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A new take on the relationship between interest rates and credit spreads

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ABSTRACT

We revisit the link between interest rates and corporate bond credit spreads by applying Rigobon's (2003) unique heteroskedasticity-based identification methodology to their interconnected dynamics through a bivariate VAR system. This different approach allows us to account for simultaneity issues and use this framework to test the various possible explanations for the credit spread – interest rate relation that have been proposed by the literature over the years. We find that credit spreads do indeed respond negatively to interest rates, a result consistent with Merton's (1974) structural model. This negative relation is robust to macroeconomic shocks, market uncertainty, business cycles, different sample periods, bond callability, and bond ratings. We also find the magnitude of the negative relation to be larger for high-yield bonds than for investment-grade bonds, and are able to rule out the option-like feature of callable bonds proposed by Duffee (1998) as the main driver of the negative nature of the relationship. These results have important portfolio and risk management implications.

KEYWORDS

Interest rates; credit spreads; identification through heteroskedasticity; simultaneity

JEL CLASSIFICATION

G12; G18; E43

The relationship between interest rates and credit spreads is of utmost importance to monetary policy makers as well as to portfolio and risk managers as both the size and the direction of credit spreads' reactions to changes in Treasury rates determine the sign and magnitude of ensuing corporate bond price movements. A portfolio manager predicting future economic growth or a downturn would be able to predict a tightening or a widening of the corporate spreads depending on whether interest rates and credit spreads are positively or negatively related.

In addition to the traditional areas where interest rate risk matters such as banking, insurance companies, pension funds and mutual funds, a new area where the nature of the relationship matters is in the emergence of Exchange-Traded Funds (ETFs) that are seeking corporate yields exposure while attempting to hedge interest rate risk, aiming for a duration close to zero. Knowing how the short rate impacts corporate credit spreads and thus various yields of differing maturities is therefore vital in such strategies.

Additionally, how credit spreads evolve over time and the underlying causes of that evolution are also essential to understanding the risk-return tradeoff in bond markets, consequences regarding bond portfolio allocation, the pricing of credit derivatives, the management of credit risk, and central financial policies implications when trying to control credit risk in bond markets.

However, examining the relationship between interest rates and credit spreads has led to a wide range of results and contradictory predictions, leaving the link between credit spreads and interest rates a still ongoing and unresolved subject of debate. Seminal theoretical papers by Merton's (1974) and Longstaff and Schwartz (1995) have predicted an inverse relationship between interest rates and credit spreads, while Leland and Toft (1996)'s model can at times predict a positive one. Subsequent empirical research in this area has included work by Duffee (1998), Bevan and Garzarelli (2000), Collin-Dufresne, Goldstein, and Martin (2001), Blanco, Brennan, and Marsh (2005), Avramov, Jostova, and Philipov (2007), Davies (2008), Ericsson, Jacobs, and Oviedo (2009), Jacoby, Liao, and Batten (2009), Neal et al. (2015), Johansson and Rehnberg (2017), Mensi et al. (2019), with the

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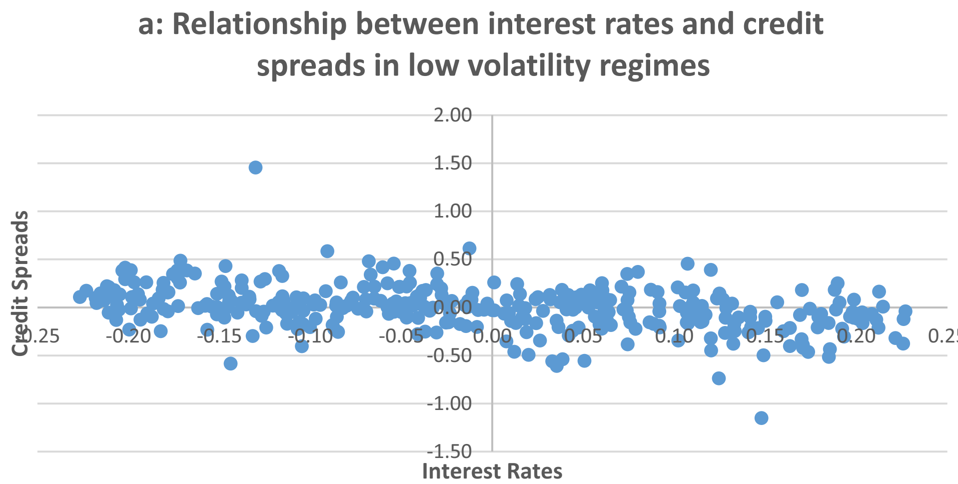
most recent investigation attempted by Li, Li, and Si (2020). Results from these empirical studies vary widely. Appendix 1 illustrates the various possible scenarios.

An important reason for the discrepancies in the results and conclusions is the fact that most empirical work involves estimating regression coefficients with credit spreads as the dependent variable and interest rates as the independent variable (possibly in the company of other variables and potential lags), with the main issue with such an approach being the potential simultaneous response of interest rates to credit spreads, as orthogonal exogenous shocks to either credit spreads or interest rates can simultaneously affect both variables, acting as confounding factors. For instance, if credit spreads and interest rates are codetermined according to a system of two structural equations, with ε_{cs} and ε_{ir} the respective error terms in the two equations of the system, then interest rates as an explanatory variable will not be independent of ε_{cs} in the credit spread equation and credit spreads as an explanatory variable will not be independent of ε_{ir} in the interest rates equation. Ignoring simultaneity in the estimation leads to biased estimates, and while imposing restrictions or the use instrumental variables can usually be used to address this problem, no economic or finance theory can help impose additional restrictions in this case and it is nearly impossible to find an instrumental variable affecting only interest rates and not credit spreads since both interest rates and credit spreads are both influenced by a set of common macroeconomic factors.

Using domestic (United States) monthly Barclay investment-grade and high-yield corporate bond indices and Treasury rates of various maturities from 1973 to 2019, we tackle this issue by adopting Rigobon's (2003) heteroskedasticity-based identification method to the possibly bidirectional interest rate - credit spread relationship. This approach allows parameter identification through the shifting of the variance of the shocks and deals with the simultaneity issue when other identification methods would otherwise not be appropriate. Applied in this setting, the identification through heteroskedasticity method delivers consistent and robust estimates of the credit spreads' reaction to interest rates.

Our approach relies on the heteroskedasticity of interest rates and credit spreads shocks. Shifts in the variance of interest rates shocks relative to that of credit spread shocks affect the covariance between credit spreads and interest rates in a manner that depends on the reaction of credit spreads to interest rates. We can thus compute the response of credit spreads based on the observed shifts in the covariance matrix. The intuition is as follows: the reaction of credit spreads becomes a stronger determinant of the covariance between credit spreads and interest rates during periods when interest rate shocks are more variable. If the variance of the interest rate shocks dominates the variance of the credit spreads shocks, the shift will make the realization of interest rates and credit spreads more precisely follow the credit spread reaction function than before. Taking a first glance at the data, Figure 1 illustrates the relationship between interest rates and credit spreads in two separate regimes: Figure 1a describes the relationship when interest rate shocks are below their mean in magnitude, while Figure 1b describes the relationship when interest rate shocks are above their mean in magnitude. In the lower volatility regime, the simultaneous determination of credit spreads and interest rates does not provide a clear reading of whether the credit spread response function is upward or downward sloping in interest rates. In the higher volatility regime, when the interest rates disturbances are more volatile, the shocks are distributed around an ellipse that stretches along the credit spread reaction function. Thus, we are better able to identify the slope of the credit spread reaction function based on changes in the covariance of credit spreads and interest rates across periods when the variance of their shocks changes.

Additionally, we plot in Figure 2 the monthly Treasury rates returns for the same period and provide visual confirmation of temporal shifts in the magnitude of the shocks, a clear display of heteroskedasticity in the data. One last quick examination of the data in Figure 3 also suggests that, while the correlation between interest rates and credit spreads tends to be negative more often than positive, it varies extensively over time both



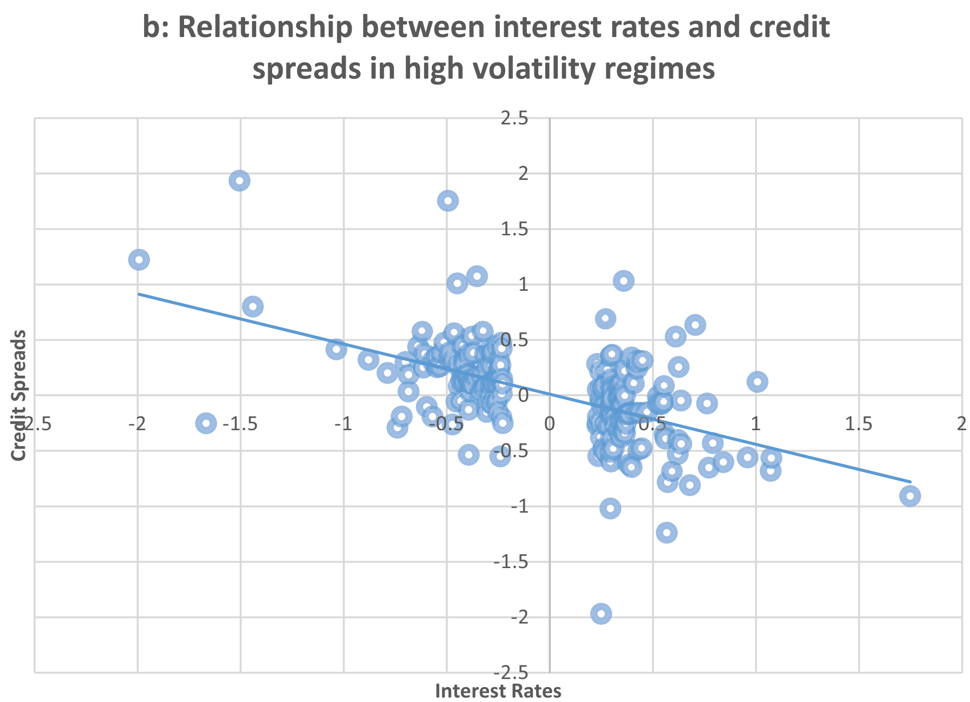


Figure 1. Joint determination of Treasury rates and investment-grade credit spreads from 1973.01 to 2019.03. Note: Figure 1a plots the joint determination of monthly returns of duration-matched Treasury rates and investment-grade credit spreads during low interest rate volatility regimes. Figure 1b plots the joint determination of Treasury rates and investment-grade credit spreads during high interest rate volatility regimes.

in size and in sign. These types of shifts in sign are explained by a shift in the relative importance of different shocks, as demonstrated earlier in Figure 1.

We find a negative response of credit spreads to interest rates, as implied by Merton's (1974) structural model. The negative relation is of economic and statistical significance, robust to macroeconomic shocks, market uncertainty, interest rates characteristics, business cycles, callability features, and bond credit ratings. We also find that the magnitude of the negative relation is larger for high-yield bonds than for investment-grade bonds, a sensible result since riskier bonds are in general more volatile and sensitive to changing economic conditions.

We also re-examine several existing explanations for the negative relation. We show that the negative relationship remains statistically significant even when the methodology is applied to a bond index devoid of any callability features, supporting King's (2002) argument that callable

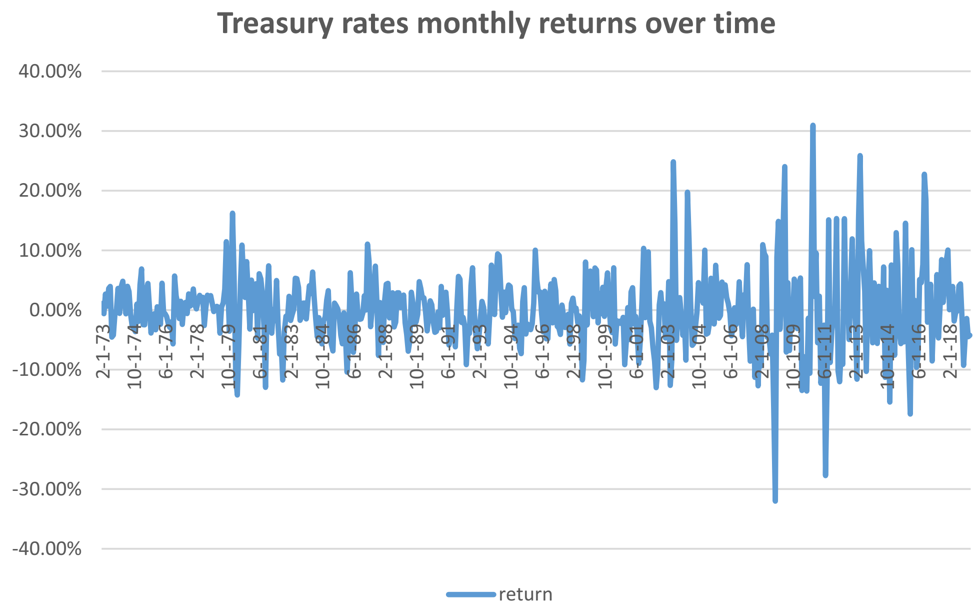


Figure 2. Treasury rates monthly returns from 1973.01 to 2019.03. Note: Figure 2 plots the monthly returns of duration-machted Treasury rates from 1973.01 to 2019.03. The monthly Treasury rates used in this study have been duration-matched with the bond indexes in the time series.

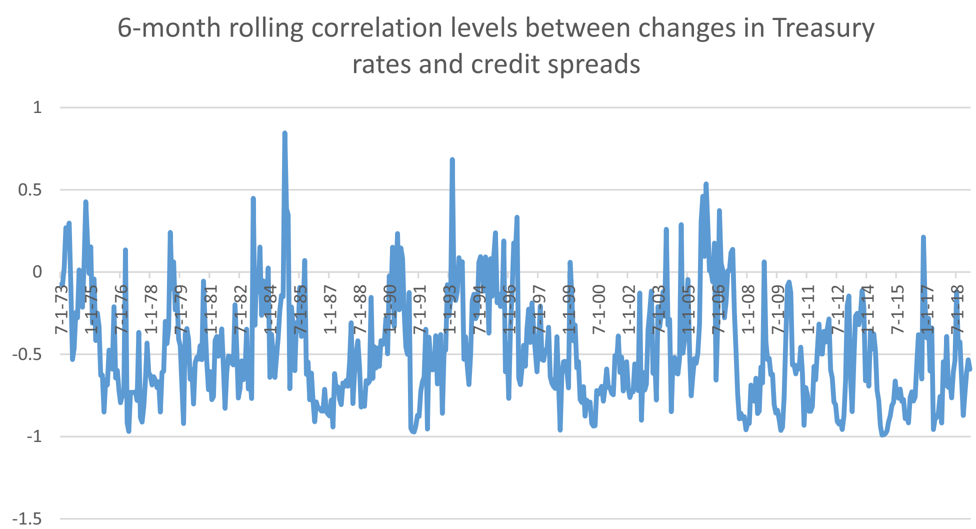


Figure 3. Correlation levels between Treasury rates and investment-grade credit spreads from 1973.01 to 2019.03. Note: This figure plots monthly returns of duration-matched Treasury rates and investment-grade credit spreads 6-month rolling correlation levels from January 1973 to March 2019.

bonds are not necessarily largely responsible for the negative relation between interest rates and credit spreads and that the effect persists even when they are removed from the sample. Collin-Dufresne, Goldstein, and Martin (2001) argue that business climate change is a significant determinant of credit spreads. We thus also test this intuition by using a two-step procedure. Interest rate and credit spread changes are first made orthogonal to changes in various macroeconomic variables, uncertainty and business cycle effects and are then run through the identification through heteroskedasticity procedure. Our results confirm with high statistical significance that, even when macroeconomic variables and business cycles are excluded from interest rates and credit spreads, a similar negative relationship remains.

The remainder of this article is organized as follows. Section I introduces the methodology used to identify the parameters through heteroskedasticity and the data employed in the study. Section II describes the different models estimated and the corresponding empirical estimates of the relationship between interest rates and credit spreads. Section III explores the validity of the callability feature explanation for the negative relation, and section IV concludes.

II. Methodology and data

In this section, we describe the methodology and data used in our empirical tests. The technique used in these different exercises follows Rigobon's (2003) method of heteroskedasticity-based identification, a procedure that allows one to account for simultaneity issues and in this setting properly capture the interaction between interest rates and credit spreads.

Methodology

When empirically estimating the relation between credit spreads and interest rates, one faces an identification challenge since both credit spreads and interest rates are endogenous variables. We address this concern by applying the heteroskedasticity-based identification method developed by Rigobon's (2003). The fundamental idea behind identification through heteroskedasticity is that with structural parameters remaining stable across different regimes, variances of structural shocks in the regimes provide additional restrictions, leading to the identification of the system. The key assumption is that the variances of structural shocks in regimes cannot change proportionally. In order to apply this method successfully, one must therefore ensure that the structural shocks exhibit some non-proportional heteroskedasticity. We first consider a bivariate VAR model without common shocks, and subsequently take various macroeconomic common shocks into account as well.

We first establish a structural bivariate VAR system to capture the interaction between interest rates and credit spreads:

$$CS_t = \alpha TB_t + \sum_{k=1}^{n} \xi_k TB_{t-k} + \sum_{k=1}^{n} \theta_k CS_{t-k} + \upsilon_t \tag{1}$$

$$TB_t = \beta CS_t + \sum_{k=1}^{n} \kappa_k CS_{t-k} + \sum_{k=1}^{n} \lambda_k TB_{t-k} + \mu_t \tag{2}$$

where TB_t and CS_t designate the Treasury rates and Corporate Bond credit spreads respectively, and where υ_t and μ_t are the structural shocks for credit spreads and interest rates. The index k represents the number of lagged terms, αstands for the impact of interest rates on credit spreads, and βrepresents the interest rate sensitivity to credit spreads. The contemporaneous reaction of credit spreads to interest rates, α, is the parameter in which we are most interested.

In this simple bivariate structural VAR model, one can think of the short rate shock as being associated with a pure risk-free rate shock, and of the credit spread shock as being associated with a pure credit default shock, hence the assumption of orthogonality. However, although the two structural shocks are independent, these orthogonal shocks can affect both interest rates and credit spreads: a shock to interest rates (credit spreads) also affects credit spreads (interest rates) through the feedback. This means that the orthogonal exogeneous structural shocks can simultaneously endogenously affect both state variables. For instance, a shock to real rates or inflation does immediately get transmitted to credit spreads and can thus be correlated with the expected future cash flows of the firm. Stated differently, the assumed independence between the two exogenous shocks does not preclude correlation between the interest rate shock and the expected future cash flows of the firm. However, recognizing the ability of potential confounding macroeconomic variables to simultaneously influence both interest rates and credit spreads, we acknowledge that the identification without common shocks in our base model is a simple one. We therefore later additionally relax the orthogonality assumption by taking common shocks into account.

It is however well known that the α and β coefficients cannot be estimated directly due to the simultaneity of the regressors. The usual approach to get around a simultaneity issue is to impose an instrumental variable or additional parameter restriction (for instance, an exclusion restriction, a sign restriction, or a long-run restriction). In this case, however, it is challenging to find an instrumental variable affecting only interest rates and not credit spreads, for the simple reason that both interest rates and credit spreads are both influenced by a set of common macroeconomic factors. No economic or finance theory can help impose additional restrictions in this case. In order to deal with these simultaneity issues, one must therefore resort to an alternative identification technique. The heteroskedasticity in the residuals of interest rates and credit spreads is used here to identify the α and β parameters.

If we insert TB_t in (2) into (1) and CS_t in (1) into (2), respectively, we obtain the reduced-form Equation (3) and Equation (4):

$$CS_t = \frac{1}{1-\alpha\beta}\left[\begin{array}{l}\sum_{k=1}^{n}(\alpha\lambda_k+\xi_k)TB_{t-k}+\sum_{k=1}^{n}(\alpha\kappa_k+\theta_k)CS_{t-k}\\ +(\alpha\mu_t+v_t)\end{array}\right] \tag{3}$$

$$TB_t = \frac{1}{1-\alpha\beta}\left[\begin{array}{l}\sum_{k=1}^{n}(\beta\xi_k+\lambda_k)TB_{t-k}+\sum_{k=1}^{n}(\beta\theta_k+\kappa_k)CS_{t-k}\\ +(\mu_t+\beta v_t)\end{array}\right] \tag{4}$$

where $\frac{1}{1-\alpha\beta}(\alpha\mu_t+v_t)$ and $\frac{1}{1-\alpha\beta}(\mu_t+\beta v_t)$ are the residuals of the reduced-form Equation (3) and Equation (4).

Based on the reduced-form VAR system, we can estimate the variance-covariance matrix of the composite innovations of Equation (3) and Equation (4) determined by:

$$\Omega = \frac{1}{(1-\alpha\beta)^2}\begin{pmatrix}\sigma_v^2+\alpha^2\sigma_\mu^2 & \beta\sigma_v^2+\alpha\sigma_\mu^2\\ & \beta^2\sigma_v^2+\sigma_\mu^2\end{pmatrix} \tag{5}$$

The variance-covariance matrix offers three equations, while there are four parameters to be estimated: $\alpha,\beta,\ \sigma_v^2,\text{and}\sigma_\mu^2$. The system is clearly underidentified and at least one additional equation is required to identify the system. We consider two regimes based on the different variance characteristics of the two structural shocks μ_t and v_t. However, it is necessary to assume that the α and β parameters remain stable across the different regimes and that the structural shocks are not correlated. For each regime, we have:

$$\Omega_i = \begin{pmatrix}\Omega_{11,i} & \Omega_{12,i}\\ & \Omega_{22,i}\end{pmatrix} = \frac{1}{(1-\alpha\beta)^2}\begin{pmatrix}\sigma_{v,i}^2+\alpha^2\sigma_{\mu,i}^2 & \beta\sigma_{v,i}^2+\alpha\sigma_{\mu,i}^2\\ & \beta^2\sigma_{v,i}^2+\sigma_{\mu,i}^2\end{pmatrix} \tag{6}$$

where each regime is represented by i = {1,2}

There are six equations provided by the variance-covariance matrices in the two regimes and six unknown parameters: $\alpha,\beta,$ $\sigma_{v,1}^2,\sigma_{v,2}^2,\sigma_{\mu,1}^2,\text{and}\sigma_{\mu,2}^2$. If the six equations are independent, then the parameters are just identified. Solving from matrix (6), α andβ must satisfy:

$$\alpha = \frac{\Omega_{12,i}-\beta\Omega_{11,i}}{\Omega_{22,i}-\beta\Omega_{12,i}} \tag{7}$$

where i= {1,2}

The β parameter can then be solved from the following equation:

$$\begin{aligned}&(\Omega_{11,1}\Omega_{12,2}-\Omega_{12,1}\Omega_{11,2})\beta^2\\ &-(\Omega_{11,1}\Omega_{22,2}-\Omega_{22,1}\Omega_{11,2})\beta\\ &+(\Omega_{12,1}\Omega_{22,2}-\Omega_{22,1}\Omega_{12,2})\\ &=0.\end{aligned} \tag{8}$$

Rigobon's (2003) shows that the α and β parameters can be consistently estimated from the variance-covariance matrices of the two regimes.[1] It is worth noting that consistency can be still achieved under some misspecification of the heteroskedasticity.[2] As in Equation (6), for the two regimes, there are six unknown parameters. Meanwhile, the variance-covariance matrix in Equation (6) provides exactly six independent moment restrictions. In this setting, we estimate these parameters using Hansen's (1982) Generalized Method of Moments (GMM).

To address potential small-sample bias concerns, we additionally implement a bootstrapping procedure and report the bootstrapped p-values for each estimate. The bootstrapping procedure

[1]See proposition 1 in Rigobon's (2003, 780).
[2]See propositions 3 and 4 in Rigobon's (2003, 783–784).

involves simulating historical data for the variables and then using these simulated time series to generate the parameters distributions through the same estimation method applied to actual historical data. Our bootstrapping procedure consists of the following four steps. First, we begin by estimating the VAR system described in Equation (3) and Equation (4) and store the reduced-form residuals for resampling. Then the α and β parameters are estimated by the GMM procedure described above. Second, we randomly draw from the stored residuals in each regime and generate two bootstrapped time series $\widehat{\mathrm{CS}_t}$and$\widehat{\mathrm{TB}_t}$ in the reduced-form VAR system. In the third step, using the bootstrapped series $\widehat{\mathrm{CS}_t}$and$\widehat{\mathrm{TB}_t}$, we re-estimate the α and β parameters via the identification through heteroskedasticity procedure. The fourth step involves repeating steps 2 and 3 a total of 1,000 times and storing the bootstrapped parameter estimate α for each iteration. Lastly, we report the bootstrapped p-values for statistical significance.

The above bivariate structural VAR model in Equation (1) and Equation (2) assumes the structural shocks to be orthogonal. However, confounding macroeconomic factors can have a simultaneous influence on both interest rates and credit spreads. We relax the orthogonality assumption by taking a common shock into account and once again empirically estimating the impact of interest rates on credit spreads. Formally we have

$$CS_t = \alpha TB_t + \sum_{k=1}^{n} \xi_k TB_{t-k} + \sum_{k=1}^{n} \theta_k CS_{t-k} + \phi_1 F_t + \nu_t \tag{9}$$

$$TB_t = \beta CS_t + \sum_{k=1}^{n} \kappa_k CS_{t-k} + \sum_{k=1}^{n} \lambda_k TB_{t-k} + \psi_1 F_t + \mu_t \tag{10}$$

where F_t represents the common shock at time t. In a first approach, we use the shocks to a set of macroeconomic variables as a proxy for the common shock. We select the following macroeconomic variables: the Inflation Rate (INF), Unemployment Rate (UER), Industrial Productivity Index (IPI) growth, Personal Disposable Income (PDI) growth, Personal Consumer Expenditures (PCE) growth, and Excess Stock Market Returns (RMRF). The common shock time series is inferred from a set of residuals of an AR (1) model fitted to each macroeconomic variable. We choose to use the residuals of an AR(1) model for the following two reasons. First, residuals of AR(1) of macroeconomic variables are a better proxy for macroeconomic news (shocks). Second, using the residuals of AR(1) of macroeconomic variables reduces the concern of spurious regression results since some macroeconomic variables are highly persistent. In a second approach, we use a business cycle dummy as a proxy for the common shock. The business cycle dummy is equal to a value of one during recession periods (shown in Figure 4) and to a value of zero during expansionary periods as defined by NBER business cycle dates. In a third approach, we use the CBOE S&P 100 volatility index (VXO) based on S&P 100 index options (OEX) and the Aruoba-Diebold-Scotti business conditions index as two proxies for market uncertainty. The main reason for choosing the VXO over the current VIX (S&P 500 index options volatility index) is the fact that the VXO goes further back in history and allows us to cover our entire sample period (while the VIX only starts on January 1st 1990). We empirically estimate Equation (9) and Equation (10) with the proxy for the common shock being only macroeconomic variable news, only the business cycle dummy, only the uncertainty measures, or all variables at once.

Additionally, we also investigate whether the reaction of credit spreads to interest rates might be related to the business climate using a two-step approach that considers macroeconomic variables, NBER business cycle dates, and market uncertainty. In a first step, we regress credit spreads and interest rates on a set of macroeconomic variables, a business cycle dummy as well as market uncertainty, described by the following two equations:

$$CS_t = const. + b_1 M_t + b_2 BC_t + b_3 U_t + \varepsilon_{cs} \tag{11}$$

$$TB_t = const. + b_1 M_t + b_2 BC_t + b_3 U_t + \varepsilon_{tb} \tag{12}$$

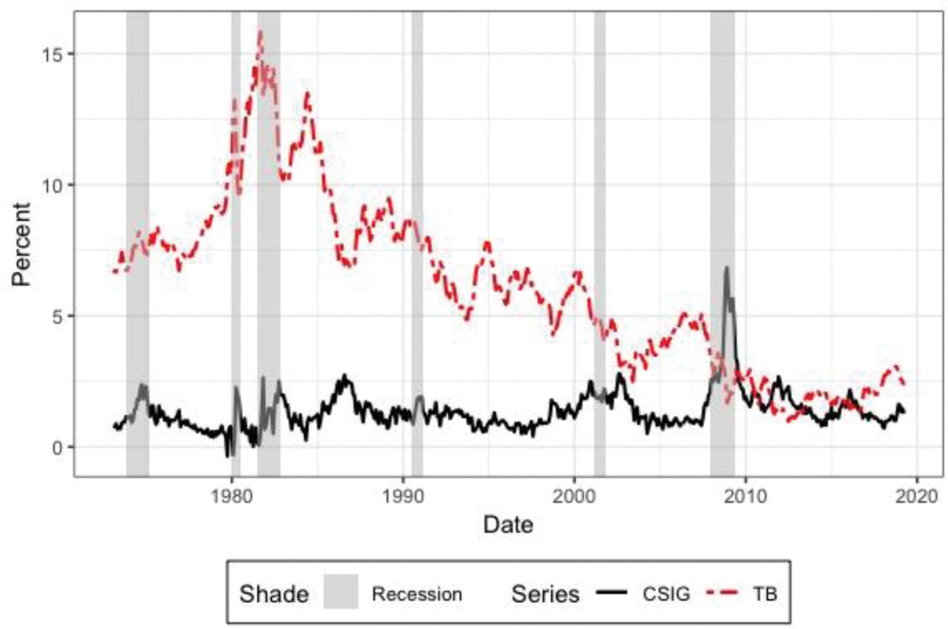


Figure 4. Treasury rates and investment-grade credit spreads from 1973.01 to 2019.03 . Note: This figure plots duration-matched Treasury rates and investment-grade credit spreads from January 1973 to March 2019. The rates are expressed in percent and reported at a monthly frequency. The shaded areas are recession periods as defined by NBER.

where M_t represents the AR(1) residuals of the vector of six macroeconomic variables previously defined, where BC_t is a business cycle dummy equal to one or zero during recessionary and expansionary periods, and where U_t includes the two uncertainty measures described earlier.

The VXO being an uncertainty indicator from financial options markets, with the Aruoba-Diebold-Scotti business conditions index being a risk measure of real business activity, this dual-element approach allows us to filter out the common factors that could potentially drive the comovements. From Equation (11) and Equation (12) we are then able to back out two sets of residualsε_{cs} and ε_{tb} that can now be seen as interest rate and credit spread changes devoid of the impact of common factors. In a second step, we examine the contemporaneous relation between ε_{cs} and ε_{tb} by means of the heteroskedasticity-based identification methodology. In a nutshell, Equation (1) through Equation (8) are revisited where CS_t andTB_t are now replaced with ε_{cs} and ε_{tb}.

Staleness in the corporate bond market is also a potential concern when examining the reaction of credit spreads to interest rates since many corporate bonds do not change hands as often as equities do, particularly in the case of high-yield bonds.[3] The consequence of bond trading staleness is the possible delay in the (re)pricing of corporate bonds following a change in the risk-free rate, implying that corporate yields could underreact to contemporaneous new risk-free rate information; this could cause the contemporaneous credit spread to appear to shrink when the spread might in fact more or less revert back to its initial level in the next period once corporate bond prices have had enough time to adjust. To address this potential issue, as a robustness check, we also estimate the impact of interest rates on credit spreads using a lagged Treasury rates series.

Data

We collect monthly yields and monthly durations on Barclay bond indices from Datastream and 3-month Treasury bill rates, 5-year Treasury bond yields and 10-year Treasury bond yields from the Saint Louis Federal Reserve. We also collect monthly corporate bond investment-grade index data spanning from 1973.01 to 2019.03 and

[3]We thank the anonymous referee for pointing out this possible issue.

monthly corporate bond high-yield index data spanning from 1993.01 to 2019.03. For purposes of computing meaningful credit spreads, we construct various duration-matched credit spread time series. More specifically, for each corporate bond index series, we create a corresponding series of risk-free (Treasury) rates by matching the bond duration in each period to that of yield curve – interpolated Treasury rates. This procedure ensures that the difference between the corporate yield and the Treasury rate is less likely to be affected by the term spread and more strictly measures the potential for default or lack thereof. Additionally, in order to test whether the callability feature of bonds might be responsible for the negative relation between interest rates and credit spreads, we also use the Bank of America – Merrill Lynch Aggregate Corporate Bond Index and the Bank of America Merrill Lynch US Bullet Corporate Excluding Yankees Index that specifically excludes Yankee and optionable bonds, with data spanning from 2003.09 to 2019.03. The Bank of America Merrill Lynch US Bullet Corporate Excluding Yankees Index is a subset of the ICE Bank of America Merrill Lynch US Corporate Index including all securities with U.S. as the country of risk, but excluding securities with embedded call or put options.

The Consumer Price Index (CPI), Unemployment Rate (UER), Industrial Productivity Index (IPI), Personal Disposable Income (PDI) and Personal Consumer Expenditure (PCE) are obtained from the Saint Louis Federal Reserve. The UER, IPI, PDI, and PCE are the monthly percentage changes in the respective variables. Inflation (INF) is the CPI monthly percentage change. Stock market excess returns (RMRF) are the value-weighted returns on all NYSE, AMEX, and NASDAQ stocks (from CRSP) minus the one-month Treasury bill rate. Macroeconomic common shocks are measured as residuals of AR(1) processes fitted to each macroeconomic variable. The CBOE S&P 100 volatility index (VXO) is obtained from the CBOE, and the Aruoba-Diebold-Scotti business conditions index (ADS) is collected from the Philadelphia Federal Reserve (e.g. Scotti 2016).

III. Relationship between interest rates and credit spreads

Properties of interest rates and credit spreads

Table 1 summarizes the monthly statistics for Treasury rates, credit spreads for investment-grade and high-yield bonds, inflation rates, CRSP

Table 1. Descriptive Statistics.

Variable	Mean	Std. Deviation	Min	Max	AR(1)
TB (%)	6.090	3.303	0.975	15.824	0.996
CS_IG (%)	1.371	0.772	−0.349	6.835	0.913
CS_HY (%)	5.487	2.573	2.453	20.463	0.963
INF (%)	0.323	0.337	−1.771	1.810	0.643
RMRF (%)	0.563	4.526	−23.240	16.100	0.060
UER (%)	6.287	1.609	3.600	10.800	0.996
IPI (% change)	0.161	0.713	−4.337	2.072	0.338
PDI (% change)	0.511	0.756	−5.584	6.186	−0.129
PCE (% change)	0.520	0.530	−2.055	2.789	−0.054
VIX	20.041	8.245	7.870	61.410	0.830
ADS	−0.107	0.789	−4.212	2.601	0.838

Table 1 summarizes monthly statistics for levels of duration-matched Treasury rates (TB), credit spreads for investment-grade bonds using Treasury rates (CS_IG), credit spreads for high-yield bonds using Treasury rates (CS_HY), and monthly statistics for inflation rate (INF), Fama-French excess market returns (RMRF), unemployment rate (UER), industrial productivity index (IPI), personal disposable income (PDI), personal consumer expenditures (PCE), the CBOE S&P100 volatility index (VXO) and the Aruoba-Diebold-Scotti business conditions index (ADS). Credit spreads are measured as yields on the corporate bond index minus the Treasury rate with matched durations. Inflation (INF), extracted from the St. Louis Federal Reserve, is the one-month percentage change in CPI. The excess return on the market (RMRF), retrieved from the Kenneth R. French Data Library, is the value-weighted return on the CRSP index minus the one-month Treasury bill rate. Unemployment rate (UER), industrial productivity Index (IPI), personal disposable income (PDI) and personal consumer expenditure (PCE) are the one-month percentage changes in each variable, also obtained from the St. Louis Federal Reserve. The CBOE S&P100 volatility index (VXO) is based on S&P 100 index options and is provided by the CBOE. The Aruoba-Diebold-Scotti business conditions index (ADS) is collected from the Philadelphia Federal Reserve. All variables are from January 1973 to March 2019, except for CSHY available from January 1993 to March 2019 and the VXO available from January 1986 to March 2019.

*AR (1) is the estimated coefficient of an AR (1) process with a constant.

value-weighted market excess returns, Unemployment Rate, Industrial Productivity Index, Personal Disposable Income, Personal Consumer Expenditure, the CBOE S&P 100 volatility index and the Aruoba-Diebold-Scotti business conditions index. The maturity-matched Treasury rates exhibit a wide spectrum of levels, ranging from 0.975% to 15.82%. Investment-grade credit spreads range from −0.349% to 6.835%, while their high-yield counterparts range from 2.453% to 20.463%. Small negative investment-grade credit spreads have been documented in the past by Bhanot and Guo (2011) and are not a cause for concern as arbitrage conditions are not violated once the bid-ask spread and liquidity are taken into account. The Treasury rate is highly persistent; its first-order autoregressive AR(1) coefficient is 0.996. Monthly average inflation is about one third of a percent with a fairly tight range, while monthly stock market excess returns – although on average close to half a percent – experience a very large array of values ranging from −23.24% to 16.10%. The rest of the statistics are in line with the findings of prior studies.

We then test for the presence of a unit root in both the interest rates and the credit spreads time series. We run the Augmented Dicky-Fuller (ADF) and the Phillips-Perron (PP) tests with a constant and a trend (untabulated to save space). The null hypothesis of a unit root is weakly rejected at the 10% significance level for Treasury rates in both ADF and PP tests. For investment-grade credit spreads, the hypothesis of a unit root is rejected at the 1% significance in both ADF and PP tests. For high-yield credit spreads, the ADF test tends to reject the unit root hypothesis while the PP test does not. Overall, the unit root tests yield mixed results. It is well known that standard unit root tests can lack power (a type II error), and while the results do not indeed provide a definite conclusion, they generally do tend to reject the unit root hypothesis. Since a non-stationary process implies an explosive volatility structure over time, Joutz, Mansi, and Maxwell (2001) argue that interest rates and credit spread cannot plausibly be non-stationary over long periods of time. Facing a similar issue on the time-series properties of book-to-market ratios, Vuolteenaho (2000) states 'I am forced to base the stationarity assumption more on economic intuition than on the clear-cut rejection of unit root tests'. However, simulations in Granger and Newbold (1974) also show that statistically significant results and high R^2 values can be obtained when two unrelated but highly persistent time series are regressed on one another, indicating that failing to take their persistence into account could lead to spurious conclusions. Granger and Newbold (1974) suggest that the rule should rather be to work with both levels and changes, and to subsequently interpret the combined results. Following Granger and Newbold (1974), we therefore use both levels and changes of interest rates and credit spreads in our estimations. The results with levels and changes are similar. In the interest of space, we only report the results pertaining to the levels and leave the results with changes available upon request.

Relation between interest rates and credit spreads: the base model

We begin with the base model without common shocks. The first step is to estimate the residual vector $[(\alpha\mu_t + v_t)/(1-\alpha\beta), (\mu_t + \beta v_t)/(1-\alpha\beta)]'$ of the reduced-form bivariate VAR model in Equations (3) and (4). Using the Bayesian Information Criterion, we determine that three lags are optimal for the investment-grade bond VAR, and that two lags are optimal for the high-yield bond VAR. The heteroskedasticity-based identification approach is motivated by the different variances of the residual vectors under different regimes. The key element in the identification process is to divide the sample into different regimes. Volatility regimes can be split in a variety of ways, all appropriate as long as the ratio of the variance of interest rate shocks in regime one $(\Omega_{11,1})$ to the variance of interest rate shocks in regime two $(\Omega_{11,2})$ remains different from the ratio of the covariance between interest rate shocks and credit spreads shocks in regime one $(\Omega_{12,1})$ to the covariance between interest rate shocks and credit spreads shocks $(\Omega_{12,2})$ in regime two. One implication is that if interest rate shocks become more volatile, the reaction of credit spreads to those interest rates will have a larger effect on the covariance between interest rates and credit spreads.

We define regimes according to the size and direction of the variance of the residuals in the reduced-form model. Interest rates and credit spreads are in regime I when both shocks are above one standard deviation over the mean. Interest rates and credit spreads are in regime II when both shocks are below one standard deviation under the mean. Finally, interest rates and credit spreads are in regime III when both shocks are within one standard deviation of the mean. Regimes I and II both capture high volatility regions of the distribution, with regime I pertaining to the upper tail and regime II to the lower tail of the distribution, while regime III captures the lower volatility region of the distribution. There are therefore two possible subsets associated with these three regimes, denoted from here on as [regime I&III] and [regime II&III]. Adopting this regime segregation method allows the capturing of the asymmetric effects of shocks on the interest rate-credit spread relation. Additionally, the different standard deviations of interest rates and credit spreads provide favourable conditions for an estimation through heteroskedasticity since the variances of interest rate shocks and credit spread shocks are not proportional. If the heteroskedasticity-based identification approach performs well, results from an estimation based on Regime I&III should be very similar to those of an estimation based on Regime II&III. The estimates from these two subsets are shown in Table 2.

Table 2. Relationship between Monthly Credit Spreads and Interest Rates/Lagged Interest Rates without Common Macroeconomic Shocks.

	α (regime I&III)	α (regime II&III)
Panel A: Investment-grade bonds		
Credit Spreads (CS_t) & Treasury Rates (TB_t)	−0.906	−1.037
	(−15.728)	(−12.633)
	[0.000]	[0.000]
Credit Spreads (CS_t) & Treasury Rates (TB_{t-1})	−1.111	−0.923
	(−3.166)	(−2.979)
	[0.022]	[0.020]
Panel B: High-yield bonds		
Credit Spreads (CS_t) & Treasury Rates (TB_t)	−4.940	−5.026
	(−3.308)	(−3.702)
	[0.032]	[0.014]
Credit Spreads (CS_t) & Treasury Rates (TB_{t-1})	6.573	−2.711
	(−4.074)	(−1.435)
	[0.044]	[0.324]

Table 2 reports regression estimates of the sensitivity of monthly credit spreads (CS_t) to Treasury rates (TB_t)/one-period lagged Treasury rates (TB_{t-1}) for the January 1973 to March 2019 period for two regimes and four different cases, with t-statistics displayed in parentheses and with the 'L' index representing up to three lags. The bootstrapped p-values are reported in brackets below the t-statistics. In regime I&III, shocks to interest rates and credit spreads are either average or significantly positive, while in regime II&III they are either average or significantly negative, as defined by their magnitude with respect to a one-sigma deviation from the mean. The model where the residuals $\alpha\mu_t + v_t$ and $+\mu_t + \beta v_t$ in the VAR system ($CS_t = (\alpha TB_L + \theta CS_L + \alpha\mu_t + v_t)/(1-\alpha\beta)$ and $TB_t = (\beta CS_L + \lambda TB_L + \mu_t + \beta v_t)/(1-\alpha\beta)$) are estimated without any extra variable(s). Panel A reports the results for investment-grade bonds, while panel B reports the results for high-yield bonds.

Table 2 reports the base model results on the relation between interest rates and credit spreads computed with the investment-grade corporate bond index (Panel A) and with the high-yield bond index (Panel B). Table 2 shows that interest rates have a significant impact on credit spreads for both investment-grade and high-yield bonds. In Panel A, for investment-grade bonds, under Regime I&III the estimated α (the credit spreads' reaction to interest rates) is −0.906 with a GMM-derived t-statistic of −15.728 and a bootstrapped p-value of 0.000. These heteroskedasticity-based results appear to confirm a significantly negative relation between credit spreads and interest rates. Under Regime II&III, our results show that the estimates are quantitatively similar to the estimates obtained under Regime I&III, suggesting that the heteroscedasticity-based identification approach is robust.

In Panel B, for high-yield bonds under Regime I&III, the credit spreads' reaction to interest rates is −4.940 with a t-statistic of −3.308 and a bootstrapped p-value of 0.032. The credit spreads' reaction is again similar under Regime II&III, suggesting that the estimation is valid and robust to both types of bonds and volatility regimes. In both panels, in all cases, the GMM-derived t-statistics and the bootstrapped p-values yield coherent conclusions. It is also worth noting that high-yield bond credit spreads additionally display a much higher sensitivity to interest rates than investment-grade bond credit spreads do, a result consistent with the ubiquitous risk-return tradeoff and with Ericsson, Jacobs, and Oviedo (2009). As a robustness check, we also perform all estimations using changes in interest rates and credit spreads. When using changes instead of their levels, we continue to observe a significant and robust negative reaction of credit spreads on interest rates regardless of the type of bonds or regime.

Lastly, as mentioned in Section I, a consequence of bond trading staleness is the possible delay in the (re)pricing of corporate bonds following a change in the risk-free rate. For instance, as Treasury rates rise in a given month, if corporate bond yields do not fully adjust immediately as a result of lower trading activity, credit spreads could first shrink in that contemporaneous month yet approximately go back to their initial levels in the next month once enough trading has occurred and bond prices have properly adjusted. Thus, as a final robustness check we also estimate the base model relation using a lagged Treasury rates series. Table 2 also shows that when running the base model again but with lagged Treasury rates instead of contemporaneous ones, interest rates still have a significant and negative impact on credit spreads in the next period for both investment-grade and high-yield bonds. Under Regime II&III, our results show the estimates are quantitatively similar to the estimates under Regime I&III.

Relation between changes in interest rates and credit spreads, with macroeconomic shocks, business cycles and market uncertianty

As described earlier in the methodology section, we here relax the structural shocks orthogonality assumption and account for a common shock that could have a simultaneous impact on both interest rates and credit spreads. The common shock is first defined as multivariate shocks to a set of macroeconomic variables, then as a business cycle dummy capturing recession and expansion periods, and two uncertainty measures. Macroeconomic conditions, business cycles and overall market uncertainty are naturally appealing factors possibly influencing the relation between interest rates and credit spreads (see Davies (2008), Delianedis and Geske (2001), Wu and Zhang (2008), Nielsen (2012), Gilchrist and Zakrajšek (2012), or Barnea and Menashe (2014)).

The negative relation could therefore be due to a combination of several factors, such as business cycles, monetary policy, time-varying risk, or liquidity. For instance, in a recession, the Federal Reserve usually gradually decreases the federal funds rate as an attempt to stimulate investments until the economy improves. Simultaneously, the worsening of the economy increases the risk of a firm through several mechanisms. From an operational point of view, sales conditions in a recession get worse and lead to low growth due to the lower demand for consumption, and as a result, uncertainty increases. From a financial point of view, the poor economic environment makes it more difficult for the firm to obtain external financing, induces a high liquidity risk, and raises financing costs. Therefore, the increase in the firm's risk could lead to a widening of the firm's corporate bonds' credit spreads. Consequently, when interest rates are decreasing, one could on average expect credit spreads to be on the rise. Conversely, in a period of economic expansion, the Federal Reserve tends to gradually increase the federal funds rate as a way of keeping inflation under control and preventing the economy from overheating. At the same time, this economic growth progressively leads to a decrease in the firm's risk both from an operational point of view (higher sales and lower uncertainty) and through decreased financing risk and costs, ultimately resulting in a narrowing of its corporate bonds' credit spreads. Therefore, when interest rates are increasing, one could on average expect credit spreads to be on the decline. For comparison purposes, we adopt the same regime segregation approach as in the previous section, and present results in Table 3.

Table 3 shows that the heteroskedasticity-based negative relation between interest rates and credit spreads still holds when accounting for common macroeconomic shocks, business cycles and economic uncertainty. In Panel A, for investment-grade bonds, under Regime I&III the estimated α is -0.935 with a t-statistic of -15.388 and a bootstrapped p-value of 0.000 when the common shock is only the vector of macroeconomic shocks, -0.895 with a t-statistic of -16.515 and a bootstrapped p-value of 0.000 when the common shock is the business cycle dummy variable, -1.024 with a t-statistic of -12.368 and a bootstrapped p-value of 0.000 when the common shock is the vector of uncertainty measures, and -1.040 with a t-statistic of -13.001 and a bootstrapped p-value

Table 3. Relationship between Monthly Interest Rates and Credit Spreads with Common Macroeconomic Shocks.

	α (regime I&III)	α (regime II&III)
Panel A: Investment-grade bonds		
Macroeconomic variables (M)	−0.935	−0.989
	(−15.388)	(−13.268)
	[0.000]	[0.000]
Business cycle dummy (BC)	−0.895	−1.014
	(−16.515)	(−13.006)
	[0.000]	[0.003]
Uncertainty measures (U)	−1.024	−1.021
	(−12.368)	(−10.142)
	[0.000]	[0.000]
Macroeconomic variables (M)	−1.040	−1.042
& Business cycle Dummy (BC)	(−13.001)	(−8.961)
& Uncertainty measures (U)	[0.000]	[0.000]
Panel B: High-yield bonds		
Macroeconomic variables (M)	−4.907	−5.019
	(−3.359)	(−3.706)
	[0.000]	[0.000]
Business cycle dummy (BC)	−4.799	−5.169
	(−3.645)	(−4.146)
	[0.013]	[0.007]
Uncertainty measures (U)	−3.126	−3.383
	(−4.245)	(−3.715)
	[0.005]	[0.004]
Macroeconomic variables (M)	−3.007	−3.276
& Business cycle dummy (BC)	(−4.052)	(−3.504)
& Uncertainty measures (U)	[0.010]	[0.010]

Table 3 reports regression estimates of the sensitivity of monthly credit spreads (CS_t) to Treasury rates (TB_t) for the January 1973 to March 2019 period for two regimes and four different cases, with macroeconomic shocks M_t obtained as residuals of AR(1) processes fitted to INF_t, $RMRF_t$, UER_t, IPI_t, PDI_t and PCE_t and a business cycle dummy (BC_t) and uncertainty measures (U_t) including VIX_t and ADS_t. The t-statistics are displayed in parentheses and the 'L' index represents up to three lags. The bootstrapped p-values are reported in brackets below the t-statistics. In regime I&III, shocks to interest rates and credit spreads are either average or significantly positive, while in regime II&III they are either average or significantly negative, as defined by their magnitude with respect to a one-sigma deviation from the mean. Case 1 is the model where the residuals $(\alpha\mu_t + v_t)/(1\text{-}\alpha\beta)$ and $(\mu_t + \beta v_t)/(1\text{-}\alpha\beta)$ in the VAR system ($CS_t=(\alpha TB_L + \theta CS_L + \gamma M_t + \alpha\mu_t + v_t)/(1\text{-}\alpha\beta)$ and $TB_t = (\beta CS_L + \lambda TB_L + \Gamma M_t + \mu_t + \beta v_t)/(1\text{-}\alpha\beta)$) are estimated with macroeconomic variable(s). Case 2 is the model where the residuals in the VAR system ($CS_t=\alpha TB_L+\theta CS_L + \phi_1 BC_t + \alpha\mu_t + v_t)/(1\text{-}\alpha\beta)$ and $TB_t=(\beta CS_L + \lambda TB_L + \psi_1 BC_t + \mu_t + \beta V_t)/(1\text{-}\alpha\beta)$) are estimated with a dummy variable BC_t set to 1 for NBER recession dates and to zero otherwise. Case 3 is the model where the residuals in the VAR system ($CS_t = (\alpha TB_L + \theta CS_L + \xi_1 U_t + \alpha\mu_t + v_t)/(1\text{-}\alpha\beta)$ and $TB_t=(\beta CS_L + \lambda TB_L + \varsigma_1 U_t + \mu_t + \beta v_t)/(1\text{-}\alpha\beta)$) are estimated with a dummy variable U_t including the CBOE volatility index VIX_t and the Aruoba-Diebold-Scotti business conditions index ADS_t. Case 4 is the model where the residuals in the VAR system ($CS_t=(\alpha TB_L + \theta CS_L + \phi_1 BC_t + \gamma Mt + \xi_1 U_t + \alpha\mu_t + v_t)/(1\text{-}\alpha\beta)$ and $TB_t=(\beta CS_L + \lambda TB_L + \psi_1 BC_t + \Gamma M_t + \varsigma_1 U_t + \mu_t + \beta v_t)/(1\text{-}\alpha\beta)$) are estimated with a business cycle dummy BC_t, macroeconomic shocks M_t and uncertainty measures U_t. Panel A reports the results for investment-grade bonds, while panel B reports the results for high-yield bonds.

of 0.000 when the common shock is the business cycle dummy and the vector of macroeconomic shocks and uncertainty measures combined.

In Panel B, for high-yield bonds, under Regime I&III, the credit spreads' reaction to interest rates is a coefficient of −4.907 with t-statistic of −3.359 and a bootstrapped p-value of 0.000 when only including the macroeconomic shocks, a coefficient of −4.799 with a t-statistic of −3.645 and a bootstrapped p-value of 0.013 when including the business cycle dummy variable, a coefficient of −3.126 with a t-statistic of −4.245 and a bootstrapped p-value of 0.005 when including uncertainty measures, and a coefficient of −3.007 with a t-statistic of −4.052 and a bootstrapped p-value of 0.010 when incorporating all the business cycle dummy, the macroeconomic shocks and uncertainty measures into the base model. Finally, just like in Table 2, the results under Regime II&III suggest that the negative relation between credit spreads and interest rates is quantitatively similar to the relation estimated under Regime I&III. The presence of common macroeconomic shocks, the effect of business cycles and the impact of financial and real business uncertainty thus does not appear to change the negative relation between interest spreads and credit spreads.[4]

Table 4 reports results of the heteroskedasticity-based relation between interest rates and credit spreads using our two-step approach described in Section I. In Panel A, for investment-grade bonds, under Regime I&III the estimated is −0.434 with a t-statistic of −6.226 and a bootstrapped p-value of 0.005 when all the business cycle dummy, the macroeconomic shocks and uncertainty measures are filtered out. In Panel B, for high-yield bonds, under Regime I&III the estimated is −1.059 with a t-statistic of −7.269 and a bootstrapped p-value of 0.002. Similarly, under Regime II&III, the estimates are quantitatively similar. In sum, the two-step approach confirms the robust negative relation between interest rates and credit spreads.

Relation between changes in interest rates and credit spreads, before and after the 2007 financial crisis

It is well known that interest rates were dramatically cut after the 2007 sub-prime financial crisis. To test

[4]We also implement the heteroskedasticity-based estimation using the two-step approach discussed in section I. We find a robust and significant negative relationship between credit spreads and interest rates consistent with the results in Tables 2 and 3. To save space, we do not report those results, but they are available upon request.

Table 4. Relationship between Monthly Credit Spreads and Interest Rates Common Macroeconomic Shocks Using a two-step Method.

	α (regime I&III)	α (regime II&III)
Panel A: Investment-grade bonds		
Credit Spreads (CS_t) & Treasury Rates (TB_t)	−0.434 (−6.226) [0.005]	−0.454 (−7.533) [0.000]
Panel B: High-yield bonds		
Credit Spreads (CS_t) & Treasury Rates (TB_t)	−1.059 (−7.269) [0.002]	−1.093 (−6.493) [0.002]

Table 4 reports regression estimates of the sensitivity of monthly credit spreads (CS_t) to Treasury rates (TB_t) for the January 1973 to March 2019 period for two regimes and four different cases, with macroeconomic shocks M_t obtained as residuals of AR(1) processes fitted to INF_t, $RMRF_t$, UER_t, IPI_t, PDI_t and PCE_t and a business cycle dummy (BC_t) and uncertainty measures (U_t) including VIX_t and ADS_t using a two-step approach. The first step is to estimate residuals ε_{cs} and ε_{tb} from $CS_t = const. + b_1M_t + b_2BC_t + b_3U_t + \varepsilon_{cs}$ and $TB_t = const. + b_1M_t + b_2BC_t + b_3U_t + \varepsilon_{tb}$. The second step is to estimate the sensitivity of credit spread to treasury rates α from the VAR system (ε_{cs}=($\alpha\varepsilon_{tb^L}$+$\theta\varepsilon_{cs^L}$+$\phi_1 BC_t$+γM_t+$\xi_1 U_t$ +$\alpha\mu_t + v_t$)/(1-αβ) and $\varepsilon_{tb} = (\beta\varepsilon_{CS^L} + \lambda\varepsilon_{tb^L} + \psi_1 BC_t + \Gamma M_t + \zeta_1 U_t$ $+\mu_t + \beta v_t$)/(1-αβ)) with a business cycle dummy BC_t, macroeconomic shocks M_t and uncertainty measures U_t The t-statistics are displayed in parentheses and the "L" index represents up to three lags. The bootstrapped p-values are reported in brackets below the t-statistics. In regime I&III, shocks to interest rates and credit spreads are either average or significantly positive, while in regime II&III they are either average or significantly negative, as defined by their magnitude with respect to a one-sigma deviation from the mean. Panel A reports the results for investment-grade bonds, while panel B reports the results for high-yield bonds.

Table 5. Relationship between Monthly Interest Rates and Credit Spreads without Common Macroeconomic Shocks before/after October 2007.

	α (regime I&III)	α (regime II&III)
Panel A: Investment-grade bonds		
January 1973 to October 2007	−0.929 (−17.243) [0.000]	−0.935 (−17.212) [0.000]
November 2007 to March 2019	−1.487 (−4.228) [0.046]	−2.970 (−3.736) [0.105]
Panel B: High-yield bonds		
January 1993 to October 2007	−2.608 (−6.337) [0.002]	−2.298 (−5.777) [0.006]
November 2007 to March 2019	−9.409 (−4.177) [0.043]	−10.665 (−5.033) [0.036]

Table 5 reports regression estimates of the sensitivity of monthly credit spreads (CS_t) to Treasury rates (TB_t) for the January 1973 to October 2007 period and November 2007 to March 2019 for two regimes and four different cases, with t-statistics displayed in parentheses and with the 'L' index representing up to three lags. The bootstrapped p-values are reported in brackets below the t-statistics. In regime I&III, shocks to interest rates and credit spreads are either average or significantly positive, while in regime II&III they are either average or significantly negative, as defined by their magnitude with respect to a one-sigma deviation from the mean. The model where the residuals $\alpha\mu_t + v_t$ and $+\mu_t + \beta v_t$ in the VAR system (CS_t =($\alpha TB_L + \theta CS_L + \alpha\mu_t + v_t$)/(1-αβ) and TB_t=($\beta CS_L + \lambda TB_L + \mu_t$ $+\beta v_t$)/(1-αβ)) are estimated without any extra variable(s). Panel A reports the results for investment-grade bonds, while panel B reports the results for high-yield bonds.

the stability of the heteroskedasticity-based identification methodology, we run the base model again but this time using two subsamples, before and after November 2007. Table 5 shows that the heteroskedasticity-based negative relation between interest rates and credit spreads holds for both the before-and-after 2007 financial crisis subsamples. In Panel A, for investment-grade bonds, under Regime I&III the estimated α is −0.929 with a t-statistic of −17.243 and a bootstrapped p-value of 0.000 before November 2007 and −1.487 with a t-statistic of −4.228 and a bootstrapped p-value of 0.046 after November 2007. In Panel B, for high-yield bonds, under Regime I&III the estimated is −2.608 with a t-statistic of −6.337 and a bootstrapped p-value of 0.002 before November 2007 and −9.409 with a t-statistic of −4.177 and a bootstrapped p-value of 0.043 after November 2007. The coefficient α is larger in the second period than in the earlier period due to lower interest rate levels, since lower levels inflate the effect of credit spreads' response to interest rates. Once again, the results under Regime II&III suggest that the negative relation between credit spreads and interest rates is quantitatively similar to the relation estimated under Regime I&III.

IV. Callability feature explanation for the negative relation examined

Given the economic and statistically significant negative relation between credit spreads and interest rates, as a last exercise, we investigate a well-known possible driver of it. Duffee (1998) reports that the negative relation between interest rates and credit spreads is weakened when the callability option is excluded from the corporate bond pool, and argues that the callability feature is a non-negligible concern in the negative relation due to the fact that corporate bond indices usually contain a large portion of callable bonds. Jacoby, Liao, and Batten (2009) use a Canadian bond index devoid of any callability characteristics and find no significant relation between interest rates and corporate bond credit spreads. Our heteroskedasticity-based estimation shows that the impact of interest rates on high-yield bond credit spreads is five times larger than on investment-grade bond credit spreads is consistent with the fact that callable bonds make up less than 1% of the investment-grade bonds pool while they make up about 70% of the high-yield bonds pool (see Aneiro 2014). Our conclusions thus at first appear to be in line with the results in Jacoby, Liao, and Batten (2009). However, King's (2002) finds that the call option value constitutes only around 2% of the par value of the average callable bond, implying that given the small contribution of the callability feature to the bond value, it would seem unlikely that this aspect of the bond would alone be responsible for the negative correlation between credit spreads and interest rates.

To further explore whether the callability feature embedded in a bond index might be a possible explanation for the large sensitivity of credit spreads to interest rates, we conduct heteroskedasticity-based estimations and tests on both the Bank of America – Merrill Lynch aggregate corporate bond index and the aggregate corporate bond index that excludes Yankee and optionable bonds, and compare the results. The sample of Bank of America – Merrill Lynch data extends from September 2003 to March 2019. We adopt the same regime separation methodology as in the previous sections, and report the results in Table 6.

Table 6 shows that, when using a corporate bond index that excludes Yankee and optionable bonds, credit spreads still respond negatively to interest rates. Under Regime I&III, the reaction of credit spreads to interest rates for the aggregate corporate bond index (with options) is −1.234 with a t-statistic of −6.119 and a bootstrapped p-value of 0.008, while the reaction of credit spreads to interest rates for the aggregate corporate bond index that excludes Yankee bonds and optionable bonds is −1.135 with a t-statistic of −5.410 and a bootstrapped p-value of 0.009; the results are quantitatively similar in Regime II&III. Our findings are thus consistent with King's (2002) since the difference between option-embedded and option-free bonds is minimal: the α parameter percentage difference between the corporate bond index with and without callable bonds is, across regimes, an average of about 4%. We can therefore conclude that a possible callability feature would not appear to affect the negative relation between credit spreads and interest rates much.

Table 6. Relationship between Monthly and Daily Interest Rates and Credit Spreads in Two Regimes for Aggregate Corporate Bond Indices with and without Options.

	α (regime I&III)	α (regime II&III)
Panel A: Corporate bond index with options		
(Monthly)	−1.234 (−6.119) [0.008]	−2.110 (−4.591) [0.063]
Panel B: Corporate bond index without options		
(Monthly)	−1.135 (−5.410) [0.009]	−2.121 (−3.950) [0.057]

Table 6 reports regression estimates of the sensitivity of monthly credit spreads (CS_t) to Treasury rates (TB_t) for the September 2003 to March 2019 period for two regimes and the base case for both the Aggregate Corporate Bond Index and the Corporate Bond Index excluding Yankee and optionable bonds. The t-statistics are displayed in parentheses and the 'L' index represents up to two lags. The bootstrapped p-values are reported in brackets below the t-statistics. In regime A, shocks to interest rates and credit spreads are either average or significantly positive, while in regime B they are either average or significantly negative, as defined by their magnitude with respect to a one-sigma deviation from the mean. The base case is the model where the residuals v_t and μ_t in the VAR system ($CS_t = (\alpha TB_L + \theta CS_L + \alpha\mu_t + v_t)/(1-\alpha\beta)$ and $TB_t = \beta CS_L + \lambda TB_L + \mu_t + \beta v_t)/(1-\alpha\beta)$) are estimated without any extra variable(s).

V. Conclusion

The relationship between interest rates and credit spreads is of paramount importance to monetary policy makers, portfolio and risk managers, the pricing of credit derivatives, the management of credit risk, as well as to any area where interest rate risk matters such as banking, insurance companies, pension funds, mutual funds, and some speciality ETFs. In this paper we re-examine the relation between government rates and corporate credit spreads by applying Rigobon's (2003) method of identification through heteroskedasticity to the issue. We find significant and robust evidence of a negative reaction of credit spreads to interest rates, in line with Merton's (1974) structural model predictions. We also show that our results are robust to a variety of factors such as different corporate bond ratings, bond callability, business cycles, market risk and various macroeconomic variables affecting the economy.

Additionally, by testing the relation using a corporate bond index devoid of callable bonds, we are also able to rule out the callability feature of corporate bonds as the main factor behind the negative correlation between Treasury rates and corporate credit spreads.

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Appendix1

The price of a bond B yielding a rate y and paying n coupons C_i at various times t_i can be expressed with continuous compounding as

$$B = \sum_{i=1}^{n} c_i e^{-yt_i} \tag{A1}$$

The corresponding duration D of the bond is

$$D = \sum_{i=1}^{n} t_i \frac{c_i e^{-yt_i}}{B} \tag{A2}$$

If we express the bond yield y as the sum of the risk-free rate r and a credit spread *cs(r)*, the bond price can instead be written as

$$B = \sum_{i=1}^{n} c_i e^{-(r+cs(r))t_i} \tag{A3}$$

Differentiating the bond price with respect to the risk-free rate r rather than to the yield y gives

$$\frac{dB}{dr} = -\sum_{i=1}^{n} c_i t_i (1 + \frac{d[cs(r)]}{dr}) e^{-yt_i} \tag{A4}$$

Combining Equations (A2) and (A4), it is straightforward to show that

$$\frac{dB}{dr} = -DB(1 + \frac{d[cs(r)]}{dr}) \tag{A5}$$

Equation (A5) implies that there are three theoretical possible cases.

First, if credit spreads respond positively to an increase in interest rates, the derivative term inside the parentheses in (A5) will be positive and the term in parentheses will be higher than one. The bond yield will thus increase by more than the increase in the risk-free rate since both of its components go up, and the bond price will therefore fall by more than it would if credit spreads and interest rates were uncorrelated.

Second, if credit spreads on average do not respond in either direction to an increase in interest rates, the derivative term inside the parentheses in (A5) will be equal to zero and the term in parentheses will be equal to one. Equation (A5) then collapses to the traditional relation between bond price changes and duration. The bond yield will increase by exactly the same amount as the risk-free rate since the credit spread or risk premium is unaffected, and the bond price will therefore fall accordingly.

Finally, if credit spreads respond negatively to an increase in interest rates, the derivative term inside the parentheses in (A5) will be negative and of the following values or range:

- Strictly between 0 and -1 and the term in parentheses will still be positive. The bond yield will thus increase by less than the increase in the risk-free rate since one of its components (the risk-free rate) goes up while the other (the credit spread) goes down by a lesser amount. The bond price will therefore fall by less than it would if credit spreads and interest rates were uncorrelated.
- Equal to -1 and the term in parentheses will be equal to zero. The bond yield will thus stay the same since one of its components (the risk-free rate) goes up while the other (the credit spread) goes down by the exact same amount. The bond price will therefore remain the same.
- Strictly less than -1 and the term in parentheses will be negative. The bond yield will thus decrease since one of its components (the risk-free rate) goes up while the other (the credit spread) goes down by more than the former. The bond price will therefore go up.