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Pricing equity-bond covariance risk: Between flight-to-quality and fear-of-missing-out[☆]

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ABSTRACT

Motivated by Merton (1973), we propose a novel bivariate intertemporal asset pricing model, which relates expected equity and bond market returns to their conditional covariance. Investors' dynamic hedging demand coincides with covariance risk, which in turn plays a central role in explaining contemporaneous time-variation in expected market returns. Our model predictions are consistent with variations in expected equity and bond returns that include flight-to-quality and fear-of-missing-out episodes, both of which coincide with low levels of equity-bond covariance. We identify determinants of time-variation in conditional covariance and thus potential drivers of flight-to-quality and fear-of-missing-out. Unanticipated changes in expected inflation, market illiquidity and stock market uncertainty predict changes in the equity-bond covariance, where the contribution of each variable is state-dependent. In particular, the non-linear effects of shocks to inflation act as a key driver.

1. Introduction

The crucial role of covariance risk in the pricing of assets can be motivated by the intertemporal capital asset pricing model (ICAPM) of Merton (1973). Reflecting investors' demand to hedge against adverse changes in the investment opportunity set, the model implies that expected asset returns depend not only on conditional variance but also on conditional covariance with state variables that are linked to time-varying investment opportunities. We propose a bivariate asset pricing model where time-varying investment opportunities are mirrored by time-variation in the conditional covariance between equities and long-term government bonds. From a dynamic hedging perspective, this is intuitive. Given time-variation in conditional equity-bond covariance, which is due to differential exposures of equities and bonds to shocks that correlate with marginal utility of wealth, multi-period investors face dynamic hedging opportunities that matter for portfolio choice.

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Changes in conditional covariance that are related to the dynamics of investors' hedging opportunities thus represent covariance risk that affects asset premia and hence expected returns.[1]

The present paper aims to answer the intriguing question whether equity-bond covariance risk is jointly priced in stock and bond markets, and if so, what are the determinants that influence covariance risk? We propose a bivariate conditional pricing model that simultaneously relates expected equity and bond market returns to the variance risk component as well as to the equity-bond covariance risk component. Our study employs monthly U.S. market observations during January 1965 and December 2017 to capture dynamics in conditional market variance and covariance between equity and bond market returns. Model estimation results provide significant evidence that covariance risk is priced in both markets. Further, we can show that the proposed equity-bond pricing relationship is consistent with two important phenomena that are both observed under low levels of equity-bond covariance. (i) Dynamic asset re-allocations within 'flight-to-quality' from equities to bonds, and (ii) re-allocations to risky assets due to 'fear-of-missing-out'.[2] While fear-of-missing-out, so far, has not been extensively covered by academics in finance, flight-to-quality has. Recent research of Baele et al. (2020) identifies global flight-to-quality episodes in association with negative equity-bond correlation and significant bond-equity return differentials. As flight-to-quality effects are supposed to correlate with liquidity effects, Baele et al. (2010) find that illiquidity proxies play a role for equity-bond correlation dynamics. Connolly et al. (2005) show that a higher probability of observing a negative equity-bond covariance coincides with high stock market uncertainty. Motivated by these studies, we control for the market uncertainty level as proxied by realized equity market volatility. Our findings show significant differences in the response of the equity and the bond market to shocks in market illiquidity across uncertainty regimes, which support the evidence of flight-to-quality from equities to bonds. During flight-to-quality, high equity market uncertainty coincides with a decline of equity prices and an increase of bond prices and realized bond returns, raising the expected return on equities and depressing the expected return on bonds.

While the public media frequently refer to 'fear-of-missing-out' in association with rising equity markets, the academic literature so far provides no explicit definition of this phenomenon. We identify and characterize fear-of-missing-out episodes by the following criteria. First, they coincide with low equity market volatility and above average equity market returns. Second, they are accompanied by a contemporaneous price depression in the bond market and a negative equity-bond covariance. In contrast to flight-to-quality, fear-of-missing-out is characterized by evident flows of funds from bonds to equities rather than from equities to bonds. The fear-of-missing-out pressure leads investors to demand lower premia and hence, to accept lower expected returns on equities. The effect on expected returns implied by both phenomena, flight-to-quality and fear-of-missing-out, can be captured by our intertemporal model that maps the pricing relations between equities and bonds.

We further focus on the economic determinants that explain time-variation in equity-bond covariance and thus are potential drivers of flight-to-quality and fear-of-missing-out effects. Guidolin and Timmermann (2006) and Guidolin and Timmermann (2007), respectively, provide reliable evidence that linear models are not able to capture time-variation in the conditional moments of equity and bond returns. To account for regime-switching dynamics, we use a threshold vector autoregressive (TVAR) model in order to assess the determinants that are likely to affect equity-bond covariance. The TVAR setting comprises shocks to stock market illiquidity, shocks to bond market illiquidity and shocks to inflation as endogenous variables and allows to estimate parameters depending on threshold regimes of expected inflation. Estimating the model shows that shocks to inflation are likely to induce changes in equity-bond covariance. This can be related to the proxy hypothesis of Fama (1981) which states that inflation is closely tied to real economic activity and consequently, shocks to inflation may act as a signal for future growth. More recently, David and Veronesi (2013) and Dergunov et al. (2016) claim that inflation shocks can be either good or bad news regarding real growth expectations. Our results show that inflation shocks in fact can represent a positive or negative signal for future economic activity depending on the level of expected inflation. The observed asymmetric signaling effect directly affects equity-bond covariance. During periods of high expected inflation, a positive shock to inflation represents bad news for both markets and reduces expected equity as well as bond returns, thereby it induces an increase in the covariance of the asset returns. During periods of low inflation, positive shocks to inflation act as a signal for improved business conditions representing good news for the equity market. At the same time, positive shocks to inflation are bad news for the bond market and depress nominal bond returns. The differential response of the equity and the bond market tends to result in a reduced level of conditional equity-bond covariance. These findings overall underline the signaling role of inflation shocks which plays a major role for equity and bond markets and makes inflation to a key macroeconomic fundamental in explaining joint dynamics in equity and bond markets and thus, time-variations in equity-bond covariance.

[1] Interestingly, the literature on the pricing of covariance risk is scarce. Notable exceptions include Rossi and Timmermann (2015), Bali (2008) and Bali and Engle (2010) who consider macro-economic and financial variables to construct the covariance risk component and find a significant premium. Other studies explicitly focus on the relation between expected returns and equity-bond covariance risk but yield contradictory results. For example, Scruggs (1998) imposes the restrictive assumption of constant covariance and concludes that the covariance risk component is not significantly priced, but reinforces the relation between the equity risk premium and conditional variance. In contrast, Scruggs and Glabadanidis (2003) assume dynamic covariances and disprove a significant improvement over single-factor models, while Gerard and Wu (2006) find a significant premium for bearing covariance risk under the assumption of time-varying conditional covariances.

[2] According to wikipedia.org, fear-of-missing-out is a social anxiety stemming from the belief that others might be experiencing satisfying events while the person experiencing the anxiety is not present. It is also defined as a fear of regret, which may lead to concerns that one might miss an opportunity for social interaction, a novel experience or a profitable investment.

The remainder of this paper is organized as follows. Section 2 presents the conditional pricing model and implications for expected equity and bond returns. Section 3 motivates variables that are likely to affect equity-bond covariance and describes the variable construction. Section 4 presents the empirical setting to identify variables that induce time-variation in equity-bond covariance. Section 5 presents the results regarding equity-bond covariance risk pricing and illustrates implications of the equity-bond pricing relations across flight-to-quality and fear-of-missing-out episodes. This section further identifies empirical determinants of time-variation in equity-bond covariance and thus, potential drivers of flight-to-quality and fear-of-missing-out effects. Section 7 concludes.

2. Pricing equity-bond covariance risk

We can express the price P of asset i at time t by

$$P_{i,t} = E_t[m_{t+1}X_{i,t+1}] \qquad \text{with} \qquad m_{t+1} = \beta\frac{u'(c_{t+1})}{u'(c_t)}, \tag{2.1}$$

where $E_t(\,\cdot\,)$ is the expectation operator conditional on information at time t, m_{t+1} represents the stochastic discount factor (SDF) and $X_{i,t+1}$ is the payoff of asset i at time $t+1$, c_t denotes consumption at time t and β is the subjective discount factor. The asset's payoff can be divided into two distinct components, the future price component and the cash flow stream.

Assuming that there exists a state variable, z_t, that contains information about the conditional distribution of asset returns and thus delivers information about future investment opportunities, the indirect utility of a representative investor also called value function, $V(\,\cdot\,)$, depends not only on wealth, W_t, but also on the state variable z_t. In this case, the maximized value of expected utility in time t of the representative investor is,

$$V(W_t, z_t) = \max_{\{c_t, c_{t+1}, \ldots, w_t, w_{t+1}, \ldots\}} \left[E_t \sum_{j=0}^{\infty} \beta^j u(c_{t+j}) \right], \tag{2.2}$$

$$\text{s.t.} \quad W_{t+1} = r^W_{t+1}(W_t - c_t), \qquad r^W_t = w'_t r_t, \qquad w'_t 1 = 1,$$

where r^W_t is the return on the wealth portfolio at time t, w_t is the vector of portfolio weights at time t and r_t is the vector of asset returns at time t. Dynamic programming reduces the infinite period problem into a two-period problem,

$$V(W_t, z_t) = \max_{\{c_t, w_t\}} \left[u(c_t) + \beta E_t \left[\max_{\{c_t, c_{t+1}, \ldots, w_t, w_{t+1}, \ldots\}} E_{t+1} \sum_{j=0}^{\infty} \beta^j u(c_{t+1+j}) \right] \right], \tag{2.3}$$

or alternatively,

$$V(W_t, z_t) = \max_{\{c_t, w_t\}} E_t[u(c_t) + \beta E_t V(W_{t+1}, z_{t+1})]. \tag{2.4}$$

At the optimum, the envelope condition, $u'(c_t) = V_W(W_t, z_t)$, holds for the SDF:

$$m_{t+1} = \beta\frac{V_W(W_{t+1}, z_{t+1})}{V_W(W_t, z_t)}. \tag{2.5}$$

Eq. (2.5) shows that the SDF depends on the state variable z_t and can be expressed as $\Lambda_t = e^{-\delta t}V_W(W_t, z_t)$ in continuous-time. The derivative yields

$$\frac{d\Lambda_t}{\Lambda_t} = -\delta dt + \frac{W_t V_{WW}(W_t, z_t)}{V_W(W_t, z_t)}\frac{dW_t}{W_t} + \frac{V_{Wz}(W_t, z_t)}{V_W(W_t, z_t)}dz_t, \tag{2.6}$$

which is the characterization of Merton's ICAPM in a continuous-time framework. The ICAPM equilibrium relation between the expected market return and market risk can be represented in a simplified form by

$$\mu_M = \lambda_M\sigma^2_M + \lambda_H\sigma_H, \tag{2.7}$$

where $\lambda_M = -WV_{WW}(W_t, z_t)/V_W(W_t, z_t)$ is commonly called the coefficient of relative risk aversion. The variance of the market return is denoted by σ^2_M and the covariance between the market return and the state variable z_t is denoted by σ_H. The coefficient λ_H is the price of covariance risk associated with state variable z_t. Hence, if state variable z_t changes stochastically over time, the investor faces additional risk due to changes in the future investment opportunity set. The risk of an asset is then decomposed into two different constituent risk parts: (i) Risk with respect to the market portfolio and (ii) risk with respect to the hedging portfolio. The expected returns of assets are related to their exposures to these two systematic risks and the associated risk premia.

We assume that long-term government bond returns provide a state variable and act as a second risk-factor. The representative investor then holds two funds, namely the equity portfolio and the bond hedging portfolio.[3] As such, we propose

[3] According to (Merton, 1973, (p. 879)), there exists at least one element in the investment opportunity set that is directly observable and changes stochastically over time, namely the interest rate. Theoretically, an asset whose return is perfectly negatively correlated with changes in the interest rate serves as a perfect hedge against changes in the investment opportunity set. Merton proposes long-term government bonds as a proxy for such an asset arguing that long-term bond returns are not perfectly, but highly correlated with interest rate changes.

the following bivariate pricing relation:

$$E_t(r_{M,t+1}) = \lambda_M\ \sigma^2_{M,t+1} + \lambda_{H,Stock}\ \sigma_{H,t+1},$$
$$E_t(r_{B,t+1}) = \lambda_B\ \sigma^2_{B,t+1} + \lambda_{H,Bond}\ \sigma_{H,t+1}. \tag{2.8}$$

Here, $r_{M,t+1}$ denotes the equity market return at time $t+1$ and $r_{B,t+1}$ denotes the bond market return at time $t+1$, $\sigma^2_{M,t+1}$ and $\sigma^2_{B,t+1}$ denote conditional equity and bond market variance and λ_M and λ_B are the corresponding market prices of risk for equities and bonds, respectively. Equity-bond conditional covariance is represented by $\sigma_{H,t+1}$. The coefficient λ_H is the market price of equity-bond covariance risk.

Model (2.8) has several implications for representative investors with constant relative risk aversion. Risk aversion implies that $\lambda_M > 0$ and $\lambda_B > 0$, i.e. investors require a reward for bearing (positive) variance risk. The economic interpretation of λ_H is more involved and depends on the (positive or negative) level of conditional covariance between equity and bond returns. In general, investors demand a premium for bearing intertemporal risk and stochastic investment opportunities as captured by time-variation in the equity-bond covariance. In sum, the resulting total risk premia in (2.8) may turn low or even negative if the covariance risk component, i.e. the hedging component, dominates. For example, if bonds (equities) provide a hedge against changes in the future investment opportunity set (particularly if $\sigma_{H,t+1} < 0$), equity (bond) investors might be even willing to pay a premium for holding the hedging asset and for the reduction of risk regarding lifetime wealth. The price for the hedging opportunities is captured by the second term (the hedging component) in our model, i.e. the part of the expected return investors are willing to give up in order to hedge their portfolio against adverse changes in the investment opportunity set. Vice versa, investors are exposed to the risk of increasing conditional equity-bond covariance and depressed hedging opportunities. Following these logics, the second term of the model reflects the part of the expected return investors demand to compensate for the risk of deteriorated hedging opportunities induced by time-variations in conditional equity-bond covariance.

3. Determinants of equity-bond covariance risk

The potential determinants of equity-bond covariance risk can be motivated by recalling the fundamental asset pricing relation in Eq. (2.1). Equity and bond prices are the discounted sum of all future cashflows, and thus, any variable that either affect the assets' payoff or the discount factor drives equity and bond returns and determines their covariance (Baele et al., 2010). In particular, a variable that affects the cashflow of either equities *or* bonds is likely to move the assets in opposite directions while a variable that affects only the discount factor is likely to move equities and bonds in the same direction. However, as most variables are supposed to affect cashflow and discount factor simultaneously, it is a hard task to theoretically derive the actual effect on equity-bond covariance. This section motivates a set of factors that are likely to affect the assets' covariance and presents the construction and data source of each economic variable under consideration.

3.1. Inflation

Equities and bonds have unique characteristics linked to their differences in the payoff structure. Stocks receive a stochastic dividend income flow, while bonds receive fixed nominal cashflows. It is rather obvious that inflation expectations impact nominal government bond returns. If expected inflation is high, bond investors demand a higher yield that compensates for alleviating the purchasing power of a bond's future cashflows. This is captured by the Fisher decomposition where the nominal bond yield is decomposed into a real interest rate component and a compensation for expected inflation. If inflation is assumed to be stochastic, an inflation risk premium rewards for inflation uncertainty. On the contrary, equities are considered as claims against real assets and should theoretically be unaffected by inflation. However, there is empirical evidence that inflation significantly affects common stocks. Pioneering empirical work of Fama and Schwert (1977) already suggests a negative relation between stock returns and inflation. The empirical evidence is still valid. Also recent studies on the inflation risk premium such as Bekaert and Wang (2010) underline that stocks act as a poor hedge against inflation risk. We decompose the inflation rate into its expected and unexpected part by

$$\widetilde{\pi}_t = E(\pi_t|F_{t-1}) + \pi^U_t, \tag{3.1}$$

where $E(\pi_t|F_{t-1})$ is the expected inflation rate from time $t-1$ to t and the disturbance term represents the unexpected component of inflation, π^U_t. As the inflation rate is approximately a random walk plus serially uncorrelated noise, by definition, the unexpected component of inflation is uncorrelated with the expected rate of inflation. In our empirical investigations, we use data on the log change in the Consumer Price Index (CPI) for All Urban Customers (All Items) obtained from the Bureau of Labor Statistics to proxy for inflation. To estimate the expected and unexpected component of inflation, we choose an autoregressive integrated moving average (ARIMA) model according to the Bayesian information criterion (BIC).[4]

[4] Assuming a constant real rate of return, Fama and Schwert (1977) approximate expected inflation as the interest rate on a Treasury bill minus the expected real return on the bill. Other studies derive inflation expectations from nominal and inflation-indexed Treasury yields or use survey data on inflation expectations. We rely on CPI data as it is available in monthly frequency over a reasonable long time horizon.

3.2. Systematic illiquidity

There is evidence that illiquidity represents a systematic risk factor in the equity market (see e.g. Amihud, 2002; Jones, 2002; Pastor and Stambaugh, 2003) and in the government bond market (see e.g. Amihud and Mendelson, 1991; Goldreich et al., 2005). Regarding the cross-market impact of illiquidity, Chordia et al. (2005) find that illiquidity on the equity and the bond market strongly covary while the recent study of Goyenko and Ukhov (2009) provides evidence that there is a lead-lag relation and bi-directional Granger causality between illiquidity in these two markets. In particular, a shock to stock market illiquidity significantly affects the bond market which is consistent with the flight-to-quality (also often referred to as flight-to-liquidity) phenomenon. In periods of financial turmoil, investors tend to exit the illiquid stock market and enter the highly liquid Treasury bond market resulting in a price pressure effect that induces negative equity-bond return correlations. Our proxy for stock market illiquidity is the measure of price impact developed by Amihud (2002) that can be easily obtained from daily data. Monthly stock market illiquidity is calculated by

$$IL_{Stock,t} = \frac{1}{D_t}\sum_{d=1}^{D_t}\frac{|r_{d,t}|}{\ln(V_{d,t})}, \tag{3.2}$$

where $r_{d,t}$ is the stock market return on day d in month t, $V_{d,t}$ is the dollar volume on day d in month t and D_t denotes the number of trading days in month t.

To capture U.S. bond market illiquidity, we use the quoted bid-ask spread which represents the most effective measure to track illiquidity changes in the Treasury bond market (see e.g. Fleming, 2003 and Goldreich et al., 2003). Using data on the 10-year Treasury note, we calculate the monthly relative bid-ask spread by

$$IL_{Bond,t} = \frac{1}{D_t}\sum_{d=1}^{D_t}\frac{Y_{B,d,t} - Y_{A,d,t}}{\frac{1}{2}(Y_{B,d,t} + Y_{A,d,t})}. \tag{3.3}$$

Here, $Y_{B,d,t}$ is the quoted bid, $Y_{A,d,t}$ is the quoted ask yield on day d in month t and D_t is the number of trading days in month t. As the bid yield is higher than the corresponding ask yield, the spread is positive and gets wider with increasing bond market illiquidity.

3.3. Stock market uncertainty

Stock market uncertainty is supposed to have important cross-market impact and to influence the joint pricing of equities and bonds. Consistent with the notion of flight-to-quality, the probability of observing a negative future equity-bond correlation is shown to be higher in times of high stock market uncertainty which directly affects the diversification benefit of equities and bonds (see e.g. Connolly et al., 2005).

We use realized volatility of the S&P 500 index as a gauge for uncertainty on the U.S. stock market. For relatively long time horizons, high-frequency intraday data is typically not available and the realized volatility estimator is based on standard deviations or variances of daily close-to-close returns. We rely on the Garman and Klass (1980) measure of realized variance that contains additional information on intraday variability by including opening-, high-, low- and closing prices. Average monthly realized variance is then calculated by

$$rv_{GK,t} = \frac{1}{D_t}\sum_{d=1}^{D_t}\left[0.5p_d^2 - (2\ln 2 - 1)q_d^2\right], \tag{3.4}$$

where $p_d = \ln(H_d/L_d)$ represents the range between high price H_d and low price L_d on day d. The open-to-close return on day d is captured by $q_d = \ln(C_d/O_d)$ where C_d denotes the closing price on day d and O_d is the opening price on day d.

4. How do economic factors affect equity-bond covariance?

Model (2.8) implies that covariance risk influences the expected return of equities and bonds. As such, factors that significantly affect conditional equity-bond covariance have an indirect impact on expected equity and bond returns. If equities and bonds exhibit different (similar) exposures to shocks in economic variables, these shocks are likely to predict a decrease (increase) in conditional covariance. We aim to identify these determinants of equity-bond covariance by using a threshold VAR that is able to capture non-linear predictability pattern. The TVAR (m) setting with $j = 1, \ldots, m$ threshold regimes is given by

$$y_t = \begin{cases} c^{(1)} + \sum_{i=1}^{p}\beta_i^{(1)}y_{t-i} + \sum_{i=1}^{q}\gamma_i^{(1)}x_{t-i} + \epsilon_t^{(1)} & \text{if } z_{t-q} \le \tau_1, \\ c^{(2)} + \sum_{i=1}^{p}\beta_i^{(2)}y_{t-i} + \sum_{i=1}^{q}\gamma_i^{(2)}x_{t-i} + \epsilon_t^{(2)} & \text{if } \tau_1 < z_{t-q} \le \tau_2, \\ \vdots & \\ c^{(m)} + \sum_{i=1}^{p}\beta_i^{(m)}y_{t-i} + \sum_{i=1}^{q}\gamma_i^{(m)}x_{t-i} + \epsilon_t^{(m)} & \text{if } z_{t-q} > \tau_{m-1}, \end{cases} \tag{4.1}$$

where $\tau_j = \{\tau_1, \ldots, \tau_{m-1}\}$ denotes the threshold value and $c^{(j)} = \left\{c^{(1)}, \ldots, c^{(m)}\right\}$ is the intercept in the j-th regime. The vector $y_t = (y_{1t}, \ldots, y_{kt})'$ contains equity and bond returns and $k-2$ additional endogenous variables, $x_t = (x_{1t}, \ldots, x_{vt})'$ is a

Table 1
Summary Statistics of Return Data. Panel A reports summary statistics as well as the Jarque Bera (JB) and Ljung Box (LB) statistics for monthly returns on the CRSP value-weighted index of NYSE, Amex or Nasdaq stocks, r_M, long-term government bond returns, $r_{B,}$ and the risk-free rate, r_f, proxied by the one-month Treasury bill. The sample period ranges from January 1965 to December 2017 resulting in 636 monthly observations. Panel B reports unconditional Pearson correlations of returns. *, ** and *** denote significance at the 10%, 5% and 1% levels, respectively.

Panel A: Summary Statistics of Returns

	Mean (%)	Median (%)	SD (%)	Skew	Kurtosis	JB	LB		
							Lag 1	Lag 5	Lag 9
r_M	0.907	1.215	4.426	-0.506	4.929	125.73***	3.21*	6.80	9.34
r_B	0.567	0.527	1.969	0.583	6.349	333.22***	58.56***	62.52***	70.57***
r_f	0.389	0.400	0.269	0.555	3.595	42.07***	602.60***	2820.50***	4843.80***

Panel B: Unconditional Correlation Matrix of Returns

	r_M	r_B	r_f
r_M	1		
r_B	0.141***	1	
	[3.60]		
r_f	-0.023	0.093**	1
	[-0.58]	[2.35]	

ν-dimensional vector of exogenous variables. Parameters p and q are the autoregressive orders of TVAR model. We assume that innovations $\epsilon_t^{(j)} = \left\{\epsilon^{(1)}, \ldots, \epsilon^{(m)}\right\}$ are serially uncorrelated with zero mean and symmetric positive definite covariance matrix Σ_j. The threshold regimes are determined by the threshold variable z_{t-q} that is assumed to be stationary and to have a continuous distribution. The delay parameter q implies that the exceeding of any threshold τ_j at time $t-q$ results in an actual change of the dynamics at time t. It is common convention in empirical applications of the TVAR to set the delay parameter to 1.[5] The signs of coefficients $\beta^{(j)}$ and $\gamma^{(j)}$ in the TVAR model determine the direction of the stock-bond covariance in each threshold regime $j = \{1, \ldots, m\}$. In general, if betas and gammas exhibit the same sign for equities and bonds, both assets exhibit similar sensitivities to these variables and the assets are likely to move together leading to an increase in conditional covariance. If the betas and gammas have different signs, the corresponding variable is likely to move equities and bonds in opposite directions which lowers covariance. Consequently, the equity-bond covariance depends on common economic variables that drive asset returns and there must be at least one dominating variable that significantly pushes equity and bond returns in opposite directions to induce negative equity-bond covariance.

5. Empirical evidence

5.1. Return summary statistics

Our sample period ranges from January 1965 to December 2017 resulting in 636 monthly observations of equity and bond returns. We measure U.S. equity returns, r_M, by the broadest possible stock market index and observe monthly value-weighted returns of all U.S. equities listed on NYSE, Amex or Nasdaq from Center for Research in Security Prices (CRSP).[6] Monthly bond returns, r_B, are proxied by the U.S. ten-year Treasury bond returns. Both series measure the return from end of month $t-1$ until end of month t. The nominal risk-free rate, r_f, is proxied by the U.S. Treasury bill with one month until maturity.

Descriptive statistics for the return data is provided in Panel A of Table 1. Typically, equity returns are more volatile than bond returns and yield higher expected returns. Over the entire sample, the average monthly return of the equity market portfolio is 0.91% which corresponds to a mean of 10.89% on an annual basis. The returns on the government bond portfolio and the risk-free rate yield a monthly average of 0.57% and 0.39%, which corresponds to an annualized average return of 6.48% and 4.68%, respectively. As one would expect, bond returns and the risk-free rate exhibit significant autocorrelations at least up to lag 9 and all series are non-normal distributed as indicated by the Jarque Bera (JB) statistics. Panel B of Table 1 reports Pearson correlations of the market return series and the corresponding t-values of a two-tailed test. The (unconditional) correlation between equity and bond market returns is positive with a value of 14.1% and highly significant. Consistent to earlier studies such as Ang and Bekaert (2007) and Campbell (1987), equity market returns are negatively correlated with the Treasury bill rate, however, not statistically significant on conventional levels. We further estimate a positive and significant correlation between government bond returns and the risk-free rate.

5 See Appendix B for further details on the estimation procedure of the TVAR model.

6 CRSP data is kindly provided by Kenneth R. French on his personal website: https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/.

5.2. Asset pricing model estimation results

The conditional model (2.8) implies that the expected equity and bond market returns are related to variance risk and equity-bond covariance risk. Thereby, the model allows to allocate a unique market price to each risk component, that is, the market price of variance risk and the market price of equity-bond covariance risk, which may potentially differ across the equity and the bond market. Our empirical investigations start with the standard version of the conditional model that postulates that the expected return is linearly related only to conditional variance. We then provide empirical evidence regarding the pricing of equity-bond covariance risk.

5.2.1. Market price of variance risk

To deliver first insights on the market price of variance risk on the equity and the bond market, we impose the constraint on $\lambda_H = 0$ in Model (2.8). We follow standard convention in tests of the ICAPM and estimate a GARCH-in-mean model to infer the risk-return relationship of equities and bonds.

Table 2 reports quasi maximum likelihood estimation (QMLE) results of the GARCH-in-mean model under the assumption of asymmetry according to Glosten et al. (1993) and Student t distributed errors. Empirical models commonly include an intercept to control for potential model misspecifications or to account for market imperfections (see e.g. Scruggs, 1998). We estimate the risk-return relation with inclusion of an intercept term in (I). As implied by the theoretical model, we further constrain the intercept to be zero in (II). Regarding the estimation of conditional variance, our results show positive and highly significant first-order autoregressive coefficients, β_M and β_B, which indicate that there is strong short-term persistence of conditional variance on both markets. The positive and significant estimate of the asymmetry parameter γ_M shows an asymmetric response of conditional variance to news. An unexpected negative equity market return (bad news) sharply increases conditional equity market variance while an unexpected positive equity market return (good news) decreases conditional equity market variance. Interestingly, the estimate of the asymmetry parameter γ_B is not significantly different from zero. This suggests that conditional bond market variance is not responsive to lagged bond market return innovations. Residual diagnostics support an appropriate fit of the time-series model.

Regarding the conditional mean equation, we observe positive market price of variance risk estimates, λ_M and λ_B. This is in line with the theoretical prediction that periods of high conditional equity and bond variance, respectively, are associated with higher expected returns. Note that λ_M and λ_B both turn statistically insignificant once the intercept is included. This is consistent with Lanne and Saikkonen (2006) who argue that the inclusion of an intercept term may distort estimates of the risk-return parameter and recommend imposing a zero restriction on the intercept term such as in the original ICAPM by Merton.

According to Glosten et al. (1993), for example, the Treasury bill rate might have significant impact on the conditional market variance and the risk-return relation. Therefore, we test whether our findings are robust regarding an inclusion of the risk-free rate as explanatory variable in the conditional mean and conditional variance equation. As shown in Table 3, the coefficient estimate $\nu_{r_f,M}$ as well as $\nu_{r_f,B}$ indicate that conditional equity and bond market variance are significantly affected by the risk-free rate. The inclusion of the risk-free rate, however, does not bias the estimation results of the remaining parameters in the variance equation of equity and bond returns. Our results on $\lambda_{r_f,M}$ show that the risk-free rate has no statistically significant impact on conditional equity market returns. In contrast, we observe a positive and significant coefficient $\lambda_{r_f,B}$. The latter findings are consistent with the reported results regarding the correlations between equity and bond returns and the risk-free rate.

Overall, our results show that the market price of variance risk is positive and economically significant implying that equity and bond investors demand higher expected returns for bearing higher conditional risk. While the statistical significance of the relation between conditional returns and conditional variance depends crucial on model restrictions regarding the intercept term, the risk-free rate does not bias the risk-return relation.

5.2.2. Market price of equity-bond covariance risk

In practice, one faces the challenge that conditional second moments are not observable. In our setting, we rely on two measures of moments. First, we assume conditional variance of stock and bond returns both to follow an asymmetric GARCH(1,1) process. Standardized residuals of the univariate GARCH models are then used to estimate the conditional stock-bond covariance according to the dynamic conditional correlation (DCC) model of Engle (2002).[7]

One of the main objectives of this study is to answer the question whether conditional equity-bond covariance is priced on the equity and on the bond market. In our pricing tests, we follow an estimation procedure similar to Bali and Engle (2010) and observe estimates of conditional equity-bond covariance in a first step. In a second step, we estimate the mean equation of equities and bonds simultaneously using seemingly unrelated regressions (SUR) to account for contemporaneously correlated error terms associated with the equity and bond equation.

Panel A of Table 4 shows the QMLE results of the DCC GARCH (1,1) model under the assumption of multivariate Student t distributed errors. A comparison of the estimated conditional variance equation parameters to those in Table 2 shows that the results do not substantially differ. Still, the coefficients β_M and β_B are positive, high in magnitude and highly

[7] For details on the estimation of conditional variance and conditional covariance see Appendix A.

Table 2
Conditional Asset Pricing Model Estimates. Estimated parameters of the system:

$$
\begin{aligned}
r_{M,t+1} &= \lambda_0 + \lambda_M \hat{\sigma}^2_{M,t+1} + \hat{\epsilon}_{M,t+1},\\
r_{B,t+1} &= \lambda_0 + \lambda_B \hat{\sigma}^2_{B,t+1} + \hat{\epsilon}_{B,t+1},\\
\hat{\sigma}^2_{M,t+1} &= \omega_M + \alpha_M \hat{\epsilon}^2_{M,t} + \gamma_M I_t \hat{\epsilon}^2_{M,t} + \beta_M \hat{\sigma}^2_{M,t},\\
\hat{\sigma}^2_{B,t+1} &= \omega_B + \alpha_B \hat{\epsilon}^2_{B,t} + \gamma_B I_t \hat{\epsilon}^2_{B,t} + \beta_B \hat{\sigma}_{B,t}.
\end{aligned}
$$

For estimation, we use monthly stock market returns on CRSP firms listed on NYSE, Amex or Nasdaq, r_M, and long-term government bond returns, r_B. Estimation results are reported with intercept (I) and with the constraint $\lambda_0 = 0$ (II). The sample period ranges from January 1965 to December 2017 resulting in 636 monthly observations. Robust t-statistics are reported in brackets, superscripts *, ** and *** denote statistical significance (at least) at the 10%, 5% and 1% level, respectively.

	Equity			Bond	
Conditional Mean	(I)	(II)		(I)	(II)
$\lambda_{0,M}$	0.007**	0	$\lambda_{0,B}$	0.002	0
	[2.509]	[-]		[0.983]	[-]
λ_M	1.484	5.274***	λ_B	8.133	13.383***
	[0.794]	[4.709]		[1.408]	[5.616]
Conditional Variance					
ω_M	0.000	0.000	ω_B	0.000	0.000
	[1.533]	[1.371]		[1.112]	[1.271]
α_M	0.058***	0.066***	α_B	0.111	0.124*
	[3.890]	[2.807]		[1.643]	[1.929]
β_M	0.769***	0.687***	β_B	0.830***	0.821***
	[8.659]	[4.414]		[7.450]	[8.246]
γ_M	0.998***	0.999***	γ_B	-0.042	-0.042
	[6.028]	[8.789]		[-0.366]	[-0.394]
Shape$_M$	8.111***	8.257	*Shape$_B$*	7.780***	7.973***
	[3.033]	[3.109]		[3.263]	[3.195]
LogLikelihood	1124.90	1121.66		1649.03	1648.18
Weighted LB Test on standardized residuals					
Lag[1][8][9]	H0 not rejected	H0 not rejected		H0 not rejected	H0 not rejected
Weighted ARCH LM Test					
ARCH Lag[3][5][7]	H0 not rejected	H0 not rejected		H0 not rejected	H0 not rejected

significant indicating that conditional variance of stock and bond returns is strongly persistent. We also find that there is a strong leverage effect for equity market returns while the response of bond market returns to lagged innovations seems to be symmetric. It should be noted that the parameters of the DCC model are both estimated to be positive with a small magnitude of $\alpha_{dcc} = 0.03$ and a large magnitude of $\beta_{dcc} = 0.96$. The sum of the DCC parameters, $(\alpha_{dcc} + \beta_{dcc} < 1)$, implies that the conditional correlations exhibit mean reversion behavior. Turning to the market prices of variance risk, we observe positive market prices of variance risk, λ_M and λ_B. Foremost, our results show that the market price of covariance risk is robust to the inclusion of a constant term, λ_0. While the statistical significance of λ_M and λ_B completely vanishes, the coefficient λ_H remains positive and significant in the equity and the bond equation.

Likelihood ratio (LR) tests are used to test whether an unrestricted model fits significantly better than variations of a restricted model with constraints on λ_0 and λ_H. The result of the χ^2-distributed LR test statistics for the model restrictions are reported in Panel B of Table 4. Regarding the restriction on the intercept λ_0, the LR-test result implies that the constant term is necessary for an adequate model specification. This is intuitive as we focus on simple returns rather than on excess returns. We further observe a p-value of less than 0.01 regarding restrictions on λ_H indicating that the additional consideration of equity-bond covariance risk yields a significantly better fit than the single-factor standard model.

Our setting, thus far, relies on conditional variance and covariance estimated from monthly asset returns derived by the DCC framework. While the use of monthly data is a standard procedure in asset pricing tests, one drawback is the bulk of past information that is not considered. To account for the information contained in higher frequency data, we perform additional tests by relating monthly expected asset returns to realized moments derived from daily asset returns. In particular, we rely on a measure of realized volatility that is constructed as the sum of past month's daily squared equity and bond returns and, similarly, past month's daily asset returns are used to derive realized equity-bond covariance. Table 5 shows that our results are robust to the alternative specifications of moments. As shown in Panel A of Table 5, the estimated parameters $\lambda_{H,M}$ and $\lambda_{H,B}$ yield positive values and statistical significance in the equity as well as in the bond equation which provides further evidence that equity-bond covariance risk plays a significant role in explaining expected returns on both markets. The LR tests in Panel B of Table 5 further confirm that including the equity-bond covariance component in the pricing model yields a significantly better fit in explaining expected asset returns.

Overall, the presented results provide robust evidence that covariance risk is priced. The significant pricing implies that conditional covariance is affected by shocks that correlate with marginal utility of wealth. If the time-variation in conditional covariance would not be affected by intertemporal risk, then investors would behave myopically in their portfolio choice and there would be no need for the second component of our model. Under the latter conditions, results regarding the pricing

Table 3
Conditional Model Estimates with Inclusion of the Risk-free Rate. Estimated parameters of the system:

$$\begin{aligned}
r_{M,t+1} &= \lambda_0 + \lambda_M \hat{\sigma}^2_{M,t+1} + \lambda_{r_f,M} r_{f,t} + \hat{\epsilon}_{M,t+1}, \\
r_{B,t+1} &= \lambda_0 + \lambda_B \hat{\sigma}^2_{B,t+1} + \lambda_{r_f,B} r_{f,t} + \hat{\epsilon}_{B,t+1}, \\
\hat{\sigma}^2_{M,t+1} &= \omega_M + \alpha_M \hat{\epsilon}^2_{M,t} + \gamma_M I_t \hat{\epsilon}^2_{M,t} + \beta_M \hat{\sigma}^2_{M,t} + \nu_{r_f,M} r_{f,t}, \\
\hat{\sigma}^2_{B,t+1} &= \omega_B + \alpha_B \hat{\epsilon}^2_{B,t} + \gamma_B I_t \hat{\epsilon}^2_{B,t} + \beta_B \hat{\sigma}^2_{B,t} + \nu_{r_f,B} r_{f,t}.
\end{aligned}$$

For estimation, we use monthly stock market returns on CRSP firms listed on NYSE, Amex or Nasdaq, r_M, long-term government bond returns, r_B, and the risk-free rate, r_f, proxied by the one-month Treasury bill. Estimation results are reported with intercept (I) and with the constraint $\lambda_0 = 0$ (II). The sample period ranges from January 1965 to December 2017 resulting in 636 monthly observations. Robust t-statistics are reported in brackets, superscripts *, ** and *** denote statistical significance (at least) at the 10%, 5% and 1% level, respectively.

	Equity			Bond	
Conditional Mean	(I)	(II)		(I)	(II)
$\lambda_{0,M}$	0.009***	0	$\lambda_{0,B}$	0.001	0
	[2.734]	[-]		[0.218]	[-]
λ_M	1.896	5.375***	λ_B	6.983	7.893**
	[0.892]	[2.946]		[1.241]	[2.400]
$\lambda_{r_f,M}$	-0.617	0.032	$\lambda_{r_f,B}$	0.541	0.582*
	[-1.065]	[0.046]		[1.532]	[1.873]
Conditional Variance					
ω_M	0.000	0.000	ω_B	0.000	0.000
	[0.902]	[1.192]		[0.653]	[0.681]
α_M	0.059***	0.071***	α_B	0.091***	0.094***
	[2.779]	[2.653]		[4.263]	[4.483]
β_M	0.740***	0.635***	β_B	0.854***	0.853***
	[5.200]	[2.972]		[10.342]	[3.413]
γ_M	0.999***	0.999***	γ_B	-0.020	-0.019
	[2.918]	[4.891]		[-0.151]	[-0.450]
$\nu_{rf,M}$	0.037	0.045	$\nu_{rf,B}$	0.002*	0.002*
	[1.633]	[1.326]		[1.655]	[1.753]
$Shape_M$	9.672**	10.261**	$Shape_B$	8.369***	8.454***
	[2.521]	[2.515]		[3.179]	[3.391]
LogLikelihood	1132.37	1128.70		1651.81	1651.77
Weighted LB Test on standardized residuals					
Lag[1][8][9]	H0 not rejected	H0 not rejected		H0 not rejected	H0 not rejected
Weighted ARCH LM Test					
ARCH Lag[3][5][7]	H0 not rejected	H0 not rejected		H0 not rejected	H0 not rejected

of conditional equity-bond covariance would lead to a statistically (and economically) insignificant pricing relation between conditional covariance and expected returns. In contrast, our results support the theoretical hypothesis that investors exhibit aversion against intertemporal risk and demand dynamic hedging which makes the equity-bond covariance component in our model indispensable. As equity-bond covariance risk matters for the stock market and the bond market, expected returns of both assets are affected by the time-variation in conditional covariance.[8]

5.3. Implications of the equity-bond pricing relationship

This section illustrates important implications of covariance risk in explaining the time-variation of expected asset returns. Our Model (2.8) captures the dynamic hedging demand of investors and is able to map the pricing effects of two market phenomena: (i) Safe haven allocations during flight-to-quality episodes and (ii) allocations to risky assets and market price rallies that occur under fear-of-missing-out.

In our setting, we assume that flight-to-quality episodes are characterized by high (above average) equity market volatility representing increased market stress and negative equity-bond covariance induced by high realized positive bond returns relative to realized equity returns (see also Baele et al., 2020 and Durand et al., 2010). Further, we identify and characterize fear-of-missing-out episodes with respect to the equity market by two criteria. First, fear-of-missing-out episodes coincide with a higher incidence of positive equity return shocks and low equity market volatility.[9] Second, the rising equity market is accompanied by a contemporaneous price depression in the bond market resulting in a high realized equity-bond return spread and negative equity-bond covariance.

Fig. 1 shows the monthly data-implied DCC conditional covariance as well as realized covariance along with the regimes of flight-to-quality and fear-of-missing-out identified according to the defined criteria. An overall look clearly reveals a time-

[8] We thank an anonymous referee for the suggestion to highlight the economic significance of our results regarding the pricing of equity-bond covariance risk.

[9] The assumption of low equity market volatility in response to positive return shocks is consistent with the strong asymmetric volatility effect on the equity market reported in Section 5.2.2.

Table 4
Pricing Equity-Bond Covariance Risk. Panel A reports simultaneously estimated parameters of the conditional equity and bond mean equation and parameter estimates of the asymmetric DCC GARCH (1,1) model assuming a multivariate Student t error distribution. Estimation results are provided with intercept (I) and with the constraint $\lambda_0 = 0$ (II). Panel B reports χ^2 statistics and p-values (in parentheses) of the likelihood ratio (LR) tests to compare model restrictions on λ_0 and λ_H. For estimation, we use monthly stock market returns on CRSP firms listed on NYSE, Amex or Nasdaq, r_M and long-term government bond returns, r_B. The sample period ranges from January 1965 to December 2017 resulting in 636 monthly observations. Robust t-statistics with HAC standard errors are reported in brackets, superscripts *, ** and *** denote statistical significance (at least) at the 10%, 5% and 1% level, respectively.

Panel A: Model Estimates

	Equity			Bond	
Mean Equation	(I)	(II)		(I)	(II)
$\lambda_{0,M}$	0.005*	0	$\lambda_{0,B}$	0.003**	0
	[1.701]	[-]		[2.513]	[-]
λ_M	0.556	1.780**	λ_B	2.201	6.090***
	[0.523]	[2.402]		[0.881]	[3.171]
$\lambda_{H,M}$	15.767**	21.123***	$\lambda_{H,B}$	9.855**	11.086***
	[2.002]	[2.881]		[2.524]	[2.852]
DCC Estimates					
ω_M	0.000***		ω_B	0.000	
	[3.121]			[0.642]	
α_M	0.068***		α_B	0.197**	
	[3.962]			[2.311]	
β_M	0.803***		β_B	0.720**	
	[17.933]			[2.383]	
γ_M	0.999***		γ_B	-0.013	
	[8.134]			[-0.076]	
$Shape_M$	10.903***		$Shape_B$	8.196***	
	[2.501]			[3.381]	
α_{DCC}	0.034				
	[0.943]				
β_{DCC}	0.956***				
	[6.373]				
$Shape_{DCC}$	9.967***				
	[4.594]				
LogLikelihood	2755.18				

Panel B: Likelihood Ratio Test Results

	χ^2	p-value
LR Test [$\lambda_0 = 0$]	8.584**	(0.0137)
LR Test [$\lambda_H = 0$]	9.334***	(0.0094)
LR Test [$\lambda_H = 0$; $\lambda_0 = 0$]	14.823***	(0.0006)

varying nature of both measures. Thereby, the DCC measure of conditional covariance is much smoother and appears to be positive and rather high from 1965 but drifts to negative values after the mid of 2001. This implies that bonds were relatively risky with respect to stocks until the millennium and then hedging effects got apparent. Further, as flight-to-quality and fear-of-missing-out effects are associated with negative covariance, the shift in conditional covariance implies that such episodes merely occurred after the millennium. Focusing on realized moments, a different picture is drawn. Besides the downward shift in equity-bond correlation and covariance, respectively, negative instances of realized moments and associated episodes of flight-to-quality and fear-of-missing-out are not a recent phenomenon but were frequently observed during the last decades.

Table 6 reports monthly expected equity and bond returns implied by Model (2.8) over the sample period from January 1965 to December 2017. Panel A reports the numerical illustrations based on sample estimates of conditional variance and conditional covariance estimated by the DCC model. As shown in the first column, the full sample average of conditional covariance is 0.0161% which corresponds to an average conditional correlation of 17.99%. Along with the conditional equity market volatility of 0.2166%, equities yield a monthly expected return of 0.7258%, on average, and a corresponding annualized expected equity premium of 4.04%.[10] The latter represents a plausible and realistic model-implied estimate of the equity premium and is consistent with documented expectations of the equity premium (see for example De Long and Magin, 2009 for an overview on equity premium expectations).

[10] For the numerical illustration, we use the following market price of variance and covariance risk estimates, $\lambda_M = 1.78$, $\lambda_B = 6.09$, $\lambda_{H,M} = 21.12$ and $\lambda_{H,B} = 11.07$ (see Table 4). The sample average of the monthly return on the risk-free asset proxied by the one-month Treasury bill is 0.3893%.

Table 5
Pricing Equity-Bond Covariance Risk based on Realized Moments. Panel A reports estimated parameters of the equity and bond mean equation. The estimation of realized moments is based on daily asset returns ranging from January 1965 to December 2017 (13198 daily observations). Model estimation results are provided with intercept (I) and with the constraint on $\lambda_0 = 0$ (II). Panel B reports χ^2 statistics and p-values (in parentheses) of the likelihood ratio (LR) tests to compare model restrictions on λ_0 and λ_H. Robust t-statistics with HAC standard errors are reported in brackets, superscripts *, ** and *** denote statistical significance (at least) at the 10%, 5% and 1% level, respectively.

Panel A: Model Estimates

	Equity			Bond	
Mean Equation	(I)	(II)		(I)	(II)
$\lambda_{0,M}$	0.007***	0	$\lambda_{0,B}$	0.004**	0
	[3.548]	[-]		[2.450]	[-]
λ_M	1.151**	2.073***	λ_B	4.501*	4.144***
	[2.035]	[3.341]		[1.865]	[4.495]
$\lambda_{H,M}$	9.820***	12.380***	$\lambda_{H,B}$	2.592**	2.991**
	[2.610]	[3.262]		[1.992]	[1.990]

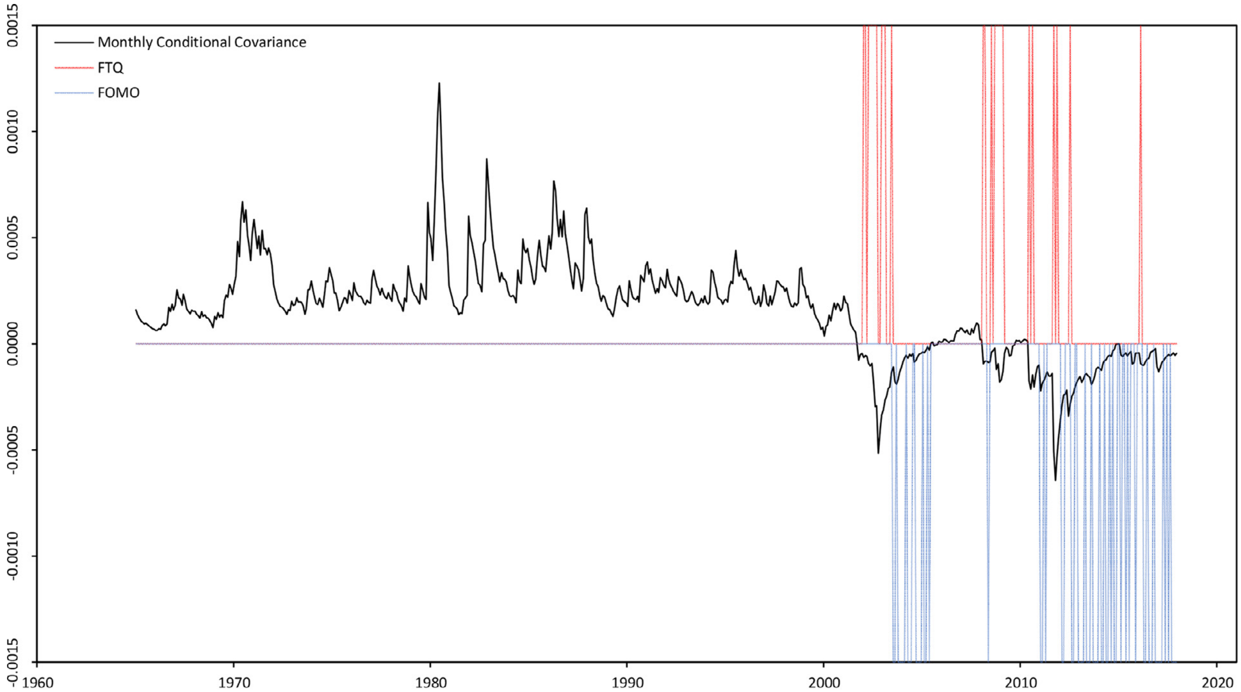
Panel B: Likelihood Ratio Test Results

	χ^2	p-value
LR Test [$\lambda_0 = 0$]	6.306**	(0.0120)
LR Test [$\lambda_H = 0$]	10.263***	(0.0059)
LR Test [$\lambda_H = 0$; $\lambda_0 = 0$]	20.028***	(0.0005)

Model-implied expected returns on the equity and the bond market across episodes of positive conditional covariance (PC) and negative conditional covariance (NC) as well as flight-to-quality (FTQ) and fear-of-missing-out (FOMO) episodes identified according to the predefined criteria are further summarized in Panel A of Table 6. Across the full sample, 478 monthly observations fall within episodes of positive conditional covariance and 158 monthly observations fall within episodes of negative conditional covariance. Negative episodes reach an average conditional covariance of -0.0124% which corresponds to an average monthly correlation of -13.74%. As the hedging effect dominates during periods of negative conditional covariance, model-implied expected returns on the bond and the equity market, in general, are lower than the expected asset returns during periods of positive conditional covariance. Across the full sample period, 27 months (4.3% of the sample) are identified as flight-to-quality episodes while fear-of-missing out episodes comprise 66 months (10.4% of the sample). As shown, flight-to-quality episodes coincide with abnormal low conditional equity-bond covariance that yield an average value of -0.0181% along with a high level of average conditional equity market volatility (0.4291%). During flight-to-quality episodes, the increasing hedging demand of risk-averse investors makes the government bond market more attractive resulting in price pressure mechanism that contemporaneously pushes up the bond prices and yields a compression of the expected bond market return. The latter effect is captured by Model (2.8) which implies a lower expected bond market return of 0.1331% relative to the high expected equity market return of 0.3815% under flight-to-quality. On the contrary, fear-of-missing-out is characterized by portfolio shifts from bonds towards equities and low average conditional equity-bond covariance of -0.0102%. The fear-of-missing-out pressure along with the higher demand of investors for risky assets results in skimpy risk premiums and a low expected equity market return of 0.0364% relative to a higher expected bond return of 0.0999%.

Baele et al. (2020) show that flight-to-quality episodes are predominantly short lived and merely last only a few days. Therefore, we further aim to identify flight-to-quality and fear-of-missing-out regimes relying on daily data. Fig. 2 graphs daily conditional covariance derived by DCC estimation along with the regimes of flight-to-quality and fear-of-missing-out. Descriptive statistics using daily conditional moments are reported in Panel B of Table 6. Across the full sample period, 7.2% of daily observations fall within flight-to-quality episodes while fear-of-missing-out days account for 10.7% of the sample. To illustrate model-implied expected returns across flight-to-quality and fear-of-missing-out episodes on a monthly basis, the sample average of daily conditional variance and covariance are also expressed in monthly terms. As such, we assume that the sample averages of flight-to-quality and fear-of-missing-out days hold on a monthly basis, i.e. we illustrate model-implied expected returns assuming that all days in a month are flight-to-quality or fear-of-missing-out days, respectively. Since the daily conditional covariance estimates yield much more dispersion over time, the model-implied expected returns differ from the estimates in Panel A. Our conclusions regarding flight-to-quality and fear-of-missing-out effects still hold. The results overall show that high equity market volatility during flight-to-quality days coincides with higher expected return on equities relative to low expected bond return. On the contrary, fear-of-missing-out leads to a compression of the expected equity return relative to the higher expected bond return.

In Panel C of Table 6, we identify flight-to-quality and fear-of-missing-out episodes using realized variance and covariance as proxies for conditional moments. Focusing on realized moments results in a higher number of flight-to-quality and fear-of-missing-out episodes. Across the sample, we observe 63 flight-to-quality months and 87 fear-of-missing-out months,



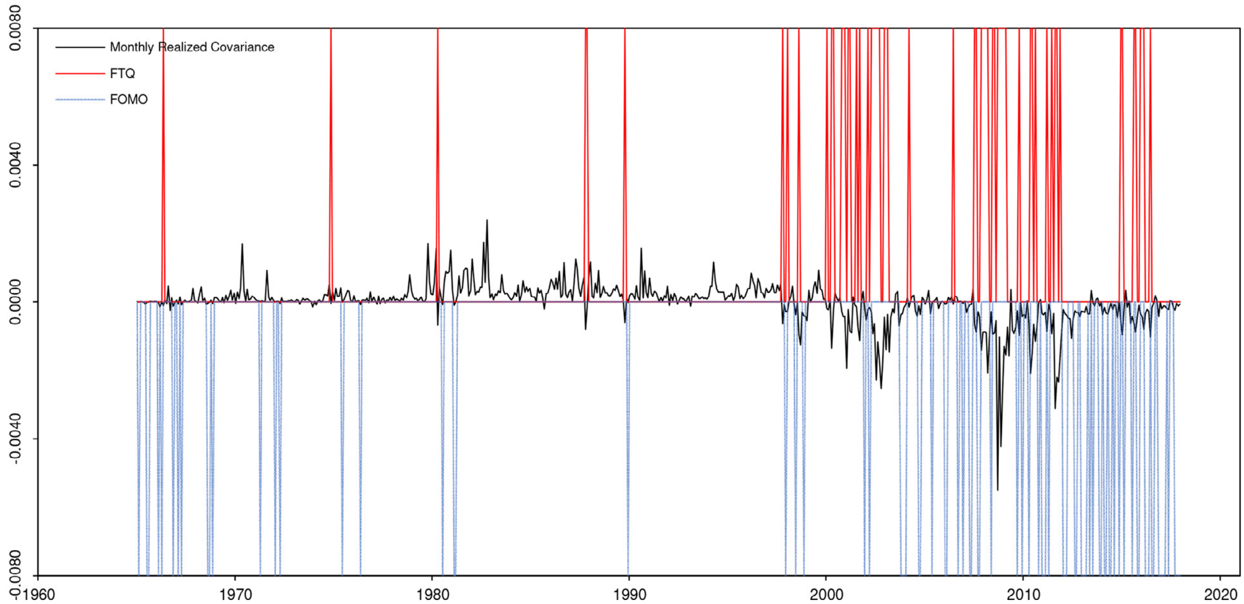


Fig. 1. Monthly Equity-Bond Covariance and Flight-to-Quality and Fear-of-Missing-Out Regimes. The upper graph plots monthly DCC conditional equity-bond covariance along with monthly flight-to-quality and fear-of-missing-out regimes identified using DCC estimates of moments. The lower graph plots monthly realized equity-bond covariance as measured by past month's daily equity and bond returns along with monthly flight-to-quality and fear-of-missing-out regimes identified by realized moments. The sample period ranges from January 1965 to December 2017 and covers 636 monthly observations and 13198 daily observations.

respectively. Regarding the model-implied expected returns across flight-to-quality and fear-of-missing-out episodes, our results remain qualitatively similar.[11] Still, flight-to-quality episodes yield high expected equity market returns of 0.2911%

[11] For the numerical illustrations regarding realized measures of moments, we rely on the market price of variance and covariance risk estimates derived in Table 5. In particular, $\lambda_M = 2.07$, $\lambda_B = 4.14$, $\lambda_{H,M} = 12.38$ and $\lambda_{H,B} = 2.99$.

Table 6
Model-Implied Expected Asset Returns under Flight-to-Quality and Fear-of-Missing-Out. Expected equity, $E_t(r_M)$, and government bond returns, $E_t(r_B)$, implied by Model (2.8) over episodes of positive covariance (PC), negative covariance (NC), flight-to-quality (FTQ) and fear-of-missing-out (FOMO). The subsample averages of equity market variance and equity-bond covariance are denoted by $\hat{\sigma}_M^2$ and $\hat{\sigma}_H$, respectively. In Panel A, monthly FTQ and FOMO episodes are identified by monthly DCC estimates of conditional variance and covariance, Panel B relies on daily conditional variance and covariance estimates to identify FTQ and FOMO regimes. Panel C relies on monthly realized moments to identify FTQ and FOMO regimes. The sample averages and the model-implied expected returns are expressed in monthly terms. The full sample period ranges from January 1965 to December 2017.

Panel A: Monthly DCC Estimates of Conditional Moments					
	Full Sample	PC	NC	FTQ	FOMO
Observations	636	478	158	27	66
$\hat{\sigma}_M^2$	0.2165%	0.2093%	0.2386%	0.4291%	0.1414%
$\hat{\sigma}_H$	0.0161%	0.0255%	-0.0124%	-0.0181%	-0.0102%
$E_t(r_M)$	0.7254%	0.9111%	0.1622%	0.3815%	0.0364%
$E_t(r_B)$	0.4176%	0.5527%	0.1124%	0.1331%	0.0999%
Panel B: Daily DCC Estimates of Conditional Moments					
	Full Sample	PC	NC	FTQ	FOMO
Observations	13198	8604	4549	948	1415
$\hat{\sigma}_M^2$	0.2244%	0.1624%	0.3366%	0.6323%	0.1232%
$\hat{\sigma}_H$	-0.0002%	0.0233%	-0.0442%	-0.0818%	-0.0173%
$E_t(r_M)$	0.3960%	0.7815%	-0.3348%	-0.6030%	-0.1468%
$E_t(r_B)$	0.2822%	0.5288%	-0.1814%	-0.8642%	0.0372%
Panel C: Monthly Realized Moments					
	Full Sample	PC	NC	FTQ	FOMO
Observations	636	398	238	63	87
$\hat{\sigma}_M^2$	0.2232%	0.1313%	0.3235%	0.7577%	0.0849%
$\hat{\sigma}_H$	-0.0016%	0.0267%	-0.0489%	-0.1033%	-0.0170%
$E_t(r_M)$	0.4422%	0.6017%	0.0643%	0.2911%	-0.0257%
$E_t(r_B)$	0.1800%	0.2572%	0.0506%	0.0052%	0.0850%

per month and low expected returns on the bond market. Fear-of-missing-out induces a low expected equity market return and implies a higher expected return on the bond market.

5.4. Covariance risk determinants

Thus far, our results show that equity-bond covariance risk is priced in the equity and the bond market and plays a significant role in explaining expected asset returns. Our subsequent objective is now to identify determinants that induce time-variation in conditional covariance and thus may also represent drivers of flight-to-quality and fear-of-missing-out effects.

5.4.1. VAR analysis

In general, economic variables that affect either stock or bond returns or the returns of both assets simultaneously may generate changes in stock-bond covariance. To identify the economic determinants, we first estimate a linear model and then use a threshold VAR to account for non-linearity as described in Section 4. Table 7 shows the results of bi-directional Granger causality tests for equity and bond returns and shocks to inflation, shocks to stock market illiquidity and shocks to bond market illiquidity as endogenous variables. We find that there is strong bi-directional causality between stock and bond returns indicating that equity market returns are able to predict bond returns, and vice versa. Stock market illiquidity proxied by the illiquidity measure of Amihud (2002) Granger causes bond market illiquidity. However, bond market illiquidity has no causality effect over stock market illiquidity. Inflation shocks significantly affect only future bond returns but seem to have no statistical significant impact on future equity returns. Overall, the observed results show that the considered variables are able to predict the direction of equity or bond returns which makes them to potential candidates to explain time-variations in equity-bond covariance.

5.4.2. Threshold VAR analysis

In the presence of non-linearities that are commonly revealed in financial time series, linear VAR findings become not reliable. Therefore, we allow the stock and bond market returns to response to shocks in the endogenous variables in a non-linear fashion. In particular, we examine whether the stock-bond return dynamics show significant differences across different states of expected inflation, π^E. For this, we first conduct likelihood ratio tests presented in Eq. B.2 to detect whether the level of expected inflation implies significant threshold effects. Panel A of Table 8 presents the results of the LR

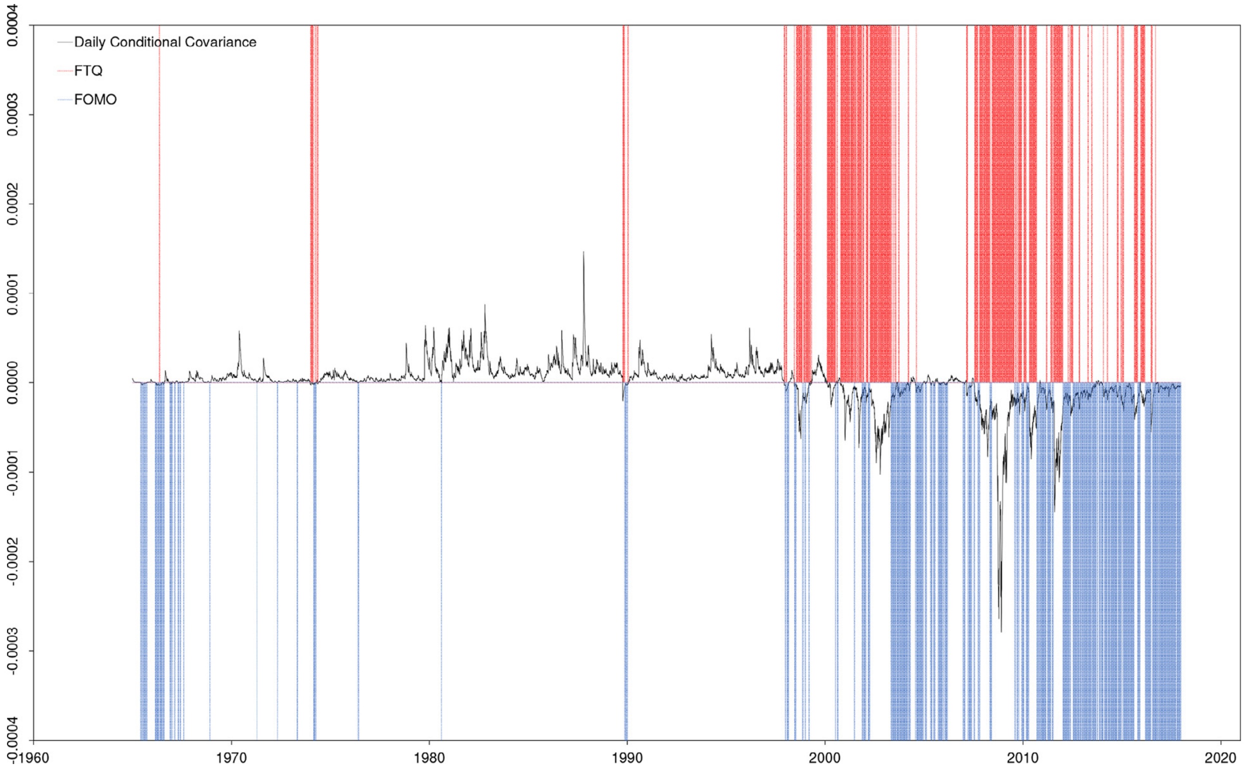


Fig. 2. Daily Equity-Bond Covariance and Flight-to-Quality and Fear-of-Missing-Out Regimes. The graph plots daily DCC conditional equity-bond covariance along with daily flight-to-quality and fear-of-missing-out regimes. The sample period ranges from January 1965 to December 2017 and covers 13198 daily observations.

Table 7
Granger Causality Tests. χ^2 statistics and p-values (in parentheses) of pairwise Granger causality tests including stock market returns, r_M, bond market returns, r_B, shocks to inflation, $(\Delta\pi)$, shocks to stock market illiquidity, (ΔIL_M), and shocks to bond market illiquidity, (ΔIL_B). Shocks to the endogenous variables are modeled by ARIMA models selected according to the BIC criterion. Bond market illiquidity is measured by the monthly quoted bid-ask spread, stock market illiquidity is proxied by the Amihud (2002) price impact measure. In each case, the null hypothesis of no Granger causality is tested. The sample period ranges from January 1965 to December 2017 resulting in 636 monthly observations. Superscripts *, ** and *** denote statistical significance (at least) at the 10%, 5% and 1% level, respectively.

	r_M	r_B	$\Delta\pi$	ΔIL_M	ΔIL_B
$r_{M,t-1}$	-	8.597***	8.241***	22.830***	3.045*
	-	(0.0035)	(0.0042)	(0.0000)	(0.0814)
$r_{B,t-1}$	6.452**	-	10.350***	1.587	20.119***
	(0.0112)	.	(0.0013)	(0.2082)	(0.0000)
$\Delta\pi_{t-1}$	0.941	11.381***	-	0.025	3.853*
	(0.3324)	(0.0008)	-	(0.8742)	(0.0501)
$\Delta IL_{M,t-1}$	116.370***	0.153	2.752*	-	6.609**
	(0.0000)	(0.6962)	(0.0976)	-	(0.0103)
$\Delta IL_{B,t-1}$	5.456**	0.814*	1.549	2.405	-
	(0.0189)	(0.0553)	(0.2137)	(0.1215)	-

tests comparing the linear VAR model to the one and two threshold model. The reported p-values are obtained by a residual bootstrap as proposed by Hansen (1999a) that is used to simulate the asymptotic distribution of the likelihood ratio test. The LR test results show that the level of expected inflation implies significant threshold effects in the data that can be captured by a TVAR model with preferably two thresholds. As described in detail in Appendix B, the threshold values are chosen according to a grid search. The lower plot in Fig. 3 illustrates all ordered (possible) threshold values that are considered within the grid search. During the threshold estimation, it is ensured that a minimum number of total sample observations (15%) lie in each threshold regime to ensure statistical inference. According to the grid search, the TVAR model minimizes

Table 8

TVAR(3) Estimation Results: Expected Inflation. Estimation results of a TVAR model with $m = 3$ threshold regimes triggered by the level of expected inflation, π^E. Endogenous variables in the TVAR include the monthly return on equities, r_M, the long-term government bond return, r_B, shocks to inflation $\Delta\pi$, shocks to stock market illiquidity, ΔIL_M, and shocks to bond market illiquidity, ΔIL_B. Panel A presents the results of the multivariate linearity test of Lo and Zivot (2001), corresponding p-values (in parentheses) are calculated by the bootstrap method of Hansen (1999a). The reported threshold values τ_1 and τ_2 are estimated by minimizing the SSE as described in Appendix B. Estimation results of the threshold VAR system are presented in Panel B. The sample period ranges from January 1965 to December 2017 resulting in 636 monthly observations. Superscripts *, ** and *** denote statistical significance (at least) at the 10%, 5% and 1% level, respectively, standard errors in brackets.

Panel A: Threshold Estimation

	Linear vs. 1 Threshold	Linear vs. 2 Thresholds
LR Test	81.58***	215.15***
	(0.0000)	(0.0000)

Estimated Thresholds: $\tau_1 = 0.0014$ $\tau_2 = 0.0042$

Panel B: Threshold VAR Estimation

	Low Expected Inflation ($\pi^E \le \tau_1$)					Medium Expected Inflation ($\tau_1 < \pi^E \le \tau_2$)					High Expected Inflation ($\pi^E > \tau_2$)				
	r_M	r_B	$\Delta\pi$	ΔIL_M	ΔIL_B	r_M	r_B	$\Delta\pi$	ΔIL_M	ΔIL_B	r_M	r_B	$\Delta\pi$	ΔIL_M	ΔIL_B
$r_{M,t-1}$	-0.0065	-0.1327***	0.0094*	0.0004	-0.0004*	-0.0074	-0.0273	0.0072**	0.0000	-0.0001	-0.1360	-0.1033***	0.0081*	0.0004	-0.0001
	[0.0944]	[0.0426]	[0.0056]	[0.0003]	[0.0002]	[0.0503]	[0.0227]	[0.0030]	[0.0002]	[0.0001]	[0.0772]	[0.0348]	[0.0045]	[0.0002]	[0.0001]
$r_{B,t-1}$	-0.0962	0.1647	-0.0151	-0.0012	0.0015***	0.1069	0.3130***	-0.0237***	0.0004	0.0006***	0.5509***	0.3467	-0.0168*	-0.0002	0.0009***
	[0.2644]	[0.1193]	[0.0155]	[0.0008]	[0.0005]	[0.1199]	[0.0541]	[0.0070]	[0.0004]	[0.0002]	[0.1536]	[0.0693]	[0.0090]	[0.0005]	[0.0003]
$\Delta\pi_{t-1}$	0.1142	-3.2125***	-0.0820	0.0027	-0.0037	-0.0828	-0.3429	-0.0225	0.0016	-0.0036	-2.6795*	-1.5268**	0.0905	0.0045	0.0004
	[1.6142]	[0.7282]	[0.0949]	[0.0052]	[0.0031]	[0.9330]	[0.4209]	[0.0549]	[0.0030]	[0.0028]	[1.3766]	[0.6210]	[0.0809]	[0.0044]	[0.0027]
$\Delta IL_{M,t-1}$	-162.03***	32.296**	-1.4591	-0.0540	0.0638	-132.87***	2.2049	-1.1498	-0.0947*	-0.0065	-91.832***	-32.903**	2.5054	0.0939	-0.0321
	[28.313]	[12.772]	[1.6647]	[0.0904]	[0.0550]	[16.157]	[7.2888]	[0.9499]	[0.0515]	[0.0314]	[30.362]	[13.697]	[1.7852]	[0.0970]	[0.0589]
$\Delta IL_{B,t-1}$	-80.607	-61.953***	3.7925	0.4286**	-0.0843	67.251***	-0.5923	2.2447	-0.1161	-0.0004	-93.558	27.841	-3.6308	1.2422***	-0.6407***
	[64.826]	[29.245]	[3.8115]	[0.2070]	[0.1258]	[24.465]	[11.036]	[1.4384]	[0.0781]	[0.0475]	[71.639]	[32.318]	[4.2120]	[0.2288]	[0.1390]
c	0.0114***	0.0047***	0.0004*	0.0000	0.0000**	0.0092***	0.0050***	0.0000	0.0000	0.0000	0.0033	0.0064	-0.0001	0.0000	0.0000
	[0.0044]	[0.0003]	[0.0003]	[0.0000]	[0.0000]	[0.0022]	[0.0050]	[0.0001]	[0.0000]	[0.0000]	[0.0036]	[0.0016]	[0.0002]	[0.0000]	[0.0000]

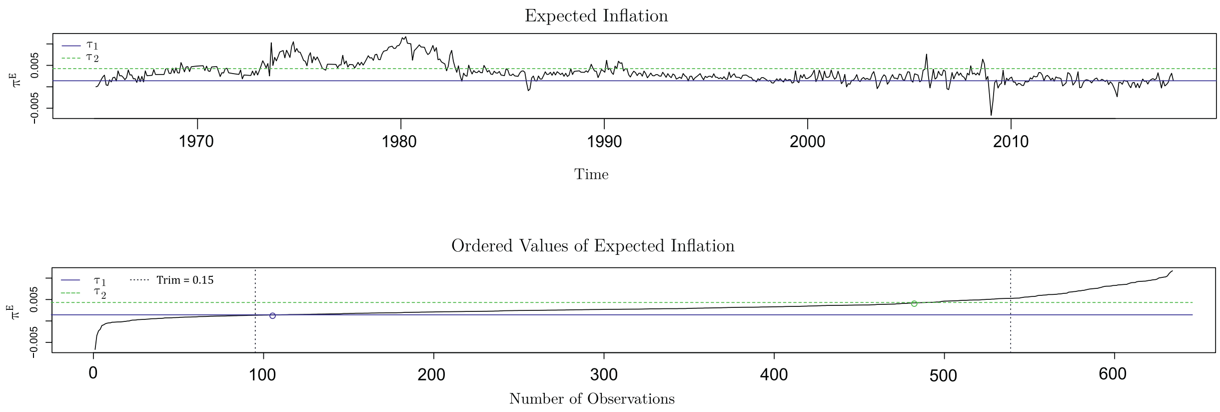


Fig. 3. Threshold Estimation: Expected Inflation. The upper graph plots monthly expected inflation, π^E, from January 1965 to December 2017. A grid search is used to estimate the lower threshold, $\tau_1 = 0.001408158$ (solid line), and the upper threshold, $\tau_1 = 0.004231543$ (dotted line), by minimizing the SSE as described in Appendix B. The lower graph illustrates the ordered values of expected inflation that are considered within the grid search. The vertical trim lines illustrate that at least 15% of sample observations lie in the low and the high threshold regime.

the SSE at threshold $\tau_1 = 0.0014$ and threshold $\tau_2 = 0.0042$ which correspond to an annualized expected inflation of 1.68% and 5.07%, respectively. The lower threshold is thus just below the 2 percent inflation objective adopted by the Federal Open Market Committee (FOMC).[12]

In the upper graph of Fig. 3, the level of expected inflation over the entire sample period is illustrated. τ_1 is represented by the solid line and the dotted line graphs the second threshold τ_2. The two thresholds divide the sample into a low (16.7% of observations), medium (59.5%) and high regime (23.8%) of expected inflation. As the graph shows, the high threshold regime covers, for example, the period of 'Great Inflation' in the 1960s and 1970s associated with abnormal high levels of expected inflation reaching a peak of 14.04% (p.a.). The graph further shows that abnormal low inflation expectations predominantly occurred in the years following the global financial crisis in 2008.

Table 8 shows the results of the TVAR model where the transitions among the different regimes of expected inflation are determined by the estimated threshold values. As one would intuitively expect, a negative response of bond market returns to shocks in inflation can be documented in each of the three threshold regimes. This indicates that positive shocks to inflation generally represent bad news for the nominal bond market and depress future returns. In contrast, our results show that the response of stock market returns is state-dependent and varies across regimes of expected inflation. In particular, we observe a negative response of stock market returns to inflation shocks when inflation expectations are high. The equity market takes positive shocks to inflation as an indication of deteriorated future business conditions leading to a higher probability of observing decreasing future equity prices and returns. In a low state of expected inflation, positive shocks to inflation predict a positive (albeit not significant) increase of equity market returns. An economic explanation is that during times of low expected inflation, equity investors take an unanticipated increase in expected inflation as a signal for future economic recovery. Thus, a positive shock to inflation represents good news for the stock market resulting in rising future equity prices. The differential response of stock and bond market returns to inflation shocks may be one explanation for observing a negative covariance in periods of low expected inflation.

Next, notice the interaction of stock market and bond market illiquidity. During low and high episodes of expected inflation, we find a strong illiquidity spillover from the bond to the stock market. In particular, a shock to bond market illiquidity leads to a significant increase in future stock market illiquidity. This cross-market illiquidity spillover may be caused by monetary policy shocks that have an immediate impact on bond illiquidity, which transmits these shocks into stock market illiquidity (see e.g. Goyenko and Ukhov, 2009). As a spillover effect cannot be observed during periods of medium expected inflation, our results indicate that bond illiquidity may indeed act as a channel to transmit monetary policy shocks to the stock market, but only in periods of abnormal low and high levels of expected inflation.

We further aim to examine whether the response to shocks to endogenous variables show significant differences across different states of stock market uncertainty. Therefore, we estimate a TVAR model with $m = 3$ threshold regimes and Garman-Klass realized stock market volatility, rv_{GK}, that triggers changes between the uncertainty regimes. The upper graph in Fig. 4 shows realized volatility over the sample period and the thresholds estimated via grid search, $\tau_1 = 0.0003$ and $\tau_2 = 0.0009$, which are illustrated by the solid line and the dotted line, respectively. The lower graph shows all possible threshold values that are considered within the grid search. The regime of low stock market uncertainty covers 33% of observations and the regime of high stock market uncertainty includes 20.2% of the sample observations.

[12] Following its January meeting in 2012, the Federal Reserve issued an FOMC statement about a 2 percent inflation target which was reaffirmed in 2016 and 2019. The FOMC publicly states that a lower inflation rate than 2 percent would be associated with 'an elevated probability of falling into deflation' while a higher rate 'would reduce the public's ability to make accurate longer-term economic and financial decisions'.

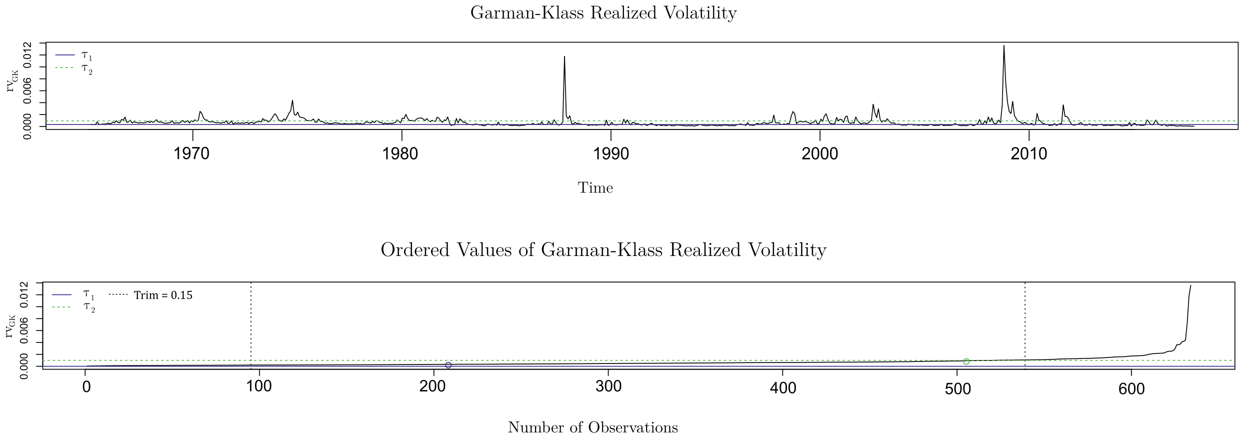


Fig. 4. Threshold Estimation: Realized Volatility. The upper figure plots monthly Garman-Klass realized volatility, rv_{GK}, from January 1965 to December 2017. The estimated lower threshold, $\tau_1 = 0.0003337665$, and the upper threshold, $\tau_2 = 0.0009469036$, are illustrated by the solid and the dotted line, respectively. The lower graph illustrates the ordered values of realized volatility that are considered within the grid search. The vertical trim lines illustrate that the low and the high threshold regime cover at least 15% of total sample observations.

The estimation results of the TVAR(3) model are presented in Table 9. In general, bond returns are positively correlated with future stock market returns. This is intuitive as equities and bonds both represent high duration assets (see e.g. Baele et al., 2010). However, this relation is only significantly present during periods of low stock market uncertainty. During periods of high uncertainty, our results show that a decline in equity market returns is associated with rising bond returns and a decline of equity-bond covariance. Stock and bond returns predominately differ in their response to bond market illiquidity shocks during periods of high stock market uncertainty. A positive shock to bond market illiquidity thereby drives stock and bond returns in opposite directions while equity and bond market returns show a similiar response to shocks to aggregate stock market illiquidity. These findings further contribute to those of Goyenko and Ukhov (2009) who investigate the linkage between stock and bond market illiquidity in a linear VAR setting that does not account for non-linear cross-market behavior.

6. Conclusion

In this article, we suggest that the pricing of stock-bond covariance risk can be seen as an important key in explaining the time-variation in expected equity and government bond returns. Risk-averse investors are willing to pay a premium for holding an asset that forms a hedge against changes in future investment opportunities. During episodes of low stock-bond covariance, the hedging benefit of the bond portfolio balances the low expected bond returns that are typically associated with flight-to-quality effects. On the contrary, allocations to risky assets under fear-of-missing-out result in low expected equity returns relative to expected bond returns. As our findings show that time-variation in the equity-bond covariance matters for expected returns of both asset classes, it is of particular interest to identify its determinants. We suggest that shocks to anticipated inflation are main drivers of future stock and bond prices. While bond returns generally show a negative response to inflation shocks, equity prices may either decrease or increase depending on the level of expected inflation. We ascribe this ambiguous effect to a non-linear role that shocks to inflation have in predicting future business conditions. Our results further suggest that equity-bond covariance is affected by systematic market illiquidity which leads to a variation in covariance across different states of uncertainty. The documented asymmetric impact of shocks and the associated joint dynamics may also be related to market participants' investment behavior as recently suggested by Li et al. (2016), Dieci et al. (2018) and Schmitt and Westerhoff (2019), for example.

As equities and bonds are major asset classes, our study has important implications regarding investors' asset allocation decisions. Equity-bond covariance risk as a proxy for changes in the investment opportunity set does not only matter for equity investors but also plays a crucial role for bond-only investors. Our findings show that the state of the economy is essential for investors to predict how unexpected inflation or unexpected changes in market liquidity will affect expected equity and bond market returns. Incorporating these findings in investment decisions may provide benefits especially under tense market conditions as characterized by low expected inflation and high uncertainty.

Appendix A. Modeling conditional variance and conditional covariance

To empirically characterize the conditional mean and conditional variance process the following system is modeled:

$$\begin{aligned} r_{M,t+1} &= \lambda_0 + \lambda_M \hat{\sigma}^2_{M,t+1} + \lambda_{H,M}\hat{\sigma}_{H,t+1} + \hat{\epsilon}_{M,t+1}; \\ r_{B,t+1} &= \lambda_0 + \lambda_B \hat{\sigma}^2_{B,t+1} + \lambda_{H,B}\hat{\sigma}_{H,t+1} + \hat{\epsilon}_{B,t+1}, \end{aligned} \tag{A.1}$$

Table 9

TVAR(3) Estimation Results: Stock Market Uncertainty. Estimation results of a TVAR model with $m = 3$ threshold regimes triggered by the level of stock market uncertainty, rv_{GK}. Endogenous variables in the TVAR include the monthly return on equities, $r_{M,}$ and the long-term government bond return, r_B, shocks to inflation $\Delta\pi$, shocks to stock market illiquidity, $\Delta IL_M$and shocks to bond market illiquidity, ΔIL_B. Panel A presents the results of the multivariate linearity test of Lo and Zivot (2001), corresponding p-values (in parentheses) are calculated by the bootstrap method of Hansen (1999a). The reported threshold values τ_1 and τ_2 are estimated by minimizing the SSE as described in Appendix B. Estimation results of the threshold VAR system are presented in Panel B. The sample period ranges from January 1965 to December 2017 resulting in 636 monthly observations. Superscripts *, ** and *** denote statistical significance (at least) at the 10%, 5% and 1% level, respectively, standard errors in brackets.

Panel A: Threshold Estimation

	Linear vs. 1 Threshold	Linear vs. 2 Thresholds
LR Test	94.69***	143.92***
	(0.0000)	(0.0000)

Estimated Thresholds: $\tau_1 = 0.0003$ $\tau_2 = 0.0009$

Panel B: Threshold VAR Estimation

	Low Stock Market Uncertainty ($rv_{GK} \leq \tau_1$)					Medium Stock Market Uncertainty ($\tau_1 < rv_{GK} \leq \tau_2$)					High Stock Market Uncertainty ($rv_{GK} > \tau_2$)				
	r_M	r_B	$\Delta\pi$	ΔIL_M	ΔIL_B	r_M	r_B	$\Delta\pi$	ΔIL_M	ΔIL_B	r_M	r_B	$\Delta\pi$	ΔIL_M	ΔIL_B
$r_{M,t-1}$	-0.1450	-0.0142***	-0.0001	0.0004	0.0000	-0.1163*	-0.0384	0.0057	0.0004*	-0.0001	0.0624	-0.1049***	0.0073**	0.0002	-0.0002**
	[0.1051]	[0.0477]	[0.0061]	[0.0003]	[0.0002]	[0.0632]	[0.0477]	[0.0061]	[0.0002]	[0.0001]	[0.0554]	[0.0251]	[0.0032]	[0.0002]	[0.0001]
$r_{B,t-1}$	0.4686*	0.4741***	-0.0174	0.0000	0.0009**	0.1024	0.2857***	-0.0150*	-0.0004	0.0008***	-0.0438	0.2779***	-0.0252***	0.0008*	0.0005*
	[0.1860]	[0.0844]	[0.0108]	[0.0006]	[0.0004]	[0.1521]	[0.0690]	[0.0088]	[0.0005]	[0.0003]	[0.1319]	[0.0599]	[0.0077]	[0.0004]	[0.0003]
$\Delta\pi_{t-1}$	-0.7874	-1.3172***	0.0169	0.0009	-0.0010	-0.1849	-0.3850	-0.1223**	-0.0060*	-0.0011	-0.7743	-2.0527***	0.1676**	0.0101**	-0.0034
	[1.3505]	[0.6128]	[0.0783]	[0.0044]	[0.0027]	[1.0511]	[0.4770]	[0.0610]	[0.0035]	[0.0021]	[1.1982]	[0.5437]	[0.0695]	[0.0039]	[0.0024]
$\Delta IL_{M,t-1}$	-61.414	25.297	-1.2873	-0.2027	0.0122	-171.91***	15.397	0.9292	-0.0375	-0.0200	-85.133***	-37.183**	-3.3253*	0.1106	-0.0447*
	[37.490]	[17.012]	[2.1749]	[0.1232]	[0.0745]	[16.376]	[7.4311]	[0.9500]	[0.0538]	[0.0583]	[22.653]	[10.280]	[1.3142]	[0.0744]	[0.0250]
$\Delta IL_{B,t-1}$	-26.600	-25.053	2.4253	-0.0381	0.0017	58.784**	-6.2839	-0.7050	0.2214**	-0.1851***	65.153	-45.646**	6.7558***	- 0.0736	0.1495
	[47.200]	[21.418]	[2.7832]	[0.1551]	[0.0938]	[28.927]	[13.126]	[1.6782]	[0.0950]	[0.0575]	[32.815]	[19.428]	[2.4348]	[0.1407]	[0.0851]
c	0.0123***	0.0043***	0.0001	0.0000	0.0000	0.0090***	0.0036***	0.0003*	0.0000	0.0000	0.0061	0.0032*	-0.0002	0.0000	0.0000
	[0.0034]	[0.0016]	[0.0002]	[0.0000]	[0.0000]	[0.0025]	[0.0011]	[0.0001]	[0.0000]	[0.0000]	[0.0039]	[0.0017]	[0.0002]	[0.0000]	[0.0000]

with

$$\hat{\sigma}^2_{M,t+1} = \omega_M + \alpha_M \hat{\epsilon}^2_{M,t} + \gamma_M I_t \hat{\epsilon}^2_{M,t} + \beta_M \hat{\sigma}^2_{M,t};$$
$$\hat{\sigma}^2_{B,t+1} = \omega_B + \alpha_B \hat{\epsilon}^2_{B,t} + \gamma_B I_t \hat{\epsilon}^2_{B,t} + \beta_B \hat{\sigma}^2_{B,t}. \tag{A.2}$$

The conditional variance equation represents the GARCH model of Glosten et al. (1993) that allows an asymmetric modeling of positive and negative shocks on conditional variance by the indicator function I that takes on value of 1 for $\epsilon \le 0$ and 0 otherwise. The so-called leverage term captures the asymmetric response and is represented by γ.

The DCC model of Engle (2002) decomposes conditional covariance such that

$$H_t = D_t R_t D_t. \tag{A.3}$$

D_t is a diagonal matrix of time-varying standard deviations from univariate GARCH models and R_t is the matrix of time-varying conditional correlations. The evolution of the correlation structure is given by

$$Q_t = (1 - \alpha_{dcc} - \beta_{dcc})\bar{Q} + \alpha_{dcc}\epsilon_{t-1}\epsilon'_{t-1} + \beta_{dcc}Q_{t-1}, \tag{A.4}$$

$$R_t = diag\{Q_t\}^{-1/2} Q_t \, diag\{Q_t\}^{-1/2}, \tag{A.5}$$

where $\bar{Q}$ is the unconditional covariance of the standardized residuals. The model assumes that conditional correlations are driven by lagged standardized residuals and an additional autoregressive term. The system is estimated by maximizing the log-likelihood function assuming that the residuals follow a Student t distribution.

Appendix B. Modeling threshold effects

In estimating the TVAR model, we assume that the threshold variable z_t is *a priori* known. If the value of the threshold τ is known with certainty, estimation of the slope coefficients can be done straightforward by using ordinary least squares (OLS) estimation. In practice, the value of the threshold is unobservable and must be estimated. The minimization of the concentrated sum of squared errors (SSE) yields the least squares estimators of the first threshold (see e.g. Hansen, 1999b):

$$\hat{\tau}_1 = \underset{\{\tau\}}{\operatorname{argmin}}\, SSE(\tau). \tag{B.1}$$

Eq. B.1 shows that computation of the least squares estimate of the threshold value involves a minimization problem. This problem can be solved through a grid search (see e.g. Balke and Fomby, 1997): The values of the threshold variable z_t are sorted with a certain percentage of smallest and largest values that are excluded to ensure a minimal percentage of observations in each regime. The remaining values contain all possible values of the threshold τ that can be used to estimate $\hat{\tau}$. For each of the possible values of τ, the SSE is estimated and the one that minimizes the SSE is chosen as the best unique threshold $\hat{\tau}$. The estimation procedure for two thresholds can be conducted in a similar way by searching for combinations of the first threshold τ_1 and the second threshold τ_2 that together minimize the SSE(τ_1, τ_2). To reduce computational effort, the second threshold can be estimated conditional on the first threshold, i.e. holding the first threshold $\hat{\tau}_1$ fixed.

In order to test for non-linear threshold effects, we use the sup-LR statistics proposed by Lo and Zivot (2001) that compares the covariance matrix of the linear model and the threshold model:

$$LR_{1m} = T(\ln(|\hat{\Sigma}_1|) - \ln(|\hat{\Sigma}_m|)). \tag{B.2}$$

Here, $\hat{\Sigma}_1$ and $\hat{\Sigma}_m$ denote the estimated residual covariance matrix of the linear VAR and the TVAR(m) with m threshold regimes, respectively, and sample size T. In our empirical application, we use the bootstrapping method of Hansen (1999b) to compute p-values of the linearity test statistics.

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