Temi di discussione

(Working Papers)

Equity tail risk in the treasury bond market

by Dario Ruzzi and Mirco Rubin

Temi di discussione

(Working Papers)

Equity tail risk in the treasury bond market

by Dario Ruzzi and Mirco Rubin

The papers published in the Temi di discussione *series describe preliminary results and are made available to the public to encourage discussion and elicit comments.*

The views expressed in the articles are those of the authors and do not involve the responsibility of the Bank.

EQUITY TAIL RISK IN THE TREASURY BOND MARKET

by Mirco Rubin[*] and Dario Ruzzi[†]

Abstract

This paper quantifies the effects of equity tail risk on the US government bond market. We estimate equity tail risk as the option-implied stock market volatility that stems from large negative jumps as in Bollerslev, Todorov and Xu (2015), and we assess its value in reduced-form predictive regressions for Treasury returns and an affine term structure model for interest rates. We document that the left tail volatility of the stock market significantly predicts one-month-ahead excess returns on Treasuries both in- and out-of-sample. The incremental value of employing equity tail risk as a return forecasting factor can increase utility for mean-variance investors trading bonds. The estimated term structure model shows that equity tail risk is priced in the US government bond market. Consistent with the theory of flight-to-safety, we find that Treasury prices increase and funds flow from equities into bonds when the perception of tail risk is higher. Our results concerning the predictive power and pricing of equity tail risk extend to major government bond markets in Europe.

Contents

[*] EDHEC Business School, 393 Promenade des Anglais, 06200 Nice, France. E-mail: mirco.rubin@edhec.edu.

[†] Fellow at Banca d'Italia, Via Nazionale, 91, 00184 Rome, Italy. E-mail: dario.ruzzi@esterni.bancaditalia.it.

1   Introduction[1]

In times of financial distress, the disengagement from risky assets, such as stocks, and the simultaneous demand for a safe haven, such as top-tier government bonds, generate a flight-to-safety (FTS) event in the capital markets. A large body of literature examines the linkages between the stock and bond markets during crisis periods and their implications for asset pricing, see Hartmann et al. (2004), Vayanos (2004), Chordia et al. (2005), Connolly et al. (2005) and Adrian et al. (2019a), among others. We add to this literature by studying how Treasury bond prices and returns respond to changes in the perceived tail risk in the stock market. If top-tier government bonds are a major beneficiary of the FTS flows occurring when the stock market is hit by heavy losses, then we expect the downside tail risk of equity to affect bond risk premia and determine both stock and bond prices during distress periods. We investigate this conjecture by considering a Gaussian affine term structure model (ATSM) for US interest rates where the pricing factors are the principal components of the yield curve combined with the risk-neutral volatility of the US stock market that stems from large negative price jumps. Further, we add to the empirical literature on bond return predictability by assessing the improvements in forecast accuracy obtained with equity tail risk and examining whether they translate into higher risk-adjusted portfolio returns. Although evidence of bond predictability based on measures of stock market uncertainty and skew has previously been found (Feunou et al., 2014; Mueller et al., 2017; Adrian et al., 2019a; Crump and Gospodinov, 2019), this is, to the best of our knowledge, the first study to assess the statistical and economic gains of using equity tail risk for predicting short-run bond risk premia and discuss the implications for pricing in a term structure model.

Understanding the dynamics of bond yields is particularly useful for forecasting financial and macro variables, for making debt and monetary policy decisions and for derivative pricing. Most

of these applications require the decomposition of yields into expectations of future short rates (averaged over the lifetime of the bond) and term premia, i.e. the additional returns required by investors for bearing the risk of long-term commitment. Gaussian affine term structure models have long been used for this purpose, see, e.g., Duffee (2002), Kim and Wright (2005) and Abrahams et al. (2016). In the setup of a Gaussian ATSM, a number of pricing factors that affect bond yields are selected and assumed to evolve according to a vector autoregressive (VAR) process of order one. The yields of different maturities are all expressed as linear functions of the factors with restrictions on the coefficients that prevent arbitrage opportunities, implying that long-term yields are merely risk-adjusted expectations of future short rates.

The selection of pricing factors typically starts by extracting from the cross-section of bond yields a given number of principal components (PCs), which are linear combinations of the rates themselves. Since the seminal work of Litterman and Scheinkman (1991), the first three PCs have been prime candidates in this regard as they generally explain over 99% of the variability in the term structure of bond yields and, due to their loadings, may be interpreted as the level, slope and curvature factor. As for the second principal component, Fama and Bliss (1987) and Campbell and Shiller (1991) showed that variables related to the slope of the yield curve are highly informative about future bond returns. Despite the important role of the level, slope and curvature, it is well established in the literature that additional factors are needed to explain the cross-section of bond returns. For this reason, the first five principal components of the US Treasury yield curve are used as pricing factors in Adrian et al. (2013), while Malik and Meldrum (2016) adopt a four-factor specification for UK government bond yields. Albeit the higher order principal components of yields have predictive power for future bond returns, in a recent study focused on the US bond market, Feunou and Fontaine (2018) show that a term structure model that includes the first three principal components and their own lags delivers better forecasts of excess returns than a specification using the first five principal components of yields as risk factors. Furthermore, several studies suggest that a great deal of information

about expected excess returns – the bond risk premium – can be found in factors that are not principal components of the yield curve. For instance, Cochrane and Piazzesi (2005) discover a new linear combination of forward rates which is a strong predictor of future excess bond returns and, based on this evidence, Cochrane and Piazzesi (2008) use it in an ATSM along with the classical level, slope and curvature factors. More recently, Cooper and Priestley (2008), Ludvigson and Ng (2009), Duffee (2011), Joslin et al. (2014), Cieslak and Povala (2015), Eriksen (2017) and Huang et al. (2019) show that valuable information about bond risk premia is located outside of the yield curve and contained, for example, in macro variables that have little or no impact on current yields but strong predictive power for future bond returns. In addition, the very recent paper by Berardi et al. (2020) finds that bond predictability provided by forward rates can be enhanced by integrating information arising from monetary policy actions, and in particular from deviations of the natural rate of interest from the real Fed Funds rate.

This paper explores the use of factors, other than combinations of yields, to drive the curve of US Treasury rates and explain bond returns. In contrast to the vast majority of previous studies, however, we draw on the literature that deals with comovement in the equity and bond markets and we consider the possibility that pricing factors of Treasury bonds are also linked to the stock market. The findings of Connolly et al. (2005) and Baele et al. (2010) indicate that measures associated with stock market uncertainty explain time variation in the stock-bond return relation and have important cross-market pricing effects.[2] Therefore, we select a risk measure which is known to predict the equity risk premium and we examine its role in the Treasury bond market. The existing literature suggests that the variance risk premium (VRP) forecasts the stock market returns at shorter horizons than do other predictors like dividend

---

[2]Connolly et al. (2005) find that when the implied volatility from equity index options, measured by the VIX, increases to a considerable extent, bond returns tend to be higher than stock returns (flight-to-quality) and the correlation between the two assets over the next month is lower. Baele et al. (2010) show that the time-varying and sometimes negative stock-bond return correlations cannot be explained by macro variables but instead by liquidity factors and the variance risk premium, which represents the compensation demanded by investors for bearing variance risk and is defined as the difference between the risk-neutral and statistical expectations of the future return variation. Although the variance risk premium is a major contributor to the stock-bond return correlation dynamics, Baele et al. (2010) find significant exposures to it only for stock but not for bond returns.

yields or price-to-earning ratios, see Bollerslev et al. (2009), Bollerslev et al. (2014) and Bekaert and Hoerova (2014), among others. In view of recent studies showing that the predictive power of the VRP for the equity risk premium stems from a jump tail risk component that captures the investors' fear of a market crash (see, e.g., Andersen et al. (2015, 2019a), Bollerslev et al. (2015) and Li and Zinna (2018)), we opt for the left jump volatility measure of Bollerslev et al. (2015) to assess the impact of equity tail events on US Treasury bonds. Building on the findings of Crump and Gospodinov (2019) that equity tail risk – as measured by the CBOE Skew Index – has strong in-sample predictive power for future Treasury bond returns, we are interested in understanding whether the forecast improvements afforded by equity tail risk continue to hold in a realistic out-of-sample forecasting setting and whether equity tail risk is priced in the term structure of US interest rates. Hence, our main contribution is to provide empirical support that equity tail risk can generate economic value in bond return predictability and can be used as a bond pricing factor in a no-arbitrage affine term structure model.[3]

As opposed to Crump and Gospodinov (2019), we do not rely on risk-neutral skewness to measure equity tail risk as the computation of moments higher than the second is prone to numerical errors and instability.[4] Instead, we rely on the procedures put forth by Bollerslev and Todorov (2011) to proxy investor fears for jump tail events. Specifically, we estimate equity tail risk with the model-free measure of left tail volatility developed by Bollerslev et al. (2015) and calculated from short-dated deep out-of-the-money put options on the S&P 500 market index. By doing so, we gauge the market's perception of jump tail risk over the following month based on the risk-neutral expectation of future return volatility associated with large negative

---

[3]We stress that our pricing methodology differs from that of Farago and Tédongap (2018), who price Treasury bonds (and many other types of assets) using a consumption-based general equilibrium model that includes a non-risk-neutralized measure of downside risk.

[4]Liu and van der Heijden (2016) discuss the difficulties associated with the computation of risk-neutral skewness using the method by Bakshi et al. (2003), on which the CBOE Skew Index is also based. They note how different approaches to the implementation of the Bakshi et al. (2003) method have led to mixed results in the literature of stock return predictability. With regard to this, the negative relationship between the Bakshi et al. (2003) measure of skewness and future returns found by Bali and Murray (2013) and Conrad et al. (2013) contrasts sharply with the positive relationship found by Rehman and Vilkov (2012) and Stilger et al. (2016).

price jumps.[5] The equity tail risk factor so obtained is by construction a measure of downside tail risk and in this it also differs from the CBOE VIX Index which is a symmetric risk measure that reflects compensation for both diffusive and jump risk. With the Bollerslev et al. (2015) measure in hand, we test whether equity tail risk is priced in the US term structure and examine whether return predictability can yield substantial gains from an investment perspective.

Our empirical analysis relies on monthly data for the US zero-coupon bond yield curve provided by Gürkaynak et al. (2007). Given the bond yield data, we construct non-overlapping monthly excess returns on Treasuries with maturities up to ten years. Data is sampled at the end of each month between January 1996 and December 2019. For the same time period, we also compute monthly estimates of equity tail risk starting from daily observations of options on the S&P 500 stock market index.[6] The econometric framework consists of reduced-form predictive regressions that use the measure of equity tail risk to forecast monthly excess Treasury returns, and a Gaussian ATSM that uses equity tail risk to drive the curve of US interest rates. Furthermore, we consider the novel three-pass method of Giglio and Xiu (2019), which delivers an estimate of a factor's risk premium that is robust to the omitted variable and measurement error problems, as an alternative to the ATSM for estimating the market price of equity tail risk and testing its relevance in the bond market.

Our results can be summarized as follows. First, there exist significant interactions between the future one-month returns of the US government bond market and the option-implied left tail volatility of the stock market.[7] The frequency at which we uncover the predictive power of

---

[5]As a robustness check, we also used a simple alternative measure of downside risk perceptions, the S&P 500 implied volatility skew (or smirk), defined as the difference between the out-of-the-money put implied volatility (with delta of 0.20) and the average of the at-the-money call and put implied volatilities (with deltas of 0.50), both calculated from options with a tenor of 30 days (Xing et al., 2010; An et al., 2014). These results, which are available upon request, are similar to those described here and obtained with the Bollerslev et al. (2015) measure.

[6]The option-implied left tail volatilities are computed daily and then the month-end value is recorded. To minimize the impact of outliers and help smooth out the estimation error, we also considered monthly estimates of equity tail risk obtained by averaging over the last five days of the month with the results being very similar to the ones reported below for their end-of-month counterparts.

[7]Adrian et al. (2019a) find that a nonlinear function of the VIX can predict both stock and bond returns at forecast horizons of about five months or longer. We show that the predictive power of the VIX for the future one-month returns on bonds is completely subsumed by the equity tail factor. Our paper relates also to the works of Feunou et al. (2014), Kaminska and Roberts-Sklar (2015), Mueller et al. (2017) and Crump and Gospodinov (2019) who document the importance of the variance risk premium and risk-neutral skewness for the government

equity tail risk for bond risk premia is considerably higher than that of the business cycle, which is normally used to interpret return predictability over forecast horizons of one quarter or longer. By contrast, the short-term predictability documented in this paper may be associated with the instantaneous reactions of market participants that, fearing a stock market crash, flock to the perceived safety of Treasuries.[8] Second, the predictability afforded by the equity tail factor continues to hold out-of-sample and can sometimes yield substantial economic value to a mean-variance investor. In fact, it is possible to achieve sizeable gains in portfolio performance when switching to a model that uses equity tail risk to predict bond returns. Third, turning to the results of the term structure model, the response of Treasury bond prices to a contemporaneous shock to the equity tail factor is shown to be positive and thus opposite to what happens in the stock market. This observation confirms the role of US government bonds as a safe haven. Fourth, equity tail risk is priced in the US term structure. We find evidence of a significant and time-varying market price of equity tail risk that has been negative on average since 2001 when Treasuries became hedges (David and Veronesi, 2013; Campbell et al., 2020). The equity tail factor's risk premium that we observe in the US government bond market is consistent with the evidence in Longstaff (2004) and Krishnamurthy and Vissing-Jorgensen (2012), who document the existence of a significant price for the safety and liquidity attributes of Treasuries. When applying the novel framework proposed by Giglio and Xiu (2019), we reject the hypothesis of weak factor for equity tail risk but we fail to find a significant market price of risk. We view this insignificance as the result of the constant-risk-premium assumption underlying the method of Giglio and Xiu (2019) that is incompatible with the estimated ATSM and empirical evidence of time-varying risk compensation in the bond market.[9] Fifth, large drops in short-term bond yields and their embedded expectations of future short rates are attributable to

---

bond market. We show that at the one-month horizon, the predictive power of equity tail risk for US Treasury returns persists even with the inclusion of the VRP of Bollerslev et al. (2014) and the CBOE Skew Index.

[8]The short-term predictability of the US term structure that we find is also in agreement with the fact that the investors' fear of a market crash decreases with the time horizon (Li and Zinna, 2018).

[9]See, for instance, Rebonato (2016) for a discussion on time-varying risk premiums in the bond market.

equity tail risk. Therefore, while the Fed asset purchase programs have been a major force in lowering longer-term yields since the global financial crisis (Kaminska and Zinna, 2018), the reduction in shorter-term yields is likely to have been caused by the investors' increased appetite for safe assets. Sixth, the strong interest rate effect of equity tail risk shocks persists even after controlling for the usual effect of monetary policy shocks and macroeconomic news releases on domestic rates. Seventh, within a flows of funds analysis inspired by the recent "Inelastic Market Hypothesis" of Gabaix and Koijen (2020), we find that equity outflows and Treasury bond inflows are associated with contemporaneous spikes of equity tail risk. These associations are observed not only at quarterly frequency with the total flows of all sectors in the economy considered by Gabaix and Koijen (2020), but also at monthly frequency with the flows of only mutual funds and exchange-traded funds, which display significant interactions with both current and previous month's level of equity tail risk. Finally, the strong and economically important role of equity tail risk – estimated from both US and national index options – extends to the Treasury bond market of the United Kingdom, Germany, Switzerland and France, while the evidence is considerably weaker in Spain and non-existent in Italy.

The remainder of the paper is structured as follows. In Section 2 we describe the bond data and the construction of the equity tail risk measure. In Section 3 we review the methodology used to assess bond return predictability and we outline the term structure modeling approach and the Giglio and Xiu (2019) three-pass method. Section 4 reports the in-sample and out-of-sample empirical results on bond return predictability and the application of equity tail risk in bond pricing. Evidence from international bond markets is also presented. Section 5 relates the results to monetary policy and to flows in and out of equities and bonds. Section 6 concludes.

2 Data

In this section we present the data sources and methods used to construct the monthly time series of excess Treasury returns and equity tail risk measure. All time series are generated over

the period January 1996 to December 2019 with data recorded at the end of each month.

2.1 Bond Returns

We compute Treasury bond returns using the Gürkaynak et al. (2007) zero-coupon bond yield curve derived from observed US government bond prices.[10] We consider maturities up to ten years, for which we construct non-overlapping one-month holding period returns.[11] Following the studies of Adrian et al. (2013), Abrahams et al. (2016) and Gargano et al. (2019), we define the monthly return of the bond with maturity n (in months) as the return from buying an n-maturity bond and selling it as an $(n-1)$-maturity bond one month later. Setting the risk-free rate equal to the $n = 1$ month yield, the monthly excess log-return at date $t+1$ (i.e., from the end of month t to the end of month $t+1$) for the generic bond with maturity n at time t gets computed as

$$rx_{t+1}^{(n-1)} \;=\; -\frac{(n-1)}{12}y_{t+1}^{(n-1)} \;+\; \frac{n}{12}y_t^{(n)} - \frac{1}{12}y_t^{(1)} \;, \tag{1}$$

where $y_t^{(i)}$ is the annualized (but not in percentage) continuously compounded yield on the zero-coupon bond with maturity i at time t, provided by Gürkaynak et al. (2007).

Table 1 provides descriptive statistics for one-month excess returns on US Treasury bonds with maturity $n = 12, 24, 36, 48, 60, 84, 120$ months.[12] A quick inspection of Panel A reveals that longer-term bonds are characterized by higher mean excess returns and higher volatility. However, the reward-to-volatility ratio, also known as Sharpe ratio, declines with the bond maturity. While all bond returns are leptokurtic, only returns on bonds with maturity up to 3

---

[10]The Gürkaynak et al. (2007) yield data are available at a daily frequency for annually spaced maturities ranging from 1 to 30 years from the Federal Reserve website `https://www.federalreserve.gov/pubs/feds/2006/200628/200628abs.html` . The parameters of the Nelson-Siegel-Svensson model used by Gürkaynak et al. (2007) are also published, thus allowing to retrieve yields for any desired maturity, including the longer ones.

[11]The advantages of using non-overlapping one-month returns instead of the more conventional overlapping one-year returns are explained in Gargano et al. (2019). Examples of these advantages include a greater number of non-overlapping observations being studied and most importantly the identification of short-lived dynamics like those characterizing the periods of stress that are at the heart of our work.

[12]Throughout the rest of the paper, the terms "returns" and "excess returns" are used interchangeably to indicate excess returns unless otherwise indicated by the particular context.

years display a strong positive skewness and a first-order autocorrelation coefficient above 0.1. Finally, as shown in Panel B, the cross-sectional correlation between bond returns is always above 0.5 with values well above 0.9 for maturities that are close to each other.

[Insert Table 1 here]

2.2 Equity Tail Risk

The equity tail risk factor of this paper corresponds to the Bollerslev et al. (2015) measure of left jump tail volatility implied by short-dated deep out-of-the-money (OTM) put options on the US stock market index.[13] This measure is essentially model-free and exploits extreme value theory to characterize the density of the risk-neutral return tails. The intuition behind it is that short-maturity OTM options remain worthless unless the investors believe that a big jump in the underlying price will occur before the option expires. Since diffusive risk does not affect their price, these contracts are fundamentally suitable to estimate jump tail risk (Bollerslev and Todorov, 2011, 2014). The calculation of the Bollerslev et al. (2015) measure is based on two parameters that must be estimated period-per-period and represent two separate sources of independent variation in the jump intensity process. The first parameter is α_t^- which controls the time-varying rate of decay, or shape, of the left tail. Lower values of α_t^- are associated with a slower rate at which the put option prices decay for successively deeper OTM contracts, implying a fatter left tail of the risk neutral density. Bollerslev and Todorov (2014) and Bollerslev et al. (2015) show that α_t^- can be estimated as follow,

$$\hat{\alpha}_t^- = \arg\min_{\alpha^-} \frac{1}{N_t^-} \sum_{i=2}^{N_t^-} \left| \log\left(\frac{O_{t,\tau}(k_{t,i})}{O_{t,\tau}(k_{t,i-1})} \right) (k_{t,i} - k_{t,i-1})^{-1} - (1 + \alpha^-) \right| , \qquad (2)$$

where $O_{t,\tau}(k)$ is the time t price of the OTM put option with time to expiration τ and (negative)

---

[13]The interested reader is directed to Bollerslev et al. (2015) for an in-depth description of the theoretical framework since here we limit ourselves to highlighting the distinctive features and to discussing the estimation and implementation procedures.

log-forward moneyness k, and N_t^- is the total number of OTM puts used in the estimation with moneyness $0 < -k_{t,1} < ... < -k_{t,N_t^-}$. The second source of variation in the jump tails comes from parameter ϕ_t^- which shifts the level of the jump intensity process through time. Given an estimate for α_t^-, the estimate of ϕ_t^- can be calculated as follows,

$$\hat{\phi}_t^- = \arg\min_{\phi^-} \frac{1}{N_t^-} \sum_{i=1}^{N_t^-} \left| \log\left(\frac{e^{r_{t,\tau}} O_{t,\tau}(k_{t,i})}{\tau F_{t,\tau}} \right) - (1+\hat{\alpha}_t^-)k_{t,i} + \log(\hat{\alpha}_t^- + 1) + \log(\hat{\alpha}_t^-) - \log(\phi^-) \right| , \tag{3}$$

where $r_{t,\tau}$ is the risk-free interest rate over the $[t, t+\tau]$ time interval, $F_{t,\tau}$ is the forward price of the underlying asset at time t and with maturity date $t+\tau$, and the rest of the notation is as before. Following Andersen et al. (2019b), we estimate α_t^- at a weekly frequency, while we allow ϕ_t^-, which is less sensitive to outliers, to vary each trading day. Furthermore, we pool data across multiple maturities for more robust estimation of both parameters.

When defining left jump tail variation, Bollerslev et al. (2015) focus on asset price moves that are unusually large relative to the current level of risk in the economy. To this end, they use a time-varying cutoff k_t for the log-jump size that identifies, for each trading day, the start of the left tail based on the market volatility level. In our study we let k_t be the threshold for a negative tail jump at the one-month horizon and we fix it at three times the maturity-normalized 30-day at-the-money Black-Scholes implied volatility at time t.[14] By substituting $\hat{\alpha}_t^-$, $\hat{\phi}_t^-$ and k_t in the expression proposed by Bollerslev et al. (2015) for the predictable risk-neutral left jump tail variation, we construct the equity tail risk measure of this paper as,

$$\text{TR}_t^{(eq)} = \sqrt{\hat{\phi}_t^- e^{-\hat{\alpha}_t^-|k_t|}(\hat{\alpha}_t^- k_t(\hat{\alpha}_t^- k_t + 2) + 2)/(\hat{\alpha}_t^-)^3} \ . \tag{4}$$

---

[14]The threshold that we use for the log-jump size, although smaller than that of Bollerslev et al. (2015) and Andersen et al. (2019b), is still able to define as jumps asset price moves of greater magnitude than those corresponding to the levels of moneyness used in Bollerslev and Todorov (2011) and considered *sufficiently "deep" in the tails to guarantee that the effect of the diffusive price components is minimal, and that the extreme value distribution provides a good approximation to the jump tail probabilities.* Nevertheless, we also considered larger values for the tail cutoff, resulting in similar, but less significant, interactions between the left tail volatility of the stock market and future bond returns. These results are available upon request.

To compute the equity tail risk measure in (4), which represents the (annualized) volatility that stems from negative return jumps greater than a threshold k_t, we rely on daily data reported by OptionMetrics IvyDB US for the European style S&P 500 equity-index options. We apply the following standard filters to our dataset. We discard options with a tenor of less than eight days or more than forty-five days. We discard options with missing prices, options with non-positive bid prices and options with non-positive bid-ask spread. The price of the surviving contracts is obtained as the average of bid and ask quotes. For each day in the sample, we retain only option tenors for which we have at least five pairs of call and put contracts with the same strike price. We exploit these cross sections to derive, via put-call parity, the underlying asset price adjusted for the dividend yield that apply to a given option tenor on a given day.[15] We discard all in-the-money options and we retain only out-of-the-money put options with volatility-adjusted log-forward moneyness less than or equal to -2.5. Finally, we omit any out-of-the-money options for which the price does not decrease with the strike price. Using the data obtained from the filtering process, we compute the end-of-month values of the S&P 500 option-implied left tail volatility $TR^{(eq)}$, which we plot in Figure 1 against the 3-month moving average of the Chicago National Activity Index (CFNAI) and the National Bureau of Economic Research (NBER) based recession periods.

[Insert Figure 1 here]

From Figure 1 it is clear that our equity tail risk measure is higher during periods of economic contraction. However, we note that $TR^{(eq)}$ spikes also in periods when the CFNAI is above its mean level, for instance during the Russian financial crisis in 1998 and the intensification of the European sovereign debt crisis in 2010 and 2011. We take this as first evidence that equity tail risk might contribute to explaining the dynamics of the US yield curve in a manner that is not

---

[15]The risk-free rates used in the estimation of $TR_t^{(eq)}$ come from the Gürkaynak et al. (2007) dataset described in Section 2.1. Data for the 30-day at-the-money implied volatility used to calculate k_t is from the volatility surface file of IvyDB OptionMetrics.

redundant with what is explained by macroeconomic variables. Now turning to the descriptive statistics reported in Table 1, we find that the annualized left tail volatility of the stock market is on average 10%.[16] We also observe that equity tail risk is positively correlated with the one-month-ahead Treasury returns. The correlation coefficient is about 0.2 across all maturities. In the next sections, we use $\text{TR}^{(eq)}$ to gauge the market's perception of jump tail risk and examine the response of US Treasury bonds to the downside tail risk of the stock market.

3   Econometric Framework

In this section we describe the techniques and evaluation criteria used to investigate the predictive content of equity tail risk for future bond returns and assess the pricing of equity tail risk in the US government bond market.

3.1   Reduced-form Predictive Regressions

The econometric framework that we adopt to evaluate bond return predictability is based on reduced-form predictive regressions that include the equity tail risk measure in (4) and, possibly, a certain number of PCs of bond yields that control for the forecasting information contained in the yield curve.[17] With respect to the yield predictors, we consider both the traditional level, slope and curvature factors, which are standard in the literature on bond return predictability, and the two higher-order principal components used by Adrian et al. (2013) to explain Treasury

---

[16]When comparing our equity tail risk measure to the VIX, we find a strong coherence between the two series but we also note that $\text{TR}^{(eq)}$ is far more persistent during post-crisis periods. We refer the reader to Section 6.1 in Bollerslev et al. (2015) for a detailed discussion of the differences between left jump tail variation and the VIX.

[17]In Section 4 we assess the in-sample explanatory power of equity tail risk for bond risk premia by controlling for other successful return predictive factors found in the literature. Specifically, we consider the Cochrane and Piazzesi (2005) bond return predictor obtained as a linear combination of forward rates, the Cieslak and Povala (2015) risk-premium factor obtained from a decomposition of Treasury yields into inflation expectations and maturity-specific interest-rate cycles, and the orthogonal component of the CBOE VIX with respect to $\text{TR}^{(eq)}$.

return variation. Therefore, our bond return prediction models take the following form,

$$rx_{t+1}^{(n-1)} = \beta_0 + \beta_1 \, \text{TR}_t^{(eq)} + \epsilon_{t+1} \, , \tag{5a}$$

$$rx_{t+1}^{(n-1)} = \beta_0 + \beta_1 \, \text{TR}_t^{(eq)} + \beta_2 \, \text{PC1}_t + \beta_3 \, \text{PC2}_t + \beta_4 \, \text{PC3}_t + \epsilon_{t+1} \, , \tag{5b}$$

$$rx_{t+1}^{(n-1)} = \beta_0 + \beta_1 \, \text{TR}_t^{(eq)} + \beta_2 \, \text{PC1}_t + \beta_3 \, \text{PC2}_t + \beta_4 \, \text{PC3}_t + \beta_5 \, \text{PC4}_t + \beta_6 \, \text{PC5}_t + \epsilon_{t+1} \, , \tag{5c}$$

where $\text{TR}^{(eq)}$ represents the perceived tail risk in the US stock market, and PC1–PC5 are the first five principal components estimated from an eigenvalue decomposition of the variance-covariance matrix of zero-coupon bond yields. We include in the analysis the univariate model of equation (5a) not only because it is a quick and inexpensive method to gauge the strength and sign of the relation between bond returns and equity tail risk, but also because simpler models might generate more accurate out-of-sample forecasts. In the following, we will assess the forecasting performance of model (5a) relative to that of the Expectation Hypothesis (EH) model. The EH assumes no predictability of bond risk premia, implying that the out-of-sample model forecasts of bond returns are equal to a recursively updated constant based on the historical return mean. The performance of models (5b) and (5c) will be compared to that of a model that includes, respectively, the first three and five PCs of bond yields alone.

The relationship between equity tail risk and bond risk premia is firstly assessed by testing the statistical significance of the coefficient of $\text{TR}^{(eq)}$ over the full sample period. The test of $\beta_1 = 0$ is carried out not only by means of conventional inference, for which we compute the Newey-West p-values with a 12-lag standard error correction, but even with the more robust inference method developed by Bauer and Hamilton (2018). The latter addresses the small-sample distortions in bond return predictive regressions that are induced, among others, by the high persistence of the predictive variables. Bauer and Hamilton (2018) propose a parametric bootstrap that generates yield curve data assuming that a given factor structure underlies the bond yields and that the relevant predictive information for bond returns is entirely contained in

the yield curve. We compute Bauer and Hamilton (2018) p-values with 5,000 artificial samples and two separate 1-month VAR processes for $\text{TR}^{(eq)}$ and the principal components of yields.[18]

To check whether the in-sample interactions between one-month-ahead bond risk premia and equity tail risk translate into positive real-time predictive ability, we consider an out-of-sample exercise in which forecasts are recursively generated at a monthly frequency based on information available only at the forecast time. We estimate the models in (5a), (5b) and (5c) – and corresponding benchmarks that do not include $\text{TR}^{(eq)}$ – recursively over expanding and rolling samples, where the first half of observations (1996:01-2007:12) constitutes the initial estimation period and the second half (2008:01-2019:12) constitutes the forecast evaluation period. Within this out-of-sample setting, we follow the approach used by Eriksen (2017) and Gargano et al. (2019), among others, and we assess both the statistical and the economic value of bond return predictability with equity tail risk. We evaluate statistical significance with the Campbell and Thompson (2008) R^2_{OS} statistic that measures the percentage reduction in mean squared prediction error (MSPE) for the out-of-sample forecasts generated by a given model relative to a benchmark. For each one of the preferred models in (5a), (5b) and (5c), we compute the Campbell and Thompson (2008) statistic as,

$$
R^2_{OS} = 1 - \frac{\sum\limits_{t=1}^{T}\left(rx_{t+1}^{(n-1)} - \widehat{rx}_{t+1}^{(n-1)}\right)^2}{\sum\limits_{t=1}^{T}\left(rx_{t+1}^{(n-1)} - \widetilde{rx}_{t+1}^{(n-1)}\right)^2} \; , \tag{6}
$$

where $\widehat{rx}_{t+1}^{(n-1)}$ and $\widetilde{rx}_{t+1}^{(n-1)}$ denote, respectively, the forecasts from one of the preferred models that include $\text{TR}^{(eq)}$ and the forecasts from its benchmark (either the PCs-only or EH model), and T is the number of out-of-sample forecasts. Positive values of R^2_{OS} indicate higher predictive

---

[18]As a robustness check, we have also evaluated the strength of the relationship between equity tail risk and future Treasury bond returns using the inference method recently proposed by Crump and Gospodinov (2019). This is a non-parametric bootstrap that accounts for the time-series and cross-sectional dependence in bond yields and generates data while remaining agnostic about the exact factor structure in the data. Based on the Crump and Gospodinov (2019) p-values computed with resampled data from 999 bootstrap replications, we continue to observe statistically significant relationships at the 0.10 level or lower across all maturities considered. Because of space considerations, these results are not reported in the paper, but are available upon request from the authors.

accuracy for the bond return prediction model that includes equity tail risk. We formally test for predictive superiority of the preferred models using the Clark and West (2007) test. This is a statistical test of the null hypothesis of $R^2_{OS} \leq 0$ against the one-sided alternative of $R^2_{OS} > 0$. Significant predictive superiority of the model that includes equity tail risk is found in case of rejection of the null. We conduct the Clark and West (2007) test by estimating the t-statistic of regressing

$$CW_{t+1} = \left(rx_{t+1}^{(n-1)} - \widetilde{rx}_{t+1}^{(n-1)} \right)^2 - \left[\left(rx_{t+1}^{(n-1)} - \widehat{rx}_{t+1}^{(n-1)} \right)^2 - \left(\widetilde{rx}_{t+1}^{(n-1)} - \widehat{rx}_{t+1}^{(n-1)} \right)^2 \right], \quad (7)$$

on a constant term, and then computing its p-value according to the Newey-West and Bauer and Hamilton (2018) inference procedures described above.[19] The statistic in (7) is the difference in the preferred and benchmark model's squared prediction errors adjusted for the upward bias induced by having to estimate the additional parameter β_1 that is 0 under the null hypothesis.

Finally, we examine the economic value of the predicting capability of the models in (5a), (5b) and (5c) by looking for sizeable risk-adjusted returns in asset allocation. To this end, we conduct a portfolio exercise with a mean-variance investor that every month allocates his or her wealth between a 1-month Treasury (risk-free) bond and an n-month Treasury (risky) bond. By solving the same expected utility maximization problem as in Eriksen (2017), at time t, the investor optimally allocates a proportion of:

$$w_t^{(n)} = \frac{1}{\gamma} \frac{\mathrm{E}_t \left[rx_{t+1}^{(n-1)} \right]}{\mathrm{Var}_t \left[rx_{t+1}^{(n-1)} \right]}, \quad (8)$$

of his or her wealth to the n-month bond, and $(1 - w_t^{(n)})$ to the 1-month bond. $\mathrm{E}_t \left[rx_{t+1}^{(n-1)} \right]$ denotes the conditional expectation of the n-month bond return, for which the investor can use the out-of-sample forecasts generated either by one of the models that include $\mathrm{TR}^{(eq)}$ or by

---

[19]We use the Bauer and Hamilton (2018) procedure to also bootstrap the p-values of the R^2_{OS} statistic.

its benchmark that does not use the equity tail factor as predictor. $\text{Var}_t\left[rx_{t+1}^{(n-1)}\right]$ denotes the conditional variance of the n-month bond return, which we estimate with the sample variance of the returns observed over the past 10 years. γ represents the investor's level of risk aversion. Following Thornton and Valente (2012) and Gargano et al. (2019), we assume a risk aversion coefficient of $\gamma = 5$ but we also consider a less risk-averse investor characterized by $\gamma = 3$. Furthermore, as in the study of Huang et al. (2019), we prevent extreme positions by restricting the weight $w_t^{(n)}$ on the risky bond to lie in the interval $[-1, 5]$, which amounts to a maximum short-sale of 100% and a maximum leverage of 400%. The investor's portfolio return realized at time $t + 1$ is given by

$$r_{\mathcal{P},t+1}^{(n)} = y_t^{(1)} + w_t^{(n)} rx_{t+1}^{(n-1)} \ . \tag{9}$$

where $y_t^{(1)}$ is the yield of the zero-coupon bond with 1-month maturity. The certainty equivalent return (CER) of the portfolio, which is defined as the average utility realized by the investor from using the optimal weights $w_t^{(n)}$, is given by

$$\text{CER}_{\mathcal{P}}^{(n)} = \mu_{\mathcal{P}}^{(n)} - \frac{\gamma}{2}\sigma_{\mathcal{P}}^{2\,(n)} \ , \tag{10}$$

where $\mu_{\mathcal{P}} = T^{-1}\sum_{t=1}^{T} r_{\mathcal{P},t+1}^{(n)}$ and $\sigma_{\mathcal{P}}^{2\,(n)} = T^{-1}\sum_{t=1}^{T}\left(r_{\mathcal{P},t+1}^{(n)} - \mu_{\mathcal{P}}\right)^2$. In order to establish whether an investor that relies on the investment signals generated by $\text{TR}^{(eq)}$ is able to improve upon the economic utility realized by an investor whose portfolio allocations do not rely on equity tail risk, we compute the difference between the CER for the investor that uses one of the preferred models in (5a), (5b) and (5c) and the CER for the investor that uses the corresponding benchmark. This difference, which we denote by $\Delta^{(n)}$ and we express in terms of an annualized percentage CER gain, can be interpreted as the portfolio management fee that an investor is willing to pay for the bond return forecasts produced with equity tail risk. Following Thornton and Valente (2012), Eriksen (2017) and Huang et al. (2019), we assess portfolio performance using also the manipulation-proof performance (MPP) measure of Goetzmann et al. (2007). For

each of the preferred models, we compute the MPP improvement relative to its benchmark as

$$\Theta^{(n)} = \frac{1}{1-\gamma}\left[\ln\left(T^{-1}\sum_{t=1}^{T}\left[\frac{1+r_{\mathcal{P},t+1,1}^{(n)}}{1+y_{t+1}^{(1)}}\right]^{1-\gamma}\right) - \ln\left(T^{-1}\sum_{t=1}^{T}\left[\frac{1+r_{\mathcal{P},t+1,0}^{(n)}}{1+y_{t+1}^{(1)}}\right]^{1-\gamma}\right)\right], \quad (11)$$

where $r_{\mathcal{P},t+1,1}^{(n)}$ and $r_{\mathcal{P},t+1,0}^{(n)}$ are the realized portfolio returns associated with the preferred and benchmark models. As with the CER gain, we report annualized percentage values for $\Theta^{(n)}$.

3.2 Term Structure Modeling

We now introduce the term structure framework adopted in this paper and we present its estimation procedure. To set up the model, we rely on the approach suggested by Adrian et al. (2013), which has the advantage that the pricing factors of bonds are not restricted to linear combinations of yields. Factors can indeed also be of different origin, such as the equity tail risk measure $\text{TR}^{(eq)}$ defined in Section 2.2. After deriving the data generating process of log excess bond returns from a dynamic asset pricing model with an exponentially affine pricing kernel, Adrian et al. (2013) propose a new regression-based estimation technique for the model parameters. The linear regressions of this simple estimator avoid the computational burden of maximum likelihood methods, which have previously been the standard approach to the pricing of interest rates.

The formulation and estimation of the Gaussian ATSM in Adrian et al. (2013) can be summarized as follows. A $K \times 1$ vector of pricing factors, $\mathbf{X}_t$, is assumed to evolve according to a VAR process of order one:

$$\mathbf{X}_{t+1} = \boldsymbol{\mu} + \boldsymbol{\phi}\mathbf{X}_t + \mathbf{v}_{t+1}, \quad (12)$$

where the shocks $\mathbf{v}_{t+1} \sim \mathcal{N}(\mathbf{0}, \boldsymbol{\Sigma})$ are conditionally Gaussian with zero mean and variance-covariance matrix $\boldsymbol{\Sigma}$. Letting $P_t^{(n)}$ denote the price of a zero-coupon bond with maturity n at

21

time t, the assumption of no-arbitrage implies the existence of a pricing kernel M_{t+1} such that,

$$P_t^{(n)} = E_t\left[M_{t+1}P_{t+1}^{(n-1)}\right] . \tag{13}$$

The pricing kernel M_{t+1} is assumed to have the following exponential form:

$$M_{t+1} = \exp\left(-r_t - \frac{1}{2}\boldsymbol{\lambda}_t'\boldsymbol{\lambda}_t - \boldsymbol{\lambda}_t'\boldsymbol{\Sigma}^{-1/2}\mathbf{v}_{t+1}\right) , \tag{14}$$

where $r_t = -\ln P_t^{(1)}$ is the continuously compounded one-period risk-free rate and $\boldsymbol{\lambda}_t$ is the $K \times 1$ vector of market prices of risk, which are affine in the factors as in Duffee (2002):

$$\boldsymbol{\lambda}_t = \boldsymbol{\Sigma}^{-1/2}(\boldsymbol{\lambda}_0 + \boldsymbol{\lambda}_1\mathbf{X}_t) . \tag{15}$$

The log excess one-period return of a bond maturing in n periods is defined as follows,

$$rx_{t+1}^{(n-1)} = \ln P_{t+1}^{(n-1)} - \ln P_t^{(n)} - r_t . \tag{16}$$

After assuming the joint normality of $\{rx_{t+1}^{(n-1)}, \mathbf{v}_{t+1}\}$, Adrian et al. (2013) derive the return generating process for log excess returns, which takes the form[20],

$$rx_{t+1}^{(n-1)} = \boldsymbol{\beta}^{(n-1)'}(\boldsymbol{\lambda}_0 + \boldsymbol{\lambda}_1\mathbf{X}_t) - \frac{1}{2}(\boldsymbol{\beta}^{(n-1)'}\boldsymbol{\Sigma}\boldsymbol{\beta}^{(n-1)} + \sigma^2) + \boldsymbol{\beta}^{(n-1)'}\mathbf{v}_{t+1} + e_{t+1}^{(n-1)} , \tag{17}$$

where the return pricing errors $e_{t+1}^{(n-1)} \sim$ i.i.d. $(0, \sigma^2)$ are conditionally independently and identically distributed with zero mean and variance σ^2. Letting N be the number of bond maturities available and T be the number of time periods at which bond returns are observed, Adrian

---

[20]For the full derivation of the data generating process see Section 2.1 in Adrian et al. (2013).

et al. (2013) rewrite equation (17) in the stacked form,

$$\mathbf{rx} = \boldsymbol{\beta}'(\boldsymbol{\lambda}_0 \boldsymbol{\iota}_T' + \boldsymbol{\lambda}_1 \mathbf{X}_-) - \frac{1}{2}(\mathbf{B}^* \text{vec}(\boldsymbol{\Sigma}) + \sigma^2 \boldsymbol{\iota}_N) \boldsymbol{\iota}_T' + \boldsymbol{\beta}' \mathbf{V} + \mathbf{E} \, , \qquad (18)$$

where $\mathbf{rx}$ is an $N \times T$ matrix of excess bond returns, $\boldsymbol{\beta} = \left[\boldsymbol{\beta}^{(1)} \, \boldsymbol{\beta}^{(2)} \, ... \, \boldsymbol{\beta}^{(N)} \right]$ is a $K \times N$ matrix of factor loadings, $\boldsymbol{\iota}_T$ and $\boldsymbol{\iota}_N$ are a $T \times 1$ and $N \times 1$ vector of ones, $\mathbf{X}_- = [\mathbf{X}_0 \, \mathbf{X}_1 \, ... \, \mathbf{X}_{T-1}]$ is a $K \times T$ matrix of lagged pricing factors, $\mathbf{B}^* = \left[\text{vec}(\boldsymbol{\beta}^{(1)} \boldsymbol{\beta}^{(1)'}) \, ... \, \text{vec}(\boldsymbol{\beta}^{(N)} \boldsymbol{\beta}^{(N)'}) \right]'$ is an $N \times K^2$ matrix, $\mathbf{V}$ is a $K \times T$ matrix and $\mathbf{E}$ is an $N \times T$ matrix.

The main novelty of the approach taken by Adrian et al. (2013) to model the term structure of interest rates is the use of ordinary least squares to estimate the parameters of equation (18). In particular, the authors propose the following three-step procedure:

1. Estimate the coefficients of the VAR model in equation (12) by ordinary least squares.[21] Stack the estimates of the innovations $\hat{\mathbf{v}}_{t+1}$ into matrix $\hat{\mathbf{V}}$ and use this to construct an estimator of the variance-covariance matrix $\hat{\boldsymbol{\Sigma}} = \hat{\mathbf{V}} \hat{\mathbf{V}}' / T$.

2. From the excess return regression equation $\mathbf{rx} = \mathbf{a} \boldsymbol{\iota}_T' + \boldsymbol{\beta}' \hat{\mathbf{V}} + \mathbf{c} \mathbf{X}_- + \mathbf{E}$, obtain estimates of $\hat{\mathbf{a}}$, $\hat{\boldsymbol{\beta}}$ and $\hat{\mathbf{c}}$. Use $\hat{\boldsymbol{\beta}}$ to construct $\hat{\mathbf{B}}^*$. Stack the residuals of the regression into matrix $\hat{\mathbf{E}}$ and use this to construct an estimator of the variance $\hat{\sigma}^2 = \text{tr}(\hat{\mathbf{E}} \hat{\mathbf{E}}') / NT$.

3. Noting from equation (18) that $\mathbf{a} = \boldsymbol{\beta}' \boldsymbol{\lambda}_0 - \frac{1}{2}(\mathbf{B}^* \text{vec}(\boldsymbol{\Sigma}) + \sigma^2 \boldsymbol{\iota}_N)$ and $\mathbf{c} = \boldsymbol{\beta}' \boldsymbol{\lambda}_1$, estimate the price of risk parameters $\boldsymbol{\lambda}_0$ and $\boldsymbol{\lambda}_1$ via cross-sectional regressions,

$$\hat{\boldsymbol{\lambda}}_0 = (\hat{\boldsymbol{\beta}} \hat{\boldsymbol{\beta}}')^{-1} \hat{\boldsymbol{\beta}} \left(\hat{\mathbf{a}} + \frac{1}{2}(\hat{\mathbf{B}}^* \text{vec}(\hat{\boldsymbol{\Sigma}}) + \hat{\sigma}^2 \boldsymbol{\iota}_N) \right) \, , \qquad (19)$$

$$\hat{\boldsymbol{\lambda}}_1 = (\hat{\boldsymbol{\beta}} \hat{\boldsymbol{\beta}}')^{-1} \hat{\boldsymbol{\beta}} \hat{\mathbf{c}} \, . \qquad (20)$$

The analytical expressions of the asymptotic variance and covariance of $\hat{\boldsymbol{\beta}}$ and $\hat{\boldsymbol{\Lambda}} = [\hat{\boldsymbol{\lambda}}_0 \, \hat{\boldsymbol{\lambda}}_1]$, which we do not report here to save space, are provided in Appendix A.1 of Adrian et al.

---

[21] For estimation purposes, Adrian et al. (2013) advise to set $\boldsymbol{\mu} = 0$ in case of zero-mean pricing factors.

(2013). From the estimated model parameters, Adrian et al. (2013) show how to generate a yield curve. Indeed, within the proposed framework, bond prices are exponentially affine in the pricing factors. Consequently, the yield of a zero-coupon bond with maturity n at time t, $y_t^{(n)}$, can be expressed as follows,

$$y_t^{(n)} = -\frac{1}{n}[a_n + \mathbf{b}_n' \mathbf{X}_t] + u_t^{(n)} \,, \tag{21}$$

where the coefficients a_n and $\mathbf{b}_n$ are obtained from the following no-arbitrage recursions,

$$a_n = a_{n-1} + \mathbf{b}_{n-1}'(\boldsymbol{\mu} - \boldsymbol{\lambda}_0) + \frac{1}{2}(\mathbf{b}_{n-1}'\boldsymbol{\Sigma}\mathbf{b}_{n-1} + \sigma^2) - \delta_0 \,, \tag{22}$$

$$\mathbf{b}_n' = \mathbf{b}_{n-1}'(\boldsymbol{\phi} - \boldsymbol{\lambda}_1) - \boldsymbol{\delta}_1' \,, \tag{23}$$

subject to the initial conditions $a_0 = 0$, $\mathbf{b}_n = \mathbf{0}$, $a_1 = -\delta_0$ and $\mathbf{b}_1 = -\boldsymbol{\delta}_1$. The parameters δ_0 and $\boldsymbol{\delta}_1$ are estimated by regressing the short rate, $r_t = -\ln P_t^{(1)}$, on a constant and contemporaneous pricing factors according to,

$$r_t = \delta_0 + \boldsymbol{\delta}_1 \mathbf{X}_t + \epsilon_t \,, \quad \epsilon_t \sim i.i.d. \ (0, \sigma_\epsilon^2) \,. \tag{24}$$

By setting the price of risk parameters $\boldsymbol{\lambda}_0$ and $\boldsymbol{\lambda}_1$ to zero in equation (22) and (23), Adrian et al. (2013) obtain a_n^{RN} and $\mathbf{b}_n^{\text{RN}}$, which they use to generate the risk-neutral yields, $y_t^{(n) \ \text{RN}}$. These yields reflect the average expected short rate over the current and the subsequent $(n-1)$ periods and are computed as follows,

$$y_t^{(n) \ \text{RN}} = \frac{1}{n}\sum_{i=0}^{n-1} \mathrm{E}_t[r_{t+i}] = -\frac{1}{n}[a_n^{\text{RN}} + \mathbf{b}_n^{\text{RN}'} \mathbf{X}_t] \,. \tag{25}$$

Given equation (21) and (25), the term premium $TP_t^{(n)}$, which is the additional compensation required for investing in long-term bonds relative to rolling over a series of short-term bonds,

can be calculated as follows,

$$TP_t^{(n)} = y_t^{(n)} - y_t^{(n) \text{ RN}} \ . \tag{26}$$

In the next sections we specify and estimate a term structure model for US interest rates following the procedure outlined above. The difference between the Gaussian ATSM in Adrian et al. (2013) and ours is that we use a different set of pricing factors. Indeed, we include in $\mathbf{X}_t$ not only the PCs of bond yields but also the equity tail factor $\text{TR}^{(eq)}$ described in Section 2.2.

3.3 Alternative Risk Premium Estimation

In this section we briefly review the method of Giglio and Xiu (2019), GX hereafter, to estimate the risk premium of an observable factor – equity tail risk in our case – which is valid even when the observed factor is measured with noise and the model does not fully account for all priced sources of risk in the economy. The new GX three-pass methodology combines principal component analysis (PCA) with two-pass regressions (Fama and MacBeth, 1973) to consistently estimate the risk premium of any observed factor. The estimator relies on a large cross section of test assets and is valid as long as PCA can recover the entire factor space of test asset returns. Unlike the term structure model described above where the pricing kernel is an exponentially affine function of the state variables and the market prices of risk are time-varying, Giglio and Xiu (2019) assume a linear stochastic discount factor and constant risk premiums. Working with a linear asset pricing model they can exploit the so-called "rotation invariance" property that allows them to estimate the risk premium γ_g of an observable factor g_t without necessarily observing or knowing all the true factors v_t entering the pricing kernel. Written in matrix form, the GX model consists of the following two equations:

$$\bar{R} = \beta\bar{V} + \bar{U} \ , \tag{27}$$

$$\bar{G} = \eta\bar{V} + \bar{Z} \ , \tag{28}$$

where $\bar{R}$ is the $n \times T$ matrix of demeaned excess returns of the test assets, $\bar{V}$ is the $p \times T$ matrix of demeaned true factors, β is the $n \times p$ matrix of factor risk exposures, $\bar{U}$ is the $n \times T$ matrix of idiosyncratic errors, $\bar{G}$ is the $d \times T$ matrix of demeaned observed factors, the risk premium of which has to be estimated, η is the $d \times p$ matrix of the loadings of the observed factors on the unobserved true factors, and $\bar{Z}$ is the $d \times T$ matrix of measurement errors. The GX estimator proceeds in three steps which can be summarized as follows:

1. *PCA step.* The first pass consists of estimating the true factors and factor risk exposures by extracting the first p principal components and their respective loadings from the cross section of test asset returns.[22] The estimators can therefore be written as:

$$\widehat{V} = T^{1/2}(\xi_1 : \xi_2 : ... : \xi_p)^\intercal \quad \text{and} \quad \widehat{\beta} = T^{-1}\bar{R}\widehat{V}^\intercal , \qquad (29)$$

where $\xi_1, ..., \xi_p$ are the eigenvectors corresponding to the largest p eigenvalues of $n^{-1}T^{-1}\bar{R}^\intercal\bar{R}$.

2. *Cross-sectional regression step.* The second pass consists of estimating the risk premia of the latent factors by running a cross-sectional ordinary least square regression of average realized excess returns, $\bar{r}$, onto the previously estimated factor loadings, $\widehat{\beta}$:

$$\widehat{\gamma} = (\widehat{\beta}^\intercal\widehat{\beta})^{-1}\widehat{\beta}^\intercal\bar{r} . \qquad (30)$$

3. *Time-series regression step.* The third pass consists of estimating the risk premia of the factors of interest by first running a time series regression of the demeaned candidate factors onto the space of the latent factors and then combining these estimates with those of the second step. The estimator $\widehat{\eta}$ of the loadings on the latent factors and the estimator

---

[22]Giglio and Xiu (2019) propose a consistent estimator of p in their Online Appendix I.1. They also demonstrate that as long as the number of principal components used is greater than or equal to the true number of factors, the estimator of the risk premium is consistent. In our empirical analysis we report results with respect not only to the number of principal components selected with the Giglio and Xiu (2019) criterion but also to higher numbers of factors to ensure robustness of the estimates.

$\widehat{\gamma}_g$ of the risk premia of the observed factors of interest can therefore be written as:

$$\widehat{\eta} = \bar{G}\widehat{V}^{\mathsf{T}}(\widehat{V}\widehat{V}^{\mathsf{T}})^{-1} \, , \tag{31}$$

$$\widehat{\gamma}_g = \widehat{\eta}\widehat{\gamma} \, . \tag{32}$$

Due to space considerations, we do not provide analytical expressions for the asymptotic variance of the risk-premium estimates and we refer the reader to Section 4 in Giglio and Xiu (2019). Another important aspect considered in the GX procedure is the noise that is contained in the observable factors and that is uncorrelated with the test asset returns. The higher the noise, the more weakly the factor is reflected in the cross section of test assets. To understand whether the factor of interest has low exposure to the fundamental factors (η is small) or whether it is dominated by noise (z_t is large), Giglio and Xiu (2019) define the R^2 of the time-series regressions in the third-pass, $R_g^2 = \frac{\widehat{\eta}\widehat{V}\widehat{V}^{\mathsf{T}}\widehat{\eta}^{\mathsf{T}}}{\bar{G}\bar{G}^{\mathsf{T}}}$. Furthermore, they provide a Wald test for the null that the observed factor g is weak by formulating the hypotheses $H_0 : \eta = 0$ vs $H_1 : \eta \neq 0$.

In our paper we apply the GX three-pass method to the whole term structure of Treasury bond returns to estimate and test the significance of the risk premium of equity tail risk. As it is standard in the literature, we use AR(1) innovations in $\text{TR}^{(eq)}$ as the observable factor g. We also report the R_g^2 and Wald p-value for the strength of the observed factor g with respect to the cross section of Treasury returns.

4   Empirical Results

In this section we present our empirical results. We first consider in Section 4.1 the full-sample least-squares estimates for the bond return prediction models with equity tail risk. We empirically show that the equity tail factor $\text{TR}^{(eq)}$ significantly predicts monthly bond returns in- and out-of-sample and the more accurate forecasts can be of economic importance for an investor facing portfolio decisions. In Section 4.2 we discuss the estimates of the Gaussian ATSM

which allow to explore in detail the effects of equity tail risk on bond prices and determine whether $TR^{(eq)}$ is a priced source of risk in the term structure of US interest rates. In Section 4.3 we use the GX three-pass regressions as an alternative method for exploring the strength and pricing of the equity tail factor $TR^{(eq)}$. Finally, Section 4.4 investigates to what extent equity tail risk affects the government bond market of countries other than the United States.

4.1 Bond Return Predictability

We start by examining the interactions between the one-month returns of US Treasury bonds and the S&P 500 option-implied volatility that stems from large negative price jumps, $TR^{(eq)}$. Using the full sample (1996:01-2019:12) of monthly data, we run the predictive regressions in (5a), (5b) and (5c), for which we report in, respectively, Panels A, B, and C of Table 2 the least-squares estimates of the slope coefficients and their corresponding p-values. Numbers at the bottom of each panel correspond to the adjusted R-squared of the predictive regressions that include and exclude $TR^{(eq)}$ as predictor, and to the p-value of an F-test of the null hypothesis that the regression that includes $TR^{(eq)}$ does not give a significantly better fit to the data than does a regression without it. In order to ease interpretation of the results, all predictors, including those discussed later, have been normalized to have a zero mean and a standard deviation of one. Here and in the rest of this section, evidence is presented for returns on the one-, two-, three-, four-, five-, seven- and ten-year Treasury bonds ($n = 12, 24, 36, 48, 60, 84, 120$ months, respectively). The results of the analysis for other maturities are available upon request.

[Insert Table 2 here]

Consider first the results of the univariate model (5a) presented in Panel A. The one-month-ahead returns of US Treasury bonds exhibit strong interactions with the perceived tail risk in the US stock market. The coefficient of the S&P 500 option-implied tail risk measure $TR^{(eq)}$ is statistically significant at well below the 0.05 level across the whole yield curve. Looking at

the size of the coefficient, we observe that the impact of equity tail risk on bond risk premia is monotonically increasing with the bond maturity. Our estimates suggest that a one standard deviation increase in the equity tail factor raises the expected annualized return on the 1-year and 10-year Treasury bonds by about 0.4% and 6%, respectively. Furthermore, we note that for all maturities considered, the sign of the coefficient is positive. This result is in sharp contrast with that obtained by Crump and Gospodinov (2019) with a conceptually very different measure of equity tail risk. It can however be explained in light of the opposite movements observed in equity and bond prices in times of stress and the considerations raised by previous studies that found a negative relation between future stock returns and option-implied volatility measures, see, e.g., Xing et al. (2010) and An et al. (2014). That is, if we believe that informed traders with negative news choose the option market to trade first, then a tail risk increase is later accompanied by lower and higher prices on, respectively, the equity and bond markets, which are slow in incorporating the information embedded in the option volatility surface. At the very least, we provide validation of this in Section 5 by showing that the funds (meaning invested moneys) of mutual funds, exchange-traded funds and households, which are known to be slow or in any case not the first to rebalance portfolios when market conditions change, flow out of equities and into Treasuries in both initial and subsequent months of an equity tail risk increase.

Since the literature on bond return predictability is more often interested in the forecasting power of a variable beyond that of the information contained in the yield curve, we now discuss the results reported in Panels B and C of Table 2. When controlling for yield curve factors with the first 3 and 5 PCs, the coefficient associated with $\text{TR}^{(eq)}$ remains positive and highly significant for all bond maturities.[23] We find strong significance not only with the standard Newey-West p-values but also with the more robust p-values computed with the bootstrap procedure of Bauer and Hamilton (2018). Furthermore, we note that the inclusion of equity tail

---

[23]In results available upon request, we also considered specifications of the regression equations (5b) and (5c) that make use of the orthogonal component of $\text{TR}^{(eq)}$ with respect to the principal components. The coefficient in front of the equity tail factor continues to be statistically significant at the 0.05 level or lower for all maturities.

risk in the predictive regressions determines sizeable changes in the adjusted R^2s, which nearly double in Panel B and increase by about 50% in Panel C. Finally, the F-test results confirm the importance of $\text{TR}^{(eq)}$ for explaining the one-month-ahead variation in bond risk premia.

In addition to our baseline regressions in (5a), (5b) and (5c), we examine whether equity tail risk remains a strong predictor of future bond returns even when controlling for other successful return forecasting factors found in the literature. Specifically, we report in Panels D and E of Table 2 the results of regressions that use the equity tail factor in combination with, respectively, the Cochrane and Piazzesi (2005) and Cieslak and Povala (2015) factors. The Cochrane and Piazzesi (2005) bond return predictor is obtained as a linear combination of forward rates, while the Cieslak and Povala (2015) risk-premium factor is obtained from a decomposition of Treasury yields into inflation expectations and maturity-specific interest-rate cycles. Due to the low correlation that exists between the covariates, Treasury risk premia continue to exhibit significant interactions with both the successful predictors found in previous studies and the equity tail factor of this paper. Finally, we report in Panel F of Table 2 the estimates of a regression that includes $\text{TR}^{(eq)}$ in combination with the CBOE VIX unspanned by $\text{TR}^{(eq)}$, the equity variance risk premium of Bollerslev et al. (2014) and the CBOE Skew Index as predictors.[24] The immediate point that stands out here is that the VIX components that are not related to our equity tail factor, i.e. continuous return variation and right jump variation, are highly insignificant for all bond maturities along the term structure. Based on this result, we can state that the VIX does not have predictive power over-and-above $\text{TR}^{(eq)}$ for future bond returns. Furthermore, our finding that higher values of $\text{TR}^{(eq)}$ forecast higher next-month returns on Treasuries is robust to the inclusion of the VRP and the CBOE Skew Index, which, according to the estimates presented, have a negative effect on bond risk premia.[25]

---

[24]It is worth mentioning that the equity tail factor $\text{TR}^{(eq)}$ can be thought of as the VIX stripped of the diffusive part of volatility and the risk of positive price jumps. Hence, we deemed it appropriate to include the orthogonal component of the VIX as a predictor that controls for the implied volatility not captured by $\text{TR}^{(eq)}$.

[25]As an additional robustness check, we also considered the risk aversion proxy and uncertainty index of Bekaert et al. (2013) and Bekaert et al. (2019). The results, which are available upon request, indicate that the predictive power of $\text{TR}^{(eq)}$ survives the inclusion of these additional controls.

We now discuss the out-of-sample performance of the models in (5a), (5b) and (5c), which predict bond returns with the S&P 500 option-implied tail risk measure $TR^{(eq)}$. The accuracy of the bond return forecasts of model (5a) is measured relative to the recursively updated forecasts from the EH model that projects returns on a constant, while the accuracy of the forecasts of models (5b) and (5c) is measured relative to the forecasts of the models that only include the principal components as predictors. Table 3 reports the Campbell and Thompson (2008) out-of-sample R^2_{OS} values for each model, alongside the p-value of the Clark and West (2007) MSPE-adjusted statistic for testing $H_0 : R^2_{OS} \leq 0$ against $H_1 : R^2_{OS} > 0$. We report results for both increasing and rolling windows of past data used in the estimation method. The out-of-sample period is 2008:01–2019:12.

[Insert Table 3 here]

Overall, the results in Table 3 suggest that the good in-sample fit provided by $TR^{(eq)}$ and discussed above translates into positive out-of-sample performance. For instance, when the benchmark is the EH model, we find that equity tail risk improves the out-of-sample bond return predictions across all maturities. The gains are in the range of 1.4% to 4.3% for both window estimations, with the largest improvements observed for medium-maturity bonds. We note that with the robust inference method developed by Bauer and Hamilton (2018) the increases in the R^2_{OS}s are statistically significant at the 0.05 level for bond maturities greater than 2 years, while the p-values of the Clark and West (2007) MSPE-adjusted statistic are lower than 10% for maturities of 5 years or longer. Similarly, we observe positive values of R^2_{OS} in Panels B and C indicating higher predictive accuracy for the bond return prediction models that include $TR^{(eq)}$ compared to their PCs-only benchmark specifications. Except for the 10-year bond, the bootstrap p-values of both R^2_{OS} and Clark and West (2007) MSPE-adjusted statistic are below 0.1, thus proving the statistical significance of the results.

Next, we examine the economic value of using equity tail risk to make one-month-ahead pre-

31

dictions of Treasury bond returns. Table 4 reports values for the CER gain (Δ) and Goetzmann et al. (2007) MPP improvement (Θ) that an investor can achieve by switching from a benchmark to a model that uses the equity tail factor $TR^{(eq)}$ to predict bond returns. For completeness we also present the Sharpe ratio of the portfolios associated with the two competing models. Results are based on the out-of-sample model forecasts produced for the period 2008:01–2019:12 with predictive models that are recursively estimated with a rolling window approach.

[Insert Table 4 here]

From an investment perspective, the results in Table 4 indicate that predicting bond returns with equity tail risk can generate substantial risk-adjusted returns. This is particularly the case for an investor that can use $TR^{(eq)}$ alongside the first 5 PCs of bond yields to predict the one-month-ahead returns of Treasuries with maturities in the range of two to seven years. Specifically, we find that the investor is willing to pay from 60 up to 370 basis points per year to switch from the 5 PCs-only benchmark to the model that forecasts bond returns also with equity tail risk. The Sharpe ratio of the portfolio associated with this model is always greater than the benchmark. To help visualize these asset allocation gains, Figure 2 displays the cumulative returns of the two trading strategies available to an investor with a risk aversion of $\gamma = 5$ that predicts bond returns with $TR^{(eq)}$ and/or the first 5 PCs of yields. By examining Panels A and B of Table 4, we see that even when the benchmark is the EH or 3 PCs-only model an investor trading some specific medium-term bonds is substantially better off following the return forecasts based on equity tail risk. In fact, the 5-year bond investor is willing to pay a fee of up to 100 basis points per year to switch to the predictive model with equity tail risk.

[Insert Figure 2 here]

Finally, we briefly discuss how the forecast performance of the models in (5a), (5b) and (5c)

32

is related to the real economy. Panels A and B of Table 5 report contemporaneous correlations between the out-of-sample forecasts of one-month-ahead Treasury bond returns and the CFNAI and the macroeconomic uncertainty index ($\mathbb{U}^{\text{MACRO}}$) constructed by Jurado et al. (2015). We note that the bond risk premia implied by any of the three models are countercyclical as they are negatively correlated with macroeconomic condition. This is a common result found in the literature on bond return predictability and is consistent with economic theories in which investors require compensation for bearing business cycle risk, see, e.g., Eriksen (2017) and references therein. In order to understand whether the models that include $\text{TR}^{(eq)}$ as predictor perform well in recessions or expansion periods, Panels C and D of Table 5 report contemporaneous correlations between the models' relative forecast and portfolio performance and the CFNAI. The relative forecast performance is defined as the difference in cumulative squared prediction error (DCSPE), while the relative portfolio performance is defined as the difference in cumulative realized utilities (DCRU). As we can see, the forecasting performance of the three models tends to be positively correlated with the CFNAI, indicating superior model performance in good times when the CFNAI is high. Looking at the relative portfolio performance gives less clear-cut results since the correlations vary substantially across maturities. In fact, asset allocation gains seem to be achievable during expansion periods for short- and medium-term bonds and during recessions for long-term bonds.

[Insert Table 5 here]

4.2 Bond Pricing in ATSM

On the basis of the significant interactions observed between future Treasury returns and the equity tail factor $\text{TR}^{(eq)}$, it is of interest to examine to what extent the left tail volatility of the stock market also affects the current level of bond prices. Figure 3 shows the time trend of Treasury bond yields against periods of elevated equity tail risk, corresponding to when

$\mathrm{TR}^{(eq)}$ is above its historical 85-th percentile. As it can be seen in the graph, many of the most remarkable declines in Treasury rates occurred at times of elevated equity tail risk. In fact, the average contemporaneous correlation between bond yields and $\mathrm{TR}^{(eq)}$ is about -0.15.

[Insert Figure 3 here]

To investigate the role of equity jump tail risk in pricing US government bonds, we now estimate the Gaussian ATSM of Section 3.2 with the inclusion of our equity tail factor in the vector of state variables. In addition to $\mathrm{TR}^{(eq)}$, however, we also need pricing factors that summarize the information contained in the yield curve. To this end, we extract the first five principal components of the US yield curve, which have proven to be remarkably effective in fitting the cross-section of bond yields and returns in Adrian et al. (2013). Based on this evidence, we let these PCs drive the interest rates of our model as well, but with a slight modification of the methodology. Indeed, in order to have pricing factors that are uncorrelated with each other, we follow Cochrane and Piazzesi (2008) and extract the principal components not from the conventional yields, but instead from the yields orthogonalized to the extra factor, which in our study is $\mathrm{TR}^{(eq)}$. By doing so, we obtain yield curve factors that are unrelated to the pricing of tail risk in the stock market, which is entirely ascribed to the $\mathrm{TR}^{(eq)}$ factor. In view of these considerations, we employ the following set of pricing factors in our Gaussian ATSM,

$$\mathbf{X}_t = \left[\mathrm{TR}_t^{(eq)}, \ \mathrm{PC1}_t, \ \mathrm{PC2}_t, \ \mathrm{PC3}_t, \ \mathrm{PC4}_t, \ \mathrm{PC5}_t \right]', \tag{33}$$

where $\mathrm{TR}^{(eq)}$ is the S&P 500 option-implied measure of left tail volatility, and PC1–PC5 are the first five principal components estimated from an eigenvalue decomposition of the covariance matrix of zero-coupon bond yields of maturities $n = 3, 6, ..., 120$ months, orthogonal to $\mathrm{TR}^{(eq)}$. All factors have mean zero and unit variance, and they are plotted in Figure 4. The panels of PC1–PC5 also present the principal components of the conventional non-orthogonalized bond

yields. We find that estimates of the factors extracted using the two yield curves track each other quite closely, with the largest differences occurring for PC2 and PC3 at the onset of the financial crisis.[26] Therefore, the orthogonalization of the rates with respect to $\text{TR}^{(eq)}$ does not appear to significantly alter the interpretation and role of the principal components in describing the characteristics of the US Treasury yield curve.

[Insert Figure 4 here]

Given the vector of state variables in (33), we estimate our Gaussian ATSM using the method put forward by Adrian et al. (2013) and discussed in Section 3.2. In particular, we use one-month excess returns for Treasury bonds with maturities $n = 6, 12, ..., 120$ months to fit the cross-section of yields. The summary statistics of the pricing errors implied by our term structure model, which accounts for equity tail risk, and a benchmark model based on only the first five PCs of the yield curve are provided in Table 6. Overall the results indicate a good fit between the data and the proposed model with equity tail risk. Indeed, both the mean and the standard deviation of our yield pricing errors remain well below a basis point for all maturities and they never exceed, in absolute value, those of the benchmark. As for the return pricing errors, we notice that explicitly including the equity tail risk factor $\text{TR}^{(eq)}$ in a Gaussian ATSM can improve the fit especially to the short end of the US yield curve. Moreover, consistent with the way Adrian et al. (2013) construct their framework for the term structure of interest rates, we observe a strong autocorrelation in the yield pricing errors and a negligible one in the return pricing errors, except for the 3-year bond. The success of our model in fitting the yield curve is shown graphically in the left panels of Figure 5. In these plots, the solid black lines of observed yields are visually indistinguishable from the dashed gray lines of model-implied yields. Similarly, the right panels of Figure 5 display the tight fit between actual and fitted

---

[26]In results available upon request, we have found significant relationships only between $\text{TR}^{(eq)}$ and PC2 and PC3 of the conventional non-orthogonalized bond yields. Both correlation coefficients were around -0.24.

excess Treasury returns. The dashed red lines plot the model-implied dynamics of bond term premia in the left panels and of the expected component of excess returns in the right panels.

[Insert Table 6 here]

[Insert Figure 5 here]

The estimation approach proposed by Adrian et al. (2013) allows for direct testing of the presence of unspanned factors, i.e. factors that do not help explain variation in Treasury returns. The specification test is implemented as a Wald test of the null hypothesis that bond return exposures to a given factor are jointly equal to zero. Letting $\boldsymbol{\beta}_i$ be the i-th column of $\boldsymbol{\beta}'$, the Wald statistic, under the null $H_0 : \boldsymbol{\beta}_i = \mathbf{0}_{N \times 1}$, is defined as follows,

$$W_{\beta_i} = \hat{\boldsymbol{\beta}}_i' \hat{\mathcal{V}}_{\beta_i}^{-1} \hat{\boldsymbol{\beta}}_i \overset{\alpha}{\sim} \chi^2(N) \ , \tag{34}$$

where $\hat{\mathcal{V}}_{\beta_i}$ is an $N \times N$ diagonal matrix that contains the estimated variances of the $\hat{\boldsymbol{\beta}}_i$ coefficient estimates.[27] The results of the Wald test on the pricing factors of both the proposed ATSM with equity tail risk and the benchmark PC-only specification are shown in Table 7. As we can see, we strongly reject the hypothesis of unspanned factor for each of our state variables. This means that the data support the use of the equity tail factor $\text{TR}^{(eq)}$, together with the yield curve factors indicated by Adrian et al. (2013), for pricing government bonds in the US market over the period $1996 - 2019$.

[Insert Table 7 here]

We now examine whether the risk factors that we use in our Gaussian ATSM are priced in the cross-section of Treasury returns. To this end, we follow Adrian et al. (2013) and perform

---

[27]See Appendix A.1 in Adrian et al. (2013) for the analytical expressions of the asymptotic variance of the estimators.

a Wald test of the null hypothesis that the market price of risk parameters associated with a given model factor are jointly equal to zero. Letting $\boldsymbol{\lambda}'_i$ be the i-th row of $\boldsymbol{\Lambda} = [\boldsymbol{\lambda}_0\ \boldsymbol{\lambda}_1]$, the Wald statistic, under the null $H_0 : \boldsymbol{\lambda}'_i = \mathbf{0}_{1 \times (K+1)}$, is defined as follows,

$$W_{\Lambda_i} = \hat{\boldsymbol{\lambda}}'_i \hat{\mathcal{V}}_{\lambda_i}^{-1} \hat{\boldsymbol{\lambda}}_i \overset{\alpha}{\sim} \chi^2(K+1) \ , \tag{35}$$

where $\hat{\mathcal{V}}_{\lambda_i}$ is a square matrix of order $(K+1)$ that contains the estimated variances of the $\hat{\boldsymbol{\lambda}}_i$ coefficient estimates.[28] In addition, in order to test whether the market prices of risk are time-varying, Adrian et al. (2013) propose the following Wald test which focuses on $\boldsymbol{\lambda}_1$ and excludes the contribution of $\boldsymbol{\lambda}_0$. Letting $\boldsymbol{\lambda}'_{1_i}$ be the i-th row of $\boldsymbol{\lambda}_1$, the Wald statistic of this second test, under the null $H_0 : \boldsymbol{\lambda}'_{1_i} = \mathbf{0}_{1 \times (K)}$, is defined as follows,

$$W_{\lambda_{1_i}} = \hat{\boldsymbol{\lambda}}'_{1_i} \hat{\mathcal{V}}_{\lambda_{1_i}}^{-1} \hat{\boldsymbol{\lambda}}_{1_i} \overset{\alpha}{\sim} \chi^2(K) \ . \tag{36}$$

In Table 8, we report the estimates and t-statistics for the market price of risk parameters in the proposed Gaussian ATSM, together with the Wald statistics and p-values for the two tests just described. Examining the first row of the table, we note that equity tail risk, as measured by exposure to $\text{TR}^{(eq)}$, is strongly priced in our term structure model with a p-value of 9.2%. We detect statistically significant time variations in the market price of equity tail risk, which are mostly explained by the level and curvature components of bond yields. Furthermore, when looking at the t-statistics in the second column of the table, we note that $\text{TR}^{(eq)}$ is an important driver of the market price of level risk. Finally, we observe that PC2 carries a significant price of risk in our term structure model. This result, together with the fact that Adrian et al. (2013) find a significant market price of slope risk only after adding an unspanned real activity factor to their framework, corroborates the hypothesis that valuable information about bond premia

---

[28]See Appendix A.1 in Adrian et al. (2013) for the analytical expressions of the asymptotic variance of the estimators.

is located outside of the yield curve.

[Insert Table 8 here]

The vector λ_t defined in equation (15) contains the time-t compensation for facing the risk introduced by each of our state variables. Figure 6 displays the time series of the estimated market price of equity tail risk. When this measure is negative (resp. positive), a positive shock to the equity tail factor $\text{TR}_t^{(eq)}$ corresponds to an unexpectedly high (resp. low) marginal value of consumption, that is a bad (resp. good) state of the economy. In this case, assets with value that increases in equity tail risk shocks earn negative (resp. positive) risk premia. In our empirical analysis we find that the sensitivity of bond prices to equity tail risk shocks, i.e. the $\beta_i^{(n-1)}$ coefficients, is positive across all maturities and the market price of equity tail risk is negative on average in the post-2001 period. These findings are compatible with Treasury bonds hedging equity tail risk shocks and earning a negative risk premium over the same period that previous studies have documented a negative stock-bond return correlation on average, see, among others, David and Veronesi (2013) and Campbell et al. (2020).

[Insert Figure 6 here]

We now discuss the impact of the state variables of our Gaussian ATSM on the pricing of Treasury bonds. The loadings of the yields on all model factors are reported in Figure 7, whereas the loadings of the expected one-month excess returns are displayed in Figure 8. From an examination of the state variables that are in common with the work of Adrian et al. (2013), we can see that our results are broadly consistent with the well-established role of these factors. Indeed, given the sign of the yield loadings on PC1, PC2 and PC3, we can argue that the first three principal components of yields preserve in our study the interpretation of, respectively, level, slope and curvature of the term structure. Moreover, the yield loadings on PC4 and PC5

are both quite small, reflecting the modest variability of bond rates explained by these factors. As can be seen from Figure 8, however, all the principal components, including the higher order ones, are important to explain variation in Treasury returns. Specifically, in line with previous findings concerning the predictability of bond returns with yield spreads, our evidence suggests that an increase in the slope factor forecasts higher expected excess returns on bonds of all maturities. Now turning to the new pricing factor that we propose in this paper, we observe from the top left panel of Figure 7 that the yield loadings on $\text{TR}^{(eq)}$ are negative across all maturities. These results imply that bond prices, which move inversely to yields, rise in response to a contemporaneous shock to the equity left tail factor. And since, by construction, $\text{TR}^{(eq)}$ is associated with a downturn in the stock market, we confirm the hypothesis that US Treasury bonds benefit from flight-to-safety flows during periods of turmoil.[29] Judging by the magnitude of the coefficients, the immediate flight-to-safety effect is stronger on shorter-term bonds. We find that a one standard deviation increase in the $\text{TR}^{(eq)}$ factor is associated with a reduction of about 40 basis point in the yields of Treasuries with maturities ranging from six months to three years. Further, it is worth noting that, according to the size of the loadings, the contemporaneous effect of the equity left tail factor on the yield curve is not negligible compared to that of the first three principal components. The expected return loadings on $\text{TR}^{(eq)}$ displayed in the top left panel of Figure 8 confirm the previously established positive relation between the left tail volatility of the stock market and the one-month-ahead risk premia of the US government bond market. These loadings, due to the convenient orthogonalization of pricing factors described at the start of this section, are equivalent to the coefficient estimates reported in Panel A of Table 2. In fact, a one standard deviation increase in the $\text{TR}^{(eq)}$ factor raises the annualized expected excess return by approximately 1% for the 2-year bond and 6% for the 10-year bond. The effect of a shock to the equity tail factor on the bond risk premia is

---

[29]In results available upon request, we found that the contemporaneous correlation between $\text{TR}^{(eq)}$ and the Fama and French (1993) market factor is -0.35. Also, there is a negative but insignificant relation between $\text{TR}^{(eq)}$ and the one-month-ahead stock market returns, as measured by the Fama and French (1993) market factor.

linearly related to the bond maturity.

[Insert Figure 7 here]

[Insert Figure 8 here]

We conclude this section by discussing how equity tail risk has affected the trend of yields, risk-neutral rates and term premia over the course of time. To this end, we calculate the component of fitted yields in equation (21) and the component of their risk-neutral counterparts in equation (25) that the model attributes to the equity left tail factor $\text{TR}^{(eq)}$. Similarly, we determine the contribution of equity tail risk to the bond term premia in equation (26) as the difference between the component of fitted yields and the component of their risk-neutral counterparts that the model ascribes to $\text{TR}^{(eq)}$. The left panels of Figure 9 illustrate the effect of the equity left tail factor $\text{TR}^{(eq)}$ on the dynamics of the 1-, 5- and 10-year Treasury yields, whereas the right panels display the effects on the expected future short rate and term premium embedded in those rates. The following remarks can be made by observing Figure 9. The effect of equity tail risk is much smaller (in absolute value) for the bond term premium than for the expectation of future short rates. Therefore, when the equity left tail factor $\text{TR}^{(eq)}$ increases, the reduction in the expected future short rate more than offsets the increase in the term premium. As a result, bond yields fall in periods of elevated equity tail risk. However, it is interesting to see that, although the same pattern is observed for all yields in Figure 3, the equity left tail factor $\text{TR}^{(eq)}$ has influenced the downward trend of rates differently depending on the bond maturity. Indeed, from the left panels of Figure 9, it appears that the dynamics of short-maturity bond yields was strongly affected by equity tail risk, whereas the response of longer-maturity rates was consistently negligible. This further corroborates our previous conclusion that short-term bonds provide a more effective shelter against equity market losses than long-term bonds do.

[Insert Figure 9 here]

To better visualize how the impact of equity tail risk varies across maturities and in time, Figure 10 shows the effect of the $\text{TR}^{(eq)}$ factor for the whole term structure calculated on selected dates: August 1998, October 2008, September 2011, and May 2013. Interest rates fell on all dates except for May 2013, when yields markedly rose with the announcement of the Federal Reserve's "taper tantrum". On that occasion, as it can be seen from the figure, $\text{TR}^{(eq)}$ did not play any role in the yield changes. On the other hand, at the peak of the 2008-09 financial crisis, we measure the impact of equity tail risk on bond yields to be larger than -200 basis points for Treasuries with maturities up to four years, while it is reduced to only -65 basis points for the 10-year Treasury. The rates showed strong downward oscillations also in the summer of 1998 and the second half of 2011, when the equity left tail factor increased in response to, respectively, the collapse of Long Term Capital Management fund and the intensification of the European sovereign debt crisis. In both these instances, the extent of the reduction in short-term bond rates that can be credited to equity tail risk is approximately 100 basis points.

[Insert Figure 10 here]

In conclusion, we can state that equity jump tail risk has been a dominant factor for the evolution of the short end of the US Treasury yield curve. In particular, while the unconventional monetary policies introduced by central banks to mitigate the severity of the financial crisis have been a major force in lowering longer-term yields (Kaminska and Zinna, 2018), the reduction in shorter-term yields can be associated with the investors' increased fear of a stock market crash.

4.3 Three-Pass Method Estimates

We now try to provide further evidence that equity tail risk matters for bond pricing using an alternative methodology to the ATSM discussed above. This is done by testing for weak factor and estimating the risk premium of equity tail risk with the novel three-pass procedure of Giglio and Xiu (2019). The results of the GX three-pass method applied to the whole term

structure of Treasury bond returns with AR(1) innovations in $\text{TR}^{(eq)}$ are reported in Table 9.

[Insert Table 9 here]

We start by examining the results reported in column $p = 5$, which corresponds to the number of principal components of bond returns selected with the criterion of Giglio and Xiu (2019).[30] For this number of latent factors, we find that the estimated risk premium of $\text{TR}^{(eq)}$ in the US government bond market is positive but not statistically different from 0 at the 10% level. We view this insignificance as the result of the constant-risk-premium assumption underlying the method of Giglio and Xiu (2019) that is incompatible with our and previous findings of time-varying risk compensation in the bond market. Nevertheless, we find evidence against the hypothesis that $\text{TR}^{(eq)}$ is measured with noise or weakly reflected in the cross section of government bond returns. In fact, the R^2 of the time-series regression in the third-pass of the GX procedure amounts to 0.08 and we reject, at the 5% significance level, the null of $\text{TR}^{(eq)}$ being a weak factor. If we now look at the estimates obtained with a higher number of latent factors, we observe robustness of our empirical results with respect to the choice of p. Even when using eight principal components, the market price of equity tail risk is still insignificant at the 0.1 level and we still reject the null of weak factor at the 0.05 level. Furthermore, we note that including the principal components beyond the sixth one does not result in further noticeable improvement in the regression R^2. On the other hand, we find that much of the information about equity tail risk is contained in the slope factor, with the R^2 that jumps from 0.01 to over 0.07 when the second principal component is included in the model.

4.4 International Evidence

In this subsection, we extend our empirical analysis of bond pricing and return predictability to the Treasury market of United Kingdom, Germany, Switzerland, France, Italy and Spain.

---

[30]See Online Appendix I.1 in Giglio and Xiu (2019) for a consistent estimator of p.

First, we explore to what extent the S&P 500 option-implied tail risk measure $\text{TR}^{(eq)}$ affects the Treasury market of countries other than the United States. Then, we estimate country-specific measures of equity tail risk and investigate the relation between these measures and the government bond market in the corresponding European country. To compute the one-month holding period returns on Treasuries in Europe, we construct a data set of end-of-month zero-coupon interest rates that extends from January 1996 to December 2018. We collect data for the United Kingdom (UK) from the Bank of England, for Germany (DE) from the Bundesbank and BIS database, for Switzerland (CH) from the Swiss National Bank and BIS database, for Italy (IT) and Spain (ES) from the BIS database, while for France (FR) we fit a Nelson-Siegel-Svensson model to the constant maturity yields from Datastream. As for the country-specific measures of equity tail risk, we follow the methodology outlined in Section 2.2 and estimate option-implied volatility that stems from large negative price jumps using daily data reported by OptionMetrics IvyDB Europe for the European style FTSE 100 (UK), DAX 30 (DE), SMI (CH), CAC 40 (FR), FTSE MIB (IT), and IBEX 35 (ES) equity-index options. Data is available from January 2002 to December 2018 for UK, DE and CH, from January 2007 to December 2018 for IT and FR, and from May 2007 to December 2018 for ES. We use option-implied left tail volatilities recorded at the end of the month for UK, DE and CH, while we use the average value over the last five days of the month for FR, IT, and ES since their less liquid option markets yield a much noisier measure of equity tail risk. Figure 11 displays the time series of these international equity tail risk measures along with the S&P 500 option-implied measure $\text{TR}^{(eq)}$. Comparing the left tail volatility of the US stock market to that of the UK, German, Swiss and French stock markets, we note a strong coherence between the series with all the correlation coefficients above 0.70. At the same time, however, there are also some important differences. In particular, we note that in 2002-03 the UK, DE and CH tail risk measures attained higher values and remained elevated for a much longer period of time than $\text{TR}^{(eq)}$, which however exhibits more pronounced peaks in the aftermath of the global financial crisis. With regard to

43

the equity tail risk measures of Italy and Spain, their series diverge quite substantially from that of the US measure with correlation coefficients of only 0.50 and 0.20, respectively.

[Insert Figure 11 here]

We begin by assessing the predictive power of the left tail volatility of the US stock market for future one-month returns on the government bond market of the European countries. To this end, we estimate the predictive regressions in (5a), (5b) and (5c) using international bond returns on the left hand side of the equations and $TR^{(eq)}$, combined with the principal components of the country-specific yield curves, on the right hand side. For each Treasury market, Table 10 reports the full-sample estimates of the coefficient of $TR^{(eq)}$ and the corresponding p-values computed with both Newey-West and Bauer and Hamilton (2018) inference procedures.

[Insert Table 10 here]

Overall, the results in Table 10 indicate that the perceived tail risk in the US stock market has significant explanatory power for future returns on Treasury bonds in the UK, Germany, Switzerland and France. When we do not control for yield curve factors in the return predictive regressions, the coefficient of $TR^{(eq)}$, assessed with the robust inference method developed by Bauer and Hamilton (2018), is statistically significant at the 0.05 level or lower for all maturities of UK, DE and CH bonds, and at the 0.10 level or lower for all maturities of FR bonds. Controlling with the first three or five principal components of bond yields does not change the results for the UK and DE Treasuries, while it reduces the significance for the longer maturities of CH and FR bonds. Consistent with the results in Table 2, the sign of the coefficient is positive, implying that higher equity tail risk is associated with an increase in the one-month-ahead bond risk premia. In contrast to the results obtained with the UK, DE, CH and FR bonds, the equity tail risk factor $TR^{(eq)}$ does not seem to help explain time variations in the bond risk premia

of Italy and Spain. In fact, the explanatory power of $\text{TR}^{(eq)}$ is never statistically significant at the 10% level for IT bonds with maturity greater than one year, and is at most significant at that level for the short-term ES bonds. These results point to the possible role that country risk may play in the identification of a safe asset when the equity market tumbles. It is indeed possible that, in periods of stress, international investors shift their holdings into instruments like the "safe" German Bund rather than debt issued by fiscally weak sovereigns, such as Italy and Spain. This is further corroborated by the fact that $\text{TR}^{(eq)}$ is strongly positively correlated with the current level of prices of DE Treasuries, while contemporaneous correlations with IT and ES bond prices are negative. Due to the mostly insignificant interactions observed in-sample between $\text{TR}^{(eq)}$ and Treasury bonds of Italy and Spain, we do not consider the out-of-sample forecast improvements afforded by equity tail risk for bond returns in these two countries. For all other countries, Table 11 reports the out-of-sample relative forecast and portfolio performance of the models in (5a), (5b) and (5c), which predict international bond returns with the S&P 500 option-implied tail risk measure $\text{TR}^{(eq)}$. Results are based on the out-of-sample setting described in Section 3.1, with predictive regressions that are recursively estimated with a rolling window approach and the assumption that the investor's level of risk aversion is $\gamma = 5$.

[Insert Table 11 here]

From an examination of the Campbell and Thompson (2008) out-of-sample R^2_{OS}s in Table 11, we note that the models that include equity tail risk systematically outperform the benchmarks in predicting returns of the UK and Germany Treasury markets. The same holds true for short- and medium-maturity bonds in Switzerland and France. The reductions in the MSPE for the forecasts generated by the model that includes $\text{TR}^{(eq)}$ are in the range of 4% to 24% for UK bond returns and in the range of 0.5% to 11% for DE bond returns. On the basis of the Clark and West (2007) test results, however, the gains of predictability in international bond returns are only marginally statistically significant. When assessing the portfolio performance afforded

45

by equity tail risk, we observe that $\text{TR}^{(eq)}$ can generate substantial risk-adjusted returns for investors trading bonds in all four countries, but especially in the UK and Germany. For instance, when the benchmark is the 3 PCs-only model, we find that an investor trading the 5-year UK (DE) Treasury bond is willing to pay approximately 165 (213) basis points per year to switch from the benchmark to the model that predicts bond returns with equity tail risk.

Having identified significant associations between the left tail volatility of the US stock market and the future returns on some of the major international government bond markets, the natural question that arises is whether equity tail risk is also a key determinant of the current level of prices of those bonds. To answer this question, we estimate the risk premium of $\text{TR}^{(eq)}$ by applying the GX three-pass method to the term structures of Treasury bonds in the UK, Germany, Switzerland, France, Italy and Spain. The results are reported in Table 12.

[Insert Table 12 here]

As we did for the US term structure, we assess robustness of the estimates by reporting results also for a higher number of latent factors than those selected with the Giglio and Xiu (2019) criterion, which points to 5 principal components for all Treasury markets except for the UK where 4 factors are selected. Examining the significance of the risk premium estimates γ_g, we can see that $\text{TR}^{(eq)}$ carries a significant price of risk in the Treasury bond market of the UK, Germany, Switzerland and France, which are the same countries that displayed strong return predictability with equity tail risk. For those countries we also tend to reject at the 0.10 level or lower the null of $\text{TR}^{(eq)}$ being a weak factor. Furthermore, it can be seen from the time-series regression R^2s that the equity left tail factor is mostly spanned by the second and, in some cases, the third principal components of the Treasury returns. As for the Italian and Spanish government bond markets, we confirm the lack of a strong connection with equity tail risk.

We end this section by relating the returns of the international government bond markets to the perceived tail risk in the stock market of the home country. We do this by running the

predictive regressions in (5a), (5b) and (5c) with the country-specific equity tail risk measures displayed in Figure 11 and estimating their risk premium with the GX three-pass procedure. Due to the limited availability of option data on the European stock market indices, we only consider the in-sample performance of the predictive models in (5a), (5b) and (5c). The full-sample estimates of the coefficients of the country-specific equity tail risk measures are reported in Table 13 while the results of the GX three-pass regression procedure are shown in Table 14.

[Insert Table 13 here]

[Insert Table 14 here]

A quick inspection of Table 13 reveals that the future one-month returns of UK, DE and CH Treasury bonds are strongly associated not only with the S&P 500 option-implied left tail factor $\text{TR}^{(eq)}$ but also with the corresponding country-specific measure of equity tail risk. On the other hand, we do not find any statistically significant relationship between the FR, IT and ES bond returns and the perceived tail risk in the stock market of the home country.[31] Finally, the results in Table 14 support our previous observations on the existence of a significant market price of equity tail risk in the Treasury bond market of UK, Germany, Switzerland and France.

In conclusion, our findings concerning the predictive power and pricing of equity tail risk are robust to alternative data sets. In fact, there is clear evidence that equity tail risk carries significant information about the dynamics of Treasury bond yields and returns not only in the US but also in major government bond markets in Europe.

---

[31]For reference, we also provide in Table 15 the in-sample results for predictive regressions that include both the US equity tail risk measure $\text{TR}^{(eq)}$ and the country-specific equivalent, orthogonalized to $\text{TR}^{(eq)}$. In short, these results suggest that the information contained in the country-specific equity tail risk measures is completely subsumed by the US equity tail factor.

5 Economic Interpretation

In this section, we relate our results of US bond pricing and return predictability based on equity tail risk to two strands of influential literature that explore factors affecting asset prices. First, since small flows lead to big and persistent price moves (Gabaix and Koijen, 2020), we consider the flows of funds (meaning invested moneys) between stocks and bonds to establish to what extent and for how long high values of our equity tail risk factor are associated with outflows from the equity market and inflows to the government bond market. Within this flows of funds analysis, we also try to characterize the sectors that buy Treasuries in times of elevated equity tail risk. Second, since we know that bond prices respond to monetary policy actions and statements, many of which happen as a result of financial stress, we consider how our equity tail risk factor is related to monetary policy shocks in order to see if the former continues to have a significant effect on interest rates after controlling for the latter.

5.1 Flows of Funds

In order to provide direct empirical evidence for a flight-to-safety interpretation of the findings in the previous sections, we study the contemporaneous and predictive relationships of our equity tail risk measure with the flows of funds (meaning invested moneys) into and out of the equity and Treasury markets.[32] We analyze flows data on two time scales: monthly and quarterly. For the monthly time scale we rely on flows provided by the Investment Company Institute (ICI) for US-domiciled open-end mutual funds and exchange-traded funds over the period 2000 to 2019. Specifically, we collect mutual funds data for Domestic Equity, World Equity, Hybrid, and Government Bond investment objectives, and ETF data for Equity, Hybrid,

---

[32]A related analysis to the one of this section is performed by Adrian et al. (2019a) and Adrian et al. (2019b), who focus only on the contemporaneous relationships between (a non-linear transformation of) the VIX index and monthly flows from two sectors, namely Mutual Funds and Money Market Funds. As described later, our analysis also involves monthly flows from the Exchange-Traded Fund (ETF) sector and quarterly flows from all sectors in the US Economy and from the Foreign Sector, including the issuance and buybacks of equities. Our analysis documents also lagged relationships at the monthly time scale.

and Government Bond investment objectives.[33] These data have the advantage of being readily available at the same (monthly) frequency as the Treasury returns and equity tail risk factor of this paper, but they only represent a rather small component of the ecosystem.[34] For this reason, we also analyze data on total flows from all sectors in the US economy and from the foreign sector to US equities and Treasuries between 1996 and 2019. Despite the high sectoral coverage offered, this data can only be obtained at the quarterly time scale from the *Financial Accounts of the United States - Z.1 Release* of the Board of Governors of the Federal Reserve. Using the same data, Gabaix and Koijen (2020), GK2020 hereafter, find evidence for the so-called "Inelastic Market Hypothesis". According to this hypothesis, as financial institutions are substantially constrained by mandate (and/or for other reasons) on the choice of their portfolio weights on all asset classes, the price elasticity of the aggregate demand of stocks is small. This implies that aggregate flows in and out of the aggregate stock market, although small compared to the total value of the equity market, have a large permanent impact on equity prices. GK2020 propose a new aggregate measure of flows to the equity market, which they call "capital flows into the stock market" (see their Section 4.7) and is computed as the weighted average of the flows to equities across all sectors. They show that this measure, which we refer to simply as "Aggregate Equity Flows", is significantly and positively correlated with the level of equity prices, survey expectations on returns ($R^2 = 0.233$), and GDP growth innovations ($R^2 = 0.045$).[35]

---

[33]For fund definitions, we refer to the ICI websites `https://www.ici.org/research/stats/iob_update/classification/iob_definitions` and `https://www.ici.org/research/stats/iob_update/classification/iob_definitions_etf` .

[34]For instance, only 6% of Treasury bonds in the US are held by mutual funds, which for this reason are referred to as "just the tip of the iceberg" by BlackRock (2020).

[35]Following GK2020, we compute Aggregate Equity Flows as the equity-share weighted average of the flows across all sectors of the US Economy and the Foreign Sector. By construction, this measure incorporates also net issuance shares buybacks. GK2020 argue that the total flows to equities, corporate bonds and government bonds of a certain sector i (divided by the total value of these assets) should be included in their measure of "capital flows into the stock market" when correctly measured, i.e. when they are associated with an elasticity of equity demand to flows of 1. If the estimated elasticity of demand of a certain sector is lower than 1, then only the pure equity flow (divided by the total value of the equity market only) should be included. Based on the estimated elasticities of demand, total capital flows are included for the following sectors: Mutual Funds, ETFs, Closed-end funds, Private Pension funds, State & local pension funds, and State & local governments. On the other hand, pure equity funds are included for the remaining sectors: Households, Foreign sector, Federal Government retirement funds, Property & Casualty insurers, Life Insurance companies, Broker dealers, and Banks. Note that a positive (resp. negative) flow in quarter t to a certain asset class, say equity, for sector i, say Mutual Funds, means that on quarter t sector i has increased (resp. decreased) its holdings of that asset class with respect to the previous quarter $t - 1$.

If the flight-to-safety interpretation of our equity tail risk measure is correct, we expect it to be positively associated with government bond fund flows and negatively associated with both stock fund flows and Aggregate Equity Flows. Motivated by the novel short-term predictability of bond returns discovered in the present study, Treasury inflows are expected to be observed even in the month following an increase in equity tail risk. Such persistence in flows, which can be seen as reflecting the fact that some investors do not rebalance their portfolios as soon as market conditions change, would provide support for the important role of equity tail risk in determining not only the present but also the one-month-ahead prices of Treasuries. To verify our conjectures, we first describe how stock and bond fund flows relate to current and previous month's level of equity tail risk. Then we extend the analysis to include the quarterly flows of sectors like households that may be characterized by delayed portfolio rebalancing and hence explain the existence of a relation between equity tail risk and flows also at lower frequencies.

Figure 12 shows the time trend of monthly flows for different types of US-domiciled funds, plotted against periods of elevated equity tail risk, corresponding to when $\text{TR}^{(eq)}$ is above its historical 85-th percentile. The "Total Equity" fund is obtained by summing up the US Equity, World Equity and Hybrid fund flows obtained from ICI. The "Equity - Government Bond" fund is obtained by subtracting from the Total Equity flows the US Government Bond flows obtained from ICI. We use net flows expressed as percentage of previous month's assets under management (AUM) for all types of funds except for "Equity - Government Bond", whose flows are shown in billions of US $. These plots clearly indicate that government bond fund flows tend to be positive when the perception of tail risk is higher, while stock fund flows tend to be negative. To measure and test the statistical strength of these relationships, we use $\text{TR}_t^{(eq)}$ as the explanatory variable in the following contemporaneous and predictive time series regressions:

$$Flow_{i,t} = \alpha_i + \beta_i \cdot \text{TR}_t^{(eq)} + \varepsilon_{i,t} \quad , \quad Flow_{i,t+1} = \alpha_i + \beta_i \cdot \text{TR}_t^{(eq)} + \varepsilon_{i,t+1} \ ,$$

where $Flow_{i,t}$ an $Flow_{i,t+1}$ are the month-t and month-$(t+1)$ net flows into type-i fund. We report the results of these time-series regressions in Table 16. The estimates reveal that our measure of equity tail risk is significantly positively correlated with bond fund flows and significantly negatively correlated with stock fund flows. This holds true in both contemporaneous and predictive regressions. Furthermore, it is interesting to see that lagging the equity tail risk measure strongly diminishes the relationship with equity fund flows but not with bond fund flows. In fact, $\mathrm{TR}_t^{(eq)}$ strongly comoves with and explains a large portion of variation in both month-t and month-$(t+1)$ bond fund flows, with a correlation of 39% and an R^2 of 15%. This persistence, which can probably be seen as reflecting the fact some of those fund managers do not rebalance their portfolios at the highest frequencies, is coherent with the prolonged positive response of US Treasury bond prices to equity tail risk documented in the previous sections. Finally, we consider how robust the explanatory and predictive ability of $\mathrm{TR}_t^{(eq)}$ for fund flows is by including in the above regressions alternative factors studied by the literatures on stock and bond return predictability. In particular, we consider the CBOE VIX and SKEW index and the VRP of Bollerslev et al. (2014), for which we report estimates in Table 17. In short, these results suggest that, amongst the candidate variables, $\mathrm{TR}_t^{(eq)}$ is the most important factor influencing stock and bond fund flows in both the present and the upcoming month.

[Insert Figure 12 here]

[Insert Table 16 here]

[Insert Table 17 here]

We now examine the quarterly relationship between $\mathrm{TR}^{(eq)}$ and Aggregate Equity Flows, which is expected to be negative. This would imply that, according to the model behind the Inelastic Market Hypothesis of GK2020, an increase of equity tail risk is positively correlated with (i) equity outflows, but also (ii) Treasuries inflows from some (or most) of the largest

51

sectors as measured by equity holdings. In particular, compatibly with the increase of Treasuries prices when equity tail risk is high, our measure should be positively correlated with flows to Treasuries by the two largest sectors by equity-ownership shares, which are Households and Mutual Funds.[36] In order to verify this, we first construct the Aggregate Equity Flows measure using data from the Z.1 Release up to 2019.Q4, and display it in Figure 13.[37]

[Insert Figure 13 here]

As the Z.1 Release only provides quarterly data on flows, we compute the within-quarter average of our monthly measure of equity tail risk ($\mathrm{TR}_t^{(eq)}$) and use it as the explanatory variable in the following regression model:

$$Flow_{i,t} = \alpha_i + \beta_i \cdot \mathrm{TR}_t^{(eq)} + \varepsilon_{i,t} \ ,$$

where the index t now refers to a specific quarter, and $Flow_{i,t}$ corresponds to the flow to equity or Treasuries for sector i. We run a separate time-series regression for each sector i and report the results in Table 18.

[Insert Table 18 here]

The first column of the table reports the estimation results of the regression where the dependent variable is the Aggregate Equity Flows measure of GK2020. The dependent variables considered in the second and third column are the flows to Treasuries from the Mutual Fund and the Households sectors, respectively. For the entire sample we find a negative and significant

---

[36]See GK2020 for a discussion of the different sectors of the US economy represented in the Z.1 Release, and the fraction of the entire US stock market they own.

[37]All vintages of the data for the Financial Accounts of the United States - Z.1 Release can be downloaded from `https://www.federalreserve.gov/releases/z1/` In our application we use the June 2020 vintage, while GK2020 use the June 2019 vintage, and therefore their data stop in 2018.

relationship between Aggregate Equity Flows and our tail risk measure, which have a correlation of -0.18, and the regression R^2 is 3.2%. Notably, this R^2 has the same order of magnitude of the R^2 when GDP news are considered as the only explanatory variable by GK2020.[38] If we only consider the post-2001 subsample, which is characterized by a mostly negative stock-bond relation, the correlation between equity tail risk and equity flows drops to -0.21, with the R^2 of the regression increasing to 4.4%. Symmetrically, we also find a positive and increasing relationship between equity tail risk and (i) flows to Treasuries from Mutual Funds only (with a p-value of 10.7% and R^2 of 1.7%), and (ii) flows to Treasuries from Households only (p-value < 1% and $R^2 = 23.3\%$). Importantly, the R^2 in this last regression is as large as the R^2 between Aggregate Equity Flows and expectation surveys on (equity) returns found by GK2020. Finally, we note that these correlations remain positive, and become stronger in the post-2001 sample, where the R^2 increases to 3.9% for Mutual funds and to 27.8% for Households.

Overall, the findings of this section are consistent with our flight-to-safety conjecture related to funds flowing form equities to Treasuries in periods of elevated equity tail risk. Furthermore, our results complement those of Adrian et al. (2019a), who concentrate only on contemporaneous relationships of the VIX index with flows from Mutual and Money Market Funds only, and those of Gabaix and Koijen (2020), who mostly focus on equity market prices and flows. Nonetheless, our analysis could be refined in the future to provide a more comprehensive understanding of the flows to equities and bonds from each sector in the Z.1 Release.

5.2   Monetary Policy Shocks

In an attempt to find a link between the actions of monetary policy (MP) in the US and our equity tail risk measure $\text{TR}^{(eq)}$, we exploit the recent dataset of Baker et al. (2020), who study the causes that trigger US stock market jumps. They identify jumps (defined as absolute

---

[38]As the variables have been standardized before running the regressions, $\hat{\beta}_i$ is also the sample correlation coefficient.

returns larger than 2.5%) at a daily level using next-day newspapers.[39] They find that the most common cause of large market movements is macroeconomic news, which triggered nearly a quarter of the jumps observed in the US from 1900 to 2019, while monetary policy and central banking jumps amount to a much smaller fraction. In terms of the implications of different jumps, they note that monetary policy jumps tend to produce a lot less follow-on volatility relative to macroeconomic news-driven jumps. The stock market jumps identified by Baker et al. (2020) can help us understand whether the behavior of our equity tail risk measure $\text{TR}^{(eq)}$ is by any means influenced by the actions of the MP makers and hence if the effect on Treasury bonds that we have found is merely a MP effect or something more than that. The answer appears to be the latter from the following considerations. In the 1996–2019 period, there are only 26 monetary jumps, which amount to 10.4% of the total number. The fact that monetary policy is not the main trigger of stock market jumps is itself an indicator that the information contained in $\text{TR}^{(eq)}$ goes beyond merely MP announcements. This can be clearly seen also in Figure 14, where the daily time series of our equity tail risk measure is plotted against the stock market jump returns driven by monetary policy. The correlation between the two series is only about 6%. This low level of correlation is not surprising at all if one considers that $\text{TR}^{(eq)}$ is, by construction, a measure of downside risk and that negative jumps account for only 23% of the jumps triggered by monetary policy. Also, the finding of Baker et al. (2020) that volatility rises less after monetary jumps than after other jumps, which can probably be explained by the predominant positive sign of these jumps combined with the well-known leverage effect, contrasts with the high persistence of $\text{TR}^{(eq)}$ observed during post-crisis periods. These are all arguments in support of our hypothesis that the effect of equity tail risk on Treasury bonds is different from that of MP actions and announcements.

[Insert Figure 14 here]

---

[39]The authors share the data which can be downloaded from their website `https://stockmarketjumps.com/`.

We now ask whether the equity tail risk factor $\text{TR}^{(eq)}$ continues to affect US Treasury bonds after accounting for the usual effect of unexpected monetary policy actions on domestic interest rates, see, e.g., Kuttner (2001), Gürkaynak et al. (2005), Ca' Zorzi et al. (2020) and Jarociński and Karadi (2020). To answer this question, we use a regression framework that measures the interest rate effects of tail risk and monetary policy shocks. Our baseline regression, which we borrow from Bekaert et al. (2020), is as follows:

$$\Delta y_t^{(n)} = \alpha + \beta^{TR}\Delta\text{TR}_t^{(eq)} + \sum_i \beta^{MP,i}\Delta\text{MP}_t^i + \gamma D_t + \sum_k \delta^k\Delta Macro_t^k + \sum_k r^k\theta_t^k + \varepsilon_t , \quad (37)$$

where $\Delta y_t^{(n)}$ is the daily change of the n-month US Treasury bond yield, $\Delta\text{TR}_t^{(eq)}$ is a proxy for pure equity tail risk shocks, ΔMP_t^i is the i-th measure of monetary policy shocks, D_t is a $\{0,1\}$ dummy variable that signals the event dates of monetary policy announcements, $\Delta Macro_t^k$ is the shock in the k-th macroeconomic series, and θ_t^k is a $\{0,1\}$ dummy variable that flags the news release days for the k-th macroeconomic series. We examine the interest rate effects of "cleansed" unexpected changes in equity tail risk by means of $\Delta\text{TR}_t^{(eq)}$, which we obtain as the residual of projecting the daily change in $\text{TR}^{(eq)}$ onto the space of the monetary policy and macroeconomic shocks.[40] To measure the effect of US monetary policy on interest rates, we mainly rely on the high-frequency shocks identified by Jarociński and Karadi (2020) with the "poor man's sign restrictions". In this case, there are two ΔMP_t^i measures in equation (37) representing, respectively, pure MP shocks and central bank (CB) information shocks, which Jarociński and Karadi (2020) separate based on the comovement of interest rates and stock prices around a monetary policy announcement. In short, a pure MP shock (resp. CB information shock) happens when negative (resp. positive) comovement between the interest rate surprise, i.e. the first principal component of rate changes in fed funds futures with maturities from 1 month to 1 year, and the stock price surprise, i.e. the change in the S&P 500, is observed

---

[40]In a similar vein, Bekaert et al. (2013) and Bekaert et al. (2020) use daily changes in risk aversion and uncertainty as proxies for unexpected changes to their variables.

in the half-hour window starting 10 minutes before and ending 20 minutes after a central bank announcement. Pure MP shocks are equal to the interest rate surprises on days when the fed funds futures and the S&P 500 moved in the opposite direction around the announcement, equal to zero otherwise. Central bank information shocks are equal to the interest rate surprises on days when the fed funds futures and the S&P 500 moved in the same direction around the announcement, equal to zero otherwise. The shocks developed by Jarociński and Karadi (2020), although available for a long period of time, do not account for the unconventional monetary policy tools introduced by central banks in the aftermath of the global financial crisis when the Fed funds rate reached the zero lower bound. Therefore, we also consider an instance of equation (37) that we estimate in the post-2008 period and where the $\Delta\mathrm{MP}_t^i$ measures are those developed by Rogers et al. (2018) who complement target rate shocks with two shocks for the non-standard policies of forward guidance and asset purchases. Specifically, the target shock is the change in yield on the current- or next-month federal funds futures contracts, as proposed by Kuttner (2001), from 15 minutes before a monetary policy announcement to 1 hour and 45 minutes afterwards. The forward guidance (FG) shock is the residual from a regression of the yield change for the fourth Eurodollar futures contract, which is a bet on the level of 3-month interest rates about 1 year hence, onto the target shock. The asset purchase (AP) shock is the residual from a regression of the yield change for the on-the-run 10-year Treasury futures onto the target and forward guidance shocks. So estimated AP shocks are meaningful only from October 2008 onwards, when they measure the jumps in long-term interest rates associated with large-scale asset purchase programs. We illustrate in the top panel of Figure 15 the two monetary policy shock measures of Jarociński and Karadi (2020) from January 1996 to May 2019, and in the bottom panel the three measures of Rogers et al. (2018) from January 1996 to December 2015 (the series of AP shocks starts in October 2008 for the aforementioned reasons). All measures are quoted in basis points.[41] For the pure MP shocks of Jarociński and Karadi

---

[41]We are very grateful to Marek Jarocinski, Refet Gürkaynak and John Rogers for sharing the data of monetary

(2020) and for the target and FG shocks of Rogers et al. (2018), a positive (resp. negative) value indicates policy tightening (resp. easing). In case of the AP shocks, a positive value, as noted by Bekaert et al. (2020), could mean an earlier-than-expected termination of the large-scale asset purchases. For the CB information shocks, a positive value indicates a better-than-expected economic outlook announcement and vice versa.

[Insert Figure 15 here]

The monetary policy day dummy D_t together with the macroeconomic shock series $\Delta Macro_t^k$ and corresponding news release day dummies θ_t^k act as control variables. In fact, we run the regression equation (37) at the daily level on all available dates. Hence, controlling for monetary policy and macroeconomic news events ensures that our interest rate effects are compatible with those of regressions that are run only on the MP event dates and in a narrow window of time around the announcement. As for the macroeconomic news surprises, we follow Bekaert et al. (2020) and collect data for the following seven series: GDP growth quarter-on-quarter, industrial production growth, unemployment rate, CPI inflation, current account balance, consumer confidence, and manufacturing confidence. The shock of each macro news release is calculated as the difference between the actual realization and the median expectation according to surveys, divided by the sample standard deviation. Daily data on the macro news announcements and corresponding survey expectations come from Bloomberg.[42]

In this analysis, interest rates and MP shocks are measured in basis points. Table 19 reports the full-sample estimates of the coefficients of $\Delta \text{TR}_t^{(eq)}$ and ΔMP_t^i, and the corresponding p-values computed with heteroskedasticity-robust standard errors.[43] The results in Panel A are obtained by estimating the regression equation (37) with the monetary policy shock measures of Jarociński and Karadi (2020). Sample period starts in January 2003, which is when data is

---

policy shock measures.

[42]We thank Nancy Xu for providing details on how to construct the macroeconomic news surprises.

[43]The regression results associated to the control variables are not reported in Table 19 for sake of space.

available for all seven macroeconomic series, and ends in May 2019 with the last available MP shocks provided by Jarociński and Karadi (2020).[44] The results in Panel B are obtained by estimating the regression equation (37) with the monetary policy shock measures of Rogers et al. (2018). In this case the sample period starts in October 2008, which is when unconventional policies became predominant, and ends in December 2015 with the last available MP shocks provided by Rogers et al. (2018). Numbers at the bottom of each panel correspond to the adjusted R-squared of the predictive regressions that include and exclude $\Delta \text{TR}_t^{(eq)}$ as covariate in the regression equation (37). In addition to the bond maturities analyzed in the previous sections, we also report results for daily changes in 3- and 6-month interest rates as it is well established in the literature that the monetary policy passes easily through short-term rates.

[Insert Table 19 here]

We start by examining the regression results obtained over the longer sample period with the MP shocks of Jarociński and Karadi (2020). As expected, the US monetary policy strongly affects domestic interest rates. The coefficient is positive and highly significant at all maturities for both pure MP and CB information shocks. For the former shock, the pass-through is over 50% at the 1-year maturity and has a peak of approximately 70% at the 3-year maturity. More relevant to the purpose of this paper is the strong negative effect of equity tail risk shocks on US Treasury rates of all maturities. This negative contemporaneous relationship between daily changes in equity tail risk and Treasury bond yields echoes the estimates obtained at lower frequency with the ATSM and confirms the flight-to-safety effect that benefits US government bonds in period of financial stress. The results of this analysis suggest that equity tail risk shocks have a large economic effect on interest rates even after accounting for monetary policy shocks. A one standard deviation shock to equity tail risk, which amounts to approximately

---

[44]In accordance with Bekaert et al. (2020) we also considered January 2000 as the start date of the sample resulting in similar results that are available upon request.

0.017, has on the 1-year US Treasury rate the same effect of an 80 basis point easing as measured by $\Delta\mathrm{MP}_t^{pure}$. The importance of equity tail risk in explaining interest rate variations is evident also from the sizeable increases in the adjusted R-squared observed when $\Delta\mathrm{TR}_t^{(eq)}$ is included in the regression. Moving on to the regression results obtained over the post-2008 sample period, we notice that equity tail risk shocks continue to significantly affect interest rates even in the presence of unconventional monetary policy shocks. Like before, the sign of the coefficient is negative and the magnitude grows with the maturity of the yields. As for the MP shocks of Rogers et al. (2018) it is worth noting that the effect of FG and AP shocks is positive and highly significant for a large number of maturities. On the contrary and not surprisingly having the Fed funds rate reached the zero lower bound, the effect of target shocks is negative and also insignificant at the short end of the curve.

6   Conclusion

In this paper, we study how US Treasury bonds respond to changes in the perceived tail risk in the stock market. We estimate equity tail risk with the risk-neutral expectation of future volatility that stems from large negative price jumps and we examine how it relates to the future one-month returns on bonds in reduced-form predictive regressions. Also, we propose an affine term structure model in which the main drivers of interest rates are the principal components of the zero-coupon yield curve and the equity tail risk factor. While earlier approaches to pricing bonds with factors other than combinations of yields have proven useful when macro variables are considered, we focus here on the observed comovement in stock and bond markets during crisis periods and use a state variable that originates in the equity option market.

The results of our main application to the US government bond and S&P 500 index option markets are summarized as follows. First, there exist significant interactions between the one-month-ahead risk premia in Treasury bonds and the left tail volatility of the stock market. Second, the strong predictive power of equity tail risk for future bond returns is confirmed

in a real-time out-of-sample exercise, where this predictability can be exploited to improve the economic utility of a mean-variance investor. Third, the left tail volatility of the stock market is a priced state variable in the US term structure. We find evidence of a significant and time-varying market price of equity tail risk that has been negative on average since 2001. Fourth, consistent with the theory of flight-to-safety, bond prices rise in response to a contemporaneous shock to the equity left tail factor. Fifth, large drops in short-term bond yields and expected future short rates are attributable to equity tail risk. Sixth, the strong interest rate effect of equity tail risk shocks persists even after controlling for the usual effect of monetary policy and macroeconomic shocks. Seventh, equity tail risk is positively correlated with aggregate equity outflows and Treasury bond inflows. Finally, our results concerning the predictive power and pricing of equity tail risk are robust to alternative data sets. When extending the analysis to major government bond markets in Europe, we find that equity tail risk carries significant information about the dynamics of Treasury bond yields and returns in United Kingdom, Germany, Switzerland and France, while the evidence is considerably weaker in Spain and non-existent in Italy.

Given our findings with a measure of downside tail risk of the stock market, a natural direction for future research would be to assess the impact on the yield curve of a tail factor implied by Treasury options. For instance, it would be interesting to see whether the downside, or even the upside, tail risk of the bond market receives compensation in a term structure model and how its pricing differs from that of equity tail risk. This would contribute to the recent literature on the auxiliary role of Treasury variance and jump risk in explaining bond risk premia, see (Wright and Zhou, 2009; Mueller et al., 2017). We leave investigation of such possibilities to future research.

References

ABRAHAMS, M., T. ADRIAN, R. K. CRUMP, E. MOENCH, AND R. YU (2016): "Decomposing real and nominal yield curves," *Journal of Monetary Economics*, 84, 182–200.

ADRIAN, T., R. CRUMP, AND E. VOGT (2019a): "Nonlinearity and Flight to Safety in the Risk-Return Trade-Off for Stocks and Bonds," *Journal of Finance*, 74, 1931–1973.

ADRIAN, T., R. K. CRUMP, AND E. MOENCH (2013): "Pricing the term structure with linear regressions," *Journal of Financial Economics*, 110, 110–138.

ADRIAN, T., D. STACKMAN, AND E. VOGT (2019b): "Global Price of Risk and Stabilization Policies," *London, Centre for Economic Policy Research.*

AN, B.-J., A. ANG, T. G. BALI, AND N. CAKICI (2014): "The Joint Cross Section of Stocks and Options," *Journal of Finance*, 69, 2279–2337.

ANDERSEN, T. G., N. FUSARI, AND V. TODOROV (2015): "The risk premia embedded in index options," *Journal of Financial Economics*, 117, 558–584.

——— (2019a): "The Pricing of Tail Risk and the Equity Premium: Evidence from International Option Markets," *Journal of Business & Economic Statistics*, forthcoming.

ANDERSEN, T. G., V. TODOROV, AND M. UBUKATA (2019b): "Tail Risk and Return Predictability for the Japanese Equity Market," *Working Paper.*

BAELE, L., G. BEKAERT, AND K. INGHELBRECHT (2010): "The determinants of stock and bond return comovements," *Review of Financial Studies*, 23, 2374–2428.

BAKER, S., N. BLOOM, S. DAVIS, AND M. SAMMON (2020): "What Triggers Stock Market Jumps?" *Working Paper.*

BAKSHI, G., N. KAPADIA, AND D. MADAN (2003): "Stock return characteristics, skew laws,

and the differential pricing of individual equity options," *The Review of Financial Studies*, 16, 101–143.

BALI, T. AND S. MURRAY (2013): "Does Risk-Neutral Skewness Predict the Cross Section of Equity Option Portfolio Returns?" *Journal of Financial and Quantitative Analysis*, 48, 1145–1171.

BAUER, M. D. AND J. D. HAMILTON (2018): "Robust Bond Risk Premia," *The Review of Financial Studies*, 31, 399–448.

BEKAERT, G., E. ENGSTROM, AND N. XU (2019): "The Time Variation in Risk Appetite and Uncertainty," *NBER Working Paper 25673*.

BEKAERT, G. AND M. HOEROVA (2014): "The VIX, the variance premium and stock market volatility," *Journal of Econometrics*, 183, 181–190.

BEKAERT, G., M. HOEROVA, AND M. LO DUCA (2013): "Risk, uncertainty and monetary policy," *Journal of Monetary Economics*, 60, 771–788.

BEKAERT, G., M. HOEROVA, AND N. XU (2020): "Risk, Uncertainty and Monetary Policy in a Global World," *Working Paper*.

BERARDI, A., M. MARKOVICH, A. PLAZZI, AND A. TAMONI (2020): "Mind the (Convergence) Gap: Bond Predictability Strikes Back!" *Management Science*, forthcoming.

BLACKROCK (2020): "Lessons from COVID-19: Overview of Financial Stability and Non-Bank Financial Institutions," Available at blackrock.com/publicpolicy: https://www.blackrock.com/corporate/literature/whitepaper/viewpoint-lessons-from-covid-overview-financial-stability-september-2020.pdf.

BOLLERSLEV, T., J. MARRONE, L. XU, AND H. ZHOU (2014): "Stock Return Predictability and Variance Risk Premia: Statistical Inference and International Evidence," *Journal of Financial and Quantitative Analysis*, 49, 633–661.

BOLLERSLEV, T., G. TAUCHEN, AND H. ZHOU (2009): "Expected stock returns and variance risk premia," *Review of Financial Studies*, 22, 4463–4492.

BOLLERSLEV, T. AND V. TODOROV (2011): "Tails, Fears, and Risk Premia," *Journal of Finance*, 66, 2165–2211.

———— (2014): "Time-varying jump tails," *Journal of Econometrics*, 66, 2165–2211.

BOLLERSLEV, T., V. TODOROV, AND L. XU (2015): "Tail risk premia and return predictability," *Journal of Financial Economics*, 118, 113–134.

CA' ZORZI, M., L. DEDOLA, G. GEORGIADIS, M. JAROCIŃSKI, L. STRACCA, AND G. STRASSER (2020): "Monetary policy and its transmission in a globalised world," *ECB Working Paper Series No 2407*.

CAMPBELL, J. AND R. J. SHILLER (1991): "Yield Spreads and Interest Rate Movements: A Bird's Eye View," *Review of Economic Studies*, 58, 495–514.

CAMPBELL, J. Y., C. PFLUEGER, AND L. M. VICEIRA (2020): "Macroeconomic Drivers of Bond and Equity Risks," *Journal of Political Economy*, 128, 3148–3185.

CAMPBELL, J. Y. AND S. B. THOMPSON (2008): "Predicting Excess Stock Returns Out of Sample: Can Anything Beat the Historical Average?" *The Review of Financial Studies*, 21, 1509–1531.

CHORDIA, T., A. SARKAR, AND A. SUBRAHMANYAM (2005): "An empirical analysis of stock and bond market liquidity," *Review of Financial Studies*, 18, 85–129.

CIESLAK, A. AND P. POVALA (2015): "Expected Returns in Treasury Bonds," *The Review of Financial Studies*, 28, 2859–2901.

CLARK, T. E. AND K. D. WEST (2007): "Approximately normal tests for equal predictive accuracy in nested models," *Journal of Econometrics*, 138, 291–311.

COCHRANE, J. H. AND M. PIAZZESI (2005): "Bond Risk Premia," *The American Economic Review*, 95, 138–160.

——— (2008): "Decomposing the Yield Curve," *Working Paper*.

CONNOLLY, R., C. STIVERS, AND L. SUN (2005): "Stock Market Uncertainty and the Stock-Bond Return Relation," *Journal of Financial and Quantitative Analysis*, 40, 161–194.

CONRAD, J., R. F. DITTMAR, AND E. GHYSELS (2013): "Ex Ante Skewness and Expected Stock Returns," *Journal of Finance*, 68, 85–124.

COOPER, I. AND R. PRIESTLEY (2008): "Time-Varying Risk Premiums and the Output Gap," *The Review of Financial Studies*, 22, 2801–2833.

CRUMP, R. K. AND N. GOSPODINOV (2019): "Deconstructing the Yield Curve," *Federal Reserve Bank of New York Staff Report*.

DAVID, A. AND P. VERONESI (2013): "What Ties Return Volatilities to Price Valuations and Fundamentals?" *Journal of Political Economy*, 121, 682–746.

DUFFEE, G. R. (2002): "Term premia and interest rate forecasts in affine models," *Journal of Finance*, 57, 405–443.

——— (2011): "Information in (and not in) the Term Structure," *The Review of Financial Studies*, 24, 2895–2934.

ERIKSEN, J. N. (2017): "Expected Business Conditions and Bond Risk Premia," *Journal of Financial and Quantitative Analysis*, 52, 1667–1703.

FAMA, E. AND R. BLISS (1987): "The Information in Long-Maturity Forward Rates," *American Economic Review*, 77, 680–692.

FAMA, E. F. AND K. R. FRENCH (1993): "Common Risk Factors in the returns on Stocks and Bonds," *Journal of Financial Economics*, 128, 234–252.

FAMA, E. F. AND J. D. MACBETH (1973): "Risk, Return, and Equilibrium: Empirical Tests," *The Journal of Political Economy*, 81, 607–636.

FARAGO, A. AND R. TÉDONGAP (2018): "Downside risks and the cross-section of asset returns," *Journal of Financial Economics*, 129, 69–86.

FEUNOU, B. AND J.-S. FONTAINE (2018): "Bond Risk Premia and Gaussian Term Structure Models," *Management Science*, 64, 1413–1439.

FEUNOU, B., J.-S. FONTAINE, A. TAAMOUTI, AND R. TÉDONGAP (2014): "Risk Premium, Variance Premium, and the Maturity Structure of Uncertainty," *Review of Finance*, 18, 219–269.

GABAIX, X. AND R. S. J. KOIJEN (2020): "In Search of the origins of Financial Fluctuations: the Inelastic Markets Hypothesis," *Working Paper*.

GARGANO, A., D. PETTENUZZO, AND A. TIMMERMANN (2019): "Bond Return Predictability: Economic Value and Links to the Macroeconomy," *Management Science*, 65, 508–540.

GIGLIO, S. AND D. XIU (2019): "Asset Pricing with Omitted Factors," *Working Paper*.

GOETZMANN, W., J. INGERSOLL, M. SPIEGEL, AND I. WELCH (2007): "Portfolio Performance Manipulation and Manipulation-proof Performance Measures," *The Review of Financial Studies*, 20, 1503–1546.

GÜRKAYNAK, R. S., B. SACK, AND E. T. SWANSON (2005): "Do Actions Speak Louder Than Words? The Response of Asset Prices to Monetary Policy Actions and Statements," *International Journal of Central Banking*, 1, 55–93.

GÜRKAYNAK, R. S., B. SACK, AND J. H. WRIGHT (2007): "The U.S. Treasury yield curve: 1961 to the present," *Journal of Monetary Economics*, 54, 2291–2304.

HARTMANN, P., S. STRAETMANS, AND C. G. DE VRIES (2004): "Asset Market Linkages in Crisis Periods," *Review of Economics and Statistics*, 86, 313–326.

HUANG, D., F. JIANG, G. TONG, AND G. ZHOU (2019): "Are Bond Returns Predictable with Real-Time Macro Data?" *Working Paper*, Available at SSRN: https://ssrn.com/abstract=3107612.

JAROCIŃSKI, M. AND P. KARADI (2020): "Deconstructing Monetary Policy Surprises – The Role of Information Shocks," *American Economic Journal: Macroeconomics*, 12, 1–43.

JOSLIN, S., M. PRIEBSCH, AND K. J. SINGLETON (2014): "Risk premiums in dynamic term structure models with unspanned macro risks," *Journal of Finance*, 69, 1197–1233.

JURADO, K., S. LUDVIGSON, AND S. NG (2015): "Measuring Uncertainty," *American Economic Review*, 105, 1177–1216.

KAMINSKA, I. AND M. ROBERTS-SKLAR (2015): "A global factor in variance risk premia and local bond pricing," *Bank of England Staff Working Paper*.

KAMINSKA, I. AND G. ZINNA (2018): "Official Demand for U.S. Debt: Implications for U.S. Real Interest Rates," *IMF Working Paper No. 14/66*.

KIM, D. H. AND J. H. WRIGHT (2005): "An Arbitrage-Free Three-Factor Term Structure Model and the Recent Behavior of Long-Term Yields and Distant-Horizon Forward Rates," *Federal Reserve Board Finance and Economics Discussion Series*.

KRISHNAMURTHY, A. AND A. VISSING-JORGENSEN (2012): "The Aggregate Demand for Treasury Debt," *Journal of Political Economy*, 120, 233–267.

KUTTNER, K. N. (2001): "Monetary policy surprises and interest rates: Evidence from the Fed funds futures market," *Journal of Monetary Economics*, 47, 523–544.

LI, J. AND G. ZINNA (2018): "The Variance Risk Premium: Components, Term Structures, and Stock Return Predictability," *Journal of Business & Economic Statistics*, 36, 411–425.

LITTERMAN, R. AND J. SCHEINKMAN (1991): "Common Factors affecting Bond Returns," *Journal of Fixed Income*, 1, 54–61.

LIU, Z. AND T. VAN DER HEIJDEN (2016): "Model-Free Risk-Neutral Moments and Proxies," *Working Paper*.

LONGSTAFF, F. (2004): "The Flight-to-Liquidity Premium in U.S. Treasury Bond Prices," *Journal of Business*, 77, 511–526.

LUDVIGSON, S. C. AND S. NG (2009): "Macro Factors in Bond Risk Premia," *The Review of Financial Studies*, 22, 5027–5067.

MALIK, S. AND A. MELDRUM (2016): "Evaluating the robustness of UK term structure decompositions using linear regression methods," *Journal of Banking and Finance*, 67, 85–102.

MUELLER, P., P. SABTCHEVSKY, A. VEDOLIN, AND P. WHELAN (2017): "Variance Risk Premia on Stocks and Bonds," *Working Paper*.

REBONATO, R. (2016): "Structural Affine Models for Yield Curve Modeling," in *Handbook of Fixed–Income Securities*, ed. by P. Veronesi, Wiley, 313–325.

REHMAN, Z. AND G. VILKOV (2012): "Risk-Neutral Skewness: Return Predictability and Its Sources," *Working Paper*, Available at SSRN: https://ssrn.com/abstract=1301648.

ROGERS, J. H., C. SCOTTI, AND J. H. WRIGHT (2018): "Unconventional Monetary Policy and International Risk Premia," *Journal of Money, Credit and Banking*, 50, 1828–1850.

STILGER, P. S., A. KOSTAKIS, AND S. POON (2016): "What Does Risk-Neutral Skewness Tell Us About Future Stock Returns?" *Management Science*, 63, 1657–2048.

THORNTON, D. AND G. VALENTE (2012): "Out-of-Sample Predictions of Bond Excess Returns and Forward Rates: An Asset Allocation Perspective," *The Review of Financial Studies*, 25, 3141–3168.

VAYANOS, D. (2004): "Flight to quality, flight to liquidity, and the pricing of risk," *NBER Working Paper*, 10327.

WRIGHT, J. H. AND H. ZHOU (2009): "Bond Risk Premia and Realized Jump Risk," *Journal of Banking and Finance*, 33, 2333–2345.

XING, Y., X. ZHANG, AND R. ZHAO (2010): "What Does the Individual Option Volatility Smirk Tell Us About Future Equity Returns?" *Journal of Financial and Quantitative Analysis*, 45, 641–662.

Table 1 – Descriptive statistics: bond risk premia and equity tail risk

	$rx_{t+1}^{(12)}$	$rx_{t+1}^{(24)}$	$rx_{t+1}^{(36)}$	$rx_{t+1}^{(48)}$	$rx_{t+1}^{(60)}$	$rx_{t+1}^{(84)}$	$rx_{t+1}^{(120)}$	$TR_t^{(eq)}$
Panel A: Descriptive Statistics								
Mean	0.389	0.965	1.534	2.066	2.548	3.359	4.240	0.101
Std. dev.	0.589	1.519	2.530	3.525	4.487	6.327	8.936	0.039
Skewness	1.373	0.484	0.143	0.010	-0.022	0.028	0.082	2.051
Kurtosis	7.592	4.624	3.911	3.710	3.767	4.190	4.957	10.020
$\rho(1)$	0.196	0.141	0.100	0.073	0.056	0.038	0.018	0.672
$\rho(6)$	0.087	-0.030	-0.078	-0.095	-0.100	-0.100	-0.090	0.272
$\rho(12)$	0.083	0.137	0.141	0.131	0.113	0.069	0.017	0.188
SR	0.660	0.636	0.606	0.586	0.568	0.531	0.475	
Panel B: Correlation Matrix								
$rx_{t+1}^{(12)}$	1.000							
$rx_{t+1}^{(24)}$	0.926	1.000						
$rx_{t+1}^{(36)}$	0.850	0.981	1.000					
$rx_{t+1}^{(48)}$	0.791	0.947	0.990	1.000				
$rx_{t+1}^{(60)}$	0.741	0.906	0.966	0.993	1.000			
$rx_{t+1}^{(84)}$	0.655	0.823	0.901	0.950	0.980	1.000		
$rx_{t+1}^{(120)}$	0.553	0.715	0.802	0.867	0.916	0.976	1.000	
$TR_t^{(eq)}$	0.207	0.175	0.172	0.176	0.182	0.192	0.193	1.000

Notes: This table contains descriptive statistics for the one-month excess US Treasury bond returns $rx_{t+1}^{(n)}$, with maturity $n = 12, 24, 36, 48, 60, 84, 120$ months, and for the S&P 500 option-implied equity tail risk measure $TR_t^{(eq)}$ used as predictor in the empirical analyses. Panel A reports the sample mean, standard deviation, skewness, kurtosis and autocorrelation coefficients of order one, six and twelve for each of the variables. Return means and standard deviations are expressed in annualized percentage terms. The annualized Sharpe ratio (SR) is also reported for the Treasury bonds. Panel B reports the correlation coefficients calculated with the future bond returns and contemporaneous $TR^{(eq)}$ factor. The sample uses end-of-month data for 1996:01–2019:12.

Table 2 – In-sample forecasts of Treasury returns with equity tail risk

		$n = 12$	$n = 24$	$n = 36$	$n = 48$	$n = 60$	$n = 84$	$n = 120$
Panel A: No control for bond return forecasting factors								
$\text{TR}_t^{(eq)}$	β	0.421	0.920	1.504	2.150	2.831	4.194	5.969
	p-value	0.000	0.001	0.001	0.002	0.002	0.003	0.007
	p-value (b)	0.012	0.040	0.027	0.018	0.011	0.003	0.001
Adj. R^2(%)		3.930	2.729	2.613	2.769	2.989	3.336	3.393
Adj. R^2(%)	no $\text{TR}^{(eq)}$	0.000	0.000	0.000	0.000	0.000	0.000	0.000
F-test		0.000	0.003	0.003	0.003	0.002	0.001	0.001
Panel B: Control for yield curve factors with 3 PCs								
$\text{TR}_t^{(eq)}$	β	0.399	0.861	1.418	2.028	2.659	3.897	5.504
	p-value	0.001	0.007	0.009	0.009	0.009	0.010	0.014
	p-value (b)	0.001	0.007	0.010	0.009	0.006	0.004	0.006
PC1_t	β	0.351	0.545	0.704	0.857	1.002	1.265	1.622
	p-value	0.015	0.119	0.201	0.252	0.287	0.334	0.371
PC2_t	β	0.190	0.630	1.060	1.480	1.889	2.662	3.695
	p-value	0.097	0.027	0.019	0.015	0.012	0.009	0.007
PC3_t	β	0.150	0.030	-0.139	-0.269	-0.339	-0.355	-0.373
	p-value	0.480	0.948	0.843	0.770	0.762	0.811	0.848
Adj. R^2(%)		7.305	4.226	3.732	3.765	3.914	4.150	4.082
Adj. R^2(%)	no $\text{TR}^{(eq)}$	4.310	2.228	1.791	1.702	1.703	1.734	1.666
F-test		0.002	0.009	0.010	0.008	0.007	0.005	0.005
Panel C: Control for yield curve factors with 5 PCs								
$\text{TR}_t^{(eq)}$	β	0.388	0.838	1.364	1.929	2.509	3.651	5.155
	p-value	0.001	0.006	0.009	0.010	0.010	0.011	0.014
	p-value (b)	0.001	0.009	0.016	0.013	0.011	0.008	0.008
PC1_t	β	0.349	0.541	0.695	0.840	0.976	1.224	1.565
	p-value	0.013	0.111	0.211	0.282	0.331	0.388	0.417
PC2_t	β	0.192	0.634	1.070	1.500	1.920	2.715	3.773
	p-value	0.100	0.023	0.016	0.015	0.014	0.012	0.009
PC3_t	β	0.152	0.036	-0.126	-0.245	-0.302	-0.294	-0.285
	p-value	0.460	0.937	0.855	0.791	0.792	0.849	0.889
PC4_t	β	0.211	0.607	1.020	1.377	1.648	1.917	1.821
	p-value	0.175	0.058	0.047	0.063	0.092	0.187	0.385
PC5_t	β	-0.158	-0.358	-0.766	-1.336	-1.961	-3.110	-4.294
	p-value	0.201	0.237	0.133	0.063	0.033	0.015	0.014
Adj. R^2(%)		8.351	5.381	5.215	5.602	6.003	6.303	5.712
Adj. R^2(%)	no $\text{TR}^{(eq)}$	5.534	3.506	3.440	3.761	4.065	4.216	3.630
F-test		0.002	0.011	0.013	0.011	0.010	0.007	0.008

Table 2 – In-sample forecasts of Treasury returns with equity tail risk (continued)

		$n = 12$	$n = 24$	$n = 36$	$n = 48$	$n = 60$	$n = 84$	$n = 120$
Panel D: Control for Cochrane-Piazzesi (CP) factor								
$\text{TR}_t^{(eq)}$	β	0.352	0.762	1.249	1.790	2.365	3.533	5.081
	p-value	0.001	0.004	0.005	0.005	0.005	0.006	0.010
CP_t	β	0.428	0.977	1.570	2.215	2.871	4.074	5.471
	p-value	0.001	0.001	0.001	0.000	0.000	0.000	0.001
Adj. $R^2_{(\%)}$		7.905	5.779	5.427	5.665	6.004	6.395	6.126
Adj. $R^2_{(\%)}$	no $\text{TR}^{(eq)}$	5.320	4.055	3.767	3.889	4.063	4.176	3.814
F-test		0.003	0.013	0.015	0.012	0.009	0.006	0.005
Panel E: Control for Cieslak-Povala (CiP) factor								
$\text{TR}_t^{(eq)}$	β	0.407	0.872	1.418	2.028	2.673	3.971	5.654
	p-value	0.001	0.004	0.005	0.004	0.004	0.004	0.007
CiP_t	β	0.269	0.947	1.670	2.385	3.073	4.363	6.148
	p-value	0.018	0.002	0.000	0.000	0.000	0.000	0.000
Adj. $R^2_{(\%)}$		5.342	5.652	5.932	6.270	6.586	6.989	7.029
Adj. $R^2_{(\%)}$	no $\text{TR}^{(eq)}$	1.679	3.226	3.632	3.830	3.942	4.019	4.004
F-test		0.001	0.004	0.005	0.004	0.003	0.002	0.002
Panel F: Control for VIX$^{\perp}$								
$\text{TR}_t^{(eq)}$	β	0.410	0.884	1.407	1.961	2.522	3.593	4.878
	p-value	0.001	0.004	0.005	0.004	0.002	0.001	0.001
$\text{VIX}_t^{\perp}$	β	0.194	0.162	0.056	-0.081	-0.254	-0.747	-1.817
	p-value	0.265	0.685	0.932	0.929	0.827	0.659	0.481
SKEW_t	β	-0.365	-0.839	-1.213	-1.484	-1.676	-1.933	-2.255
	p-value	0.033	0.049	0.079	0.112	0.144	0.201	0.269
VRP_t	β	-0.115	-0.317	-0.674	-1.171	-1.786	-3.252	-5.697
	p-value	0.399	0.357	0.214	0.097	0.032	0.002	0.000
Adj. $R^2_{(\%)}$		9.666	5.322	4.124	3.919	4.109	4.886	5.991
Adj. $R^2_{(\%)}$	no $\text{TR}^{(eq)}$	6.079	2.922	1.966	1.763	1.898	2.619	3.919
F-test		0.001	0.005	0.007	0.007	0.006	0.006	0.008

Notes: This table reports the slope estimates and p-values from predictive regressions of one-month US Treasury bond returns on the S&P 500 option-implied equity tail risk measure $\text{TR}^{(eq)}$. n denotes the bond maturity in months. Panel A reports the results of a regression that only uses $\text{TR}^{(eq)}$ as predictor. Panels B to F report the results of regressions that control for bond return predictors identified in the literature: PC1 – PC5 are the first five principal components extracted from the Treasury bond yields, CP is the Cochrane and Piazzesi (2005) bond return predictor obtained as a linear combination of forward rates, CiP is the Cieslak and Povala (2015) risk-premium factor obtained from a decomposition of Treasury yields into inflation expectations and maturity-specific interest-rate cycles, VIX$^{\perp}$ is the orthogonal component of the CBOE VIX with respect to $\text{TR}^{(eq)}$, VRP is the equity variance risk premium of Bollerslev et al. (2014), and SKEW is the CBOE Skew Index. All predictors have been normalized to have mean zero and unit variance. For all predictors we report the Newey-West p-values computed with a 12-lag standard error correction. In addition, for the $\text{TR}^{(eq)}$ factor used alone or alongside the principal components in the predictive regressions, we report the p-value (b) computed with the bootstrap procedure of Bauer and Hamilton (2018). For each regression we report the adjusted R-squared in percentage. This measure is also reported for a regression that excludes the $\text{TR}^{(eq)}$ factor as predictor. We also report the p-value of an F-test of the null hypothesis that the regression that includes the $\text{TR}^{(eq)}$ as predictor does not give a significantly better fit to the data than does a regression without it. The in-sample period is 1996:01–2019:12.

Table 3 – Out-of-sample forecasts of Treasury returns with equity tail risk

		$n = 12$	$n = 24$	$n = 36$	$n = 48$	$n = 60$	$n = 84$	$n = 120$
Panel A: Benchmark predictor is EH model (no predictability)								
Panel A1: Increasing windows								
R^2_{OS} (%)		2.045	2.867	3.698	4.212	4.284	3.466	1.707
p-value	(CW)	0.120	0.100	0.085	0.070	0.056	0.030	0.009
p-value (b)	(CW)	0.155	0.198	0.123	0.102	0.095	0.073	0.102
p-value (b)	(R^2_{OS})	0.076	0.068	0.016	0.010	0.007	0.005	0.023
Panel A2: Rolling windows								
R^2_{OS} (%)		1.800	2.750	3.517	3.955	3.978	3.124	1.357
p-value	(CW)	0.123	0.098	0.078	0.060	0.043	0.016	0.004
p-value (b)	(CW)	0.163	0.202	0.124	0.095	0.085	0.065	0.097
p-value (b)	(R^2_{OS})	0.093	0.074	0.020	0.012	0.011	0.010	0.038
Panel B: Benchmark predictor is 3 PCs-only model								
Panel B1: Increasing windows								
R^2_{OS} (%)		3.897	3.082	3.471	3.794	3.773	2.952	1.393
p-value	(CW)	0.010	0.018	0.021	0.018	0.012	0.004	0.014
p-value (b)	(CW)	0.015	0.035	0.040	0.037	0.034	0.047	0.110
p-value (b)	(R^2_{OS})	0.002	0.005	0.004	0.003	0.003	0.008	0.039
Panel B2: Rolling windows								
R^2_{OS} (%)		2.799	2.578	3.175	3.567	3.597	2.862	1.305
p-value	(CW)	0.036	0.028	0.017	0.010	0.006	0.008	0.084
p-value (b)	(CW)	0.035	0.036	0.028	0.025	0.022	0.042	0.101
p-value (b)	(R^2_{OS})	0.008	0.013	0.006	0.005	0.005	0.012	0.052
Panel C: Benchmark predictor is 5 PCs-only model								
Panel C1: Increasing windows								
R^2_{OS} (%)		2.559	2.802	3.034	3.099	2.930	2.050	0.606
p-value	(CW)	0.053	0.089	0.098	0.093	0.080	0.042	0.020
p-value (b)	(CW)	0.029	0.055	0.067	0.073	0.069	0.086	0.149
p-value (b)	(R^2_{OS})	0.008	0.008	0.006	0.005	0.009	0.021	0.103
Panel C2: Rolling windows								
R^2_{OS} (%)		2.966	3.751	3.980	4.015	3.800	2.825	1.300
p-value	(CW)	0.060	0.052	0.046	0.034	0.019	0.004	0.067
p-value (b)	(CW)	0.034	0.037	0.043	0.040	0.041	0.048	0.108
p-value (b)	(R^2_{OS})	0.009	0.005	0.003	0.002	0.004	0.013	0.055

Notes: This table reports the Campbell and Thompson (2008) out-of-sample R^2_{OS}s of predicting one-month returns on the n-month US Treasury bond with the S&P 500 option-implied equity tail risk measure $\text{TR}^{(eq)}$. These R^2_{OS} statistics represent the percentage reduction in the MSPE for the forecasts generated by a preferred model that includes $\text{TR}^{(eq)}$ relative to a benchmark that does not use it as predictor. Panel A: the preferred model uses the $\text{TR}^{(eq)}$ factor alone, while the benchmark model complies with the expectation hypothesis that assumes no predictability of bond returns. Panel B: the preferred model includes $\text{TR}^{(eq)}$ and the first 3 principal components of bond yields, while the benchmark model only includes the 3 principal components. Panel C: the preferred model includes $\text{TR}^{(eq)}$ and the first 5 principal components of bond yields, while the benchmark model only includes the 5 principal components. Predictive regressions are recursively estimated with both expanding and rolling window approach. The out-of-sample period is 2008:01–2019:12. Statistical significance for R^2_{OS} is based on the p-value of the Clark and West (2007) MSPE-adjusted statistic (CW) for testing $H_0 : R^2_{OS} \leq 0$ against $H_1 : R^2_{OS} > 0$. For the CW statistics we report both the Newey-West p-value computed with a 12-lag standard error correction and the p-value (b) computed with the bootstrap procedure of Bauer and Hamilton (2018). For the out-of-sample R^2_{OS} we only report the bootstrap p-value (b).

Table 4 – Asset allocation gains of equity tail risk

	$n=12$	$n=24$	$n=36$	$n=48$	$n=60$	$n=84$	$n=120$
Panel A: Benchmark predictor is EH model (no predictability)							
Panel A1: Risk aversion $\gamma=3$							
Δ (%)	0.096	−0.359	−0.307	−0.017	0.908	0.908	−2.753
Θ (%)	0.094	−0.366	−0.322	0.004	0.990	1.431	−2.990
$\text{SR}^{(1)}$	1.063	0.881	0.854	0.811	0.769	0.681	0.508
$\text{SR}^{(0)}$	0.895	0.888	0.853	0.787	0.720	0.645	0.570
Panel A2: Risk aversion $\gamma=5$							
Δ (%)	0.033	−0.233	0.189	1.418	0.822	−1.419	−4.918
Θ (%)	0.029	−0.253	0.219	1.535	1.091	−0.149	−5.108
$\text{SR}^{(1)}$	1.079	0.908	0.859	0.829	0.761	0.650	0.479
$\text{SR}^{(0)}$	0.895	0.888	0.827	0.727	0.716	0.675	0.602
Panel B: Benchmark predictor is 3 PCs-only model							
Panel B1: Risk aversion $\gamma=3$							
Δ (%)	−0.305	−0.926	−0.594	0.532	1.077	1.773	−1.072
Θ (%)	−0.307	−0.928	−0.587	0.528	1.039	1.797	−0.939
$\text{SR}^{(1)}$	1.400	0.951	0.890	0.903	0.830	0.707	0.499
$\text{SR}^{(0)}$	1.260	1.111	0.986	0.892	0.782	0.611	0.572
Panel B2: Risk aversion $\gamma=5$							
Δ (%)	−0.252	−0.693	−0.294	0.900	1.334	1.618	−1.541
Θ (%)	−0.257	−0.695	−0.290	0.917	1.356	1.657	−0.480
$\text{SR}^{(1)}$	1.405	0.941	0.907	0.900	0.819	0.701	0.448
$\text{SR}^{(0)}$	1.246	1.101	0.998	0.848	0.707	0.576	0.534
Panel C: Benchmark predictor is 5 PCs-only model							
Panel C1: Risk aversion $\gamma=3$							
Δ (%)	−0.260	0.674	1.244	2.059	3.556	3.175	−1.318
Θ (%)	−0.263	0.673	1.244	2.119	3.703	3.164	−1.964
$\text{SR}^{(1)}$	1.451	1.074	1.025	1.014	1.014	0.910	0.575
$\text{SR}^{(0)}$	1.249	0.976	0.934	0.962	0.865	0.772	0.617
Panel C2: Risk aversion $\gamma=5$							
Δ (%)	−0.281	0.594	1.115	1.721	2.541	0.825	−1.559
Θ (%)	−0.286	0.594	1.143	1.866	2.927	0.604	−0.862
$\text{SR}^{(1)}$	1.454	1.060	0.999	0.984	0.963	0.825	0.557
$\text{SR}^{(0)}$	1.275	0.979	0.929	0.904	0.831	0.787	0.549

Notes: This table reports the asset allocation gains of predicting one-month US Treasury bond returns with the S&P 500 option-implied equity tail risk measure $\text{TR}^{(eq)}$. n denotes the maturity of the bond in months. We assume a mean-variance investor with risk aversion $\gamma=3$ or $\gamma=5$ that every month allocates his or her wealth between a 1-month Treasury (risk-free) bond and an n-month Treasury bond. Investment decisions are based on the expected return forecasts of the n-month bond which are generated by a preferred model that includes $\text{TR}^{(eq)}$ as predictor or by a benchmark that does not use it. Panel A: the preferred model uses the $\text{TR}^{(eq)}$ factor alone, while the benchmark model complies with the expectation hypothesis that assumes no predictability of bond returns. Panel B (resp. C): the preferred model includes $\text{TR}^{(eq)}$ and the first three (resp. five) principal components of bond yields, while the benchmark model only includes the principal components. Predictive models are recursively estimated with a rolling window approach. The (out-of-sample) investment period is 2008:01–2019:12. We report two measures for the performance of the preferred model relative to that of the benchmark model: certainty equivalent return gain (Δ) and Goetzmann et al. (2007) manipulation-proof performance improvement (Θ). Both measures are expressed in annualized percentage terms. The annualized Sharpe ratio of the portfolios associated with the preferred model ($\text{SR}^{(1)}$) and the benchmark ($\text{SR}^{(0)}$) are also reported.

Table 5 – Expected returns, forecasting performance and macroeconomic condition

	$n = 12$	$n = 24$	$n = 36$	$n = 48$	$n = 60$	$n = 84$	$n = 120$
Panel A: $\rho(\mathbb{E}_t[\text{RX}_{t+1}^{(n)}], \text{CFNAI}_t)$							
$\text{TR}^{(eq)}$	-0.667	-0.648	-0.635	-0.622	-0.603	-0.556	-0.492
$\text{TR}^{(eq)} + 3\text{PCs}$	-0.471	-0.430	-0.414	-0.409	-0.405	-0.387	-0.334
$\text{TR}^{(eq)} + 5\text{PCs}$	-0.331	-0.168	-0.098	-0.081	-0.087	-0.124	-0.188
Panel B: $\rho(\mathbb{E}_t[\text{RX}_{t+1}^{(n)}], \mathbb{U}_t^{\text{MACRO}})$							
$\text{TR}^{(eq)}$	0.716	0.676	0.650	0.630	0.608	0.559	0.496
$\text{TR}^{(eq)} + 3\text{PCs}$	0.569	0.544	0.528	0.521	0.516	0.496	0.442
$\text{TR}^{(eq)} + 5\text{PCs}$	0.505	0.353	0.277	0.257	0.264	0.306	0.372
Panel C: $\rho(\text{DCSPE}_t, \text{CFNAI}_t)$							
$\text{TR}^{(eq)}$	-0.371	-0.188	-0.013	0.100	0.165	0.213	0.160
$\text{TR}^{(eq)} + 3\text{PCs}$	0.408	0.394	0.394	0.391	0.378	0.321	0.194
$\text{TR}^{(eq)} + 5\text{PCs}$	0.357	0.395	0.388	0.384	0.379	0.327	0.189
Panel D: $\rho(\text{DCRU}_t, \text{CFNAI}_t)$							
$\text{TR}^{(eq)}$	0.217	0.298	-0.013	0.224	0.044	-0.322	-0.449
$\text{TR}^{(eq)} + 3\text{PCs}$	0.406	0.170	0.009	0.218	0.174	0.122	-0.175
$\text{TR}^{(eq)} + 5\text{PCs}$	0.244	0.231	0.411	0.442	0.423	-0.024	-0.181

Notes: This table reports contemporaneous correlations between economic variables and the expected bond risk premia and forecasting performance obtained with the S&P 500 option-implied equity tail risk measure $\text{TR}^{(eq)}$. n denotes the bond maturity in months. Panels A and B report contemporaneous correlations between the out-of-sample forecasts of the one-month-ahead Treasury bond returns obtained by one of the three models that use $\text{TR}^{(eq)}$ as predictor and the Chicago Fed National Activity Index (CFNAI) and the macroeconomic uncertainty index ($\mathbb{U}^{\text{MACRO}}$) constructed by Jurado et al. (2015). Panels C and D report contemporaneous correlations between relative forecast and portfolio performance obtained by one of the three models that use $\text{TR}^{(eq)}$ as predictor (relative to its benchmark that does not use $\text{TR}^{(eq)}$ to predict bond returns) and the CFNAI. Relative forecast performance is defined as the difference in cumulative squared prediction error (DCSPE) and portfolio performance is defined as the difference in cumulative realized utilities (DCRU). The out-of-sample evaluation period is 2008:01–2019:12. The predictive models are recursively estimated with a rolling window approach. The investor's risk aversion coefficient is $\gamma = 5$.

Table 6 – Fit diagnostics of the ATSM with equity tail risk

Panel A: Equity Tail Risk ATSM

	$n = 12$	$n = 24$	$n = 36$	$n = 60$	$n = 84$	$n = 120$
Panel A1: Yield Pricing Errors						
Mean	−0.002	0.000	0.000	−0.002	−0.001	−0.002
Standard Deviation	0.004	0.005	0.003	0.004	0.003	0.006
Skewness	−0.390	0.779	0.119	−0.311	0.413	−0.429
Kurtosis	4.162	4.163	2.047	3.635	2.769	3.509
$\rho(1)$	0.877	0.805	0.910	0.899	0.845	0.863
$\rho(6)$	0.551	0.369	0.787	0.583	0.481	0.499
Panel A2: Return Pricing Errors						
Mean	0.000	0.002	−0.002	−0.005	0.004	−0.027
Standard Deviation	0.044	0.072	0.067	0.111	0.118	0.394
Skewness	−0.322	−0.488	−0.537	0.044	−0.201	−0.211
Kurtosis	5.807	7.212	14.160	5.989	6.385	5.008
$\rho(1)$	0.048	0.045	0.258	0.020	−0.072	−0.015
$\rho(6)$	0.152	0.215	0.283	0.020	0.136	0.051

Panel B: PC-only ATSM

	$n = 12$	$n = 24$	$n = 36$	$n = 60$	$n = 84$	$n = 120$
Panel B1: Yield Pricing Errors						
Mean	−0.004	−0.001	−0.001	−0.003	−0.003	−0.002
Standard Deviation	0.005	0.005	0.003	0.005	0.003	0.006
Skewness	−0.096	0.744	−0.142	−0.143	0.048	−0.434
Kurtosis	3.754	4.106	1.888	3.158	2.152	3.563
$\rho(1)$	0.906	0.813	0.949	0.922	0.897	0.860
$\rho(6)$	0.615	0.398	0.872	0.651	0.692	0.540
Panel B2: Return Pricing Errors						
Mean	−0.001	0.002	−0.004	−0.009	−0.001	−0.015
Standard Deviation	0.049	0.074	0.066	0.124	0.114	0.384
Skewness	−0.413	−0.466	−0.741	−0.081	0.130	−0.217
Kurtosis	5.628	7.908	13.689	5.975	6.487	5.424
$\rho(1)$	0.129	0.014	0.344	0.079	−0.186	−0.083
$\rho(6)$	0.109	0.217	0.337	0.002	0.138	0.037

Notes: This table contains the summary statistics of the pricing errors implied by the Gaussian ATSM that includes the S&P 500 option-implied equity tail risk measure $\text{TR}^{(eq)}$ (Panel A) and by the benchmark model that only uses the first five PCs of the yield curve (Panel B). Models are estimated over the period 1996 to 2019. Reported are the sample mean, standard deviation, skewness, kurtosis and the autocorrelation coefficients of order one and six. Panels A1 and B1: properties of the yield pricing errors $\hat{u}$. Panels A2 and B2: properties of the return pricing errors $\hat{e}$. n denotes the maturity of the bonds in months.

Table 7 – Factor risk exposures in the ATSM with equity tail risk

Factor	Equity Tail Risk ATSM		PC-only ATSM	
	W_{β_i}	p-value	W_{β_i}	p-value
TR$^{(eq)}$	9520240.543	0.000	-	-
PC1	32833939.666	0.000	34906004.697	0.000
PC2	6017848.042	0.000	6474375.636	0.000
PC3	987085.382	0.000	1000091.019	0.000
PC4	186350.666	0.000	188058.261	0.000
PC5	35266.896	0.000	35190.169	0.000

Notes: This table provides the Wald statistics and corresponding p-values for the Wald test of whether the exposures of bond returns to a given model factor are jointly zero. Under the null $H_0 : \boldsymbol{\beta}_i = \mathbf{0}_{N \times 1}$ the i-th pricing factor is unspanned, i.e. Treasury returns are not exposed to it. The test is conducted on the pricing factors of both the proposed ATSM specified with the S&P 500 option-implied equity tail risk measure TR$^{(eq)}$, and a benchmark PC-only model specification.

Table 8 – Market prices of risk in the ATSM with equity tail risk

Factor	λ_0	$\lambda_{1,1}$	$\lambda_{1,2}$	$\lambda_{1,3}$	$\lambda_{1,4}$	$\lambda_{1,5}$	$\lambda_{1,6}$	W_{Λ_i}	$W_{\lambda_{1_i}}$
$\text{TR}^{(eq)}$	0.138	-0.175	0.419	0.111	-0.410	-0.091	0.224	12.268	11.958
	(0.926)	(-1.134)	(2.459)	(0.743)	(-2.469)	(-0.618)	(1.445)	(0.092)	(0.063)
PC1	0.004	-0.055	0.053	0.001	-0.060	-0.031	0.018	12.241	12.238
	(0.178)	(-2.192)	(1.927)	(0.049)	(-2.252)	(-1.287)	(0.714)	(0.093)	(0.057)
PC2	-0.046	0.019	-0.097	-0.052	0.121	0.016	-0.091	14.516	13.940
	(-1.129)	(0.442)	(-2.106)	(-1.274)	(2.695)	(0.384)	(-2.155)	(0.043)	(0.030)
PC3	0.006	0.033	-0.149	0.023	0.038	0.070	-0.066	12.061	11.934
	(0.121)	(0.671)	(-2.872)	(0.483)	(0.755)	(1.499)	(-1.360)	(0.099)	(0.063)
PC4	0.020	-0.043	-0.062	0.084	-0.029	-0.037	-0.077	18.709	18.330
	(0.595)	(-1.282)	(-1.828)	(2.480)	(-0.871)	(-1.094)	(-2.277)	(0.009)	(0.005)
PC5	-0.068	-0.003	-0.039	-0.113	0.046	-0.037	-0.136	15.537	13.904
	(-1.388)	(-0.068)	(-0.747)	(-2.289)	(0.904)	(-0.754)	(-2.724)	(0.030)	(0.031)

Notes: This table provides the estimates of the market price of risk parameters $\boldsymbol{\lambda}_0$ and $\boldsymbol{\lambda}_1$ in equation (15) for the Gaussian ATSM specified with the S&P 500 option-implied equity tail risk measure $\text{TR}^{(eq)}$. Estimated t-statistics are reported in parentheses. Wald statistics for tests of the rows of $\boldsymbol{\Lambda}$ and of $\boldsymbol{\lambda}_1$ being different from zero are reported along each row, with the corresponding p-values in parentheses below. The null hypothesis underlying W_{Λ_i} is that the risk related to a given factor is not priced in the term structure model. The null hypothesis underlying $W_{\lambda_{1_i}}$ is that the price of risk associated with a given factor does not vary over time.

Table 9 – Market price of equity tail risk with GX procedure

	$p=1$	$p=2$	$p=3$	$p=4$	$p=5$	$p=6$	$p=7$	$p=8$
γ_g	0.010	0.026	0.026	0.024	0.024	0.026	0.024	0.024
	(0.009)	(0.016)	(0.016)	(0.016)	(0.016)	(0.017)	(0.017)	(0.017)
R_g^2	0.006	0.078	0.078	0.081	0.081	0.098	0.105	0.106
p-value g weak	0.241	0.012	0.027	0.035	0.034	0.021	0.038	0.044

Notes: This table reports the results of the three-pass regression procedure of Giglio and Xiu (2019) to estimate the risk premium of the S&P 500 option-implied equity tail risk measure $\mathrm{TR}^{(eq)}$ in the US Treasury bond market. p denotes the number of latent factors used in the three-pass estimator. For each number of latent factors, we report the estimate of the market price of risk γ_g of the observable factor g with standard errors in parentheses, the R-squared of the time series regression of the observable factor g onto the p latent factors, and the p-value of the Wald test of testing the null hypothesis that the observable factor is weak. We use AR(1) innovations in $\mathrm{TR}^{(eq)}$ as the factor g. * (resp. **, and ***) denote statistical significance at the 10% (resp. 5%, and 1%) level.

Table 10 – In-sample forecasts of international bond returns with equity tail risk

		$n = 12$	$n = 24$	$n = 36$	$n = 48$	$n = 60$	$n = 84$	$n = 120$
Panel A: No control for bond return forecasting factors								
UK	β	0.975	1.806	2.450	3.002	3.549	4.520	5.754
	p-value	0.001	0.000	0.000	0.000	0.000	0.000	0.000
	p-value (b)	0.000	0.000	0.000	0.000	0.000	0.000	0.000
DE	β	0.542	1.030	1.448	1.827	2.172	2.758	3.378
	p-value	0.002	0.001	0.001	0.001	0.002	0.004	0.009
	p-value (b)	0.000	0.001	0.001	0.003	0.002	0.010	0.026
CH	β	0.547	0.654	0.799	1.033	1.295	1.776	2.397
	p-value	0.036	0.002	0.000	0.001	0.001	0.002	0.009
	p-value (b)	0.000	0.011	0.035	0.037	0.032	0.034	0.047
FR	β	0.468	0.893	1.231	1.511	1.754	2.170	2.667
	p-value	0.003	0.003	0.004	0.007	0.012	0.035	0.097
	p-value (b)	0.003	0.008	0.010	0.014	0.024	0.042	0.083
IT	β	0.402	0.454	0.679	1.008	1.336	1.811	2.084
	p-value	0.103	0.343	0.350	0.285	0.237	0.205	0.240
	p-value (b)	0.116	0.417	0.402	0.317	0.269	0.245	0.285
ES	β	0.619	1.179	1.662	2.079	2.445	3.067	3.866
	p-value	0.000	0.000	0.000	0.001	0.002	0.005	0.011
	p-value (b)	0.017	0.045	0.054	0.072	0.085	0.112	0.156
Panel B: Control for yield curve factors with 3 PCs (country-specific)								
UK	β	0.966	1.758	2.351	2.862	3.376	4.289	5.460
	p-value	0.001	0.000	0.000	0.000	0.000	0.000	0.000
	p-value (b)	0.000	0.000	0.000	0.000	0.000	0.000	0.001
DE	β	0.548	1.009	1.393	1.732	2.034	2.527	3.001
	p-value	0.002	0.001	0.001	0.002	0.003	0.007	0.022
	p-value (b)	0.000	0.000	0.001	0.003	0.004	0.010	0.035
CH	β	0.559	0.693	0.828	1.008	1.194	1.523	1.992
	p-value	0.034	0.003	0.001	0.002	0.004	0.011	0.036
	p-value (b)	0.000	0.007	0.030	0.041	0.041	0.055	0.074
FR	β	0.452	0.830	1.099	1.295	1.447	1.678	1.923
	p-value	0.007	0.010	0.015	0.028	0.050	0.123	0.265
	p-value (b)	0.000	0.002	0.007	0.019	0.035	0.094	0.222
IT	β	0.446	0.597	0.841	1.117	1.344	1.549	1.374
	p-value	0.111	0.283	0.312	0.288	0.272	0.290	0.427
	p-value (b)	0.068	0.269	0.299	0.279	0.260	0.318	0.469
ES	β	0.500	1.015	1.416	1.746	2.031	2.512	3.127
	p-value	0.003	0.003	0.008	0.014	0.020	0.031	0.050
	p-value (b)	0.051	0.082	0.111	0.143	0.170	0.199	0.253

Table 10 – In-sample forecasts of international bond returns with equity tail risk (continued)

		$n = 12$	$n = 24$	$n = 36$	$n = 48$	$n = 60$	$n = 84$	$n = 120$
Panel C: Control for yield curve factors with 5 PCs (country-specific)								
UK	β	0.941	1.752	2.343	2.877	3.431	4.481	5.876
	p-value	0.002	0.000	0.000	0.000	0.000	0.000	0.001
	p-value (b)	0.000	0.000	0.000	0.000	0.000	0.000	0.000
DE	β	0.479	0.908	1.279	1.615	1.915	2.399	2.846
	p-value	0.000	0.000	0.000	0.001	0.002	0.006	0.023
	p-value (b)	0.000	0.001	0.003	0.006	0.008	0.017	0.044
CH	β	0.464	0.605	0.767	0.939	1.081	1.281	1.585
	p-value	0.014	0.001	0.001	0.005	0.010	0.027	0.080
	p-value (b)	0.000	0.018	0.047	0.057	0.068	0.110	0.155
FR	β	0.441	0.817	1.093	1.298	1.454	1.673	1.856
	p-value	0.016	0.015	0.017	0.026	0.047	0.127	0.297
	p-value (b)	0.000	0.003	0.007	0.017	0.034	0.096	0.234
IT	β	0.586	0.837	1.134	1.426	1.657	1.900	1.882
	p-value	0.027	0.099	0.123	0.119	0.118	0.140	0.237
	p-value (b)	0.017	0.115	0.155	0.170	0.170	0.214	0.331
ES	β	0.678	1.189	1.605	2.009	2.395	3.085	3.957
	p-value	0.008	0.009	0.012	0.015	0.017	0.027	0.050
	p-value (b)	0.006	0.039	0.071	0.094	0.100	0.118	0.155

Notes: This table reports the slope estimates and p-values associated with the S&P 500 option-implied equity tail risk measure $\text{TR}^{(eq)}$ used in return predictive regressions of Treasury bonds of United Kingdom (UK), Germany (DE), Switzerland (CH), France (FR), Italy (IT), and Spain (ES). n denotes the bond maturity in months. Panel A reports the results of a regression that only uses $\text{TR}_t^{(eq)}$ as predictor. Panel B (resp. C) reports the results of a predictive regression that controls for country-specific yield curve factors represented by the first three (resp. five) principal components of Treasury bond yields. Predictors have been normalized to have mean zero and unit variance. We report the Newey-West p-values computed with a 12-lag standard error correction, and the p-value (b) computed with the bootstrap procedure of Bauer and Hamilton (2018). The in-sample period is 1996:01–2018:12.

Table 11 – Out-of-sample forecasts of international bond returns with equity tail risk

		$n = 12$	$n = 24$	$n = 36$	$n = 48$	$n = 60$	$n = 84$	$n = 120$
Panel A: No control for bond return forecasting factors								
UK	R^2_{OS} (%)	24.245	18.207	14.287	12.136	10.904	8.411	5.991
	p-value	0.103	0.078	0.064	0.056	0.051	0.044	0.034
	Δ (%)	0.009	0.243	1.012	2.093	3.433	1.786	−4.959
	Θ (%)	0.007	0.264	1.110	2.284	3.774	2.419	−5.765
DE	R^2_{OS} (%)	9.637	7.644	6.923	6.498	6.038	4.941	3.278
	p-value	0.046	0.046	0.041	0.034	0.028	0.020	0.014
	Δ (%)	−0.011	0.070	0.188	0.420	0.785	1.359	0.121
	Θ (%)	−0.011	0.072	0.220	0.505	0.986	1.858	0.800
CH	R^2_{OS} (%)	9.422	5.735	2.465	2.594	3.182	3.362	2.476
	p-value	0.100	0.056	0.033	0.032	0.030	0.016	0.001
	Δ (%)	0.105	0.332	0.061	−0.192	0.070	0.112	1.241
	Θ (%)	0.104	0.330	0.059	−0.251	0.028	0.183	1.972
FR	R^2_{OS} (%)	7.269	5.474	4.397	3.480	2.757	1.763	0.754
	p-value	0.102	0.116	0.118	0.117	0.120	0.139	0.196
	Δ (%)	−0.001	0.005	0.080	0.140	0.140	0.321	−3.606
	Θ (%)	−0.001	0.004	0.093	0.178	0.250	0.640	−4.526
Panel B: Control for yield curve factors with 3 PCs (country-specific)								
UK	R^2_{OS} (%)	20.834	14.966	11.143	9.289	8.254	6.173	4.187
	p-value	0.096	0.097	0.097	0.090	0.081	0.063	0.049
	Δ (%)	0.422	0.449	0.526	1.553	1.649	0.868	−1.859
	Θ (%)	0.435	0.503	0.621	1.680	1.794	1.076	−0.406
DE	R^2_{OS} (%)	7.717	5.934	5.218	4.500	3.714	2.205	0.545
	p-value	0.084	0.103	0.105	0.101	0.096	0.089	0.112
	Δ (%)	0.285	1.671	2.281	2.433	2.134	1.769	0.151
	Θ (%)	0.284	1.677	2.301	2.497	2.243	2.053	0.123
CH	R^2_{OS} (%)	8.870	5.372	2.211	1.918	1.832	0.927	−0.577
	p-value	0.102	0.071	0.081	0.102	0.111	0.106	0.223
	Δ (%)	0.839	0.566	1.104	1.175	1.184	0.941	0.235
	Θ (%)	0.839	0.572	1.120	1.203	1.232	1.056	0.086
FR	R^2_{OS} (%)	6.493	4.489	3.136	1.950	1.009	−0.249	−1.334
	p-value	0.115	0.151	0.173	0.197	0.231	0.339	0.621
	Δ (%)	0.017	−0.239	−0.194	−0.196	−0.594	−2.188	−4.100
	Θ (%)	0.019	−0.237	−0.153	−0.066	−0.359	−1.748	−3.270

Table 11 – Out-of-sample forecasts of international bond returns with equity tail risk (continued)

		$n=12$	$n=24$	$n=36$	$n=48$	$n=60$	$n=84$	$n=120$
Panel C: Control for yield curve factors with 5 PCs (country-specific)								
UK	R^2_{OS} (%)	20.461	15.758	12.521	11.005	10.215	8.208	5.754
	p-value	0.096	0.086	0.080	0.072	0.063	0.049	0.043
	Δ (%)	0.481	0.701	0.497	1.682	2.288	0.996	1.044
	Θ (%)	0.494	0.761	0.586	1.773	2.266	0.793	0.954
DE	R^2_{OS} (%)	10.968	8.402	6.647	5.373	4.320	2.580	0.694
	p-value	0.030	0.048	0.051	0.051	0.051	0.054	0.107
	Δ (%)	0.036	−0.207	−0.311	0.138	0.428	0.053	−0.889
	Θ (%)	0.036	−0.209	−0.294	0.190	0.473	0.197	−1.056
CH	R^2_{OS} (%)	8.631	3.860	1.082	0.770	0.775	0.395	−0.737
	p-value	0.059	0.027	0.060	0.097	0.116	0.136	0.484
	Δ (%)	−0.114	0.398	0.593	0.543	0.611	0.639	0.112
	Θ (%)	−0.114	0.397	0.605	0.562	0.617	0.623	−0.176
FR	R^2_{OS} (%)	7.846	5.277	3.554	2.268	1.283	−0.110	−1.416
	p-value	0.103	0.149	0.179	0.204	0.233	0.334	0.666
	Δ (%)	−0.058	−0.101	0.766	1.339	0.783	−0.557	−3.398
	Θ (%)	−0.057	−0.091	0.801	1.483	1.050	−0.090	−3.877

Notes: This table reports the Campbell and Thompson (2008) out-of-sample R^2_{OS}s of predicting one-month Treasury bond returns in United Kingdom (UK), Germany (DE), Switzerland (CH), and France (FR) with the S&P 500 option-implied equity tail risk measure $\text{TR}^{(eq)}$. These R^2_{OS} statistics represent the percentage reduction in the MSPE for the forecasts generated by a preferred model that includes $\text{TR}^{(eq)}$ relative to a benchmark that does not use it as predictor. The preferred model uses the $\text{TR}^{(eq)}$ factor alone in Panel A, and alongside the country-specific first three (resp. five) principal components of bond yields in Panel B (resp. C). Statistical significance for R^2_{OS} is based on the Clark and West (2007) MSPE-adjusted statistic, for which we report Newey-West p-values computed with a 12-lag standard error correction. To assess the portfolio performance afforded by $\text{TR}^{(eq)}$ relative to the benchmark models, we report the certainty equivalent return gain (Δ) and Goetzmann et al. (2007) manipulation-proof performance improvement (Θ) in annualized percentage terms. The out-of-sample period is 2007:07–2018:12. Predictive regressions are recursively estimated with a rolling window approach. The investor's risk aversion coefficient γ is set equal to 5.

Table 12 – Market price of equity tail risk in international bond markets

		$p = 1$	$p = 2$	$p = 3$	$p = 4$	$p = 5$	$p = 6$	$p = 7$	$p = 8$
UK	γ_g	0.015	0.028*	0.032*	0.032*	0.035*	0.035*	0.035*	0.036*
		(0.011)	(0.016)	(0.019)	(0.019)	(0.021)	(0.020)	(0.021)	(0.021)
	R_g^2	0.013	0.061	0.071	0.071	0.095	0.096	0.103	0.104
	p-value g weak	0.089	0.037	0.071	0.121	0.013	0.018	0.008	0.015
DE	γ_g	0.039**	0.047**	0.051**	0.055**	0.054**	0.055**	0.052*	0.052*
		(0.018)	(0.023)	(0.026)	(0.027)	(0.027)	(0.028)	(0.028)	(0.028)
	R_g^2	0.041	0.121	0.160	0.161	0.163	0.165	0.172	0.172
	p-value g weak	0.005	0.003	0.002	0.004	0.004	0.004	0.003	0.003
CH	γ_g	0.027**	0.033**	0.032**	0.040**	0.049***	0.051**	0.067**	0.083**
		(0.014)	(0.016)	(0.016)	(0.017)	(0.018)	(0.024)	(0.033)	(0.038)
	R_g^2	0.023	0.051	0.051	0.069	0.073	0.073	0.094	0.130
	p-value g weak	0.026	0.004	0.013	0.005	0.005	0.006	0.014	0.016
FR	γ_g	0.023	0.059**	0.059**	0.064**	0.079**	0.089**	0.089**	0.091**
		(0.015)	(0.028)	(0.028)	(0.029)	(0.032)	(0.035)	(0.035)	(0.036)
	R_g^2	0.017	0.109	0.110	0.116	0.127	0.133	0.133	0.135
	p-value g weak	0.082	0.011	0.029	0.043	0.032	0.045	0.064	0.094
IT	γ_g	−0.014	−0.012	−0.011	−0.012	−0.013	−0.015	−0.017	−0.017
		(0.009)	(0.010)	(0.010)	(0.010)	(0.010)	(0.011)	(0.012)	(0.012)
	R_g^2	0.009	0.021	0.024	0.028	0.029	0.033	0.037	0.040
	p-value g weak	0.106	0.119	0.206	0.288	0.416	0.408	0.461	0.357
ES	γ_g	−0.004	0.007	0.008	0.010	0.004	0.035	0.032	0.039
		(0.007)	(0.013)	(0.014)	(0.017)	(0.021)	(0.026)	(0.027)	(0.026)
	R_g^2	0.001	0.023	0.030	0.030	0.031	0.046	0.048	0.060
	p-value g weak	0.536	0.147	0.235	0.370	0.425	0.334	0.301	0.219

Notes: This table reports the results of the three-pass regression procedure of Giglio and Xiu (2019) to estimate the risk premium of the S&P 500 option-implied equity tail risk measure $\text{TR}^{(eq)}$ in the Treasury bond market of United Kingdom (UK), Germany (DE), Switzerland (CH), France (FR), Italy (IT), and Spain (ES). p denotes the number of latent factors used in the three-pass estimator. For each number of latent factors, we report the estimate of the market price of risk γ_g of the observable factor g with standard errors in parentheses, the R-squared of the time series regression of the observable factor g onto the p latent factors, and the p-value of the Wald test of testing the null hypothesis that the observable factor is weak. We use AR(1) innovations in $\text{TR}^{(eq)}$ as the factor g. * (resp. **, and ***) denote statistical significance at the 10% (resp. 5%, and 1%) level.

Table 13 – In-sample forecasts of international bond returns with country-specific equity tail risk

		$n = 12$	$n = 24$	$n = 36$	$n = 48$	$n = 60$	$n = 84$	$n = 120$
Panel A: No control for bond return forecasting factors								
UK	β	0.864	1.612	2.290	2.955	3.623	4.810	6.137
	p-value	0.004	0.000	0.000	0.000	0.000	0.002	0.016
	p-value (b)	0.000	0.000	0.000	0.000	0.000	0.001	0.001
DE	β	0.581	1.128	1.563	1.927	2.231	2.667	2.909
	p-value	0.000	0.000	0.001	0.002	0.006	0.018	0.065
	p-value (b)	0.001	0.002	0.004	0.006	0.010	0.022	0.048
CH	β	0.600	0.741	0.826	1.008	1.270	1.921	3.002
	p-value	0.117	0.012	0.009	0.016	0.015	0.010	0.005
	p-value (b)	0.000	0.003	0.035	0.059	0.049	0.023	0.012
FR	β	0.432	0.561	0.558	0.557	0.614	0.966	2.124
	p-value	0.017	0.107	0.221	0.296	0.308	0.217	0.099
	p-value (b)	0.008	0.115	0.310	0.458	0.517	0.479	0.327
IT	β	1.205	1.837	2.076	2.105	2.048	1.920	1.931
	p-value	0.000	0.007	0.046	0.123	0.218	0.379	0.494
	p-value (b)	0.000	0.028	0.123	0.219	0.306	0.436	0.524
ES	β	0.726	0.752	0.560	0.515	0.531	0.487	0.187
	p-value	0.295	0.439	0.672	0.765	0.803	0.868	0.963
	p-value (b)	0.127	0.492	0.749	0.804	0.831	0.892	0.972
Panel B: Control for yield curve factors with 3 PCs (country-specific)								
UK	β	0.758	1.348	1.862	2.386	2.924	3.851	4.847
	p-value	0.015	0.001	0.001	0.002	0.006	0.034	0.094
	p-value (b)	0.000	0.000	0.000	0.001	0.001	0.004	0.012
DE	β	0.634	1.160	1.512	1.754	1.915	2.036	1.798
	p-value	0.000	0.001	0.007	0.025	0.055	0.148	0.366
	p-value (b)	0.000	0.001	0.005	0.012	0.030	0.097	0.293
CH	β	0.588	0.783	0.860	0.948	1.076	1.469	2.308
	p-value	0.139	0.019	0.004	0.009	0.022	0.045	0.039
	p-value (b)	0.000	0.002	0.034	0.074	0.094	0.096	0.065
FR	β	0.320	0.280	0.076	-0.138	-0.293	-0.346	0.283
	p-value	0.105	0.483	0.885	0.826	0.688	0.735	0.868
	p-value (b)	0.062	0.468	0.892	0.861	0.767	0.816	0.907
IT	β	0.603	0.458	0.099	-0.298	-0.646	-1.088	-1.191
	p-value	0.061	0.621	0.941	0.852	0.717	0.607	0.652
	p-value (b)	0.049	0.605	0.944	0.868	0.768	0.689	0.713
ES	β	0.419	0.197	-0.188	-0.366	-0.444	-0.628	-1.127
	p-value	0.555	0.845	0.892	0.841	0.846	0.843	0.798
	p-value (b)	0.371	0.854	0.911	0.858	0.869	0.858	0.832

Table 13 – In-sample forecasts of international bond returns with country-specific equity tail risk (cont.)

		$n = 12$	$n = 24$	$n = 36$	$n = 48$	$n = 60$	$n = 84$	$n = 120$
Panel C: Control for yield curve factors with 5 PCs (country-specific)								
UK	β	0.747	1.346	1.847	2.360	2.894	3.849	4.944
	p-value	0.018	0.002	0.001	0.001	0.005	0.032	0.093
	p-value (b)	0.000	0.000	0.001	0.001	0.001	0.003	0.011
DE	β	0.604	1.151	1.514	1.751	1.903	2.018	1.819
	p-value	0.000	0.001	0.009	0.028	0.059	0.156	0.370
	p-value (b)	0.000	0.001	0.007	0.013	0.036	0.107	0.297
CH	β	0.515	0.729	0.815	0.886	0.987	1.342	2.175
	p-value	0.015	0.000	0.001	0.014	0.036	0.046	0.017
	p-value (b)	0.000	0.002	0.042	0.100	0.122	0.132	0.080
FR	β	0.254	0.086	−0.291	−0.672	−0.970	−1.247	−0.977
	p-value	0.174	0.810	0.511	0.201	0.132	0.209	0.574
	p-value (b)	0.138	0.825	0.636	0.413	0.355	0.411	0.680
IT	β	0.639	0.669	0.545	0.353	0.149	−0.196	−0.476
	p-value	0.066	0.467	0.677	0.821	0.932	0.924	0.854
	p-value (b)	0.037	0.443	0.691	0.841	0.945	0.948	0.884
ES	β	0.430	0.287	−0.055	−0.177	−0.149	0.004	0.145
	p-value	0.509	0.787	0.970	0.924	0.947	0.999	0.972
	p-value (b)	0.354	0.793	0.973	0.933	0.955	0.999	0.983

Notes: This table reports the slope estimates and p-values associated with country-specific equity tail risk measures used in return predictive regressions of Treasury bonds in United Kingdom (UK), Germany (DE), Switzerland (CH), France (FR), Italy (IT), and Spain (ES). n denotes the maturity of the bonds in months. The country-specific equity tail risk measures are calculated using options on the FTSE 100 (UK), DAX (DE), SMI (CH), CAC 40 (FR), FTSE MIB (IT) and IBEX 35 (ES) equity index. Panel A reports the results of a regression that only uses the country-specific equity tail risk measure as predictor. Panel B (resp. C) reports the results of a predictive regression that controls for country-specific yield curve factors represented by the first three (resp. five) principal components of Treasury bond yields. All predictors have been normalized to have mean zero and unit variance. We report the Newey-West p-values computed with a 12-lag standard error correction, and the p-value (b) computed with the bootstrap procedure of Bauer and Hamilton (2018). The in-sample period is 2002:01–2018:12 in UK, DE and CH, 2007:01–2018:12 in IT and FR, 2007:05–2018:12 in ES.

Table 14 – Market price of country-specific equity tail risk in international bond markets

		$p=1$	$p=2$	$p=3$	$p=4$	$p=5$	$p=6$	$p=7$	$p=8$
UK	γ_g	0.029*	0.057*	0.053*	0.053*	0.053*	0.053*	0.057*	0.056*
		(0.016)	(0.029)	(0.028)	(0.028)	(0.031)	(0.031)	(0.031)	(0.031)
	R_g^2	0.033	0.104	0.135	0.137	0.168	0.168	0.174	0.174
	p-value g weak	0.005	0.003	0.004	0.009	0.001	0.001	0.002	0.003
DE	γ_g	0.047**	0.059*	0.063*	0.063*	0.063*	0.061*	0.060*	0.067*
		(0.022)	(0.031)	(0.035)	(0.035)	(0.034)	(0.035)	(0.034)	(0.036)
	R_g^2	0.055	0.145	0.197	0.197	0.199	0.231	0.231	0.242
	p-value g weak	0.004	0.005	0.003	0.008	0.001	0.000	0.000	0.000
CH	γ_g	0.050**	0.060**	0.059**	0.074***	0.078**	0.074**	0.139**	0.144**
		(0.020)	(0.024)	(0.024)	(0.027)	(0.031)	(0.036)	(0.056)	(0.057)
	R_g^2	0.055	0.080	0.086	0.114	0.114	0.114	0.191	0.194
	p-value g weak	0.001	0.001	0.003	0.001	0.003	0.007	0.002	0.004
FR	γ_g	0.045	0.142*	0.144*	0.165*	0.163*	0.163**	0.173**	0.173**
		(0.031)	(0.077)	(0.078)	(0.085)	(0.085)	(0.083)	(0.087)	(0.087)
	R_g^2	0.037	0.244	0.253	0.285	0.301	0.340	0.358	0.358
	p-value g weak	0.060	0.023	0.050	0.064	0.077	0.020	0.001	0.001
IT	γ_g	−0.017	−0.017*	−0.015	0.005	0.006	0.007	0.009	0.008
		(0.010)	(0.009)	(0.011)	(0.028)	(0.029)	(0.030)	(0.031)	(0.031)
	R_g^2	0.020	0.020	0.022	0.065	0.066	0.069	0.078	0.079
	p-value g weak	0.120	0.227	0.378	0.031	0.035	0.056	0.150	0.171
ES	γ_g	0.009	0.018	0.013	−0.010	0.012	0.075	0.083	0.102
		(0.009)	(0.020)	(0.023)	(0.029)	(0.036)	(0.089)	(0.093)	(0.093)
	R_g^2	0.004	0.008	0.021	0.029	0.033	0.048	0.054	0.076
	p-value g weak	0.264	0.504	0.467	0.448	0.556	0.691	0.747	0.001

Notes: This table reports the results of the three-pass regression procedure of Giglio and Xiu (2019) to estimate the risk premium of country-specific equity tail risk measures in the Treasury bond market of United Kingdom (UK), Germany (DE), Switzerland (CH), France (FR), Italy (IT), and Spain (ES). The country-specific equity tail risk measures are calculated using options on the FTSE 100 (UK), DAX (DE), SMI (CH), CAC 40 (FR), FTSE MIB (IT) and IBEX 35 (ES) equity index. p denotes the number of latent factors used in the three-pass estimator. For each number of latent factors, we report the estimate of the market price of risk γ_g of the observable factor g with standard errors in parentheses, the R-squared of the time series regression of the observable factor g onto the p latent factors, and the p-value of the Wald test of testing the null hypothesis that the observable factor is weak. We use AR(1) innovations in the country-specific equity tail risk measures as factors g. * (resp. **, and ***) denote statistical significance at the 10% (resp. 5%, and 1%) level.

Table 15 – In-sample forecasts of int. bond returns with US and country-specific equity tail risk

		$n=12$	$n=24$	$n=36$	$n=48$	$n=60$	$n=84$	$n=120$
UK	β	1.136	2.073	2.797	3.465	4.162	5.486	7.143
	p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	$\beta^\perp$	0.038	0.121	0.335	0.588	0.816	1.126	1.279
	p-value$^\perp$	0.832	0.729	0.420	0.211	0.171	0.288	0.492
DE	β	0.710	1.399	2.018	2.588	3.106	3.979	4.896
	p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	$\beta^\perp$	0.111	0.196	0.192	0.137	0.049	-0.209	-0.783
	p-value$^\perp$	0.525	0.642	0.759	0.863	0.958	0.861	0.622
CH	β	0.670	0.829	1.015	1.346	1.754	2.608	3.786
	p-value	0.025	0.000	0.000	0.000	0.000	0.000	0.000
	$\beta^\perp$	0.181	0.223	0.158	0.087	0.052	0.123	0.479
	p-value$^\perp$	0.300	0.272	0.627	0.846	0.925	0.864	0.589
FR	β	0.629	1.066	1.409	1.720	2.017	2.581	3.379
	p-value	0.001	0.009	0.019	0.031	0.045	0.084	0.155
	$\beta^\perp$	-0.073	-0.389	-0.799	-1.167	-1.429	-1.549	-0.699
	p-value$^\perp$	0.672	0.344	0.232	0.205	0.217	0.324	0.731
IT	β	0.800	0.831	1.127	1.635	2.186	3.078	3.725
	p-value	0.002	0.193	0.247	0.184	0.127	0.077	0.080
	$\beta^\perp$	0.927	1.643	1.745	1.480	1.088	0.412	0.044
	p-value$^\perp$	0.019	0.073	0.208	0.407	0.609	0.877	0.989
ES	β	0.791	1.674	2.450	3.145	3.781	4.932	6.532
	p-value	0.000	0.000	0.000	0.000	0.000	0.001	0.003
	$\beta^\perp$	0.569	0.402	0.037	-0.161	-0.283	-0.580	-1.235
	p-value$^\perp$	0.432	0.672	0.976	0.921	0.890	0.840	0.760

Notes: This table reports the slope estimates and p-values associated with the US and country-specific equity tail risk measures used in return predictive regressions of Treasury bonds in United Kingdom (UK), Germany (DE), Switzerland (CH), France (FR), Italy (IT), and Spain (ES). n denotes the maturity of the bonds in months. The US measure corresponds to the S&P 500 option-implied equity tail risk factor $\mathrm{TR}^{(eq)}$. The country-specific measures are calculated using options on the FTSE 100 (UK), DAX (DE), SMI (CH), CAC 40 (FR), FTSE MIB (IT) and IBEX 35 (ES) equity index, and they have been orthogonalized with respect to the US measure $\mathrm{TR}^{(eq)}$. The slope estimates and p-values associated with the country-specific measures are denoted respectively as $\beta^\perp$ and p-value$^\perp$. We report the Newey-West p-values computed with a 12-lag standard error correction. The in-sample period is 2002:01–2018:12 in UK, DE and CH, 2007:01–2018:12 in IT and FR, 2007:05–2018:12 in ES.

Table 16 – Monthly fund flows and equity tail risk

Sample: 2000-2019	**Contemporaneous**		**Predictive**	
LHS variable: $TR_t^{(eq)}$	β p-value	Adj. $R^2{(\%)}$	β p-value	Adj. $R^2{(\%)}$
US Government Bond	0.394 0.000	15.155	0.386 0.000	14.555
US Equity	−0.321 0.000	9.898	−0.145 0.038	1.683
World Equity	−0.493 0.000	24.018	−0.400 0.000	15.647
Hybrid	−0.378 0.000	13.922	−0.257 0.005	6.196
Total Equity	−0.460 0.000	20.799	−0.283 0.000	7.621
Equity - Government Bond ($ flow)	−0.448 0.000	19.762	−0.275 0.000	7.174

Notes: This table reports the slope estimates, their p-values and the adjusted R-squared in percentage for the contemporaneous time series regressions $Flow_{i,t} = \alpha_i + \beta_i \cdot \text{TR}_t^{(eq)} + \varepsilon_{i,t}$ and for the predictive regressions $Flow_{i,t+1} = \alpha_i + \beta_i \cdot \text{TR}_t^{(eq)} + \varepsilon_{i,t+1}$, where $\text{TR}_t^{(eq)}$ are the monthly values of the S&P 500 option-implied equity tail risk measure and $Flow_{i,t}$ are the monthly values of US-domiciled open-end mutual fund and ETF flows into type-i funds indicated in the left column. Source of flows data: the Investment Company Institute (ICI). The "Total Equity" category is obtained by summing up the US Equity, World Equity and Hybrid fund flows obtained from ICI. The "Equity - Government Bond" category is obtained by subtracting from the Total Equity flows the US Government Bond flows obtained from ICI. We use flows expressed as percentage of previous month's fund AUM for all types of funds except for "Equity - Government Bond", whose flows are measured in millions of US $. We report Newey-West p-values computed with a 12-lag standard error correction. The sample period is 2000:01–2019:12. For convenience, both left and right hand variables have been standardized.

Table 17 – Monthly fund flows and equity tail risk - Controls

		Contemporaneous					Predictive				
		(i)	(ii)	(iii)	(iv)	(v)	(i)	(ii)	(iii)	(iv)	(v)
US Government Bond											
$\text{TR}_t^{(eq)}$	β	0.394				0.396	0.386				0.415
	p-val	0.000				0.000	0.000				0.000
VIX_t	β		0.399			0.289		0.336			0.113
	p-val		0.000			0.017		0.000			0.243
SKEW_t	β			−0.023		0.207			0.015		0.115
	p-val			0.837		0.028			0.884		0.249
VRP_t	β				−0.119	−0.014				−0.030	0.087
	p-val				0.025	0.863				0.468	0.098
Adj. R^2	(%)	15.155	15.595	−0.371	1.005	17.697	14.555	10.922	−0.398	−0.329	14.840
US Equity											
$\text{TR}_t^{(eq)}$	β	−0.321				−0.317	−0.145				−0.188
	p-val	0.000				0.000	0.038				0.002
VIX_t	β		−0.242			−0.088		−0.032			0.121
	p-val		0.001			0.592		0.577			0.236
SKEW_t	β			−0.093		−0.168			−0.137		−0.055
	p-val			0.297		0.173			0.089		0.444
VRP_t	β				0.120	0.028				−0.080	−0.142
	p-val				0.019	0.653				0.137	0.018
Adj. R^2	(%)	9.898	5.450	0.450	1.031	10.208	1.683	−0.318	1.467	0.227	4.890
World Equity											
$\text{TR}_t^{(eq)}$	β	−0.493				−0.480	−0.400				−0.392
	p-val	0.000				0.000	0.000				0.000
VIX_t	β		−0.484			−0.397		−0.375			−0.193
	p-val		0.000			0.000		0.000			0.074
SKEW_t	β			−0.027		−0.339			0.009		−0.147
	p-val			0.778		0.000			0.922		0.179
VRP_t	β				0.208	0.081				0.148	0.041
	p-val				0.059	0.196				0.052	0.371
Adj. R^2	(%)	24.018	23.133	−0.351	3.936	30.485	15.647	13.728	−0.414	1.790	16.301
Hybrid											
$\text{TR}_t^{(eq)}$	β	−0.378				−0.285	−0.257				−0.204
	p-val	0.000				0.000	0.005				0.005
VIX_t	β		−0.326			−0.282		−0.190			−0.160
	p-val		0.005			0.015		0.098			0.179
SKEW_t	β			−0.104		−0.316			−0.128		−0.250
	p-val			0.398		0.011			0.288		0.034
VRP_t	β				0.430	0.354				0.263	0.205
	p-val				0.000	0.000				0.000	0.000
Adj. R^2	(%)	13.922	10.243	0.667	18.149	28.744	6.196	3.200	1.230	6.511	11.720

Table 17 – Monthly fund flows and equity tail risk - Controls (continued)

		Contemporaneous					Predictive				
		(i)	(ii)	(iii)	(iv)	(v)	(i)	(ii)	(iii)	(iv)	(v)
Total Equity											
$\text{TR}_t^{(eq)}$	β	−0.460				−0.430	−0.283				−0.299
	p-val	0.000				0.000	0.000				0.000
VIX_t	β		−0.391			−0.246		−0.181			−0.002
	p-val		0.000			0.085		0.012			0.984
SKEW_t	β			−0.095		−0.290			−0.117		−0.128
	p-val			0.313		0.014			0.170		0.154
VRP_t	β				0.250	0.130				0.049	−0.041
	p-val				0.000	0.019				0.412	0.456
Adj. R^2	(%)	20.799	14.929	0.482	5.841	25.010	7.621	2.881	0.958	−0.185	8.193
Equity - Government Bond ($ flow)											
$\text{TR}_t^{(eq)}$	β	−0.448				−0.415	−0.275				−0.283
	p-val	0.000				0.000	0.000				0.000
VIX_t	β		−0.397			−0.175		−0.213			−0.015
	p-val		0.000			0.222		0.002			0.916
SKEW_t	β			−0.020		−0.161			−0.034		−0.054
	p-val			0.845		0.203			0.699		0.632
VRP_t	β				0.247	0.131				0.061	−0.021
	p-val				0.000	0.012				0.204	0.625
Adj. R^2	(%)	19.762	15.388	−0.383	5.683	21.659	7.174	4.149	−0.307	−0.046	6.215

Notes: This table reports the slope estimates, their p-values and the adjusted R-squared in percentage for the contemporaneous time series regressions $Flow_{i,t} = \alpha_i + \boldsymbol{\beta}_i' \cdot \mathbf{X}_t + \varepsilon_{i,t}$ and for the predictive regressions $Flow_{i,t+1} = \alpha_i + \boldsymbol{\beta}_i' \cdot \mathbf{X}_t + \varepsilon_{i,t+1}$, where $\mathbf{X}_t$ includes the monthly values of the S&P 500 option-implied equity tail risk measure $\text{TR}^{(eq)}$ and/or a number of control variables – the CBOE VIX and SKEW index and the VRP of Bollerslev et al. (2014) – and $Flow_{i,t}$ are the monthly values of US-domiciled open-end mutual fund and ETF flows into type-i funds indicated in bold at the top of each panel. Source of flows data: the Investment Company Institute (ICI). The "Total Equity" category is obtained by summing up the US Equity, World Equity and Hybrid fund flows obtained from ICI. The "Equity - Government Bond" category is obtained by subtracting from the Total Equity flows the US Government Bond flows obtained from ICI. We use flows expressed as percentage of previous month's fund AUM for all types of funds except for "Equity - Government Bond", whose flows are measured in millions of US $. The column headers (i)-(v) indicate different models that include in $\mathbf{X}_t$ different sets of explanatory variables selected from those indicated in the left column. Due to the high correlation that exists between $\text{TR}^{(eq)}$ and VIX, we deploy the orthogonal component of the VIX with respect to $\text{TR}^{(eq)}$ in model (v). We report Newey-West p-values computed with a 12-lag standard error correction. The sample period is 2000:01–2019:12. For convenience, both left and right hand variables have been standardized.

Table 18 – Quarterly flows by different sectors in the economy and equity tail risk

Sector (i)	Flow to Equities by all sectors	Flow to Treasuries by Mutual Funds	Flow to Treasuries by Households
Full sample: 1996.Q1 - 2019.Q4			
β_i	-0.180*	0.129	0.483***
	(0.105)	(0.105)	(0.092)
R_i^2	0.032	0.017	0.233
Post-2001 sample: 2002.Q1 - 2019.Q4			
β_i	-0.210*	0.197	0.527***
	(0.117)	(0.120)	(0.104)
R_i^2	0.044	0.039	0.278

Notes: This table reports the β_i estimates, their OLS standard errors (in brackets) and R^2 for the contemporaneous time series regressions $Flow_{it} = \alpha_i + \beta_i \cdot \text{TR}_t^{(eq)} + \varepsilon_{it}$, where $\text{TR}_t^{(eq)}$ are the quarterly values of the S&P 500 option-implied equity tail risk measure, computed as averages of the end-of-month observations within each quarter. $Flow_{it}$ is the Aggregate Equity Flows (column 1), Treasury flows of Mutual Funds only (column 2), and Treasury flows of Mutual Funds only (column 3) as defined by Gabaix and Koijen (2020). The upper panel report results for the full sample (1996.Q1 - 2019.Q4), while the bottom panel report results for the post-2001 sample (2002.Q1 - 2019.Q4). $***$, $**$, and $*$ denote statistical significance at the 1%, 5%, and 10% level for a t-statistic for the test of the null $\beta_i = 0$. For convenience, all series have been standardized to have mean zero and unit variance before running the regressions, and therefore the estimated values of β_i are equal to the sample correlation between $Flow_{it}$ and $TR_t^{(eq)}$. Source of flows data: *Financial Accounts of the United States - Z.1 Release*, vintage June 2020, available at `https://www.federalreserve.gov/releases/z1/`.

Table 19 – Interest rate effects of monetary policy and equity tail risk shocks

		$n=3$	$n=6$	$n=12$	$n=24$	$n=36$	$n=48$	$n=60$	$n=84$	$n=120$
Panel A: Monetary policy shock measures developed by Jarociński and Karadi (2020). Sample: 2003–2019										
$\Delta \text{TR}^{(eq)}$	β	-8.230	-14.232	-23.885	-37.131	-45.203	-50.247	-53.518	-57.220	-59.315
	p-value	0.136	0.006	0.000	0.000	0.000	0.000	0.000	0.000	0.000
ΔMP^{pure}	β	0.337	0.409	0.535	0.667	0.692	0.667	0.624	0.530	0.411
	p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.002
ΔMP^{info}	β	1.542	1.404	1.281	1.236	1.197	1.123	1.031	0.844	0.608
	p-value	0.031	0.007	0.000	0.000	0.000	0.000	0.000	0.000	0.002
Adj. $R^2_{(\%)}$		2.706	4.336	5.328	5.610	5.490	5.256	5.039	4.765	4.583
Adj. $R^2_{(\%)}$	no $\Delta \text{TR}^{(eq)}$	2.614	3.849	4.089	3.739	3.277	2.788	2.369	1.799	1.364
Panel B: Monetary policy shock measures developed by Rogers et al. (2018). Sample: 2008–2015										
$\Delta \text{TR}^{(eq)}$	β	-8.488	-14.196	-24.391	-40.325	-51.650	-59.813	-65.825	-73.748	-79.646
	p-value	0.245	0.025	0.000	0.000	0.000	0.000	0.000	0.000	0.000
$\Delta \text{MP}^{target}$	β	-0.244	-0.247	-0.296	-0.476	-0.675	-0.841	-0.958	-1.050	-0.940
	p-value	0.437	0.383	0.248	0.061	0.009	0.001	0.000	0.000	0.003
ΔMP^{FG}	β	0.178	0.267	0.441	0.738	0.947	1.078	1.150	1.171	1.043
	p-value	0.053	0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.000
ΔMP^{AP}	β	0.031	0.048	0.130	0.384	0.650	0.873	1.039	1.222	1.267
	p-value	0.751	0.572	0.100	0.000	0.000	0.000	0.000	0.000	0.000
Adj. $R^2_{(\%)}$		1.217	3.485	10.173	12.740	13.669	14.497	15.064	15.341	14.403
Adj. $R^2_{(\%)}$	no $\Delta \text{TR}^{(eq)}$	0.987	2.214	5.933	7.860	8.756	9.438	9.822	9.744	8.381

Notes: This table reports the slope estimates and p-values from contemporaneous regressions of daily yield changes of the n-month US Treasury bond on US monetary policy and equity tail risk shocks, with the latter corresponding to daily changes in the S&P 500 option-implied tail risk measure $\text{TR}^{(eq)}$. Panel A reports the results of a regression that includes, besides control variables, the pure MP shocks (ΔMP^{pure}) and central bank information shocks (ΔMP^{info}) identified by Jarociński and Karadi (2020) and the orthogonalized equity tail risk shocks ($\Delta \text{TR}^{(eq)}$) with respect to all other shocks. Sample is 2003:01–2019:05. Panel B reports the results of a regression that includes, besides control variables, the target shocks ($\Delta \text{MP}^{target}$), forward guidance shocks (ΔMP^{FG}) and asset purchase shocks (ΔMP^{AP}) identified by Rogers et al. (2018) and the orthogonalized equity tail risk shocks ($\Delta \text{TR}^{(eq)}$) with respect to all other shocks. Sample is 2008:10–2015:12. For all monetary policy shocks and equity tail risk shocks we report p-values computed with heteroskedasticity-robust standard errors. For each regression we report the adjusted R-squared in percentage. This measure is also reported for a regression that excludes $\Delta \text{TR}^{(eq)}$ as covariate.

Figure 1 – Time series of the S&P 500 option-implied equity tail risk measure
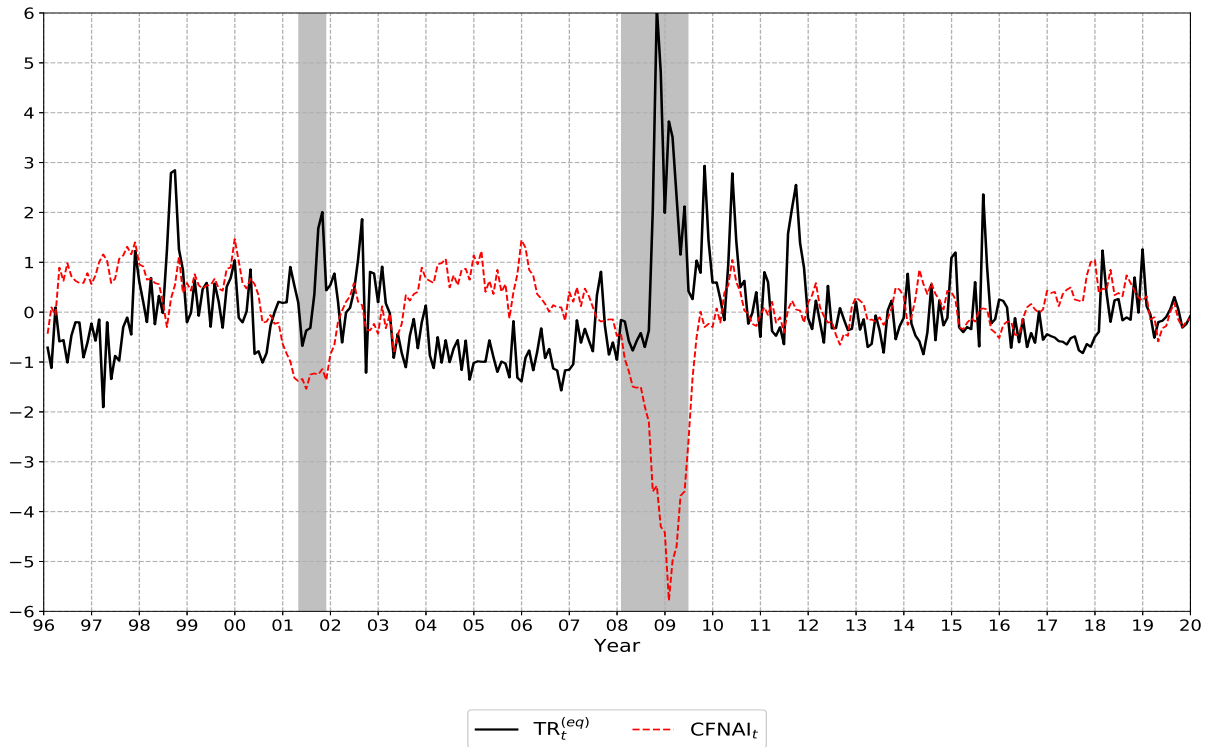
The figure displays the end-of-month values of the S&P 500 option-implied equity tail risk measure ($\text{TR}_t^{(eq)}$) and 3-month moving average of the Chicago National Activity Index (CFNAI_t) from January 1996 to December 2019. For convenience, both series have been normalized to have mean zero and unit variance. Contemporaneous correlation between $\text{TR}^{(eq)}$ and CFNAI is -0.49. Vertical gray bars denote the National Bureau of Economic Research (NBER) based recession periods.

Figure 2 – Cumulative returns of competing strategies
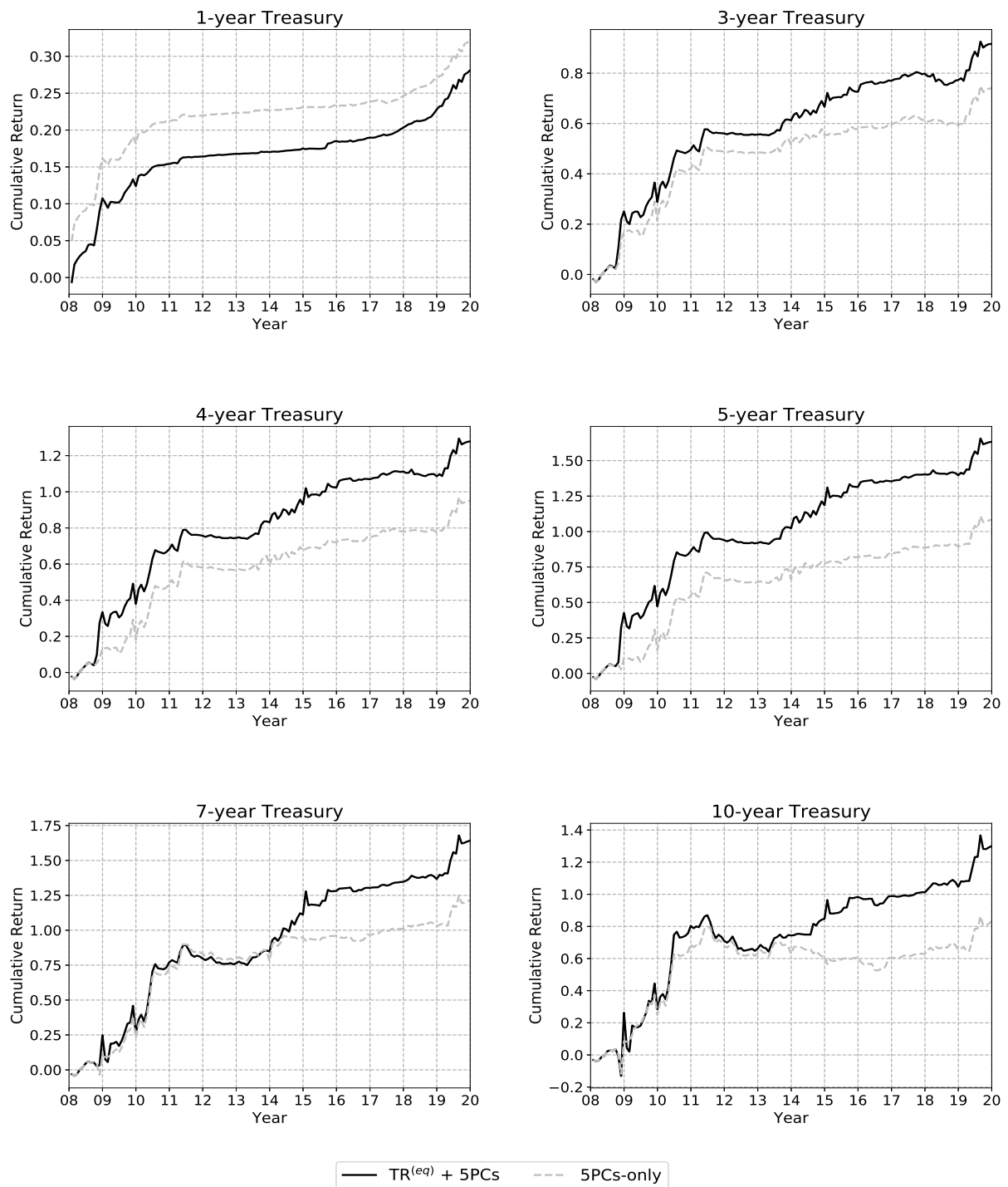
The figure illustrates the cumulative returns of a portfolio formed using the return forecasts delivered by a model that includes both $\text{TR}^{(eq)}$ and the first 5 PCs of bond yields as predictors (solid black line), and a portfolio formed using the return forecasts delivered by a 5 PCs-only benchmark (dashed gray line). Predictive models are recursively estimated with a rolling window approach. The (out-of-sample) investment period is 2008:01–2019:12. The investor's risk aversion coefficient is $\gamma = 5$.

94

Figure 3 – Time series of US Treasury bond yields
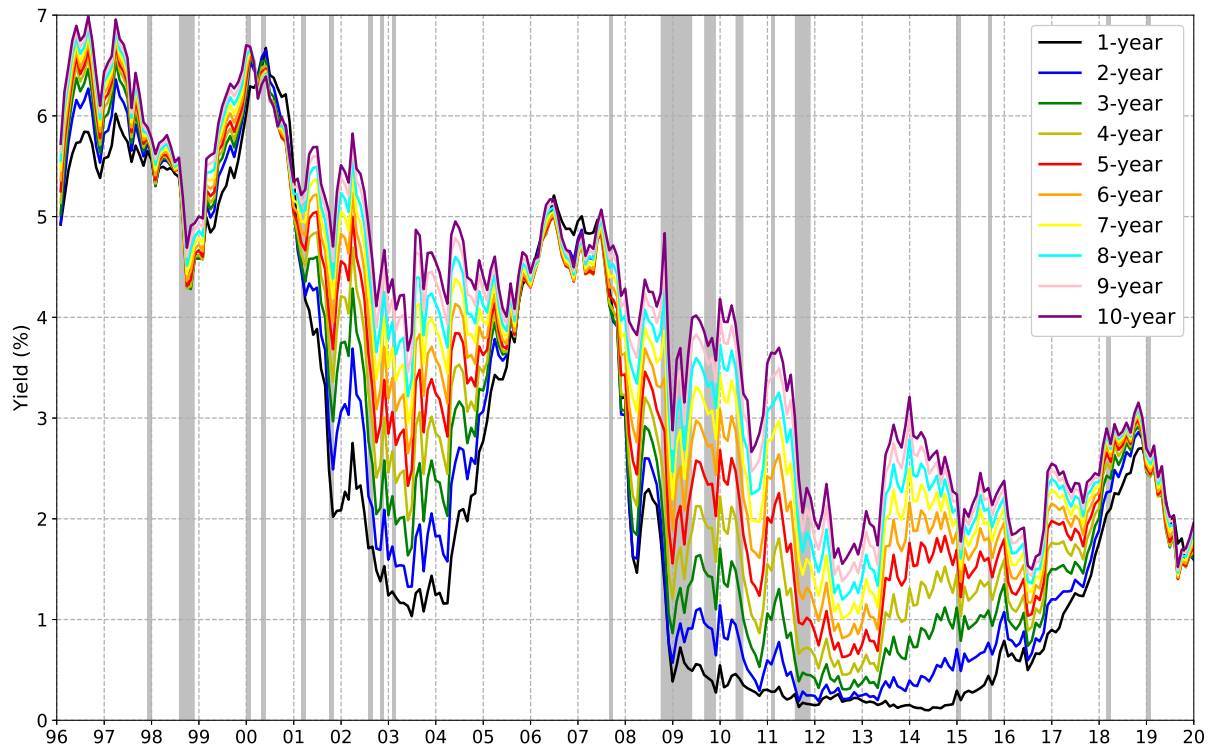
The figure displays the end-of-month values of 1- to 10-year Treasury bond yields from January 1996 to December 2019. Vertical gray bars indicate periods of elevated (>= 85%-ile) equity tail risk implied by S&P 500 index options.

Figure 4 – Time series of the pricing factors of US Treasuries
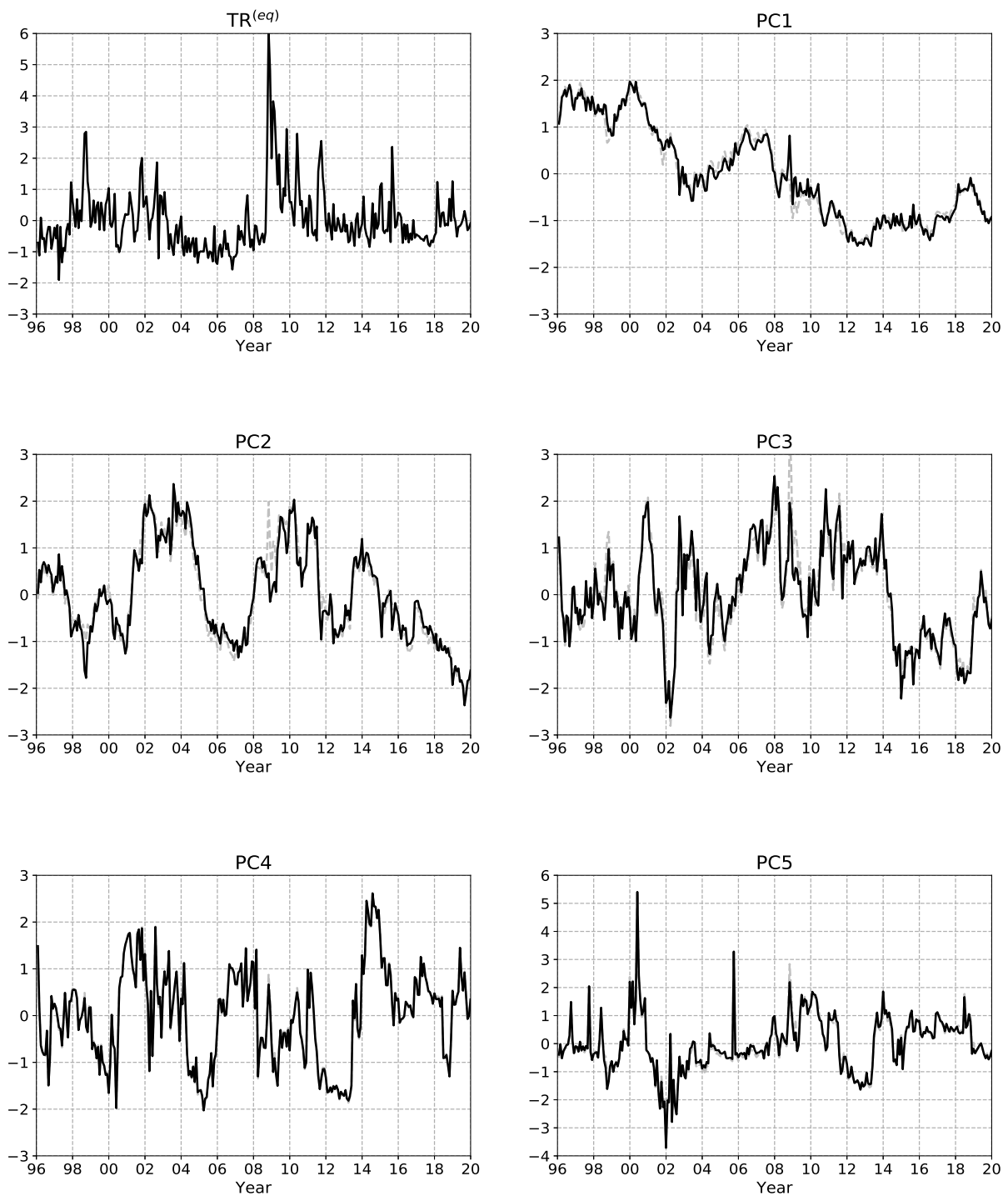
The figure displays the monthly time series of the pricing factors of the proposed Gaussian ATSM with equity tail risk. The top-left panel shows the S&P 500 option-implied equity tail risk factor $TR^{(eq)}$. The remaining panels show the first five principal components extracted from the US Treasury yields orthogonal to the $TR^{(eq)}$ factor. The light-colored dashed lines show the principal components extracted from non-orthogonalized yields, which however are not used as pricing factors in our model. All factors have been normalized to have mean zero and unit variance.

Figure 5 – Observed and model-implied US Treasury bond yields and returns
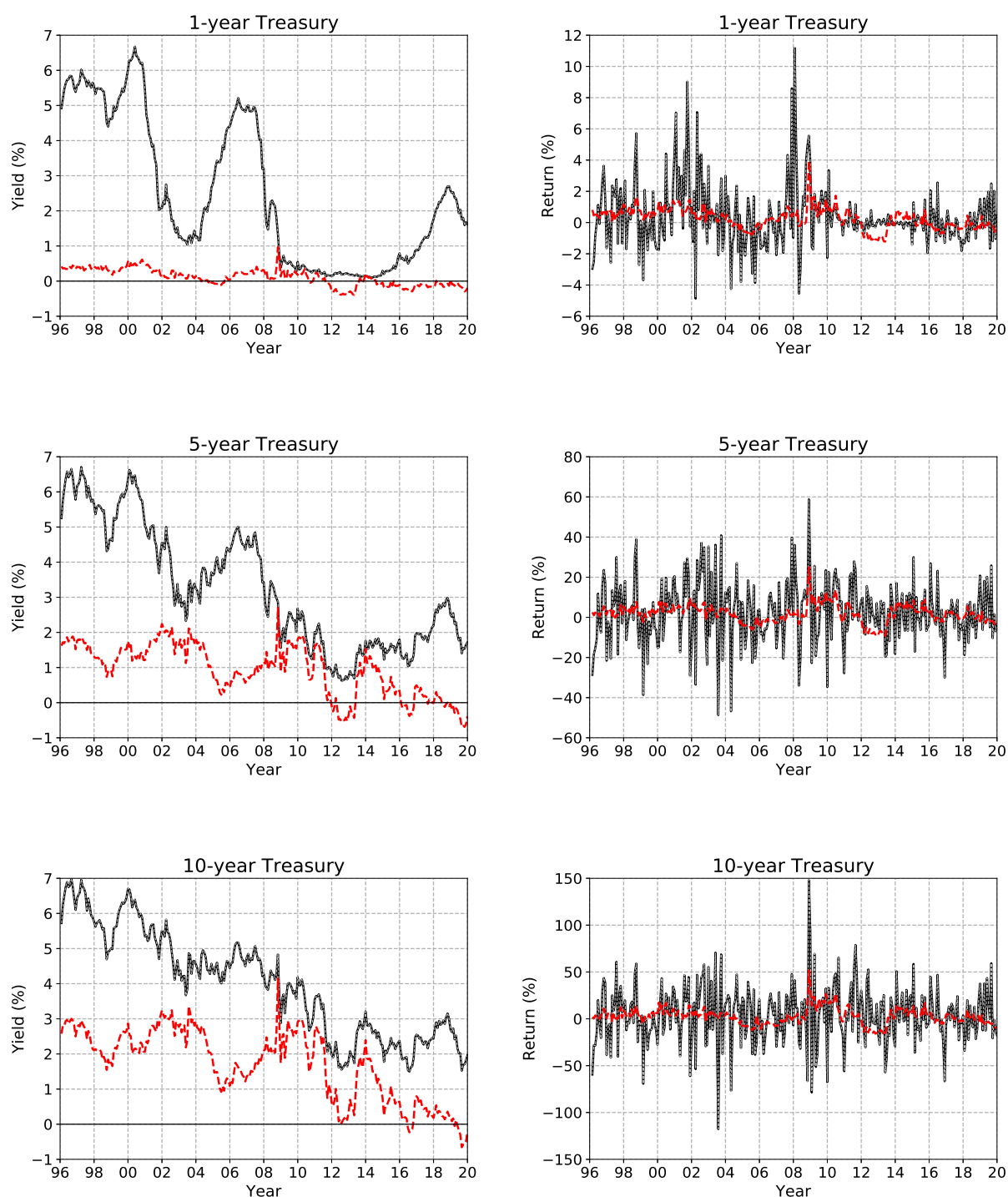
The figure displays the observed and model-implied time series of yields and one-month excess returns on US Treasury bonds with 1-, 5- and 10-year maturities. In the left panels, the solid black lines show the observed yields, the dashed gray lines plot the model-implied yields, while the dashed red lines indicate the model-implied term premia. In the right panels, the solid black lines show the observed excess returns, the dashed gray lines plot the model-implied excess returns, while the dashed red lines indicate the model-implied expected excess returns.

Figure 6 – Time-varying market price of equity tail risk
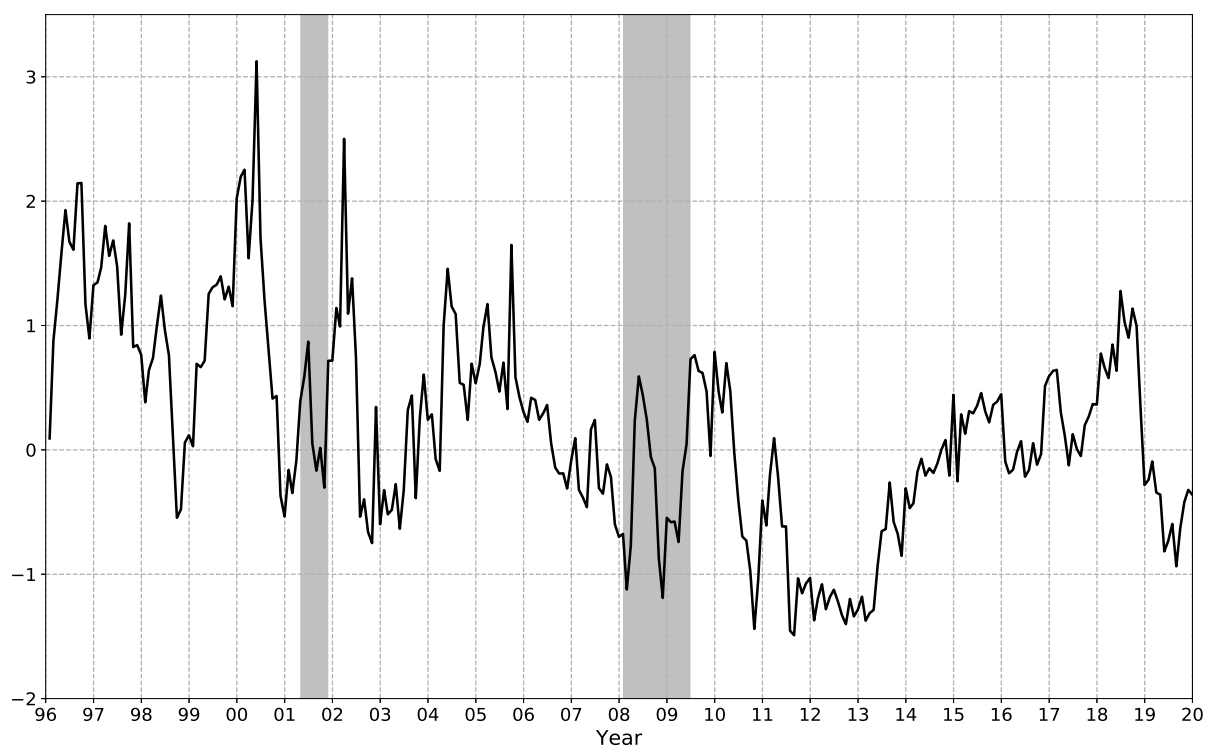
The figure displays the monthly time series of the market price of equity tail risk estimated with the proposed Gaussian ATSM. For each day in the sample, this measure corresponds to the element in vector $\boldsymbol{\lambda}_t$ defined in equation (15) that is associated with the risk factor $\mathrm{TR}_t^{(eq)}$. Vertical gray bars denote the NBER based recession periods.

Figure 7 – Model-implied yield loadings on the pricing factors of US Treasuries
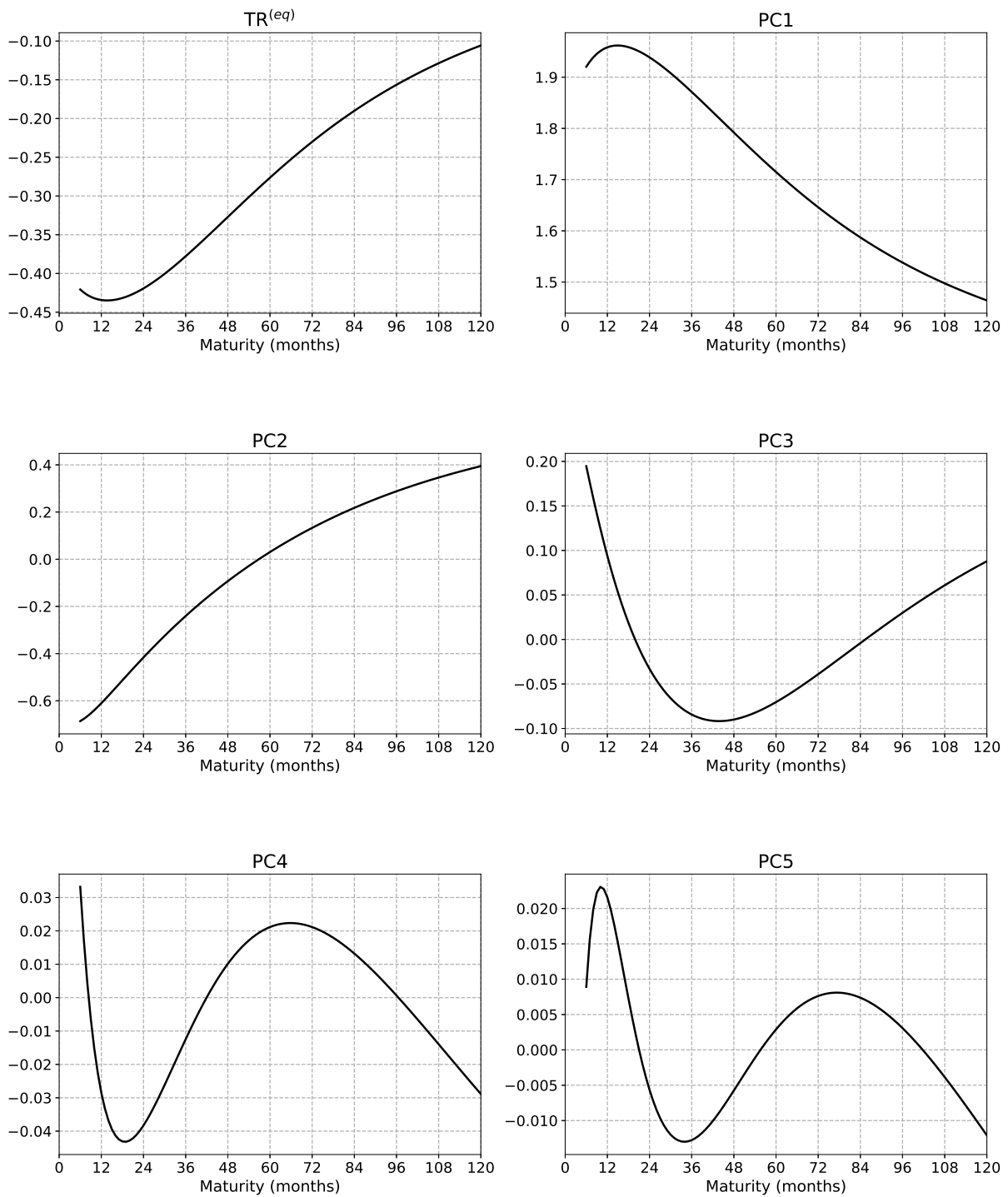
The figure displays the model-implied yield loadings on the pricing factors of the proposed ATSM with equity tail risk. These coefficients are calculated as $-(1/n)\mathbf{b}_n$ and can be interpreted as the response of the n-month yield (expressed in annualized percentage terms) to a contemporaneous shock to the respective factor. $\text{TR}^{(eq)}$ represents the S&P 500 option-implied equity tail risk factor, normalized to have mean zero and unit variance. PC1 – PC5 denote the first five standardized principal components extracted from the US Treasury yields orthogonal with respect to the $\text{TR}^{(eq)}$ factor.

Figure 8 – Model-implied return loadings on the pricing factors of US Treasuries
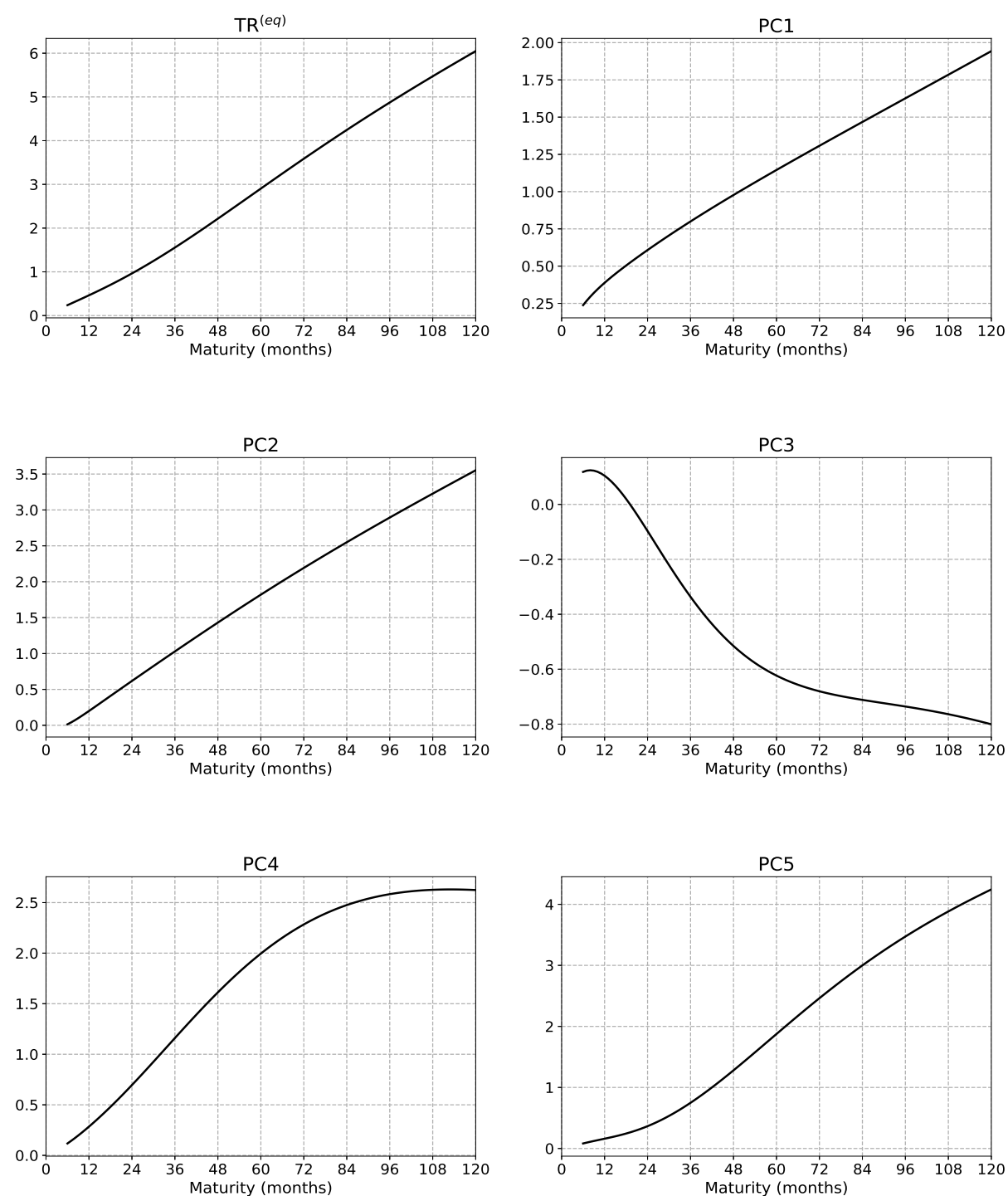
The figure displays the model-implied excess return loadings on the pricing factors of the proposed ATSM with equity tail risk. These coefficients are calculated as $\mathbf{b}_n'\boldsymbol{\lambda}_1$ and can be interpreted as the response of the expected one-month excess return (expressed in annualized percentage terms) on the n-month bond to a contemporaneous shock to the respective factor. $\text{TR}^{(eq)}$ represents the S&P 500 option-implied equity tail risk factor, normalized to have mean zero and unit variance. PC1 – PC5 denote the first five standardized principal components extracted from the US Treasury yields orthogonal with respect to the $\text{TR}^{(eq)}$ factor.

Figure 9 – Impact over time of equity tail risk on US Treasury bond yields and components
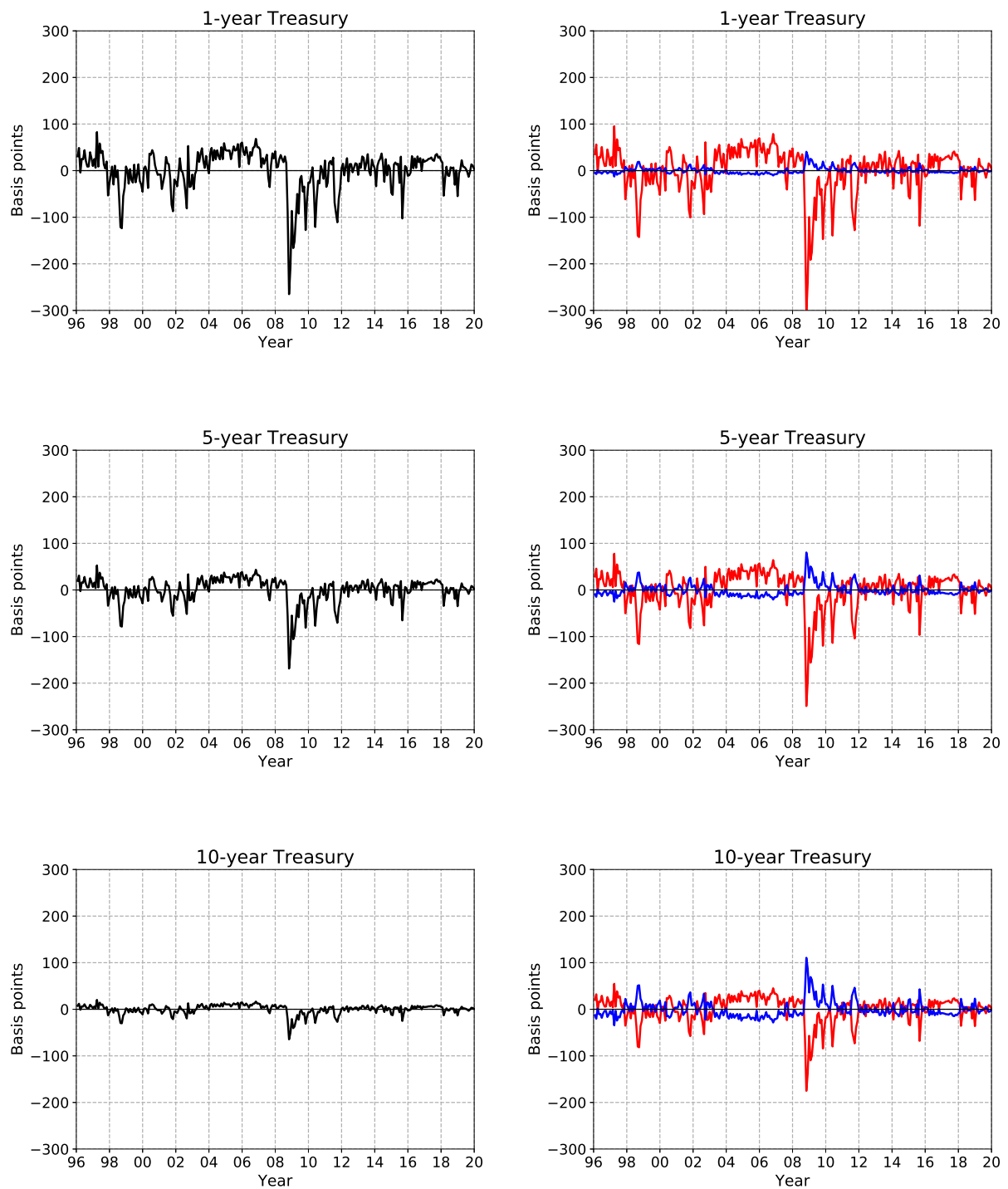
The figure displays the impact over time of the S&P 500 option-implied equity tail risk factor $\text{TR}_t^{(eq)}$ on the 1-, 5- and 10-year US Treasury bond yields (black lines) and on their two components, i.e average expected future short rate (red lines) and term premium (blue lines).

Figure 10 – Impact of equity tail risk on US Treasury bond yields
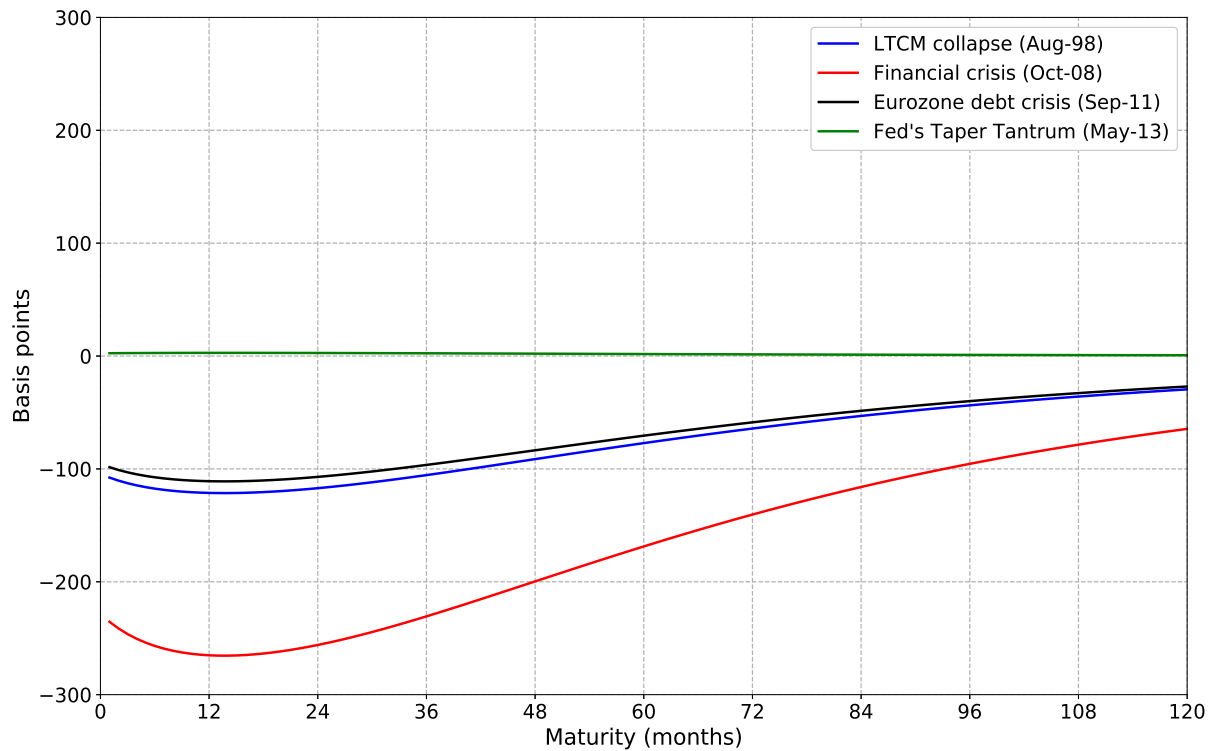
The figure displays the impact (in basis points) of the S&P 500 option-implied equity tail risk factor $\mathrm{TR}_t^{(eq)}$ on the term structure of US interest rates for selected dates: Russian financial crisis and collapse of Long Term Capital Management fund (Aug-98), onset of 2008-09 financial crisis with bankruptcy of Lehman Brothers (Oct-08), intensification of European sovereign debt crisis (Sep-11), announcement of the Federal Reserve's "taper tantrum" (May-13). Interest rates fell on all dates except for May-13, when yields markedly rose.

Figure 11 – Time series of international equity tail risk measures
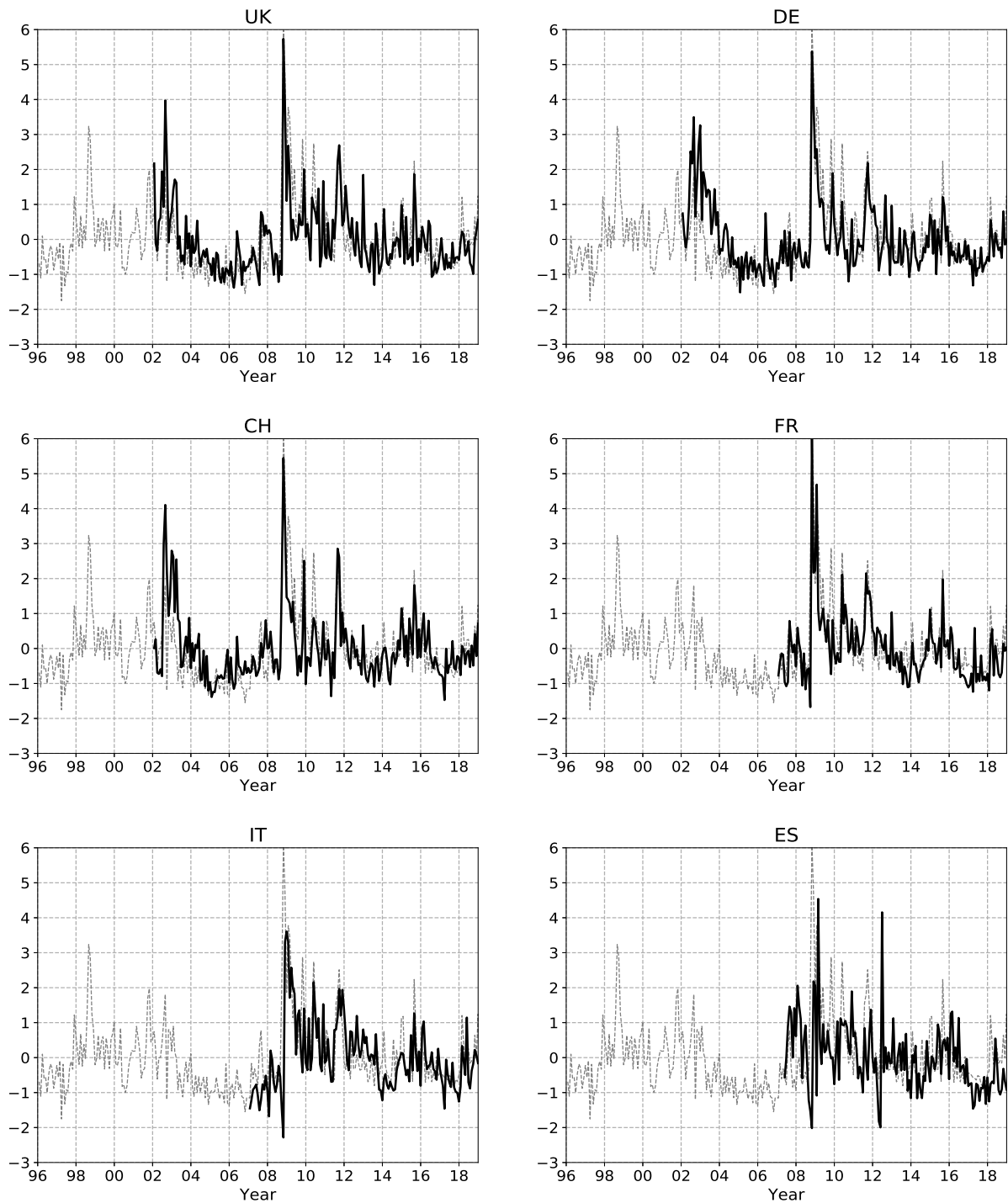
The figure displays the international equity tail risk measures calculated using options on the FTSE 100 (UK), DAX (DE), SMI (CH), CAC 40 (FR), FTSE MIB (IT) and IBEX 35 (ES) equity index. All series have been normalized to have mean zero and unit variance. The solid black lines show the equity tail risk measure of the country of interest, while the dashed gray lines show, for comparison, the S&P 500 option-implied equity tail risk measure $\text{TR}^{(eq)}$.

Figure 12 – Monthly fund flows
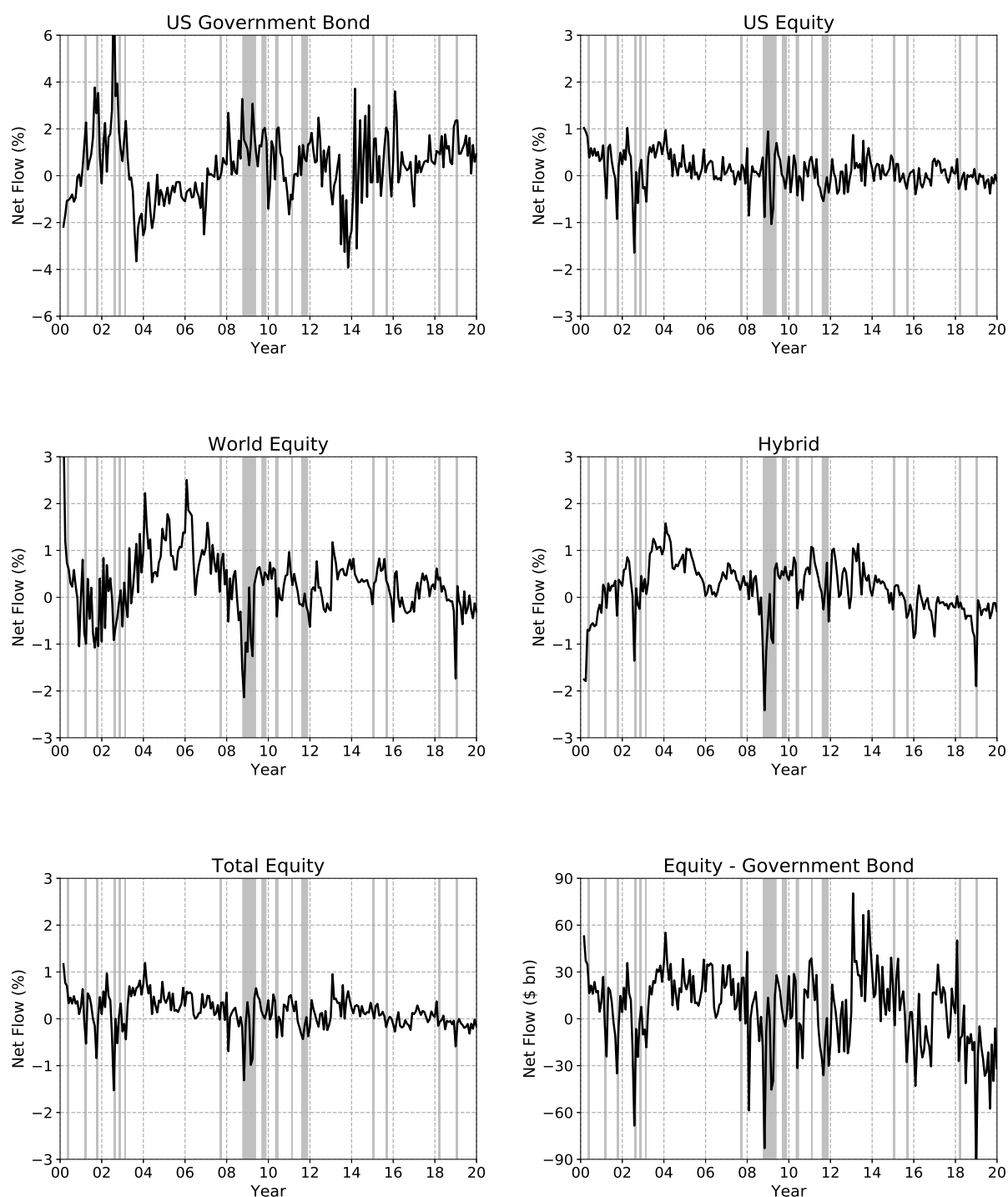
The figure displays the monthly time series of US-domiciled open-end mutual fund and ETF flows into the types of funds indicated by the subplot titles. Displayed values are from January 2000 to December 2019. Vertical gray bars indicate periods of elevated ($\geq 85\%$-ile) equity tail risk implied by S&P 500 index options ($\text{TR}^{(eq)}$). Source of flows data: the Investment Company Institute (ICI). The "Total Equity" category is obtained by summing up the US Equity, World Equity and Hybrid fund flows obtained from ICI. The "Equity - Government Bond" category is obtained by subtracting from the Total Equity flows the US Government Bond flows obtained from ICI. We show flows expressed as percentage of previous month's fund AUM for all types of funds except for "Equity - Government Bond", whose flows are shown in billions of US $.

Figure 13 – S&P 500 option-implied equity tail risk and Aggregate Equity Flows (quarterly)
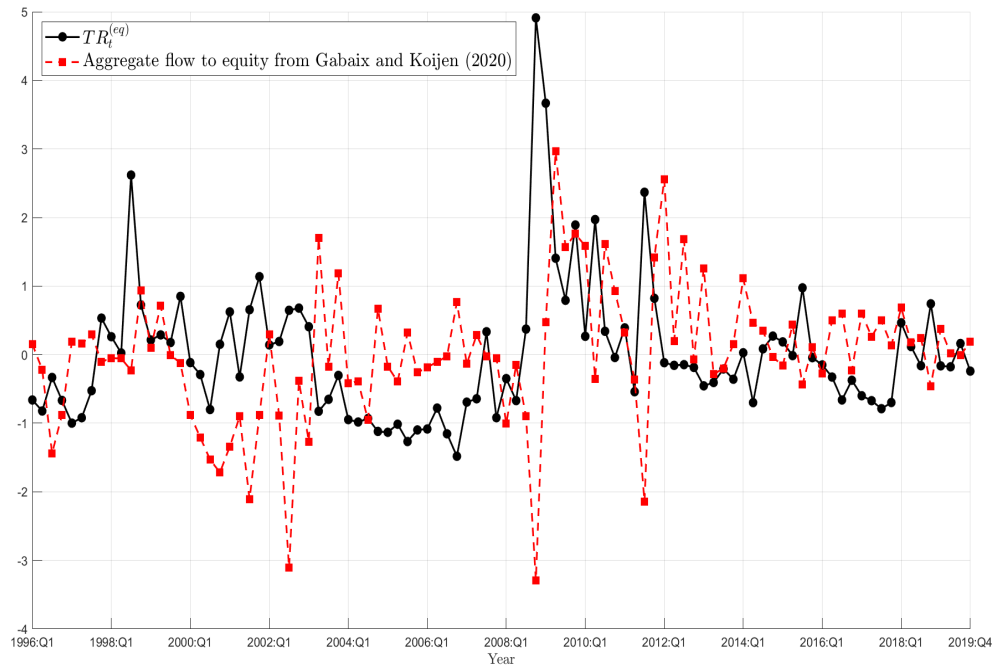
The figure displays the quarterly time series the S&P 500 option-implied equity tail risk measure ($\mathrm{TR}_t^{(eq)}$), computed as averages of the end-of-month observations within each quarter (red dashed line), and Aggregate Equity Flows (black continuous line) as computed by Gabaix and Koijen (2020). The sample period is 1990.Q1 - 2019:Q4. For convenience, both series have been standardized to have mean zero and unit variance. Source of flows data: *Financial Accounts of the United States - Z.1 Release*, vintage June 2020, available at `https://www.federalreserve.gov/releases/z1/`.

Figure 14 – Equity tail risk vs monetary-policy-driven jumps
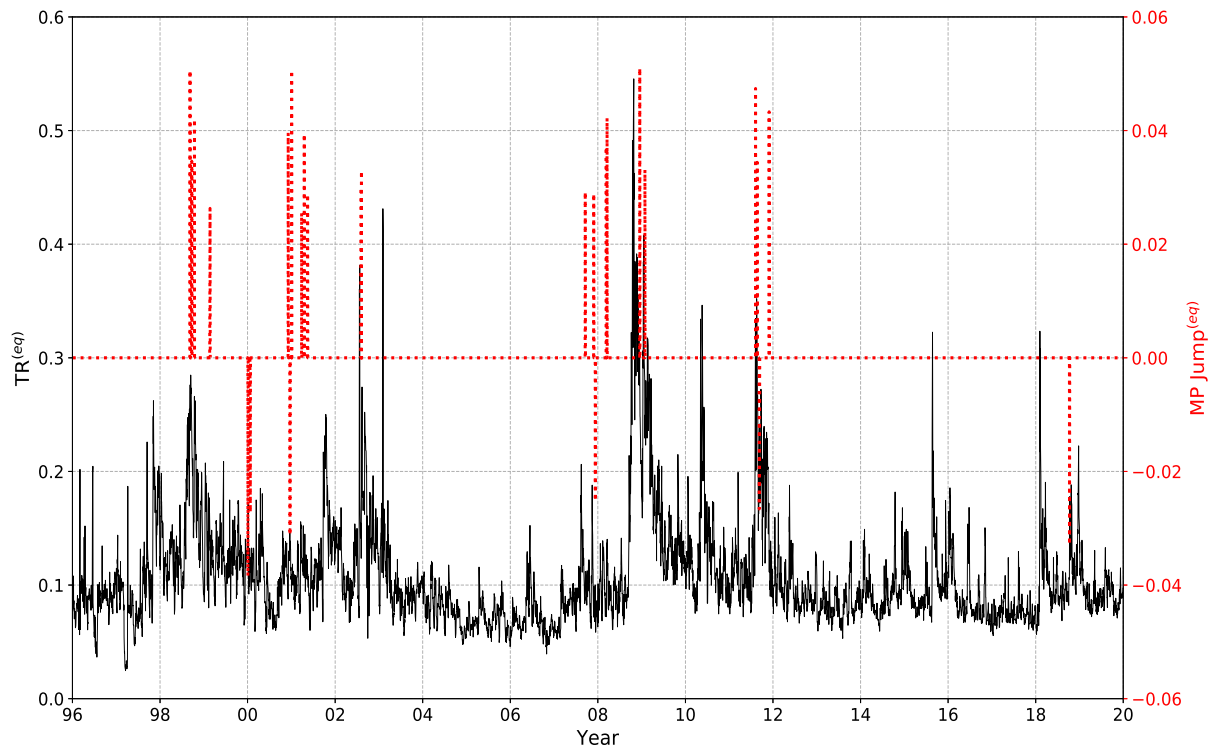
The figure displays the daily time series of the S&P 500 option-implied equity tail risk measure $TR_t^{(eq)}$ (left y-axis, solid black line) and of the US stock market jump returns triggered by monetary policy and identified by Baker et al. (2020) (right y-axis, dashed red line) from January 1996 to December 2019. Contemporaneous correlation between the two series is 0.06.

Figure 15 – Monetary policy shocks

(a) Measures developed by Jarociński and Karadi (2020)

(b) Measures developed by Rogers et al. (2018)
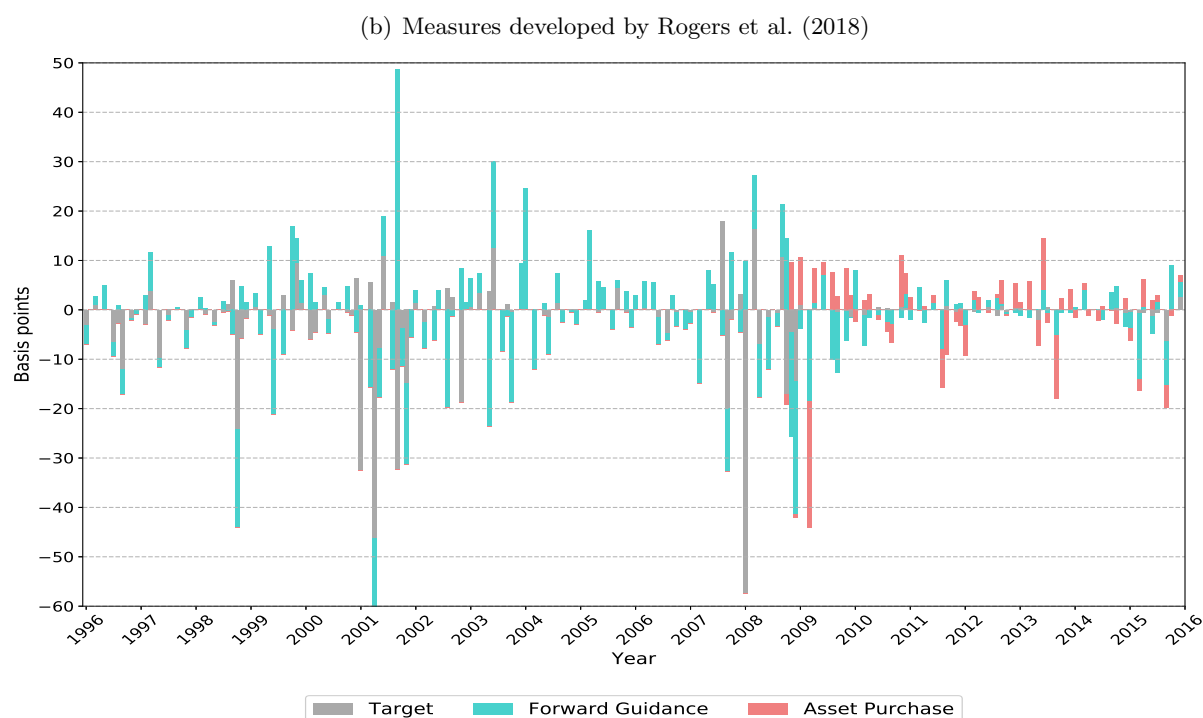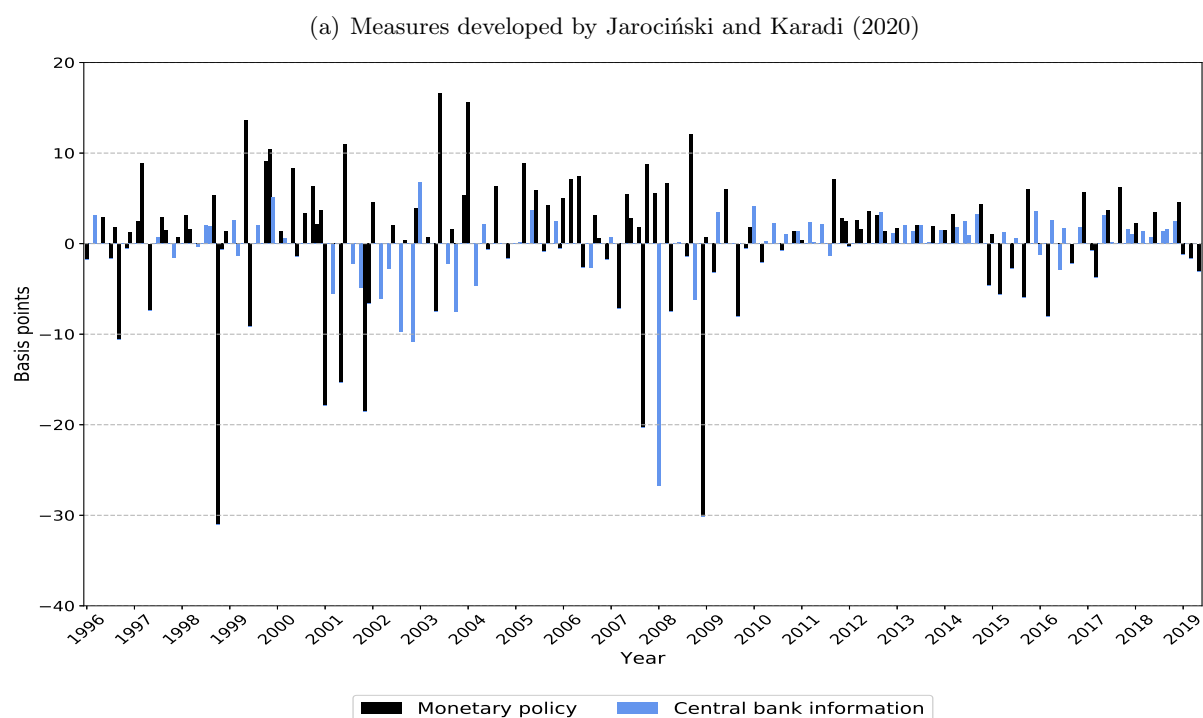
The figure displays the time series of the monetary policy shock measures developed by Jarociński and Karadi (2020) and Rogers et al. (2018). Data are aggregated to the monthly frequency. In any month with no announcement, the shock is zero. In any month with multiple announcements, the shocks are added up within that month. Panel A shows the "pure" monetary policy shocks (black bars) and central bank information shocks (blue bars) identified by Jarociński and Karadi (2020) from January 1996 to May 2019. Panel B shows the target shocks (gray bars), forward guidance shocks (turquoise bars) and asset purchase shocks (coral bars) identified by Rogers et al. (2018) from January 1996 to December 2015.

RECENTLY PUBLISHED "TEMI" (*)

N. 1287 – *Court efficiency and aggregate productivity: the credit channel*, by Guzmán González-Torres and Giacomo Rodano (July 2020).

N. 1288 – *The time-varying risk of Italian GDP*, by Fabio Busetti, Michele Caivano, Davide Delle Monache and Claudia Pacella (July 2020).

N. 1289 – *Trade shocks and credit reallocation*, by Stefano Federico, Fadi Hassan and Veronica Rappoport (July 2020).

N. 1290 – *The impact of the IRB approach on the relationship between the cost of credit for public companies and financial market conditions*, by Raffaele Gallo (July 2020).

N. 1291 – *An economic assessment of the evolution of the corporate tax system in Italy*, by Ernesto Zangari (September 2020).

N. 1292 – *Asymmetric information in corporate lending: evidence from SME bond markets*, by Alessandra Iannamorelli, Stefano Nobili, Antonio Scalia and Luana Zaccaria (September 2020).

N. 1293 – *Fiscal space and the size of fiscal multiplier*, by Luca Metelli and Kevin Pallara (September 2020).

N. 1294 – *Prudential policies, credit supply and house prices: evidence from Italy*, by Pierluigi Bologna, Wanda Cornacchia and Maddalena Galardo (September 2020).

N. 1295 – *How loose, how tight? A measure of monetary and fiscal stance for the euro area*, by Nicoletta Batini, Alessandro Cantelmo, Giovanni Melina and Stefania Villa (September 2020).

N. 1296 – *Price dividend ratio and long-run stock returns: a score driven state space model*, by Davide Delle Monache, Ivan Petrella and Fabrizio Venditti (September 2020).

N. 1297 – *Workforce aging, pension reforms, and firm outcomes*, by Francesca Carta, Francesco D'Amuri and Till von Wachter (September 2020).

N. 1298 – *Anti-poverty measures in Italy: a microsimulation analysis*, by Nicola Curci, Giuseppe Grasso, Pasquale Recchia and Marco Savegnago (September 2020).

N. 1299 – *Forecasting US recessions: the role of economic uncertainty*, by Valerio Ercolani and Filippo Natoli (September 2020).

N. 1300 – *Demographics and the natural real interest rate: historical and projected paths for the euro area*, by Andrea Papetti (November 2020).

N. 1301 – *A quantitative analysis of distortions in managerial forecasts*, by Yueran Ma, Tiziano Ropele, David Sraer and David Thesmar (November 2020).

N. 1302 – *Bargaining power and the Phillips curve: a micro-macro analysis*, by Marco J. Lombardi, Marianna Riggi and Eliana Viviano (November 2020).

N. 1303 – *The effects of structural reforms: Evidence from Italy*, by Emanuela Ciapanna, Sauro Mocetti and Alessandro Notarpietro (November 2020).

N. 1304 – *Consumption and Wealth: New Evidence from Italy*, by Riccardo De Bonis, Danilo Liberati, John Muellbauer and Concetta Rondinelli (November 2020).

N. 1305 – *Do details matter? An analysis of the Italian personal income tax*, by Martino Tasso (November 2020).

N. 1306 – *Effects of eligibility for central bank purchases on corporate bond spreads*, by Taneli Mäkinen, Fan Li, Andrea Mercatanti and Andrea Silvestrini (November 2020).

2018

ACCETTURO A., V. DI GIACINTO, G. MICUCCI and M. PAGNINI, *Geography, productivity and trade: does selection explain why some locations are more productive than others?,* Journal of Regional Science, v. 58, 5, pp. 949-979, **WP 910 (April 2013).**

ADAMOPOULOU A. and E. KAYA, *Young adults living with their parents and the influence of peers,* Oxford Bulletin of Economics and Statistics,v. 80, pp. 689-713, **WP 1038 (November 2015).**

ANDINI M., E. CIANI, G. DE BLASIO, A. D'IGNAZIO and V. SILVESTRINI, *Targeting with machine learning: an application to a tax rebate program in Italy,* Journal of Economic Behavior & Organization, v. 156, pp. 86-102, **WP 1158 (December 2017).**

BARONE G., G. DE BLASIO and S. MOCETTI, *The real effects of credit crunch in the great recession: evidence from Italian provinces,* Regional Science and Urban Economics, v. 70, pp. 352-59, **WP 1057 (March 2016).**

BELOTTI F. and G. ILARDI *Consistent inference in fixed-effects stochastic frontier models,* Journal of Econometrics, v. 202, 2, pp. 161-177, **WP 1147 (October 2017).**

BERTON F., S. MOCETTI, A. PRESBITERO and M. RICHIARDI, *Banks, firms, and jobs,* Review of Financial Studies, v.31, 6, pp. 2113-2156, **WP 1097 (February 2017).**

BOFONDI M., L. CARPINELLI and E. SETTE, *Credit supply during a sovereign debt crisis,* Journal of the European Economic Association, v.16, 3, pp. 696-729, **WP 909 (April 2013).**

BOKAN N., A. GERALI, S. GOMES, P. JACQUINOT and M. PISANI, *EAGLE-FLI: a macroeconomic model of banking and financial interdependence in the euro area,* Economic Modelling, v. 69, C, pp. 249-280, **WP 1064 (April 2016).**

BRILLI Y. and M. TONELLO, *Does increasing compulsory education reduce or displace adolescent crime? New evidence from administrative and victimization data,* CESifo Economic Studies, v. 64, 1, pp. 15–4, **WP 1008 (April 2015).**

BUONO I. and S. FORMAI *The heterogeneous response of domestic sales and exports to bank credit shocks,* Journal of International Economics, v. 113, pp. 55-73, **WP 1066 (March 2018).**

BURLON L., A. GERALI, A. NOTARPIETRO and M. PISANI, *Non-standard monetary policy, asset prices and macroprudential policy in a monetary union,* Journal of International Money and Finance, v. 88, pp. 25-53, **WP 1089 (October 2016).**

CARTA F. and M. DE PHLIPPIS, *You've Come a long way, baby. Husbands' commuting time and family labour supply,* Regional Science and Urban Economics, v. 69, pp. 25-37, **WP 1003 (March 2015).**

CARTA F. and L. RIZZICA, *Early kindergarten, maternal labor supply and children's outcomes: evidence from Italy,* Journal of Public Economics, v. 158, pp. 79-102, **WP 1030 (October 2015).**

CASIRAGHI M., E. GAIOTTI, L. RODANO and A. SECCHI, *A "Reverse Robin Hood"? The distributional implications of non-standard monetary policy for Italian households,* Journal of International Money and Finance, v. 85, pp. 215-235, **WP 1077 (July 2016).**

CIANI E. and C. DEIANA, *No Free lunch, buddy: housing transfers and informal care later in life,* Review of Economics of the Household, v.16, 4, pp. 971-1001, **WP 1117 (June 2017).**

CIPRIANI M., A. GUARINO, G. GUAZZAROTTI, F. TAGLIATI and S. FISHER, *Informational contagion in the laboratory,* Review of Finance, v. 22, 3, pp. 877-904, **WP 1063 (April 2016).**

DE BLASIO G, S. DE MITRI, S. D'IGNAZIO, P. FINALDI RUSSO and L. STOPPANI, *Public guarantees to SME borrowing. A RDD evaluation,* Journal of Banking & Finance, v. 96, pp. 73-86, **WP 1111 (April 2017).**

GERALI A., A. LOCARNO, A. NOTARPIETRO and M. PISANI, *The sovereign crisis and Italy's potential output,* Journal of Policy Modeling, v. 40, 2, pp. 418-433, **WP 1010 (June 2015).**

LIBERATI D., *An estimated DSGE model with search and matching frictions in the credit market,* International Journal of Monetary Economics and Finance (IJMEF), v. 11, 6, pp. 567-617, **WP 986 (November 2014).**

LINARELLO A., *Direct and indirect effects of trade liberalization: evidence from Chile,* Journal of Development Economics, v. 134, pp. 160-175, **WP 994 (December 2014).**

NATOLI F. and L. SIGALOTTI, *Tail co-movement in inflation expectations as an indicator of anchoring,* International Journal of Central Banking, v. 14, 1, pp. 35-71, **WP 1025 (July 2015).**

NUCCI F. and M. RIGGI, *Labor force participation, wage rigidities, and inflation,* Journal of Macroeconomics, v. 55, 3 pp. 274-292, **WP 1054 (March 2016).**

RIGON M. and F. ZANETTI, *Optimal monetary policy and fiscal policy interaction in a non_ricardian economy,* International Journal of Central Banking, v. 14 3, pp. 389-436, **WP 1155 (December 2017).**

SEGURA A., *Why did sponsor banks rescue their SIVs?,* Review of Finance, v. 22, 2, pp. 661-697, **WP 1100 (February 2017).**

2019

ALBANESE G., M. CIOFFI and P. TOMMASINO, *Legislators' behaviour and electoral rules: evidence from an Italian reform,* European Journal of Political Economy, v. 59, pp. 423-444, **WP 1135 (September 2017).**

APRIGLIANO V., G. ARDIZZI and L. MONTEFORTE, *Using the payment system data to forecast the economic activity,* International Journal of Central Banking, v. 15, 4, pp. 55-80, **WP 1098 (February 2017).**

ARNAUDO D., G. MICUCCI, M. RIGON and P. ROSSI, *Should I stay or should I go? Firms' mobility across banks in the aftermath of the financial crisis,* Italian Economic Journal / Rivista italiana degli economisti, v. 5, 1, pp. 17-37, **WP 1086 (October 2016).**

BASSO G., F. D'AMURI and G. PERI, *Immigrants, labor market dynamics and adjustment to shocks in the euro area,* IMF Economic Review, v. 67, 3, pp. 528-572, **WP 1195 (November 2018).**

BATINI N., G. MELINA and S. VILLA, *Fiscal buffers, private debt, and recession: the good, the bad and the ugly,* Journal of Macroeconomics, v. 62, **WP 1186 (July 2018).**

BURLON L., A. NOTARPIETRO and M. PISANI, *Macroeconomic effects of an open-ended asset purchase programme,* Journal of Policy Modeling, v. 41, 6, pp. 1144-1159, **WP 1185 (July 2018).**

BUSETTI F. and M. CAIVANO, *Low frequency drivers of the real interest rate: empirical evidence for advanced economies,* International Finance, v. 22, 2, pp. 171-185, **WP 1132 (September 2017).**

CAPPELLETTI G., G. GUAZZAROTTI and P. TOMMASINO, *Tax deferral and mutual fund inflows: evidence from a quasi-natural experiment,* Fiscal Studies, v. 40, 2, pp. 211-237, **WP 938 (November 2013).**

CARDANI R., A. PACCAGNINI and S. VILLA, *Forecasting with instabilities: an application to DSGE models with financial frictions,* Journal of Macroeconomics, v. 61, **WP 1234 (September 2019).**

CHIADES P., L. GRECO, V. MENGOTTO, L. MORETTI and P. VALBONESI, *Fiscal consolidation by intergovernmental transfers cuts? The unpleasant effect on expenditure arrears,* Economic Modelling, v. 77, pp. 266-275, **WP 1076 (July 2016).**

CIANI E., F. DAVID and G. DE BLASIO, *Local responses to labor demand shocks: a re-assessment of the case of Italy,* Regional Science and Urban Economics, v. 75, pp. 1-21, **WP 1112 (April 2017).**

CIANI E. and P. FISHER, *Dif-in-dif estimators of multiplicative treatment effects,* Journal of Econometric Methods, v. 8. 1, pp. 1-10, **WP 985 (November 2014).**

CIAPANNA E. and M. TABOGA, *Bayesian analysis of coefficient instability in dynamic regressions,* Econometrics, MDPI, Open Access Journal, v. 7, 3, pp.1-32, **WP 836 (November 2011).**

COLETTA M., R. DE BONIS and S. PIERMATTEI, *Household debt in OECD countries: the role of supply-side and demand-side factors,* Social Indicators Research, v. 143, 3, pp. 1185–1217, **WP 989 (November 2014).**

COVA P., P. PAGANO and M. PISANI, *Domestic and international effects of the Eurosystem Expanded Asset Purchase Programme,* IMF Economic Review, v. 67, 2, pp. 315-348, **WP 1036 (October 2015).**

ERCOLANI V. and J. VALLE E AZEVEDO, *How can the government spending multiplier be small at the zero lower bound?,* Macroeconomic Dynamics, v. 23, 8. pp. 3457-2482, **WP 1174 (April 2018).**

FERRERO G., M. GROSS and S. NERI, *On secular stagnation and low interest rates: demography matters,* International Finance, v. 22, 3, pp. 262-278, **WP 1137 (September 2017).**

FOA G., L. GAMBACORTA, L. GUISO and P. E. MISTRULLI, *The supply side of household finance,* Review of Financial Studies, v.32, 10, pp. 3762-3798, **WP 1044 (November 2015).**

GIORDANO C., M. MARINUCCI and A. SILVESTRINI, *The macro determinants of firms' and households' investment: evidence from Italy,* Economic Modelling, v. 78, pp. 118-133, **WP 1167 (March 2018).**

GOMELLINI M., D. PELLEGRINO and F. GIFFONI, *Human capital and urban growth in Italy,1981-2001,* Review of Urban & Regional Development Studies, v. 31, 2, pp. 77-101, **WP 1127 (July 2017).**

MAGRI S., *Are lenders using risk-based pricing in the Italian consumer loan market? The effect of the 2008 crisis,* Journal of Credit Risk, v. 15, 1, pp. 27-65, **WP 1164 (January 2018).**

MERCATANTI A., T. MAKINEN and A. SILVESTRINI, *The role of financial factors for european corporate investment,* Journal of International Money and Finance, v. 96, pp. 246-258, **WP 1148 (October 2017).**

MIGLIETTA A., C. PICILLO and M. PIETRUNTI, *The impact of margin policies on the Italian repo market,* The North American Journal of Economics and Finance, v. 50, **WP 1028 (October 2015).**

MONTEFORTE L. and V. RAPONI, *Short-term forecasts of economic activity: are fortnightly factors useful?,* Journal of Forecasting, v. 38, 3, pp. 207-221, **WP 1177 (June 2018).**

NERI S. and A. NOTARPIETRO, *Collateral constraints, the zero lower bound, and the debt–deflation mechanism,* Economics Letters, v. 174, pp. 144-148, **WP 1040 (November 2015).**

PANCRAZI R. and M. PIETRUNTI, *Natural expectations and home equity extraction,* Journal of Housing Economics , v. 46, 4, **WP 984 (November 2014).**

PEREDA FERNANDEZ S., *Teachers and cheaters. Just an anagram?,* Journal of Human Capital, v. 13, 4, pp. 635-669, **WP 1047 (January 2016).**

RIGGI M., *Capital destruction, jobless recoveries, and the discipline device role of unemployment,* Macroeconomic Dynamics, v. 23, 2, pp. 590-624, **WP 871 (July 2012).**

2020

ALESSANDRI P. and M. BOTTERO, *Bank lending in uncertain times,* R European Economic Review, V. 128, **WP 1109 (April 2017).**

ANTUNES A. and V. ERCOLANI, *Public debt expansions and the dynamics of the household borrowing constraint,* Review of Economic Dynamics, v. 37, pp. 1-32, **WP 1268 (March 2020).**

ARDUINI T., E. PATACCHINI and E. RAINONE, *Treatment effects with heterogeneous externalities,* Journal of Business & Economic Statistics, , v. 38, 4, pp. 826-838, **WP 974 (October 2014).**

BRIPI F., D. LOSCHIAVO and D. REVELLI, *Services trade and credit frictions: evidence with matched bank – firm data,* The World Economy, v. 43, 5, pp. 1216-1252, **WP 1110 (April 2017).**

BRONZINI R., G. CARAMELLINO and S. MAGRI, *Venture capitalists at work: a Diff-in-Diff approach at late-stages of the screening process,* Journal of Business Venturing, v. 35, 3, **WP 1131 (September 2017).**

COIBION O., Y. GORODNICHENKO and T. ROPELE, *Inflation expectations and firms' decisions: new causal evidence,* Quarterly Journal of Economics, v. 135, 1, pp. 165-219, **WP 1219 (April 2019).**

CORSELLO F. and V. NISPI LANDI, *Labor market and financial shocks: a time-varying analysis,* Journal of Money, Credit and Banking, v. 52, 4, pp. 777-801, **WP 1179 (June 2018).**

COVA P. and F. NATOLI, *The risk-taking channel of international financial flows,* Journal of International Money and Finance, v. 102, **WP 1152 (December 2017).**

D'IGNAZIO A. and C. MENON, *The causal effect of credit Guarantees for SMEs: evidence from Italy,* The Scandinavian Journal of Economics, v. 122, 1, pp. 191-218, **WP 900 (February 2013).**

ERCOLANI V. and F. NATOLI, *Forecasting US recessions: the role of economic uncertainty,* Economics Letters, v. 193, **WP 1299 (October 2020).**

MAKINEN T., L. SARNO and G. ZINNA, *Risky bank guarantees,* Journal of Financial Economics, v. 136, 2, pp. 490-522, **WP 1232 (July 2019).**

NISPI LANDI V., *Capital controls spillovers,* Journal of International Money and Finance, v. 109, **WP 1184 (July 2018).**

RAINONE E. and F. VACIRCA, *Estimating the money market microstructure with negative and zero interest rates,* Quantitative Finance, v. 20, 2, pp. 207-234, **WP 1059 (March 2016).**

RIZZICA L., *Raising aspirations and higher education. Evidence from the UK's widening participation policy,* Journal of Labor Economics, v. 38, 1, pp. 183-214, **WP 1188 (September 2018).**

SANTIONI, R., F. SCHIANTARELLI and P. STRAHAN, *Internal capital markets in times of crisis: the benefit of group affiliation*, Review of Finance, v. 24, 4, pp. 773-811, **WP 1146 (October 2017).**

SCHIANTARELLI F., M. STACCHINI and P. STRAHAN, *Bank Quality, judicial efficiency and loan repayment delays in Italy,* Journal of Finance , v. 75, 4, pp. 2139-2178, **WP 1072 (July 2016).**

FORTHCOMING

ALBANESE G., G. DE BLASIO and A. LOCATELLI, *Does EU regional policy promote local TFP growth? Evidence from the Italian Mezzogiorno,* Papers in Regional Science, **WP 1253 (December 2019).**

BALTRUNAITE A., C. GIORGIANTONIO, S. MOCETTI and T. ORLANDO, *Discretion and supplier selection in public procurement*, Journal of Law, Economics, and Organization, **WP 1178 (June 2018).**

BOLOGNA P., A. MIGLIETTA and A. SEGURA, *Contagion in the CoCos market? A case study of two stress events,* International Journal of Central Banking, **WP 1201 (November 2018).**

BOTTERO M., F. MEZZANOTTI and S. LENZU, *Sovereign debt exposure and the Bank Lending Channel: impact on credit supply and the real economy,* Journal of International Economics, **WP 1032 (October 2015).**

BRONZINI R., S. MOCETTI and M. MONGARDINI, *The economic effects of big events: evidence from the Great Jubilee 2000 in Rome,* Journal of Regional Science, **WP 1208 (February 2019).**

COVA P., P. PAGANO, A. NOTARPIETRO and M. PISANI, *Secular stagnation, R&D, public investment and monetary policy: a global-model perspective,* Macroeconomic Dynamics, **WP 1156 (December 2017).**

DEL PRETE S. and S. FEDERICO, *Do links between banks matter for bilateral trade? Evidence from financial crises,* Review of World Economics, **WP 1217 (April 2019).**

FIDORA M., C. GIORDANO and M. SCHMITZ, *Real exchange rate misalignments in the Euro Area,* Open Economies Review, **WP 1162 (January 2018).**

GERALI A. and S. NERI, *Natural rates across the Atlantic,* Journal of Macroeconomics, **WP 1140 (September 2017).**

LI F., A. MERCATANTI, T. MAKINEN and A. SILVESTRINI, *A regression discontinuity design for ordinal running variables: evaluating central bank purchases of corporate bonds,* Annals of Applied Statistics, **WP 1213 (March 2019).**

LIBERATI D. and M. LOBERTO, *Taxation and housing markets with search frictions,* Journal of Housing Economics, **WP 1105 (March 2017).**

LOSCHIAVO D., *Household debt and income inequality: evidence from Italian survey data,* Review of Income and Wealth, **WP 1095 (January 2017).**

METELLI L. and F. NATOLI, *The international transmission of US tax shocks: a proxy-SVAR approach,* IMF Economic Review, **WP 1223 (June 2019).**

MOCETTI S., G. ROMA and E. RUBOLINO, *Knocking on parents' doors: regulation and intergenerational mobility,* Journal of Human Resources, **WP 1182 (July 2018).**

MODENA F., E. RETTORE and G. M. TANZI, *The effect of grants on university dropout rates: evidence from the Italian case,* Journal of Human Capital, **WP 1193 (September 2018).**

NISPI LANDI V. and A. SCHIAVONE, *The effectiveness of capital controls,* Open Economies Review, **WP 1200 (November 2018).**

PEREDA FERNANDEZ S., *Copula-based random effects models for clustered data,* Journal of Business & Economic Statistics, **WP 1092 (January 2017).**

PERICOLI M., *On risk factors of the stock–bond correlation,* International Finance, **WP 1198 (November 2018).**

PERICOLI M. and M. TABOGA, *Nearly exact Bayesian estimation of non-linear no-arbitrage term-structure models,* Journal of Financial Econometrics, **WP 1189 (September 2018).**

RAINONE E., *The network nature of otc interest rates,* Journal of Financial Markets, **WP 1022 (July 2015).**