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# Stocks and bonds: Flight-to-safety for ever?

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This paper gives new insights about flight-to-safety from stocks to bonds, asking whether the strength of this phenomenon remains the same in the current environment of low yields. The motivations lie in the conjecture that when yields are low, the traditional motives of flight-to-safety (wealth protection, liquidity) could not be sufficient, inducing weaker flight-to-safety events. Empirical applications using data for U.S. government bonds and the S&P 500 index, show indeed that when yields are low, the strength of flight-to-safety from stocks to bonds weakens. This result holds, even when controlling for the effects of traditional flight-to-safety factors including the VIX, the TED spreads and the overall level of illiquidity in the stock market. Moreover, we develop a bivariate model of flight-to-safety transfers that measures to what extent the strength of flight-to-safety from stocks to bonds is related to the strength of flight-to-safety from stocks to other safe haven assets (gold and currencies). Results show that when the strength of flight-to-safety from stocks to bonds decreases the strength of flight-to-safety from stocks to these safe haven assets increases. This result holds only in the low-yield environment, suggesting a kind of substitution effect of save haven assets, similar to the reaching for yield behavior.


## 1. Introduction

The correlation between the returns on government bonds and stock indices has been deeply scrutinized in the literature. The main motivation lies in the fact that these two assets are considered not only as complementary but also as substitutes, and the level and dynamics of their return's correlation are important elements for asset allocation decisions. Theoretically, uncertainties about growth and inflation are the main drivers of this correlation via their impact on both the equity risk premium and the term premium (Ilmanen, 2003). Indeed, when uncertainty about growth raises, the equity risk premium increases, depressing stock market, while bond prices boom in response to a drop in the term premium. This leads to a negative correlation between the returns on stocks and bonds. Moreover, a positive correlation arises from increased uncertainty about expected inflation, via the impact of the latter on the common interest rate factor that drives stock and bond prices (Li, 2002). Of major importance are episodes of pronounced negative correlation between these two assets, referred to as flight-to-safety (hereafter FTS), with large decline (rise) in stock (bond) prices. FTS refers to a sudden increase in appetite for safe assets relative to risky assets. Typically, it is a combination of a preference for safe assets (low volatility, downside risk), high

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quality assets (low default) and highly liquid assets. A recent literature pioneered by the seminal paper of Vayanos (2004) has analyzed FTS episodes, both theoretically and empirically.

Economic theories of investor FTS include Vayanos (2004), Caballero and Krishnamurthy (2008) and Brunnermeier and Pedersen (2009), to cite but a few. Vayanos (2004) develops an equilibrium model with assets differing in their liquidity, and where asset managers are subject to funding constraints that (endogenously) depend on the level of market volatility. When volatility increases, fund managers face redemption risk they tend to mitigate by allocating more to relatively safer assets, generating FTS.[1] Caballero and Krishnamurthy (2008) build a model where FTS episodes arise not only from the risk about asset payoffs, but also from (Knightian) uncertainty about the states of the world. In their model, facing market turmoil and limited aggregate liquidity, uncertainty-averse agents with max–min preferences consider the most unfavorable scenario among all possible ones. This leads them to project liquidity shortages and to switch from risky to safe assets. Using the relation between market liquidity and trader's funding liquidity, Brunnermeier and Pedersen (2009) develop a model in which deterioration of market liquidity pushes speculators to mostly provide liquidity in safer securities (with lower margins), leading to an increase in the liquidity differential between safe and risky securities, an evidence of FTS.

On the empirical side, Baur and Lucey (2009) propose a test of FTS from stocks to bonds, with applications to eight developed countries. Their results evidence the existence of FTS episodes that coincide with crisis periods, and which appear to be country-specific with a common occurrence among countries. Baele et al. (2015) provide many interesting stylized facts about FTS episodes from stock to bond markets, using daily data for 23 countries. They found, among other things, that FTS days comprise less than 3% of the sample, and in those days, bond returns exceed stock returns by 2.5 to 4% on average. Moreover, FTS episodes coincide with increases in the VIX and the TED spreads, decreases in sentiment and appreciations of Yen and Swiss franc. Both real activity and inflation decrease immediately (and year after) following a FTS spell.

The objective of this paper is to provide additional stylized facts about FTS. Precisely, we investigate whether bond yield regimes (low or high yield environment) can affect the strength of FTS between stocks and bonds. Indeed, market participants usually consider Treasury bonds as attractive in times of market stress, not only for their low level of default risk, but also for their high levels of liquidity. But our intuition is that low nominal yield can potentially jeopardizes the desirability of treasury bonds in FTS episodes. This research question is important for portfolio managers to evaluate whether the well-known diversification benefits of FTS continue to hold in a low-yield environment, when low inflation and expansionary monetary policies push yields to historically low levels.[2] In relation to the existing literature, our approach goes beyond the traditional motives of FTS (wealth protection, liquidity) asking if they remain sufficient in the current context of low yields. In other words, (i) when yields are low, do investors still find it rational in times of stress to rebalance their equity portfolios in favor of bonds? (ii) Are there some transfers to other more profitable safe havens, such as gold or currencies? To our knowledge, this is the first paper that addresses these two issues about FTS.

To provide answers to the first research question, we build on Ghysels et al. (2016) and Aslanidis and Christiansen (2017) and use an econometric model based on dynamic quantile regression that helps measuring the strength of FTS from stocks to bonds. The model draws on the conditional autoregressive value at risk (CAViaR) specification of Engle and Manganelli (2004) for the estimation of an extreme upper quantile of the distribution of $r_t^{(bs)} = r_t^{(b)} - r_t^{(s)}$, with $r_t^{(b)}$ the returns on government bond and $r_t^{(s)}$ the returns on a representative stock index. Remark that the excess returns $r_t^{(bs)}$ take extreme values for FTS events, i.e, when realized bond (stock) returns are located in the upper (lower) tail of its conditional distribution. Hence, the upper extreme quantile of $r_t^{(bs)}$ can be viewed as a measure of the strength of FTS.[3] We consider an extended version of this CAViaR model including a low-yield environment dummy variable. The coefficient of this dummy variable when statistically different from zero and negative (positive) is the evidence that in low-yield environment, the strength of FTS from stocks to bonds decreases (increases).

Empirical results using data for U.S. government bonds and the S&P 500 index show that the strength of FTS is related to the level of yields. This result holds for all maturities (10-year, 5-year and 2-year). For illustration, with the 10-year maturity bond, when yields are lower than 2%, the strength of FTS from stocks to bonds decreases, suggesting less strong FTS events in low-yield environment. For the medium 5-year (resp. short term 2-year) maturity, we observe the same result when yields are lower than 1% (resp. 0.5%). It is worth noting that these results remain statistically significant, even when controlling for the effects of traditional flight-to-safety factors including the VIX, the TED spreads and the overall level of illiquidity in the stock market.

[1] In the literature FTS episodes refers to both flight-to-quality and flight-to-liquidity episodes. The difference between them results from the economic motives (preference for less risky assets or preference for liquidity) that lead investors rebalancing their portfolios in time of increased uncertainty. Beber et al. (2009) deeply analyzes both episodes in the Euro-area bond market. In this paper we do not focus on these motives and consider the FTS phenomenon, globally.

[2] U.S. nominal interest rates remained low since 2007–2008 as the result of low inflation and low neutral real interest rate estimates. To support the economic recovery from the Great Recession, the Federal Reserve held the federal funds rate near zero for over seven years and acquired large holdings of longer-term securities. Despite these extraordinary measures, real GDP has grown at only a modest pace during the recovery. Commentators and policymakers have described this combination of low growth and low-interest rates as a "new normal" for the U.S. economy. Some observers, such as Rogoff (2015), trace these development to persistent, but ultimately transitory, debt deleveraging and borrowing headwinds in the wake of the global financial crisis. Some others, like Summers (2014), see these developments as more structural and symptomatic of "secular stagnation", i.e., a confluence of structural changes persistently weakening GDP growth and lowering interest rates.

[3] Note that we focus only on measuring the strength of FTS and do not consider identifying FTS events as in Ghysels et al. (2016) and Aslanidis and Christiansen (2017). FTS days can indeed be identified as the days corresponding to a quantile exception, i.e., when $r_t^{(bs)}$ is higher than its extreme upper conditional quantile.

Equipped with these results, we focus on the second research question, i.e., whether the observed decreases in the strength of FTS from stocks to bonds, can be explained by some transfers to other more profitable safe haven assets. We thus build on the VAR for VaR (vector autoregressive model for value at risk) model of White et al. (2015). Precisely, we consider a bivariate CAViaR model for the joint dynamics of the upper extreme quantiles of $r_t^{(bs)}$ and $r_t^{(as)}$ with $r_t^{(as)} = r_t^{(a)} - r_t^{(s)}$, and $r_t^{(a)}$ the returns on an alternative (to bonds) safe haven assets such as gold or currencies. This model helps measuring to what extent the strength of FTS from stocks to bonds is related to the strength of FTS from stocks to other safe haven assets (gold, Swiss Franc and Japanese Yen). Results show that when the strength of FTS from stocks to bonds decreases, the strength of FTS from stocks to these alternative safe haven assets increases. This result holds only in the low-yield environment, suggesting a kind of substitution effect of safe haven assets in stress episodes, similar to the reaching for yield behavior.

The rest of the paper is organized as follows. In Section 2, we develop and estimate (using U.S. data) a model that relates the strength of FTS from stocks to bonds to the state of the world as measured by the level of yields. Section 3 is devoted to the bivariate model that relates the strength of FTS from stocks to bonds to the strength of FTS from stocks to other safe haven assets. The last Section concludes the paper.

## 2. Strength of FTS and low-yield environment

### 2.1. The econometric model

Traditional econometric models to measure the strength of FTS are based on the so-called tail-dependence coefficient. Formally, let $r_t^{(s)}$ and $r_t^{(b)}$ be the returns at time $t$ for a given country in its stock index and benchmark government bond, respectively. Denote $Q_t^{(j)}(\alpha), j \in \{s, b\}$, the $\alpha$-quantile at time $t$ of $r_t^{(j)}, 0 < \alpha < 1$, conditional on the information set $\mathcal{F}_t$ available at time $t$. The tail-dependence coefficient measures the dependence between the lower tail of $r_t^{(s)}$ and the upper tail of $r_t^{(b)}$, and is given by

$$\tau^{b|s} = \lim_{\alpha \to 1} \Pr\left(r_t^{(b)} > Q_t^{(b)}(\alpha) \middle| r_t^{(s)} < Q_t^{(s)}(1-\alpha)\right). \quad (1)$$

The tail-dependence coefficient $\tau^{b|s}$ lies between zero and one. It takes value zero (one) in the case of full tail-independence (dependence), corresponding to the complete absence (presence) of a flight-to-safety event from stocks to bonds. In the literature, there are two different approaches to make inference on the tail-dependence coefficient $\tau^{b|s}$, stemming from the multivariate extreme value theory (EVT). The first one is linked to the theory of copulas which offers a fully parametric approach to specify the bivariate probability distribution of any couple of asset returns. From this distribution, estimating and testing for the significance of the tail-dependence coefficient is straightforward within the maximum likelihood framework (McNeil et al., 2005; Hua and Joe, 2011). The second approach is semi parametric and consists in transposing some results in univariate EVT to the bivariate or multivariate case (Ledford and Tawn, 1996; Draisma et al., 2004; Poon et al., 2004; Hartmann et al., 2004). More recently, van Oordt and Chen (2012) introduce a linear regression model to estimate the tail-dependence parameter $\tau^{b|s}$. The advantage of the regression approach arises from its simplicity regarding the estimation, which can be achieved via the method of ordinary least squares (OLS), available on common econometric software.[4]

The above contributions have the common property that they produce an unconditional measure of the tail-dependence coefficient. Since our goal in this paper is to investigate whether a variable measuring yield regimes (high or low) can affect the strength of a flight-to-safety event from stocks to bonds, we need a conditional model for the tail-dependence coefficient. Note that such a conditional framework was introduced in the literature by Patton (2006) in the context of copulas theory, to test for the asymmetry in the dependence between exchange rates. The approach of Cappiello et al. (2014) can also be used to measure the impact of exogenous dummy variables on the probability of flight-to-safety.

Although these two approaches are attractive, we follow Ghysels et al. (2016) and Aslanidis and Christiansen (2017) and opt to measure the strength of FTS using simple dynamic quantile regression with target variable being $r_t^{(bs)} = r_t^{(b)} - r_t^{(s)}$, where again $r_t^{(b)}$ is the return on government bond and $r_t^{(s)}$ is the return on a representative stock index. It is worth noting that the excess returns $r_t^{(bs)}$ take positive extreme values with realized large negative stock returns concomitant to large positive bond returns, an evidence of FTS. Thus, the magnitude of an extreme upper-quantile of the excess return $r_t^{(bs)}$ is a natural proxy of the strength or intensity of FTS events. Obviously, the level of this extreme quantile should be high (low) in FTS (non-FTS) days, and can be considered as a barometer of wealth rebalancing across the two markets. Let $Q_t^{(bs)}(\alpha), \alpha = 99\%$ be the extreme upper quantile of $r_t^{(bs)}$ at the risk level $\alpha$. We consider the following specification for $Q_t^{(bs)}(\alpha) \equiv Q_t^{(bs)}(\alpha; \theta)$

$$Q_t^{(bs)}(\alpha) = \theta_0 + \theta_1 Q_{t-1}^{(bs)}(\alpha) + \theta_2 r_{t-1}^{(bs)} \mathbb{I}\left(r_{t-1}^{(bs)} < 0\right) + \theta_3 r_{t-1}^{(bs)} \mathbb{I}\left(r_{t-1}^{(bs)} \geqslant 0\right), \quad (2)$$

[4] See also Cappiello et al. (2014) for a similar approach.

with $\mathbb{I}(.)$ the usual indicator function. This specification corresponds to the asymmetric slope version of the CAViaR model of Engle and Manganelli (2004) that offers a parsimonious specification to model quantiles for heteroskedastic time series. As already stressed, the quantile $Q_t^{(bs)}(\alpha)$ can be viewed as a measure of the strength of FTS from stocks to bonds, since larger values are indicative of a more leptokurtic conditional distribution of the excess returns $r_t^{(bs)}$. The main advantage of this semi-parametric model is that, one does not need to specify the full conditional distribution of the excess returns, as for example in a GARCH-type methodology. The parameters of the model are estimated by minimizing with respect to the unknown parameters the "tick" loss function of Koenker and Bassett (1978), i.e.,

$$\widehat{\theta} = \arg\min_{\theta} T^{-1} \sum_{t=2}^{T} \left( \alpha - \mathbb{I}\left( u_t^{(bs)} < 0 \right) \right) u_t^{(bs)}, \tag{3}$$

$$u_t^{(bs)} = r_t^{(bs)} - Q_t^{(bs)}(\alpha), \tag{4}$$

with $T$ the sample size. Under weak regularity assumptions, Engle and Manganelli (2004) show that

$$\sqrt{T} A_T^{-1/2} D_T \left( \widehat{\theta} - \theta_0 \right) \longrightarrow N(0,1), \tag{5}$$

where

$$A_T = \mathbb{E}\left( T^{-1} \alpha(1-\alpha) \sum_{t=1}^{T} \nabla' Q_t^{(bs)}(\alpha) \nabla Q_t^{(bs)}(\alpha) \right), \tag{6}$$

$$D_T = \mathbb{E}\left( T^{-1} \sum_{t=1}^{T} h_t(0|\mathcal{F}_t) \nabla' Q_t^{(bs)}(\alpha) \nabla Q_t^{(bs)}(\alpha) \right), \tag{7}$$

with $h_t(0|\mathcal{F}_t)$ the conditional density of the quantile residuals $u_t^{(bs)}$, and $\nabla Q_t^{(bs)}(\alpha)$ the vector of derivative of $Q_t^{(bs)}(\alpha)$ with respect to the parameter vector $\theta$. Inference about the parameters can thus be conducted using (5), with consistent estimates of $A_T$ and $D_T$.

To evaluate the impact of low-yield environment to the strength of FTS, we consider an extended version of the CAViaR model in (2) corresponding to the following specification

$$Q_t^{(bs)}(\alpha) = \theta_0 + \theta_1 Q_{t-1}^{(bs)}(\alpha) + \theta_2 r_{t-1}^{(bs)} \mathbb{I}\left( r_{t-1}^{(bs)} < 0 \right) + \theta_3 r_{t-1}^{(bs)} \mathbb{I}\left( r_{t-1}^{(bs)} \geqslant 0 \right) + \delta \mathbb{I}\left( i_t < \bar{i} \right), \tag{8}$$

where $i_t$ is the value of the bond yield at time $t$, and $\bar{i}$ an exogenous threshold. As $Q_t^{(bs)}(\alpha)$ is a measure of the strength of FTS, the parameter $\delta$ when statistically different from zero is the evidence that there exists a relation between yield regimes and the intensity of FTS from stocks to bonds. Moreover in the case of significance, a negative (positive) value for the estimate $\widehat{\delta}$ means that in low-yield environment, the strength of FTS from stocks to bonds decreases (increases).

Let us note that correct specification of both models in (2), (8) can be tested relying on the dynamic quantile (DQ) test of Engle and Manganelli (2004). The related null hypothesis checks for an orthogonality condition between the centered process of quantile-exception equal to $Hit_t(\theta_0) = \mathbb{I}\left( r_t^{(bs)} > Q_t^{(bs)(\alpha)} \right) - (1-\alpha)$ and a set $X_t(\theta_0)$ of K instruments. Under the null hypothesis of a correctly specified dynamic quantile model, the authors show that[5]

$$DQ = \frac{Hit\left(\hat{\theta}\right) X\left(\hat{\theta}\right) \left( \hat{M}_T \hat{M}_T' \right) X'\left(\hat{\theta}\right) Hit'\left(\hat{\theta}\right)}{\alpha(1-\alpha)} \underset{T\to\infty}{\to} \chi^2(K), \tag{9}$$

with $\widehat{M}_T$ given by the difference between $X'\left(\widehat{\theta}\right)$ and a function of the gradient of $\widehat{Q}_t^{(bs)}(\alpha) \equiv Q_t^{(bs)}\left(\alpha; \widehat{\theta}\right)$.

### 2.2. Data and descriptive statistics

Before presenting the estimation results of the extended CAViaR model in (8) that helps measuring the impact of yield regimes on the strength of FTS, this subsection provides descriptive statistics for the input variables and gives some graphical illustrations of FTS through our sample.

Our dataset includes weekly total return prices on U.S. government bonds and the S&P 500 index over the period ranging from February 2, 1990 to November 23, 2018, with a total of $T = 1504$ observations. Empirical papers on the subject use either daily, weekly or monthly data. For instance, Baur and Lucey (2009) and Baele et al. (2015) use daily data, while Ilmanen (2003) and Li (2002) use both daily and monthly data. Daily, weekly and monthly data are covered in Baur and McDermott (2010). We make the choice of weekly data for a main reason. Indeed, all the papers cited above operated in

[5] See the reference for more details on the DQ test.

a framework where the main objective is to check for the occurrence of FTS phenomenons. In such a context, using high-frequency data is appropriate because the sharp rise in bond returns that follows a sharp decline in equity returns is often contemporary, and hence is more significant when measured at the daily frequency. Our approach here is different because we are not trying to detect the occurrence of FTS events, but rather their magnitudes. In such a context, the use of a lower frequency (weekly or monthly) makes it possible to better measure the magnitude of FTS events, which is not only limited to capital flows occurring the day of the fall in the equity market, but also those caused by market participants the following days.[6]

To analyze the sensitivity of our results to the maturity of bonds, we consider three different maturities, i.e., long (10-year), medium (5-year) and short (2-year). Fig. B.1 in Appendix displays the dynamics of prices over the sample for the four assets. For the S&P 500 index, we observe the typical two bear markets (2000–2003 and 2007–2009) corresponding to the dot-com crash and the global financial crisis, respectively. In these market turmoils characterized by a large drop in the stocks index prices, the prices of bonds were rising, a symptom of a FTS event from stocks to bonds.

Table 1 gives some descriptive statistics for the corresponding weekly returns. The S&P 500 index has higher average mean than that of the bonds, indicating that overall investing in stocks is more profitable over the sample period. But this is at the cost of a higher risk as measured by the volatility or standard deviation. Indeed, on a annualized basis, the volatility of the stock market is equal to 16.29%, with the same statistics taking values 1.68%, 4.25%, and 7.16% for the 2-year, 5-year and 10-year U.S. government bond returns. The figure is the same when risk is measured as the probability of loss. Indeed, the kurtosis of the S&P 500 index is equal to 8.40 and higher than that of the three bonds, suggesting a significant tail-risk for the former asset. The minimum values of the weekly returns over the sample confirm this result.

Fig. 1 displays the U.S. stock–bond correlation estimated on rolling-window samples of size $n = 52$ (one year of weekly data). At the beginning of the sample, in the 1990s, the correlation fluctuated around a positive average level. Consistent with the literature mentioned above (Li, 2002), this positive level of correlation arises from increased uncertainty about expected inflation, following high and volatile inflation (shocks in oil prices) in the previous decades (1970s, 1980s). The correlation became negative since the 2000s, and fluctuated around the average value of $-30\%$. Uncertainties about growth and earnings can partly explain this dynamic, with bonds appearing to be good hedges against stocks. Note that the hedging property is related to the uncorrelatedness or the existence of negative correlation between stocks and bonds in all states of the world, and hence differs from FTS phenomenons which capture uncorrelatedness or negative correlation only in a market crash (Baur and Lucey, 2010). Indeed, as recently analyzed by Baele and Van Holle (2017), the negative and persistent level of correlation since the 2000s should not be attributed to an increase in the frequency of FTS events, but rather to the prolonged period of accommodating monetary policy. Precisely, they show that in times of low inflation, central bank policies that seek to stimulate economic growth by loosening money supply, lead to a negative correlation between stocks and bonds. Indeed, in low inflation environment, investors would be mainly concerned about deflationary risks and central banks are constrained by the zero lower bound. In such environment, a negative inflation shock leads to higher risk aversion and a fall of equity prices, while the accommodating monetary policy, by unconventional measures such as forward guidance and asset purchases, leads to a flattened yield curve and a rise in bond prices. Given these elements, asking whether the strength of FTS from stocks to bonds remains the same in the current context of low yields, is not irrelevant, even when the correlation between stocks and bonds is empirically negative.

Fig. 2 displays the incidences of FTS through our sample. Precisely, we compute our variable of interest $r_t^{(bs)} = r_t^{(b)} - r_t^{(s)}$, with $r_t^{(b)}$ the returns on the 10-year government bond and $r_t^{(s)}$ the returns on the S&P500 index. As already stressed the excess returns $r_t^{(bs)}$ take extreme values for FTS events, i.e, when realized bond (stock) returns are high (low). Hence, we use a threshold $\gamma$ we set to 3% and define an FTS indicator as follows[7]

$$\text{FTS-Indicator}_t = \begin{cases} r_t^{(bs)} & \text{if} \quad r_t^{(bs)} > \gamma \\ 0 & \text{else.} \end{cases}$$

We observe in this figure that FTS events occur mainly in crisis periods, with the FTS indicator taking large values. Indeed, the FTS indicator clearly identifies well known episodes of financial crisis including the 1997 Asian crisis, the Russian crisis and LTCM debacle in 1998, the 2001–2002 dot-com crash, the 2007–2008 global financial crisis and the 2011–2012 European sovereign debt crisis. Table 2 displays with respect to the threshold $\gamma$ some statistics for the FTS indicator variable, including the frequency of FTS, the average value and the standard deviation. The frequency of FTS occurrence is equal to 3.35% for the largest value of $\gamma$, and as expected the means and standard deviations have increasing values with respect to $\gamma$.

Although Fig. 2 and Table 2 are informative on the frequency and strength of FTS, they offer only an unconditional analysis that does not take into account the states of the world or the information available at each date. In the next sub-section, our objective is to provide such an analysis by asking the following question: conditional on the information available at any

[6] We choose weekly instead of monthly data as almost all our econometric models are about quantile regression that needs enough data to provide consistent estimates of parameters.

[7] We vary the threshold $\gamma$ and give some summary statistics for our FTS indicator in Table 2.

**Table 1**
Summary statistics for returns.

| | Avg Mean | Min | Max | Std. dev. | Skewness | Kurtosis |
|---|---|---|---|---|---|---|
| 2-year bond | 0.0810 | −1.1939 | 1.2693 | 0.2296 | 0.2528 | 6.1805 |
| 5-year bond | 0.1029 | −2.4731 | 2.1606 | 0.5784 | −0.2068 | 4.0178 |
| 10-year bond | 0.1159 | −4.2460 | 4.8254 | 0.9751 | −0.2821 | 3.9623 |
| S&P 500 | 0.2152 | −18.1405 | 12.0919 | 2.2176 | −0.5017 | 8.4075 |

Notes: The table displays some main statistics for the weekly returns on the assets. The data covers the period ranging from February 2, 1990 to November 23, 2018, with a total of $T = 1504$ observations. Values in the first four columns are in percentage. Min (Max) refers to the minimum (maximum) returns, and Std. dev. the standard deviation.

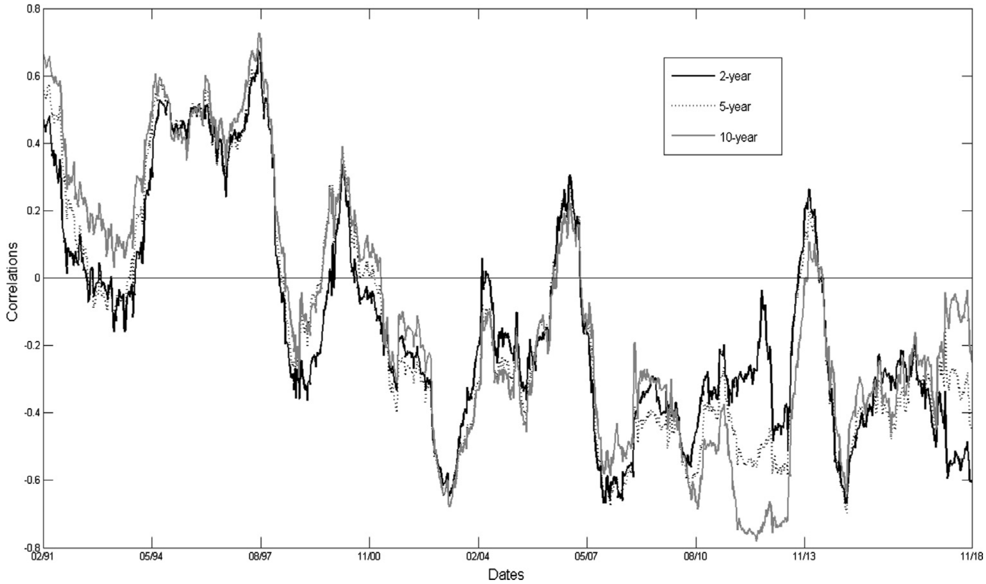


**Fig. 1.** Rolling-window estimates of U.S. stock–bond correlation.

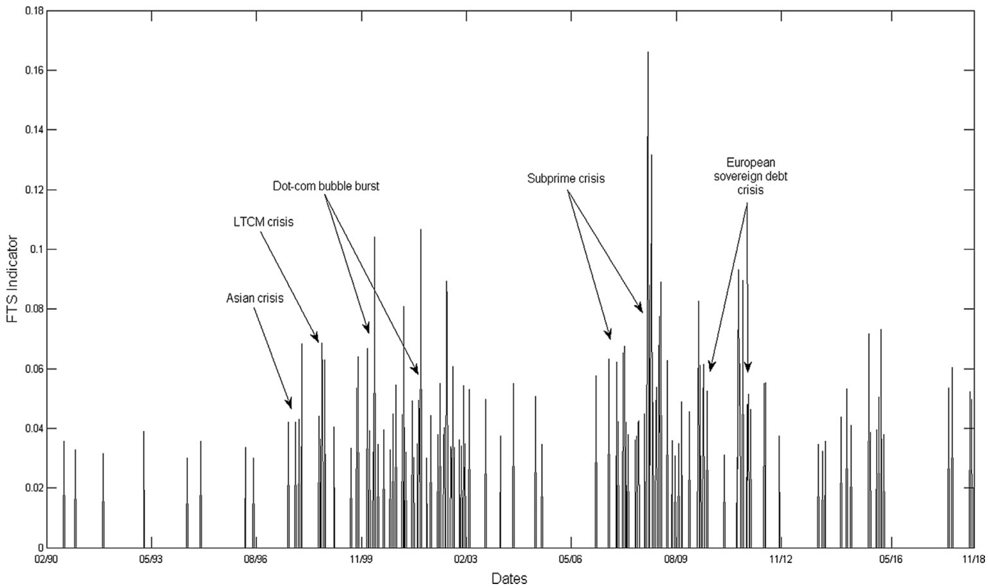


**Fig. 2.** Historical evidences of FTS.

**Table 2**
Summary statistics for FTS indicator.

| | $\gamma = 2\%$ | $\gamma = 3\%$ | $\gamma = 4\%$ | $\gamma = 5\%$ |
|---|---|---|---|---|
| Frequency of FTS (%) | 16.1390 | 8.4420 | 5.4004 | 3.3520 |
| Mean of FTS indicator | 0.0385 | 0.0512 | 0.0605 | 0.0702 |
| Std. dev. of FTS indicator | 0.0204 | 0.0212 | 0.0215 | 0.0222 |

Notes: The table displays some main statistics for the FTS indicator variable. The data covers the period ranging from February 2, 1990 to November 23, 2018, with a total of $T = 1504$ observations. Std. dev. refers to the standard deviation.

given date, is the strength of FTS dependent on the level of bond's yields? As stressed in Section 2.1, we provide answer to this question via the dynamic quantile regression as specified in (8).

### 2.3. Estimation results

Table 3 gives the estimation results of the extended CAViaR model in (8) with the quantile level set to 99%. Recall that this model relates the strength of FTS as measured by an extreme upper-quantile of $r_t^{(bs)}$ to the level of bond yields (low-yield environment).[8]

Results are displayed for the longest maturity (10-year government bond), with the parameter estimates followed in parentheses by their standard deviations. The threshold parameter $\bar{i}$ is set to 2%, meaning that the low-yield environment corresponds to the case where the 10-year U.S. government bond is lower than 2%. [9]

Model [1] is the benchmark regression, i.e., the usual CAViaR model, while model [2] corresponds to the same model extended by including as an explanatory variable, a dummy variable measuring low-yield environment ($i_t < \bar{i}$), with $i_t$ the yields on the 10-year U.S. Government bond and $\bar{i} = 2\%$. Models [3] to [5] are estimated for robustness checks controlling model [2] for the effects of traditional factors of FTS.

Let us stress that these factors are those identified in the literature to impact the comovements between stock and bond returns, and potentially the occurrence/strength of FTS from stocks to bonds. Indeed, in standard rational pricing models, the fundamental factors or determinants driving stock and bond returns either affect cash flows or discount rates. Hence, the literature has identified business cycle variables that can influence both fixed income and equity returns via cash-flow growth and/or discount rates such as inflation, output-gaps, short-term interest rates, the term premium, economic uncertainty and risk aversion. But as shown by Baele et al. (2010) these factors fail to explain the conditional correlation between stock and bond returns.

Other macro-financial variables are identified by Baele et al. (2010) as significant determinants of stock and bond returns, and hence appear as potential factors of the FTS phenomenon. First, they find that the VIX implied volatility measure as a proxy for stock market uncertainty is negatively related to stock and bond return comovements, hence confirming the results in Connolly et al. (2005). Second, consistent with Goyenko (2006), their empirical results highlight the role of stock market illiquidity in explaining the correlation between stock and bond returns. The mechanism behind this relation goes through the link between negative liquidity shocks in the stock market and expected returns. Indeed, if stock market liquidity is priced, a negative liquidity shock increases expected returns, with a decrease in stock prices and a flow of funds into treasuries (flight-to-liquidity) that decreases (increases) yields (returns). Note that the authors also consider as a potential determinant, the level of illiquidity in the bond market, which however does not appear significant in explaining the comovement between stock and bond returns.

Results in Baele et al. (2015) also provide some guidance about other potential determinants of FTS from stocks to bonds. Focusing directly in identifying FTS events, instead of measuring correlations between stock and bond returns, they find that FTS episodes coincide with increases in the VIX and the TED spreads.

Based on these stylized facts, our results for the core quantile regression in Table 3 are controlled for the effects of three different variables: the VIX (model [3]), the TED spreads (model [4]) and the level of illiquidity in the stock market (model [5]).[10] For the latter variable, we follow Amihud (2002) and approximate the level of illiquidity by the average value over the week of the ratio of daily absolute stock returns to its dollar volume. As argued by Amihud (2002), this measure can be interpreted as the price response associated with one dollar of trading volume, thus serving as a rough measure of price impact.

For each model in Table 3, the last panel provides statistics for specification tests, including the frequency of quantile-exceptions, the DQ test statistics for correct specification and the corresponding p-values.[11] For the computation of the DQ test statistics, we use as instruments $X\left(\widehat{\theta}\right)$ (see Eq. (9)) the 10 lagged values of the estimated process of quantile-exceptions.

[8] Fig. B.2 in Appendix displays the three time series of U.S. government bond yields over the sample. We observe that the low-yield environment is located at the end of the sample, as there is globally a downward trend in all series as the result of successive easing monetary policies linked to a continuous disinflation.

[9] We consider only this value for ease of presentation. Moreover, results available from the authors upon request show that the effect of yield regimes on the strength of FTS is weak for other values of $\bar{i}$, i.e., $\bar{i} = 3\%, 3.5\%, 4\%$.

[10] We consider the first differences of these variables rather than their levels, because differentiating helps reducing the level of persistence that characterizes these variables and which can jeopardize the inference.

[11] For a quantile risk level of $\alpha = 99\%$, the frequency of quantile-exceptions should be close to $1 - \alpha = 1\%$ for a correctly specified dynamic quantile model.

**Table 3**
Strength of FTS and low yields: S&P 500 & 10-year U.S. Government bond.

| | [1] | [2] | [3] | [4] | [5] |
|---|---|---|---|---|---|
| $\theta_0$ | 0.0092* (0.0056) | 0.0116*** (0.0033) | 0.0018 (0.0011) | 0.0048* (0.0026) | 0.0045*** (0.0017) |
| $\theta_1$ | 0.7184*** (0.0911) | 0.6934*** (0.0636) | 0.8445*** (0.0591) | 0.8644*** (0.0622) | 0.7108*** (0.0407) |
| $\theta_2$ | −0.1675 (0.1419) | −0.1107 (0.1210) | −0.3511*** (0.0847) | −0.0243 (0.1173) | −0.2727*** (0.0986) |
| $\theta_3$ | 0.8841*** (0.1437) | 0.8781*** (0.1204) | 0.1571* (0.0835) | 0.4408** (0.1859) | 0.8326*** (0.1180) |
| $\delta$ | | −0.0082*** (0.0018) | −0.0020*** (0.0008) | −0.0035** (0.0017) | −0.0046*** (0.0017) |
| ΔVIX | | | 0.0052*** (0.0005) | | |
| ΔTED Spreads | | | | 0.0419*** (0.0141) | |
| Δilliquidity | | | | | 0.0202** (0.0080) |
| Specification Test | | | | | |
| Hit-Frequency | 0.0093 | 0.0106 | 0.0100 | 0.0100 | 0.0100 |
| DQ-Stat | 1.1196 | 5.6116 | 1.4975 | 1.3695 | 11.0653 |
| DQ-Pvalue | 0.9997 | 0.8468 | 0.9989 | 0.9993 | 0.3525 |

Notes: This table displays the results (parameter estimates followed by standard errors in parentheses) of different CAViaR models (at the risk level $\alpha = 99\%$) with the dependent variable being the returns on 10-year U.S. Government bond in excess of the returns on S&P500. Model [1] refers to the usual CAViaR model, while model [2] corresponds to an extended CAViaR model that includes (as explanatory variable) a dummy variable measuring low-yield environment ($i_t < \bar{i}$), with $i_t$ the yields on the 10-year U.S. Government bond and $\bar{i} = 2\%$. Models [3] to [5] are similar to model [2] with an additional control variable. The last panel provides relevant statistics for the test of correct specification, including the frequencies of Hit, the dynamic quantile (DQ) test statistics and the associated p-values. All estimations are performed using weekly data ranging from February 2, 1990 to November 23, 2018, with a total of $T = 1504$ observations. Significances at 1%, 5% and 10% are emphasized by ***, ** and *, respectively.

Note that we do not consider a model that includes all control variables at the same time. The main reason is to avoid a model that is affected by over-parametrization.[12]

The first important result in Table 3 is that all models do a good job in measuring the strength of FTS as given by the upper-quantile of the excess returns $r_t^{(bs)}$. Indeed, the frequencies of quantile exceptions (or Hit frequencies) are close to $1 - \alpha = 1\%$. Moreover the p-values of the DQ test are higher than 5% suggesting a correct conditional calibration of the dynamic quantile models. The second result to underline is that the autoregressive coefficient $\theta_1$ is always highly significant, meaning that there exists clustering in the tails, even at the weekly frequency. We also observe that while the coefficient $\theta_3$ is always significant, the coefficient $\theta_2$ is insignificant, except in two cases. Hence, positive returns seem to drive the dynamics of the upper-quantile of the excess returns $r_t^{(bs)}$, while negative returns do not play any role in much cases.

Focusing on our parameter of interest $\delta$, results show that this parameter is negative and significant in all models. We deduce from this result that the strength of FTS from stocks to bonds decreases at very low levels of yields. So, our conjecture that when yields are low, the traditional motives of FTS (wealth protection, liquidity) could not be sufficient, inducing weaker FTS events, seems to hold at least on the U.S. market and for the longest bond maturity considered (10-year).

Fig. 3 displays for model [2] the yields impact curve computed in the same spirit as the news impact curve of Engle and Manganelli (2004). For different values of the yield, the curve displays the strength of FTS from stocks to bonds as measured by the dynamic quantiles estimated in (8), keeping each of the first three explanatory variables, $Q_{t-1}^{(bs)}(\alpha), r_{t-1}^{(bs)}\mathbb{I}\left(r_{t-1}^{(bs)} < 0\right)$, and $r_{t-1}^{(bs)}\mathbb{I}\left(r_{t-1}^{(bs)} \geqslant 0\right)$, at its average value over the sample. We observe the asymmetry of the curve with jumps in the value of the strength at the threshold value $\bar{i} = 2\%$, which is the result of the retained specification in (8). To give more insights about the magnitude of the jump, we display in Fig. 3 the quantiles of order 49% and 65% of the strength of FTS. The former (latter) quantile is the lower (upper) bound of the yields impact curve. The difference between the orders is equal to 16%, meaning that the strength of FTS decreases by more than one decile when moving from high-yield environment to low-yield environment.

It is worth noting that all control variables are positive and statistically significant. For the VIX and the TED spreads, these results are in line with those obtained by Baele et al. (2015). Indeed, they report that a rise in the implicit volatility and the TED spread, seem to be concomitant to FTS episodes. Our results confirm that the variations of these variables also impact positively the strength or intensity of FTS. Regarding the illiquidity variable, this result shows that stock liquidity shortages do not only explain negative correlations (Baele et al., 2010) between the returns on stock and bond, but also extreme negative correlations corresponding to FTS events. Let us stress that our parameter of interest $\delta$ that measures the impact of low yield environment on the strength of FTS has estimated values that decrease when controlling for the macro-financial variables. However, it remains statistically significant in all configurations.

Tables B.1 and B.2 in Appendix display the results for the 5-year and the 2-year U.S. government bonds, respectively. The presentation is similar to that of Table 3. As in Table 3, we cannot reject the null hypothesis of a correctly specified dynamic quantile regression model for the models considered, except model [5] for the 2-year government bond. Moreover, the

[12] Empirical results show indeed that this model fails the correct specification test of the dynamic quantile model.

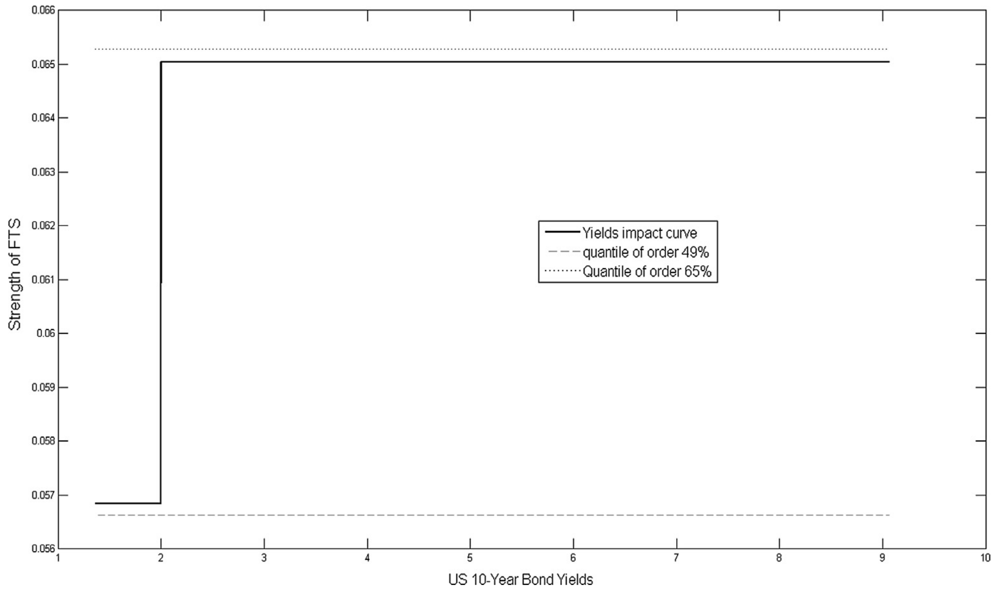


**Fig. 3.** Dynamics of the yields impact curve.

autoregressive parameter $\theta_1$ appears always significant suggesting temporal dependence in quantile dynamics. Regarding the parameter of interest $\delta$, the results are qualitatively similar to those in Table 3, but the magnitude of the estimates are lower than the ones obtained in Table 3, mainly for the 2-year government bond. As a consequence, the result that the strength of FTS from stocks to bonds decreases at very low levels of yields, seems to operate at all maturities, but to a greater extent at the highest maturities (10-year and 5-year government bonds). Indeed, FTS episodes are much more pronounced on the 10-year (5-year) maturity due to its relative liquidity. As a result, the decrease of the FTS strength is more likely to operate at the highest maturities.

## 3. Bond alternatives and flight-to-safety transfers

This section tackles the issue of FTS transfers across markets. Formally, we built a bivariate dynamic quantile model that measures to what extent the strength of FTS from stocks to bonds is related to the strength of FTS from stocks to another safe haven, such as gold or currencies. By doing so, our objective is to check whether the observed decreases in the strength of FTS from stocks to bonds when yields are low, can be explained by some transfers to other more profitable safe havens. We describe the econometric model in the first part of the section, and the last part presents and analyzes the empirical results.

### *3.1. The econometric model*

Since our goal is to measure to what extent low-yield environment impacts the dependence between the strength of FTS from stocks to bonds and the same phenomenon from stocks to gold (or currencies), a simple way to proceed would be to estimate in a first step both levels of strength using the dynamic quantile model as specified in (2), then to estimate in a second step a linear model that relates both time series. To be more precise, let $\widehat{Q}_t^{(bs)}(\alpha)$ be the fitted value of the quantile from (2) which measures the strength of FTS from stocks to bonds at time $t$. Similarly, we denote $\widehat{Q}_t^{(as)}(\alpha)$ the estimated quantile of $r_t^{(as)} = r_t^{(a)} - r_t^{(s)}$ at time $t$, where $r_t^{(a)}$ is the return on an alternative (to bonds) safe haven asset like gold or currencies. The following linear model which can be estimated by the ordinary least squares (OLS) method can be used to provide an answer to our second research question, i.e.,

$$\widehat{Q}_t^{(as)}(\alpha) = \beta_0 + \beta_1 \widehat{Q}_{t-1}^{(bs)}(\alpha) + \beta_2 \widehat{Q}_{t-1}^{(bs)}(\alpha)\mathbb{I}\left(i_{t-1} < \bar{i}\right). \tag{10}$$

Indeed, if the parameter $\beta_2$ is statistically significant and negative, this means that the observed decrease in the strength of FTS from stocks to bonds in low-yield environment as evidenced in Section 2, leads to an increase in the strength of FTS from stocks to the considered alternative safe haven asset (gold or currencies).

Nevertheless, two main reasons prevent the use of such a two-step estimation procedure. Firstly, to proceed in this way assumes the independence between the two models of quantile regression from which the two time series measuring the strength of FTS are extracted. This is a quite strong assumption, as the strength of FTS, which is linked to wealth re-balancing is likely to have dynamics that is correlated across markets. Secondly, the second-step OLS regression as specified in (10) would be affected by the estimation errors in the two quantile regressions, rendering obsolete the usual tool of OLS inference.

To avoid these two shortcomings, we build on the VAR (vector autoregressive model) for VaR (value at risk) of White et al. (2015), and consider modeling in a one step the joint dynamics of both upper-extreme quantiles. The model writes

$$\begin{cases} Q_t^{(as)}(\alpha) = c_1 + a_{11}\left|r_{t-1}^{(as)}\right| + a_{12}\left|r_{t-1}^{(bs)}\right| + b_{11}Q_{t-1}^{(as)}(\alpha) + b_{12}Q_{t-1}^{(bs)}(\alpha) + \rho Q_{t-1}^{(bs)}(\alpha)\mathbb{I}\left(i_{t-1} \leqslant \bar{i}\right) \\ Q_t^{(bs)}(\alpha) = c_2 + a_{21}\left|r_{t-1}^{(as)}\right| + a_{22}\left|r_{t-1}^{(bs)}\right| + b_{21}Q_{t-1}^{(as)}(\alpha) + b_{22}Q_{t-1}^{(bs)}(\alpha), \end{cases} \tag{11}$$

where again $Q_t^{(bs)}(\alpha)$ is the upper-quantile of $r_t^{(bs)}$ at the risk level $\alpha$, and $Q_t^{(as)}(\alpha)$ the upper-quantile of $r_t^{(as)}$ at the same risk level. Recall that both $Q_t^{(bs)}(\alpha)$ and $Q_t^{(as)}(\alpha)$ measure the strength of FTS, the first from stocks to bonds, and the second from stocks to an alternative safe haven. The bivariate specification thus captures the link between these two forms of FTS. In a matrix notation, the model is equal to

$$Q_t(\alpha) = c + A|r_{t-1}| + BQ_{t-1}(\alpha) + D\widetilde{Q}_{t-1}(\alpha), \tag{12}$$

with $c = (c_1, c_2)'$, $|r_t| = \left(\left|r_t^{(as)}\right|, \left|r_t^{(bs)}\right|\right)'$, and

$$Q_t(\alpha) = \left(Q_t^{(as)}(\alpha), Q_t^{(bs)}(\alpha)\right)', \tag{13}$$

$$\widetilde{Q}_t(\alpha) = \left(Q_t^{(as)}(\alpha), Q_t^{(bs)}(\alpha)\mathbb{I}\left(i_t < \bar{i}\right)\right)', \tag{14}$$

where the matrices $A, B$, and $D$ are given by

$$A = \begin{pmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{pmatrix}, B = \begin{pmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{pmatrix}, D = \begin{pmatrix} 0 & \rho \\ 0 & 0 \end{pmatrix}. \tag{15}$$

Apart from the last term in the first equation of (11) or equivalently the last term in (12), this specification corresponds to the VAR for VaR model of White et al. (2015) which has many potential applications in co-tail risk analysis. This last term is crucial in our context, as it allows us to provide an answer to our second research question. Indeed, if the parameter $\rho$ is negative and statistically significant, this means that when yields are low ($i_{t-1} \leqslant \bar{i}$) a decrease in the strength of FTS from stocks to bonds leads to an increase in the FTS from stocks to the alternative (to bond) safe haven asset, and this increase is higher than what prevails (statistically significant or not) in high-yield environment. This result would be the evidence of a FTS transfer across markets in low-yield environment.

Note that independence between the dynamics of both quantiles can be easily tested by checking for the joint nullity of off-diagonal elements in the matrices $A, B$ and $D$. The corresponding null hypothesis is defined as

$$\mathbb{H}_0 : a_{12} = 0, b_{12} = 0, \rho = 0, a_{21} = 0, b_{21} = 0. \tag{16}$$

With an appropriately chosen matrix $R$ of dimension $(5, p)$, the Wald test statistics is equal to

$$W = \left(R\widehat{\psi}\right)'\left[R\widehat{\Omega}R'\right]^{-1}\left(R\widehat{\psi}\right), \tag{17}$$

with $\widehat{\Omega}$ the estimated covariance matrix of $\widehat{\psi}$, where $\psi$ is the vector of parameters of length $p = 11$, i.e., $\psi = (c_1, a_{11}, a_{12}, b_{11}, b_{12}, \rho, c_2, a_{21}, a_{22}, b_{22}, b_{21})'$. Remark that when the null hypothesis is not rejected at the usual nominal risk levels, this means that the dynamics of both quantiles are not related, and the two equations can be estimated separately using the univariate CAViaR specification. In our framework, this case corresponds to the absence of dependence between both FTS phenomenons. Say differently, when the null hypothesis holds, the FTS from stocks to bonds is not related to the FTS from stocks to the alternative safe haven asset.

### 3.2. Estimation results

We provide estimates of the parameters $\psi$ in the bivariate dynamic quantile model using gold and two currencies, that is, the Japanese Yen (JPY) and the Switzerland Franc (CHF), as alternative (to bonds) safe haven assets.

The safe haven nature of gold has been deeply analyzed in the academic literature. Early contributions are Baur and Lucey (2010) and Baur and McDermott (2010). Baur and Lucey (2010) scrutinize both constant and time-varying dependencies between the returns on gold and the returns on international stock indexes (U.S., U.K. and German). Their empirical analyzes show evidence that gold is a safe haven asset in times of market turmoil. The same conclusion is obtained by Baur and McDermott (2010) who stress that gold reduces the effect of highly adverse stock market movements in most developed countries worldwide, and can be viewed as an asset that helps stabilizing the financial system. This figure is nuanced by Hood and Malik (2013) who show that gold serves the function of safe haven, which seems to disappear in periods of extreme high volatility. Nevertheless, two more recent papers confirm the role of gold as safe haven. For instance, using the more sophisticated smooth transition regression tool, Beckmann et al. (2015) confirm the figure which appears to be market-specific. Moreover, Baur and McDermott (2016) confirm the safe haven nature by linking the decision to buy gold to behavioral biases associated with gold's history as a currency. Their empirical analysis shows that gold was a strong safe haven in the aftermath of September 11, 2001 and the Lehman bankruptcy in September 2008.

The safe haven property of JPY and CHF currencies has also been covered by the financial literature. For instance, Ranaldo and Söderlind (2010) using a factor specification to model linear and non-linear linkages between currencies and stocks markets, show that the Swiss franc and Japanese Yen appreciate against the U.S. dollar when U.S. stock prices decrease. They report that these effects last from a few hours to several days, and are more pronounced for the Yen during the great financial crisis. Theoretically, there is no clear consensus on the determinants of this phenomenon, except for a positive net foreign asset position (Habib and Stracca, 2012). As argued by Habib and Stracca (2014), this difficulty arises from the changing motives and investor's categories that drive currencies FTS, and the mixed results obtained in the empirical applications can be viewed as a proof of their assertion. For instance, de Carvalho Filho (2015) finds that CHF appreciations during market turmoil are associated to significant capital inflows, while the results in Yesin (2016) suggest an insignificant relation between appreciations and capital inflows. These latter results seem to hold for the JPY currency, with exchange rate movements arising mainly from derivative trading, without capital inflows (Botman et al., 2013). Beyond this debate, there is nevertheless a consensus in the literature that recognizes the property of safe haven asset to these two currencies.

Table 4 displays the results of the bivariate CAViaR models for the 10-year U.S. government bond, while Tables B.3 and B.4 in Appendix display the same results for the 5-year and 2-year government bonds, respectively. We use weekly data over the same time period as in Section 2, i.e., from February 2, 1990 to November 23, 2018, with a total of $T = 1504$ observations. We set the quantile risk level at $\alpha = 99\%$, and the yield threshold $\bar{i}$ to $2\%, 1\%$ and $0.5\%$ for the 10-year, 5-year and 2-year, respectively. The three tables present the results only for the first equation including our parameter of interest $\rho$ (see Eq. (11)). For each parameter, we report the estimates followed in parentheses by the standard deviations. The last column gives the Wald test statistics of the joint nullity of off-diagonal elements in the system followed in brackets by the corresponding p-values.

First, with results in Table 4, it appears that in all configurations, the Wald test rejects the null hypothesis of the nullity of off-diagonal elements in the bivariate dynamic quantile model at the nominal significance level of 5%. We deduce that the dynamics of both quantiles are linked. Economically, this means that the strength of FTS from stocks to bonds is related to the strength of FTS from stocks to the three alternative safe haven assets, regardless of the direction of causality. This result confirms the relevance of using a one-step approach that assumes the dependence between the dynamics of the two quantiles.

Second, the parameter $b_{12}$ is, in all cases, insignificant. Recall that this parameter measures to what extent the strength of FTS from stocks to bonds impacts the strength of FTS from stocks to the alternative asset, in only high-yield environment. This result suggests that when yields are high, a decrease (or an increase) in the strength of FTS from stocks to bonds does not have any predictive content for the strength of FTS from stocks to each of the alternative asset.

Lastly, focusing on our parameter of interest $\rho$, it appears overall negative and significant at the $1\%$ (resp. $10\%$) significance level, when one considers CHF (resp. gold) as the alternative safe haven asset. For instance, with CHF, the estimate of $\rho$ is equal to $\widehat{\rho} = -0.1581$. As a consequence, the negative relation between the strength of FTS from stocks to bonds and the strength of FTS from stocks to CHF is reinforced, when the 10-year government bond yield is lower than $\bar{i} = 2\%$. This is a clear-cut evidence of FTS transfer in a low-yield environment. To give insights about the magnitude of this relation, Table 5 displays with respect to the 10-year U.S. government bond yield environment (high versus low) the elasticity (in %) of the strength of FTS from stocks to CHF ($Q_t^{(as)}(\alpha)$), as a function of the strength of FTS from stocks to bonds ($Q_t^{(bs)}(\alpha)$). The elasticities are computed using the output from the estimation of the first equation in (11), taking $Q_t^{(as)}$ as a function of $Q_t^{(bs)}$, yielding

$$\mathcal{E}_{\widehat{Q}^{(as)}}\left(\widehat{Q}^{(bs)}\right) = \frac{\widehat{Q}^{(bs)}}{\widehat{Q}^{(as)}} \frac{\partial \widehat{Q}^{(as)}}{\partial \widehat{Q}^{(bs)}} = \begin{cases} \frac{\widehat{Q}^{(bs)}}{\widehat{Q}^{(as)}} \widehat{b}_{12} & \text{if} \quad \text{High-yield environment} \\ \frac{\widehat{Q}^{(bs)}}{\widehat{Q}^{(as)}} \left(\widehat{b}_{12} + \widehat{\rho}\right) & \text{if} \quad \text{Low-yield environment} \end{cases} \tag{18}$$

The elasticities in Table 5 are displayed for some selected values of $\widehat{Q}^{(bs)}$ corresponding to its deciles. We observe that the reported values in low-yield environment are much higher (in absolute value) than their counterparts in high-yield environment. For instance, the average value of these elasticities are equal to $-8.33\%$ (resp. $-25.91\%$) in high (resp. low)-yield environment, suggesting that a $1\%$ decrease in the strength of FTS from stocks to bonds leads on average to an increase of $8.33\%$ (resp. $25.91\%$) in the strength of FTS from stocks to CHF. This difference is noticeable and validates the hypothesis of FTS transfer across markets in low-yield environment.

This result of FTS transfers or substitutions across markets in low-yield environment is reminiscent of the reaching for yield behavior documented in the literature. This behavior which does not depend on the level of stress in the stock market is materialized by investors chasing yield by overinvesting (underinvesting) in riskier (safer) bond instruments in low-yield environment (Acharya and Naqvi, 2015; Choi and Kronlund, 2018; Di Maggio and Kacperczyk, 2017; Hanson and Stein, 2015). For instance, Acharya and Naqvi (2015) build a theoretical model in which, in the absence of any agency problems, managers reduce their holdings of liquid assets (money market instruments) when yields are low and subsequently increase

**Table 4**
FTS transfers and low yields: 10-year U.S. government bond with $\alpha = 99\%$.

| $c_1$ | $a_{11}$ | $a_{12}$ | $b_{11}$ | $b_{12}$ | $\rho$ | Wald |
|---|---|---|---|---|---|---|
| | | | Gold | | | |
| 0.0070 (0.0064) | 0.6328*** (0.1922) | 0.3210** (0.1486) | 0.6756*** (0.2235) | −0.0000 (0.2067) | −0.1045* (0.0583) | 12.4164 [0.0295] |
| | | | JPY | | | |
| 0.0244 (0.0157) | 0.5308 (0.3738) | 0.4734 (0.6244) | 0.1185 (0.2279) | 0.3492 (0.4269) | −0.2641 (0.2124) | 20.2571 [0.0011] |
| | | | CHF | | | |
| 0.0144** (0.0073) | −0.1281 (0.1598) | 0.7502** (0.3287) | 0.7246*** (0.1406) | −0.0749 (0.0649) | −0.1581*** (0.0491) | 45.0007 [0.0000] |

Notes: This table displays the results (parameter estimates followed by standard errors in parentheses) of the first equation of the bivariate dynamic quantile model in (11) assuming three different alternative (to bonds) safe haven assets. The last column gives the Wald test statistics of the joint nullity of off diagonal elements in the system followed in brackets by the corresponding p-values. Results are presented for the quantile level $\alpha = 99\%$. The threshold $\bar{i}$ is set to 2%. All estimations are performed using weekly data ranging from February 2, 1990 to November 23, 2018, with a total of $T = 1504$ observations. Significances at 1%, 5% and 10% are emphasized by ***, ** and *, respectively.

**Table 5**
Elasticity of the strength of FTS from stocks to CHF as a function of the strength of FTS from stocks to bonds.

| Deciles of $Q_t^{(bs)}(\alpha)$ | Elasticity (in %) of $Q_t^{(as)}(\alpha)$ | |
|---|---|---|
| | High-yield environment | Low-yield environment |
| 0.0402 | −3.8730 | −12.0504 |
| 0.0470 | −5.0909 | −15.8396 |
| 0.0514 | −6.5815 | −20.4775 |
| 0.0561 | −6.0503 | −18.8249 |
| 0.0608 | −18.3706 | −57.1578 |
| 0.0683 | −6.9960 | −21.7673 |
| 0.0774 | −12.8503 | −39.9820 |
| 0.0888 | −6.2996 | −19.6003 |
| 0.1038 | −8.8580 | −27.5608 |
| Average value | −8.3300 | −25.9179 |

Notes: This table displays with respect to the 10-year U.S. government bond yield environment (high versus low) the elasticity (in %) of the strength of FTS from stocks to CHF ($Q_t^{(as)}(\alpha)$), as a function of the strength of FTS from stocks to bonds ($Q_t^{(bs)}(\alpha)$). Results are obtained using Eq. (18) along with the output of the estimated bi-variate dynamic quantile model as displayed in the last panel of Table 4. The elasticities are presented for some selected values (deciles) of the strength of FTS from stocks to bonds.

their investments made in risky and safer assets. They interpret this result as a substitution effect whereby managers who are maximizing the expected profit of intermediaries hold liquid assets up to the point where the marginal benefit of holding an additional unit of a safe asset just equals the corresponding marginal cost. In the same vain, Di Maggio and Kacperczyk (2017) focusing on the U.S. money fund industry, empirically find that in response to policies that maintain zero interest rates, money funds invest in riskier asset classes. Moreover, Hanson and Stein (2015) show that in low-yield environment, investors rebalance their portfolios toward longer-term bonds in an effort to keep their overall portfolio yield from declining too much. This mechanism raises the prices of long-term bonds and lowers long-term real yields and forward rates. Choi and Kronlund (2018) highlight the same phenomenon in the corporate bond universe. They show that in low-yield environment, U.S. corporate bond mutual funds reach for yield tilting portfolios toward bonds with yields higher than the benchmarks.

Our results of FTS transfers can thus be viewed as a kind of substitution effect of safe haven assets in stress episodes, similar to the reaching for yield behavior, with investors arbitraging between the safer government bond instruments and other safe haven assets like currencies and gold.

Tables B.3 and B.4 display the estimation results of the first equation of the bi-variate dynamic quantile model in (11) for the other two bond maturities, i.e., 5-year and 2-year respectively. The presentation is similar to that of Table 4. For the 5-year (resp. 2-year) maturity the low-yield environment corresponds to yields lower than $\bar{i} = 1\%$ (resp. $\bar{i} = 0.5\%$). Results in Table B.3 are slightly different when compared to those reported in Table 4. For our parameter of interest $\rho$, CHF appears one again as the candidate safe haven asset, but results do not longer support FTS transfers when considering gold as safe haven asset. Lastly, for the 2-year government bond, only JPY appears as an alternative (to bonds) safe haven asset in low-yield environment. Thus, from the viewpoint of robustness across maturities, CHF appears as the safe haven asset that most benefits from the reaching for yield behavior as described above. This safe haven transfer on the CHF is far from neutral, since it participated to the Swiss Franc appreciation that the Swiss National Bank has tried to limit through exchange rate interventions and increasing foreign reserves.

## 4. Conclusion

This explores the phenomenon of flight-to-safety from stocks to bonds in the U.S. markets. The main objective is to assess the strength of this stylized fact in line of the current environment of low yields. Indeed, non conventional monetary policies over the last decade have pushed U.S. government bond yields to historically low levels, and rationalizes the question of whether the traditional motives of flight-to-safety, i.e., wealth protection and liquidity, are still sufficient for investors to rebalance their equity portfolios in favor of bonds in market turmoils. To explore this issue, we develop a dynamic quantile model that models the strength of flight-to-safety from stocks to bonds. An augmented version of this regression, with low-yield regime as additional predictor, helps to evaluate the impact of the latter. Empirical applications using weekly data for the S&P 500 index and three U.S. government bonds, show that when yields are low, the strength of flight-to-safety from stocks to bonds decreases. This result holds, even when controlling for the effects of traditional flight-to-safety factors including the VIX, the TED spreads and the overall level of illiquidity in the stock market.

As an extension of these results, we check via a bivariate dynamic quantile model, whether the observed decreases of the strength of flight-to-safety from stocks to bonds, are related to some transfers to other more profitable safe haven assets. Using gold and two safe haven currencies (Swiss Franc and Japanese Yen) as alternative assets, results show that when U.S. government bond yields are low, a decrease in the strength of flight-to-safety from stocks to bonds leads to an increase in the flight-to-safety from stocks to these safe haven assets. This result suggests a kind of substitution effect of safe haven assets in low-yield environment, similar to the reaching for yield behavior, with investors arbitrating between the safer government bond instruments and other safe haven assets like currencies and gold.

The question of whether a low yield environment modifies FTS strength is crucial for academics, policy makers and practitioners. For academics and policy makers that have to consider all the implications of the shortage of safe assets as well as the externalities of unconventional monetary policies on financial stability. For practitioners, especially asset managers in portfolio construction and risk managers in extreme risk follow-up, as FTS strength reduction can have important consequences in asset allocation and risk management. Lastly, these results are also important for central bankers as the transfers imply currencies appreciation and the related negative externalities.

## Appendix A. Estimation and inference of the bivariate dynamic quantile model

Estimation of the system of equations in (11) can be achieved minimizing the sum of the quantile loss functions related to the two equations, yielding

$$\widehat{\psi} = \arg\min_{\psi} T^{-1}\sum_{t=2}^{T}\left\{\left(\alpha - \mathbb{I}\left(u_t^{(bs)} < 0\right)\right)u_t^{(bs)} + \left(\alpha - \mathbb{I}\left(u_t^{(as)} < 0\right)\right)u_t^{(as)}\right\} \tag{19}$$

where $\psi = (c_1, a_{11}, a_{12}, b_{11}, b_{12}, \rho, c_2, a_{21}, a_{22}, b_{22}, b_{21})'$ is the vector of length $p = 11$ with elements the unknown parameters, $u_t^{(bs)} = r_t^{(bs)} - Q_t^{(bs)}(\alpha)$ and $u_t^{(as)} = r_t^{(as)} - Q_t^{(as)}(\alpha)$ the quantile residuals. This likelihood-based objective function assumes that the vector of quantile residuals $\left(u_t^{(bs)}, u_t^{(as)}\right)'$ has independent components each following an asymmetric double exponential random variable (Komunjer, 2005), and the estimation method can be viewed as a quasi maximum likelihood, when this assumption does not hold.

Inference about the parameters is conducted using the asymptotic distribution of $\widehat{\psi}$ as provided by White et al. (2015). By making explicit the dependence of the quantiles to the vector of parameters, i.e., $Q_t^{(bs)}(\alpha) = Q_t^{(bs)}(\alpha;\psi)$, and $Q_t^{(as)}(\alpha) = Q_t^{(as)}(\alpha;\psi)$, we have

$$T^{1/2}\left(\widehat{\psi} - \psi^*\right) \longrightarrow N\left(0, M^{*-1}V^*M^{*-1}\right), \tag{20}$$

with

$$M^* = \mathbb{E}\left[f_t^{(bs)}(0)\nabla Q_t^{(bs)}(\alpha;\psi^*)\nabla' Q_t^{(bs)}(\alpha;\psi^*)\right] + \mathbb{E}\left[f_t^{(as)}(0)\nabla Q_t^{(as)}(\alpha;\psi^*)\nabla' Q_t^{(as)}(\alpha;\psi^*)\right], \tag{21}$$

$$V^* = \mathbb{E}(\eta_t^*\eta_t^{*\prime}), \tag{22}$$

$$\eta_t^* = \nabla Q_t^{(bs)}(\alpha;\psi^*)\left[\alpha - \mathbb{I}\left(r_t^{(bs)} < Q_t^{(bs)}(\alpha;\psi^*)\right)\right] + \nabla Q_t^{(as)}(\alpha;\psi^*)\left[\alpha - \mathbb{I}\left(r_t^{(as)} < Q_t^{(as)}(\alpha;\psi^*)\right)\right] \tag{23}$$

where $\nabla Q_t^{(j)}(\alpha;\psi^*), j \in \{(bs),(as)\}$, are the $p \times 1$ gradient vector of $Q_t^{(j)}(\alpha;\psi^*)$ with respect to $\psi^*$, and $f_t^{(j)}(0)$ the conditional density of the residuals $u_t^{(j)}$.

A consistent estimator of the asymptotic covariance matrix $M^{*-1}V^*M^{*-1}$ is obtained using consistent estimators of $M^*$ and $V^*$, with

$$\widehat{V}_T = T^{-1}\sum_{t=1}^{T}\widehat{\eta}_t\widehat{\eta}_t' \tag{24}$$

$$\widehat{\eta}_t = \nabla Q_t^{(bs)}\left(\alpha;\widehat{\psi}\right)\left[\alpha - \mathbb{I}\left(r_t^{(bs)} < Q_t^{(bs)}\left(\alpha;\widehat{\psi}\right)\right)\right] + \nabla Q_t^{(as)}\left(\alpha;\widehat{\psi}\right)\left[\alpha - \mathbb{I}\left(r_t^{(as)} < Q_t^{(as)}\left(\alpha;\widehat{\psi}\right)\right)\right] \tag{25}$$

$$\widehat{M}_T = T^{-1}\sum_{t=1}^{T}\left\{\left(2\widehat{c}_T^{(bs)}\right)^{-1}\mathbb{I}\left(-\widehat{c}_T^{(bs)} \leqslant u_t^{(bs)} \leqslant \widehat{c}_T^{(bs)}\right)\nabla Q_t^{(bs)}\left(\alpha;\widehat{\psi}\right)\nabla' Q_t^{(bs)}\left(\alpha;\widehat{\psi}\right) + \left(2\widehat{c}_T^{(as)}\right)^{-1}\mathbb{I}\left(-\widehat{c}_T^{(as)} \leqslant u_t^{(as)} \leqslant \widehat{c}_T^{(as)}\right)\nabla Q_t^{(as)}\left(\alpha;\widehat{\psi}\right)\nabla' Q_t^{(as)}\left(\alpha;\widehat{\psi}\right)\right\}, \tag{26}$$

where the terms $\left(2\widehat{c}_T^{(bs)}\right)^{-1}\mathbb{I}\left(-\widehat{c}_T^{(bs)} \leqslant u_t^{(bs)} \leqslant \widehat{c}_T^{(bs)}\right)$ and $\left(2\widehat{c}_T^{(as)}\right)^{-1}\mathbb{I}\left(-\widehat{c}_T^{(as)} \leqslant u_t^{(as)} \leqslant \widehat{c}_T^{(as)}\right)$ are taken as the estimators of $f_t^{(bs)}(0)$ and $f_t^{(as)}(0)$, respectively, with $\widehat{c}_T^{(bs)}$ and $\widehat{c}_T^{(as)}$ two bandwidth parameters. We follow White et al. (2015) setting values to these two parameters as

$$\widehat{c}_T^{(j)} = \kappa^{(j)}\left[\Phi^{-1}(\alpha + h_T) - \Phi^{-1}(\alpha - h_T)\right], \tag{27}$$

with

$$h_T = T^{-1/3}\left(\Phi^{-1}(1-0.05/2)\right)^{2/3}\left(\frac{1.5\left(\phi\left(\Phi^{-1}(\alpha)\right)\right)^2}{2\left(\Phi^{-1}(\alpha)\right)^2+1}\right)^{1/3}, \tag{28}$$

where $\phi(.)$ and $\Phi(.)$ are the p.d.f. and the c.d.f. of the standard normal distribution, and $\kappa^{(j)}$ the median absolute deviation of the quantile residual series $u_t^{(j)}, j \in \{(bs),(as)\}$.

## Appendix B. Additional tables and figures

See Figs. B.1 and B.2 and Tables B.1–B.4.

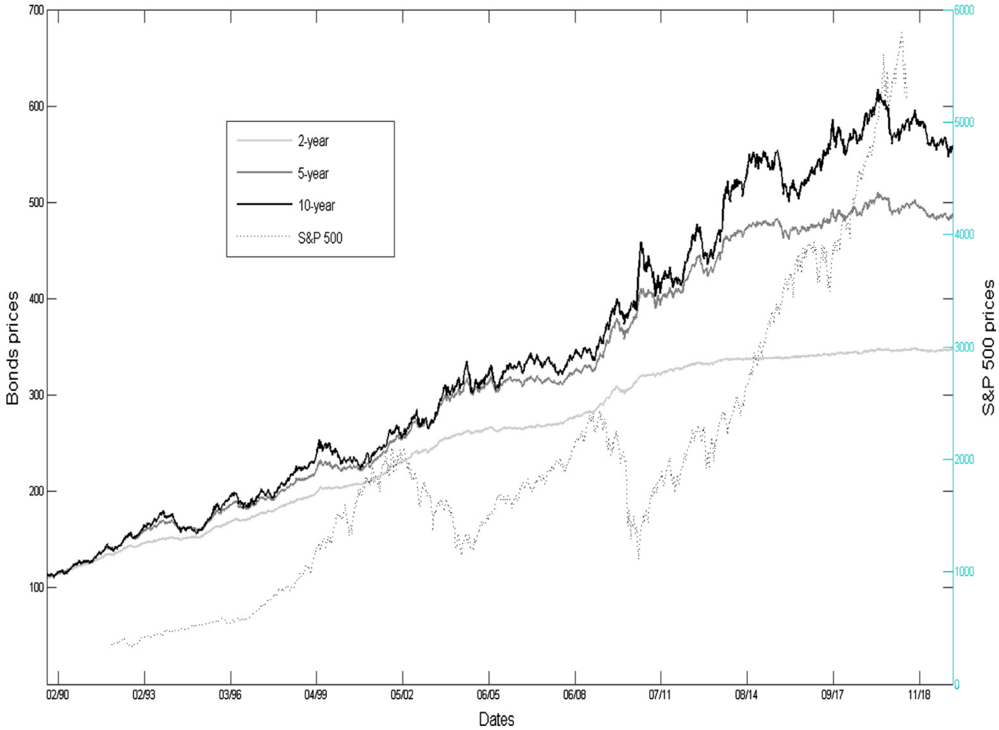


**Fig. B.1.** Dynamics of asset prices.

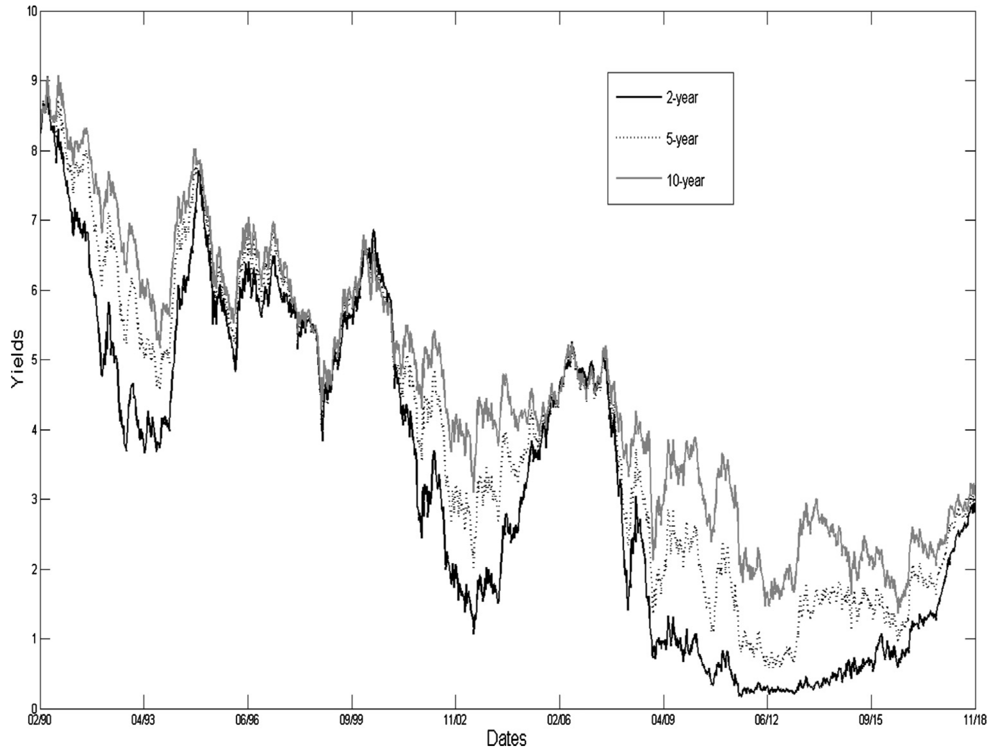


**Fig. B.2.** Dynamics of U.S. government bond yields.

**Table B.1**
Strength of FTS and low yields: S&P 500 & 5-year U.S. Government bond.

| | [1] | [2] | [3] | [4] | [5] |
|---|---|---|---|---|---|
| $\theta_0$ | $0.0077^{**}$ (0.0038) | $0.0085^{***}$ (0.0027) | 0.0012 (0.0008) | $0.0052^{**}$ (0.0021) | $0.0032^{**}$ (0.0013) |
| $\theta_1$ | $0.7091^{***}$ (0.0676) | $0.7034^{***}$ (0.0529) | $0.8593^{***}$ (0.0628) | $0.8140^{***}$ (0.0394) | $0.6974^{***}$ (0.0372) |
| $\theta_2$ | $-0.2023^{*}$ (0.1160) | −0.1572 (0.1055) | $-0.3146^{***}$ (0.0964) | −0.0732 (0.1073) | $-0.3190^{***}$ (0.1018) |
| $\theta_3$ | $1.0159^{***}$ (0.1057) | $1.0095^{***}$ (0.0929) | 0.1623 (0.1296) | $0.6982^{***}$ (0.1586) | $1.0333^{***}$ (0.0706) |
| $\delta$ | | $-0.0059^{***}$ (0.0013) | $-0.0017^{*}$ (0.0009) | $-0.0043^{***}$ (0.0013) | $-0.0060^{***}$ (0.0011) |
| ΔVIX | | | $0.0048^{***}$ (0.0003) | | |
| ΔTED Spreads | | | | $0.0264^{***}$ (0.0095) | |
| Δilliquidity | | | | | $0.0193^{***}$ (0.0074) |
| Specification Test | | | | | |
| Hit-Frequency | 0.0100 | 0.0100 | 0.0100 | 0.0106 | 0.0106 |
| DQ-Stat | 6.1155 | 6.1339 | 5.9797 | 5.8923 | 10.1434 |
| DQ-Pvalue | 0.8055 | 0.8039 | 0.8170 | 0.8242 | 0.4280 |

Notes: This table displays the results (parameter estimates followed by standard errors in parentheses) of different CAViaR models (at the risk level $\alpha = 99\%$) with the dependent variable being the returns on 5-year U.S. Government bond in excess of the returns on S&P500. Model [1] refers to the usual CAViaR model, while model [2] corresponds to an extended CAViaR model that includes (as explanatory variable) a dummy variable measuring low-yield environment ($i_t < \bar{i}$), with $i_t$ the yields on the 5-year U.S. Government bond and $\bar{i} = 1\%$. Models [3] to [5] are similar to model [2] with an additional control variable. The last panel provides relevant statistics for the test of correct specification, including the frequencies of Hit, the dynamic quantile (DQ) test statistics and the associated p-values. All estimations are performed using weekly data ranging from February 2, 1990 to November 23, 2018, with a total of $T = 1504$ observations. Significances at 1%, 5% and 10% are emphasized by ***, ** and *, respectively.

**Table B.2**
Strength of FTS and low yields: S&P 500 & 2-year U.S. Government bond.

| | [1] | [2] | [3] | [4] | [5] |
|---|---|---|---|---|---|
| $\theta_0$ | 0.0089** (0.0044) | 0.0094** (0.0037) | 0.0015*** (0.0004) | 0.0072** (0.0036) | 0.0039* (0.0024) |
| $\theta_1$ | 0.6669*** (0.0817) | 0.6614*** (0.0868) | 0.7890*** (0.0300) | 0.7427*** (0.0638) | 0.6370*** (0.0613) |
| $\theta_2$ | −0.1951 (0.1328) | −0.1778 (0.1334) | −0.4400*** (0.0413) | −0.1013 (0.1171) | −0.4198*** (0.1232) |
| $\theta_3$ | 1.1474*** (0.1061) | 1.1447*** (0.0911) | 0.2514*** (0.0969) | 0.9577*** (0.1659) | 1.2027*** (0.0744) |
| $\delta$ | | −0.0035** (0.0015) | −0.0019*** (0.0005) | −0.0030* (0.0018) | −0.0039*** (0.0013) |
| ΔVIX | | | 0.0052*** (0.0002) | | |
| ΔTED Spreads | | | | 0.0207* (0.0113) | |
| Δilliquidity | | | | | 0.0189** (0.0087) |
| | | | Specification Test | | |
| Hit-Frequency | 0.0100 | 0.0100 | 0.0113 | 0.0100 | 0.0093 |
| DQ-Stat | 1.4615 | 1.4966 | 5.5504 | 1.4499 | 26.9351 |
| DQ-Pvalue | 0.9991 | 0.9989 | 0.8515 | 0.9991 | 0.0027 |

Notes: This table displays the results (parameter estimates followed by standard errors in parentheses) of different CAViaR models (at the risk level $\alpha = 99\%$) with the dependent variable being the returns on 2-year U.S. Government bond in excess of the returns on S&P500. Model [1] refers to the usual CAViaR model, while model [2] corresponds to an extended CAViaR model that includes (as explanatory variable) a dummy variable measuring low-yield environment ($i_t < \bar{i}$), with $i_t$ the yields on the 2-year U.S. Government bond and $\bar{i} = 0.5\%$. Models [3] to [5] are similar to model [2] with an additional control variable. The last panel provides relevant statistics for the test of correct specification, including the frequencies of Hit, the dynamic quantile (DQ) test statistics and the associated p-values. All estimations are performed using weekly data ranging from February 2, 1990 to November 23, 2018, with a total of $T = 1504$ observations. Significances at 1%, 5% and 10% are emphasized by ***, ** and *, respectively.

**Table B.3**
FTS transfers and low yields: 5-year U.S. government bond with $\alpha = 99\%$.

| $c_1$ | $a_{11}$ | $a_{12}$ | $b_{11}$ | $b_{12}$ | $\rho$ | Wald |
|---|---|---|---|---|---|---|
| | | | Gold | | | |
| 0.0028 (0.0044) | 0.4846 (0.4784) | 0.3563 (0.5062) | 0.8390 (0.8005) | −0.1006 (0.9432) | −0.0702 (0.0973) | 13.0449 [0.0230] |
| | | | JPY | | | |
| 0.0182** (0.0074) | 0.0370 (0.2510) | 0.7520 (0.5974) | 0.0643 (0.2626) | 0.7198*** (0.2715) | −0.3381 (0.2551) | 16.3927 [0.0058] |
| | | | CHF | | | |
| 0.0088** (0.0034) | −0.3141** (0.1297) | 1.1268*** (0.4368) | 0.9172*** (0.1940) | −0.2425 (0.2469) | −0.1607* (0.0864) | 225.4224 [0.0000] |

Notes: This table displays the results (parameter estimates followed by standard errors in parentheses) of the first equation of the bivariate dynamic quantile model in (11) assuming three different alternative (to bonds) safe haven assets. The last column gives the Wald test statistics of the joint nullity of off diagonal elements in the system followed in brackets by the corresponding p-values. Results are presented for the quantile level $\alpha = 99\%$. The threshold $\bar{i}$ is set to 1%. All estimations are performed using weekly data ranging from February 2, 1990 to November 23, 2018, with a total of $T = 1504$ observations. Significances at 1%, 5% and 10% are emphasized by ***, ** and *, respectively.

**Table B.4**
FTS transfers and low yields: 2-year U.S. government bond with $\alpha = 99\%$.

| $c_1$ | $a_{11}$ | $a_{12}$ | $b_{11}$ | $b_{12}$ | $\rho$ | Wald |
|---|---|---|---|---|---|---|
| | | | Gold | | | |
| 0.0025 (0.0074) | 0.4966* (0.2559) | 0.3537 (0.8120) | 0.8039 (0.7159) | −0.0553 (1.2764) | −0.0100 (0.0496) | 7.9622 [0.1583] |
| | | | JPY | | | |
| 0.0328 (0.0239) | −0.4757 (0.3159) | 1.5022 (1.3989) | −0.0801 (0.3747) | 0.7508* (0.4636) | −0.4246** (0.2127) | 43.0533 [0.0000] |
| | | | CHF | | | |
| 0.0109 (0.0111) | −0.2053 (0.2157) | 1.0546* (0.5689) | 0.5892 (1.5411) | 0.1056 (1.7635) | −0.0428 (0.0947) | 18.1854 [0.0027] |

Notes: This table displays the results (parameter estimates followed by standard errors in parentheses) of the first equation of the bivariate dynamic quantile model in (11) assuming three different alternative (to bonds) safe haven assets. The last column gives the Wald test statistics of the joint nullity of off diagonal elements in the system followed in brackets by the corresponding p-values. Results are presented for the quantile level $\alpha = 99\%$. The threshold $\bar{i}$ is set to 0.5%. All estimations are performed using weekly data ranging from February 2, 1990 to November 23, 2018, with a total of $T = 1504$ observations. Significances at 1%, 5% and 10% are emphasized by ***, ** and *, respectively.

## Appendix C. Supplementary material

Supplementary data associated with this article can be found, in the online version, at https://doi.org/10.1016/j.jimonfin.2019.03.002.

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