International Stock Return Predictability: Is the Role of U.S. Time-Varying?

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Abstract

This study investigates the predictability of 11 industrialized stock returns with emphasis on the role of U.S. returns. Using monthly data spanning 1980:2 to 2014:12, we show that there exist multiple structural breaks and nonlinearities in the data. Therefore, we employ methods that are capable of accounting for these and at the same time date stamping the periods of causal relationship between the U.S. returns and those of the other countries. First we implement a subsample analysis which relies on the set of models, data set and sample range as in Rapach et al. (2013). Our results show that while the U.S. returns played a strong predictive role based on the OLS pairwise Granger causality predictive regression and news-diffusion models, it played no role based on the pooled version of the OLS model and its role based on the adaptive elastic net model is weak relative to Switzerland. Second, we implement our preferred model: a bootstrap rolling window approach using our newly updated data on stock returns for each countries, and find that U.S. stock return has significant predictive ability for all the countries at certain sub-periods. Given these results, it would be misleading to rely on results based on constant-parameter linear models that assume that the relationship between the U.S. returns and those of other industrialized countries are permanent, since the relationship is, in fact, time-varying, and holds only at specific periods.

Keywords: Stock returns, predictability, structural breaks, nonlinearity, time varying causality

JEL Classification: C32, G10, G15

1. Introduction

The recent financial and economic crisis has heightened research and policy attention to the stock market dynamics, in particular its predictability. This is because of the potential spill over effects from the stock markets to the real sector and the fact that they help in predicting output and inflation by acting as leading indicators (Stock and Watson, 2003). Therefore, to design appropriate policies in advance for avoiding any impending crisis, there is need to predict stock returns accurately. There has been evidence of the U.S. and other international stock returns in-sample and out-of-sample predictability in a number of studies (Rapach and Wohar, 2006; Ang and Bekaert, 2007; Rapach and Zhou 2013; Henkel, et. al., 2011; Ferreira and Santa-Clara, 2011; Dangl and Halling, 2012; Gupta and Modise, 2012; Rapach et al., 2013 e.t.c.). However, this has been questioned in few other studies (Bossaerts and Hillion, 1999; Goyal and Welch, 2003; Goyal and Welch 2008). Also the question of which variables have predictive ability is still an on-going debate. Common predictors in the literature include: valuation ratios (Campbell and Shiller, 1998), the dividend yield (Rozeff, 1984; Henkel, et. al., 2011; Rapach et al., 2013), the

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short interest rate (Ang and Bekaert, 2007; Dangl and Halling, 2012; Henkel, et. al., 2011; Rapach et al., 2013), the default premium (Fama and Bliss, 1987; Campbell, 1987; Fama and French, 1989), the slope of the term structure (Keim and Stambaugh, 1986; Campbell, 1987; Fama and French, 1989), long term yield and dividend-payout ratio (Dangl and Halling, 2012; Gupta and Modise, 2012), earnings growth (Ferreira and Santa-Clara, 2011); price-dividend and price-earnings ratio (Ferreira and Santa-Clara, 201; Gupta and Modise, 2012), debt ceiling and government shutdown (Aye et al., forthcoming) among others.

This study focuses on the lagged U.S. returns uncovered as a new predictor in Rapach et al. (2013). Using monthly data from 1980:2 to 2010:12 on 11 industrialized countries, Rapach et al. (2013) show that in many non-U.S. industrialized countries lagged U.S. returns significantly predict returns better than those countries' own economic variables, while lagged non-U.S. returns exhibit limited predictive power with respect to U.S. returns. Using news diffusion model, they show that U.S. return shocks are only fully reflected in equity prices outside of the U.S. with a lag. The economic rationale for including lagged U.S. returns as a predictor is based on the argument that returns in one country can predict returns in a trading-partner country if a two-country Lucas-tree framework with gradual information diffusion is employed (Hong et al., 2007; Rizona, 2010). Therefore, given that U.S. has the largest equity market in the world in terms of market capitalisation, and is a trading partner for many countries, the market is likely to receive the most attention from investors, consequently causing a gradual diffusion of information on the global macroeconomic fundamentals from the U.S. market to other countries' markets (Rapach et al., 2013).

The current paper contributes to the international stock returns predictability literature by re-examining the in-sample predictive role of the lagged U.S. stock returns in a time varying framework. Specifically, we employ a bootstrap rolling window approach. Results in Rapach et al., (2013) are based on estimations from ordinary least squares (OLS), adaptive elastic nets and generalised method of moments (GMM) which are based on full samples. The use of full sample is based on the assumption that model parameters are constant over time. However, in an ever changing socioeconomic environment, this assumption may be quite restrictive. The assumption hardly ever holds and is a puzzling topic for economic empirical studies (Granger 1996). The presence of structural breaks and nonlinearities as is common with financial variables would therefore invalidate any conclusions from the full sample in-sample predictive estimations or the standard Granger causality results. A number of ways have been devised to account for structural breaks in economic relationships. The most common practice would be to test for the presence of structural breaks in advance and modify the estimation in various ways, for example, with the use of dummy variables or sample splitting. However, it has been argued that these methods can introduce some pre-test bias (Balcilar et al., 2010). This notwithstanding, we first perform subsample analyses using the same models in Rapach et al. (2013). Other methods to account for structural breaks include recursive estimation, time varying parameter (TVP), regime switching and rolling estimations. Recursive and TVP estimations are similar, as both keep the lower end of the estimation window while moving forward with a growing window. As the window grows, it accumulates more information and when they reach the last observation, they will be equivalent to the full sample estimation (Inglesi-Lotz et al., 2014). Recursive and TVP methods are not optimal in the case of multiple structural breaks since the impact of previous breaks on the later ones will not be isolated. To accommodate parameter variability in this case, the rolling estimation is a preferable option since the estimations are based only on the most recent portion of the data. Our bootstrap rolling window approach is robust to small samples and presence of multiple structural breaks and nonlinearities while also providing evidence of existence or otherwise of temporal causal relationship (in-sample predictability over time) between U.S. stock returns and international stock returns. Understanding the predictive role of the lagged U.S. returns has implications for asset international pricing models, hedging and investing behaviour and choices.

2. Data and Methodology

As earlier stated, we started by performing subsample analyses using OLS, adaptive elastic nets and GMM. For the estimation of these models we use data on excess stock returns, 3-month Treasury bill rates and dividend yield from 11 industrialized countries: Australia, Canada, France, Germany, Italy, Japan, Netherlands, Sweden, Switzerland, United Kingdom and United States. These are the same data sets and sample range in Rapach et al. (2013) as we do not have access to all the series for all the countries. The summary statistics and original sources of these data are provided in Rapach et al. (2013).

However, for the rolling window estimation, we use updated excess stock returns from the 11 countries. We compute each country's equity premium (i.e. excess returns) as stock return less the annualized rate of the 3-month Treasury bill rate. The stock returns are computed as the first log differences of the stock prices of the relevant countries. The stock price and 3-month Treasury bill rates data are obtained from Thomson Reuters Datastream. The sample covers the period 1980:2 to 2014:12 after transformations with the exception of that of Sweden which span from 1982:3 to 2014:12. The starting and ending periods are determined by the availability of the 3-month Treasury bill rates data. We keep the stock returns in their respective national currencies to enable us analyse the predictive power of lagged U.S. returns for the other countries' returns.

As the OLS regressions, adaptive elastic nets and News-diffusion models only serve as a precursor to our preferred method, the bootstrap rolling window approach, we do not discuss them here.[1] So we turn to the bootstrap rolling window approach. Here the null hypothesis is Granger non-causality from U.S. returns to international returns. The assumption is that there is no causality (or predictive power) from international returns to U.S. returns, because of its large equity market concentration and a major trading partner for many countries. The joint parameter restriction associated with the Granger non-causality test in a VAR framework can be examined with the *Wald*, Likelihood ratio (*LR*) and Lagrange multiplier (*LM*) statistics based on the assumption that the underlying series is stationary, which is the case in this study, given the nature of the data transformation (see Figure 1). Hence, we do not use the Toda and Yamamoto (1995) procedure for testing for Granger causality.

Building on the standard Granger non-causality test, we use a residual based (*RB*) bootstrap test rather than standard asymptotic tests while accounting for the fact that international returns has no in-sample predictability for U.S. returns. Following Balcilar and Ozdemir (2013) and Balcilar et al. (2010, 2013), we use the *RB* based modified-*LR* statistics to examine the causality between U.S. returns and international returns.

The bootstrap modified-*LR* Granger causality can be demonstrated starting with a bivariate VAR(p) process of the form:

$$y_t = \Phi_0 + \Phi_1 y_{t-1} + ... + \Phi_p y_{t-p} + \varepsilon_t,\ t = 1,2...,T, \tag{1}$$

[1] Interested readers may consult Rapach et al. (2013) for the details on these models.

where $\varepsilon_t = (\varepsilon_{1t}, \varepsilon_{2t})'$ is a white noise process with zero mean and covariance matrix Σ and *p* is the lag order of the process. We use the Schwarz Information Criterion (*SIC*) to select the optimal lag order *p* in the empirical section. For simplification, let y be partitioned into two sub-vectors, y_1 (U.S. returns) and y_2 (international returns). Hence, equation (1) can be rewritten in a matrix format as follows:

$$\begin{bmatrix} y_{1t} \\ y_{2t} \end{bmatrix} = \begin{bmatrix} \varphi_{10} \\ \varphi_{20} \end{bmatrix} + \begin{bmatrix} \varphi_{11}(L) & 0 \\ \varphi_{21}(L) & \varphi_{22}(L) \end{bmatrix} \begin{bmatrix} y_{1t} \\ y_{2t} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{bmatrix}, \quad (2)$$

where $\phi_{ij}(L) = \sum_{k=1}^{p+1} \phi_{ij,k} L^k$, $i, j = 1,2$ and L is the lag operator such that $L^k y_{it} = y_{it-k}$, $i = 1,2$. The restriction $\varphi_{12}(L) = 0$ in equation (2) is due to the exogeneity assumption of the U.S. stock returns. We test the null hypothesis that U.S. returns does not Granger cause international by imposing zero restrictions: $\varphi_{21,i} = 0$ for $i = 1,2,\ldots,p$. This implies that if the joint zero restrictions under the null hypothesis:

$$H_0 : \varphi_{21,1} = \varphi_{21,2} = \ldots = \varphi_{21,p} = 0 . \quad (3)$$

are not rejected, then U.S. returns does not cause or contain predictive ability for international returns. If the hypothesis in equation (3) is rejected, then U.S. returns Granger causes international returns. The causality hypothesis in equation (3) can be tested using a number of testing techniques. However, this study uses the bootstrap approach which uses critical or *p* values generated from the empirical distribution derived for the particular test using the sample data.

Structural changes shift the parameters and the pattern of the causal relationship may change over time. To deal with structural changes and parameter non-constancy, this paper applies the bootstrap causality test to rolling window subsamples for $t = \tau - l + 1, \tau - l, \ldots, \tau$, $\tau = l, l+1, \ldots, T$, where l is the size of the rolling window.[2] We apply the causality test to each subsample in each step, providing a (T − l) sequence of causality tests instead of only one. This also allows us to detect whether U.S. returns has led international returns over time. We test for the existence of structural breaks using Bai-Perron (2003) tests for multiple structural breaks and for nonlinearity using the Brock, Dechert and Scheinkman (BDS, 1996) test.

3 Results

3.1 Preliminary analysis

The plots of the monthly country excess stock returns are shown in Figure 1. These show that all the series are stationary and this is not surprising given that the stock returns upon which excess stock returns are calculated are the differenced first natural logs of stock prices. We also present the summary statistics for the monthly excess returns (in percent) for the 11 countries in Table 1. During the sample period, Sweden has the highest average returns (0.40%) followed by Switzerland and U.S. while Australia has the least (-0.10%). Italy displays the greatest volatility over the sample period. All countries have positive autocorrelation with Switzerland displaying

[2] More technical details on the approach we use can be found in Balcilar et al. (2010, 2013).

the largest value (0.18) while U.K. display the smallest autocorrelation (0.02). With respect to the Sharpe ratio computed as the ratio of the mean to the standard deviation, Switzerland has the largest value (0.08) while Australia had the least value (-0.02).

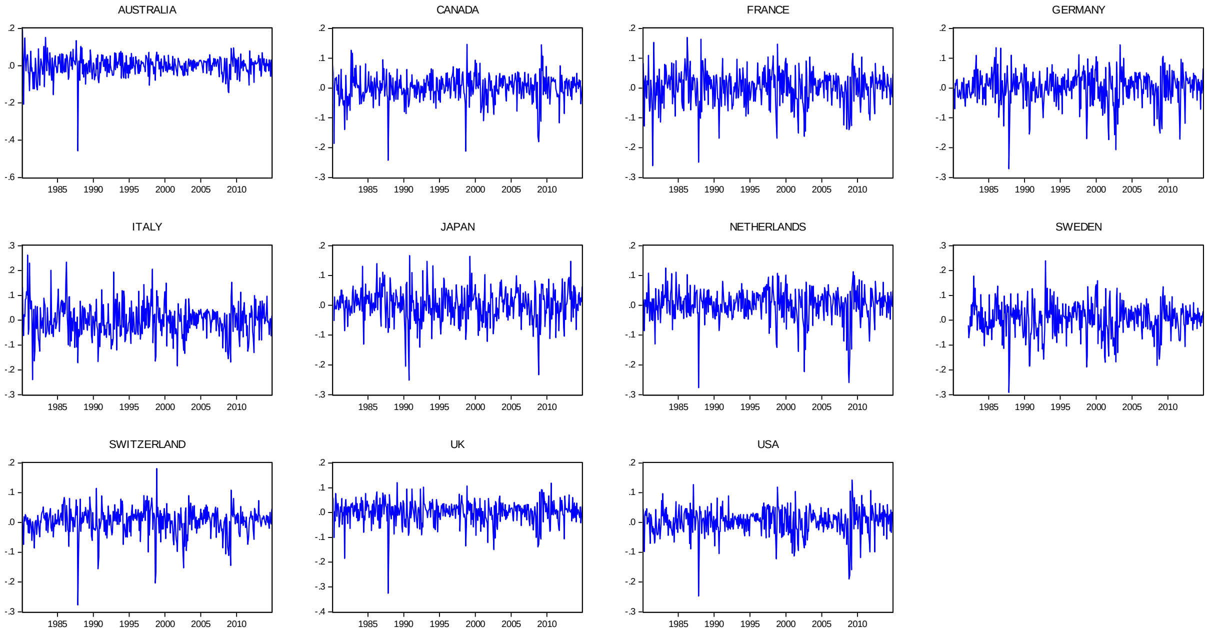

Figure 1: Equity premium of the 11 industrialized countries

Table 1: Summary statistics of monthly country excess stock returns

Country	Mean	Standard Deviation	Minimum	Maximum	Autocorrelation	Sharpe Ratio
Australia	-0.10	5.35	-45.82	19.27	0.08	-0.02
Canada	0.07	4.60	-24.26	14.69	0.12	0.02
France	0.15	5.79	-26.10	16.93	0.12	0.03
Germany	0.16	5.43	-27.16	14.55	0.11	0.03
Italy	0.01	6.82	-24.00	26.26	0.12	0.00
Japan	0.09	5.55	-25.12	16.74	0.12	0.02
Netherlands	0.23	5.31	-27.66	12.50	0.12	0.04
Sweden	0.40	6.63	-29.07	23.88	0.16	0.06
Switzerland	0.39	4.56	-27.78	18.11	0.18	0.08
United Kingdom	0.09	4.72	-32.57	12.11	0.02	0.02
United States	0.29	4.56	-24.72	14.30	0.06	0.06

Prior to estimating the relevant models in Rapach et al. (2013), we perform the Bai and Perron (2003) multiple break test. For the U.S. equity premium, the Bai-Perron test is performed by regressing the equity premium of the U.S. on a constant only, and is reported in Table A1. We find evidence of 5 significant break points in the U.S. equity premium. Based on these we extract 3 subsamples (1982:09-2000:08 and 2000:09-2010:12; 1982:09-2002:09 and 2002:10-2010:12; 1982:09-2007:5 and 2007:6-2010:12) and perform subsample analysis instead of the full sample (1980:2 to 2010:12) analysis as in Rapach et al. (2013).

Further, the condition for using the rolling window causality testing approach also depends on the evidence of instability in the relationships. Therefore, we also test for the presence of structural breaks and linear dependence in each pair of the return series. For structural breaks test we regress country *i* returns on a constant, one lag of U.S. returns and one lag of country *i* returns. The results are also presented in Table A1. In most cases, we observe as many as five significant breaks. The results for the BDS test, presented in Table A2, is based on the residuals of a regression of country *i* returns on a constant, one lag of U.S. returns and one lag of country *i* returns. In all cases except for the Netherlands, the null hypothesis of independently and identically distributed (*i.i.d.*) residuals are rejected implying the presence of omitted nonlinear structure which was not captured by the linear specification, and hence there is nonlinearity in the relationship between the stock returns of the US and the other economy under consideration. With the presence of both structural breaks and nonlinearities, the assumption of constant parameters over time as in full sample predictive regressions or standard Granger causality tests is no longer valid. Hence, we proceed with the subsample analysis and rolling window regression approach.

3.2 Subsample results

The OLS estimates of the benchmark predictive regression of national three-month Treasury bill rate ($\beta_{i,b}$) and log dividend yield ($\beta_{i,d}$) on equity premium for each country *i* are reported in Table A3. The estimates are reported in columns 1, 2, 4, 5, 7 and 8 with their corresponding t-statistics (based on heteroskedasticity-robust standard errors) in parentheses.[3] We also report the corresponding R^2 statistics. The values in parentheses under the R^2 statistics are the χ^2 statistics for testing the null hypothesis that $\beta_{i,b} = \beta_{i,d} = 0$, implying no return predictability for country *i*. For brevity, we highlight the coefficient estimates and R^2 statistics that are significant at the 10% level or better in bold fonts. Overall, based on the wild bootstrapped *p*-values, we observe a more predictive ability of the nominal interest rate than the dividend yield consistent with findings in Rapach et al. (2013). However, in contrasts to their results, we obtain more robust estimates and significant results for both variables and for more countries. For instance, while dividend yield was a significant return predictor for only U.K in Rapach et al. (2013), here it is significant return predictor for at least 5 countries in all the subsamples with exception of the most recent periods. With respect to the R^2 statistics, a value near 0.5% indicates economically significant return predictor (Kandel and Stambaugh, 1996; Campbell and Thompson, 2008). Our results show evidence of R^2 statistics above 1% in general. Our R^2 statistics are also far larger than those reported in Rapach et al. (2013). For example while their largest R^2 is 2.6% for U.K., we have 14.99% for U.K. and 27.19% (the largest in our results) for Sweden in the 2007:6-2010:12 sub-period. Also the null hypothesis of no return predictability indicated by the χ^2 statistics are rejected for more countries in each subsample analysis than in Rapach et al. (2013).

[3] To conserve space we do not report the wild bootstrapped *p*-values here but these are available from authors upon request.

A pooled version of the predictive regression which imposes $\beta_{i,b} = \overline{\beta}_b$ and $\beta_{i,d} = \overline{\beta}_d$ for all i while allowing for country-specific constants as reported in the last but two rows also produced a completely different result with respect to the size and significance of the coefficients, R^2 and χ^2 statistics. No significant results on these were found in Rapach et al. (2013). The signs here are however consistent with theirs with negative and positive coefficients for nominal interest rate and dividend yield respectively. These findings are not surprising given that we account for structural breaks in our analysis.

In Table A4, we report the results on the lead-lag relationship i.e. the pairwise Granger causality between country *i* and country *j* returns. These are obtained from a specification that allows us to include lagged country *i* and lagged country j excess returns as predictors of country *i* returns while controlling for predictive ability of national economic variables using the nominal interest rate and dividend yield. With exception of Japan and Switzerland, U.S. returns exhibit significant predictive power for all other countries returns at one sub-period or the other. It significantly predicts returns in 34 out of 66 cases (including the pooled version) lagging slightly behind Sweden with 35 significant coefficients and has the largest coefficient in 15 cases following Switzerland with 17 cases. However, only Swedish returns out of the 10 non-U.S. returns consistently shows predictive ability for U.S. returns except in the last sub-period (i.e. 5 out of 6 cases) while Switzerland and Australia show significant predictive power for the U.S. returns once. Moreover relatively large values for U.S. returns in the last column compared to its values on the last but one row is an indication of U.S. leading role in the international equity market consistent with Rapach et al. (2013). These results may justify our exogeneity assumption for the U.S. returns in the rolling window estimations to be discussed later. We note however that based on the average estimates and pooled model results, U.S. and Switzerland appear to be competing with each other.

Next we allow for more general specification (augmented VAR(1) model) by including all the 11 countries lagged returns in addition to the national economic variables and estimating same with pooled OLS (Ang and Bakaert, 2007; Hjalmarsson, 2010) and adaptive elastic net (Zou and Zhang, 2009; Ghosh, 2011) approaches meant to improve the power of the test and precision of estimates. This specification allows us to control for all other country returns when testing for causality. Table A5 reports the pairwise Granger causality results from the pooled version while Table A6 reports results from elastic net alongside with their bias-corrected wild bootstrapped 90% confidence intervals. In Table A5, we find no significant role for the U.S. returns over international returns at any sub-period. Instead, Switzerland exhibits the strongest and positive predictive power followed by Sweden while Netherland exhibits a negative predictive role. Slightly similar results are obtained in Table A6 with Switzerland still maintaining the leading and stronger role (27 out of 66 cases), some other countries now coming into the picture while U.S. plays fewer (8 out of 66 cases) and weaker predictive role. These findings contrast those in Rapach et al. (2013) where U.S. maintained the leading and stronger predictive role.

Finally on the subsample analysis, we estimate a news-diffusion model that allows for a return shock from one country to be fully incorporated into another country with a lag, thereby permitting cross-country information frictions (Rapach et al., 2013). The two-step GMM parameter estimates alongside with their heteroskedasticity-robust t-statistics in parenthesis are presented in Table A7.[4] The estimates $\tilde{\beta}_{i,b}$ and $\tilde{\beta}_{i,d}$ relates to the national Treasury bill rate and

[4] The asymptotic GMM p-values upon which the significance of the t-statistics is based are available from authors upon request. The fact that we use asymptotic p-values instead of a bootstrapped one due to high computational costs requires some caution in the result interpretation as noted in Rapach et al. (2013).

dividend yield respectively. The key structural parameter estimates in the news-diffusion model, $\tilde{\lambda}_{i,USA}$ measures the total impact of a unit of U.S. return shock on country *i* returns, while $\tilde{\theta}_{i,USA}$ is the diffusion parameter that measures the proportion of the total impact of U.S. return shock contemporaneously incorporated into country *i* returns.[5] Larger $\tilde{\lambda}_{i,USA}$ is an indication of stronger economic links while smaller $\tilde{\theta}_{i,USA}$ indicates greater information frictions. Both cases suggest greater predictive ability of lagged U.S. returns. Focusing on the key parameters, evidence from Table A7 shows that the null hypothesis that $\tilde{\lambda}_{i,USA} = 0$ is rejected at 1% for all countries at all sub-periods in favour of the alternative hypothesis that $\tilde{\lambda}_{i,USA} > 0$. This suggests the statistically and economically significant link between each countries equity market and that of U.S. This is consistent with Rapach et al. (2013). The null hypothesis $\tilde{\theta}_{i,USA} = 1$ is rejected in favour of its alternative $\tilde{\theta}_{i,USA} < 1$ in 48 out of 66 cases. Although this provides evidence of international information frictions, our findings are not as overwhelming as in Rapach et al. (2013) with 100% rejection. However, consistent with information frictions in the international equity markets, all the pooled estimates of $\tilde{\lambda}_{i,USA}$ ($\tilde{\theta}_{i,USA}$) are significantly greater than zero (less than one) thus supporting that non-U.S. returns underreact to U.S. return shocks an indication of the predictive ability of lagged U.S. returns over the other countries returns. Also the rejection of the null hypothesis that $\tilde{\beta}_{i,USA} = 0$ in favour of $\tilde{\beta}_{i,USA} > 0$ in a number of cases including the pooled model implies that information friction is one of the key sources of predictive ability of the U.S. returns.

3.3 Results based on time varying bootstrap rolling causality

In this section we present the results from the bootstrap rolling window results as this is not only capable of handling multiple structural breaks but also accounts for nonlinearities in the causal relationships as well as robust to small sample sizes.

Two important decisions that must be made prior to estimation of the rolling window approach are the window size and lag order selection. With respect to window size, there is no strict selection criterion; however there is a trade-off between the accuracy of the parameter estimates and the representativeness of the model over the subsample period. On one hand, a small window size reduces heterogeneity and improves the representativeness of parameters, but it may reduce parameter accuracy by increasing the standard errors of estimates. On the other hand, a large window size may improve the accuracy of estimates, but reduces the representativeness of the model, especially in the presence of heterogeneity. Through Monte Carlo simulations, Pesaran and Timmermann (2005) showed that the bias in autoregressive (AR) parameters is minimized with window size around 10–20 when there are frequent breaks as in our case. Therefore we use a rolling window of small size of 24 months and apply bootstrap technique to each window so as to estimate the tests with better precision.

The rolling window method uses a fixed length moving window sequentially from the beginning to the end of the sample by adding one observation from ahead and dropping one from behind, where each rolling window subsample includes l observations. To investigate potential changes

[5] We note that to identify the structural parameters of the news-diffusion model, we assume following Rapach et al. (2013) that $\theta_{USA,i} = 1$ and $\lambda_{USA,i} = 0$ which respectively implies that lagged non-U.S. returns do not predict U.S. returns and shocks arising from the non-U.S. countries do not affect U.S. returns.

in the causality relationships, we estimate the bootstrap value of observed LR-statistics rolling over the whole sample period 1980:2 to 2014:12, except Sweden for which the sample period is from 1982:3 to 2014:12. That is, we estimate the VAR model in equation (1) for a time span of 24 months rolling through $t = \tau\text{-}23, \tau\text{-}22, \ldots, \tau, \quad \tau = 24, \ldots, T$. The bootstrap LR-test uses the p-values obtained from 1000 replications. We use one lag in each of the VAR model is estimations as determined by the SIC criterion.

The bootstrap p-values pertaining to the null hypothesis that U.S. returns does not have predictive power over country *i* returns are presented in Figures 2 to 11. Non-causality in each rolling subsample estimate is evaluated at a 10% level to guard against the low power of the test. It can be observed that in all cases, the p-values change substantially over the sample. Figure 2 shows the bootstrap p-values of the rolling test statistics testing the null hypothesis that the U.S. returns does not Granger cause or have predictive power for Australia returns. The null hypothesis is rejected at 10% significance level during the following sub-periods: 1982:2 -1983:8, 1988:11-1989:1, 2006:1-2006:2, 2008:3, 2008:5-2008:12 and 2011:10-2012:5. The null hypothesis cannot be rejected for the rest of the sample periods. The estimation results for Canada shown in Figure 3 indicates that the null hypothesis that the U.S. returns does not have predictive power for Canada returns is rejected at 10% level during the 1982:2-1985:2, 1992:5-1993:3, 1999:2-1996, 1999:9-1999:10, 2003:3, 2008:2-2008:12, 2014:4, 2011:10-2011:12, 2012:3 and 2014:12 sub-periods. For France, the results as presented in Figure 4 provides evidence of rejection of the null hypothesis during the following sub-periods: 1995:3, 1995:7, 2005:5, 2000:7-2000:9, 2004:12-2005:2, 2005:5, 2005:9, 2011:2, 2011:4, 2011:10, 2013:10-2014:11.

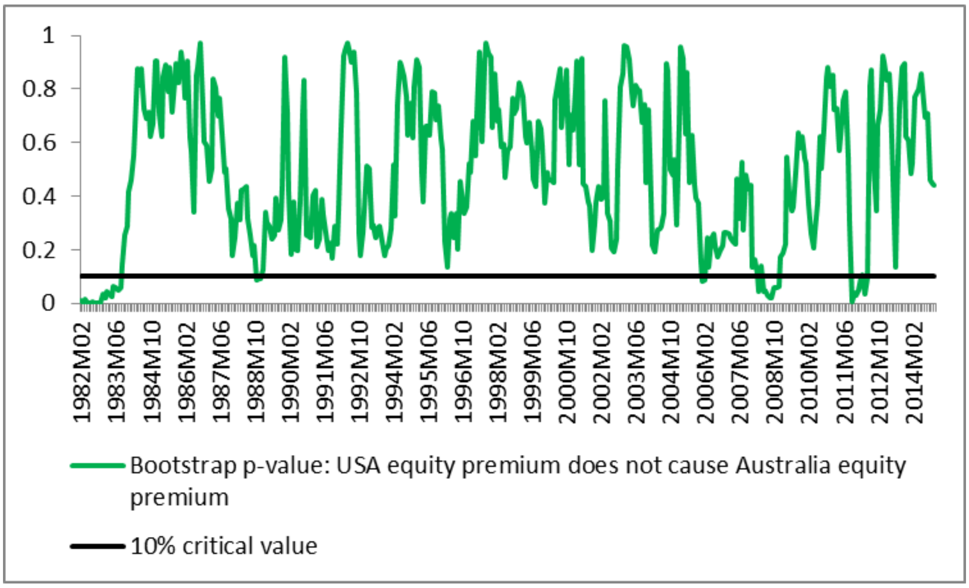

Figure 2: Rolling window bootstrap p-value: USA equity premium does not Granger cause Australia equity premium

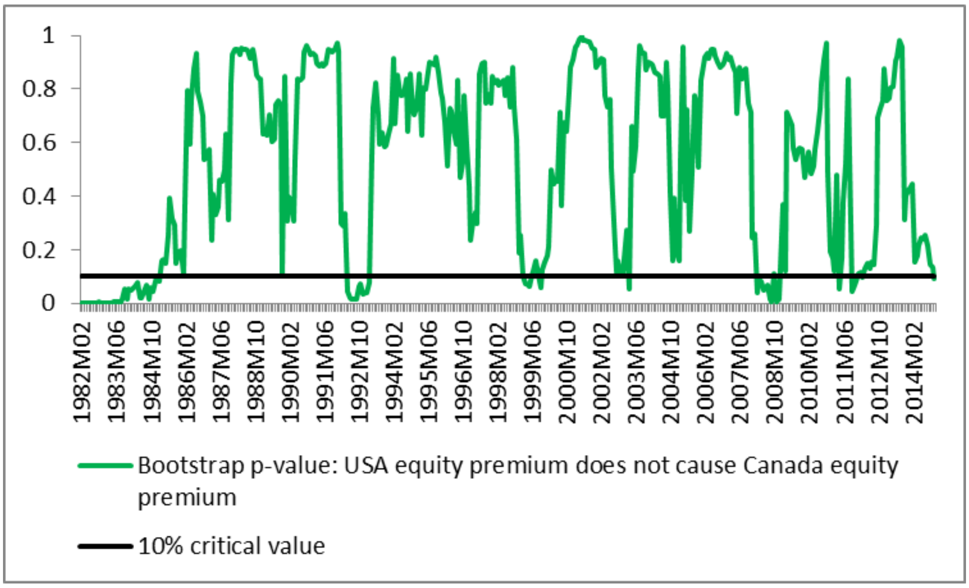

Figure 3: Rolling window bootstrap p-value: USA equity premium does not Granger cause Canada equity premium

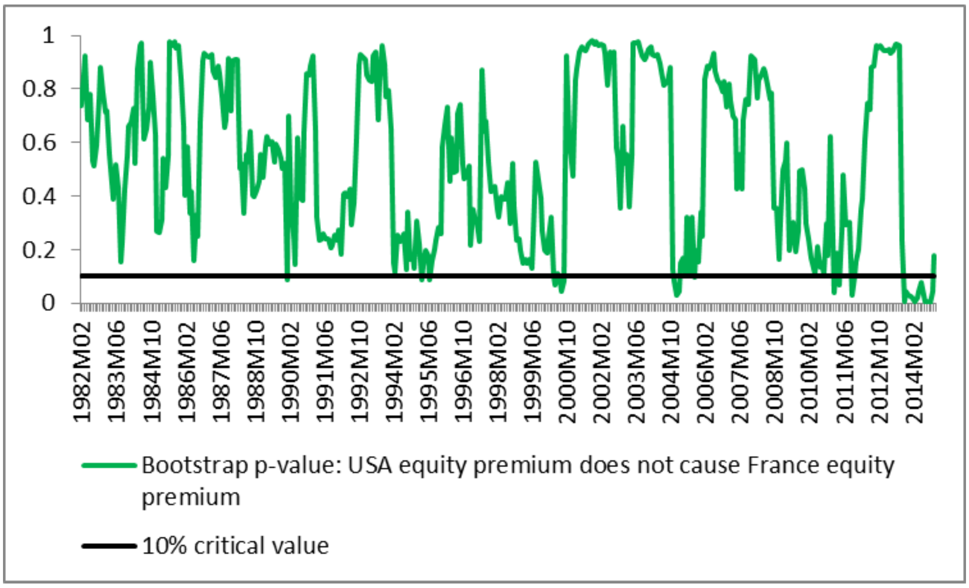

Figure 4: Rolling window bootstrap p-value: USA equity premium does not Granger cause France equity premium

The estimation result for Germany is plotted in Figure 5. The results show that the null hypothesis that U.S. returns does not Granger-cause Germany returns is rejected at 10% significance level in the 1982:11-1983:5, 1984:1-1984:6, 1984:12-1985:1, 1990:11-1991:12, 1992:2-1992:8, 1994:10-1995:7, 19995:11, 2004:11-2005:5, 2008:9, 2008:11-2009:1, 2009:5-2010:11, 2011:10, 2013:10-2014:11 sub-periods. For Italy depicted in Figure 6, the null hypothesis is rejected during 1983:6, 1983:8-1983:9, 1991:3-1992:11, 1993:1, 1994:10-1994:12, 1995:3-1996:3, 1998:10-2000:8, 2004:1-2004:7, 2004:10-2006:1, 2006:4-2006:5, 2008:11-2008:12, 2009:5, 2010:4-2010:5 and 2013:12-2014:3 sub-periods while the remaining sample periods, it cannot be rejected. The null hypothesis that U.S. returns has no predictive ability for the Japan returns as presented in Figure 7 is rejected for a number of sub-periods: 1982:5-1982:9, 1982:11-1983:9, 1983:11-1984:1, 1988:9-1988:11, 19892, 1989:5-1989:11, 1991:1-1992:9, 1998:8, 2004:3-2004:10, 2005:1-2005:3, 2005:5, 2007:12-2008:12, 2011:4 and 2011:11. For the Netherlands shown in Figure 8, the null hypothesis is rejected at 10% level during the 1982:12-1983:5, 1986:4-1986:1986:7, 1991:3-1991:9, 1992:2-1992:4, 1992:6-1992:9, 1994:3, 1995:3-1995:4, 1995:7, 1996:6-1996:7, 1997:2, 2000:4-2000:9, 2001:1, 2001:4, 2008:9-2008:12, 2009:5-2009:7, 2009:9, 2010:4-2010:5, 2010:11, 2013:10-2013:11 and 2014:1-2014:3 sub-periods while the null cannot be rejected for the other periods.

As can be seen in Figure 9, the null hypothesis that U.S. returns does Granger cause the equity premium in Sweden is rejected at 10% level for few sub-periods. The rejections are observed for 1984:3-1984:5, 1987:12-1989:5, 1990:11, 1991:2-1992:8, 2005:1 and 2008:12-2014:12 sub-periods. Switzerland on the other hand had massive rejections occurring during 1982:2-1984:6, 1986:11-1987:7, 1987:9-1987:10, 1989:7-1989:10, 1991:4-1991:6, 1991:8-1991:9, 1991:11-1991:12, 1992:2-1992:9, 1994:3, 1995:7, 1999:12-2000:5, 2004:7, 2004:10-2005:4, 2007:7, 2008:12, 2009:3, 2009:5-2009:7 and 2010:2-2010:4 sub-periods as can be seen in Figure 10. For the United Kingdom as shown in Figure 11, the null hypothesis that U.S. returns does not predict its returns is rejected at 10% level for a number of sub-periods: 1982:2-1983:9, 1985:7, 1986:10, 1986:10, 1986:12, 1987:2, 1988:12-1989:2, 1994:3-1994:8, 1995:2-1995:4, 1997:10, 2008:2-2008:12 and 2011:10-2012:4.

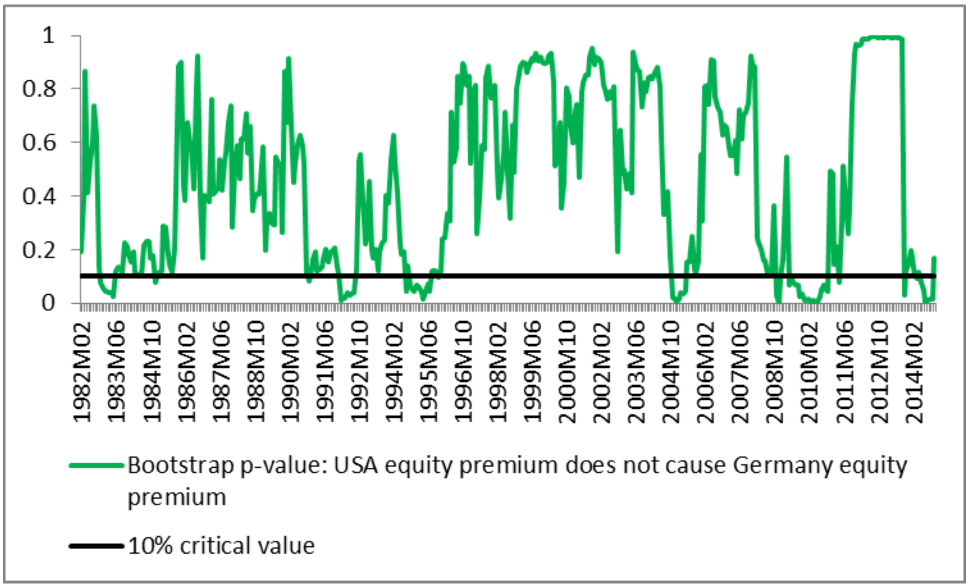

Figure 5: Rolling window bootstrap p-value: USA equity premium does not Granger cause Germany equity premium

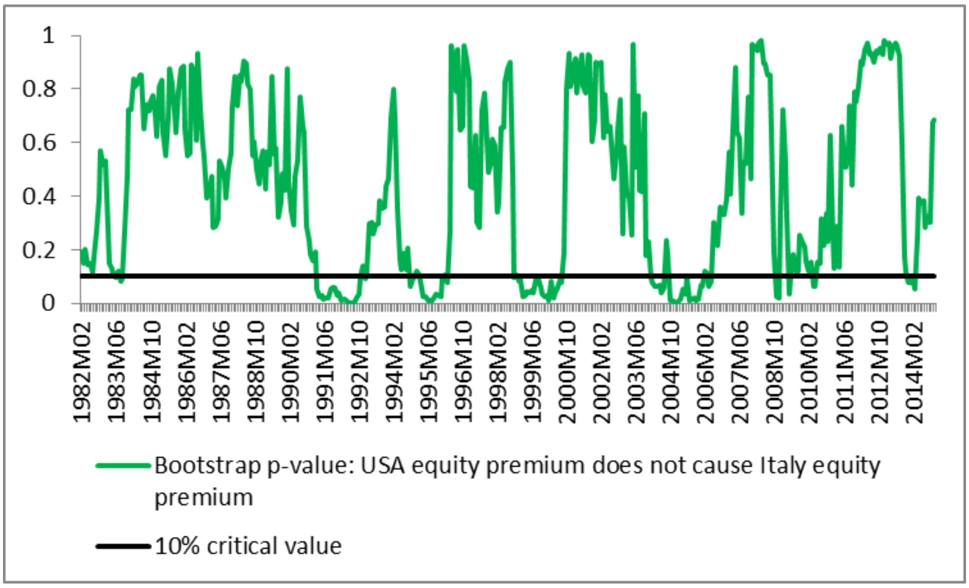

Figure 6: Rolling window bootstrap p-value: USA equity premium does not Granger cause Italy equity premium

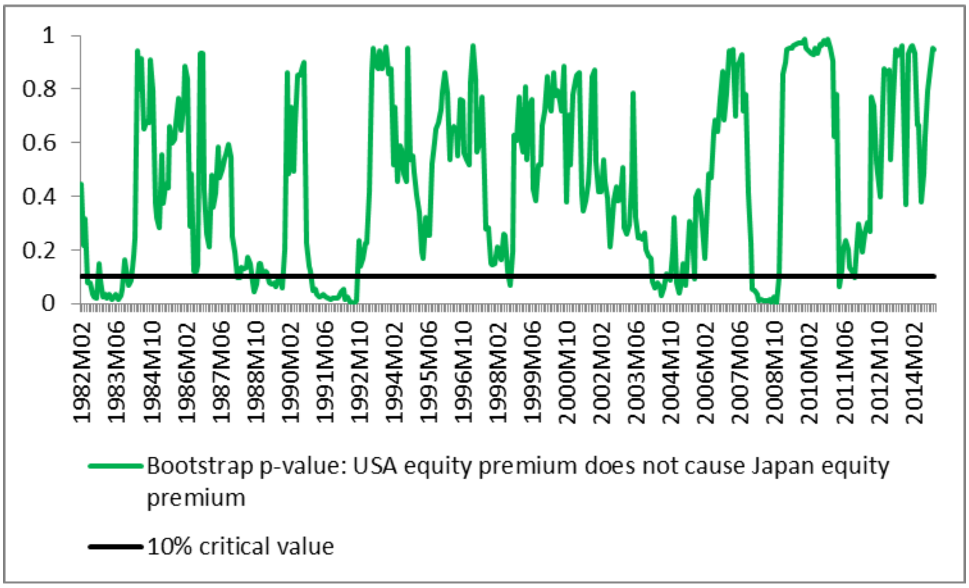

Figure 7: Rolling window bootstrap p-value: USA equity premium does not Granger cause Japan equity premium

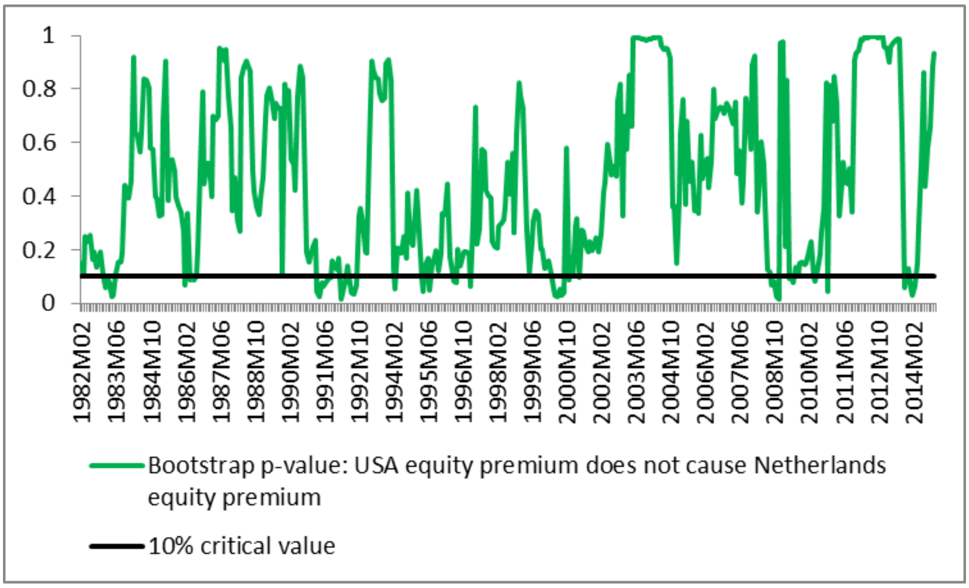

Figure 8: Rolling window bootstrap p-value: USA equity premium does not Granger cause Netherlands equity premium

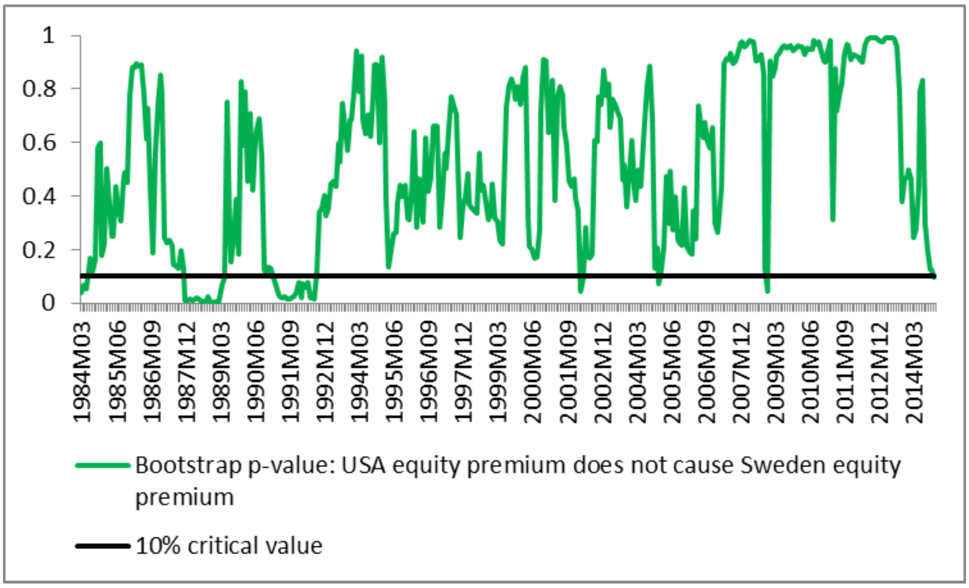

Figure 9: Rolling window bootstrap p-value: USA equity premium does not Granger cause Sweden equity premium

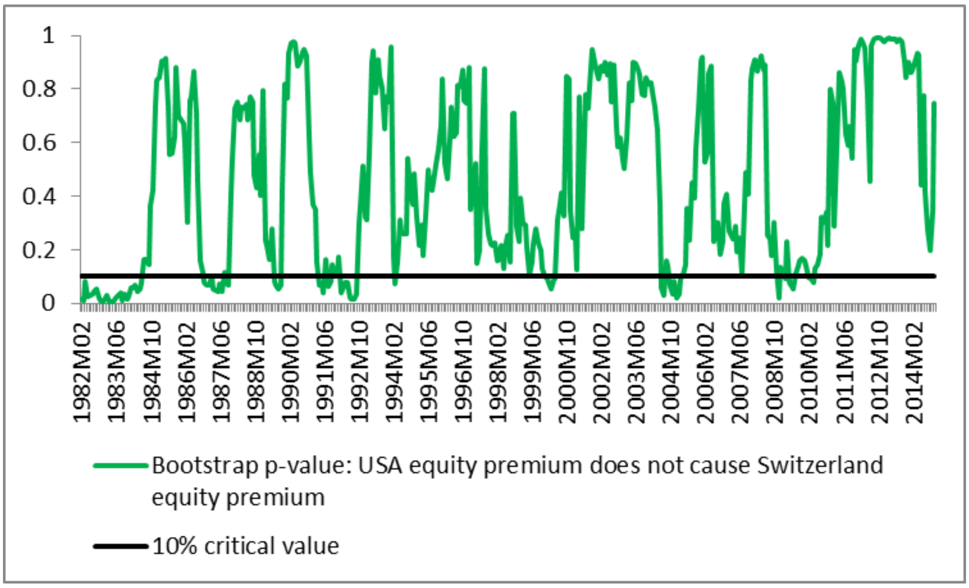

Figure 10: Rolling window bootstrap p-value: USA equity premium does not Granger cause Switzerland equity premium

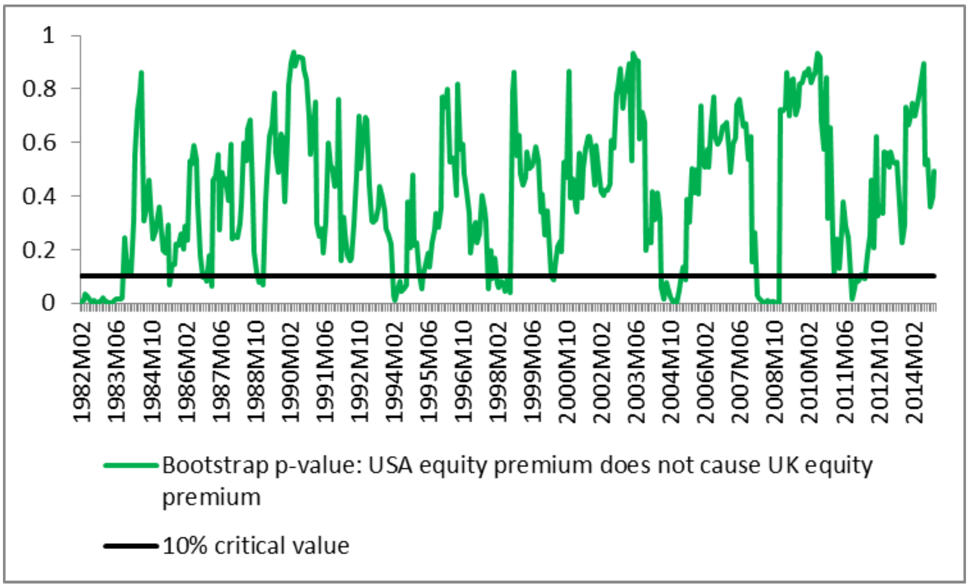

Figure 11: Rolling window bootstrap p-value: USA equity premium does not Granger cause UK equity premium

These periods that the U.S. returns had predictive power for international returns may be associated with key market, technological and regulatory events in the U.S. stock market. Remarkable market events include the 1987 Black Monday stock market crash, 13 Oct 1989 mini-crash caused by failed leveraged buyout of United Airlines, early 1990s recession caused by invasion of Kuwait by Iraq in July 1990, which led to oil price increases and about 18% fall in Dow Jones Industrial Average (DJIA) in three months, the 1997-2000 dot-com bubble burst leading to the collapse of a technology bubble and stock market crash, world economic effects arising from the 2001 September 11 attacks, the stock market downturn of 2002, 2007 Quant crash, United States bear market of 2007–09 declared in June 2008 when the DJIA fell 20% from its 11 October 2007 high, 2007-2008 subprime credit crisis periods, 2010 Flash Crash when the DJIA suffers its worst intra-day point loss, dropping nearly 1,000 points before partially recovering (Credit Suisse Derivative Strategy cited in Business Insider Inc., 2015; Wikipedia, 2015).

The regulatory events include the 1996 NASDAQ litigation, 1997 Order handling rules that prompted rise of Electronic Communication Networks (ECNs) for transaction costs reduction, the 1999 Regulation of Alternative Trading Systems (ATS) which allows ECNS to operate as broker dealers without exchange registration and eliminates any market making obligations and 9 April 2001 Decimalization that facilitated smaller lots and market automation. Further the 2005 Regulation of the National Market System (NMS II) which was formed to compile the consolidated book, forced price competition across exchanges, one cent price increments and access rules for facilitating sharing of market data such as quotations is another important regulation in the U.S. stock market. Other regulations during the significant sub-periods in our sample include the 2008 Short Sale Bans – a temporary ban to prevent "bear raids", 2010 Circuit Breakers, trading pauses to prevent wild price swings and the 2011 Uptick Rule which restricts short selling.

With respect to technological events, the 1980's program trading, that is the simultaneous trading of a portfolio of stocks, as opposed to buying or selling just one stock at a time, 1988 Small Order Execution System (SOES)—Nasdaq automation— automatically executes small orders against the best quotations, making greater volume and efficiency in trading possible, 1999 Instinet Order Management System (OMS) first Execution management systems (EMS) platform and 2001 Credit Suisse (CS) Advanced Execution Services (AES) launch (Credit Suisse Derivative Strategy cited in Business Insider Inc., 2015) are among the few that could have affected the U.S. stock market and hence spill over to the international stock markets. Other events that may have affected the stock market in the U.S. between 2012 and 2014 include the 2012 Presidential election, September 13, 2012 Federal Reserve announcement of a third round of quantitative easing (QE3) (Fawley and Nelly, 2013) and the continued debate on Fiscal Cliff.

4. Conclusion

This study analyse the lead-lag relationship among 11 industrialized country (Australia, Canada, France, Germany, Italy, Japan, Netherlands, Sweden, Switzerland, United Kingdom and United States) stock returns with specific aim of identifying the predictive role of the U.S return. We use the national economic variables (dividend yield and 3-month Treasury bill rates) as control variables. Our data is monthly data covering the 1980:2 to 2014 period for all countries except Sweden for which data is available only from 1982:3 to 2014:12. Although, the idea behind this study is based on Rapach et al. (2013), we contribute by accounting for structural breaks and nonlinearities that pose challenge to financial time series data since these properties invalidate results from full sample standard Granger causality tests. This we do by employing two different approaches: a subsample analysis that are based on the same set of models (OLS, Adaptive elastic net and News-diffusion models) estimated in Rapach et al. (2013) and a bootstrap rolling window causality test. The rolling window approach does not only account for multiple structural breaks, it is capable of dating exactly the periods for which the U.S. returns has predictive power for the international returns and it is robust to small sample size.

To determine the suitability of these two approaches, we first conduct multiple structural breaks and linear dependency tests. We find the existence of multiple structural breaks and nonlinearities in the data. Given this outcome we proceed first with the subsample analysis using the same data set and sample range as in Rapach et al. (2013). The subsample results based on the pairwise Granger causality predictive regression and the News-diffusion model in general support the findings in Rapach et al. (2013): the lagged U.S returns has predictive power over other countries returns and that information friction plays a key role in the impact of U.S. return shocks on other countries. However, in contrast to Rapach et al. (2013) we do not find much evidence of the U.S. returns predictive power when using the pooled OLS and adaptive elastic net models. Also we obtain more robust estimates in almost all cases than they did. It is also important to note that in all the estimations, the results vary from one sub-period to the other both in terms of size and significance.

Based on our new updated data set and the bootstrap rolling window approach, we are able to reject the null hypothesis that the U.S. returns does not have predictive ability for the other country returns at 10% level of significance. For instance, this holds for Australia during 1982:2 - 1983:8, 1988:11-1989:1, 2006:1-2006:2, 2008:3, 2008:5-2008:12 and 2011:10-2012:5 sub-periods. For Japan it is rejected during 1982:5-1982:9, 1982:11-1983:9, 1983:11-1984:1, 1988:9-1988:11, 19892, 1989:5-1989:11, 1991:1-1992:9, 1998:8, 2004:3-2004:10, 2005:1-2005:3, 2005:5, 2007:12-2008:12, 2011:4 and 2011:11 sub-periods. For Switzerland it is rejected during 1982:2-1984:6, 1986:11-1987:7, 1987:9-1987:10, 1989:7-1989:10, 1991:4-1991:6, 1991:8-1991:9, 1991:11-1991:12, 1992:2-1992:9, 1994:3, 1995:7, 1999:12-2000:5, 2004:7, 2004:10-2005:4, 2007:7, 2008:12, 2009:3, 2009:5-2009:7 and 2010:2-2010:4 sub-periods. The time variation in the causal relationship between the U.S. returns and international returns invalidates any results based on the linear models since these assume a permanent relationship. Hence, this feature needs to be taken into account when modeling and predicting stock returns. More so, the fact that international returns are predictable is interesting given that they act as leading indicators in the economy and hence serve as a source of useful information for policy makers and investors as to where the economy might be heading. The significant predictive role of the U.S. returns on the rest of the countries returns also has implications for asset international pricing models, hedging and investing behaviour and choices. We could not control for fundamentals by using same national economic variables as in Rapach et al. (2013) in the rolling window estimations due to data unavailability for all countries, therefore we suggest that future studies should incorporate these once they become available.

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Appendix

Table A1: Multiple Structural Break Tests

Country	No. of breaks	Estimated break dates				
		1st	2nd	3rd	4th	5th
Australia	5	1982M08	1987M11	1990M12	2007M05	2009M01
Canada	5	1982M08	1998M11	2000M10	2002M12	2009M01
France	5	1998M11	2000M10	2002M11	2007M07	2009M04
Germany	5	1987M01	1992M12	1998M03	2003M05	2009M01
Italy	5	1984M06	1986M05	1990M08	1992M11	1994M07
Japan	5	1990M08	1992M12	2002M07	2008M12	2012M07
Netherlands	2	2001M08	2003M07	-	-	-
Sweden	5	1989M09	1992M12	2000M04	2002M11	2006M06
Switzerland	3	1996M09	1998M08	2000M04	-	-
United Kingdom	5	1982M08	1987M09	1990M12	2001M07	2009M01
United States[a]	5	1982M08	2000M09	2002M10	2007M06	2009M03

Note: [a] is obtained by regressing U.S. equity premium on a constant.

Table A2. BDS Linear Dependence Tests

Country(i)	Dimension									
	2		3		4		5		6	
	Statistics	P-value	Statistics	P-value	Statistics	P-value	Statistics	P-value	Statistics	P-value
AUS	-1.18E-05	0.959	-7.26E-07	0.999	1.04E-05	0.990	1.00E-05	0.994	-1.37E-05	0.994
CAN	0.011	0.009	0.029	0.000	0.034	0.000	0.039	0.000	0.038	0.000
FRA	0.016	0.000	0.032	0.000	0.042	0.000	0.045	0.000	0.045	0.000
DEU	0.024	0.000	0.043	0.000	0.054	0.000	0.060	0.000	0.060	0.000
ITA	0.012	0.001	0.021	0.000	0.032	0.000	0.036	0.000	0.037	0.000
JPN	0.004	0.309	0.012	0.056	0.020	0.005	0.023	0.002	0.023	0.001
NLD	0.023	0.0002	0.041	0.000	0.049	0.000	0.047	0.000	0.043	0.000
SWE	0.015	0.0002	0.028	0.000	0.039	0.000	0.044	0.000	0.0433	0.000
CHE	0.019	0.0002	0.033	0.000	0.042	0.000	0.046	0.000	0.047	0.000
GBR	0.022	0.0002	0.040	0.000	0.047	0.000	0.051	0.000	0.052	0.000

Table A3: Benchmark Predictive Regression Model Results

	1982:9-2000:8			2000:9-2010:12			1982:9-2002:9		
Country (i)	$\hat{\beta}_{i,b}$	$\hat{\beta}_{i,d}$	R^2 (%)	$\hat{\beta}_{i,b}$	$\hat{\beta}_{i,d}$	R^2 (%)	$\hat{\beta}_{i,b}$	$\hat{\beta}_{i,d}$	R^2 (%)
Australia	-0.03	2.03	0.44	**-0.96**	-1.50	5.76	-0.02	2.14	0.58
	(-0.2)	(0.47)	(0.41)	(-1.98)	(-0.43)	(5.01)	(-0.11)	(0.52)	(0.87)
Canada	**-0.32**	1.65	1.73	**-0.74**	-0.46	4.63	**-0.39**	**3.64**	2.94
	(-1.73)	(0.91)	(3.76)	(-2.65)	(-0.24)	(7.2)	(-2.17)	(2.12)	(4.99)
France	**-0.43**	**4.40**	**2.46**	**-1.42**	-1.75	**8.61**	-0.19	**3.38**	1.43
	(-2.36)	(2.45)	(6.43)	(-2.72)	(-0.6)	(10.81)	(-0.99)	(1.8)	(4.08)
Germany	-0.47	2.60	1.79	**-1.67**	-3.24	**9.38**	-0.30	3.03	1.29
	(-1.68)	(1.31)	(2.87)	(-3.97)	(-1.11)	(15.79)	(-1.05)	(1.55)	(2.4)
Italy	-0.05	-0.34	0.13	**-1.18**	-1.79	**6.27**	0.12	-1.93	0.82
	(-0.32)	(-0.18)	(0.25)	(-2.67)	(-0.7)	(7.53)	(1.09)	(-1.14)	(1.91)
Japan	0.04	**1.90**	**1.44**	**-5.63**	1.06	**5.76**	0.16	**1.55**	0.92
	(0.2)	(2.28)	(5.25)	(-2.7)	(0.63)	(8)	(0.92)	(1.93)	(4.17)
Netherlands	**-0.66**	**2.98**	**4.62**	**-1.69**	-2.14	**12.53**	**-0.47**	**3.05**	**2.91**
	(-4.06)	(2.35)	(16.53)	(-3.66)	(-0.87)	(15.08)	(-2.51)	(2.53)	(8.02)
Sweden	**-0.40**	**4.51**	**2.64**	**-1.74**	1.23	**14.41**	-0.04	2.12	0.57
	(-2.49)	(1.8)	(6.27)	(-3.87)	(0.52)	(17.85)	(-0.25)	(0.88)	(0.89)
Switzerland	**-0.43**	1.90	**2.49**	**-1.01**	-1.47	**4.62**	**-0.33**	**2.30**	**1.67**
	(-2.59)	(1.59)	(7.08)	(-2.69)	(-0.74)	(7.3)	(-2.02)	(2.01)	(5.83)
United Kingdom	**-0.23**	**3.99**	2.47	**-0.54**	0.45	**4.95**	**-0.17**	**4.75**	**4.11**
	(-1.57)	(2.12)	(4.55)	(-1.77)	(0.13)	(6.06)	(-1.16)	(3.04)	(10.89)
United States	-0.10	0.53	0.18	-0.15	2.45	2.26	-0.02	1.53	2.07
	(-0.58)	(0.57)	(0.42)	(-0.72)	(0.84)	(1.83)	(-0.11)	(1.79)	(4.59)
Pooled	**-0.17**	**1.47**	**1.06**	**-1.03**	-0.82	**6.09**	-0.03	**1.45**	**0.71**
	(-2.09)	(2.28)	(7.12)	(-4.82)	(-0.49)	(23.69)	(-0.41)	(2.52)	(6.55)

	2002:10-2010:12			1982:9-2007:5			2007:6-2010:12		
Country (i)	$\hat{\beta}_{i,b}$	$\hat{\beta}_{i,d}$	R^2 (%)	$\hat{\beta}_{i,b}$	$\hat{\beta}_{i,d}$	R^2 (%)	$\hat{\beta}_{i,b}$	$\hat{\beta}_{i,d}$	R^2 (%)
Australia	**-1.33**	-5.08	**9.15**	-0.05	2.43	0.58	**-1.56**	-3.21	**16.81**
	(-2.14)	(-1.1)	(5.26)	(-0.37)	(0.62)	(0.53)	(-2.27)	(-0.62)	(7.4)
Canada	**-0.50**	-3.35	4.31	**-0.42**	**3.67**	**3.55**	**-1.26**	-7.02	**10.34**
	(-1.79)	(-1.59)	(4.99)	(-2.71)	(2.25)	(7.42)	(-2.7)	(-1.11)	(7.32)
France	**-1.28**	-3.13	**7.19**	-0.16	**3.00**	**1.64**	**-1.35**	1.43	**14.64**
	(-2.42)	(-0.99)	(5.96)	(-1.57)	(2.37)	(5.66)	(-2.37)	(0.28)	(7.93)
Germany	**-1.43**	-3.45	**8.07**	-0.44	2.88	1.50	**-1.82**	-2.42	**17.76**
	(-2.94)	(-1.13)	(8.7)	(-1.68)	(1.55)	(2.92)	(-3.3)	(-0.43)	(11.46)
Italy	**-0.99**	-2.79	5.82	-0.01	-0.14	0.01	**-1.39**	1.22	**11.98**
	(-2.11)	(-0.92)	(4.75)	(-0.07)	(-0.11)	(0.01)	(-2.69)	(0.29)	(7.38)
Japan	**-6.90**	-0.10	**9.79**	0.11	**1.82**	**1.18**	-5.87	5.32	**11.88**
	(-3.13)	(-0.06)	(9.77)	(0.71)	(2.38)	(5.65)	(-0.93)	(1.01)	(9.38)
Netherlands	**-1.54**	-2.89	**13.70**	**-0.36**	**2.61**	**2.37**	**-1.73**	0.01	**19.96**
	(-2.95)	(-1.02)	(8.91)	(-2.59)	(2.31)	(7.86)	(-2.95)	(0)	(8.9)
Sweden	**-1.42**	-1.27	**11.05**	-0.08	2.83	1.32	**-2.08**	2.42	**27.19**
	(-2.71)	(-0.44)	(7.88)	(-0.93)	(1.73)	(3.88)	(-3.55)	(0.66)	(12.85)
Switzerland	-0.91	-2.47	3.53	**-0.36**	**2.62**	**2.25**	-1.26	-0.49	5.90
	(-1.79)	(-1.25)	(4.16)	(-2.58)	(2.24)	(7.83)	(-1.44)	(-0.08)	(3.45)
United Kingdom	**-0.61**	-3.38	5.35	**-0.23**	**4.88**	**3.89**	**-0.98**	-1.30	**14.99**
	(-1.93)	(-0.78)	(3.99)	(-1.76)	(3.24)	(11.3)	(-2.68)	(-0.29)	(7.77)
United States	-0.21	-1.36	0.60	-0.14	1.65	1.69	-0.90	-1.08	3.94
	(-1.02)	(-0.33)	(1.04)	(-0.97)	(2.01)	(4.35)	(-1.59)	(-0.16)	(3.44)
Pooled	**-0.90**	-2.66	**5.81**	**-0.08**	**1.56**	**0.89**	**-1.38**	0.06	**13.20**
	(-3.47)	(-1.31)	(15.03)	(-1.28)	(3.05)	(9.71)	(-3.13)	(0.02)	(10.03)

Table A4: Pairwise Granger Causality Test for First Subsample: 1982:9-2000:8 and 2000:9-2010:12

					1982:9-2000:8						
Country(i)	$\hat{\beta}_{i,AUS}$	$\hat{\beta}_{i,CAN}$	$\hat{\beta}_{i,FRA}$	$\hat{\beta}_{i,DEU}$	$\hat{\beta}_{i,ITA}$	$\hat{\beta}_{i,JPN}$	$\hat{\beta}_{i,NLD}$	$\hat{\beta}_{i,SWE}$	$\hat{\beta}_{i,CHE}$	$\hat{\beta}_{i,GBR}$	$\hat{\beta}_{i,USA}$
AUS		0.09	**0.15**	**0.17**	**0.08**	**0.10**	0.11	**0.08**	0.05	0.06	0.12
		(0.85)	(1.78)	(2.04)	(1.82)	(1.58)	(1.1)	(1.64)	(0.64)	(0.62)	(1.12)
CAN	0.00		0.02	-0.04	0.00	0.00	-0.10	0.07	-0.06	0.00	0.02
	(-0.03)		(0.24)	(-0.6)	(0.04)	(-0.03)	(-1.2)	(1.59)	(-0.69)	(-0.05)	(0.2)
FRA	0.01	0.04		-0.08	0.00	-0.01	-0.07	**0.12**	0.03	0.05	0.11
	(0.14)	(0.39)		(-0.79)	(-0.02)	(-0.16)	(-0.49)	(1.68)	(0.27)	(0.34)	(0.94)
DEU	-0.05	0.10	**0.17**		**0.13**	0.01	0.11	**0.11**	0.17	0.07	0.15
	(-0.42)	(0.91)	(1.6)		(2.24)	(0.11)	(0.93)	(1.84)	(1.3)	(0.61)	(1.2)
ITA	-0.07	0.08	**0.18**	0.10		-0.02	-0.09	0.05	0.18	0.15	0.09
	(-0.77)	(0.71)	(1.73)	(0.77)		(-0.19)	(-0.61)	(0.62)	(1.28)	(1.29)	(0.8)
JPN	-0.01	0.09	**0.12**	-0.06	0.03		0.01	0.07	0.02	**0.12**	0.07
	(-0.1)	(0.91)	(1.62)	(-0.75)	(0.49)		(0.06)	(1.08)	(0.23)	(1.41)	(0.67)
NLD	0.09	**0.27**	**0.16**	0.06	0.06	0.03		**0.13**	**0.25**	0.17	**0.25**
	(0.86)	(2.48)	(2.15)	(0.68)	(1.18)	(0.52)		(2.21)	(2.17)	(1.35)	(2.2)
SWE	-0.05	**0.30**	0.11	0.15	**0.13**	0.02	0.05		0.15	**0.22**	**0.31**
	(-0.38)	(2.52)	(1.1)	(1.3)	(1.33)	(0.25)	(0.37)		(1.22)	(1.66)	(2.22)
CHE	0.02	0.05	0.02	-0.04	0.01	-0.04	-0.02	**0.13**		0.06	0.12
	(0.25)	(0.44)	(0.19)	(-0.37)	(0.27)	(-0.8)	(-0.22)	(2.64)		(0.63)	(0.98)
GBR	0.04	0.09	0.03	-0.09	0.00	0.05	-0.12	0.03	-0.05		0.10
	(0.53)	(0.84)	(0.33)	(-1.1)	(0.05)	(0.84)	(-1.12)	(0.67)	(-0.61)		(0.73)
USA	0.04	0.07	0.00	-0.05	0.03	-0.05	-0.04	0.05	-0.04	0.02	
	(0.43)	(0.61)	(-0.06)	(-0.75)	(0.79)	(-1.08)	(-0.48)	(1.18)	(-0.42)	(0.18)	
Average	0.00	0.11	0.08	-0.01	0.04	0.00	-0.03	0.08	0.07	0.08	0.12
Pooled	0.00	**0.11**	**0.09**	0.01	**0.05**	0.01	-0.01	**0.09**	0.06	0.09	**0.13**
	(-0.04)	(1.42)	(1.61)	(0.21)	(1.27)	(0.3)	(-0.19)	(2.38)	(0.78)	(1.33)	(1.75)
					2000:9-2010:12						
Country(i)	$\hat{\beta}_{i,AUS}$	$\hat{\beta}_{i,CAN}$	$\hat{\beta}_{i,FRA}$	$\hat{\beta}_{i,DEU}$	$\hat{\beta}_{i,ITA}$	$\hat{\beta}_{i,JPN}$	$\hat{\beta}_{i,NLD}$	$\hat{\beta}_{i,SWE}$	$\hat{\beta}_{i,CHE}$	$\hat{\beta}_{i,GBR}$	$\hat{\beta}_{i,USA}$
AUS		0.04	0.00	-0.01	-0.04	0.06	-0.01	0.11	**0.16**	0.02	0.09
		(0.31)	(0.03)	(-0.14)	(-0.49)	(0.7)	(-0.12)	(1.4)	(1.48)	(0.15)	(0.59)
CAN	0.18		**0.19**	**0.15**	0.10	**0.18**	0.12	**0.25**	**0.25**	**0.22**	**0.29**
	(1.29)		(1.74)	(1.76)	(0.95)	(1.85)	(1.2)	(3.59)	(2.12)	(1.56)	(2)
FRA	**0.37**	-0.01		0.14	-0.43	**0.17**	-0.21	0.18	**0.56**	0.15	0.31
	(1.56)	(-0.04)		(0.61)	(-2.05)	(1.38)	(-0.68)	(1.15)	(2.19)	(0.47)	(1.2)
DEU	**0.46**	0.07	0.03		-0.33	**0.23**	-0.25	0.20	**0.51**	0.21	**0.47**
	(1.86)	(0.4)	(0.11)		(-1.68)	(1.83)	(-0.92)	(1.06)	(1.92)	(0.72)	(1.81)
ITA	**0.57**	0.11	**0.69**	**0.34**		**0.20**	0.12	**0.28**	**0.54**	**0.46**	**0.50**
	(2.78)	(0.7)	(3.34)	(2.07)		(1.66)	(0.61)	(2.25)	(3.03)	(1.78)	(2.52)
JPN	0.06	0.11	0.08	0.10	0.01		0.09	0.04	**0.22**	0.08	0.06
	(0.4)	(0.77)	(0.75)	(1.19)	(0.07)		(0.83)	(0.39)	(1.7)	(0.56)	(0.46)
NLD	**0.43**	0.14	0.48	**0.46**	0.01	**0.28**		**0.34**	**0.68**	**0.52**	**0.59**
	(1.87)	(0.95)	(1.54)	(2.04)	(0.07)	(2.15)		(2.19)	(2.54)	(1.81)	(2.85)
SWE	0.23	0.11	0.08	0.05	-0.09	0.16	-0.08		0.24	0.04	**0.32**
	(0.92)	(0.59)	(0.37)	(0.25)	(-0.54)	(1.03)	(-0.4)		(1.23)	(0.15)	(1.42)
CHE	0.16	0.00	-0.11	-0.05	-0.18	**0.16**	-0.18	0.05		0.02	0.08
	(1.22)	(-0.05)	(-0.79)	(-0.38)	(-1.63)	(1.99)	(-1.22)	(0.49)		(0.13)	(0.58)
GBR	**0.27**	-0.02	0.12	0.16	-0.09	**0.14**	-0.10	**0.21**	**0.38**		**0.28**
	(1.63)	(-0.15)	(0.58)	(1.1)	(-0.55)	(1.48)	(-0.58)	(1.86)	(2.5)		(1.55)
USA	**0.30**	0.05	-0.04	-0.06	-0.16	**0.16**	-0.07	**0.19**	0.19	0.08	
	(1.58)	(0.24)	(-0.2)	(-0.44)	(-1.09)	(1.57)	(-0.38)	(1.65)	(1.33)	(0.31)	
Average	0.30	0.06	0.15	0.13	-0.12	0.17	-0.06	0.17	0.36	0.18	0.29
Pooled	**0.31**	0.08	**0.12**	**0.11**	-0.06	**0.19**	0.00	**0.18**	**0.33**	**0.17**	**0.26**
	(2.05)	(0.63)	(1.7)	(2)	(-0.75)	(1.95)	(-0.04)	(2.97)	(3.15)	(1.25)	(2.34)

Table A4: Pairwise Granger Causality Test for Second Subsample: 1982:9-2002:9 and 2002:10-2010:12 Contd.

	1982:9-2002:9										
Country(*i*)	$\hat{\beta}_{i,AUS}$	$\hat{\beta}_{i,CAN}$	$\hat{\beta}_{i,FRA}$	$\hat{\beta}_{i,DEU}$	$\hat{\beta}_{i,ITA}$	$\hat{\beta}_{i,JPN}$	$\hat{\beta}_{i,NLD}$	$\hat{\beta}_{i,SWE}$	$\hat{\beta}_{i,CHE}$	$\hat{\beta}_{i,GBR}$	$\hat{\beta}_{i,USA}$
AUS		0.11	**0.15**	**0.18**	**0.08**	**0.11**	0.10	**0.09**	0.07	0.08	**0.13**
		(1.3)	(2.04)	(2.26)	(1.85)	(1.79)	(1.17)	(2)	(0.91)	(0.82)	(1.38)
CAN	-0.01		0.06	-0.01	0.02	0.02	-0.08	**0.09**	-0.04	0.01	0.03
	(-0.21)		(0.87)	(-0.11)	(0.34)	(0.38)	(-0.96)	(2.12)	(-0.39)	(0.13)	(0.34)
FRA	-0.01	0.02		-0.04	-0.01	0.01	-0.07	**0.14**	0.04	0.03	0.10
	(-0.12)	(0.21)		(-0.39)	(-0.15)	(0.17)	(-0.5)	(1.84)	(0.31)	(0.24)	(0.85)
DEU	-0.06	0.11	**0.21**		**0.12**	0.06	0.10	**0.15**	0.17	0.08	**0.16**
	(-0.51)	(1.15)	(1.99)		(2.09)	(0.8)	(0.83)	(2.27)	(1.36)	(0.7)	(1.48)
ITA	-0.08	0.06	**0.21**	0.12		0.00	-0.08	0.05	**0.17**	0.14	0.09
	(-0.88)	(0.6)	(1.99)	(1.04)		(0.01)	(-0.62)	(0.73)	(1.32)	(1.25)	(0.87)
JPN	-0.02	0.07	**0.12**	-0.04	0.03		0.02	0.07	0.04	**0.12**	0.05
	(-0.3)	(0.84)	(1.78)	(-0.5)	(0.55)		(0.32)	(1.17)	(0.52)	(1.47)	(0.52)
NLD	0.07	**0.26**	**0.22**	**0.15**	0.07	0.07		**0.17**	**0.27**	**0.19**	**0.28**
	(0.76)	(2.92)	(2.86)	(1.59)	(1.36)	(1.29)		(2.75)	(2.38)	(1.58)	(2.75)
SWE	-0.08	**0.26**	**0.14**	**0.17**	0.12	0.04	0.04		0.13	**0.21**	**0.29**
	(-0.6)	(2.36)	(1.5)	(1.56)	(1.27)	(0.49)	(0.32)		(1.13)	(1.63)	(2.16)
CHE	0.01	0.06	0.06	0.03	0.03	-0.01	0.01	**0.15**		0.08	0.14
	(0.14)	(0.64)	(0.68)	(0.29)	(0.65)	(-0.19)	(0.12)	(3.32)		(0.9)	(1.25)
GBR	0.03	0.08	0.06	-0.04	0.01	0.07	-0.10	0.05	-0.03		0.09
	(0.44)	(0.94)	(0.68)	(-0.57)	(0.24)	(1.26)	(-1)	(1.1)	(-0.41)		(0.76)
USA	0.03	0.10	0.03	-0.03	0.04	-0.02	-0.04	**0.08**	-0.03	0.02	
	(0.35)	(0.9)	(0.5)	(-0.4)	(0.94)	(-0.41)	(-0.45)	(1.67)	(-0.27)	(0.19)	
Average	-0.01	0.10	0.11	0.03	0.04	0.02	-0.02	0.10	0.07	0.09	0.12
Pooled	-0.01	**0.10**	**0.12**	0.05	**0.05**	0.04	0.00	**0.11**	0.07	**0.09**	**0.13**
	(-0.22)	(1.57)	(2.24)	(0.82)	(1.44)	(0.87)	(-0.05)	(3.16)	(1.02)	(1.46)	(1.93)

	2002:10-2010:12										
Country(*i*)	$\hat{\beta}_{i,AUS}$	$\hat{\beta}_{i,CAN}$	$\hat{\beta}_{i,FRA}$	$\hat{\beta}_{i,DEU}$	$\hat{\beta}_{i,ITA}$	$\hat{\beta}_{i,JPN}$	$\hat{\beta}_{i,NLD}$	$\hat{\beta}_{i,SWE}$	$\hat{\beta}_{i,CHE}$	$\hat{\beta}_{i,GBR}$	$\hat{\beta}_{i,USA}$
AUS		-0.07	-0.12	-0.09	-0.08	0.00	-0.03	0.08	0.12	-0.07	0.03
		(-0.37)	(-0.98)	(-0.96)	(-1)	(0)	(-0.27)	(0.91)	(0.99)	(-0.43)	(0.14)
CAN	**0.26**		**0.19**	**0.21**	0.13	0.09	**0.22**	**0.28**	**0.29**	**0.26**	**0.37**
	(1.63)		(1.64)	(2.42)	(1.07)	(0.81)	(2.07)	(3.88)	(2.48)	(1.82)	(2.48)
FRA	**0.48**	0.02		0.13	-0.32	0.03	0.06	0.21	**0.82**	0.31	**0.44**
	(1.89)	(0.1)		(0.56)	(-1.56)	(0.27)	(0.19)	(1.34)	(3.11)	(0.95)	(1.65)
DEU	0.49	-0.02	-0.34		-0.31	0.07	-0.14	0.06	**0.59**	0.21	**0.47**
	(1.74)	(-0.09)	(-1.02)		(-1.54)	(0.6)	(-0.48)	(0.27)	(1.93)	(0.74)	(1.62)
ITA	**0.70**	0.20	**0.72**	**0.27**		0.11	0.23	**0.34**	**0.69**	**0.56**	**0.65**
	(3.02)	(0.92)	(3.47)	(2.01)		(0.8)	(1.06)	(2.61)	(3.51)	(1.9)	(2.82)
JPN	0.18	0.22	0.06	0.09	0.00		0.11	0.05	**0.26**	0.08	0.15
	(1.04)	(1.12)	(0.51)	(0.96)	(0.01)		(0.82)	(0.47)	(1.84)	(0.48)	(0.92)
NLD	**0.40**	0.03	0.21	0.32	-0.07	0.13		0.23	**0.65**	0.39	**0.57**
	(1.53)	(0.13)	(0.57)	(1.35)	(-0.28)	(1.01)		(1.33)	(2.4)	(1.32)	(2.31)
SWE	0.28	0.10	0.09	0.09	-0.02	0.02	0.15		0.44	0.15	**0.37**
	(1.01)	(0.44)	(0.42)	(0.53)	(-0.11)	(0.11)	(0.81)		(1.91)	(0.62)	(1.59)
CHE	0.20	-0.03	-0.27	-0.20	-0.31	0.09	-0.16	-0.01		0.00	0.08
	(1.29)	(-0.19)	(-1.6)	(-1.41)	(-2.6)	(1.02)	(-0.98)	(-0.07)		(0)	(0.49)
GBR	**0.34**	-0.08	0.06	0.11	-0.10	0.04	-0.03	**0.22**	**0.44**		**0.37**
	(1.72)	(-0.44)	(0.3)	(0.8)	(-0.54)	(0.41)	(-0.16)	(1.9)	(2.67)		(1.71)
USA	0.29	-0.01	-0.10	0.02	-0.16	0.02	0.03	**0.21**	**0.26**	0.13	
	(1.33)	(-0.05)	(-0.59)	(0.16)	(-0.98)	(0.23)	(0.14)	(1.75)	(1.67)	(0.46)	
Average	0.36	0.04	0.06	0.10	-0.11	0.06	0.05	0.16	0.44	0.21	0.35
Pooled	**0.37**	0.07	0.07	**0.10**	-0.06	0.07	0.07	**0.18**	**0.41**	0.19	**0.33**
	(2.37)	(0.45)	(0.76)	(1.52)	(-0.63)	(0.76)	(0.67)	(2.74)	(3.38)	(1.3)	(2.53)

Table A4: Pairwise Granger Causality Test for Second Subsample: 1982:9-2007:5 and 2007:6-2010:12 Contd.

					1982:9-2007:5						
Country(i)	$\hat{\beta}_{i,AUS}$	$\hat{\beta}_{i,CAN}$	$\hat{\beta}_{i,FRA}$	$\hat{\beta}_{i,DEU}$	$\hat{\beta}_{i,ITA}$	$\hat{\beta}_{i,JPN}$	$\hat{\beta}_{i,NLD}$	$\hat{\beta}_{i,SWE}$	$\hat{\beta}_{i,CHE}$	$\hat{\beta}_{i,GBR}$	$\hat{\beta}_{i,USA}$
AUS		0.10	**0.14**	**0.15**	**0.08**	**0.09**	0.09	**0.09**	0.08	0.09	**0.13**
		(1.25)	(2.03)	(2.34)	(1.87)	(1.71)	(1.27)	(2.08)	(1.04)	(1)	(1.44)
CAN	0.00		0.07	0.03	0.02	0.01	-0.02	**0.10**	0.01	0.04	0.08
	(-0.08)		(1.25)	(0.57)	(0.47)	(0.15)	(-0.26)	(2.51)	(0.08)	(0.55)	(0.91)
FRA	0.00	0.00		-0.03	-0.02	0.01	-0.06	**0.12**	0.07	0.04	0.11
	(0.04)	(0)		(-0.31)	(-0.37)	(0.11)	(-0.46)	(1.72)	(0.58)	(0.27)	(1.01)
DEU	-0.03	0.09	**0.18**		**0.10**	0.05	0.07	**0.13**	**0.21**	0.09	**0.19**
	(-0.26)	(0.92)	(1.74)		(1.68)	(0.81)	(0.65)	(2.02)	(1.66)	(0.75)	(1.63)
ITA	-0.05	0.06	**0.20**	0.13		0.01	-0.04	0.07	**0.18**	**0.15**	0.12
	(-0.63)	(0.66)	(2.12)	(1.23)		(0.07)	(-0.34)	(1.13)	(1.49)	(1.41)	(1.19)
JPN	-0.01	0.09	**0.13**	0.00	0.03		0.05	0.07	0.07	**0.13**	0.07
	(-0.21)	(1.14)	(1.99)	(-0.01)	(0.55)		(0.73)	(1.27)	(0.94)	(1.69)	(0.84)
NLD	0.08	**0.20**	**0.19**	**0.13**	0.05	0.06		**0.15**	**0.28**	**0.18**	**0.27**
	(0.83)	(2.24)	(2.51)	(1.49)	(0.91)	(1.25)		(2.5)	(2.61)	(1.52)	(2.72)
SWE	-0.06	**0.22**	0.10	0.11	0.10	0.03	0.01		0.11	0.17	**0.27**
	(-0.48)	(2.07)	(1.09)	(1.14)	(1.02)	(0.38)	(0.05)		(1)	(1.39)	(2.12)
CHE	0.02	0.03	0.04	0.02	0.02	0.00	0.00	**0.13**		0.08	0.13
	(0.21)	(0.35)	(0.46)	(0.21)	(0.32)	(-0.06)	(0)	(2.86)		(0.93)	(1.27)
GBR	0.04	0.05	0.05	-0.02	0.01	0.06	-0.09	0.05	-0.01		0.10
	(0.56)	(0.65)	(0.65)	(-0.27)	(0.12)	(1.16)	(-0.95)	(1.14)	(-0.12)		(0.93)
USA	0.03	0.04	0.03	-0.02	0.03	-0.03	-0.03	**0.07**	-0.01	0.03	
	(0.34)	(0.39)	(0.4)	(-0.35)	(0.76)	(-0.8)	(-0.47)	(1.66)	(-0.13)	(0.28)	
Average	0.00	0.08	0.10	0.04	0.03	0.02	-0.01	0.09	0.09	0.09	0.13
Pooled	0.00	**0.08**	**0.10**	0.05	0.04	0.03	0.00	**0.10**	**0.08**	**0.10**	**0.14**
	(-0.04)	(1.32)	(2.18)	(0.99)	(1.14)	(0.81)	(0.01)	(3.08)	(1.36)	(1.68)	(2.24)

					2007:6-2010:12						
Country(i)	$\hat{\beta}_{i,AUS}$	$\hat{\beta}_{i,CAN}$	$\hat{\beta}_{i,FRA}$	$\hat{\beta}_{i,DEU}$	$\hat{\beta}_{i,ITA}$	$\hat{\beta}_{i,JPN}$	$\hat{\beta}_{i,NLD}$	$\hat{\beta}_{i,SWE}$	$\hat{\beta}_{i,CHE}$	$\hat{\beta}_{i,GBR}$	$\hat{\beta}_{i,USA}$
AUS		-0.04	-0.26	-0.30	-0.23	0.05	-0.14	0.10	0.06	-0.26	-0.06
		(-0.88)	(-2.75)	(-1.28)	(0)	(0.36)	(-1.55)	(0)	(0.22)	(-1.35)	(-0.62)
CAN	0.19		0.05	0.13	0.03	**0.27**	0.04	**0.38**	0.18	0.08	0.25
	(0.78)		(0.46)	(0.62)	(0.35)	(2.46)	(0.22)	(3.63)	(0)	(0)	(1.59)
FRA	0.75	0.22		-0.03	-0.86	0.18	-0.09	0.28	1.30	0.39	**0.55**
	(3.08)	(0)		(0)	(-8.98)	(1.27)	(0)	(0)	(2.21)	(1.58)	(14.04)
DEU	0.68	0.14	-0.23		-0.39	0.23	-0.20	0.22	0.80	0.15	**0.47**
	(1.88)	(0)	(0)		(-3.21)	(1.44)	(-6.14)	(0.77)	(1.59)	(0)	(3.32)
ITA	**0.91**	0.40	**1.46**	**0.51**		0.32	0.14	0.40	1.39	0.79	0.84
	(3.91)	(0)	(12.27)	(13.24)		(2.19)	(0.51)	(0)	(0)	(2.42)	(0)
JPN	0.25	0.33	0.04	0.15	0.00		0.13	0.05	0.23	0.07	0.21
	(0.96)	(0)	(0.31)	(0.98)	(0.05)		(0.75)	(0)	(1.18)	(0)	(1.74)
NLD	0.68	**0.48**	**0.41**	**0.45**	0.11	**0.42**		0.47	**0.92**	0.57	**0.95**
	(2.66)	(3.94)	(3.45)	(3.3)	(0)	(3.31)		(0)	(3.8)	(2.78)	(11.28)
SWE	0.35	0.27	0.09	0.08	0.06	0.33	0.12		0.57	0.18	**0.39**
	(0.91)	(0)	(0.62)	(0.54)	(0.66)	(2.11)	(0.85)		(2.01)	(1.92)	(15.62)
CHE	0.20	0.05	-0.43	-0.33	-0.49	0.06	-0.26	0.06		-0.18	0.01
	(1.19)	(0.48)	(-6.27)	(-1.52)	(0)	(0.62)	(-1.14)	(0)		(-1.35)	(0.14)
GBR	0.48	0.02	-0.11	-0.08	-0.29	0.11	-0.19	0.23	**0.67**		**0.43**
	(1.66)	(0)	(-0.34)	(-0.91)	(-7.57)	(0.86)	(0)	(0)	(3.95)		(2.66)
USA	0.52	0.28	-0.21	-0.02	-0.26	0.21	0.01	0.35	0.44	0.02	
	(1.5)	(0)	(-7.84)	(-0.1)	(-2.38)	(1.66)	(0)	(1.9)	(1.29)	(0)	
Average	0.50	0.22	0.11	0.09	-0.21	0.21	-0.03	0.24	0.65	0.21	0.41
Pooled	**0.46**	0.23	0.02	0.05	-0.12	0.21	-0.02	**0.25**	**0.54**	0.14	**0.38**
	(2.53)	(1.19)	(0.14)	(0.43)	(-1.11)	(1.46)	(-0.1)	(2.43)	(2.38)	(0.77)	(2.46)

Table A5: Estimation Results for the Pooled General Model Specification

$\hat{\hat{\beta}}_{i,AUS}$	$\hat{\hat{\beta}}_{i,CAN}$	$\hat{\hat{\beta}}_{i,FRA}$	$\hat{\hat{\beta}}_{i,DEU}$	$\hat{\hat{\beta}}_{i,ITA}$	$\hat{\hat{\beta}}_{i,JPN}$	$\hat{\hat{\beta}}_{i,NLD}$	$\hat{\hat{\beta}}_{i,SWE}$	$\hat{\hat{\beta}}_{i,CHE}$	$\hat{\hat{\beta}}_{i,GBR}$	$\hat{\hat{\beta}}_{i,USA}$
					1982:9-2000:8					
-0.07	0.09	0.07	-0.03	0.03	-0.02	**-0.15**	**0.07**	0.00	0.060	0.09
[-0.19, 0.06]	[-0.06, 0.23]	[-0.05, 0.18]	[-0.14, 0.08]	[-0.04, 0.1]	[-0.09, 0.05]	[-0.28, -0.01]	[0.01, 0.14]	[-0.15, 0.16]	[-0.09, 0.21]	[-0.05, 0.24]
					2000:9-2010:12					
0.21	-0.06	0.02	0	-0.21	0.1	-0.19	0.12	**0.28**	0.08	0.14
[-0.06, 0.46]	[-0.25, 0.12]	[-0.16, 0.21]	[-0.15, 0.17]	[-0.37, -0.06]	[-0.06, 0.27]	[-0.41, 0.02]	[-0.02, 0.27]	[0.03, 0.52]	[-0.18, 0.33]	[-0.07, 0.34]
					1982:9-2002:9					
-0.08	0.07	0.09	0	0.02	0	**-0.16**	**0.08**	0	0.06	0.09
[-0.2, 0.03]	[-0.06, 0.19]	[-0.02, 0.2]	[-0.12, 0.11]	[-0.05, 0.08]	[-0.07, 0.08]	[-0.29, -0.03]	[0.02, 0.15]	[-0.14, 0.15]	[-0.08, 0.2]	[-0.06, 0.22]
					2002:10-2010:12					
0.3	-0.03	-0.15	-0.07	**-0.24**	-0.05	-0.11	**0.18**	**0.41**	0.097	0.2
[0.02, 0.6]	[-0.27, 0.2]	[-0.34, 0.04]	[-0.25, 0.1]	[-0.41, -0.06]	[-0.19, 0.09]	[-0.34, 0.13]	[0.02, 0.34]	[0.16, 0.67]	[-0.17, 0.37]	[-0.02, 0.43]
					1982:9-2007:5					
-0.06	0.03	0.07	0	0	0	**-0.15**	**0.08**	0.02	0.058	0.11
[-0.18, 0.06]	[-0.1, 0.15]	[-0.03, 0.18]	[-0.1, 0.1]	[-0.06, 0.07]	[-0.07, 0.07]	[-0.26, -0.04]	[0.01, 0.14]	[-0.11, 0.15]	[-0.07, 0.19]	[-0.03, 0.24]
					2007:6-2010:12					
0.28	0.16	-0.12	-0.13	**-0.26**	0.03	-0.23	**0.29**	**0.59**	0.045	0.09
[-0.04, 0.6]	[-0.14, 0.46]	[-0.36, 0.11]	[-0.36, 0.09]	[-0.49, -0.03]	[-0.2, 0.27]	[-0.55, 0.09]	[0.09, 0.48]	[0.26, 0.94]	[-0.34, 0.43]	[-0.16, 0.33]

Table A6: Adaptive Elastic Net Results for General Model Specification: 1982:9-2000:8 and 2000:9-2010:12

1982:9-2000:8

Country (i)	$\hat{\beta}^*_{i,\text{AUS}}$	$\hat{\beta}^*_{i,\text{CAN}}$	$\hat{\beta}^*_{i,\text{FRA}}$	$\hat{\beta}^*_{i,\text{DEU}}$	$\hat{\beta}^*_{i,\text{ITA}}$	$\hat{\beta}^*_{i,\text{JPN}}$	$\hat{\beta}^*_{i,\text{NLD}}$	$\hat{\beta}^*_{i,\text{SWE}}$	$\hat{\beta}^*_{i,\text{CHE}}$	$\hat{\beta}^*_{i,\text{GBR}}$	$\hat{\beta}^*_{i,\text{USA}}$
AUS		0.00	0.04	**0.14**	0.00	0.03	0.00	0.00	-0.07	0.00	0.00
			[-0.06, 0.17]	[0.02, 0.34]		[-0.01, 0.11]			[-0.27, 0.05]		
CAN	0.00		0.01	0.00	0.00	0.00	**-0.10**	**0.08**	0.00	0.00	0.00
			[-0.04, 0.07]				[-0.26, -0.04]	[0.05, 0.17]	[-0.08, 0.08]		
FRA	0.00	0.00		-0.02	0.00	0.00	-0.01	**0.12**	0.00	0.00	0.03
				[-0.13, 0.05]			[-0.13, 0.06]	[0.04, 0.24]			[-0.03, 0.13]
DEU	-0.06	0.00	0.04		**0.04**	0.00	0.00	**0.05**	0.03	0.00	0.03
	[-0.19, 0]	[-0.03, 0.03]	[-0.01, 0.11]		[0.02, 0.11]			[0.02, 0.12]	[-0.03, 0.1]		[-0.01, 0.12]
ITA	**-0.14**	0.06	**0.16**	0.00		0.00	**-0.35**	0.00	**0.20**	**0.18**	0.00
	[-0.34, -0.06]	[-0.06, 0.24]	[0.03, 0.38]				[-0.7, -0.23]		[0.07, 0.45]	[0.01, 0.46]	
JPN	-0.05	0.00	**0.18**	**-0.22**	0.00		0.00	0.06	0.00	0.102	0.00
	[-0.18, 0.02]	[-0.13, 0.14]	[0.06, 0.36]	[-0.43, -0.11]				[-0.02, 0.18]		[-0.02, 0.27]	
NLD	0.00	**0.17**	0.02	0.00	0.00	0.00		0.06	0.10	0.00	0.00
		[0.05, 0.36]	[-0.03, 0.1]					[0, 0.15]	[-0.02, 0.29]		
SWE	**-0.26**	**0.37**	0.00	0.11	0.09	0.00	**-0.26**		0.00	0.20	0.11
	[-0.5, -0.1]	[0.14, 0.66]		[-0.03, 0.3]	[-0.06, 0.25]		[-0.63, -0.05]			[0, 0.47]	[-0.1, 0.33]
CHE	0.00	0.00	0.00	0.00	0.00	**-0.04**	-0.01	**0.12**		0.00	0.06
				[-0.07, 0.06]		[-0.13, -0.01]	[-0.1, 0.04]	[0.07, 0.22]			[-0.03, 0.2]
GBR	0.00	0.07	0.05	-0.07	0.00	0.00	**-0.10**	0.03	0.00		0.03
		[-0.02, 0.21]	[-0.02, 0.17]	[-0.19, 0]		[-0.04, 0.04]	[-0.25, -0.04]	[-0.01, 0.1]			[-0.05, 0.13]
USA	0.00	0.00	0.00	-0.05	0.01	**-0.03**	0.00	**0.03**	0.00	0.00	
				[-0.15, 0.01]	[-0.02, 0.06]	[-0.09, -0.01]		[0.01, 0.09]			
Average	-0.05	0.07	0.05	-0.03	0.01	-0.01	-0.08	0.06	0.03	0.05	0.03

2000:9-2010:12

Country (i)	$\hat{\beta}^*_{i,\text{AUS}}$	$\hat{\beta}^*_{i,\text{CAN}}$	$\hat{\beta}^*_{i,\text{FRA}}$	$\hat{\beta}^*_{i,\text{DEU}}$	$\hat{\beta}^*_{i,\text{ITA}}$	$\hat{\beta}^*_{i,\text{JPN}}$	$\hat{\beta}^*_{i,\text{NLD}}$	$\hat{\beta}^*_{i,\text{SWE}}$	$\hat{\beta}^*_{i,\text{CHE}}$	$\hat{\beta}^*_{i,\text{GBR}}$	$\hat{\beta}^*_{i,\text{USA}}$
AUS		0.00	0.00	0.00	0.00	0.00	0.00	0.06	0.12	0.00	0.00
								[-0.03, 0.15]	[-0.04, 0.29]		
CAN	0.00		0.00	0.00	0.00	0.01	0.00	**0.23**	0.00	0.00	0.00
						[-0.07, 0.07]		[0.16, 0.36]			
FRA	**0.30**	0.00		0.00	**-0.31**	0.00	**-0.27**	0.07	**0.51**	0.00	0.07
	[0.11, 0.65]				[-0.65, -0.12]		[-0.71, -0.01]	[-0.05, 0.24]	[0.28, 0.95]		[-0.13, 0.29]
DEU	**0.36**	0.00	0.00		**-0.40**	0.00	**-0.35**	0.00	**0.51**	0.00	**0.31**
	[0.16, 0.8]				[-0.82, -0.23]		[-0.87, -0.16]		[0.32, 1.04]		[0.1, 0.74]
ITA	**0.43**	-0.08	0.47	0.00		0.00	**-0.43**	0.08	0.30	0.00	0.16
	[0.16, 0.8]	[-0.32, 0.08]	[0, 1.1]				[-0.98, -0.05]	[-0.08, 0.28]	[-0.02, 0.71]		[-0.11, 0.5]

JPN	0.00	0.03 [-0.13, 0.19]	0.00	0.00	**-0.09** [-0.31, -0.03]		0.00	0.00	**0.30** [0.18, 0.57]	0.000	0.00
NLD	0.00	0.00	0.00	0.16 [-0.08, 0.51]	**-0.28** [-0.65, -0.1]	0.12 [-0.03, 0.3]		0.00	**0.40** [0.13, 0.85]	0.04 [-0.16, 0.3]	**0.31** [0.07, 0.7]
SWE	0.00	0.00	0.00	0.00	-0.07 [-0.26, 0.01]	0.00	-0.04 [-0.24, 0.09]		0.00	0.00	**0.16** [0.04, 0.48]
CHE	0.12 [0, 0.34]	0.00	0.00	0.00	**-0.17** [-0.42, -0.07]	**0.12** [0.02, 0.25]	**-0.18** [-0.46, -0.07]	0.08 [-0.01, 0.22]		0.10 [-0.04, 0.35]	0.01 [-0.1, 0.11]
GBR	**0.12** [0.03, 0.33]	0.00	0.00	0.00	**-0.14** [-0.35, -0.02]	0.00	**-0.33** [-0.7, -0.15]	**0.19** [0.07, 0.4]	**0.40** [0.22, 0.76]		0.01 [-0.16, 0.15]
USA	**0.21** [0.1, 0.47]	0.00	0.00	-0.05 [-0.23, 0.05]	**-0.17** [-0.41, -0.09]	0.03 [-0.03, 0.11]	**-0.15** [-0.45, -0.02]	**0.21** [0.13, 0.44]	**0.18** [0.07, 0.48]	0.05 [-0.07, 0.22]	
Average	0.15	-0.01	0.05	0.01	-0.16	0.03	-0.18	0.09	0.26	0.02	0.10

Table A6: Adaptive Elastic Net Results for General Model Specification: 1982:9-2002:9 and 2002:10-2010:12 Contd.

						1982:9-2002:9					
Country (i)	$\hat{\beta}^*_{i\,,\mathrm{AUS}}$	$\hat{\beta}^*_{i\,,\mathrm{CAN}}$	$\hat{\beta}^*_{i\,,\mathrm{FRA}}$	$\hat{\beta}^*_{i\,,\mathrm{DEU}}$	$\hat{\beta}^*_{i\,,\mathrm{ITA}}$	$\hat{\beta}^*_{i\,,\mathrm{JPN}}$	$\hat{\beta}^*_{i\,,\mathrm{NLD}}$	$\hat{\beta}^*_{i\,,\mathrm{SWE}}$	$\hat{\beta}^*_{i\,,\mathrm{CHE}}$	$\hat{\beta}^*_{i\,,\mathrm{GBR}}$	$\hat{\beta}^*_{i\,,\mathrm{USA}}$
AUS		0.00	0.02	**0.10**	0.00	0.03	0.00	0.00	0.00	0.00	0.00
			[-0.05, 0.11]	[0.03, 0.25]		[0, 0.09]			[-0.11, 0.08]		
CAN	0.00		0.07	0.00	0.00	0.00	**-0.17**	**0.11**	0.00	0.00	0.00
			[-0.01, 0.18]				[-0.34, -0.07]	[0.05, 0.2]			
FRA	0.00	0.00		0.00	0.00	0.00	0.00	**0.13**	0.00	0.00	0.00
								[0.08, 0.24]			
DEU	-0.04	0.00	**0.08**		0.00	0.00	0.00	**0.09**	0.00	0.00	0.00
	[-0.17, 0.02]		[0.01, 0.21]					[0.04, 0.21]			
ITA	**-0.13**	0.00	**0.19**	0.03		0.00	**-0.33**	0.00	**0.18**	**0.17**	0.00
	[-0.31, -0.06]		[0.06, 0.42]	[-0.06, 0.16]			[-0.69, -0.24]		[0.07, 0.43]	[0.03, 0.45]	
JPN	**-0.07**	0.00	**0.16**	**-0.17**	0.00		0.00	**0.06**	0.00	**0.106**	0.00
	[-0.2, -0.01]		[0.08, 0.32]	[-0.36, -0.1]				[0.005, 0.16]		[0.01, 0.26]	
NLD	-0.03	**0.16**	**0.09**	0.00	0.00	0.00		**0.11**	0.10	0.00	0.00
	[-0.15, 0.06]	[0.05, 0.33]	[0.01, 0.22]					[0.03, 0.21]	[-0.02, 0.28]		
SWE	**-0.25**	**0.27**	0.00	0.14	0.08	0.00	**-0.28**		0.00	0.19	0.14
	[-0.49, -0.11]	[0.09, 0.53]		[-0.01, 0.35]	[-0.07, 0.25]		[-0.64, -0.06]			[-0.01, 0.47]	[-0.1, 0.39]
CHE	0.00	0.00	0.00	0.00	0.00	0.00	0.00	**0.14**		0.00	0.00
								[0.09, 0.25]			
GBR	0.00	0.07	0.09	-0.05	0.00	0.04	**-0.17**	0.05	0.00		0.02
		[-0.04, 0.2]	[-0.03, 0.24]	[-0.16, 0.04]		[-0.03, 0.12]	[-0.33, -0.06]	[-0.02, 0.14]			[-0.09, 0.12]
USA	0.00	0.00	0.00	0.00	0.00	0.00	0.00	**0.03**	0.00	0.00	
							[-0.07, 0.04]	[0.01, 0.09]			
Average	-0.05	0.05	0.07	0.00	0.01	0.00	-0.09	0.07	0.03	0.05	0.02
						2002:10-2010:12					
Country (i)	$\hat{\beta}^*_{i\,,\mathrm{AUS}}$	$\hat{\beta}^*_{i\,,\mathrm{CAN}}$	$\hat{\beta}^*_{i\,,\mathrm{FRA}}$	$\hat{\beta}^*_{i\,,\mathrm{DEU}}$	$\hat{\beta}^*_{i\,,\mathrm{ITA}}$	$\hat{\beta}^*_{i\,,\mathrm{JPN}}$	$\hat{\beta}^*_{i\,,\mathrm{NLD}}$	$\hat{\beta}^*_{i\,,\mathrm{SWE}}$	$\hat{\beta}^*_{i\,,\mathrm{CHE}}$	$\hat{\beta}^*_{i\,,\mathrm{GBR}}$	$\hat{\beta}^*_{i\,,\mathrm{USA}}$
AUS		0.00	**-0.38**	**-0.12**	0.00	0.00	0.00	**0.20**	**0.37**	0.00	0.00
			[-0.86, -0.32]	[-0.35, -0.02]				[0.09, 0.47]	[0.25, 0.8]		
CAN	0.00		**-0.29**	0.00	0.00	0.00	0.00	**0.34**	0.08	0.00	**0.21**
			[-0.67, -0.19]					[0.15, 0.59]	[-0.02, 0.28]		[0.06, 0.51]
FRA	**0.21**	0.00		0.00	**-0.29**	0.00	0.00	0.00	**0.50**	0.00	0.00

	[0.09, 0.54]				[-0.68, -0.27]				[0.43, 0.85]		
DEU	**0.54**	-0.18	-0.31		**-0.48**	-0.06	-0.26	0.04	**0.59**	0.17	**0.47**
	[0.11, 1.05]	[-0.5, 0.09]	[-0.85, 0.11]		[-0.87, -0.19]	[-0.26, 0.1]	[-0.71, 0.1]	[-0.17, 0.29]	[0.25, 1.08]	[-0.19, 0.63]	[0.1, 0.97]
ITA	**0.52**	0.00	0.05	-0.16		-0.09	-0.25	**0.21**	**0.45**	0.00	**0.24**
	[0.24, 0.95]		[-0.16, 0.37]	[-0.48, 0.02]		[-0.3, 0.01]	[-0.71, 0.03]	[0.09, 0.48]	[0.2, 0.9]		[0, 0.62]
JPN	0.01	0.24	-0.21	0.00	-0.14		0.00	0.00	**0.51**	0.00	0.00
	[-0.16, 0.17]	[-0.04, 0.62]	[-0.62, 0.03]		[-0.4, 0.02]				[0.33, 0.93]		
NLD	0.02	0.00	0.00	0.00	**-0.31**	0.00		0.00	**0.46**	0.00	**0.36**
	[-0.12, 0.16]				[-0.7, -0.2]				[0.3, 0.89]		[0.18, 0.79]
SWE	0.00	0.00	0.00	0.00	-0.03	0.00	0.00		**0.15**	0.00	0.03
					[-0.16, 0.01]				[0.06, 0.39]		[-0.2, 0.24]
CHE	**0.23**	0.00	0.00	0.00	**-0.24**	0.00	0.00	0.00		0.00	0.02
	[0.14, 0.54]				[-0.56, -0.23]						[-0.09, 0.12]
GBR	0.11	0.00	0.00	0.00	**-0.21**	0.00	**-0.20**	**0.13**	**0.38**		0.08
	[0, 0.34]				[-0.48, -0.18]		[-0.52, -0.08]	[0.05, 0.33]	[0.25, 0.77]		[-0.07, 0.32]
USA	**0.30**	0.00	**-0.41**	0.00	-0.12	**-0.07**	0.00	**0.30**	**0.32**	0.04	
	[0.18, 0.65]		[-0.9, -0.28]		[-0.34, 0.03]	[-0.21, -0.02]		[0.14, 0.59]	[0.16, 0.74]	[-0.19, 0.31]	
Average	0.19	0.01	-0.12	-0.02	-0.18	-0.02	-0.07	0.10	0.35	0.02	0.14

Table A6: Adaptive Elastic Net Results for General Model Specification: 1982:9-2007:5 and 2007:6-2010:12 Contd.

1982:9-2007:5											
Country (*i*)	$\hat{\beta}^*_{i,\text{AUS}}$	$\hat{\beta}^*_{i,\text{CAN}}$	$\hat{\beta}^*_{i,\text{FRA}}$	$\hat{\beta}^*_{i,\text{DEU}}$	$\hat{\beta}^*_{i,\text{ITA}}$	$\hat{\beta}^*_{i,\text{JPN}}$	$\hat{\beta}^*_{i,\text{NLD}}$	$\hat{\beta}^*_{i,\text{SWE}}$	$\hat{\beta}^*_{i,\text{CHE}}$	$\hat{\beta}^*_{i,\text{GBR}}$	$\hat{\beta}^*_{i,\text{USA}}$
AUS		0.00	0.01	**0.10**	0.00	0.01	0.00	0.00	0.00	0.00	0.00
			[-0.05, 0.07]	[0.04, 0.22]		[-0.01, 0.05]					
CAN	0.00		**0.04**	0.00	0.00	0.00	**-0.07**	**0.11**	0.00	0.00	0.00
			[0, 0.13]				[-0.19, -0.03]	[0.06, 0.19]			
FRA	0.00	0.00		0.00	0.00	0.00	-0.01	**0.10**	0.00	0.00	0.03
							[-0.11, 0.03]	[0.07, 0.2]			[-0.03, 0.1]
DEU	-0.08	0.00	0.06		0.01	0.00	**-0.03**	0.08	0.08	0.00	0.09
	[-0.25, 0.03]		[-0.05, 0.21]		[-0.04, 0.07]		[-0.17, 0.07]	[0, 0.19]	[-0.044, 0.26]		[-0.05, 0.26]
ITA	**-0.12**	0.00	**0.18**	0.06		0.00	**-0.35**	0.01	**0.17**	**0.17**	0.00
	[-0.29, -0.04]		[0.05, 0.38]	[-0.03, 0.2]			[-0.67, -0.25]	[-0.04, 0.07]	[0.05, 0.38]	[0.03, 0.42]	
JPN	-0.03	0.00	**0.14**	**-0.08**	0.00		0.00	0.01	0.00	0.07	0.00
	[-0.11, 0.01]		[0.08, 0.31]	[-0.22, -0.05]				[-0.03, 0.07]		[0, 0.19]	
NLD	0.00	0.07	0.05	0.00	0.00	0.00		**0.09**	**0.14**	0.00	0.04
		[-0.03, 0.19]	[-0.02, 0.15]					[0.01, 0.19]	[0, 0.34]		[-0.04, 0.15]
SWE	**-0.16**	**0.18**	0.00	0.08	0.06	0.00	**-0.19**		0.00	0.12	**0.18**
	[-0.37, -0.06]	[0.05, 0.39]		[-0.03, 0.25]	[-0.06, 0.2]		[-0.49, -0.08]			[-0.01, 0.32]	[0.02, 0.41]
CHE	0.00	0.00	0.00	0.00	0.00	0.00	0.00	**0.11**		0.00	0.05
								[0.06, 0.19]			[-0.04, 0.14]
GBR	0.00	0.00	0.06	0.00	0.00	0.016	**-0.16**	0.05	0.00		0.08
			[-0.03, 0.19]			[-0.03, 0.07]	[-0.33, -0.09]	[-0.01, 0.13]			[-0.03, 0.22]
USA	0.00	0.00	0.00	0.00	0.00	-0.02	**-0.05**	**0.07**	0.00	0.00	
				[-0.05, 0.04]		[-0.07, 0.01]	[-0.15, -0.01]	[0.04, 0.15]			
Average	-0.04	0.02	0.05	0.01	0.01	0.00	-0.09	0.06	0.04	0.04	0.05

2007:6-2010:12											
Country (*i*)	$\hat{\beta}^*_{i,\text{AUS}}$	$\hat{\beta}^*_{i,\text{CAN}}$	$\hat{\beta}^*_{i,\text{FRA}}$	$\hat{\beta}^*_{i,\text{DEU}}$	$\hat{\beta}^*_{i,\text{ITA}}$	$\hat{\beta}^*_{i,\text{JPN}}$	$\hat{\beta}^*_{i,\text{NLD}}$	$\hat{\beta}^*_{i,\text{SWE}}$	$\hat{\beta}^*_{i,\text{CHE}}$	$\hat{\beta}^*_{i,\text{GBR}}$	$\hat{\beta}^*_{i,\text{USA}}$
AUS		0.01	0.00	**-0.34**	**-0.23**	0.00	0.00	**0.36**	**0.53**	-0.17	0.00
		[-0.22, 0.24]		[-0.86, -0.1]	[-0.55, -0.08]			[0.22, 0.7]	[0.3, 1.16]	[-0.6, 0.07]	
CAN	0.00		0.00	0.00	0.00	0.00	0.00	**0.33**	0.00	0.00	0.00
								[0.22, 0.59]			
FRA	0.23	0.20		-0.18	**-0.51**	-0.01	**-0.37**	**0.34**	**0.96**	0.00	0.00
	[0, 0.58]	[-0.04, 0.62]		[-0.5, 0]	[-0.95, -0.34]	[-0.24, 0.14]	[-0.92, -0.07]	[0.23, 0.67]	[0.83, 1.56]		
DEU	**0.42**	0.07	-0.07		**-0.34**	0.00	**-0.41**	**0.21**	**0.69**	0.00	0.00

	[0.22, 0.92]	[-0.16, 0.38]	[-0.22, 0.01]		[-0.72, -0.32]		[-1, -0.12]	[0.1, 0.52]	[0.463, 1.41]		
ITA	**0.25**	0.21	0.00	0.00		0.00	**-0.49**	**0.33**	**0.99**	0.00	0.00
	[0.05, 0.66]	[-0.05, 0.65]					[-1.22, -0.13]	[0.19, 0.64]	[0.74, 1.66]		
JPN	0.00	0.17	0.00	0.05	0.00		0.00	0.00	0.04	0.00	0.00
		[-0.05, 0.51]		[-0.05, 0.16]					[-0.14, 0.18]		
NLD	0.00	0.34	0.00	0.00	**-0.40**	0.00		**0.37**	**0.92**	0.00	0.16
		[-0.02, 0.85]			[-0.87, -0.11]			[0.23, 0.64]	[0.59, 1.57]		[-0.15, 0.52]
SWE	0.00	0.00	**-0.62**	0.00	0.00	0.00	0.00		**0.90**	0.00	0.00
			[-1.35, -0.58]						[0.75, 1.92]		
CHE	**0.27**	**0.23**	0.00	**-0.28**	**-0.28**	0.00	**-0.34**	**0.32**		0.00	0.00
	[0.06, 0.6]	[0.05, 0.59]		[-0.66, -0.1]	[-0.52, -0.16]		[-0.82, -0.11]	[0.2, 0.6]			
GBR	0.00	0.00	0.00	**-0.05**	**-0.28**	0.000	**-0.18**	**0.22**	**0.66**		0.00
				[-0.2, 0.04]	[-0.62, -0.34]		[-0.5, -0.02]	[0.17, 0.46]	[0.63, 1.31]		
USA	0.00	**0.26**	-0.20	0.00	**-0.41**	0.00	-0.23	**0.50**	**0.71**	0.00	
		[0.09, 0.67]	[-0.66, 0.08]		[-0.92, -0.31]		[-0.71, 0.06]	[0.31, 0.93]	[0.51, 1.5]		
Average	0.12	0.15	-0.09	-0.05	-0.22	0.00	-0.20	0.26	0.59	0.00	0.02

Table A7: News-Diffusion Model Parameter Estimates

i	1982:9-2000:8				
	$\tilde{\beta}_{i,b}$	$\tilde{\beta}_{i,d}$	$\tilde{\lambda}_{i,USA}$	$\tilde{\theta}_{i,USA}$	$\tilde{\beta}_{i,USA}$
AUS	0.12	-2.56	**0.55**	0.89	0.06
	(1.11)	(-1.10)	(4.08)	(-0.81)	(0.71)
CAN	-0.01	-0.82	**0.83**	**0.91**	**0.08**
	(-0.08)	(-0.44)	(9.89)	(-1.61)	(1.45)
FRA	-0.21	**2.36**	**0.90**	**0.78**	**0.20**
	(-1.10)	(1.26)	(7.02)	(-2.94)	(2.25)
DEU	-0.26	1.58	**0.79**	**0.74**	**0.20**
	(-0.05)	(0.76)	(4.96)	(-2.33)	(1.73)
ITA	0.00	-0.32	**0.69**	**0.80**	0.14
	(0.01)	(-0.15)	(3.62)	(-1.42)	(1.09)
JPN	0.10	**1.39**	**0.54**	0.83	0.09
	(0.44)	(1.48)	(3.35)	(-1.02)	(0.82)
NLD	**-0.47**	1.65	**0.94**	**0.75**	**0.23**
	(-2.88)	(1.09)	(7.29)	(-3.10)	(2.31)
SWE	**-0.25**	1.70	**1.16**	**0.62**	**0.44**
	(-1.28)	(0.63)	(6.82)	(-5.35)	(3.57)
CHE	**-0.21**	0.48	**0.94**	**0.78**	**0.21**
	(-1.63)	(0.37)	(7.92)	(-2.86)	(2.26)
GBR	-1.10	1.63	**0.85**	**0.85**	**0.13**
	(-0.81)	(0.96)	(8.83)	(-2.11)	(1.76)
USA	0.18	-0.86			
	(1.12)	(-0.90)			
Pooled	**-0.18**	-0.12	**0.86**	**0.84**	**0.13**
	(-3.78)	(-0.27)	(18.60)	(-5.39)	(4.55)

i	2000:9-2010:12				
	$\tilde{\beta}_{i,b}$	$\tilde{\beta}_{i,d}$	$\tilde{\lambda}_{i,USA}$	$\tilde{\theta}_{i,USA}$	$\tilde{\beta}_{i,USA}$
AUS	0.02	**6.41**	**0.68**	0.92	0.05
	(0.06)	(1.78)	(8.25)	(-0.72)	(0.68)
CAN	-0.43	**5.12**	**0.85**	**0.8**	**0.17**
	(-1.2)	(2.32)	(8.62)	(-2.05)	(1.75)
FRA	-0.34	3.96	**0.93**	1.02	-0.02
	(-0.81)	(1.21)	(8.91)	(0.22)	(-0.22)
DEU	**-0.83**	1.41	**1**	1.04	-0.04
	(-2.02)	(0.49)	(7.71)	(0.37)	(-0.38)
ITA	-0.17	**5.11**	**1.03**	0.91	0.09
	(-0.42)	(1.62)	(7.93)	(-1.15)	(1.04)
JPN	-1.58	**3.59**	**0.67**	0.91	0.06
	(-0.77)	(1.56)	(4.72)	(-0.53)	(0.49)
NLD	-0.32	**4.42**	**1.11**	0.89	0.12
	(-0.95)	(1.5)	(8.09)	(-1.13)	(1.02)
SWE	**-0.79**	**7.88**	**1.12**	0.99	0.01
	(-2.09)	(2.54)	(6.67)	(-0.09)	(0.09)
CHE	**-0.7**	1.5	**0.71**	0.95	0.04
	(-1.72)	(0.73)	(8.31)	(-0.51)	(0.49)
GBR	-0.15	**6.45**	**0.77**	0.98	0.01
	(-0.63)	(2.03)	(9.41)	(-0.18)	(0.18)
USA	-0.08	**7.68**			
	(-0.29)	(2.51)			
Pooled	**-0.84**	-0.84	**0.86**	**0.95**	**0.04**
	(-5.88)	(-0.98)	(27.28)	(-1.55)	(1.49)

i	1982:9-2002:9				
	$\tilde{\beta}_{i,b}$	$\tilde{\beta}_{i,d}$	$\tilde{\lambda}_{i,USA}$	$\tilde{\theta}_{i,USA}$	$\tilde{\beta}_{i,USA}$
AUS	0.14	-2.22	**0.55**	0.9	0.05
	(1.39)	(-0.98)	(5.11)	(-0.87)	(0.78)
CAN	-0.03	0.67	**0.88**	**0.91**	0.08
	(-0.19)	(0.37)	(13.34)	(-2.02)	(1.85)
FRA	-0.05	**2.54**	**0.97**	**0.81**	**0.19**
	(-0.3)	(1.49)	(9.41)	(-3.08)	(2.54)
DEU	-0.23	**3.46**	**0.9**	**0.79**	**0.19**
	(-0.94)	(1.69)	(7.11)	(-2.41)	(1.97)
ITA	0.11	-0.5	**0.76**	**0.85**	0.12
	(0.9)	(-0.27)	(4.93)	(-1.33)	(1.11)
JPN	0.2	**1.15**	**0.54**	0.92	0.04
	(1.02)	(1.33)	(4.04)	(-0.49)	(0.44)
NLD	**-0.39**	**2.99**	**1**	**0.78**	**0.22**
	(-2.53)	(2.24)	(9.65)	(-3.37)	(2.69)
SWE	0.04	0.72	**1.26**	**0.67**	**0.42**
	(0.25)	(0.31)	(9.5)	(-5.47)	(4.11)
CHE	**-0.2**	**2.1**	**0.95**	**0.8**	**0.2**
	(-1.65)	(1.7)	(10.27)	(-3.21)	(2.63)
GBR	-0.07	**2.97**	**0.82**	**0.88**	**0.09**
	(-0.58)	(2.02)	(10.09)	(-1.68)	(1.48)
USA	0.17	0.48			
	(1.05)	(0.55)			
Pooled	0.04	**0.55**	**0.89**	**0.86**	**0.13**
	(0.79)	(1.4)	(21.03)	(-5.37)	(4.62)

i	2002:10-2010:12				
	$\tilde{\beta}_{i,b}$	$\tilde{\beta}_{i,d}$	$\tilde{\lambda}_{i,USA}$	$\tilde{\theta}_{i,USA}$	$\tilde{\beta}_{i,USA}$
AUS	-0.11	0.53	**0.84**	**0.85**	**0.12**
	(-0.2)	(0.09)	(7.87)	(-1.5)	(1.35)
CAN	-0.17	-0.78	**0.86**	**0.76**	0.2
	(-0.34)	(-0.24)	(5.69)	(-1.69)	(1.39)
FRA	-0.31	-1.04	**1.01**	0.9	0.1
	(-0.59)	(-0.23)	(8.41)	(-1.1)	(1.01)
DEU	-0.39	-1.4	**1.14**	0.91	0.1
	(-0.73)	(-0.3)	(6.69)	(-0.87)	(0.79)
ITA	-0.14	-1.08	**1.03**	0.89	0.12
	(-0.25)	(-0.28)	(7.03)	(-1.13)	(1)
JPN	**-4.25**	-0.25	**0.8**	0.85	0.12
	(-1.66)	(-0.09)	(4.69)	(-1.08)	(0.93)
NLD	-0.24	-0.23	**1.22**	**0.81**	**0.23**
	(-0.5)	(-0.06)	(7.37)	(-1.93)	(1.63)
SWE	-0.55	1.47	**0.92**	1.01	-0.01
	(-0.98)	(0.35)	(3.91)	(0.07)	(-0.07)
CHE	-0.5	-1.57	**0.82**	0.89	0.09
	(-0.75)	(-0.54)	(7.66)	(-1.07)	(0.98)
GBR	-0.06	1.59	**0.87**	0.9	0.09
	(-0.19)	(0.32)	(7.43)	(-0.94)	(0.85)
USA	-0.23	-1.2			
	(-0.68)	(-0.24)			
Pooled	**-0.66**	-3.08	**0.88**	**0.93**	**0.06**
	(-4.98)	(-3.18)	(22.35)	(-1.48)	(1.41)

	1982:9-2007:5									
i	$\tilde{\beta}_{i,b}$	$\tilde{\beta}_{i,d}$	$\tilde{\lambda}_{i,USA}$	$\tilde{\theta}_{i,USA}$	$\tilde{\beta}_{i,USA}$	i	$\tilde{\beta}_{i,b}$	$\tilde{\beta}_{i,d}$	$\tilde{\lambda}_{i,USA}$	$\tilde{\theta}_{i,USA}$	$\tilde{\beta}_{i,USA}$
AUS	0.11	-2.31	**0.58**	**0.88**	0.07	NLD	-0.14	**1.58**	**1.06**	**0.79**	**0.22**
	(1.22)	(-1.14)	(6.02)	(-1.3)	(1.15)		(-1.08)	(1.34)	(10.92)	(-3.78)	(3.07)
CAN	-0.1	0.52	**0.87**	**0.88**	**0.11**	SWE	-0.02	0.74	**1.27**	**0.71**	**0.37**
	(-0.73)	(0.33)	(14.6)	(-2.95)	(2.64)		(-0.2)	(0.45)	(10.33)	(-5)	(3.93)

FRA	0	1.45	**1**	**0.82**	**0.18**	CHE	-0.13	**1.46**	**0.97**	**0.79**	**0.2**
	(0.02)	(1.17)	(10.72)	(-3.36)	(2.8)		(-1.19)	(1.36)	(11.25)	(-3.87)	(3.14)
DEU	-0.16	1.85	**1.01**	**0.81**	**0.19**	GBR	-0.08	**2.52**	**0.84**	**0.87**	**0.11**
	(-0.69)	(1.03)	(8.25)	(-2.72)	(2.27)		(-0.72)	(1.86)	(11.04)	(-2.21)	(1.91)
ITA	0.02	0.4	**0.82**	**0.83**	**0.14**	USA	0.09	0.24			
	(0.24)	(0.28)	(6.1)	(-1.92)	(1.57)		(0.72)	(0.32)			
JPN	0.12	**1.43**	**0.59**	**0.84**	**0.09**	Pooled	**-0.1**	**0.62**	**0.9**	**0.85**	**0.14**
	(0.68)	(1.76)	(4.93)	(-1.31)	(1.1)		(-2.31)	(1.92)	(23.9)	(-6.94)	(5.99)