# Predictability in Equity Markets: A Quantile Approach

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**Abstract**

In this thesis we examine the predictability of equity premiums using international lagged excess returns. Rapach et al. (2013) shows that lagged excess returns of different countries, especially the U.S., have significant forecasting power when predicting equity premiums. This paper extends on the results of Rapach et al. (2013) by showing, with the use of quantile regression, that the relationships found by Rapach et al. (2013) also hold in other parts of the distribution besides the mean, especially in the lower tails. Furthermore we present that the U.S. continues to be one of the countries with the most predictive power regardless of the specific part of the distribution. However the out-of-sample predictive power, measured with adjusted versions of the Diebold-Mariano statistic, is less visible for the tails of the distribution than it is for the mean.

# Contents

# 1 Introduction

Stock return predictability has been a subject that has received a lot of attention over the years. The possibility of predicting returns is of great importance for major financial institutions such as banks and investment companies. These institutions are of course interested in getting high returns without taking unnecessary high risk. Because of this, there has been a lot of research on the possibility of predicting returns. Although there are still some criticisms, a lot of researchers have provided results that do give firm reasons to believe that returns are (at least to some extent) predictable. Ferson and Harvey (1991) for instance find that returns are predictable but that this isn't a result of market inefficiency but due to changes in risk exposures. Solnik (1993) uses the predictive parts of returns to create a trading strategy which performs better than standard market portfolios. Pesaran and Timmermann (1995) also conclude that predictability is so strong that it could have been exploited by investors in the 1970s. Rapach et al. (2013) show that excess returns of a selection of industrialized countries are predictable by using lagged excess returns from other countries. In particular a significant lead-lag relationship is found between the United States (U.S.) and the individual industrialized non-U.S. countries, both in-sample and out-of-sample. This relationship is consistent with the lag with which relevant information spreads from the U.S. to the other markets as is formally investigated by the researchers with a news-diffusion model.

In this thesis we use the relationship found by Rapach et al. (2013) to predict different types of excess returns. In particular we investigate whether the results hold when we differentiate between positive and negative excess returns and if they hold over different quantiles. The lower quantiles are directly linked to downside risk via the concept of Value-At-Risk. In order to estimate the different quantiles we use quantile regression which is used (or a variation hereof) by other researchers in a similar setting such as by Engle and Manganelli (1999). The distinction between positive and negative excess returns is analyzed via regular ordinary least squares (OLS) in-sample and by the use of logit models out-of-sample.

Although there has been a lot of research on the shape of the distribution of returns, there has been less so in forecasting specific quantiles (although it definitely has been done e.g. Clements et al. (2008)). Lead-lag relationships between countries appear to have barely been used by researchers to forecast specific quantiles, which is why this thesis adds to the existing literature. The possibility to predict specific quantiles by using the lead-lag relationship can also be used by financial institutions for predicting their Value-At-Risk and to predict very high excess returns via the upper quantiles.

The analysis of the distinction between positive and negative excess returns shows that negative equity premiums are more easily predicted with lagged international excess returns than positive equity premiums. The quantile analysis supports this. We find, using quantile regression on the $10^{th}$, $25^{th}$, $75^{th}$ and $90^{th}$ quantile, that the predictive power of the U.S. (as found by Rapach et al. (2013) for the mean), also holds for different parts of the distribution. Especially the lower excess returns are predictable by using lagged international excess returns, which is explainable by risk averseness of traders. We also perform an out-of-sample analysis by using an adjusted form (as introduced by Ge (2015)) of the standard Diebold-Mariano test statistic of equal forecasting accuracy (Diebold and Mariano (2002)). This also shows that, although the out-of-sample predictive power of the U.S. isn't exceptionally strong, lower excess returns are more easily predicted than higher excess returns.

This thesis uses the research of Rapach et al. (2013) as a guideline. We first replicate their major results and then make extensions in the form named above.

## 2 Data

The used data is given on the website of the author of the reference paper[1]. The variables that are used in almost all the models are the excess return, the risk-free rate and the log dividend yield for each of the countries of interest. The countries that will be discussed are: Australia (AUS), Canada (CAN), France (FRA), Germany (DEU), Italy (ITA), Japan (JPN), the Netherlands (NLD), Sweden (SWE), Switzerland (CHE), the United Kingdom (GBR), and the United States (USA).

The excess returns are computed by taking the return as measured by a country's value weighted broad stock market index and deducting the risk-free rate. The risk-free rate is approximated by the three-month Treasury bill rate. The log dividend yield is the logarithm of the dividend yield (dividend per share divided by the price per share) based on an average of the dividends of the current and preceding eleven months. Although the analysis will be done on a monthly basis, the return data needs to be daily available to correct for closing time differences between markets. This gives us a time window from February 1980 until December 2010. Also noteworthy is that the returns are based on the country's national currency. This allows us to work without an exchange rate risk premium and, because of interest rate parity, this shouldn't differ from the currency-hedged returns (Solnik (1993)).

Summary statistics of the monthly excess returns are given in table 13 in the Appendix.

## 3 Methodology

For the methodology, we first discuss the replicating part. Thereafter we discuss the extensions that we make for the paper.

### 3.1 Replication

#### 3.1.1 Benchmark Model

In order to find the lead-lag relationship between countries we first create a benchmark model to see if lagged values of the country's own risk-free interest rate and the log dividend yield have a significant influence on the future excess returns. Thus the benchmark model is of the form

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

In which $r_{i,t+1}$ is the excess return for country $i$ at month $t+1$, $bill_{i,t}$ is the three-month Treasury bill rate (risk-free rate) for country $i$ at month $t$ and $dy_{i,t}$ is the log dividend yield for country $i$ at month $t$.

In order to judge the significance of the coefficients we use heteroskedasticity-robust standard errors (White (1980)) to compute the $t$-statistics. The $p$-values that correspond to these coefficients are computed by a wild bootstrap procedure based on Gonçalves and Kilian (2004) and Cavaliere et al. (2010). By using this procedure we take simultaneous correlations between variables into account and take care of conditional heteroskedasticity and Stambaugh (1999) bias. Since we expect there to be a negative coefficient for the Treasury bill rate and a positive coefficient for the dividend yield we compute the $p$-values based on a one-sided alternative, thus $\beta_{i,b} < 0$ and $\beta_{i,d} > 0$. We expect this since the excess returns are computed by deducting the Treasury bill rate and because dividends are likely to be higher when stock prices rise. Besides testing for the individual significance of the coefficients we also do a joint chi-squared test for the null-hypotheses $\beta_{i,b} = \beta_{i,d} = 0$.

[1]Data is available at *http://sites.slu.edu/rapachde/home/research* which in turn is largely from Global Financial Data

For model (1) we also do a pooled estimation technique for which we set the restriction that $\beta_{i,b}$ and $\beta_{i,d}$ should be the same across all countries $i$. The $t$-statistics for this model are based on a GMM procedure that takes simultaneous correlations and heteroskedasticity into account.

As a final adaption of model (1) we estimate this model by using the USA benchmark variables for each country instead of the country specific variables. This means that we replace $bill_{i,t}$ by $bill_{USA,t}$ and $dy_{i,t}$ by $dy_{USA,t}$ in equation (1). For this version of the model we use the same procedures as before to compute the $p$-values and $t$-statistics and to perform a pooled estimation.

### 3.1.2 International Returns-Based Predictive Model

We now investigate whether excess returns of one country can predict the excess returns of another country in the next period. We do so by expanding (1) with lagged excess returns. The model is thus now given by

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

In this model not only the lagged excess returns of country $j$ are taken into account when predicting the returns of country $i$ but also country $i$'s own lagged excess returns. We do this because returns are autocorrelated and simultaneously correlated between countries, causing biased results when excluding the countries' own lagged excess returns. Also note that in this model we have to take closing times between markets into account such that we don't get spurious results because of the same reasons as why we include $r_{i,t}$ for country $i$. We thus remove the last day from each month in some regressions such that this problem does not occur. For an overview of the different market's opening and closing times and whether to exclude the last day for the regression in model (2), see tables 14 and 15 in the Appendix.

In the same way as in the benchmark model, we use heteroskedasticity robust $t$-statistics and wild bootstrapped $p$-values to test the significance of $\beta_{i,j}$. These $p$-values are based on the one-sided alternative that $\beta_{i,j}$ is positive, since this can be interpreted as lags of adjustment in equity prices of country $i$ to relevant information for this country, captured by country $j$'s equity prices. As for the benchmark model, we also perform a pooled estimation in which $\beta_{i,i}$, $\beta_{i,j}$, $\beta_{i,b}$ and $\beta_{i,d}$ are to remain constant for all $i \neq j$.

Finally, we adjust (2) for extra economic variables. After all, it may very well be that some of the returns can still be explained by other national variables instead of international returns. Therefore we also consider the following five extra variables: term spread, inflation rate, industrial production growth, real exchange rate growth and real oil price growth. We now thus have seven economic variables which are likely correlated. We therefore re-estimate (2) with the first two principal components of these seven variables instead of using $bill_{i,t}$ and $dy_{i,t}$ to accommodate for the extra effects that these national economic variables might have.

### 3.1.3 More General International Returns-Based Predictive Model

Next, we estimate a VAR(1) model which takes the excess returns of all the countries of interest into account simultaneously, instead of just one of the countries. The model is then of the form

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

This model will not be estimated by standard OLS since there are a lot of correlated regressors which would lead to weak tests and non-precise estimates of coefficients. Therefore we use two different approaches. First we do a pooled approach which may increase efficiency at the cost of a bias and secondly we perform an adaptive elastic net procedure (Zou and Zhang (2009), Ghosh (2011)). The pooled approach simply sets the restrictions that $\beta_{i,i}$, $\beta_{i,j}$, $\beta_{i,b}$ and $\beta_{i,d}$ are to remain constant for all $i$. For the coefficients of this model we will also estimate 90% confidence intervals based on the wild bootstrapped $p$-values.

The adaptive elastic net procedure is a procedure which allows us to estimate (3) while selecting the most important variables. The procedure solves the following problem

$$\min_{\beta_i} \sum_{t=0}^{T-1} (r_{i,t+1} - x_t'\beta_i)^2 + \lambda_1 \sum_{k=1}^{K} \omega_k |\beta_{i,k}| + \lambda_2 \sum_{k=1}^{K} \beta_{i,k}^2. \tag{4}$$

Here $x_t$ are all the standardized K predictor variables in model (3) and $\beta_i$ are the corresponding K parameters with weights $\omega$ for the first penalty term. $\lambda_1$ and $\lambda_2$ correspond to LASSO and ridge penalty terms respectively. The weights are of the form $\omega_k = |\hat{\beta}_{i,k}|^{-\gamma}$ with $\gamma > 0$ (Zou (2006)). After selecting $\lambda_1$, $\lambda_2$ and $\gamma$ using five-fold cross-validation we solve (4) using the Friedman et al. (2010) algorithm. As for the pooling model, we create bias-corrected wild bootstrapped 90% confidence intervals for the $\beta_{i,j}$ coefficients.

### 3.1.4 News-Diffusion Model

In order to investigate whether lagged international excess returns have predictive power due to information frictions, we estimate a news diffusion model of the form

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

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

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

$$\mu_{j,t} = \beta_{j,0} + \beta_{j,b}bill_{j,t} + \beta_{j,d}dy_{j,t}. \tag{8}$$

Thus $\mu_{i,t}$ is the expected excess return according to our original economic variables for country $i$. $\lambda_{i,j}$ and $\theta_{i,j}$ are the structural parameters which measure the impact of a shock of country $j$ excess returns on country $i$, and the proportion of the total impact of a shock of country $j$ simultaneously incorporated in the excess returns of country $i$, respectively. $u_{i,t+1}$ and $u_{j,t+1}$ are the non-autocorrelated error terms. These terms are also assumed to not be simultaneously correlated with each other.

The structural parameters are not unrestricted in this model. This can be seen by solving equation (6) for $u_{j,t+1}$ and substituting it into equation (5). After all, this gives us

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

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

If we are now interested in predicting equity premiums using lagged excess returns from other countries, we have to make sure that the coefficient of $r_{j,t}$ is non-zero. This means that $\lambda_{i,j}$ can't be zero and $\theta_{i,j}$ can't be equal to one. But this is fine, since $\lambda_{i,j}$ will be non-zero if country $j$ shocks affect country $i$ and $\theta_{i,j}$ will be smaller then one in the case of information frictions.

Since we are mostly interested in the leading role that the U.S. plays, we estimate the model for $j$ being the U.S. and $i$ being one of the other countries from our sample. In order to do this estimation we make the assumptions that $\theta_{USA,i} = 1$ and $\lambda_{USA,i} = 0$, meaning that the shocks of other countries do not predict and affect the U.S returns respectively. This simplified news-diffusion model is then given by

$$r_{USA,t+1} = x'_{USA,t}\beta_{USA} + u_{USA,t+1} \tag{11}$$

$$r_{i,t+1} = x'_{i,t}\beta_i + \theta_{i,USA}\lambda_{i,USA}u_{USA,t+1} + (1-\theta_{i,USA})\lambda_{i,USA}u_{USA,t} + u_{i,t+1}. \tag{12}$$

Here $i$ is any of the non-U.S. countries from our sample, $x_{i,t} = (1, bill_{i,t}, dy_{i,t})'$ and $\beta_i$ are it's corresponding parameters. $\phi$ contains all the 53 parameters in a vector: $\phi = (\beta'_{USA}, \beta'_{i,AUS}, \theta_{AUS,USA}, \lambda_{AUS,USA}, ..., \lambda_{GBR,USA})'$. We estimate these parameters using two-step GMM based on the following 73 moment conditions:

$$E[x_{USA,t}u_{USA,t+1}(\phi)] = 0 \tag{13}$$

$$E[(bill_{i,t}, dy_{i,t})'u_{USA,t+1}(\phi)] = 0 \qquad \forall i \tag{14}$$

$$E[(x'_{i,t}, u_{USA,t+1}(\phi), u_{USA,t}(\phi))'u_{i,t+1}(\phi)] = 0 \qquad \forall i. \tag{15}$$

We are mostly interested in the structural parameters of the model so we focus on the significance tests for these variables (even though we will also test $\beta_{i,b}$ and $\beta_{i,d}$ against the same alternatives as before). We test the significance of the structural parameters against the expected alternatives: $\lambda_{i,USA} > 0$ such that the U.S influences the other markets and $\theta_{i,USA} < 1$ such that we have information frictions. The $p$-values are in this model not estimated with the wild-bootstrapped procedure but with the asymptotic GMM procedure. To be able to easily compare the coefficients of model (2) with the coefficients implied by the news-diffusion model we compute $\hat{\beta}_{i,USA} = (1-\hat{\theta}_{i,USA})\hat{\lambda}_{i,USA}$. The $p$-values for these coefficients are based on the one-sided alternative that the coefficient is positive and it's standard errors are computed using the delta method.

Finally we also do a pooled estimation of the news-diffusion model. This implies that $\beta_{i,b}$ and $\beta_{i,d}$ are constant across all countries and $\lambda_{i,USA}$ and $\theta_{i,USA}$ are constant across all non-U.S. countries.

### 3.1.5 Out-of-Sample Analysis

To test whether the in-sample result also hold out-of-sample, we make three models which use U.S. lagged excess returns and let it compete versus three corresponding benchmark models. The three benchmarks that are used to compare these forecasts with are the following three models:

$$B1: \qquad r_{i,t+1} = \beta_{i,0} + \epsilon_{i,t+1} \tag{16}$$

$$B2: \qquad r_{i,t+1} = \beta_{i,0} + \beta_{i,i}r_{i,t} + \epsilon_{i,t+1} \tag{17}$$

$$B3: \qquad r_{i,t+1} = \beta_{i,0} + \beta_{i,b}bill_{i,t} + \beta_{i,d}dy_{i,t} + \epsilon_{i,t+1}. \tag{18}$$

Note that here again $i$ refers to all non-U.S. countries. The models that we use to compete against these benchmarks are these same models but now include lagged U.S. excess returns. The parameters for these models can be recursively estimated with OLS for every $t$. In order to get sufficient data for the first forecast we take a forecast sample from January 1985 until December 2010.

The out-of-sample forecasts are now compared using the out-of-sample $R^2$ statistic ($R^2_{OS}$) (Campbell and Thompson (2008)) which measures the reduction in mean squared forecast error (MSFE). In order to test if this reduction is significant, we test whether $R^2_{OS} = 0$ against the alternative that $R^2_{OS} > 0$ using the Clark and West (2007) $MSFE - adjusted$ statistic. This is an adjusted version of the standard Diebold-Mariano statistic (Diebold and Mariano (2002)) to account for nested forecasts.

For the out-of-sample analysis we also perform a pooled estimation in which $\beta_{i,USA}$ is the same for all non-U.S. countries. We do this because this reduces how much the parameters change over time according to Hjalmarsson (2010).

## 3.2 Extensions

The extensions are focused on seeing whether the relationships found in Rapach et al. (2013) hold among different types of excess returns. We make distinctions based on positive and negative excess returns, and on different quantiles of the excess returns distribution. We do both an in-sample and out-of-sample analysis for these two distinctions.

### 3.2.1 Positive and Negative Excess Returns

The first distinction focuses on the difference between positive and negative excess returns. The in-sample analysis fits models (1) and (2) for positive and negative excess returns separately. Thus we first select the $r_{i,t+1}$ values that are only positive (negative) and take the corresponding lagged values of the predictors of models (1) and (2). Note that these corresponding lagged values do not necessarily need to be positive (negative). The estimation procedure is then exactly the same as for models (1) and (2) but now with a different dependent variable. However we now make use of $p$-values computed from the heteroskedasticity-robust $t$-statistics instead of wild-bootstrapped $p$-values for ease of computation. Also, since we are only interested in checking whether the same countries as before continue to have large predictive power, we do not need to perform a pooled estimation of these models. The $t$-tests will be against the same one-sided alternatives as before.

For the out-of-sample analysis we have to be more careful than just splitting the dependent variable and selecting the corresponding lagged values. After all, if we would do so and make predictions we would implicitly assume to know whether the future excess return is either positive or negative. Therefore we do not use regular OLS models but logit models. The logit models are of the following form:

$$r_{i,t+1} = x'_{i,t}\beta_i + \epsilon_{i,t+1} \tag{19}$$

$$y_{i,t+1} = \begin{cases} 0 & \text{if} \quad r_{i,t+1} \leq 0 \\ 1 & \text{if} \quad r_{i,t+1} > 0. \end{cases} \tag{20}$$

Here $x'_{i,t}\beta_i$ refers to the predictor variables and parameters in the benchmark and competing models as specified in (16), (17) and (18). We use these models to predict whether the excess returns will be positive or negative one period ahead. We then compare the percentage of correctly predicted ones and zeros (positive and negative excess returns) and the total percentage of correct predictions.

### 3.2.2 Quantile Analysis

For the quantile analysis we estimate the main models for different conditional quantiles to see whether the relations found in the mean via OLS also hold in different parts of the distribution. For this we make use of quantile regression. This means that we estimate a linear model for the conditional quantile $\tau$ as $Q_r(\tau|x) = x'\beta(\tau)$. For the in-sample analysis this means that we first choose $x'\beta(\tau)$ to correspond to the benchmark model as specified in (1) and then to the international returns-based predictive model as specified in (2). To estimate $\beta(\tau)$ for these models we can solve the following optimization problem for each of the (combination of) countries (Koenker (2005))

$$\min_{\beta \in \mathcal{R}^P} \sum_{i=1}^{n} \rho_\tau(r_i - x'_i\beta). \tag{21}$$

Here $p$ denotes the amount of explanatory variables, $0 < \tau < 1$ denotes the $\tau^{th}$ quantile, $n$ is the amount of available observations, $r_i$ is the excess return for observation $i$, $x_i$ are the explanatory variables for observation $i$ and $\rho_\tau(.)$ is the quantile loss function given by $\rho_\tau(u) = u(\tau - I(u < 0))$, where $I(.)$ is an indicator function. In order to judge the fit of the model we make use of the Pseudo-$R^2$ statistic which can be computed as

$$R^2 = 1 - \frac{\sum_{i=1}^{n} \rho_\tau(r_i - \hat{x_i}'\hat{\beta})}{\sum_{i=1}^{n} \rho_\tau(r_i - \bar{x_i}'\bar{\beta})} \tag{22}$$

where $\bar{x_i}'\bar{\beta}$ denotes the fit of the restricted model with only a constant and $\hat{x_i}'\hat{\beta}$ being the fit of the unrestricted model of interest. To test the significance of the coefficients we use standard $p$-values from the $t$-statistics based on the same one-sided alternatives as before.

For the out-of-sample analysis we fit again the three benchmark models and their corresponding competing models as specified in (16), (17) and (18) but now for the conditional quantiles $\tau$. We iteratively estimate the models via (21) and use this to make forecasts. In order to compare these forecasts we again can't make use of the standard Diebold-Mariano statistic. In the OLS setting we solved this with the $MSFE-adjusted$ statistic. For quantile regression we have a similar adjusted form of the Diebold-Mariano statistic as shown by Ge (2015). We thus use this to compare the competing models with the baseline models. For all of the in-sample and out-of-sample models we use a value of 0.10, 0.25, 0.75 and 0.90 for $\tau$ in order to check both the lower and upper tails of the distribution.

# 4 Results

Similarly to the methodology section we first show the results from the replication and thereafter the results from the extensions.

## 4.1 Replication

### 4.1.1 Benchmark Model

As is expected from the benchmark regression results from table 1, almost all of the $\hat{\beta}_{i,b}$ estimates are negative and almost all of the $\hat{\beta}_{i,d}$ estimates are positive. However, there are only few cases in which these coefficients are significant and $\hat{\beta}_{i,b}$ is more often significant than $\hat{\beta}_{i,d}$. The $R^2$ statistics are often low, as is also expected, but values of 1% or higher can have reasonable economic significance as is the case for Canada, the Netherlands and the United Kingdom.

Noteworthy here is that we expect to have the exact same coefficients as Rapach et al. (2013) but $\hat{\beta}_{i,b}$ for Sweden and the $R^2$ for the pooled regression are different. In which the first difference is probably a round-off error and the latter one is likely a type-o since Rapach et al. (2013) has -0,01 for Sweden's $\hat{\beta}_{i,b}$ and 1,35% for the pooled regression's $R^2$. Also the bootstrapped $p$-values aren't always exactly the same but this is of course expected as this relies on random draws. This will be present in every table relying on bootstrapped $p$-values.

In table 16 in the Appendix we show the results for the benchmark model but with lagged economic variables of the U.S. for each country. We see that in general the country's own lagged variables are more important than those of the U.S.. Apart from this, the results are quite similar to the ones found in table

1. The benchmark predictive model thus provides some economically significant predictive power for a few countries but the predictive power is limited.

Table 1: Benchmark Predictive Regression Model

| Country | $\hat{\beta}_{i,b}$ | $\hat{\beta}_{i,d}$ | $R^2$ | Country | $\hat{\beta}_{i,b}$ | $\hat{\beta}_{i,d}$ | $R^2$ |
|---|---|---|---|---|---|---|---|
| AUS | -0.05 | 0.68 | 0.13% | NLD | -0.32* | 1.82 | 1.72%* |
| | (-0.49) | (0.29) | (0.26) | | (-2.54) | (1.81) | (6.48) |
| | [0.27] | [0.60] | [0.91] | | [0.02] | [0.11] | [0.07] |
| CAN | -0.23* | 1.44 | 2.58%* | SWE | -0.02 | 1.18 | 0.45% |
| | (-2.42) | (1.22) | (6.47) | | (-0.19) | (1.24) | (1.54) |
| | [0.02] | [0.34] | [0.07] | | [0.46] | [0.26] | [0.53] |
| FRA | -0.09 | 0.92 | 0.31% | CHE | -0.15 | 0.23 | 0.55% |
| | (-1.00) | (0.86) | (1.09) | | (-1.32) | (0.25) | (2.01) |
| | [0.23] | [0.45] | [0.66] | | [0.11] | [0.65] | [0.46] |
| DEU | -0.33* | 1.68 | 1.24% | GBR | -0.16* | 3.71* | 2.60%* |
| | (-1.86) | (1.24) | (3.78) | | (-1.67) | (2.90) | (8.75) |
| | [0.10] | [0.22] | [0.21] | | [0.06] | [0.01] | [0.02] |
| ITA | -0.01 | -0.69 | 0.14% | USA | -0.19 | 1.61 | 1.51% |
| | (-0.08) | (-0.59) | (0.37) | | (-1.66) | (2.03) | (4.15) |
| | [0.45] | [0.88] | [0.86] | | [0.12] | [0.12] | [0.24] |
| JPN | 0.04 | 0.41 | 0.10% | Pooled | -0.06 | 0.53 | 0.35% |
| | (0.32) | (0.68) | (0.59) | | (-1.06) | (1.20) | (2.06) |
| | [0.61] | [0.51] | [0.81] | | [0.14] | [0.20] | [0.32] |

This table shows the coefficients, $R^2$ statistics, $t$-statistics and $p$-values of the benchmark regression model (1). The $t$-statistics are reported in parentheses and the $p$-values are given between the brackets. The number in parentheses below the $R^2$ statistics are joint $\chi^2$ tests. * indicates significance at the 10% level or better.

### 4.1.2 International Returns-Based Predictive Model

As can be seen from table 2 almost all of the $\hat{\beta}_{i,j}$ estimates in the international returns-based predictive model are positive as is consistent with adjustment delays from country $i$ to relevant information from country $j$. Furthermore we see that the U.S. has the largest predictive power by having the most significant $\hat{\beta}_{i,j}$ estimates for all $j$. The opposite however is not true: non-U.S. countries have only limited predictive power for the U.S since there are only two significant $\hat{\beta}_{USA,j}$ estimates. Sweden is one of the two countries that does have predictive power for the U.S. and we see that Swedish excess returns have more often a significant effect than other countries. Also notable is that Swiss excess returns appear to have more predictive power than the other countries, having a significant effect for seven countries. We also see that the $R^2$ values are higher than in table 1 meaning that including lagged country excess returns improves the predictive power of our models.

Some inconsistencies are present in the results of table 2 compared to the corresponding results in Rapach et al. (2013). The $t$-statistic for $\hat{\beta}_{NLD,USA}$ differs slightly, which is probably a round-off error and $\hat{\beta}_{CHE,ITA}$ is positive in the Internet Appendix of Rapach et al. (2013), although this appears to be a type-o since the results do correspond to the table in the main paper of Rapach et al. (2013). What is also noteworthy is that we have an extra significant $\hat{\beta}_{i,j}$ estimate compared to Rapach et al. (2013) due to the randomness of the bootstrapping procedure. $\hat{\beta}_{CAN,JPN}$ is significant in our case but it isn't for Rapach et al. (2013). This one difference doesn't change the interpretation of the results as much but the conclusion based on this table could change if more of these changes would have been present.

Table 17 in the Appendix show the results when we take extra controlling variables into account. These results are very similar to the results in table 2 as again almost all of the $\hat{\beta}_{i,j}$ estimates are positive and the U.S. has the most predictive power. Important to note is thus that adding lagged international country equity premiums improves predictive power of the models and that the role of the U.S. is the largest.

Table 2: International Returns-Based Predictive Model

| Country | $\hat{\beta}_{i,AUS}$ | $\hat{\beta}_{i,CAN}$ | $\hat{\beta}_{i,FRA}$ | $\hat{\beta}_{i,DEU}$ | $\hat{\beta}_{i,ITA}$ | $\hat{\beta}_{i,JPN}$ | $\hat{\beta}_{i,NLD}$ | $\hat{\beta}_{i,SWE}$ | $\hat{\beta}_{i,CHE}$ | $\hat{\beta}_{i,GBR}$ | $\hat{\beta}_{i,USA}$ |
|---|---|---|---|---|---|---|---|---|---|---|---|
| AUS | | 0.11* | 0.12* | 0.13* | 0.08* | 0.10* | 0.13* | 0.08* | 0.11* | 0.07 | 0.20* |
| | | (1.35) | (1.96) | (2.06) | (2.24) | (1.91) | (1.77) | (1.91) | (1.67) | (0.94) | (2.34) |
| | | [0.10] | [0.03] | [0.02] | [0.02] | [0.03] | [0.06] | [0.04] | [0.06] | [0.19] | [0.01] |
| | | 0.95% | 1.70% | 1.84% | 1.48% | 1.27% | 1.59% | 1.12% | 1.08% | 0.67% | 2.34% |
| CAN | 0.05 | | 0.06 | 0.06 | 0.06* | 0.06* | 0.06 | 0.15* | 0.08 | 0.07 | 0.21* |
| | (0.84) | | (1.21) | (1.24) | (1.53) | (1.26) | (0.79) | (3.73) | (1.00) | (0.99) | (2.19) |
| | [0.21] | | [0.11] | [0.11] | [0.07] | [0.09] | [0.23] | [0.00] | [0.18] | [0.16] | [0.01] |
| | 4.13% | | 4.37% | 4.34% | 4.59% | 4.35% | 4.20% | 7.24% | 4.35% | 4.27% | 5.58% |
| FRA | 0.01 | -0.01 | | -0.03 | -0.05 | 0.04 | 0.00 | 0.14* | 0.16* | 0.03 | 0.12 |
| | (0.15) | (-0.15) | | (-0.31) | (-0.91) | (0.53) | (0.02) | (2.27) | (1.47) | (0.26) | (1.28) |
| | [0.44] | [0.55] | | [0.62] | [0.81] | [0.32] | [0.48] | [0.01] | [0.09] | [0.41] | [0.11] |
| | 2.14% | 2.14% | | 2.17% | 2.36% | 2.24% | 2.13% | 3.92% | 2.94% | 2.17% | 2.64% |
| DEU | 0.03 | 0.09 | 0.13* | | 0.06 | 0.09* | 0.06 | 0.14* | 0.26* | 0.07 | 0.22* |
| | (0.37) | (1.11) | (1.49) | | (1.29) | (1.43) | (0.55) | (2.49) | (2.26) | (0.77) | (2.33) |
| | [0.37] | [0.14] | [0.07] | | [0.10] | [0.08] | [0.30] | [0.01] | [0.01] | [0.23] | [0.01] |
| | 2.20% | 2.50% | 2.84% | | 2.47% | 2.73% | 2.25% | 3.78% | 3.99% | 2.35% | 3.86% |
| ITA | -0.01 | 0.06 | 0.16* | 0.11 | | 0.05 | -0.06 | 0.06 | 0.21* | 0.15* | 0.15* |
| | (-0.07) | (0.66) | (1.63) | (1.21) | | (0.72) | (-0.59) | (0.99) | (1.84) | (1.48) | (1.59) |
| | [0.52] | [0.27] | [0.06] | [0.12] | | [0.26] | [0.71] | [0.16] | [0.04] | [0.08] | [0.07] |
| | 0.77% | 0.89% | 1.91% | 1.32% | | 0.91% | 0.91% | 1.02% | 2.15% | 1.50% | 1.46% |
| JPN | 0.04 | 0.12* | 0.11* | 0.02 | 0.03 | | 0.07 | 0.09* | 0.11* | 0.11* | 0.11* |
| | (0.70) | (1.70) | (2.07) | (0.44) | (0.78) | | (1.17) | (1.77) | (1.61) | (1.71) | (1.48) |
| | [0.26] | [0.05] | [0.02] | [0.35] | [0.23] | | [0.14] | [0.04] | [0.07] | [0.05] | [0.07] |
| | 1.75% | 2.51% | 2.65% | 1.68% | 1.78% | | 2.02% | 2.55% | 2.34% | 2.43% | 2.28% |
| NLD | 0.10* | 0.15* | 0.15* | 0.15* | 0.05 | 0.11* | | 0.16* | 0.33* | 0.11 | 0.32* |
| | (1.46) | (1.95) | (2.20) | (1.79) | (1.05) | (2.12) | | (2.76) | (3.28) | (1.11) | (3.70) |
| | [0.10] | [0.04] | [0.02] | [0.04] | [0.15] | [0.01] | | [0.00] | [0.00] | [0.15] | [0.00] |
| | 3.46% | 3.88% | 3.94% | 3.77% | 3.03% | 3.78% | | 4.99% | 6.16% | 3.21% | 6.09% |
| SWE | -0.03 | 0.16* | 0.05 | 0.08 | 0.08 | 0.06 | 0.01 | | 0.12 | 0.10 | 0.23* |
| | (-0.31) | (1.75) | (0.58) | (0.88) | (1.09) | (0.76) | (0.13) | | (1.23) | (0.90) | (2.22) |
| | [0.60] | [0.05] | [0.29] | [0.20] | [0.15] | [0.24] | [0.45] | | [0.13] | [0.21] | [0.02] |
| | 3.02% | 3.91% | 3.08% | 3.21% | 3.46% | 3.15% | 2.99% | | 3.43% | 3.27% | 4.54% |
| CHE | 0.03 | 0.03 | 0.005 | -0.02 | -0.003 | 0.02 | -0.01 | 0.13* | | 0.02 | 0.14* |
| | (0.50) | (0.41) | (0.07) | (-0.20) | (-0.08) | (0.51) | (-0.08) | (3.14) | | (0.32) | (1.67) |
| | [0.32] | [0.35] | [0.49] | [0.58] | [0.54] | [0.31] | [0.51] | [0.00] | | [0.36] | [0.05] |
| | 3.70% | 3.69% | 3.63% | 3.64% | 3.63% | 3.69% | 3.63% | 5.75% | | 3.66% | 4.54% |
| GBR | 0.11* | 0.08 | 0.08 | 0.02 | 0.01 | 0.09* | -0.02 | 0.09* | 0.11* | | 0.23* |
| | (1.74) | (1.02) | (1.17) | (0.26) | (0.24) | (1.85) | (-0.18) | (2.03) | (1.42) | | (2.26) |
| | [0.05] | [0.18] | [0.13] | [0.40] | [0.42] | [0.04] | [0.56] | [0.02] | [0.09] | | [0.01] |
| | 3.51% | 3.00% | 3.15% | 2.66% | 2.65% | 3.49% | 2.65% | 3.72% | 3.24% | | 4.82% |
| USA | 0.06 | 0.03 | 0.01 | -0.01 | 0.06* | -0.0003 | 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) | |
| | [0.19] | [0.40] | [0.43] | [0.59] | [0.08] | [0.50] | [0.45] | [0.01] | [0.34] | [0.44] | |
| | 2.24% | 1.97% | 1.95% | 1.95% | 2.55% | 1.93% | 1.95% | 3.28% | 2.01% | 1.95% | |
| Average | 0.04 | 0.08 | 0.09 | 0.05 | 0.04 | 0.06 | 0.03 | 0.11 | 0.15 | 0.08 | 0.19 |
| Pooled | 0.03 | 0.07* | 0.08* | 0.05 | 0.04* | 0.06* | 0.02 | 0.11* | 0.13* | 0.08* | 0.17* |
| | (0.65) | (1.34) | (2.02) | (1.08) | (1.32) | (1.52) | (0.42) | (3.56) | (2.22) | (1.45) | (2.98) |
| | [0.28] | [0.10] | [0.02] | [0.15] | [0.10] | [0.06] | [0.34] | [0.00] | [0.02] | [0.09] | [0.00] |
| | 1.69% | 1.70% | 1.87% | 1.69% | 2.01% | 1.80% | 1.49% | 2.59% | 2.12% | 1.88% | 2.72% |

This table shows the coefficients, $R^2$ statistics, $t$-statistics and $p$-values of the international returns-based predictive model (2). The $t$-statistics are reported in parentheses and the $p$-values are given between the brackets. Below these $p$-values are the $R^2$ statistics. "Average" is the column average of the $\hat{\beta}_{i,j}$ estimates. * indicates significance at the 10% level or better.

### 4.1.3 More General International Returns-Based Predictive Model

Table 3: Pooled Method for More General International Returns-Based Predictive Model

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

This table shows the results of the pooled estimation approach for the more general international returns-based predictive model (3). The 90% wild bootstrapped confidence intervals are shown in brackets and * indicates significance at the 10% level or better.

The results of the pooled method for the more general international returns-based predictive model in table 3 are expected when we look back at the results of table 2. Sweden and the U.S. appear to have large predictive power for the pooled model. However the Netherlands also has a significance influence while this was almost never the case in table 2. These results fully correspond to the results in Rapach et al. (2013).

Table 4: Adaptive Elastic Net for More General International Returns-Based Predictive Model

| Country | $\hat{\beta}_{i,AUS}$ | $\hat{\beta}_{i,CAN}$ | $\hat{\beta}_{i,FRA}$ | $\hat{\beta}_{i,DEU}$ | $\hat{\beta}_{i,ITA}$ | $\hat{\beta}_{i,JPN}$ | $\hat{\beta}_{i,NLD}$ | $\hat{\beta}_{i,SWE}$ | $\hat{\beta}_{i,CHE}$ | $\hat{\beta}_{i,GBR}$ | $\hat{\beta}_{i,USA}$ |
|---|---|---|---|---|---|---|---|---|---|---|---|
| AUS | | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.13* |
| | | | | | | | | | | | [0.06,0.26] |
| CAN | 0 | | 0 | 0 | 0 | 0 | -0.02 | 0.11* | 0 | 0 | 0.08* |
| | | | | | | | [-0.10,0.02] | [0.07,0.19] | | | [0.01,0.19] |
| FRA | 0 | 0 | | 0 | 0 | 0 | 0 | 0.11* | 0.04 | 0 | 0 |
| | | | | | | | | [0.06,0.21] | [-0.04,0.13] | | |
| DEU | 0 | 0 | 0 | | 0 | 0 | -0.07 | 0.07* | 0.09 | 0 | 0.12* |
| | | | | | | | [-0.21,-0.02] | [0.01,0.17] | [-0.01,0.25] | | [0.01,0.28] |
| ITA | -0.07 | 0 | 0.15 | 0.05 | | 0 | -0.43* | 0 | 0.28* | 0.17* | 0.06 |
| | [-0.22,0.01] | | [-0.01,0.36] | [-0.07,0.20] | | | [-0.73,-0.26] | | [0.08,0.54] | [0.01,0.41] | [-0.06,0.23] |
| JPN | 0 | 0.04 | 0.05* | 0 | 0 | | 0 | 0.04 | 0 | 0 | 0 |
| | | [-0.02,0.11] | [0.01,0.13] | | | | | [-0.004,0.11] | | | |
| NLD | 0 | 0 | 0 | 0 | 0 | 0.03 | | 0.09* | 0.20* | -0.04 | 0.21* |
| | | | | | | [-0.02,0.11] | | [0.01,0.18] | [0.06,0.39] | [-0.19,0.06] | [0.07,0.39] |
| SWE | -0.12* | 0.06 | 0 | 0 | 0.07 | 0 | -0.13 | | 0 | 0 | 0.31* |
| | [-0.3,-0.002] | [-0.05,0.20] | | | [-0.03,0.19] | | [-0.36,0.003] | | | | [0.13,0.56] |
| CHE | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.11* | | 0 | 0.08 |
| | | | | | | | | [0.06,0.19] | | | [-0.001,0.19] |
| GBR | 0.03 | -0.0002 | 0.02 | -0.02 | 0 | 0.04 | -0.13* | 0.06* | 0.02 | | 0.18* |
| | [-0.05,0.12] | [-0.10,0.07] | [-0.05,0.12] | [-0.10,0.05] | | [-0.02,0.11] | [-0.29,-0.04] | [0.01,0.14] | [-0.08,0.14] | | [0.06,0.38] |
| USA | 0.01 | 0 | 0 | -0.06* | 0.03 | 0 | 0 | 0.09* | 0 | 0 | |
| | [-0.06,0.08] | | | [-0.17,-0.01] | [-0.01,0.10] | | | [0.04,0.17] | | | |
| Average | -0.02 | 0.01 | 0.02 | -0.004 | 0.01 | 0.005 | -0.10 | 0.06 | 0.05 | 0.02 | 0.11 |

This table shows the results of the adaptive elastic net estimation approach for the more general international returns-based predictive model (3). The 90% wild bootstrapped confidence intervals are shown in brackets and * indicates significance at the 10% level or better. "Average" is the column average of the $\hat{\beta}_{i,j}$ estimates.

The results in table 4, where we estimate the same model but with the adaptive elastic net approach, are in line with the results found in tables 3 and 2. The U.S. seems to play an important role, being selected the most often together with Sweden. However the average coefficient of the USA is almost twice the size of the Swedish average coefficient such that the U.S. has a much larger influence on average. Also Switzerland and the Netherlands seem to be selected often where the former is in line with table 2 and the latter isn't. Note however that Dutch excess returns always have a negative influence and the Swiss excess returns a positive influence. Both are significant in two cases, but since Dutch excess returns didn't have much predictive power in table 2 we believe that the predictive ability of Dutch equity premiums isn't that strong. Even though the average coefficient for the Netherlands is (in absolute value) quite high.

The results found in this table differ a bit from the corresponding results in Rapach et al. (2013). This is of course the result of the randomness in the solving of the adaptive elastic net procedure. Running the procedure multiple times gives us different results and sometimes they correspond closer to the results in Rapach et al. (2013) and sometimes they correspond a bit less. Most noteworthy is that the significance differs for three coefficients. $\hat{\beta}_{ITA,FRA}$ and $\hat{\beta}_{CHE,USA}$ estimates aren't significant in our results but are for Rapach et al. (2013). The opposite is true for the $\hat{\beta}_{USA,DEU}$ estimate.

The results of tables 3 and 4 confirm that the U.S has a big leading international role and that Sweden, although not as much as the U.S., also has high predictive power.

### 4.1.4 News-Diffusion Model

Table 5: News-Diffusion Model

| Country | $\hat{\beta}_{i,b}$ | $\hat{\beta}_{i,d}$ | $\hat{\theta}_{i,USA}$ | $\hat{\lambda}_{i,USA}$ | $\hat{\beta}_{i,USA}$ | Country | $\hat{\beta}_{i,b}$ | $\hat{\beta}_{i,d}$ | $\hat{\theta}_{i,USA}$ | $\hat{\lambda}_{i,USA}$ | $\hat{\beta}_{i,USA}$ |
|---|---|---|---|---|---|---|---|---|---|---|---|
| AUS | 0.01 | -0.70 | 0.88* | 0.70* | 0.09* | NLD | -0.20* | 2.35* | 0.82* | 1.02* | 0.18* |
| | (0.17) | (-0.51) | (-1.95) | (9.45) | (1.74) | | (-1.90) | (2.50) | (-3.77) | (14.98) | (3.26) |
| CAN | -0.22* | 1.71* | 0.88* | 0.91* | 0.11* | SWE | -0.04 | 2.43* | 0.76* | 1.08* | 0.26* |
| | (-2.61) | (1.55) | (-3.14) | (16.59) | (2.82) | | (-0.54) | (2.64) | (-3.90) | (10.80) | (3.20) |
| FRA | -0.08 | 1.19* | 0.86* | 0.96* | 0.13* | CHE | -0.13* | 1.35* | 0.82* | 0.90* | 0.16* |
| | (-1.04) | (1.30) | (-2.96) | (13.94) | (2.61) | | (-1.54) | (1.64) | (-3.82) | (14.24) | (3.27) |
| DEU | -0.31* | 2.26* | 0.84* | 0.96* | 0.16* | GBR | -0.16* | 3.78* | 0.91* | 0.80* | 0.07* |
| | (-2.03) | (1.86) | (-2.84) | (11.15) | (2.50) | | (-2.17) | (3.63) | (-1.83) | (13.50) | (1.66) |
| ITA | 0.04 | 0.56 | 0.85* | 0.83* | 0.12* | USA | -0.20* | 1.43* | | | |
| | (0.49) | (0.50) | (-1.97) | (7.43) | (1.67) | | (-2.02) | (2.02) | | | |
| JPN | 0.07 | 0.98* | 0.85* | 0.65* | 0.10* | Pooled | -0.08* | 0.37* | 0.86* | 0.90* | 0.12* |
| | (0.55) | (1.86) | (-1.78) | (7.65) | (1.53) | | (-2.02) | (1.31) | (-6.65) | (27.53) | (5.83) |

This table shows the estimates of the news-diffusion model parameters as specified in (11) and (12). The $t$-statistics are shown in parentheses. * Indicates significance at the 10% level or better. The $\hat{\beta}_{i,USA}$ estimates are computed by $\hat{\beta}_{i,USA} = (1 - \hat{\theta}_{i,USA})\hat{\lambda}_{i,USA}$

The news-diffusion parameters are shown in table 5. The $\hat{\lambda}_{i,USA}$ parameters show that other markets are dependent on the U.S. market since all of these estimates are significant. Furthermore the $\hat{\theta}_{i,USA}$ estimates are also all significantly smaller than one, corresponding to information frictions between the U.S. markets and the other markets. Since the $\hat{\beta}_{i,USA}$ estimates are also significant for all countries, we know that lagged U.S. excess returns have predictive power for the other markets. These $\hat{\beta}_{i,USA}$ estimates are however lower then the corresponding estimates in table 2 meaning that not all of the predictive power is due to information frictions. These results are exactly the same as the results from Rapach et al. (2013), besides a round-off difference for the $t$-statistic of the $\hat{\lambda}_{CAN,USA}$ estimate.

The news-diffusion model shows us that the predictive power of the U.S. is, although not completely, due to international information frictions between markets.

### 4.1.5 Out-of-Sample Analysis

Table 6: Out-of-Sample Analysis for Three Baseline and Competing Models

| | B1 | | B2 | | B3 | |
|---|---|---|---|---|---|---|
| Country | $R^2_{OS}$ | $R^2_{OS}, Pooled$ | $R^2_{OS}$ | $R^2_{OS}, Pooled$ | $R^2_{OS}$ | $R^2_{OS}, Pooled$ |
| AUS | -0.69%* | 0.50%* | -0.27%* | 0.71%* | -0.58%* | 0.18% |
| | (1.49) | (1.60) | (1.42) | (3.58) | (1.46) | (0.77) |
| | [0.07] | [0.06] | [0.08] | [0.00] | [0.07] | [0.22] |
| CAN | 1.30%* | 1.86%* | -1.94% | 0.34%* | 2.48%* | 5.43%* |
| | (2.36) | (2.18) | (0.85) | (1.99) | (2.60) | (2.78) |
| | [0.01] | [0.01] | [0.20] | [0.02] | [0.00] | [0.00] |
| FRA | 1.52%* | 1.91%* | 0.09% | 1.28%* | 1.56%* | 4.36%* |
| | (1.90) | (2.12) | (0.54) | (1.96) | (1.91) | (2.76) |
| | [0.03] | [0.02] | [0.29] | [0.02] | [0.03] | [0.00] |
| DEU | 1.57%* | 1.98%* | 0.99%* | 2.23%* | 1.59%* | 3.37%* |
| | (1.78) | (1.91) | (1.58) | (1.84) | (1.80) | (2.35) |
| | [0.04] | [0.03] | [0.06] | [0.03] | [0.04] | [0.01] |
| ITA | 0.92%* | 1.54%* | 0.36% | 1.76%* | 0.81%* | 3.26%* |
| | (1.54) | (2.05) | (1.00) | (4.33) | (1.47) | (1.62) |
| | [0.06] | [0.02] | [0.16] | [0.00] | [0.07] | [0.05] |
| JPN | 0.82%* | 1.30%* | 0.14% | 1.65%* | 0.95%* | 3.68%* |
| | (1.33) | (1.65) | (0.90) | (2.74) | (1.40) | (1.41) |
| | [0.09] | [0.05] | [0.18] | [0.00] | [0.08] | [0.08] |
| NLD | 3.81%* | 3.88%* | 3.52%* | 3.66%* | 3.54%* | 6.72%* |
| | (2.62) | (2.58) | (3.35) | (2.35) | (2.58) | (3.52) |
| | [0.00] | [0.00] | [0.00] | [0.01] | [0.01] | [0.00] |
| SWE | 2.90%* | 2.76%* | 1.09%* | 1.83%* | 3.35%* | 4.59%* |
| | (2.25) | (2.31) | (1.59) | (2.79) | (2.38) | (3.35) |
| | [0.01] | [0.01] | [0.06] | [0.00] | [0.01] | [0.00] |
| CHE | 2.64%* | 2.95%* | 0.14% | 1.69%* | 2.68%* | 4.66%* |
| | (2.45) | (2.40) | (0.94) | (2.90) | (2.53) | (2.77) |
| | [0.01] | [0.01] | [0.17] | [0.00] | [0.01] | [0.00] |
| GBR | 0.28% | 0.43%* | 0.74%* | 3.24%* | 0.47% | 1.22%* |
| | (0.97) | (1.34) | (1.29) | (1.31) | (1.12) | (2.53) |
| | [0.17] | [0.09] | [0.10] | [0.09] | [0.13] | [0.01] |
| Average | 1.51% | 1.91% | 0.49% | 1.84% | 1.68% | 3.75% |

This table shows the out-of-sample $R^2$ statistic ($R^2_{OS}$ Campbell and Thompson (2008)) for our predictive models versus the three corresponding baseline models: B1, B2 and B3. The three baseline models are the constant expected return model (16), the AR model (17) and the benchmark predictive model (18). In parentheses is the $MFSE - adjusted$ statistic of Clark and West (2007) and the corresponding $p$-values are in brackets. * Indicates significance at the 10% level or better. "Average" is the column average of the $R^2_{OS}$ estimates.

From the out-of-sample results in table 6 we can see that on average the model that does take lagged U.S. excess returns into account provides better forecasts (in the sense of a lower MSFE) than models that do not take this information into account. This result becomes more clear when we look at the pooled statistics. These are in all of the cases positive and in all but one cases they are significant at the 10% lever or better. The important role of the U.S. that we found in the in-sample results thus appears to also hold out-of-sample based on these results. Interestingly enough, the $R^2_{OS}$ statistics are significantly positive for Australia for all three baseline models, even tough the statistics themselves are negative. This is due to the comparison of nested forecasts as done in this procedure.

The results are almost exactly the same as the corresponding results in the Appendix and main paper of

Rapach et al. (2013). The only differences found are some differences in rounding and type-o's. These are the $t$-statistics for Australia for the pooled statistic in baseline 2 and for the regular statistic in baseline 3. Also in baseline 2 is a difference in the $R^2_{OS}$ for the United Kingdom.

Table 6 showed us that the predictive power of the U.S. is not limited to an in-sample setting. The predictive power is also very much visible in the out-of-sample setting.

## 4.2 Positive and Negative Excess Return Models Extension

### 4.2.1 Benchmark Model

First we discuss the results of the analysis that separates positive and negative excess returns. The results of the benchmark model for positive excess returns can be found in table 7.

Table 7: Benchmark Positive Excess Return Predictive Regression Model

| Country | $\hat{\beta}_{i,b}$ | $\hat{\beta}_{i,d}$ | $R^2$ | Country | $\hat{\beta}_{i,b}$ | $\hat{\beta}_{i,d}$ | $R^2$ |
|---|---|---|---|---|---|---|---|
| AUS | 0.13 | 1.54* | 7.95%* | NLD | -0.25* | 1.07 | 3.39%* |
| | (2.45) | (1.33) | (8.98) | | (-2.62) | (1.28) | (3.82) |
| | [0.99] | [0.09] | [0.00] | | [0.00] | [0.10] | [0.02] |
| CAN | 0.01 | 0.14 | 0.13% | SWE | 0.12 | 1.33* | 3.32%* |
| | (0.18) | (0.16) | (0.13) | | (1.63) | (1.38) | (3.52) |
| | [0.57] | [0.44] | [0.88] | | [0.95] | [0.08] | [0.03] |
| FRA | -0.04 | 1.43* | 1.97% | CHE | 0.04 | -0.78 | 0.74% |
| | (-0.55) | (1.84) | (2.10) | | (0.41) | (-1.29) | (0.82) |
| | [0.29] | [0.03] | [0.13] | | [0.66] | [0.90] | [0.44] |
| GER | -0.40* | 1.51* | 5.18%* | GBR | -0.08 | 3.05* | 6.88%* |
| | (-2.65) | (1.32) | (5.68) | | (-1.20) | (3.84) | (8.08) |
| | [0.00] | [0.09] | [0.00] | | [0.11] | [0.00] | [0.00] |
| ITA | 0.13 | -1.06 | 4.11%* | USA | -0.02 | 0.50 | 0.44% |
| | (1.84) | (-0.77) | (4.05) | | (-0.25) | (0.77) | (0.48) |
| | [0.97] | [0.78] | [0.02] | | [0.40] | [0.22] | [0.62] |
| JPN | -0.08 | -0.86 | 1.25% | | | | |
| | (-0.82) | (-1.75) | (1.21) | | | | |
| | [0.21] | [0.96] | [0.30] | | | | |

This table shows the coefficients, $R^2$ statistics, $t$-statistics and $p$-values of the benchmark regression model (1) but only for positive excess returns. The $t$-statistics are reported in parentheses and the $p$-values are given between the brackets. The number in parentheses below the $R^2$ statistics are joint $\chi^2$ tests. * indicates significance at the 10% level or better.

What stands out from this table is that we get much higher $R^2$ values than in the regular benchmark results in table 1. What is also different compared to the results in table 1, is that the $\hat{\beta}_{i,b}$ coefficients are now less often negative and the $\hat{\beta}_{i,d}$ coefficients are now less often positive. However in most cases the coefficients still take the sign that is to be expected ($\hat{\beta}_{i,b} < 0$ and $\hat{\beta}_{i,d} > 0$). In fact in table 18 in the Appendix, which shows the model for negative excess returns, we see that this pattern is more consistent and we also see lower $R^2$ values. This may mean that we are capable of explaining positive excess returns better than negative excess returns or at least with the benchmark variables. This is also indicated by the fact that the $\hat{\beta}_{i,b}$ and $\hat{\beta}_{i,d}$ coefficients are less often significant in table 18 in the Appendix compared to the estimates in table 7. The benchmark variables thus appear to explain positive excess returns better.

### 4.2.2 International Returns-Based Predictive Model

Table 8: International Positive Excess Returns-Based Predictive Model

| Country | $\hat{\beta}_{i,AUS}$ | $\hat{\beta}_{i,CAN}$ | $\hat{\beta}_{i,FRA}$ | $\hat{\beta}_{i,DEU}$ | $\hat{\beta}_{i,ITA}$ | $\hat{\beta}_{i,JPN}$ | $\hat{\beta}_{i,NLD}$ | $\hat{\beta}_{i,SWE}$ | $\hat{\beta}_{i,CHE}$ | $\hat{\beta}_{i,GBR}$ | $\hat{\beta}_{i,USA}$ |
|---|---|---|---|---|---|---|---|---|---|---|---|
| AUS | | -0.09 | -0.04 | -0.03 | -0.07 | -0.04 | 0.004 | -0.04 | -0.01 | -0.02 | -0.02 |
| | | (-1.95) | (-0.67) | (-0.53) | (-2.66) | (-1.11) | (0.06) | (-1.06) | (-0.18) | (-0.39) | (-0.38) |
| | | [0.97] | [0.75] | [0.70] | [1.00] | [0.87] | [0.47] | [0.85] | [0.57] | [0.65] | [0.65] |
| | | 9.45% | 8.44% | 8.17% | 10.36% | 8.57% | 7.96% | 8.50% | 7.97% | 8.04% | 8.04% |
| CAN | 0.01 | | -0.01 | 0.02 | 0.0001 | -0.02 | -0.03 | 0.05* | -0.01 | 0.05 | 0.02 |
| | (0.15) | | (-0.11) | (0.40) | (0.003) | (-0.68) | (-0.52) | (1.57) | (-0.10) | (0.82) | (0.33) |
| | [0.44] | | [0.54] | [0.34] | [0.50] | [0.75] | [0.70] | [0.06] | [0.54] | [0.21] | [0.37] |
| | 0.16% | | 0.16% | 0.25% | 0.15% | 0.37% | 0.36% | 1.72% | 0.16% | 0.55% | 0.22% |
| FRA | -0.01 | -0.06 | | -0.04 | -0.02 | 0.08 | -0.10 | 0.06 | 0.02 | 0.06 | 0.04 |
| | (-0.15) | (-0.95) | | (-0.63) | (-0.38) | (1.23) | (-0.96) | (0.95) | (0.21) | (0.54) | (0.49) |
| | [0.56] | [0.83] | | [0.74] | [0.65] | [0.11] | [0.83] | [0.17] | [0.42] | [0.29] | [0.31] |
| | 2.61% | 2.98% | | 2.87% | 2.67% | 3.95% | 3.74% | 3.53% | 2.63% | 2.88% | 2.76% |
| DEU | -0.01 | 0.02 | -0.04 | | 0.04 | 0.04 | -0.10 | 0.05 | 0.04 | -0.06 | 0.12* |
| | (-0.24) | (0.27) | (-0.53) | | (1.01) | (0.85) | (-1.15) | (0.98) | (0.40) | (-0.76) | (1.58) |
| | [0.60] | [0.39] | [0.70] | | [0.16] | [0.20] | [0.87] | [0.16] | [0.34] | [0.78] | [0.06] |
| | 8.56% | 8.56% | 8.73% | | 9.07% | 8.86% | 9.42% | 9.06% | 8.64% | 8.85% | 9.88% |
| ITA | 0.05 | -0.06 | -0.01 | -0.10 | | -0.11 | -0.10 | -0.08 | -0.01 | 0.12 | -0.02 |
| | (0.56) | (-0.60) | (-0.12) | (-1.08) | | (-1.50) | (-0.87) | (-1.50) | (-0.06) | (1.12) | (-0.20) |
| | [0.29] | [0.72] | [0.55] | [0.86] | | [0.93] | [0.81] | [0.93] | [0.53] | [0.13] | [0.58] |
| | 4.80% | 4.83% | 4.65% | 5.39% | | 5.63% | 5.30% | 5.61% | 4.65% | 5.46% | 4.66% |
| JPN | 0.00 | 0.03 | 0.002 | -0.11 | -0.02 | | -0.07 | 0.01 | -0.05 | 0.06 | 0.04 |
| | (-0.001) | (0.61) | (0.04) | (-1.95) | (-0.46) | | (-1.35) | (0.19) | (-0.80) | (0.81) | (0.59) |
| | [0.50] | [0.27] | [0.48] | [0.97] | [0.68] | | [0.91] | [0.42] | [0.79] | [0.21] | [0.28] |
| | 2.49% | 2.64% | 2.49% | 4.75% | 2.65% | | 3.22% | 2.51% | 2.80% | 2.87% | 2.65% |
| NLD | -0.004 | 0.01 | 0.04 | -0.01 | 0.02 | 0.06* | | 0.07* | 0.14* | 0.06 | 0.08 |
| | (-0.08) | (0.15) | (0.86) | (-0.19) | (0.51) | (1.73) | | (1.47) | (2.13) | (0.85) | (1.10) |
| | [0.53] | [0.44] | [0.20] | [0.58] | [0.31] | [0.04] | | [0.07] | [0.02] | [0.20] | [0.13] |
| | 3.41% | 3.42% | 3.66% | 3.43% | 3.53% | 4.41% | | 5.08% | 5.37% | 3.74% | 3.96% |
| SWE | 0.03 | 0.07 | -0.04 | -0.06 | 0.09* | 0.02 | -0.09 | | 0.02 | 0.05 | 0.05 |
| | (0.32) | (0.84) | (-0.57) | (-0.83) | (1.36) | (0.29) | (-0.99) | | (0.17) | (0.45) | (0.48) |
| | [0.37] | [0.20] | [0.71] | [0.80] | [0.09] | [0.39] | [0.84] | | [0.43] | [0.33] | [0.31] |
| | 3.39% | 3.70% | 3.49% | 3.70% | 5.21% | 3.38% | 3.98% | | 3.36% | 3.49% | 3.49% |
| CHE | 0.03 | -0.07 | 0.002 | -0.01 | 0.01 | 0.01 | -0.07 | 0.08* | | 0.02 | 0.06 |
| | (0.61) | (-1.36) | (0.03) | (-0.21) | (0.16) | (0.22) | (-1.42) | (2.87) | | (0.40) | (1.03) |
| | [0.27] | [0.91] | [0.49] | [0.58] | [0.44] | [0.41] | [0.92] | [0.00] | | [0.34] | [0.15] |
| | 1.06% | 1.84% | 0.86% | 0.88% | 0.87% | 0.88% | 1.69% | 4.01% | | 0.93% | 1.48% |
| GBR | 0.04 | -0.03 | 0.002 | -0.05 | -0.04 | 0.02 | -0.11 | -0.03 | -0.10 | | 0.02 |
| | (0.88) | (-0.61) | (0.06) | (-1.22) | (-1.60) | (0.66) | (-2.12) | (-1.09) | (-1.99) | | (0.33) |
| | [0.19] | [0.73] | [0.48] | [0.89] | [0.95] | [0.26] | [0.98] | [0.86] | [0.98] | | [0.37] |
| | 7.99% | 7.77% | 7.57% | 8.31% | 8.54% | 7.78% | 10.21% | 8.20% | 9.30% | | 7.62% |
| USA | 0.06* | 0.002 | 0.03 | 0.02 | 0.01 | -0.01 | 0.01 | 0.03 | -0.01 | 0.002 | |
| | (1.40) | (0.02) | (0.60) | (0.38) | (0.34) | (-0.24) | (0.10) | (1.00) | (-0.11) | (0.03) | |
| | [0.08] | [0.49] | [0.27] | [0.35] | [0.37] | [0.59] | [0.46] | [0.16] | [0.55] | [0.49] | |
| | 3.77% | 2.81% | 3.02% | 2.88% | 2.88% | 2.83% | 2.81% | 3.39% | 2.81% | 2.81% | |
| Average | 0.02 | -0.02 | -0.01 | -0.04 | 0.002 | 0.004 | -0.07 | 0.02 | 0.00 | 0.03 | 0.04 |

This table shows the coefficients, $R^2$ statistics, $t$-statistics and $p$-values of the international returns-based predictive model (2) for positive excess returns. The $t$-statistics are reported in parentheses and the $p$-values are given between the brackets. Below these $p$-values are the $R^2$ statistics. "Average" is the column average of the $\hat{\beta}_{i,j}$ estimates. * indicates significance at the 10% level or better.

In table 8 we show the results for the international returns-based predictive model for positive excess returns (table 19 in the Appendix shows the results for negative excess returns). We see now that the pattern of high $R^2$ values for positive excess returns and lower for negative excess returns has disappeared. In fact we now see that the negative excess return models have on average higher $R^2$ values and have more significant coefficients than the positive excess return models. Apparently, the lead-lag relationships give us more information about negative excess returns than about positive excess returns. Furthermore we see that in both tables 8 and 19 the average coefficient of the U.S. is the highest among all the countries. This is in line with the large predictive power of the U.S. that we found in table 2 and the other replication results. Thus while the benchmark variables give us more information about the positive excess returns, the lead-lag relationships among countries give us more information about the negative excess returns. On top of that we see that the U.S. continues to have the highest predictive power.

### 4.2.3 Out-of-Sample Analysis

Table 9: Out-of-Sample Analysis for Three Logit Models

| | | B1 | C1 | B2 | C2 | B3 | C3 |
|---|---|---|---|---|---|---|---|
| AUS | % 0 | 0.00% | 14.73% | 7.75% | 12.40% | 13.18% | 11.63% |
| | % 1 | 97.27% | 81.97% | 90.16% | 81.97% | 87.43% | 86.34% |
| | % total | 57.05% | 54.17% | 56.09% | 53.21% | 56.73% | 55.45% |
| CAN | % 0 | 23.13% | 35.82% | 22.39% | 36.57% | 30.60% | 31.34% |
| | % 1 | 76.40% | 70.22% | 76.97% | 66.85% | 72.47% | 73.60% |
| | % total | 53.53% | 55.45% | 53.53% | 53.85% | 54.49% | 55.45% |
| FRA | % 0 | 0.00% | 7.69% | 8.46% | 13.08% | 0.77% | 3.08% |
| | % 1 | 100.00% | 95.05% | 95.60% | 94.51% | 96.70% | 97.25% |
| | % total | 58.33% | 58.65% | 59.29% | 60.58% | 56.73% | 58.01% |
| DEU | % 0 | 0.00% | 7.52% | 7.52% | 9.02% | 1.50% | 6.02% |
| | % 1 | 100.00% | 95.53% | 96.65% | 93.85% | 99.44% | 98.32% |
| | % total | 57.37% | 58.01% | 58.65% | 57.69% | 57.69% | 58.97% |
| ITA | % 0 | 17.33% | 27.33% | 36.67% | 36.00% | 26.00% | 30.67% |
| | % 1 | 77.78% | 72.84% | 62.35% | 64.20% | 72.84% | 69.75% |
| | % total | 48.72% | 50.96% | 50.00% | 50.64% | 50.32% | 50.96% |
| JPN | % 0 | 0.00% | 10.39% | 17.53% | 19.48% | 12.34% | 19.48% |
| | % 1 | 100.00% | 91.14% | 82.91% | 82.28% | 89.24% | 79.75% |
| | % total | 50.64% | 51.28% | 50.64% | 51.28% | 51.28% | 50.00% |
| NLD | % 0 | 0.00% | 0.00% | 0.00% | 0.78% | 41.09% | 40.31% |
| | % 1 | 100.00% | 100.00% | 99.45% | 98.36% | 71.04% | 70.49% |
| | % total | 58.65% | 58.65% | 58.33% | 58.01% | 58.65% | 58.01% |
| SWE | % 0 | 4.55% | 18.94% | 14.39% | 21.97% | 4.55% | 11.36% |
| | % 1 | 95.56% | 82.22% | 91.11% | 81.11% | 91.11% | 84.44% |
| | % total | 57.05% | 55.45% | 58.65% | 56.09% | 54.49% | 53.53% |
| CHE | % 0 | 0.00% | 9.76% | 10.57% | 12.20% | 21.95% | 24.39% |
| | % 1 | 100.00% | 87.83% | 91.01% | 86.77% | 84.13% | 81.48% |
| | % total | 60.58% | 57.05% | 59.29% | 57.37% | 59.62% | 58.97% |
| GBR | % 0 | 0.00% | 0.00% | 1.56% | 1.56% | 2.34% | 2.34% |
| | % 1 | 100.00% | 100.00% | 96.74% | 95.11% | 98.91% | 98.91% |
| | % total | 58.97% | 58.97% | 57.69% | 56.73% | 59.29% | 59.29% |
| Average | % 0 | 4.50% | 13.22% | 12.68% | 16.31% | 15.43% | 18.06% |
| | % 1 | 94.70% | 87.68% | 88.30% | 84.50% | 86.33% | 84.03% |
| | % total | 56.09% | 55.86% | 56.22% | 55.55% | 55.93% | 55.86% |

This table shows the out-of-sample performance of the logit models based on the three baseline and competing models. The three baseline models are the constant expected return model (16), the AR model (17) and the benchmark predictive model (18) and C1, C2 and C3 are the corresponding competing models. The numbers shown are the percentage of correctly predicted zeros (negative excess returns), ones (positive excess returns) and total values.

In table 9 we see the out-of-sample performance of the logit models. We see that in all the models we predict more positive excess returns correct than negative. This can be due to the fact that we have more positive excess returns in our data leading to a positive constant in each model. Since the predictive power of the other variables is limited we predict ones quite often because of this. Furthermore we see that the U.S. appears to have some predictive power but not a lot. After all, we see that on average the total percentage of correct predictions is lower for the competing models than for the baseline models. However, the percentage of correctly predicted negative excess returns is on average always higher for the competing models. This is in line with what we found in the in-sample results where we saw that international lead-lag relationships had more information about negative excess returns than about positive excess returns. Thus although the U.S. may have predictive power, it is probably mostly about negative excess returns.

## 4.3 Quantile Regression Models Extension

### 4.3.1 Benchmark Model

Table 10 and tables 20, 21 and 22 in the Appendix show the results of the benchmark quantile regression models for the $10^{th}$ and $90^{th}$, $75^{th}$ and $25^{th}$ quantile respectively.

Table 10: Benchmark Predictive Quantile Regression Model for $10^{th}$ Quantile

| Country | $\hat{\beta}_{i,b}$ | $\hat{\beta}_{i,d}$ | Pseudo-$R^2$ | Country | $\hat{\beta}_{i,b}$ | $\hat{\beta}_{i,d}$ | Pseudo-$R^2$ |
|---|---|---|---|---|---|---|---|
| AUS | -0.10 | -2.19 | 1.40% | NLD | -0.31 | 1.95 | 0.29% |
| | (-0.82) | (-0.99) | - | | (-1.01) | (0.89) | - |
| | [0.21] | [0.84] | - | | [0.16] | [0.19] | - |
| CAN | -0.23* | 2.02* | 2.51% | SWE | 0.05 | 1.90 | 0.49% |
| | (-1.69) | (1.29) | - | | (0.35) | (1.03) | - |
| | [0.05] | [0.10] | - | | [0.64] | [0.15] | - |
| FRA | -0.04 | 0.88 | 0.23% | CHE | 0.06 | 1.17 | 0.49% |
| | (-0.28) | (0.51) | - | | (0.29) | (0.77) | - |
| | [0.39] | [0.30] | - | | [0.61] | [0.22] | - |
| GER | -0.20 | 2.01 | 0.22% | GBR | -0.12 | 1.09 | 0.29% |
| | (-0.56) | (0.72) | - | | (-0.66) | (0.42) | - |
| | [0.29] | [0.24] | - | | [0.26] | [0.34] | - |
| ITA | -0.17* | -0.33 | 1.12% | USA | -0.19 | 2.35* | 1.11% |
| | (-1.68) | (-0.21) | - | | (-0.94) | (1.48) | - |
| | [0.05] | [0.58] | - | | [0.17] | [0.07] | - |
| JPN | 0.14 | 1.99* | 1.14% | | | | |
| | (0.69) | (1.82) | - | | | | |
| | [0.75] | [0.03] | - | | | | |

This table shows the coefficients, Pseudo-$R^2$ statistics, $t$-statistics and $p$-values of the benchmark quantile regression model (1) for the $10^{th}$ quantile. The $t$-statistics are reported in parentheses and the $p$-values are given between the brackets. * indicates significance at the 10% level or better.

We see that in tables 10, 21 and 22 the benchmark coefficients have mostly their expected sign as discussed before. However this pattern is less visible in table 20. Furthermore it is noteworthy that the Pseudo-$R^2$ values are on average quite a bit higher for the $90^{th}$ quantile than for the lower quantiles. This is in line with our earlier findings where we have seen that the $R^2$ values are higher for positive excess returns in the benchmark model than for the negative excess returns. There is of course an indirect link between positive excess returns and the upper quantiles and negative excess returns and the lower quantiles. However when we look at the amount of significant coefficients it's harder to see a pattern since the amount of significant coefficients for the $90^{th}$ quantile is 7, for the $10^{th}$ quantile is 5 but for the $25^{th}$ quantile it is 11. Also when we compare to the OLS results of table 1 we see that the OLS benchmark had 5 significant coefficients and an average $R^2$ value which is higher than the Pseudo-$R^2$ values of all quantiles except the $90^{th}$. So based on the results of our positive/negative distinction and Pseudo-$R^2$ values we might say that the benchmark variables have some more information about higher excess returns but this is not so much supported by the amount of significant coefficients in the quantile models. The predictive power of the benchmark variables is therefore not very dependent on the specific part of the distribution.

### 4.3.2 International Returns-Based Predictive Model

Table 11: International Excess Returns-Based Predictive Model for $10^{th}$ quantile

| Country | $\hat{\beta}_{i,AUS}$ | $\hat{\beta}_{i,CAN}$ | $\hat{\beta}_{i,FRA}$ | $\hat{\beta}_{i,DEU}$ | $\hat{\beta}_{i,ITA}$ | $\hat{\beta}_{i,JPN}$ | $\hat{\beta}_{i,NLD}$ | $\hat{\beta}_{i,SWE}$ | $\hat{\beta}_{i,CHE}$ | $\hat{\beta}_{i,GBR}$ | $\hat{\beta}_{i,USA}$ |
|---|---|---|---|---|---|---|---|---|---|---|---|
| AUS | | 0.25* | 0.14* | 0.12* | 0.13* | 0.06 | 0.08 | 0.09 | 0.20* | 0.09 | 0.19* |
| | | (2.49) | (1.58) | (1.56) | (1.99) | (0.71) | (0.83) | (1.14) | (1.96) | (0.74) | (1.86) |
| | | [0.01] | [0.06] | [0.06] | [0.02] | [0.24] | [0.20] | [0.13] | [0.03] | [0.23] | [0.03] |
| | | 3.46% | 3.76% | 3.01% | 3.45% | 2.49% | 2.60% | 2.32% | 3.04% | 2.52% | 4.35% |
| CAN | 0.05 | | 0.12* | 0.03 | 0.13* | 0.14* | 0.14* | 0.21* | 0.25* | -0.01 | 0.26* |
| | (0.58) | | (1.61) | (0.36) | (2.08) | (1.86) | (1.48) | (3.38) | (2.90) | (-0.21) | (1.84) |
| | [0.28] | | [0.05] | [0.36] | [0.02] | [0.03] | [0.07] | [0.00] | [0.00] | [0.58] | [0.03] |
| | 5.67% | | 6.32% | 4.32% | 6.30% | 6.37% | 5.92% | 7.92% | 6.80% | 5.58% | 7.05% |
| FRA | 0.03 | 0.05 | | -0.16 | -0.07 | 0.16* | -0.002 | 0.12* | 0.20* | -0.10 | 0.26* |
| | (0.33) | (0.44) | | (-1.13) | (-0.79) | (1.75) | (-0.15) | (1.32) | (1.48) | (-0.70) | (1.80) |
| | [0.37] | [0.33] | | [0.87] | [0.78] | [0.04] | [0.56] | [0.09] | [0.07] | [0.76] | [0.04] |
| | 2.49% | 2.58% | | 3.18% | 2.95% | 3.34% | 2.47% | 3.19% | 4.20% | 2.65% | 3.19% |
| DEU | 0.04 | 0.14 | 0.30* | | 0.02 | 0.25* | 0.35* | 0.25* | 0.45* | 0.17 | 0.29* |
| | (0.34) | (0.85) | (2.87) | | (0.19) | (2.40) | (2.04) | (2.17) | (2.68) | (0.97) | (1.58) |
| | [0.37] | [0.20] | [0.00] | | [0.42] | [0.01] | [0.02] | [0.02] | [0.00] | [0.17] | [0.06] |
| | 3.27% | 3.62% | 5.04% | | 3.29% | 6.88% | 4.00% | 5.03% | 6.76% | 3.61% | 4.61% |
| ITA | -0.07 | 0.26* | 0.40* | 0.19* | | 0.08 | 0.12 | 0.05 | 0.33* | 0.31* | 0.39* |
| | (-0.61) | (2.15) | (3.33) | (1.48) | | (0.67) | (1.10) | (0.54) | (2.16) | (2.27) | (3.78) |
| | [0.73] | [0.02] | [0.00] | [0.07] | | [0.25] | [0.14] | [0.29] | [0.02] | [0.01] | [0.00] |
| | 0.27% | 2.41% | 4.39% | 2.09% | | 1.38% | 1.50% | 1.22% | 3.16% | 3.36% | 4.43% |
| JPN | 0.003 | 0.15* | 0.21* | 0.14* | 0.08 | | 0.21* | 0.16* | 0.04 | 0.15* | 0.06 |
| | (0.10) | (1.39) | (2.46) | (1.55) | (1.09) | | (2.21) | (2.19) | (0.38) | (1.45) | (0.57) |
| | [0.46] | [0.08] | [0.01] | [0.06] | [0.14] | | [0.01] | [0.01] | [0.35] | [0.07] | [0.28] |
| | 3.67% | 4.05% | 4.59% | 4.08% | 3.93% | | 4.05% | 4.96% | 3.74% | 3.92% | 3.83% |
| NLD | 0.15 | 0.24* | 0.23* | 0.25* | -0.12 | 0.23* | | 0.14* | 0.45* | 0.10 | 0.49* |
| | (1.02) | (1.64) | (1.78) | (1.76) | (-1.34) | (2.08) | | (1.33) | (2.83) | (0.59) | (2.97) |
| | [0.15] | [0.05] | [0.04] | [0.04] | [0.91] | [0.02] | | [0.09] | [0.00] | [0.28] | [0.00] |
| | 4.91% | 5.25% | 5.23% | 4.79% | 4.80% | 4.84% | | 4.61% | 7.38% | 4.59% | 7.29% |
| SWE | 0.07 | 0.14 | 0.26* | 0.32* | 0.11 | 0.02 | 0.15 | | 0.22* | 0.17 | 0.25* |
| | (0.53) | (0.99) | (2.38) | (2.84) | (1.07) | (0.22) | (1.07) | | (1.60) | (1.07) | (1.59) |
| | [0.30] | [0.16] | [0.01] | [0.00] | [0.14] | [0.41] | [0.14] | | [0.05] | [0.14] | [0.06] |
| | 6.70% | 7.17% | 7.86% | 8.30% | 6.49% | 6.39% | 7.01% | | 7.94% | 7.12% | 7.70% |
| CHE | 0.03 | 0.08 | -0.06 | -0.10 | 0.03 | 0.01 | 0.04 | 0.13* | | 0.02 | 0.16 |
| | (0.33) | (0.81) | (-0.57) | (-0.96) | (0.43) | (0.14) | (0.34) | (1.76) | | (0.19) | (1.26) |
| | [0.37] | [0.21] | [0.72] | [0.83] | [0.33] | [0.44] | [0.37] | [0.04] | | [0.42] | [0.10] |
| | 7.13% | 7.51% | 7.16% | 7.40% | 7.10% | 7.08% | 7.14% | 7.72% | | 7.15% | 8.18% |
| GBR | 0.05 | 0.04 | 0.19* | 0.16* | 0.02 | 0.11 | 0.20* | 0.25* | 0.35* | | 0.28* |
| | (0.49) | (0.34) | (1.84) | (1.45) | (0.32) | (0.98) | (1.48) | (3.53) | (3.21) | | (1.83) |
| | [0.31] | [0.37] | [0.03] | [0.07] | [0.37] | [0.16] | [0.07] | [0.00] | [0.00] | | [0.03] |
| | 2.99% | 3.03% | 3.98% | 3.23% | 2.86% | 3.33% | 3.51% | 6.33% | 5.60% | | 4.29% |
| USA | 0.11 | 0.19* | -0.05 | -0.01 | 0.05 | 0.06 | 0.02 | 0.08 | 0.14 | 0.03 | |
| | (1.21) | (1.75) | (-0.65) | (-0.21) | (0.77) | (0.75) | (0.26) | (1.11) | (1.11) | (0.34) | |
| | [0.11] | [0.04] | [0.74] | [0.58] | [0.22] | [0.23] | [0.40] | [0.13] | [0.13] | [0.37] | |
| | 6.00% | 6.21% | 4.88% | 5.25% | 5.56% | 5.68% | 5.31% | 5.68% | 5.80% | 5.28% | |
| Average | 0.05 | 0.15 | 0.18 | 0.09 | 0.04 | 0.11 | 0.13 | 0.15 | 0.26 | 0.09 | 0.26 |

This table shows the coefficients, Pseudo-$R^2$ statistics, $t$-statistics and $p$-values of the international returns-based predictive model (2) for the $10^{th}$ quantile. The $t$-statistics are reported in parentheses and the $p$-values are given between the brackets. Below these $p$-values are the Pseudo-$R^2$ statistics. "Average" is the column average of the $\hat{\beta}_{i,j}$ estimates. * indicates significance at the 10% level or better.

The results in table 11 and tables 23, 24 and 25 in the Appendix show the results of the predictive quantile regression models with lagged international excess returns. Our results here fit very well with the results that we found in the positive and negative distinction. We see much higher Pseudo-$R^2$ values for the $10^{th}$ and $25^{th}$ quantile than for the $75^{th}$ and $90^{th}$ quantile, meaning that the lagged international excess returns contain more information about the lower excess returns than about the higher excess returns. This is also supported by the amount of significant variables since the lower the quantile, the higher the amount of significant variables.

When we look at the size of the average coefficients in the tables, we see that not only the U.S. but also Switzerland and Sweden have large values here. In fact, Switzerland has a higher average coefficient than the U.S. in both tables 24 and 25. However, when we compare how often the coefficients are significant among these three countries, then Switzerland performs the worst and Sweden performs the best. It is noteworthy to see that the U.S. and Sweden are less often significant in each of the different quantiles than in the OLS setting, but that this difference is the smallest when we compare the $10^{th}$ quantile to the OLS models.

Summarizing these results we see that the predictive power is overall a lot higher for lower excess returns than for higher excess returns and that besides the U.S. also Switzerland and Sweden have large predictive power.

### 4.3.3 Out-of-Sample Analysis

Table 12: Out-of-Sample Analysis for Three Baseline and Competing Models for $10^{th}$ quantile

| Country | B1 Adj-DM | B2 Adj-DM | B3 Adj-DM | Country | B1 Adj-DM | B2 Adj-DM | B3 Adj-DM |
|---|---|---|---|---|---|---|---|
| AUS | 1.29* | -2.28 | 1.36* | NLD | -0.14 | 4.07* | -0.32 |
| | [0.10] | [0.99] | [0.09] | | [0.56] | [0.00] | [0.62] |
| CAN | 1.35* | -2.12 | -4.88 | SWE | -0.57 | 4.66* | 4.71* |
| | [0.09] | [0.98] | [1.00] | | [0.72] | [0.00] | [0.00] |
| FRA | 2.00* | -2.68 | 4.59* | CHE | 2.00 | -2.68 | 4.59 |
| | [0.02] | [1.00] | [0.00] | | [0.81] | [1.00] | [0.78] |
| DEU | -0.48 | -0.62 | -5.54 | GBR | 4.10* | 6.78* | 4.41* |
| | [0.69] | [0.73] | [1.00] | | [0.00] | [0.00] | [0.00] |
| ITA | 0.35 | -0.90 | 0.74 | Average | 1.08 | 0.73 | 0.87 |
| | [0.37] | [0.82] | [0.23] | | | | |
| JPN | 3.77* | 2.99* | 4.37* | | | | |
| | [0.00] | [0.00] | [0.00] | | | | |

This table shows the adjusted DM-statistic (as introduced by Ge (2015)) for our predictive models versus the three corresponding baseline models: B1, B2 and B3. The three baseline models are the constant expected return model (16), the AR model (17) and the benchmark predictive model (18) for the $10^{th}$ quantile. In brackets are the corresponding $p$-values. * Indicates significance at the 10% level or better. "Average" is the column average of the adjusted DM-statistic estimates.

In table 12 and tables 26, 27 and 28 in the Appendix we show the results of our out-of-sample quantile analysis. We see that the average adjusted DM-statistics is positive in 7 out of 12 cases. This means that our lagged U.S. excess returns have some but not much out-of-sample predictive power. This can also be seen by the fact that the adjusted DM-statistics are more often positive than negative but are not significant in a lot of cases, as opposed to the results in table 6 where almost all statistics are significant and positive. However, we see for the lower quantiles that we have more significant adjusted DM-statistics than for the higher quantiles, which fits with what we found in the previous results. To be precise: the $10^{th}$ quantile has 14 significant test statistics, the $25^{th}$ and $75^{th}$ quantile both have 7 and the $90^{th}$ quantile only has 4. The lead-lag relationship again appears to be stronger among the lower excess returns but the out-of-sample predictive power is less visible for the tails of the distribution than it is for the mean.

# 5 Conclusion & Discussion

In this thesis we examine the lead-lag relationship between excess returns of different countries. Rapach et al. (2013) shows, and we confirm his results here, that the U.S. plays the largest role in predicting the excess returns of other countries and that this is at least partially due to international information frictions between markets. The leading role of the U.S. holds for the mean both in-sample and out-of-sample and the U.S. equity premium should therefore be taken into account when trying to predict excess returns as an addition to regular economic variables.

We show, as an extension to Rapach et al. (2013), that the U.S. continues to be one of the countries with the largest predictive power among our countries of interest, when we look at other parts of the distribution besides the mean. In fact, when we look at the tails of the distribution (more specifically the $10^{th}$, $25^{th}$, $75^{th}$ and $90^{th}$ quantile) we can still see that especially in-sample lead-lag relationships continue to hold. Moreover the lead-lag relationship of international excess returns appears to be a lot stronger for lower/negative excess returns both in-sample and out-of-sample. A reason for this is that markets react stronger to losses than gains due to risk averseness of traders. So when traders see negative equity premiums in foreign markets they may react stronger in their own markets since they're more afraid of spillovers when it regards losses than when it regards gains. We thus strongly recommend to take lagged U.S. excess returns into account when predicting the Value-At-Risk statistic in addition to regular national economic predictors such as dividend yield and the risk-free interest rate.

We do the analysis about the lead-lag relationships for the other parts of the distribution here only for the $10^{th}$, $25^{th}$, $75^{th}$ and $90^{th}$ quantile and for positive and negative excess returns. One could say that these results are dependent on the specific quantiles chosen, so it is interesting to examine whether the relationships found in this paper also hold in other quantiles. One can also try to see whether the predictive power of the U.S. is still existent when we include more national economic variables, as we have done for the in-sample analysis for the mean of the distribution with the factor model. Besides these researches, one can investigate whether the lead-lag relationships found in this paper hold for the option market. It could be expected that these relationships not only hold for the risk premium in equity markets (after all the risk premium is equal to the equity premium or the excess return) but also hold for the risk premium in option markets. As a final limitation to this research I'd like to add that the results here differ quite a bit across countries and that including more countries can improve the robustness of the results found in this paper. Thus a research regarding the same relationships across multiple countries would also be an interesting addition to the current literature.

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# Appendix

Table 13: Summary Statistics of Excess Returns

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

This table shows the summary statistics of the excess returns (in percent) for our countries of interest. The sharpe ratio is defined as the mean of the excess return divided by its standard deviation.

Table 14: Information on Used Return Indexes and Market Times

| Country | Global Financial Data series name | Coverage | Opening/closing times |
|---|---|---|---|
| AUS | ASX Accumulation Index - All Ordinaries | 500 largest companies listed on Australian Securities Exchange | 7:00pm/1:00am |
| CAN | Canada S&P/TSX-300 Total Return Index | 300 largest companies listed on Toronto Stock Exchange | 9:30am/4:00pm |
| FRA | CAC All-Tradable Total Return Index | 250 largest companies listed on Paris Stock Exchange | 3:00am/11:30am |
| GER | CDAX Total Return Index | All companies listed on Frankfurt Stock Exchange | 3:00am/2:00pm |
| ITA | BCI Global Return Index | All companies listed on Borsa Italiana | 3:00am/11:30am |
| JPN | Nikko Securities Composite Total Return | All companies listed on Tokyo and Osaka Stock Exchanges | 7:00pm/1:00am |
| NLD | All-Share Return Index | All companies listed on Amsterdam Stock Exchange | 3:00am/11:30am |
| SWE | OMX Stockholm Benchmark Gross Index | 80–100 largest/most-traded stocks on Stockholm Stock Exchange | 3:00am/11:30am |
| CHE | Swiss Performance Index | 400 largest companies listed on Swiss Exchange | 3:00am/11:20am |
| GBR | FTSE All-Share Return Index | All companies listed on London Stock Exchange | 3:00am/11:30am |
| USA | S&P 500 Total Return Index | 500 largest companies on NYSE/AMEX/NASDAQ | 9:30am/4:00pm |

This table shows the used series from Global Financial Data and what the coverage of these series is. It also shows the markets opening and closing times in Eastern Standard Time.

Table 15: Exclusion Table

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

This table shows whether we need to exclude the last day for a certain country combination in order to get valid results. 1 means that we can use all data in the return index and a 0 means that we have to exclude the last day in order to make sure the market's closing and opening times don't interfere with our results. The row refers to dependent variable and the column to the independent variable.

Table 16: U.S. Predictors Based Predictive Regression Model

| Country | $\hat{\beta}_{i,b}$ | $\hat{\beta}_{i,d}$ | $R^2$ | Country | $\hat{\beta}_{i,b}$ | $\hat{\beta}_{i,d}$ | $R^2$ |
|---|---|---|---|---|---|---|---|
| AUS | -0.20* | 0.79 | 0.95% | NLD | -0.03 | 0.88 | 0.38% |
| | (-1.83) | (1.19) | (3.38) | | (-0.22) | (1.03) | (1.53) |
| | [0.05] | [0.25] | [0.24] | | [0.56] | [0.34] | [0.55] |
| CAN | -0.29* | 0.99 | 2.42%* | SWE | -0.05 | 1.41 | 0.60% |
| | (-2.39) | (1.13) | (6.22) | | (-0.36) | (1.22) | (2.12) |
| | [0.01] | [0.34] | [0.08] | | [0.46] | [0.23] | [0.39] |
| FRA | -0.05 | 0.33 | 0.04% | CHE | -0.08 | 0.57 | 0.22% |
| | (-0.34) | (0.36) | (0.15) | | (-0.87) | (0.78) | (0.79) |
| | [0.47] | [0.55] | [0.94] | | [0.29] | [0.46] | [0.75] |
| DEU | -0.05 | 0.66 | 0.15% | GBR | -0.16 | 1.72* | 1.49%* |
| | (-0.39) | (0.67) | (0.50) | | (-1.45) | (2.51) | (6.38) |
| | [0.47] | [0.46] | [0.83] | | [0.14] | [0.02] | [0.06] |
| ITA | 0.06 | 0.02 | 0.07% | USA | -0.19 | 1.61 | 1.51% |
| | (0.30) | (0.02) | (0.18) | | (-1.66) | (2.03) | (4.15) |
| | [0.70] | [0.61] | [0.91] | | [0.10] | [0.11] | [0.24] |
| JPN | -0.03 | 0.68 | 0.21% | Pool | -0.10 | 0.88 | 0.44% |
| | (-0.26) | (0.80) | (0.93) | | (-0.97) | (1.25) | (1.57) |
| | [0.50] | [0.31] | [0.64] | | [0.29] | [0.30] | [0.57] |

This table shows the coefficients, $R^2$ statistics, $t$-statistics and $p$-values of the benchmark regression model (1) but with USA economic variables instead of that of the country itself. The $t$-statistics are reported in parentheses and the $p$-values are given between the brackets. The number in parentheses below the $R^2$ statistics are joint $\chi^2$ tests. * indicates significance at the 10% level or better.

Table 17: Pairwise Granger Causality Tests for Extra Controlling Variables

| Country | $\hat{\beta}_{i,AUS}$ | $\hat{\beta}_{i,CAN}$ | $\hat{\beta}_{i,FRA}$ | $\hat{\beta}_{i,DEU}$ | $\hat{\beta}_{i,ITA}$ | $\hat{\beta}_{i,JPN}$ | $\hat{\beta}_{i,NLD}$ | $\hat{\beta}_{i,SWE}$ | $\hat{\beta}_{i,CHE}$ | $\hat{\beta}_{i,GBR}$ | $\hat{\beta}_{i,USA}$ |
|---|---|---|---|---|---|---|---|---|---|---|---|
| AUS | | 0.10 | 0.12* | 0.13* | 0.08* | 0.09* | 0.13* | 0.08* | 0.11* | 0.07 | 0.20* |
| | | (1.29) | (1.88) | (1.99) | (2.26) | (1.88) | (1.74) | (1.86) | (1.57) | (0.89) | (2.24) |
| | | [0.11] | [0.02] | [0.02] | [0.01] | [0.03] | [0.04] | [0.04] | [0.05] | [0.19] | [0.01] |
| | | 0.96% | 1.58% | 1.77% | 1.49% | 1.21% | 1.62% | 1.09% | 1.02% | 0.66% | 2.26% |
| CAN | 0.04 | | 0.05 | 0.05 | 0.05 | 0.05 | 0.04 | 0.15* | 0.07 | 0.07 | 0.21* |
| | (0.69) | | (1.06) | (1.09) | (1.25) | (1.08) | (0.62) | (3.68) | (0.89) | (0.99) | (2.14) |
| | [0.26] | | [0.15] | [0.14] | [0.11] | [0.14] | [0.27] | [0.00] | [0.20] | [0.16] | [0.01] |
| | 2.89% | | 3.08% | 3.07% | 3.23% | 3.05% | 2.92% | 6.03% | 3.08% | 3.07% | 4.31% |
| FRA | 0.01 | 0.002 | | -0.02 | -0.04 | 0.04 | 0.02 | 0.15* | 0.16* | 0.04 | 0.12 |
| | (0.18) | (0.02) | | (-0.20) | (-0.78) | (0.61) | (0.17) | (2.50) | (1.56) | (0.32) | (1.28) |
| | [0.44] | [0.50] | | [0.58] | [0.76] | [0.29] | [0.42] | [0.01] | [0.07] | [0.36] | [0.12] |
| | 1.79% | 1.78% | | 1.79% | 1.94% | 1.91% | 1.79% | 3.92% | 2.67% | 1.83% | 2.29% |
| DEU | 0.03 | 0.10 | 0.12* | | 0.06* | 0.10* | 0.08 | 0.16* | 0.25* | 0.09 | 0.22* |
| | (0.45) | (1.25) | (1.40) | | (1.38) | (1.58) | (0.77) | (2.73) | (2.23) | (0.96) | (2.29) |
| | [0.35] | [0.12] | [0.09] | | [0.10] | [0.06] | [0.25] | [0.00] | [0.01] | [0.17] | [0.01] |
| | 1.39% | 1.77% | 1.91% | | 1.69% | 2.08% | 1.51% | 3.39% | 3.10% | 1.63% | 3.00% |
| ITA | -0.001 | 0.06 | 0.16* | 0.12 | | 0.05 | -0.03 | 0.07 | 0.22* | 0.15* | 0.13* |
| | (-0.01) | (0.66) | (1.58) | (1.31) | | (0.69) | (-0.27) | (1.07) | (1.98) | (1.45) | (1.36) |
| | [0.52] | [0.28] | [0.08] | [0.12] | | [0.28] | [0.60] | [0.16] | [0.04] | [0.07] | [0.10] |
| | 2.30% | 2.43% | 3.34% | 2.89% | | 2.43% | 2.33% | 2.60% | 3.81% | 3.03% | 2.80% |
| JPN | 0.04 | 0.12* | 0.11* | 0.03 | 0.03 | | 0.08 | 0.09* | 0.11* | 0.12* | 0.11* |
| | (0.70) | (1.72) | (2.03) | (0.52) | (0.83) | | (1.31) | (1.80) | (1.61) | (1.77) | (1.47) |
| | [0.26] | [0.05] | [0.03] | [0.33] | [0.21] | | [0.11] | [0.04] | [0.07] | [0.05] | [0.08] |
| | 1.90% | 2.68% | 2.78% | 1.85% | 1.95% | | 2.27% | 2.75% | 2.50% | 2.63% | 2.42% |
| NLD | 0.10 | 0.15* | 0.14* | 0.15* | 0.04 | 0.12* | | 0.17* | 0.32* | 0.12 | 0.33* |
| | (1.38) | (1.88) | (2.00) | (1.68) | (0.97) | (2.38) | | (2.96) | (3.04) | (1.19) | (3.46) |
| | [0.11] | [0.04] | [0.02] | [0.05] | [0.18] | [0.01] | | [0.00] | [0.00] | [0.12] | [0.00] |
| | 2.53% | 2.98% | 2.83% | 2.77% | 2.09% | 3.09% | | 4.42% | 5.00% | 2.36% | 5.01% |
| SWE | -0.04 | 0.15* | 0.03 | 0.06 | 0.08 | 0.05 | -0.005 | | 0.10 | 0.09 | 0.23* |
| | (-0.42) | (1.65) | (0.40) | (0.73) | (1.03) | (0.69) | (-0.05) | | (1.01) | (0.86) | (2.15) |
| | [0.66] | [0.07] | [0.36] | [0.27] | [0.20] | [0.29] | [0.53] | | [0.19] | [0.22] | [0.03] |
| | 2.47% | 3.26% | 2.44% | 2.56% | 2.84% | 2.53% | 2.40% | | 2.69% | 2.67% | 3.88% |
| CHE | 0.03 | 0.03 | 0.003 | -0.004 | 0.005 | 0.03 | 0.02 | 0.13* | | 0.03 | 0.13* |
| | (0.53) | (0.43) | (0.04) | (-0.05) | (0.13) | (0.63) | (0.33) | (3.32) | | (0.44) | (1.48) |
| | [0.33] | [0.35] | [0.48] | [0.54] | [0.45] | [0.29] | [0.39] | [0.00] | | [0.34] | [0.08] |
| | 4.39% | 4.38% | 4.31% | 4.31% | 4.32% | 4.41% | 4.34% | 6.70% | | 4.36% | 5.04% |
| GBR | 0.09 | 0.06 | 0.05 | -0.001 | -0.003 | 0.08* | -0.03 | 0.09* | 0.09 | | 0.22* |
| | (1.26) | (0.81) | (0.74) | (-0.01) | (-0.09) | (1.58) | (-0.37) | (2.07) | (1.19) | | (2.04) |
| | [0.14] | [0.24] | [0.25] | [0.50] | [0.54] | [0.07] | [0.64] | [0.02] | [0.13] | | [0.03] |
| | 0.72% | 0.43% | 0.39% | 0.18% | 0.18% | 0.80% | 0.24% | 1.32% | 0.59% | | 2.02% |
| USA | 0.06 | 0.04 | 0.002 | -0.02 | 0.05* | -0.001 | 0.01 | 0.09* | 0.03 | 0.02 | |
| | (1.06) | (0.39) | (0.04) | (-0.31) | (1.41) | (-0.02) | (0.15) | (2.27) | (0.35) | (0.23) | |
| | [0.18] | [0.34] | [0.48] | [0.61] | [0.09] | [0.50] | [0.44] | [0.01] | [0.37] | [0.41] | |
| | 1.21% | 0.94% | 0.87% | 0.90% | 1.41% | 0.87% | 0.88% | 2.18% | 0.92% | 0.89% | |
| Average | 0.04 | 0.08 | 0.08 | 0.05 | 0.04 | 0.06 | 0.03 | 0.12 | 0.15 | 0.08 | 0.19 |
| Pooled | 0.03 | 0.07 | 0.08* | 0.05 | 0.03 | 0.06* | 0.02 | 0.11* | 0.13* | 0.08* | 0.17* |
| | (0.63) | (1.32) | (1.88) | (1.02) | (1.22) | (1.51) | (0.36) | (3.50) | (2.18) | (1.45) | (2.93) |
| | [0.29] | [0.12] | [0.03] | [0.17] | [0.13] | [0.07] | [0.37] | [0.00] | [0.02] | [0.09] | [0.00] |
| | 1.45% | 1.50% | 1.64% | 1.47% | 1.55% | 1.52% | 1.28% | 2.42% | 1.87% | 1.72% | 2.55% |

This table shows the coefficients, $R^2$ statistics, $t$-statistics and $p$-values of the international returns-based predictive model (2) for extra controlling variables. The $t$-statistics are reported in parentheses and the $p$-values are given between the brackets. Below these $p$-values are the $R^2$ statistics. "Average" is the column average of the $\hat{\beta}_{i,j}$ estimates. * indicates significance at the 10% level or better.

Table 18: Benchmark Negative Excess Return Predictive Regression Model

| Country | $\hat{\beta}_{i,b}$ | $\hat{\beta}_{i,d}$ | $R^2$ | Country | $\hat{\beta}_{i,b}$ | $\hat{\beta}_{i,d}$ | $R^2$ |
|---|---|---|---|---|---|---|---|
| AUS | -0.12 | 1.33 | 0.78% | NLD | 0.11 | -0.44 | 0.34% |
| | (-0.61) | (0.31) | (0.61) | | (0.77) | (-0.39) | (0.25) |
| | [0.27] | [0.38] | [0.54] | | [0.78] | [0.65] | [0.78] |
| CAN | -0.14 | 1.19 | 1.55% | SWE | -0.03 | 1.01 | 0.82% |
| | (-1.24) | (0.89) | (1.27) | | (-0.40) | (1.19) | (0.66) |
| | [0.11] | [0.19] | [0.28] | | [0.34] | [0.12] | [0.52] |
| FRA | -0.004 | 0.39 | 0.11% | CHE | -0.01 | 2.32* | 3.44%* |
| | (-0.05) | (0.35) | (0.09) | | (-0.06) | (1.88) | (2.58) |
| | [0.48] | [0.36] | [0.91] | | [0.48] | [0.03] | [0.08] |
| GER | 0.14 | 0.53 | 1.23% | GBR | -0.15 | 1.66 | 1.37% |
| | (0.75) | (0.37) | (0.97) | | (-1.27) | (1.02) | (1.01) |
| | [0.77] | [0.36] | [0.38] | | [0.10] | [0.15] | [0.37] |
| ITA | -0.07 | 0.06 | 1.13% | USA | 0.09 | 0.05 | 1.08% |
| | (-1.27) | (0.07) | (1.00) | | (0.77) | (0.07) | (0.80) |
| | [0.10] | [0.47] | [0.37] | | [0.78] | [0.47] | [0.45] |
| JPN | 0.06 | 0.89* | 1.04% | | | | |
| | (0.47) | (1.35) | (0.91) | | | | |
| | [0.68] | [0.09] | [0.41] | | | | |

This table shows the coefficients, $R^2$ statistics, $t$-statistics and $p$-values of the benchmark regression model (1) but only for negative excess returns. The $t$-statistics are reported in parentheses and the $p$-values are given between the brackets. The number in parentheses below the $R^2$ statistics are joint $\chi^2$ tests. * indicates significance at the 10% level or better.

Table 19: International Negative Excess Returns-Based Predictive Model

| Country | $\hat{\beta}_{i,AUS}$ | $\hat{\beta}_{i,CAN}$ | $\hat{\beta}_{i,FRA}$ | $\hat{\beta}_{i,DEU}$ | $\hat{\beta}_{i,ITA}$ | $\hat{\beta}_{i,JPN}$ | $\hat{\beta}_{i,NLD}$ | $\hat{\beta}_{i,SWE}$ | $\hat{\beta}_{i,CHE}$ | $\hat{\beta}_{i,GBR}$ | $\hat{\beta}_{i,USA}$ |
|---|---|---|---|---|---|---|---|---|---|---|---|
| AUS | | 0.21* | 0.11* | 0.11* | 0.06* | 0.09* | 0.15* | 0.03 | 0.07 | -0.01 | 0.28* |
| | | (2.01) | (1.60) | (1.52) | (1.84) | (1.83) | (1.76) | (0.71) | (0.97) | (-0.11) | (2.57) |
| | | [0.02] | [0.05] | [0.06] | [0.03] | [0.03] | [0.04] | [0.24] | [0.17] | [0.54] | [0.01] |
| | | 4.53% | 3.06% | 2.87% | 2.40% | 2.76% | 3.99% | 1.70% | 1.90% | 1.56% | 6.48% |
| CAN | -0.08 | | -0.02 | -0.04 | -0.02 | 0.03 | -0.01 | -0.03 | -0.06 | -0.22 | 0.04 |
| | (-1.05) | | (-0.44) | (-0.78) | (-0.32) | (0.55) | (-0.16) | (-0.54) | (-0.54) | (-2.50) | (0.28) |
| | [0.85] | | [0.67] | [0.78] | [0.62] | [0.29] | [0.56] | [0.71] | [0.71] | [0.99] | [0.39] |
| | 6.53% | | 5.85% | 5.97% | 5.82% | 5.88% | 5.78% | 5.93% | 6.09% | 10.27% | 5.85% |
| FRA | -0.03 | 0.03 | | -0.16 | -0.06 | 0.06 | -0.02 | 0.01 | 0.02 | -0.11 | 0.02 |
| | (-0.42) | (0.44) | | (-1.43) | (-0.97) | (0.95) | (-0.19) | (0.10) | (0.23) | (-1.05) | (0.24) |
| | [0.66] | [0.33] | | [0.92] | [0.83] | [0.17] | [0.58] | [0.46] | [0.41] | [0.85] | [0.41] |
| | 4.21% | 4.22% | | 5.87% | 4.84% | 4.61% | 4.15% | 4.12% | 4.16% | 5.38% | 4.15% |
| DEU | 0.02 | 0.08 | 0.15* | | -0.01 | 0.19* | 0.08 | 0.12* | 0.18* | 0.02 | 0.14* |
| | (0.30) | (1.08) | (1.64) | | (-0.19) | (3.47) | (0.76) | (2.19) | (1.43) | (0.16) | (1.76) |
| | [0.38] | [0.14] | [0.05] | | [0.57] | [0.00] | [0.22] | [0.01] | [0.08] | [0.44] | [0.04] |
| | 4.82% | 5.32% | 5.99% | | 4.77% | 9.54% | 5.13% | 6.74% | 6.35% | 4.78% | 6.06% |
| ITA | 0.02 | 0.10* | 0.21* | 0.16* | | 0.03 | 0.13* | 0.04 | 0.17* | 0.19* | 0.16* |
| | (0.45) | (1.45) | (2.18) | (2.07) | | (0.54) | (1.69) | (0.80) | (1.97) | (2.32) | (2.03) |
| | [0.33] | [0.07] | [0.01] | [0.02] | | [0.30] | [0.05] | [0.21] | [0.02] | [0.01] | [0.02] |
| | 1.23% | 2.41% | 6.37% | 4.48% | | 1.30% | 3.23% | 1.47% | 4.00% | 5.01% | 3.75% |
| JPN | -0.02 | 0.07 | 0.07* | 0.06 | 0.04 | | 0.06 | 0.05 | 0.01 | 0.04 | 0.09 |
| | (-0.32) | (0.91) | (1.30) | (1.15) | (1.15) | | (0.87) | (0.99) | (0.14) | (0.60) | (1.12) |
| | [0.62] | [0.18] | [0.10] | [0.13] | [0.13] | | [0.19] | [0.16] | [0.45] | [0.27] | [0.13] |
| | 5.14% | 5.81% | 5.98% | 5.88% | 5.69% | | 5.79% | 5.74% | 5.09% | 5.34% | 5.99% |
| NLD | 0.07 | 0.14* | 0.08 | 0.10 | -0.11 | 0.12* | | 0.03 | 0.16 | 0.03 | 0.23* |
| | (0.98) | (2.02) | (0.85) | (1.01) | (-2.05) | (1.98) | | (0.32) | (1.25) | (0.22) | (2.79) |
| | [0.16] | [0.02] | [0.20] | [0.16] | [0.98] | [0.02] | | [0.37] | [0.11] | [0.41] | [0.00] |
| | 9.40% | 10.55% | 9.32% | 9.61% | 10.91% | 10.67% | | 8.98% | 10.18% | 8.94% | 11.70% |
| SWE | 0.04 | 0.11* | 0.20* | 0.20* | 0.03 | 0.05 | 0.11* | | 0.17* | 0.12* | 0.17* |
| | (0.57) | (1.35) | (2.32) | (2.78) | (0.53) | (0.70) | (1.31) | | (1.96) | (1.35) | (1.84) |
| | [0.29] | [0.09] | [0.01] | [0.00] | [0.30] | [0.24] | [0.10] | | [0.03] | [0.09] | [0.03] |
| | 12.51% | 13.36% | 15.66% | 15.68% | 12.50% | 12.65% | 13.33% | | 14.21% | 13.31% | 14.13% |
| CHE | 0.01 | 0.10 | 0.17* | 0.07 | 0.04* | 0.08* | 0.06 | 0.03 | | 0.06 | 0.21* |
| | (0.12) | (1.26) | (1.61) | (0.76) | (1.35) | (1.45) | (0.59) | (0.67) | | (0.88) | (1.95) |
| | [0.45] | [0.10] | [0.05] | [0.22] | [0.09] | [0.07] | [0.28] | [0.25] | | [0.19] | [0.03] |
| | 11.15% | 12.48% | 14.45% | 11.71% | 11.74% | 12.07% | 11.46% | 11.30% | | 11.49% | 14.16% |
| GBR | 0.01 | 0.15* | 0.14 | 0.21* | -0.01 | 0.09* | 0.24* | 0.15* | 0.21* | | 0.32* |
| | (0.14) | (1.55) | (1.25) | (1.84) | (-0.21) | (1.40) | (1.73) | (2.59) | (2.37) | | (2.34) |
| | [0.44] | [0.06] | [0.11] | [0.03] | [0.58] | [0.08] | [0.04] | [0.00] | [0.01] | | [0.01] |
| | 4.76% | 6.82% | 7.10% | 9.26% | 4.78% | 5.84% | 9.07% | 7.82% | 7.88% | | 11.50% |
| USA | 0.09* | 0.22* | 0.03 | -0.01 | -0.02 | 0.08* | 0.10 | -0.04 | 0.05 | -0.07 | |
| | (1.42) | (2.02) | (0.56) | (-0.13) | (-0.65) | (1.66) | (1.26) | (-0.76) | (0.46) | (-0.65) | |
| | [0.08] | [0.02] | [0.29] | [0.55] | [0.74] | [0.05] | [0.10] | [0.78] | [0.32] | [0.74] | |
| | 6.72% | 9.67% | 5.65% | 5.53% | 5.71% | 6.84% | 6.75% | 5.85% | 5.72% | 5.97% | |
| Average | 0.01 | 0.12 | 0.11 | 0.07 | -0.01 | 0.08 | 0.09 | 0.04 | 0.10 | 0.004 | 0.17 |

This table shows the coefficients, $R^2$ statistics, $t$-statistics and $p$-values of the international returns-based predictive model (2) for negative excess returns. The $t$-statistics are reported in parentheses and the $p$-values are given between the brackets. Below these $p$-values are the $R^2$ statistics. "Average" is the column average of the $\hat{\beta}_{i,j}$ estimates. * indicates significance at the 10% level or better.

Table 20: Benchmark Predictive Quantile Regression Model for $90^{th}$ Quantile

| Country | $\hat{\beta}_{i,b}$ | $\hat{\beta}_{i,d}$ | $R^2$ | Country | $\hat{\beta}_{i,b}$ | $\hat{\beta}_{i,d}$ | $R^2$ |
|---|---|---|---|---|---|---|---|
| AUS | 0.10 | 2.62* | 1.95% | NLD | -0.56* | 2.82* | 3.08% |
| | (1.10) | (1.54) | - | | (-3.44) | (2.46) | - |
| | [0.86] | [0.06] | - | | [0.00] | [0.01] | - |
| CAN | 0.08 | 0.41 | 0.72% | SWE | 0.22 | 1.86 | 1.79% |
| | (0.83) | (0.36) | - | | (1.42) | (1.10) | - |
| | [0.80] | [0.36] | - | | [0.92] | [0.14] | - |
| FRA | 0.003 | -0.08 | 0.01% | CHE | 0.03 | -2.29 | 0.88% |
| | (0.03) | (-0.06) | - | | (0.16) | (-1.77) | - |
| | [0.51] | [0.53] | - | | [0.56] | [0.96] | - |
| GER | -0.62* | 2.63* | 1.99% | GBR | -0.06 | 4.01* | 3.69% |
| | (-3.13) | (1.75) | - | | (-0.50) | (2.25) | - |
| | [0.00] | [0.04] | - | | [0.31] | [0.01] | - |
| ITA | 0.10 | -2.01 | 2.22% | USA | -0.24* | 1.38 | 1.34% |
| | (0.91) | (-1.23) | - | | (-1.64) | (1.25) | - |
| | [0.82] | [0.89] | - | | [0.05] | [0.11] | - |
| JPN | -0.04 | -0.39 | 0.16% | | | | |
| | (-0.17) | (-0.30) | - | | | | |
| | [0.43] | [0.62] | - | | | | |

This table shows the coefficients, Pseudo-$R^2$ statistics, $t$-statistics and $p$-values of the benchmark quantile regression model (1) for the $90^{th}$ quantile. The $t$-statistics are reported in parentheses and the $p$-values are given between the brackets. * indicates significance at the 10% level or better.

Table 21: Benchmark Predictive Quantile Regression Model for $75^{th}$ Quantile

| Country | $\hat{\beta}_{i,b}$ | $\hat{\beta}_{i,d}$ | $R^2$ | Country | $\hat{\beta}_{i,b}$ | $\hat{\beta}_{i,d}$ | $R^2$ |
|---|---|---|---|---|---|---|---|
| AUS | 0.07 | 1.49 | 0.66% | NLD | -0.36* | 2.18* | 1.69% |
| | (1.16) | (1.26) | - | | (-3.07) | (2.46) | - |
| | [0.88] | [0.10] | - | | [0.00] | [0.01] | - |
| CAN | -0.15* | 0.51 | 1.38% | SWE | 0.05 | 0.26 | 0.10% |
| | (-2.11) | (0.61) | - | | (0.59) | (0.24) | - |
| | [0.02] | [0.27] | - | | [0.72] | [0.40] | - |
| FRA | -0.13 | 1.51* | 0.42% | CHE | -0.10 | -0.69 | 0.76% |
| | (-1.23) | (1.30) | - | | (-1.02) | (-0.85) | - |
| | [0.11] | [0.10] | - | | [0.15] | [0.80] | - |
| GER | -0.43* | 0.54 | 2.03% | GBR | -0.21* | 4.32* | 1.93% |
| | (-3.05) | (0.52) | - | | (-2.79) | (4.25) | - |
| | [0.00] | [0.30] | - | | [0.00] | [0.00] | - |
| ITA | 0.10 | -0.32 | 0.55% | USA | -0.12 | 0.73 | 0.37% |
| | (1.53) | (-0.34) | - | | (-1.09) | (0.88) | - |
| | [0.94] | [0.63] | - | | [0.14] | [0.19] | - |
| JPN | -0.25* | -0.98 | 0.73% | | | | |
| | (-2.73) | (-1.75) | - | | | | |
| | [0.00] | [0.96] | - | | | | |

This table shows the coefficients, Pseudo-$R^2$ statistics, $t$-statistics and $p$-values of the benchmark quantile regression model (1) for the $75^{th}$ quantile. The $t$-statistics are reported in parentheses and the $p$-values are given between the brackets. * indicates significance at the 10% level or better.

Table 22: Benchmark Predictive Quantile Regression Model for $25^{th}$ Quantile

| Country | $\hat{\beta}_{i,b}$ | $\hat{\beta}_{i,d}$ | $R^2$ | Country | $\hat{\beta}_{i,b}$ | $\hat{\beta}_{i,d}$ | $R^2$ |
|---|---|---|---|---|---|---|---|
| AUS | -0.02 | -2.27 | 0.91% | NLD | -0.29* | 2.79* | 1.06% |
| | (-0.23) | (-1.43) | - | | (-1.76) | (2.33) | - |
| | [0.41] | [0.92] | - | | [0.04] | [0.01] | - |
| CAN | -0.22* | 0.78 | 1.47% | SWE | -0.18* | 1.76* | 1.55% |
| | (-2.59) | (0.77) | - | | (-2.44) | (1.86) | - |
| | [0.00] | [0.22] | - | | [0.01] | [0.03] | - |
| FRA | -0.18 | 1.64 | 0.19% | CHE | -0.27* | 1.07 | 0.84% |
| | (-1.26) | (1.07) | - | | (-1.77) | (0.90) | - |
| | [0.10] | [0.14] | - | | [0.04] | [0.18] | - |
| GER | -0.11 | 1.58 | 0.39% | GBR | -0.21* | 3.93* | 1.14% |
| | (-0.57) | (1.13) | - | | (-1.77) | (2.38) | - |
| | [0.28] | [0.13] | - | | [0.04] | [0.01] | - |
| ITA | -0.03 | 0.33 | 0.10% | USA | -0.31* | 2.00* | 1.57% |
| | (-0.45) | (0.30) | - | | (-2.99) | (2.60) | - |
| | [0.33] | [0.38] | - | | [0.00] | [0.00] | - |
| JPN | 0.34 | 1.80* | 1.62% | | | | |
| | (2.50) | (2.39) | - | | | | |
| | [0.99] | [0.01] | - | | | | |

This table shows the coefficients, Pseudo-$R^2$ statistics, $t$-statistics and $p$-values of the benchmark quantile regression model (1) for the $25^{th}$ quantile. The $t$-statistics are reported in parentheses and the $p$-values are given between the brackets. * indicates significance at the 10% level or better.

Table 23: International Excess Returns-Based Predictive Model for $90^{th}$ quantile

| Country | $\hat{\beta}_{i,AUS}$ | $\hat{\beta}_{i,CAN}$ | $\hat{\beta}_{i,FRA}$ | $\hat{\beta}_{i,DEU}$ | $\hat{\beta}_{i,ITA}$ | $\hat{\beta}_{i,JPN}$ | $\hat{\beta}_{i,NLD}$ | $\hat{\beta}_{i,SWE}$ | $\hat{\beta}_{i,CHE}$ | $\hat{\beta}_{i,GBR}$ | $\hat{\beta}_{i,USA}$ |
|---|---|---|---|---|---|---|---|---|---|---|---|
| AUS | | -0.09 | 0.04 | -0.05 | -0.01 | 0.04 | -0.05 | -0.01 | 0.01 | 0.11* | 0.05 |
| | | (-1.09) | (0.67) | (-0.73) | (-0.23) | (0.68) | (-0.71) | (-0.19) | (0.17) | (1.38) | (0.62) |
| | | [0.86] | [0.25] | [0.77] | [0.59] | [0.25] | [0.76] | [0.57] | [0.43] | [0.08] | [0.27] |
| | | 2.49% | 2.07% | 2.02% | 2.02% | 1.96% | 1.98% | 1.97% | 1.95% | 2.57% | 1.99% |
| CAN | 0.15* | | 0.05 | 0.05 | 0.04 | 0.07 | -0.02 | 0.12* | 0.07 | 0.22* | 0.17* |
| | (1.93) | | (0.81) | (0.79) | (0.74) | (1.07) | (-0.29) | (2.24) | (0.75) | (2.40) | (2.08) |
| | [0.03] | | [0.21] | [0.22] | [0.23] | [0.14] | [0.62] | [0.01] | [0.23] | [0.01] | [0.02] |
| | 1.56% | | 1.19% | 1.02% | 1.40% | 1.03% | 0.96% | 3.09% | 0.97% | 2.14% | 1.40% |
| FRA | 0.06 | -0.09 | | -0.02 | 0.01 | 0.10 | -0.19 | 0.06 | 0.10 | 0.08 | 0.13 |
| | (0.62) | (-0.91) | | (-0.22) | (0.10) | (1.27) | (-1.82) | (0.82) | (0.81) | (0.75) | (1.10) |
| | [0.27] | [0.82] | | [0.59] | [0.46] | [0.10] | [0.97] | [0.21] | [0.21] | [0.23] | [0.14] |
| | 0.19% | 0.02% | | 0.05% | 0.04% | 0.87% | 0.89% | 0.54% | 0.30% | 0.08% | 0.40% |
| DEU | -0.0002 | 0.07 | 0.07 | | 0.12* | 0.02 | -0.01 | 0.13* | 0.18* | -0.01 | 0.27* |
| | (-0.51) | (0.81) | (0.88) | | (1.91) | (0.38) | (-0.17) | (1.97) | (1.57) | (-0.19) | (2.73) |
| | [0.69] | [0.21] | [0.19] | | [0.03] | [0.35] | [0.57] | [0.02] | [0.06] | [0.58] | [0.00] |
| | 2.72% | 2.77% | 2.76% | | 3.67% | 2.85% | 2.73% | 3.65% | 3.04% | 2.74% | 4.17% |
| ITA | 0.09 | 0.003 | 0.09 | 0.01 | | -0.13 | -0.10 | 0.06 | 0.21* | 0.11 | 0.05 |
| | (0.72) | (0.12) | (0.69) | (0.20) | | (-1.03) | (-0.77) | (0.62) | (1.54) | (0.69) | (0.36) |
| | [0.24] | [0.45] | [0.24] | [0.42] | | [0.85] | [0.78] | [0.27] | [0.06] | [0.24] | [0.36] |
| | 2.58% | 2.44% | 2.72% | 2.45% | | 2.46% | 2.47% | 2.23% | 2.94% | 2.80% | 2.47% |
| JPN | 0.11 | 0.16* | 0.06 | -0.13 | -0.001 | | -0.04 | 0.06 | 0.07 | 0.13 | 0.14 |
| | (1.05) | (1.36) | (0.60) | (-1.23) | (-0.11) | | (-0.44) | (0.64) | (0.55) | (1.13) | (1.14) |
| | [0.15] | [0.09] | [0.27] | [0.89] | [0.54] | | [0.67] | [0.26] | [0.29] | [0.13] | [0.13] |
| | 0.63% | 0.58% | 0.38% | 0.81% | 0.23% | | 0.41% | 0.58% | 0.32% | 0.89% | 0.64% |
| NLD | 0.004 | 0.12* | 0.13* | 0.001 | 0.04 | 0.11* | | 0.14* | 0.21* | 0.11 | 0.37* |
| | (0.16) | (1.30) | (1.61) | (0.09) | (0.77) | (1.60) | | (2.03) | (1.75) | (1.05) | (3.77) |
| | [0.44] | [0.10] | [0.05] | [0.46] | [0.22] | [0.06] | | [0.02] | [0.04] | [0.15] | [0.00] |
| | 3.20% | 3.46% | 3.78% | 3.19% | 3.52% | 3.79% | | 5.09% | 3.95% | 3.47% | 5.36% |
| SWE | -0.09 | 0.15 | 0.003 | -0.28 | 0.06 | 0.002 | -0.24 | | 0.04 | 0.13 | 0.28* |
| | (-0.69) | (1.10) | (0.23) | (-2.06) | (0.60) | (0.16) | (-1.69) | | (0.29) | (1.00) | (1.86) |
| | [0.75] | [0.14] | [0.41] | [0.98] | [0.28] | [0.44] | [0.95] | | [0.39] | [0.16] | [0.03] |
| | 1.99% | 2.22% | 1.95% | 2.67% | 2.09% | 1.96% | 2.32% | | 1.97% | 2.22% | 3.02% |
| CHE | 0.07 | -0.12 | -0.002 | -0.06 | 0.05 | -0.06 | -0.08 | 0.20* | | 0.18* | 0.18* |
| | (0.90) | (-1.30) | (-0.07) | (-0.63) | (0.84) | (-0.81) | (-0.85) | (3.72) | | (1.85) | (1.47) |
| | [0.18] | [0.90] | [0.53] | [0.73] | [0.20] | [0.79] | [0.80] | [0.00] | | [0.03] | [0.07] |
| | 1.09% | 1.27% | 0.94% | 1.01% | 1.18% | 1.04% | 1.38% | 4.50% | | 1.83% | 1.42% |
| GBR | 0.13* | 0.07 | 0.01 | -0.09 | -0.01 | 0.04 | -0.17 | -0.001 | -0.01 | | 0.15* |
| | (1.59) | (0.84) | (0.22) | (-1.14) | (-0.29) | (0.58) | (-2.78) | (-0.08) | (-0.20) | | (1.47) |
| | [0.06] | [0.20] | [0.41] | [0.87] | [0.61] | [0.28] | [1.00] | [0.53] | [0.58] | | [0.07] |
| | 5.77% | 5.29% | 5.28% | 5.82% | 5.26% | 5.33% | 6.27% | 5.27% | 5.33% | | 5.79% |
| USA | 0.03 | 0.12 | 0.06 | 0.04 | 0.14* | 0.02 | 0.04 | 0.05 | 0.05 | 0.06 | |
| | (0.48) | (1.15) | (0.93) | (0.65) | (2.89) | (0.44) | (0.50) | (0.87) | (0.63) | (0.65) | |
| | [0.31] | [0.13] | [0.18] | [0.26] | [0.00] | [0.33] | [0.31] | [0.19] | [0.26] | [0.26] | |
| | 2.68% | 2.73% | 2.92% | 2.63% | 4.45% | 2.46% | 2.25% | 3.04% | 2.75% | 2.58% | |
| Average | 0.06 | 0.04 | 0.05 | -0.05 | 0.04 | 0.02 | -0.09 | 0.08 | 0.09 | 0.11 | 0.18 |

This table shows the coefficients, Pseudo-$R^2$ statistics, $t$-statistics and $p$-values of the international returns-based predictive model (2) for the $90^{th}$ quantile. The $t$-statistics are reported in parentheses and the $p$-values are given between the brackets. Below these $p$-values are the Pseudo-$R^2$ statistics. "Average" is the column average of the $\hat{\beta}_{i,j}$ estimates. * indicates significance at the 10% level or better.

Table 24: International Excess Returns-Based Predictive Model for $75^{th}$ quantile

| Country | $\hat{\beta}_{i,AUS}$ | $\hat{\beta}_{i,CAN}$ | $\hat{\beta}_{i,FRA}$ | $\hat{\beta}_{i,DEU}$ | $\hat{\beta}_{i,ITA}$ | $\hat{\beta}_{i,JPN}$ | $\hat{\beta}_{i,NLD}$ | $\hat{\beta}_{i,SWE}$ | $\hat{\beta}_{i,CHE}$ | $\hat{\beta}_{i,GBR}$ | $\hat{\beta}_{i,USA}$ |
|---|---|---|---|---|---|---|---|---|---|---|---|
| AUS | | -0.11 | 0.01 | -0.04 | -0.04 | 0.01 | -0.05 | -0.01 | 0.04 | 0.03 | -0.02 |
| | | (-1.82) | (0.26) | (-0.81) | (-1.15) | (0.15) | (-0.91) | (-0.22) | (0.62) | (0.45) | (-0.25) |
| | | [0.97] | [0.40] | [0.79] | [0.87] | [0.44] | [0.82] | [0.59] | [0.27] | [0.32] | [0.60] |
| | | 1.46% | 0.75% | 0.84% | 0.97% | 0.72% | 0.82% | 0.75% | 0.79% | 0.73% | 0.74% |
| CAN | 0.05 | | 0.09* | 0.08* | 0.05* | 0.08* | 0.12* | 0.13* | 0.10* | 0.19* | 0.17* |
| | (1.01) | | (1.99) | (1.70) | (1.35) | (1.95) | (2.40) | (3.30) | (1.52) | (3.02) | (2.27) |
| | [0.16] | | [0.02] | [0.04] | [0.09] | [0.03] | [0.01] | [0.00] | [0.06] | [0.00] | [0.01] |
| | 1.69% | | 1.97% | 1.98% | 1.69% | 1.69% | 2.04% | 3.59% | 1.78% | 3.04% | 2.74% |
| FRA | -0.03 | -0.16 | | -0.04 | -0.08 | 0.01 | -0.21 | 0.10* | 0.11 | 0.03 | -0.05 |
| | (-0.40) | (-2.13) | | (-0.49) | (-1.39) | (0.24) | (-2.46) | (1.65) | (1.24) | (0.31) | (-0.54) |
| | [0.66] | [0.98] | | [0.69] | [0.92] | [0.40] | [0.99] | [0.05] | [0.11] | [0.38] | [0.71] |
| | 0.47% | 1.09% | | 0.47% | 0.85% | 0.46% | 0.91% | 0.79% | 0.69% | 0.45% | 0.50% |
| DEU | 0.004 | 0.04 | 0.02 | | 0.05 | -0.02 | -0.04 | 0.06 | 0.20* | 0.02 | 0.16* |
| | (0.16) | (0.58) | (0.31) | | (1.17) | (-0.33) | (-0.61) | (0.99) | (2.20) | (0.32) | (1.80) |
| | [0.44] | [0.28] | [0.38] | | [0.12] | [0.63] | [0.73] | [0.16] | [0.01] | [0.38] | [0.04] |
| | 2.06% | 2.18% | 2.09% | | 2.41% | 2.11% | 2.11% | 2.15% | 2.79% | 2.08% | 2.55% |
| ITA | 0.10 | -0.01 | 0.08 | 0.03 | | 0.05 | -0.19 | 0.11* | 0.19* | 0.24* | 0.14* |
| | (1.28) | (-0.20) | (0.92) | (0.37) | | (0.59) | (-2.05) | (1.74) | (2.04) | (2.97) | (1.63) |
| | [0.10] | [0.58] | [0.18] | [0.36] | | [0.28] | [0.98] | [0.04] | [0.02] | [0.00] | [0.05] |
| | 0.91% | 0.67% | 0.79% | 0.74% | | 0.73% | 0.96% | 0.79% | 1.08% | 1.60% | 1.07% |
| JPN | 0.06 | 0.11* | 0.08* | 0.04 | 0.002 | | 0.05 | 0.09* | 0.16* | 0.11* | 0.10* |
| | (1.09) | (1.95) | (1.58) | (0.94) | (0.09) | | (1.00) | (2.37) | (2.66) | (1.91) | (1.77) |
| | [0.14] | [0.03] | [0.06] | [0.17] | [0.46] | | [0.16] | [0.01] | [0.00] | [0.03] | [0.04] |
| | 0.94% | 1.54% | 1.06% | 0.84% | 0.74% | | 0.94% | 1.89% | 1.53% | 1.37% | 1.31% |
| NLD | 0.001 | -0.05 | 0.08 | 0.01 | 0.01 | 0.02 | | 0.15* | 0.24* | 0.14* | 0.17* |
| | (0.10) | (-0.86) | (1.27) | (0.24) | (0.38) | (0.38) | | (2.90) | (2.64) | (1.59) | (1.85) |
| | [0.46] | [0.81] | [0.10] | [0.40] | [0.35] | [0.35] | | [0.00] | [0.00] | [0.06] | [0.03] |
| | 1.69% | 1.82% | 2.19% | 1.72% | 1.74% | 1.71% | | 3.27% | 2.80% | 2.02% | 2.31% |
| SWE | -0.09 | 0.11 | -0.10 | -0.09 | 0.04 | 0.07 | -0.16 | | -0.08 | 0.03 | 0.10 |
| | (-0.99) | (1.20) | (-1.16) | (-1.03) | (0.71) | (0.93) | (-1.78) | | (-0.78) | (0.28) | (1.02) |
| | [0.84] | [0.12] | [0.88] | [0.85] | [0.24] | [0.18] | [0.96] | | [0.78] | [0.39] | [0.15] |
| | 0.23% | 0.34% | 0.39% | 0.30% | 0.35% | 0.25% | 0.49% | | 0.23% | 0.13% | 0.27% |
| CHE | 0.02 | -0.08 | -0.10 | -0.09 | -0.04 | 0.01 | -0.08 | 0.13* | | -0.06 | 0.03 |
| | (0.50) | (-1.56) | (-1.92) | (-1.66) | (-1.15) | (0.19) | (-1.28) | (3.13) | | (-1.01) | (0.45) |
| | [0.31] | [0.94] | [0.97] | [0.95] | [0.87] | [0.42] | [0.90] | [0.00] | | [0.84] | [0.33] |
| | 1.56% | 1.73% | 1.96% | 2.00% | 1.74% | 1.49% | 1.74% | 2.61% | | 1.70% | 1.51% |
| GBR | 0.08* | -0.001 | 0.005 | -0.10 | -0.01 | 0.02 | -0.22 | -0.02 | -0.07 | | -0.01 |
| | (1.41) | (-0.09) | (0.18) | (-2.20) | (-0.30) | (0.43) | (-3.22) | (-0.58) | (-1.19) | | (-0.20) |
| | [0.08] | [0.53] | [0.43] | [0.99] | [0.62] | [0.34] | [1.00] | [0.72] | [0.88] | | [0.58] |
| | 2.55% | 2.14% | 2.15% | 2.33% | 2.17% | 2.21% | 3.50% | 2.23% | 2.20% | | 2.14% |
| USA | 0.01 | -0.19 | -0.004 | -0.04 | 0.01 | -0.05 | -0.01 | 0.13* | -0.02 | 0.04 | |
| | (0.20) | (-2.24) | (-0.13) | (-0.64) | (0.22) | (-0.92) | (-0.23) | (2.62) | (-0.24) | (0.51) | |
| | [0.42] | [0.99] | [0.55] | [0.74] | [0.41] | [0.82] | [0.59] | [0.00] | [0.60] | [0.30] | |
| | 0.54% | 1.33% | 0.63% | 0.77% | 0.66% | 0.79% | 0.66% | 1.44% | 0.69% | 0.71% | |
| Average | 0.02 | -0.04 | 0.02 | -0.02 | 0.00 | 0.02 | -0.08 | 0.09 | 0.09 | 0.08 | 0.08 |

This table shows the coefficients, Pseudo-$R^2$ statistics, $t$-statistics and $p$-values of the international returns-based predictive model (2) for the $75^{th}$ quantile. The $t$-statistics are reported in parentheses and the $p$-values are given between the brackets. Below these $p$-values are the Pseudo-$R^2$ statistics. "Average" is the column average of the $\hat{\beta}_{i,j}$ estimates. * indicates significance at the 10% level or better.

Table 25: International Excess Returns-Based Predictive Model for $25^{th}$ quantile

| Country | $\hat{\beta}_{i,AUS}$ | $\hat{\beta}_{i,CAN}$ | $\hat{\beta}_{i,FRA}$ | $\hat{\beta}_{i,DEU}$ | $\hat{\beta}_{i,ITA}$ | $\hat{\beta}_{i,JPN}$ | $\hat{\beta}_{i,NLD}$ | $\hat{\beta}_{i,SWE}$ | $\hat{\beta}_{i,CHE}$ | $\hat{\beta}_{i,GBR}$ | $\hat{\beta}_{i,USA}$ |
|---|---|---|---|---|---|---|---|---|---|---|---|
| AUS | | 0.19* | 0.19* | 0.22* | 0.13* | 0.12* | 0.15* | 0.14* | 0.21* | 0.14* | 0.29* |
| | | (2.48) | (2.92) | (4.22) | (2.93) | (1.91) | (2.09) | (2.90) | (2.81) | (1.65) | (3.36) |
| | | [0.01] | [0.00] | [0.00] | [0.00] | [0.03] | [0.02] | [0.00] | [0.00] | [0.05] | [0.00] |
| | | 2.59% | 3.00% | 3.24% | 3.80% | 2.13% | 2.17% | 2.93% | 2.85% | 2.13% | 3.16% |
| CAN | 0.13* | | -0.01 | -0.001 | 0.08* | 0.04 | 0.01 | 0.13* | 0.04 | -0.02 | 0.21* |
| | (1.82) | | (-0.25) | (-0.14) | (1.64) | (0.66) | (0.19) | (2.59) | (0.55) | (-0.29) | (2.62) |
| | [0.03] | | [0.60] | [0.56] | [0.05] | [0.25] | [0.42] | [0.00] | [0.29] | [0.62] | [0.00] |
| | 3.08% | | 2.73% | 2.72% | 3.41% | 2.79% | 2.73% | 4.21% | 2.80% | 2.74% | 3.44% |
| FRA | -0.02 | -0.02 | | -0.05 | -0.03 | -0.10 | 0.04 | 0.07 | 0.08 | -0.03 | -0.01 |
| | (-0.23) | (-0.29) | | (-0.44) | (-0.37) | (-1.19) | (0.38) | (0.80) | (0.64) | (-0.31) | (-0.15) |
| | [0.59] | [0.61] | | [0.67] | [0.65] | [0.88] | [0.35] | [0.21] | [0.26] | [0.62] | [0.56] |
| | 2.14% | 2.19% | | 2.19% | 2.17% | 2.38% | 2.23% | 2.53% | 2.35% | 2.17% | 2.15% |
| DEU | 0.02 | -0.02 | 0.03 | | 0.02 | 0.01 | 0.16* | 0.11* | 0.39* | 0.11 | 0.03 |
| | (0.36) | (-0.31) | (0.43) | | (0.34) | (0.17) | (1.64) | (1.67) | (3.55) | (1.07) | (0.33) |
| | [0.36] | [0.62] | [0.33] | | [0.37] | [0.43] | [0.05] | [0.05] | [0.00] | [0.14] | [0.37] |
| | 2.08% | 2.05% | 2.09% | | 2.10% | 2.06% | 2.52% | 2.75% | 3.38% | 1.93% | 2.09% |
| ITA | -0.03 | 0.04 | 0.17* | 0.28* | | 0.09 | 0.005 | 0.15* | 0.37* | 0.17* | 0.07 |
| | (-0.38) | (0.46) | (1.88) | (3.32) | | (1.14) | (0.11) | (2.09) | (3.52) | (1.62) | (0.67) |
| | [0.65] | [0.32] | [0.03] | [0.00] | | [0.13] | [0.46] | [0.02] | [0.00] | [0.05] | [0.25] |
| | 0.16% | 0.17% | 0.96% | 1.47% | | 0.46% | 0.13% | 0.76% | 1.70% | 0.57% | 0.26% |
| JPN | 0.02 | 0.04 | 0.08* | 0.05 | 0.01 | | 0.04 | 0.04 | 0.03 | 0.01 | 0.001 |
| | (0.30) | (0.59) | (1.29) | (0.85) | (0.25) | | (0.66) | (0.77) | (0.41) | (0.19) | (0.24) |
| | [0.38] | [0.28] | [0.10] | [0.20] | [0.40] | | [0.25] | [0.22] | [0.34] | [0.42] | [0.41] |
| | 3.46% | 3.53% | 3.79% | 3.57% | 3.45% | | 3.56% | 3.56% | 3.48% | 3.44% | 3.44% |
| NLD | 0.16* | 0.15* | 0.10 | 0.16* | 0.06 | 0.03 | | 0.11* | 0.36* | 0.07 | 0.30* |
| | (2.05) | (1.56) | (1.14) | (1.80) | (0.97) | (0.53) | | (1.75) | (2.95) | (0.64) | (2.99) |
| | [0.02] | [0.06] | [0.13] | [0.04] | [0.17] | [0.30] | | [0.04] | [0.00] | [0.26] | [0.00] |
| | 3.27% | 3.09% | 2.79% | 2.86% | 2.53% | 2.48% | | 3.35% | 3.96% | 2.50% | 4.05% |
| SWE | -0.02 | 0.13* | 0.09 | 0.13* | -0.01 | -0.02 | 0.04 | | 0.18* | 0.12 | 0.21* |
| | (-0.29) | (1.51) | (1.23) | (1.58) | (-0.28) | (-0.35) | (0.53) | | (1.66) | (1.25) | (2.20) |
| | [0.61] | [0.07] | [0.11] | [0.06] | [0.61] | [0.64] | [0.30] | | [0.05] | [0.11] | [0.01] |
| | 3.65% | 3.92% | 3.78% | 4.16% | 3.58% | 3.58% | 3.62% | | 3.98% | 3.80% | 4.40% |
| CHE | 0.001 | 0.03 | -0.08 | -0.05 | -0.004 | -0.02 | -0.001 | 0.08* | | 0.04 | 0.11 |
| | (0.24) | (0.51) | (-1.28) | (-0.73) | (-0.17) | (-0.43) | (-0.15) | (1.58) | | (0.52) | (1.28) |
| | [0.40] | [0.31] | [0.90] | [0.77] | [0.57] | [0.67] | [0.56] | [0.06] | | [0.30] | [0.10] |
| | 5.06% | 5.18% | 5.30% | 5.30% | 5.07% | 5.10% | 5.06% | 5.65% | | 5.11% | 5.34% |
| GBR | 0.09 | 0.08 | 0.04 | 0.03 | 0.04 | 0.06 | 0.04 | 0.16* | 0.22* | | 0.25* |
| | (1.09) | (0.94) | (0.57) | (0.54) | (0.72) | (0.90) | (0.46) | (3.24) | (2.66) | | (2.76) |
| | [0.14] | [0.17] | [0.29] | [0.30] | [0.24] | [0.18] | [0.32] | [0.00] | [0.00] | | [0.00] |
| | 1.85% | 1.84% | 1.79% | 1.70% | 1.70% | 1.75% | 1.70% | 3.71% | 2.96% | | 3.20% |
| USA | 0.12* | 0.07 | -0.04 | -0.02 | 0.09* | -0.001 | 0.04 | 0.09* | 0.15* | 0.10* | |
| | (1.69) | (0.89) | (-0.58) | (-0.33) | (2.24) | (-0.21) | (0.63) | (1.74) | (2.21) | (1.48) | |
| | [0.05] | [0.19] | [0.72] | [0.63] | [0.01] | [0.58] | [0.26] | [0.04] | [0.01] | [0.07] | |
| | 2.22% | 1.98% | 1.96% | 1.88% | 2.74% | 1.87% | 1.97% | 2.53% | 2.59% | 2.04% | |
| Average | 0.05 | 0.07 | 0.06 | 0.08 | 0.04 | 0.02 | 0.05 | 0.11 | 0.20 | 0.07 | 0.15 |

This table shows the coefficients, Pseudo-$R^2$ statistics, $t$-statistics and $p$-values of the international returns-based predictive model (2) for the $25^{th}$ quantile. The $t$-statistics are reported in parentheses and the $p$-values are given between the brackets. Below these $p$-values are the Pseudo-$R^2$ statistics. "Average" is the column average of the $\hat{\beta}_{i,j}$ estimates. * indicates significance at the 10% level or better.

Table 26: Out-of-Sample Analysis for Three Baseline and Competing Models for $90^{th}$ quantile

| Country | B1 Adj-DM | B2 Adj-DM | B3 Adj-DM | Country | B1 Adj-DM | B2 Adj-DM | B3 Adj-DM |
|---|---|---|---|---|---|---|---|
| AUS | -1.69 | -1.22 | 0.25 | NLD | 0.03 | -0.89 | 0.17 |
| | [0.95] | [0.89] | [0.40] | | [0.49] | [0.81] | [0.43] |
| CAN | -1.82 | -1.22 | -0.08 | SWE | 1.00 | 1.00 | 1.36* |
| | [0.97] | [0.89] | [0.53] | | [0.16] | [0.16] | [0.09] |
| FRA | 0.30 | 0.72 | 1.05 | CHE | -0.29 | 1.44* | 0.04 |
| | [0.38] | [0.24] | [0.15] | | [0.61] | [0.08] | [0.48] |
| DEU | -0.57 | -0.48 | 0.55 | GBR | 1.14 | 1.43* | 0.64 |
| | [0.72] | [0.68] | [0.29] | | [0.13] | [0.08] | [0.26] |
| ITA | 0.91 | -1.26 | -1.88 | Average | -0.08 | -0.02 | 0.37 |
| | [0.18] | [0.90] | [0.97] | | | | |
| JPN | 0.16 | 0.33 | 1.61* | | | | |
| | [0.44] | [0.37] | [0.05] | | | | |

This table shows the adjusted DM-statistic (as introduced by Ge (2015)) for our predictive models versus the three corresponding baseline models: B1, B2 and B3. The three baseline models are the constant expected return model (16), the AR model (17) and the benchmark predictive model (18) for the $90^{th}$ quantile. In brackets are the corresponding $p$-values. * Indicates significance at the 10% level or better. "Average" is the column average of the adjusted DM-statistic estimates.

Table 27: Out-of-Sample Analysis for Three Baseline and Competing Models for $75^{th}$ quantile

| Country | B1 Adj-DM | B2 Adj-DM | B3 Adj-DM | Country | B1 Adj-DM | B2 Adj-DM | B3 Adj-DM |
|---|---|---|---|---|---|---|---|
| AUS | 3.06* | 3.23* | 1.68* | NLD | 0.28 | 0.94 | -0.40 |
| | [0.00] | [0.00] | [0.05] | | [0.39] | [0.17] | [0.66] |
| CAN | -1.89 | 0.78 | 0.56 | SWE | 1.60* | 2.01* | 1.10 |
| | [0.97] | [0.22] | [0.29] | | [0.06] | [0.02] | [0.14] |
| FRA | -0.40 | 0.58 | -0.05 | CHE | 0.43 | -1.03 | -1.58 |
| | [0.66] | [0.28] | [0.52] | | [0.33] | [0.85] | [0.94] |
| DEU | 2.62* | 1.44* | 1.22 | GBR | -1.38 | -0.71 | -0.01 |
| | [0.00] | [0.08] | [0.11] | | [0.92] | [0.76] | [0.51] |
| ITA | 0.96 | -2.22 | -1.62 | Average | 0.64 | 0.57 | 0.20 |
| | [0.17] | [0.99] | [0.95] | | | | |
| JPN | 1.09 | 0.68 | 1.14 | | | | |
| | [0.14] | [0.25] | [0.13] | | | | |

This table shows the adjusted DM-statistic (as introduced by Ge (2015)) for our predictive models versus the three corresponding baseline models: B1, B2 and B3. The three baseline models are the constant expected return model (16), the AR model (17) and the benchmark predictive model (18) for the $75^{th}$ quantile. In brackets are the corresponding $p$-values. * Indicates significance at the 10% level or better. "Average" is the column average of the adjusted DM-statistic estimates.

Table 28: Out-of-Sample Analysis for Three Baseline and Competing Models for $25^{th}$ quantile

| Country | B1 Adj-DM | B2 Adj-DM | B3 Adj-DM | Country | B1 Adj-DM | B2 Adj-DM | B3 Adj-DM |
|---|---|---|---|---|---|---|---|
| AUS | 0.30 | 2.29* | 0.88 | NLD | -4.63 | -2.95 | -2.84 |
| | [0.38] | [0.01] | [0.19] | | [1.00] | [1.00] | [1.00] |
| CAN | -2.63 | -2.97 | -2.19 | SWE | 1.26 | 2.07* | 0.18 |
| | [1.00] | [1.00] | [0.99] | | [0.10] | [0.02] | [0.43] |
| FRA | 2.59* | -2.84 | 3.31* | CHE | -0.25 | -1.82 | -1.24 |
| | [0.00] | [1.00] | [0.00] | | [0.60] | [0.97] | [0.89] |
| DEU | -0.71 | -1.27 | -0.15 | GBR | -4.60 | -3.21 | -4.03 |
| | [0.76] | [0.90] | [0.56] | | [1.00] | [1.00] | [1.00] |
| ITA | -1.87 | -2.58 | 2.59* | Average | -0.73 | -1.23 | -0.02 |
| | [0.97] | [1.00] | [0.00] | | | | |
| JPN | 3.26* | 1.02 | 3.31* | | | | |
| | [0.00] | [0.15] | [0.00] | | | | |

This table shows the adjusted DM-statistic (as introduced by Ge (2015)) for our predictive models versus the three corresponding baseline models: B1, B2 and B3. The three baseline models are the constant expected return model (16), the AR model (17) and the benchmark predictive model (18) for the $25^{th}$ quantile. In brackets are the corresponding $p$-values. * Indicates significance at the 10% level or better. "Average" is the column average of the adjusted DM-statistic estimates.