0.38)	(−0.83)	(0.00)	(−1.74)	(0.45)	(0.59)	(0.24)	(1.81)		(−1.28)	(0.82)
GBR	0.13	−0.01	0.06	0.04	0.07	0.14	0.12	0.16	0.14		0.19*
	1.07)	(−0.07)	(0.68)	(0.50)	(1.10)	(1.86)	(1.22)	(2.26)	(1.38)		(1.55)
USA	0.07	−0.21	0.08	0.18	0.13	0.08	0.18	0.15	0.07	−0.11	
	0.75)	(−1.47)	(0.84)	(1.63)	(1.85)	(1.11)	(1.49)	(1.99)	(0.51)	(−0.86)	
Average	0.11	−0.06	0.13	0.07	0.08	0.06	0.11	0.15	0.21	−0.05	0.21
Pooled	0.12	−0.07	0.12	0.09	0.08*	0.05	0.12*	0.15*	0.21*	−0.03	0.20*
	(1.11)	(−0.65)	(1.26)	(0.87)	(1.42)	(0.38)	(1.31)	(2.37)	(1.59)	(−0.26)	(1.67)

The most dominant predictors when only using the positive excess returns are the U.S. and Switzerland, with seven and six out of ten $\hat{\beta}_{i,j}$ being significant respectively. Both the U.S. and Swiss estimates have an average value of 0.21. The USA has six estimates with a value larger or equal to 0.23. For Switzerland five estimates are larger or equal to 0.20. The strong predictive ability of these two countries is also notable in the pooled estimates. The estimates $\hat{\hat{\beta}}_{i,CHE}$ and $\hat{\hat{\beta}}_{i,USA}$ are the largest with values of 0.21 and 0.20 respectively. The other countries do not have strong predictive ability. The Canadian $\beta_{i,CAN}$ estimates are noteworthy, because most of these values are negative, which differs from the overall estimates. However, none of these Canadian estimates are significant, which shows that the estimates are not robust. Another exceptional finding is that the Swedish and Dutch excess returns are relatively easily predictable when using country j's positive lagged excess returns as predictors, with eight significant $\beta_{SWE,j}$ and five significant $\beta_{NLD,j}$ estimates.

When comparing the results of Table 7 to the full sample results, we see that the USA and Switzerland remain dominant predictors when only using the positive lagged excess returns. Furthermore, one Swedish $\beta_{i,SWE}$ estimate is significant when only using positive lagged excess returns, which is different from the nine significant results when using the full sample. As mentioned before, the differences in the number of significant estimates between the extensions and replications are partly caused by the difference in the p-value computation, but the overall comparison of a country being a strong or weak predictor still holds.

Table 8: Impact of Negative Lagged Excess Returns

The table reports the $\beta_{i,j}$ estimates of regression (7), so only when using negative lagged country j's excess returns (and the corresponding number data). In the parenthesis below the coefficient estimates, heteroskedasticity-robust t-statistic are shown for testing $H_0 : \beta_{i,j} = 0$ against $H_a : \beta_{i,j} > 0$. Furthermore, the asterisk indicates significance at a 10% significance level according to the moving block bootstrapped p-values.

1	2	3	4	5	6	7	8	9	10	11	12
i	$\hat{\beta}_{i,AUS}$	$\hat{\beta}_{i,CAN}$	$\hat{\beta}_{i,FRA}$	$\hat{\beta}_{i,DEU}$	$\hat{\beta}_{i,ITA}$	$\hat{\beta}_{i,JPN}$	$\hat{\beta}_{i,NLD}$	$\hat{\beta}_{i,SWE}$	$\hat{\beta}_{i,CHE}$	$\hat{\beta}_{i,GBR}$	$\hat{\beta}_{i,USA}$
AUS		0.12	0.15	0.10	0.14	0.12	0.19*	0.12	0.04	0.17*	0.22*
		(0.76)	(1.32)	(0.78)	(1.31)	(0.92)	(1.34)	(1.21)	(0.34)	(1.08)	(1.00)
CAN	−0.06		−0.01	0.01	0.16	0.14	0.10	0.04	−0.004	0.08	0.14
	(−0.75)		(−0.08)	(0.05)	(1.77)	(1.25)	(0.67)	(0.38)	(−0.03)	(0.55)	(0.69)
FRA	−0.05	0.20*		−0.07	0.15	0.11	0.08	0.08	0.31*	0.28*	0.11
	(−0.39)	(1.31)		(−0.44)	(1.02)	(0.71)	(0.44)	(0.59)	(1.53)	(1.71)	(0.58)
DEU	0.09	0.27*	−0.15		0.16	0.26*	0.16	0.21	0.56*	0.29*	0.30*
	(0.56)	(1.68)	(−0.79)		(1.55)	(1.55)	(0.69)	(1.40)	(2.54)	(1.40)	(1.24)
ITA	−0.10	0.18*	0.21*	0.21*		0.21*	0.08	0.05	0.20*	0.11	0.12
	(−0.81)	(1.20)	(1.06)	(1.22)		(1.36)	(0.46)	(0.38)	(1.16)	(0.62)	(0.61)
JPN	0.08	0.15*	0.03	0.05	0.01		0.31*	0.07	0.13	0.10	0.18*
	(1.00)	(1.20)	(0.33)	(0.42)	(0.06)		(2.32)	(0.57)	(0.97)	(0.83)	(1.10)
NLD	0.13	0.32*	0.14	0.35*	0.18	0.18*		0.17	0.73*	0.53*	0.58*
	(0.83)	(1.95)	(1.01)	(2.11)	(1.68)	(1.33)		(1.35)	(3.81)	(2.70)	(2.72)
SWE	0.13	0.40*	0.09	0.09	−0.02	0.14	0.05		0.45*	0.003	0.23*
	(0.94)	(2.48)	(0.43)	(0.47)	(−0.15)	(0.75)	(0.20)		(2.20)	(0.01)	(0.97)
CHE	−0.03	0.23*	−0.12	0.28*	0.07	0.05	0.19	0.05		0.35*	0.25*
	(−0.26)	(1.52)	(−0.77)	(1.82)	(0.69)	(0.43)	(1.20)	(0.44)		(2.19)	(1.44)
GBR	0.07	0.21*	0.11	0.10	0.15	0.11	0.21	0.08	0.32*		0.71*
	(0.54)	(1.54)	(0.75)	(0.73)	(1.52)	(0.95)	(1.11)	(0.71)	(1.98)		(2.97)
USA	0.14	0.19	0.02	−0.01	0.20	0.11	0.15	0.04	0.05	0.11	
	(1.27)	(1.03)	(0.12)	(−0.13)	(1.91)	(1.05)	(0.83)	(0.37)	(0.32)	(0.62)	
Average	0.04	0.23	0.05	0.11	0.12	0.14	0.15	0.09	0.28	0.20	0.28
Pooled	0.03	0.21*	0.05	0.08	0.12*	0.14	0.14	0.09	0.23*	0.16	0.22
	(0.22)	(1.62)	(0.42)	(0.60)	(1.36)	(1.01)	(0.89)	(0.91)	(1.33)	(1.26)	(1.23)

Furthermore, the results when only using negative excess returns, as mentioned in equation (7), are shown in Table 8. Of the 110 regressions, 99 estimates are positive, of which 35 significant. A notable result is that Canada has the most significant $\beta_{i,CAN}$ estimates, with eighth out of ten significant estimates. The average value of the estimates is 0.23 and six estimates are larger or equal to 0.20. The significance of Canada is remarkable if we compare it to the results in Table 3 and Table 7, so when only using the lagged negative excess returns, Canada has large predictive ability. The U.S. and Switzerland remain dominant predictors, with seven and six significant $\beta_{i,j}$ estimates respectively. The average value of the USA estimates is 0.28 and six estimates are larger or equal than 0.22. Swedish estimates also have an average value of 0.28 and six estimates are larger or equal to 0.20. The pooled estimates indeed show large values for $\hat{\bar{\beta}}_{i,CAN}$, $\hat{\bar{\beta}}_{i,CHE}$ and $\hat{\bar{\beta}}_{i,USA}$, which corresponds to these three countries having most significant estimates. Furthermore, the Dutch excess returns are again relatively easy predictable, with six significant estimates of $\beta_{NLD,j}$.

4.2.2 Predictability of High and Low Volatility Regimes

Next, we look at if the country j's lagged excess returns have significant effect on country i's excess returns if only the observations corresponding to the months where the lagged country j's monthly returns have high volatility are used. The results are shown in Table 9.

Table 9: Impact of Months with High Volatility

The table reports the $\beta_{i,j}$ estimates of regression (8), so only when using lagged country j's monthly excess returns corresponding to months with volatility being larger than the average monthly volatility in the sample (and the corresponding data). In the parenthesis below the coefficient estimates, heteroskedasticity-robust t-statistic are shown for testing $H_0 : \beta_{i,j} = 0$ against $H_a : \beta_{i,j} > 0$. Furthermore, the asterisk indicates significance at a 10% significance level according to the moving block bootstrapped p-values.

1	2	3	4	5	6	7	8	9	10	11	12
i	$\hat{\beta}_{i,AUS}$	$\hat{\beta}_{i,CAN}$	$\hat{\beta}_{i,FRA}$	$\hat{\beta}_{i,DEU}$	$\hat{\beta}_{i,ITA}$	$\hat{\beta}_{i,JPN}$	$\hat{\beta}_{i,NLD}$	$\hat{\beta}_{i,SWE}$	$\hat{\beta}_{i,CHE}$	$\hat{\beta}_{i,GBR}$	$\hat{\beta}_{i,USA}$
AUS		−0.003	0.12	0.01	0.08	0.05	0.05	0.12	0.10	0.05	0.21*
		(−0.03)	(1.43)	(0.09)	(1.84)	(0.94)	(0.49)	(2.16)	(1.10)	(0.51)	(1.36)
CAN	0.09		0.03	0.04	0.09	0.14*	0.09	0.14	−0.08	0.12	0.16*
	(1.09)		(0.59)	(0.56)	(1.91)	(2.72)	(0.95)	(2.88)	(−0.71)	(1.30)	(1.03)
FRA	0.07	−0.002		0.02	−0.04	0.08	0.05	0.15	0.25*	0.13*	0.13*
	(0.70)	(−0.02)		(0.10)	(−0.65)	(0.81)	(0.30)	(1.41)	(1.39)	(0.68)	(0.69)
DEU	0.06	0.12*	−0.01		0.05	0.13*	−0.05	0.15	0.39*	0.25*	0.38*
	(0.55)	(1.13)	(−0.10)		(0.97)	(1.65)	(−0.30)	(1.45)	(1.98)	(1.68)	(2.40)
ITA	−0.02	0.03	0.43*	0.22*		0.10*	−0.06	0.14*	0.33*	0.25*	0.14*
	(−0.20)	(0.27)	(3.19)	(1.25)		(1.05)	(−0.43)	(1.72)	(1.97)	(1.74)	(1.02)
JPN	0.05	0.05	0.10	0.05	−0.01		0.01	0.15*	0.13*	0.17*	0.17*
	(0.64)	(0.54)	(1.39)	(0.73)	(−0.26)		(0.15)	(2.15)	(1.30)	(1.75)	(1.54)
NLD	0.16*	0.18*	0.17	0.32*	0.09	0.21*		0.20*	0.45*	0.34*	0.49*
	(1.72)	(1.55)	(1.82)	(2.20)	(1.91)	(2.98)		(2.38)	(2.42)	(2.15)	(3.48)
SWE	0.14*	0.13*	0.01	−0.10	0.16*	0.06	−0.02		0.15*	0.12*	0.25*
	(1.45)	(1.09)	(0.08)	(−0.75)	(1.84)	(0.59)	(−0.09)		(0.98)	(0.73)	(1.68)
CHE	0.08	0.01	−0.11	−0.11	−0.01	0.08	−0.06	0.09		−0.02	0.27*
	(0.95)	(0.09)	(−1.16)	(−1.01)	(−0.27)	(1.33)	(−0.51)	(1.45)		(−0.12)	(1.75)
GBR	0.10	0.14*	0.06	−0.03	0.01	0.11	0.06	0.01	0.04		0.38*
	(1.13)	(1.37)	(0.92)	(−0.29)	(0.32)	(1.72)	(0.40)	(0.19)	(0.31)		(2.06)
USA	0.08	−0.02	−0.001	0.01	0.12	0.12	0.02	0.07	−0.02	0.08	
	(1.04)	(−0.13)	(−0.02)	(0.12)	(2.72)	(2.45)	(0.18)	(1.18)	(−0.17)	(0.68)	
Average	0.08	0.06	0.08	0.04	0.05	0.11	0.01	0.12	0.17	0.15	0.26
Pooled	0.07*	0.06	0.08*	0.03	0.06*	0.11*	0.02	0.12*	0.15*	0.14*	0.22*
	(1.29)	(0.90)	(2.23)	(0.65)	(2.02)	(2.01)	(0.29)	(3.19)	(2.17)	(1.85)	(2.57)

In general, we see that out of the 110 regressions, 88 estimates are positive and 39 significant. The general predictability thus is higher than when only using positive or negative lagged excess returns. The U.S. and Switzerland are again dominant predictors, with ten and six significant $\beta_{i,j}$ estimates respectively. Six of the $\beta_{i,USA}$ estimates are larger or equal to 0.20 and the average $\beta_{i,USA}$ estimate is 0.26. The Swiss estimates are often lower, but still mostly above 0.15 with an average value of 0.17. Next to these two countries, the British lagged excess returns in months of high volatility are also good predictors, as six $\beta_{i,GBR}$ estimates are significant and have an average value of 0.15. The large predictive ability of the U.S. when using excess returns in months with high volatility reflects in the pooled estimate $\hat{\bar{\beta}}_{i,USA}$ of 0.22, which is the largest value. Furthermore, the Dutch and Swedish excess returns are again relatively easy predictable, with eigth $\beta_{NLD,j}$ and six $\beta_{SWE,j}$ being significant.

Table 10: Impact of Months with Low Volatility

The table reports the $\beta_{i,j}$ estimates of regression (9), so only when using lagged country j's monthly excess returns corresponding to months with volatility being below the average monthly volatility of the sample (and the corresponding data). In the parenthesis below the coefficient estimates, heteroskedasticity-robust t-statistic are shown for testing $H_0 : \beta_{i,j} = 0$ against $H_a : \beta_{i,j} > 0$. Furthermore, the asterisk indicates significance at a 10% significance level according to the moving block bootstrapped p-values.

1	2	3	4	5	6	7	8	9	10	11	12
i	$\hat{\beta}_{i,AUS}$	$\hat{\beta}_{i,CAN}$	$\hat{\beta}_{i,FRA}$	$\hat{\beta}_{i,DEU}$	$\hat{\beta}_{i,ITA}$	$\hat{\beta}_{i,JPN}$	$\hat{\beta}_{i,NLD}$	$\hat{\beta}_{i,SWE}$	$\hat{\beta}_{i,CHE}$	$\hat{\beta}_{i,GBR}$	$\hat{\beta}_{i,USA}$
AUS		0.25*	0.12*	0.25*	0.07	0.17*	0.16*	0.03	0.13*	0.10	0.19*
		(2.10)	(1.19)	(2.02)	(1.28)	(1.57)	(1.82)	(0.36)	(1.25)	(0.79)	(2.06)
CAN	0.01		0.08	0.07	0.003	−0.08	−0.01	0.13	0.19*	0.03	0.25*
	(0.11)		(0.92)	(0.96)	(0.05)	(−0.96)	(−0.09)	(1.99)	(1.65)	(0.27)	(2.05)
FRA	−0.08	0.02		−0.01	−0.06	−0.01	−0.03	0.13*	0.19*	−0.03	0.02
	(−0.78)	(0.18)		(−0.08)	(−0.60)	(−0.12)	(−0.23)	(1.75)	(1.38)	(−0.24)	(0.21)
DEU	−0.05	0.06	0.24*		0.08	0.01	0.12*	0.09	0.21*	−0.09	0.01
	(−0.54)	(0.56)	(2.24)		(0.92)	(0.11)	(1.04)	(1.36)	(1.48)	(−0.81)	(0.12)
ITA	0.09*	0.20*	−0.06	0.07		0.07	−0.06	−0.06	0.29*	0.08*	0.06
	(0.71)	(1.42)	(−0.52)	(0.58)		(0.63)	(−0.40)	(−0.60)	(1.79)	(0.51)	(0.45)
JPN	−0.003	0.20*	0.12	0.003	0.11		0.02	0.003	0.14*	0.03	−0.03
	(−0.03)	(1.82)	(1.62)	(0.04)	(1.40)		(0.27)	(0.05)	(1.35)	(0.29)	(−0.30)
NLD	0.02	0.13*	0.13	−0.04	−0.04	−0.09		0.09	0.22*	−0.06	0.12*
	(0.25)	(1.22)	(1.31)	(−0.42)	(−0.46)	(−1.24)		(1.17)	(1.85)	(−0.48)	(1.14)
SWE	−0.31	0.22*	0.11*	0.14*	−0.08	0.09	0.01		0.13*	0.04	0.12*
	(−2.69)	(1.55)	(1.00)	(1.27)	(−0.77)	(0.77)	(0.06)		(0.97)	(0.30)	(0.90)
CHE	−0.05	0.03	0.09	0.003	0.004	−0.07	−0.001	0.15		−0.04	−0.04
	(−0.64)	(0.24)	(0.80)	(0.03)	(0.06)	(−0.92)	(−0.02)	(2.61)		(−0.41)	(−0.41)
GBR	0.09	0.03	0.10	0.004	−0.01	0.08	−0.13	0.16*	0.08		0.08
	(0.97)	(0.28)	(0.81)	(0.04)	(−0.22)	(0.87)	(−1.32)	(2.28)	(0.74)		(0.64)
USA	0.01	0.08	0.03	−0.06	−0.06	−0.20*	−0.01	0.08	0.04	−0.05	
	(0.13)	(0.70)	(0.36)	(−0.84)	(−1.18)	(−2.79)	(−0.13)	(1.30)	(0.36)	(−0.42)	
Average	−0.03	0.12	0.10	0.04	0.002	−0.004	0.01	0.08	0.16	0.00	0.08
Pooled	−0.03	0.11*	0.07	0.04	0.004	−0.01	−0.00	0.06*	0.15*	0.01	0.06
	(−0.45)	(1.30)	(1.28)	(0.64)	(0.08)	(−0.11)	(−0.05)	(1.36)	(1.81)	(0.13)	(0.79)

Furthermore, we look at the predictive ability of country j's lagged excess returns when only using observations matching the lagged excess returns corresponding to the months where the monthly volatility is below the average monthly volatility. The results are reported in Table 10. Out of the 110 regressions, 78 estimates are positive of which 29 are significant. This shows that, in general, the lagged excess returns corresponding to the months with low volatility have less predictive ability. The only significant predictor when using lagged excess returns in months of low volatility is Switzerland. Eighth of the ten $\hat{\beta}_{i,CHE}$ are significant and the average value of the estimates is 0.16. In comparison to Table 9, British and U.S. lagged excess returns in months of low volatility have a lot less predictive ability, now having one and four significant $\beta_{i,j}$ estimates respectively. The Dutch excess returns are also harder to predict when using lagged country j's excess returns corresponding to the month of low volatility for country j; only three $\beta_{NLD,j}$ estimate are significant. The Swedish excess returns are a bit easier to predict with five significant $\beta_{SWE,j}$ estimates. Furthermore, he dominant predictive ability of Switzerland reflects in the largest pooled $\bar{\beta}_{i,CHE}$ estimate, being 0.15.

The main result is that the predictive ability of lagged returns in months with high volatility have more predictive ability than lagged returns in months with low volatility, especially for the U.S. Ramchand and Susmel (1998) find that high volatility in the U.S. markets leads to more correlations between the U.S. and other international markets compared to a low volatility state of the U.S. markets. This explains the result of the lagged U.S. excess returns having ten significant $\hat{\beta}_{i,USA}$ in months of high volatility and only four significant estimates in months of low volatility.

4.2.3 Predictability in Times of U.S. Recession

Because lagged US excess returns show to have a significant effect on different countries' excess returns, we further investigate this predictive ability. The results in Table 11 and Table 12 show the significance of the lagged US returns as predictor for another country i, when only using the recession months and months of economic growth as observations for the regressors respectively.

Based on the results, it becomes clear that the lagged U.S. excess returns corresponding to times of U.S. recession have more significant predictive ability than lagged U.S. returns corresponding to times of U.S. economic growth. When using data during US recessions, nine out of ten times the $\beta_{i,USA}$ estimate is significant, while during a U.S. growing economy only four estimates are significant. During recession, the volatility is often higher. More volatility in the U.S. leads to more correlation with other international stock markets as Ramchand and Susmel (1998) conclude, thus this could give an explanation to the strong predictive ability of data in recessions and weak predictive ability of data during economic growth. Moreover, the impact on the Dutch excess returns is significant for both cases, because we see that they are easily predictable in general as discussed before.

Table 11: Impact of Lagged U.S. Excess Returns in Times of US Recession

The table reports the $\beta_{i,USA}$ estimates of regression (10), so only when using lagged US monthly excess returns corresponding to the months of US recession (and the corresponding data). In the parenthesis below the coefficient estimates, heteroskedasticity-robust t-statistic are shown for testing $H_0 : \beta_{i,j} = 0$ against $H_a : \beta_{i,j} > 0$. Furthermore, the asterisk indicates significance at a 10% significance level according to the moving block bootstrapped p-values.

	AUS	CAN	FRA	DEU	ITA	JPN	NLD	SWE	CHE	GBR
$\hat{\beta}_{i,USA}$	0.44*	0.76*	0.25*	0.52*	0.54*	0.42*	0.77*	0.39*	0.34	0.71*
	(2.14)	(2.68)	(1.34)	(2.44)	(2.39)	(1.93)	(2.92)	(1.88)	(1.92)	(3.47)

Table 12: Impact of Lagged U.S. Excess Returns in Times of a Growing US Economy

The table reports the $\beta_{i,USA}$ estimates of regression (11), so only when using lagged US monthly excess returns corresponding to the months of US economic growth (and the corresponding data). In the parenthesis below the coefficient estimates, heteroskedasticity-robust t-statistic are shown for testing $H_0 : \beta_{i,j} = 0$ against $H_a : \beta_{i,j} > 0$. Furthermore, the asterisk indicates significance at a 10% significance level according to the moving block bootstrapped p-values.

	AUS	CAN	FRA	DEU	ITA	JPN	NLD	SWE	CHE	GBR
$\hat{\beta}_{i,USA}$	0.10*	0.04	0.06	0.14*	0.02	0.01	0.21*	0.16*	0.08	0.07
	(1.09)	(0.49)	(0.61)	(1.32)	(0.19)	(0.18)	(2.15)	(1.26)	(0.86)	(0.59)

Table 13: US Recession Benchmark Regression

This table shows estimates of the benchmark regression as described in equation (12). The second and sixth column contain the estimates for the coefficient of the Treasury bill rate with the heteroskedasticity-robust t-statistic, testing $H_0 : \beta_{i,b} = 0$ against $H_a : \beta_{i,b} < 0$, in the parentheses below and the third and seventh columns show the estimates for the coefficient of the log dividend yield with again the t-statistics, testing $H_0 : \beta_{i,d} = 0$ against $H_a : \beta_{i,d} > 0$, in the parentheses below. In the fourth and eighth column, the R^2 statistic for every regression is shown. In the parenthesis below these R^2 statistics, the χ^2 statistic for testing $H_0 : \beta_{i,b} = \beta_{i,d} = 0$ are stated. Furthermore, the pooled estimates are shown, which impose the restriction that $\beta_{i,b} = \bar{\beta}_b$ and $\beta_{i,d} = \bar{\beta}_d$. The asterisk indicates significance on 10% or better, based on the moving block bootstrapped p-values testing the same hypothesis as the t-statistics.

1 i	2 $\hat{\beta}_{i,b}$	3 $\hat{\beta}_{i,d}$	4 R^2	5 i	6 $\hat{\beta}_{i,b}$	7 $\hat{\beta}_{i,d}$	8 R^2
Australia	−0.31	4.43	3.76%	Netherlands	−0.25	4.21*	3.95%
	(−1.51)	(1.34)	(2.57)		(−0.75)	(1.66)	(2.95)
Canada	−0.22	2.10	2.56%	Sweden	−0.01	2.06	0.81%
	(−1.12)	(0.80)	(1.25)		(−0.03)	(0.70)	(0.59)
France	−0.17	4.86*	6.02%	Switzerland	−0.19	5.90*	6.98%
	(−0.75)	(1.69)	(3.83)		(−0.68)	(2.26)	(5.42)
Germany	−0.55*	9.05*	11.45%	United Kingdom	−0.12	5.35*	4.98%
	(−1.36)	(2.42)	(6.82)		(−0.63)	(1.96)	(4.60)
Italy	0.17	3.08	1.51%	United States	−0.32	3.88*	4.90%
	(0.96)	(0.90)	(1.03)		(−1.15)	(1.67)	(2.91)
Japan	0.40	2.71*	3.11%	Pooled	−0.05	2.33*	2.30%
	(1.72)	(1.05)	(4.35)		(−0.34)	(2.51)	(6.51)

Furthermore, because results in Table 2 show significance for some of the conventional national economic variables used for the benchmark regression, we also check the significance of these variables during US recession and US economic growth. The results are reported in Table 13 and Table 14.

We see that when making the distinction for U.S. recession and U.S. economic growth, the $\hat{\beta}_{i,b}$ are all negative except for Italy and Japan (both during recession and economic growth), but all $\hat{\beta}_{i,b}$ estimates are positive which is different when using the whole sample. The Treasury bill rate is in general a better predictor in times of U.S. economic growth with seven significant estimates respectively versus only the one significant estimate when using data during the U.S. recession. The log dividend yield is a dominant predictor in both estimations, as there are seven significant estimates when using data during US recession and nine significant estimates when using data during economic growth.

Table 14: US Growing Economy Benchmark Regression

This table shows estimates of the benchmark regression as described in equation (13). The second and sixth column contain the estimates for the coefficient of the Treasury bill rate with the heteroskedasticity-robust t-statistic, testing $H_0 : \beta_{i,b} = 0$ against $H_a : \beta_{i,b} < 0$, in the parentheses below and the third and seventh columns show the estimates for the coefficient of the log dividend yield with again the t-statistics, testing $H_0 : \beta_{i,d} = 0$ against $H_a : \beta_{i,d} > 0$, in the parentheses below. In the fourth and eighth column, the R^2 statistic for every regression is shown. In the parenthesis below these R^2 statistics, the χ^2 statistic for testing $H_0 : \beta_{i,b} = \beta_{i,d} = 0$ are stated. Furthermore, the pooled estimates are shown, which impose the restriction that $\beta_{i,b} = \bar{\beta}_b$ and $\beta_{i,d} = \bar{\beta}_d$. The asterisk indicates significance on 10% or better, based on the moving block bootstrapped p-values testing the same hypothesis as the t-statistics.

1 i	2 $\hat{\beta}_{i,b}$	3 $\hat{\beta}_{i,d}$	4 R^2	5 i	6 $\hat{\beta}_{i,b}$	7 $\hat{\beta}_{i,d}$	8 R^2
Australia	−0.07	3.74*	1.30%	Netherlands	−0.32*	2.26*	2.07%
	(−0.53)	(0.94)	(1.18)		(−2.70)	(2.04)	(7.52)
Canada	−0.26*	2.17*	2.93%	Sweden	−0.02	2.29*	1.41%
	(−2.90)	(1.74)	(8.82)		(−0.28)	(1.93)	(3.86)
France	−0.09*	1.23*	0.41%	Switzerland	−0.17*	0.82	0.60%
	(−1.02)	(0.97)	(1.41)		(−1.56)	(0.80)	(2.45)
Germany	−0.25*	1.51*	0.71%	United Kingdom	−0.21*	4.61*	3.75%
	(−1.42)	(1.06)	(2.03)		(−1.98)	(3.23)	(10.70)
Italy	0.04	0.07	0.10%	United States	−0.18*	1.64*	1.64%
	(0.50)	(0.06)	(0.27)		(−1.74)	(2.06)	(4.45)
Japan	0.10	1.08*	0.64%	Pooled	−0.05	1.03*	0.55%
	(0.89)	(1.65)	(3.06)		(−0.91)	(1.99)	(4.24)

Furthermore, the R^2 statistics during U.S. recession are all relatively high (mostly above 3%) as can be seen in Table 13, especially for regressions with significant parameters. For the regressions during U.S. economic growth, the R^2 statistics as reported in Table 14 are generally lower, but are still mostly above 1% when a coefficient in the regression is significant.

4.2.4 Sensitivity Analysis

The results of the sensitivity analysis are shown in Table 15. We see that the results are consistent with respect to the selection of the block size. For the first four extensions, at most two of the 110 estimates have different result for the significance when changing the block size from five to three and ten. For the last two extension, at most one of the ten estimates is different when changing the benchmark block size to three or ten.

Table 15: Sensitivity Analysis Moving Block Bootstrap

The percentages of equally made conclusions for the significance of $\beta_{i,j}$ when using different block sizes L compared to the benchmark size five are shown in the table. The results are per extension.

	Positive	Negative	High VIX	Low VIX	US Recession	US Growth
L = 3	0.98	0.98	0.98	1.00	1.00	1.00
L = 5	1.00	1.00	1.00	1.00	1.00	1.00
L = 10	0.99	0.99	0.99	0.99	1.00	0.90

5 Conclusion

The findings in our paper are in line with conclusions from previous research conducted by Rapach et al. (2013). The strong predictive ability of the United States' lagged excess returns is clear, both when considering the Granger causality as well as the number of times the United States is chosen as a predictor by the adaptive elastic net in the general model. Furthermore, we find approximately equal predictive ability when using positive or negative lagged excess returns in terms of overall significance although for some countries the predictive ability differs substantially when making this distinction. Canada in particular, shows very strong predictive ability when using negative lagged excess returns with eight out of nine estimates being significant. When using positive lagged excess return, none of the Canadian estimates are significant which indicates no predictive ability at all. When differing in the magnitude of monthly volatility, there is a strong indication that the predictive ability of lagged excess returns in months of high volatility is larger than the predictive ability of lagged excess returns in months of low volatility. Especially the United Kingdom and the United States have stronger predictive ability when using months with high volatility as predictors. From the last extension, looking at the distinction between the U.S. recession months and the months where the U.S. economy was growing, we find a larger international predictive ability of the U.S. lagged excess returns in times of recession and economic growth.

In this research, we examined the predictive ability for the excess returns for the whole market. In order to understand the drivers of this lead-lag relationships in the international stock markets, making a distinction for specific sectors will explain this international correlation more clearly. For example, one could examine the predictive ability of the U.S. car industry for the German car industry. Furthermore, for more further research, one could examine differentiating between more extreme returns and investigate the predictive power of these tail events. Additionally, in recent years, China and other Asian countries have become prominent global economies. In this paper, only Japan is considered due to the availability of data. In order to make a more comprehensive research it is suggested to include more Asian countries in the analyses when enough data becomes available.

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A Appendix

Table 16: Impact of Lagged US Excess Returns in Times of US Recession

This table reports the closing times of all countries, according to the Eastern Standard Time.

	AUS	CAN	FRA	DEU	ITA	JPN	NLD	SWE	CHE	GBR	USA
Closing Time	1:00am	4:00pm	11:30am	2:00pm	11:30am	1:00am	11:30am	11:30am	11:20am	11:30am	4:00pm

B Appendix

Table 17: Impact of Positive Returns

The table reports the $\beta_{i,j}$ estimates of regression (6), so only when using positive lagged country j's excess returns (and the corresponding data). In the parenthesis below the coefficient estimates, heteroskedasticity-robust t-statistic are shown for testing $H_0 : \beta_{i,j} = 0$ against $H_a : \beta_{i,j} > 0$. Furthermore, the asterisk indicates significance at a 10% significance level according to the moving block bootstrapped p-values. In the brackets, the moving block bootstrapped p-values are reported for testing the same hypothesis as the t-statistic. Below the p-values, the R^2 statistics is showed in percentages.

1	2	3	4	5	6	7	8	9	10	11	12
i	$\hat{\beta}_{i,AUS}$	$\hat{\beta}_{i,CAN}$	$\hat{\beta}_{i,FRA}$	$\hat{\beta}_{i,DEU}$	$\hat{\beta}_{i,ITA}$	$\hat{\beta}_{i,JPN}$	$\hat{\beta}_{i,NLD}$	$\hat{\beta}_{i,SWE}$	$\hat{\beta}_{i,CHE}$	$\hat{\beta}_{i,GBR}$	$\hat{\beta}_{i,USA}$
AUS		−0.02	0.13	0.22	0.01	0.07	0.25*	0.07	0.09	−0.04	0.13
		(−0.18)	(1.05)	(2.05)	(0.23)	(0.93)	(1.94)	(0.93)	(0.75)	(−0.26)	(1.09)
		[0.88]	[0.37]	[0.16]	[0.95]	[0.63]	[0.09]	[0.69]	[0.48]	[0.77]	[0.31]
		4.63	4.26	5.77	4.62	7.77	4.81	4.25	5.21	1.61	6.03
CAN	0.14		0.13	0.22	0.12	0.09	0.21	0.25	0.08	−0.02	0.32*
	1.30)		(1.68)	(2.52)	(1.98)	(1.26)	(2.00)	(3.32)	(0.70)	(−0.20)	(2.90)
	[0.24]		[0.37]	[0.15]	[0.52]	[0.52]	[0.14]	[0.17]	[0.44]	[0.83]	[0.01]
	7.93		9.91	11.98	7.81	10.16	5.15	13.52	5.97	6.01	8.42
FRA	0.18*	−0.17*		0.00	0.01	0.06	0.10	0.18	0.25*	−0.26*	0.23*
	1.32)	(−1.07)		(−0.01)	(0.14)	(0.48)	(0.62)	(1.87)	(1.58)	(−1.44)	(1.56)
	[0.06]	[0.07]		[0.99]	[0.94]	[0.56]	[0.40]	[0.17]	[0.00]	[0.00]	[0.01]
	6.26	4.41		3.56	4.70	3.78	3.15	7.02	6.43	5.96	4.35
DEU	0.02	−0.07	0.12		0.03	0.03	0.14	0.16	0.24*	−0.14	0.23*
	0.16)	(−0.47)	(0.82)		(0.45)	(0.34)	(0.99)	(1.71)	(1.57)	(−0.98)	(1.48)
	[0.79]	[0.40]	[0.37]		[0.82]	[0.76]	[0.24]	[0.26]	[0.02]	[0.11]	[0.01]
	3.63	3.52	9.15		3.13	6.79	2.58	6.40	5.53	4.43	6.33
ITA	0.18*	−0.06	0.23*	−0.05		−0.23*	−0.13	0.13	0.50*	0.08	0.24*
	0.94)	(−0.29)	(1.44)	(−0.33)		(−1.64)	(−0.68)	(1.19)	(2.47)	(0.38)	(1.25)
	[0.02]	[0.40]	[0.01]	[0.59]		[0.00]	[0.11]	[0.22]	[0.00]	[0.23]	[0.00]
	1.86	1.56	3.24	2.09		4.59	1.89	2.76	5.22	2.28	2.38
JPN	0.14	−0.05	0.04	0.04	0.02		0.10	0.07	0.18*	0.05	0.11
	0.99)	(−0.37)	(0.34)	(0.44)	(0.25)		(0.83)	(0.82)	(1.09)	(0.35)	(0.71)
	[0.10]	[0.55]	[0.73]	[0.67]	[0.92]		[0.32]	[0.57]	[0.04]	[0.57]	[0.23]
	5.79	3.28	4.20	1.61	3.13		2.59	3.75	2.18	2.48	1.81
NLD	0.19*	0.01	0.24	0.06	0.14	0.11		0.24*	0.35*	−0.04	0.28*
	1.74)	(0.08)	(2.15)	(0.47)	(2.00)	(1.27)		(2.48)	(2.42)	(−0.29)	(2.03)
	[0.08]	[0.91]	[0.10]	[0.63]	[0.39]	[0.35]		[0.10]	[0.00]	[0.67]	[0.00]
	8.01	9.03	12.02	9.88	6.71	12.01		12.98	9.54	9.07	11.80
SWE	−0.03	0.04	0.25*	0.20*	0.26*	0.16*	0.17*		0.20*	0.11	0.29*
	−0.14)	(0.20)	(2.06)	(1.62)	(1.99)	(1.18)	(1.04)		(1.15)	(0.66)	(1.52)
	[0.74]	[0.58]	[0.01]	[0.03]	[0.02]	[0.06]	[0.05]		[0.01]	[0.12]	[0.00]
	5.42	6.66	7.68	5.14	9.51	5.21	7.73		7.50	6.61	9.38
CHE	0.04	−0.09	0.00	−0.19	0.03	0.05	0.03	0.12		−0.13	0.10
	0.38)	(−0.83)	(0.00)	(−1.74)	(0.45)	(0.59)	(0.24)	(1.81)		(−1.28)	(0.82)
	[0.77]	[0.45]	[1.00]	[0.23]	[0.86]	[0.76]	[0.84]	[0.50]		[0.29]	[0.41]
	5.40	9.57	8.19	11.36	3.29	6.33	6.01	9.22		9.21	9.04
GBR	0.13	−0.01	0.06	0.04	0.07	0.14	0.12	0.16	0.14		0.19
	1.07)	(−0.07)	(0.68)	(0.50)	(1.10)	(1.86)	(1.22)	(2.26)	(1.38)		(1.55)
	[0.36]	[0.94]	[0.69]	[0.79]	[0.73]	[0.31]	[0.41]	[0.38]	[0.21]		[0.14]
	9.02	3.88	5.37	4.69	5.25	6.46	3.73	10.09	6.21		6.39
USA	0.07	−0.21	0.08	0.18	0.13	0.08	0.18	0.15	0.07	−0.11	
	0.75)	(−1.47)	(0.84)	(1.63)	(1.85)	(1.11)	(1.49)	(1.99)	(0.51)	(−0.86)	
	[0.58]	[0.10]	[0.60]	[0.28]	[0.50]	[0.60]	[0.23]	[0.42]	[0.57]	[0.36]	
	5.06	7.32	4.46	5.37	6.14	2.82	3.98	9.82	4.32	5.20	
Average	0.11	−0.06	0.13	0.07	0.08	0.06	0.11	0.15	0.21	−0.05	0.21
Pooled	0.12	−0.07	0.12	0.09	0.08*	0.05	0.12*	0.15*	0.21*	−0.03	0.20*
	1.11)	(−0.65)	(1.26)	(0.87)	(1.42)	(0.38)	(1.31)	(2.37)	(1.59)	(−0.26)	(1.67)

Table 18: Impact of Negative Returns

The table reports the $\beta_{i,j}$ estimates of regression (7), so only when using negative lagged country j's excess returns (and the corresponding data). In the parenthesis below the coefficient estimates, heteroskedasticity-robust t-statistic are shown for testing $H_0 : \beta_{i,j} = 0$ against $H_a : \beta_{i,j} > 0$. Furthermore, the asterisk indicates significance at a 10% significance level according to the moving block bootstrapped p-values. In the brackets, the moving block bootstrapped p-values are reported for testing the same hypothesis as the t-statistic. Below the p-values, the R^2 statistics is showed in percentages.

1	2	3	4	5	6	7	8	9	10	11	12
i	$\hat{\beta}_{i,AUS}$	$\hat{\beta}_{i,CAN}$	$\hat{\beta}_{i,FRA}$	$\hat{\beta}_{i,DEU}$	$\hat{\beta}_{i,ITA}$	$\hat{\beta}_{i,JPN}$	$\hat{\beta}_{i,NLD}$	$\hat{\beta}_{i,SWE}$	$\hat{\beta}_{i,CHE}$	$\hat{\beta}_{i,GBR}$	$\hat{\beta}_{i,USA}$
AUS		0.12	0.15	0.10	0.14	0.12	0.19	0.12	0.04	0.17	0.22*
		(0.76)	(1.32)	(0.78)	(1.31)	(0.92)	(1.34)	(1.21)	(0.34)	(1.08)	(1.00)
		[0.29]	[0.20]	[0.43]	[0.30]	[0.27]	[0.12]	[0.38]	[0.64]	[0.11]	[0.03]
		1.95	2.56	1.58	4.55	2.60	2.88	3.22	2.62	2.21	3.35
CAN	−0.06		−0.01	0.01	0.16	0.14	0.10	0.04	0.00	0.08	0.14
	(−0.75)		(−0.08)	(0.05)	(1.77)	(1.25)	(0.67)	(0.38)	(−0.03)	(0.55)	(0.69)
	[0.66]		[0.95]	[0.97]	[0.33]	[0.26]	[0.49]	[0.83]	[0.97]	[0.53]	[0.34]
	4.22		2.68	2.72	5.25	2.30	6.08	5.24	4.10	3.91	6.39
FRA	−0.05	0.20		−0.07	0.15	0.11	0.08	0.08	0.31*	0.28*	0.11
	(−0.39)	(1.31)		(−0.44)	(1.02)	(0.71)	(0.44)	(0.59)	(1.53)	(1.71)	(0.58)
	[0.71]	[0.11]		[0.70]	[0.37]	[0.33]	[0.63]	[0.63]	[0.03]	[0.05]	[0.39]
	1.90	3.68		3.87	4.58	3.43	6.24	2.85	5.28	2.79	4.21
DEU	0.09	0.27*	−0.15		0.16	0.26*	0.16	0.21	0.56*	0.29*	0.30*
	(0.56)	(1.68)	(−0.79)		(1.55)	(1.55)	(0.69)	(1.40)	(2.54)	(1.40)	(1.24)
	[0.51]	[0.02]	[0.35]		[0.32]	[0.03]	[0.40]	[0.25]	[0.00]	[0.03]	[0.01]
	2.67	5.32	1.89		5.05	3.11	6.20	4.63	8.84	3.86	4.93
ITA	−0.10	0.18*	0.21	0.21		0.21*	0.08	0.05	0.20*	0.11	0.12
	(−0.81)	(1.20)	(1.06)	(1.22)		(1.36)	(0.46)	(0.38)	(1.16)	(0.62)	(0.61)
	[0.31]	[0.04]	[0.10]	[0.10]		[0.08]	[0.50]	[0.75]	[0.06]	[0.27]	[0.22]
	4.84	1.88	4.07	2.95		1.59	3.72	8.19	4.62	3.14	2.51
JPN	0.08	0.15	0.03	0.05	0.01		0.31*	0.07	0.13	0.10	0.18*
	(1.00)	(1.20)	(0.33)	(0.42)	(0.06)		(2.32)	(0.57)	(0.97)	(0.83)	(1.10)
	[0.54]	[0.19]	[0.79]	[0.71]	[0.97]		[0.03]	[0.71]	[0.26]	[0.39]	[0.09]
	2.65	2.91	3.23	3.96	1.75		5.76	2.43	4.51	4.21	4.02
NLD	0.13	0.32*	0.14	0.35*	0.18	0.18		0.17	0.73*	0.53*	0.58*
	(0.83)	(1.95)	(1.01)	(2.11)	(1.68)	(1.33)		(1.35)	(3.81)	(2.70)	(2.72)
	[0.34]	[0.02]	[0.33]	[0.06]	[0.26]	[0.17]		[0.39]	[0.00]	[0.00]	[0.00]
	2.63	4.31	2.70	4.67	7.19	2.11		5.86	11.75	5.25	6.31
SWE	0.13	0.40*	0.09	0.09	−0.02	0.14	0.05		0.45*	0.00	0.23*
	(0.94)	(2.48)	(0.43)	(0.47)	(−0.15)	(0.75)	(0.20)		(2.20)	(0.01)	(0.97)
	[0.23]	[0.00]	[0.54]	[0.55]	[0.87]	[0.23]	[0.71]		[0.00]	[0.98]	[0.01]
	8.34	8.57	5.51	9.64	6.60	8.15	7.05		7.27	6.02	4.33
CHE	−0.03	0.23*	−0.12	0.28	0.07	0.05	0.19	0.05		0.35*	0.25*
	(−0.26)	(1.52)	(−0.77)	(1.82)	(0.69)	(0.43)	(1.20)	(0.44)		(2.19)	(1.44)
	[0.82]	[0.07]	[0.50]	[0.16]	[0.72]	[0.73]	[0.30]	[0.80]		[0.02]	[0.06]
	9.18	4.62	5.88	4.86	9.74	7.44	6.32	7.40		5.09	4.01
GBR	0.07	0.21	0.11	0.10	0.15	0.11	0.21	0.08	0.32*		0.71*
	(0.54)	(1.54)	(0.75)	(0.73)	(1.52)	(0.95)	(1.11)	(0.71)	(1.98)		(2.97)
	[0.63]	[0.11]	[0.49]	[0.59]	[0.40]	[0.43]	[0.31]	[0.67]	[0.06]		[0.00]
	2.20	5.49	4.43	5.94	7.18	3.85	9.29	5.19	6.22		10.88
USA	0.14	0.19	0.02	−0.01	0.20	0.11	0.15	0.04	0.05	0.11	
	(1.27)	(1.03)	(0.12)	(−0.13)	(1.91)	(1.05)	(0.83)	(0.37)	(0.32)	(0.62)	
	[0.47]	[0.27]	[0.94]	[0.94]	[0.33]	[0.44]	[0.49]	[0.86]	[0.80]	[0.58]	
	3.77	3.18	4.45	6.23	5.74	6.31	9.01	2.29	3.74	2.17	
Average	0.04	0.23	0.05	0.11	0.12	0.14	0.15	0.09	0.28	0.20	0.28
Pooled	0.03	0.21*	0.05	0.08	0.12*	0.14	0.14	0.09	0.23*	0.16	0.22
	(0.22)	(1.62)	(0.42)	(0.60)	(1.36)	(1.01)	(0.89)	(0.91)	(1.33)	(1.26)	(1.23)

Table 19: Impact of Months with High Volatility

The table reports the $\beta_{i,j}$ estimates of regression (8), so only when using lagged country j's monthly excess returns corresponding to months with volatility being larger than the average monthly volatility in the sample (and the corresponding data). In the parenthesis below the coefficient estimates, heteroskedasticity-robust t-statistic are shown for testing $H_0 : \beta_{i,j} = 0$ against $H_a : \beta_{i,j} > 0$. Furthermore, the asterisk indicates significance at a 10% significance level according to the moving block bootstrapped p-values. In the brackets, the moving block bootstrapped p-values are reported for testing the same hypothesis as the t-statistic. Below the p-values, the R^2 statistics is showed in percentages.

1	2	3	4	5	6	7	8	9	10	11	12
i	$\hat{\beta}_{i,AUS}$	$\hat{\beta}_{i,CAN}$	$\hat{\beta}_{i,FRA}$	$\hat{\beta}_{i,DEU}$	$\hat{\beta}_{i,ITA}$	$\hat{\beta}_{i,JPN}$	$\hat{\beta}_{i,NLD}$	$\hat{\beta}_{i,SWE}$	$\hat{\beta}_{i,CHE}$	$\hat{\beta}_{i,GBR}$	$\hat{\beta}_{i,USA}$
AUS		0.00	0.12	0.01	0.08	0.05	0.05	0.12	0.10	0.05	0.21*
		(−0.03)	(1.43)	(0.09)	(1.84)	(0.94)	(0.49)	(2.16)	(1.10)	(0.51)	(1.36)
		[0.97]	[0.28]	[0.95]	[0.44]	[0.52]	[0.58]	[0.29]	[0.20]	[0.58]	[0.02]
		6.92	9.10	2.53	6.66	4.05	7.35	4.61	2.77	2.96	4.95
CAN	0.09		0.03	0.04	0.09	0.14*	0.09	0.14	−0.08	0.12	0.16
	(1.09)		(0.59)	(0.56)	(1.91)	(2.72)	(0.95)	(2.88)	(−0.71)	(1.30)	(1.03)
	[0.32]		[0.76]	[0.73]	[0.48]	[0.09]	[0.47]	[0.27]	[0.32]	[0.24]	[0.19]
	5.03		9.95	6.66	8.21	10.50	8.82	12.37	6.71	3.34	6.05
FRA	0.07	0.00		0.02	−0.04	0.08	0.05	0.15	0.25*	0.13	0.13*
	(0.70)	(−0.02)		(0.10)	(−0.65)	(0.81)	(0.30)	(1.41)	(1.39)	(0.68)	(0.69)
	[0.30]	[0.98]		[0.90]	[0.75]	[0.39]	[0.63]	[0.22]	[0.00]	[0.12]	[0.09]
	4.93	3.11		4.55	2.34	4.73	3.88	6.14	4.95	5.81	7.49
DEU	0.06	0.12*	−0.01		0.05	0.13	−0.05	0.15	0.39*	0.25*	0.38*
	(0.55)	(1.13)	(−0.10)		(0.97)	(1.65)	(−0.30)	(1.45)	(1.98)	(1.68)	(2.40)
	[0.40]	[0.06]	[0.94]		[0.73]	[0.13]	[0.72]	[0.30]	[0.00]	[0.00]	[0.00]
	7.72	5.19	3.27		3.01	5.51	3.27	5.28	5.67	5.15	8.13
ITA	−0.02	0.03	0.43*	0.22*		0.10	−0.06	0.14*	0.33*	0.25*	0.14*
	(−0.20)	(0.27)	(3.19)	(1.25)		(1.05)	(−0.43)	(1.72)	(1.97)	(1.74)	(1.02)
	[0.73]	[0.54]	[0.00]	[0.00]		[0.11]	[0.39]	[0.08]	[0.00]	[0.00]	[0.01]
	3.82	3.01	11.04	5.59		4.41	4.78	5.71	5.60	6.52	6.47
JPN	0.05	0.05	0.10	0.05	−0.01		0.01	0.15	0.13*	0.17*	0.17*
	(0.64)	(0.54)	(1.39)	(0.73)	(−0.26)		(0.15)	(2.15)	(1.30)	(1.75)	(1.54)
	[0.42]	[0.42]	[0.21]	[0.54]	[0.89]		[0.87]	[0.17]	[0.04]	[0.01]	[0.01]
	4.29	6.39	3.28	3.67	3.15		8.47	4.90	3.05	4.33	7.55
NLD	0.16	0.18*	0.17	0.32*	0.09	0.21*		0.20	0.45*	0.34*	0.49*
	(1.72)	(1.55)	(1.82)	(2.20)	(1.91)	(2.98)		(2.38)	(2.42)	(2.15)	(3.48)
	[0.11]	[0.03]	[0.21]	[0.04]	[0.49]	[0.02]		[0.17]	[0.00]	[0.01]	[0.00]
	11.96	9.59	6.49	6.33	5.29	8.65		8.06	8.52	6.17	12.03
SWE	0.14*	0.13*	0.01	−0.10	0.16*	0.06	−0.02		0.15*	0.12*	0.25*
	(1.45)	(1.09)	(0.08)	(−0.75)	(1.84)	(0.59)	(−0.09)		(0.98)	(0.73)	(1.68)
	[0.03]	[0.02]	[0.91]	[0.32]	[0.07]	[0.40]	[0.86]		[0.02]	[0.06]	[0.00]
	10.83	8.69	5.24	5.95	10.52	3.60	5.56		5.00	6.35	11.39
CHE	0.08	0.01	−0.11	−0.11	−0.01	0.08	−0.06	0.09		−0.02	0.27*
	(0.95)	(0.09)	(−1.16)	(−1.01)	(−0.27)	(1.33)	(−0.51)	(1.45)		(−0.12)	(1.75)
	[0.40]	[0.94]	[0.46]	[0.58]	[0.92]	[0.48]	[0.71]	[0.58]		[0.90]	[0.03]
	10.36	12.48	14.00	11.38	7.94	14.33	9.84	11.41		13.13	12.19
GBR	0.10	0.14	0.06	−0.03	0.01	0.11	0.06	0.01	0.04		0.38*
	(1.13)	(1.37)	(0.92)	(−0.29)	(0.32)	(1.72)	(0.40)	(0.19)	(0.31)		(2.06)
	[0.27]	[0.14]	[0.68]	[0.87]	[0.91]	[0.27]	[0.73]	[0.95]	[0.74]		[0.00]
	8.48	5.21	5.58	7.56	2.83	7.92	3.34	6.81	8.58		9.70
USA	0.08	−0.02	0.00	0.01	0.12	0.12	0.02	0.07	−0.02	0.08	
	(1.04)	(−0.13)	(−0.02)	(0.12)	(2.72)	(2.45)	(0.18)	(1.18)	(−0.17)	(0.68)	
	[0.53]	[0.88]	[0.99]	[0.95]	[0.37]	[0.28]	[0.89]	[0.69]	[0.89]	[0.57]	
	6.31	4.15	5.64	6.25	7.47	10.45	4.42	8.78	4.72	2.30	
Average	0.08	0.06	0.08	0.04	0.05	0.11	0.01	0.12	0.17	0.15	0.26
Pooled	0.07*	0.06	0.08*	0.03	0.06*	0.11*	0.02	0.12*	0.15*	0.14*	0.22*
	(1.29)	(0.90)	(2.23)	(0.65)	(2.02)	(2.01)	(0.29)	(3.19)	(2.17)	(1.85)	(2.57)

Table 20: Impact of Months with Low Volatility

The table reports the $\beta_{i,j}$ estimates of regression (9), so only when using lagged country j's monthly excess returns corresponding to months with volatility being below the average monthly volatility of the sample (and the corresponding data). In the parenthesis below the coefficient estimates, heteroskedasticity-robust t-statistic are shown for testing $H_0 : \beta_{i,j} = 0$ against $H_a : \beta_{i,j} > 0$. Furthermore, the asterisk indicates significance at a 10% significance level according to the moving block bootstrapped p-values. In the brackets, the moving block bootstrapped p-values are reported for testing the same hypothesis as the t-statistic. Below the p-values, the R^2 statistics is showed in percentages.

1	2	3	4	5	6	7	8	9	10	11	12
i	$\hat{\beta}_{i,AUS}$	$\hat{\beta}_{i,CAN}$	$\hat{\beta}_{i,FRA}$	$\hat{\beta}_{i,DEU}$	$\hat{\beta}_{i,ITA}$	$\hat{\beta}_{i,JPN}$	$\hat{\beta}_{i,NLD}$	$\hat{\beta}_{i,SWE}$	$\hat{\beta}_{i,CHE}$	$\hat{\beta}_{i,GBR}$	$\hat{\beta}_{i,USA}$
AUS		0.25*	0.12	0.25*	0.07	0.17*	0.16*	0.03	0.13	0.10	0.19*
		(2.10)	(1.19)	(2.02)	(1.28)	(1.57)	(1.82)	(0.36)	(1.25)	(0.79)	(2.06)
		[0.01]	[0.20]	[0.02]	[0.53]	[0.08]	[0.08]	[0.82]	[0.11]	[0.27]	[0.02]
		3.96	2.50	4.07	1.78	1.81	5.09	1.63	1.85	2.00	3.05
CAN	0.01		0.08	0.07	0.00	−0.08	−0.01	0.13	0.19*	0.03	0.25*
	(0.11)		(0.92)	(0.96)	(0.05)	(−0.96)	(−0.09)	(1.99)	(1.65)	(0.27)	(2.05)
	[0.94]		[0.45]	[0.49]	[0.98]	[0.41]	[0.93]	[0.33]	[0.05]	[0.74]	[0.02]
	6.91		4.17	9.42	5.02	7.58	3.96	6.81	7.69	9.20	7.04
FRA	−0.08	0.02		−0.01	−0.06	−0.01	−0.03	0.13	0.19*	−0.03	0.02
	(−0.78)	(0.18)		(−0.08)	(−0.60)	(−0.12)	(−0.23)	(1.75)	(1.38)	(−0.24)	(0.21)
	[0.35]	[0.80]		[0.92]	[0.60]	[0.84]	[0.78]	[0.20]	[0.01]	[0.66]	[0.79]
	3.31	5.00		3.04	5.41	2.67	3.64	3.77	4.63	6.84	1.97
DEU	−0.05	0.06	0.24*		0.08	0.01	0.12	0.09	0.21*	−0.09	0.01
	(−0.54)	(0.56)	(2.24)		(0.92)	(0.11)	(1.04)	(1.36)	(1.48)	(−0.81)	(0.12)
	[0.60]	[0.43]	[0.02]		[0.51]	[0.91]	[0.19]	[0.42]	[0.01]	[0.24]	[0.86]
	0.99	2.67	5.85		3.82	3.10	4.37	4.88	4.87	4.29	4.47
ITA	0.09	0.20*	−0.06	0.07		0.07	−0.06	−0.06	0.29*	0.08	0.06
	(0.71)	(1.42)	(−0.52)	(0.58)		(0.63)	(−0.40)	(−0.60)	(1.79)	(0.51)	(0.45)
	[0.16]	[0.00]	[0.45]	[0.38]		[0.34]	[0.39]	[0.50]	[0.00]	[0.19]	[0.27]
	1.63	2.63	1.59	0.90		3.59	3.24	0.90	3.79	1.19	0.55
JPN	0.00	0.20*	0.12	0.00	0.11		0.02	0.00	0.14*	0.03	−0.03
	(−0.03)	(1.82)	(1.62)	(0.04)	(1.40)		(0.27)	(0.05)	(1.35)	(0.29)	(−0.30)
	[0.97]	[0.02]	[0.24]	[0.96]	[0.38]		[0.77]	[0.97]	[0.08]	[0.73]	[0.70]
	1.39	3.35	3.99	3.12	2.96		1.10	6.03	3.46	2.27	0.73
NLD	0.02	0.13	0.13	−0.04	−0.04	−0.09		0.09	0.22*	−0.06	0.12
	(0.25)	(1.22)	(1.31)	(−0.42)	(−0.46)	(−1.24)		(1.17)	(1.85)	(−0.48)	(1.14)
	[0.80]	[0.18]	[0.27]	[0.74]	[0.78]	[0.32]		[0.50]	[0.03]	[0.49]	[0.15]
	2.08	3.82	7.03	8.88	7.49	9.34		7.90	7.87	8.40	9.66
SWE	−0.31*	0.22*	0.11	0.14*	−0.08	0.09	0.01		0.13*	0.04	0.12*
	(−2.69)	(1.55)	(1.00)	(1.27)	(−0.77)	(0.77)	(0.06)		(0.97)	(0.30)	(0.90)
	[0.00]	[0.00]	[0.15]	[0.04]	[0.43]	[0.23]	[0.91]		[0.05]	[0.54]	[0.05]
	5.85	5.09	6.16	6.64	7.11	8.98	6.37		6.86	5.00	4.12
CHE	−0.05	0.03	0.09	0.00	0.00	−0.07	0.00	0.15		−0.04	−0.04
	(−0.64)	(0.24)	(0.80)	(0.03)	(0.06)	(−0.92)	(−0.02)	(2.61)		(−0.41)	(−0.41)
	[0.66]	[0.74]	[0.46]	[0.98]	[0.98]	[0.47]	[0.99]	[0.27]		[0.69]	[0.66]
	3.29	3.73	3.89	3.61	4.51	4.22	3.96	6.11		4.17	3.97
GBR	0.09	0.03	0.10	0.00	−0.01	0.08	−0.13	0.16	0.08		0.08
	(0.97)	(0.28)	(0.81)	(0.04)	(−0.22)	(0.87)	(−1.32)	(2.28)	(0.74)		(0.64)
	[0.43]	[0.74]	[0.34]	[0.97]	[0.92]	[0.46]	[0.23]	[0.19]	[0.43]		[0.36]
	4.87	7.37	7.24	6.81	7.45	5.22	9.04	7.67	5.87		5.40
USA	0.01	0.08	0.03	−0.06	−0.06	−0.20*	−0.01	0.08	0.04	−0.05	
	(0.13)	(0.70)	(0.36)	(−0.84)	(−1.18)	(−2.79)	(−0.13)	(1.30)	(0.36)	(−0.42)	
	[0.91]	[0.46]	[0.79]	[0.53]	[0.64]	[0.05]	[0.92]	[0.54]	[0.68]	[0.62]	
	3.80	6.16	4.38	7.00	6.68	9.01	7.34	7.31	5.95	5.78	
Average	−0.03	0.12	0.10	0.04	0.00	0.00	0.01	0.08	0.16	0.00	0.08
Pooled	−0.03	0.11*	0.07	0.04	0.00	−0.01	0.00	0.06*	0.15*	0.01	0.06
	(−0.45)	(1.30)	(1.28)	(0.64)	(0.08)	(−0.11)	(−0.05)	(1.36)	(1.81)	(0.13)	(0.79)

Table 21: Impact of Lagged US Excess Returns in Times of US Recession

The table reports the $\beta_{i,USA}$ estimates of regression (10), so only when using lagged US monthly excess returns corresponding to the months of US recession (and the corresponding data). In the parenthesis below the coefficient estimates, heteroskedasticity-robust t-statistic are shown for testing $H_0 : \beta_{i,j} = 0$ against $H_a : \beta_{i,j} > 0$. Furthermore, the asterisk indicates significance at a 10% significance level according to the moving block bootstrapped p-values. In the brackets, the moving block bootstrapped p-values are reported for testing the same hypothesis as the t-statistic. Below the p-values, the R^2 statistics is showed in percentages.

	AUS	CAN	FRA	DEU	ITA	JPN	NLD	SWE	CHE	GBR
$\hat{\beta}_{i,USA}$	0.44^*	0.76^*	0.25^*	0.52^*	0.54^*	0.42^*	0.77^*	0.39^*	0.34	0.71^*
	(2.14)	(2.68)	(1.34)	(2.44)	(2.39)	(1.93)	(2.92)	(1.88)	(1.92)	(3.47)
	[0.01]	[0.00]	[0.05]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.07]	[0.00]
	18.87	23.22	13.74	23.14	17.56	13.95	21.71	11.32	21.86	24.07

Table 22: Impact of Lagged US Excess Returns in Times of a Growing US Economy

The table reports the $\beta_{i,USA}$ estimates of regression (11), so only when using lagged US monthly excess returns corresponding to the months of US economic growth (and the corresponding data). In the parenthesis below the coefficient estimates, heteroskedasticity-robust t-statistic are shown for testing $H_0 : \beta_{i,j} = 0$ against $H_a : \beta_{i,j} > 0$. Furthermore, the asterisk indicates significance at a 10% significance level according to the moving block bootstrapped p-values.

	AUS	CAN	FRA	DEU	ITA	JPN	NLD	SWE	CHE	GBR
$\hat{\beta}_{i,USA}$	0.10^*	0.04	0.06	0.14^*	0.02	0.01	0.21^*	0.16^*	0.08	0.07
	(1.09)	(0.49)	(0.61)	(1.32)	(0.19)	(0.18)	(2.15)	(1.26)	(0.86)	(0.59)
	[0.05]	[0.29]	[0.13]	[0.01]	[0.32]	[0.39]	[0.00]	[0.00]	[0.11]	[0.20]
	3.42	4.58	3.75	4.01	1.93	3.10	7.33	6.95	5.46	5.98

Table 23: U.S. Recession Benchmark Regression

This table shows estimates of the benchmark regression as described in equation (12). The second and sixth column contain the estimates for the coefficient of the Treasury bill rate with the heteroskedasticity-robust t-statistic, testing $H_0 : \beta_{i,b} = 0$ against $H_a : \beta_{i,b} < 0$, in the parentheses below and the third and seventh columns show the estimates for the coefficient of the log dividend yield with again the t-statistics, testing $H_0 : \beta_{i,d} = 0$ against $H_a : \beta_{i,d} > 0$, in the parentheses below. In the fourth and eighth column, the R^2 statistic for every regression is shown. In the parenthesis below these R^2 statistics, the χ^2 statistic for testing $H_0 : \beta_{i,b} = \beta_{i,d} = 0$ are stated. Furthermore, the pooled estimates are shown, which impose the restriction that $\beta_{i,b} = \bar{\beta}_b$ and $\beta_{i,d} = \bar{\beta}_d$. The asterisk indicates significance on 10% or better, based on the moving block bootstrapped p-values testing the same hypothesis as the t-statistics. In the brackets, the moving block bootstrapped p-values are reported

1	2	3	4	5	6	7	8
i	$\hat{\beta}_{i,b}$	$\hat{\beta}_{i,d}$	R^2	i	$\hat{\beta}_{i,b}$	$\hat{\beta}_{i,d}$	R^2
Australia	−0.31	4.43	3.76%	Netherlands	−0.25	4.21*	3.95%
	(−1.51)	(1.34)	(2.57)		(−0.75)	(1.66)	(2.95)
	[0.10]	[0.13]			[0.22]	[0.04]	
Canada	−0.22	2.10	2.56%	Sweden	−0.01	2.06	0.81%
	(−1.12)	(0.80)	(1.25)		(−0.03)	(0.70)	(0.59)
	[0.12]	[0.20]			[0.41]	[0.18]	
France	−0.17	4.86*	6.02%	Switzerland	−0.19	5.90*	6.98%
	(−0.75)	(1.69)	(3.83)		(−0.68)	(2.26)	(5.42)
	[0.21]	[0.04]			[0.26]	[0.02]	
Germany	−0.55*	9.05*	11.45%	United Kingdom	−0.12	5.35*	4.98%
	(−1.36)	(2.42)	(6.82)		(−0.63)	(1.96)	(4.60)
	[0.04]	[0.00]			[0.31]	[0.06]	
Italy	0.17	3.08	1.51%	United States	−0.32	3.88*	4.90%
	(0.96)	(0.90)	(1.03)		(−1.15)	(1.67)	(2.91)
	[0.73]	[0.12]			[0.15]	[0.04]	
Japan	0.40	2.71*	3.11%	Pooled	−0.05	2.33*	2.30%
	(1.72)	(1.05)	(4.35)		(−0.34)	(2.51)	(6.51)
	[0.80]	[0.09]					

Table 24: U.S. Growing Economy Benchmark Regression

This table shows estimates of the benchmark regression as described in equation (13). The second and sixth column contain the estimates for the coefficient of the Treasury bill rate with the heteroskedasticity-robust t-statistic, testing $H_0 : \beta_{i,b} = 0$ against $H_a : \beta_{i,b} < 0$, in the parentheses below and the third and seventh columns show the estimates for the coefficient of the log dividend yield with again the t-statistics, testing $H_0 : \beta_{i,d} = 0$ against $H_a : \beta_{i,d} > 0$, in the parentheses below. In the fourth and eighth column, the R^2 statistic for every regression is shown. In the parenthesis below these R^2 statistics, the χ^2 statistic for testing $H_0 : \beta_{i,b} = \beta_{i,d} = 0$ are stated. Furthermore, the pooled estimates are shown, which impose the restriction that $\beta_{i,b} = \bar{\beta}_b$ and $\beta_{i,d} = \bar{\beta}_d$. The asterisk indicates significance on 10% or better, based on the moving block bootstrapped p-values testing the same hypothesis as the t-statistics. In the brackets, the moving block bootstrapped p-values are reported

1	2	3	4	5	6	7	8
i	$\hat{\beta}_{i,b}$	$\hat{\beta}_{i,d}$	R^2	i	$\hat{\beta}_{i,b}$	$\hat{\beta}_{i,d}$	R^2
Australia	−0.07	3.74*	1.30%	Netherlands	−0.32*	2.26*	2.07%
	(−0.53)	(0.94)	(1.18)		(−2.70)	(2.04)	(7.52)
	[0.18]	[0.02]			[0.00	[0.01]	
Canada	−0.26*	2.17*	2.93%	Sweden	−0.02	2.29*	1.41%
	(−2.90)	(1.74)	(8.82)		(−0.28)	(1.93)	(3.86)
	[0.00]	[0.03]			[0.12	[0.00]	
France	−0.09*	1.23*	0.41%	Switzerland	−0.17*	0.82	0.60%
	(−1.02)	(0.97)	(1.41)		(−1.56)	(0.80)	(2.45)
	[0.06]	[0.09]			[0.06]	[0.24]	
Germany	−0.25*	1.51*	0.71%	United Kingdom	−0.21*	4.61*	3.75%
	(−1.42)	(1.06)	(2.03)		(−1.98)	(3.23)	(10.70)
	[0.03]	[0.09]			[0.01]	[0.00]	
Italy	0.04	0.07	0.10%	United States	−0.18*	1.64*	1.64%
	(0.50)	(0.06)	(0.27)		(−1.74)	(2.06)	(4.45)
	[0.40]	[0.45]			[0.03]	[0.03]	
Japan	0.10	1.08*	0.64%	Pooled	−0.05	1.03*	0.55%
	(0.89)	(1.65)	(3.06)		(−0.91)	(1.99)	(4.24)
	[0.36]	[0.05]					