NBER WORKING PAPER SERIES

FLIGHTS TO SAFETY

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Working Paper 19095
http://www.nber.org/papers/w19095

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
May 2013

The authors greatly benefited from discussions with seminar participants at Antwerp University, the National Bank of Belgium, the University of the Basque Country, and Tilburg University, and in particular with Hans Dewachter, Eric Ghysels, Frank de Jong, and Joost Driessen. Baele, Bekaert, and Inghelbrecht gratefully acknowledge financial support from the National Bank of Belgium and Inquire Europe. The opinions expressed are those of the authors and do not necessarily reflect views of the National Bank of Belgium or the Federal Reserve System or the National Bureau of Economic Research.

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NBER Working Paper No. 19095
May 2013
JEL No. E43,E44,G11,G12,G14

ABSTRACT

Despite a large and growing theoretical literature on flights to safety, there does not appear to exist an empirical characterization of flight-to-safety (FTS) episodes. Using only data on bond and stock returns, we identify and characterize flight to safety episodes for 23 countries. On average, FTS days comprise less than 5% of the sample, and bond returns exceed equity returns by 2 to 3%. The majority of FTS events are country-specific not global. FTS episodes coincide with increases in the VIX, decreases in consumer sentiment indicators and appreciations of the Yen, Swiss franc, and US dollar. The financial, basic materials and industrial industries under-perform in FTS episodes, but the telecom industry outperforms. Money market instruments, corporate bonds, and commodity prices (with the exception of metals, including gold) face abnormal negative returns in FTS episodes. Liquidity deteriorates on FTS days both in the bond and equity markets. Both economic growth and inflation decline right after and up to a year following a FTS spell.

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1 Introduction

In periods of market stress, the financial press interprets extreme and inverse market movements in the bond and equity markets often as “flights to safety” or “flights to quality.” In particular, between August 2004 and June 2012, a period marred by a global financial crisis, the Financial Times referred 805 times to “Flight(s)-to-Quality” and 533 times to “Flight(s)-to-Safety.”

There is an active theoretical academic literature studying such phenomena. In Vayanos (2004)‘s model, risk averse investment managers fear redemptions during high volatility periods and therefore an increase in volatility may lead to a “flight-to-liquidity.” At the same time, their risk aversion also increases, leading to a “flight-to-safety,” meaning that they require higher risk premiums, which in turn drives down the prices of risky assets (a flight to quality). In Caballero and Krishnamurthy (2008), Knightian uncertainty may lead agents to shed risky assets in favor of uncontingent and safe claims when aggregate liquidity is low thereby provoking a flight to quality or safety. Brunnermeier and Pedersen (2009) study a model in which speculators, who provide market liquidity, have margin requirements increasing in volatility. They show how margin requirements can help cause a liquidity spiral following a bad shock, where liquidity deteriorates in all markets, but also a flight to quality, which they define as a sharp drop in liquidity provision for the high margin, more volatile assets. Representative agent models can also generate “flights-to-safety.” In the consumption based asset pricing literature (e.g. Barsky (1989); Bekaert et al. (2009)) a flight to safety is typically defined as the joint occurrence of higher economic uncertainty (viewed as exogenous) with lower equity prices (through a cash flow or risk premium effect) and low real rates (through a precautionary savings effect).

These articles seem to treat flights to quality, safety and/or liquidity as Justice Potter treated porn: we know it when we see it. However, to be able to test and refute a diverse set of theoretical models, an empirical characterization of flight to safety episodes would appear essential. The goal of our paper is to define, detect and characterize flight-to-safety episodes for 23 countries. In doing so, we only use high frequency data on the prototypical risky asset (a well-diversified equity index) and the prototypical safe and liquid asset (the benchmark Treasury bond). Beber et al. (2009) use the Euro-area government bond market to show that in times of market stress, investors demand liquidity rather than credit quality. Longstaff (2004), focusing on the US Treasury market, shows that the liquidity premium in Treasury bonds can represent up to 15% of their value. In other words, flights to safety may be as much or more about flights to liquidity than about flights to quality.

It is therefore important to focus on a liquid bond benchmark in our work. To define a flight to safety, referred to as FTS henceforth, we use the simple observation that it happens during periods of market stress (high equity market volatility), entails a large and positive bond return, a large and negative equity return, and negative high-frequency correlations between bond and stock returns. Note that stock and bond returns are likely positively correlated outside the flights-to-safety periods as both represent high duration assets. Negative aggregate demand shocks may also entail negative stock-bond return correlations but will only be identified as FTS when accompanied by substantial market stress.

We use a plethora of econometric techniques, detailed in Sections 2.2 and 2.3, to identify flight-to-safety episodes from these features. In Section 2.4, we then analyze the identified flight to safety episodes in 23 countries in more detail. We find that FTS episodes comprise less than 5% of the sample on average, and bond returns exceed equity returns by about 2 to 3% on FTS days. Only a minority of FTS events can be characterized as global (less than 30% for most countries). FTS episodes coincide with increases in the VIX, decreases in consumer sentiment indicators in the US, Germany and the OECD and appreciations of the yen, the Swiss franc, and the US dollar. Finally, in section 3, we characterize the dynamic cross-correlations between flights to safety and the financial and economic environment. We compute flight to safety betas for equity and bond portfolios, and for commodity futures contracts, controlling for systematic exposures to the broad equity and bond markets. The financial, basic materials and industrial industries under-perform in FTS episodes, but the telecom industry outperforms. Large cap stocks outperform small cap stocks. For the bond market, we find that both money market instruments and corporate bonds face abnormal negative returns during FTS episodes. Most commodity prices decrease sharply during FTS episodes, whereas the gold price measured in dollars increases slightly. We also investigate the link with the macro-economy. Both economic growth and inflation decline right after and up to a year following a FTS spell.

There are, of course, a number of empirical papers that bear some indirect relation to what we attempt to accomplish. Baele et al. (2010) show that a dynamic factor model with standard fundamental factors fails to provide a satisfactory fit for stock and bond return comovements. The ability of the model to capture episodes of negative stock-bond return correlations only improves when stock-bond illiquidity factors (potentially capturing "flight-to-liquidity") and the VIX (potentially capturing "flight-to-safety") are included. Connolly et al. (2005) and Bansal et al. (2010) show that high stock market uncertainty is associated with low correlations between between stock and bond returns, and higher bond returns at high frequencies. Goyenko and Sarkissian (2012) define a flight to liquidity and/or quality using illiquidity in short-term (non-benchmark) US Treasuries and show that it affects future stock returns around the globe. Baur and Lucey (2009) define a flight to quality as a period in which stock and bond returns decrease in a falling stock market and differentiate it from contagion, where asset markets move in the same direction. They define the 1997 Asian crisis and the 1998 Russian crisis as flight to safety episodes. The recent financial crisis also sparked a literature on indicators of financial instability and systemic risk which are indirectly related to our flight to safety indicator. The majority of those articles use data from the financial sector only (see e.g. Acharya et al. (2011); Adrian and Brunnermeier (2011); Allen et al. (2012); Brownlees and Engle (2010)), but Hollo et al. (2012) use a wider set of stress indicators and we revisit their methodology in Section 2.2.2.

We compute flight to safety betas for equity and bond portfolios, and for commodity futures contracts, controlling for systematic exposures to the broad equity and bond markets. The financial, basic materials and industrial industries underperform in FTS episodes, but the telecom industry outperforms. Large cap stocks outperform small cap stocks. The regressions include controls for systematic exposure.“ Otherwise the last sentence just hangs by itself.

2 Identifying Flight-to-Safety Episodes

2.1 Data and Overview

Our dataset consists of daily stock and 10-year government bond returns for 23 countries over the period January 1980 till January 2012. Our sample includes two countries from North-America (US, Canada), 18 European countries (Austria, Belgium, Czech Republic, Denmark, France, Finland, Germany, Greece, Ireland, Italy, Netherlands, Norway, Poland, Portugal, Spain, Sweden, Switzerland, UK), as well as Australia, Japan, and New-Zealand. We use Datastream International's total market indices to calculate daily total returns denominated in local currency, and their 10-year benchmark bond indices to calculate government bond returns. For the countries in the euro zone, we use returns denominated in their original (pre-1999) currencies (rather than in synthetic euros), but German government bonds serve as the benchmark. For the other European countries, local government bonds serve as benchmark bonds. More details as well as summary statistics can be found in the online Appendix.

2.2 Measures of Flights to Safety

Our goal is to use only these bond and stock return data to identify a flight-to-safety episode. That is, ultimately we seek to create a $[0, 1]$ *FTS dummy variable* that identifies whether on a particular day a FTS took place. Given the theoretical literature, the symptoms of a flight to safety are rather easy to describe: market stress (high equity and perhaps bond return volatility), a simultaneous high bond and low equity return, low (negative) correlation between bond and equity returns. We use 4 different methodologies to create *FTS indicators*, numbers in $[0, 1]$ that reflect the likelihood of a FTS occurring that day. The indicators can be turned into a FTS dummy using a simple classification rule. The first two methodologies turn the incidence of (a subset of) the symptoms into a [0,1] FTS indicator, with 1 indicating a sure FTS episode, and 0 indicating with certainty that no FTS took place. The last two use a regime switching model to identify the probability of a flight to safety based on its symptoms. In the following sub-sections, we detail these various approaches, whereas section 2.3 discusses how to aggregate the 4 different indicators into one aggregate FTS indicator.

2.2.1 A Flight-to-Safety Threshold Model

Our simplest measure identifies a flight-to-safety event as a day with both an (extreme) negative stock return and an (extreme) positive bond return. The flight-to-safety indicator FTS for country i at time t is calculated as:

$$FTS_{i,t} = I\left\{r^b_{i,t} > z_{i,b}\right\} \times I\left\{r^s_{i,t} < z_{i,s}\right\} \tag{2.1}$$

where I is the indicator function, and $r^b_{i,t}$ and $r^s_{i,t}$ the time t returns in country i for respectively its benchmark government bond and equity market. We allow for different values for the country-specific thresholds $z_{i,b}$ and $z_{i,s}$. Because flights-to-safety are typically associated with large drops (increases) in equity (bond) prices, we use thresholds to model $z_{i,b}$ and $z_{i,s}$:

$$z_{i,b} = \kappa \times \sigma_{i,b} \qquad\qquad z_{i,s} = -\kappa \times \sigma_{i,s} \tag{2.2}$$

where $\sigma_{i,b}$ and $\sigma_{i,s}$ are the full-sample country-specific return volatilities for bond and stock returns, respectively, and κ ranges between 0 and 4 with intervals of 0.5. Consequently, equity (bond) returns must be κ standard deviations below (above) zero before we identify a day to be a FTS day.

Table 1 reports the incidence of FTS under the simple threshold model for different threshold levels κ. We focus on the fractional number of instances (as a percent of the (country-specific) total number of observations) because the number of observations across countries varies. The number of FTS instances decreases rapidly with the threshold level, from about 1/4th of the sample for $\kappa = 0$ to mostly less than 3% for $\kappa = 1$. Less than half a percent of days experience bond and stock returns that are simultaneously 2 standard deviations above/below zero, respectively. To benchmark these numbers we conducted a small simulation experiment. Imagine that bond and stock returns are normally distributed with their means, standard deviations and correlations equal to the ensemble averages (the average of the respective statistics across countries) over the full sample of 23 countries[1]. In such a world, we would expect flights to safety to be quite rare compared to the real world with fat tails, negative skewness and time-varying correlations. The last line in the table reports FTS numbers for the simulated data. It is reasonable to expect that extreme FTS events are more common in the data than predicted by the unconditional multivariate normal distribution. However, until $\kappa = 1$, the percentage of FTS instances in the data is actually lower than predicted by the normal model. This suggests to use a $\kappa > 1$ for our definition of a FTS.

To get a sense of what happens on such extreme days, we also compute the average difference between bond and equity returns on flight to safety days. This return impact, averaged over the various countries, is reported on the last row of Table 1. It increases from 1.20% for $\kappa = 0$ to 3.19% for $\kappa = 1$ to more than 5% for $\kappa = 2$. On extreme FTS days, when $\kappa = 4$, the return impact increases to 9.28% on average.

2.2.2 Ordinal FTS Index

Here we quantify the various FTS symptoms extracted from bond and equity returns, and use the joint information about their severity to create a composite FTS index. We use 6 individual variables, either positively (+) or negatively (-) related to FTS incidence:

- The difference between the bond and stock return (+)
- The difference between the bond return minus its 250 moving average and the equity return minus its 250 days moving average (+)
- The short-term stock-bond return correlation (-)

[1] The equally-weighted unconditional annualized equity and bond return means (volatilities) in percent are 10.78 (19.5) and 7.39 (5.83) respectively. To annualize, we assume there are 252 trading days per year. The average correlation is -0.09.

- The difference between the short and long-term stock-bond return correlation (-)
- The short-term equity return volatility (+)
- The difference between the short and long-term equity return volatility (+)

Most of these variables are self explanatory. Because the macro-economic environment may affect returns and correlations, we also consider return and correlation measures relative to time-varying historical benchmarks (250 day moving averages).

To estimate the short and long-term volatilities and correlations, we use a simple kernel method. Given a sample from $t = 1, .., T$, the kernel method calculates stock and bond return variances and their pairwise covariance/correlation at any normalized point $\tau \in (0, 1)$ as:

$$\begin{aligned} \sigma^2_{i,\tau} &= \textstyle\sum_{t=1}^{T} K_h\left(t/T - \tau\right) r^2_{i,t}, \qquad i = s, b \\ \sigma_{s,b,\tau} &= \textstyle\sum_{t=1}^{T} K_h\left(t/T - \tau\right) r_{s,t} r_{b,t} \\ \rho_{s,b,\tau} &= \sigma_{s,b,\tau} / \sqrt{\sigma^2_{b,\tau}\sigma^2_{s,\tau}} \end{aligned}$$

where $K_h(z) = K(z/h)/h$ is the kernel with bandwidth $h > 0$. The kernel determines how the different observations are weighted. We use a two-sided Gaussian kernel with bandwidths of respectively 5 (short-term) and 250 (long-term) days (expressed as a fraction of the total sample size T):

$$K(z) = \frac{1}{\sqrt{2\pi}} exp\left(\frac{z^2}{2}\right)$$

Thus, the bandwidth can be viewed as the standard deviation of the distribution, and determines how much weight is given to returns either in the distant past or future. For instance, for a bandwidth of 5 days, about 90% of the probability mass is allocated to observations ±6 days away from the current observation; for a bandwidth of 250 days, it takes ±320 days to cover 90% of the probability mass[2]. We use a two-sided symmetric kernel rather than a one-sided and/or non-symmetric kernel because, in general, the bias from two-sided symmetric kernels is lower than for one-sided filters (see e.g. Ang and Kristensen (2012)).

We combine observations on the 6 FTS-sensitive variables into one composite FTS indicator using the "ordinal" approach developed in Hollo et al. (2012), who propose a composite measure of systemic stress in the financial system. As a first step, we rank the observations on variables that increase with FTS (bond minus

[2] To ensure that the weights sum to one in a finite sample, we divide by their sum.

stock returns, this difference minus its 250-day moving average, short-term equity market volatility, and the difference between short and long-term equity market volatility) from low to high, and those that decrease with the likelihood of FTS (short-term stock-bond correlation, difference between short and long-term stock bond correlation) from high to low. Next, we replace each observation for variable i by its ranking number $\zeta_{i,t}$ divided by the total number of observations T, i.e. $\psi_{i,t} = \zeta_{i,t}/T$, so that values close to one (zero) are associated with a larger (lower) likelihood of FTS. For instance, a value of 0.95 at time t_0 for, say, short-term equity return volatility would mean that only 5 percent of observations over the full sample have a short-term equity volatility that is larger or equal than the time t_0 value. Finally, we take at each point in time the average of the ordinal numbers for each of the six FTS variables[3].

The ordinal approach yields numbers for each variable that can be interpreted as a cumulative density function probability, but it does not tell us necessarily the probability of a flight to safety. For example, numbers very close to 1 such as 0.99 and 0.98 strongly suggest the occurrence of a FTS, but whether a number of say 0.80 represents a FTS or not is not immediately clear. Despite the imperfect correlation between the different variables, the maximum ordinal numbers for the composite index are quite close to 1 for all 23 countries, varying between 0.9775 and 0.9996. To transform these ordinal numbers into a FTS ordinal indicator, we first collect the ordinal numbers of the days that satisfy all the "mild" FTS –symptoms. In particular, these are days featuring:

1. A positive bond-stock return difference
2. A positive difference between the bond return minus its 250 day moving average and the stock return minus its 250 day moving average
3. A negative short-term stock-bond return correlation
4. A negative difference between the short and long-term stock-bond return correlation
5. A value for short-term equity return volatility that is more than one standard deviation above its unconditional value (that is, larger than double the unconditional standard deviation)

[3]We also considered taking into account the correlation between the various variables as suggested by Hollo et al. (2012), where higher time series correlations between the stress-sensitive variables increase the stress indicator's value. However, our inference regarding FTS episodes was not materially affected by this change.

6. A positive difference between the short and long-term equity return volatility.

We view the minimum of this set of ordinal index values as a threshold. All observations with an ordinal number below this threshold get a FTS Ordinal Indicator value equal to zero. It would appear unlikely that such days can be characterized as flights to safety. For observations with an ordinal number above the threshold, we set the FTS Ordinal Indicator equal to one minus the percentage of "false positives", calculated as the percentage of observations with an ordinal number above the observed ordinal number that are not matching our FTS criteria. The number of false positives will be substantial for observations with relatively low ordinal numbers (but still above the minimum threshold) but close to zero for observations with ordinal numbers close to 1.

The left panel of Figure 1 plots the original FTS Ordinal index values and corresponding threshold levels for the US, Germany, and the UK; the right panel shows the derived FTS ordinal indicator. We view this indicator as an estimate of the probability that a particular day was a FTS, so that a standard classification rule suggests a FTS event when that probability is larger than 0.5. Values with a probability larger than 50% are depicted in black, values below 50% in light gray. The percentage of days that have an ordinal indicator value above the threshold ranges from 6% of the total sample for Germany to 9% for the UK. Of those observations, about 65% have a FTS probability larger than 50% in the UK, compared to about 75% in the US. In Germany, this proportion even exceeds 98%.

We further characterize FTS incidence with the ordinal indicator in Table 2. The threshold levels show a tight range across countries with a minimum of 0.65 and a maximum of 0.80. The mean is 0.72. The percentage of sample observations above the threshold equals 10.5% with an interquartile range of 9.3%-11.4%. The raw ordinal index values seem to display consistent behavior across countries. Our indicator is also influenced by the number of false positives above the threshold value. Therefore, the third column shows the percentage of observations above the threshold that have a FTS ordinal indicator larger than 50%. The mean is 52.9% and the interquartile range is 39.1%-64.9%. Germany proved to be an outlier with 98.7% and the minimum value of 18.59% is observed for the Czech Republic. The final column assesses how rare FTS episodes are according to this indicator. The percentage of observations with a FTS ordinal indicator larger than 50% as a percentage of total sample is 5.2% on average, with an interquartile range of 4.6%-6.3%. The range is quite tight across countries (the minimum is 2.7%, the maximum is 7.9%).

2.2.3 A Univariate Regime-Switching FTS Model

Define $y_{i,t} = r^b_{i,t} - r^s_{i,t}$, with $r^s_{i,t}$ the stock return for country i and $r^b_{i,t}$ the return on the benchmark government bond for that country. We model $y_{i,t}$ as a three-state regime-switching (RS) model. We need two regimes to model low and high volatility that are typically identified in RS models for equity returns (see Ang and Bekaert (2002) and Perez-Quiros and Timmermann (2001)). The third regime then functions as the FTS regime. The regime variable follows a Markov Chain with constant transition probabilities. Let the current regime be indexed by υ.

$$y_{i,t} = \mu_{i,\upsilon} + \sigma_{i,\upsilon}\epsilon_{i,t} \tag{2.3}$$

with $\epsilon_{i,t} \sim N(0,1)$. The means and volatilities can take on 3 values. Of course, in a FTS, $y_{i,t}$ should be high. To identify regime 3 as the flight-to-safety regime, we impose its mean to be positive and higher than the means in the other two regimes, i.e. $\mu_{i,3} > 0, \mu_{i,3} > \mu_{i,1}, \mu_{i,3} > \mu_{i,2}$. The transition probability matrix, Φ_i, is 3×3, where each probability p_{kj} represents $P[S_{i,t} = k | S_{i,t-1} = j]$, with $k, j \in \{1,2,3\}$:

$$\Phi_i = \begin{pmatrix} p^i_{11} & p^i_{21} & (1 - p^i_{11} - p^i_{21}) \\ p^i_{12} & p^i_{22} & (1 - p^i_{12} - p^i_{22}) \\ (1 - p^i_{23} - p^i_{33}) & p^i_{23} & p^i_{33} \end{pmatrix} \tag{2.4}$$

Panel A of Table 3 reports the estimation results. The first column reports detailed estimation results for the US, followed by the average estimate and interquartile range across all 23 countries. Regime 1 is characterized by low volatility, and a significantly negative bond-stock return difference for all countries. This is in line with the expectation that equities outperform bonds in tranquil times. Regime 2 corresponds to the intermediate volatility regime, and also features a mostly negative bond-stock return difference, yet typically of a smaller magnitude than in regime 1 and often not statistically significant. Annualized volatility is about double as high in regime 2 than in regime 1 (20.1% versus 10.5%).

The volatility in regime 3, the FTS regime, is on average more than 47%, which is more than 2.35 (4.5) times higher than in regime 2 (1). Looking at the interquartile range, the bottom volatility quartile of the FTS regime is nearly double as high as the top volatility quartile of regime 2. The mean bond-stock return difference amounts to about 0.25% on average (significantly different from zero at the 5% (10%) level in 11 (16) of the 23 countries), with an interquartile range of [0.198%; 0.271%]. While this is a relatively small number, the effect is substantially higher on days that the FTS jumps to the "on" state (1.09% on average, with an interquartile range of 0.73%-1.33%).

The FTS regime is the least persistent regime (with an average probability of staying of 94.7% versus 98.1% for regime 1 and 96.7% for regime 2). To classify a day as a FTS-event, we require the smoothed probability of the FTS regime to be larger than 0.5, even though there are three regimes.[4] The average FTS spell lasts 26.4 days. The large interquartile range (35.2 versus 17.2 days) reflects the substantial cross-sectional dispersion in the average FTS regime durations across countries. There are an average of 26 FTS spells in the sample. This number is somewhat hard to interpret as the sample period varies between 23 years and less than 13 years across different countries. Yet, most of the spells occur in the second half of the sample, and the number is useful to compare across different models.

2.2.4 A Bivariate Regime-Switching FTS Model

The univariate RS FTS model uses minimal information to identify FTS episodes, namely days of relatively high differences between bond and stock returns. While for most countries, the FTS regime means were quite substantially above zero, it is still possible that such a high difference occurs on days when both bonds and equities decrease in value, but the equity market, the more volatile market, declines by more. To make such cases less likely, and to incorporate more identifying information, we estimate the following bivariate model for stock and bond returns in each country (we remove the country subscript i for ease of notation):

$$
\begin{aligned}
r_{s,t} &= \alpha_0 + \alpha_1 J_{s,t}^{lh} + \alpha_2 J_{s,t}^{hl} + \alpha_3 \left(J_t^{FTS} + v S_t^{FTS}\right) + \varepsilon_{s,t}, & (2.5)\\
& \quad \varepsilon_{s,t} \sim N\left(0, h_s\left(S_t^s\right)\right) & (2.6)\\
r_{b,t} &= \beta_0 + \beta_1 J_{b,t}^{lh} + \beta_2 J_{b,t}^{hl} + \beta_3 \left(J_t^{FTS} + v S_t^{FTS}\right) + \\
& \quad \left(\beta_4 + \beta_5 S_t^{FTS}\right) r_{s,t} + \varepsilon_{b,t},\ \varepsilon_{b,t} \sim N\left(0, \theta_{t-1} h_b\left(S_t^b\right)\right) & (2.7)
\end{aligned}
$$

The variance of the stock return shock follows a two-state regime-switching model with latent regime variable S_t^s. The variance of the bond return shock has two components, one due to a spillover from the equity market, and a bond-specific part. The latter follows a two-state regime-switching square-root model with latent

[4] The percentage of FTS days would increase on average with about 1 percent of daily observations if we were to use 1/3 rather than 1/2 as a classification rule. Testing whether a third regime is necessary is complicated because of the presence of nuisance parameters under the null (see e.g. Davies (1987)), and therefore omitted.

regime variable S_t^b; θ_{t-1} is the lagged bond yield[5]. The "jump" terms $J_{s,t}^{lh}$ and $J_{s,t}^{hl}$ are equal to 1 when the equity return shock variance switches regimes (from low to high or high to low), and zero otherwise. We expect α_1 to be negative and α_2 to be positive. $J_{b,t}^{lh}$ and $J_{b,t}^{hl}$ are defined in a similar way (but depend on the bond return shock variance). Without the jump terms, regime switching models such as the one described above often identify negative means in the high volatility regime. However, we would expect that there is a negative return when the regime jumps from low to high volatility but that the higher volatility regime features expected returns higher not lower than the low volatility regime. The jump terms have this implication with $\alpha_1 < 0$ and $\alpha_2 > 0$. There is a mostly unexpected negative (positive) return when the regime switches from the low (high) volatility to the high (low) volatility regime. Within the high volatility regime, there is some expectation that a positive jump will occur driving the mean higher than in the low volatility regime where there is a chance of a jump to a high volatility regime. This intuition was first explored and analyzed in Mayfield (2004).

The structure so far describes a fairly standard regime switching model for bond and stock returns, but would not allow us to identify flights to safety. Our identification for the flight to safety regime uses information on the means of bonds versus equities, on equity return volatility and on the correlation between bond and stock returns. Let S_t^{FTS} be a latent regime variable that equals 1 on FTS days and zero otherwise. We impose $\alpha_3 < 0$ (stock markets drop during FTS episodes), $\beta_3 > 0$ (bond prices increase during FTS), and $\beta_5 < 0$ (the covariance between stocks and bonds decreases during FTS episodes). It is conceivable that a flight to safety lasts a while, but it is unlikely that the returns will continue to be as extreme as on the first day. Therefore we introduce the J_t^{FTS} variable, which is 1 on the first day of a FTS-regime and zero otherwise, and the $\upsilon-$parameter. The α_3 and β_3 effects are only experienced "in full" on the first day but with υ restricted to be in $(0, 1)$, the negative (positive) flight-to-safety effect on equity (bond) returns is allowed to decline after the first day. We assume S_t^b and S_t^{FTS} to be independent Markov chain processes. For S_t^s, we assume that the equity volatility regime is always in the high volatility state, given that we experience a FTS episode:

$$\Pr\left(S_t^s = 1 \middle| S_{t-1}^s, S_t^{FTS} = 1\right) = 1 \tag{2.8}$$

Panel B of Table 3 summarizes the estimation results. The jump terms have

[5] By making the bond return shock variance a function of the (lagged) interest rate level, we avoid that the high volatility regime is only observed in the first years of sample, as the early 1980s is a period of high interest rates.

the expected signs for the equity market (and are mostly significant) but for bond returns, the results are more mixed. We clearly identify a high and low volatility regime for both the bond and the stock market, with volatilities typically about twice as high in the high volatility regime. In terms of the parameters governing the FTS regime, we find that α_3 is -7.863% in the US, and -5.03% on average, with a substantial interquartile range ([-7.42%, -1.29%]). Not surprisingly, the υ-scaling parameter is mostly rather small (interquartile range of [0.015,0.062]), indicating that a FTS mostly only induces one day of heavy losses[6]. For bond returns, β_3 is 0.72% on average, but it is also often drawn to the lower boundary of zero. Finally, we do find that β_5 is statistically significantly negative, indicating that a FTS induces a negative covariance between bond and stock returns (or at least one lower than the covariance in non-FTS regimes). As reflected by the average and interquartile values for β_4, the average stock-bond correlation in 'normal' times is relatively close to zero in our sample, but positive on average.

To identify a FTS day, we use the standard classification rule that the smoothed FTS regime probability be larger than 0.5. We do find that the bivariate model predicts FTS spells to last substantially longer than in the univariate model, namely an average of 89.9 days in the US and 86.6 days on average in all countries (but with a substantial interquartile range of [58-101]). The number of FTS spells is on average even smaller than for the univariate model, but there are more spells in the US (24) relative to the univariate model (18).

2.3 Aggregate FTS Incidence

At this point, we have transformed data on bond and stock returns and simple information about the "symptoms" of a FTS into 4 noisy indicators on the presence of a FTS day. All 4 indicators are between 0 and 1 and can be interpreted as a measure of the probability of observing a FTS event. For the FTS threshold approach, we select $\kappa = 1.5$ as the preferred method to make FTS episodes suitably rare relative to what we expect from a normal distribution (see Section 2.2.1). This also gives an incidence of FTS days somewhat similar to that of the Ordinal FTS indicator. In general, these two methods yield a relatively low incidence of FTS days, whereas the regime-switching approach delivers relatively persistent FTS regimes and classifies more days as FTS events. Table 4 (right hand side columns) reports the average number of days classified as a FTS for the 4 approaches. For most countries, the proportion of time spent in a FTS-episode increases monotonically moving from the

[6] The average value for ν (0.156) is higher than the value for the top quartile because a small number of countries have a value of ν close to one (but also a low absolute value for α_3).

threshold indicator (0.96% on average) to the ordinal indicator (4%), then to the univariate RS model (9.76%) and finally the bivariate RS model (14.83%). Within each method, the interquartile ranges are quite tight, ranging from 0.74%-1.16% for the threshold indicator to 2.6%-5.3% for the ordinal indicator to 8%-11.9% and 13%-17.7% for the univariate and bivariate RS models, respectively.

To infer whether a particular day suffered a flight to safety episode, we must use the imperfect information given in the indicators to come up with a binary classification. There is of course a large literature on classification that suggests that the optimal rule (in the sense that it minimizes misclassification) is to classify the population based on the relative probability. Given that there are two regimes, a probability of a flight to safety higher than 0.5 would lead to the conclusion that there is a flight to safety.

To aggregate the information in the 4 indicators, we use two methods. A first naive aggregator is simply to average the probabilities at each point in time; this constitutes the first aggregate FTS indicator. When that average is above 0.5, we conclude there is a flight to safety, and set the average FTS dummy equal to 1. A second method, which leans more on the extant literature on regime classification based on qualitative variables (see e.g. Gilbert (1968)), recognizes that if three of the 4 variables indicate a flight to safety, we should be rather confident a flight to safety indeed occurred. We extract the joint probability that at least 3 out of our 4 indicators identify a FTS on a particular day from a multivariate Bernoulli distribution using the method proposed by Teugels (1990) (see Appendix A for technical details). This computation requires not only the probabilities of the 4 Bernoulli random variables at each point in time but also their covariances. It goes without saying that inference based on the 4 different indicators is likely to be positively correlated. Sample correlations between the 4 dummies vary roughly between 20% and 65%. In these day by day computations, we use full sample estimates of the covariances between the different FTS dummies (the underlying Bernoulli variables), which we estimate using the usual 50% classification rule as explained above. We then set the joint FTS dummy equal to one when that joint probability is larger than 50%, and zero otherwise.

Given these two aggregation methods, we record the proportion of time spent in a FTS episode in Table 4 (left columns). The average proportion is 4.70% (interquartile range of 3.21%-6.38%) using the average joint measure and 1.98% (interquartile range of 0.78%-2.91%) using the joint probability measure. In Table 5, we report the "return impact" (bond return minus equity return) both on FTS and non-FTS days. The rarer nature of FTS episodes under the joint probability measure translates into a higher return impact of 2.97% on FTS days versus 1.76% for the average measure. The interquartile range for the return impact is relatively tight for both measures. As expected, on non-FTS days, the return impact is slightly negative (-0.08%), reflecting the on average higher return on stocks than on bonds in tranquil times.

Figure 2 plots the aggregate FTS measures for the US. The top panel plots the average FTS indicator together with the corresponding FTS dummy. The bottom panel plots the joint probability aggregate indicator and the corresponding joint FTS dummy. Both measures largely select the same periods as FTS episodes, and the dummy variables are highly correlated at 85.2% . The main difference between the two measures is that FTS episodes are slightly longer lasting for the average measure than for the more demanding joint measure. Generally, the joint probability measures on FTS dates are rather close to one. The final two columns of Table 5 report the correlation between the average and joint FTS dummies, both at the daily and weekly frequency. The daily correlation between both measures for the US is near the top of the range among our different countries. On average, the correlation is 66% with an interquartile range of 60.5%-75.3%. The weekly FTS measures are dummies with a value equal to one if at least one day within that week is a FTS day according to that specific indicator, and zero otherwise. Weekly correlations are quite a bit higher than daily correlations, suggesting that the different indicators do tend to select similar FTS spells, with small timing and persistence differences. We further characterize FTS in Section 2.4.

2.4 Characterizing FTS Episodes

To characterize the nature of FTS episodes, we investigate returns before, on and after FTS episodes; examine their comovement across countries and how they correlate with alternative indicators of market stress, uncertainty and risk aversion. Figure 3 plots returns in the equity and bond market as well as the difference between the bond and equity return, averaged over the 23 countries, ranging from 30 days before to 30 days after a FTS event. In the graphs on the left, FTS is identified using the average measure, in the graphs on the right the joint probability FTS measure is used. The solid lines take all FTS days into account, even if the previous day was also a FTS day. The dotted lines show returns and return impact around the first day of a FTS spell only. The solid lines indicate that the FTS events are characterized by very sudden simultaneous drops in the equity market and increases in the bond market, as expected. For the average (joint probability) measure, the average equity return is -1.49% (-2.49%) and the average bond return is +0.28% (0.49%). These FTS-events do seem to occur in periods when equity returns are already slightly negative and bond returns slightly positive. Somewhat oddly, just before the start of a FTS episode, we see somewhat substantial positive equity returns and negative bond returns (see the dotted line).

Figure 4 plots the percentage of countries experiencing a FTS at each point in time. The FTS dummies clearly select well known global crises as global FTS events, including the October 1987 crash, the 1997 Asian crisis, the Russian crisis and LTCM debacle in 1998, the Lehman Brothers collapse and several spells during the European sovereign debt crisis. Defining a global FTS as one where at least two thirds of our countries experience a FTS, there are a total of 109 days of global FTS according to the average measure, but only 39 days according to the joint probability measure. In Table 6, we report the proportion of FTS spells that are global in nature. The cross-country average of local FTS spells that are global in nature amounts to 32.5% for the average measure and 24.5% for the joint measure. The interquartile ranges are 21.0%-30.8% and 14.5%-23.3%, respectively. Large developed countries such as the US, the UK and Germany (reported separately) feature a relatively low proportion of global spells, suggesting they are more subject to idiosyncratic flights to safety. While the interquartile ranges are relatively tight, a number of small countries, such as Norway, the Czech Republic and Poland have a very high proportion of global FTS episodes (more than 70% under the average measure).

Our FTS measures require minimal data inputs and provide a high frequency reading of flight to safety episodes. Of course, there are other financial indicators that may allow identification of a flight to safety episode. We therefore investigate the comovement between our FTS dummies and three types of alternative stress indicators. The first set comprises implied volatility indices on major indices: the US S&P500 (VIX), the UK FTSE100 (VFTS), the German DAX (VDAX), and the Japanese Nikkei 225 (VXJ). The US VIX index is generally viewed as a fear index. We use daily changes in the indices as the dependent variable in a regression on our FTS dummies. Second, we investigate a series of sentiment/confidence indicators. The sentiment variables include the Baker and Wurgler (2006) sentiment indicator (purged of business cycle fluctuations) and the Michigan consumer sentiment index which measure sentiment in the US; the Ifo Business Climate indicator (which measures sentiment in Germany) and the (country-specific) OECD consumer confidence indicators (seasonally-adjusted). We use changes in these indices as the dependent variable. Because these sentiment variables are only available on a monthly basis, we regress them on the fraction of FTS days within the month (expressed in %). Finally, we regress percentage changes in the value of three safe haven currency values (i.e. the Swiss Franc, the Japanese Yen, and the US Dollar) on the FTS indicator using daily data. Note that the currencies are expressed in domestic currency units per unit of the safe currency and positive values indicate an appreciation of the safe currency. For this exercise, we leave out the particular currency's country.

Table 7 shows the results for the joint probability FTS measure. We relegate the (very similar) results for the average measure to an online appendix. We show slope parameter estimates for the US, Germany and the UK, as well as the average, standard deviation and top/bottom quartile parameter estimates across all 23 countries. The last column shows the number of countries for which the parameter estimates are significant.

The VIX increases by 3.28% on average when the US experiences a FTS. The effect of local FTS on the US VIX is significant at the 10 (5) percent level in 20 (17) of the countries. When country-specific implied volatilities (VIX for US, Canada; VFTS for the UK; VDAX for the other European countries; VJX for Japan, Australia and New Zealand) are used, however, the FTS effect increases in magnitude and becomes significant in all countries.

There is clear evidence of a significant decline in consumer and business sentiment during FTS episodes. The Baker-Wurgler sentiment indicator and the Michigan consumer sentiment decrease significantly when there is FTS in the US. The Michigan index also reacts significantly to flight to safety instances in Germany and the UK, despite these countries witnessing only a limited number of global flights to safety (see Table 6). There are another 6 countries whose FTS episodes have a significant effect on the Michigan index, but only 3 additional significant coefficients for the regression involving the Baker-Wurgler index. The Ifo business climate indicator declines significantly in times of FTS for all countries. This is somewhat surprising as this indicator measures the German business climate. A FTS negatively affects OECD consumer confidence in 20 countries, as measured by the country-specific OECD indicator of consumer sentiment. Thus, the Ifo business climate and OECD leading indicators seem linked to FTS events across the globe.

There is also strong evidence of a flight to safe haven currencies in times of a FTS. On average, during a FTS day, the Swiss Franc appreciates by 0.43%, the Japanese Yen by 0.85%, and the US Dollar by 0.39%. The appreciation of the Yen is significant following a FTS in all 22 countries, compared to in 19 and in 20 countries for the Swiss Franc and US dollar, respectively.

3 FTS and the Economic and Financial Environment

In this section, we examine the comovement of FTS spells with a large number of financial and economic variables. Our goal is to document comovements rather than to look for causality. All of our reported results use the joint FTS dummy, with the results using the average measure relegated to the online appendix. The results are very similar across the two measures. Unless otherwise mentioned, the format of our tables is identical across different classes of variables. We show the estimates for the US, Germany and UK, as well as the average, standard deviation and top/bottom quartile estimates across all 23 countries.

Before we begin, we provide one illustration of the importance of FTS. It is to be expected that bond and stock returns, the two major asset classes, are positively correlated as they both represent long duration assets. Over our sample period, which starts fairly late in 1980, this correlation is nonetheless negative for 19 out of 23 countries. It is conceivable that this negative correlation is mainly caused by the relatively high incidence of FTS in the last 30 years. If such a "FTS-heavy" era is not likely to occur again in the near future, investors may want to re-assess the computation of the bond-stock return correlation. To assess the importance of FTS events for this important statistic, we eliminated FTS events (using the joint measure) in each country from the sample and recomputed the stock-bond return correlation. The stock-bond return correlation is -2.4% on average in "normal" periods with an interquartile range of [-7.6%, 3.5%]) and -9.12% overall (interquartile range of [-13.1%,-5.3%]). The absolute difference between correlations in normal and FTS times is on average 41%, with a relative tight interquartile range ([32.9%, 55.5%]). Thus, FTS events indeed render the bond-equity return correlation (substantially) more negative. Using the average measure, the correlation is in fact mostly positive when FTS days are excluded.

3.1 FTS and Equity Portfolios

To assess the FTS "beta" of different equity portfolios, we regress their daily returns on the FTS dummy, but also on two controls for "standard" systematic risk, the world market return and the local stock market return, both measured in local currency units. As a consequence, the FTS beta must be interpreted as the abnormal return earned during FTS episodes, controlling for normal beta risk. Importantly, it does not indicate which portfolios perform best or worst during FTS spells, as portfolios with positive (negative) FTS betas may have also high (low) market betas, making them perform overall relatively poorly (well) during a FTS spell. We also estimated a specification with interactions between the FTS indicator and the benchmark returns, but this specification often runs into multi-collinearity problems and the results are therefore omitted.

Table 8 reports the FTS betas for 10 local industry portfolios (using the Datastream industry classification) and local style portfolios (large caps, mid caps, small caps, value and growth, from MSCI). The style portfolios also include a SMB portfolio (i.e. the return on the small cap portfolio minus the return on the large cap portfolio) and a HML portfolio (i.e. the return on the value portfolio minus the return on the growth portfolio).

For the industry portfolios, there are three industries (financials, basic materials and industrials) which show globally significant underperformance during a FTS, even controlling for their "normal" betas. The inter-quartile range is negative for these industries and the FTS beta statistically significant in many countries. The only "defensive" industry is telecom, which increases by 36.5 bps on a FTS-day, controlling for its normal beta. Other industries show strong but country-specific results. For instance, the technology sector significantly outperforms in the US, but underperforms in Germany and the UK. In terms of style portfolios, large cap portfolios have positive FTS betas, whereas small cap portfolios have negative FTS betas. Value portfolios tend to have negative FTS betas and growth portfolios positive ones, but the betas are small and the results are statistically weaker than for the size portfolios. This is naturally confirmed when we look at spread portfolios, where the SMB portfolio has an average FTS beta of about -50 basis points (significant in 16 out of 23 countries), but the HML portfolio only has a FTS beta of -14 basis points (significant in 11 countries). Perhaps the size results can also be interpreted as a flight to quality in terms of larger, well-known companies.

3.2 FTS and Bond Portfolios

In Table 9, we focus on how FTS events affect the bond markets. Panel A reports how bond yields and spreads react during FTS episodes. Because interest rates are highly persistent and appear to be on a downward trend over the sample period, a regression of yields on an FTS dummy may just record the lower interest rates prevailing in the FTS-heavy later part of the sample. We therefore measure yields and spreads relative to their moving averages over the most recent 150 days. We construct the level, slope and curvature factors from 3-month T-bill rates and 5- and 10-year bond yields in the usual fashion (see the Table notes for details).

On average, the nominal government bond yield curve shifts down, flattens and becomes less hump-shaped in times of FTS (our curvature factor is decreasing in the degree of curvature). Nominal government bond yields decline significantly in all but some southern European countries (e.g. Greece, Portugal and Italy), which see significant increases in their government bond yields. This is consistent with a FTS from those countries towards safer countries (like Germany and the US). Central banks seem to respond to FTS episodes, as the targeted interest rate declines considerably in most countries. Turning to corporate spreads, we see mixed results for the spreads between yields on AAA-rated corporate bond and those on 10-year government bonds: most developed countries (e.g. US, UK, Germany) observe a significant widening of those spreads, likely reflecting both higher credit risk premiums and higher liquidity premiums during a FTS. In contrast, certain non-core European countries (e.g. Belgium, Italy, Spain, Greece, Portugal) and New Zealand see those spreads narrowing, likely reflecting the fact that local investors prefer highly-rated regional corporate bonds above local government bonds in times of FTS. The corporate bond indices are only available for the US, Japan, Canada, Australia and the Eurozone as a whole; we therefore use the Euro-zone corporate bond index for European countries and the Australian corporate bond index for New Zealand. Finally, we find a significant increase in the BBB-AAA spread for all but 3 countries.

In unreported results, we also examine inflation-indexed government bond yields from seven countries for which such data is available: US, UK, Japan, Canada, Sweden, Australia, and France. For the majority of the countries, nominal government bond yields decline by much more than real yields do.[7] This indicates a decrease in inflation expectations or inflation risk premiums in such times (see Section 3.5 for a thorough discussion on the comovement between FTS episodes and the macroeconomy) in addition to a drop in the real yield. For Canada, however, the real yield curve shifts up while the nominal yield curve shifts down during a FTS episode whereas for Japan the real yield decrease is larger than the nominal yield decrease but only the latter is significant.

Panel B of Table 9 reports the FTS betas for daily returns on the bond portfolios. We follow a similar procedure as for equity returns and control for the exposure to the long-term benchmark bond portfolio in each regression. For corporate bond returns, we also control for the local stock market return. The bond portfolios include JP Morgan Libor-based cash indices with maturities of 1, 2, 3, 6 and 12 months, benchmark Datastream government bond indices with maturities of 2, 5,

[7]When we compare the reaction of both nominal and real bond yields to FTS, we restrict the sample for the nominal bond yields to the (slightly) shorter period real bond yields are available.

7, 10, 20 and 30 years, and Bank of America/Merrill-Lynch corporate bond indices for AAA, AA, A and BBB rating groups, which have somewhat limited country coverage (see above). All returns are daily and denominated in the local currency.

For the US and UK, there is a pronounced pattern that during FTS episodes, shorter-term bonds underperform the benchmark 10-year government bond, while the longer-term 30-year bond outperforms. This pattern largely remains when looking across all countries but becomes less pronounced. Corporate bonds underperform after controlling for their exposures to the stock market and the government bond market; the underperformance is more significant for lower-rated bonds, although the FTS betas of A- and BBB-rated bonds are quantitatively similar. The finding that AAA bonds slightly over-perform on average is driven entirely by Japan; when Japan is excluded, AAA bonds also underperform with a FTS beta of -0.042. It is interesting to note that the betas of corporate bonds with respect to the long-term government bonds are around 0.4 and slightly smaller for lower ratings, whereas the equity betas are minuscule. Hence, corporate bonds almost surely outperform equities during FTS-episodes.

Finally, in Panel C we consider two types of spread portfolios, including two term spread portfolios consisting of a long position in the 10-year government bond and a short position in either the 1-month cash index or the 2-year government bond, and two default spread portfolios consisting of a long position in the AAA corporate bond index (benchmark government bond) and a short position in the BBB corporate bond index (the AAA corporate bond index). The first type of portfolios would perform well when the yield curve steepens, while the second type of portfolio would perform well when default risks or default risk premiums rise. We find that the term spread portfolios generally outperform, consistent with the finding in Panel B that longer-term bonds outperform shorter-term instruments. Turning to the default spread portfolios, the government-AAA portfolio outperforms on FTS days for the US, consistent with fears of increased default risks on those days, but underperforms on average across countries; the average underperformance is largely driven by investor preferences for the regional high-quality corporate bonds over local government bonds in some non-core European countries and New Zealand as mentioned above. In contrast, the AAA-BBB spread portfolio consistently delivers positive abnormal returns on FTS days for all countries.

3.3 FTS and Liquidity

3.3.1 Bond Market Liquidity

Benchmark Treasury bonds are attractive in times of market stress not only for their low level of default risk, but also for their (perceived) high levels of liquidity. Longstaff (2004) shows that the liquidity premium in Treasury bonds can amount up to more than 15 percent of their value. Beber et al. (2009) find that while investors value both the credit quality and liquidity of bonds, they care most about their liquidity in times of stock market stress. Of course, it is unclear whether the supply of liquidity in the Treasury bond market is present when it is most necessary. It is also not likely present for all bonds. Chordia et al. (2005) find that the liquidity in the Treasury market overall deteriorates during crisis periods. Goyenko and Ukhov (2009) show that bid-ask spreads on Treasury bills and bonds increase during recessions, especially for off-the-run long-term bonds.

Our analysis of how bond (il)liquidity is correlated with FTS is severely hampered by data availability. We therefore only show results for the US. Our first illiquidity measure was proposed by Goyenko and Ukhov (2009), and used more recently in Baele et al. (2010) and Goyenko et al. (2011). It is the average of proportional quoted spreads[8] of off-the-run US Treasury bonds with a maturity of at most 1 year (in percent).[9] This measure is available at the monthly frequency from the start of our sample (1980) till December 2010. The monthly average spread is calculated for each security and then equal weighted across securities. Our daily FTS measures are transformed to monthly indicators by taking the proportion of FTS days within a month. Because the proportional spread is clearly non-stationary over our sample, decreasing from over 0.09% in the early 1980s to less than 0.01% more recently, our estimations use the spread relative to a 6-month moving average as the dependent variable (multiplied by 100). As Panel A of Table 10 shows, we observe a positive and significant increase in the proportional spread on FTS days, relative to a 6-month moving average.

As a second measure, we use the off/on-the-run spread, calculated as the negative of the daily yield difference between an on-the-run Treasury bond and a synthetic off-the-run Treasury security with the same coupon rate and maturity date.[10] On-the-run bonds tend to trade at a premium (lower yield) because investors appreciate their higher liquidity relative to off-the-run bonds (see e.g. Jordan and Jordan (1997),

[8] The proportional spread is calculated as the difference between ask and bid prices scaled by the midpoint of the posted quote.

[9] We would like to thank Ruslan Goyenko for making this series available to us.

[10] See Section 6 in Gurkaynak et al. (2007) for a discussion on how to calculate the synthetic yields. Our measure is adjusted for auction cycle effects.

Krishnamurthy (2002), and Graveline and McBrady (2011)). Pasquariello and Vega (2009), among others, show that the off-on-the run spread increases in times of higher perceived uncertainty surrounding U.S. monetary policy and macroeconomic fundamentals. The second row of Panel A of Table 10 shows that the off-on-the-run spread increases from about 14 basis points in "normal" times to more than 24 basis points on FTS days (with the change significant at the 1% level).

As a third measure, we use the root mean squared distance between observed yields on Treasury bonds with maturities between 1 and 10 years and those implied by the smoothed zero coupon yield curve proposed by Gurkaynak et al. (2007). This cross-sectional "price deviation" measure was developed by Hu et al. (2012), who argue that it primarily measures liquidity supply. When arbitrageurs have unrestricted risk-bearing capacity, they can supply ample liquidity and can quickly eliminate deviations between bond yields and their fundamental values as proxied by the fitted yield curve. When their risk-bearing capacity is impaired, liquidity is imperfect and substantial deviations can appear. Fontaine and Garcia (2012) propose a similar measure. Hu et al. (2012) show that their "noise measure" is small in normal times but increases substantially during market crises. The noise measure is on average only 3.6 basis points, but increases to over 10 basis points during crises. Yet, this measure also shows a long-term trend downwards from the early 80s till the end of the 90s. We therefore investigate its value relative to a 150-day moving average. The final row of Panel A shows that the noise measure increases on FTS days relative to its 150-day moving average with about 1.2 basis points (significant at the 1% level).

Our overall findings on bond liquidity are consistent with the detailed results in a recent paper by Engle et al. (2012), who use (high-frequency) order book data for on the run 2, 5, and 10 year notes from early 2006 till mid-2010. They analyze Treasury bond liquidity in stress times using a FTS threshold measure inspired by this paper to identify stress. They find trading volume, the number of trades, and net buying volume to be substantially higher on FTS days, especially for shorter-term (2-year) notes. However, they find market depth, a measure of the willingness to provide liquidity, to be much lower on FTS days, and to thin out more quickly for the 5 and 10-year notes than for the 2 year notes. The combination of decreasing depth and high price volatility on FTS days suggests that even though liquidity demand shoots up, high market volatility makes dealers substantially more conservative with their liquidity supply, as they attempt to reduce adverse execution risk. Hence, this paper concludes that insufficient liquidity supply causes bond market illiquidity in stress times.

3.3.2 Equity Market Liquidity

Brunnermeier and Pedersen (2009) develop a theory where a (severe) market shock interacts with (evaporating) funding and market liquidity, with liquidity provision being curtailed particularly in volatile assets such as equities. The extant empirical work seems to confirm this intuition. Chordia et al. (2005) find that equity market liquidity deteriorates together with that in the Treasury market during crisis periods; Naes et al. (2011) find that equity market liquidity systematically decreases during (and even before) economic recessions.

Here, we link our FTS measures to three measures of equity market illiquidity, namely the effective tick measure developed in Goyenko et al. (2009)and Holden (2009), the price impact measure of Amihud (2002), and the reversal measure of Pastor and Stambaugh (2003). Goyenko et al. (2009) and Holden (2009) estimate the effective bid-ask spread from prices using a price clustering model. The "Effective Tick measure" is the probability-weighted average of potential effective spread sizes within a number of price-clustering regimes divided by the average price in the examined time interval. Amihud (2002) examines the average ratio of the daily absolute return to the dollar trading volume on that day, which measures the daily price impact of order flow. Pastor and Stambaugh (2003) use a complex regression procedure involving daily firm returns and signed dollar volume to measure (innovations in) price reversals, both at the firm and market levels. In the tradition of Roll (1984), price reversals are interpreted to reflect the bid-ask spread. Aggregate measures for each of these indicators are equally-weighted averages of monthly firm-level estimates that are in turn estimated using daily firm-level data within a month. Unreported time series graphs reveal that the Amihud and Pastor-Stambaugh series are stationary, so we report level regression results. However, the effective tick measure starts a downward trend at the end of the 80s-early 90s, rendering the series non-stationary. We therefore investigate the series relative to a 6-month moving average.

Results in Panel B of Table 10 suggest that illiquidity in the US equity market increases substantially and significantly during FTS. The FTS coefficients are very large relative to the means in normal periods, as reflected by the constants in the regressions. Do note that the monthly nature of the data implies that the full estimated effect will never materialize, as this measures the effect of a month in which all days are FTS. This never happens; the maximum is in fact 0.65, which occurred in November 2008.

3.4 FTS and Commodities

In Table 11, we report regression coefficients from a regression of the daily S&P GSCI benchmark commodity index returns on the joint FTS dummy while controlling for global equity market exposure. These returns reflect the returns on commodity futures contracts worldwide. We consider broad indices (Commodity Total, Energy, Industrial Metals, Precious Metals, Agriculture, Livestock) and subindices (Crude Oil, Brent Crude Oil and Gold). The table has the exact same structure as the previous tables for bonds and equities, except for the last but one column, which reports the average exposure (beta) to global equity market returns. We note that commodity prices generally decline on FTS days, ranging from on average minus 14 basis points for Livestock to minus 84 basis points for Brent Crude Oil. The decrease is statistically significant for the great majority of country/commodity pairs. There is one, not entirely surprising, exception: precious metals and its main component, gold. Both have positive FTS betas of on average 32 and 35 basis points, respectively. In both cases, the interquartile ranges are strictly positive, and the FTS betas are significant in 14 and 15 of the 23 countries. Note, however, that all commodities, even precious metals and gold, have positive global market betas, ranging from 0.11 for Livestock to more than 0.5 for Industrial Metals and Brent Crude oil. Because the market return on FTS days will generally be (very) negative, the total drop in value of the various commodities will be even more severe than the estimated FTS effect. Similarly, the positive (marginal) FTS effect for precious metals and gold will erode because both are positively exposed to (negative) market returns. In fact, when we do not control for equity market exposure,[11] the FTS betas for precious metals (gold) drop to on average 1 (9) basis points, and are only statistically significant in 2 (1) countries.

3.5 FTS Episodes and the Macroeconomy

In Table 12, we investigate the contemporaneous comovement between FTS episodes and the real economy. We regress a number of real economy variables on the fraction of days of FTS instances within the month (expressed in decimals). We investigate the following variables: inflation, industrial production growth (IP), the unemployment rate and the OECD leading indicator (available monthly); GDP growth and investment/GDP (available quarterly). For inflation, IP growth, GDP growth, the unemployment rate and investment growth, we also have survey forecasts (Consensus Economics) and we use both the mean and the standard deviation of individual

[11] These results are available in an online appendix.

forecasts (available monthly, in %). The growth variables are computed as the next quarter value relative to the current value (in %). The unemployment rate (in %), the OECD leading indicator, investment/GDP (in %) and the survey forecast variables are computed as absolute differences between the next quarter value and the current value. In the lines with "future variables", we regress the cumulative one year growth or increase in the economic variables on the fraction of days of FTS instances within the month (expressed in decimals). The cumulative one year growth in GDP, industrial production and CPI (inflation) is computed as the next year value relative to the current value (in %). The increase in the unemployment rate (in %), the OECD leading indicator, and investment/GDP (in %) is computed as the absolute difference between the next year value and the current value.

Inflation is significantly lower right after FTS episodes for most countries. GDP and IP growth decrease significantly immediately following FTS episodes for respectively 16 and 12 countries. The average growth and the interquartile range across countries is strictly negative. Unemployment increases significantly for 10 out of 23 countries. The mean survey forecasts reveal a significant and negative effect for the real growth variables and a significant and positive effect for unemployment and this is true for most countries (although forecasts data are not available for all countries/variables). Forecast uncertainty (as measured by the standard deviation of individual forecasts) does not change significantly during FTS episodes.

Inflation also declines significantly the year after FTS for most countries. FTS predicts negative one-year growth in industrial production and GDP for all countries. The effect is significant for the majority of countries. Unemployment increases substantially the year following a FTS spell. Note that the economic magnitudes are very large. For example, US GDP growth is predicted to be 4.9% lower if all days within a month are categorized as a FTS (that is, the FTS incidence is 100%, but recall its maximum is 65%). Finally, high FTS incidence predicts an increase in the OECD leading indicator one year from now. Of course, recall that the contemporaneous (one quarter ahead) response of the OECD indicator to a FTS spell was negative. As the OECD aims to predict the business cycle with a 6 to 9 months lead, this suggests that the economy is expected to rebound within two years. However, while significant in the US, UK and Germany, we do not observe this phenomenon for all countries.

4 Conclusions

We define a flight to safety event as a day where bond returns are positive, equity returns are negative, the stock bond return correlation is negative and there is market stress as reflected in a relatively large equity return volatility. Using only data on equity and bond returns, we identify FTS episodes in 23 countries. On average, FTS episodes comprise less than 5% of the sample, and bond returns exceed equity returns by about 2 to 3%. FTS events are mostly country-specific as less than 30% can be characterized as global. Nevertheless, our methodology identifies major market crashes, such as October 1987, the Russia crisis in 1998 and the Lehman bankruptcy as FTS episodes. FTS episodes coincide with increases in the VIX, decreases in consumer sentiment indicators in the US, Germany and the OECD and appreciations of the Yen, the Swiss franc, and the US dollar. The financial, basic materials and industrial industries under-perform in FTS episodes, but the telecom industry outperforms. Money market securities and corporate bonds have negative "FTS-betas". Liquidity deteriorates on FTS days both in the bond and equity markets. Most commodity prices decrease sharply during FTS episodes, whereas the gold price measured in dollars increases slightly. Both economic growth and inflation decrease immediately following a FTS spell, and this decrease extends to at least one year after the spell.

We hope that our results will provide useful input to theorists positing theories regarding the origin and dynamics of flights to safety, or to asset pricers attempting to uncover major tail events that may drive differences in expected returns across different stocks and/or asset classes. They could also inspire portfolio and risk managers to look for portfolio strategies that may help insure against FTS-events.

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A Calculation of Joint Indicator

Assume $\{X_i, i = 1, 2, ..., n\}$ is a sequence of Bernoulli random variables, where

$$P\{X_i = 0\} = q_i, \quad P\{X_i = 1\} = p_i$$

where $0 < p_i = 1 - q_i < 1$. The multivariate Bernoulli distribution is then represented by

$$p_{k_1,k_2,...,k_n} := P\{X_1 = k_1, X_2 = k_2, ..., X_n = k_n\}$$

where $k_i \in \{0, 1\}$ and $i = 1, 2, ..., n$. Let $\mathbf{p^{(n)}}$ be a vector containing the probabilities of the 2^n possible combinations of the n individual binary indicators. To define $\mathbf{p^{(n)}}$, we write k (with $1 \leq k \leq 2^n$) as a binary expansion:

$$k = 1 + \sum_{i=1}^{n} k_i 2^{i-1}$$

where $k_i \in \{0, 1\}$. This expansion induces a 1-1 correspondence

$$k \leftrightarrow (k_1, k_2, ..., k_n)$$

so that

$$p_k^{(n)} = p_{k_1,k_2,...,k_n}, \qquad 1 \leq k \leq 2^n$$

Teugels (1990) shows that $\mathbf{p^{(n)}}$ can be calculated as:

$$\mathbf{p^{(n)}} = \begin{bmatrix} 1 & 1 \\ -p_n & q_n \end{bmatrix} \otimes \begin{bmatrix} 1 & 1 \\ -p_{n-1} & q_{n-1} \end{bmatrix} \otimes ... \otimes \begin{bmatrix} 1 & 1 \\ -p_1 & q_1 \end{bmatrix} \sigma^{(\mathbf{n})}$$

where $\sigma^{(\mathbf{n})} = \left(\sigma_1^{(n)}, \sigma_2^{(n)}, ..., \sigma_{2^n}^{(n)}\right)^T$ is the vector of central moments than can be calculated as

$$\sigma_k^{(n)} = E\left[\prod_{i=1}^{n} (X_i - p_i)^{k_i}\right]$$

In our application, $n = 4$. Here, p_1 corresponds to the FTS indicator on a particular day generated from our FTS threshold model. We use p_2 to represent the Ordinal FTS indicator, while p_3 and p_4 are the smoothed probabilities that the univariate and bivariate RS models signal FTS, respectively. The Bernoulli variables X_i, $i = 1, .., 4$ are set to 1 when $p_i > 0.5$, and zero otherwise. The vector of central moments $\sigma_k^{(n)}$ is estimated over the full sample. Our joint FTS dummy is set to one when on that particular day the probability that at least 3 FTS measures signal a FTS is larger than 50%, i.e. when $p_{1,1,1,1} + p_{1,1,1,0} + p_{1,1,0,1} + p_{1,0,1,1} + p_{0,1,1,1} > 0.5$.

Table 1: Flights-to-Safety Dummy

This table reports the number of FTS days as a percentage of total observations. For a given threshold level κ, we identify a Flight-to-Safety episode as a day when the bond return is κ standard deviations above zero while at the same time the equity return for that country is κ standard deviations below zero. The standard deviations for bond and stock returns are country-specific and calculated over the full sample. The simulation line indicates the percentage FTS days when data are drawn from a bivariate normal distribution with means, standard deviations, and correlation equal to the average of these statistics across countries. The last line reports, for different levels of κ, the average return impact, measured as the difference between the daily bond and stock return (in %), on FTS days.

	Percentage # FTS Instances, $\kappa = 1, .., 4$								
	0	0.5	1	1.5	2	2.5	3	3.5	4
US	21.82	6.70	2.41	0.90	0.42	0.22	0.12	0.07	0.04
Germany	24.20	7.02	3.20	1.19	0.45	0.27	0.12	0.06	0.04
UK	23.44	6.45	1.97	0.63	0.25	0.11	0.05	0.04	0.02
Switzerland	31.25	6.24	2.02	0.74	0.30	0.20	0.12	0.06	0.01
Japan	29.01	8.23	2.21	0.61	0.18	0.04	0.03	0.00	0.00
Canada	24.00	6.75	2.19	0.69	0.28	0.18	0.08	0.03	0.03
Sweden	26.08	8.00	2.12	0.58	0.13	0.08	0.05	0.00	0.00
Australia	25.32	7.64	2.35	0.88	0.35	0.12	0.03	0.02	0.02
Denmark	25.56	7.55	2.15	0.67	0.32	0.12	0.02	0.02	0.00
France	26.73	8.13	3.07	1.31	0.43	0.23	0.08	0.06	0.01
Belgium	26.13	7.17	2.82	1.06	0.37	0.23	0.10	0.06	0.05
Italy	28.01	8.55	2.90	1.28	0.44	0.26	0.13	0.02	0.02
New Zealand	26.16	8.26	2.37	0.72	0.20	0.15	0.07	0.02	0.02
Netherlands	26.60	7.80	3.14	1.23	0.38	0.22	0.11	0.05	0.04
Ireland	26.64	7.17	2.64	1.08	0.37	0.18	0.08	0.05	0.04
Spain	27.00	9.07	3.55	1.46	0.54	0.29	0.15	0.06	0.05
Austria	24.98	6.53	2.58	1.16	0.44	0.22	0.11	0.05	0.04
Czech Republic	27.48	8.30	2.67	0.84	0.27	0.17	0.04	0.02	0.02
Finland	27.52	9.30	3.31	1.12	0.27	0.14	0.06	0.02	0.02
Greece	28.44	8.88	2.76	0.87	0.29	0.16	0.07	0.02	0.00
Norway	26.34	7.62	2.34	0.74	0.40	0.24	0.12	0.04	0.02
Poland	28.54	9.43	3.01	0.94	0.32	0.15	0.06	0.02	0.00
Portugal	27.91	8.59	3.49	1.27	0.43	0.24	0.14	0.07	0.03
Average	26.49	7.80	2.66	0.96	0.34	0.18	0.08	0.04	0.02
Simulation	27.31	11.16	3.27	0.66	0.09	$<$0.01	$<$0.001	$<$0.001	$<$0.001
Average return Impact	1.20	2.19	3.19	4.20	5.31	6.15	7.09	8.54	9.28

Table 2: The Ordinal FTS Indicator

This table reports summary statistics for the Ordinal FTS Indicator discussed in Section 2.2.2. The first column reports summary statistics for the threshold level, calculated as the minimum of the ordinal numbers on days that satisfy a set of "mild" FTS conditions. Column 2 reports the percentage of observations that have an ordinal number above this threshold. Column 3 reports how much of those observations have an ordinal indicator larger than 50% (calculated as 1 minus the percentage of false positives, i.e. the percentage of observations with an ordinal number above the threshold that are not meeting our FTS criteria). Column 4 shows the percentage of observations in the full sample that have an ordinal FTS indicator larger than 50%.

	Threshold Level	% observation > Threshold	% (obs > threshold) with indicator > 0.5	% obs with indicator > 0.5
US	0.772	6.9%	75.4%	5.2%
Germany	0.781	6.5%	98.7%	6.4%
UK	0.728	9.0%	65.3%	5.9%
Mean	0.723	10.5%	52.9%	5.2%
Median	0.723	10.3%	57.0%	5.1%
Min	0.650	4.8%	18.6%	2.7%
Max	0.804	19.3%	98.7%	7.9%
Interquartile	0.710	9.3%	39.1%	4.6%
Range	0.728	11.4%	64.9%	6.3%

Table 3: Estimation Results Regime-Switching FTS models

Panel A presents the estimation results for the Univariate 3-state Regime-Switching model described in Section 2.2.3. Panel B reports estimation results for the Bivariate Regime-Switching FTS model with jump terms as described in Section 2.2.4. We show detailed estimation results for the US, as well as the average and top/bottom quartile parameter estimates across all 23 countries. ***, **, and * represent statistical significance at the 1, 5, and 10 percent level, respectively. The FTS duration is expressed in days.

Panel A: Univariate 3-state RS FTS Model

	US	**Average**	**6th**	**17th**
Regime-dependent Intercepts (expressed in daily %)				
μ_1	-0.046***	-0.057	-0.079	-0.039
μ_2	-0.014	-0.020	-0.050	-0.007
μ_3	0.218*	0.249	0.198	0.271
Annualized Volatility Estimates				
σ_1	0.097***	0.105	0.087	0.122
σ_2	0.195***	0.201	0.166	0.217
σ_3	0.465***	0.473	0.408	0.498
FTS duration	36.3	26.7	17.2	35.3
# spells	18	26.4	17	31

Panel B: Bivariate RS FTS Model

	US	**Average**	**6th**	**17th**
Equity: Intercept + Jump Terms (expressed in daily %)				
α_0	0,076***	0.069	0.050	0.085
α_1	-1.275**	-2.359	-2.053	-0.246
α_2	1,732***	3.020	1.257	1.989
Bond: Intercept + Jump Terms (expressed in daily %)				
β_0	0,02***	0.030	0.029	0.033
β_1	-0.360	-0.775	-0.923	-0.327
β_2	-0.691***	-0.242	-0.578	0.068
FTS Estimates (expressed in daily %)				
α_3	-7,863***	-5.0286	-7.4159	-1.2872
β_3	0.0001	0.7237	0.0179	0.6736
ν	0,012***	0.1561	0.0146	0.0615
Beta Estimates				
β_4	0,178***	0.0307	-0.0055	0.0382
β_5	-0,344***	-0.1667	-0.1974	-0.1114
Annualized Volatility Estimates				
$h_s\left(S_t^s = 1\right)$	0,104***	0.1100	0.0930	0.1316
$h_s\left(S_t^s = 2\right)$	0,255***	0.2860	0.2464	0.3245
$h_s\left(S_t^b = 1\right)$	0,021***	0.0157	0.0132	0.0180
$h_s\left(S_t^b = 2\right)$	0,048***	0.0357	0.0314	0.0382
FTS duration	89.9	86.6	58.0	101.3
# spells	24	16.0	10.0	18.5

Table 4: Percentage Number of FTS Instances

This table reports the percentage number of days that a FTS is observed according to our two aggregate indicators (columns 1 and 2) and four individual indicators (columns 3 to 6).

	Aggregate Indicators		Individual Indicators			
Country	Average	Joint Prob.	Threshold	Ordinal	Univ RS	Bivar RS
US	3.91	2.87	0.90	5.17	7.98	21.74
Germany	4.95	3.94	1.19	6.37	11.31	26.77
UK	5.22	3.51	0.63	5.86	9.40	23.17
Switzerland	3.02	2.05	0.74	5.68	7.05	6.95
Japan	1.34	0.45	0.61	3.07	5.49	12.96
Canada	4.36	2.05	0.69	4.74	8.56	19.26
Sweden	6.41	2.91	0.58	6.66	14.59	28.24
Australia	3.21	0.78	0.88	1.80	3.72	17.71
Denmark	6.55	1.53	0.67	2.42	12.00	17.74
France	4.59	2.96	1.31	6.34	7.85	17.32
Belgium	7.11	3.21	1.06	4.34	8.83	16.66
Italy	4.42	2.13	1.28	3.28	8.17	10.16
New Zealand	0.81	0.22	0.72	1.82	1.99	1.78
Netherlands	9.60	3.89	1.23	5.29	12.18	17.26
Ireland	6.38	2.31	1.08	3.69	8.89	14.29
Spain	7.87	3.12	1.46	5.67	12.09	23.73
Austria	6.15	2.34	1.16	3.08	11.91	14.50
Czech Republic	1.53	0.31	0.84	2.59	2.96	5.55
Finland	7.73	1.79	1.12	4.76	19.20	14.80
Greece	5.33	1.06	0.87	2.52	19.75	13.08
Norway	0.58	0.04	0.74	0.16	10.83	0.12
Poland	1.45	0.29	0.94	2.07	10.88	3.46
Portugal	5.52	1.82	1.27	4.65	8.85	13.75
Average	4.70	1.98	0.96	4.00	9.76	14.83
Median	4.82	2.05	0.92	4.17	9.14	14.81
Min	0.58	0.04	0.58	0.16	1.99	0.12
Max	9.60	3.94	1.46	6.66	19.75	28.24
Interquartile	3.21	0.78	0.74	2.59	7.98	12.96
Range	6.38	2.91	1.16	5.29	11.91	17.74

Table 5: Return Impact on FTS Days

This table reports the return impact - the difference between the bond and stock return - on FTS and non-FTS days. FTS days are days when the average or joint FTS probability is larger than 50%. The final two columns report the correlation between the joint and average FTS dummies at the daily and weekly frequency, respectively.

	Return Impact on FTS and non-FTS days				correlation of joint with average FTS dummy	
	Average measure		Joint Prob. Measure			
	FTS	non-FTS	FTS	non-FTS	daily	weekly
US	2.53%	-0.12%	2.86%	-0.10%	85.2%	92.4%
Germany	2.46%	-0.14%	2.63%	-0.12%	88.8%	93.5%
UK	1.99%	-0.12%	2.44%	-0.10%	81.3%	90.3%
Average	1.76%	-0.08%	2.97%	-0.07%	66.0%	81.0%
Min	0.42%	-0.18%	1.54%	-0.13%	32.1%	66.0%
Max	5.27%	-0.02%	5.12%	-0.01%	88.8%	93.5%
Interquartile	0.80%	-0.09%	2.40%	-0.10%	60.5%	76.5%
Range	2.37%	-0.06%	3.46%	-0.05%	75.3%	89.2%

Table 6: The Incidence of Global FTS

This table reports how many of the local FTS days are global in nature. At the left, FTS instances are identified using the average measure, at the right using the joint measure. We define a FTS event to be global when at least two-thirds of all countries experience a FTS on that same day. We report country-specific statistics for the US, Germany, and the UK, and summary statistics (average, min, max, interquartile range) for our full sample of 23 countries.

	Average Measure			Joint Prob. Measure		
	# FTS	# global	% global	# FTS	# global	% global
US	327	84	25.7%	240	30	12.5%
Germany	414	99	23.9%	330	39	11.8%
UK	437	103	23.6%	294	39	13.3%
Average	341.3	82.7	32.5%	166	29	24.5%
Min	29	22	13.4%	3	2	10.5%
Max	804	108	75.9%	330	39	66.7%
Interquartile	209	66	21.0%	65	19	14.5%
Range	437	101	30.8%	244	38	23.3%

Table 7: FTS Dummies and Alternative Stress Indicators

This table reports estimates from a regression of changes in implied volatility measures, sentiment variables and safe have currency values on the joint aggregate FTS dummy (instances). Implied volatility measures (i.e. VIX and country-specific measures (VIX for US, Canada; VFTS for the UK; VDAX for the other European countries: VJX for Japan, Australia and New Zealand)) and safe haven currency values (i.e. the Swiss Franc, the Japanese Yen and the US dollar) are available on a daily basis and are regressed on the FTS dummy. The sentiment variables are available on a monthly basis and are regressed on the fraction of FTS days within the month (expressed in %). Implied volatility and sentiment variables are expressed in absolute changes. The currency values are expressed in percentage changes (country currency per unit of safe currency). The sentiment variables include the Baker-Wurgler sentiment indicator (purged of business cycle fluctuations) and the Michigan consumer sentiment index which measure sentiment in the US, the Ifo Business Climate indicator (sentiment in Germany) and the (country-specific) OECD consumer confidence indicator (seasonally-adjusted). We show slope parameter estimates for the US, Germany and UK, as well as the average, standard deviation and top/bottom quartile parameter estimates across all 23 countries. The last column shows the number of countries for which the parameters estimates are significant at the 10% level. ***, **, and * represent statistical significance at the 1, 5 and 10 percent level, respectively.

	US	Germany	UK	Mean	Std	6th	17th	Sign.
Implied Volatility								
VIX	3.276***	1.813***	1.543***	2.107	1.156	1.399	2.330	20
Country-Specific	3.276***	2.177***	2.411***	2.868	1.503	1.837	3.626	23
Sentiment								
Baker-Wurgler	-1.123*	-0.233	-0.603	-1.615	3.088	-1.123	-0.066	5
Michigan	-3.229	-4.422***	-4.864**	-6.605	9.700	-4.694	-2.464	7
Ifo Business	-3.105***	-2.883***	-3.163***	-4.809	3.743	-5.110	-2.912	21
OECD	-0.413***	-0.393***	-0.258***	-0.463	0.429	-0.718	-0.234	19
Currencies								
Swiss Franc	0.060	0.162***	0.263***	0.429	0.566	0.111	0.357	19
Japanese Yen	0.196***	0.308***	0.487***	0.849	0.809	0.355	0.708	22
US Dollar	-	0.005	0.104**	0.394	0.585	0.091	0.399	20

Table 8: FTS and Equity Portfolios

This table reports estimates from a regression of stock portfolio returns on the joint aggregate FTS indicator. The stock portfolios include Datastream industry portfolios (10 industry classification) and MSCI style portfolios (large caps, mid caps, small caps, value and growth). The style portfolios also include a SMB portfolio (i.e. return of small cap portfolio minus return of large cap portfolio) and a HML portfolio (i.e. return of value portfolio minus return of growth portfolio). The portfolio returns are expressed in percentages on a daily basis and are denominated in their original currencies. In the regressions, we control for beta risk by adding a global factor (world market return) and a local factor (local stock market return). We show slope parameter estimates for the US, Germany and UK, as well as the average, standard deviation and top/bottom quartile parameter estimates across all 23 countries. The last column shows the number of countries for which the parameters estimates are significant at the 10 percent level. ***, **, and * represent statistical significance at the 1, 5 and 10 percent level, respectively.

	US	**Germany**	**UK**	**Mean**	**Std**	**6th**	**17th**	**Sign.**
Industry Portfolios								
Oil & Gas	-0.077	-0.267	0.085	-0.188	0.665	-0.377	0.154	10
Basic Materials	-0.303***	-0.055	-0.315**	-0.253	0.537	-0.372	-0.055	11
Industrials	-0.103**	-0.040	-0.027	-0.213	0.429	-0.491	-0.073	15
Consumer Goods	0.227**	-0.107	0.072	-0.177	0.423	-0.421	0.109	10
Health Care	0.225***	0.015	0.162***	-0.093	0.435	-0.188	0.087	6
Consumer Services	0.152***	0.002	0.020	-0.189	0.541	-0.256	0.116	7
Telecom	0.272***	0.423**	0.315***	0.365	0.609	0.176	0.481	15
Utilities	-0.101	-0.090	0.040	-0.213	0.784	-0.295	0.116	8
Financials	-0.368***	-0.246**	-0.264***	-0.346	0.521	-0.553	-0.240	18
Technology	0.140	-0.079	-0.473***	-0.131	0.491	-0.300	0.174	8
Style Portfolios								
Large Cap	0.029***	-0.141	0.047***	0.144	0.346	-0.022	0.154	13
Mid Cap	-0.140***	-0.343***	-0.217***	-0.284	0.441	-0.271	-0.069	12
Small Cap	-0.188***	-0.164***	-0.256***	-0.350	0.327	-0.414	-0.188	16
Value	-0.063	-0.290	0.054	-0.047	0.228	-0.122	0.024	7
Growth	0.066**	0.017	0.012	0.097	0.211	0.004	0.175	7
SMB	-0.216***	-0.022**	-0.304***	-0.502	0.588	-0.734	-0.216	16
HML	-0.129*	-0.307	0.042	-0.144	0.380	-0.352	0.028	11

Table 9: FTS and Bonds

This table reports regression coefficients from a regression of bond yields, spreads and portfolio returns on the joint FTS indicator. Panel A shows the results for the bond yields and spreads. For the yields, we consider the level, slope and curvature factor of the yield curve. The level factor is identified as the average of the 3 month bill rate, and the 5 and 10 year government bond yields; the slope factor as the 10 year goverment bond yield minus the 3 month bill rate; the curvature factor as the sum of the 10 year goverment bond yield and the 3 month bill rate minus two times the 5 year goverment bond yield. We also show results for the 10 year benchmark government bond yields and the monetary policy target rates. For the spreads, we consider two default spread measures, the yield on the AAA portfolio minus the 10 year bond yield, and the yield on the BBB portfolio minus the yield on the AAA portfolio. The bond yields and spreads are expressed relative to a 150 days moving average. We do not add control variables to the regressions reported in Panel A. Panel B shows the results for individual bond portfolio returns. The bond portfolios include JP Morgan cash indices (1, 3, 6 and 12 months), benchmark Datastream government bond indices (2, 5, 20 and 30 year) and BOFA ML coporate bond indices (with respectively AAA, AA, A and BBB ratings). The corporate bond indices are only available for the US, Japan, Canada, Australia and the Eurozone as a whole. We use the Eurozone corporate bond index for regressions with FTS indicators of European countries and the corporate bond index of Australia for the regression with the FTS indicator of New Zealand. In Panel C, we consider 4 spread portfolio returns: the 10 year government bond return minus the 1 month cash return, the 10 year goverment bond return minus the 2 year goverment bond return, the 10 year goverment bond return minus the AAA portfolio return, and the return on the BBB portfolio minus the return on the AAA portfolio. Thus, the first 2 portfolios primarily reacts to changes in the term spread, and the latter 2 to changes in default risk. In the regressions of Panel B and C, we control for the 10 year benchmark government bond return. In the regressions for the corporate bonds, we also control for the local stock market return. All yields, spreads and returns are daily and denominated in local currency. We show slope parameter estimates for the US, Germany and UK, as well as the average, standard deviation and top/bottom quartile parameter estimates across all 23 countries. The last 2 columns show respectively the number of countries for which the parameters estimates are significant at the 10 percent level and the number of countries for which data is available. ***, **, and * represent statistical significance at the 1, 5 and 10 percent level, respectively.

	US	Germany	UK	Mean	Std	6th	17th	Sign.	Obs
Panel A: Yields and spreads									
Gov Level	-0.403***	-0.292***	-0.302***	-0.118	0.461	-0.305	-0.179	21	23
Gov Slope	-0.169***	-0.153***	-0.051	-0.145	0.329	-0.250	-0.052	16	23
Gov Curvature	0.334***	0.361***	0.349***	0.217	0.670	0.183	0.411	20	23
Gov 10 Year	-0.472***	-0.309***	-0.269***	-0.158	0.475	-0.405	-0.193	21	23
MP Target Rates	-0.161***	-0.151***	-0.183***	-0.131	0.204	-0.172	-0.034	17	23
AAA - Gov 10 Year	0.420***	0.130***	0.120***	0.040	0.421	-0.093	0.244	20	23
BBB - AAA	0.425***	0.684***	0.666***	0.529	0.310	0.322	0.766	20	23
Panel B: Bond portfolio returns									
Cash 1 Month	-0.007***	-0.005***	-0.009***	-0.007	0.003	-0.010	-0.006	15	17
Cash 3 Month	-0.007***	-0.004***	-0.009***	-0.007	0.003	-0.009	-0.005	15	17
Cash 6 Month	-0.007***	-0.003***	-0.010***	-0.007	0.005	-0.010	-0.004	14	17
Cash 12 Month	-0.010**	-0.001	-0.009**	-0.006	0.007	-0.012	-0.002	7	16
Gov 2 Year	-0.020**	0.010**	-0.004	-0.008	0.039	-0.027	0.009	12	21
Gov 5 Year	-0.003	0.035***	0.022*	0.031	0.063	-0.003	0.035	10	23
Gov 20 Year	-	-0.021	0.129***	0.020	0.070	-0.021	0.060	3	9
Gov 30 Year	0.175***	-0.015	0.201***	0.049	0.078	-0.015	0.054	4	12

	US	Germany	UK	Mean	Std	6th	17th	Sign.	Obs
Panel B: Bond portfolio returns (continued)									
AAA	-0.024	-0.008	-0.022	0.031	0.355	-0.048	-0.013	1	23
AA	-0.056***	-0.046**	-0.053***	-0.005	0.364	-0.070	-0.047	19	23
A	-0.079***	-0.079***	-0.093***	-0.064	0.375	-0.144	-0.091	21	23
BBB	-0.080***	-0.068**	-0.086***	-0.060	0.384	-0.151	-0.086	20	23
Panel C: Spread portfolio returns									
Gov 10 Year - Cash 1 Month	0.007***	0.005***	0.009***	0.007	0.003	0.005	0.009	15	17
Gov 10 Year - 2 Year	0.020**	-0.010**	0.004	-0.004	0.067	-0.010	0.020	13	23
Gov 10 Year - AAA	0.028**	0.006	-0.008	-0.121	0.372	-0.145	0.006	10	23
AAA - BBB	0.051*	0.060**	0.054*	0.079	0.077	0.041	0.093	14	23

Table 10: Liquidity and FTS

This table reports slope parameter estimates from a regression of US bond (Panel A) and equity market (Panel B) illiquidity measures on the joint FTS dummy (instances). Our bond market illiquidity measures are (1) the monthly effective spread, a cross-sectional monthly average of proportional quoted spreads of Treasury bonds with a maturity of at most one year (in %), (2) the daily Treasury on/off-the-run spread, calculated as minus the daily difference in yield between an on-the-run Treasury bond and a synthetic off-the-run Treasury security with the same coupon rate and maturity data (in basis points), and (3) the 'noise' measure of Hu et al. (2012). Our equity market illiquidity measures are monthly cross-sectional averages of (1) the effective tick measure from **?**, (2) Amihud (2002)'s price impact measure, and (3) the negative of the Pastor and Stambaugh (2003) price impact measure. When the measures are non-stationary over the sample, we use values relative to either a 150-day or 6 month moving average. The regressions only feature a constant and the FTS measure as dependent variable. When the illiquidity measure is only available at the monthly frequency, we relate it to the percentage of FTS days within that month. ***, **, and * represent statistical significance at the 1, 5 and 10 percent level, respectively.

	Level	
	α	β_{FTS}
Panel A: Bond Illiquidity Measures		
Proportional Spread	-0.11***	0.43***
Treasury On/Off-the-run Premiums	14.36***	10.02***
Noise Measure Hu, Pan, Wang (2012)	-0.12***	1.20***
Panel B: Equity Illiquidity Measures		
Effective Tick	-0.04**	0.62***
Amihud	2.46***	8.03***
(negative of) Pastor-Stambaugh	0.02***	0.22***

Table 11: FTS and Commodity Prices

This table reports regression coefficients from a regression of the S&P GSCI benchmark commodity index returns (in US$) on the joint FTS dummy and the global equity market return (in US$) as control. We consider broad indices (Commodity Total, Energy, Industrial Metals, Precious Metals, Agriculture, Livestock) and subindices (Crude Oil, Brent Crude Oil and Gold). The returns are expressed in percent on a daily basis and are denominated in US$. We show FTS slope parameter estimates for the US, Germany and UK, as well as the average, standard deviation and top/bottom quartile parameter estimates across all 23 countries. The last two columns report the average market beta as well as the number of countries for which the FTS slope parameter estimates are significant at the 10 percent level, respectively. ***, **, and * represent statistical significance at the 1, 5 and 10 percent level, respectively.

	US	**Germany**	**UK**	**Mean**	**Std**	**6th**	**17th**	**Beta**	**Sign.**
Commodity Total	-0.414***	-0.290***	-0.418***	-0.621	0.397	-0.843	-0.364	0.276	20
Energy	-0.514***	-0.371***	-0.473***	-0.736	0.435	-1.026	-0.459	0.290	21
Industrial Metals	-0.108	-0.209**	-0.361***	-0.488	0.402	-0.609	-0.251	0.523	19
Precious Metals	0.419***	0.347***	0.212**	0.324	0.364	0.209	0.397	0.202	14
Agriculture	-0.174*	-0.087	-0.236**	-0.271	0.527	-0.343	-0.100	0.247	12
Livestock	-0.106*	-0.114**	-0.203***	-0.140	0.222	-0.178	-0.094	0.106	13
Crude Oil	-0.687***	-0.469***	-0.580***	-0.839	0.473	-1.125	-0.525	0.307	21
Brent Crude Oil	-0.543***	-0.180	-0.310*	-0.637	0.555	-0.713	-0.310	0.546	16
Gold	0.427***	0.359***	0.242**	0.350	0.333	0.228	0.417	0.162	15

Table 12: FTS and the Real Economy

This table reports regression coefficients from a regression of the real economy variables on the fraction of days of FTS instances (based on the the joint FTS indicator) within the month (expressed in decimals). The real economy variables include inflation, industrial production growth (IP), the unemployment rate and the OECD leading indicator (available monthly); GDP growth and investment/GDP (available quarterly). For inflation, IP growth, GDP growth, unemployment rate and investment growth, we also use the mean of survey forecasts and the standard deviation of the individual forecasts (available monthly, in %). The growth variables are computed as the next quarter value relative to the current value (in %). The unemployment rate (in %), the OECD leading indicator, investment/GDP (in %) and the forecast variables are computed as absolute differences between the next quarter value and the current value. Future values of the different values are cumulative one year growth rates, calculated as next year's value relative to the current value (in %) for GDP, IP, and CPI, and as the absolute difference between the next year value and the current value in case of the unemployment rate (in %), the OECD leading indicator, and investment growth. We show slope parameter estimates for the US, Germany and UK, as well as the average, standard deviation and top/bottom quartile parameter estimates across all 23 countries. The next to column shows the number of countries for which the parameters estimates are significant at the 10 percent level. The last column shows the number of countries for which the real economy is available. ***, **, and * represent statistical significance at the 1, 5 and 10 percent level, respectively, using Newey-West standard errors (using eiither 6 quarterly or 24 monthly lags).

	US	Germany	UK	Mean	Std	6th	17th	Sign.	Obs
Inflation	-1.391**	-0.946***	-1.051***	-2.420	3.207	-2.392	-1.051	19	23
Inflation Forecast Mean	-1.632	-0.547	-1.320**	-1.431	2.101	-1.406	-0.400	6	21
Inflation Forecast St. Dev.	0.115	0.008	0.117	-0.005	0.253	-0.034	0.105	0	12
Future Inflation	-3.930***	-3.144***	-3.599**	-7.933	7.613	-8.834	-3.497	21	23
IP Growth	-3.341*	-4.529**	-2.564**	-13.027	29.330	-6.514	-3.341	12	14
IP Growth Forecast Mean	-3.783*	-3.571*	-1.912*	-4.563	6.665	-3.783	-1.862	11	19
IP Growth Forecast St. Dev.	0.423	0.234	-0.037	0.781	1.183	-0.004	0.478	1	12
Future IP Growth	-9.856***	-4.041	-5.944	-22.473	42.383	-11.625	-4.366	8	14
GDP Growth	-2.452**	-3.014**	-1.911	-8.550	17.314	-6.883	-2.018	16	23
GDP Growth Forecast Mean	-1.749*	-1.720**	-1.149*	-2.133	3.185	-1.914	-1.099	16	21
GDP Growth Forecast St. Dev.	0.109	0.077	-0.020	-0.133	0.729	-0.007	0.109	1	12
Future GDP Growth	-4.909	-6.632***	-5.683	-17.316	25.781	-15.989	-4.601	15	23
Unemployment	0.883*	0.290	0.165	0.557	0.608	0.174	0.883	10	23
Unemployment Forecast Mean	0.911	0.293	0.529	0.592	0.306	0.337	0.555	2	7
Unemployment Forecast St. Dev.	0.075	-0.027	0.059	0.057	0.097	-0.027	0.075	0	7
Future Unemployment	3.033**	0.536	0.713	2.802	3.803	0.713	3.033	11	23
Investment/GDP	-1.003*	-0.341	-0.338	2.993	24.425	-2.063	-0.058	7	20
Investment Growth Forecast Mean	-5.617	-4.619	-2.324*	-10.396	19.211	-11.721	-2.710	9	12
Investment Growth Forecast St. Dev.	0.968**	-0.182	-0.179	1.871	5.558	-0.179	0.968	2	12
Future Investment/GDP	-2.391	-0.394	-2.408***	-27.667	101.572	-10.632	-0.747	7	20
OECD Leading Indicator	-1.014	-0.661	-0.570	-1.625	2.271	-1.788	-0.570	12	23
Future OECD Leading Indicator	2.245*	3.172*	1.174	1.196	3.440	-0.861	2.245	6	23

Figure 1: Ordinal Indicator: US, Germany, and UK

The left panels plot the ordinal FTS indices for the US, Germany, and UK together with the minimum threshold level, calculated as the minimum of all ordinal values for which the minimal FTS conditions hold . The right panels plot the derived ordinal FTS indicator. Values with a value above 0.5 are depicted in black, values below 0.5 in light grey.

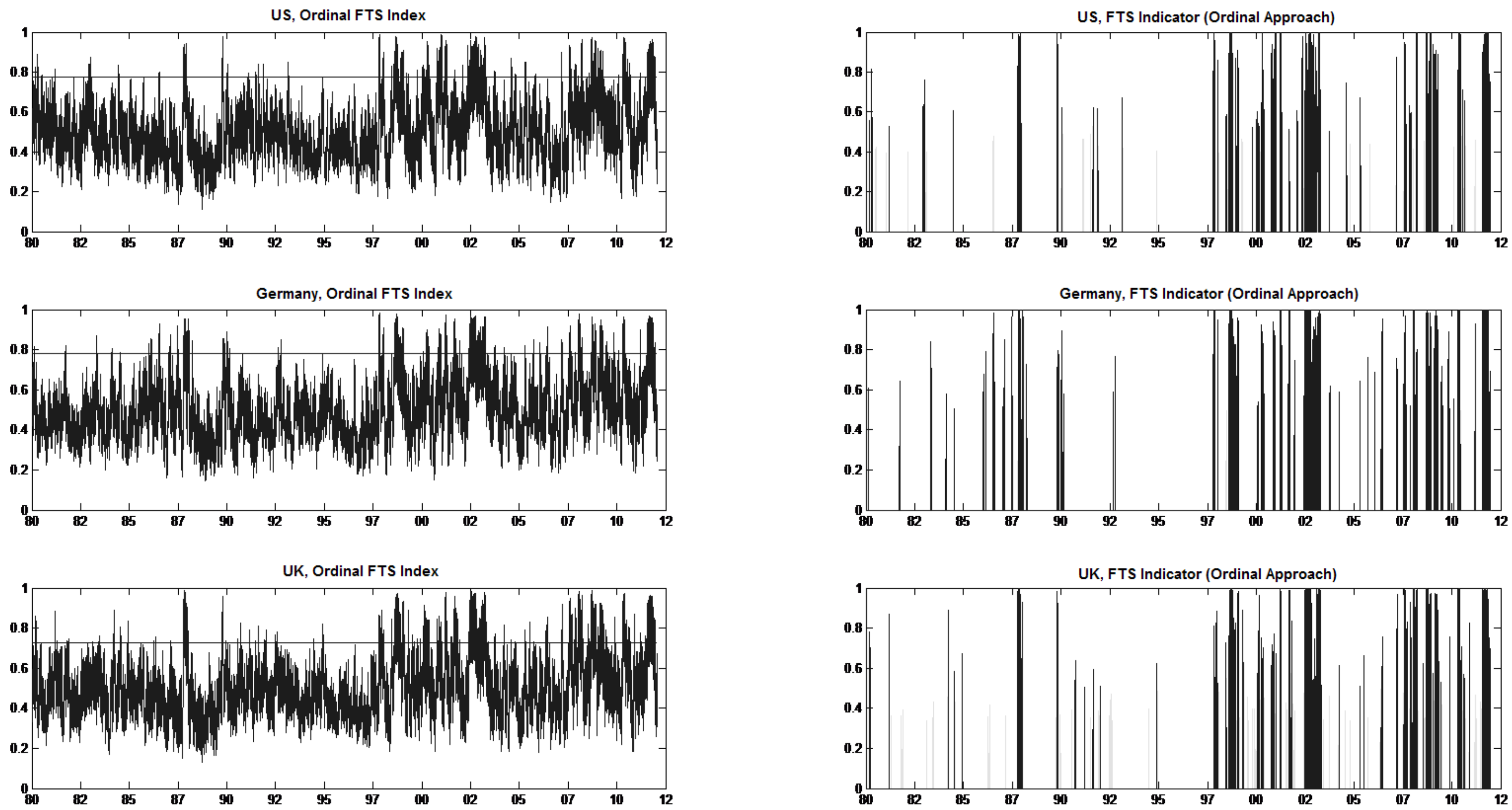

Figure 2: Aggregate FTS Indicator and Dummy, US

The top panel of this figure plots the average FTS indicator together with the corresponding FTS dummy for the US. The dummy is equal to one when the average indicator is larger than 50%, and zero otherwise. The bottom panel plots the joint FTS probability measure together with its corresponding joint FTS dummy.

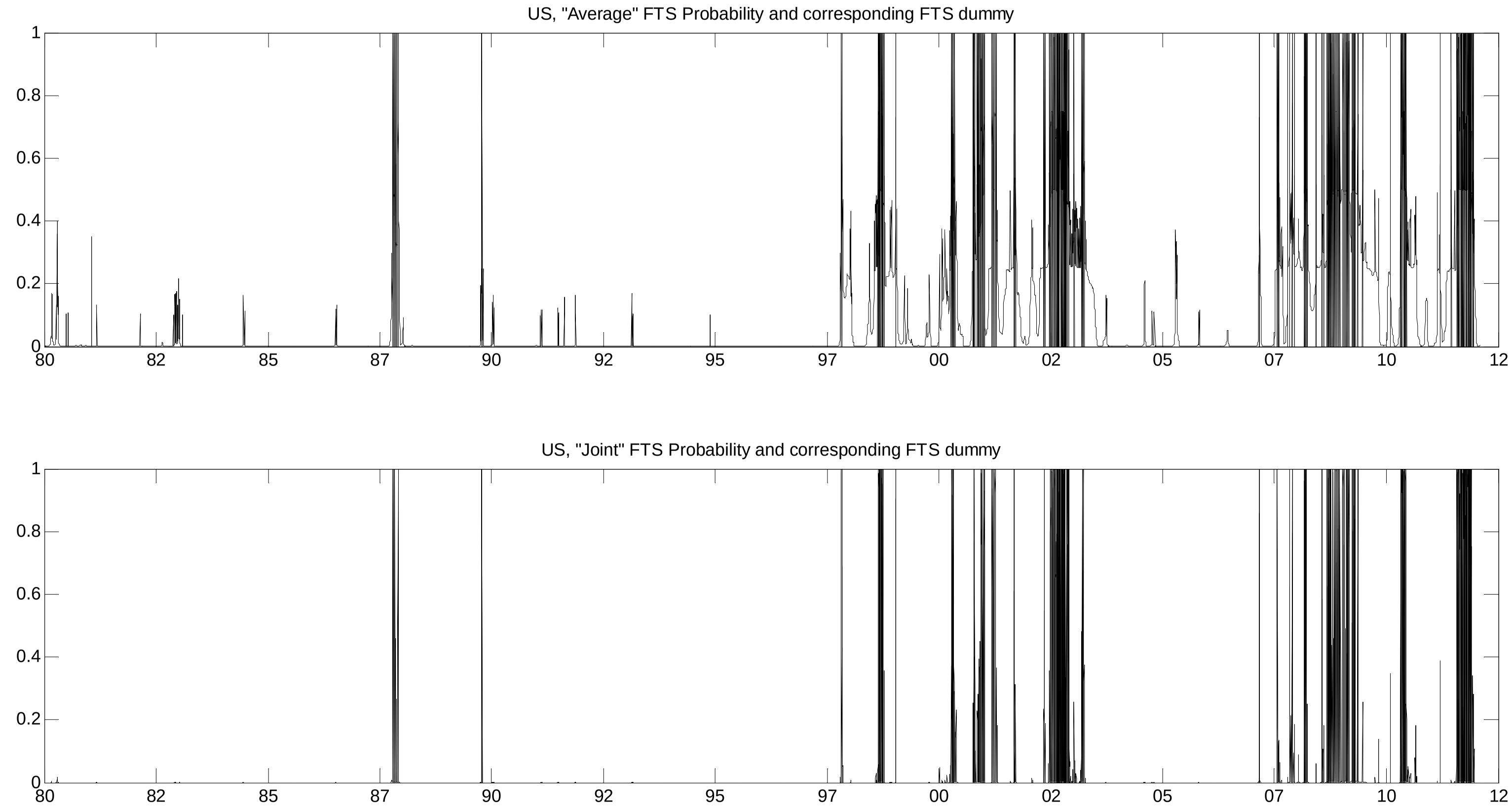

Figure 3: Return Impact before/on/after FTS days

This figure plots returns (in percent) in the equity and bond market as well as the difference between the bond and equity return, averaged over the 23 countries, ranging from 30 days before to 30 days after a FTS event. In the graphs on the left, FTS is identified using the average FTS dummy, in the graphs on the right the joint FTS dummy is used. The solid lines take all FTS days into account, the dotted lines show returns and return impact around the first day of a FTS spell only.

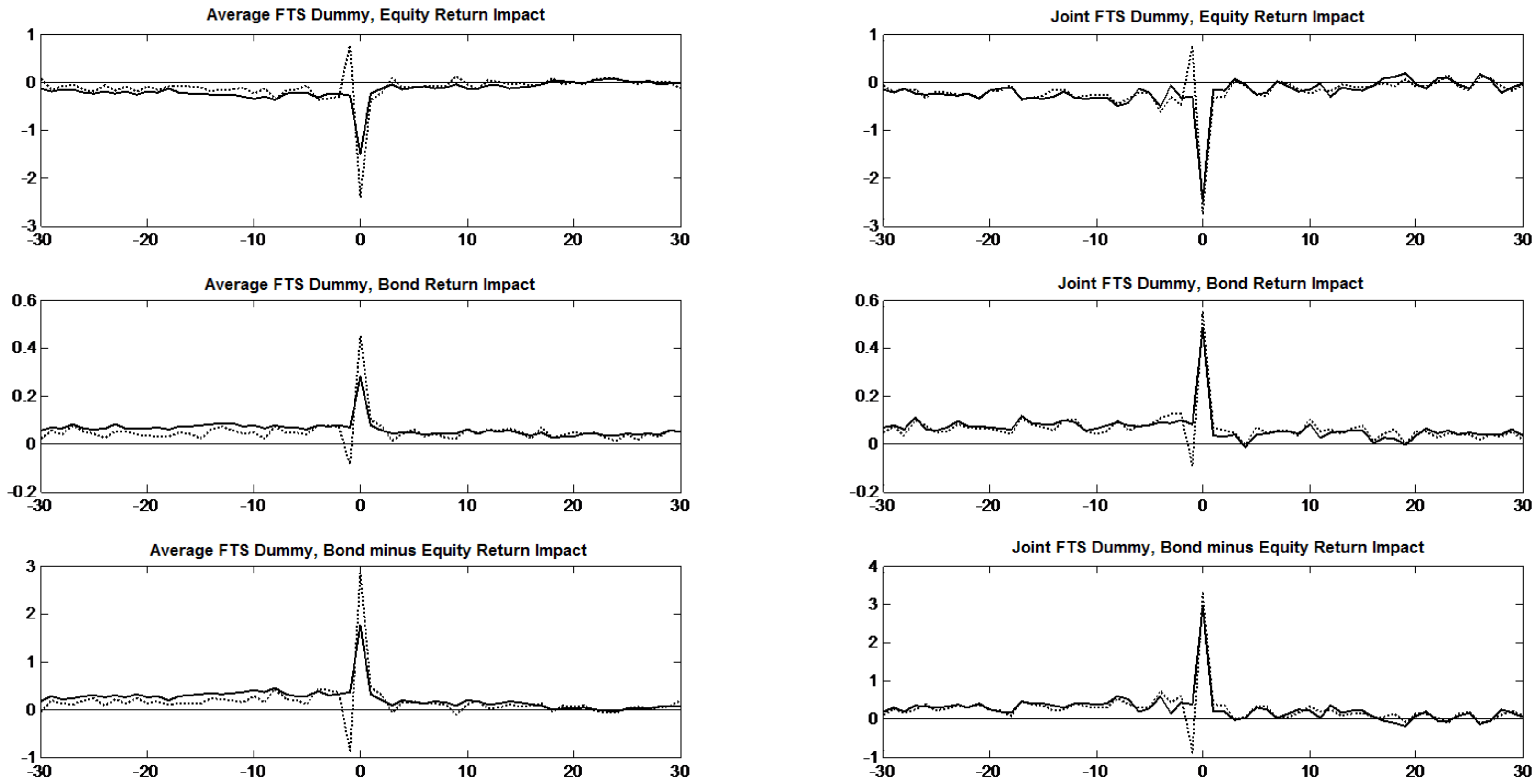

Figure 4: Percentage of Countries in FTS

This Figure plots the equally-weighted percentage of countries experiencing a FTS at each point in time. In the top panel, FTS is identified using the average FTS dummy, while in the bottom panel the joint FTS dummy is used.