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Research

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Empirical Evidence on the Stock–Bond Correlation

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The correlation between stock and bond returns is a cornerstone of asset allocation decisions. History reveals abrupt regime shifts in correlation after long periods of relative stability. We investigate the drivers of the correlation between stocks and bonds and find that inflation, real rates, and government creditworthiness are important explanatory variables. We examine the implications of a shift in the stock–bond correlation and find that increases are associated with higher multi-asset portfolio risk and higher bond risk premia.

Keywords: bonds; correlation; inflation; interest rates; stocks

Introduction

The correlation between stocks and bonds is an essential driver of any asset allocation decision. It impacts not only the overall risk of a diversified multi-asset class portfolio but also the risk premia one should expect to receive for taking risk in different asset classes. The obstacle one faces when estimating the correlation between stocks and bonds is that it fluctuates extensively across periods. Volatility of asset classes can vary widely inside of a business cycle but remain relatively stable over longer horizons. Correlations between stocks and bonds may persist with the same sign for extended periods, before eventually reversing. For example, the average correlation between stocks and bonds was 0.35 in the United States between 1970 and 1999 and then was −0.29 between 2000 and 2023. The effect of these variations can be seen in Figure 1. Keeping equity and bond mean returns and volatilities constant at the full sample values, the figure shows that the correlation in the first three decades leads to a volatility of 10.5% per annum for the 60/40 portfolio, whereas this decreases to 8.4% with the correlation realized in the post-1999 period.

In times when allocations to government bonds reduce overall portfolio risk, it would make sense that the expected returns on bonds are low or even negative. Investors may be prepared to pay for (imperfect) insurance against equity market downturns. In other words, the bond risk premium (also sometimes called the term premium), that is, the additional return that investors are expected to earn from investing in Treasury

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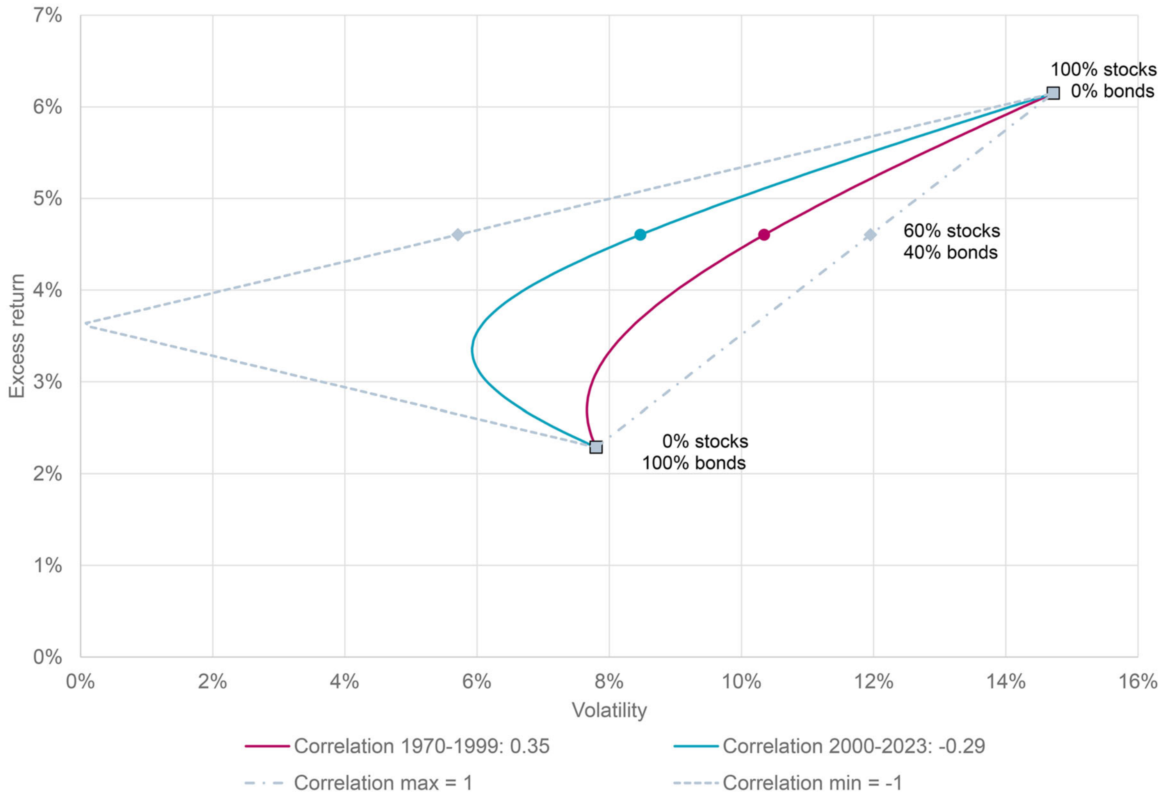
PL Credits: 2.0

Figure 1. Multi-Asset Portfolio Risk and Return for Different Stock–Bond Correlation



Notes: Authors' average standard deviation and excess returns from January 1970 to June 2023. Pearson correlation coefficient of monthly returns computed between January 1970 and December 1999 and between January 2000 and June 2023.

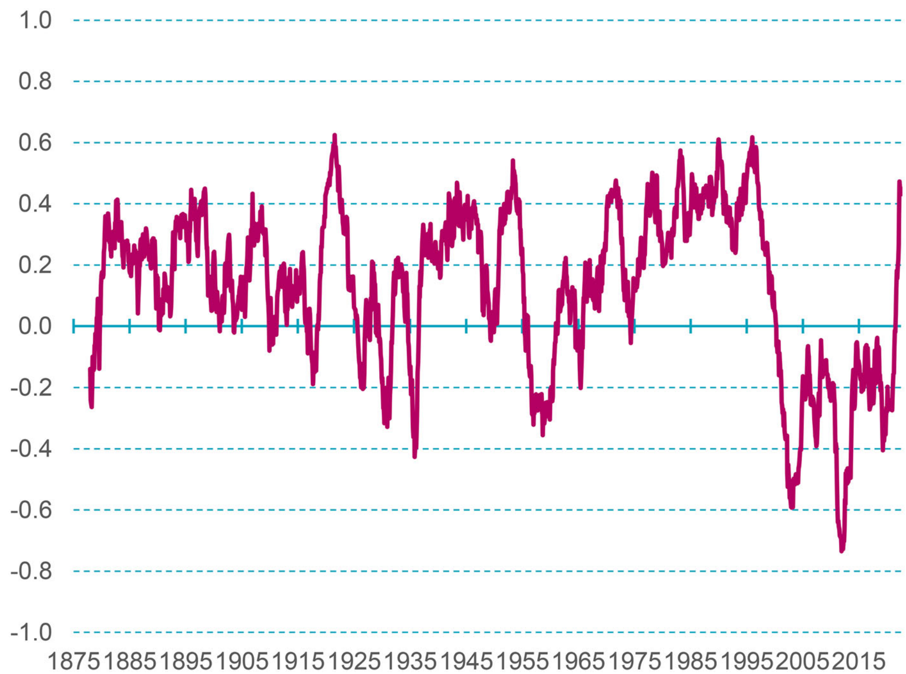
bonds rather than Treasury bills, may become negative in times when the stock–bond correlation is negative.

Today's market participants have little experience, perhaps except for the last two years, investing in an environment where the correlation between stocks and bonds is positive. Given that a shift in level or even the sign of the correlation between stocks and bonds can last for decades, short historical data periods (i.e., 10 or even 20 years) are of little help to understand the drivers of co-movements between stocks and bonds. To resolve this, our analyses use multiple decades of historical data across multiple countries. Figure 2 contains the time series of correlations for the United States using data starting in 1875. Researchers have several choices on how to calculate the stock–bond correlation. The effects of some of these choices are described with more detail in Online Appendix A, where we argue that using the Spearman rank correlation instead of the conventional Pearson correlation helps to obtain a more robust estimate of the stock–bond correlation. Figure 2 shows that the stock–bond correlation tends to be positive or close to zero. Exceptions with a correlation below –0.2 occur in the early 1930s, in the late 1950s, and during most of the 2000s.[1]

The main question that we aim to answer is whether we can better understand what characterizes periods in which the stock–bond correlation is above or, alternatively, below zero and how this affects multi-asset portfolio risk and the bond risk premium. This means that our goal is to *explain* stock–bond correlations with economically motivated variables. This also means that we leave *forecasting* the stock–bond correlation for future research. We start by formulating theoretical drivers of the stock–bond correlation, estimate these using our historical dataset, and link these to the prevailing monetary and macroeconomic environment. Additional empirical evidence from other countries complements our insights from U.S. financial markets.

Our findings can be summarized as follows. First, we observe that the stock–bond correlation varies

Figure 2. Stock–Bond Correlation for the United States



Notes: Spearman rank correlation based on monthly returns for the U.S. equity market and government bonds with 10-year maturity. Rolling window estimation using 36 monthly observations over the period January 1875 to June 2023.
Source: Authors, Global Financial Data.

considerably over time, both in magnitude and sign. Second, before 1951, real risk-free rates and inflation had no discernable impact on the stock–bond correlation.[2] After 1951, as central banks started to adopt countercyclical monetary policies, we find remarkably similar patterns across developed markets: the stock–bond correlation tends to be high during periods when inflation and real risk-free rates are high. This relation tends to be absent in countries where government bonds have a lower credit rating. Third, we find that the sign and magnitude of the stock–bond correlation play a significant role to estimate portfolio risk. Moreover, bond risk premia are positively related to estimates of the stock–bond correlation, as is implied by the capital asset pricing model (CAPM).

Our contribution is threefold. First, we provide long-run empirical evidence on the economic drivers of the correlation between stocks and bonds in three major developed markets.[3] Second, we examine the impact of the credit quality of government bond markets on the stock–bond correlation and its drivers, which as far as we know has not been explored in the literature. Third, our results extend the work of Ilmanen (2003) and confirm the existence of a positive relation between stock–bond correlation and risk premia.

Theoretical Drivers of the Stock–Bond Correlation

We can derive the drivers of the stock–bond correlation by modeling the returns using factors that affect their valuations.[4] We assume that government bond yields (y) contain three components: the expected short real interest rate (rr) and inflation (π) until maturity of the bond and the bond risk premium (brp) for holding bonds instead of short-term Treasury bills.[5] Since the current bond yield is known, the unexpected part of the bond return comes from changes in the three components:

$$r_{t+1}^{b} \approx \alpha^{b} - \beta_{rr}^{b}\Delta_{t+1}rr - \beta_{\pi}^{b}\Delta_{t+1}\pi - \beta_{brp}^{b}\Delta_{t+1}brp \qquad (1)$$

We expect that each of the β-s in Equation (1) are positive.

We assume that equity yields contain four components: the expected short real interest rate (rr) and inflation (π) over the life of the stock, the expected growth rate of dividends (g), and the equity risk premium (erp).[6] Since the current dividend (or earnings) yield is known, the unexpected part of the equity return comes from changes in the four components:

$$r^e_{t+1} \approx \alpha^e - \beta^e_{rr}\Delta_{t+1}rr - \beta^e_{\pi}\Delta_{t+1}\pi - \beta^e_{erp}\Delta_{t+1}erp + \beta^e_{g}\Delta_{t+1}g \tag{2}$$

We again expect that each of the β-s are positive.

This leads to the following covariance between stock and bond returns:

$$\begin{aligned} cov\left\{r^b_{t+1}, r^e_{t+1}\right\} &= \beta^b_{rr}\beta^e_{rr}\sigma^2_{rr} + \beta^b_{\pi}\beta^e_{\pi}\sigma^2_{\pi} + \left(\beta^b_{rr}\beta^e_{\pi} + \beta^b_{\pi}\beta^e_{rr}\right)\sigma_{rr,\pi} + \ldots \\ &\ldots + \beta^b_{rr}\beta^e_{erp}\sigma_{rr,erp} - \beta^b_{rr}\beta^e_{g}\sigma_{rr,g} + \beta^b_{\pi}\beta^e_{erp}\sigma_{\pi,erp} - \beta^b_{\pi}\beta^e_{g}\sigma_{\pi,g} + \ldots \\ &\ldots + \beta^b_{brp}\beta^e_{rr}\sigma_{brp,rr} + \beta^b_{brp}\beta^e_{\pi}\sigma_{brp,\pi} + \beta^b_{brp}\beta^e_{erp}\sigma_{brp,erp} - \beta^b_{brp}\beta^e_{g}\sigma_{brp,g}. \end{aligned} \tag{3}$$

This formula indicates that the volatility of real interest rate changes and inflation changes should have a positive effect on the stock–bond correlation. For each of the other nine components, the effect depends on the sign of the covariance of the cross-terms. Since we expect all betas to be positive, the coefficients of the decomposition are also positive, except for those related to the expected growth rate of cash flows. Correlation is effectively a volatility-scaled covariance, so any driver of correlation will have the same directional impact on covariance; see Brixton et al. (2023). We give economic intuition for the components of Equation (3).

First, a higher variance of real interest rates should also generate a higher correlation in bonds and equity prices, as higher (lower) real interest rates lead to lower (high) values of future cash flows of both stocks and bonds, all other things equal. More variability in real interest rates then leads to equity and bond returns in the same direction.

Second, ceteris paribus, a higher variance of changes in expected inflation should generate larger co-movements in bonds and equity prices. This is consistent with Brixton et al. (2023). However, the inflation level, the time-series variance of inflation, and forward-looking uncertainty around future inflation are positively related, which may make it empirically difficult to disentangle. Friedman (1977) states that higher inflation is accompanied by higher policy uncertainty. High inflation often leads to countercyclical monetary policy, inducing abrupt changes in economic policies or even political unrest, and thus wide uncertainty regarding future inflation. Ball (1992) presents a model where expected inflation is more uncertain when it is high. When inflation is around the central bank's ambition level, it is expected to be stable. However, when inflation is high, it is hard to predict how and how fast the central bank will react. The central bank wants to curb inflation but will be reluctant to create deflation given the concern of recession. The positive relation between the level and variability is known as the Friedman–Ball hypothesis.[7] Note that forward-looking uncertainty can also be high when short-term realized volatility is low. David and Veronesi (2016) find that inflation uncertainty, measured by the dispersion of survey forecasts, contains different information from the realized inflation time-series volatility.

Finally, we have a series of cross-terms that affect the stock–bond correlation. Since real interest rates and inflation are the only variables that affect both stock and bond prices, there is no variance term for the other variables. For example, there is no variance term of economic growth. Instead, the sign of the covariance of economic growth with inflation and real rates determines its effect on the correlation between stocks and bonds. Stock returns are expected to increase with economic growth through the corporate earnings channel, but the relation of economic growth with inflation and real rates is not a priori clear, see, for example, Cukierman et al. (1993). On the other hand, bond returns are in the short run negatively correlated with economic growth; see Ilmanen (2011). Well-documented episodes of stagflation during the 1970s illustrate this point. Similarly, divergences in the risk premia of bonds and equities should reduce the correlation between stocks and bonds. Episodes of divergence between bond and equity risk premia have been more common in the years since 2000. During episodes of increased risk aversion (i.e., 2000, 2008, 2020) bond risk premia compress while equity risk premia expand. Such a relation depends on bonds being considered as "safe haven" assets. However, the assumption that sovereign bonds are "safe haven" assets is not always correct. Campbell, Pflueger, and Viceira (2020) develop a model where bonds can switch from safe to risky assets. If the correlation between inflation and output gap is negative, then bonds become risky assets and are positively correlated with equities. On the other hand, if inflation is positively correlated with the output gap, then bonds are a safe asset and negatively correlated with equities. David and Veronesi (2016) highlight the importance of the macroeconomic environment to understand the impact of inflation on the correlation between stocks and bonds. In low-inflation environments, an increase in inflation has a small negative impact on the pricing of bonds but is good news for equity markets, as it signals higher growth and lower equity risk premia. Baele and Van Holle (2017) emphasize the importance of monetary policy during low-inflation environments. In high-inflation environments, the correlation between stocks and bonds is always positive. When inflation is low, it is the conjunction of low inflation and loose monetary policy that creates a negative correlation between stocks and bonds.

The Appendix contains details of our data sources. Here, we give a broad overview of our choice of data series for each of the theoretical factors that we distinguish. For bonds, we use Adrian, Crump, and Moench (2013) for the bond risk premium, the average of the past 10-year inflation as the inflation forecast, and the observed government bond yields to obtain the expected short-term real interest rates. For expected inflation, we later also use the survey of the University of Michigan, which is a one-year inflation expectation. For equities, we take the risk premium from Damodaran (2023), and for growth we use the average of the past 10-year growth in industrial production.

Drivers of the Stock–Bond Correlation

Due to data availability, we can only estimate the theoretical model developed in "Theoretical Drivers of the Stock–Bond Correlation" over a relatively recent sample starting in 1961. For our deep historical sample starting in 1875 (shown in Figure 2), we are limited to examining a smaller set of potential drivers: inflation and real rates.[8] We continue by examining the drivers of the stock–bond correlation internationally for the G7 countries and for five large emerging markets. Finally, we show that using uncertainty in inflation forecasts further improves our understanding of the variability of the stock–bond correlation.

Empirical Results. Descriptive statistics on the sample starting in 1875 can be found in Table OB1 in Online Appendix B. The data on each of the theoretical drivers discussed in "Theoretical Drivers of the Stock–Bond Correlation" is not available over long historical periods. Therefore, we limit ourselves to realized inflation levels (see, e.g., Ilmanen 2003) and the real interest rates that have been shown to be helpful in explaining the stock–bond correlation in the literature; see, for example, Yang, Zhou, and Wang (2009) and Wu et al. (2022).[9] Regimes with high interest rates are associated with higher stock–bond correlation, as interest rates are then more important in determining stock and bond returns. As discussed in "Theoretical Drivers of the Stock–Bond Correlation," the level and uncertainty of inflation are highly related and difficult to disentangle.

Table 1 contains the results of regression models to explain the stock–bond correlation for the United States, the United Kingdom, and France over 36-month periods. For each country, we have three columns with regression results. The first column contains the full-sample results, which start in 1875 for the United States, in 1801 for the United Kingdom, and in 1871 for France. The second column contains the sample until 1951. The third column contains the post-1951 period, or the modern sample that is likely to be more representative of the current environment. The reason to choose 1951 as a breakpoint is the Treasury Accord of 1951, which is often used as a regime shift in U.S. fixed-income markets, and many empirical studies start afterward.

For the United States, both inflation and the real rate are significant over the full sample period. As expected, the effect of inflation is positive (coefficient = 4.48, t statistic = 4.04) and the effect of the real rate is also positive (coefficient = 4.36, t statistic = 3.47). The explanatory power of the model is limited, with an adjusted R^2 of 0.19. When we examine the two subperiods, it becomes clear that the explanatory power is solely due to the modern, post-1951 sample. The adjusted R^2 is only 0.01 for the 1875–1951 sample, and both explanatory variables are insignificant. Over the more recent period, the adjusted R^2 is markedly higher at 0.39, and both explanatory variables are statistically significant (inflation t statistic = 3.82, real rate t statistic = 4.17). We perform a statistical test to examine whether the parameters during the first subsample, which are positive but not statistically significant, are different from the parameters in the second subsample. The p value of this F test is 0.019, indicating that the parameters are indeed significantly different from each other.[10]

For the United Kingdom, there is no statistical significance for inflation over the full sample (t statistic = 1.01), but the real rate is (t statistic = 2.03). The explanatory power of the model is low, with an R^2 of only 0.05. For the historical sample, both coefficient estimates are positive, but they are not statistically significant (inflation t statistic = 1.40, real rate t statistic = 1.52), and the explanatory power is weak, with an adjusted R^2 of 0.04. For the modern sample, we find that both inflation and real rate are positive and statistically significant (inflation t statistic = 3.59, real rate t statistic = 2.95). While the coefficients are similar to those in the United States, the explanatory power for the United Kingdom is lower, at 0.25. A statistical test for differences in coefficient estimates over the two subsamples does not reject

Table 1. Explaining the Stock–Bond Correlation over the Long Term

	United States			United Kingdom			France		
Start	1875	1875	1952	1801	1801	1952	1871	1871	1952
End	2023	1951	2023	2023	1951	2023	2023	1951	2023
Intercept	–0.05	0.15	–0.20	0.27	0.30	–0.06	0.12	0.44	–0.12
t statistic	*–0.77*	***2.12***	***–2.36***	***5.68***	***4.55***	*–0.73*	*1.90*	***4.35***	*–1.57*
Inflation	4.48	0.96	5.66	0.75	2.61	3.80	2.28	–2.80	3.42
t statistic	***4.04***	*0.55*	***3.82***	*1.01*	*1.40*	***3.59***	***2.60***	*–0.95*	***3.53***
Real rate	4.36	0.70	7.35	1.88	2.88	3.70	2.78	–2.02	7.01
t statistic	***3.47***	*0.44*	***4.17***	***2.03***	*1.52*	***2.95***	***3.32***	*–0.69*	***6.06***
Adj R^2	0.19	0.01	0.39	0.05	0.04	0.25	0.09	0.19	0.42
Equality (*p* value)		**0.019**			0.853			**0.004**	

Notes: Dependent variable is the 36-month Spearman rank correlation between stock and bond markets over the full sample period (starting dates for United States: January 1875, United Kingdom: January 1801, France: January 1871, same end date: June 2023), over a historical sample until December 1951, and over a modern sample starting in January 1952. Independent variables are measured as averages over the same 36-month period as the dependent variable. The *t* statistics use Newey and West (1987) standard errors with 35 overlapping observations. Bold *t* statistics indicate statistical significance at the 5% level. The bottom row contains the *p* value corresponding to the *F* test for equality of the coefficients for inflation and real rate over the two subsample periods.
Source: Authors.

the null hypothesis of equal coefficients, with a *p* value of 0.853. The reason is that while the coefficients are not statistically significant over the first subsample, they are similar in magnitude to those estimated over the modern sample. The results of France are like those of the United States and the United Kingdom.[11] Over the full sample both inflation and real rates are significant, over the first subsample they are both insignificant, and over the modern sample they are again significant. The explanatory power is low over the full sample (0.09) and the historical subsample (0.19) but reaches 0.42 over the modern subsample. The coefficients are significantly different over the first and second subsample, with a *p* value of 0.004.

Our results are consistent with the approach of Baele and Van Holle (2017), which uses monetary policy to understand time variations in the correlation between stocks and bonds. A countercyclical monetary policy in periods of low inflation implies that the central bank's monetary policy will be primarily guided by growth and unemployment. Central bank policies over the last twenty years reflect well this environment. Inflation is less of a concern to central bankers, and lower growth will directly lead to lower real rates, and conversely, higher growth will lead to higher real rates. Therefore, bonds will become countercyclical assets with very attractive hedging characteristics. Bonds will benefit not only from lower inflation and real rates but also from declining risk premia and therefore will be negatively correlated with equity. However, in the absence of countercyclical policies, lower inflation alone is not sufficient to create a negative stock–bond correlation. A structural shift in central bank policies occurred after World War II as countercyclical monetary policies seeking to balance inflation and unemployment became commonplace. In the United States, Bordo (2007) notes that the Fed regained its independence with the Treasury-Fed Accord of 1951 and "*began following a deliberate countercyclical policy under the directorship of William McChesney Martin.*" Before World War II, the Fed monetary policy was dictated by either the gold standard (see Elwell 2012) or the real bill doctrine, which resulted in monetary policies that at best were cycle-agnostic and often were pro-cyclical. Taylor (1999) uses his eponymous rule to explain monetary policy and finds that inflation and output gap do not explain real interest rates set by the Fed during the 1879 to 1914 period. On the other hand, Taylor finds that since the 1950s the output gap and inflation played an increasingly important role in explaining changes in Fed policy rates. Therefore, the seemingly surprising lack of relation between inflation and stock–bond correlation that we observe before during our historical sample could simply illustrate that countercyclical monetary policy has become the norm, but absent these policies it is not clear that we would observe such a strong relation among inflation, real rates, and the stock–bond correlation.

Because of data availability to estimate the theoretical drivers of the stock–bond correlation, we focus exclusively on the modern sample in the remainder of this section. Our sample starts a little later, in

1961, as this is the starting date of the bond risk premium estimates from Adrian, Crump, and Moench (2013) that we use.[12]

Table 2 contains the estimation results over the period from 1961 to 2023. The first column, labeled with "Theoretical," includes each of the factors from Equation (3).[13] About half of the correlations have a statistically significant coefficient with the expected sign. For example, a positive correlation between the change in bond and equity risk premia is associated with a positive effect on the stock–bond correlation (coefficient = 0.74, t statistic = 3.76). The relation between bond risk and equity risk premia can change significantly over time. During periods of higher inflation uncertainty, government bonds behave more like risky assets, which impacts positively the stock–bond correlation. The correlation between the bond risk premium and growth is the only one with a statistically significant estimate of the wrong sign (coefficient = 0.56, t statistic = 2.53). The volatility of expected inflation has a negative sign, contrary to the theoretical model's predictions, but is not statistically significant (coefficient = −0.47, t statistic = −0.66). This may be due to the difficulty of obtaining a reliable proxy for inflation uncertainty. We show in the following section that for a similar model based on survey-based measures of inflation uncertainty, the volatility of expected inflation has a positive sign and is statistically significant. The volatility of the real short interest rate has a statistically significant positive coefficient (coefficient = 0.21, t statistic = 3.16).

The next column, labeled with "Empirical," contains only two purely empirically motivated level variables, which we also used over the historical samples in Table 1. The level of realized inflation and real interest rate are statistically significant and have t values well above two.[14] The explanatory power of this simple two-parameter model, as measured by the adjusted R^2, is 0.52, whereas the explanatory power of the theoretical model with eleven parameters is 0.63. Although lacking theoretical support, our simple "empirical" model can explain a large share of the time-variation of the stock–bond correlation.[15] This suggests that the Friedman–Ball hypothesis is valid for both inflation and real rates. Higher inflation levels and real rate levels come with higher inflation and real rate uncertainty. Therefore, in the absence of a precise measure of inflation and real rates uncertainty, the levels of inflation and real rates do a very good job of capturing uncertainty.

The final column contains the combination of the theoretical and empirically motivated variables. The same sign and statistical significance of both

Table 2. Explaining the 36-Month Stock–Bond Correlation

	Theoretical		Empirical		Combination	
	Coeff.	t statistic	Coeff.	t statistic	Coeff.	t statistic
ρ (*brp*, *erp*)	0.74	***3.76***	–		0.34	***3.67***
ρ (*brp*, π)	0.08	*0.57*	–		0.03	*0.26*
ρ (*brp*, *rr*)	−0.08	*−0.82*	–		−0.16	*−2.83*
ρ (*brp*, g)	0.56	*2.53*	–		0.25	*2.03*
ρ (π, *erp*)	−0.03	*−0.30*	–		−0.04	*−0.49*
ρ (π, *g*)	−0.18	*−1.49*	–		−0.01	*−0.14*
ρ (*rr*, *erp*)	0.62	***4.65***	–		0.62	***7.05***
ρ (*rr*, π)	0.28	***2.99***	–		0.30	***3.31***
ρ (*rr*, *g*)	0.07	*0.46*	–		−0.24	***−2.22***
σ (π)	−0.47	*−0.66*	–		0.62	*0.96*
σ (*rr*)	0.21	***3.16***	–		−0.18	*−1.84*
μ (π)	–	–	7.72	***4.73***	9.99	***6.28***
μ (*rr*)	–	–	9.39	***5.25***	9.31	***7.85***
Adjusted R^2	0.63		0.52		0.79	

Notes: Dependent variable is the 36-month Spearman rank correlation between U.S. stock and bond markets over the period June 1961 to June 2023. Each component from Equation (3) is shown here, where correlations are indicated with ρ, volatilities with σ, and ex-post averages with μ. The components are as follows: bond risk premium (brp), equity risk premium (erp), real interest rate (rr), growth (g), and inflation (π). The column "Coeff" the estimated coefficients, and the t statistics use Newey and West (1987) standard errors with 35 overlapping observations. t statistics in bold are significant at the 5% level and of the expected sign.
Source: Authors.

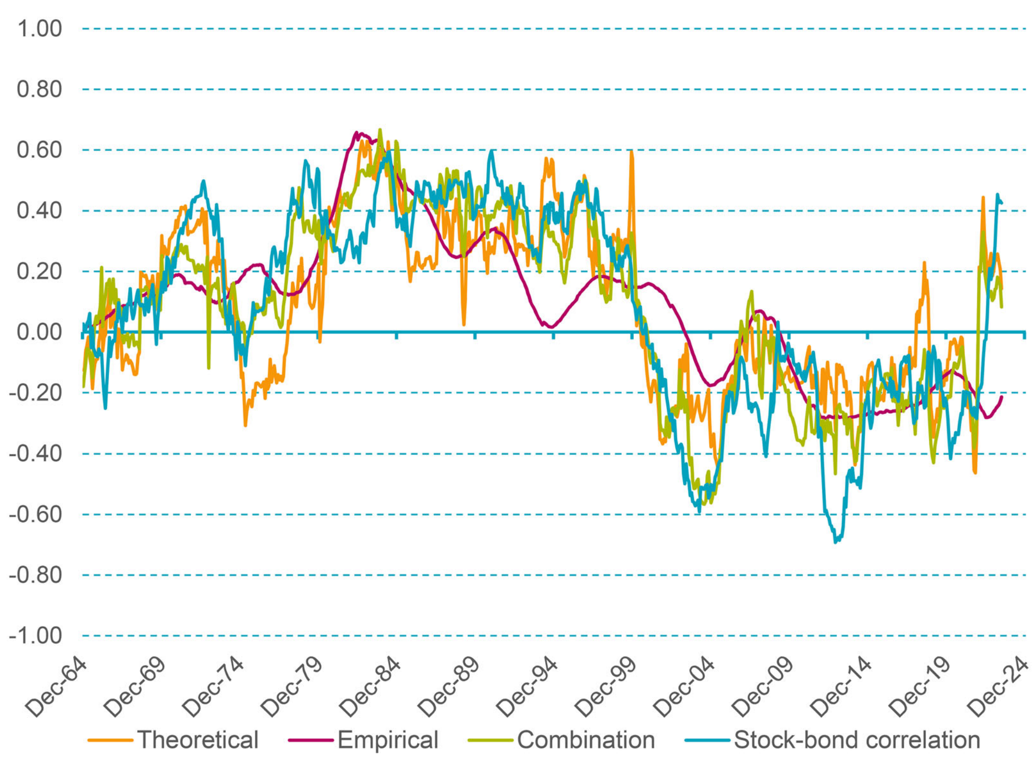
empirical level variables are still there, indicating that they are not subsumed by the theoretically motivated variables. Again, four are statistically significant with the expected sign, of which three are the same as in the model in the first column. Both volatilities are statistically insignificant, possibly because of the positive association between the level and volatility of inflation. The adjusted R^2 is 0.79, about 0.16 higher than the model without the level variables.

Figure 3 illustrates the three models' ability to explain the stock–bond correlation. The theoretical model follows the estimated stock–bond correlation closely most of the time. It is late to turn positive during the second half of the 1970s. It picks up very well the sign switch in the late 1990s and captures the spike in correlation we experienced after the COVID-19 crisis. The empirical model also captures the general level of the stock–bond correlation. It leads to much smoother estimates and does not adjust as quickly during regime shifts. As expected, the combined model shows a very good fit with the observed U.S. stock–bond correlation over this period.

These empirical results indicate that the theoretically motivated variables can explain a large part of the time-series variation of the stock–bond correlation and are preferred over a simple model with the level of inflation and the real rate. At the same time, for many countries outside the United States, several of these theoretically motivated explanatory variables are difficult to obtain or estimate. Our results suggest that practitioners who aim to analyze international financial markets can rely on the easier-to-obtain levels of inflation and the real rate. Even though the explanatory power is somewhat lower, it can explain about half the time-series variation in the stock–bond correlation. In the next subsection, we examine the international dimension of our results.

International Evidence from Developed and Emerging Markets. Because we do not have data on each of the theoretically motivated variables for our international sample, we perform the regression analyses on the two empirically motivated level variables, inflation and real rates, which we found to give reasonably good results for the United

Figure 3. Fit of the Explanatory Models for the Stock–Bond Correlation



Notes: Figure shows the stock–bond correlation and the explanatory values based on the theoretically motivated model, the empirically motivated model, and the combination of the two, as well as the U.S. stock–bond correlation, calculated as the Spearman correlation over rolling 36-month periods over the period June 1961 to June 2023.
Source: Authors.

States in the previous section. We repeat this for the six other countries that make up the G7: Canada, France, Germany, Italy, Japan, and the United Kingdom. In addition, we add five large emerging markets that have a substantial data history of both investable government bonds and equity markets: Brazil, Malaysia, Mexico, South Africa, and Thailand. Since the sample period is now shortened to start in 1987 for the other developed markets, we also include the United States over the same sample period.[16] The samples for the emerging markets start later, mostly at the turn of the millennium and at the latest in January 2002.

Table 3 shows the model with only realized inflation and real rates. We see that over this shorter estimation period, both variables for the United States are still statistically significant, with *t* values of 2.77 and 2.79. For three out of six other G7 countries, the coefficient for inflation is also statistically significant. It seems that inflation is somewhat less important in this sample that starts in 1988, as the inflationary periods from the 1970s are not included. The real rates are significant for all G7 countries except Italy, where it has a *t* value of 1.43. The explanatory power for Italy is rather low, with an adjusted R^2 of only 0.12. This may be related to its creditworthiness during the European sovereign debt crisis, where Italian government bonds traded as a risky instead of a safe asset. The distribution of its S&P credit rating is displayed below the R^2 in Table 3, where this increased riskiness can be observed.

To examine whether the low explanatory power is characteristic of countries with lower credit ratings, we extend our sample with five large emerging markets that have sufficiently long histories of local-currency government bond and equity market returns. The frequency of the credit ratings is displayed at the bottom of Table 3. Of the five emerging markets, Malaysia has been the least credit-risky, as it was A-rated for most of the sample period, while the four other countries mostly were BBB- or BB-rated. For four out of five countries, the explanatory power of inflation and the real rate is low, with R^2 values below 0.20. The only exception is Mexico, which has an R^2 of 0.43, similar to that of the United States. This may have to do with the partial integration of financial markets of these two geographical neighbors. The results for the United States hold up for countries with safe-haven characteristics, but generally not for riskier countries. In this instance, researchers on international financial markets cannot automatically extrapolate the U.S. results but need to take the credit quality of the country into account. This difference is an important insight for practitioners who want to apply the model outside the United States, something that is

Table 3. Explaining the 36-Month Stock–Bond Correlation: International Evidence

	G7 countries							Emerging markets				
	CA	FR	DE	IT	JP	UK	US	BR	MY	MX	ZA	TH
Inflation	5.51	−2.00	18.87	1.52	14.67	10.92	14.27	−0.60	27.51	8.49	2.90	2.25
t statistic	*0.73*	*−0.14*	***3.61***	*0.42*	***2.49***	***3.48***	***2.77***	*−0.16*	*1.76*	***4.16***	*1.48*	*0.70*
Real rate	11.47	8.62	4.66	3.40	9.96	5.01	8.57	−0.83	23.56	6.51	−0.25	7.46
t statistic	***3.77***	***2.50***	***2.10***	*1.43*	***2.93***	***2.29***	***2.79***	*−0.53*	*1.48*	***4.53***	*−0.12*	*1.56*
Intercept	−0.24	−0.07	−0.48	0.15	−0.35	−0.27	−0.46	0.43	−0.55	−0.21	0.16	−0.02
t statistic	*−1.85*	*−0.38*	*−3.10*	*1.26*	*−6.93*	*−2.18*	*−3.34*	*1.38*	*−1.18*	*−1.98*	*1.27*	*−0.32*
Adjusted R^2	0.60	0.31	0.42	0.12	0.58	0.41	0.40	0.01	0.19	0.43	0.05	0.18
Credit rating	AAA	AAA	AAA	A	AA	AAA	AAA	BB	A	BBB	BBB	BBB
AAA	72	67	100	0	36	78	64	0	0	0	0	0
AA	28	33	0	50	39	22	36	0	0	0	0	0
A	0	0	0	17	25	0	0	0	91	0	0	0
BBB	0	0	0	33	0	0	0	30	9	96	57	100
BB (or lower)	0	0	0	0	0	0	0	61	0	4	43	0

Notes: Dependent variable is the 36-month Spearman rank correlation between stock and bond markets for the G7 over the period January 1988 to June 2023. CA = Canada, FR = France, DE = Germany, JP = Japan, UK = United Kingdom, US = United States. For emerging markets, BR = Brazil (start January 2002), MY = Malaysia (start January 2002), MX = Mexico (start January 2002), ZA = South Africa (start July 1994), TH = Thailand (start = February 2001). Independent variables are measured as averages over the same 36-month period as the dependent variable. The rows with "*t* statistic" contain *t* statistics using Newey and West (1987) standard errors using 35 overlapping observations. Bold indicates statistical significance at the 5% level. Credit rating contains the average S&P credit rating over the sample period. The distribution of credit ratings is displayed in the bottom five rows, in percentages.
Source: Authors.

often disregarded in the finance literature (see, e.g., Karolyi 2016).

These international results confirm to a large extent our observations for the United States, as the inflation and the realized real return on the Treasury bill are important drivers of the stock–bond correlation over the period from 1987 to 2023 for countries with a relatively safe government bond market.

Uncertainty in Inflation Expectations. So far, our series on expected inflation has been the past 10-year average. However, for a shorter sample period, we can also make use of surveys of expected inflation. This allows us to infer not only the *level* of expected inflation but also the *uncertainty* surrounding the expectation by examining the dispersion of inflation expectations of the respondents. This may be a better measure of inflation risk than the time-series volatility of inflation, especially in case of inflation shocks; see David and Veronesi (2013).[17]

Therefore, in the theoretical model we use the expected inflation from the Michigan survey, which is available from 1978 onward, instead of the past 10-year realized inflation. We also replace the time-series volatility of inflation with the cross-sectional dispersion of inflation expectations.[18] We leave the two variables from the empirical model unchanged. Table 4 contains the new estimation results.

An important difference with our previous model shown in Table 2 is that the coefficient for the volatility of expected inflation is now positive and statistically significant. Most other explanatory variables have the same sign as in Table 2, but more are statistically significant. The explanatory power increases from 0.63 in Table 2 to 0.82 in Table 4. The combination model shows that the coefficients for inflation level and real risk-free rate remain significant when survey inflation expectations are used. Several coefficients that were significant in the first column are no longer significant. Their role is taken over by the two important empirically motivated variables. The explanatory power of the combined model reaches even 0.88. Figure OB2 in Online Appendix B illustrates the fit of these models over time.

Investment Implications

In this section, we analyze the investment implications in more detail. The first and most straightforward implication concerns the risk of multi-asset portfolios. The second implication that we discuss is the link of the stock–bond correlation with the expected bond risk premium, extending the important work of Ilmanen (2003).

Time-Varying Risk of a Multi-Asset Portfolio. A higher correlation between stocks and bonds implies a higher risk for multi-asset or balanced portfolios that many institutional and retail investors hold. Figure 4 shows the 36-month volatility of the 60/40 stock/bond portfolio on the vertical axis as a function of the stock–bond correlation measured over the same period on the horizontal axis.[19] This empirical analysis complements the hypothetical portfolio analysis in Brixton et al. (2023). The colors of the dots represent the two different regimes: 1970–1999 and 2000–2023. The first period shows a stock–bond correlation of +0.35, while it is –0.29 in the second period. The scatterplot is far from a straight line, indicating that the explanatory power of the stock–bond correlation for portfolio risk is not perfect, as in the theoretical example of Figure 1 where we held volatilities constant. Time variation in bond and especially equity volatility also plays an important role for portfolio risk.

During the first regime, with the positive stock–bond correlation, the volatility of the 60/40 portfolio was close to 10.5%. During the second regime, with the negative stock–bond correlation, the volatility of the 60/40 portfolio declined to 8.4%. This decline can be partially attributed both to a decline in bond volatility (from 8.2% to 7.3%; see Table 5) and a switching sign of the stock–bond correlation. A multi-asset investor who aims to keep their risk profile constant may need to reduce the allocation to equities in times of a positive stock–bond correlation. Holding volatilities constant over the entire sample, a return to the first subsample positive correlation between stocks and bonds requires that 60/40 investors reduce their equity position by 25% (i.e., invest in a 35/65 portfolio) to arrive at the same portfolio risk.[20]

Changes in the correlation between stocks and bonds should also affect the contribution of the sources of the variance in a multi-asset portfolio. Table 5 contains the variance decomposition of the portfolio volatility in equity, bond, and correlation risk. Indeed, during the negative stock–bond correlation regime, more than 100% of the variance of a multi-asset portfolio can be ascribed to equities, as bond investments reduce overall portfolio variance. During the positive stock–bond correlation regime, the contribution of bonds to total portfolio risk is positive. The empirical and theoretical models that we developed in "Theoretical Drivers of the Stock–Bond Correlation" explain current levels of the stock–bond correlation with contemporaneous macroeconomic

Table 4. Explaining the 36-Month Stock–Bond Correlation with Survey Expectations

	Theoretical		Empirical		Combination	
	Coeff.	*t* statistic	Coeff.	*t* statistic	Coeff.	*t* statistic
ρ (*brp*, *erp*)	0.44	***2.96***			0.25	*1.84*
ρ (*brp*, *π*)	0.57	***3.46***			0.42	***2.57***
ρ (*brp*, *rr*)	0.23	*1.81*			0.07	*0.60*
ρ (*brp*, g)	0.56	*4.24*			0.40	*2.52*
ρ (*π**, *erp*)	0.40	***2.19***			0.40	***2.08***
ρ (*π**, *g*)	−0.44	***−2.00***			0.01	*0.02*
ρ (*rr*, *erp*)	0.77	***5.33***			0.95	***6.28***
ρ (*rr*, *π*)	1.41	***7.35***			0.20	*0.64*
ρ (*rr*, *g*)	−0.63	***−2.76***			−0.37	*−1.73*
σ (*π**)	4.76	***2.96***			4.01	***3.55***
σ (*rr*)	0.11	***3.64***			−0.09	*−1.50*
μ (*π*)			6.33	***2.90***	7.36	***3.28***
μ (*rr*)			10.10	***4.48***	7.63	***4.12***
Adjusted R^2	0.82		0.55		0.88	

Notes: Dependent variable is the 36-month Spearman rank correlation between U.S. stock and bond markets over the period January 1978 to June 2023. Each component from Equation (3) is shown here, where correlations are indicated with ρ, volatilities with σ, and ex-post averages with μ. π* refers to the expected inflation from the Michigan survey, and its volatility is the cross-sectional volatility of the estimates. The column "Coeff." contains the estimated coefficients, and "*t* statistic" contains the corresponding *t* statistics using Newey and West (1987) standard errors using 35 overlapping observations.
Source: Authors.

Figure 4. Relation between Stock–Bond Correlation and Portfolio Risk

Notes: Average of standard deviation and Pearson correlation coefficient of monthly returns computed over 36-month rolling windows ending January 1970 to June 2023.
Source: Authors.

Table 5. Risk and Return of the 60/40 Stock–Bond Portfolio

	1970–2023			1970–1999			2000–2023		
Stock–bond correlation	0.07			0.35			−0.29		
Bond premium ACM (%)	1.7			2.4			0.9		
	Stock	Bond	60/40	Stock	Bond	60/40	Stock	Bond	60/40
Excess return (%)	6.0	2.1	4.7	5.7	1.6	4.3	6.4	2.8	5.3
Volatility (%)	14.8	7.8	9.6	14.8	8.2	10.5	14.7	7.3	8.4
Sharpe ratio	0.51	0.28	0.59	0.45	0.20	0.45	0.58	0.37	0.77
Variance decomposition									
Equity (%)	100	0	89	100	0	71	100	0	111
Bond (%)	0	100	12	0	100	11	0	100	14
Stock–bond correlation (%)	0	0	−1	0	0	18	0	0	−25

*Notes:*Top panel: Average of 36-month excess returns, standard deviation, Sharpe ratio, and Pearson correlation coefficient of monthly returns computed over 36-month overlapping windows ending January 1970 to June 2023. Bottom panel: Decomposition of the 60/40 portfolio variance into equity, bonds, and equity-bonds co-movements. $100\% = \frac{60\%^2\sigma^2(\text{stocks})}{\sigma^2(60/40)} + \frac{40\%^2\sigma^2(\text{bonds})}{\sigma^2(60/40)} + \frac{2\cdot 60\%\cdot 40\%\cdot\sigma(\text{stocks})\sigma(\text{bonds})\rho(\text{stocks, bonds})}{\sigma^2(60/40)}$. Each of the three variance components is computed over 36-month rolling windows ending January 1970 to June 2023. We take the average of each component during each period. This explains why the sign of the stock–bond correlation is slightly positive over the full sample period, while it is slightly negative for the variance decomposition. ACM = Adrian, Crump, and Moench models.
Source: Authors, Federal Reserve Bank of New York

variables. To forecast the stock–bond correlation, one needs to be able to forecast these macroeconomic variables, which is beyond the scope of this paper. However, our research outlines the importance of changing macroeconomic environments to understand the risk of multi-asset class portfolios. For example, the coefficient estimates of the empirical model in Table 2 indicate that a 1% increase in both inflation and real rates results in a +0.17 increase in the correlation between stocks and bonds. In turn, this can lead to an increase of 0.8% to 1.7% in the risk of a 60/40 portfolio, depending on the starting stock–bond correlation.[21] Therefore, reliable macroeconomic forecasts are a critical input for cross-asset class risk management and in the absence of reliable macroeconomic forecast one should use macro scenario analysis and stress tests.

The *increase* in total risk due to stock–bond correlation concerns investors who are not affected by the present value of their liabilities. However, for multi-asset investors with long-dated unhedged bond-like liabilities, such as pension funds and life insurance companies, an increase in the stock–bond correlation would also *decrease* their solvency risk, as stocks now better hedge liability risk. In our analysis of bond risk premia, we assume that the marginal investor does not have unhedged bond-like liabilities.[22]

The Bond Risk Premium. A higher stock–bond correlation makes bonds a riskier investment for multi-asset investors. It could increase the bond risk premium that investors require for holding bonds instead of short-term Treasury bills. This can also be seen from the CAPM:

$$E\{R_{bonds} - R_{riskfree}\} = \beta \times E\{R_{market} - R_{riskfree}\}$$

where

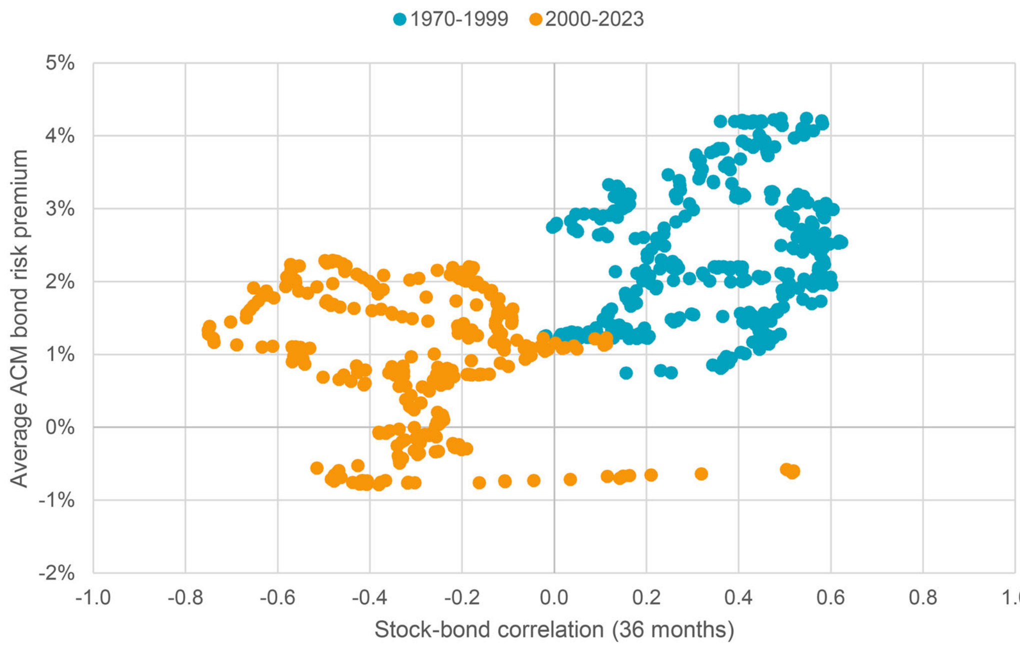
$$\beta = \frac{cov\{R_{bonds}, R_{market}\}}{var\{R_{market}\}} = \frac{\sigma_{bonds}}{\sigma_{market}} \times \rho_{bonds,\,market}$$

Stated differently, the bond risk premium is a function of bond volatility, the correlation of bond returns with the market, and the Sharpe ratio of the market:

$$E\{R_{bonds} - R_{riskfree}\} = \sigma_{bonds} \times \rho_{bonds,\,market} \times \frac{E\{R_{market} - R_{riskfree}\}}{\sigma_{market}}$$

Given the higher volatility of equity relative to bonds, equity markets play a dominant role in the variation of the market portfolio. Therefore, one can assume that variations in the correlation between bond returns and the *market* returns are closely related to variations in the correlation between bond returns and *stock* returns. A higher correlation implies a higher CAPM-implied risk premia for bonds; see Singer and Terhaar (1997). However, there are other theories for the bond risk premium, such as an inflation-risk premium or preferred habitat by long-term investors such as pension funds, insurance

Figure 5. Relation between the Stock–Bond Correlation and the Bond Risk Premium



Notes: Average of Adrian, Crump, and Moench (2013) risk premia, average stock–bond correlation of monthly returns over 36-month overlapping windows ending January 1970 to June 2023.
Source: Authors, Federal Reserve Bank of New York.

companies, and sovereign wealth funds; see Vayanos and Vila (2021).

We can also try to directly estimate the expected bond risk premium without taking the CAPM as a starting point. This is not a straightforward exercise. The expected bond risk premium earned by a buy-and-hold investor in a government bond with negligible default risk is the difference between the current bond yield and the projected return of rolling over short-term Treasury bills until the maturity of the bond.[23] The Federal Reserve updates two models for the U.S. bond risk premium (i.e., the expected return difference of holding a 10-year government bond or on rolling over Treasury bills for the coming 10 years). Adrian, Crump, and Moench (2013) and Kim and Wright (2005) developed empirical models to capture risk premia embedded in bond yields.[24]

Figure 5 shows that the bond risk premium tends to be higher when the correlation between stocks and bonds is higher. This is consistent with our earlier reasoning based on the CAPM that investors need to be compensated for bond risk when it co-moves positively with equity market risk. However, an alternative explanation is that bond volatility tends to be higher in periods with a high stock–bond correlation, and the higher bond risk premium is caused by higher stand-alone bond volatility and is unrelated to the correlation with equity markets. The Friedman–Ball hypothesis states that increases in inflation should occur in conjunction with higher inflation *uncertainty*, which could lead to higher bond risk and therefore a higher bond risk premium unrelated to co-movements with equity markets.

In Table 6, we show the estimation results of a regression of the average bond risk premium over 36-month periods against both the stock–bond correlation and the volatility of bonds over the same 36-month periods. This regression shows that, when controlling for bond risk, the bond risk premium is significantly related to the stock–bond correlation over the entire sample period from 1970 to 2023. The relation is weaker within each subsample and is no longer significant in the second subsample. This suggests that meaningful long-term regime shifts in the stock–bond correlation are important for the bond risk premium, but within a given regime smaller variations are less relevant. Nevertheless, it is striking that a bond risk premium model built on the CAPM (through the effect of a time-varying stock–bond correlation on the bond market's market beta) and a bond risk premium model that uses only the term

Table 6. Explaining ACM Bond Risk Premium

		ACM bond risk premium								
		1970–2023			1970–1999			2000–2023		
Bond volatility	Coeff.	0.33		0.28	0.23		0.22	0.42		0.42
	t statistic	4.2		5.1	3.7		4.3	5.7		6.0
Stock–bond correlation	Coeff.		0.02	0.01		0.01	0.01		−0.01	−0.01
	t statistic		3.2	3.5		1.5	1.8		−1.4	−1.3
Intercept	Coeff.	−0.8%	1.6%	−0.5%	0.6%	1.9%	0.2%	−2.2%	0.7%	−2.4%
	t statistic	−1.2	7.2	−1.2	1.1	4.7	0.4	−3.5	2.3	−3.5
R^2 (%)		0.35	0.30	0.54	0.37	0.07	0.42	0.41	0.05	0.45
Observations		642	642	642	360	360	360	282	282	282

Notes: Dependent variable average of 10-year ACM bond risk premia over 36-month overlapping windows. First independent variable: standard deviation of 10-year Treasury bond monthly return computed over the same 36-month periods as the dependent variable. Second independent variable: correlation between stocks and bonds, computed using monthly returns over the same 36 months periods as the dependent variable windows ending January 1970 to June 2023. The column "Coeff." contains the estimated coefficients, and "*t* statistic" contains the corresponding *t* statistics using Newey and West (1987) standard errors using 36 overlapping observations. ACM = Adrian, Crump, and Moench models.
Source: Authors.

structure of interest rates empirically lead to the same conclusion that an increase in stock–bond correlation is associated with a higher bond risk premium.

Conclusions

In this study, we aim to economically explain stock–bond correlations. Our deep historical data starting in 1875 for the United States (and even 1801 for the United Kingdom) indicates that positive stock–bond correlation regimes have been more common than negative ones. Our results indicate the presence of a structural break in the explanatory power of our models' variables. Since 1951, as central bank policies became increasingly countercyclical, periods of high inflation and high real risk-free rates are associated with a higher correlation between stocks and bonds.

Our theoretically motivated model with eleven variables explains a larger share of the variance than the empirically motivated variables inflation and real risk-free rate. However, with only two independent variables the empirical model provides a good framework to understand fluctuation in the correlation between stocks and bonds. International data confirm that our simple empirical model works well outside the United States. For countries where government bonds are considered riskier, stock–bond correlations tend to be more positive and inflation and real interest rates do not impact its variation over time. This outlines the importance of government creditworthiness in understanding the drivers of the stock–bond correlation.

Our results have important implications for multi-asset investors. Historical regimes with positive stock–bond correlation are associated with higher multi-asset portfolio risk. Therefore, secular changes in inflation and the real rate level can materially impact multi-asset portfolio risk. This implies that good risk management practices should include the analysis of different macroeconomic scenarios resulting in variations of the stock–bond correlation level. In addition, we find that bond risk premiums are positively related to the stock–bond correlation. This may be an indication that the CAPM has a stronger empirical basis across than within asset classes.

Appendix: Data and Measurement

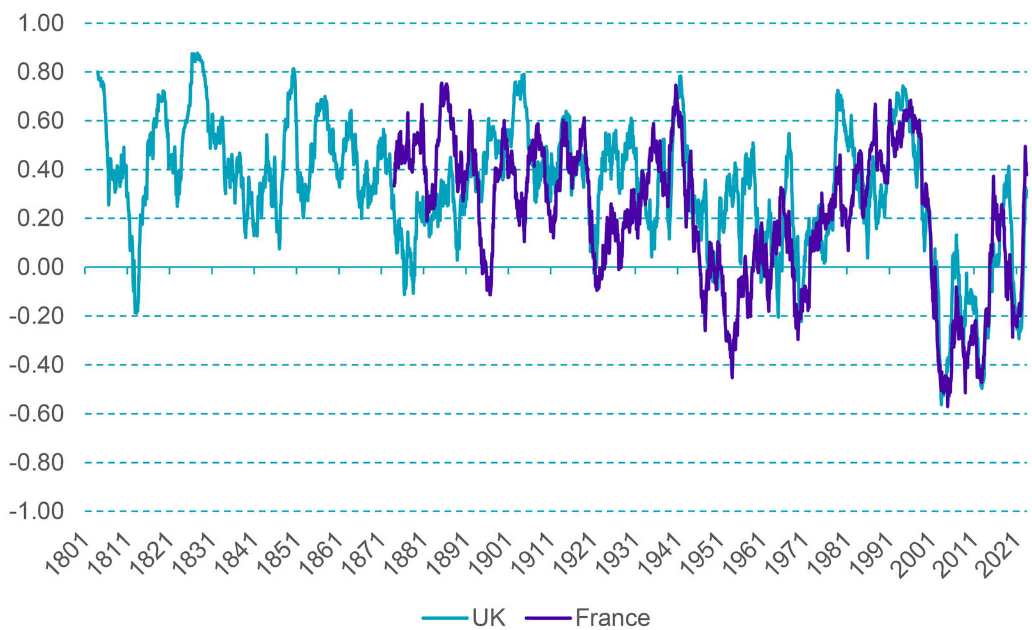
Data

Our main analysis makes use of long-term financial market data from the United States. These data are available on the monthly frequency over the period 1875 to 2021 and are sourced from Global Financial Data. Figure 1 in the main text shows the 36-month rolling-window correlation over our sample period.[25] We also obtain data on consumer price inflation and short-term nominal interest rates from Global Financial Data. For the international extension, we use the same source to obtain data for financial markets in the United Kingdom and France. For additional information on data sources, see Table A1. The stock–bond correlation for the United Kingdom and France can be found in Figure A1. Notice that there

Table A1. Data Sources for the Deep Historical Sample

Country	Series	Source	Code	Period	Freq
US	Stocks	GFD	_SPXTRD	1876–2023	Month
	Bonds	GFD	IGUSA10D	1876–2023	Month
	Bills	GFD	IPUSAC3D	1876–2023	Month
	Inflation	GFD	CPUSAM	1876–2023	Month
UK	Stocks	GFD	_TFTASD	1801–2023	Month
	Bonds	GFD	IGGBR10D	1801–2023	Month
	Bills	GFD	IPGBR3D	1801–2023	Month
	Inflation	GFD	CPGBRM	1801–1914	Year
				1915–2023	Month
France	Stocks	GFD	TRSBF250D	1871–2023	Month
	Bonds	GFD	IGFRA10D	1871–2023	Month
	Bills	GFD	IDFRAD	1871–1930	Irregular
			ITFRA3D	1931–1935	Quarter
				1936–2023	Month
	Inflation	GFD	CPFRAM	1871–1914	Year
				1915–2023	Month

Figure A1. Stock–Bond Correlation for the United Kingdom and France



Notes: Spearman rank correlation based on monthly returns for the US equity market and government bonds with 10-year maturity. Rolling-window estimation using 36-month observations.
Source: Authors, Global Financial Data.

is more commonality in the stock–bond correlation over the past 50 years than in the period before.

The more detailed analyses on possible explanations of the stock–bond correlation start in June 1961, a little more than a decade after the Treasury-Fed Accord of March 1951. For this period, we make use of different data sources that are open-source available, which facilitates replication of these results. The daily and monthly stock market data are from the online data library of Kenneth French. Monthly 10-year zero-coupon bonds are from the online database

Table A2. Data Sources for the G7 Countries

Country	Series	Source	Code
Canada	Stocks	Bloomberg	GDDLCA
1987	Bonds	Bloomberg	JPMTCA
	Bills	DataStream	ECCAD1M
	Inflation	FRED	CANCPIALLMINMEI
France	Stocks	Bloomberg	GDDLFR
1987	Bonds	Bloomberg	JPMTFR
	Bills	DataStream	ECFFR1M
	Inflation	FRED	FRACPIALLMINMEI
Germany	Stocks	Bloomberg	GDDLGR
1987	Bonds	Bloomberg	JPMTWG
	Bills	DataStream	ECWGM1M
	Inflation	FRED	DEUCPIALLMINMEI
Italy	Stocks	Bloomberg	GDDLIT
1987	Bonds	Bloomberg	JPMTIT
	Bills	DataStream	ECITL1M
	Inflation	FRED	ITACPIALLMINMEI
Japan	Stocks	Bloomberg	GDDLJN
1987	Bonds	Bloomberg	JPMTJPN
	Bills	DataStream	ECJAP1M
	Inflation	Bloomberg	OEJPGABM
U.K.	Stocks	Bloomberg	GDDLUK
1987	Bonds	Bloomberg	JPMTUK
	Bills	DataStream	ECUKP1M
	Inflation	FRED	GBRCPIALLMINMEI
U.S.	Stocks	Bloomberg	GDDLUS
1987	Bonds	Bloomberg	JPMTUS
	Bills	DataStream	ECUSD1M
	Inflation	FRED	USACPIALLMINMEI

of McCulloch, based on McCulloch and Kwon (1993), until August 1971, when we use daily data from the online database of the Federal Reserve, based on Gürkaynak, Sack, and Wright (2007). In addition, we use data on industrial production, from Federal Reserve Economic Data (FRED) from the St Louis Federal Reserve Bank. We use the Adrian, Crump, and Moench (2013) risk premia, sourced from the Federal Reserve Bank of New York. We take the U.S. equity risk premium from Damodaran. See for more details in Damodaran (2023).

Table A2 contains the data sources for our international analysis using data of G7 countries starting in 1987, while Table A3 contains information on the five emerging countries.

Descriptive Statistics

One of the challenges with the stock–bond correlation is that it is not an observable characteristic, but it must be estimated from stock and bond returns.[26] This requires several empirical choices that may affect the estimated stock–bond correlation at any point in time.

First, the data frequency is important. Should we use daily, weekly, monthly, quarterly, annually, or even lower frequency return data? This is not a trivial choice and may impact the results. For example, Czasonis, Kritzman, and Turkington (2021) report

Table A3. Data Sources for the Five Emerging Countries

Country	Series	Source	Code
Brazil	Stocks	Datastream	MSBRAZL
2002	Bonds	Datastream	JGEMBBR
	Bills	Datastream	BRPRE3M & TRBR3MT
	Inflation	Datastream	BRCONPRCF
Malaysia	Stocks	Datastream	MSMALFL
2002	Bonds	Datastream	JGEMBMY
	Bills	Datastream	TRMY3MT
	Inflation	Datastream	MYCONPRCF
Mexico	Stocks	Datastream	MSMEXFL
2002	Bonds	Datastream	JGEMBMX
	Bills	Datastream	MXI60C.. & TRMX3MT
	Inflation	FRED	MEXCPIALLMINMEI
South Africa	Stocks	Datastream	MSBRAZL
1994	Bonds	Datastream	JPMSASR
	Bills	Datastream	SATBL3M
	Inflation	FRED	ZAFCPIALLMINMEI
Thailand	Stocks	DataStream	MSTHAFL
2001	Bonds	Datastream	JGEMBTH
	Bills	Datastream	TRTH3MT & THBON3MT
	Inflation	Datastream	THCONPRCF

that the stock–bond correlation over the period 1926 to 2019 has been 0.07 using monthly data, but it increases to 0.11, to 0.17, and even to 0.21 when the return frequency is increased to annually, every three years, or every five years, respectively. Auto- and cross-correlation patterns in stock and bond returns cause these differences. These may be truly in the data but could also be caused by different times that the stock and bond markets close, especially for the daily frequency. To obtain the stock–bond correlation for lower frequencies (or longer horizons), it is also possible to estimate a vector autoregressive model on higher-frequency data and iterate until the longer horizon result is obtained (see, e.g., Campbell and Viceira 2002). Such method is sensitive to the correct specification of the high-frequency model that is the basis for the extrapolation. Also, the historical period over which the model is estimated can be important, especially in the case of time-varying parameters or regime shifts.

Second, the period over which the correlation is measured needs to be chosen and typically depends on the data frequency. For example, the daily return frequency is often combined with a monthly or quarterly measurement period. The stock–bond correlation is then estimated based on about 21 or 63 daily observations. For weekly returns, measurement periods typically range from a half-year (26 observations) to three years (156 observations) and for monthly returns from one year (12 observations) to five years (60 observations). Lower-frequency returns, such as annual or even triannual, need much longer periods for reliable correlation estimates such that the reliable measurement of variation over time in the stock–bond correlation is challenging. To increase the number of observations of the stock–bond correlation, overlapping samples can be used. When performing regression analysis on such overlapping data, standard errors need to be adjusted to account for the overlapping periods. The longer the measurement period is, the lower the estimation error, but the fewer independent periods are available given a historical dataset. For measurement periods longer than a year, the use of overlapping samples in combination with Newey and West (1987) standard errors is commonly applied.

Third, there may be influential observations that create a so-called "ghost effect," that is, these single observations cause the stock–bond correlation to jump up or down only for the estimation periods in which they are included; see Alexander (2008). Ways to reduce the effect of influential observations is to use the Spearman *rank* correlation instead of the usual Pearson correlation. An alternative solution is to first detect the influential data points, for example, through the turbulence indicator (Kritzman and Li 2010), and cap or remove them altogether from the dataset. The latter method involves additional subjective modeling choices. Therefore, we prefer the use of the Spearman rank correlation. Both the Pearson and Spearman rank correlation suffer from a disadvantage that it adjusts for the average return of stocks and bonds over the measurement period. For example, a positive *average* stock return and a negative *average* bond return over the measurement period may be perceived by investors as an indication of a negative stock–bond correlation, even though it is the *deviation* from the average that counts.[27]

Finally, the choice of the equity and bond portfolio may affect the results. Common choices are the market-capitalization weighted equity market index and nominal (zero-coupon) government bonds with a 10-year remaining maturity. We also use these for our base case analysis. However, one could also choose alternative equity indices that focus on certain styles such as large-cap or small-cap, value or growth, and low-risk or high-risk. Alternative bond indices are the market-capitalization weighted government bond index, short- or long-maturity bonds, or inflation-linked instead of nominal bonds.

For our main analysis, we choose a monthly return frequency and an estimation period of 36 months, we use the Spearman rank correlation, the market-capitalization weighted equity market index, and 10-year zero-coupon nominal bond index. This is also the basis of Figure 2 in the main text. In Online Appendix A, we show the sensitivity of the choices on frequency and estimation period for the stock–bond correlation, as well as the choice of correlation metric.

Editor's Note

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Notes

1. This figure is a backward (to 1875) and forward (to 2023) extension of Rankin and Idil (2014), who cover the period 1900 to 2012.

2. We use real risk-free rate here as the return on short-term Treasury bills minus the realized inflation, so it is an ex-post real return and not an ex-ante real interest rate.

3. This extends the work of Andersson, Krylova, and Vähämaa (2008), Yang, Zhou, and Wang (2009), Baele, Bekaert, and Inghelbrecht (2010), Rankin and Idil (2014), David and Veronesi (2016), Campbell, Sunderam, and Viceira (2017), Campbell, Pflueger, and Viceira (2020), Cieslak and Pang (2021), and Brixton et al. (2023), among others.

4. There are several ways to do this. For example, Brixton et al. (2023) use growth and inflation, whereas Campbell and Ammer (1993) distinguish, like us, also real rates and inflation.

5. The price of a bond with maturity N can be written as $P_t = \frac{1}{(1+rr_t+\pi_t+brp_t)^N}$. The natural log of the bond price is $\ln(P_t) = -N \ \ln(1 + rr_t + \pi_t + brp_t) \approx -N(rr_t + \pi_t + brp_t)$. The (log) bond return over short holding periods can be approximated as $r^b_{t+1} \approx -N(\Delta_{t+1}rr + \Delta_{t+1}\pi + \Delta_{t+1}brp)$.

6. The price of a stock yielding $1 of cashflows growing at a constant rate in perpetuity is $S_t = \frac{1}{rr_t+\pi_t+erp_t-g_t}$. As with bonds, we can take logs and take the first difference to obtain (log) stock returns.

7. Empirical evidence on the Friedman–Ball hypothesis is generally confirmatory; see, e.g., Okun (1971), Logue and Willett (1976), Ball, Cecchetti, and Gordon (1990), Holland (1995), and Grier and Perry (1998).

8. Baltussen et al. (2023) also use a sample period starting in 1875 to examine the effect of inflation on asset class and factor returns. However, they do not link their results to the stock–bond correlation.

9. Yang, Zhou, and Wang (2009) find that the level of nominal interest rates and inflation are important drivers of the stock–bond correlation, whereas we prefer splitting the nominal rate into a real rate and inflation, as not to “double count” inflation expectations embedded in bond yields. Wu et al. (2022) find that real yields are important for the stock–bond correlation when using a machine-learning approach.

10. We also performed Chow breakpoint tests and found a peak in the test statistic around 1955. However, this test statistic also peaks, and at an even higher level, in the early 2000s.

11. Starting our analysis around 1870 for the United Kingdom does not bring the results more in line with the United States.

12. To facilitate replication of our results, we proceed with publicly available data from here. This has only small effects on the estimated stock–bond correlation.

13. We have replaced the covariances in Equation (3) with correlation and the variances with the standard deviation. This is common in the literature; see, for example, Brixton et al. (2023). The results are similar, but the covariance between the bond risk premium and growth is no longer statistically significant, and the variance of the expected inflation changes to positive and is statistically significant.

14. Note that the estimated parameters are now slightly different, as we switched our data sources from Global Financial Data to publicly available datasets. Due to data limitations, the sample period is also slightly shorter, starting in 1961 rather than 1952.

15. Our aim is to economically *explain* the time-variation in the stock–bond correlation. We do not aim to find the best *predictive* model for the stock–bond correlation, for which we would need to perform a proper out-of-sample analysis. As prediction is not the main goal, we leave such analysis for future research. We do not include an autoregressive term, as this does not help explain the sign and level of the stock–bond correlation.

16. Tables A2 and A3 in the Appendix contain the data sources for the G7 and emerging market samples.

17. The correlation between the 36-month average inflation and inflation volatility is 0.03 over the period 1978–2023, while the correlation between 36-month average inflation forecasts and dispersion in inflation forecasts is 0.78 over the same period. Because of this high correlation, we orthogonalize dispersion in the regression model.

18. Figure OB1 in Online Appendix B shows the descriptive statistics of the median expected inflation and its cross-sectional standard deviation.

19. While we used the zero-coupon bond yields in the previous section, we use the return on par bonds in this section. Although the par bonds have a time-varying duration that depends on the yield level, it is a better approximation of real-world government bond portfolios. Data source for par bond yields and returns is Swinkels (2023), sheet “improved US 1947.” We use GFD for stocks (ticker _SPXTRD) and the risk-free rate (ITUSA3CMD). In Section 4, we also make use of the Pearson instead of Spearman rank correlation, as the former allows for an exact decomposition of the total portfolio variance.

20. This is an illustration to show the economic impact of increasing correlation between stocks and bonds. We are not suggesting that one should use ex-post volatility realizations to forecast risk.

21. To arrive at 0.17, we multiply the two coefficients, 7.72 and 9.39, of the empirical model in Table 2 with 1%, the increase in inflation and real rates. We can then examine the change in portfolio risk for the period 1970–1999 by increasing the correlation from 0.35 to 0.52. This leads to an increase in portfolio volatility of 1.7%. For the period 2000–2023, an increase from −0.29 to −0.12 leads to an increase in portfolio volatility of 0.8%.

22. For a more detailed exposition of asset allocation for investors with liabilities, we refer to Leibowitz (1986), Elton and Gruber (1992), Blake (1999), and Campbell and Viceira (2002).

23. This is different from taking the term *spread*, which is the difference between the yield of a Treasury bond and a Treasury bill. Such an approach would ignore that expected short rates detract from the spread to arrive at a bond risk premium. The correlation between the term spread and the bond risk premium is positive, but low, at 0.36.

24. Kim and Wright (2005) develop a statistical model that includes survey data to compute the implied bond risk premium. Figure OB3 in Online Appendix B shows that the two bond risk premium models exhibit disparities in the short run. Despite these short-term disparities, both models point to a very similar long-run pattern: a secular decline in the bond risk premium since the mid-1990s. The reason we only use the bond risk premium estimates by Adrian, Crump, and Moench (2013) is that their data start in the 1960s, while the Kim and Wright (2005) model estimates start only in the 1990s. Using their estimates would mean that we cannot include a large part of the regime with positive stock–bond correlations. Figure OB3 also contains the expected bond risk premium constructed by subtracting the expected short interest rate from surveys from the current long-term yield. This model-free approach of estimating the bond risk premium shows mostly a similar pattern as the model-based estimates. The disadvantage of this survey-based estimate is also its shorter data history and lower frequency as the surveys are updated semiannually.

25. Correlation estimates are bound to be in the range of −1 to 1. To make them more suited to serve as the dependent variable in regression models, sometimes the Fisher transformation of the correlation is used: $\tilde{\rho} = \frac{1}{2} ln\left(\frac{1+\rho}{1-\rho}\right)$. We do not use this transformation in our further analyses, as the differences are small for correlations that do not exceed ±0.75. For such values, the Fisher transformation would be ±0.97.

26. An alternative to using bond returns is to use changes in the bond yield, as for example in Rankin and Idil (2014). The difference is that bond returns include both the level and the change in yields. Most of the variability comes from the changes in bond yields, such that differences between the results based on this choice are typically small.

27. This specific aspect could also be solved by calculating an alternative to the correlation by plugging in zero instead of the sample averages, so replace $\sum_{i=1}^{N} (x_i - \overline{x})(y_i - \overline{y})$ by $\sum_{i=1}^{N} (x_i)(y_i)$ in the numerator and a similar adjustment in the denominator of the correlation formula. Another alternative, which uses forward-looking information, would be to use the full sample averages of *x* and *y*, as advocated by Zhao et al. (2021).

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