J. Int. Financ. Markets Inst. Money 62 (2019) 53–73

Contents lists available at ScienceDirect

Journal of International Financial Markets, Institutions & Money

journal homepage: www.elsevier.com/locate/intfin

Sovereign bond return prediction with realized higher moments ☆

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ARTICLE INFO

Article history:
Received 1 February 2019
Accepted 18 May 2019
Available online 29 May 2019

JEL classification:
C1
G10
G15
G17

Keywords:
Sovereign bond markets
High-frequency data
Realized higher moments
Hyper-skewness
Hyper-kurtosis
Out-of-sample prediction

ABSTRACT

This paper analyzes whether realized higher moments are able to predict out-of-sample sovereign bond returns using high-frequency data from the European bond market. We study bond return predictability over tranquil and crisis periods and across core and periphery markets at the index and country level. We provide fresh evidence that realized kurtosis is the dominant predictor of subsequent returns among higher moments and other predictors such as CDS spreads, short-term interest rates and implied stock market volatility. Our findings further underline that sovereign bond return predictability is stronger during crisis periods and more pronounced for bonds of lower credit ratings.

1. Introduction

Asset return predictability has a long tradition in finance which goes back to the work of Dow (1920). One of the most prominent variables explored in the literature is return variance. Classical mean-variance portfolio analysis focuses on the first two moments of returns under the assumption that the distributions of asset returns follow a normal distribution (Lintner, 1965). However, asset returns exhibit asymmetries (especially those of bonds which are skewed by nature) and are fat-tailed relative to a normal distribution, justifying the need to examine higher moments in predictive regression models and asset pricing frameworks. Arditti (1967), Kraus and Litzenberger (1976), and Kane (1982) extend the standard mean-variance portfolio theory to incorporate the effect of skewness on valuation. They propose a three-moment asset pricing

☆ Papavassiliou would like to acknowledge the support of University College Dublin for financial assistance under grant number SF1258. We would like to thank two anonymous referees as well as Guido Mantovani, Kim Cuong Ly, and conference participants at the 2019 Financial Management Association (FMA) European Conference, and the INFINITI 2019 Conference on International Finance (both in Glasgow) for helpful comments. All omissions and errors remain with the authors.
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https://doi.org/10.1016/j.intfin.2019.05.002
1042-4431/

model in which investors show preference to positive skewness and an aversion to variance and find that assets that increase a portfolio's skewness are more desirable and must generate lower expected returns.

Recent empirical work provides evidence that higher moments of the return distribution are important in pricing securities. It is worth mentioning that the bulk of studies rely on in-sample prediction which does not necessarily imply out-of-sample predictability. There is a number of recent studies that have analyzed the forecasting power of higher moments, i.e. skewness and kurtosis, for stocks and corporate bonds mainly from the U.S. markets (Dittmar, 2002; Xing et al., 2010; Amaya et al., 2015; Bai et al., 2016). Nevertheless, no study has addressed the issue of out-of-sample forecasting performance of higher moments for sovereign bond market returns and we aim at filling this gap in the related literature.[1]

Our study contributes to this strand of research in a number of ways. First, we analyze for the first time whether higher moments are able to predict out-of-sample sovereign bond returns using data from the European bond market. Following the realized volatility literature, we construct realized higher moments as well as realized hyper moments that have been proposed only recently. Second, we employ a rich and detailed high-frequency dataset provided by MTS (Mercato dei Titoli di Stato), Europe's premier electronic fixed-income trading market for euro-denominated government bonds. High-frequency data facilitate the construction of more efficient volatility measures compared to data of lower frequencies, such as monthly or daily. Moreover, our rich high-frequency dataset allows the construction of realized higher moments from intraday returns as opposed to ordinary higher moments constructed from asset returns sampled at lower frequencies.

To construct higher moments, we use the daily realized variance approach popularized by Andersen and Bollerslev (1998) and Andersen et al. (2001) who show that high-frequency returns allow for the construction of more efficient model-free *ex-post* volatility measurements via cumulative squared intraday returns. As Gargano et al. (2019) argue, focusing on the higher-frequency not only expands the number of non-overlapping observations, which in turn helps to minimize parameter estimation error, but also allows the identification of short-term dynamics in the lower moments of bond returns which cannot be captured by models of lower frequency. This is an important consideration especially during periods of stress such as the European sovereign debt crisis period.

Third, our data sample includes both tranquil and crisis periods, thus it provides an ideal laboratory to study bond return predictability over different states of the economy. Along these lines, we provide fresh evidence on bond return predictability across core and periphery European markets.[2] Fourth, we study the out-of-sample forecasting performance of higher moments in comparison to a set of alternative predictors. Specifically, we employ relative spread and quoted depth liquidity measures which are able to capture the tightness and depth liquidity dimensions. Previous research has shown that there is strong bidirectional causality between liquidity and returns and that liquidity is a priced risk factor (Amihud and Mendelson, 1986; Pástor and Stambaugh, 2003; Goyenko et al., 2011). In addition, Kinateder and Wagner (2017) document that country-specific bond liquidity as well as market liquidity are both priced in the European Monetary Union (EMU) sovereign bond market. Our third and fourth alternative predictors are the 3-month Euribor rate and the VIX volatility index which have shown to be good predictors of expected returns (Whaley, 2000; Batten and Hogan, 2003). Moreover, we employ principal component analysis (PCA) to construct a novel common risk factor extracted from realized volatility, realized skewness, and realized kurtosis, in line with Bai et al. (2016). As previous work finds evidence for CDS spreads and a first-order autoregressive term to be efficient predictors of bond returns, we also include those variables as additional predictors in our empirical analysis (Duffie, 1999; Bao et al., 2011; Fontana and Scheicher, 2016). Finally, our study investigates if realized higher moments are useful for time-series forecasting of future returns. As Amaya et al. (2015) argue, although there is evidence on the cross-section of equity returns, there is lack of evidence on time-series forecasting with higher moments.

For our set of predictors, we analyze the relative out-of-sample forecasting performance of each predictor compared to a naïve forecast using the historical average of bond returns. As it is widely acknowledged, it is hard to beat the historical average in out-of-sample forecasts (see Welch and Goyal, 2008 for a discussion). The historical average model corresponds to the restricted version of the predictive regression model, thus our approach yields nested forecasts. More specifically, we perform a horse race among the various realized higher moments and alternative predictors, which allows us to evaluate the out-of-sample forecasting power of these variables in a comprehensive manner. One of the potential problems when forecasting bond returns could be the fact that predictability is sample dependent. As a result, we study predictability in different economic conditions, i.e. before and during the European sovereign debt crisis.

Our study is motivated by the unique market features of the sovereign bond market and investors' perceptions of risk. Although firms that issue stocks exhibit limited exposure to default risk, issuers of sovereign debt are susceptible to default risk which affects the determination of sovereign bond returns over time. This is particularly important during episodes of market turmoil where the long-term debt sustainability of countries may be challenged. Moreover, bondholders exhibit higher sensitivity to downside risk than stockholders and may ask for higher compensation in the form of a greater future return (Bai et al., 2016).

Why should one expect sovereign bond returns to be predictable using higher moments? The answer lies within the nature of the bond return distribution. As sovereign bond returns may have skewed and leptokurtic distributions, relying only on standard deviation to capture the variability of returns is inadequate. Therefore, we should consider higher-order

[1] The study by Fujiwara et al. (2013) investigates asymmetries in the distribution of government bond returns and although it provides some evidence on the relationship between bond returns and the coefficient of skewness, it does not address the issue of out-of-sample forecasting performance of higher moments.

[2] Periphery countries are those that borrowed money from their European counterparts and the International Monetary Fund in order to avoid default during the European sovereign debt crisis.

moments as more efficient measures of dispersion and variability. A relative discussion is provided by Cont (2001). Moreover, the fact that the normal distribution assigns very small probabilities to extreme market episodes that in reality occur much more often than predicted by normality assumptions, necessitates the use of higher moments that are able to capture extreme outcomes in asymmetric bond return distributions (Xiong and Idzorek, 2011; Neuberger, 2012).

Essentially, high skewness should coincide with a low prospective return (Brunnermeier et al., 2007; Barberis and Huang, 2008). A possible explanation is provided by Bali et al. (2011) and Bordalo et al. (2013), namely that securities with negative (positive) skewness are undervalued (overvalued). Moreover, negative skewness indicates greater exposure to downside risk, thus assets with negatively skewed returns should require higher returns. Garrett and Sobel (1999) and Walker and Young (2001) argue that it is the level of skewness in the payoffs that intrigues participants. Kurtosis, on the other hand, should exhibit a positive relationship with expected returns as rational investors will seek for protection in order to undertake additional amounts of excessive kurtosis (Dittmar, 2002). Bai et al. (2016) argue that investors are averse to kurtosis and prefer securities with lower probability mass in the tails of the distribution, that is, there is preference for lower kurtosis. Blau and Whitby (2016) find that stocks with high idiosyncratic kurtosis underperform stocks with low idiosyncratic kurtosis, even after controlling for idiosyncratic volatility and skewness.

Our main findings are summarized as follows: (a) realized kurtosis is the dominant predictor for GIPS countries especially during the crisis period[3]; (b) realized volatility outperforms realized skewness and realized kurtosis for non-GIPS countries in the crisis period; (c) liquidity and a first-order autoregressive term are the only alternative predictors which outperform realized kurtosis for GIPS countries during the crisis at both the index and country level; (d) sovereign bond return predictability is stronger during periods of market turmoil and more pronounced for bonds of lower credit ratings, such as those of Greece and Portugal; (e) sovereign bond returns are hardly predictable during tranquil periods.

The rest of the paper is organized as follows. Section 2 discusses the related literature. Section 3 presents the empirical methodology and describes the dataset employed. Section 4 discusses the empirical results. Finally, Section 5 concludes the paper.

2. Related literature

The academic literature on asset return predictability using higher moments is scarce and in fact non-existent for sovereign bond markets. In this section, we provide a selective literature review on related studies from various financial markets. Not only we refer to previous studies that have dealt with asset return predictability using higher moments, but also to studies that have examined the cross-sectional relations between higher moments and future asset returns. In doing so, we aim at putting into perspective the significant role higher moments play in explaining asset subsequent returns.

Earlier research on the relationship between higher moments and asset returns has mainly focused on the stock market. Welch and Goyal (2008) study the in-sample and out-of-sample performance of linear regressions that predict the equity premium with variables suggested by the academic literature and find that most predictors exhibit poor and unstable out-of-sample results. Rapach et al. (2010) using forecast combining methods find that the out-of-sample predictive ability of a selection of economic variables (dividend-price ratio, stock variance, Treasury bill rate, inflation, among others) is quite satisfactory over a number of periods. Ang et al. (2006) and Conrad et al. (2013) find a negative link between stock returns and idiosyncratic volatility and Fu (2009) shows that there is a significant positive relation between conditional volatility and expected stock returns. Xing et al. (2010) and Conrad et al. (2013) find a negative relationship between skewness and expected stock returns, whereas Bali et al. (2011) find a positive but statistically insignificant relationship, thus evidence in relation to the third higher moment can be regarded as inconclusive.[4] A significant negative relation between skewness and subsequent returns essentially means that more negatively skewed securities will exhibit higher subsequent returns. Conrad et al. (2013) provide additional evidence that the relation between idiosyncratic skewness and subsequent returns persists even after controlling for differences in covariance, coskewness, and cokurtosis.

Khademalomoom et al. (2019) propose a higher moments GARCH model to study the out-of-sample predictability for exchange rates during the period 2004–2014. In addition, the authors consider the fifth and sixth higher moments, i.e. hyper-skewness and hyper-kurtosis. The authors find that the higher moments GARCH model shows better forecasting performance (both statistical as well as economic) than the ordinary GARCH model.

Neuberger (2012) proposes a definition of the realized third moment that is computed from high-frequency returns and from option returns and demonstrates that the skewness of equity index returns increases with horizons up to a year and its magnitude is economically significant. Evidence on the role kurtosis plays in predicting stock returns is scarce and mainly confirms kurtosis importance in pricing individual stocks (Dittmar, 2002; Conrad et al., 2013; Amaya et al., 2015). As Conrad et al. (2013) demonstrate, this relation persists after controlling for firm characteristics, such as beta, size, and book-to-market ratios, and adjustment for the Fama and French (1993) risk factors. Jondeau et al. (2018) show that the

[3] We use the acronym GIPS to refer to the distressed economies of Greece, Italy, Portugal and Spain which was popularized during the European sovereign debt crisis. Correspondingly, the acronym non-GIPS refers to the core eurozone economies.

[4] Regarding coskeweness – an asset's return comovement with volatility - studies have shown that it matters significantly in predicting equity returns (Harvey and Siddique, 2000; Chang et al., 2013). Theoretical explanations on the role coskeweness plays in determining the cross-section of stock returns is provided by Kraus and Litzenberger (1976) among others.

value-weighted average of stock skewness is the best predictor of future market returns and also economically significant out-of-sample.

Bai et al. (2016, 2019) study whether the distributional characteristics of corporate bonds predict cross-sectional differences in future bond returns. Using a detailed dataset of corporate bond returns for the period 1973–2012, they document a significantly positive link between volatility and expected returns and a negative link between skewness and expected returns, even after controlling for credit rating, maturity, size, and liquidity risk of corporate bonds. Moreover, the significance of the cross-sectional relationship between kurtosis and future returns appears to be weak both from a statistical and economic point of view.

There are a few more studies on the cross-sectional determinants of corporate bond returns such as those of Fama and French (1993) and Gebhardt et al. (2005) which provide evidence that default and term premia, as well as their corresponding betas, are significantly related to bond returns after controlling for various bond characteristics. Lin et al. (2011), Acharya et al. (2013), and Bongaerts et al. (2017) focus on liquidity risk considerations in the corporate bond market and show that expected liquidity and liquidity risk are priced factors in the cross-section of corporate bond returns. Finally, Chordia et al. (2015) and Choi and Kim (2018) investigate the importance of equity market anomalies in relation to the cross-section of corporate bond returns.

Evidence on sovereign bond markets mainly focuses on the in-sample predictability of short to medium-term bond returns using variables such as forward spreads (Fama and Bliss, 1987; Cochrane and Piazzesi, 2005), yield spreads (Campbell and Shiller, 1991), factors extracted from the cross-section of macroeconomic variables (Ludvigson and Ng, 2009), or simply using basic measures of forecast accuracy (Kunze et al., 2017). Fujiwara et al. (2013) study conditional asymmetries in government bond excess returns for five developed markets - Canada, Germany, Japan, U.K. and the U.S. – and find that positive bond returns are associated with negative skewness and that bond liquidity is able to forecast skewness with a positive sign. Chiang (2016) explores properties of third moments – skewness and coskewness – in discrete holding-period Treasury and corporate bond returns and finds that longer maturity bonds have lower skewness and coskewness with respect to a bond market index. Moreover, bonds of lower quality exhibit lower skewness but higher coskewness with respect to a broad-based bond index than higher quality bonds. To the best of our knowledge, there is no previous work dealing with the importance of higher moments in predicting sovereign bond returns in an out-of-sample setting and we hope that our study will shed some light on this open issue.

3. Methodology and data

This section provides (a) the predictive regression approach and the statistical as well as economic criteria used to evaluate out-of-sample predictions of the market return, along with results of economic significance of the predictive regressions; (b) the theoretical framework upon which the construction of realized higher moments is based, as well as a description of our methodological approach; (c) a description of the dataset and data handling procedures; (d) a discussion on the alternative predictors used and the rationale for their inclusion in the empirical analysis.

3.1. Predictive regression model

To predict the one-step-ahead bond market return we use a predictive regression model of the following form in line with Rapach et al. (2010) and Ferreira and Santa-Clara (2011):

$$R_{b,t+1} = \alpha + \beta z_t + \varepsilon_{t+1}, \tag{1}$$

where z_t denotes the predictive variable, $R_{b,t+1}$ is the sovereign bond return of country b at time $t+1$, and ε_{t+1} denotes the error term. Our set of predictive variables includes realized higher moments as well as alternative predictors, which are presented in Sections 3.2 and 3.4. We generate out-of-sample predictions by applying a recursive window with initial length q_0, that is, we use $t = 1, \ldots, q$ observations from a sample consisting of T observations, where $1 \leqslant t \leqslant q \leqslant T-1$, to estimate

$$R_{b,t} = \alpha + \beta z_{t-1} + \varepsilon_t. \tag{2}$$

In a second step, we predict the first out-of-sample sovereign bond market return at day $q+1$:

$$\widehat{R}_{b,q+1} = \widehat{\alpha} + \widehat{\beta} z_q, \tag{3}$$

where $\widehat{\alpha}$ and $\widehat{\beta}$ are the estimated coefficients of Eq. (2). The aforementioned procedure described in Eqs. (2) and (3) is repeated by expanding the recursive window from time $q = q_0, \ldots, T-1$ which yields a sequence of $T - q_0$ out-of-sample sovereign bond return predictions.

3.1.1. Statistical significance

To evaluate the statistical accuracy of out-of-sample predictions, we employ the out-of-sample R-squared, OOS-R^2 proposed by Campbell and Thompson (2008) as well as the Clark and West (2007) MSPE-adjusted statistic. The OOS-R^2 measures the mean squared prediction error (MSPE) of an out-of-sample forecast from a predictive regression relative to a given benchmark, which in our case is the historical average return. Formally, it is defined as

$$\text{OOS-}R^2 = 1 - \frac{MSPE_{PR}}{MSPE_{HA}}, \tag{4}$$

where $\text{OOS-}R^2 \in [-\infty; 1]$ with

$$MSPE_{PR} = \frac{1}{T - q_0} \sum_{t=q_0}^{T-1} \left(R_{b,t+1} - \widehat{R}_{b,t+1}\right)^2, \tag{5}$$

where $MSPE_{PR}$ is the mean squared prediction error of the unrestricted predictive regression model and $\widehat{R}_{b,t+1}$ denotes the predicted bond market return, whilst

$$MSPE_{HA} = \frac{1}{T - q_0} \sum_{t=q_0}^{T-1} \left(R_{b,t+1} - \overline{R}_{b,t+1}\right)^2, \tag{6}$$

where $MSPE_{HA}$ is the mean squared prediction error of the restricted benchmark model and $\overline{R}_{b,t+1}$ is the rolling estimate of the historical average bond market return. Eq. (6) implies that the benchmark is based on a sovereign bond return prediction consistent with a random walk model with drift, where negative (positive) values of $\text{OOS-}R^2$ indicate that the predictive model underperforms (outperforms) the benchmark (Jordan et al., 2014).

Clark and West (2007) propose an adjustment in the point estimate of the difference between MSPEs of two competing models in terms of the noise associated with the larger model's forecast. Along these lines, the statistical inference of our out-of-sample predictions is evaluated using the Clark-West MSPE-adjusted statistic, as the authors demonstrate that the original MSPE statistic is not asymptotically normally distributed. The Clark-West MSPE-adjusted statistic is conveniently computed by defining

$$\widehat{f}_{t+1} = \left(R_{b,t+1} - \overline{R}_{b,t+1}\right)^2 - \left[\left(R_{b,t+1} - \widehat{R}_{b,t+1}\right)^2 - \left(\overline{R}_{b,t+1} - \widehat{R}_{b,t+1}\right)^2\right], \tag{7}$$

where period t forecasts of $R_{b,t+1}$ from the parsimonious model (i.e. historical average) and the larger model defined in Eq. (2) that nests the parsimonious one are denoted as $\overline{R}_{b,t+1}$ and $\widehat{R}_{b,t+1}$, respectively. The one-sided test for MSPEs which is denoted t-DM thereafter, involves regressing $\widehat{f}_{t+1}$ on a constant and using the resulting t-statistic for a coefficient lower than or equal to zero. Rejection of the null hypothesis $\left(H_0 : \text{OOS-}R^2 \leqslant 0\right)$ implies that the MSPE of the predictive model is significantly lower than the MSPE of the historical average.

3.1.2. Economic significance

Next, we address the issue of economic significance since predictive regressions having a positive $OOS\text{-}R^2$ do not necessarily produce positive gains for investors in terms of higher portfolio returns (see for example Campbell and Thompson, 2008). Another limitation of $OOS\text{-}R^2$ is the fact that it does not consider the risk an investor has to bear over his out-of-sample investment horizon (Rapach et al., 2010). Since $OOS\text{-}R^2$ is based on the MSPE, it may overestimate the effect of extreme outliers.

In order to address this problem, we follow the literature and compute the utility gain for a mean-variance investor who daily allocates his portfolio between the risk-free short-term interest rate and (risky) sovereign bonds (see Campbell and Thompson, 2008; Rapach et al., 2010; Ferreira and Santa-Clara, 2011; Zhu and Zhu, 2013; Jordan et al., 2014). The resulting return of this two-asset portfolio is

$$R_{p,t+1} = \left(1 - \omega_{b,t+1}\right) R_{f,t+1} + \omega_{b,t+1} R_{b,t+1}, \tag{8}$$

where $R_{f,t+1}$ denotes the short-term risk-free rate, which is proxied by the 3-month Euribor. As a result, the next day's optimal portfolio weights of sovereign bonds, $\omega^*_{b,t+1}$, are calculated at the end of day t considering an investor's relative risk aversion γ and the next day's prediction from the historical average, $\overline{R}_{b,t+1}$, and our predictive model, $\widehat{R}_{b,t+1}$, respectively. The optimal weights for the historical average, $\omega^*_{HA,t}$, and the predictive model, $\omega^*_{PR,t}$, are (Rapach et al., 2010; Zhu and Zhu, 2013)

$$\omega^*_{HA,t} = \frac{\overline{R}_{b,t+1} - R_{f,t+1}}{\gamma \hat{\sigma}^2_{b,t+1}} \tag{9}$$

and

$$\omega^*_{PR,t} = \frac{\widehat{R}_{b,t+1} - R_{f,t+1}}{\gamma \hat{\sigma}^2_{b,t+1}}. \tag{10}$$

As in Campbell and Thompson (2008), we use a rolling window with size q_0 to estimate $\hat{\sigma}^2_{b,t+1}$ and impose the following constraint for the portfolio weight of sovereign bonds: $0 \leqslant \omega_{b,t+1} \leqslant 1.5$. Given optimal portfolio weights, the estimated utility, U_{HA}, for a mean-variance investor using the historical average is

$$U_{HA} = \frac{1}{T - q_0} \sum_{t=q_0}^{T-1} \left[R_{HA,t+1} - \frac{\gamma}{2} \omega_{HA,t+1}^{*2} \sigma_{HA,t+1}^2 \right], \tag{11}$$

where $R_{HA,t+1}$ and $\sigma_{HA,t+1}^2$ are the *ex-post* return and variance from a portfolio defined in Eq. (8) based on portfolio weights in Eq. (9).

The utility gain, U_{PR}, for a mean-variance investor using our predictive regression model is

$$U_{PR} = \frac{1}{T - q_0} \sum_{t=q_0}^{T-1} \left[R_{PR,t+1} - \frac{\gamma}{2} \omega_{PR,t+1}^{*2} \sigma_{PR,t+1}^2 \right], \tag{12}$$

where $R_{PR,t+1}$ and $\sigma_{PR,t+1}^2$ are the *ex-post* return and variance from a portfolio defined in Eq. (8) based on portfolio weights in Eq. (10). Given that, the average annualized percentage utility gain, ΔU, is

$$\Delta U = (U_{PR} - U_{HA}) \times 25,000. \tag{13}$$

3.2. Realized higher moments

We construct higher moments computed from intraday returns. Merton (1980) was the first to note that as the sampling frequency increases to infinity, volatility estimates become more efficient. Given this logic, we use the realized variance approach popularized by Andersen and Bollerslev (1998) and Andersen et al. (2001, 2003) to obtain improved daily volatility measures. Following Andersen et al. (2005) the stochastic differential equation can conveniently express continuous-time volatility models:

$$dP_t = \mu_t dt + \sigma_t dW_t, \tag{14}$$

where W_t denotes a standard Brownian motion, μ_t is a predictable drift term of finite variation and P_t denotes the asset price. The one-period continuously compounded return for the price process in Eq. (8) is given by

$$R_t \equiv \ln(P_t) - \ln(P_{t-1}) = \int_{t-1}^{t} \mu_u du + \int_{t-1}^{t} \sigma_u dW_u. \tag{15}$$

The one-period returns are Gaussian with conditional mean equal to $\int_{t-1}^{t} \mu_u du$ and conditional variance equal to integrated volatility,

$$IV_t \equiv \int_{t-1}^{t} \sigma_u^2 du \tag{16}$$

which is a natural measure of the *ex-post* return variability. Following the theory of quadratic variation, daily realized variance on day t is obtained by summing squares of high-frequency returns:

$$Var_t^{realized} = \sum_{i=1}^{N_t} R_{b,i}^2, \tag{17}$$

where $i = 1, \ldots, N_t$ denotes number of 5-min intraday returns $R_{b,i}$ within each trading day t, which is used to construct daily moments. Daily realized volatility is obtained using the square-root of the variance series and converges uniformly in probability to IV_t:

$$Vol_t^{realized} = \sqrt{\sum_{i=1}^{N_t} R_{b,i}^2}. \tag{18}$$

These model-free types of measures provide more efficient *ex-post* observations on the realized return variation than more conventional sample variances which are based on return observations of lower frequencies (Barndorff-Nielsen and Shephard, 2002). Along these lines, we construct daily realized variance measures by the summation of squared 5-min intraday returns.

Next, we introduce model-free estimates of higher moments based on the methodology proposed by Amaya et al. (2015). For this purpose, we use 5-min returns $R_{b,i}$ to construct *ex-post* realized daily skewness and kurtosis measures as follows:

$$Skew_t^{realized} = \frac{N_t^{1/2} \sum_{i=1}^{N_t} R_{b,i}^3}{\left(Var_t^{realized} \right)^{3/2}} \tag{19}$$

and

$$Kurt_t^{realized} = \frac{N_t \sum_{i=1}^{N_t} R_{b,i}^4}{\left(Var_t^{realized} \right)^{2}}. \tag{20}$$

Amaya et al. (2015) verify with the use of Monte Carlo simulations that the measurement of the realized higher moments is reliable in finite samples and that it is robust to the presence of market microstructure noise as well as to quote discontinuities.[5]

Apart from the third moment (skewness) and the fourth moment (kurtosis), Khademalomoom et al. (2019) discuss the usage of so-called hyper moments, which provide additional information to the aforementioned moments. For robustness, we also consider these moments as potential predictors of sovereign bond returns.

Realized hyper-skewness (fifth moment) accounts for asymmetric sensitivity of realized kurtosis (Khademalomoom et al., 2019):

$$HSkew_t^{realized} = \frac{N_t^{3/2}\sum_{i=1}^{N_t} R_{b,i}^5}{\left(Var_t^{realized}\right)^{5/2}}. \tag{21}$$

Realized hyper-kurtosis (sixth moment) evaluates the tails and peakedness relative to the Gaussian distribution (Khademalomoom et al., 2019):

$$HKurt_t^{realized} = \frac{N_t^{2}\sum_{i=1}^{N_t} R_{b,i}^6}{\left(Var_t^{realized}\right)^{3}}. \tag{22}$$

All realized higher moments and realized hyper moments and sovereign bond returns have been constructed at both the country and index level. Daily sovereign bond returns and realized higher moments are aggregated in order to obtain an aggregate equally-weighted market index measure for periphery (GIPS) and core (non-GIPS) countries.[6]

3.3. Data

Our dataset is provided by the MTS market which is the largest quote-driven interdealer electronic fixed-income market for euro-denominated government bonds.[7] It covers the period from January 2008 to December 2010 and includes both tranquil and crisis periods. We consider November 2009 as the beginning of the European sovereign debt crisis following Greece's sovereign debt downgrade by Fitch. Our high-frequency dataset consists of the following ten countries: Austria, Belgium, Finland, France, Germany, Greece, Italy, the Netherlands, Portugal, and Spain. It contains the three best bid and ask quotations throughout the trading day, time-stamped to the nearest second. Our analysis is focused on the most heavily traded 10-year fixed-coupon bearing benchmark from each country. Our dataset has been filtered to consider quotes recorded during regular trading hours from 8:15 am to 5:30 pm CET. Overall, the dataset consists of 85,456 5-min sovereign bond prices (number of 5-min prices per trading day (112) times dates in the sample (763)). We have further filtered the dataset to exclude pre-sessional and end-of-day quotations to deal with microstructure effects and have discarded quotes with zero and negative bid-ask spreads.

We employ midpoints of bid-ask quotes as price measures which are less noisy measures of the efficient price than are transaction prices, as they do not suffer from bid-ask bounce microstructure effects (Bandi and Russell, 2006). We construct 5-min returns from the linearly interpolated logarithmic midpoint of the continuously recorded bid and ask quotes.[8] The selection of 5-min returns as the optimal sampling frequency has become standard practice in the literature as it balances both measurement error and microstructure biases (Andersen et al., 2001). Daily sovereign bond returns are computed as the summation of the 5-min intraday returns for each benchmark bond.

Table 1a reports descriptive statistics for daily sovereign bond returns and realized higher moments of all markets in the pre-crisis period. The average daily bond returns range from 0.03 percent to 0.05 percent. All return series are clearly stationary based on the Augmented Dickey-Fuller (ADF) unit root test using the Schwarz (SIC) information criterion. The mild lag-one autocorrelation as described by the Ljung-Box Q test is positive for all countries and takes on its highest value for Greece (14.68) and its lowest value for the Netherlands (0.0003). The average realized volatility lies in the vicinity of 0.3 to 0.4 percent for all countries displaying no unique pattern for countries either within the core or peripheral region. There is evidence of lag-one autocorrelation in all volatility series which rejects the white noise hypothesis for all benchmark bonds, in line with the findings of previous studies from U.S. and European equity markets (Ebens, 1999; Papavassiliou, 2013). The ADF unit root tests reject the null hypothesis of a unit root for all countries as judged by the 1 or 5 percent level critical value. The average realized skewness is negative and all benchmark bonds have an average realized kurtosis higher than six. All realized skewness and kurtosis series are clearly stationary and exhibit mild lag-one autocorrelation. The

[5] Further results on the limiting process of higher realized moments are summarized by Amaya et al. (2015). For example, authors show that realized skewness in the limit does not capture skewness arising from correlation between return and variance innovations.

[6] We prefer to use equally-weighted market indices than market value-weighted ones for the following reasons. First, value-weighted series tend to underestimate results for periods with high volatility and low liquidity (Pástor and Stambaugh, 2003). Our crisis period exhibits these features especially for the GIPS countries. Second, value-weighted series do not exhibit flight-to-quality effects which are dominant during crisis periods as investors rebalance their portfolios towards more liquid assets. Third, value-weighted series tend to underestimate the liquidity premium as Liu (2006) shows. Nevertheless, the aforementioned studies conclude that equally-weighted and value-weighted methods yield remarkably similar results.

[7] According to Persaud (2006) the market share of MTS stands at 88.7 percent.

[8] We have taken into account bond excess returns using the 1-month German T-bill rate in line with Gargano et al. (2019)

Table 1a

Descriptive statistics in the pre-crisis period. This table presents descriptive statistics for daily returns and realized higher moments in the pre-crisis period (January 2008 - October 2009). Panel A depicts the mean, standard deviation, maximum, minimum, Augmented Dickey-Fuller (ADF) unit root tests and the lag-one Ljung-Box Q test of daily bond returns. Panels B, C, D, E, and F report the corresponding statistics for daily realized volatility, daily realized skewness, daily realized kurtosis, daily realized hyper-skewness, and daily realized hyper-kurtosis, respectively. Daily bond returns and realized higher moments are calculated from 5-min intraday returns. The ADF test uses the Schwarz Information Criterion (SIC) for lag length selection. ***, **, and * denote statistical significance at the 1, 5, and 10 percent level, respectively.

	Austria	Belgium	Finland	France	Germany	Greece	Italy	Netherlands	Portugal	Spain
Panel A: Daily Returns										
Mean	0.0004	0.0004	0.0003	0.0003	0.0003	0.0005	0.0003	0.0003	0.0003	0.0003
Std.Dev.	0.003	0.003	0.003	0.004	0.004	0.004	0.003	0.003	0.003	0.003
Max.	0.012	0.008	0.011	0.011	0.015	0.022	0.013	0.010	0.011	0.010
Min.	−0.013	−0.011	−0.014	−0.013	−0.013	−0.025	−0.017	−0.014	−0.015	−0.012
ADF(SIC)	−19.62***	−20.12***	−19.76***	−21.87***	−21.27***	−17.80***	−19.49***	−21.63***	−19.94***	−21.46***
Q(1)	4.37**	2.04	2.68	0.03	0.07	14.68***	4.35**	0.0003	1.85	0.002
Panel B: Realized Volatility										
Mean	0.004	0.003	0.003	0.004	0.004	0.004	0.003	0.003	0.004	0.003
Std.Dev.	0.002	0.001	0.002	0.001	0.001	0.002	0.001	0.001	0.002	0.001
Max.	0.016	0.011	0.012	0.021	0.022	0.012	0.011	0.010	0.019	0.010
Min.	0.0005	0.001	0.0003	0.0009	0.0008	0.0007	0.0002	0.001	0.0003	0.0009
ADF(SIC)	−2.96**	−5.79***	−3.38**	−5.14***	−6.10***	−3.76***	−3.99***	−5.66***	−4.17***	−5.35***
Q(1)	140.68***	103.91***	203.26***	71.74***	33.99***	109.67***	106.23***	117.32***	86.52***	129.13***
Panel C: Realized Skewness										
Mean	−0.066	−0.024	−0.023	0.026	−0.045	−0.018	−0.012	−0.018	−0.0008	−0.008
Std.Dev.	1.056	0.951	1.191	1.016	1.029	1.350	1.009	1.081	1.080	1.173
Max.	3.738	3.240	7.104	8.736	5.880	5.913	4.846	6.282	4.262	7.886
Min.	−5.363	−3.298	−5.880	−3.144	−5.635	−5.968	−3.965	−6.553	−4.873	−7.075
ADF(SIC)	−20.54***	−20.99***	−20.75***	−21.88***	−20.27***	−18.95***	−21.18***	−21.08***	−19.88***	−23.88***
Q(1)	1.14	0.69	1.50	0.93	1.60	10.67***	0.18	0.42	2.90*	0.0003
Panel D: Realized Kurtosis										
Mean	7.597	5.788	6.973	5.690	5.710	8.812	5.909	5.949	7.054	6.524
Std.Dev.	6.053	3.566	6.294	5.603	4.857	6.860	4.330	5.185	5.164	6.496
Max.	56.331	31.026	66.719	86.432	49.803	53.537	38.676	57.694	43.945	77.376
Min.	2.565	2.536	2.531	2.353	2.595	2.649	2.483	2.199	2.612	2.477
ADF(SIC)	−18.37***	−20.51***	−19.91***	−22.79***	−19.66***	−19.46***	−21.20***	−22.27***	−22.21***	−29.10***
Q(1)	10.48***	1.37	5.78**	2.09	0.06	8.78***	0.08	0.28	0.45	0.18
Panel E: Realized Hyper-Skewness										
Mean	−3.711	−1.371	−2.142	2.809	−0.817	−2.834	0.228	−1.023	0.986	0.235
Std.Dev.	41.162	26.346	57.306	53.284	39.562	58.117	36.245	46.256	38.059	61.603
Max.	174.768	120.032	617.979	856.628	416.838	339.921	303.054	409.336	247.007	742.313
Min.	−319.627	−170.307	−451.437	−159.881	−422.614	−468.029	−230.481	−512.546	−304.073	−595.411
ADF(SIC)	−20.24***	−21.51***	−22.3***	−24.57***	−20.26***	−20.89***	−22.32***	−21.71***	−20.81***	−31.15***
Q(1)	1.69	0.12	0.01	0.04	0.01	3.63*	0.63	0.00	0.61	0.02
Panel F: Realized Hyper-Kurtosis										
Mean	155.578	89.057	154.954	104.372	98.587	210.606	100.811	110.515	139.111	144.316
Std.Dev.	338.441	155.427	447.501	479.522	302.512	417.581	238.739	351.172	262.022	510.879
Max.	3525.278	1450.168	5742.741	8495.157	3647.789	4114.823	2424.383	4580.928	2438.985	7160.778
Min.	8.687	8.819	8.799	7.457	9.172	9.839	8.826	6.555	9.262	8.064
ADF(SIC)	−19.11***	−21.24***	−21.29***	−24.14***	−19.94***	−21.74***	−21.59***	−22.23***	−22.68***	−36.63***
Q(1)	5.94**	0.17	1.26	0.25	0.02	1.63	0.02	0.35	1.16	0.15

autocorrelation structure will adjust in the crisis period especially for GIPS countries. Realized hyper-skewness takes on more negative values than realized skewness and is more noisy as it exhibits much higher standard deviation. Similar to realized skewness it is clearly stationary and exhibits mild lag-one autocorrelation. Realized hyper-kurtosis takes on positive and much higher mean and standard deviation values than realized kurtosis, and both measures exhibit a similar autocorrelation structure.

Table 1b reports the corresponding descriptive statistics for the crisis period. The average daily return plummets in most countries during the crisis period, and even down to minus two percent in Greece. Mean daily returns for GIPS countries become negative and those of non-GIPS countries remain positive but lower than those in the pre-crisis period. Realized volatility intensifies during the crisis for GIPS countries but remains constant or decreases for non-GIPS countries. According to O'Sullivan and Papavassiliou (2018b) this result can be attributed to lowered trading intensity for non-GIPS bonds during the crisis and to the role played by hedge funds and derivatives markets that helped reduce volatility.

Mean realized skewness becomes more negative for GIPS countries during the crisis and mean realized kurtosis nearly triples for Greece and Portugal while it increases by roughly 50 percent for Italy and Spain. The finding that bonds of lower quality exhibit lower skewness than bonds of higher quality is in line with the evidence provided by Chiang (2016) from the U.S. Treasury and corporate bond market. We also note that high-kurtosis bonds have lower credit ratings than low-kurtosis

Table 1b

Descriptive statistics in the crisis period. This table presents descriptive statistics for daily returns and realized higher moments in the crisis period (November 2009 - December 2010). Panel A depicts the mean, standard deviation, maximum, minimum, Augmented Dickey-Fuller (ADF) unit root tests and the lag-one Ljung-Box Q test of daily bond returns. Panels B, C, D, E, and F report the corresponding statistics for daily realized volatility, daily realized skewness, daily realized kurtosis, daily realized hyper-skewness, and daily realized hyper-kurtosis, respectively. Daily bond returns and realized higher moments are calculated from 5-min intraday returns. The ADF test uses the Schwarz Information Criterion (SIC) for lag length selection. ***, **, and * denote statistical significance at the 1, 5, and 10 percent level, respectively.

	Austria	Belgium	Finland	France	Germany	Greece	Italy	Netherlands	Portugal	Spain
Panel A: Daily Returns										
Mean	7.46e-05	6.25e-05	0.0002	0.0002	0.0002	−0.002	−5.60e-05	0.0003	−0.001	−1.39e-05
Std.Dev.	0.003	0.003	0.002	0.002	0.003	0.010	0.003	0.003	0.006	0.004
Max.	0.008	0.010	0.008	0.008	0.008	0.034	0.015	0.008	0.026	0.019
Min.	−0.015	−0.012	−0.008	−0.009	−0.011	−0.054	−0.016	−0.010	−0.025	−0.013
ADF(SIC)	−15.30***	−14.95***	−16.09***	−16.32***	−15.47***	−13.48***	−13.59***	−15.68***	−13.35***	−12.87***
Q(1)	3.44*	4.59**	0.96	0.38	2.68	17.28***	5.57**	1.96	16.79***	12.15***
Panel B: Realized Volatility										
Mean	0.003	0.003	0.003	0.003	0.003	0.007	0.003	0.003	0.005	0.004
Std.Dev.	0.001	0.002	0.0009	0.001	0.001	0.005	0.002	0.0009	0.003	0.002
Max.	0.008	0.015	0.008	0.007	0.011	0.027	0.016	0.007	0.014	0.014
Min.	0.0009	0.0003	0.0002	0.0001	0.0005	5.63e-05	0.0001	0.0005	0.0004	0.001
ADF(SIC)	−10.06***	−4.55***	−5.43***	−3.37**	−7.49***	−7.28***	−6.29***	−3.74***	−7.87***	−5.54***
Q(1)	70.38***	53.07***	38.35***	28.27***	35.20***	51.41***	72.81***	57.83***	29.63***	120.08***
Panel C: Realized Skewness										
Mean	−0.081	−0.016	−0.008	−0.018	0.023	−0.553	−0.158	0.077	−0.148	−0.133
Std.Dev.	1.168	1.182	1.149	1.051	0.989	3.344	1.311	0.925	2.591	1.442
Max.	5.845	4.466	3.529	4.507	3.705	10.528	4.193	4.137	8.704	7.728
Min.	−4.950	−5.208	−7.493	−7.553	−4.311	−10.583	−4.563	−3.281	−10.046	−5.253
ADF(SIC)	−17.09***	−15.29***	−16.78***	−16.27***	−15.34***	−13.25***	−16.00***	−16.16***	−16.78***	−15.99***
Q(1)	0.0002	2.40	0.84	0.65	3.32*	16.76***	0.95	0.88	0.18	1.06
Panel D: Realized Kurtosis										
Mean	7.803	7.666	6.628	5.958	5.806	22.933	9.823	5.819	17.446	9.438
Std.Dev.	6.034	7.021	6.565	5.608	5.212	20.885	7.752	4.717	15.767	7.464
Max.	56.234	47.013	71.563	68.393	48.756	112.002	48.532	36.648	104.981	66.481
Min.	2.777	2.567	2.432	2.435	2.504	3.329	2.899	2.399	3.135	2.648
ADF(SIC)	−13.94***	−16.91***	−5.91***	−17.50***	−18.18***	−5.10***	−16.12***	−13.97***	−5.56***	−15.29***
Q(1)	11.24***	0.0001	4.35**	0.22	1.29	71.37***	0.47	11.43***	4.88**	3.56*
Panel E: Realized Hyper-Skewness										
Mean	−4.427	−1.919	−3.234	−2.649	−0.941	−36.674	−6.622	2.047	−7.552	−6.114
Std.Dev.	50.512	52.778	56.279	49.511	29.808	249.901	59.141	29.415	173.126	66.636
Max.	268.564	250.066	173.979	250.346	177.192	1174.995	298.783	200.985	851.569	586.393
Min.	−427.616	−374.794	−675.141	−632.335	−192.511	−1185.297	−274.104	−170.374	−1092.182	−380.226
ADF(SIC)	−7.92***	−16.19***	−17.31***	−17.02***	−16.34***	−13.86***	−16.26***	−16.42***	−17.48***	−16.85***
Q(1)	0.64	0.43	0.07	0.00	0.51	11.93***	0.21	0.41	0.64	0.02
Panel F: Realized Hyper-Kurtosis										
Mean	172.071	184.246	147.128	115.479	102.191	1207.171	259.145	99.539	743.189	243.834
Std.Dev.	355.583	411.971	459.643	398.536	265.694	2086.987	450.569	223.135	1397.899	478.528
Max.	4024.108	3229.387	6385.622	5882.507	2546.585	12544.00	2692.109	1689.976	11372.26	5257.032
Min.	10.501	8.893	8.106	8.472	9.671	13.383	12.753	7.631	14.768	10.577
ADF(SIC)	−15.53***	−17.30***	−6.02***	−17.45***	−19.38***	−7.48***	−16.67***	−14.04***	−16.56***	−16.56***
Q(1)	2.44	0.14	0.25	0.18	0.47	61.46***	0.00	10.89***	0.00	0.24

bonds, a result inconsistent with the evidence from the corporate bond market documented by Bai et al. (2016). Lower kurtosis bonds exhibit higher returns and high kurtosis bonds exhibit lower returns. For instance, all GIPS countries (especially Greece) exhibit much higher kurtosis values than non-GIPS countries and at the same time exhibit the lowest mean returns. These results are consistent with Dittmar (2002) who finds that risk-averse investors prefer high returns and low kurtosis. Mean realized hyper-skewness becomes more negative for almost all countries during the crisis and more volatile for GIPS countries. Realized hyper-kurtosis takes on much larger mean and standard deviation values during the crisis especially for the GIPS countries, showing that it is responsive to extreme market episodes.

3.4. Alternative predictors

In this section, we describe the set of alternative predictors that we analyze in comparison to realized higher moments.

Bond Liquidity:

Our first alternative predictor is liquidity. Previous research has examined the dynamic interactions of liquidity and returns in stock and bond markets (Amihud and Mendelson, 1986; Hasbrouck, 1991; Krishnamurthy, 2002; Goyenko et al., 2011). Results point towards the existence of a bidirectional causal relationship between liquidity and returns. During periods of market turmoil liquidity dries-up and investors ask for higher returns as compensation for higher risk. Pástor and Stambaugh (2003) and Acharya and Pedersen (2005) find that liquidity is priced and future stock returns are robustly related to innovations in aggregate liquidity. Evidence on the pricing implications of liquidity in government bond markets is provided by Goyenko et al. (2011) (U.S. Treasury market) and O'Sullivan and Papavassiliou (2018a) (European bond market). Kinateder and Wagner (2017) find that country-specific bond liquidity as well as market liquidity are both priced in the EMU sovereign bond market. In addition, Kinateder et al. (2017) document increased predictive power of liquidity-based forecasting models during times of crisis.

We have constructed the following liquidity measures that are able to capture both tightness and depth liquidity dimensions:

- *Relative or proportional spread:* It is defined as the best bid-ask spread divided by the midpoint of the bid and ask quotes, i.e. $100(A_{it} - B_{it}/M_{it})$, where A_{it} and B_{it} denote the ask and bid price, respectively. The midpoint is computed as $M_{it} = (A_{it} + B_{it})/2$

- *Quoted depth:* It is defined as best bid size plus best ask size, where size is related to the quantity of bonds bid or offered at the posted bid or offer prices

Short-term Interest Rate:

As proxy for our second predictor, namely the short-term interest rate, we use the 3-month euro interbank offered rate (Euribor), provided by the Organization for Economic Co-operation and Development and retrieved from the FRED Economic Database of the Federal Reserve Bank of St. Louis. Since changes in interest rates negatively affect the present value of a bond's future cash flows, we consider the 3-month Euribor as alternative predictor for subsequent bond returns. Previous work of Batten and Hogan (2003) document a promising role for short-term interest rates in predicting contemporaneous returns of Australian Eurobonds.

Implied Stock Market Volatility:

Our third alternative predictor is the Chicago Board Options Exchange (CBOE) implied volatility index (VIX). VIX is a popular measure of the stock market's expectation of volatility implied by highly liquid S&P 500 index options. We rely on daily data from the VIX index which has emerged as the industry standard as a measure of risk-neutral expected variance. The VIX index has been termed as "market gauge of fear" (Whaley, 2000). We regard VIX as potential predictor since jumps in VIX indicate increased uncertainty. In times of increased uncertainty, investors may reduce stock market positions and transfer their funds to sovereign bond markets. As a result, changes in VIX may affect sovereign bond returns.

Common Risk Factor:

Finally, using principal component analysis, we construct a novel common risk factor based on the distributional characteristics of sovereign bonds using the first principal component extracted from realized volatility, realized skewness, and realized kurtosis, in line with Bai et al. (2016). Our aim is to show that the common risk factor can represent sources of common return variation that cannot be captured by the other alternative predictors. Bai et al. (2016) show that such common factors contain additional predictive power beyond standard predictors as they can capture the downside risk of corporate bonds reflected in higher credit and liquidity risk.

Credit Default Swaps (CDS) Spread:

A Credit Default Swap (CDS) is the most popular credit derivative which provides insurance against a default by a sovereign entity. It has been shown that there is a close theoretical link between CDS spreads and bond yield spreads if the two quantities are viewed as a pure measure of credit risk (Duffie, 1999; Hull et al., 2004). As Fontana and Scheicher (2016) argue, since September 2008 the euro-area sovereign CDS market has attracted widespread attention with tensions peaked via flight-to-safety episodes that took place in May 2010, when global investors initiated large scale sell-offs of risky assets. Kim et al. (2016) examine the predictive power of the CDS-bond basis for future corporate bond returns and find a strong relation which can help bring corporate bond prices closer to their fundamental values. The aforementioned studies demonstrate that CDS spreads can prove to be good predictors of subsequent sovereign bond returns. We employ average daily euro-area CDS spreads as a potential predictor of future bond returns, obtained from Thomson Reuters Datastream.

Autoregressive Model:

Bao et al. (2011) stress that bond prices may react in a delayed manner to new information due to illiquidity. As a result, there can be autoregressive (AR) behavior in bond returns. Our previous findings in Tables 1 and 2 show that especially in the crisis period, returns of GIPS countries exhibit significant first-order serial correlation. Therefore, we consider an AR(1) term as alternative predictor of bond returns.

4. Empirical analysis

In this section, we study the ability of realized higher moments to provide statistically accurate out-of-sample forecasts of the bond market return for GIPS and non-GIPS regions at both the index and country level. Apart from higher moments, we consider a set of alternative predictors described in Section 3.4. Our return forecasts are based on recursively updated parameter estimates of Eq. (2). More specifically, we use an expanding window of initial size $q_0 = 60$, which is updated daily with new information. Economic significance analysis considers an investor with risk aversion of $\gamma = 3$, which is widely used in the literature (see e.g. Campbell and Thompson, 2008; Rapach et al., 2010; Jordan et al., 2014). All forecasts are performed for a horizon of one day and the out-of-sample forecasting period spans the dates from March 31, 2008 to December 30, 2010. The out-of-sample forecasting performance is evaluated by comparing the unrestricted predictive regression model to a restricted benchmark model (historical mean of market return). As explained previously in Section 3, we use the OOS-R^2 in conjunction with the Clark-West MSPE-adjusted statistic to analyze whether the predictive regression model is able to achieve a statistically significant lower MSPE than the historical average return benchmark model.

4.1. Preliminary analysis

Before we present the results of the horse race among realized higher moments and alternative predictors, we discuss findings of a simple correlation analysis. Table 2 reports correlation coefficients among realized higher moments and alternative predictors of sovereign bond returns during pre-crisis and crisis periods for GIPS and non-GIPS countries.

In all sub-periods, hyper-skewness and hyper-kurtosis are highly correlated (coefficients larger than 0.8) with realized skewness and kurtosis, respectively. Therefore, we expect them to behave similarly over pre-crisis and crisis periods. In addition, the first three moments (i.e. realized volatility, realized skewness, realized kurtosis) show only weak correlation with one another. Another interesting observation is the correlation behavior between our uncertainty proxies, i.e. VIX and CDS. This pair exhibits a high correlation in the pre-crisis sample (0.701) and a quite low correlation in the crisis sample (0.170). This difference may be explained by the fact that CDS spreads reflect the market expectation that the issuer will default and take into account liquidity risk, whilst the VIX, which is calculated from equity options, may not capture that information. As liquidity deteriorates during the crisis, the two variables will become less strongly correlated with one another.

4.2. Out-of-sample prediction results at the index level

4.2.1. Statistical significance

Table 3a presents OOS-R^2 for daily forecasts of the sovereign bond returns from predictive regressions relative to the historical average benchmark forecasting model. A predictor outperforms the other predictors in the model if it can generate an OOS-R^2 which is significantly different from zero and exhibits the highest OOS-R^2 among the other predictors. The results show that within higher moments realized kurtosis outperforms the other moments in the full sample for GIPS countries and beats the historical mean. All realized higher moments perform poorly for non-GIPS countries in the full sample but also in the pre-crisis sample, failing to beat the historical average return. The same holds for GIPS countries in the pre-crisis period whose OOS-R^2 values are negative and statistically insignificant. However, realized higher moments are able to predict GIPS and non-GIPS expected sovereign bond returns more accurately during the crisis period. Realized volatility outperforms realized skewness and kurtosis for non-GIPS markets, whereas kurtosis is the dominant predictor for GIPS countries during the crisis, beating the historical average return in a statistically significant manner. Realized skewness is statistically insignificant in explaining bond returns out-of-sample. Realized hyper-skewness is also statistically insignificant across all samples whilst realized hyper-kurtosis performs satisfactorily for GIPS countries in both the crisis and the full sample, however, it cannot outperform realized kurtosis.

Apart from these results, we analyze the evolution of forecasting performance from day to day. For this purpose, Fig. 1 plots the cumulative squared prediction errors of the out-of-sample forecasts of realized higher moments and realized hyper moments against the historical average over time, for GIPS and non-GIPS countries. Negative values indicate that higher moments are able to beat the historical average. The results for GIPS countries show that in the pre-crisis period, realized kurtosis and realized hyper-kurtosis are the only predictors that partly (around September 2008) provide forecasting gains. However, in the crisis period, all predictors show increased forecasting performance from March 2010 onwards. At this time, the European Commission announced that Greece will get financial aid and shortly thereafter the first bailout package for Greece was approved. Interestingly, not all moments react with the same intensity to these news. The highest immediate impact on forecasting performance is documented for realized kurtosis, whereas realized skewness only shows an immediate mild forecasting gain which increases over time. For non-GIPS countries we document smaller fluctuations of forecasting performance over time. In this sample, realized kurtosis is the only predictor which outperforms the historical average, where the best results are documented in June 2009.

It is important to show whether higher moments dominate the alternative predictors. Our results reveal that liquidity as measured by the quoted depth along with the autoregressive term are the only predictors which marginally outperform realized kurtosis for GIPS countries during the crisis period. They are also statistically significant at the 10 and 1 percent level respectively for GIPS in the full sample but only the AR(1) term outperforms realized kurtosis and realized hyper-kurtosis. These results are in line with those of Kinateder et al. (2017) who find that during periods of financial turmoil, liquidity in the

Table 2
Correlation matrix. The table reports correlation coefficients among realized higher moments (realized volatility (R-Volatility), realized skewness (R-Skewness), realized kurtosis (R-Kurtosis), realized hyper-skewness (RH-Skewness), realized hyper-kurtosis (RH-Kurtosis)) and alternative predictors of sovereign bond returns (relative spread (RS), quoted depth (QD), VIX index, 3-month Euribor (Eur), common risk factor (PCA), CDS spread (CDS) and an autoregressive AR(1) term) for GIPS and non-GIPS countries during pre-crisis and crisis periods. The pre-crisis period spans the dates from January 2008 to October 2009, whilst the crisis period extends from November 2009 to December 2010.

	R-Volatility	R-Skewness	R-Kurtosis	RH-Skewness	RH-Kurtosis	RS	QD	VIX	Eur	PCA	CDS
Panel A: Pre-crisis (GIPS)											
R-Volatility	1.000										
R-Skewness	−0.095	1.000									
R-Kurtosis	0.195	−0.025	1.000								
RH-Skewness	−0.061	0.855	−0.012	1.000							
RH-Kurtosis	0.119	0.008	0.932	−0.021	1.000						
RS	0.716	−0.107	0.180	−0.108	0.126	1.000					
QD	−0.509	0.126	−0.130	0.093	−0.094	−0.639	1.000				
VIX	0.662	−0.061	0.065	−0.065	0.027	0.825	−0.482	1.000			
Eur	−0.075	−0.052	−0.070	−0.018	−0.056	−0.148	0.383	−0.014	1.000		
PCA	0.801	−0.398	0.597	−0.387	0.488	0.584	−0.419	0.492	−0.008	1.000	
CDS	0.581	−0.045	0.153	−0.070	0.087	0.794	−0.620	0.701	−0.516	0.489	1.000
Panel B: Pre-crisis (non-GIPS)											
R-Volatility	1.00										
R-Skewness	−0.120	1.000									
R-Kurtosis	0.104	0.044	1.000								
RH-Skewness	−0.087	0.838	0.047	1.000							
RH-Kurtosis	0.058	0.028	0.886	0.086	1.000						
RS	0.637	−0.064	0.052	−0.050	0.028	1.000					
QD	−0.376	0.098	0.013	0.097	0.023	−0.603	1.000				
VIX	0.627	−0.032	−0.005	−0.052	−0.030	0.806	−0.416	1.000			
Eur	0.049	−0.027	0.081	0.001	0.079	−0.215	0.503	−0.014	1.000		
PCA	0.794	−0.416	0.556	−0.389	0.429	0.485	−0.287	0.434	0.093	1.000	
CDS	0.500	−0.040	0.025	−0.047	−0.014	0.791	−0.585	0.701	−0.516	0.351	1.000
Panel C: Crisis (GIPS)											
R-Volatility	1.000										
R-Skewness	−0.159	1.000									
R-Kurtosis	0.332	−0.131	1.000								
RH-Skewness	−0.153	0.881	−0.143	1.000							
RH-Kurtosis	0.260	−0.118	0.954	−0.123	1.000						
RS	0.415	−0.112	0.606	−0.099	0.494	1.000					
QD	−0.434	0.078	−0.474	0.066	−0.361	−0.723	1.000				
VIX	0.079	0.043	0.391	−0.030	0.392	0.343	−0.149	1.000			
Eur	0.076	−0.080	0.078	−0.075	−0.037	0.373	−0.395	−0.168	1.000		
PCA	0.702	−0.425	0.794	−0.456	0.709	0.650	−0.542	0.267	0.175	1.000	
CDS	0.307	−0.117	0.428	−0.106	0.294	0.789	−0.638	0.170	0.738	0.440	1.000
Panel D: Crisis (non-GIPS)											
R-Volatility	1.000										
R-Skewness	−0.161	1.000									
R-Kurtosis	0.244	−0.070	1.000								
RH-Skewness	−0.103	0.862	−0.179	1.000							
RH-Kurtosis	0.205	−0.107	0.955	−0.259	1.000						
RS	0.587	−0.029	0.161	−0.014	0.127	1.000					
QD	−0.283	0.006	−0.135	0.018	−0.113	−0.437	1.000				
VIX	0.319	0.010	0.017	−0.018	0.009	0.569	−0.142	1.000			
Eur	0.322	−0.111	−0.140	−0.037	−0.128	0.027	−0.328	−0.168	1.000		
PCA	0.760	−0.488	0.705	−0.538	0.664	0.422	−0.237	0.184	0.157	1.000	
CDS	0.522	−0.087	−0.117	−0.009	−0.116	0.438	−0.361	0.170	0.738	0.246	1.000

European bond market is involved more heavily in the pricing schemes of investors than in calm periods. They are also consistent with the findings of O'Sullivan and Papavassiliou (2018a) who show that liquidity risk was of primary importance in the European sovereign debt crisis period especially for the GIPS countries.[9] Bai et al. (2019) also provide evidence that liquidity risk positively predicts variation in future corporate bond returns. Liquidity proxied by the relative spread also performs well for GIPS countries in the crisis period as its OOS-R^2 takes on statistically significant values at the 10 percent level.

Interestingly, VIX and the common risk factor extracted from PCA are able to explain GIPS sovereign bond returns during the crisis quite accurately as they provide statistically significant forecasts at the 10 and 5 percent level, respectively. However, they perform poorly for non-GIPS countries in both periods. It can be said that our common risk factor of realized higher moments generates large risk premia during episodes of market turmoil confirming previous results by Bai et al. (2016) from

[9] In contrast to these findings Oliveira et al. (2012) find an insignificant role for the liquidity risk factor in explaining the evolution of credit spreads during both calm and crisis periods in the eurozone bond market.

Table 3a

Out-of-sample bond return prediction at the index level: Statistical Significance. This table presents OOS-R^2 for daily forecasts of the sovereign bond returns from predictive regressions relative to the historical average benchmark forecasting model. Daily sovereign bond returns, daily realized higher moments, daily realized hyper moments, and alternative predictors are constructed as equally-weighted market indices. Daily realized higher moments (R-Volatility, R-Skewness, R-Kurtosis) and daily realized hyper moments (RH-Skewness, RH-Kurtosis) are constructed using 5-min intraday bond returns. Relative spread (RS) is defined as the best bid-ask spread divided by the midpoint of the bid and ask quotes. Quoted depth (QD) is defined as the summation of best bid size and best ask size (quantity of securities bid or offered for sale at the posted bid and offer prices). VIX is the CBOE volatility index derived from highly liquid S&P 500 index options. The 3-month Euribor rate (Eur) is the short-term euro interbank offered rate. PCA corresponds to the first principal component extracted from all three realized higher moments. CDS spread (CDS) is the daily average euro-area spread. AR(1) is a first-order autoregressive term. GIPS refers to the countries of Greece, Italy, Portugal, and Spain. non-GIPS refers to the countries of Austria, Belgium, Finland, France, Germany, and the Netherlands. Statistical significance is based on Clark and West's (2007) adjusted-DM test, *t*-DM. All forecasts are based on a 60-day recursive (expanding) window. ***, **, and * denote statistical significance for the out-of-sample forecasts at the 1, 5, and 10 percent level, respectively. *t*-DM is the one-sided test statistic. The associated critical values are: 2.33 (1 percent level); 1.64 (5 percent level); 1.25 (10 percent level). The full sample period spans the dates from January 2008 to December 2010. November 2009 corresponds to the beginning of the crisis sample.

		Full sample (Jan 08-Dec 10)		Pre-crisis (Jan 08-Oct 09)		Crisis (Nov 09-Dec 10)	
		GIPS	Non-GIPS	GIPS	Non-GIPS	GIPS	Non-GIPS
AR(1)	OOS-R^2	1.98	−0.68	−0.24	−1.03	3.55	0.03
	t-DM	3.47***	−0.63	0.93	−0.79	3.79***	0.33
R-Volatility	OOS-R^2	0.05	−0.33	−0.70	−0.78	0.58	0.56
	t-DM	0.60	−0.27	−0.84	−1.04	0.91	1.77*
R-Skewness	OOS-R^2	0.25	−0.48	−0.17	−0.64	0.54	−0.15
	t-DM	1.23	−1.37	0.21	−1.18	1.21	−2.06
R-Kurtosis	OOS-R^2	0.65	−0.16	−0.02	0.27	1.13	−1.02
	t-DM	2.04**	0.54	0.69	0.96	1.86**	−0.80
RH-Skewness	OOS-R^2	−0.22	−0.45	−0.09	−0.60	−0.31	−0.15
	t-DM	0.27	−1.37	0.26	−1.16	0.18	−1.77
RH-Kurtosis	OOS-R^2	0.23	−0.54	−0.38	−0.67	0.66	−0.27
	t-DM	1.54*	−0.74	0.13	−0.56	1.64**	−1.07
RS	OOS-R^2	0.01	−0.72	−1.17	−1.06	0.86	−0.05
	t-DM	0.82	−2.44	−1.81	−2.60	1.49*	−0.80
QD	OOS-R^2	0.48	−0.31	−0.71	−0.44	1.32	−0.04
	t-DM	1.49*	−0.72	−0.39	−0.68	2.20**	−0.17
VIX	OOS-R^2	−0.71	−1.65	−2.23	−2.39	0.36	−0.14
	t-DM	−0.60	−1.96	−1.47	−2.15	1.52*	−0.08
Eur	OOS-R^2	−0.97	−1.38	−1.59	−1.82	−0.53	−0.50
	t-DM	−0.33	−1.23	−0.09	−1.64	−0.74	0.23
PCA	OOS-R^2	0.89	−0.07	−0.27	−0.15	1.71	0.09
	t-DM	1.79**	0.59	0.26	0.27	1.79**	0.74
CDS	OOS-R^2	−0.65	−1.47	−2.59	−2.26	0.72	0.13
	t-DM	0.66	−1.52	−1.07	−2.72	1.48*	0.78

the corporate bond market. The common risk factor also performs well for GIPS countries in the full sample and manages to outperform realized hyper-kurtosis. The 3-month Euribor is the only variable that fails to provide accurate forecasts across GIPS and non-GIPS country returns in all sample periods. CDS spread performs satisfactorily only for GIPS countries in the crisis, as it is able to capture the increased default risk of those countries. A very interesting finding in our analysis is that our alternative predictors provide accurate return forecasts for GIPS countries only during the crisis period. It seems that these predictors are able to capture the bond return variability during periods of stress where liquidity evaporates quickly leading to market-wide effects, whereas they perform poorly during calm periods of lower market uncertainty.

Fig. 2 plots the corresponding cumulative squared prediction errors of the out-of-sample forecasts of alternative predictors against the historical average for GIPS and non-GIPS countries and confirms the findings presented in Table 3a. The results for GIPS countries indicate that both liquidity measures as well as the common risk factor and the AR(1) term show increased predictability from March 2010 onwards, which is similar to the findings of realized higher moments given in Fig. 1. For non-GIPS countries, no measure is able to beat the historical average. There is a mild exception for the common risk factor which is able to provide marginally better forecasting performance at some point in time.

In conclusion, we provide evidence that bond return predictability is stronger during crisis periods than during tranquil periods in line with earlier studies from stock markets (Henkel et al., 2011; Dangl and Halling, 2012). We also show that GIPS bonds that exhibit predictability also exhibit higher probabilities of financial distress, in line with evidence from the corporate bond market (Downing et al., 2009). Kurtosis measures the bimodality of the distribution, or the probability mass in the tails of the distribution (Neuberger, 2012). Therefore, kurtosis as opposed to variance is able to capture the probability of extreme outcomes that are far away from the mean. Kurtosis sensitivity to extreme states can explain its strong predictive performance during the crisis period for the distressed economies of Greece, Italy, Portugal, and Spain.

4.2.2. Economic significance

Table 3b presents the average annualized percentage utility gain from the out-of-sample bond return prediction at the index level. Positive values indicate that the investor earns a utility gain in the form of a positive risk-adjusted portfolio return compared to the historical average. In fact, the higher the utility gain, the higher is the economic significance in terms

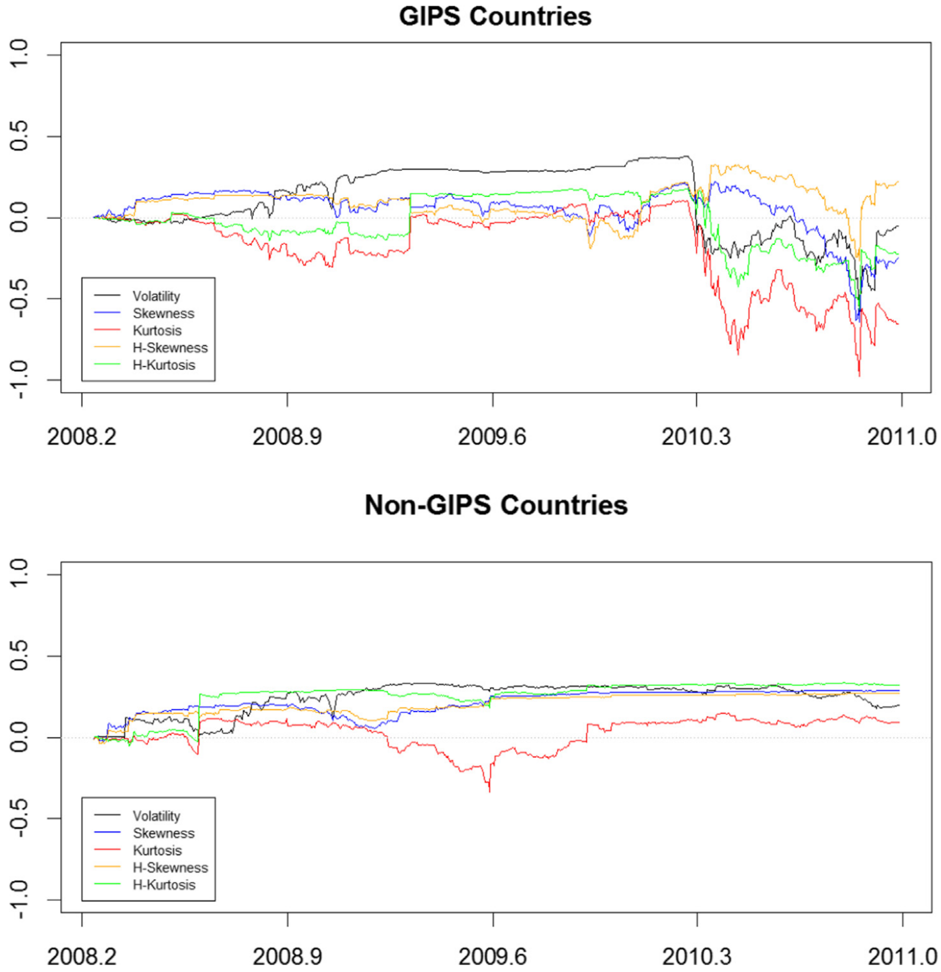

Fig. 1. The Figure plots the cumulative difference between the squared prediction error of the predictive model using a higher moment (i.e. realized volatility, realized skewness, realized kurtosis, realized hyper-skewness, or realized hyper-kurtosis) and the squared prediction error of the historical average model. The top plot shows results for GIPS countries and the bottom plot contains non-GIPS countries. Negative values indicate that higher moments are able to beat the historical average. All calculations are based on percentage logarithmic returns and a 60-day recursive window. The sample period is from January 2008 to December 2010.

of positive portfolio returns. We provide evidence that during the crisis period almost all alternative predictors and realized higher moments exhibit positive risk-adjusted portfolio returns compared to the historical average for GIPS countries. The AR(1) term exhibits the highest average annualized percentage utility gain of all, followed by the common risk factor. The results differ substantially for non-GIPS countries where realized higher moments (with the exception of volatility) and liquidity take on negative values showing that investors have realized utility losses during the crisis. On the contrary, the role of the 3-month Euribor and that of CDS spread gain importance during the crisis for non-GIPS countries. This finding complements that of Fontana and Scheicher (2016) who find a negative basis in 2009 and early 2010 for Portugal and Greece due to flight to liquidity effects that have lowered government bond spreads in periods of market turmoil.

In the pre-crisis period the economic importance of liquidity, VIX, and CDS spread is lowered for GIPS and non-GIPS countries. Realized skewness and realized hyper-skewness offer utility gains to GIPS countries only whilst realized kurtosis and realized hyper-kurtosis offer higher risk-adjusted portfolio returns to non-GIPS than GIPS countries.

4.3. Out-of-sample prediction results at the country level

4.3.1. Statistical significance

In this section, we present the out-of-sample prediction results at the country level. Panel A of Table 4a depicts the results for the full sample. Realized volatility and skewness perform poorly for all countries (with the exception of Greece) failing to beat the historical average return. These results are in line with those of Welch and Goyal (2008) and Zhu and Zhu (2013) from the U.S. stock market but contradict those of Rapach et al. (2010), Jordan et al. (2014), and Jondeau et al. (2018) who

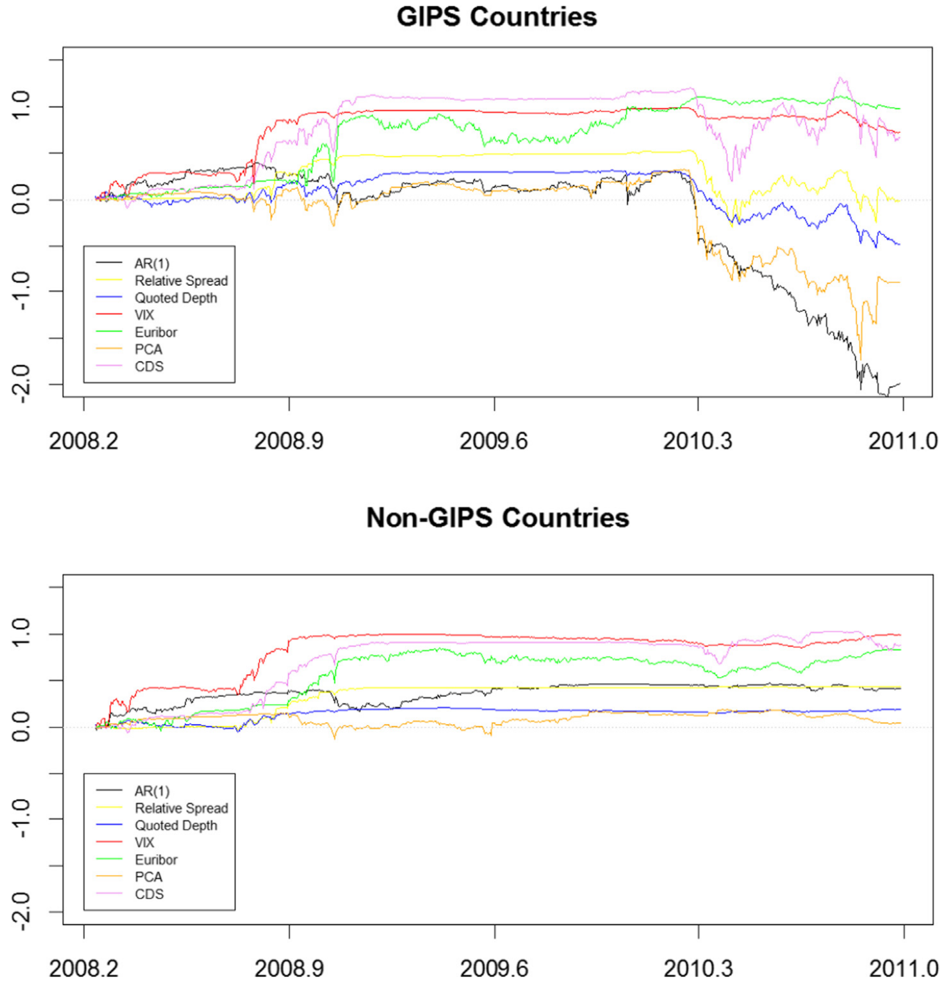

Fig. 2. The Figure plots the cumulative difference between the squared prediction error of the predictive model using an alternative predictor (i.e. AR(1), relative spread, quoted depth, S&P 500 implied volatility (VIX), 3-month Euribor, first principal component (PCA) of daily realized higher moments, or the CDS spread) and the squared prediction error of the historical average model. The top plot shows results for GIPS countries and the bottom plot contains non-GIPS countries. Negative values indicate that the alternative predictors are able to beat the historical average. All calculations are based on percentage logarithmic returns and a 60-day recursive window. The sample period is from January 2008 to December 2010.

find that variance and skewness measures accurately predict subsequent stock returns.[10] Our evidence is also inconsistent with the findings of Bai et al. (2016) who find a statistically significant relation between volatility and future corporate bond returns. Only realized skewness for Greece is statistically significant in explaining sovereign bond returns at the 5 percent level. Realized kurtosis does a better job in explaining sovereign bond returns out-of-sample especially for Greece and to a lesser extent for Belgium and the Netherlands. Realized hyper-skewness performs poorly for all countries whilst realized hyper-kurtosis predicts accurately Greek and Italian sovereign bond returns.

The AR(1) term is statistically significant in explaining bond returns of the GIPS countries and manages to outperform all realized higher moments and alternative predictors. Liquidity's importance as an alternative predictor is lowered in the full sample as its OOS-R^2 beats the historical average only for Portugal – both relative spread and quoted depth are statistically significant at the 5 and 1 percent level, respectively - and Austria, nevertheless it outperforms all realized higher moments of these two countries. VIX index and the 3-month Euribor fail to provide accurate forecasts in the full sample for both core and periphery countries. The common risk factor is able to capture bond return variability for Greece, Portugal, and Belgium however, it outperforms realized higher moments only for the country of Belgium. This result is in line with the findings of Bai et al. (2016, 2019) who show that common risk factors of corporate bond returns perform well during downturns

[10] We acknowledge the fact that due to lack of international evidence from sovereign bond markets we inevitably rely on comparisons with other financial markets. Moreover, our empirical results are not directly comparable to those from other markets, not only because of differences in asset specific characteristics but also due to differences across forecasting approaches and evaluation methods.

Table 3b

Out-of-sample bond return prediction at the index level: Economic Significance. This table presents the average annualized percentage utility gain (see Eq. (13)), ΔU, in percentage points. Utility gains are computed as the difference between forecasts using the predictive regression and forecasts using the historical average for a mean-variance investor with relative risk aversion coefficient of $\gamma = 3$, and portfolio weights of the bond return restricted to the interval between 0 and 1.5 (see Campbell and Thompson (2008)). Positive values indicate that the investor earns a utility gain in the form of a positive risk-adjusted portfolio return compared to the historical average. Daily sovereign bond returns, daily realized higher moments (R-Volatility, R-Skewness, R-Kurtosis), daily realized hyper moments (RH-Skewness, RH-Kurtosis) and alternative predictors (First-order autoregressive term AR(1), Relative Spread (RS), Quoted Depth (QD), VIX index (VIX), 3-month Euribor (Eur), common risk factor (PCA), CDS spread (CDS)) are constructed as equally-weighted market indices. All forecasts are based on a 60-day recursive (expanding) window. The full sample period spans the dates from January 2008 to December 2010. November 2009 corresponds to the beginning of the crisis sample.

	Full sample (Jan 08-Dec 10)		Pre-crisis (Jan 08-Oct 09)		Crisis (Nov 09-Dec 10)	
	GIPS	Non-GIPS	GIPS	Non-GIPS	GIPS	Non-GIPS
AR(1)	0.6998	−0.0407	0.3022	−0.1043	1.1776	0.0358
R-Volatility	−0.0004	0.0144	−0.0294	−0.2317	0.0344	0.3101
R-Skewness	0.0770	−0.1155	0.0810	−0.1723	0.0723	−0.0472
R-Kurtosis	0.1079	0.2503	0.1388	0.4652	0.0708	−0.0080
RH-Skewness	−0.0833	−0.1339	0.0314	−0.2062	−0.2212	−0.0469
RH-Kurtosis	0.0634	0.0328	0.0474	0.0947	0.0826	−0.0415
RS	0.0375	−0.1033	−0.0300	−0.1887	0.1187	−0.0006
QD	0.0838	0.0295	−0.0174	0.0094	0.2053	0.0536
VIX	−0.0191	−0.1787	−0.1184	−0.4851	0.1002	0.1896
Eur	0.3128	0.3774	0.6257	0.1545	−0.0631	0.6453
PCA	0.1131	0.1919	0.0251	0.1199	0.2187	0.2785
CDS	−0.0196	−0.0205	−0.0965	−0.4672	0.0729	0.5164

of the economy. The CDS spread works well for Portugal only and takes on small and statistically insignificant values for the rest of the countries.

The full sample analysis does not provide a clear picture as it includes both pre-crisis and crisis periods. Examining out-of-sample return predictability for crisis and non-crisis periods in isolation will resolve any ambiguity in the interpretation of results. Panel B of Table 4a presents the results for the pre-crisis period. It seems that Greece is the only country for which bond subsequent returns can be predicted accurately by both higher moments and alternative predictors. Realized skewness and kurtosis are statistically significant at the 5 percent level beating the historical mean return. Realized hyper-skewness and realized hyper-kurtosis are able to explain the Greek bond returns only but take on smaller values than the realized skewness and kurtosis measures. These results are comparable to those of Boyer et al. (2010), Bali and Murray (2013), Conrad et al. (2013), and Amaya et al. (2015). The common risk factor and the autoregressive AR(1) term also perform well for Greece as they beat the historical mean and take on slightly higher values than realized skewness. Apart from Greece, realized kurtosis is positively and significantly related to future bond returns for the Netherlands, whilst liquidity proxied by the quoted depth outperforms realized higher moments for Austria. The CDS spread seems to be totally ineffective in predicting bond returns pre-crisis.

Panel C of Table 4a presents the results of the crisis period. Within higher moments realized kurtosis and realized hyper-kurtosis outperform the other moments especially those of the GIPS countries and beat the historical mean, confirming our previous results at the index level. Realized kurtosis works quite well for Greece, Italy, and Portugal as it is able to capture the probability of extreme market outcomes such as those witnessed in the distressed economies of the South. Realized skewness is statistically significant for Greece only showing that being the most vulnerable country within the GIPS group it drives the euro crash risk. On the contrary, realized hyper-skewness shows no power at all in predicting bond returns. Realized volatility accurately predicts subsequent sovereign bond returns for Portugal and Spain and outperforms realized skewness for both countries and realized kurtosis for Spain, however it fails to beat the historical mean for the rest of the countries.

Liquidity's importance in the crisis period is manifested in Greece and Portugal only, whereas it fails to outperform the historical mean return in Italy and Spain. Interestingly, both the relative spread and quoted depth outperform realized kurtosis and realized volatility in Portugal. Liquidity regardless of whether it is proxied by spread-based or depth-based measures is statistically insignificant for all countries in the non-GIPS region. VIX index and the 3-month Euribor perform poorly similar to the prediction results in the pre-crisis and the full sample period. The common risk factor in Greece, Portugal, and Belgium is able to explain subsequent bond returns in a statistically significant manner during the crisis confirming the findings of the full sample analysis as well as those of the index level analysis. The CDS spread performs satisfactorily for Portugal whose default risk was heightened during this period. Among the alternative predictors, the AR(1) term clearly outperforms all realized higher moments of the GIPS countries showing that it is arguably the fundamental predictor of subsequent bond returns during the crisis.

4.3.2. Economic significance

Table 4b presents the average annualized percentage utility gains from the out-of-sample predictions at the country level. On average, the results confirm those of Table 3b at the index level. In the crisis sample the autoregressive AR(1) term takes

Table 4a
Out-of-sample bond return prediction at the country level: Statistical Significance. This table presents OOS-R^2 for daily forecasts of the sovereign bond returns from predictive regressions relative to the historical average benchmark forecasting model. Daily realized higher moments (R-Volatility, R-Skewness, R-Kurtosis) and daily realized hyper moments (RH-Skewness, RH-Kurtosis) are constructed using 5-min intraday bond returns. Relative spread (RS) is defined as the best bid-ask spread divided by the midpoint of the bid and ask quotes. Quoted depth (QD) is defined as the summation of best bid size and best ask size (quantity of securities bid or offered for sale at the posted bid and offer prices). VIX is the CBOE volatility index derived from highly liquid S&P 500 index options. The 3-month Euribor rate (Eur) is the short-term euro interbank offered rate. PCA corresponds to the first principal component extracted from all three realized higher moments. CDS spread (CDS) is the daily average euro-area spread. AR(1) is a first-order autoregressive term. Statistical significance is based on Clark and West's (2007) adjusted-DM test, *t*-DM. All forecasts are based on a 60-day recursive (expanding) window. ***, **, and * denote statistical significance for the out-of-sample forecasts at the 1, 5, and 10 percent level, respectively. *t*-DM is the one-sided test statistic. The associated critical values are: 2.33 (1 percent level); 1.64 (5 percent level); 1.25 (10 percent level). The full sample period spans the dates from January 2008 to December 2010. November 2009 corresponds to the beginning of the crisis sample. Panel A reports the results for the full sample, whilst Panels B and C report the corresponding results for the pre-crisis and crisis periods, respectively.

		Austria	Belgium	Finland	France	Germany	Greece	Italy	Netherlands	Portugal	Spain
Panel A: Full Sample (Jan 08-Dec 10)											
AR(1)	OOS-R^2	−0.03	0.09	−0.22	−0.81	−0.81	5.00	0.69	−0.71	2.85	0.58
	t-DM	0.66	1.10	0.56	−1.56	−0.95	2.92***	2.40***	−1.36	3.08***	1.17
R-Volatility	OOS-R^2	−0.51	0.48	−0.29	−0.35	−0.34	1.92	−1.18	−0.42	0.54	0.27
	t-DM	0.69	1.21	0.89	−1.29	−0.98	1.07	−2.06	−0.18	1.10	1.01
R-Skewness	OOS-R^2	−0.31	−0.12	−0.13	−0.78	−0.58	1.76	−0.04	−0.49	−0.07	0.02
	t-DM	−0.25	0.40	0.67	−1.82	−1.37	2.31**	0.71	−1.53	0.35	0.70
R-Kurtosis	OOS-R^2	−0.51	0.09	−0.17	−4.01	−0.47	1.15	0.14	0.17	0.52	−0.35
	t-DM	−0.89	1.34*	0.40	−1.00	0.79	2.13**	1.23	1.51*	1.18	0.03
RH-Skewness	OOS-R^2	−0.44	−0.13	−0.23	−1.55	−0.64	0.08	−0.09	−0.59	−0.64	−0.08
	t-DM	−0.44	0.39	0.35	−2.09	−0.88	0.85	−0.17	−1.10	−1.25	0.40
RH-Kurtosis	OOS-R^2	−0.90	−0.20	−0.20	−19.48	−1.13	0.69	0.17	−0.12	−0.21	−0.26
	t-DM	−1.01	1.07	0.51	−1.02	1.22	2.15**	1.43*	1.23	0.31	0.41
RS	OOS-R^2	−1.53	−0.55	−0.92	−1.04	−1.65	0.50	−0.62	−0.39	1.10	−0.66
	t-DM	−0.51	−1.80	−0.26	−1.67	−1.16	1.18	−1.08	−1.78	1.88**	−0.46
QD	OOS-R^2	0.49	−0.52	−0.25	−0.34	−0.23	0.24	−0.44	−0.20	1.15	−0.33
	t-DM	1.93**	−1.06	−1.34	−0.37	−0.21	0.70	−1.24	−0.59	2.34***	−0.71
VIX	OOS-R^2	−1.78	−1.70	−0.93	−1.97	−1.34	0.10	−1.27	−1.50	−0.83	−0.84
	t-DM	−0.50	−1.51	−0.59	−2.24	−1.04	0.52	−1.82	−0.77	−0.54	−0.53
Eur	OOS-R^2	−1.45	−1.48	−1.65	−1.58	−1.52	−0.19	−1.43	−1.14	−0.55	−1.01
	t-DM	−0.12	−0.91	−2.05	−1.21	−1.15	0.66	−0.65	−0.59	−0.77	−0.22
PCA	OOS-R^2	−0.31	0.94	−0.61	−0.94	−0.31	3.88	−0.20	−0.29	1.38	−0.15
	t-DM	0.17	1.92**	−1.56	−2.15	0.28	1.89**	0.29	−1.46	1.80**	0.18
CDS	OOS-R^2	−2.20	−1.62	−1.53	−1.67	−1.33	−0.65	−1.47	−1.59	0.22	−1.70
	t-DM	−1.09	−0.93	−0.33	−1.93	−0.29	0.74	−1.35	−0.90	1.27*	−1.01
Panel B: Pre-Crisis (Jan 08-Oct 09)											
AR(1)	OOS-R^2	−0.21	−0.39	−0.22	−1.09	−1.29	2.16	0.22	−1.17	−1.12	−0.89
	t-DM	0.23	0.44	0.47	−1.48	−1.21	1.71**	1.40*	−1.46	0.01	−1.02
R-Volatility	OOS-R^2	−0.70	0.05	0.10	−0.49	−0.54	−0.50	−0.78	−0.41	−0.42	−0.61
	t-DM	0.66	0.63	1.19	−1.40	−1.25	−0.07	−1.64	0.11	−0.12	−0.96
R-Skewness	OOS-R^2	−0.36	−0.47	0.03	−1.08	−0.82	0.74	−0.44	−0.74	−0.49	−0.42
	t-DM	−0.44	−0.54	0.76	−2.44	−1.27	1.67**	−0.31	−1.39	−0.69	−1.08
R-Kurtosis	OOS-R^2	−0.61	−0.42	0.28	−5.50	−0.21	0.58	−0.13	0.25	−0.63	−0.43
	t-DM	−0.58	0.39	1.20	−0.99	1.20	1.90**	0.37	1.46*	−1.17	0.56
RH-Skewness	OOS-R^2	−0.29	−0.58	−0.25	−2.15	−0.92	0.30	−0.31	−1.03	−0.39	−0.31
	t-DM	−0.15	−1.39	0.34	−2.15	−0.87	1.41*	−1.70	−1.25	−0.99	−0.29
RH-Kurtosis	OOS-R^2	−1.03	−0.92	0.02	−26.96	−1.37	0.43	−0.17	−0.32	−0.56	−0.59
	t-DM	−0.64	0.05	1.05	−1.03	0.77	1.75**	0.27	1.1	−1.61	0.44
RS	OOS-R^2	−2.05	−0.79	−1.23	−1.38	−2.44	−1.09	−1.06	−0.60	−0.81	−1.43
	t-DM	−0.49	−1.75	−0.21	−1.74	−1.21	−0.69	−2.43	−1.76	0.34	−0.61
QD	OOS-R^2	0.75	−0.82	−0.25	−0.40	−0.14	−0.50	−0.75	−0.31	−0.31	−0.46
	t-DM	2.09**	−0.98	−1.03	−0.20	0.13	−0.74	−1.10	−0.56	−0.21	−0.27
VIX	OOS-R^2	−1.96	−2.62	−1.18	−2.69	−1.90	−1.68	−2.25	−2.45	−2.53	−2.04
	t-DM	−0.31	−1.49	−0.43	−2.36	−0.96	−1.51	−1.84	−0.78	−0.43	−0.63
Eur	OOS-R^2	−1.37	−2.03	−2.26	−2.10	−2.21	−2.01	−1.85	−1.77	−2.07	−1.44
	t-DM	−0.06	−0.92	−2.30	−1.29	−1.27	0.26	−0.47	−0.92	−1.69	0.11
PCA	OOS-R^2	−0.29	0.26	−0.83	−1.29	−0.20	1.17	−0.37	−0.53	−0.49	−0.55
	t-DM	0.29	0.92	−1.50	−2.25	0.51	1.85**	−0.15	−1.90	0.07	−0.41
CDS	OOS-R^2	−2.85	−3.04	−2.17	−2.35	−1.89	−2.43	−2.40	−2.27	−2.88	−2.62
	t-DM	−1.33	−1.80	−0.98	−2.58	−0.58	−0.59	−2.08	−1.91	−1.28	−0.49
Panel C: Crisis (Nov 09-Dec 10)											
AR(1)	OOS-R^2	0.45	0.81	−0.21	−0.10	0.19	5.71	1.24	−0.02	4.61	1.72
	t-DM	1.09	1.37*	0.34	−1.07	0.85	3.08***	1.81**	0.06	3.25***	1.49**
R-Volatility	OOS-R^2	−0.01	1.12	−1.17	0.02	0.04	2.54	−1.65	−0.45	0.97	0.96
	t-DM	0.39	1.10	−1.05	0.25	0.38	1.18	−1.46	−1.29	1.29*	1.32*

(*continued on next page*)

Table 4a (*continued*)

		Austria	Belgium	Finland	France	Germany	Greece	Italy	Netherlands	Portugal	Spain
R-Skewness	OOS-R^2	−0.17	0.39	−0.50	0.00	−0.07	2.02	0.44	−0.12	0.11	0.37
	t-DM	0.04	1.10	−0.16	0.50	−0.90	2.16**	1.18	−0.70	0.57	1.14
R-Kurtosis	OOS-R^2	−0.27	0.85	−1.19	−0.14	−1.00	1.29	0.46	0.06	1.03	−0.29
	t-DM	−0.96	1.55*	−1.33	−2.07	−2.46	2.25**	1.27*	0.56	1.30*	−1.07
RH-Skewness	OOS-R^2	−0.84	0.54	−0.20	0.02	−0.05	0.02	0.18	0.07	−0.76	0.11
	t-DM	−0.53	1.26	0.05	0.43	−0.14	0.65	0.8	0.70	−1.04	0.62
RH-Kurtosis	OOS-R^2	−0.55	0.85	−0.70	0.00	−0.62	0.75	0.58	0.19	−0.05	−0.01
	t-DM	−0.80	1.45*	−0.82	0.42	−2.16	2.22**	1.43*	0.92	0.46	0.04
RS	OOS-R^2	−0.17	−0.20	−0.21	−0.13	−0.02	0.91	−0.10	−0.07	1.96	−0.06
	t-DM	−0.89	−0.83	−0.73	−0.14	−2.42	1.55*	0.32	−0.44	1.94**	0.15
QD	OOS-R^2	−0.22	−0.07	−0.23	−0.20	−0.43	0.43	−0.07	−0.04	1.80	−0.22
	t-DM	0.43	−0.76	−0.93	−3.27	−0.68	0.92	−0.86	−0.22	2.60***	−2.05
VIX	OOS-R^2	−1.33	−0.35	−0.37	−0.11	−0.20	0.55	−0.12	−0.07	−0.07	0.10
	t-DM	−0.50	−0.34	−0.91	0.01	−0.91	1.15	−0.54	−0.08	−0.39	0.71
Eur	OOS-R^2	−1.65	−0.68	−0.26	−0.22	−0.12	0.26	−0.94	−0.19	0.13	−0.68
	t-DM	−0.15	−0.26	0.03	0.34	0.27	0.77	−0.47	0.44	0.63	−0.89
PCA	OOS-R^2	−0.37	1.94	−0.10	−0.01	−0.55	4.57	0.01	0.08	2.22	0.16
	t-DM	−0.42	1.72**	−0.97	0.17	−1.06	2.07**	0.54	0.87	1.90**	0.65
CDS	OOS-R^2	−0.49	0.46	−0.06	0.09	−0.16	−0.21	−0.37	−0.56	1.60	−0.98
	t-DM	0.04	0.84	0.79	0.73	0.60	1.04	0.01	0.38	1.70*	−0.95

on its largest positive values for Greece, Italy, Portugal, and Spain, whereas it exhibits small utility gains for the non-GIPS countries. It seems that investors are compensated with higher positive portfolio returns for undertaking additional amounts of risk by investing in bonds of lower credit ratings. Realized skewness and realized kurtosis mainly offer increased utility benefits to those investors with holdings in GIPS benchmark securities. The economic significance of realized hyper-skewness and realized hyper-kurtosis does not differ dramatically from that of realized skewness and kurtosis. We get mixed results for liquidity as we are unable to detect a clear pattern within the crisis sample. VIX and the 3-month Euribor are more economically meaningful for the non-GIPS countries whilst the common risk factor offers more consistent benefits for the GIPS countries. The CDS spread although it exhibits positive returns compared to the historical average for GIPS countries (with the exception of Greece), it offers higher utility gains for non-GIPS countries, such as Finland, Germany, and the Netherlands. This result is in line with that of Billio et al. (2013) who show that on average the expected loss ratio of government debt of periphery countries is much higher than the corresponding expected loss ratio of core eurozone countries.

Similar to findings at the index level, in the pre-crisis period the role of CDS spread, VIX, and the common risk factor is less important in terms of percentage utility gains achieved than that documented in the crisis sample. The 3-month Euribor's economic significance increases in the pre-crisis period compared to the crisis period for GIPS countries and declines for non-GIPS countries. Theoretical developments on the valuation of risky debt proposed by Longstaff and Schwartz (1995) predict a negative correlation between credit spreads and interest rates. This finding has been empirically confirmed by Duffee (1998) and Collin-Dufresne et al. (2001), among others. This partly explains the 3-month Euribor's economic significance pre-crisis as it is negatively correlated with the CDS spread.

Again we get mixed results for spread-based and depth-based liquidity as it behaves erratically over pre-crisis and crisis periods. Realized hyper-skewness offers smaller utility gains in the pre-crisis period, and those gains are equally shared across core and periphery countries. Realized hyper-kurtosis and realized kurtosis measures offer enhanced utility gains for non-GIPS countries pre-crisis whilst realized volatility exhibits higher portfolio returns for GIPS countries (with the exception of Spain) pre-crisis. Although the AR(1) term takes on smaller values pre-crisis, it offers economically significant returns for GIPS countries (with the exception of Spain). For non-GIPS countries, we get mixed results for the AR(1) term as we observe large economic gains for Finland and losses for France and Germany.

5. Conclusions

To the best of our knowledge, this paper is the first to investigate whether the distributional characteristics of sovereign bonds predict time series of future bond returns. In particular, we contribute to the return prediction literature by studying the out-of-sample predictability of sovereign bond returns using realized higher moments and realized hyper moments. We use a rich and comprehensive high-frequency dataset from the MTS bond market which facilitates the construction of model-free realized higher moments from intraday returns, in line with the realized volatility theory. We study both tranquil and crisis periods and analyze the predictive accuracy of realized higher moments across core and periphery eurozone countries.

Overall, our analysis implies that it is not easy for higher moments to beat the historical average return. Another interesting implication is that the degree of bond return predictability depends on market conditions, that is, it differs between calm periods and periods of market turmoil. Moreover, we provide evidence that alternative economic predictors such as

Table 4b

Out-of-sample bond return prediction at the country level: Economic Significance. This table presents the average annualized percentage utility gain (see Eq. (13)), ΔU, in percentage points. Utility gains are computed as difference between forecasts using the predictive regression and forecasts using the historical average for a mean-variance investor with relative risk aversion coefficient of $\gamma = 3$, and portfolio weights of the bond return restricted to the interval between 0 and 1.5 (see Campbell and Thompson (2008)). Positive values indicate that the investor earns a utility gain in the form of a positive risk-adjusted portfolio return compared to the historical average. Variables are: daily realized higher moments (R-Volatility, R-Skewness, R-Kurtosis), daily realized hyper moments (RH-Skewness, RH-Kurtosis) and alternative predictors (First-order autoregresive term AR(1), Relative Spread (RS), Quoted Depth (QD), VIX index (VIX), 3-month Euribor (Eur), common risk factor (PCA), CDS spread (CDS)). All forecasts are based on a 60-day recursive (expanding) window. The full sample period spans the dates from January 2008 to December 2010. November 2009 corresponds to the beginning of the crisis sample. Panel A reports the results for the full sample, whilst Panels B and C report the corresponding results for the pre-crisis and crisis periods, respectively.

	Austria	Belgium	Finland	France	Germany	Greece	Italy	Netherlands	Portugal	Spain
Panel A: Full Sample (Jan 08-Dec 10)										
AR(1)	0.1951	0.2536	0.3686	−0.2055	−0.2258	1.0495	0.7814	0.0227	0.8004	0.5157
R-Volatility	0.1300	0.4326	0.2997	−0.0644	0.0000	−0.1510	−0.1035	0.0135	−0.0150	0.4288
R-Skewness	0.0343	0.0689	0.1686	−0.1383	−0.1778	0.0675	0.1081	−0.1071	−0.0364	0.1883
R-Kurtosis	−0.0321	0.2385	0.1226	−0.1098	0.0235	0.0064	0.0274	0.2858	0.0048	−0.0316
RH-Skewness	−0.0017	0.0020	−0.0020	−0.2959	−0.1602	−0.2616	−0.0370	−0.1387	−0.1104	0.1625
RH-Kurtosis	−0.0157	0.1353	0.1025	−0.1517	−0.0085	−0.0249	0.0132	0.1036	−0.0188	0.0096
RS	−0.0042	−0.0616	0.2141	−0.0767	−0.1150	−0.0509	0.0646	−0.0705	0.0965	0.1118
QD	0.4450	−0.0139	0.0595	−0.0693	0.2596	0.0009	−0.0299	−0.0094	0.1309	−0.0716
VIX	0.1698	−0.1694	0.0830	−0.2027	−0.0517	−0.0163	−0.1591	−0.0370	0.0382	−0.0111
Eur	0.6055	0.3331	−0.0328	0.1380	0.0667	0.1177	0.4781	0.4237	−0.0017	0.4906
PCA	−0.0680	0.2131	−0.1039	−0.1476	−0.0748	0.5654	−0.0411	−0.0527	0.1543	−0.0474
CDS	−0.0132	−0.1436	0.6168	−0.1838	0.3989	−0.0386	−0.1330	0.2051	0.0000	0.1020
Panel B: Pre-Crisis (Jan 08-Oct 09)										
AR(1)	0.0527	0.1357	0.6017	−0.3542	−0.4758	0.6547	0.5835	0.0452	0.0266	−0.1158
R-Volatility	0.1129	0.1727	0.9340	−0.1577	−0.1069	0.0157	−0.0839	0.1688	0.0082	0.0114
R-Skewness	0.0249	−0.0339	0.2616	−0.3059	−0.3064	0.2366	0.0367	−0.1616	−0.0005	−0.0822
R-Kurtosis	−0.0235	0.2718	0.2664	−0.1702	0.1906	0.1398	0.0095	0.3756	−0.0079	0.0309
RH-Skewness	−0.0475	−0.1210	−0.0400	−0.5566	−0.2856	0.0833	−0.0945	−0.2761	−0.0358	−0.0485
RH-Kurtosis	−0.0263	0.1495	0.1751	−0.2834	0.0929	0.0839	−0.0208	0.0867	−0.0225	−0.0036
RS	0.0157	−0.1365	0.5603	−0.2225	−0.2055	−0.0552	−0.0990	−0.0666	0.0600	0.1609
QD	0.6458	−0.0297	0.0801	−0.0614	0.4157	−0.0199	−0.0359	−0.0455	0.0879	−0.0332
VIX	0.1219	−0.4641	0.3919	−0.5096	0.0279	−0.0354	−0.3364	−0.1805	0.1106	−0.0226
Eur	0.7642	0.2976	−0.4271	−0.1294	−0.2084	0.3025	0.6244	0.1768	0.0266	0.7617
PCA	−0.0604	0.0542	−0.1729	−0.2688	−0.0417	0.2438	−0.0771	−0.1104	−0.1021	−0.1146
CDS	−0.1084	−0.4862	0.5503	−0.5369	0.3414	−0.0168	−0.3038	−0.2156	−0.0796	0.1520
Panel C: Crisis (Nov 09-Dec 10)										
AR(1)	0.3663	0.3954	0.0884	−0.0267	0.0748	1.5239	1.0192	−0.0043	1.7303	1.2747
R-Volatility	0.1507	0.7449	−0.4626	0.0476	0.1285	−0.3513	−0.1269	−0.1731	−0.0428	0.9305
R-Skewness	0.0456	0.1925	0.0569	0.0631	−0.0233	−0.1356	0.1939	−0.0415	−0.0796	0.5135
R-Kurtosis	−0.0425	0.1985	−0.0503	−0.0373	−0.1774	−0.1539	0.0489	0.1780	0.0200	−0.1067
RH-Skewness	0.0534	0.1498	0.0436	0.0174	−0.0094	−0.6762	0.0321	0.0265	−0.2001	0.4159
RH-Kurtosis	−0.0029	0.1184	0.0153	0.0066	−0.1304	−0.1557	0.0541	0.1239	−0.0143	0.0256
RS	−0.0281	0.0284	−0.2020	0.0985	−0.0063	−0.0458	0.2612	−0.0752	0.1404	0.0528
QD	0.2036	0.0050	0.0348	−0.0787	0.0720	0.0258	−0.0226	0.0339	0.1825	−0.1177
VIX	0.2273	0.1847	−0.2883	0.1662	−0.1474	0.0066	0.0540	0.1355	−0.0489	0.0027
Eur	0.4148	0.3759	0.4411	0.4593	0.3974	−0.1045	0.3022	0.7205	−0.0358	0.1648
PCA	−0.0771	0.4042	−0.0208	−0.0021	−0.1146	0.9521	0.0021	0.0167	0.4625	0.0333
CDS	0.1012	0.2681	0.6969	0.2408	0.4680	−0.0649	0.0723	0.7108	0.0957	0.0420

CDS spreads, short-term interest rates, and the VIX index do not usually provide statistically significant forecasting gains compared to realized higher moments. However, the first-order autoregressive term outperforms quite often the realized higher moments, especially those of GIPS countries during the crisis sample.

Our findings in the pre-crisis period reveal that all realized higher moments perform poorly for GIPS and non-GIPS countries at the index level, whereas at the country level Greece is the only country for which bond returns are predictable using higher moments and alternative predictors. The most interesting results pertain to the crisis period. Among higher moments realized kurtosis is the dominant predictor for GIPS countries. Liquidity gains significance in the crisis period as it outperforms realized kurtosis for GIPS countries whilst the VIX index, the CDS spread, and the common risk factor extracted from realized higher moments are also able to explain GIPS subsequent returns quite accurately during the crisis. Our analysis also offers useful insights on the economic significance of prediction results across core and periphery countries. In conclusion, we provide solid evidence that sovereign bond return predictability using realized higher moments is more pronounced in the crisis period and is mainly manifested in the benchmark securities of distressed eurozone economies.

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