

Global macro matters

The stock/bond correlation: Increasing amid inflation, but not a regime change

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Faith in the traditional 60% stock/40% bond portfolio has been shaken further in recent months as a step-up in inflation and interest rates threatens to violate the negative stock/bond correlation underpinning the diversification properties of a multi-asset portfolio.¹ This backlash comes at a time when the balanced portfolio is under increased scrutiny because of the historically low income generated by fixed income securities; some have argued that this low income not only dampens overall portfolio returns in normal times but also accentuates the limitations of bonds as effective equity shock absorbers. Although we acknowledge that returns for balanced portfolios are unlikely to reach their long-run averages, less is clear on how the stock/bond correlation is expected to evolve and impact portfolio outcomes.

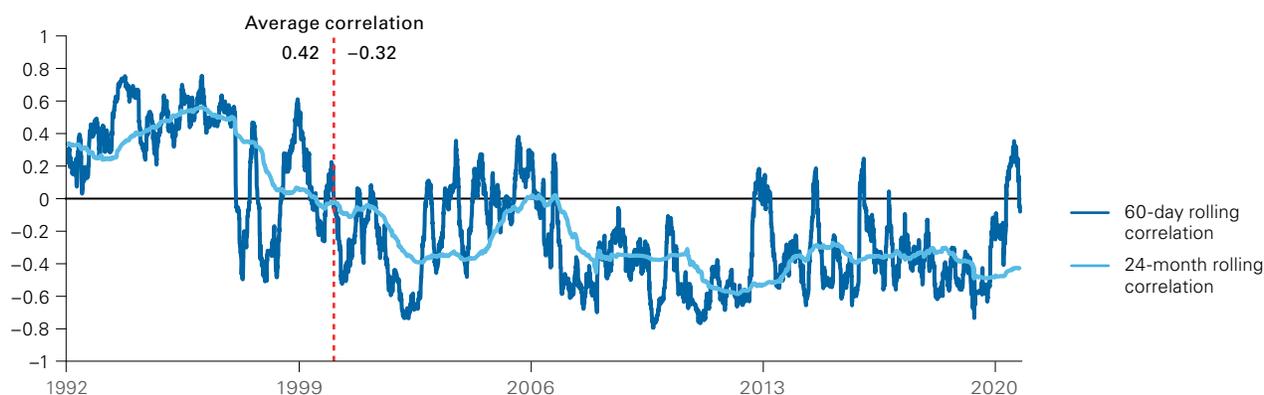
In this paper, we use machine learning techniques to assess the likelihood of entering into a new, higher-correlation regime. We find that a return to the pre-2000s positive correlation regime is unlikely but that a higher inflation outlook under the Federal Reserve's new flexible average inflation targeting (FAIT) framework could still

increase correlations modestly over the next five years. Though this may imply a slight increase in expected portfolio volatility across the investment horizon, a persistently negative correlation regime still suggests that diversification benefits will persist, albeit less than in the recent past. In addition, for a long-term investor, we find that a higher stock/bond correlation has virtually no impact on either the expectations for or the uncertainty of long-term portfolio outcomes, which are primarily determined by the strategic asset allocation decision.

Rising correlation in perspective

The diversification benefits offered by a traditional balanced portfolio have come under fire in recent months. Critics have pointed to the sharp shifts in stock/bond correlation dynamics from negative to positive at the start of the pandemic and, more recently, over the past month (see the dark-blue line in **Figure 1**) as a counter to the ballast that bonds offer. History suggests that such fluctuations in correlations are not uncommon, especially when viewed using daily data over short time horizons.

Figure 1. Short-term correlation time-varies, though regimes tend to stick for years



Sources: Vanguard, using data from Refinitiv.

¹ A negative correlation implies a tendency for stock and bond returns to move in opposite directions.

Instead, these are historically transient events that do not undermine the diversification benefits of bonds over the longer term, which is more important for strategic asset allocation decisions. A comparison of the 60-day and 24-month rolling correlation in Figure 1 exemplifies this point: In spite of temporary fluctuations in the higher-frequency correlation numbers, the longer-term stock/bond relationship has remained predominantly negative since the early 2000s.

Drivers of stock/bond correlation

Despite the longer-term negative correlation trend, we recognize that the recent sharp upward turn in short-term correlation dynamics against the backdrop of potentially higher inflation has sparked concern about whether this foreshadows a more permanent shift in correlation regimes—and, by implication, the death of the 60/40 portfolio. To determine how correlation could evolve, we sought to first explore the macroeconomic factors that could affect the underlying components of stock and bond returns, then we used a machine learning technique to identify the most important factors.

We began with a framework similar to that of Ilmanen (2003), which decomposes the expected stock and bond return equations per the following:

$$P_{stock} = E \left[\sum_{t=1}^{\infty} \left(\frac{1 + G}{1 + Y_t + ERP_t} \right)^t * D \right]$$

$$P_{bond} = E \left[\sum_{t=1}^T \frac{C_t}{(1 + Y_t)^t} + \frac{100}{(1 + Y_T)^T} \right]$$

where (P_{stock}) and (P_{bond}) refer to the return of stocks and bonds, (G) refers to the expected growth rate of dividends (D), (Y) reflects expectations of future short-term rates and the required bond risk premium, (ERP) is the required equity risk premium embedded in the discount rate for stocks in addition to the bond risk premium, and (C) and 100 refer to the fixed cash flows coming from regular coupon streams and par value 100 of a bond.

As indicated in the equation, stocks and bonds have both shared and contrary elements that cause them to move together or to decouple. Inflation shocks, for instance, are likely to cause correlation to increase because of the impact on short-term interest rates; this is a common exposure shared by both asset classes. Growth and volatility shocks, on the other hand, are likely to create a wedge between stock and bond performance because of the impact on future dividend streams and the equity risk premium. **Figure 2** summarizes the key dimensions by which economic fundamentals can affect stock and bond movements and lists the 35 potential variables we considered in our machine learning test set to capture those shocks over time.

Figure 2. The drivers of stock/bond correlation

Economic factor	Rationale	Variables considered for machine learning testing
Inflation	Inflation shocks are associated with positive stock/bond correlation because higher inflation directly raises expected future short rates and inflation-related bond risk premiums (Y_t), thereby hurting bonds. Meanwhile, the negative effect on equities through the common discount rate factor (Y_t) tends to dominate any positive changes in cash flow expectations (G) that come during periods of high inflation (Ilmanen, 2003).	<ul style="list-style-type: none"> • Trailing 10-year annualized changes in headline CPI • Trailing 10-year annualized changes in core CPI • One-year change in headline CPI • One-year change in core CPI
Uncertainty	<p>An increase in uncertainty about the outlook for inflation will increase stock/bond correlation by raising the discount factor (Y_t) common to stocks and bonds.</p> <p>An increase in uncertainty about the outlook for growth, on the other hand, will decrease the correlation as the equity risk premium increases, depressing stock prices, while the bond term premium declines, increasing bond prices.</p>	<ul style="list-style-type: none"> • Trailing 10-year annualized standard deviation of annual changes in headline CPI • Trailing 10-year annualized standard deviation of annual changes in core CPI • Trailing 10-year annualized standard deviation of annual changes in industrial production • Trailing 10-year annualized standard deviation of monthly changes in nonfarm payrolls • Survey of Professional Forecasters (SPF) headline inflation forecast dispersion • SPF core inflation forecast dispersion • SPF industrial production forecast dispersion • SPF nonfarm payrolls forecast dispersion • SPF unemployment rate forecast dispersion
Volatility	Equity volatility is likely to trigger stocks and bonds to move in opposite directions, as flight-to-quality episodes often increase the required equity risk premiums (reducing stock prices) and reduce bond risk premiums (increasing bond prices).	<ul style="list-style-type: none"> • Trailing 10-year annualized standard deviation of Standard & Poor's 500 Index total returns • One-year annualized standard deviation of S&P 500 Index total returns • CBOE VIX • S&P 500 Index futures contract trading volume
Growth	Growth news is likely to cause a wedge between stock and bond performance. If G rises in cyclical expansions, stocks benefit but bonds do not—in fact, they may be hurt by the impact of growth on yields.	<ul style="list-style-type: none"> • One-year change in U.S. real industrial production • Output gap • Natural logarithm of nonfarm payrolls • U-3 unemployment rate • U-6 unemployment rate capturing underutilization • 3-month/10-year Treasury yield spread • 2-year/10-year Treasury yield spread • TED spread (3-month LIBOR–3-month Treasury bill) • National Bureau of Economic Research business cycle dating • Corporate profits after tax
Policy	Higher real yields increase the common discount rate (Y_t) factor shared by equities and bonds and are therefore associated with positive stock/bond correlation unless accompanied by strong earnings growth (G).	<ul style="list-style-type: none"> • Real 10-year Treasury yields • Real federal funds rate • Nominal federal funds rate • M2 money supply • Monetary policy gap (versus neutral rate) • Monetary policy gap (versus Taylor rule) • Federal Reserve balance sheet as a percentage of outstanding bonds • Federal Reserve balance sheet as a percentage of GDP

Notes: CBOE VIX refers to the Chicago Board Options Exchange volatility index. It is used to reflect the market's expectation of volatility based on Standard & Poor's 500 Index options. U-3 unemployment rate, the most commonly reported rate of unemployment, captures the total number of unemployed, while the U-6 rate also includes underutilized workers. M2 is a measure of the money supply that includes cash, checking deposits, and easily convertible near money. Monetary policy gap (versus neutral rate) refers to the difference between the actual real federal funds policy rate and the neutral rate. Monetary policy gap (versus Taylor rule) refers to the difference between the actual nominal federal funds policy rate and the policy rate implied by the Taylor rule. The Taylor rule is a simple monetary policy rule that prescribes how a central bank should adjust its interest rate policy instrument in a systematic manner in response to developments in inflation and macroeconomic activity.

Source: Vanguard.

To narrow down our selection of potential variables, we used a random forest machine learning algorithm to identify the most important features that have determined stock/bond correlation regimes historically. Unlike approaches such as dynamic conditional correlation or dynamic factor model (Figure 3), our machine learning technique allows us to capture the nonlinear relationship

among the different variables and ultimately select factors that have the highest ability to predict the correlation level over time. The choice of decision tree models rather than other supervised machine learning algorithms allows us to rank the importance of the macro determinants in explaining the changes in correlation regimes.

Figure 3. An evaluation of existing models used to predict correlation

Approach	Model	Description	Limitations
Time series modeling	Dynamic conditional correlation (DCC)	DCC is one of the more popular models used to capture the time-varying structure of financial market co-movements. Under this approach, correlation parameters are estimated according to a GARCH-type structure, which models volatility for each of the assets (Engle, 2002).	Little is known about the main determinants of the stock/bond co-movements.
Linear regression	Dynamic factor model (DFM)	In DFM, macro variables are predefined and included in the regression used to model the time variation in correlation.	This model assumes that the interrelationships among the various input factors are static and linear.

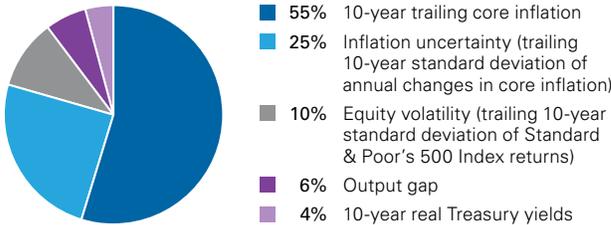
Note: GARCH, or generalized autoregressive conditional heteroskedasticity, is a statistical modeling technique used to help model the volatility of returns on financial assets.

Source: Vanguard.

Figure 4 reveals the five most important variables explaining the correlation trends from 1950 to 2021 as indicated by the feature-selection mechanism of our random forest algorithm. Among these five factors, we find that the prevailing inflation backdrop, as represented by the 10-year trailing inflation rate, is by far the most influential driver of the equity/bond correlation level, where positive shocks in inflation tend to drive periods of positive stock/bond correlation regimes and vice versa.² As a case in point, Figure 5 compares the correlation regimes during the 1970s hyperinflationary environment and the high-inflation environments of the 1950s and 1990s with the post-2000 backdrop. The 1950s, 1970s, and 1990s were associated with a highly positive stock/bond correlation, and post-2000 was associated with a persistent negative correlation regime.

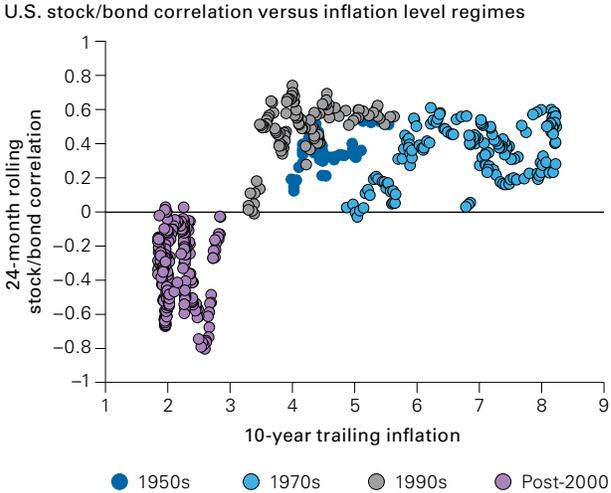
This relationship reaffirms our hypothesis: Given the common exposure that stocks and bonds have to inflation, higher inflation increases correlation by dampening nominal bond prices and reducing expectations of real earnings growth for equities. By contrast, factors such as equity volatility and economic growth tend to cause stocks and bonds to move in opposite directions and can help explain the cyclical time variation in correlation dynamics during the post-2000 negative stock/bond correlation regime.

Figure 4. 10-year trailing inflation proves to be the most important variable determining correlation level over time



Note: By training a random forest model on our data set, the model object we obtain can tell us which were the most important variables in the training; that is, which of them have the most influence on the target variable, which in this case is the rolling 24-month correlation from January 1950 to April 2021. Sources: Vanguard, using data from Refinitiv and Global Financial Data.

Figure 5. High inflation as seen during the 1950s, 1970s, and 1990s is associated with positive correlation regimes



Sources: Vanguard, using data from Refinitiv and Global Financial Data.

² Although long-term inflation is the most influential driver of correlation level because they trend together, other factors have increased importance in explaining changes in correlation. For more information on methodology, see our forthcoming research paper, *Forecasting U.S. Equity and Bond Correlation – A Machine Learning Approach*, in Volume 4, Issue 1 of *The Journal of Financial Data Science*, which is scheduled to be published in February 2022.

Testing the out-of-sample forecasting ability of the model

Figure 6 illustrates the goodness-of-fit of our model using the five factors combined, with an out-of-sample evaluation over the past five years returning a root mean squared error (RMSE) between the actual and predicted correlation of around 0.11, implying a high degree of accuracy of the model.

Figure 6. An out-of-sample test reveals a high degree of accuracy of our nonlinear machine learning model

Nonlinear machine learning out-of-sample: RMSE = 0.11



Notes: We used data over 260 months to train the data set and allow the gradient boosting algorithm to learn the dynamic relationship among the factors, after which the test set or out-of-sample set over the last five years was used to check for the robustness of the model. RMSE is a frequently used statistical measure of the differences between values predicted by a model and the values actually observed.

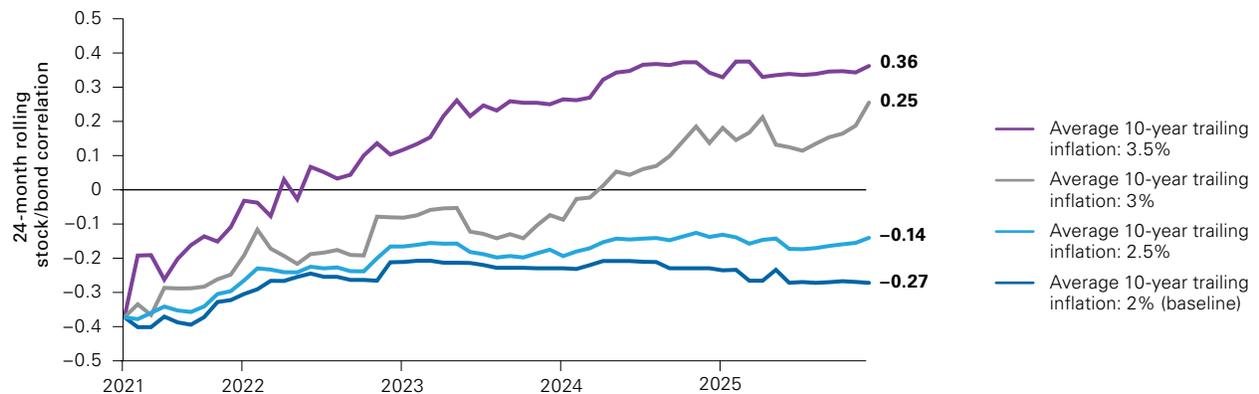
Sources: Vanguard, using data from Refinitiv and Global Financial Data.

Scenario analysis: A modestly higher but still negative correlation regime

With inflation proving to be a key driver of stock/bond correlation regime change, some investors have become concerned that aggressive fiscal support today, alongside pent-up demand and supply-chain constraints, may lead to a permanently higher inflation regime and, by implication, a positive stock/bond correlation regime. Using our five-factor model, we explore the potential inflation scenarios that could break the existing negative correlation regime, and we weigh the likelihood of those scenarios happening.

As our simulations in Figure 7 show, 10-year trailing inflation would have to be around 3% on average over the next five years to have a significant impact on correlation regimes. Importantly, the criterion listed here is the 10-year trailing inflation rate rather than the one-year annual inflation rate, highlighting the extended period of time that high inflation would have to be sustained before having a significant impact on correlation. Specifically, for 10-year trailing inflation to average 3% over the next five years, annual core inflation would have to be maintained at the minimum rate of 5.7% over the same period.

Figure 7. What will it take to break correlation into positive territory?

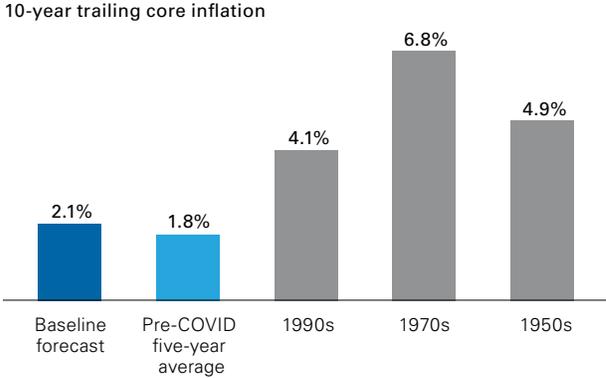


Source: Vanguard.

Such a scenario would be possible only if the Fed were to lose the ability to anchor inflation or if inflationary expectations were to spiral out of control on the back of massive liquidity injections—both of which we see as quite unlikely. Even if we were to factor in a more persistent-than-expected spike in inflationary pressures—for example, if we were to get a modest upside surprise in fiscal stimulus and a Fed that proves to be moderately more tolerant to inflation under the FAIT framework—we would expect annual core CPI inflation to rise to only 2.7% by the end of 2022. Such an increase would take the 10-year trailing inflation rate about 30 basis points higher than its pre-COVID five-year average of 1.8%.

This rate would be considerably lower than the inflation scenarios seen during the pre-2000 positive correlation regimes, where 10-year trailing inflation averaged around 5.3% (Figure 8). And it certainly falls short of the long-term inflation threshold needed to push correlation permanently into positive territory. Against this backdrop, we expect correlation to move modestly higher in the coming years as reflation takes place but nonetheless remain in negative territory, around -0.27, at the end of the next five years as inflation settles around the Fed’s 2% target.

Figure 8. Inflation, yes; hyperinflation, no

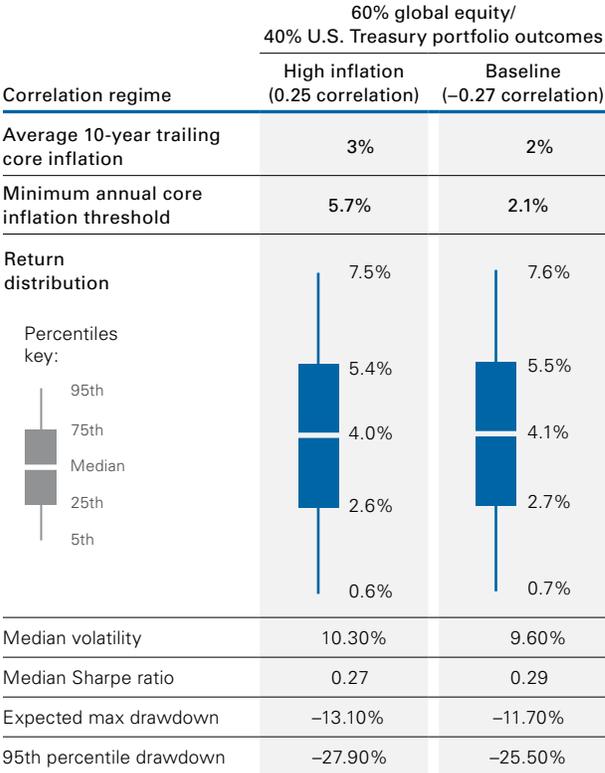


Sources: Vanguard calculations, using data from Refinitiv.

Portfolio implications under various correlation regimes

Using the range of correlation simulations in Figure 7, we examined the impact on portfolios by comparing the risk and return simulations of a 60/40 portfolio under our baseline and high-inflation (10-year trailing inflation at 3% or higher; annual inflation minimum at 5.7% or higher) scenarios. As Figure 9 shows, the correlation regime affects the volatility or fluctuations in portfolio values across the investment time horizon (as seen in the expected maximum drawdown and median volatility), whereby a 60/40 portfolio under our baseline negative correlation regime will have lower volatility and smaller tail-risk events than that of a 60/40 portfolio under the high-inflation positive correlation regime. However, long-term portfolio outcomes do not seem to vary much across the different correlation regimes, suggesting that the strategic decision of the stock/bond mix ultimately remains the primary determinant of dispersion in end outcomes, regardless of correlation.³

Figure 9. Correlation regimes affect the volatility in portfolio values but not end-of-horizon outcomes



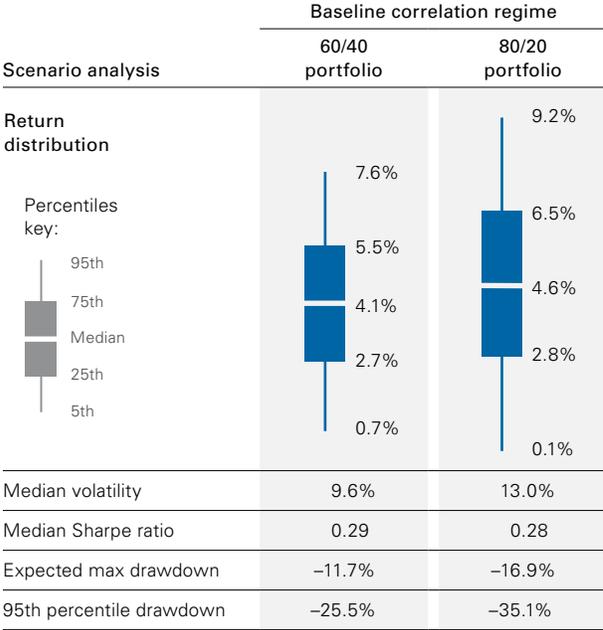
Notes: The Sharpe ratio is a measure of risk-adjusted returns, describing how much excess return one can receive for the volatility of holding a riskier asset. A higher Sharpe ratio indicates higher risk-adjusted returns.

Source: Vanguard simulations.

³ Dispersion is a measure of the uncertainty in ending portfolio outcomes and can be measured as the difference between the 95th and 5th percentiles.

Comparing the 60/40 portfolio with an 80/20 portfolio reaffirms this point (Figure 10). The variation in risk and return dynamics, for instance, proves to be significantly greater when comparing a 60/40 portfolio with an 80/20 portfolio than it is for a 60/40 portfolio under different correlation regimes. The reason for this lies in the individual distributions of the two asset classes. U.S. Treasury bonds have a very narrow range of annualized outcomes, characterized by low volatility, whereas equity return dispersion is comparatively wider, with much higher volatility. Equity valuations, which are the primary driver of this risk, tend to be very persistent but also prone to abrupt declines because of rapid repricing of risk premium. This combination creates a wide set of potential outcomes that the stock/bond correlation cannot materially change. Long-term investors concerned about the portfolio outcome at the end of their investment horizon should therefore calibrate their asset allocation based on return goals and risk tolerance rather than on expected correlation regime shifts.

Figure 10. The strategic asset allocation decision is the primary determinant for long-term portfolio outcomes



Notes: The Sharpe ratio is a measure of risk-adjusted returns, describing how much excess return one can receive for the volatility of holding a riskier asset. A higher Sharpe ratio indicates higher risk-adjusted returns.
Source: Vanguard simulations.

Conclusion

Criticism of the traditional balanced stock/bond portfolio has ramped up in recent months on the back of a potential correlation regime switch that would negate the diversification properties of bonds. Using nonlinear machine learning techniques such as the random forest and gradient boosting regressor, we have explored the drivers of correlation regimes and conclude that higher inflation could increase correlations modestly. However, a return to a positive correlation regime of the pre-2000 era is unlikely absent an environment where 10-year trailing inflation averages 3% over the next five years. Although modestly higher correlation implies that portfolio volatility may edge slightly higher, a persistently negative regime suggests that the diversification properties of a balanced portfolio are likely to remain intact. Additionally, for a long-term investor, we find that higher correlations have very little impact on expectations for and uncertainty in long-term portfolio outcomes, which are primarily determined by the strategic asset allocation decision.

References

- Engle, Robert, 2002. Dynamic Conditional Correlation: A Simple Class of Multivariate Generalized Autoregressive Conditional Heteroskedasticity Models. *Journal of Business & Economic Statistics* 20(3): 339–350.
- Friedman, Jerome H., 2002. Stochastic Gradient Boosting. *Computational Statistics and Data Analysis* 38(4): 367–378.
- Ilmanen, Antti, 2003. Stock-Bond Correlations. *The Journal of Fixed Income* 13(2): 55–66.
- Rankin, Ewan, and Muhammed Shah Idil, 2014. A Century of Stock-Bond Correlations. *Reserve Bank of Australia Bulletin*. September: 67–74.
- Svetnik, Vladimir, Andy Liaw, Christopher Tong, J. Christopher Culberson, Robert P. Sheridan, and Bradley P. Feuston, 2003. Random Forest: A Classification and Regression Tool for Compound Classification and QSAR Modeling. *Journal of Chemical Information and Computer Sciences* 43(6): 1947–1958.
- Tirelli, Tina, and Daniela Pessani, 2011. Importance of Feature Selection in Decision-Tree and Artificial-Neural-Network Ecological Applications. *Alburnus Alburnus Alborella: A Practical Example. Ecological Informatics* 6(5): 309–315.
- Zhou, Lina, Shimei Pan, Jianwu Wang, and Athanasios V. Vasilakos, 2017. Machine Learning on Big Data: Opportunities and Challenges. *Neurocomputing* 237(C): 350–361.

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