International Tail Risk and World Fear*

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November 21, 2017

Abstract

We examine the pricing of tail risk in international stock markets. We find that the tail risk of different countries is highly integrated. Introducing a new *World Fear* index, we find that local and global aggregate market returns are mainly driven by global tail risk rather than local tail risk. World fear is also priced in the cross-section of stock returns. Buying stocks with high sensitivities to World Fear while selling stocks with low sensitivities generates excess returns of up to 2.72% per month.

JEL classification: G01, G11, G12, G17

Keywords: Jump Risk; Tail Risk; International Stock Market Returns; Return Predictability; International Asset Pricing; Factor Models

*We thank Yufeng Han (EFA discussant), Fabian Hollstein, Michael Stutzer (MFA discussant) as well as participants at the meeting of the Eastern Finance Association (2017) and Midwestern Finance Association (2017) and the research seminar in Leibniz University Hannover (2016) for valuable comments. Contact: nguyen@fmt.uni-hannover.de (D.B.B Nguyen), prokopczuk@fmt.uni-hannover.de (M. Prokopczuk) and c.wese-simen@icmacentre.ac.uk (C. Wese Simen).

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I Introduction

"Not every business cycle has a financial crisis.

Frequently they do."

— Kenneth Arrow

The study of tail risk has been the focus of recent studies, especially since past years have been marked by times of financial distress like the burst of the dot-com bubble, the Lehman default, the great recession followed by the European debt crisis and the Chinese stock market crash.

In this paper, we examine the pricing of tail risk in international equity markets. We begin by analyzing the tail risk of each country and analyze their comovements. Motivated by the finding that tail risk comoves across countries, we construct a global version of tail risk which we call World Fear (WF). We then investigate the asset implication of World Fear for international stock returns both in the time-series and the cross-section.

Our key findings can be summarized as follows. First, there is a positive and significant relationship between World Fear and future aggregate market returns around the globe. A one-standard-deviation increase in World Fear predicts an increase of future excess returns by up to 8.46% at the one year horizon. The explanatory power in terms of R^2 is highest for the one year horizon with values between 3.57% and 18.10%. We also find that World Fear is a strong predictor of the cross-section of stock returns for most countries. Stocks that have a high exposure to World Fear significantly outperform stocks with low exposure by 1.06%, 1.28%, 2.72%, 0.97% and 1.00% per month in Canada, France, Germany, Italy and the U.K., respectively. Overall, we document a positive and statistically significant risk premium associated with World Fear for international markets. We present a potential explanation for the predictive power of World Fear. To achieve this goal, we explore the link between World Fear and the real economy.

Our empirical results establish that an increase in World Fear is followed by higher unemployment in subsequent months for all countries followed by a slow recovery.

The modeling of tail risk can be generally separated into two strands of literature. The first is based on option implied measures. Using deep-out-of-the-money and short maturity options of the S&P 500 index, Bollerslev et al. (2015) decompose the variance risk premium into a premium for diffusive and a premium for large movements referred to as jump tail variation or fear. Cremers et al. (2015) use at-the-money S&P 500 straddles to capture jump and volatility risk portfolios. More precisely, they relate jump and volatility risk to the Black-Scholes greeks and create mimicking portfolios by ensuring that they are market-neutral, vega-neutral (vega-positive) and gamma-positive (gamma-neutral) for the jump (volatility) factor. The second stream relies on underlying return data. For instance, Bollerslev & Todorov (2011) use high-frequency S&P 500 index returns in order to quantify the tail risk of the S&P 500. Kelly & Jiang (2014) use the cross-section of stock returns in the U.S. to estimate the tail risk of the equity market.

While the data set for options is limited for international countries, papers using tail risk estimation based on returns data mainly focus on the U.S. We contribute to the literature by providing international evidence of tail risk based on returns data.[1]

Our work adds to the growing literature that analyzes the predictability of returns in an international context. For instance, Ang & Bekaert (2007) study the predictive power of traditional predictors such as dividend yields and short rates in international countries. Bollerslev et al. (2014) introduce the global variance risk premium and show that it outperforms the local variance risk premium in predicting aggregate local market returns. Relative to these studies, we introduce a new predictor, which we denote World

[1] When we started this project, we could not find any study that focused on tail risk in international markets. After completing the current version of our paper, we have become aware of Wang (2015), which also examines international markets.

Fear, and contribute to the literature on international return predictability of both the aggregate market and the cross-section of stock returns. The impact of World Fear is both economically and statistically significant.

The rest of the paper is organized as follows. Section II describes our data set and methodology. Section III discusses the results related to local and global tail risk. Section IV analyzes a possible economic mechanism. Section V presents robustness tests and Section VI concludes.

II Data and Methodology

A Data

Our primary data set contains stock returns of the G-7 countries: Canada, France, Germany, Italy, Japan, the U.K. and the U.S. This choice is motivated by the economic importance of these countries on the one hand, and data availability on the other. Equity price and market capitalization data are obtained from Datastream except for the U.S. data which are from the Center for Research in Security Prices (CRSP). We include the universe of stocks from the major exchanges for each country, which are defined as the exchanges in which the majority of the stocks are traded. Canada, France, Italy and the U.K. have a single major exchange while there are two for Germany (Frankfurt and Xetra) and Japan (Osaka and Tokyo), and three for the U.S. (AMEX, NYSE and NASDAQ).

The data span the period from January 2000 to December 2015, including a total of 4,023 trading days. Most companies are from the U.S. with a median of about 5,000 stocks over the whole sample period, followed by Japan with a median of around 3,500.

Italy has the smallest number of equities with a median of just 274.[2] CRSP total returns (including dividends) are obtained directly from CRSP for the U.S. while local returns are calculated using total return indices for the remaining countries from Datastream. We conduct our analyses in U.S. dollar returns. We convert the returns into U.S. dollar returns using the corresponding exchange rates from Datastream.

Following existing studies such as Lesmond (2005) and Lee (2011), we include all listed and delisted companies and exclude Depository Receipts (DRs), Real Estate Investment Trusts (REITs) and preferred stocks from Datastream. For the U.S. market, we only include stocks with share codes 10 and 11, following Kelly & Jiang (2014). As in Hou et al. (2011) and Lee (2011) , we exclude anomalous observations. More specifically, if the current or past return, r_t or r_{t-1}, are higher than 300% and $(1+r_t)(1+r_{t-1})-1 < 50\%$ both r_t and r_{t-1} are set missing.[3] Moreover, we require a minimum number of return observations per trading day. If more than 90% of the stocks have zero returns on a day, the day is declared as non-trading and dropped (see, e.g., Amihud (2002), Lesmond (2005) and Lee (2011)). Lastly, we require a minimum price in order to exclude illiquid stocks. We follow Lee (2011) and set the lower limit at 0.01.

Table 1 summarizes descriptive statistics for the daily returns of the cross-section of the individual countries. We report means, standard deviations, selected quantiles, skewness and kurtosis. The average cross-sectional median return is close to zero.[4] The

[2]Even though equity data goes back as far as 1980, we focus on the most recent years. This choice is motivated by data availability. The year 1980 starts with just under 8,000 stocks across all countries from which around 4,000 are U.S. equities. Starting in 2000, the sample size rises to above 15,000. Moreover, for our robustness checks, some predictor variables, e.g. the implied volatility indices, are available starting in 2000 only.

[3]The cutoff level of 300% employed in extant studies is somewhat arbitrary. As robustness check, we therefore also estimate JKTR using raw data without the 300% return cutoff. The correlations of JKTR based on raw and cleaned data are essentially 100% and the return predictability regressions deliver qualitatively and quantitatively similar results. We also experiment with cutoff values of 100% and 200% and lower limits of 0.05 and 0.10. The correlation coefficients with our main estimates vary between 98.96% and 100% and the return predictability regressions again deliver qualitatively and quantitatively similar results.

[4]Even though the mean returns are relatively high for Canada, France and Germany, the medians are

cross-sectional distribution exhibits both high skewness and high kurtosis. In the subsequent analysis we rely on the decay of the tail rather than the higher moments to proxy for tail risk.

B Estimation of Tail Risk

This section briefly describes the estimation procedure of the tail risk introduced by Kelly & Jiang (2014), from now on referred to as JKTR. The tail risk is measured by the tail parameter of the tail distribution. The distribution of equity index returns is assumed to obey a potentially time-varying power law and the tail parameter is estimated from the cross-section of returns. The tail probability distribution of an asset's return is given by:

$$P(r^*_{i,t+1} < R | r^*_{i,t+1} < u_t; \mathbb{F}_t) = \left(\frac{R}{u_t}\right)^{-a_i/\lambda_t} \tag{1}$$

where $r^*_{i,t}$ is the return of asset i on day t, $\mathbb{F}_t$ is the information set at time t and u_t is the tail threshold, where $R < u_t < 0$.[5] The JKTR is estimated by the power law estimator of Hill (1975) using the cross-section of daily return observations for all stocks at time t:

$$JKTR_t = \frac{1}{K_t} \sum_{i=1}^{K_t} log(r^*_{i,t}) - log(u_t) \tag{2}$$

where K_t is the total number of daily returns falling below the threshold u_t for period t. Facing the trade-off between a sufficiently low threshold and an appropriate number

both of lower magnitude and in line with the remaining countries. The average cross-sectional median return varies between -0.1% and -0.01%. Since the row Mean takes the average return both in the cross-section and the time series, it is sensitive to outlier returns. When removing the outliers (0.1% and 99.9% percentiles), we find values of 0.09%, 0.06% and 0.06% for Canada, France and Germany, respectively. As noted above, we also experimented with alternative cutoffs for our empirical analysis and show that our results are robust and hence not driven by the outliers.

[5] We rely on simple returns for our estimation, i.e. $r^*_{i,t} = (P_{i,t}/P_{i,t-1}) - 1$, where $P_{i,t}$ is the total return price index of asset i on day t. We denote the returns with a superscript $(^*)$ since we work with excess returns later denoted as $r_{i,t}$.

of observations below it, the threshold is fixed to the 5% quantile of the cross-sectional return distribution using a month of daily return data (Kelly & Jiang, 2014). The JKTR can be interpreted as a rate of decay in the left tail since a higher λ_t results into a fatter left tail.

III International Tail Risk

A Estimation Results

To get an initial impression about the characteristics of international tail risk, we investigate the time series of JKTR for each country separately. Figure 1 plots monthly estimated tail risk time series for the seven countries for the period from January 2000 to December 2015. Recessions are indicated by shaded areas defined by the National Bureau of Economic Research (NBER) and the Organisation for Economic Co-operation and Development (OECD).[6] Table 2 reports summary statistics for tail risk for each country in Panel A, mean differences in Panel B and sample correlations in Panel C. The tail risk is time-varying and has its own dynamics for each country. The JKTR of Canada, France, Germany, Italy, Japan, the U.K. and the U.S. are on average 0.47, 0.59, 0.58, 0.33, 0.39, 0.54 and 0.41 over the whole sample, respectively.[7] The tail risk of France is the highest with an average value of 0.59. Italy has the lowest tail risk followed by the Japan and the U.S. with marginally higher tail risk. We examine the relationship between the level

[6]For the non-U.S. countries we rely on recession indicators from the OECD which are determined by the same methodology established by the NBER until 2008, and use a simplified version afterwards.

[7]For comparison, (standard) normal distributed returns show a JTKR value of 0.21. Returns following a t-distribution with $3, 5$ or 10 degrees of freedom exhibit JKTR values of 0.41, 0.32 and 0.26, respectively. The corresponding p-value or probability of a $3 - \sigma$ event is 0.13% for the standard normal distribution. For the t-distributions with 3, 5 or 10 degrees of freedom the probabilities are 0.72%, 0.59% and 0.37%, respectively. The estimates are means obtained by applying the Hill estimator to random samples with the according distributions. We repeat the procedure 10,000 times for an exemplary country with 500 stocks and 20 daily return observations in a month.

of tail risk and its price as a risk factor in the cross-section in Section III.E.

The tail risks for all countries except for Japan are moderately persistent with first-order autocorrelations of typically 50% and as high as 83% for Germany. While Kelly & Jiang (2014) show the predictive power of the U.S. tail risk for the stock market, we investigate the predictive power for the other countries in Section III.D.

Kelly & Jiang (2014) find for the U.S. that the tail risk is countercyclical and stays flat during the financial crisis in 2007-2009. This may seem surprising. They argue that volatility is predictable over short horizons for that time and that the JKTR is a volatility-adjusted measure. The time-varying threshold u_t is viewed as a proxy for market volatility with a correlation of 60%. The effect of dramatic changes in volatility is absorbed by the time-varying threshold and hence the JKTR is unaffected. Figure 2 illustrates this feature of the JKTR. The JKTR for the U.S. for example is very similar during both relatively calm (09/2003) and turbulent (09/2008) times. The obtained estimates are $JKTR_{2003} = JKTR_{2008} = 0.38$, indicating equally heavy tails. But the relatively low estimate during the financial crisis is due to the time-varying threshold and the resulting volatility adjustment. The tail distribution is plotted for the two identical JKTR estimates but different thresholds. By utilizing a lower threshold the tail becomes drastically fatter as it is the case during the financial crisis. The JKTR is hence a volatility-adjusted measure.[8]

Similar to the U.S., the tail risk of the remaining countries does not show clear peaks in the times of financial distress indicated by the OECD. The tail risk measures of France and Germany show the highest fluctuations, exhibiting low values at the beginning of

[8]In this paper we focus on the asset implications of tail risk and World Fear rather than the relationship or differences concerning tail risk and volatility. Nonetheless, we control for two volatility factors in our asset pricing tests in Section III.E and thus show that the stocks' sensitivity to World Fear contains information about future excess returns beyond that of volatility.

the sample which are more than doubled by the end of the sample, while the tail risk measure of Italy is rather stable. These findings are also supported by the high (low) standard deviations. Looking at the reported correlations in more detail, we observe that the correlations are positive for the tail risk of all countries (except for the pair Canada–Germany). Canada and the U.K. show the highest correlation coefficient with a value of 0.70. The JTKR of the U.K. and the U.S. are also highly correlated, with a value of 0.63. With correlation coefficients as low as 0.09, the tail risk of Germany and the U.K. exhibit the lowest overall correlation with other countries. Overall, the markets show a positive contemporaneous relation. We investigate whether there is a lead-lag relationship between the tail risk of the countries in Section III.B.

B Granger Causality

After examining each country individually, we now turn to lead-lag relationships of international tail risk. In order to further quantify the interactions between international tail risks, we estimate vector autoregressive (VAR) models and perform a series of Granger causality tests (Granger, 1969).[9] In the following model:

$$\begin{pmatrix} JKTR_t^i \\ JKTR_t^j \end{pmatrix} = \begin{pmatrix} \alpha_{1,0} \\ \alpha_{2,0} \end{pmatrix} + \sum_{p=1}^{P} \begin{pmatrix} \beta_{1,p} & \gamma_{1,p} \\ \beta_{2,p} & \gamma_{2,p} \end{pmatrix} \begin{pmatrix} JKTR_{t-p}^i \\ JKTR_{t-p}^j \end{pmatrix} + \begin{pmatrix} \epsilon_{i,t} \\ \epsilon_{j,t} \end{pmatrix} \tag{3}$$

the null hypothesis that tail risk JKTR of country i does not Granger-cause the tail risk of country j is rejected if the coefficients of the lagged terms of country i in the equation of country j are not jointly equal to zero. The joint significance of the coefficients is tested using an F-test. The optimal lag order P is chosen according to the Bayesian

[9] To ascertain that the series are stationary, the Phillips-Perron test and the Augmented Dickey-Fuller test are performed. We test the null hypothesis that the time series has a unit-root against the alternative of stationarity. The null can be rejected for all countries using both tests.

Information Criterion (BIC).

The results can be summarized as follows.[10] In 21 out of the 42 bivariate relationships, the null is rejected, suggesting high interaction of the countries' tail risk rather than the tail risk of all countries being driven by the tail risk of one country. The tail risk of every country both Granger-causes the tail risk of another country and is Granger-caused by another country as well, even though the significance and the number of significant lead-lag relationships vary from country to country. The results are similar to the ones from the correlation analysis in Section III.A where a positive and significant correlation is found between the tail risks of the countries. This makes sense economically, especially since the period has long phases of financial distress, i.e. the Lehman Default and the European debt crisis. The results can be confirmed by estimating a multivariate VAR model for all seven countries and running corresponding Granger causality tests.[11]

The overall implication of these findings is that there is high interdependence of tail risk in the G-7 countries with no explicit direction of causality.

C World Fear

Several studies investigate the integration of international financial markets and provide both empirical and theoretical evidence for an increase especially for developed countries (King & Levine, 1993; Levine, 1997; Rajan & Zingales, 1998; Sarazervos, 1998; Beck et al., 2000; Edison et al., 2002; Levine et al., 2000; De Guevara et al., 2007). Further, the transmission of shocks across borders often referred to as volatility spillover and contagion (Lin et al., 1994; Hamao et al., 1990; Allen & Gale, 2000; Karolyi, 2003) is documented by various studies for the financial crisis 2007-2009 and the European debt

[10] Detailed results are provided in the Online Appendix (Tables 7 and 8) .
[11] These results are available upon request.

crisis (Bekaert et al., 2014; Dungey & Gajurel, 2015).

Given the high level of integration of developed markets and the presence of volatility spillover effects in addition to the contemporaneous and lead-lag correlation we find, the question arises whether the tail risk of one country is relevant for market and stock returns or whether global tail risk is more important. We estimate the *World Fear Index* as a proxy for global tail risk as the average of the individual tail risk estimates of each country:

$$WF_t = \frac{1}{7}\sum_{j=1}^{7} JKTR_t^j \tag{4}$$

where $JKTR_t^j$ is the tail risk of country j.[12] Figure 3 displays the time series and descriptive statistics are reported in the last column of Panel A in Table 2. World Fear has an average value of 0.47. The index has similar dynamics to the countries France, the U.K. and the U.S. The last row of Panel C in Table 2 presents the correlation between the World Fear index and the tail risk of the individual countries. It is highly correlated to the JKTR of countries such as France, the U.K. and the U.S., with correlation coefficients as high as 90% and moderately correlated to the remaining countries, with values between 56% and 64%. We find that World Fear exhibits an $AR(1)$ coefficient of 0.55. Due to the high autocorrelation and the resemblance to local tail risk the question arises whether World Fear is a good predictor or an even better predictor than local tail risk for future returns both in the time-series and the cross-section for the different countries.[13]

[12] We also considered World Fear defined as the market capitalization weighted average of the individual tail risk estimates following Bollerslev et al. (2014), which leads to qualitatively similar but somewhat weaker results.

[13] We provide further evidence of a common component in the tail risk of individual countries by regressing the JKTR on our World Fear index. Table 9 in the Online Appendix shows that World Fear has strong explanatory power for the JKTR across all countries. The slope coefficient is positive and statistically significant at the 1% level for all countries and the adj. R^2 varies between 31% and 81%. Our findings are in line with the high positive contemporaneous correlations.

D Time-Series Return Predictability

Recent literature finds for the U.S. that high (low) tail risk is associated with relatively high (low) market returns in the future (see, e.g., Kelly & Jiang (2014), Bollerslev et al. (2014) and Bollerslev et al. (2015)). We test whether this finding holds outside of the U.S. The following regression model is estimated separately for each country:

$$r_{j,t+h} = a_{j,h} + b_{j,h} TR_t + \epsilon_{j,t+h} \tag{5}$$

where $r_{j,t+h}$ is the continuously compounded market excess return in country j over the horizon h and TR is either the local tail risk of country j, $JTKR_j$ or World Fear, WF. Monthly returns are in excess of the monthly return of the 1-month U.S. Treasury bill yield. In order to account for overlapping observations we use Hodrick (1992) standard errors with lags equal to the return horizon expressed in months. For the adjusted R^2 values, we conduct a bootstrap in order to obtain statistical significance following Welch & Goyal (2008). The following data generating process under the null is assumed:

$$r_{j,t+h} = a_{j,h} + u_{1,j,t+h} \tag{6}$$

$$TR_{t+1} = \alpha_j + \beta_j TR_t + u_{2,j,t+h} \tag{7}$$

We obtain pseudo time series for both the future excess returns and TR time series by drawing with replacement from the residuals simultaneously. We hence preserve the cross-correlation structure of the residuals in the predictive regressions and the autoregressive models. We then compute the in-sample adjusted R^2 for the pseudo sample. We repeat this process 5,000 times and obtain an empirical distribution and critical values for the adjusted R^2. We focus our discussion on the estimated slope coefficients, their statistical significance and the forecast accuracy of the regressions as measured by the adjusted R^2.

Table 3 reports the results for the JKTR. We find that local tail risk is generally not a statistically significant predictor of future aggregate market returns. The degree of predictability starts out quite low, with R^2 values close to zero for all countries at the one month horizon. Only for France (Germany), it is statistically significant at the three month and six month (three month) horizon with adj. R^2 values up to 4.95% (3.58%), which are statisticall significant as well.[14]

Replacing JTKR with WF dramatically increases the forecasting performance concerning both the statistical significance of the predictor and the explanatory power, which is consistent with the overall positive correlation and strong lead-lag interdependencies we find. The results are reported in Table 4.

World Fear is a statistically significant predictor for future local market returns in six out of seven countries at the three month to one year horizons and for all countries at the two year horizon.[15] At the one year horizon, the adj. R^2 vary between 3.57% and 18.10%. A one-standard-deviation increase (4.20%) in World Fear predicts an increase in futures market excess returns of 4.95%, 5.92%, 6.35%, 5.44%, 8.46%, 4.47%, 5.33% and 5.47% for Canada, France, Germany, Italy, Japan, the U.K. and the U.S., respectively.[16]

[14]This result for the U.S. is in contrast to Kelly & Jiang (2014). However, their sample period differs from ours. If we consider the same period from 1963 to 2015, we obtain similar results as theirs. Details are provided in the Online Appendix (Table 10). Figure 5 of the Online Appendix shows the time series of tail risk together with the market return over the next three years, similar to Figure 1 in Kelly & Jiang (2014). Our results suggest that tail risk is more integrated in recent years and the tail risk of other developed countries plays a more important role for the market returns of a country than local tail risk.

[15]Figure 7 in the Online Appendix plots the realized aggregate market returns against the fitted values from our predictive regressions. Both time series are standardized to have mean zero and standard deviation of one. One can observe that the fitted values closely follows the realized ones. Inoue & Kilian (2005) argue that one-sided t-tests are asymptotically more powerful than tests of equal predictive accuracy or test of forecast encompassing. Due to our relatively small sample and the knowledge of the theoretical sign of the slope coefficient, we feel confident on applying the one-sided test, which would yield even stronger evidence of predictive power for World Fear, while results remain unchanged for the local tail risk. The asymptotic critical values are 1.28, 1.64 and 2.33 for the 10%, 5% and 1% significance level, respectively.

[16]For comparison, Kelly & Jiang (2014) finds that a one-standard-deviation increase of tail risk leads

The adj. R^2 values are generally higher when relying on WF instead of $JKTR$ and they are all statistically significant for horizons longer than one month.[17] And for France and Germany, we find that $JKTR$ has higher explanatory power than global tail risk for short horizons up to six months. Economically, this means that France and Germany (and their tail risk) are less sensitive to foreign developed countries in general and the aggregate market returns of these countries mainly depend on their own tail risk. This makes sense since a relatively large part of our sample covers the European debt crisis and France and Germany as the economically strongest members of the European Union are more affected by the Euro-zone rather than crisis periods in other countries. Nonetheless, the market returns of developed countries in general are strongly predicted by World Fear.

We also find that World Fear as a proxy for global tail risk is a strong predictor for future global market returns (last column in Table 4). The slope coefficient is statistically significant for all horizons and the adj. R^2 range from 1.65% at the one month horizon to 6.96% at the one year horizon, which are all statistically significant as well.

Having investigated the in-sample predictability, we now turn to an out-of-sample exercise. As argued by Welch & Goyal (2008), it is not sufficient to only investigate in-sample tests since most of the predictors are unable to consistently forecast the equity premium out-of-sample. Most of their examined models underperform the recursive mean model out-of-sample. Similar to them we use the historical mean as a benchmark for our models. The historical mean is given by:

$$\bar{r}_{t+h} = \frac{1}{t}\sum_{j=1}^{t} r_j \tag{8}$$

to future excess returns of 4.5% for the U.S. and the period from 1963 until 2010.

[17]There an exception: For Canada, the adj. R^2 is not statistically significant at the six month horizon.

using return observations until t. Following Campbell & Thompson (2008), we evaluate our models using the out-of-sample R^2 which measures the differences in mean squared prediction errors (MSPE) for the predictive model and the historical mean model, and is given by:

$$R^2_{OOS} = 1 - \frac{\sum_{t=s}^{T}(r_{t+1} - \hat{r}_{t+1})^2}{\sum_{t=s}^{T}(r_{t+1} - \bar{r}_{t+1})^2} \tag{9}$$

where $\hat{r}_{t+1}$ stands for the out-of-sample forecast obtained from model (5) using the data until t, s is the break point splitting the whole sample for the out-of-sample analysis. Positive values for R^2_{OOS} indicate that the predictor outperforms the historical mean model in terms of the MSPE. We further test whether World Fear significantly outperforms the historical mean using the Clark & West (2007) augmented test, i.e. testing the null of $R^2_{OOS} \leq 0$. Under the null hypothesis, the MSPE-adjusted test statistic of Clark & West (2007) follows a standard normal distribution. Defining

$$f_{t+1} = (r_{t+1} - \bar{r}_{t+1})^2 - \left[(r_{t+1} - \hat{r}_{t+1})^2 - (\bar{r}_{t+1} - \hat{r}_{t+1})^2\right] \tag{10}$$

and regressing f_{t+1} on a constant, i.e. $f_{t+1} = \alpha + \epsilon_{t+1}$, the MSPE-adjusted test statistic is equal to the t-statistic of the constant. Following Rapach & Wohar (2006), Welch & Goyal (2008), Clark & McCracken (2012) and Rapach et al. (2013), we rely on bootstrapped p-values instead of the asymptotic distribution. The procedure is the same as for the bootstrapped critical values for the in-sample adjusted R^2. By using this approach we guard against biases that could arise because of our relatively small sample, the high serial autocorrelation of our World Fear index and the overlapping observations for long horizons.

Table 5 reports the results for the same period as the in-sample analysis using 120 observations for the initial estimation. We focus on World Fear, which has shown the strongest overall predictive power. World Fear has good out-of-sample forecasting performance for the majority of the countries considered. At all horizons except for the one year horizon, at least five out of the seven countries exhibit positive R^2_{OOS} values. At the three month horizon and two year horizons, World Fear significantly beats the historical mean in all countries.[18] Similar to our in-sample analysis, World Fear is also able to predict future global market returns out-of-sample for all horizons. The test statistic shows statistical significance for all horizons except for the one year horizon. Overall, the results suggest that World Fear has predictive power for market returns of the G-7 countries both in-sample and out-of-sample.

E World Fear and the Cross-Section of Stock Returns

In the framework of the ICAPM, relevant risk factors should predict future investment opportunities and price the cross-section of returns. We now test the latter condition. If investors are averse to World Fear, and World Fear is priced, we expect a positive risk premium. Stocks with low loadings on World Fear measure can be used as hedges and hence should have higher prices and lower expected returns. As in Kelly & Jiang (2014) we estimate the sensitivities to the tails for the individual stocks using the same predictive regression model as in Equation (5) but replace the market excess returns with the excess stock return of individual stocks. The stock returns are all measured in U.S.

[18]Figure 8 in the Online Appendix plots the performance of our out-of-sample predictive regressions. Following Welch & Goyal (2008) we plot the difference between the cumulative squared prediction errors of the historical mean model and our prediction model using World Fear. An increase (a decrease) in the line indicates that our model outperforms (underperforms) the historical mean model. One can observe that our model shows rather weak performance in the beginning but outperforms the benchmark especially during the financial crisis, indicated by the shaded area, where a sharp increase is present for all plots. The performance of both models are similar in the ending, where the lines are rather flat.

dollars.

Each month, the tail risk loadings are estimated for each stock in regressions using the most recent 60 observations. The stocks are then sorted into equally weighted portfolios based on the estimated loadings whereby firms with the lowest coefficient are in the first decile portfolio and firms with the highest coefficients are in the tenth decile portfolio. Excess returns of the portfolios are tracked over the subsequent month. The analysis is out-of-sample in the sense that there is no overlap between the data used for the beta estimation and the data used to compute the excess return of the portfolio. High minus low portfolio returns are then regressed on risk factors in order to test whether these returns merely reflect passive exposure to standard factors. We rely on the state of the art Fama & French (1993) three-factor model (FF3) :

$$r_{i,t} = \alpha_i + \beta_{Mkt} Mkt_t + \beta_{SMB} SMB_t + \beta_{HML} HML_t + \epsilon_{i,t} \tag{11}$$

where MKT stands for the market excess return, and SMB and HML stand for Small Minus Big and High Minus Low, respectively. These factors measure historical excess returns of small caps over big caps and of value stocks over growth stocks. We construct country specific factors for non–U.S. countries following the method described on Kenneth R. French's website and use the available ones for the U.S.[19]

Lastly, in order to quantify the risk premium associated with tail risks, cross-sectional

[19] Website: http://mba.tuck.dartmouth.edu/pages/facult/ken.french. We find that the size premium is close to zero and statistically insignificant for the majority of countries. The value premia on the under hand are all positive and statistically significant at the 1% level. These findings are consistent with the results of Fama & French (2016).

Fama–MacBeth regressions are conducted using the estimated betas.[20]

$$r_{i,t+1} = \gamma + \gamma_{JKTR}\beta_{JKTR,i,t} + \epsilon_{i,t} \tag{12}$$

$$r_{i,t+1} = \gamma + \gamma_{JKTR}\beta_{JKTR,i,t} + \gamma_{Control}Control_{i,t} + \epsilon_{i,t} \tag{13}$$

We control for further firm characteristics, which are the sensitivity to the market return, the logarithmic size ($Size$), the book-to-market ratio (BTM), the momentum (measured as the return from the past twelve months excluding the most recent month) (Mom) and the illiquidity (Liq) following Amihud (2002). These variables have been shown to be priced in the cross-section of stock returns (Jegadeesh & Titman, 1993; Amihud, 2002; Fama & French, 2008; Jiang & Yao, 2013). Since World Fear captures the global downside risk, we examine the interaction between our index and further downside measures by including the downside beta of Ang et al. (2006a) and coskewness of Harvey & Siddique (2000) as control variables. We also include the idiosyncratic volatility effect of (Ang et al., 2006b) and the aggregate volatility effect of (Ang et al., 2006a). For the computation of downside beta ($DownsideBeta$), coskewness ($Coskewness$), idiosyncratic volatility ($iVol$) and aggregatve volatility ($Aggr.Vol$), we rely on monthly observations over the past 60 months, similar to the estimation of our World Fear betas (Kelly & Jiang, 2014). The vector $\gamma_{Control}$ presents the risk premia associated with the additional control variables. Table 6 reports the results for the portfolio sorts, simple Fama–MacBeth regressions and multiple Fama–MacBeth regressions in Panels A, B and C, respectively.

Sorting returns by the exposure to WF and buying the decile portfolio with high loadings and selling the decile portfolio with low loadings yields a positive and statistically

[20] For our cross-sectional analysis, we winsorize the variables at 1st and 99th percentile to restrict the effect of outliers (Fama & French, 2008; Baltussen et al., 2015). Also, we use Shanken (1992) corrected standard errors in order to take into account measurement error in beta.

significant spread excess return for five countries: Canada, France, Germany, Italy, the U.K. with values of 1.06%, 1.28%, 2.72%, 0.97% and 1.00% per month, respectively.[21] The risk-adjusted returns are very similar to the raw returns, suggesting that the returns cannot be explained by the Fama & French (1993) risk factors.

Turning next to the cross-sectional regressions, we find positive risk premia for the same five countries: Canada, France, Germany, Italy and the U.K., which are statistically significant at the 5% level. The risk premia for the sensitivity to World Fear remain statistically significant when controlling for the sensitivity to the excess market return, market capitalization, book-to-market ratio, momentum, illiquidity, downside risk and volatility measures. The t-statistics for World Fear in the multiple regressions for Canada, France, Germany and Italy all exceed the rigorous threshold of 3 as recommended by Harvey et al. (2016) and hence give statistical evidence for the proposed asset pricing factor.

The results confirm that market participants seem to be crash averse and avoid stocks which are highly sensitive towards World Fear in the majority of countries. Stocks with higher tail risk earn higher average future and risk-adjusted returns. World Fear is able to predict future aggregate market returns and explain the cross-section of stock returns for most countries.

[21] Figure 6 in the Online Appendix displays the average returns of the decile portfolios for the seven countries. The returns are generally increasing from the first to the tenth decile portfolio for the countries except for Japan and the U.S. for which we do not find a significant spread. The spread may seem quite large, especially for France or Germany but such magnitudes are not uncommon for option trading strategies and option strategies are closely related to tail risk in our analysis. Kelly & Jiang (2014) relate the trading strategy based on the exposure to tail risk to delta-hedged equity put options and shows that both are closely related, where returns of up to 16.70% per month may be generated through the option strategy. Goyal & Saretto (2009) find that sorting by the difference between historical realized volatility and ATM implied volatility leads to a delta-hedged option spread return of 2.70% or straddle returns of 22.70% per month. Cao & Han (2013) sort options by stock (idiosyncratic) volatility and find an option spread delta-hedged return of 1.20% (1.40%) per month.

IV Economic Mechanism

In this section, we investigate one economic mechanism which could drive the reported return predictability of the JKTR. If asset pricing effects are channeled by uncertainty shocks, JKTR must have a direct impact on aggregate real economic outcomes. Following Kelly & Jiang (2014) we study the effect of tail risk on the real economy proxied by the unemployment for the G-7 countries. Unemployment rates for the G-7 countries are obtained from Datastream. We focus on the World Fear index and its effect on unemployment over the next year.[22]

Figure 4 shows the cross-correlations between World Fear in month t, and unemployment of the G-7 countries in month $t+0$ to $t+12$. It shows that there is a positive and significant contemporaneous correlation for most countries, which remains both positive and statistically significant over the subsequent months but slowly disappears when the horizon reaches twelve months. For Canada, Japan, the U.K. and the U.S., there is an immediate increase in unemployment followed by an increase in tail risk with correlation coefficients of 0.22, 0.25, 0.12 and 0.19 at the one month horizon, respectively, which are all statistically significant. The cross-correlations (and t-statistics) then slowly fall for the four countries and reach values close to zero at the twelve month horizon. Only for the U.K. the correlation is negative (-0.13). For France, Germany and Italy, the cross-correlation is positive and increases over the first four months and then drops for longer horizons. The highest correlation is reached at the three, four and two month horizons with values of 0.16, 0.17 and 0.22 for France, Germany and Italy, respectively, which are again all statistically significant.

Economically, an increase in World Fear is followed by an immediate increase in

[22]We focus on World Fear because it is shown to be the overall strongest predictor for local market returns. The unemployment rate is detrended using the Hodrick-Prescott filter.

unemployment and hence a contraction in economic activity within the subsequent year, followed by a slow recovery. We are hence able to extend the results from previous literature for the U.S. to further major countries using our introduced World Fear index.

V Robustness

A Return Predictability

In order to further assess the robustness of the tail risk's return predictability, we repeat the simple regressions in local returns and run multiple regressions including alternative predictors. All tables are reported in the Online Appendix, and discussed in the following.

U.S. Dollar vs Local Currencies

The analysis in the predictability Section III.D focuses on market returns expressed in U.S. dollar. However, it might be worth repeating this analysis from the perspective of a local investor. To be more specific, we rely on local returns rather than U.S. returns and explore the extent to which they can be predicted by World Fear. The monthly returns of non-U.S. countries are in excess of local three month interest rates obtained from Datastream.[23] These results are presented in Table 11 of the Online Appendix. The World Fear index is statistically significant and positive for six out of seven countries at the three month and one year horizon and for all seven countries at the two year horizon. The magnitudes of the explanatory power in terms of adj. R^2 are similar to our main results. The robustness tests hence support our main findings in Section III.D.

[23] We use the Canadian Dollar, Euro, Japanese Yen and Sterling 3-Month Deposit rates for Canada, the European countries, Japan and the U.K., respectively.

Controlling for other Predictors

For the additional predictors, we include option implied measures, macroeconomic variables and asset-related variables.

We include the dividend-price ratio, given as the difference between the log of 12-month trailing dividends and the log of prices (see, for example, Cochrane (2008), Welch & Goyal (2008) and Cochrane (2011)). The inflation rate is defined as changes in the consumer price index and we further include the volatility indices for each country (see, for example, Bollerslev et al. (2009) and Drechsler & Yaron (2011)).[24] All data are obtained from Datastream.

The control variables show in general low correlations with the tail risk. Only the implied volatilities exhibit moderate correlations with the tail risk with absolute values of 39% to 54%, see Table 12 of the Online Appendix.[25] For the sake of brevity, we focus on the one year horizon and additionally report Wald tests for the joint significance of our predictors.[26] Results for the regressions can be found in Table 13 of the Online Appendix and can be summarized as follows: when including the volatility indices, the World Fear index remains significantly positive at the one year horizon. WF still helps in predicting future market returns in the same six countries as before and the adj. R^2 reach higher values of 7.72% to 22.24%. Additionally including the inflation of the individual countries leaves the World Fear index positive and statistically significant and the adj. R^2 can generally be further increased. Lastly, when adding the dividend-price ratio, World Fear

[24] For Italy, dividend yield data is available starting in 2009 only. We hence exclude the regressions including the dividend-price ratio for Italy from the robustness tests. Further, there is no data available for the volatility index before 2010. We hence use the Euro Stoxx 50 Volatility as a proxy. For Canada, we combine the data of the MVX and the VICX using the data from MVX for the period from December 2002 to September 2009 and data from the VICX from October 2009 until December 2015.

[25] The findings are consistent with Kelly & Jiang (2014) who find significant correlations of their tail risk measure with option implied measures and a negative relationship with the option implied volatility.

[26] Results for alternative horizons are qualitatively similar and available on upon request.

remains a statistically significant predictor for three of the six countries. Even though the t-statistics are reduced somewhat compared to the simple and multiple regressions for France and the U.K., when controlling for the dividend-price ratio, the Wald tests for their joint significance are highly significant with test statistics above 10. Hence, the dividend yield is not able to fully span the predictive power of World Fear. In general, the Wald tests support the joint significance of the predictor variables for all countries.

Finite Sample Bias

In our predictive regressions in Section III.D we rely on Hodrick (1992) standard errors for the slope coefficients and bootstrapped p-values for the adj. R^2. While Hodrick (1992) standard errors take into account the impact of data overlap, they do not address the issue of persistence in the World Fear index. In order to take into account the finite sample bias and the potential Stambaugh (1999) bias, we apply the same bootstrap method for our OLS slope coefficients in the predictive regressions. As shown by Ang & Bekaert (2007) and Kelly & Jiang (2014), Hodrick (1992) standard errors are the most conservative when taking into account overlapping observations and the bootstrap standard errors of Welch & Goyal (2008) produce even stronger statistical significance for the slope coefficients. In unreported results, we also find that the p-values of all coefficients based on Hodrick (1992) standard errors are higher than the corresponding bootstrapped p-values. Only for France and the one month horizon the bootstrapped p-value is higher but the coefficient is statistically insignificant according to both p-values.

Alternative Thresholds

In our main analysis we define the tail of the cross-sectional distribution of a monthly pool of daily returns as the 5% quantile, which is fixed across the sample period and across countries. We now consider alternative thresholds to show that our results are robust against the chosen estimation procedure. This is especially relevant since the number of firms varies for the different countries with a median number of firms between 274 and 5000.

Table 14 of the Online Appendix presents the return predictability regressions of aggregate market returns for the one year horizon using our introduced World Fear index.[27] The threshold is fixed as the 6% and 7% quantile of the cross-sectional distribution.[28] We find that World Fear remains a statistically significant predictor of future market returns for the majority of countries just as in our main analysis and is further able to predict global market returns. The adj. R^2 show similar magnitudes to our main results and are all statistically significant as well.

Table 15 reports the results for the Fama–MacBeth regressions using the World Fear index, which are based on the alternative thresholds. The results are qualitatively and quantitatively similar to our main analysis. Hence, our findings for both the time-series and cross-sectional predictive power of World Fear are robust to the estimation procedure.

B Sorts and the Cross-Section of Stock Returns

In this section, we investigate whether the relation between World Fear betas and returns is robust to our factor choices. In Section III.E we use local Fama & French (1993) factors for the individual countries. Griffin (2002) argues that country-specific three-factor models have more explanatory power for average stock returns than international or world versions but their data sample only covers the period from January 1981 to December 1995. Fama & French (2012) compare local and global models and suggest

[27] Results are qualitatively similar for alternative horizons.

[28] Due to the relatively small sample size of Italy, we choose to increase the threshold and include more observations rather than the opposite.

rather using local models in order to explain regional portfolio returns.

Nonetheless, we repeat the sorts as in Section III.E but control for global Fama & French (1993) risk factors instead of local factors using the data provided by the Kenneth R. French data library.[29] We find FF3 alphas of 1.06%, 1.11%, 3.30%, 1.04% and 1.13% for Canada, France, Germany, Italy and the U.K., respectively, which are all statistically significant. The findings are qualitatively similar to our main findings.

C Foreign Tail Risk

In Section III.B we analyze the interaction between the different countries, comparing each country's tail risk. It is also of particular interest how the individual tail risk and aggregate tail risk of the other countries interact. We therefore decompose the World Fear into one country's own tail risk and the aggregate tail risk of the remaining countries, which we denote as foreign tail risk $Foreign$. We then compare the ability of predicting market and stock returns of local tail risk $JKTR$ and our World Fear index with foreign tail risk $Foreign$.

In this section, we investigate the predictive power of $Foreign$ for aggregate market returns and its pricing in the stock markets. The results for the predictive regressions are reported in Table 16.[30] Foreign tail risk is a stronger predictor than local tail risk in terms of explanatory power for most countries. The adj. R^2 can generally be increased for the remaining countries and horizons. The slope coefficient is also statistically significant for most countries. At the six month, one year and two year horizons, foreign tail risk is statistically significant for five out of seven countries, respectively. At the one year

[29]Website: Http://mba.tuck.dartmouth.edu/pages/facult/ken.french.

[30]Table 17 of the Online Appendix presents the explanatory power of the regressions relying on $JKTR$, WF or $Foreign$ in the terms of explanatory power (adj. R^2) and allows for a more convenient comparison.

horizon, the adj. R^2 vary between 0.35% and 19.39% for those countries, which are all statistically significant. The explanatory power is highest for Japan for all horizons, indicating that especially Japan is sensitive to the tail risk of other countries. Even though the explanatory power is higher for some countries when relying on foreign tail risk, our World Fear index has a stronger overall predictive power across the countries.

We also repeat the cross-sectional analysis but estimate the sensitivity of individual stocks to foreign tail risk rather than World Fear. The results are reported in Table 18 of the Online Appendix. We find that sorting by $Foreign$ loadings yields positive and statistically significant (at the 5% level or lower) spreads for Germany, Italy and the U.K. As argued above, foreign tail risk has more predictive power for some countries, which leads to the stronger statistical significance of the spreads but has a less overall predictive power across countries. These findings are consistent with our results from the aggregate market return predictions. The results for the Fama–MacBeth regressions are similar to the ones using WF.

VI Conclusion

The aim of the present paper is to analyze tail risk internationally. We investigate the interaction between the tail risk of different developed countries and combine them to capture global tail risk. We show that the local tail risk is highly integrated across developed countries. While local tail risk does not help to predict future market returns, foreign tail risk and World Fear do. The return predictability is economically and statistically strong, both in-sample and out-of-sample when using World Fear. Further, sorting stocks by World Fear exposure generates positive excess returns for the majority of countries. The results are similar for both foreign and global tail risk. Our results are found to be robust after testing various variations of the examined models.

Overall, we conclude that global tail risk is a useful predictor of market returns while local tail risk generally does not predict future returns. An increase of World Fear has an impact on future aggregate economic activity such as unemployment which presents potential channels through which World Fear influences asset prices.

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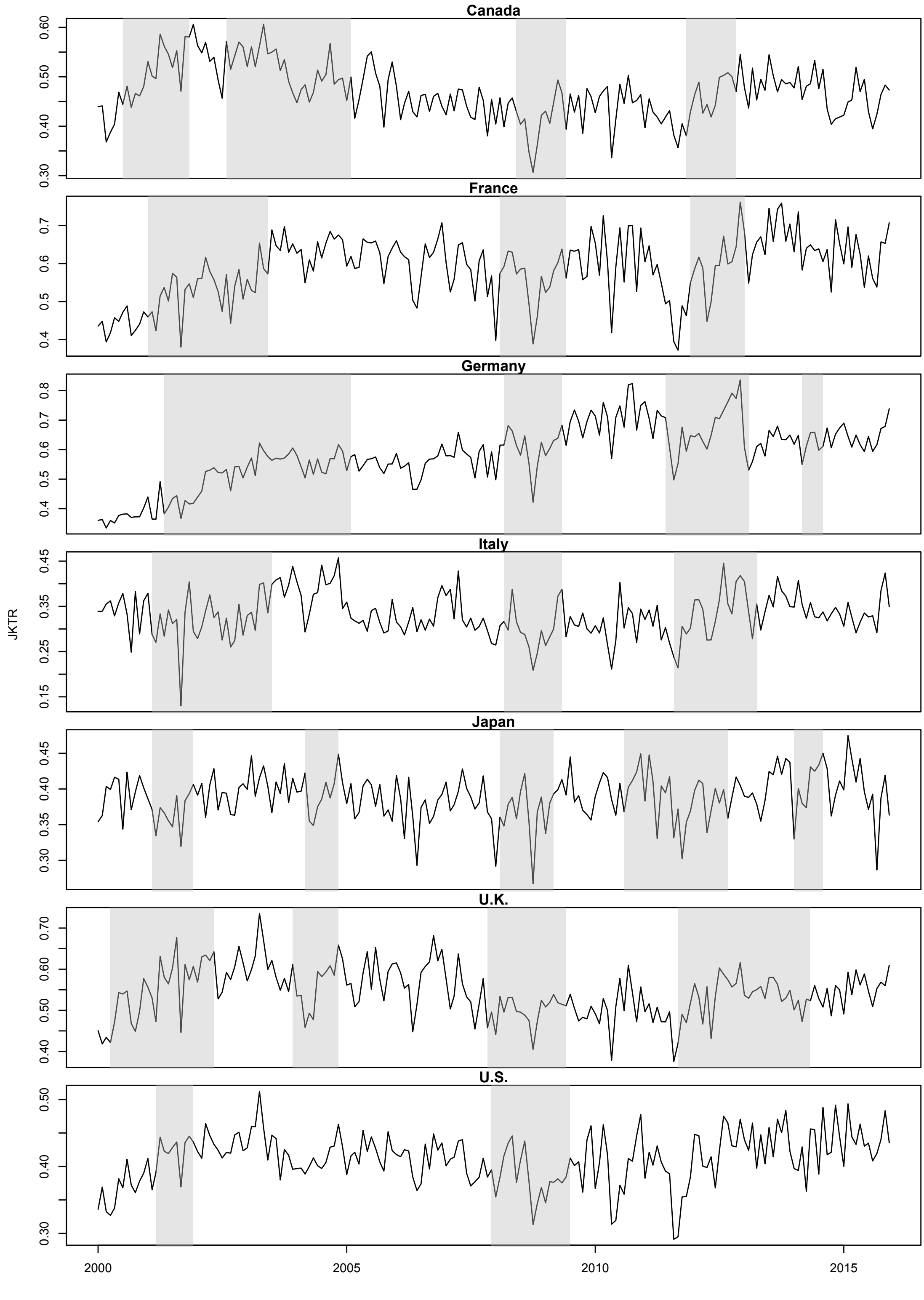

Figure 1: JKTR of G-7 Countries

This figure shows the monthly time series of the JKTR of the primary data set, the G-7 countries, for the period from January 2000 to December 2015. The shaded area indicates the recession defined by NBER and OECD for the U.S. and the remaining countries, respectively.

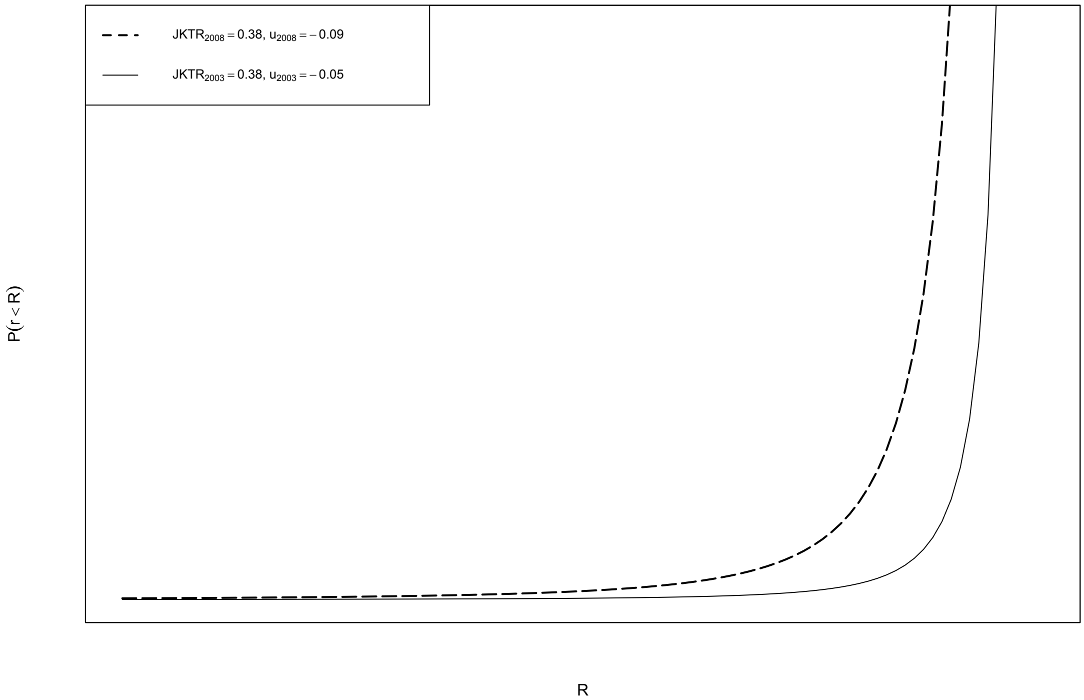

Figure 2: Tail of Return Distribution

This figure shows tail probability distribution of the U.S. using decay parameter and thresholds of both a relatively calm period (2003) and during the financial crisis (2008).

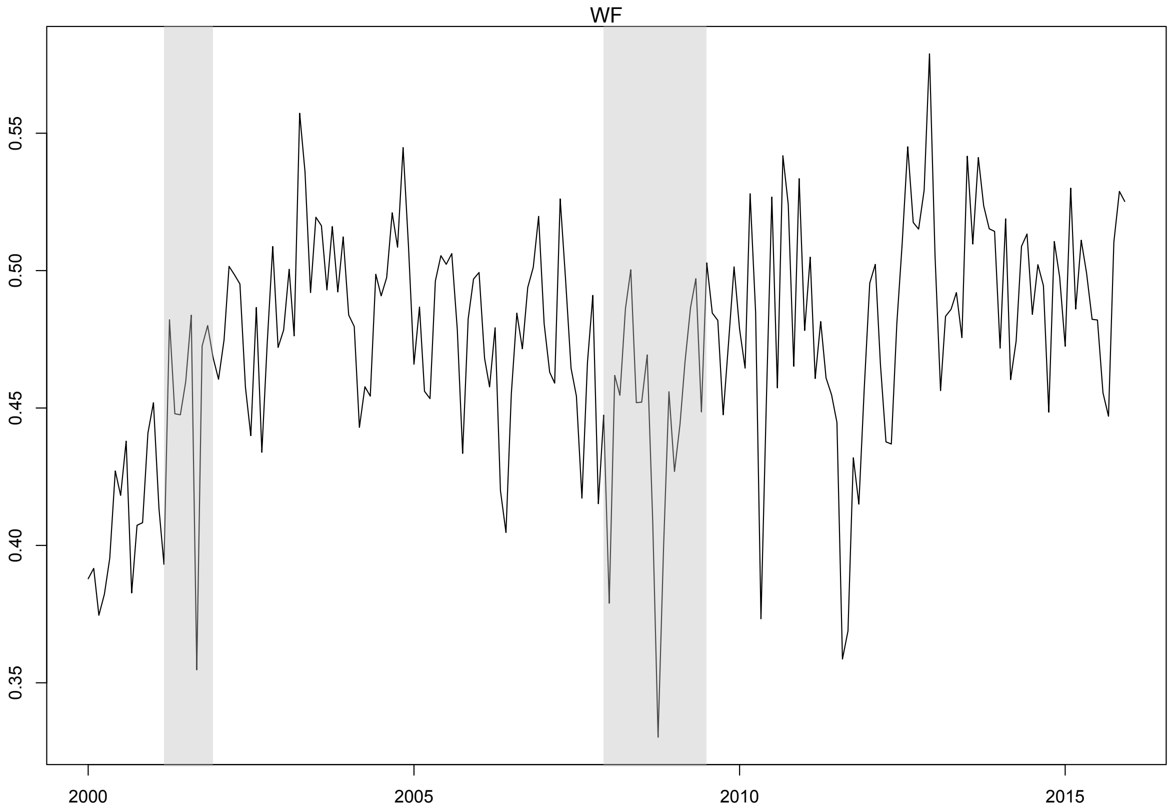

Figure 3: World Fear (2000-2015)

This figure shows the monthly time series of World Fear, for the period from January 2000 to December 2015. The shaded area indicates the recession defined by NBER.

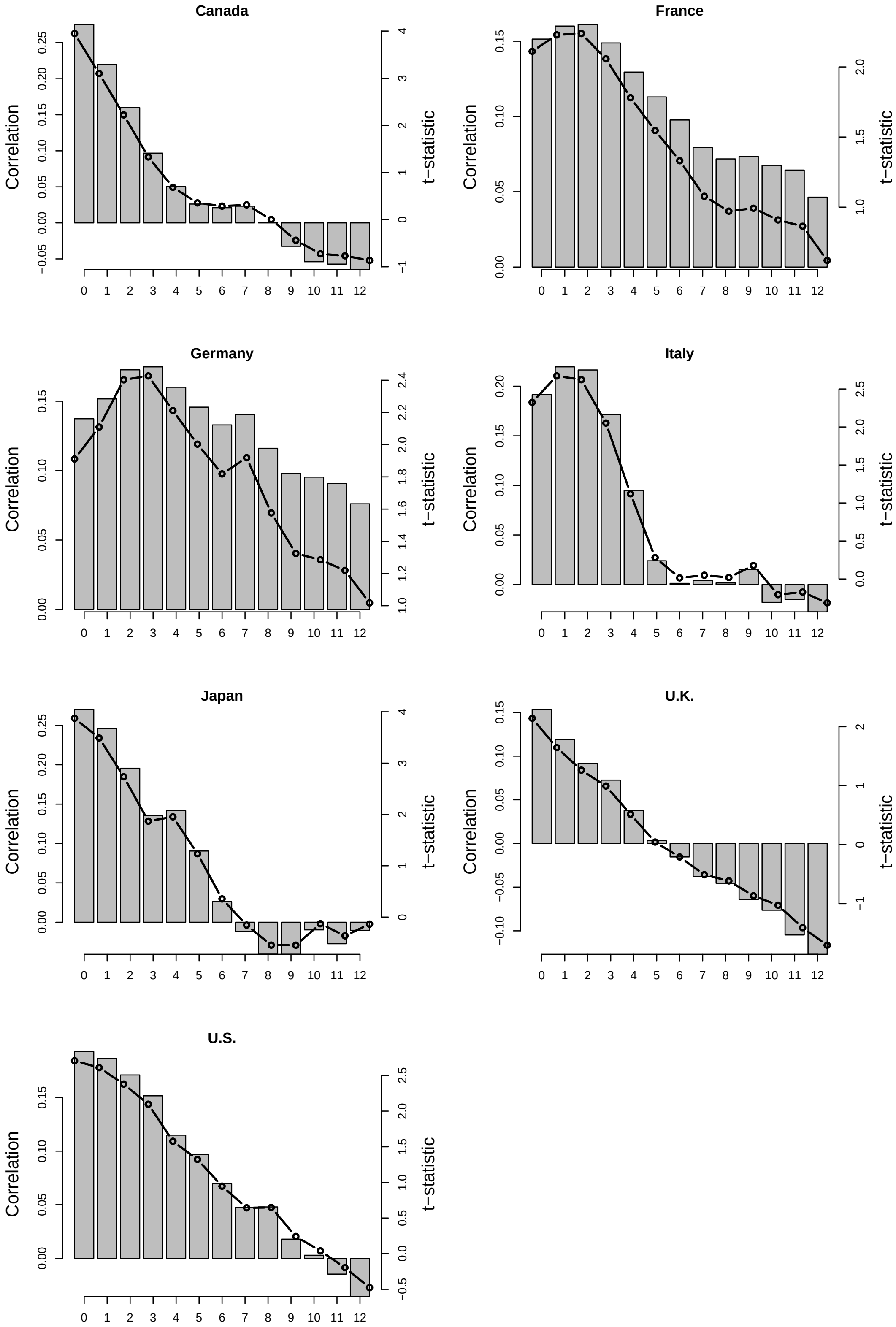

Figure 4: Correlogram: World Fear and Unemployment

This figure plots the percentage correlation (bars corresponding to the left axis) between the estimated World Fear at month t with unemployment rates in month $t+i$ for $i = 0, ..., 12$ and t-statistics (line plot corresponding to right axis).

Table 1: Summary Statistics of Returns for G-7 Countries

This table presents descriptive statistics for the daily returns in *U.S. dollar currency* of the G-7 countries for the period from January 2000 until December 2015. We report time-series averages of selected quantiles (5%, 25%, 50% 75%, 95%), the mean, the standard deviation (SD), the skewness and the kurtosis of the cross-sectional return distribution.

	Canada	France	Germany	Italy	Japan	U.K.	U.S.
5%	−0.0576	−0.0362	−0.0513	−0.0303	−0.0371	−0.0381	−0.0499
25%	−0.0113	−0.0048	−0.0085	−0.0108	−0.0110	−0.0040	−0.0141
Mean	0.0015	0.0010	0.0036	0.0001	0.0005	0.0003	0.0007
Median	−0.0004	−0.0001	−0.0001	−0.0011	−0.0006	−0.0002	−0.0004
75%	0.0104	0.0042	0.0068	0.0090	0.0098	0.0026	0.0134
95%	0.0633	0.0403	0.0534	0.0333	0.0406	0.0378	0.0530
SD	0.0569	0.0477	0.1536	0.0238	0.0301	0.0415	0.0410
Skewness	3.5611	3.9073	8.6135	1.3311	2.6654	4.3906	3.8432
Kurtosis	82.6331	131.8120	268.8520	19.9402	77.2840	151.5709	137.9877

Table 2: Descriptive Statistics for JKTR of G-7 Countries and World Fear

This table presents descriptive statistics for the JKTR and World Fear in Panel A, mean differences between tail risks of two countries or World Fear in Panel B and correlations in Panel C. The investigated countries are Canada, France, Germany, Italy, Japan, the U.K. and the U.S. over the period from January 2000 until December 2015. Mean describes the time-series average of the JKTR, SD stands for the standard deviation, Min and Max are the minimum and maximum values of the JKTR and AR(1) stands for the first-order autocorrelation.

	Canada	France	Germany	Italy	Japan	U.K.	U.S.	WF
Panel A: Descriptive Statistics								
Mean	0.47	0.59	0.58	0.33	0.39	0.54	0.41	0.47
SD	0.05	0.08	0.10	0.05	0.03	0.06	0.04	0.04
Min	0.31	0.37	0.33	0.13	0.27	0.38	0.29	0.33
Max	0.61	0.76	0.84	0.46	0.47	0.74	0.51	0.58
AR(1)	0.66	0.58	0.83	0.43	0.26	0.54	0.50	0.55
Panel B: Mean Differences								
Canada								
France	−0.12							
Germany	−0.11	0.00						
Italy	0.14	0.25	0.25					
Japan	0.08	0.20	0.19	−0.06				
U.K.	−0.07	0.04	0.04	−0.21	−0.15			
U.S.	0.06	0.17	0.17	−0.08	−0.02	0.13		
WF	−0.00	0.11	0.11	−0.14	−0.08	0.07	−0.06	
Panel C: Correlations								
Canada								
France	0.33							
Germany	−0.10	0.65						
Italy	0.38	0.55	0.19					
Japan	0.31	0.44	0.25	0.38				
U.K.	0.70	0.52	0.09	0.44	0.30			
U.S.	0.58	0.61	0.32	0.40	0.43	0.63		
WF	0.56	0.90	0.64	0.64	0.56	0.71	0.77	

Table 3: Return Predictability Regressions

This table presents results for monthly return predictive regressions of value-weighted market index returns in *U.S. dollar currency* over horizons from one month to two years. The investigated countries are the G-7 countries over the period from January 2000 until December 2015. The predictor is the JKTR of the country [name in column]. Robust Hodrick (1992) standard errors are reported in parentheses using lags equal to the prediction horizon expressed in months. Stars indicate significance of the estimates: * significant at $p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$. We report bootstrapped p-values below the corresponding adjusted R^2.

	Canada	France	Germany	Italy	Japan	U.K.	U.S.
Intercept	−0.0335	−0.0289	−0.0346	−0.0430	0.0155	−0.0203	−0.0141
	(0.0465)	(0.0346)	(0.0279)	(0.0353)	(0.0397)	(0.0342)	(0.0441)
$JKTR_{1Month}$	0.0834	0.0551	0.0683	0.1350	−0.0394	0.0439	0.0425
	(0.0959)	(0.0560)	(0.0456)	(0.1013)	(0.1011)	(0.0602)	(0.1040)
adj. R^2	0.0003	0.0004	0.0064	0.0053	−0.0045	−0.0023	−0.0040
	{0.3582}	{0.3532}	{0.1646}	{0.1618}	{0.7138}	{0.4392}	{0.7152}
Intercept	−0.0541	−0.1403	−0.1183	−0.1211	−0.0221	−0.0734	0.0283
	(0.1083)	(0.0867)	(0.0775)	(0.0867)	(0.0785)	(0.0836)	(0.1018)
$JKTR_{3Month}$	0.1534	0.2576*	0.2299*	0.3813	0.0596	0.1573	−0.0434
	(0.2192)	(0.1387)	(0.1277)	(0.2428)	(0.1982)	(0.1450)	(0.2390)
adj. R^2	0.0001	0.0342	0.0358	0.0206	−0.0049	0.0054	−0.0049
	{0.1558}	{0.0072}	{0.0018}	{0.1880}	{0.1652}	{0.0250}	{0.3294}
Intercept	−0.0446	−0.2437	−0.1723	−0.1535	−0.0855	−0.1523	0.0929
	(0.2044)	(0.1537)	(0.1463)	(0.1474)	(0.1300)	(0.1488)	(0.1649)
$JKTR_{6Month}$	0.1763	0.4554*	0.3566	0.5050	0.2311	0.3300	−0.1707
	(0.4099)	(0.2436)	(0.2431)	(0.4031)	(0.3200)	(0.2556)	(0.3840)
adj. R^2	−0.0022	0.0495	0.0391	0.0151	−0.0024	0.0143	−0.0027
	{0.4334}	{0.0014}	{0.0032}	{0.0540}	{0.4010}	{0.0576}	{0.4738}
Intercept	−0.1413	−0.3237	−0.2715	−0.1197	−0.2246	−0.2865	−0.0930
	(0.3870)	(0.2728)	(0.2986)	(0.2552)	(0.2286)	(0.2803)	(0.2396)
$JKTR_{1Year}$	0.4765	0.6423	0.6082	0.4527	0.6283	0.6387	0.3525
	(0.7691)	(0.4280)	(0.5013)	(0.6672)	(0.5539)	(0.4778)	(0.5496)
adj. R^2	0.0058	0.0467	0.0568	0.0032	0.0044	0.0294	−0.0006
	{0.1558}	{0.0072}	{0.0018}	{0.1880}	{0.1652}	{0.0250}	{0.3294}
Intercept	−0.4688	−0.2806	−0.2187	0.0008	−0.2518	−0.2482	−0.0625
	(0.6795)	(0.3245)	(0.4948)	(0.4169)	(0.3188)	(0.4599)	(0.3548)
$JKTR_{2Year}$	1.4462	0.7089	0.7224	0.2561	0.8180	0.7241	0.4647
	(1.3363)	(0.4920)	(0.8508)	(1.0254)	(0.7468)	(0.7767)	(0.7862)
adj. R^2	0.0408	0.0244	0.0371	−0.0046	0.0027	0.0152	−0.0024
	{0.0094}	{0.0172}	{0.0058}	{0.6166}	{0.2132}	{0.0586}	{0.4088}

Table 4: Return Predictability – World Fear

This table presents results for monthly return predictive regressions of value-weighted market index returns in *U.S. dollar currency* over horizons from one month to two years. The investigated countries are the G-7 countries over the period from January 2000 until December 2015. The predictor is World Fear WF. Robust Hodrick (1992) standard errors are reported in parentheses using lags equal to the prediction horizon expressed in months. Stars indicate significance of the estimates: * significant at $p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$. We report bootstrapped p-values below the corresponding adjusted R^2.

	Canada	France	Germany	Italy	Japan	U.K.	U.S.	Global
Intercept	−0.0682	−0.0462	−0.0758	−0.0783	−0.1140**	−0.0583	−0.0642	−0.0731*
	(0.0581)	(0.0548)	(0.0629)	(0.0589)	(0.0402)	(0.0439)	(0.0459)	(0.0441)
WF_{1Month}	0.1563	0.1049	0.1711	0.1690	0.2415**	0.1307	0.1431	0.1614*
	(0.1191)	(0.1126)	(0.1286)	(0.1221)	(0.0823)	(0.0898)	(0.0940)	(0.0901)
adj. R^2	0.0064	−0.0001	0.0068	0.0070	0.0418	0.0074	0.0125	0.0165
	{0.1844}	{0.3604}	{0.1744}	{0.1544}	{0.0020}	{0.1238}	{0.0842}	{0.0484}
Intercept	−0.1320	−0.2026	−0.2667*	−0.2678**	−0.3551**	−0.1682*	−0.1863*	−0.2114**
	(0.1239)	(0.1321)	(0.1532)	(0.1338)	(0.1161)	(0.0971)	(0.1055)	(0.1004)
WF_{3Month}	0.3177	0.4503*	0.5969*	0.5768**	0.7540**	0.3814*	0.4168*	0.4695**
	(0.2495)	(0.2687)	(0.3106)	(0.2747)	(0.2379)	(0.1976)	(0.2134)	(0.2031)
adj. R^2	0.0085	0.0254	0.0401	0.0389	0.1197	0.0243	0.0393	0.0458
	{0.0702}	{0.0374}	{0.0084}	{0.0046}	{0.0000}	{0.0206}	{0.0068}	{0.0016}
Intercept	−0.1464	−0.3936*	−0.3775	−0.3915*	−0.5524**	−0.2484	−0.2759	−0.3126*
	(0.2256)	(0.2275)	(0.2518)	(0.2239)	(0.1929)	(0.1631)	(0.1847)	(0.1763)
WF_{6Month}	0.3909	0.8802*	0.8721*	0.8562*	1.1788**	0.5822*	0.6323*	0.7104**
	(0.4520)	(0.4584)	(0.5068)	(0.4555)	(0.3950)	(0.3298)	(0.3709)	(0.3536)
adj. R^2	0.0040	0.0467	0.0382	0.0385	0.1323	0.0232	0.0392	0.0431
	{0.1766}	{0.0028}	{0.0090}	{0.0028}	{0.0000}	{0.0136}	{0.0048}	{0.0030}
Intercept	−0.4728	−0.6148	−0.6333	−0.5810	−0.9304**	−0.4424	−0.5470*	−0.5616*
	(0.4007)	(0.3918)	(0.4102)	(0.3858)	(0.2894)	(0.2814)	(0.2886)	(0.2922)
WF_{1Year}	1.1783	1.4106*	1.5128*	1.2950*	2.0134***	1.0644*	1.2690**	1.3029**
	(0.7976)	(0.7817)	(0.8140)	(0.7745)	(0.5927)	(0.5601)	(0.5714)	(0.5765)
adj. R^2	0.0357	0.0586	0.0572	0.0477	0.1810	0.0397	0.0746	0.0696
	{0.0094}	{0.0042}	{0.0040}	{0.0072}	{0.0000}	{0.0098}	{0.0004}	{0.0012}
Intercept	−0.4872	−0.7790*	−0.7084	−0.7181	−0.9859**	−0.5848	−0.6424*	−0.6696*
	(0.4346)	(0.4484)	(0.4954)	(0.4426)	(0.3552)	(0.3583)	(0.3359)	(0.3422)
WF_{2Year}	1.4868*	1.9320**	1.9238**	1.7079**	2.2345**	1.5517**	1.6367**	1.7044**
	(0.8469)	(0.8398)	(0.9319)	(0.8384)	(0.7151)	(0.6765)	(0.6246)	(0.6373)
adj. R^2	0.0236	0.0530	0.0434	0.0394	0.1209	0.0389	0.0527	0.0550
	{0.0204}	{0.0012}	{0.0048}	{0.0038}	{0.0000}	{0.0080}	{0.0022}	{0.0020}

Table 5: Return Predictability Regressions – Out-of-Sample R^2

This table presents results for monthly out-of-sample return forecasts. Out-of-sample R^2 from predictive regressions of value-weighted market index excess returns in *U.S. dollar currency* over a one month, three months, six months, one year and two year horizons are reported. The investigated countries are Canada, France, Germany, Italy, Japan, the U.K. and the U.S. over the period from January 2000 until December 2015. To obtain statistical significance we conduct a Clark & West (2007) MSPE test. The null hypothesis is the recursive mean model outperforming the predictive model, i.e. $R_{OOS} \leq 0$. We rely on bootstrapped critical values instead of the asymptotic distribution. In each month t (beginning at $t = 120$), we estimate rolling univariate forecasting regressions of monthly market returns on the lagged World Fear index WF. Stars indicate significance of the estimates: * significant at $p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

	Canada	France	Germany	Italy	Japan	U.K.	U.S.	Global
1 Month	-0.0016	0.0041^{*}	0.0100^{*}	0.0109^{**}	0.0071^{*}	0.0123^{**}	0.0185^{**}	0.0151^{**}
	(0.1398)	(0.0936)	(0.0674)	(0.0492)	(0.0744)	(0.0416)	(0.0276)	(0.0242)
3 Month	0.0013^{*}	0.0243^{**}	0.0232^{**}	0.0247^{**}	0.0294^{*}	0.0217^{**}	0.0305^{**}	0.0151^{***}
	(0.0926)	(0.0290)	(0.0258)	(0.0170)	(0.0672)	(0.0204)	(0.0112)	(0.0080)
6 Month	-0.0006	0.0108^{*}	0.0014	-0.0033	0.0420^{**}	0.0077^{*}	0.0050^{*}	0.0151^{*}
	(0.1234)	(0.0818)	(0.1206)	(0.1834)	(0.0206)	(0.0578)	(0.0952)	(0.0612)
1 Year	-0.0142	-0.0156	-0.0227	-0.0234	0.0658^{**}	0.0002	-0.0041	0.0151
	(0.4176)	(0.4396)	(0.6270)	(0.6188)	(0.0218)	(0.1474)	(0.2280)	(0.2032)
2 Year	0.0168^{**}	0.0284^{**}	0.0281^{**}	0.0176^{**}	0.0199^{*}	0.0260^{**}	0.0085^{*}	0.0151^{**}
	(0.0308)	(0.0200)	(0.0172)	(0.0356)	(0.0630)	(0.0162)	(0.0700)	(0.0456)

Table 6: Portfolio Sorts and Fama–MacBeth Regressions – World Fear

This table presents results from portfolio sorts based on WF. The investigated countries are the G-7 countries over the period from January 2000 until December 2015. Quintile portfolios are formed based on WF betas for each country. Betas are calculated in predictive regressions using the most recent 60 returns measured in *U.S. Dollars*. We then track 1 month out-of-sample equally weighted holding period returns. We report the average returns of the high minus low portfolio in the first row of Panel A. *FF3* report alphas from the Fama & French (1993) 3 factor model. In Panel B, Intercept and γ_{WF} are means of the coefficients from the cross-sectional regressions of individual stock returns on an intercept and the World Fear loadings. Panel C additionally includes the market loading, $log(Size)$, book-to-market ratios (BTM), prior returns (Mom), illiquidity (Liq), aggregate Volatility ($Aggr.Vol$), coskewness ($Coskewness$), downside beta ($DownsideBeta$) and idiosyncratic volatility ($iVol$) of individual stocks in the cross-sectional regressions. The according mean coefficients γ_{Market}, γ_{Size}, γ_{BTM}, γ_{Mom}, γ_{Liq}, $\gamma_{Aggr.Vol}$, $\gamma_{Coskewness}$, $\gamma_{DownsideBeta}$ and γ_{iVol} are reported. For the cross-sectional regressions, we apply the Shanken (1992) correction. Stars indicate significance of the estimates: * significant at $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

	Canada	France	Germany	Italy	Japan	U.K.	U.S.
Panel A: Portfolio Sorts							
Average return	0.0106*	0.0128***	0.0272***	0.0097*	−0.0007	0.0100*	0.0009
	(0.0057)	(0.0048)	(0.0066)	(0.0050)	(0.0046)	(0.0055)	(0.0042)
FF3	0.0118**	0.0106**	0.0298***	0.0116**	0.0028	0.0112*	−0.0027
	(0.0054)	(0.0045)	(0.0067)	(0.0050)	(0.0037)	(0.0059)	(0.0037)
Panel B: Simple Fama–MacBeth Regressions							
(Intercept)	0.0061	0.0030	0.0043	−0.0048	0.0053	−0.0019	0.0055
	(0.0062)	(0.0046)	(0.0049)	(0.0059)	(0.0037)	(0.0051)	(0.0040)
γ_{WF}	0.0004**	0.0015***	0.0000***	0.0016**	0.0001	0.0009**	0.0003
	(0.0002)	(0.0004)	(0.0000)	(0.0006)	(0.0004)	(0.0004)	(0.0004)
Panel C: Multiple Fama–MacBeth Regressions							
(Intercept)	−0.0073	0.0011	0.0065	0.0015	−0.0000	−0.0031	0.0064
	(0.0055)	(0.0061)	(0.0059)	(0.0061)	(0.0044)	(0.0053)	(0.0062)
γ_{WF}	0.0015***	0.0034***	0.0022***	0.0027***	0.0011*	0.0011*	0.0005
	(0.0004)	(0.0007)	(0.0007)	(0.0008)	(0.0006)	(0.0006)	(0.0006)
γ_{Market}	−0.0077**	−0.0025	−0.0066*	−0.0014	0.0022	0.0006	0.0029
	(0.0031)	(0.0036)	(0.0036)	(0.0045)	(0.0020)	(0.0022)	(0.0019)
γ_{Size}	0.0006	0.0001	−0.0003	−0.0001	−0.0001	0.0012**	0.0001
	(0.0005)	(0.0006)	(0.0005)	(0.0007)	(0.0005)	(0.0005)	(0.0004)
γ_{BTM}	0.0124***	0.0065***	0.0025**	0.0045***	0.0060***	0.0078***	−0.0019*
	(0.0013)	(0.0015)	(0.0011)	(0.0011)	(0.0008)	(0.0009)	(0.0010)
γ_{Mom}	0.0037	0.0044	0.0092*	0.0031	−0.0027	0.0060	−0.0035
	(0.0047)	(0.0044)	(0.0047)	(0.0067)	(0.0032)	(0.0045)	(0.0031)
γ_{Liq}	0.0001	−0.0013	−0.0004	−0.0013	0.0002	0.0001	−0.2129
	(0.0001)	(0.0012)	(0.0003)	(0.0035)	(0.0004)	(0.0002)	(0.1539)
$\gamma_{Aggr.Vol}$	0.0661	−0.4776***	−0.0011	−0.4340	−0.0658	−0.0901	0.0139
	(0.1142)	(0.1547)	(0.1895)	(0.2728)	(0.1856)	(0.1250)	(0.0957)
$\gamma_{Coskewness}$	−0.0001	0.0010	0.0014*	0.0015*	0.0002	−0.0003	−0.0001
	(0.0005)	(0.0006)	(0.0008)	(0.0008)	(0.0002)	(0.0004)	(0.0002)
$\gamma_{DownsideBeta}$	−0.0001	−0.0012	0.0102***	−0.0006	0.0009	−0.0037*	−0.0016
	(0.0017)	(0.0026)	(0.0036)	(0.0034)	(0.0012)	(0.0019)	(0.0011)
γ_{iVol}	0.0137	−0.0404	−0.0438*	−0.0809***	−0.0323*	−0.0586***	−0.0254
	(0.0182)	(0.0256)	(0.0245)	(0.0278)	(0.0187)	(0.0143)	(0.0169)

International Tail Risk and World Fear

Online Appendix

A Additional Figures

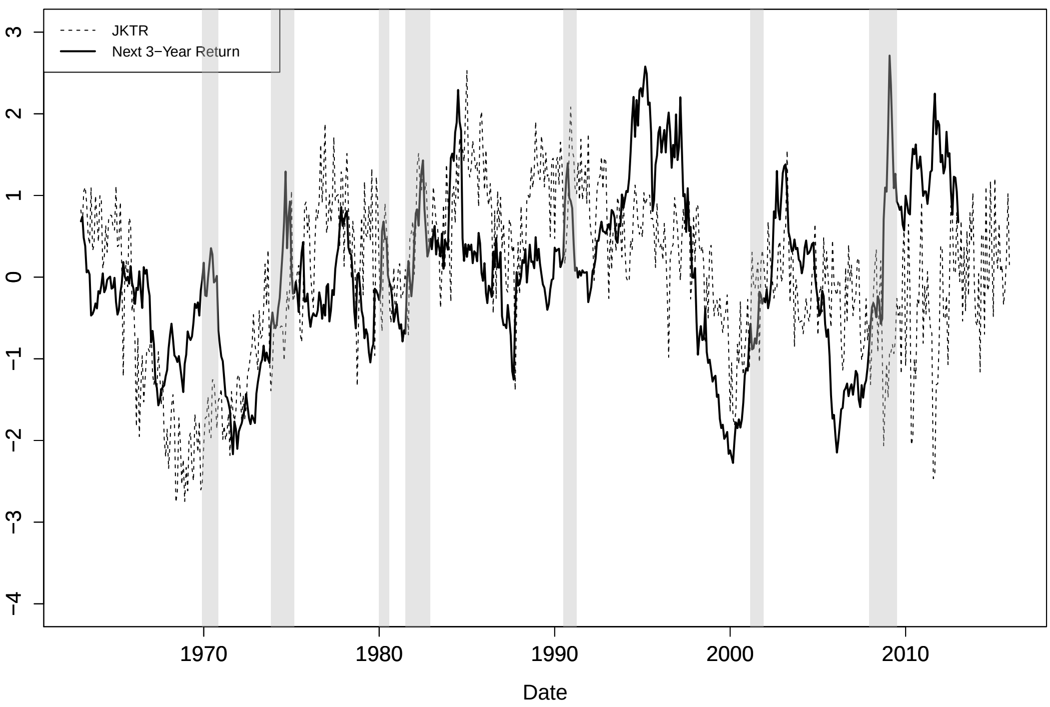

Figure 5: JKTR and Subsequent Market Returns for the U.S. (1963-2015)

This figure shows the monthly time series of the JKTR for the U.S. for the period from 1963 to 2015. Also plotted in each month is the realized market return over the three years following the current month. The shaded areas present recessions defined by NBER. Both series are scaled to have mean zero and variance one.

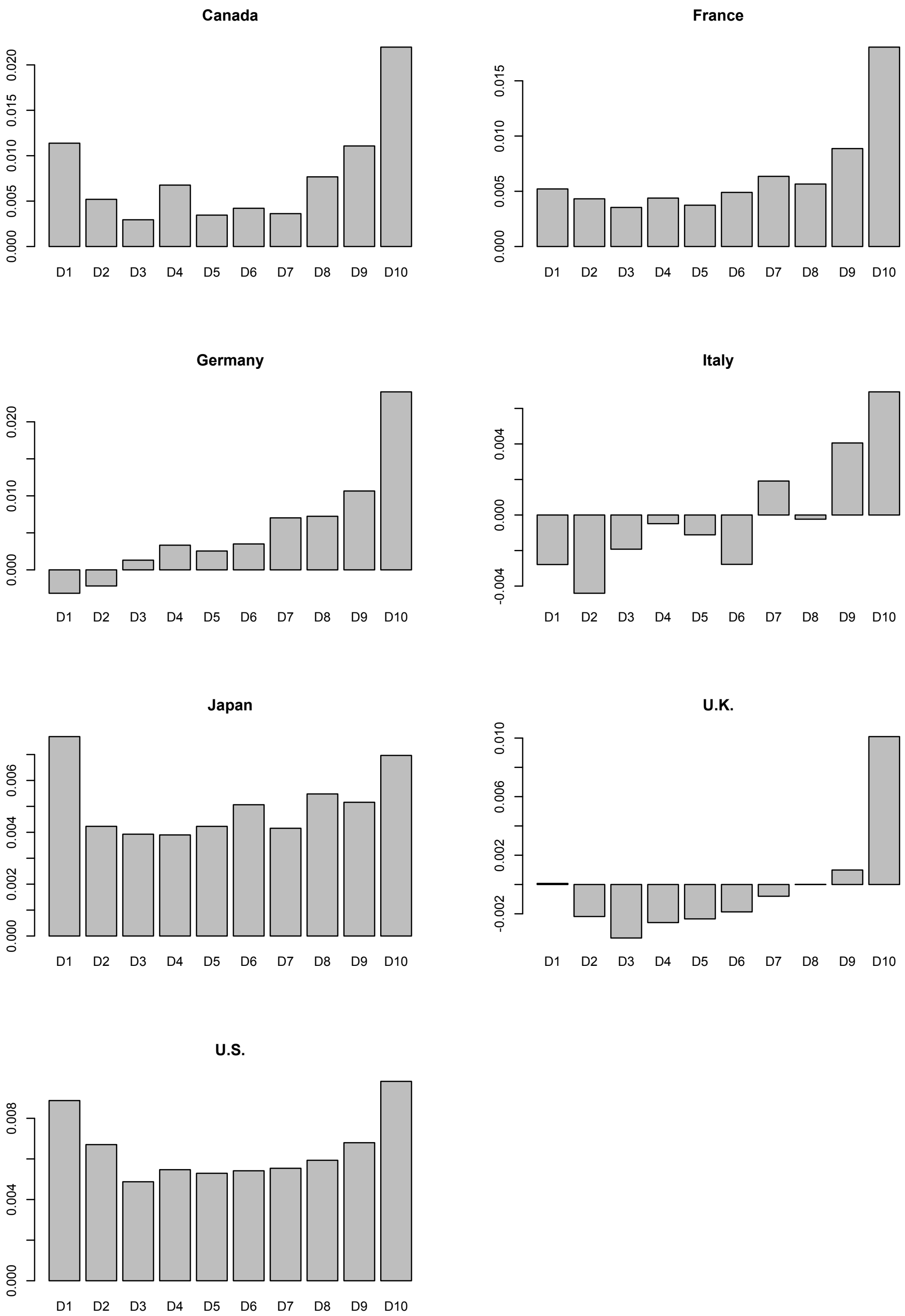

Figure 6: Average Return of Decile Portfolios

This figure shows average return of decile portfolios. Each month, the World Fear loadings are estimated for each stock in regressions using the most recent 60 observations. Stocks are sorted into equally weighted portfolios based on the estimated loadings whereby firms with the lowest coefficient are in the first decile portfolio and firms with the highest coefficients are in the tenth decile portfolio.

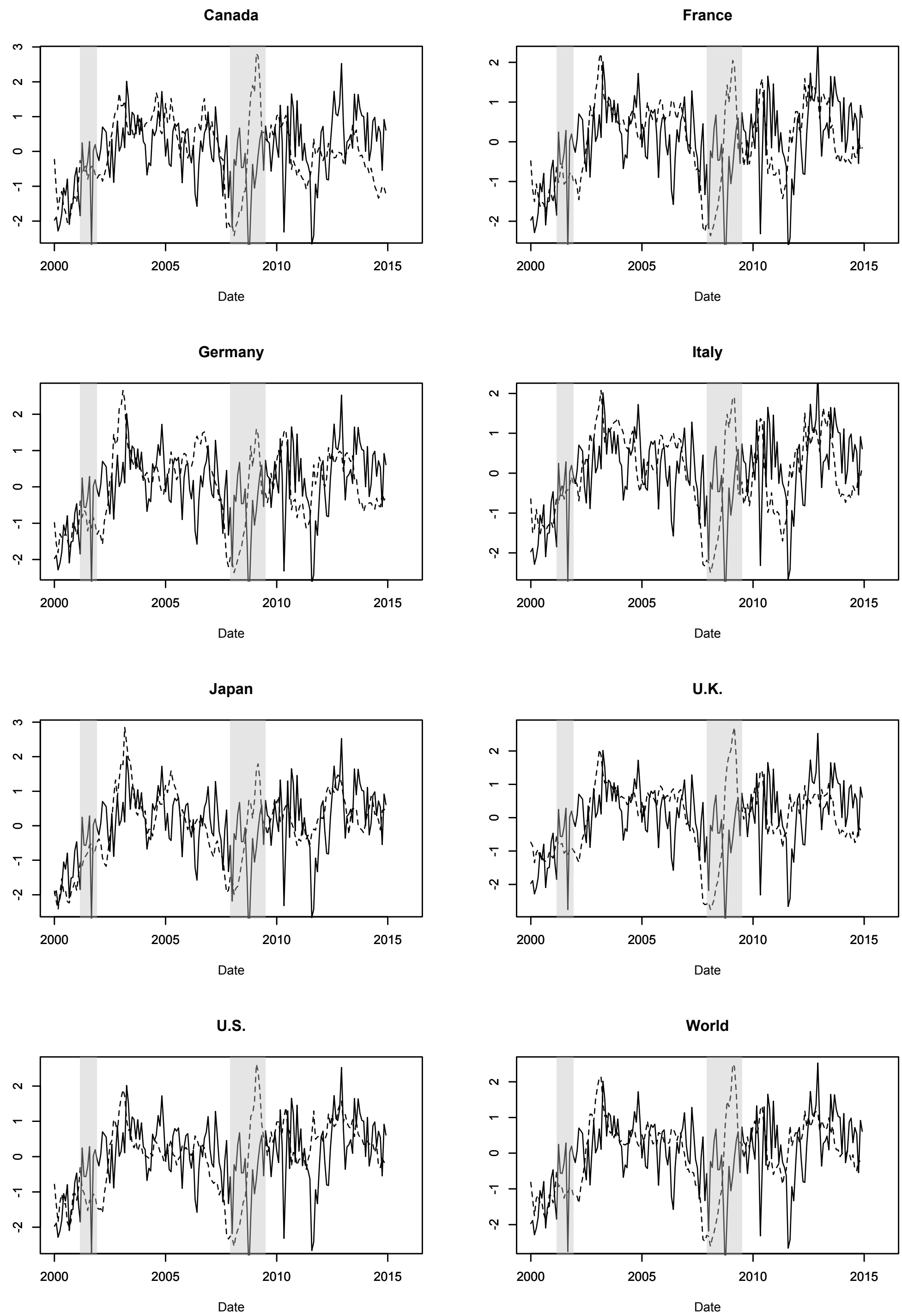

Figure 7: Expected Market Returns vs. Realized Market Returns

This figure plots the market returns over the next twelves months (dotted line) and the expected market returns over the same period (solid line). Expected market returns are the fitted values from the predictive regressions. The shaded areas present recessions defined by NBER.

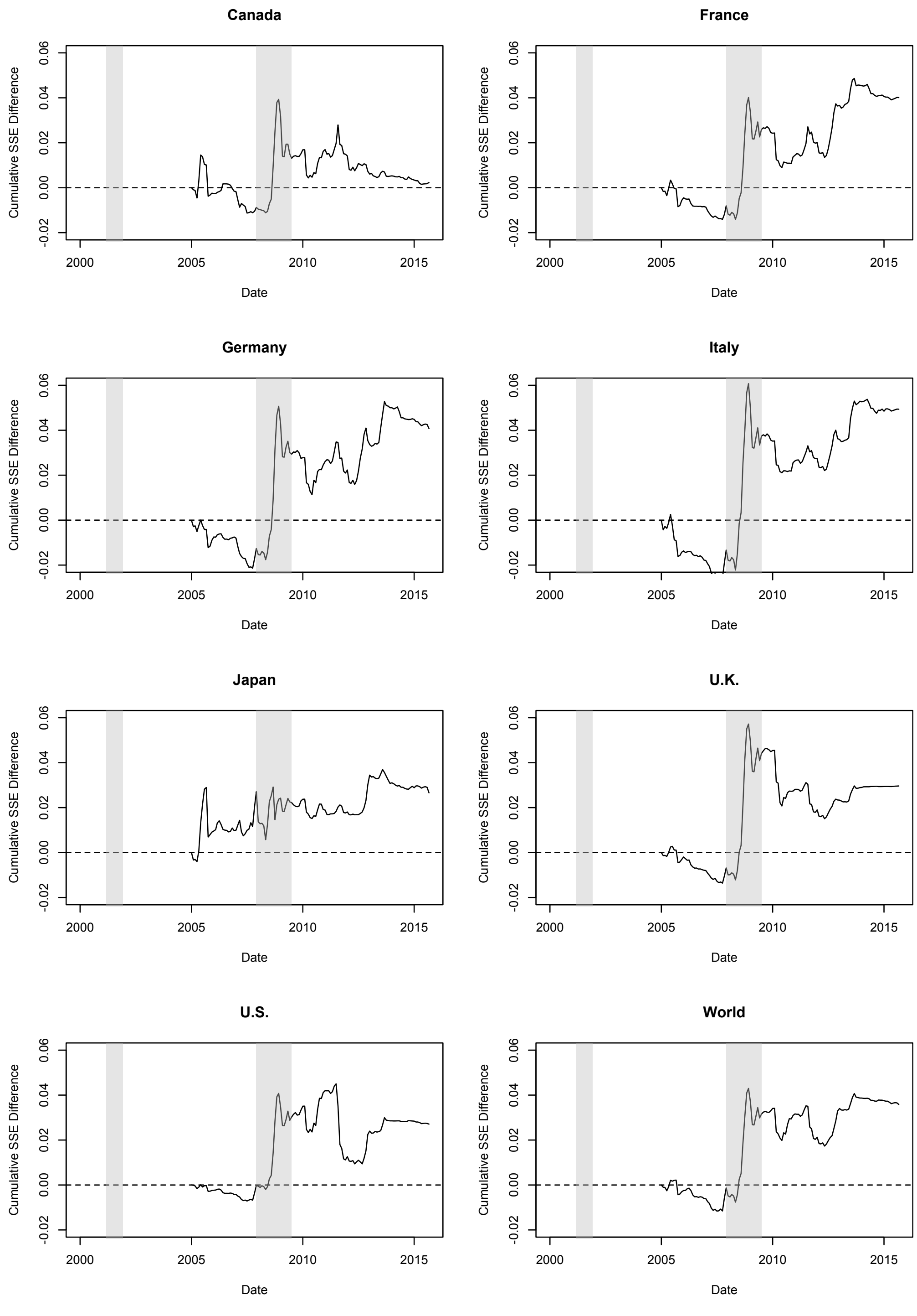

Figure 8: Performance of Predictors – Out-of-Sample

This figure shows the out-of-sample performance of predictive regressions for the three month horizon. We plot the cumulative squared prediction errors of the historical mean model minus the cumulative squared prediction error of our prediction model using WF. An increase (a decrease) in the line indicates that our model outperforms (underperforms) the historical mean model. The shaded areas present recessions defined by NBER.

B Additional Tables

Table 7: Granger Causality

This table presents the results for Granger causality tests between the JKTR. The investigated countries are the G-7 countries over the period from January 2000 until December 2015. We test the null hypothesis that the JKTR of one individual country is not Granger-caused by the JKTR of the remaining countries. We report the F-statistic with the corresponding p-values below. Stars indicate significance of the estimates: * significant at $p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

	Canada	France	Germany	Italy	Japan	U.K.	U.S.
1 Month	2.8730***	2.0862*	3.5633***	1.1326	2.2581**	3.2466***	1.8821*
	0.0087	0.0522	0.0017	0.3409	0.0358	0.0036	0.0806
3 Month	1.2240	1.7376**	1.8430**	0.7861	0.8719	1.6875**	0.9474
	0.2330	0.0282	0.0170	0.7186	0.6137	0.0356	0.5200
6 Month	0.9144	1.1466	1.1095	0.8401	0.8828	1.0288	0.6753
	0.6151	0.2560	0.3036	0.7360	0.6679	0.4234	0.9285
1 Year	0.5977	0.7839	0.8342	0.8551	0.8924	0.7858	0.7954
	0.9964	0.9023	0.8315	0.7955	0.7228	0.9000	0.8881

Table 8: Granger Causality – Bivariate

This table presents results for Granger causality tests between the JKTR of two individual countries. The investigated countries are the G-7 countries over the period from January 2000 until December 2015. We test the null hypothesis that the JKTR of one individual country does not Granger-cause the JKTR of another country. We report the lag order chosen by the Bayesian Information Criterion (BIC), the F-statistic and the corresponding p-values. Stars indicate significance of the estimates: * significant at $p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

	Lag	F-statistic	p-value
Canada → France	3	0.1997	0.8966
France → Canada	3	3.7589**	0.0111
Canada → Germany	1	10.5611***	0.0013
Germany → Canada	1	10.1047***	0.0016
Canada → Italy	2	1.0075	0.3661
Italy → Canada	2	1.9082	0.1498
Canada → Japan	1	3.0531*	0.0814
Japan → Canada	1	6.6604**	0.0102
Canada → U.K.	1	3.2235*	0.0734
U.K. → Canada	1	0.5604	0.4546
Canada → U.S.	1	2.6836	0.1022
U.S. → Canada	1	0.9627	0.3271
France → Germany	3	3.7109**	0.0118
Germany → France	3	1.6399	0.1798
France → Italy	2	2.2752	0.1042
Italy → France	2	0.2593	0.7718
France → Japan	1	8.4291***	0.0039
Japan → France	1	6.0887**	0.0140
France → U.K.	3	2.9467**	0.0329
U.K. → France	3	0.6926	0.5570
France → U.S.	2	0.5589	0.5723
U.S. → France	2	2.3000	0.1017
Germany → Italy	1	0.0312	0.8599
Italy → Germany	1	10.6340***	0.0012
Germany → Japan	1	3.8502*	0.0505
Japan → Germany	1	7.8163***	0.0054
Germany → U.K.	1	6.8772***	0.0091
U.K. → Germany	1	11.4396***	0.0008
Germany → U.S.	3	0.1829	0.9080
U.S. → Germany	3	2.4459*	0.0636
Italy → Japan	1	7.3125***	0.0072
Japan → Italy	1	0.8912	0.3457
Italy → U.K.	1	0.6702	0.4135
U.K. → Italy	1	1.7429	0.1876
Italy → U.S.	1	0.5526	0.4577
U.S. → Italy	1	0.1029	0.7486
Japan → U.K.	1	7.2711***	0.0073
U.K. → Japan	1	1.9872	0.1595
Japan → U.S.	1	1.1260	0.2893
U.S. → Japan	1	4.4459**	0.0356
U.K. → U.S.	1	7.8834***	0.0052
U.S. → U.K.	1	0.5805	0.4466

Table 9: JTKR vs. World Fear

This table reports results from the following regression: $JKTR_{i,t} = a_i + b_i WF_t + \epsilon_{i,t}$ where $JKTR_{i,t}$ is the tail risk of country i at time t, WF_t is World Fear at time t and $\epsilon_{i,t}$ is the error term. Stars indicate significance of the estimates: * significant at $p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

	Canada	France	Germany	Italy	Japan	U.K.	U.S.
Intercept	0.1278***	−0.2582***	−0.1665**	−0.0231	0.1822***	0.0589*	0.0790***
	(0.0368)	(0.0297)	(0.0653)	(0.0306)	(0.0221)	(0.0355)	(0.0201)
WF	0.7228***	1.7826***	1.5833***	0.7476***	0.4368***	1.0233***	0.7036***
	(0.0774)	(0.0626)	(0.1375)	(0.0645)	(0.0466)	(0.0747)	(0.0423)
adj. R^2	0.3109	0.8090	0.4078	0.4113	0.3128	0.4945	0.5907

Table 10: Return Predictability U.S. (1963-2015)

This table presents results for monthly return predictive regressions of CRSP value-weighted market index returns over horizons from one month to five years. The period starts in 1963 following Kelly & Jiang (2014) but is extended until 2015 in Panel A. Panel B reports results for the same period as Kelly & Jiang (2014) while Panel C investigates the period from 1963 to 1979. Robust Hodrick (1992) standard errors are reported in parentheses using lags equal to the prediction horizon expressed in months. Stars indicate significance of the estimates: * significant at $p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

	1 Month	1 Year	2 Year	3 Year	5 Year
Panel C: 1963-2015					
(Intercept)	-0.0259^{*}	-0.2242	-0.4157	-0.7320^{*}	-1.3684^{**}
	(0.0144)	(0.1479)	(0.2939)	(0.4311)	(0.6800)
JKTR	0.0816^{**}	0.7955^{**}	1.5392^{**}	2.5963^{**}	4.8275^{**}
	(0.0326)	(0.3366)	(0.6696)	(0.9831)	(1.5473)
adj. R^2	0.0088	0.0649	0.1105	0.1850	0.2262
Panel B: 1963-2010					
(Intercept)	-0.0304^{**}	-0.2722^{*}	-0.5494^{*}	-0.9769^{**}	-1.6229^{**}
	(0.0145)	(0.1578)	(0.3105)	(0.4605)	(0.7323)
JTKR	0.0921^{**}	0.8967^{**}	1.8132^{**}	3.1107^{**}	5.3930^{**}
	(0.0329)	(0.3581)	(0.7064)	(1.0487)	(1.6532)
adj. R^2	0.0115	0.0797	0.1524	0.2580	0.2895
Panel C: 1963-1979					
(Intercept)	-0.0187	-0.0716	-0.2098	-0.3796	-0.7782
	(0.0177)	(0.2080)	(0.3941)	(0.5692)	(0.8154)
JKTR	0.0640	0.3801	0.9099	1.4917	2.8872^{*}
	(0.0420)	(0.4942)	(0.9108)	(1.2949)	(1.7418)
adj. R^2	0.0041	0.0193	0.0611	0.1703	0.2892

Table 11: Return Predictability Regressions – Local Market Returns

This table presents results for monthly return predictive regressions of value-weighted market index returns in *local currencies* over horizons from one month to two years. The investigated countries are the G-7 countries over the period from January 2000 until December 2015. The predictor is World Fear. Robust Hodrick (1992) standard errors are reported in parentheses using lags equal to the prediction horizon expressed in months. Stars indicate significance of the estimates: * significant at $p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

	Canada	France	Germany	Italy	Japan	U.K.	U.S.	Global
Intercept	−0.0705*	−0.0263	−0.0488	−0.0496	−0.1286**	−0.0090	−0.0705*	−0.0731*
	(0.0371)	(0.0400)	(0.0476)	(0.0473)	(0.0406)	(0.0312)	(0.0371)	(0.0441)
WF_{1Month}	0.1565**	0.0605	0.1090	0.1061	0.2770**	0.0232	0.1565**	0.1614*
	(0.0757)	(0.0823)	(0.0982)	(0.0980)	(0.0848)	(0.0642)	(0.0757)	(0.0901)
adj. R^2	0.0219	−0.0028	0.0011	0.0012	0.0480	−0.0047	0.0219	0.0165
	{0.0352}	{0.5244}	{0.3336}	{0.2912}	{0.0020}	{0.7428}	{0.0388}	{0.0484}
Intercept	−0.1214	−0.1650*	−0.2149**	−0.1977**	−0.3811***	−0.0769	−0.1214	−0.2114**
	(0.0824)	(0.0879)	(0.1073)	(0.0982)	(0.1028)	(0.0729)	(0.0824)	(0.1004)
WF_{3Month}	0.2803*	0.3638**	0.4716**	0.4200**	0.8254***	0.1755	0.2803*	0.4695**
	(0.1658)	(0.1783)	(0.2179)	(0.2018)	(0.2144)	(0.1491)	(0.1658)	(0.2031)
adj. R^2	0.0168	0.0227	0.0313	0.0287	0.1080	0.0053	0.0168	0.0458
	{0.0310}	{0.0656}	{0.0192}	{0.0226}	{0.0000}	{0.1494}	{0.0422}	{0.0016}
Intercept	−0.1429	−0.3449**	−0.3309*	−0.3364*	−0.5606**	−0.1389	−0.1429	−0.3126*
	(0.1502)	(0.1692)	(0.1925)	(0.1895)	(0.1789)	(0.1326)	(0.1502)	(0.1763)
WF_{6Month}	0.3512	0.7602**	0.7377*	0.7180*	1.2295**	0.3209	0.3512	0.7104**
	(0.3006)	(0.3413)	(0.3907)	(0.3861)	(0.3732)	(0.2693)	(0.3006)	(0.3536)
adj. R^2	0.0099	0.0474	0.0351	0.0381	0.0969	0.0097	0.0099	0.0431
	{0.0984}	{0.0088}	{0.0164}	{0.0074}	{0.0000}	{0.0880}	{0.1012}	{0.0030}
Intercept	−0.4599*	−0.6299**	−0.6454**	−0.6414*	−1.0495***	−0.2871	−0.4599*	−0.5616*
	(0.2644)	(0.3014)	(0.3212)	(0.3300)	(0.2850)	(0.2321)	(0.2644)	(0.2922)
WF_{1Year}	1.0779**	1.4067**	1.4590**	1.3757**	2.3297***	0.6707	1.0779**	1.3029**
	(0.5241)	(0.5997)	(0.6400)	(0.6653)	(0.5883)	(0.4618)	(0.5241)	(0.5765)
adj. R^2	0.0655	0.0718	0.0669	0.0683	0.1545	0.0234	0.0655	0.0696
	{0.0010}	{0.0022}	{0.0016}	{0.0014}	{0.0000}	{0.0346}	{0.0022}	{0.0012}
Intercept	−0.5610**	−1.0187**	−1.0369**	−1.0910**	−1.2951***	−0.4167	−0.5610**	−0.6696*
	(0.2735)	(0.3896)	(0.4462)	(0.3956)	(0.3432)	(0.3100)	(0.2735)	(0.3422)
WF_{2Year}	1.4460**	2.3433**	2.4230**	2.3856**	3.0019***	1.0381*	1.4460**	1.7044**
	(0.5260)	(0.7280)	(0.8420)	(0.7487)	(0.6870)	(0.5722)	(0.5260)	(0.6373)
adj. R^2	0.0553	0.0863	0.0849	0.0869	0.1076	0.0265	0.0553	0.0550
	{0.0022}	{0.0000}	{0.0006}	{0.0000}	{0.0000}	{0.0300}	{0.0016}	{0.0020}

Table 12: Correlation of Control Variables

This table presents sample correlations between World Fear and the country specific control variables for the period from January 2000 until December 2015. The control variables are the implied volatility IV, the inflation $Inflation$ and the dividend-price ratio $log(D/P)$.

	Canada	France	Germany	Italy	Japan	U.K.	U.S.
IV	−0.5352	−0.4197	−0.3857	−0.4081	−0.4346	−0.5085	−0.5203
Inflation	−0.0214	−0.0446	0.0898	−0.0895	0.1853	0.0741	0.0320
log(D/P)	0.2129	0.1900	0.1126		0.1463	0.2303	0.2135

Table 13: Return Predictability Regressions – Control Variables

This table presents robustness checks for return predictive regressions of value-weighted market index returns in *Dollar currencies* for the one year horizon. The investigated countries are the G-7 countries over the period from January 2000 until December 2015. The control variables are the implied volatility IV, the inflation $Inflation$ and the dividend-price ratio $log(D/P)$. Robust Hodrick (1992) standard errors are reported in parentheses using lags equal to the prediction horizon. Stars indicate significance of the estimates: * significant at $p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$. The Wald row reports the Wald test statistic for the joint significance of the tail risk and the control variable.

	Canada	France	Germany	Italy	Japan	U.K.	U.S.
Intercept	−0.6848	−1.2227**	−1.3307**	−1.2710**	−1.2853***	−0.9481**	−1.1753***
	(0.5245)	(0.5119)	(0.5540)	(0.4960)	(0.3456)	(0.3530)	(0.3501)
WF	1.2925	2.2238**	2.4407**	2.2151**	2.4796***	1.8009**	2.1929***
	(0.9775)	(0.9086)	(0.9724)	(0.8854)	(0.6245)	(0.6207)	(0.6298)
IV	0.0108**	0.0096*	0.0107*	0.0103**	0.0052	0.0078	0.0092**
	(0.0047)	(0.0054)	(0.0056)	(0.0051)	(0.0040)	(0.0051)	(0.0043)
adj. R^2	0.0772	0.1554	0.1889	0.1812	0.2224	0.0999	0.1908
Wald	5.6101	6.3545	6.6916	7.0476	15.7972	8.4224	12.4457
Intercept	−0.6578	−1.1575**	−1.3267**	−1.1655**	−1.3157***	−0.9467**	−1.0788**
	(0.5173)	(0.5128)	(0.5530)	(0.4831)	(0.3469)	(0.3529)	(0.3400)
WF	1.2591	2.1617**	2.4555**	2.0901**	2.5625***	1.8205**	2.0857***
	(0.9685)	(0.9101)	(0.9764)	(0.8678)	(0.6340)	(0.6237)	(0.6171)
IV	0.0104**	0.0093*	0.0105*	0.0098*	0.0049	0.0076	0.0079*
	(0.0047)	(0.0054)	(0.0056)	(0.0052)	(0.0041)	(0.0051)	(0.0044)
Inflation	−3.1697	−23.2123*	−4.9216	−21.6222*	−10.8589	−4.5471	−9.7053**
	(2.8307)	(12.4961)	(3.1089)	(12.5540)	(7.0593)	(4.6159)	(4.8193)
adj. R^2	0.0732	0.1812	0.1881	0.2065	0.2341	0.1009	0.2101
Wald	6.8105	9.8944	7.1857	8.5866	16.8375	8.9156	13.8955
Intercept	−2.8098**	0.5776	−0.3319	0.4479	−0.4126	1.5047	1.3131
	(1.3290)	(1.1981)	(1.2046)	(1.3607)	(0.6138)	(1.0620)	(1.0547)
WF	1.6765	1.2534	2.0481*	0.8441	2.1228**	0.7214	1.1241*
	(1.0134)	(1.0135)	(1.0919)	(0.9153)	(0.6535)	(0.7376)	(0.6143)
IV	0.0198**	0.0039	0.0079	0.0029	0.0021	0.0013	0.0031
	(0.0065)	(0.0062)	(0.0064)	(0.0081)	(0.0042)	(0.0046)	(0.0044)
Inflation	−4.4572	−18.9839	−4.1975	−12.8134	−11.8963*	−6.9369	−6.4796
	(2.9815)	(12.4498)	(3.1846)	(7.7342)	(6.9385)	(4.1969)	(5.0998)
log(D/P)	−0.4840*	0.3477	0.2037	0.2633	0.1443	0.5253**	0.4618**
	(0.2690)	(0.2315)	(0.2081)	(0.3462)	(0.0915)	(0.2317)	(0.2204)
adj. R^2	0.2228	0.2893	0.2360	0.0252	0.3147	0.2614	0.4199
Wald	11.0415	10.6539	8.6090	6.9029	18.3215	15.3518	14.9004

Table 14: Return Predictability Regressions – Alternative Thresholds

This table presents robustness checks for return predictive regressions of value-weighted market index returns in *Dollar currencies* for the one year horizon. The investigated countries are the G-7 countries over the period from January 2000 until December 2015. The predictor variables are the World Fear indices $WF_{0.06}$ and $WF_{0.07}$, which are based on a threshold of 6% and 7%, respectively. Robust Hodrick (1992) standard errors are reported in parentheses using lags equal to the prediction horizon. Stars indicate significance of the estimates: * significant at $p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

	Canada	France	Germany	Italy	Japan	U.K.	U.S.	Global.
Intercept	−0.5288	−0.6217	−0.6480	−0.6222	−0.9420**	−0.4598	−0.5229*	−0.5674*
	(0.4100)	(0.4002)	(0.4207)	(0.4022)	(0.2963)	(0.2989)	(0.2932)	(0.3014)
$WF_{0.06}$	1.2480	1.3715*	1.4855*	1.3301*	1.9611***	1.0596*	1.1719**	1.2656**
	(0.7851)	(0.7671)	(0.8059)	(0.7736)	(0.5855)	(0.5714)	(0.5589)	(0.5722)
adj. R^2	0.0426	0.0574	0.0573	0.0528	0.1784	0.0411	0.0654	0.0681
	{0.0066}	{0.0058}	{0.0044}	{0.0056}	{0.0000}	{0.0106}	{0.0024}	{0.0004}
Intercept	−0.5281	−0.5810	−0.6084	−0.6161	−0.9052**	−0.4397	−0.4764	−0.5357*
	(0.4123)	(0.4034)	(0.4260)	(0.4128)	(0.2983)	(0.3110)	(0.2944)	(0.3063)
$WF_{0.07}$	1.2004	1.2407*	1.3527*	1.2688*	1.8159**	0.9808*	1.0371*	1.1563**
	(0.7595)	(0.7437)	(0.7878)	(0.7624)	(0.5684)	(0.5721)	(0.5407)	(0.5600)
adj. R^2	0.0420	0.0495	0.0501	0.0511	0.1627	0.0371	0.0538	0.0600
	{0.0064}	{0.0082}	{0.0072}	{0.0070}	{0.0000}	{0.0144}	{0.0050}	{0.0018}

Table 15: Fama–MacBeth Regressions – Alternative Thresholds

This table reports results for Fama–MacBeth Regressions based on World Fear loadings and alternative thresholds of 6% and 7%. Intercept and γ_{WF} are means of the coefficients from the cross-sectional regressions of individual stock returns on an intercept and the tail risk loadings. We apply the Shanken (1992) correction. Stars indicate significance of the estimates: * significant at $p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

	Canada	France	Germany	Italy	Japan	U.K.	U.S.
Panel A: Threshold 6%							
Intercept	0.0060	0.0030	0.0043	−0.0050	0.0053	−0.0018	0.0055
	(0.0061)	(0.0045)	(0.0049)	(0.0058)	(0.0037)	(0.0050)	(0.0039)
γ_{WF}	0.0004**	0.0014***	0.0000**	0.0016**	0.0001	0.0008**	0.0003
	(0.0002)	(0.0004)	(0.0000)	(0.0007)	(0.0004)	(0.0004)	(0.0004)
Panel B: Threshold 7%							
Intercept	0.0061	0.0030	0.0043	−0.0051	0.0053	−0.0016	0.0055
	(0.0061)	(0.0045)	(0.0049)	(0.0058)	(0.0037)	(0.0050)	(0.0039)
γ_{WF}	0.0004**	0.0015***	0.0000**	0.0016**	0.0002	0.0008**	0.0003
	(0.0002)	(0.0004)	(0.0000)	(0.0007)	(0.0004)	(0.0004)	(0.0004)

Table 16: Return Predictability – Foreign Tail Risk

This table presents results for monthly return predictive regressions of value-weighted market index returns in *U.S. dollar currency* over horizons from one month to two years. The investigated countries are the G-7 countries over the period from January 2000 until December 2015. The predictor is the foreign tail risk *Foreign* of the country [name in column]. Robust Hodrick (1992) standard errors are reported in parentheses using lags equal to the prediction horizon expressed in months. Stars indicate significance of the estimates: * significant at $p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$. We report bootstrapped p-values below the corresponding adjusted R^2.

	Canada	France	Germany	Italy	Japan	U.K.	U.S.
Intercept	−0.0613	−0.0471	−0.0594	−0.0731	−0.1152**	−0.0583	−0.0666
	(0.0532)	(0.0594)	(0.0662)	(0.0585)	(0.0389)	(0.0416)	(0.0440)
$Foreign_{1Month}$	0.1415	0.1111	0.1419	0.1506	0.2371**	0.1341	0.1450
	(0.1086)	(0.1277)	(0.1412)	(0.1157)	(0.0773)	(0.0874)	(0.0881)
adj. R^2	0.0054	−0.0007	0.0023	0.0055	0.0494	0.0083	0.0150
	{0.2044}	{0.3908}	{0.2878}	{0.1858}	{0.0008}	{0.1174}	{0.0606}
Intercept	−0.1199	−0.1980	−0.2127	−0.2578**	−0.3515**	−0.1637*	−0.2030**
	(0.1151)	(0.1420)	(0.1632)	(0.1304)	(0.1122)	(0.0915)	(0.1016)
$Foreign_{3Month}$	0.2917	0.4586	0.5018	0.5289**	0.7250**	0.3813**	0.4426**
	(0.2315)	(0.3023)	(0.3449)	(0.2560)	(0.2229)	(0.1917)	(0.2008)
adj. R^2	0.0078	0.0194	0.0242	0.0360	0.1339	0.0249	0.0506
	{0.0808}	{0.0562}	{0.0284}	{0.0066}	{0.0000}	{0.0200}	{0.0034}
Intercept	−0.1330	−0.4031*	−0.2891	−0.3826*	−0.5409**	−0.2272	−0.3079*
	(0.2118)	(0.2436)	(0.2778)	(0.2180)	(0.1850)	(0.1571)	(0.1789)
$Foreign_{6Month}$	0.3625	0.9370*	0.7119	0.7973*	1.1216**	0.5509*	0.6851*
	(0.4249)	(0.5139)	(0.5844)	(0.4245)	(0.3677)	(0.3280)	(0.3506)
adj. R^2	0.0036	0.0405	0.0213	0.0369	0.1450	0.0207	0.0528
	{0.1894}	{0.0056}	{0.0370}	{0.0028}	{0.0000}	{0.0190}	{0.0006}
Intercept	−0.4405	−0.6635	−0.4839	−0.6009	−0.8988**	−0.3976	−0.5677**
	(0.3721)	(0.4176)	(0.4478)	(0.3839)	(0.2726)	(0.2686)	(0.2830)
$Foreign_{1Year}$	1.1093	1.5758*	1.2427	1.2734*	1.8907***	0.9941*	1.2848**
	(0.7424)	(0.8728)	(0.9277)	(0.7413)	(0.5415)	(0.5534)	(0.5472)
adj. R^2	0.0354	0.0567	0.0333	0.0514	0.1939	0.0347	0.0860
	{0.0100}	{0.0044}	{0.0178}	{0.0066}	{0.0000}	{0.0134}	{0.0002}
Intercept	−0.3497	−0.9124*	−0.5389	−0.7805*	−0.9446**	−0.5583	−0.6691**
	(0.3724)	(0.5060)	(0.6300)	(0.4070)	(0.3312)	(0.3435)	(0.3323)
$Foreign_{2Year}$	1.1946	2.3044**	1.6232	1.7529**	2.0852**	1.5350**	1.6572**
	(0.7406)	(0.9998)	(1.2650)	(0.7486)	(0.6459)	(0.6769)	(0.6055)
adj. R^2	0.0153	0.0596	0.0265	0.0468	0.1284	0.0383	0.0611
	{0.0450}	{0.0012}	{0.0192}	{0.0020}	{0.0000}	{0.0088}	{0.0010}

Table 17: Return Predictability – Adj. R^2

This table presents results for monthly return predictive regressions of value-weighted market index returns in *U.S. dollar currency* over horizons from one month to two years. The investigated countries are the G-7 countries over the period from January 2000 until December 2015. The predictors are JKT, WF and $Foreign$. We report the adjusted R^2.

	Canada	France	Germany	Italy	Japan	U.K.	U.S.
$JKTR_{1Month}$	0.0003	0.0004	0.0064	0.0053	−0.0045	−0.0023	−0.0040
WF_{1Month}	0.0064	−0.0001	0.0068	0.0070	0.0418	0.0074	0.0125
$Foreign_{1Month}$	0.0054	−0.0007	0.0023	0.0055	0.0494	0.0083	0.0150
$JKTR_{3Month}$	0.0001	0.0342	0.0358	0.0206	−0.0049	0.0054	−0.0049
WF_{3Month}	0.0085	0.0254	0.0401	0.0389	0.1197	0.0243	0.0393
$Foreign_{3Month}$	0.0078	0.0194	0.0242	0.0360	0.1339	0.0249	0.0506
$JKTR_{6Month}$	−0.0022	0.0495	0.0391	0.0151	−0.0024	0.0143	−0.0027
WF_{6Month}	0.0040	0.0467	0.0382	0.0385	0.1323	0.0232	0.0392
$Foreign_{6Month}$	0.0036	0.0405	0.0213	0.0369	0.1450	0.0207	0.0528
$JKTR_{1Year}$	0.0058	0.0467	0.0568	0.0032	0.0044	0.0294	−0.0006
WF_{1Year}	0.0357	0.0586	0.0572	0.0477	0.1810	0.0397	0.0746
$Foreign_{1Year}$	0.0354	0.0567	0.0333	0.0514	0.1939	0.0347	0.0860
$JKTR_{2Year}$	0.0408	0.0244	0.0371	−0.0046	0.0027	0.0152	−0.0024
WF_{2Year}	0.0236	0.0530	0.0434	0.0394	0.1209	0.0389	0.0527
$Foreign_{2Year}$	0.0153	0.0596	0.0265	0.0468	0.1284	0.0383	0.0611

Table 18: Portfolio Sorts and Fama–MacBeth Regressions – Foreign Tail Risk

This table presents results from portfolio sorts based on *Foreign*. The investigated countries are the G-7 countries over the period from January 2000 until December 2015. Decile portfolios are formed based on *Foreign* betas for each country. Betas are calculated in predictive regressions using the most recent 60 returns measured in *U.S. Dollars*. We then track 1 month out-of-sample equally weighted holding period returns. We report the average returns of the high minus low portfolio in the first row of Panel A. *FF3* report alphas from the Fama & French (1993) 3 factor model. In Panel B, Intercept and $\gamma_{Foreign}$ are means of the coefficients from the cross-sectional regressions of individual stock returns on an intercept and the foreign tail risk loadings. Panel C additionally includes the market loading, $log(Size)$, book-to-market ratios (BTM), prior returns (Mom), illiquidity (Liq), aggregate Volatility ($Aggr.Vol$), coskewness ($Coskewness$), downside beta ($DownsideBeta$) and idiosyncratic volatility ($iVol$) of individual stocks in the cross-sectional regressions. The according mean coefficients γ_{Market}, γ_{Size}, γ_{BTM}, γ_{Mom}, γ_{Liq}, $\gamma_{Aggr.Vol}$, $\gamma_{Coskewness}$, $\gamma_{DownsideBeta}$ and γ_{iVol} are reported. For the cross-sectional regressions, we apply the Shanken (1992) correction. Stars indicate significance of the estimates: * significant at $p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

	Canada	France	Germany	Italy	Japan	U.K.	U.S.
Panel A: Portfolio Sorts							
Average return	0.0089	0.0036	0.0292***	0.0147***	−0.0015	0.0139**	0.0017
	(0.0059)	(0.0050)	(0.0070)	(0.0048)	(0.0046)	(0.0057)	(0.0043)
FF3	0.0102*	0.0013	0.0320***	0.0163***	0.0021	0.0157**	−0.0021
	(0.0058)	(0.0047)	(0.0074)	(0.0049)	(0.0038)	(0.0062)	(0.0036)
Panel B: Simple Fama–MacBeth Regressions							
(Intercept)	0.0061	0.0033	0.0043	−0.0051	0.0054	−0.0028	0.0051
	(0.0061)	(0.0045)	(0.0049)	(0.0059)	(0.0037)	(0.0051)	(0.0039)
$\gamma_{Foreign}$	0.0004**	0.0013***	0.0000***	0.0020***	−0.0000	0.0012***	0.0004
	(0.0002)	(0.0003)	(0.0000)	(0.0007)	(0.0004)	(0.0004)	(0.0004)
Panel C: Multiple Fama–MacBeth Regressions							
(Intercept)	−0.0074	−0.0008	0.0062	0.0017	−0.0001	−0.0025	0.0073
	(0.0054)	(0.0060)	(0.0060)	(0.0060)	(0.0044)	(0.0054)	(0.0062)
$\gamma_{Foreign}$	0.0013***	0.0022***	0.0022***	0.0034***	0.0010	0.0020***	0.0007
	(0.0004)	(0.0007)	(0.0007)	(0.0009)	(0.0007)	(0.0006)	(0.0007)
γ_{Market}	−0.0078**	−0.0047	−0.0053	−0.0023	0.0022	−0.0001	0.0024
	(0.0031)	(0.0036)	(0.0036)	(0.0045)	(0.0020)	(0.0021)	(0.0019)
γ_{Size}	0.0005	0.0003	−0.0003	−0.0001	−0.0001	0.0011**	0.0000
	(0.0005)	(0.0006)	(0.0005)	(0.0007)	(0.0005)	(0.0005)	(0.0004)
γ_{BTM}	0.0125***	0.0061***	0.0024**	0.0046***	0.0060***	0.0077***	−0.0018*
	(0.0013)	(0.0015)	(0.0011)	(0.0011)	(0.0008)	(0.0009)	(0.0010)
γ_{Mom}	0.0039	0.0042	0.0089*	0.0048	−0.0026	0.0058	−0.0035
	(0.0046)	(0.0044)	(0.0048)	(0.0066)	(0.0032)	(0.0045)	(0.0031)
γ_{Liq}	0.0001	−0.0017	−0.0004	−0.0000	0.0001	0.0001	−0.2271
	(0.0001)	(0.0012)	(0.0003)	(0.0036)	(0.0004)	(0.0002)	(0.1542)
$\gamma_{Aggr.Vol}$	0.0589	−0.2738*	−0.0170	−0.4710*	−0.0328	−0.1476	−0.0204
	(0.1139)	(0.1552)	(0.1876)	(0.2725)	(0.1852)	(0.1203)	(0.0949)
$\gamma_{Coskewness}$	−0.0000	0.0007	0.0013	0.0016*	0.0002	−0.0002	−0.0001
	(0.0005)	(0.0006)	(0.0008)	(0.0008)	(0.0002)	(0.0004)	(0.0002)
$\gamma_{DownsideBeta}$	0.0001	0.0010	0.0092**	−0.0004	0.0009	−0.0037**	−0.0018*
	(0.0017)	(0.0025)	(0.0036)	(0.0034)	(0.0012)	(0.0019)	(0.0011)
γ_{iVol}	0.0163	−0.0274	−0.0452*	−0.0807***	−0.0326*	−0.0605***	−0.0295*
	(0.0180)	(0.0255)	(0.0245)	(0.0276)	(0.0187)	(0.0144)	(0.0168)