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Stocks and Bonds: Flight-to-Safety for Ever?

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Abstract

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 US 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. 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 gold increases. This result is more pronounced in the current low-yield environment, suggesting a shift in the historical attractiveness of bonds as safe haven.

JEL Codes: G11, G12, E43, E44
Keywords: Bonds stocks relationship, Flight-to-Safety, Low-yield environment, Bond alternatives, Currencies, Gold.

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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. 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 uncertainty is modelled by the stochastic volatility of asset payoffs. Investors are considered as fund managers with their managing wealth subject to withdrawals when the fund performance falls below an exogenous threshold. The model generates FTS associated to time of high uncertainty due to increased liquidity premia.[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

[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.

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, a rise in the implicit volatility and the Ted spread, liquidity shortages, and decreases in consumer sentiment indicators, seem to be concomitant to FTS episodes.

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. 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, low inflation and expansionary monetary policies, that pushes 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 crisis 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.

[2]US 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 US 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.

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 US 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), but to a lesser extent for the medium (5-year) and short (2-year) maturities. For illustration, with the 10-year maturity bond, when yields are lower than 2%, the upper extreme quantile of $r_t^{(bs)}$ at the 99% (97.5%) level decreases, suggesting less strong FTS events in low-yield environment. For the medium 5-year maturity, we observe the same result at both quantile risk levels (99%,97.5%) when the yields are lower than 1%, but the results are less significant. Lastly, for the short 2-year maturity, the result holds only at the highest quantile risk level 99% when yields are lower than 0.5%.

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 gold increases. This result holds only in

[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.

the current low-yield environment, suggesting a shift in the historical attractiveness of bonds as safe haven asset.

The rest of the paper is organized as follows. In Section 2, we develop and estimate (using US 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 havens. The last Section concludes the paper.

2 Strength of FTS and low yield environment

2.1 The 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 α-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

$$\tau^{b|s} = \lim_{\alpha \to 0} \Pr\left(r_t^{(b)} > Q_t^{(b)}(1-\alpha) \,\middle|\, r_t^{(s)} < Q_t^{(s)}(\alpha) \right). \tag{1}$$

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 $Q_t^{(bs)}(\alpha)$, $\alpha \in \{99\%, 97.5\%\}$ be the extreme upper quantile of $r_t^{(bs)}$ at the risk level α. We consider the following specification for $Q_t^{(bs)}(\alpha) \equiv Q_t^{(bs)}(\alpha; \theta)$

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

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

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

"tick" loss function of Koenker and Bassett (1978), i.e.,

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

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

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

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

where

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

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

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 θ. 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

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

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 δ 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 $Hit_t(\theta_0) = \mathbb{I}(r_t^{(bs)} > Q_t^{(bs)}) - \alpha$ and a set $X_t(\theta_0)$ of instruments. Under the null hypothesis of a correctly specified dynamic quantile model, the authors show that[5]

$$DQ = \frac{Hit(\widehat{\theta})X(\widehat{\theta})(\widehat{M}_T\widehat{M}'_T)X'(\widehat{\theta})Hit'(\widehat{\theta})}{\alpha\,(1-\alpha)}, \tag{9}$$

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

2.2 Estimation results

In this section we estimate the extended dynamic quantile regression in (8) using US stocks and bonds data. Our dataset includes weekly total return prices on US government bonds and the S&P 500 index over the period ranging from January 4, 1988 to October 4, 2017, with a total of $T = 1551$ observations. We use weekly instead of daily data, as there may be a delay or time-lag in the FTS phenomenon which can be understated using daily returns. Indeed, the US treasuries market is opened almost 24 hours a day, while the time slot for the opening of the US stock market (S&P 500) runs from 8:30AM to 4:15PM. 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). Figure A.1 in Appendix displays the dynamics of prices over the sample for these 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. We also note the short-lived crisis of the year 1998. 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: Summary statistics for returns

	Avg Mean	Min	Max	Std. dev.	Skewness	Kurtosis
2-year bond	0.0840	−0.9872	1.2875	0.2236	0.3428	5.7407
5-year bond	0.1079	−2.4127	2.2838	0.5678	−0.0252	3.8936
10-year bond	0.1222	−3.6750	5.8112	0.9684	0.0888	4.6514
S&P 500	0.2133	−18.2911	18.0641	2.2043	−0.6372	12.5165

Notes: The table displays some main statistics for the weekly returns on the assets. The data covers the period ranging from January 4, 1988 to October 4, 2017, with a total of $T = 1551$ observations. Values in the first four columns are in percentage. Min (Max) refers to the minimum (maximum) returns, and Std. dev. the standard deviation.

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 a the cost

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

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 15%, with the same statistics taking values 1.58%, 4.03%, and 7% for the 2-year, 5-year and 10-year US government bond returns. The figure is more pronounced when risk is measured as the probability of loss. Indeed, the kurtosis of the S&P 500 index is equal to 12.5 and much 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.

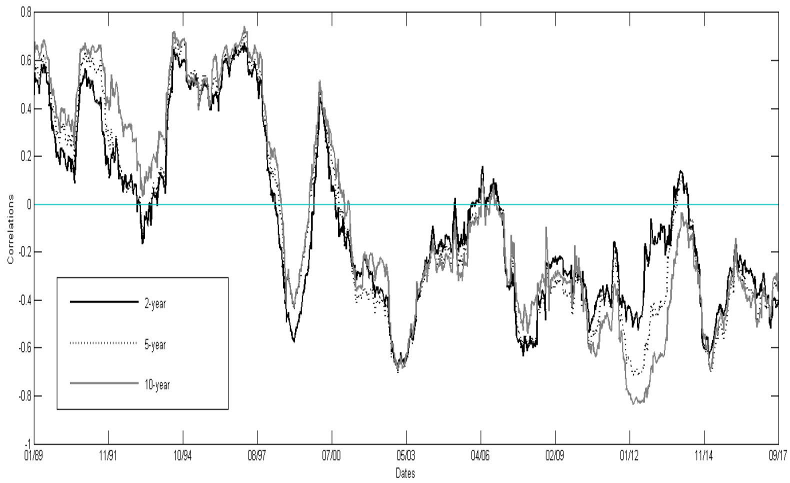

Figure 1: Rolling-window estimates of US stock-bond correlation

Figure 1 displays the US 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 rose into negative territory 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, 2010a). 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. Table 2 below gives the estimation results of the extended CAViaR model in (8). 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).[6] Results are displayed for the longest maturity (10-year government bond), with the parameter estimates followed in parentheses by their standard deviations. The benchmark regression refers to the usual CAViaR model, while the others correspond to an extended model that includes (as explanatory variable) a dummy variable measuring low-yield environment, i.e., $\mathbb{I}(i_t < \bar{i})$, with $\bar{i} \in \{2\%, 3\%, 4\%, 5\%\}$. Panel A presents the results for $\alpha = 99\%$, and Panels B and C for $\alpha = 97.5\%$ and $\alpha = 95\%$, respectively, with α the upper-quantile level. For each model, we also report the frequency of quantile-exceptions, the DQ test statistics for correct specification and the corresponding p-values. For the computation of the DQ test statistics, we use as instruments $X(\widehat{\theta})$ (see equation 9) the 10 lagged values of the estimated process of quantile-exceptions.

The first important result 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 $1-\alpha$. 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 θ_1 is always highly significant, meaning that there exists clustering in the tails,

[6] Figure A.2 in Appendix displays the three time series of US 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 desinflation.

Table 2: Strength of FTS and low yields: S&P 500 & 10-year US Government bond

	Benchmark	$\bar{i} = 2\%$	$\bar{i} = 3\%$	$\bar{i} = 4\%$	$\bar{i} = 5\%$
			$\alpha = 99\%$		
θ_0	0.0086*** (0.0025)	0.0084*** (0.0023)	0.0080*** (0.0016)	0.0084*** (0.0027)	0.0068*** (0.0017)
θ_1	0.7610*** (0.0508)	0.7674*** (0.0379)	0.7804*** (0.0340)	0.7493*** (0.0628)	0.7870*** (0.0422)
θ_2	0.0295 (0.1252)	0.0359 (0.0886)	0.0525 (0.0837)	0.0164 (0.1256)	0.1511 (0.0973)
θ_3	0.8558*** (0.1437)	0.8478*** (0.1144)	0.8289*** (0.1145)	0.8547*** (0.1722)	0.7945*** (0.1317)
δ		−0.0049*** (0.0011)	−0.0026*** (0.0009)	0.0013 (0.0025)	0.0027* (0.0016)
Hit-Frequency	0.0103	0.0103	0.0103	0.0110	0.0097
DQ-Stat	10.0077	4.7106	5.2698	9.0515	5.5039
DQ-Pvalue	0.4398	0.9097	0.8724	0.5272	0.8551
			$\alpha = 97.5\%$		
θ_0	0.0044*** (0.0014)	0.0046*** (0.0016)	0.0046*** (0.0011)	0.0049*** (0.0015)	0.0051*** (0.0017)
θ_1	0.8068*** (0.0619)	0.8008*** (0.0611)	0.8004*** (0.0453)	0.7919*** (0.0720)	0.7584*** (0.0787)
θ_2	−0.0093 (0.1255)	0.0031 (0.1220)	−0.0144 (0.1126)	−0.0030 (0.1421)	−0.0568 (0.1323)
θ_3	0.6370** (0.2489)	0.6841*** (0.2160)	0.6608*** (0.1832)	0.6736** (0.2784)	0.7456*** (0.2730)
δ		−0.0021** (0.0008)	−0.0017** (0.0007)	0.0002 (0.0011)	0.0010 (0.0010)
Hit-Frequency	0.0258	0.0258	0.0258	0.0239	0.0264
DQ-Stat	6.8358	6.4014	5.5767	7.2692	4.0875
DQ-Pvalue	0.7408	0.7805	0.8495	0.6998	0.9433
			$\alpha = 95\%$		
θ_0	0.0023*** (0.0006)	0.0022** (0.0010)	0.0024*** (0.0006)	0.0020*** (0.0007)	0.0024*** (0.0005)
θ_1	0.8601*** (0.0526)	0.8791*** (0.0453)	0.8733*** (0.0492)	0.8701*** (0.0396)	0.8618*** (0.0446)
θ_2	−0.0100 (0.0881)	0.0227 (0.0783)	0.0172 (0.0702)	0.0197 (0.0876)	0.0248 (0.0737)
θ_3	0.3426** (0.1599)	0.3213** (0.1636)	0.3206** (0.1503)	0.3505*** (0.1314)	0.3472** (0.1369)
δ		−0.0006 (0.0004)	−0.0005 (0.0004)	0.0004 (0.0005)	0.0005 (0.0005)
Hit-Frequency	0.0503	0.0490	0.0503	0.0516	0.0496
DQ-Stat	4.4097	5.8681	5.3243	5.2166	7.0039
DQ-Pvalue	0.9270	0.8262	0.8685	0.8762	0.7251

Notes: This table displays the results (parameter estimates followed by standard errors in parentheses) of different CAViaR models with the dependent variable being the returns on 10-year US Government bond in excess of the returns on S&P 500. The benchmark regression refers to the usual CAViaR model, while the others correspond to an extended CAViaR model that includes (as explanatory variable) a dummy variable measuring low-yield environment ($i_t < \bar{i}$). Statistics for the test of correct specification are also displayed, including the frequencies of Hit, the dynamic quantile (DQ) test statistics and the associated p-values. Panel A, B and C report the results for $\alpha = 99\%$, $\alpha = 97.5\%$ and $\alpha = 95\%$, respectively, with α the upper-quantile risk level. All estimations are performed using weekly data ranging from January 15, 1988 to September 29, 2017, with a total of $T = 1551$ observations. Significances at 1%, 5% and 10% are emphasized by ***, ** and *, respectively.

even at the weekly frequency. We also observe that while the coefficient θ_3 is always very significant, the coefficient θ_2 is overall insignificant. 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.

Lastly, focusing on our parameter of interest δ, results in Panel A and B show that this parameter is negative and significant for yield thresholds $\bar{i}$ equal to 2% and 3%. For $\bar{i} \geq 4\%$ the same parameter is positive and insignificant in many cases. 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 US market and for the longest bond maturity considered (10-year).

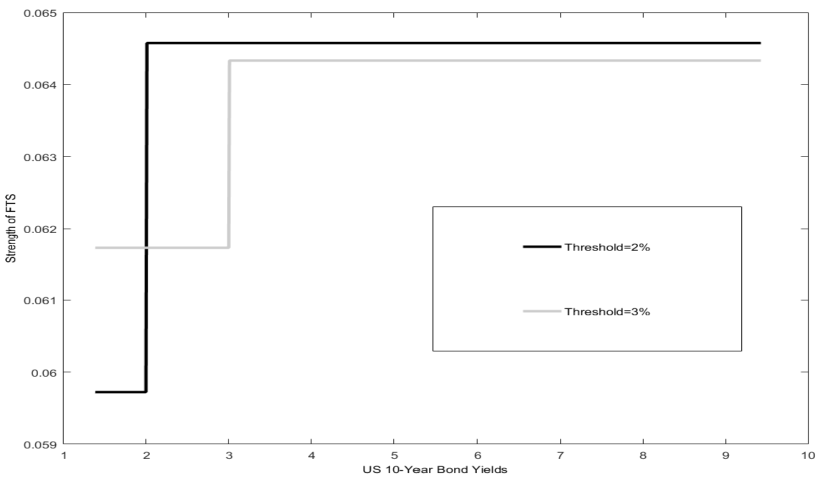

Figure 2: Yields Impact Curve: $\alpha = 99\%$

Figure 2 displays the yields impact curves computed in the same spirit as the news impact curve of Engle and Manganelli (2004). For different values of the yield, each 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, $Q_{t-1}^{(bs)}(\alpha)$, $r_{t-1}^{(bs)}\mathbb{I}(r_{t-1}^{(bs)} < 0)$, and $r_{t-1}^{(bs)}\mathbb{I}(r_{t-1}^{(bs)} \geq 0)$, at its average value over the sample. We observe the asymmetry of both curves with jumps in the value of the strength at the threshold value $\bar{i}$, which is the result of the retained specification in (8). Moreover and importantly, the asymmetry appears stronger at the lowest value of the yield threshold $\bar{i}$.

Tables A.1 and A.2 in Appendix display the results for the 5-year and the 2-year US government bonds, respectively. The presentation is similar to that of Table 2. As in Table 2, we cannot reject the null hypothesis of a correctly specified dynamic quantile regression model for each of the model considered. Moreover, the autoregressive parameter θ_1 appears always significant suggesting temporal dependence in quantile dynamics. Regarding the parameter estimates, the results are qualitatively similar to those in Table 2, except for our parameter of interest δ which is significant at the nominal significance level of 10% in some cases for the 5-year government bond (notably at the threshold $\bar{i} = 1\%, 2\%$) and significant in only one case for the 2-year government bond at the lowest threshold ($\bar{i} = 0.5\%$). To conclude, 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 maturity (10-year government bond). Indeed, FTS episodes are much more pronounced on the 10-year maturity due to its relative liquidity. As a result, the decrease of the FTS strength is more likely to operate at this maturity. The estimated value of the parameter θ_0 (the constant) in the quantile regression (8), which gives an indication of the average value of the strength of FTS, gives more insights on the point (see Tables 2, A.1 and A.2). We observe that the estimated value of this parameter is higher for the 10-year largest maturity (0.86%) than for the other maturities (0.58% and 0.55% for the 5-year and 2-year 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 model

We build on the VAR (vector autoregressive model) for VaR (value at risk) of White et al. (2015), and consider modeling 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 asset like gold or currencies. The model writes

$$\begin{cases} Q_t^{(as)}(\alpha) = c_1 + a_{11}\left|r_{t-1}^{(as)}\right| + a_{12}\left|r_{t-1}^{(bs)}\right| + b_{11}Q_{t-1}^{(as)}(\alpha) + b_{12}Q_{t-1}^{(bs)}(\alpha) + \rho Q_{t-1}^{(bs)}(\alpha)\,\mathbb{I}\left(i_{t-1} \leq \bar{i}\right) \\ Q_t^{(bs)}(\alpha) = c_2 + a_{21}\left|r_{t-1}^{(as)}\right| + a_{22}\left|r_{t-1}^{(bs)}\right| + b_{21}Q_{t-1}^{(as)}(\alpha) + b_{22}Q_{t-1}^{(bs)}(\alpha), \end{cases} \tag{10}$$

where again $Q_t^{(bs)}(\alpha)$ is the upper-quantile of $r_t^{(bs)}$ at the risk level α, 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

$$Q_t(\alpha) = c + A\left|r_{t-1}\right| + BQ_{t-1}(\alpha) + D\widetilde{Q}_{t-1}(\alpha), \tag{11}$$

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

$$Q_t(\alpha) = \left(Q_t^{(as)}(\alpha), Q_t^{(bs)}(\alpha)\right)', \tag{12}$$

$$\widetilde{Q}_t(\alpha) = \left(Q_t^{(as)}(\alpha), Q_t^{(bs)}(\alpha)\,\mathbb{I}\left(i_t < \bar{i}\right)\right)', \tag{13}$$

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

$$A = \begin{pmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{pmatrix}, \quad B = \begin{pmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{pmatrix}, \quad D = \begin{pmatrix} 0 & \rho \\ 0 & 0 \end{pmatrix}. \tag{14}$$

Apart from the last term in the first equation of (10) or equivalently the last term in (11), 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 ρ is negative and statistically significant, this means that when yields are low ($i_{t-1} \leq \bar{i}$) 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.

Estimation of the system of equations in (10) can be achieved minimizing the sum of the quantile loss functions related to the two equations, yielding

$$\widehat{\psi} \;=\; \arg\min_{\psi}\, T^{-1}\sum_{t=2}^{T}\{(\alpha - \mathbb{I}(u_t^{(bs)} < 0))u_t^{(bs)} + (\alpha - \mathbb{I}(u_t^{(as)} < 0))u_t^{(as)}\} \tag{15}$$

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 $(u_t^{(bs)}, u_t^{(as)})'$ 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

$$T^{1/2}(\widehat{\psi} - \psi^*) \longrightarrow N\left(0, M^{*-1}V^*M^{*-1}\right), \tag{16}$$

with

$$\begin{aligned} M^* &= \mathbb{E}[f_t^{(bs)}(0)\,\nabla Q_t^{(bs)}(\alpha;\psi^*)\,\nabla' Q_t^{(bs)}(\alpha;\psi^*)] + \\ &\quad \mathbb{E}[f_t^{(as)}(0)\,\nabla Q_t^{(as)}(\alpha;\psi^*)\,\nabla' Q_t^{(as)}(\alpha;\psi^*)], \end{aligned} \tag{17}$$

$$V^* = \mathbb{E}(\eta_t^* \eta_t^{*\prime}), \tag{18}$$

$$\begin{aligned} \eta_t^* &= \nabla Q_t^{(bs)}(\alpha;\psi^*)[\alpha - \mathbb{I}(r_t^{(bs)} < Q_t^{(bs)}(\alpha;\psi^*))] + \\ &\quad \nabla Q_t^{(as)}(\alpha;\psi^*)[\alpha - \mathbb{I}(r_t^{(as)} < Q_t^{(as)}(\alpha;\psi^*))] \end{aligned} \tag{19}$$

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 ψ^*, 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

$$\widehat{V}_T = T^{-1}\sum_{t=1}^{T} \widehat{\eta}_t \widehat{\eta}_t' \tag{20}$$

$$\begin{aligned} \widehat{\eta}_t &= \nabla Q_t^{(bs)}(\alpha;\widehat{\psi})[\alpha - \mathbb{I}(r_t^{(bs)} < Q_t^{(bs)}(\alpha;\widehat{\psi})] + \\ &\quad \nabla Q_t^{(as)}(\alpha;\widehat{\psi})[\alpha - \mathbb{I}(r_t^{(as)} < Q_t^{(as)}(\alpha;\widehat{\psi})] \end{aligned} \tag{21}$$

$$\begin{aligned} \widehat{M}_T &= T^{-1}\sum_{t=1}^{T}\Big\{(2\widehat{c}_T^{(bs)})^{-1}\mathbb{I}(-\widehat{c}_T^{(bs)} \le u_t^{(bs)} \le \widehat{c}_T^{(bs)})\nabla Q_t^{(bs)}(\alpha;\widehat{\psi})\nabla' Q_t^{(bs)}(\alpha;\widehat{\psi}) + \\ &\quad (2\widehat{c}_T^{(as)})^{-1}\mathbb{I}(-\widehat{c}_T^{(as)} \le u_t^{(as)} \le \widehat{c}_T^{(as)})\nabla Q_t^{(as)}(\alpha;\widehat{\psi})\nabla' Q_t^{(as)}(\alpha;\widehat{\psi})\Big\}, \end{aligned} \tag{22}$$

where the terms $(2\widehat{c}_T^{(bs)})^{-1}\mathbb{I}(-\widehat{c}_T^{(bs)} \leq u_t^{(bs)} \leq \widehat{c}_T^{(bs)})$ and $(2\widehat{c}_T^{(as)})^{-1}\mathbb{I}(-\widehat{c}_T^{(as)} \leq u_t^{(as)} \leq \widehat{c}_T^{(as)})$ 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

$$\widehat{c}_T^{(j)} = \kappa^{(j)} \left[\Phi^{-1}(\alpha + h_T) - \Phi^{-1}(\alpha - h_T)\right], \tag{23}$$

with

$$h_T = T^{-1/3}\left(\Phi^{-1}(1 - 0.05/2)\right)^{2/3}\left(\frac{1.5\left(\phi\left(\Phi^{-1}(\alpha)\right)\right)^2}{2\left(\Phi^{-1}(\alpha)\right)^2 + 1}\right)^{1/3}, \tag{24}$$

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 $u_t^{(j)}$, $j \in \{(bs), (as)\}$.

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

$$\mathbb{H}_0 : a_{12} = 0, b_{12} = 0, \rho = 0, a_{21} = 0, b_{21} = 0. \tag{25}$$

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

$$W = (R\widehat{\psi})'[R\widehat{\Omega}R']^{-1}(R\widehat{\psi}), \tag{26}$$

with $\widehat{\Omega} = T^{-1}\widehat{M}^{-1}\widehat{V}\widehat{M}^{-1}$ the estimated covariance matrix of $\widehat{\psi}$. 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 causality 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 ψ 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 (2010b) and Baur and McDermott (2010).

Baur and Lucey (2010b) scrutinize both constant and time-varying dependencies between the returns on gold and the returns on international stock indexes (US, UK 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. Using the more sophisticated smooth transition regression tool, Beckmann et al. (2015) confirm these results which appear to be market-specific. Note, however, that this figure is nuanced by Hood and Malik (2013). The authors show that gold serves the function of safe haven, which seems to disappear in periods of extreme high volatility.

The safe haven property of JPY and CHF currencies has also been covered by the financial literature. 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 to these two currencies.

Table 3 below displays the results of the bivariate CAViaR models. We use weekly data over the same time period as in the last section, i.e., from January 15, 1988 to September 29, 2017, with a total of $T = 1551$ observations. As our goal is to analyze FTS transfers, we only consider the configurations corresponding to strong decreases in the FTS from stocks to bonds as evidenced in the last section (see Tables 2, A.1 and A.2). Precisely, 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, 2-year, respectively. The Table presents the results only for the first equation including our parameter of interest ρ (see equation (10)). 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

Table 3: FTS transfers and low yields (US): $\alpha = 99\%$

10-year Government Bond ($\bar{i} = 2\%$)

	c_1	a_{11}	a_{12}	b_{11}	b_{12}	ρ	Wald
Gold	0.0057***	0.7021**	0.2499	0.7680***	−0.0816	−0.1598**	18.9583
	(0.0025)	(0.3630)	(0.3027)	(0.0917)	(0.0998)	(0.0844)	[0.0020]
JPY	0.0152*	−0.3959	1.2379**	0.5833***	0.0728	−0.0946	76.0178
	(0.0084)	(0.2732)	(0.6028)	(0.1763)	(0.1901)	(0.0673)	[0.0000]
CHF	0.0120	−0.1607	0.7472	0.8419***	−0.1370*	−0.1307	30.0509
	(0.0107)	(0.3157)	(0.5708)	(0.1476)	(0.0791)	(0.1181)	[0.0000]

5-year Government Bond ($\bar{i} = 1\%$)

	c_1	a_{11}	a_{12}	b_{11}	b_{12}	ρ	Wald
Gold	0.0053***	0.6843**	0.5930**	0.7303***	−0.0954	−0.2687***	121.6488
	(0.0020)	(0.3178)	(0.2522)	(0.1566)	(0.1474)	(0.0986)	[0.0000]
JPY	0.0288	−0.4686	1.5574	−0.1849	0.8176	−0.4875	89.4198
	(0.0620)	(0.8077)	(1.9629)	(0.4271)	(1.5330)	(0.4668)	[0.0000]
CHF	0.0235	0.8413	0.0000	0.0712	0.3988**	−0.3301	33.3419
	(0.0163)	(0.8604)	(1.0757)	(0.3616)	(0.1647)	(0.2588)	[0.0000]

2-year Government Bond ($\bar{i} = 0.5\%$)

	c_1	a_{11}	a_{12}	b_{11}	b_{12}	ρ	Wald
Gold	0.0068**	0.5461	0.8010***	0.8021***	−0.2220	−0.1590**	56.8127
	(0.0033)	(0.3659)	(0.3095)	(0.2150)	(0.2726)	(0.0681)	[0.0000]
JPY	0.0088	−0.3016	1.2812	0.7761	−0.0839	−0.1434	76.1848
	(0.0365)	(0.8853)	(1.9823)	(1.2754)	(0.8409)	(0.2830)	[0.0000]
CHF	0.0118	0.1564	0.4158	0.3911	0.2977	0.1865	9.3848
	(0.0140)	(0.5007)	(1.8313)	(0.7778)	(0.5515)	(0.4529)	[0.0947]

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 (10) 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%, 1% and 0.5% for the 10-year, 5-year and 2-year government bonds. All estimations are performed using weekly data ranging from January 15, 1988 to September 29, 2017, with a total of $T = 1551$ observations. Significances at 1%, 5% and 10% are emphasized by ***, ** and *, respectively.

of off-diagonal elements in the system followed in brackets by the corresponding p-values.

First, it appears that in all configurations except one, 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 1%. 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. Second, the parameter b_{12} is, in most 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. The only exceptions occur with the alternative safe haven asset being CHF, for the 10-year and 5-year government bonds.

Lastly, focusing on our parameter of interest ρ, it appears overall negative and significant at the 5% significance level, when one considers gold as alternative safe haven asset. For instance, with the 10-year government bond, the estimate of ρ is equal to $\widehat{\rho} = -0.1598$. As a consequence, the relation between the strength of FTS from stocks to bonds (as shown in the last section) and the FTS from stocks to gold 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, as ρ is negative. Results are qualitatively similar for the 5-year (2-year) government bonds when the corresponding yield is lower than $\bar{i} = 1\%$ ($\bar{i} = 0.5\%$). Lastly, results do not support FTS transfers when considering JPY and CHF as alternative (to bonds) safe haven assets. Indeed, the parameter ρ is insignificant in all configurations for these two assets. This FTS transfer on gold instead of usual "safe haven" currencies may be related to the low level of the US dollar over the last decade. Since gold is traded in dollars, for international investors, the gold price may have seemed relatively more attractive.

4 Conclusion

This explores the phenomenon of flight-to-safety from stocks to bonds in the US 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 US 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 US government bonds, show that when yields are low, the strength of flight-to-safety from stocks to bonds decreases. This result holds at all maturities considered (10-year, 5-year, 2-year), but to a greater extent at the highest maturity.

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 US 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 gold. This evidence of flight-to-safety transfers seems to operate at all bond maturities. In contrast, the empirical investigations do not favor a flight-to-safety transfer to the two safe haven currencies.

A Appendix: Additional Tables and Figures

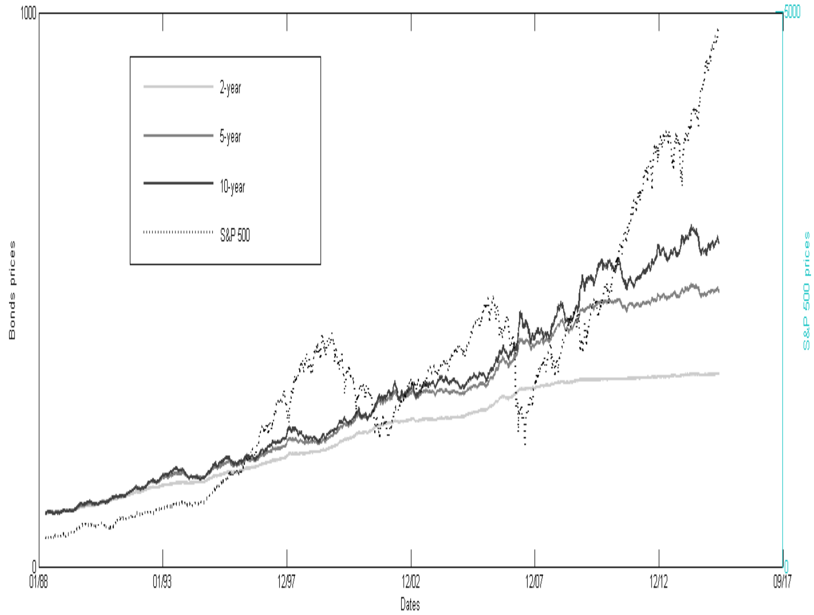

Figure A.1: Dynamics of asset prices

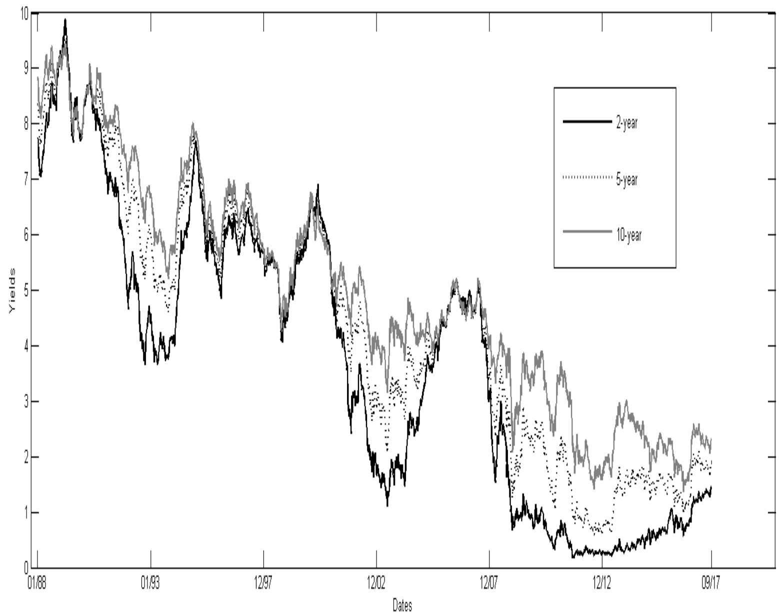

Figure A.2: Dynamics of US government bond yields

Table A.1: Strength of FTS and low yields: S&P 500 & 5-year US Government bond

	Benchmark	$\bar{i} = 1\%$	$\bar{i} = 2\%$	$\bar{i} = 3\%$	$\bar{i} = 4\%$
		$\alpha = 99\%$			
θ_0	0.0058***	0.0059***	0.0059***	0.0058***	0.0058***
	(0.0010)	(0.0015)	(0.0014)	(0.0010)	(0.0010)
θ_1	0.8101***	0.7928***	0.7943***	0.8086***	0.8111***
	(0.0227)	(0.0311)	(0.0293)	(0.0251)	(0.0228)
θ_2	0.1511**	0.0414	0.0433	0.1448*	0.1525**
	(0.0696)	(0.1000)	(0.0917)	(0.0838)	(0.0741)
θ_3	0.8886***	0.9222***	0.9199***	0.8976***	0.8895***
	(0.0838)	(0.1116)	(0.1059)	(0.1033)	(0.0927)
δ		−0.0020*	−0.0020*	−0.0001	−0.0000
		(0.0011)	(0.0011)	(0.0011)	(0.0008)
Hit-Frequency	0.0097	0.0097	0.0097	0.0097	0.0103
DQ-Stat	5.8829	9.7949	5.8306	5.8604	9.2821
DQ-Pvalue	0.8250	0.4587	0.8293	0.8269	0.5056
		$\alpha = 97.5\%$			
θ_0	0.0047***	0.0042***	0.0045***	0.0046***	0.0047***
	(0.0010)	(0.0013)	(0.0010)	(0.0010)	(0.0009)
θ_1	0.8070***	0.8174***	0.8076***	0.7950***	0.8065***
	(0.0599)	(0.0785)	(0.0593)	(0.0618)	(0.0599)
θ_2	0.0564	0.0466	0.0363	0.0110	0.0452
	(0.1132)	(0.1047)	(0.1005)	(0.1258)	(0.1146)
θ_3	0.6511**	0.6722	0.6976**	0.7116**	0.6525**
	(0.2877)	(0.4520)	(0.3129)	(0.3228)	(0.2852)
δ		−0.0019	−0.0017*	−0.0003	−0.0001
		(0.0013)	(0.0010)	(0.0010)	(0.0009)
Hit-Frequency	0.0258	0.0258	0.0258	0.0264	0.0251
DQ-Stat	7.9803	5.0806	4.6447	5.3015	3.4711
DQ-Pvalue	0.6308	0.8857	0.9136	0.8702	0.9681
		$\alpha = 95\%$			
θ_0	0.0020***	0.0020***	0.0021***	0.0020***	0.0020***
	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0004)
θ_1	0.8706***	0.8706***	0.8860***	0.8725***	0.8741***
	(0.0453)	(0.0455)	(0.0433)	(0.0504)	(0.0449)
θ_2	0.0042	0.0042	0.0376	0.0062	0.0248
	(0.1011)	(0.0978)	(0.0723)	(0.1161)	(0.0775)
θ_3	0.3321**	0.3320**	0.3087**	0.3281**	0.3314**
	(0.1435)	(0.1458)	(0.1331)	(0.1442)	(0.1414)
δ		−0.0004	−0.0005	−0.0001	0.0001
		(0.0006)	(0.0004)	(0.0004)	(0.0004)
Hit-Frequency	0.0509	0.0503	0.0516	0.0503	0.0503
DQ-Stat	4.7443	3.4235	2.3370	7.4845	5.9763
DQ-Pvalue	0.9076	0.9696	0.9930	0.6790	0.8172

Notes: This table displays the results (parameter estimates followed by standard errors in parentheses) of different CAViaR models with the dependent variable being the returns on 5-year US Government bond in excess of the returns on S&P 500. The benchmark regression refers to the usual CAViaR model, while the others correspond to an extended CAViaR model that includes (as explanatory variable) a dummy variable measuring low-yield environment ($i_t < \bar{i}$). Statistics for the test of correct specification are also displayed, including the frequencies of Hit, the dynamic quantile (DQ) test statistics and the associated p-values. Panel A, B and C report the results for $\alpha = 99\%$, $\alpha = 97.5\%$ and $\alpha = 95\%$, respectively, with α the upper-quantile risk level. All estimations are performed using weekly data ranging from January 15, 1988 to September 29, 2017, with a total of $T = 1551$ observations. Significances at 1%, 5% and 10% are emphasized by ***, ** and *, respectively.

Table A.2: Strength of FTS and low yields: S&P 500 & 2-year US Government bond

	Benchmark	$\bar{i} = 0.5\%$	$\bar{i} = 1\%$	$\bar{i} = 2\%$	$\bar{i} = 3\%$
		$\alpha = 99\%$			
θ_0	0.0055*** (0.0013)	0.0062*** (0.0013)	0.0074*** (0.0013)	0.0055*** (0.0014)	0.0058*** (0.0023)
θ_1	0.8134*** (0.0430)	0.7642*** (0.0253)	0.7594*** (0.0423)	0.8137*** (0.0507)	0.8030*** (0.0579)
θ_2	0.1715** (0.0850)	0.0031 (0.1510)	0.0101 (0.1458)	0.1726* (0.0980)	0.0994 (0.1581)
θ_3	0.8769*** (0.2154)	1.0849*** (0.1177)	0.9503*** (0.2622)	0.8733*** (0.2562)	0.8112*** (0.2512)
δ		−0.0035*** (0.0009)	−0.0022 (0.0014)	0.0000 (0.0010)	0.0003 (0.0011)
Hit-Frequency	0.0103	0.0110	0.0103	0.0097	0.0103
DQ-Stat	13.4383	9.1505	5.5963	14.7503	13.2982
DQ-Pvalue	0.2002	0.5179	0.8480	0.1414	0.2075
		$\alpha = 97.5\%$			
θ_0	0.0040*** (0.0010)	0.0043*** (0.0010)	0.0044*** (0.0012)	0.0040*** (0.0010)	0.0040*** (0.0010)
θ_1	0.8448*** (0.0471)	0.8342*** (0.0489)	0.8237*** (0.0531)	0.8464*** (0.0463)	0.8443*** (0.0467)
θ_2	0.1391** (0.0645)	0.1242* (0.0667)	0.0822 (0.0917)	0.1392** (0.0677)	0.1335** (0.0653)
θ_3	0.5624** (0.2212)	0.5917** (0.2607)	0.6087*** (0.2213)	0.5536*** (0.2154)	0.5477*** (0.2118)
δ		−0.0008 (0.0008)	−0.0009 (0.0007)	−0.0002 (0.0006)	0.0001 (0.0006)
Hit-Frequency	0.0258	0.0258	0.0271	0.0251	0.0258
DQ-Stat	3.5442	3.4077	6.1886	4.8946	3.4247
DQ-Pvalue	0.9656	0.9701	0.7992	0.8981	0.9696
		$\alpha = 95\%$			
θ_0	0.0024*** (0.0006)	0.0024*** (0.0006)	0.0023*** (0.0006)	0.0023*** (0.0005)	0.0023*** (0.0006)
θ_1	0.8763*** (0.0409)	0.8797*** (0.0388)	0.8835*** (0.0371)	0.8822*** (0.0344)	0.8852*** (0.0369)
θ_2	0.0661 (0.0499)	0.0749 (0.0461)	0.0552 (0.0498)	0.0642 (0.0499)	0.0593 (0.0477)
θ_3	0.3370*** (0.1273)	0.3327*** (0.1201)	0.3081*** (0.1092)	0.3334*** (0.1103)	0.3132*** (0.1090)
δ		0.0001 (0.0004)	−0.0002 (0.0004)	−0.0003 (0.0003)	−0.0002 (0.0003)
Hit-Frequency	0.0503	0.0503	0.0509	0.0496	0.0503
DQ-Stat	3.9047	3.4280	4.4762	4.8623	3.6974
DQ-Pvalue	0.9515	0.9695	0.9233	0.9002	0.9600

Notes: This table displays the results (parameter estimates followed by standard errors in parentheses) of different CAViaR models with the dependent variable being the returns on 2-year US Government bond in excess of the returns on S&P 500. The benchmark regression refers to the usual CAViaR model, while the others correspond to an extended CAViaR model that includes (as explanatory variable) a dummy variable measuring low-yield environment ($i_t < \bar{i}$). Statistics for the test of correct specification are also displayed, including the frequencies of Hit, the dynamic quantile (DQ) test statistics and the associated p-values. Panel A, B and C report the results for $\alpha = 99\%$, $\alpha = 97.5\%$ and $\alpha = 95\%$, respectively, with α the upper-quantile risk level. All estimations are performed using weekly data ranging from January 15, 1988 to September 29, 2017, with a total of $T = 1551$ observations. Significances at 1%, 5% and 10% are emphasized by ***, ** and *, respectively.

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