Graham Capital Management
Research Note, August 2021

Macro-Economic Drivers of the Bond-Stock Correlation

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Abstract
We seek to develop a quantitative framework to assess how macro-economic shocks impact the stock-bond correlation. In particular, we examine how these shocks drive long periods of either positive or negative bond-stock correlation. We find that the positive correlation observed from 1972 to 1999 is attributable to high inflation shocks coupled with a hawkish Fed policy. The negative correlation observed from 2000 to 2020 can be attributed to recurring negative growth shocks and concerns over economic strength. Accordingly, our findings cast doubt on the conventional wisdom that one can always trust bonds to hedge losses in stocks. Instead, we find that the hedging property of bonds is highly dependent on the source of macroeconomic shocks driving losses in stocks.

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1. Introduction

Over the past two decades, the stock-bond correlation has usually been negative and has been a major boon for investors who own both stocks and bonds. In periods when stocks performed very poorly, gains from bonds usually helped offset equity losses. While investors have become accustomed to this negative stock-bond correlation, we find significant periods historically where the correlation has been positive. Further, we demonstrate that in periods where stocks lose money, the economic driver of the losses will also influence the stock-bond correlation: If losses are driven by concerns over growth (as they usually have been over the last two decades), gains from bonds may partially offset losses from stocks. In contrast, if stock market declines are driven by concerns about inflation or hawkish monetary policy, stocks and bonds may lose money simultaneously.

Looking at a long-term time series of the stock-bond correlation, we can observe many interesting patterns:

- The long run average correlation is close to zero, and in fact is slightly positive, contrary to the common belief that the correlation is negative.
- Even though the average long-term correlation is close to zero, actual correlation values are rarely at zero.
- Actual correlation values tend to fall into strong positive or strong negative regimes, typically multi-year or decades-long.
- From our knowledge of financial and macro history, we can associate periods of positive correlation with periods of high inflation and/or active monetary policy, while periods of negative correlation exist mostly when growth shocks dominate, and monetary policy is very accommodative.

Armed with these insights, we seek to develop a quantitative framework to assess how macro shocks impact the stock-bond correlation and, in particular, relate the long correlation cycles to macroeconomic regimes. Furthermore, we seek to identify the response of the yield curve and stocks to macroeconomic shocks. In the context of a linear model, the objective is to find a matrix that maps inflation, growth, and monetary policy shocks to the responses of stocks and bonds.

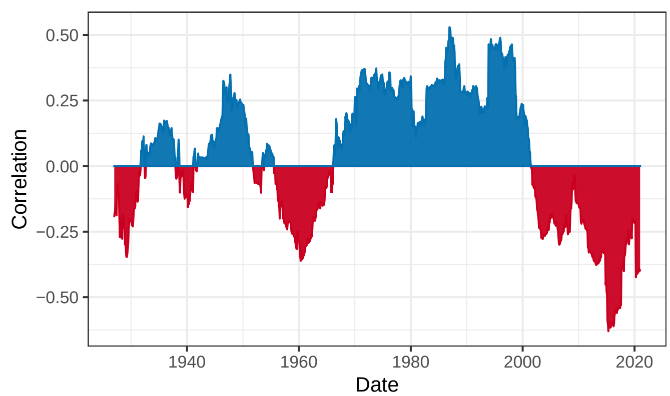


Figure 1. Rolling 5y Stock-Bond Correlation S&P Correlation to US 10Y(average correlation = 0.04)

2. Building a Framework

Ideally, we would run regressions of stock and bond returns on macro variables, estimating a model F such that:

$$\text{Market Data} = F(\text{Macro Data})$$

The challenge with this approach is that macro variables are measured with delay and at a much lower frequency (at most monthly) than market data. As such, a standard regression may be misleading. Furthermore, such data is subject to revisions and is sometimes challenging to obtain historically. In particular, the lack of daily observations can obscure the information from macroeconomic time series because markets move daily in response to changes in economic expectations, even when there are no time series updates. This is especially true for monetary policy information.

For example, financial markets collapsed during the first week of March 2020, while macro data releases showed no signs of weakness for at least another month. Of course, markets tumbled as market participants forecasted a severe economic slowdown due to the COVID-19 global pandemic. A naïve analysis would invert the causality and conclude that the market collapse caused the economic downturn rather than the other way around.

The key to solving this problem is to realize that we can still estimate the model F using market data and our rich a priori knowledge of the market *reaction function*. For instance, if we assume that a given yield curve and stock market response could only result from a growth shock, then any time we see that behavior in the data, we would catalog the event as a growth shock. The stylized assumptions that we use to build our model include the following:

1. Economic growth shocks tend to move stocks and bonds in opposite directions: positive economic growth shocks drive stocks up and bonds down and vice-versa for negative economic growth shocks.
2. Monetary policy shocks move stocks and bonds in the same direction. In particular, hawkish Fed moves increase yields, flatten the curve, and bring stocks down.
3. Affine term structure models help us quantify term premia dynamics and their relationship with macro fundamentals. In general, we need two kinds of 'risk premia' to explain bond dynamics:
   (a) During negative growth shocks, yields and stocks go down. This is the 'good' or hedging side of bonds and further reinforces the negative stock-bond correlation;
   (b) Stocks and yields go in opposite direction with inflation and monetary policy shocks. This is the 'bad' side of bonds that reinforces the positive stock-bond correlation

By characterizing multiple market responses to macroeconomic shocks, we create a mapping between macro shocks and shocks to market variables and use the market data plus the mapping to identify macro shocks.

2.1 Defining the Macroeconomic Factors

Similar to Cieslak and Pang (2020), we define four latent macroeconomic factors, and then identify these factors indirectly through yield changes using stylized facts. The four factors are defined as follows:

- **Growth**
  The Growth factor corresponds to changes in bond and stock prices driven by changes in the current state of growth in the economy. Following our first stylized assumption, we assume shocks to growth result in increases in stock prices due to expectations of higher future profits. Positive shocks also cause increases in bond yields (decreases in bond prices). This contributes negatively to bond-stock correlation.
- **Monetary Policy/Inflation**
  Following our second stylized assumption, the Monetary Policy or Inflation factor relates changes in prices to changes in the current state of monetary policy. Positive or hawkish shocks to monetary policy cause a drop in stock prices and an increase in bond yields. This contributes positively to bond-stock correlation. Here we assume that central bank policy moves up or down in tandem with inflation.
- **Hedging Premium**
  The Hedging Premium factor is a time-varying risk premium that investors demand to compensate for risks arising from future negative shocks to growth. Following our third stylized assumption, an increase in this premium causes stocks to fall and bond yields to drop because investors dump stocks to go to the safety of bonds. This is the classic 'risk-off' factor. It impacts correlation negatively.
- **Common Premium** - The Common Premium factor is a time-varying risk premium required to compensate investors for risks arising from future positive shocks to monetary policy (unexpected increases in the short rate). According to our third stylized assumption, increases in this factor cause an increase in bond yields (drop in prices) and a decline in stock prices, with an associated rise in positive correlation.

Because these factors are not directly observable, we use a time series of zero-coupon bond yields and S&P 500 dividend yields to indirectly identify them, as previously established by Cieslak and Pang (2020). We describe this approach in more details and elaborate further on the specifics of our model in the Appendix.

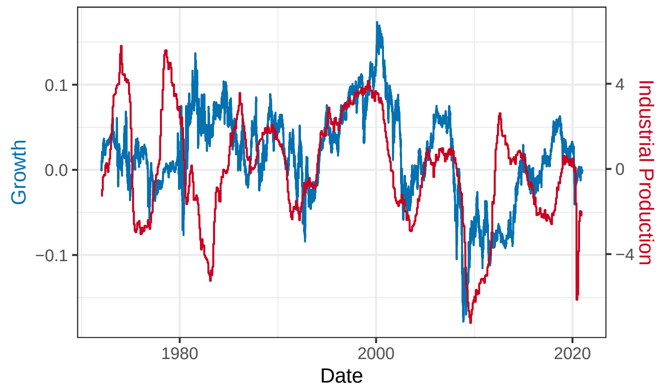
3. Model Results

Figures 2a and 2b show the historical contributions of the Growth and Monetary Policy factors respectively to the S&P 500 yield when fitting the model to data from 1972 to 2020. Please refer to the appendix for details on how these historical contributions are estimated.

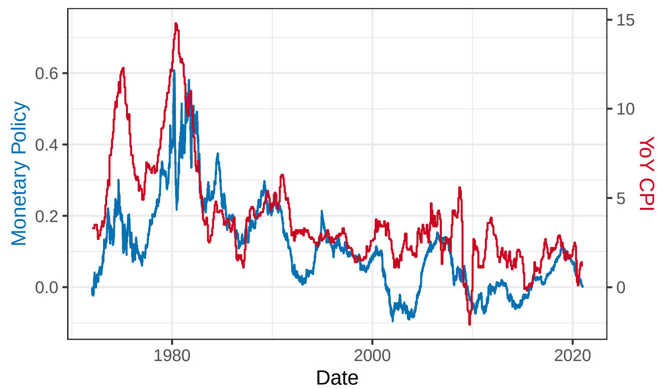
Because the Growth and Monetary Policy factors are theoretically related to current conditions, we would hope to be able to loosely tie them directly to observable low frequency economic data. We compare the Growth factor to rolling three-year average US industrial production in Figure 2a, noting a reasonable similarity. In Figure 2b, we also see similarity between the Monetary Policy factor and year-over-year CPI growth.

The Hedging and Common factors in Figure 2c are more challenging to match to observable economic data due to the fact they represent expected compensation for future risks. However, we observe that the Hedging Premium has grown considerably over the last 20 years, coinciding with the increased prevalence (at least anecdotally) of risk-on/risk-off market behavior. Additionally, we see that the Common Premium increased sharply from the 1970s to the mid-1980s when monetary policy was particularly restrictive and has generally decreased since then.

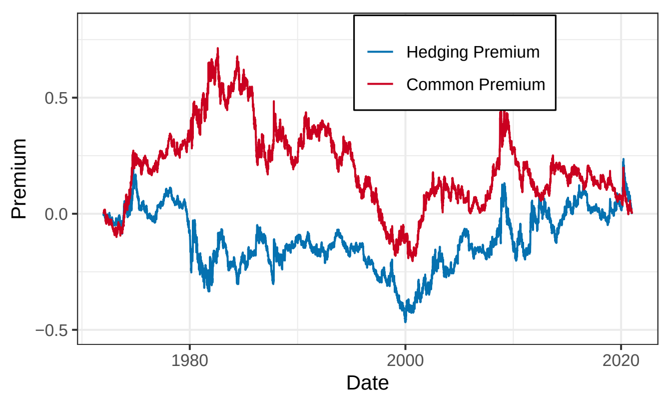
Next, we fit the same model to two sub-periods: 1) 1972 to 1999 when the bond-stock correlation was generally positive, and 2) 2000 to 2020 when the correlation was generally negative. In Figure 2d we decompose the correlation between the S&P 500 and the US 10y zero-coupon bond during these periods into the components coming from each of the four factors.



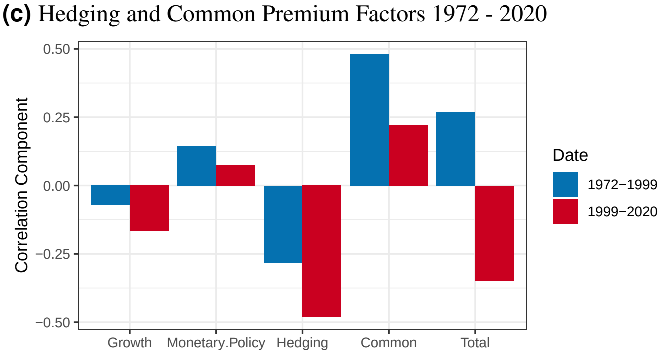
(a) Growth Factor 1972 - 2020



(b) Monetary Policy Factor 1972 - 2020



(c) Hedging and Common Premium Factors 1972 - 2020



(d) S&P 500 and US 10y Z-Bond Correlation Components

The most significant drivers of the difference between pre-2000 and post-2000 bond-stock correlation are the Hedging and Common Premia. The pre-2000 Common Premium component was more than twice as large as its post-2000 counterpart, probably reflecting concerns about tight monetary policy and higher inflation volatility, especially in the '70s and '80s.

Conversely, the Hedging Premium was significantly more negative in the post-2000 period, subtracting an additional 20% from the pre-2000 bond-stock correlation. This can probably be attributed to investor concerns arising from major deflationary shocks during the DotCom collapse and the 2008 Financial Crisis.

Put another way, the positive bond-stock correlation in the pre-2000 period was driven chiefly by concerns about restrictive monetary policy and inflation. In contrast, in the post-2000 period, investors seemed to be primarily preoccupied with concerns about current and future growth.

4. Shock Scenarios

	S&P 500	Bonds	60/40
Growth	-7.19%	8.02%	-1.11%
Monetary Policy	-9.24%	-3.77%	-7.05%
Hedging Premium	-15.30%	8.54%	-5.76%
Common Premium	-16.43%	-5.40%	-12.02%

Table 1. Impact of 2 Standard Deviation Shock over 1y.

Here we use the results from the full sample to examine what would happen to a traditional 60/40 portfolio (60% S&P 500, 40% bonds) in the case of two standard deviation shocks to each factor. We assume the bond allocation is split between the 5y and 10y US Z-bonds to match the approximate 6.5 year duration of the Bloomberg Barclays US Aggregate Index, and we assume nominal growth in dividends of 3% per year.

Table 1 shows the estimated results. For an investor managing a portfolio over the past twenty years, the Growth and Hedging shock scenarios seem somewhat familiar: Concerns about current or future economic strength cause investors to flee stocks for bonds. Stocks lose significant money, but bonds soften the blow.

However, the Common shock scenario is less familiar. Like the Hedging Premium shock, stocks lose money under a shock to the Common Premium. The difference is that bonds also face considerable losses. This kind of Common Premium shock scenario runs counter to the idea that bonds can be trusted to hedge significant losses in stocks.

5. Conclusion

Because periods of large equity drawdowns over the last two decades have chiefly been driven by the Growth and Hedging factors, it has become conventional wisdom that investors can expect large equity losses to be offset by gains in fixed income. But there is no guarantee that this would always be the case. If future declines in stock prices were to come chiefly from concerns over current or future monetary constriction or inflation, it is unlikely that bonds will soften the blow.

The obvious contributor to the relative dearth of Common or Monetary Policy shocks over the last 20 years is an accommodating and predictable Fed policy. The US 1y yield declined approximately 600 bps from January 2000 to December 2020, perhaps alleviating any market concerns about the likelihood of permanent upward monetary policy shocks during that period.

While yields may decline from current levels, it seems highly unlikely that central banks will replicate another 600 bps of loosening with short-term rates near zero. This asymmetry means the very negative bond-stock correlation of the last twenty years might be less helpful over the next twenty years.

References

A. Cieslak and H. Pang. Common Shocks in Stocks and Bonds. Working Paper 28184, National Bureau of Economic Research, December 2020. URL http://www.nber.org/papers/w28184.

R. S. Gürkaynak, B. Sack, and J. H. Wright. The U.S. Treasury yield curve: 1961 to the present. *Journal of Monetary Economics*, 54(8):2291–2304, 2007. ISSN 0304-3932. doi: https://doi.org/10.1016/j.jmoneco.2007.06.029. URL https://www.sciencedirect.com/science/article/pii/S0304393207000840.

Appendix

The historical decomposition of a VAR measures the permanent effect of error term shocks on variables. Consider a VAR of the form:

$$Y_t = \alpha + \phi Y_{t-1} + A\omega_t$$

Where α is a vector of intercept terms and ω_t is a vector of uncorrelated standard normal random variables. We can restate this VAR in terms of the starting vector Y_0 and subsequent shocks $\omega_1, \omega_2, \ldots \omega_t$ as:

$$Y_t = \phi^t Y_0 + \alpha \sum_{n=0}^{t-1} \phi^n + \sum_{n=0}^{t-1} \phi^n A\omega_{t-n}$$

The part of Y_t that can be attributable to $\omega_1(k), \omega_2(k), \ldots, \omega_t(k)$ is the historical decomposition coming from shock term k, where $\omega_s(k)$ is the k^{th} element of the vector ω_s. Denote this historical decomposition as $Y_t^{(k)}$. Then

$$Y_1(k) = A_{:,k}\omega_1(k)$$

Where $A_{:,k}$ is the k^{th} column of A. Given this $Y_1^{(k)}$, we can iterate to get $Y_t^{(k)}$ using

$$Y_t^{(k)} = A_{:,k}\omega_t(k) + \phi Y_{t-1}^{(k)}$$

Modeling the Factors

Because our factors are not directly observable, we use a time series of zero-coupon bond yields and S&P 500 dividend yields to indirectly identify them. To do this, we first denote Y_t as a 4×1 vector of yields on day t, where $Y_t(1)$ is the 2y zero-coupon US Treasury yield, $Y_t(2)$ is the 5y yield, $Y_t(3)$ is the 10y yield, and $Y_t(4)$ is the log of the S&P 500 dividend yield. That is,

$$Y_t(4) = \log(D_t/P_t)$$

where D_t are the dollar dividends paid by the S&P 500 over the past year, and P_t is the index price. Data comes from Bloomberg and the zero-coupon yield data set constructed by Gürkaynak et al. (2007).

We denote our four factors on day t as $F_t = [g_t, m_t, h_t, c_t]'$, where g_t is the level of the Growth factor, m_t is the Monetary Policy factor, h_t is the Hedging Premium factor, and c_t is the Common Premium factor. We model the factors as

$$F_t = \alpha + \phi F_{t-1} + \omega_t$$

where ω_t is a 4×1 vector of uncorrelated standard normal random variables. We then have a reduced-form model for changes in yields, given as

$$\Delta Y_t = \gamma + H\Delta Y_{t-1} + \epsilon_t$$

the link between the factors and the reduced-form model is

$$\Delta Y_t = AF_t$$

with the following identities:

$$\begin{aligned} \gamma &= A\alpha \\ H &= A\phi \\ \epsilon_t &= A\omega_t \end{aligned}$$

We can then re-state the reduced-form model as:

$$\Delta Y_t = \gamma + H\Delta Y_{t-1} + A\omega_t$$

We are particularly concerned with shocks ω_t to the factors over time, since this will drive all the unexpected variation in the yield levels. Ideally, we could invert the relationship between ω_t and Y_t to get the shocks to the factors directly:

$$\omega_t = A^{-1}(\Delta Y_t - \gamma - H\Delta Y_{t-1})$$

However, this requires a condition that isn't met: We would need to be able to observe the factors F_t directly in order to estimate the matrix A. We can't identify the factors directly because the factors are latent, and we're trying to infer these unobservable factors via the observable yields.

Instead, we estimate can A using certain stylized facts that lead to constraints on the signs and relative sizes of its components. First, we denote the components of A as :

$$A = \begin{bmatrix} {a_g}^{(2)} & {a_m}^{(2)} & {a_h}^{(2)} & {a_c}^{(2)} \\ {a_g}^{(5)} & {a_m}^{(5)} & {a_h}^{(5)} & {a_c}^{(5)} \\ {a_g}^{(10)} & {a_m}^{(10} & {a_h}^{(10)} & {a_c}^{(10)} \\ {a_g}^{s} & {a_m}^{s} & {a_h}^{s} & {a_c}^{s} \end{bmatrix}$$

Where ${a_g}^{(n)}$ is the n-year zero coupon bond yield's loading on the Growth factor, and ${a_g}^s$ the loading of the S&P 500 yield. The sub-scripts m, h, and c similarly denote the loadings on the Monetary Policy, Hedging Premium, and Common Premium factors, respectively.

Following directly from our factor definitions above, we constrain the signs on the components of A as:

$$\text{sign}(A) = \begin{bmatrix} + & + & - & + \\ + & + & - & + \\ + & + & - & + \\ - & + & + & + \end{bmatrix}$$

We also constrain the relative magnitudes of the loadings for the zero-coupon yields. First, we require that ${a_m}^{(n)} \geq {a_m}^{(n+j)}, j > 0$. In other words, Monetary Policy shocks have higher impact on the short end of the yield curve than the long end. This follows from our second stylized assumption.

Second, we require that $|{a_{h/c}}^{(n)}| \leq |{a_{h/c}}^{(n+j)}|, j > 0$. This comes from the general view of practitioners that bond term premia seem to be larger and more volatile at the longer end of the yield curve.

Third, we require that $a_g^{(2)} \geq {a_g}^{(10)}$ and ${a_g}^{(5)} \geq {a_g}^{(10)}$. The reason for this constraint is that, similar to the Monetary Policy factor loadings ${a_m}^{(n)}$, long-term yields might reflect gradual dissipation in short-term growth shocks. Like Cieslak and Pang, we do not restrict the relationship between ${a_g}^{(2)}$ and ${a_g}^{(5)}$.

To apply these stylized facts, we first note that since ω_t are assumed to be standard normal random variables, it follows that:

$$\text{Cov}(\Delta Y_t) = AA'$$

We then use an optimization routine to find A that minimizes the squared difference between the elements of $\text{Cov}(\Delta Y_t)$ and AA', subject to the sign and inequality constraints on A. Once we estimate A, we can derive the latent shocks factors using $\omega_t = A^{-1}(\Delta Y_t - \gamma - H\Delta Y_{t-1})$, where $\tilde{A}$ is our estimate of the true parameter A.

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