



Institut ekonomických studií Fakulta sociálních věd Univerzita Karlova v Praze

> Opletalova 26 110 00 Praha 1

E-mail : ies@fsv.cuni.cz http://ies.fsv.cuni.cz

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# Time-Varying Pricing of Risk in Sovereign Bond Futures Returns\* Barbora Malinska<sup>a</sup>

<sup>a</sup>Institute of Economic Studies, Faculty of Social Sciences, Charles University in Prague, Smetanovo nabrezi 6, 111 01 Prague 1, Czech Republic Email (corresponding author): <u>malinska.barbora@gmail.com</u>

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# Abstract:

We examine time-varying explanatory power of realized moments on subsequent bond futures excess returns using more than 12 years of high-frequency data from U.S. and German sovereign bond markets. We detect realized volatility and realized kurtosis to carry valuable information for next-day open-close excess returns on the U.S. market which is not priced in traditional bond return predictors such as term or default spreads. Most importantly, we reveal the bond excess return predictability to be significantly dynamic and to increase during crisis period. Whereas the realized volatlity reveals to have negative effect on next-day excess returns, effect of realized kurtosis is switching from positive effect in the time of 2007-2009 financial crisis to negative values after 2014.

# JEL: C32, C55, G12

**Keywords:** Realized moments, bond pricing, risk-return trade-off, high-frequency data, time-varying coeffcients

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\*An online appendix with data and code is available at meta-analysis.cz/forward.

# 1 Introduction

The risk-return relationship challenging the traditionally widely accepted principle of no predictability of returns has been studied much more intensively on equity markets as compared to sovereign bond markets. Despite large number of empirical studies, there is no clear consensus on the existence or nature of the inter-temporal risk-return relationship as the results were often ambiguous or even contradictory.

Starting from a very general asset pricing principle, as comprehensively summarized by Cochrane (2009), price of an asset must be equal to the present value of future cash flows arising out of holding the asset. An investor always compares future payoffs related to an asset discounted to present value in order to reflect her impatience in consumption and aversion to risk. This consumption-based model has been serving as a starting point to most factor asset pricing models since they are in essence trying to tie the discount factor to various variables trying to capture the risk of future cash flows.

However, existing empirical literature on risk-return trade-off appears to lead to ambiguous and often even contradictory results. Primary motivation of this paper is to address potential sources of these inconsistencies and to provide with comprehensive analysis of risk-return tradeoff on sovereign markets. First, we address measuring the risk and we aim to add to the very scarce literature on the predictability of government bonds returns going beyond the standard mean-variance dimension. With respect to the different nature and risk profile of bond investments as compared to equities, different sensitivities towards risk of bondholders and significant proportion of bonds in investors' portfolios, the proper study of the predictability of returns using realized moments minimizing exante estimation errors is highly relevant. Second, we believe that assumption of constant relationship between risk factors and returns does not reflect the real situation on the market. Thus, conclusions on the presence and nature of the predictive power of risk factors are extremely sensitive on choice of the time period covered in the analysis as well as the actual length of the period. Therefore, we assess the return predictability using time-varying coefficient analysis on 12 years of daily data in order to address the potentially dynamic nature of the relationship. Further, we examine the risk-return relationship over the entire term structure of all available tenors on U.S. and German sovereign bond futures market. Since the short-end and long-end tenors represent largely different investment propositions, we expect also the nature and dynamics of the risk-return relationship to differ.

Classic literature related to predictability of bond returns challenging the expectation hypothesis include significant portion of literature claiming that term spreads carry significant predictive power for bond returns. These influential works such as Fama (1976), Fama (1984), Fama and French (1989) or Campbell and Shiller (1991) are built upon the hypothesis that the term spread reflects the term risk premium compensating investors for their exposure to interest rate (or discount rate) and duration risks. In addition to the term spread, Fama and French (1989) find bond market default spread to contribute to stock and bond returns predictions. Further, Fama and Bliss (1987) found certain predictive power of spread of forward rates and one-year yields for bond excess returns. In the past decade, number of studies surged as a reaction on the work by Cochrane and Piazzesi (2005) who show the predictability of U.S. bond returns using a tent-shaped linear combination of forward rates on monthly data. Since

their work became to a large extent a benchmark study in this field, multiple authors enhanced the Cochrane-Piazzesi approach by adding additional factors improving the predictive power such as Wright and Zhou (2009) who augmented the original model by multiple volatility measures (e.g. realized volatility, implied volatility, jumps-related measures) and concluded that jump-related measures improved the excess bond return predictability significantly. More recent works challenging the study by Cochrane and Piazzesi (2005) include the work by Adrian et al. (2013) who introduce a three-step ordinary least squares estimator to the pricing of interest rates and claim to outperform the benchmark by Cochrane and Piazzesi (2005).

As already mentioned the empirical literature of the risk-return trade-off is significantly dominated by the studies of equity markets often leading to ambiguous results. The fact that the literature has not reached a consensus regarding the existence and nature of the risk-return relationship on equity markets might be also caused by the concept of risk taken into account in the respective analyses. Bali and Peng (2006) argued that since conditional volatility of returns is unobservable, different approaches to its estimation might be responsible for differences in the empirical evidence. Therefore, incorporation of realized measures appears as a natural next step to mitigate at least one potential source of inconsistencies of the empirical literature.

Since Andersen and Bollerslev (1998) or Andersen et al. (2003) made volatility observable by introduction of realized volatility concept, authors such as Bali and Peng (2006) confronted the intertemporal risk-return analysis using both latent- and observable-volatility approaches and inspected risk-return tradeoff using high-frequency S&P 500 cash index data. Further, a comprehensive analysis of high-frequency causality between equity returns and volatility was carried out by Dufour et al. (2012). With respect to clear lack of consensus in empirical evidence of existence and nature of the link between return and risk, i.e. whether there is a causal link from return to volatility (also called leverage effect in literature), from volatility to return (also called volatility feedback phenomenon) or whether the link is instantaneous, Dufour et al. (2012) started his study with a complex inspection of Granger-causality of risk and return measures with varying conclusions according to different volatility measures used.

Further, Mueller and Whelan (2017) performed an empirical analysis of relationship between volatility risk and expected returns both in case of equities and U.S. bond market with a conclusion that neither implied nor realized variance did not exhibit a predictive ability for returns, but their spread (variance risk premia) did.

There were also works exploring the role of various volatility components or volatility-related state variables in explaining future excess returns. Among others, Adrian and Rosenberg (2008) documented that excess stock returns are not only governed by covariation of the assets returns with the market returns but there is also a contribution of state variables related to volatility. Adding to the academic debates a practitioners' angle, Amromin and Sharpe (2012) conducted a survey among stock investors and showed that the risk-return link was perceived differently under different macroeconomic conditions. For example, in case of macroeconomic expansion investors tend to expect high returns and low volatility (i.e. that risk and return are inversely correlated), which is in contradiction to standard theory that high volatility is remunerated by higher expected returns.

In addition to traditional risk-return trade-off, there has been a surge of literature exploring

relationship between equity returns and higher moments of return distributions (namely skewness and kurtosis). Early work connecting skewness and stock returns was the theory of Kraus and Litzenberger (1976) who claimed coskewness to determine cross-section of stock returns. Recently, there were multiple empirical works focusing on relationship between skewness and expected returns predominantly on equity markets elaborating on later theoretical concepts claiming negative relationship between skewness and expected returns.

One of these is the work by Mitton and Vorkink (2007) who take into account also behavioural biases of investors, meaning that investors' preferences are heterogeneous. The authors argue that in addition to "traditional" investors there are also "lottery-type" investors preferring assets with positively skewed return distributions, and therefore, returns to these lottery-type stocks deteriorate due to overpricing. According to Mitton and Vorkink (2007), the overpricing is not arbitraged due to short-selling restrictions.

Similarly, theory by Barberis and Huang (2008) arrives to similar conclusions though by different reasoning. The authors revisit the cumulative prospect theory by Kahneman and Tversky (1979) which states that investors' utility functions are concave over gains and convex over losses. Barberis and Huang (2008) amend the theory in terms of its probability weighting component reflecting the tendency of investors to overshoot the probability of extreme outcomes. This again leads to willingness of investors to overpay for the positively skewed assets, in other words, that a stock's skewness is priced and affects excess returns. Other theoretical pieces of work supporting risk-averse investor's preference for positively skewed assets include Scott and Horvath (1980), Kimball et al. (1990) or Ebert and Wiesen (2011). Theoretical works assessing relation of higher moment (i.e. kurtosis) and investors' preferences are even more scarce, most referenced works include Kimball et al. (1990), Dittmar (2002) or Haas (2007) suggesting investor aversion to kurtosis.

In contrast to theoretical consensus of negative effect of skewness on (equity) returns, empirical evidence is rather ambiguous. Negative effect of skewness on future equity returns was documented by Kumar (2009) who confirms the lottery-type stocks to underperform or by Bali et al. (2011). Bali et al. (2011) find significant negative effect of occurence of extreme (lotterytype) returns on future returns and by that succeed to explain puzzling negative return-volatility effect found by Ang et al. (2006) or Ang et al. (2009). Further, negative correlation between expected idiosyncratic skewness and stock returns was demonstrated by Boyer et al. (2009), and effect of ex ante moments on expected stock returns was inspected by Conrad et al. (2013). Further, significant effect of skewness (or gambling preference) on equity option returns was found by Bali and Murray (2013), Boyer and Vorkink (2014) or Byun and Kim (2016). Informational content of realized moments for future stock return were examined by Amaya et al. (2015) who found significant power of realized skewness to predict cross-section of equity returns. From the relevant recent studies, Jondeau et al. (2019) found that monthly average return skewness across firms performs well in future market return predictions. As far as other than equity market is concerned, Fernandez-Perez et al. (2018) detected skewness to be valuable predictor of commodity futures returns. In contrast, some studies find also positive relationship between skewness and stock returns (e.g. Rehman and Vilkov (2012)). Recently, Shen et al. (2018) revisits the explanatory power of higher moments on stock returns on daily frequency concluding that skewness lacks any explanatory power for future returns. As compared to skewness, kurtosis has attracted less attention. Recently, Chen et al. (2019) finds empirical evidence against expected positive relationship between kurtosis and expected returns on stock market. The authors explain the detected negative effect of kurtosis on stock returns by lottery preference of the investors.

Also for sovereign bonds, enhancing the risk-return relationship by inclusion of higher moments (such as skewness and kurtosis) are likely to add additional explanatory power for future returns. As noted by Fujiwara et al. (2013), the asymmetry of government bond returns implies that mean and variance are not sufficient to describe risk.

To our best knowledge, Kinateder and Papavassiliou (2019) is the only work analyzing the predictability of bond returns by realized moments. However, the authors use different methodology and focus on returns of European sovereign 10-year bonds over a 2-year period and conclude that the only moment valuable for return prediction is kurtosis.

With an ambition to provide the readers with a comprehensive and robust study which will bring results valid beyond short periods or a concrete maturity we approach the task as follows. First, having on hand an extensive high-frequency dataset, we start with careful inspection of statistical properties of government bond returns over the entire term structure on the U.S. and German market. Second, we analyze how the return and realized moments co-move across the markets and maturities. Third, we estimate whether and how the realized moments help to predict the excess returns, and how the conclusions differ across markets, maturities, sub-periods and data frequencies.

The rest of the paper is organized as follows. Section 2 outlines the methodology of construction of the realized moments and introduces the form of the model analyzing the link between realized moments and future bond returns both in static and dynamic settings. Section 3 presents the dataset along with detailed descriptive and correlation analysis of both U.S. and German sovereign markets. The estimation results are discussed in Section 5 and Section 6 concludes.

# 2 Methodology

As Cochrane (2009) reminds, the recent empirical literature revisiting expectation hypothesis gradually arrived to broader application of multi-factor models for explanation of future returns (rather than models relying on market betas of the respective assets). In fixed income context, more recent works show bond returns to be predictable to some extent. Cornerstone of asset pricing is the reflection of investors' concerns about states of world which have impact on their returns in their investment decisions. In other words, that investors face the trade-off between average returns and (bad) states of the world. In case of factor pricing models, the factor variables should be the indicators of these bad states of world (Cochrane, 2009).

Since the relevant literature is nearly silent on this topic, we perceive the rigorous analysis of link between return moments and bond prices to be meaningful adding to the bond-related literature. We also believe that analysis of risk-return relationship for bonds across different maturities is contributive since bonds with different maturities are traded on different market segments and the respective risk-return relationship might be perceived (and also grounded) differently.

#### 2.1 Realized moments

#### 2.1.1 Realized variance

Inspecting (and also modeling and forecasting) volatility is complicated by the fact that the actual volatility is not directly observable. Therefore, researchers developed multiple approaches relying on strict parametric assumptions to capture the latency of volatility. These methodologies include autoregressive conditional heteroskedasticity (ARCH) or stochastic volatility (SV) models, or alternatively, option-based implied volatility measures. As Andersen and Teräsvirta (2009) summarize, in order to approximate current and future levels of volatility, some literature also employs historical volatility measures (i.e. backward-looking sample return standard deviation), which generally do not provide with outcomes consistent with basic properties of volatility (such as mean reversion).

Thanks to availability of high-frequency data on various financial assets and to increasing computational power needed for efficient processing of large-scale datasets, we can observe stronger presence of model-free data-driven volatility measurements to the detriment of parametric conditional volatility models. As Andersen and Bollerslev (1998) or Andersen et al. (2003) show realized volatility measures based on intra-day data bring significant reduction in noise and improve stability of the results as compared to the measures relying on daily return observations.

We use medRV estimator as formulated by Andersen et al. (2012) constructed as:

$$medRV_t = \frac{\pi}{6 - 4\sqrt{3} + \pi} \left(\frac{N}{N - 2}\right) \sum_{i=2}^{N-1} med(|r_{t,i-1}|, |r_{t,i}|, |r_{t,i+1}|)^2$$
(1)

where  $r_{t,i}$  generally represents the *i*-th return on trading day *t* and *N* is the number of equispaced returns on the trading day. We work also with associated volatility measure medRVol referring to square root of medRV.

As discussed in Andersen et al. (2012), medRV performs better compared to bi-power or multi-power RV measures in terms of robustness in finite sample with respect to jumps and occurrence of spurious zero returns caused by quote or trade price duplicates.

Within robustness checks we also employ realized variance measure as formulated by Andersen et al. (2003):

$$RV_t = \sum_{i=1}^{N} r_{t,i} r'_{t,i}$$
(2)

where  $r_{t,i}$  generally represents the *i*-th return on trading day *t* and *N* is the number of equispaced returns on the trading day. Analogously, measure *RVol* refers to square root of *RV*.

#### 2.1.2 Realized skewness

As Jondeau et al. (2019) recalls, skewness reflecting occurrence of extreme events can be associated with concepts such as tail risk (e.g. Bollerslev et al. (2015)) or disaster risk (e.g. Kozhan et al. (2013)). Motivated also by up-to-date practice to include skewness of returns as an additional risk factor, we include its realized measure to our fixed income risk-return analysis.

Similarly as in case of volatility measure, we suspect varying approaches to skewness estimation as one of the possible sources of result inconsistencies of empirical analyses of skewnessreturn relationship. Therefore, thanks to availability of high-frequency data we use realized skewness measure which was first introduced by Neuberger (2012). Specifically, we construct the measure following Amaya et al. (2015):

$$rSkew_t = \frac{\sqrt{N}\sum_{i=1}^{N} (r_{t,i})^3}{RV_t^{3/2}}$$
(3)

in which  $r_{t,i}$  generally represents the *i*-th return on trading day *t*, *N* is the number of equispaced returns on the trading day and  $RV_t$  refers to realized variance.

#### 2.1.3 Realized kurtosis

Similarly as in case of lower moments, problematic measurement (or estimation) of the fourth moment might be responsible for scarceness and ambiguity of empirical literature testing moment predictive power with respect to future asset returns. Again, having high-frequency data at our disposal, in construction of realized kurtosis we follow the pioneering work by Amaya et al. (2015):

$$rKurt_{t} = \frac{N\sum_{i=1}^{N} (r_{t,i})^{4}}{RV_{t}^{2}}$$
(4)

in which  $r_{t,i}$  generally represents the *i*-th return on trading day *t*, *N* is the number of equispaced returns on the trading day and  $RV_t$  refers to realized variance.

#### 2.1.4 Constant-coefficient model

Before we move to the core time-varying analysis, we start with constant-coefficient model of risk-return relationship on sovereign bond markets. Majority of the aforementioned literature studies cross-section of asset returns. We focus on time series analysis of importance of realized moments in predicting bond futures excess returns across maturities and markets. We hypothesise, individual realized moments to be risk factors which are priced separately. In order to filter out the effects already priced in traditionally used risk factors, we augment our basic model by multiple control variables. For final model specification we have decided to use similar logic to traditional Fama-French bond factors being able to capture business cycle fluctuations. We restrict ourselves to additional two control variables which proved to be priced in (bond) excess returns - term spread and default spread. The former is in our case defined as difference between yields on 10-year Treasury bond and 3-month Treasury bill, whereas the default spread is calculated as difference between yields on BAA-rated and AAA-rated U.S. corporate bonds. Following Bali and Peng (2006), we extend the basic model with a lagged return to mitigate the potential spurious effect due to serial correlation in returns. Thus, final full-scope model with all the control variables is constructed as follows:

$$r_{t+1} = \alpha + \beta_1 R Vol_t + \beta_2 R Skew_t + \beta_3 R Kurt_t + \gamma_1 r_t + \gamma_2 \Delta Term_t + \gamma_3 \Delta Def_t + \epsilon_t$$
(5)

where  $r_{t+1}$  is bond excess return and the explanatory variables refer to realized measures of volatility, skewness and kurtosis, respectively, as defined in the preceding section. The control variables refer to lagged excess return, first-differenced term spread and first-differenced default spread, respectively.

#### 2.1.5 Time-varying coefficient model

In order to inspect the time variation of the effect of individual risk factors on future returns, we use the time-varying linear regression, which is attracting more and more attention in financial research. As mentioned above, our ambition is to challenge the findings in previous risk-return relationship studies which appear to be largely dependent on selection of the particular asset and time period. We hypothesise that assumption of risk-return parameters to be constant might not be true and the relationships between the variables might vary, especially in case of our extensive data set covering 12 years. Non-parametric models robust to the functional misspecification of the relationships between the analyzed variables would be natural candidates to tackle this issue. However, these are vulnerable to "curse of dimensionality" (Casas and Fernandez-Casal, 2019) and often do not provide the recipients with a straightforward inference. Therefore, semi-parametric models where the coefficients change over time in a specified manner allow for more flexibility than parametric linear model without the drawbacks of the fully non-parametric methods.

Generally, the time-varying coefficient linear model (TVC) is specified as follows:

$$y_t = x_t^{\mathsf{T}} \beta(z_t) + u_t, t = 1, ..., T$$
 (6)

where  $y_t$  is the dependent variable,  $x_t$  is the vector of independent variables, and  $u_t$  is the disturbance term with  $E(u_t|x_t) = 0$  and  $E(u_t^2|x_t) = \sigma^2$ . As compared to the constantcoefficient linear model,  $\beta(z_t)$  represent the regression coefficients being the unknown functions of time or of a random variable changing with time. In our work, we will focus on the former case<sup>1</sup>, where the smoothing variable corresponds to the time rescaled to interval [0, 1], i.e.  $z_t = \tau = t/T$ . Pioneering work in this field was Robinson (1989) who analysed the time-varying parameter linear models using stationary variables. The framework was extended also for nonstationary case among others by Cai (2007). Recently, the time-varying coefficient methodology was applied by Chen et al. (2019) who enhanced the Heterogenous Autoregressive Model for realized volatility forecasting developed by Corsi (2009).

In our case, we employ time-varying OLS using the local constant kernel method (in the literature known as Nadaraya-Watson estimator). In this case,  $\beta(t)$  is approximated by a constant at each point in time (t) and the local constant Nadaraya-Watson estimator solves the

<sup>&</sup>lt;sup>1</sup>Comprehensive literature review on the latter approach can be found in Casas and Fernandez-Casal (2019).

following minimization problem:

$$\arg\min_{\theta} \sum_{t=1}^{T} [y_t - x_t^{\mathsf{T}} \theta]^2 K_b(z_t - z) \tag{7}$$

where the kernel  $K_b(z_t - z) = \frac{1}{b}K(\frac{z_t - z}{b})$  weights the local regressions within a chosen bandwith, and the optimized  $\theta^*$  represents the local constant estimator of  $\beta(z_t)$ . Details on the theoretical framework of the estimation procedure can be found in Cai (2007). The set of dependent and independent variables is identical as in case of the constant-coefficient model as presented above. Therefore, our time-varying coefficient model is expressed by:

$$r_{t+1} = \alpha_t + \beta_{1t}RVol_t + \beta_{2t}RSkew_t + \beta_{3t}RKurt_t + \gamma_{1t}r_t + \gamma_{2t}\Delta Term_t + \gamma_{3t}\Delta Def_t + \epsilon_t \quad (8)$$

where  $r_{t+1}$  is bond excess return and the explanatory variables refer to realized measures of volatility, skewness and kurtosis, respectively, as defined above. The control variables refer to lagged excess return, first-differenced term spread and first-differenced default spread, respectively, and  $\alpha$ ,  $\beta$ , and  $\gamma$  coefficients are time-varying.

## 3 Data

#### 3.1 US Treasury and German sovereign bond futures prices

For our analysis we use 1-minute U.S. Treasury and German futures data (active contracts) from Tick Data, Inc.<sup>2</sup> database. We examine contracts for each U.S. Treasury and German benchmark tenors traded at the world's leading electronic platform CME Globex and Eurex, respectively. The corresponding tickers and tenors are summarized in the following table.

CME Global ticker	Eurex ticker	Underlying tenor
TU	BZ	2 years
FV	BL	5 years
TY	BN	10 years
US	BX	30 years

Table 1: Summary of analyzed bond futures

There are multiple benefits of analyzing futures instead of cash market in order to examine the risk-return relationship. First, as long as this paper applies data-driven methodology in order to estimate volatility (as well as higher moments), immediate availability of clean 1minute high-frequency futures data from renowned database is extremely beneficial. Second, observing situation on U.S. bond market in past decade, futures market has been gaining relative importance to the cash market<sup>3</sup>. Third, due to delivery mechanism of U.S. Treasury futures contracts, futures prices are tightly linked to underlying bond prices (and yields), and moreover, also due to lower transaction costs, futures market was detected to be dominant to cash market in reaction to news and price discovery process (see e.g. Brandt et al. (2007), Andersen et al.

<sup>&</sup>lt;sup>2</sup>http://www.tickdata.com/

 $<sup>^3 \</sup>rm See$  The New Treasury Market Paradigm, CME Group, June 2016, available at https://www.cmegroup.com/education/files/new-treasury-market-paradigm.pdf.

(2007) or Engle (1998)). Panzarino et al. (2016) found that volatility on the futures market tends to spread to cash market, whereas the reverse flow is rather much weaker.

For our analysis we restrict ourselves to futures price observations in the period from September 2005 to November 2017. The selection of the inspected timeframe is beneficial, as long as throughout the entire period the U.S. futures contracts have consistent specifics and delivery conditions especially in terms of annual coupon rate of the underlying bond contract which changed to 6% in 2000. Further, for this period we gain a complete series for all tenors both on the U.S. and German markets. We believe that 12 years of 1-minute high-frequency observations covering also turbulent period of the 2007-2009 financial crisis represent wide variety possible market situations reflected in various risk-return regimes on the respective markets.

The raw high-frequency data on futures prices are clean and validated by TickData inhouse system. However, we need to perform several more steps in order to acquire solid and representative time series for meaningful calculation of realized moments and open-close logreturns used for the analysis. First step is to exclude non-active days such as weekends or public holidays. We also drop days having only a single unique futures price observation during the trading day. This procedure leaves us with 3,099 days. Due to operation of trading electronic platform CME Globex, significant trading activity is observable also outside the CME trading hours (07:20 - 14:00 CT). Therefore, we decide to extend the interval for purposes of realized moments calculation by two hours on each pole and to define the trading day for our purposes from 05:20 CT to 16:00 CT in order to include all significant activity to our calculations. Moreover, this window includes the regular announcements issued by Federal Reserve System, European Central Bank and other relevant authorities which represent significant determinants of changes on the sovereign market.

Based on the findings in the relevant literature (summarized in e.g. Liu et al. (2015), Hansen and Lunde (2006)), we aggregate our data to 5-minutes sampling interval in order to benefit from optimal trade-off between bias and variance, which leaves us with final number of 1,083,527 and 892,102 observations for the U.S. and German markets, respectively.

Using the final dataset, we calculate open-close log-returns and realized moments (variance, skewness and kurtosis) for each tenor. It should be noted that the moments were satisfactorily tested for stationarity in order to reject the unit-root contamination of the regressions. Descriptive statistics of the daily returns and realized moments are provided in the Table 2.

Both mean daily returns and mean realized volatility of the U.S. Treasury futures are increasing with maturity. Mean of the realized skewness is clearly negative for all maturities and increasing in absolute value with maturity. For all maturities we observe significant autocorrelation in realized volatility corresponding to the known concept of volatility clustering and standard deviation of realized volatility series increasing with the underlying tenor.

Similar observations apply also for the German futures. Mean daily returns, mean realized volatility as well as standard deviation of realized volatility increase with the maturity. Correlation with the first lag is even more pronounced in the realized volatility of the German futures returns as compared to the U.S. Treasury. However, mean realized skewness does not show any common trend with the maturity of the underlying bonds.

Open-close returns and realized moments in weekly frequency of the 10-year U.S. and Ger-

man bond futures prices are summarized in Figures 4 and 5, respectively. Despite our basic model is estimated on daily data, we aggregate the variables also to weekly and monthly frequency for better detection of dynamics of the moments over the inspected period. Whereas weekly log-returns and realized volatility are aggregated by summations of the respective daily observations, weekly measures of realized skewness and kurtosis correspond to weekly means. As mentioned above, instead of explaining real returns we comply with best practice in the literature and work with excess returns earned above risk-free three-month T-bill rate.

	Mean	Median	Std	Skew	Kurt	AR(1)
Panel A: U.S. Treasury						
Daily returns						
2-year (TU)	0.001	0.000	0.086	-0.866	14.881	-0.075
5-year (FV)	0.002	0.000	0.228	-0.308	6.217	-0.048
10-year (TY)	0.004	0.000	0.346	0.056	4.912	-0.034
30-year (US)	0.008	0.013	0.607	1.064	17.826	-0.015
Realized volatility						
2-year (TU)	0.082	0.075	0.047	2.377	11.416	0.551
5-year (FV)	0.187	0.174	0.103	1.580	5.532	0.506
10-year (TY)	0.303	0.280	0.150	1.434	5.065	0.463
30-year (US)	0.532	0.520	0.246	1.322	8.550	0.377
Realized skewness						
2-year (TU)	-0.104	0.000	2.601	-0.929	14.701	0.003
5-year (FV)	-0.217	-0.033	3.144	-0.856	8.870	0.013
10-year (TY)	-0.225	-0.046	2.894	-0.880	9.648	0.012
30-year (US)	-0.243	-0.050	2.526	-1.308	12.319	0.003
Realized kurtosis						
2-year (TU)	18.570	6.210	34.044	4.449	23.754	-0.030
5-year (FV)	22.425	8.055	39.518	3.734	16.071	-0.036
10-year (TY)	20.033	7.653	35.718	3.996	17.997	-0.048
30-year (US)	17.489	7.652	30.753	4.645	25.426	-0.054
Panel B: Germany						
Daily returns						
2-year (BZ)	0.002	0.000	0.081	-0.289	9.538	-0.040
5-year (BL)	0.005	0.008	0.233	-0.840	8.126	-0.015
10-year (BN)	0.009	0.012	0.384	-0.267	3.146	-0.006
30-year (BX)	0.015	0.020	0.817	0.046	3.588	-0.001
Realized volatility						
2-year (BZ)	0.071	0.059	0.037	2.381	8.250	0.859
5-year (BL)	0.182	0.162	0.079	1.861	5.714	0.811
10-year (BN)	0.310	0.283	0.119	2.831	27.615	0.711
30-year (BX)	0.654	0.602	0.270	1.874	7.319	0.717
Realized skewness						
2-year (BZ)	-0.088	-0.025	2.090	-1.369	22.781	0.015
5-year (BL)	-0.069	-0.028	2.514	-0.923	17.375	-0.004
10-year (BN)	-0.137	-0.066	2.477	-1.218	13.805	-0.004
30-year (BX)	-0.095	-0.021	2.263	-0.371	7.648	0.015
Realized kurtosis						
2-year (BZ)	14.245	7.757	25.806	6.607	51.116	0.056
5-year (BL)	17.323	9.048	3.254	5.968	40.945	0.024
10-year (BN)	17.820	9.776	28.890	5.744	38.911	0.002
	19.298		22.245	4.667	29.915	0.040

Table 2: Descriptive statistics of returns and realized moments of U.S. Treasury and German bond futures

The upward sloping term structure of realized volatility valid for both U.S. and German securities is apparent also in Figure 1 where we show monthly median realized volatilities for individual tenors on both markets. The monthly aggregations exhibit similiar pattern across maturities differing in rather in levels.

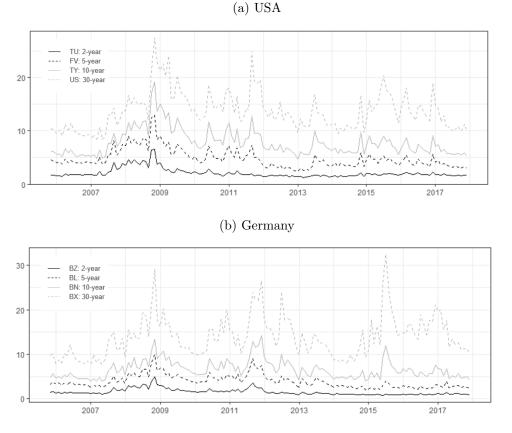


Figure 1: Monthly median realized volatility. Note: Monthly median realized volatility calculated as summation from daily non-overlapping data.

We further inspect comovement in terms of intra-market correlations of individual moments but also comovement of the moments on the U.S. and German market or across maturities. The detailed correlation table of daily data is provided in Appendix (Table 8). First, we look at the correlation of individual moments of U.S. Treasury futures returns across maturities. As expected, the returns are strongly correlated across maturities with the intensity of the link decreasing with increasing maturity differential. The same observation applies also for median realized volatilities (as already suggested by common trends in Figure 1) as well as for realized skewness and realized kurtosis. Further, we observe practically zero (or very weak) correlation between returns and volatility as well as between volatility and realized kurtosis. On the contrary, the correlation between returns and realized skewness is relatively strong (with the strongest relationship within corresponding tenors). The identical conclusions apply also for German futures. The significant postive correlation between returns and realized skewness is even stronger than in case of U.S. Treasury futures (by ca. 10-15 percentage points). Finally we also inspect the cross-market correlations. Returns are strongly positively correlated across maturities with the strongest positive correlation of 10-year tenors. The link between U.S. and German sovereign market is even stronger in terms of volatility with correlation decreasing with increasing maturities differential. Correlation of higher moments across the markets is much weaker as compared to returns and volatility achieving appprox. 20-30% and 10-20% for realized skewness and realized kurtosis, respectively.

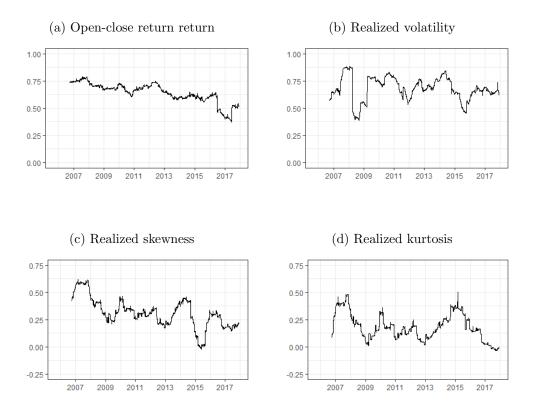


Figure 2: Dynamic correlation between returns and realized moments of 10-year U.S. and German bond futures. Rolling correlation coefficients calculated from rolling windows of 250 days.

Figure 2 illustrates 1-year (250-day) rolling correlation coefficients of returns and individual moments for the 10-year tenors on both markets. We observe very strong correlation of openclose return throughout the entire period with a slightly decreasing trend. On the other hand, the dynamic correlation of realized volatility is more variable over the period, but most of the time well-above 50%. For the sake of completeness, we show also rolling correlations of higher moments. We find the dynamic correlation of skewness to be rather decreasing in time with correlation over 50% present in 2007 (i.e. at start of global financial crisis). Realized kurtosis does not reveal any clear conclusion since the dynamic 1-year correlation remains week over the entire period. With respect to our inter-temporal analysis, as outlined in Equation 2.1.4, we also inspect the 250-day dynamic correlations of the realized moments with the next day open-close returns. For illustration we provide the time series of the rolling correlation for the 10-year Treasury in Figure 3 whereas the identical plots for remaining assets are shown in the Appendix.

Before we move to description of control variables, we show the sample of dependent and independent variables, i.e. returns and the second, the third and the fourth moments. All moments for 10-year tenors (i.e. TY and BN tickers) on both markets are plotted in Figures 4 and 5 (for better illustration we aggregate the daily data to weekly frequency).

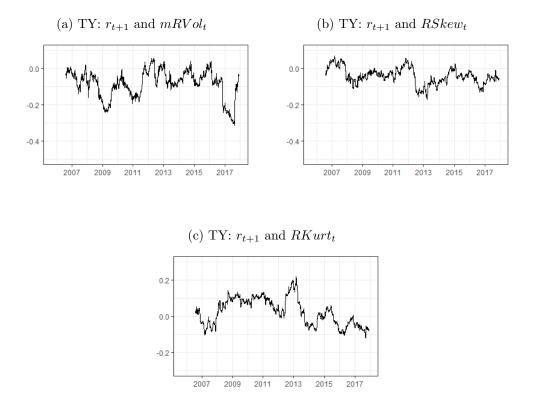


Figure 3: 10-year U.S. Treasury futures: Dynamic correlations of realized moments with next day open-close return.

From Figure 5b is evident, that the German 10-year tenor futures (as well as the underlying bonds) experienced multiple turbulent periods as compared to the U.S. Treasury, which were shorter but not much less intense as compared to the 2007-2009 financial crisis. First, we observe significant increase in volatility in 2012 as an effect of "whatever-it-takes" message of the European Central Bank<sup>4</sup>. Most recent spikes in volatility in 2015 correspond to the period when ECB (similarly as other central banks) initiated a quantitative easing (by asset purchase programmes) in order to address the long period of very low inflation. The asset purchase programme extended the existing programmes of ECB of private sector assets purchases by purchases of sovereign bonds.

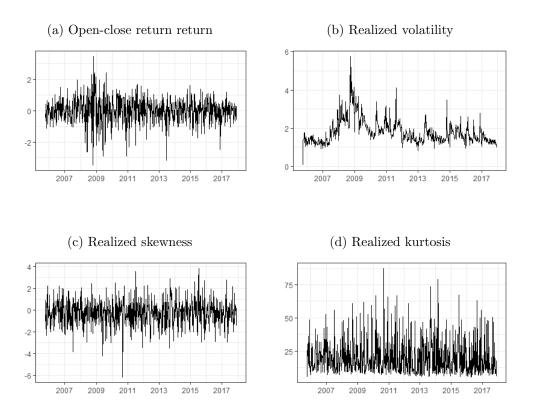


Figure 4: 10-year U.S. Treasury futures (weekly). Note: Note: Weekly log-returns and realized volatility are aggregated by summations of the respective daily observations, weekly measures of realized skewness and kurtosis correspond to weekly means.

<sup>&</sup>lt;sup>4</sup>Speech by Mario Draghi, President of the European Central Bank at the Global Investment Conference in London 26 July 2012: https://www.ecb.europa.eu/press/key/date/2012/html/sp120726.en.html

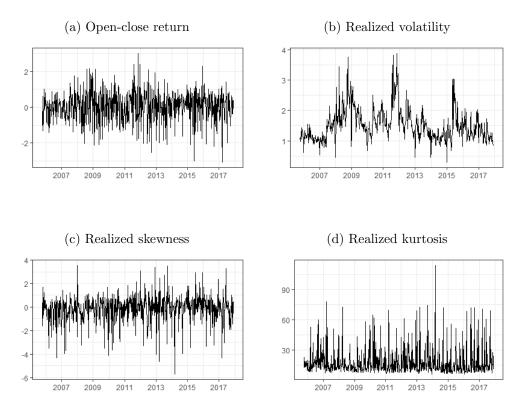


Figure 5: 10-year German bonds futures (weekly). Note: Weekly log-returns and realized volatility are aggregated by summations of the respective daily observations, weekly measures of realized skewness and kurtosis correspond to weekly means.

#### 3.2 Control variables

As mentioned earlier, we include control factors proved in the bond return literature to have a certain explanatory power for future returns - term spread and default spread. We follow Bali and Peng (2006) who define the spreads as difference between yields on the 10-year Treasury bond and 3-month T-bill, and difference in long-term Moodys BAA-rated and AAA-rated corporate bond yields, respectively. The respective daily yields were obtained from Federal Reserve Bank of St. Louis<sup>5</sup>. Control variables for German market were constructed identically and obtained from Bloomberg database<sup>6</sup>. Term spreads and default spreads for the U.S. and German markets are displayed in Figures 6 and 7 (for better illustration in weekly frequency).

It is apparent that the spread developments have been reflecting business conditions in the country. Significant flattening of U.S. yield curve (i.e. term spread decreasing to - or even below - zero) has been usually a signal for a forthcoming economic slowdown (Estrella, 2005). Since term spreads are proxy for (unobservable) term premiums investors require for their exposure to longer maturity, term spreads tend to follow the business cycle (Domian and Reichenstein, 1998). Thus, term premiums (and term spreads) increase under poor business conditions and decrease in prosperity. Similarly, default spreads widen during recessions since

<sup>&</sup>lt;sup>5</sup>Link to databank: https://fred.stlouisfed.org/categories/22. Weekly and monthly observations were in line with FRED practice constructed as averages. Possible missing observations completed by linear interpolations.

<sup>&</sup>lt;sup>6</sup>Tickers: GTDEM3MO Corp (3-month), GTDEM10YR Corp (10-year), ER10 (EURO AAA Corporate yields), ER40 (EURO BBB Corporate yields)

investors' demand for safer bonds pushes the top-rated yields down. On contrary, when the economy starts to recover and investors trust increases they again shift their interest also to lower-rated bonds which again narrows the default spread<sup>7</sup>. In order to ensure stationarity of the series, we employ first-differenced term and default spreads in our model (refer to Equation 2.1.4).

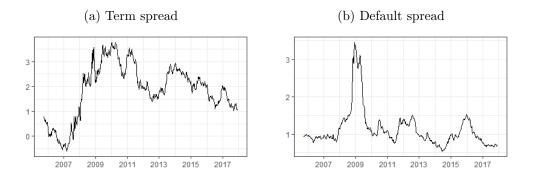


Figure 6: U.S. market control variables: Term spread and default spread (weekly)

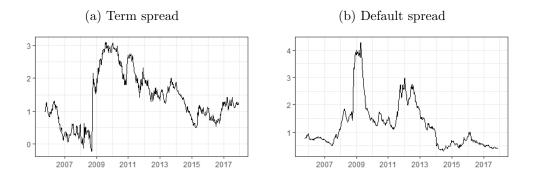


Figure 7: German market control variables: Term spread and default spread (weekly)

# 4 Results

This section sets forth empirical evidence of (time-varying) inter-temporal risk-return relationship on the sovereign markets in the USA and Germany. We start with standard constantcoefficient approach and discuss explanatory power of realized moments for next-day open-close excess returns for U.S. Treasury futures prices over the whole sample. The U.S. market findings are further confronted with empirical evidence of German data. Subsequently we move to the

 $<sup>^{7}\</sup>mathrm{It}$  is worth noting that the same economic conditions are captured by dividend yields (Fama and French, 1989).

key focus of our empirical analysis - the time-variability of explanatory power of individual factors for next day excess returns. Finally, we discuss our findings in the context of the evidence found by existing relevant literature.

#### 4.1 Constant-coefficient model

#### 4.1.1 US Treasury

Table 3 summarizes the estimation results of model specified in Equation 2.1.4 based on daily frequency for all inspected tenors. Except for the shortest maturity, the negative effect of median realized volatility on the next-day open-close return was found for all the tenors. The contribution of volatility on future returns is not captured by the control variables which proved to be significant for future returns as concluded by existing studies. Consistently with the existing evidence, the effect of changes in term spread is significant in explaining the next-day returns while the default spread turns out to be insignificant. Unsurprisingly, we find significantly negative link between today's and tomorrow's open-close return which is usually found in the higher frequency data due to random flow of sales and purchases of the asset causing a bounce between the bid and ask prices<sup>8</sup>.

	2-year TU	5-year FV	10-year TY	30-year US
(Intercept)	-0.003	0.016	0.041 **	0.057 *
	(0.003)	(0.008)	(0.014)	(0.026)
mRVol	-0.015	-0.105 **	-0.144 ***	-0.102 *
	(0.030)	(0.037)	(0.038)	(0.041)
RSkew	0.000	-0.001	-0.002	-0.002
	(0.001)	(0.001)	(0.002)	(0.005)
RKurt	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Ret	-0.066 ***	-0.060 **	-0.063 **	-0.066 **
	(0.020)	(0.021)	(0.022)	(0.022)
$\Delta$ Term spread	-0.039	-0.191 **	-0.441 ***	-1.009 ***
-	(0.024)	(0.070)	(0.111)	(0.197)
$\Delta Default spread$	0.005	0.111	-0.178	0.098
-	(0.073)	(0.192)	(0.291)	(0.510)
$\mathbb{R}^2$	0.7%	0.8%	1.2%	1.0%

(Standard errors in parentheses) \*\*\* p < 0.001; \*\* p < 0.01; \* p < 0.05

Table 3: Effect of realized moments and control variables on one-day ahead open-close excess returns (daily).

Similarly as Bali and Peng (2006), we note that with respect to the noisiness of the daily data,  $R^2$  oscillating around 1% is satisfactory and consistent with other empirical studies of daily asset returns.

Contrary to some recent studies, we do not find any significant evidence of contribution of the higher realized moments. We assign this to multiple factors. First, the studies concluding a predictive power of realized higher moments (mainly skewness) focus on cross-section analysis of equities (e.g. Amaya et al. (2015) or Jondeau et al. (2019)). Second, it is evident that data frequency matters since we also detect a certain predictive power of higher moments (concretely

 $<sup>^{8}</sup>$ We also performed the estimation at lower frequencies (weekly and monthly). In these cases the past-return lacked an explanatory power for future returns.

realized kurtosis) on future returns on weekly frequency<sup>9</sup>. Here we comply with Shen et al. (2018) who also found evidence against significant explanatory power of realized skewness for future returns as the authors performed their analysis on daily data.

	2-year TU	5-year FV	10-year TY	30-year US
(Intercept)	-0.004	0.058	0.109 *	0.097
	(0.015)	(0.036)	(0.049)	(0.070)
mRVol	-0.028	-0.213 *	-0.259 **	-0.183 *
	(0.088)	(0.102)	(0.097)	(0.090)
RSkew	-0.004	-0.002	-0.005	0.000
	(0.003)	(0.006)	(0.009)	(0.015)
RKurt	0.000 *	0.001	0.001	0.002
	(0.000)	(0.000)	(0.001)	(0.001)
Ret	-0.064	-0.043	-0.007	0.023
	(0.047)	(0.048)	(0.049)	(0.049)
$\Delta$ Term spread	0.014	0.044	-0.027	-0.151
	(0.059)	(0.136)	(0.198)	(0.288)
$\Delta Default spread$	-0.019	0.266	-0.434	0.073
	(0.204)	(0.457)	(0.650)	(0.939)
$\mathbb{R}^2$	2.5%	1.9%	2.0%	1.7%

(Standard errors in parentheses) \*\*\* p < 0.001; \*\* p < 0.01; \* p < 0.05

Table 4: Effect of realized moments and control variables on one-day ahead open-close excess returns (daily): subsample April 1, 2007 - March 31, 2009.

Motivated by most probably different extent of return predictability during the global financial crisis period (Kinateder and Papavassiliou, 2019), we estimate the model outlined in Equation 2.1.4 using a subsample starting April 1, 2007 and ending March 31, 2009 and summarize the results in Table 4.

Again, we observe negative effect of median realized volatility on the next-day excess return in case of all tenors except for the 2-year T-Bills. In the crisis period, volatility remains to be the only significant predictor as the contribution of the control variables turns to be insignificant. Here we comply with Kinateder and Papavassiliou (2019) who found European bond returns to be more predictable during crisis periods, however we differ in the realized moment detected to be a valuable predictor<sup>10</sup>.

When we look at the post-crisis subsample from April 2009 to November 2017 (as summarized in Table 5), control variables - past return and first-differenced term spread - turn out to be significant across all maturities. But also in this case, median realized volatility remains to show significantly negative impact on future excess returns for all tenors this time except the longest one.

It is worth noting, that we do not find any evidence of significant informative contribution of higher realized moments for future returns in any of the analyzed sub-samples.

#### 4.1.2 Germany

Having the corresponding dataset covering the same maturities also for German sovereign market at our disposal, we perform the similar analysis of the inter-temporal risk-return relationship

<sup>&</sup>lt;sup>9</sup>In this paper we focus on daily model. Estimation results on weekly frequency are available upon request.

<sup>&</sup>lt;sup>10</sup>Kinateder and Papavassiliou (2019) found realized kurtosis to be the best predictor for European 10-year bond returns over the inspected 2-year period.

	2-year TU	5-year FV	10-year TY	30-year US
(Intercept)	0.006	0.023 *	0.046 **	0.057
	(0.004)	(0.009)	(0.016)	(0.032)
mRVol	-0.097 *	-0.143 **	-0.154 **	-0.089
	(0.045)	(0.049)	(0.049)	(0.053)
RSkew	0.000	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.003)	(0.006)
RKurt	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Ret	-0.078 **	-0.131 ***	-0.197 ***	-0.182 ***
	(0.028)	(0.029)	(0.031)	(0.029)
$\Delta$ Term spread	-0.099 ***	-0.607 ***	-1.443 ***	-2.833 ***
	(0.029)	(0.111)	(0.194)	(0.360)
$\Delta Default spread$	0.026	-0.008	-0.022	-0.065
	(0.069)	(0.227)	(0.359)	(0.694)
$\mathbb{R}^2$	1.0%	1.8%	2.8%	2.5%

(Standard errors in parentheses) \*\*\* p < 0.001; \*\* p < 0.01; \* p < 0.05

Table 5: Effect of realized moments and control variables on one-day ahead open-close excess returns (daily): subsample April 1, 2009 - November 30, 2017.

as in case of the U.S. Treasury market. Estimation results are presented in the Table 6. Contrary to the U.S. market, we found no evidence of the independent variables outlined in the Equation 2.1.4 having any explanatory power for next-day excess returns.

	2-year BZ	5-year BL	10-year BN	30-year BX
(Intercept)	-0.002	-0.009	0.000	0.030
	(0.003)	(0.011)	(0.020)	(0.041)
mRVol	0.025	0.062	0.016	-0.055
	(0.041)	(0.054)	(0.059)	(0.055)
RSkew	0.000	0.002	0.004	0.013
	(0.001)	(0.002)	(0.004)	(0.008)
RKurt	0.000	0.000	0.000	0.001
	(0.000)	(0.000)	(0.000)	(0.001)
Ret	-0.029	-0.032	-0.035	-0.048
	(0.024)	(0.028)	(0.027)	(0.026)
$\Delta$ Term spread	0.025	-0.028	-0.220	-0.607 *
-	(0.027)	(0.084)	(0.148)	(0.306)
$\Delta Default spread$	0.059	-0.109	-0.287	-0.011
	(0.044)	(0.127)	(0.210)	(0.446)
$\mathbb{R}^2$	0.3%	0.1%	0.2%	0.3%

(Standard errors in parentheses) \*\*\* p < 0.001; \*\* p < 0.01; \* p < 0.05

Table 6: Effect of realized moments and control variables on one-day ahead open-close excess returns (daily).

#### 4.2 Time-varying coefficient model

In the previous section, we observe that the detected relationship is most probably distinctly variable in time which might lead to inconsistencies and ambiguity of the existing empirical evidence performed on shorter periods. Therefore, we take advantage of our unique dataset, especially in terms of the length of the covered period, and look at the variability of the risk-return tradeoff in more detail. As described previously, we employ the time-varying coefficient model as specified in Equation 2.1.5. Time-varying coefficients including 90% confidence band for the U.S. Treasury 10-year tenor are plotted in Figure 8 together with the constant OLS estimate (red line).

We recall that in the classic OLS setting, only median realized volatility, excess return and differenced term spread were detected as significant for the next day excess return of 10-year Treasury bonds futures. As we see in Figure 8a, the time-varying effect of realized volatility is negative (with minor exceptions) throughout the sample period. In line with the crisis subsample analysis presented earlier, we observe the crisis period of 2007 - 2009 to show significant effect, i.e. the 90% confidence band is entirely below zero. Then, after 5-year period of no evidence of significantly negative return-volatility relationship, the time-varying coefficient incl. its confidence band return to negative values in 2014. Since then, the mid point estimate has been declining (but with widening confidence band).

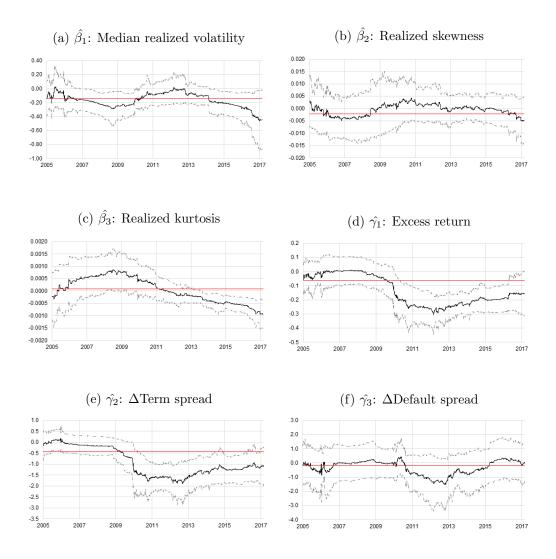


Figure 8: Time-varying coefficients for 10-year Treasury returns. Dotted lines represent 90% confidence bands. Red line indicates constant-coefficient OLS estimate.

Even in TVC setting, realized skewness does not show any significant contribution to the next day return. The coefficient estimate is oscillating around zero over the entire sample period. On the other hand, in case of realized kurtosis, time-varying coefficient methodology reveals a lot more than standard OLS. Figure 8c shows that in the 12-year sample period there are extensive periods of positive and negative effects of realized kurtosis on the next day excess return. We see that around the year 2009 there is a significantly positive effect of the

realized kurtosis on the next day return. On the contrary, since 2013 we found significantly negative effect of kurtosis, moreover with relatively narrow 90% confidence band. We conclude that especially in case of the fourth moment, the insignificance of the constant-coefficient OLS estimate over the entire period 2005-2017 is misleading.

As far as the control variables are concerned, we observe significantly negative autoregressive effect of excess returns since 2010. Similarly, the first-differenced term spread has significantly negative effect on future returns since 2010. The remaining control variable, the first-differenced default spread, does not show any significant effect since the confidence band always includes zero.

Summary of the results for all tenors is provided in Table 7 and plots of time-varying coefficients for the remaining tenors are provided in the Appendix.

TU: 2-year (daily)	Min	1st quartile	Median	Mean	3rd quartile	Max
Intercept	-0.031	-0.005	0.001	-0.002	0.007	0.167
mRVol	-0.276	-0.096	-0.038	-0.041	0.046	0.179
RSkew	-0.003	-0.001	0.000	0.000	0.000	0.001
RKurt	0.000	0.000	0.000	0.000	0.000	0.000
Ret	-0.156	-0.132	-0.078	-0.086	-0.056	0.005
$\Delta$ Term spread	-0.140	-0.072	-0.050	-0.050	-0.036	0.060
$\Delta$ Default spread	-0.160	-0.032	-0.004	-0.003	0.030	0.182
$R^2$	2.1%					
FV: 5-year (daily)	Min	1st quartile	Median	Mean	3rd quartile	Мах
Intercept	-0.022	0.009	0.019	0.023	0.037	0.062
mRVol	-0.411	-0.199	-0.118	-0.136	-0.068	0.058
RSkew	-0.003	0.000	0.000	0.000	0.000	0.002
RKurt	-0.001	0.000	0.000	0.000	0.000	0.001
Ret	-0.204	-0.154	-0.114	-0.103	-0.038	0.015
$\Delta$ Term spread	-0.669	-0.555	-0.505	-0.354	-0.076	0.153
$\Delta$ Default spread	-0.731	-0.371	-0.072	-0.059	0.349	0.530
$R^2$	2.2%					
TY: 10-year (daily)	Min	1st quartile	Median	Mean	3rd quartile	Max
Intercept	-0.019	0.025	0.045	0.050	0.075	0.118
mRVol	-0.461	-0.234	-0.162	-0.165	-0.082	0.028
RSkew	-0.005	-0.002	0.000	-0.001	0.001	0.004
RKurt	-0.001	0.000	0.000	0.000	0.001	0.001
Ret	-0.308	-0.232	-0.184	-0.137	-0.205	0.010
$\Delta$ Term spread	-1.900	-1.458	-1.155	-0.910	-0.170	0.175
$\Delta$ Default spread	-1.510	-0.684	-0.139	-0.327	0.041	0.456
$R^2$	2.8%					
US: 30-year (daily)	Min	1st quartile	Median	Mean	3rd quartile	Max
Intercept	-0.020	0.029	0.060	0.062	0.087	0.196
mRVol	-0.363	-0.152	-0.126	-0.109	-0.034	0.061
RSkew	-0.014	-0.007	-0.003	-0.001	0.004	0.013
RKurt	-0.002	-0.001	0.000	0.000	0.001	0.002
Ret	-0.387	-0.166	-0.101	-0.121	-0.029	0.004
$\Delta$ Term spread	-4.947	-2.982	-2.022	-1.941	-0.349	0.262
$\Delta$ Default spread	-2.524	-0.538	0.156	-0.154	0.581	1.195
$R^2$	2.8%					

Table 7: Summary statistics of time-varying coefficients (US Treasury)

Interestingly, the results both in terms of value development as well as significance development in time, is similar across the tenors of U.S. Treasury bond futures. Effect of realized volatility on future returns is significantly negative in the period of global financial crisis of 2007-2009 in case of longer tenors, i.e. 10-year and 30-year. A bit weaker outcome was detected in case of the 5-year tenor, where the upper limit of the confidence band oscillates very close to zero around the year 2009. For the shortest tenor (2-year) we observe results consistent with OLS estimation on the 2007-2009 subsample and conclude that no significant effect of volatility on next day return was detected. However, since 2014, we observe negative effect of realized volatility on future returns and this effect appears to be significant for all the tenors. Further, the absence of any significant effect of realized skewness on next day return is valid for all the tenors. On the contrary, we find very interesting results in case of realized kurtosis with coefficients switching from positive (approximately between 2007 and 2009) to negative values (after 2013). Furthermore, we find the negative effect of the fourth moment on next day openclose return to steadily amplify in absolute value. Despite its changing nature throughout the sample, we agree with conclusions of Kinateder and Papavassiliou (2019) who found realized kurtosis to be an important predictor of future sovereign bond returns.

Our results indicate that if there is a evidence of a risk-return trade-off, the priced "risk" element in the risk-return trade-off is most probably dominantly defined by volatility and kurtosis (on top of the standard control variables). Importance of higher moments for the general notion of risk is something which was already described in the literature. However, compared to other studies we benefit for an extraordinarily long period covered in our analysis which allows us to inspect the time variability of the pricing of the risk factor in future returns. The observations made on the 12-year series of time-varying coefficients are in line with the recent works focused shorter periods or different assets. We remind that different nature of the link between realized moments and future returns was also found by Chen et al. (2019) on the Chinese stock market since the investor's behaviour tend to change in time of crisis period. Similarly, Kinateder and Papavassiliou (2019) find more profound results when they separate crisis and non-crisis subsamples when evaluating predictability of European bond returns.

Last but not least we are turning to the control variables. Here again, we find similar patterns across the term structure with the exception for the 2-year tenor which is perceived to resemble rather the cash market. For the medium and long tenors we find significantly negative auto-regressive effect since approximately 2010. Further, we observe significant contribution of differenced term spread on next day returns since 2010. We observe that in periods where the term spread proved to be significant, the true value is most probably well below the classic OLS estimate. And finally, consistent with the constant-coefficient OLS, default spread lacks any explanatory power over the entire sample.

We performed the same estimation of time-varying coefficients for the German bond futures<sup>11</sup>. As compared to the U.S. Treasury, the periods of significance of individual realized moments for next day open-close excess returns are substantially shorter as compared to the U.S. Treasury (see plot in the Appendix). Interestingly, volatility is not significant in case of any maturity. From the realized moments, skewness appears to be the most promising. Equally for all maturities, there is a period around 2008, where we can observe the 90% confidence band below zero. However, later the sign of the effect significantly changes and around 2012 we observe on the contrary positive effect of realized skewness on the next day return. Further, for the shorter tenors (2-year and 5-year) we can see the negative effect of kurtosis around 2007-2008. From the control variables, only the differenced default spread appears to be contributive approx. in the period 2011-2013.

<sup>&</sup>lt;sup>11</sup>Summary statistics of time-varying coefficients are provided in the Appendix.

# 5 Conclusion

We extend the existing literature of bond return predictability in multiple dimensions. We introduce additional factors having a significant effect on next day excess returns which is not already explained by traditionally used predictive variables. Further, we detect strong time-variability of risk-return relationship on sovereign markets which might be probably responsible for inconsistencies of the existing empirical evidence covering different time periods and sample sizes.

We show that realized moments are valuable predictors of next day open-close excess returns of U.S. Treasury bond futures. Namely, realized volatility and realized kurtosis carry significant information for subsequent returns which is not priced by commonly used factors such as term and default spreads. Over the whole period, we find significant (negative) predictive power of realized volatility whereas the effect of realized kurtosis changes from positive (around 2008) to significantly negative impact detected between 2013 and 2017. Interestingly, the dynamics of bond futures return predictability evolves similarly over the entire term structure of the U.S. Treasury futures (except for 2-year underlying tenor). Surprisingly, we cannot extend the conclusions also to German market where we found no robust evidence of predictability of the bond futures returns.

Besides bond return predictability, we find the moments to be strongly correlated over the entire term structure on each market. Moreover, we reveal significant (dynamic) positive correlation of returns German and U.S. sovereign market as well as respective realized volatilities. Interestingly, we also find that realized volatility forms upward-sloping term structure on both markets.

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# Appendix

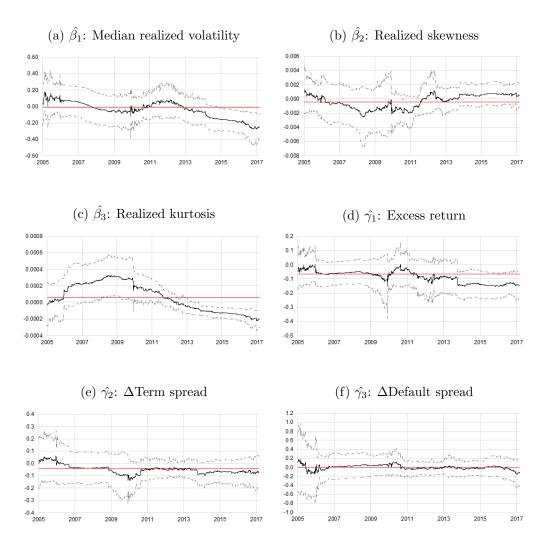


Figure 9: Time-varying coefficients for 2-year Treasury returns. Dotted lines represent 90% confidence bands. Red line indicates constant-coefficient OLS estimate.

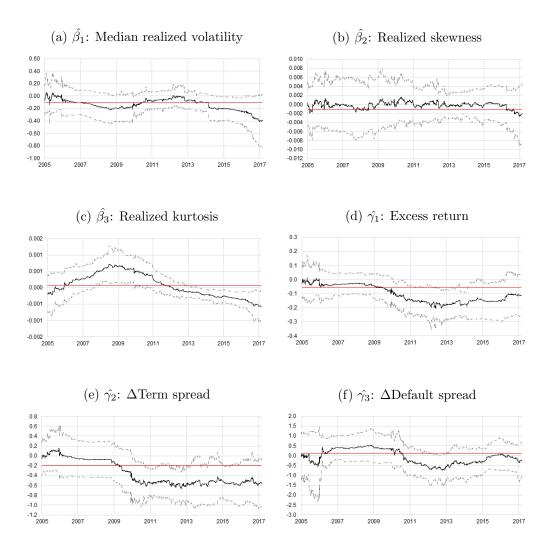


Figure 10: Time-varying coefficients for 5-year Treasury returns. Dotted lines represent 90% confidence bands. Red line indicates constant-coefficient OLS estimate.

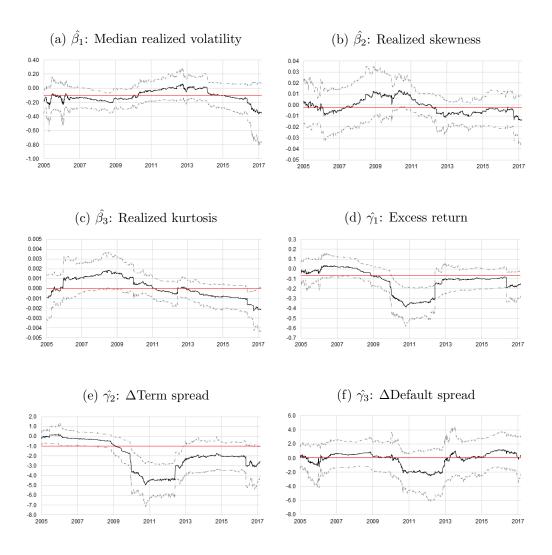


Figure 11: Time-varying coefficients for 30-year Treasury returns. Dotted lines represent 90% confidence bands. Red line indicates constant-coefficient OLS estimate.

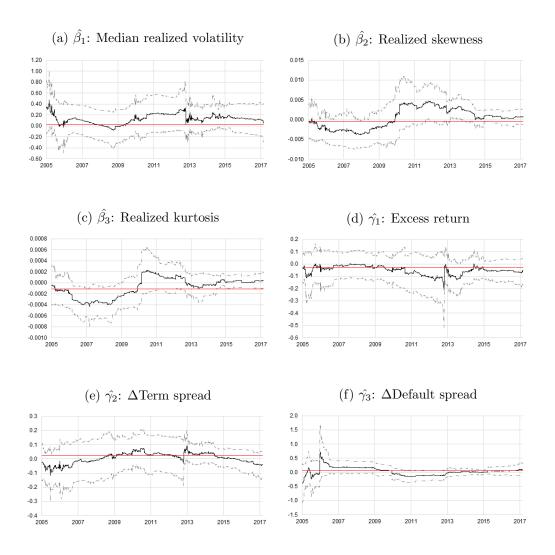


Figure 12: Time-varying coefficients for 2-year German bond returns. Dotted lines represent 90% confidence bands. Red line indicates constant-coefficient OLS estimate.

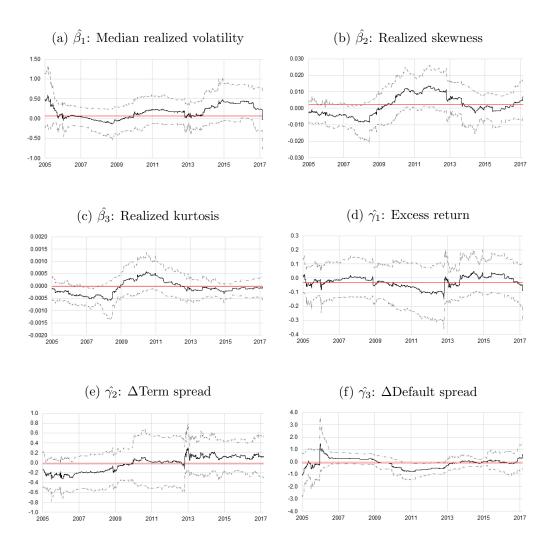


Figure 13: Time-varying coefficients for 5-year German bond returns. Dotted lines represent 90% confidence bands. Red line indicates constant-coefficient OLS estimate.

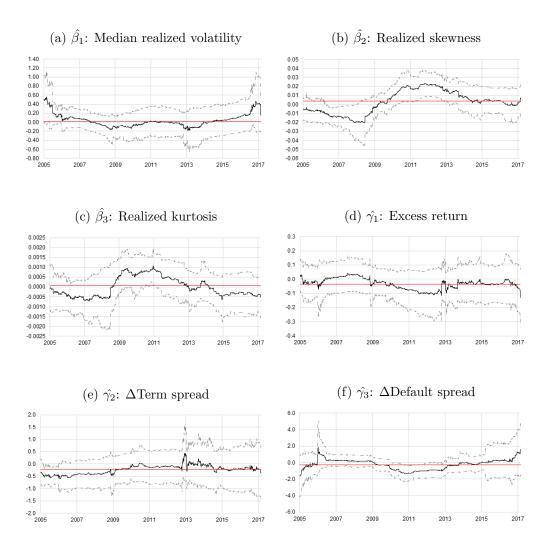


Figure 14: Time-varying coefficients for 10-year German bond returns. Dotted lines represent 90% confidence bands. Red line indicates constant-coefficient OLS estimate.

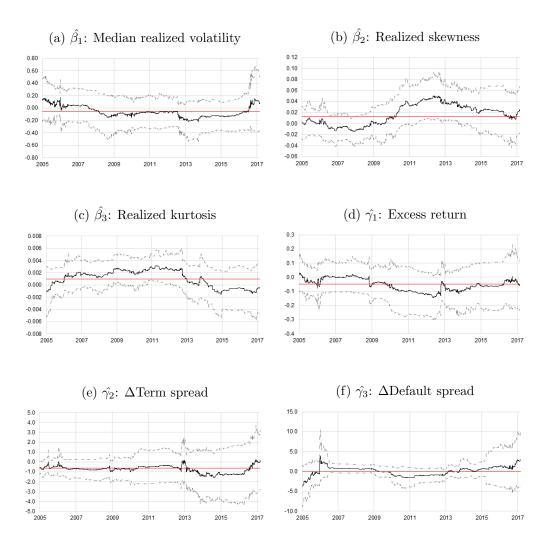


Figure 15: Time-varying coefficients for 30-year German bond returns. Dotted lines represent 90% confidence bands. Red line indicates constant-coefficient OLS estimate.

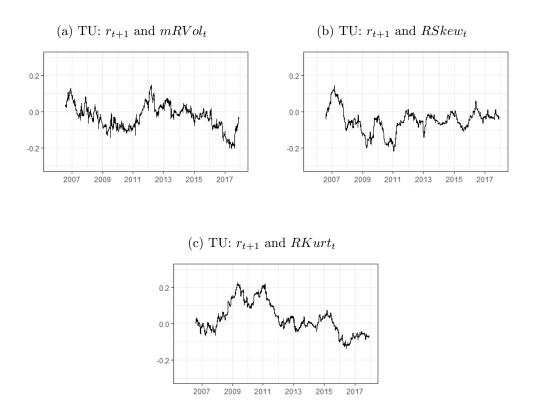


Figure 16: 2-year U.S. Treasury futures: Dynamic correlations of realized moments with next day open-close return.

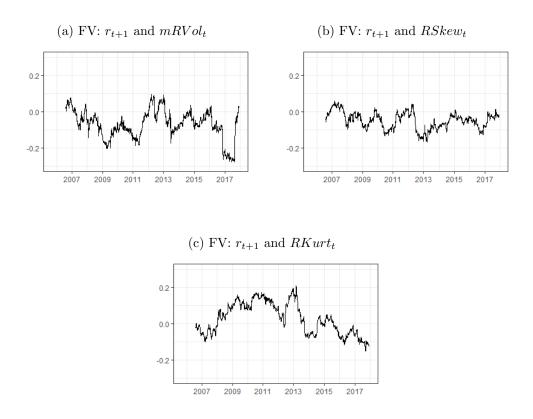


Figure 17: 5-year U.S. Treasury futures: Dynamic correlations of realized moments with next day open-close return.

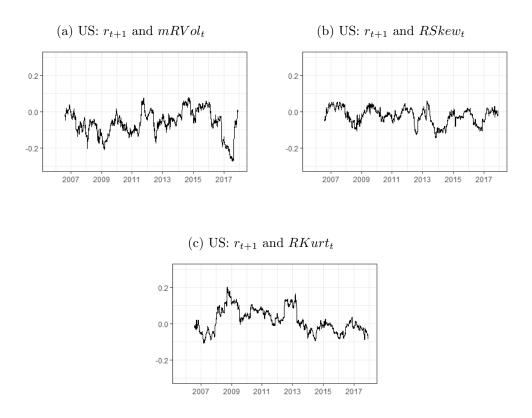


Figure 18: 30-year U.S. Treasury futures: Dynamic correlations of realized moments with next day open-close return.

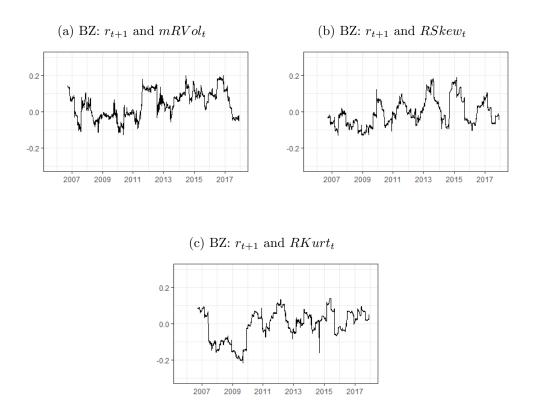


Figure 19: 2-year German bond futures: Dynamic correlations of realized moments with next day open-close return.

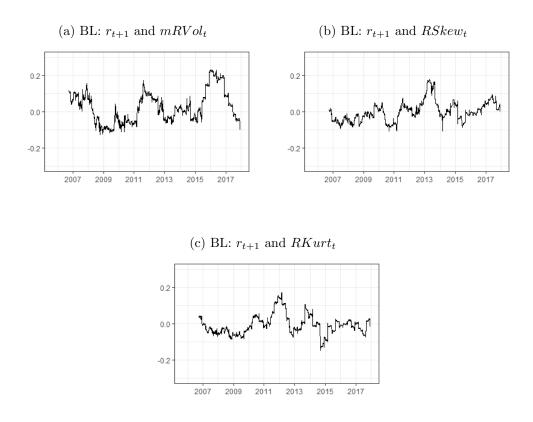


Figure 20: 5-year German bond futures: Dynamic correlations of realized moments with next day open-close return.

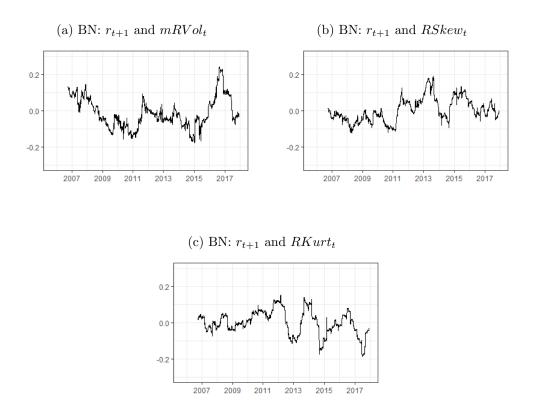


Figure 21: 10-year German bond futures: Dynamic correlations of realized moments with next day open-close return.

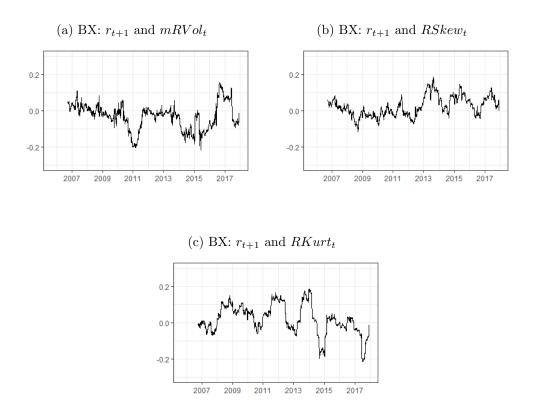


Figure 22: 30-year German bond futures: Dynamic correlations of realized moments with next day open-close return.

	1.00 0.93 0.76 0.02 0.01 0.01 0.01	$\begin{array}{c} 1.00\\ 0.86\\ 0.01\\ 0.00\\ 0.00\\ 0.01\end{array}$	1.00 0.01 0.00 0.00 -0.01	$\begin{array}{c} 1.00\\ 0.91\\ 0.83\\ 0.68\end{array}$	$\begin{array}{c} 1.00\\ 0.95\\ 0.83\end{array}$	1.00 0.93	1.00								
m 10 1 10 10	$\begin{array}{c} 0.46 \\ 0.52 \\ 0.48 \\ 0.43 \\ -0.10 \end{array}$	0.38 0.47 0.50 0.45 -0.06	$\begin{array}{c} 0.24\\ 0.35\\ 0.39\\ 0.46\\ 0.00\end{array}$	$\begin{array}{c} 0.03 \\ 0.05 \\ 0.04 \\ 0.05 \\ -0.13 \end{array}$	$\begin{array}{c} 0.04 \\ 0.06 \\ 0.05 \\ 0.05 \\ -0.11 \end{array}$	$\begin{array}{c} 0.04 \\ 0.06 \\ 0.05 \\ 0.06 \\ -0.16 \end{array}$	$\begin{array}{c} 0.04 \\ 0.06 \\ 0.06 \\ 0.07 \\ -0.20 \end{array}$	$1.00 \\ 0.74 \\ 0.70 \\ 0.57 \\ -0.21$	1.00 0.90 0.78 -0.17	$1.00 \\ 0.86 \\ -0.15$	1.00-0.14	1.00			
	-0.12 -0.09 -0.11 0.47 0.52	-0.07 -0.10 -0.10 0.46 0.55	-0.04 -0.05 -0.05 0.40 0.52	-0.14 -0.12 -0.15 0.04 0.01	-0.13 -0.10 -0.14 0.04 0.00	-0.14 -0.12 -0.15 0.05 0.01	-0.16 -0.13 -0.18 0.05 0.01	-0.15 -0.14 -0.16 0.19 0.17	-0.27 -0.21 -0.26 0.20 0.22	-0.20 -0.28 -0.30 0.20 0.23	-0.22 -0.27 -0.37 0.20 0.24	$\begin{array}{c} 0.72 \\ 0.68 \\ 0.57 \\ 0.01 \\ 0.01 \end{array}$	1.00 0.88 0.78 0.02 0.02	1.00 0.86 0.03 0.03	$1.00 \\ 0.02 \\ 0.00 $
0.43 0.33 0.01 -0.01 -0.01	0.57 0.45 0.01 -0.02 -0.02	0.63 0.52 0.00 -0.04	0.63 0.57 0.00 -0.03 -0.04	-0.01 -0.01 0.74 0.58 0.42 0.31	-0.02 -0.02 0.76 0.69 0.56	-0.02 -0.02 0.73 0.68 0.68	-0.02 -0.02 0.55 0.63 0.71	0.18 0.02 0.02 0.02	0.26 0.23 0.00 0.00	0.27 0.24 0.00 -0.01 -0.01	0.30 0.28 -0.01 -0.02	0.01 0.01 0.01 -0.01 -0.02	0.02 -0.01 0.01 0.00	$0.02 \\ 0.01 \\ $	0.00 0.00 0.01 0.00 0.00
-0.04 0.15 0.16 0.19 0.00 0.00 0.00 0.00	-0.05 0.15 0.20 0.24 0.24 -0.01 0.00 0.00 0.00	-0.06 0.15 0.21 0.25 0.26 0.00 0.00 0.00 0.00	-0.06 0.14 0.20 0.25 -0.25 -0.01 -0.01 -0.01	$\begin{array}{c} 0.31\\ 0.03\\ 0.01\\ 0.00\\ 0.00\\ 0.10\\ 0.10\\ 0.02\\ 0.01\\ 0.01\\ 0.10\\ 0.10 \end{array}$	$\begin{array}{c} 0.42\\ 0.05\\ 0.03\\ 0.03\\ 0.01\\ 0.11\\ 0.11\\ 0.03\\ 0.02\\ 0.02\\ 0.12\end{array}$	$\begin{array}{c} 0.53\\ 0.05\\ 0.06\\ 0.04\\ 0.03\\ 0.01\\ 0.01\\ 0.01\\ 0.01\\ 0.01\\ 0.01\end{array}$	$\begin{array}{c} 0.65\\ 0.04\\ 0.04\\ 0.03\\ 0.03\\ 0.02\\ 0.03\\ 0.03\\ 0.03\\ 0.03\\ 0.03\\ 0.10\end{array}$	$\begin{array}{c} 0.01\\ 0.18\\ 0.18\\ 0.18\\ 0.23\\ 0.23\\ 0.23\\ 0.03\\ 0.03\\ 0.03\\ 0.03\end{array}$	$\begin{array}{c} 0.00\\ 0.18\\ 0.23\\ 0.29\\ 0.29\\ 0.03\\ 0.01\\ 0.01\end{array}$	$\begin{array}{c} 0.00\\ 0.18\\ 0.23\\ 0.31\\ 0.32\\ 0.03\\ 0.02\\ 0.01\\ 0.01\end{array}$	-0.01 0.17 0.23 0.30 0.02 0.02 0.00 0.00	-0.02 0.04 0.03 0.01 0.01 0.01 0.12 0.12 0.12	$\begin{array}{c} 0.00\\ 0.05\\ 0.04\\ 0.01\\ 0.01\\ 0.01\\ 0.02\\ 0.12\\ 0.16\\ 0.14\\ 0.14\end{array}$	0.00 0.05 0.03 0.01 0.01 0.01 0.17 0.17 0.16	-0.01 0.03 0.00 0.02 -0.03 0.05 0.15 0.15 0.15
BZ ret 1.00 0.67 0.67 0.67 0.61 0.02 0.02 0.02 0.03 0.46 0.46 0.46 0.38 0.38 0.38 0.38 0.38 0.13 0.13 0.13 0.13 0.13 0.13 0.02 0.02 0.02 0.02 0.02 0.02 0.02 0.0	BL ref ref. 1.00 1.00 1.00 1.00 1.00 1.00 1.00 1.0	BN ret 	<b>BX</b> ret 1.00 -0.03 -0.04 -0.05 0.38 0.44 0.58 0.48 0.58 0.48 0.58 0.48 0.58	BZ mRVol 1.00 0.91 0.65 0.41 0.65 0.02 -0.03 -0.03 0.14 0.03 0.14	BL mRVol 1.00 0.56 0.02 0.01 0.01 0.00 0.15 0.03 0.15	BN mRVol 1.00 0.03 0.00 0.00 0.00 0.00 0.00 0.00	BX mRVol 1.00 0.04 0.03 0.03 0.03 0.00 0.01 0.05 0.03	BZ RSkew 1.00 0.64 0.54 0.54 0.46 -0.15 -0.15	BL RSkew 1.00 0.59 0.58 0.59 0.59 -0.16 -0.18	BN RSkew 0.68 -0.14 -0.25 -0.25 -0.16	BX RSkew 1.00 -0.12 -0.21 -0.15	BZ RKurt 1.00 0.59 0.47 0.38	BL RKurt 1.00 0.86 0.61	BN RKurt 1.00 0.68	BX RKurt 1.00

BZ: 2-year (daily)	Min	1st quartile	Median	Mean	3rd quartile	Max
Intercept	-0.048	-0.015	-0.005	-0.008	-0.002	0.012
mRVol	-0.076	0.080	0.129	0.129	0.182	0.472
RSkew	-0.004	-0.002	0.000	0.000	0.003	0.005
RKurt	0.000	0.000	0.000	0.000	0.000	0.000
Ret	-0.212	-0.072	-0.051	-0.053	-0.025	0.003
$\Delta$ Term spread	-0.119	-0.018	0.009	0.005	0.034	0.094
$\Delta$ Default spread	-0.391	-0.070	0.027	0.035	0.137	0.721
$R^2$	2.9%					
BL: 5-year (daily)	Min	1st quartile	Median	Mean	3rd quartile	Max
Intercept	-0.114	-0.041	-0.024	-0.022	-0.004	0.039
mRVol	-0.136	0.037	0.166	0.165	0.266	0.601
RSkew	-0.009	-0.003	0.001	0.002	0.006	0.013
RKurt	-0.001	0.000	0.000	0.000	0.000	0.001
Ret	-0.151	-0.053	-0.022	-0.028	0.003	0.049
$\Delta$ Term spread	-0.335	-0.185	0.017	-0.020	0.111	0.306
$\Delta$ Default spread	-1.084	-0.446	-0.073	-0.102	0.205	1.479
$R^2$	1.7%					
BN: 10-year (daily)	Min	1st quartile	Median	Mean	3rd quartile	Max
Intercept	-0.160	-0.026	0.008	-0.002	0.028	0.074
mRVol	-0.192	-0.058	0.009	0.038	0.086	0.564
RSkew	-0.021	-0.007	0.003	0.003	0.014	0.024
RKurt	-0.001	0.000	0.000	0.000	0.000	0.001
Ret	-0.131	-0.057	-0.031	-0.032	-0.008	0.042
$\Delta$ Term spread	-0.603	-0.401	-0.199	-0.225	-0.103	0.444
$\Delta$ Default spread	-1.609	-0.809	-0.101	-0.198	0.216	1.880
$R^2$	1.5%					
BX: 30-year (daily)	Min	1st quartile	Median	Mean	3rd quartile	Max
Intercept	-0.153	-0.026	0.039	0.034	0.110	0.173
mRVol	-0.227	-0.125	-0.077	-0.060	0.014	0.171
RSkew	-0.015	0.000	0.019	0.016	0.033	0.050
RKurt	-0.002	0.000	0.001	0.001	0.002	0.003
Ret	-0.144	-0.091	-0.056	-0.053	-0.016	0.032
$\Delta$ Term spread	-1.587	-0.899	-0.706	-0.733	-0.497	0.290
$\Delta$ Default spread	-3.765	-0.897	0.372	0.089	0.738	3.991
$R^2$	1.3%					

Table 9: Summary statistics of time-varying coefficients (Germany)

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Univerzita Karlova v Praze, Fakulta sociálních věd Institut ekonomických studií [UK FSV – IES] Praha 1, Opletalova 26 E-mail : ies@fsv.cuni.cz http://ies.fsv.cuni.cz