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When Diversification Fades: a Firm Level Perspective of Stock and Corporate Bond Correlations

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ABSTRACT

This paper examines the evolving relationship between corporate bond and stock returns in the euro area from 2007 to 2025. While theory predicts negative (or at least lower) correlations during periods of market stress and negative demand shocks, empirical evidence shows substantial instability over time. We construct equity and corporate bond indices using a strictly matched issuer universe, such that the constituent firms are identical across the two indices. We then analyse their correlation dynamics across major euro area markets using Dynamic Conditional Correlation models. Results indicate that correlations, historically negative, have since 2009 gradually trended toward neutrality, but can shift in either direction rapidly. We show that the discount-rate channel emerges as the dominant driver of co-movement in both low- and high-inflation environments. By contrast, financial stress reduces correlations – consistent with flight-to-quality dynamics –only in low-inflation regimes but not in high inflation regimes. This indicates that investors cannot rely on policy-induced compression in discount rates to generate cross-asset arbitrage opportunities in favour of bonds when inflation is high.

Keywords: DCC Correlation, Corporate Bonds, Asset Allocation, Equity Returns, Monetary Policy

JEL classification: G12, G14, E43, E52

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NON-TECHNICAL SUMMARY

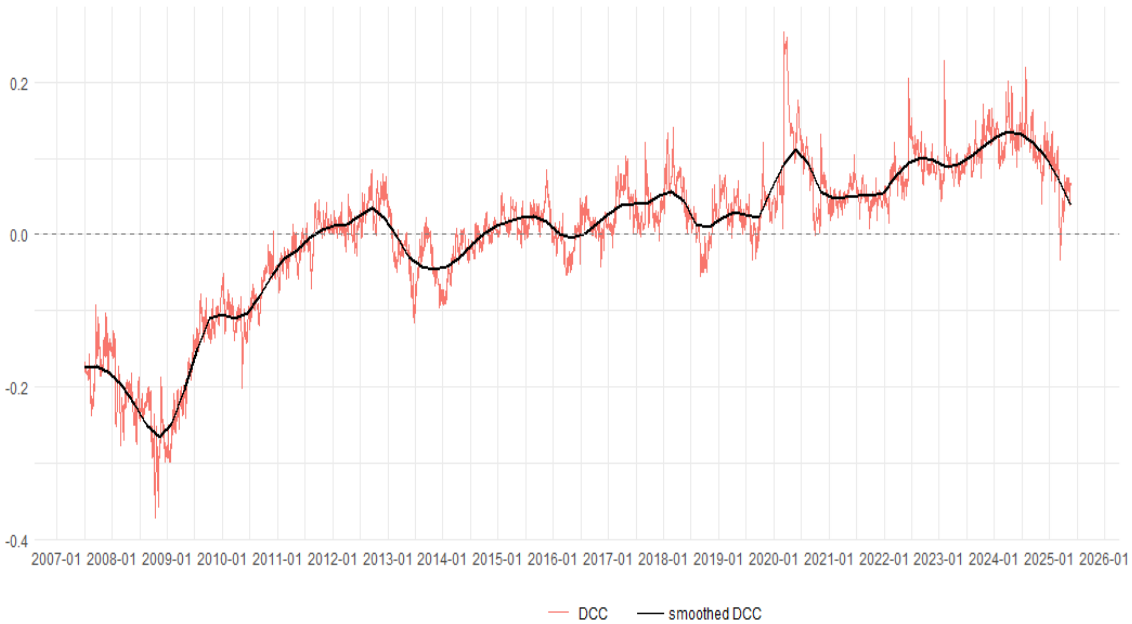
This paper studies how corporate bond returns and stock returns move together in the euro area over the period 2007–2025, focusing on a key issue for investors: whether combining these assets still provides diversification benefits. Traditionally, bonds are viewed as relatively safe investments, while equities are riskier but offer higher expected returns. When their returns are negatively correlated – as was the case for many decades – investors can reduce overall risk by holding both assets.

However, the paper shows that this relationship is neither stable nor guaranteed. In theory and past evidence, stock–bond correlations tend to turn negative during periods of financial stress due to a "flight-to-safety" mechanism: investors shift away from risky equities toward safer bonds. Yet since the global financial crisis, this pattern has gradually weakened. Correlations have moved closer to zero and have become more volatile, suggesting that diversification benefits are less possible and reliable than previously assumed.

A key contribution of the paper is its firm-level perspective. Instead of relying on aggregate indices, we examine the relationship between stocks and bonds issued by the same firms. This approach removes composition biases (a common limitation in similar studies) and offers a clearer view of the underlying economic mechanisms. The analysis covers major euro area countries and uses daily data, capturing high-frequency market dynamics.

The findings reveal strong time variation in correlations, driven primarily by macroeconomic conditions. The most important mechanism is the "discount-rate channel." When inflation expectations rise or monetary policy tightens (leading to higher real interest rates), both bond and equity valuations tend to fall at the same time. This creates a positive correlation between the two asset classes. Conversely, declines in rates can support both markets simultaneously.

Figure 1. The daily mean correlations (DCCs) of price changes across all NFC CAC40 stock-corporate bond pairs



Note: The DCCs of price changes for individual corporate bond-stock pairs are averaged across all NFC CAC40 issuers (red line) and then smoothed (black line).

The role of financial stress is more complex. In low-inflation environments, increased financial stress reduces correlations because investors move toward safer assets, restoring diversification benefits. However, in high-inflation regimes this mechanism breaks down. Central banks, focused on controlling inflation, are less able to respond to financial stress with accommodative policies. As a result, bonds do not necessarily provide protection against falling stock prices.

Overall, the paper concludes that the weakening of stock–bond diversification is not just cyclical but depends critically on the macro-financial regime, especially inflation and monetary policy. In high-inflation environments, stock–bond correlations tend to increase, reducing diversification benefits. This has important implications for portfolio management, risk management, and policymaking. In particular, it suggests that investors can no longer rely on the traditional negative relationship between equities and bonds to hedge risks. Standard investment strategies based on stable negative correlations between stocks and bonds may need to be reconsidered in a world of higher and more volatile inflation.

Quand la diversification s'estompe : une analyse au niveau des entreprises des corrélations entre actions et obligations

RÉSUMÉ

Cet article examine l'évolution de la corrélation entre les rendements des obligations d'entreprises et ceux des actions dans la zone euro sur la période 2007–2025. Alors que la théorie prévoit des corrélations négatives (ou du moins affaiblies) en période de stress de marché et de chocs de demande négatifs, les données empiriques montrent une forte instabilité au cours du temps. Nous construisons des indices actions et obligations d'entreprises à partir d'un univers d'émetteurs strictement identique, de sorte que les entreprises constituant les deux indices sont exactement les mêmes. Nous analysons ensuite la dynamique de leurs corrélations sur les principaux marchés de la zone euro à l'aide de modèles de corrélation conditionnelle dynamique (Dynamic Conditional Correlation, DCC). Les résultats indiquent que les corrélations, historiquement négatives, ont progressivement évolué vers la neutralité depuis 2009, tout en pouvant varier rapidement. Nous montrons que le canal des taux d'actualisation s'impose comme le principal facteur expliquant les co-mouvements, aussi bien en environnement de faible inflation que de forte inflation. En revanche, le stress financier réduit les corrélations — conformément à une dynamique de fuite vers la qualité — seulement dans les régimes de faible inflation, mais pas en régime de forte inflation : lorsque l'inflation est élevée, les investisseurs ne peuvent pas compter sur une baisse des taux d'actualisation induite par la politique monétaire pour générer des opportunités d'arbitrage en faveur des obligations.

Mots-clés : corrélation DCC ; obligations d'entreprises ; allocation d'actifs ; rendements des actions ; politique monétaire

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1. Introduction

The relationship between bond and stock returns remains fundamental for practitioners concerned with portfolio construction, diversification and risk management. While bonds provide safer income and low volatility, equities compensate higher risk with potential of superior returns. Their joint inclusion is often expected to generate diversification benefits, although the correlation between the two asset classes varies substantially across economic regimes.

Theory, consistent with the “flight-to-safety” mechanism, predicts that correlations between stock–bond prices become negative during periods of market stress, as investors reallocate from equities toward safer fixed-income instruments. Empirical work supports this behavior: Connolly et al. (2005) and Chiang et al. (2015) document significantly negative correlations during market drawdowns and early recoveries, reinforcing their role as a key diversification channel (see also Lin et al., 2018; Molenaar et al., 2024).

Yet negative correlations are not structurally guaranteed. Historically, stock–bond co-movement was frequently positive, particularly in high-growth or inflationary environments. Baele et al. (2010) show that correlations were predominantly positive from the 1970s to the 1990s, before a well-documented structural break toward negative territory (Andersson et al., 2008; Jammazi et al., 2015; Lin et al., 2018). Chiang et al. (2015) and Baele and van Holle (2017) identify the turning point around 1998–1999. More recently, the ECB tightening cycle since 2022 renewed expectations of increasing correlations, as rate hikes depress both bond prices and equity valuations. In 2022, both markets declined simultaneously for the first time in decades (Forgan, 2024).

A series of shorter episodes – Covid-19 market disruption (2020), the SVB banking stress (2023), and the Bank of Japan’s unexpected rate hike (2024) – also generated temporary shifts in stock-bond dynamics. Against this backdrop, the present study investigates the evolution of corporate bond–stock correlations from mid-2007 to mid-2025, with particular attention to the determinants of correlation in a context where negative co-movement can no longer be taken as given. The contribution of this study is twofold: a joint macro- and micro-level approach with a focus on correlations between securities issued by the same firm.

Although the literature on aggregate stock–government bond interactions is extensive, firm–level stock–corporate bond relationships remain understudied. Data limitations partly explain this gap. We address it by examining return interdependencies between corporate bonds and equities issued by the same non–financial firms, thereby providing a more realistic basis for asset allocation and risk assessment.

The empirical analysis relies on Dynamic Conditional Correlation (DCC) models at both the firm and aggregate levels. This approach mitigates composition bias inherent in standard equity and bond indices and captures potential cross-firm heterogeneity. The dataset encompasses the major euro area markets – with particular attention on the French CAC 40 – and spans from mid-2007 to mid-2025. Moreover, existing research typically analyses low-frequency determinants (e.g., monthly GDP or inflation indicators), yet today’s financial environment is driven by higher–frequency market dynamics. To reflect this reality, we relate daily corporate bond–stock correlations to daily variations in inflation expectations, monetary policy stance, and financial stress using market proxies. These high–frequency interactions are crucial for understanding short–term financing decisions, arbitrage opportunities, and investors’ diversification capacity.

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The findings reveal pronounced time variation in correlations. Across the largest euro area markets, correlations that were generally negative after 2007 have trended toward neutrality since 2009 and can shift rapidly between positive and negative values. Patterns are broadly consistent across countries, with slightly higher (less negative) correlations in Italy and Spain. Correlations usually tend to rise – reducing diversification benefits – when inflation expectations increase, monetary policy becomes more restrictive, or financial stress diminishes (only in low inflationary environment). These results carry important implications for investors, policymakers and analysts monitoring financial markets at high frequency or trying to analyze policy decision impacts on markets. In particular, standard investment strategies based on stable negative correlations between stocks and bonds may need to be reconsidered in a world of higher and more volatile inflation.

The remainder of the article is structured as follows: Section 2 reviews the theoretical and empirical literature; Section 3 presents the dataset and index construction; Section 4 describes methodological approach for calculating correlations; Section 5 provides main results and discusses the drivers of correlation dynamics; final section concludes.

2. Why stock-bond correlation is (not always) negative?

2.1. Factors influencing stock-bond correlations

The well-known flight-to-safety is the first mechanism behind negative correlation: risk-off investors sell risky assets such as equity to buy safer assets, such as bonds (usually govies) to secure portfolios. This mechanism tends to lower equity prices and increase bond prices in risk-off environment. It consistently induces negative correlations (Connelly et al., 2005; Andersson et al., 2008; Asgharian et al., 2016; Lin et al., 2018). Equity volatility in particular widens the divergence between asset classes.

However, this may not be always the case. From asset pricing theory, the interaction between stock and bond returns stems from discounted cash-flow valuation: asset prices reflect expected future cash flows discounted by the risk-free rate and a risk premium (ECB, 2022). Thus, if expected dividends and risk premia are unchanged, rising risk-free rates depress both bond prices and equity valuations, generating a positive correlation. Therefore, any rise in inflation expectation corrected by tightening of monetary policy should push stock-bond price correlation upward.

Nevertheless, stocks and bonds differ in their cash-flow structures and then in their sensitivities to real rates, inflation expectations and risk premia. Bonds, delivering fixed nominal payments, are more sensitive to real-rate and inflation shocks, whereas equities should respond more strongly to risk-premium fluctuations. Consequently, changes in discount-rate components can strengthen or weaken stock-bond co-movement depending on the nature of the underlying shock. Model calibrations for stock-bond price correlation therefore vary widely: post-2000 settings often assume negative correlations (−0.2 to −0.5) reflecting the historical “flight-to-safety”.

Empirically, numerous studies confirm that inflation, interest rates, growth or inflation expectations and financial stress shape stock–bond correlation dynamics. Periods of high inflation expectations are generally associated with positive correlations (Ilmanen, 2003; Andersson et al., 2007; Conrad & Sturmer, 2017; Molenaar et al., 2024) as then discount-rate effects dominate. Christiansen & Ranaldo (2007) and Baele & van Holle (2017) show that correlations are consistently positive under high-inflation regimes, whereas negative correlations prevail when inflation is low and stable (Andersson et al., 2008).

Monetary policy is thus major driver. Tightening typically raises yields and depresses equities, creating positive correlations, especially for long-duration bonds (Baele et al., 2010; Lin et al., 2018). Campbell et al. (2014) link the post-2000 negative correlation regime to accommodative monetary policy, while Asgharian et al. (2016) note that quantitative easing softened this pattern. The literature also distinguishes between pure monetary policy shocks and information shocks, which have opposite effects on stock–bond co-movement (Jarocinski & Karadi, 2020).

Growth expectations generate more ambiguous effects. Strong economic optimism can produce positive correlations (McMillan, 2019; Chiang et al., 2015), while negative growth surprises may generate negative correlations as equities fall and bonds benefit from expected monetary easing. Yet overall, growth has a weaker influence than inflation and interest rates (Andersson et al., 2007; Molenaar et al., 2024).

2.2. Empirical research on high-frequency firm-level correlations is scarce

Most empirical studies rely on monthly or quarterly data (e.g., Andersson et al., 2008; Baele et al., 2010; Conrad & Sturmer, 2017; Kelly et al., 2023). High-frequency relationships are less explored, despite their relevance for modern markets. DCC-MIDAS approaches (Perego & Vermeulen, 2016; Asgharian et al., 2016; Nieto & Rodriguez, 2015) partly address this, but still map daily correlations to lower-frequency macro variables.

Moreover, research on corporate bond–stock correlations – especially for bonds and equities issued by the same firm – remains scarce. Existing contributions include Nieto & Rodriguez (2015), Kelly et al. (2023) and McMillan (2019). To date, no multi-country study examines firm-level stock–corporate bond correlations in the euro area.

The Modigliani–Miller (MM) theorem establishes that, under perfect market conditions, a firm's value is independent of its capital structure – that is, the mix of debt and equity used to finance its assets. Although MM does not explicitly model stock–bond correlations, its implications are highly relevant for understanding the joint behavior of corporate debt and equity returns. Considering extension of Merton's (1974), its structural model states that the value of both equity and debt is a direct function of the firm's underlying asset value. When firm value rises, equity prices appreciate, and default risk declines, which raises corporate bond prices. Conversely, when firm value falls, equity prices decline and default risk increases, reducing bond prices. The model therefore predicts positive stock–bond co-movement when changes in the discount factor affect both assets (leverage effect) and during deteriorating macroeconomic conditions, such as recessions, when rising default risk simultaneously lowers stock and bond valuations.

This paper tries to overcome two main difficulties. First, analytical research on flight-to-safety is often made between government bonds and stock markets which is a restricted view: the measured arbitrage is not only between stock and bonds but more between private firm and public government. To overcome this bias, we propose to study the correlation at firm level but also between indices that do not suffer composition bias; in other terms, even on aggregate we consider the same basket of issuers with the same counterparty risk. Second, the aggregate analysis may be affected by firm-level characteristics. Back to Merton (1974), the leverage of firms composing the corporate and stock indices may affect the level of the correlation. Higher leverage should limit arbitrage opportunities between stock and bonds and maintain positive correlation. Conversely, lower leverage should induce more negative correlation.

As already mentioned, Nieto and Rodriguez (2015) provide one of the few firm-level analyses of stock–bond co-movement using daily data. Relying on a DCC-GARCH framework, the authors investigate the dynamic correlation between a firm's equity returns and the returns of its own corporate bonds. Their results reveal substantial time variation in correlations, which respond not only to macro-financial drivers but also to security-specific characteristics. In particular, correlations increase with measures of firm leverage and default risk, and are sensitive to bond attributes such as residual maturity, coupon rate, and credit quality. The study finds that correlations tend to be more positive when macroeconomic conditions dominate idiosyncratic risk – particularly during periods of high interest rate or inflation expectations – while episodes of financial stress and heightened equity volatility tend to reduce correlations. Overall, the paper highlights the importance of combining firm-specific determinants with broader macro-financial factors to understand the behaviour of corporate stock–bond correlations at high frequency.

The impact of firm-level characteristic is also indirectly shown as well by Kelly et al. (2023). Their analysis demonstrates that the co-movement of corporate bonds and equities is strongly conditioned by the credit risk profile of the issuing firms. For investment-grade bonds, return dynamics are primarily driven by interest rate and inflation shocks, leading to positive correlations. This phenomenon is reinforced for high-yield bonds that behave more like equity-like instruments: their correlations with stock returns tighten further during periods of macroeconomic expansion and increase even more during episodes of heightened credit risk or market stress.

3. Data and indices construction

3.1 Sample selection

We restrict our analysis to non-financial corporations (NFCs) included in the primary equity indices of the five largest euro area markets. Financial institutions are excluded because their business models, regulatory environment, and funding structures – high leverage, short-term market funding, and distinct balance-sheet risk – lead to pricing dynamics that are not directly comparable with those of NFCs. Their exclusion ensures a more homogeneous sample and a cleaner identification of stock–bond co-movements within the corporate sector.

The focus on Germany (DAX), France (CAC40), Italy (FTSE MIB), Spain (IBEX35) and the Netherlands (AEX) reflects the limited liquidity and insufficient number of daily observations in smaller euro area markets. These indices jointly account for approximately 75–85% of domestic market capitalisation, ensuring that our sample captures the dominant share of market activity.

To construct a consistent stock–bond dataset for each country, we retain only the bonds issued by firms that are constituents of the respective equity index. A firm contributes observations only during the periods in which it is included in the index; its bonds are accordingly matched over the same periods. This approach ensures perfect temporal alignment between the equity and bond universes.

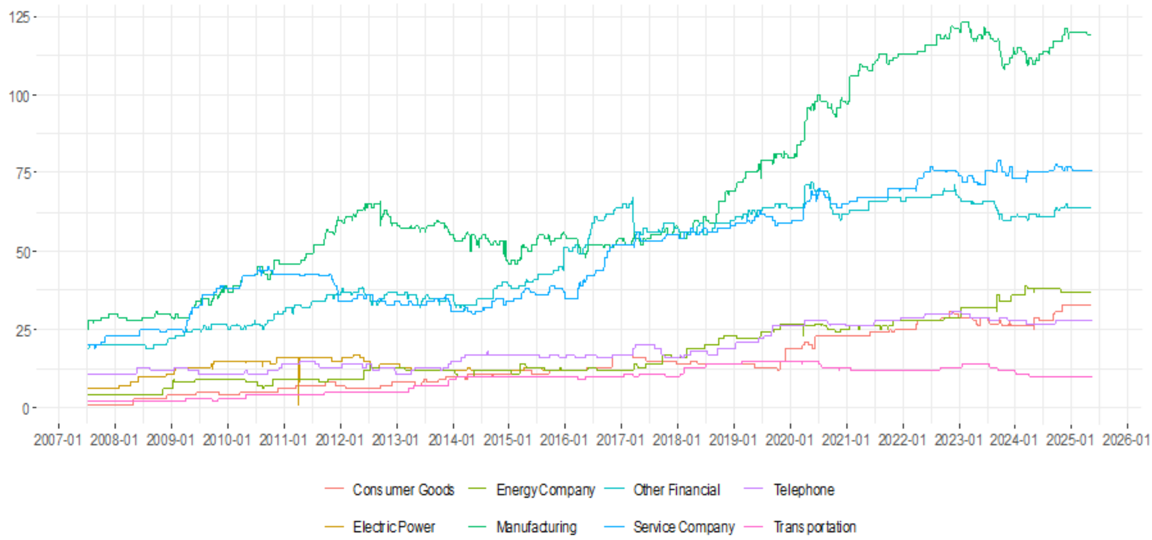
To obtain a homogeneous and liquid set of NFC bonds, we apply several filters. We retain only euro-denominated securities, as foreign-currency bonds are influenced by non-euro-area monetary policies. We exclude short-term instruments by restricting the sample to bonds with original maturities above one year and below 50 years (as in Sandulescu, 2022; Kelly et al., 2023). Bonds with issuance amounts below €50 million are removed due to their limited liquidity. Moreover, following Gilchrist and Mojon (2014) and Nieto and Rodriguez (2015), we retain only fixed- and zero-coupon bonds without embedded options (non-callable, non-puttable, non-convertible). Finally, observations with residual maturities below six months are discarded to avoid price convergence effects close to redemption.

These filters yield a sample of liquid, euro-denominated corporate bonds with meaningful daily price variation. For France alone, this results in slightly more than one million daily stock–bond pairs from mid-2007 to May 2025. As illustrated in Figure 1, the number of outstanding bonds issued by CAC40

NFCs varies considerably over time, with the largest increases observed among manufacturing and, to a lesser extent, services firms.

Annex 1 presents additional descriptive statistics for corporate bonds issued by CAC40 non-financial firms. Both the average residual maturity and the distribution of maturities vary moderately over time (Annex 1.1). Maturities tend to lengthen during low-interest-rate environments but shorten again following the post-Covid-19 tightening cycle. The overall dispersion of average bond yields remains limited (Annex 1.2), indicating that differences in maturity or other idiosyncratic structures translate into only modest yield heterogeneity.

Figure 1. Number of issued corporate bonds by NFC CAC40 companies in the compiled data sample by issuer sector

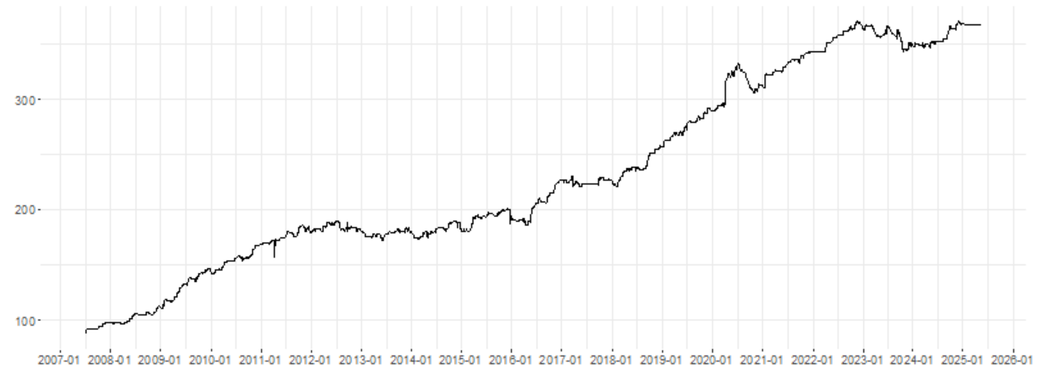


Note: the overall number of bond-stock pairs is provided after the homogenization of sample as explained above.

Figure 2 illustrates that the number of corporate bond-stock pairs in our dataset has been gradually increasing since 2007 in the case of France[1]. However, even at the beginning of the sample period, there were approximately 100 French bond-stock pairs, providing a sufficiently large dataset to derive reliable insights into the interdependencies between corporate bonds and stocks. Interestingly, Annex 2 shows that the composed bond price indices evolve in a rather similar manner, implying that there are potentially market-wide factors that are driving the bond prices. Still, there are some periods when the differences between the bond price indices widen considerably, so the idiosyncratic factors are also in-play.

Figure 2. Number of NFC CAC40 corporate bond and stock pairs included in the data sample

[1] This increase can be in some part related to two main reasons: the number of bonds issued by non-financial companies included in CAC40 list has increased and / or we could not retrieve all matured corporate bonds that were outstanding before the end of the sample period due to the technical restrictions of data provider. Some issuers are also excluded from our sample if there are no bonds that meet the criteria described in section 3.1. We can not firmly conclude which effect is dominating during time.

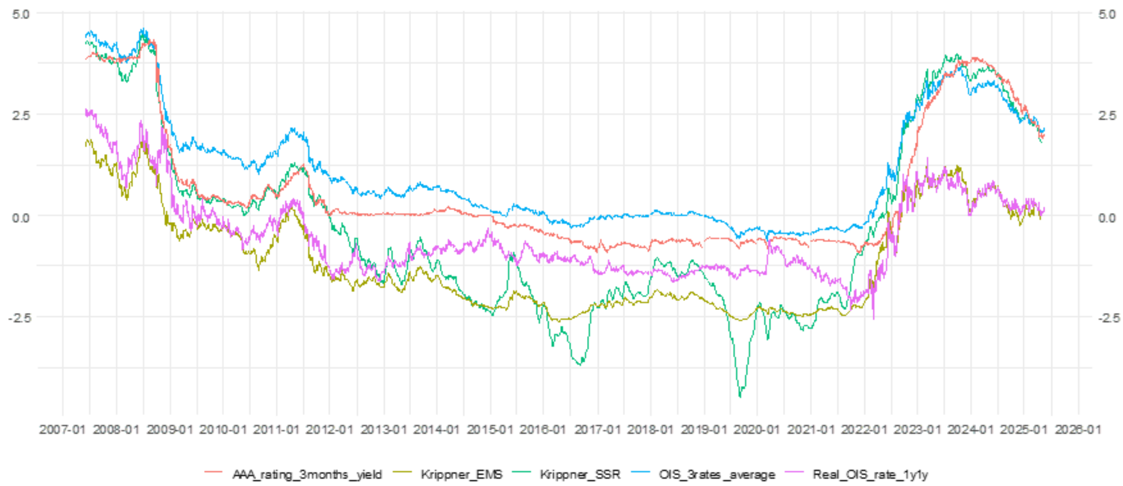


Note: the daily overall number of bond-stock pairs is provided after the homogenization of sample as explained above.

To examine how monetary policy affects bond–stock return correlations, we rely on several daily monetary policy indicators. We first use the Shadow Short Rate (SSR) and the Effective Monetary Stimulus (EMS) developed by Krippner (2020), the former capturing the overall stance of policy and the latter measuring deviations from a neutral benchmark. Shadow rates are widely used in the literature when studying unconventional monetary policy (e.g., Hadood and Gokmenoglu, 2020). We also test fully market-based measures, including a real 1-year/1-year rate (nominal OIS minus inflation swap of equal maturity) and a simple average of nominal OIS rates across 3-month, 2-year and 10-year maturities.

Although these indicators differ in levels, their time profiles are broadly similar (Figure 3). Nominal indicators generally lie above real rates, while the gap between EMS and the SSR primarily reflects the stability of the estimated neutral rate. Given the close alignment in first differences, we expect DCC model results to be robust to the choice of indicator. The most pronounced policy shifts occur during the 2007–2008 monetary cycle and the tightening cycle that began in late 2022, whereas movements in the remaining years are comparatively limited.

Figure 3. Euro area monetary policy indicators, in %



Notes: SSR is Shadow short rate (calculated by Krippner, 2020) is a synthetic interest rate reflecting the overall stance of monetary policy. EMS is Effective monetary stimulus (calculated also by Krippner, 2020) that reflects the deviation of policy from a neutral benchmark.

3.2 Construction of unbiased stock-bond market indices

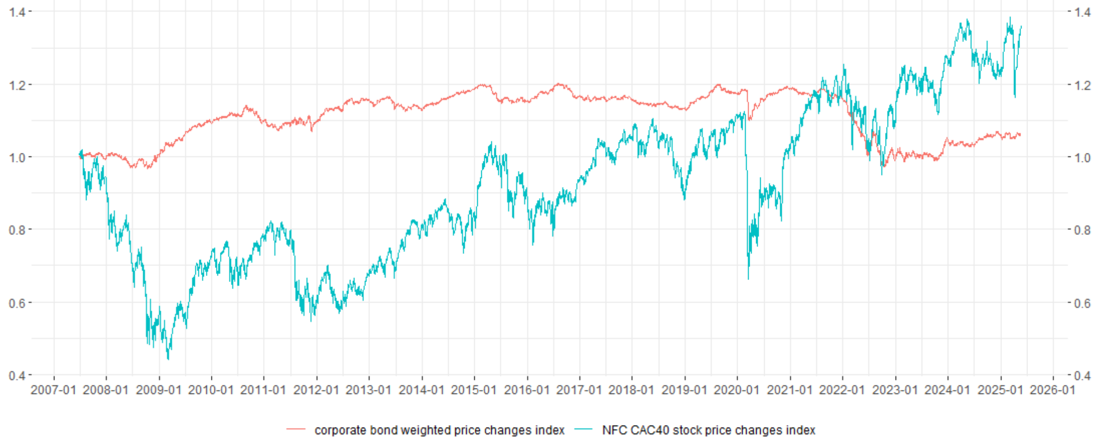
We build indices for both asset classes at a daily frequency as portfolio cumulative returns as in Molenaar et al. (2024), for each asset class $u \in \{stock; bonds\}$:

$$r_{u,t} = \left[\sum_{i=1}^{n_u} w_{i,t}\left(\frac{P_{i,t}}{P_{i,t-1}} - 1\right)\right] \text{for } u \in \{s, b\} \quad (1)$$

where $w_{i,t} = \frac{A_{i,t}}{\sum_{j=1}^{n_u} A_{j,t}}$, $A_{i,t}$ is the market capitalization of stock *i* for $u = s$ and the issued amount of bond *i* for $u = b$. This approach mirrors standard market-capitalisation weighting practices used in equity and bond index construction (Perego and Vermeulen, 2016). The weighted price index at date *t* is then $I_{u,t} = \sum_{k=1}^{t} r_{u,k}$.[2]

Figure 4 shows that price indexes for France trend upward over the sample, except for the sharp decline in 2022 driven by monetary policy tightening, which strongly affected bond valuations. The stock index, by contrast, exhibits higher volatility: it collapsed during the 2007–2008 financial crisis, and during Covid episode in 2020 but grew more strongly than corporate bond indices thereafter.

Figure 4. Weighted corporate bond and stock indices (2007-07-01 = 1)



4. Modelling dynamic corporate bond-stock correlations

4.1. Controlling for market betas in Dynamic conditional correlation

A wide range of empirical strategies has been used to study stock–bond interlinkages, including rolling-window correlations (Ilmanen, 2003; Andersson et al., 2008; McMillan, 2019; Molenaar et al., 2024), GARCH-type and DCC models (Connolly et al., 2005; Chiang et al., 2015; Nieto and Rodriguez, 2015), MIDAS-based specifications (Baele et al., 2010; Asgharian et al., 2016; Perego and Vermeulen, 2016; Baele and van Holle, 2017; Allard et al., 2020), as well as copula (Jammazi et al., 2015), wavelet (Lin et al., 2018), and factor-based approaches (Kelly et al., 2023).

Given our objective of capturing daily correlations at the micro level, we pre-filter each return according to their market beta in a two-dimensional VAR such as:

$$\begin{bmatrix} r_{s,t} - r_t^f \\ r_{b,i,t} - r_t^f \end{bmatrix}_j = \begin{bmatrix} \alpha_s \\ \alpha_{b,i} \end{bmatrix}_j + \begin{bmatrix} \beta_{s,j} & 0 \\ 0 & \beta_{b,i,j} \end{bmatrix} \begin{bmatrix} r_{s,t} - r_t^f \\ r_{b,t} - r_t^f \end{bmatrix} + \begin{bmatrix} \epsilon_{s,t-1} \\ \epsilon_{b,i,t-1} \end{bmatrix}_j \quad (2)$$

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[2] We also construct total returns, incorporating reinvested dividends (for equities) and coupon income (for bonds) yet empirical evidence shows that total-return-based and price-based correlations are typically nearly identical (Asgharian et al., 2016).

where $\begin{bmatrix} r_{s,t} - r_t^f \\ r_{b,i,t} - r_t^f \end{bmatrix}_j$ denote stock and bond excess returns for each stock-bond pair *i* of firm *j*. $\begin{bmatrix} r_{s,t} - r_t^f \\ r_{b,t} - r_t^f \end{bmatrix}$ denote the market excess returns. r_t^f is the risk-free rate proxied by the spot OIS rate.

Note that for a given firm, there are several pairs *i* as soon as there are different bonds issued for a given firm *j* but only one stock. From equation (2) we obtain the $\beta_{s,j}$ of the stock market of firm *j* and $\bar{\beta}_{b,j} = \frac{1}{N}\sum_{i=1}^{N} \beta_{b,i,j}$ is the average β of the bonds issued by firm *j*.

The residuals from (2) serve as inputs to the DCC-GARCH model. Each return series is first fitted with a univariate GARCH(1,1). To simplify notation, we do not explicitly indicate *j* subscript that implicitly applies to all equations:

$$h_{u,i,t} = \omega_{u,i} + \alpha_{u,i}^{h} \epsilon_{u,i,t-1}^{2} + \beta_{u,i}^{h} h_{u,i,t-1} \tag{3}$$

for $u \in \{s, b\}$.

Let $D_{i,t} = diag(\sqrt{h_{s,i,t}}, \sqrt{h_{b,i,t}})$. The standardized residuals are $\varepsilon_{i,t} = D_{i,t}^{-1}\epsilon_{i,t}$. The unconditional correlation is

$$\bar{R}_i = \frac{1}{T}\sum_{t=1}^{T} \varepsilon_{i,t}\varepsilon_{i,t}{}' \tag{4}$$

The correlation matrix evolves according to the standard DCC (1,1) structure

$$R_{i,t} = (1 - a - b)\bar{R}_i + a\left(\varepsilon_{i,t-1}\varepsilon_{i,t-1}'\right) + bR_{i,t-1} \tag{5}$$

where a measures the sensitivity of correlations to recent shocks and b governs correlation persistence. This two-step estimation yields a time series of daily conditional correlations between stock and bond returns, controlling for the market beta of each pair *i* for firm *j*.

4.2. Explanatory factors behind the changing links between corporate bonds and stocks

To identify the factors driving the daily co-movements between corporate bonds and stocks, we regress the estimated daily DCC correlations on a set of high-frequency explanatory variables. Our objective is to explain correlation dynamics using lagged daily information, consistent with what investors could observe in real time when making portfolio decisions. Unlike Asgharian et al. (2016), we do not embed macro-financial variables directly within the DCC estimation but adopt a two-step framework for two main reasons.

First, our dataset contains hundreds of stock–bond pairs per country, which makes maximum-likelihood estimation of a DCC model with multiple exogenous variables computationally prohibitive and prone to convergence issues. Second, a panel regression framework allows for the inclusion of bond fixed effects, which is far more difficult to implement within a multivariate GARCH structure given the large number of parameters involved.

Because correlation coefficients are inherently bounded within the range [-1, +1], while the explanatory variables are not, we apply the Fisher transformation to each bond-stock pair *i*:

$$\tilde{R}_{i,j,t} = \frac{1}{2} \times \ln\left(\frac{1+R_{i,j,t}}{1-R_{i,j,t}}\right) \tag{6}$$

This transformation is standard in the literature (Chiang et al., 2015; Perego and Vermeulen, 2016; Baele and van Holle, 2017; Lin et al., 2018). The transformed series $\tilde{R}_{i,t}$ serves as the dependent variable in our panel regressions.

We estimate a panel model with bond fixed effects (887 bonds in the CAC40 sample), while also considering firm fixed effects as a robustness check. To control for persistence in correlations, we follow Perego and Vermeulen (2016) and include the lagged dependent variable. The baseline regression takes the form:

$$\Delta\tilde{R}_{i,j,t} = \alpha_j + \beta_0\Delta\tilde{R}_{i,j,t-1} + \beta_1\Delta FSS_{t-1} + \beta_2\Delta INF_{t-1} + \beta_3\Delta MPS_{t-1} + \delta X_{j,t} + u_{i,t} \tag{7}$$

where:

ΔFSS – daily change in the ECB indicator of financial system stress (probability of simultaneous default of two or more large European banks);

ΔINF – daily change in the euro area 1year/1year inflation expectations;

ΔMPS – daily change in the euro area 1year/1year real OIS rate;

$X_{j,t}$ – firm specific variables such as bond residual maturity

Changes in inflation expectations directly affect bond yields and discount rates, while their effect on stock returns is theoretically ambiguous: higher inflation may depress stock prices via the discount rate channel but may also increase expected nominal cash flows.

Similarly, changes in the monetary policy stance affect both asset classes through discount rate channels, although the real-rate measure ensures that we do not mechanically confound policy with inflation shocks. Notably, inflation expectations and real OIS rates exhibit only modest correlation (<0.4), mitigating multicollinearity concerns and reflecting the fact that monetary policy may react differently to supply- versus demand-driven inflation shocks.

Finally, an increase in financial system stress is typically associated with a decline in stock prices – due to higher risk premia – and simultaneously with higher demand for safe assets, leading to rising bond prices. Higher stress should therefore be associated with lower stock–bond correlations. We use the ECB's financial stress measure because it is available daily, highly reactive, and independent of stock or bond return variances, avoiding endogeneity problems that would arise if volatility-based measures were used instead (given the GARCH structure underlying our DCC estimates).

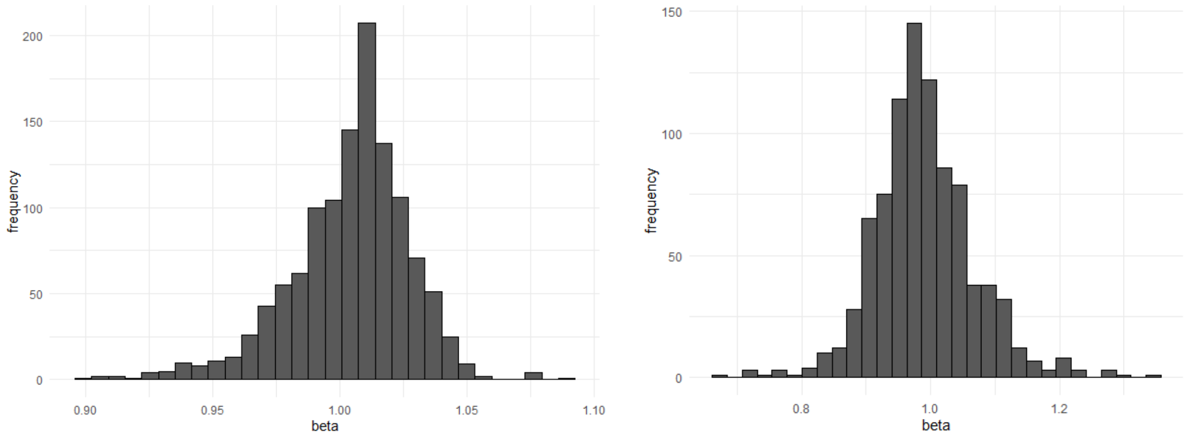
5. Results

5.1. Dynamic correlations estimations: strong heterogeneity at the firm level

As regards the first step in our estimation (equation 2), the obtained betas for excess returns are somewhat wider for the case of CAC40 stocks than bonds, underlying higher heterogeneity across stocks as regards market sensitivity. For corporate bonds, we see that betas are more concentrated around 1 (Figure 5). This demonstrates the importance of neutralizing overall market dynamics to properly measure stock-bond correlation at the micro level. Very similar findings are also obtained for corporate bonds-stocks of other four largest euro area markets (Annex 3).

Figure 5. The betas for French <u>corporate bond</u> excess returns (LHS) and for <u>stock</u> excess returns (RHS)

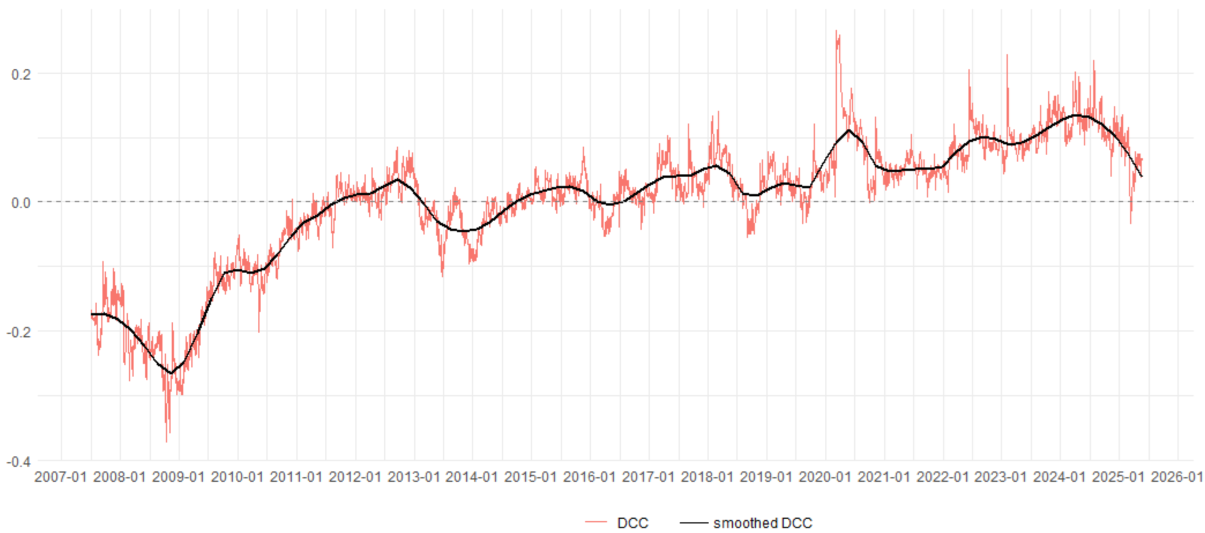
betas for corporate bond excess returns betas for stock excess returns



Notes: Betas are estimated as under formula (2). The price changes of bonds and stocks are included in this analysis only when their issuer was constituent of the main French stock index (CAC40) and is NFC. The estimates are shown for the bonds whose standard deviation of DCC was statistically significantly different from 0, as described in section 3.1.

We then concentrate on the weighted-mean DCC line aggregated across all pairs of CAC40 stocks-corporate bonds (Figure 6). After the GFC characterized by negative correlation, we observe a increasing trend since 2009. We see on average that the correlation is not so high, even at temporary peaks, hardly reaching 0.25 when positive, and -0.35 during GFC. Since 2012, this correlation stayed at rather neutral and subdued levels, albeit there are some evident changes in either direction. Although there are some cross-country differences, this positive trend after the end of GFC is also visible for other four major euro area markets (Annex 4).

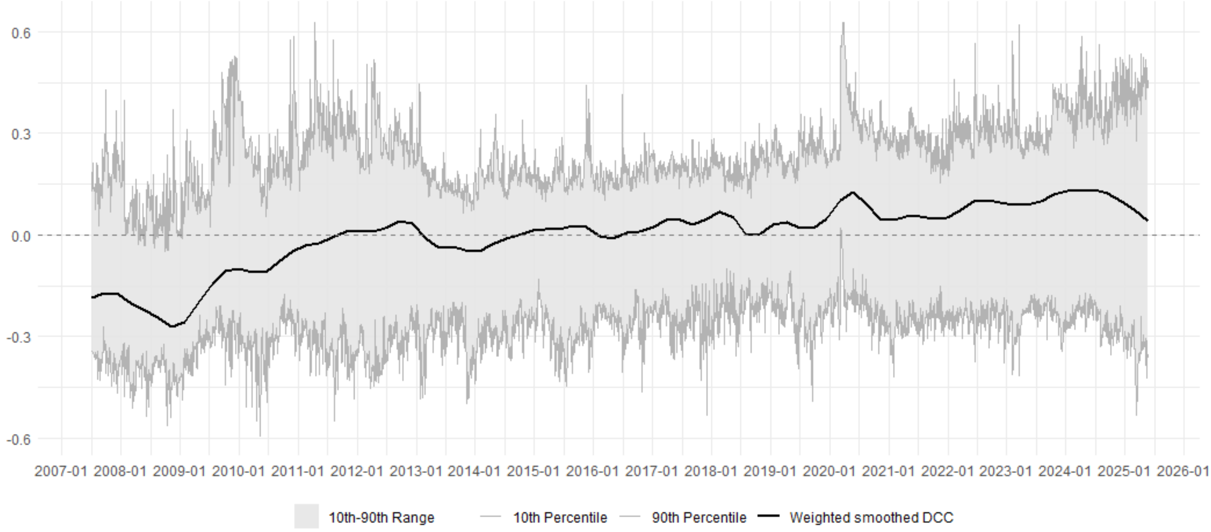
Figure 6. The daily mean DCCs of price changes across all NFC CAC40 stock-corporate bond pairs



Notes: The DCCs of price changes for individual corporate bond-stock pairs are averaged across all NFC CAC40 issuers (red line). The smoothing of the mean line (black line) is applied using the LOESS method with a fixed span parameter (degree of smoothing) of 0.2.

Looking at the dispersion of all estimated DCCs across CAC40 firms (Figure 7), it reveals that there is a wide range of DCC values. For instance, even when the mean DCC line implies overall negative correlation until 2012, the correlations of some pairs of corporate bonds-stocks are positive. This heterogeneity justifies the necessity to better understand the underlying forces of these correlations at firm level.

Figure 7. The range of DCCs for different NFC CAC40 stock-corporate bond pairs and the smoothed weighted mean line



Notes: The DCCs of price changes for individual corporate bond-stock pairs are averaged daily for each NFC CAC40 stock issuer. The percentiles are calculated on the daily basis. Several issuers were excluded to avoid bond-stock pairs that appear up just for several months due to either a short sample period or temporary exclusion from the CAC40 index, which would otherwise distort the smoothening of the lines. The smoothed mean line is averaged by the respective issued weight of each corporate bond.

5.2. What moves correlations at firm-level?

Table 1 reports the parameter estimates for Equation (7). Over the full sample period, high-frequency (daily) variations in inflation expectations and real short-term interest rates (OIS) are the only statistically significant determinants of stock–bond correlations. The estimated coefficients on both variables are positive, indicating that firm-level stock–bond correlations increase in response to upward revisions in inflation expectations and to a tightening in the expected monetary policy stance, as proxied by changes in real OIS rates.

These results are consistent with a discount-rate channel, whereby shifts in expected inflation and real rates jointly affect the discount factor applied to both equity and bond cash flows. An increase in expected inflation and/or real rates raises discount rates, generating co-movements in asset prices and thus higher correlations.

During the 2022 monetary policy tightening episode, the persistence of strong equity market performance alongside a rapid increase in policy rates was widely interpreted as a potential sign of equity market overvaluation. However, such aggregate-level evidence may be misleading due to composition effects embedded in broad equity and bond indices, as well as the dominant focus over government bond–equity index correlations. Our firm-level evidence suggests that, once these aggregation biases are mitigated, asset price dynamics are consistent with rational repricing along the expected discount-rate channel. In other words, investors appear to have internalized the implications of tighter expected monetary policy for discount rates, even if this was not immediately apparent in aggregate market indicators. This finding is corroborated by sub-sample estimations of Equation (7), which show that the effect is verified in the high-inflation regime.

In addition, the same mechanism operates in the low-inflation regime. In this environment, monetary policy easing – associated with declining inflation expectations – tends to impact equity–bond correlations through a reduction in discount rates and an upward revision of expected future cash flows. Notably, the magnitude of the discount-rate channel is even stronger (i.e. higher betas) in low-inflation regimes, pointing to an asymmetry: asset prices respond more strongly to decreases in discount rates than to comparable increases, reflecting some convexity in market expectations.

In the low-inflation regime, financial stress exerts a negative and statistically significant effect on stock–bond correlations, consistent with a flight-to-quality or arbitrage channel. By contrast, this effect is not significant in the medium- or high-inflation sub-samples. We interpret this result as evidence that, in high-inflation environments, market participants anticipate a constrained monetary policy reaction function. In particular, central banks – such as the European Central Bank – prioritize price stability, limiting their ability to respond to financial stress through accommodative policy measures.

As a result, the arbitrage channel is effectively muted in high-inflation regimes, and the discount-rate channel becomes the dominant transmission mechanism. Put differently, when financial stress materializes in a high-inflation environment, investors cannot rely on policy-induced compression in discount rates to generate cross-asset arbitrage opportunities between equities and bonds.

Finally, this effect dominates in the aggregate results: controlling for bond characteristics such as average maturity does not yield a statistically significant impact on firm-level equity–bond correlations, further supporting the primacy of the channels described above.

Table 1. Results of the panel regression model (equation 7) of the daily change of Fisher-transformed DCC values between residual of NFC CAC40 stock and bond excess price changes for different sample periods

variable	full sample period	lower inflation	medium inflation	higher inflation
lag of dependent	-0.28825 (0.00267)***	-0.29470 (0.00459)***	-0.25830 (0.00464)***	-0.30522 (0.00463)***
residual maturity	0.00001 (0.00002)	0.00001 (0.00002)	-0.00002 (0.00003)	0.00001 (0.00004)
financial system stress	-0.00028 (0.00023)	-0.00113 (0.00045)**	0.00056 (0.00062)	0.00003 (0.00046)
EA inflation 1y1y	0.27121 (0.11008)**	0.55803 (0.24530)**	0.09314 (0.22945)	0.32404 (0.16334)**
real OIS 1y1y	0.14634 (0.06528)**	0.35902 (0.16949)**	0.06396 (0.13689)	0.17442 (0.09254)*
number of instruments	887	685	771	651

The effects described above for France are rather similar for other euro area countries, ie with stronger effects on lowest and highest inflation periods, although there are specific differences for various indicators across countries (Annex 5).

Conclusion

This paper provides new evidence on the dynamics of stock–bond correlations in the euro area by adopting a firm-level perspective and high-frequency methodology. Using a large panel of corporate bond–equity pairs and Dynamic Conditional Correlation models, we document substantial time variation in correlations and show that their behaviour cannot be fully understood only through aggregate index-based approaches. In particular, the correlation between stock-corporate bond returns tended, on average, to increase since the GFC and fluctuated at rather neutral levels from around 2012.

Our main contribution is to demonstrate the central role of the discount-rate channel in driving stock–bond co-movement at the firm level. Across both low- and high-inflation regimes, changes in inflation expectations and real interest rates emerge as the primary determinants of correlations, inducing stronger co-movement between corporate bond and equity returns. By contrast, the traditional arbitrage or flight-to-quality channel – whereby financial stress leads to negative correlations – is only operative in low-inflation environments. This asymmetry has important implications. In high-inflation regimes, stock–bond correlations do not decrease, thus limiting diversification benefits, as monetary policy is constrained in its ability to respond to financial stress. Central banks – such as the European Central Bank – are exclusively focused on restoring price stability, limiting the scope for policy easing expectations that would otherwise support cross-asset hedging dynamics. As a result, financial stress episodes may be amplified, with fewer opportunities for investors to offset losses across asset classes.

Methodologically, our results also highlight the importance of addressing composition bias – a common limitation in similar studies. By focusing on bonds and equities issued by the same firms, we show that aggregate correlations may obscure underlying mechanisms and lead to misleading interpretations of market dynamics. Firm-level analysis reveals a more coherent picture in which asset prices adjust consistently to expected discount-rate changes, even when aggregate indicators suggest apparent disconnects.

This research suggests avenues for future research by further exploring the role of firm-specific characteristics, such as leverage or credit risk, in shaping correlation dynamics across regimes. Interestingly, we did not find meaningful effect of changing residual maturities of bonds on the daily correlations. It could also be extended to financial firms with bond characteristics that are more complex than NFC bond characteristics.

Overall, our findings suggest that the erosion of stock–bond diversification is not merely cyclical but depends critically on the macro-financial regime. In particular, high-inflation environments fundamentally alter the arbitrage channels, with important consequences for portfolio allocation, risk management, and the conduct of monetary policy.

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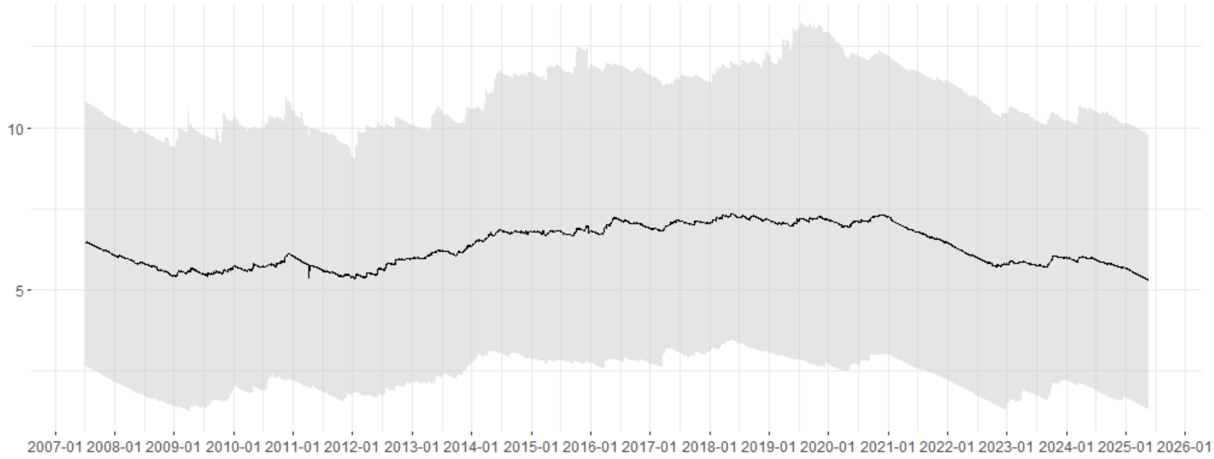
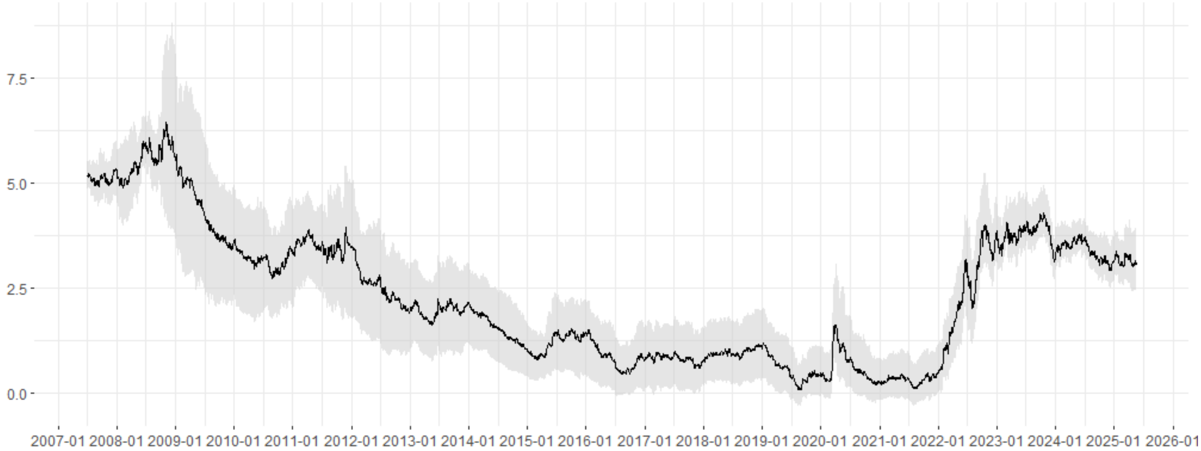
ANNEXES

Annex 1. Descriptive statistics of NFC CAC40 companies' corporate bonds during time

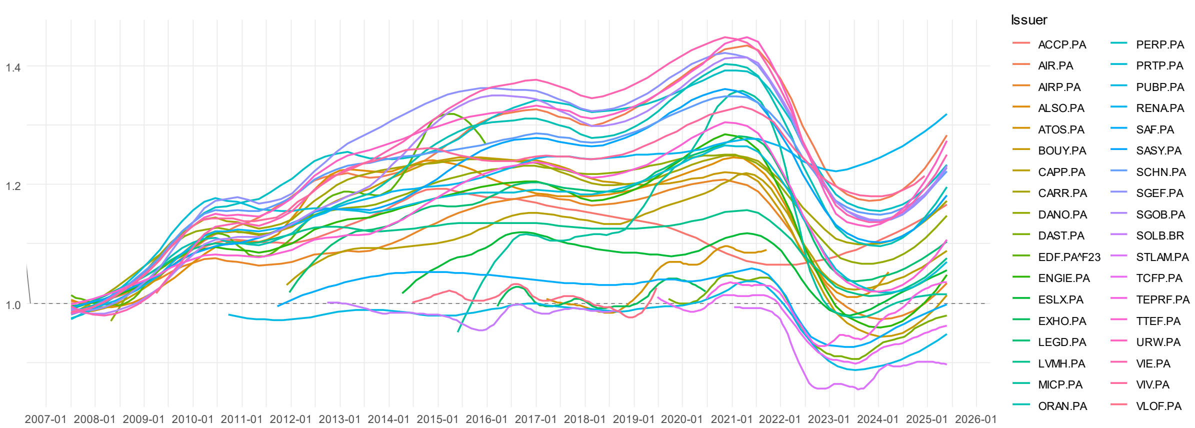
Annex 1.1. 10th (lower), mean and 90th (higher) **residual maturity percentiles** for corporate bonds of NFC CAC40 companies' every day



Annex 1.2. 10th (lower), mean and 90th (higher) **yield percentiles** for corporate bonds of NFC CAC40 companies' every day



Annex 2. French bond indices composed from daily price changes for each NFC CAC40 issuer (starting date = 1)

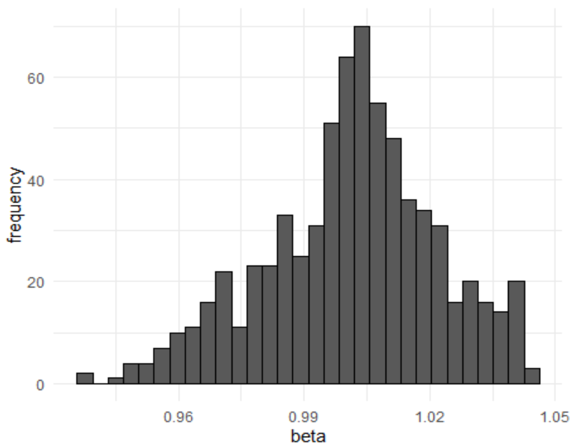


Note: To avoid indices that show up just for several months and then disappear, we require the index to have at least one year or un-interrupted time-series. The lines represent the smoothed indices by using the LOESS method with a fixed span parameter (i.e., degree of smoothing) of 0.2.

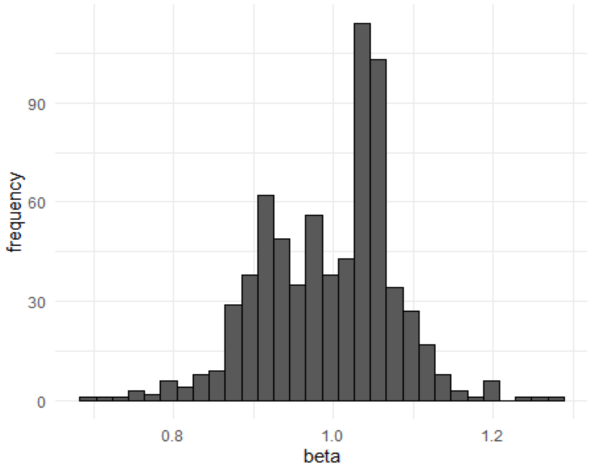
Annex 3. The betas for <u>corporate bond</u> excess returns (LHS) and for <u>stock</u> excess returns (RHS) for different countries

i) German DAX index issuers:

betas for corporate bond excess returns

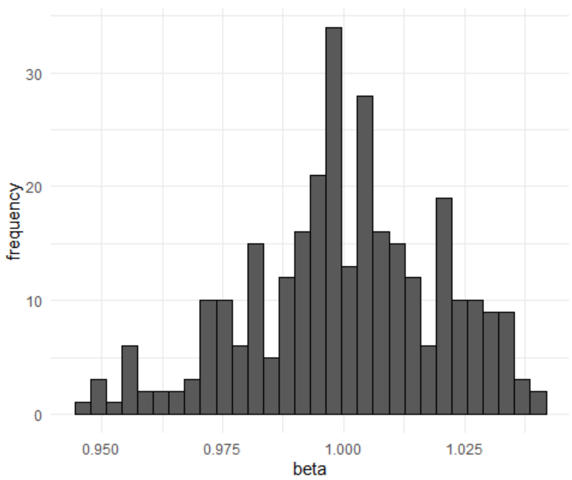


betas for stock excess returns

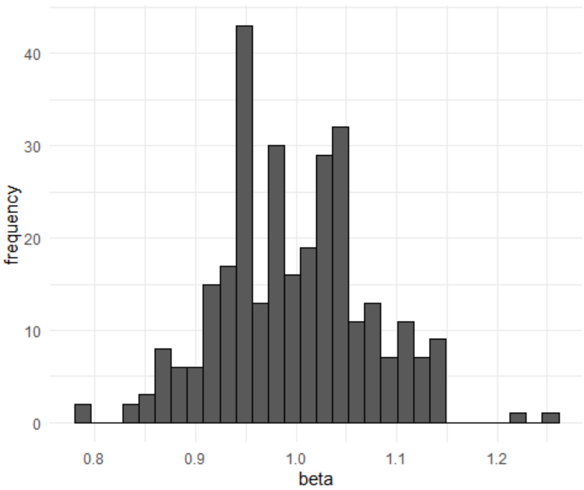


ii) Italian FTSE MIB index issuers:

betas for corporate bond excess returns



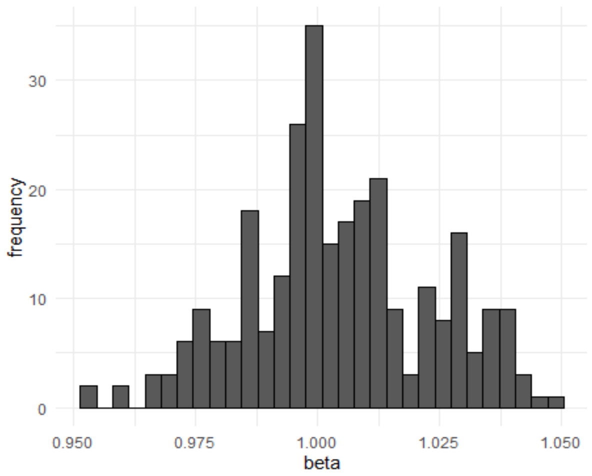
betas for stock excess returns

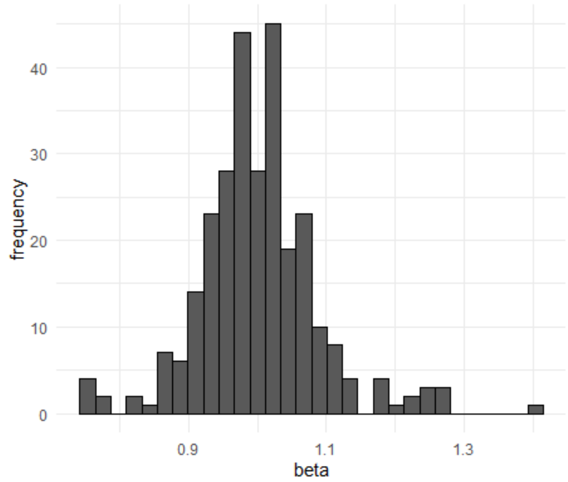


iii) Spanish IBEX35 index issuers:

betas for corporate bond excess returns

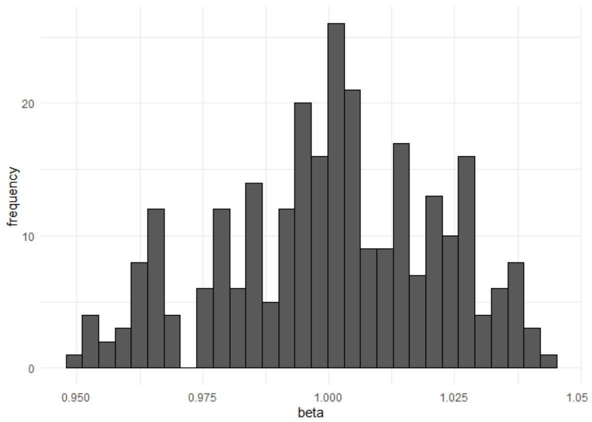
betas for stock excess returns



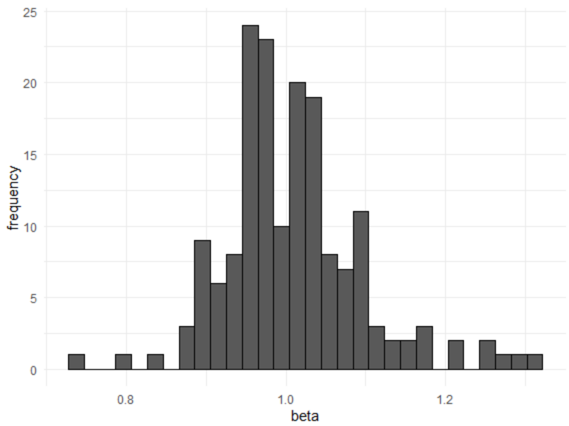


iv) The Netherlands AEX index issuers:

betas for corporate bond excess returns



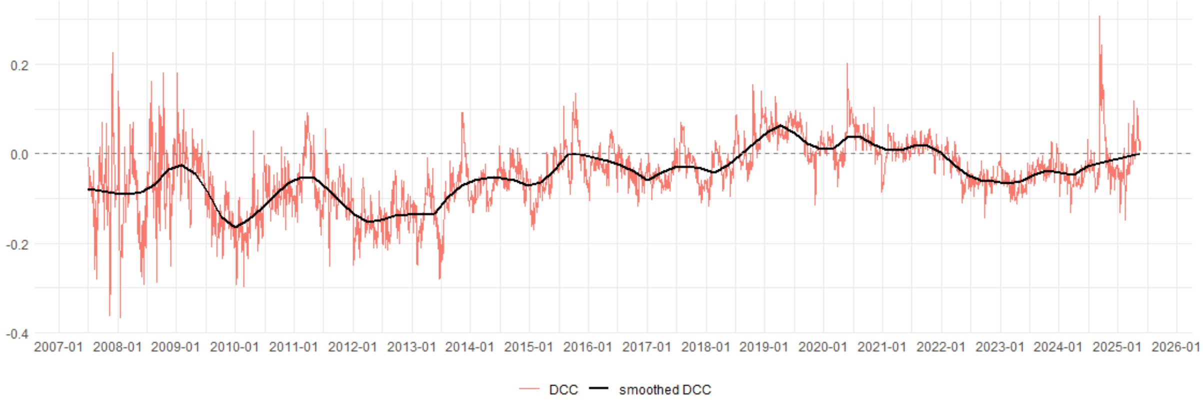
betas for stock excess returns



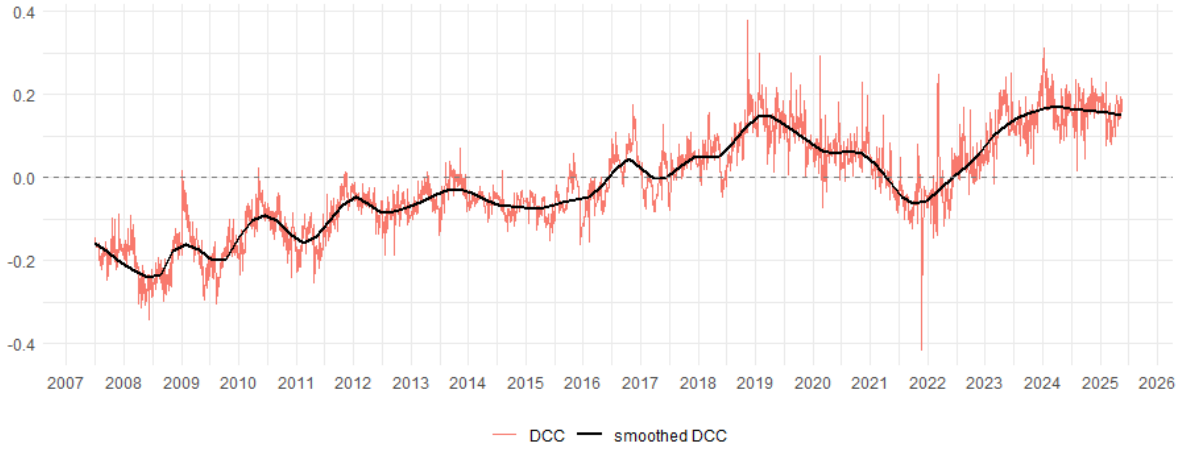
Notes: Betas are estimated as under formula (2). The price changes of bonds and stocks are included in this analysis only when their issuer was constituent of the main stock index (CAC40) and is NFC for a particular country. The estimates are shown for the bonds whose standard deviation of DCC was statistically significantly different from 0, as described in section 3.1.

Annex 4. The daily mean DCCs of price changes across all stock-corporate bond pairs for different countries

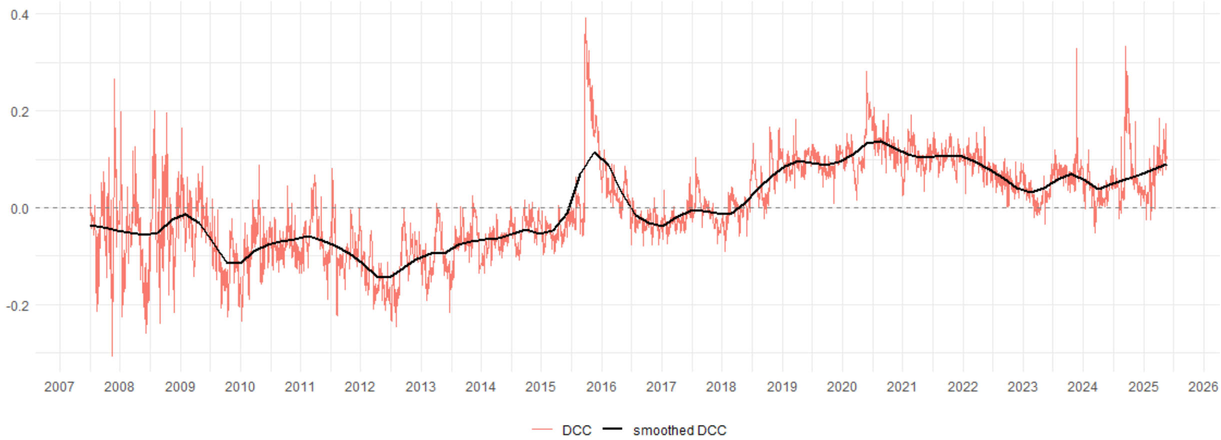
i) German DAX index issuers:



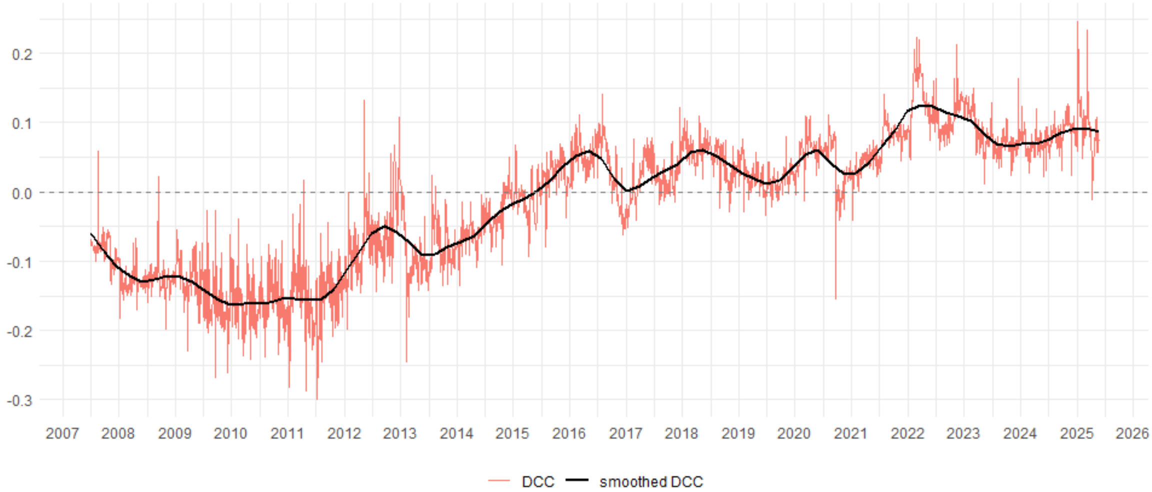
ii) Italian FTSE MIB index issuers:



iii) Spanish IBEX35 index issuers:



iv) The Netherlands AEX index issuers:



Notes: The DCCs of price changes for individual corporate bond-stock pairs are averaged across all index (red line) from a particular country's issuers. The smoothing of the mean line (black line) is applied using the LOESS method with a fixed span parameter (degree of smoothing) of 0.2.

Annex 5. Results of the panel regression model (equation 7) of the daily change of Fisher-transformed DCC values between residual of stock and bond excess price changes for different sample periods of different stock index

i) Germany:

variable	full sample period	lower inflation	medium inflation	higher inflation
lag of dependent	-0.20530 (0.01771)***	-0.17015 (0.01874)***	-0.22328 (0.01720)***	-0.27959 (0.01728)***
residual maturity	0.00001 (0.00001)	0.00001 (0.00002)	0.00002 (0.00003)	-0.00001 (0.00001)
financial system stress	-0.00012 (0.00030)	-0.00039 (0.00023)*	-0.00009 (0.00012)	0.00022 (0.00043)
EA inflation 1y1y	0.14670 (0.13308)	0.29363 (0.16592)*	0.30929 (0.19181)	0.07061 (0.11146)
real OIS 1y1y	0.13186 (0.07142)*	0.26256 (0.11580)**	0.06250 (0.12589)	0.11442 (0.05968)*
number of instruments	605	470	601	533

ii) Italy:

variable	full sample period	lower inflation	medium inflation	higher inflation
lag of dependent	-0.24676 (0.03520)***	-0.20178 (0.02714)***	-0.23852 (0.04340)***	-0.27325 (0.02646)***
residual maturity	0.00001 (0.00001)	0.00000 (0.00001)	-0.00001 (0.00001)	0.00001 (0.00001)
financial system stress	-0.00026 (0.00032)	-0.00176 (0.00068)**	-0.00040 (0.00027)	0.00056 (0.00039)
EA inflation 1y1y	0.20144 (0.10990)*	0.40587 (0.18384)**	0.08414 (0.10524)	0.18418 (0.09512)*
real OIS 1y1y	0.22460 (0.12772)*	0.26569 (0.14178)*	-0.13257 (0.11529)	0.24569 (0.12327)*
number of instruments	273	238	270	230

iii) Spain:

variable	full sample period	lower inflation	medium inflation	higher inflation
lag of dependent	-0.25933 (0.03231)***	-0.19771 (0.02228)***	-0.26993 (0.02914)***	-0.29380 (0.04147)***
residual maturity	0.00001 (0.00002)	0.00003 (0.00002)	0.00000 (0.00001)	0.00002 (0.00001)
financial system stress	-0.00003 (0.00037)	-0.00010 (0.00046)	0.00048 (0.00035)	0.00006 (0.00042)
EA inflation 1y1y	0.44230 (0.24043)*	0.76704 (0.28981)***	0.01215 (0.20481)	0.47204 (0.24479)*
real OIS 1y1y	0.04582 (0.12425)	0.30494 (0.19178)	-0.00673 (0.24103)	0.18366 (0.09977)*
number of instruments	250	210	248	206

iv) The Netherlands:

variable	full sample period	lower inflation	medium inflation	higher inflation
lag of dependent	-0.31318 (0.02877)***	-0.31135 (0.03422)***	-0.31215 (0.02652)***	-0.31886 (0.02580)***

residual maturity	0.00001 (0.00001)	0.00002 (0.00001)	-0.00002 (0.00001)	0.00001 (0.00002)
financial system stress	-0.00102 (0.00056)*	-0.00149 (0.00078)*	0.00043 (0.00038)	-0.00074 (0.00089)
EA inflation 1y1y	0.26329 (0.27175)	0.73087 (0.39748)*	0.18842 (0.26508)	0.24857 (0.15597)
real OIS 1y1y	0.20127 (0.11656)*	0.57042 (0.21477)***	0.01233 (0.15263)	0.148744 (0.07825)*
number of instruments	214	175	212	196

Notes: The first line for each variable denotes the estimate of the effect of the independent variable specified on the left-hand side. The second line (in parentheses) shows standard error. Asterisks indicate statistical significance at the 10% (*), 5% (**) and 1% (***) levels. To account for heteroscedasticity and within-cluster correlation in standard errors, we estimate our model using clustered standard errors at the stock level. Stock-fixed effects are used for the panel model estimation. The dependent variable is the Fisher-transformed daily DCCs values.