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Asset prices and time-varying persistence of consumption growth*

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ABSTRACT

Inspired by results in the macro literature, we consider a model in which the correlation between shocks to consumption and to expected future consumption growth is nonzero and varies over time. Combined with a precautionary savings effect, the model embeds time variation in consumption growth persistence, which provides an alternative explanation why the correlation between stock and bond returns fluctuates over time. The time-variation also derives changes in the volatility of stock returns, the so-called "leverage effect," and the predictive relation between bond yields and future stock returns. We find strong empirical support for all of these predictions.

Keywords: Consumption persistence, long-run risk, stock/bond correlation, leverage effect

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I. Introduction

When consumers reduce spending, is this an indication of a higher or a lower future consumption growth rate? Whether such consumption shocks are persistent or anti-persistent is a difficult question, in part because competing theories have opposite predictions. The well-known challenge of measuring expected consumption growth (e.g., Schorfheide, Song, and Yaron 2018) makes an empirical answer to the question elusive as well.

Nevertheless, the question is important because a nonzero correlation has significant implications for asset prices. Using the long-run risk (LRR) framework of Bansal and Yaron (2004), we show that a positive correlation between consumption growth shocks and future expected growth rates lowers the correlation between bond and stock returns. Since these shocks – current and expected future cash flows – are two main drivers of equity values, a positive correlation further increases the volatility of stock returns. This correlation also affects the so-called "leverage effect," the relationship between stock returns and volatility shocks, and the degree with which bond yields predict future stock returns.

We devise an empirical strategy that uses higher frequency asset price data to overcome some of the challenges in analyzing a conditional correlation involving the latent expected consumption growth process. Using this approach, we show that the stock/bond return correlation is more negative when the correlation between current and future expected consumption growth shocks is more positive, providing a new explanation of why the correlation between bond and stock returns may vary over time. Furthermore, we find that the stock/bond correlation is related to stock market volatility, the stock market leverage effect, and the predictability of stock returns in the ways predicted by our model.

In our model, consumption persistence has two sources. One is the slow variation in the expected consumption growth process, as postulated by Bansal and Yaron (2004). This process generates a moderately positive autocorrelation in consumption growth that decays very gradually with the horizon. The other is the correlation between current and expected consumption growth shocks, which we refer to for brevity as consumption growth persistence or CGP. By including both sources, it is possible to induce time variation in CGP while maintaining the long-run positive autocorrelation that is critical for matching the moments of asset returns.

Macroeconomic models provide many reasons why CGP is unlikely to be zero. Transient shocks to productivity (Kaltenbrunner and Lochstoer 2010), to income (Hall and Mishkin 1982), or to uncertainty (Basu and Bundick 2017) can all drive consumption higher in the short run, while at the same time decreasing long-term consumption growth. A negative CGP is thus a natural outcome of the mean-reverting nature of these shocks.

In contrast, models that incorporate permanent shocks generally imply higher persistence, as is the case in the production economy of Kaltenbrunner and Lochstoer (2010). Separately, in the macro literature on the income/consumption relation, Campbell and Deaton (1989) find that consumption underreacts to permanent income shocks. In both cases, the positive CGP results from frictions that induce gradual adjustment to permanent shocks.

The empirical macro literature is abundant with evidence that both permanent and transitory shocks are necessary to explain observed patterns of persistence. Friedman (1957) observes that income and consumption likely contains both permanent and transitory components, an idea formalized by Beveridge and Nelson (1981), Watson (1986), and Clark (1987), among others. Furthermore, the relative importance of these shocks likely varies over time, as there appear to be multiple sources of uncertainly that affect macroeconomic and financial variables to different degrees (Jurado, Ludvigson, and Ng 2015). Intuitively, then, if the most volatile shocks are transitory (e.g., pandemics, oil shocks), CGP will become negative. When permanent shocks (e.g., technology, climate change) dominate, CGP turns positive.

Our model, building on Bansal and Yaron (2004), is a stylized way to capture the net effect of these mechanisms. While preserving the core features of LRR models –

the phenomenon that consumption growth at long horizons is positively autocorrelated – our model allows for the possibility that consumption growth may in some environments display mean reversion, which is an expected outcome when macro risks are transient. By allowing for additional flexibility in the persistence of consumption growth, our model is able to explain some conditional moments that the standard LRR model cannot.

By including this additional flexibility, our model generates a number of new predictions. One is that CGP should be an important driver of the correlation between the returns on stocks and bonds. The logic is straightforward: Changes in expected consumption growth drive interest rates due to intertemporal smoothing, while changes in realized growth affect cash flows. Therefore, a positive CGP gives rise to a higher correlation between interest rates and cash flows, resulting in a lower (and likely negative) correlation between bond and stock returns. Therefore, our model predicts that consumption growth autocorrelation decreases with the stock/bond correlation.

The model also implies that a higher CGP will raise stock market volatility. This is because current and expected future cash flows are two primary drivers of equity valuation.[1] When these shocks are positively correlated, their effects will be amplified, and market volatility will rise. The testable implication is that market volatility is decreasing in the stock/bond return correlation.

An additional feature of our model is the incorporation of a negative correlation between shocks to consumption growth and its volatility. Allowing this correlation to be nonzero is an attempt to reconcile the standard LRR model with the presence of a precautionary savings motive, which is found in a number of studies, including Carroll (1997) and Basu and Bundick (2017). A nonzero CGP amplifies the effects of the correlation between consumption shocks and volatility by linking volatility shocks to expected future consumption growth shocks. Since a higher CGP also implies a lower stock/bond return correlation, the model implies that the strength of the predictive relation between volatility and future consumption growth will vary with the stock/bond correlation. This

[1]Shocks to expected consumption growth have both cash flow and discount rate effects, which affect equities with opposite signs. Our calibration strongly implies that the cash flow effects dominate.

mechanism also suggests that the stock market leverage effect will be magnified (i.e., made more negative) by a higher CGP. An additional prediction of our model is that the stock/bond correlation and the stock market leverage effect will be positively related.

Finally, our model implies a particular relationship between interest rates and future stock market returns. Empirically, the weakness of the predictive relationship presents something of a puzzle, as it is suggested by most macro-finance models. Our model suggests that the strength of such a relationship should depend on CGP. Since bond yields are closely related to the level of expected consumption growth, they are more strongly related to consumption volatility – which drives the market risk premium – when CGP is high. When CGP is low, our model implies that yields should have little predictive power for future market returns, which may account for the weak unconditional relationship. The testable prediction is that yields will predict market returns more strongly when the stock/bond return correlation is low.

Our empirical findings are consistent with these model predictions. We first show that consumption growth autocorrelations are decreasing with the stock/bond return correlation. As in all LRR models, expected consumption growth is closely linked to the real interest rate. Thus, a higher CGP is implied by a higher correlation between interest rates and consumption growth. Empirically, we find that lower stock/bond correlations imply a stronger relation between consumption and interest rate shocks, which is additional evidence of the relation between the stock/bond correlation and CGP. These two results justify the use of the stock/bond return correlation, which can be measured at high frequency using daily data as a proxy for CGP.

We then turn to the strong link between CGP and the stock market leverage effect. This link implies that the stock/bond return correlation and the leverage effect should be positively related, which we confirm in the data. Therefore, the leverage effect should also be able to proxy for time-varying persistence in consumption growth. It appears to do this as well, though with lower significance. We, therefore, use the stock market leverage effect to supplement the stock/bond correlation when testing additional implications of our model.

CGP should also be positively related to market volatility. Specifically, the model implies that the stock/bond correlation should have a negative interactive effect with macroeconomic uncertainty. We confirm this relationship using several uncertainty measures, namely the macro uncertainty of Jurado, Ludvigson, and Ng (2015), the monetary policy uncertainty of Baker, Bloom, and Davis (2016), and a simple measure of consumption growth variance. These results are consistent with our prediction that CGP modulates the correlation between shocks to volatility and expected future consumption growth.

Our final set of results demonstrate that the stock/bond correlation is an important state variable for the predictive relation between yields and future stock returns. We test the predictive relationship by interacting the yields with the stock/bond correlation. Overall, while the negative unconditional predictive relationship is weak as documented in prior work, we report strong conditional relationship. As the stock/bond correlation drops, the negative relationship strengthens, consistent with our model. The insignificant unconditional relation, which is at odds with the predictions of many models, is therefore a natural result of the stock/bond correlation being positive over much of our sample.

In the next section, we describe and calibrate our model. Section III describes our data and strategies for measuring latent processes. Section IV presents our empirical results, and Section V concludes.

II. The model

1. Consumption growth dynamics

Our model is a generalization of the standard framework of Bansal and Yaron (2004). In our baseline specification, the representative agent has Epstein and Zin (1991) preferences, and consumption growth (Δc_{t+1}) has a persistent time-varying component x_t and time-varying uncertainty σ_t^2:

$$\Delta c_{t+1} = \mu + x_t + \sigma_t \epsilon_{c,t+1} \tag{1}$$
$$x_{t+1} = p_1 x_t + \phi_x \sigma_t \epsilon_{x,t+1}$$
$$\sigma_{t+1}^2 = s_0 + s_1 \sigma_t^2 + \sigma_v \sigma_t \epsilon_{v,t+1}$$

Note that we depart slightly from Bansal and Yaron (2004) in that the volatility of the consumption variance depends on the level of the consumption volatility. This type assumption is standard in the option pricing literature and ensures that the variance remains positive under reasonable parameter specifications.[2] However, our primary motivation for this assumption is that it will allow for analytical solutions even when we induce correlations to the three shocks. Otherwise, we believe that it has minimal effects relative to the constant volatility-of-variance specification of Bansal and Yaron (2004). Under the assumption that the three shocks in the model are uncorrelated, Bansal and Yaron (2004) show that the wealth-consumption ratio is linear in x_t and σ_t^2. Similarly, in our baseline model we have

$$z_t = A_0 + A_1 x_t + A_2 \sigma_t^2, \tag{2}$$

where the constants A_0 and A_1 are positive, while A_2 is negative. As is standard, valuations are therefore raised by greater expected consumption growth and reduced, via a discount rate effect, by higher volatility.

Our generalized models deviate from Bansal and Yaron in several important dimensions. First, we allow shocks to consumption growth ($\epsilon_{c,t+1}$) and expected long-run consumption growth ($\epsilon_{x,t+1}$) to be stochastically correlated. We refer to this correlation as consumption growth persistence, or CGP, given that it determines whether a shock to current consumption growth is associated with higher or lower consumption growth in the future. This correlation, which we denote as ρ_t, follows a stochastic process that will be specified below.

As discussed in the introduction, allowing for a stochastic correlation can be viewed

[2]In the continuous time version of the model, the required Feller condition would be $2s_0 s_1/(1-s_1) > \sigma_v^2$.

as a reduced form approach to modeling time variation in the relative importance of permanent and transitory shocks. For example, in the production economy of Kaltenbrunner and Lochstoer (2010), the assumption of permanent productivity shocks results in a positive CGP, while transitory shocks generate a negative CGP. This results from differences in how investment (and therefore consumption) responds to changing productivity and how adjustment costs and mean reversion induce trends in future output. Given our view that both types of shocks are likely, either effect could dominate depending on which type of shock is currently more volatile. Furthermore, this phenomenon is not limited to shocks to productivity. Permanent and transitory shocks to income generate similar responses, as discussed, for example, by Hall and Mishkin (1982) and Campbell and Deaton (1989).

We also deviate from Bansal and Yaron by allowing consumption growth shocks to be correlated with consumption variance shocks. A negative correlation is a natural result of a precautionary savings motive, which has been confirmed empirically in a number of studies, including Carroll and Samwick (1998) and Basu and Bundick (2017). We assume this correlation, denoted ϱ_{ps}, is constant.

Finally, given that consumption growth shocks are correlated with shocks to expected growth rates (ρ_t) and to consumption volatility (ϱ_{ps}), it is natural to expect a nonzero correlation between shocks to expected consumption growth and consumption volatility. For example, an increase in precautionary savings induced by greater uncertainty should reduce current consumption, as households increase their savings and lead to a rise in expected long-run consumption growth as uncertainty wanes and consumption returns to normal. Empirically, a nonzero correlation between σ_t and x_t is found by Nakamura, Sergeyev, and Steinsson (2017), who show that it tends to be more negative during economic contractions. In another work, Parker and Preston (2005) find significant evidence, using household survey data to measure the relative importance of precautionary savings, that the precautionary motive explains the predictable component of consumption growth.

In the interest of parsimony, we avoid introducing unnecessary additional parameters by assuming that this correlation between shocks to consumption volatility and expected consumption growth is equal to the product $\rho_t \varrho_{ps}$.[3]

Closing the model requires a specification of the dynamics of CGP, or ρ_t. To obtain closed-form solutions, we parameterize the covariance, rather than correlation, between $\epsilon_{c,t}$ and $\epsilon_{x,t}$ as an autoregressive process. The covariance, $p_t = \text{Cov}_t\left(\epsilon_{c,t+1}, \epsilon_{x,t+1}\right)$, follows

$$p_{t+1} = \omega_0 + \omega_1 p_t + \sigma_p \sigma_t \epsilon_{p,t+1}, \tag{6}$$

where, for simplicity, we assume that $\epsilon_{p,t+1}$ is uncorrelated with other shocks.

Given the same preference assumptions as Bansal and Yaron, the price-to-consumption ratio z_t can be represented as a linear function of long-run expected consumption growth (x_t), the variance of consumption growth (σ_t^2), and the leverage covariance (p_t). That is,

$$z_t = A_0 + A_1 x_t + A_2 \sigma_t^2 + A_3 p_t. \tag{7}$$

In the appendix, we derive the values for A_0, A_1, A_2, and A_3. Under conventional parameter assumptions ($\gamma > 1$ and $\psi > 1$), we find that $A_1 > 0$ and $A_2 < 0$, which is consistent with the model of Bansal and Yaron and with our baseline specification. In addition, we find that $A_3 < 0$, implying that the price-consumption ratio is lower when CGP is higher.

We refer to the above specification as the "consumption-only" model, given that it solely describes the dynamics of consumption. As is standard, we extend this model further by adding a dividend process. In this model, which we label as the "full" model, dividend growth is specified as

$$\Delta d_{t+1} = \mu_d + \phi_d x_t + \sigma_t \varphi_{cd} \epsilon_{c,t+1} + \sigma_t \varphi_d \epsilon_{d,t+1}, \tag{8}$$

where $\epsilon_{d,t+1}$ is assumed to be uncorrelated with other shocks. Therefore, dividend growth shares similarities with consumption because of its dependence on the long-run growth

[3] This correlation structure is consistent with the assumption that there are three orthonormal shocks, $[u_{c,t}\ u_{x,t}\ u_{v,t}]$, that drive the shocks to the three state variables via

$$\epsilon_{c,t} = u_{c,t} \tag{3}$$

$$\epsilon_{x,t} = \rho_t u_{c,t} + \sqrt{1-\rho_t^2}\, u_{x,t} \tag{4}$$

$$\epsilon_{v,t} = \varrho_{ps} u_{c,t} + \sqrt{1-\varrho_{ps}^2}\, u_{v,t} \tag{5}$$

process x_t, and its sensitivity to the consumption growth shock $\epsilon_{c,t}$. The strength of this commonality is determined by the values of ϕ_d and φ_{cd} relative to the volatility of dividend-specific shocks, determined by φ_d.

We define the return on the market portfolio as

$$R_{m,t+1} = \kappa_0 + \kappa_1 z_{m,t+1} - z_{m,t} + \Delta d_{t+1}, \tag{9}$$

where z_m is the price-dividend ratio of that portfolio and where κ_0 and κ_1 are constants of the log linearization. Similar to the wealth-consumption ratio, we can verify the conjecture that the price-dividend ratio is a linear function of the three state variables. We show in the appendix that the signs of the coefficients match those of equation (7).

2. Calibration

We perform a calibration of the model to examine its quantitative implications. In doing so, our priority is to match the parameters of Bansal and Yaron (2004) as closely as possible. In our baseline model, in which correlations are all zero, most parameters are equal to their counterparts in that paper. The only exception is the volatility-of-variance parameter σ_v, because of how we specify the volatility of the σ_t^2 process. We set this parameter to the value that equates the unconditional volatility-of-variance with the constant value assumed by Bansal and Yaron.

The generalized specifications require, in addition, several correlation parameters. These include the three parameters of the CGP (p_t) process in equation (6), the constant correlation parameter ϱ_{ps}, as well as two parameters (φ_c and φ_{cd}) that determine the correlation between consumption and dividend shocks. Because of the difficulty in estimating unconditional means, we assume that the mean of the p_t process is zero, which implies that $\omega_0 = 0$. The slope (ω_1) and volatility (σ_p) parameters are chosen to match the volatility and first-order serial correlation of the covariances between stock returns and bond yields. This is justified by the strong relation between these covariances and the p_t process, as shown in the following section. For our primary specification, we set the precautionary savings parameter ϱ_{ps} equal to -0.3 following the results of Basu and Bundick

(2017), but we also show results for two alternative specifications by setting ϱ_{ps} equal to -0.2 and -0.5. We choose the persistence of long-run growth to match the correlation between stock and bond returns. The persistence and volatility of variance parameters are chosen to match the stock market leverage correlation and beta. Estimates from the data are based on annual data and use real yields and stock returns. The variance model used is described in the empirical section. The assumed parameters are summarized in Panel A of Table I.

Panel B compares the asset moments generated by our three specifications. These include the baseline model, in which correlations are set to zero, the consumption-only model, in which the total wealth portfolio is assumed to be the stock market portfolio, and the full model, which incorporates a dividend process. For each specification, we generate one million observations and evaluate the first two moments of stock and bond returns, as well as several other relevant asset pricing moments. The unconditional moments generated by the simulations are generally comparable to those of other standard LRR models, aside from the correlations and stock market leverage beta.

3. Stock/bond return correlation

This section shows strong implications of CGP for the contemporaneous relationship between stock and bond returns (the SB correlation), which suggests a new explanation for why the SB correlation may vary over time. Establishing the relationship to the CGP is important for our purpose because it would imply that the stock/bond correlation is a good proxy for ρ_t, particularly given that the correlation can be computed as long as bond and stock returns are available.

To establish the relationship between CGP and the SB correlation, it helps first to understand how bond yields, stock returns, and stock variances are affected. Here, we explain these relationships, which are summarized in Table II.

We first consider the two channels that drive SB correlations under the baseline model, in which ρ_t is assumed to be zero. The first is through shocks to the expected consumption growth ($\epsilon_{x,t+1}$). If this shock is positive, higher expected future cash flows will lead to higher stock returns. Bond yields will also increase as the demand for money rises through the intertemporal consumption smoothing motive. Therefore, stock and bond returns will have opposite responses, implying a negative SB correlation.

The second channel is through shocks to consumption growth uncertainty ($\epsilon_{v,t+1}$). The stock market return variance will rise following a positive uncertainty shock, which also raises risk premia and lowers valuations. At the same time, bond yields will drop as higher consumption risk induces households to reduce their holdings of risky assets and replace them with riskless bonds. Therefore, an increase in uncertainty leads to stock and bond prices moving in the opposite direction. The negative SB correlation that results from this channel is often referred to as the 'flight-to-quality' phenomenon.

Panel A of Table II shows that the first channel is much stronger than the second. The correlation between yield changes and shocks to expected consumption growth is around 0.98. In contrast, the correlation between yield changes and volatility shocks is just -0.18. Notably, both channels both imply a negative correlation between bond and stock returns since lower yields imply higher bond returns.

While our generalized models exhibit the same negative SB correlation on average, CGP causes this correlation to vary over time. For example, this correlation should increase when ρ_t is negative. To see this, suppose there is a positive expected consumption growth shock ($\epsilon_{x,t+1} > 0$). This shock is likely to coincide with a decline in current consumption. In this case, bond yields will increase as the economy expects higher future growth, while the negative shock to current consumption will lower equity values. While the net effect may be that equity values rise due to higher expected long-run growth, the rise will be moderated by the negative shock to current consumption. A negative ρ_t will therefore lead to a SB correlation that is less negative than usual, perhaps even slightly positive.

This channel is amplified by the negative relationship between uncertainty shocks ($\epsilon_{v,t+1}$) and consumption growth shocks ($\epsilon_{c,t+1}$), which captures a precautionary savings motive. Unconditionally, a positive uncertainty shock will lower stock valuation and bond yields since uncertainty shocks lower current consumption. When ρ_t is positive, precautionary savings will further reduce the SB correlation, as a positive uncertainty shock is likely to be associated with lower expected consumption growth. In contrast, when ρ_t is negative, this shock is more likely to increase expected future growth, which would have ambiguous effects on stock and bond valuations. An uncertainty shock could even increase the stock/bond return correlation, although below, we show that the magnitude of this effect is not likely to be quantitatively large.

The first two panels of Figure 1 show how the SB correlation varies as a function of the model state variables. Panel (a) shows the relationship between the SB correlation and the ρ_t process for the consumption-only model, while panel (b) presents corresponding results for the full model. In both, we show correlations for several different fixed levels of the precautionary savings parameter ϱ_{ps}. For comparison, each panel includes a flat line indicating the constant correlation obtained under the baseline model, in which all shocks are uncorrelated. It is worth noting that the baseline does not match the empirical observation that the SB correlation is time varying.[4]

We derive these relationships using closed-form solutions for the variances of stock returns, bond yields, as well as for the covariance between the two. We show in the appendix that all three may be expressed as linear combinations of σ_t^2 and p_t. Furthermore, both the covariance and the two variances are increasing in consumption growth volatility and in p_t. The stock/bond return correlation, therefore, is a univariate function of just ρ_t. However, whether this function is increasing or decreasing in ρ_t is not straightforward and must be addressed using our calibrated model.

The figure confirms the negative relation between ρ_t and the SB correlation. In both panels, one for the consumption-only model and one for the full model, the SB correlation is slightly convex in ρ_t, and in both cases, the value of the precautionary savings parameter

[4]For example, Connolly, Stivers, and Sun (2005) and Baele, Bekaert, and Inghelbrecht (2010) report a negative relationship between SB correlations and stock market uncertainty. Campbell, Pflueger, and Viceira (2020), among others, report a decreasing trend in SB correlations.

ϱ_{ps} has relatively little effect. Lastly, while low values of CGP are associated with positive SB correlations in both models, positive SB correlations are rarer in the full model.

This relationship is also shown in the simulation result in Panel B of Table II, which examines the "correlation of correlations." While the figure shows that the relation between ρ_t and the SB correlation is slightly nonlinear, the table is useful in that it assesses the goodness of fit of a linear projection of the SB correlation onto ρ_t. For both the consumption-only model and the full model, the relationship between ρ_t and SB correlation is extremely negative, with correlations below -0.99. Thus, our model suggests that the SB correlation is a very good proxy for the less easily observed ρ_t process.

4. Stock market volatility and the leverage effect

Time-varying CGP also has implications for stock market volatility and the time-varying "leverage effect" in the stock market, which refers to the negative relationship between stock returns and stock volatility shocks. While robust, the relationship is nevertheless time-varying, as demonstrated by Pyun (2019).

First, high CGP will raise stock return variance. Stock returns depend positively on both current consumption and future expected consumption shocks. A positive correlation between these shocks magnifies their risk, while a negative correlation reduces risk due to a hedging effect. Thus, the model implies that the variance of stock returns will increase with CGP. This is formalized with an analytical result, which we prove in the appendix, which is that

$$\mathrm{Var}_t(R_{m,t+1}) = V_2\sigma_t^2 + V_3 p_t, \tag{10}$$

where $V_2, V_3 > 0$.

Second, higher CGP will strengthen the negative relationship between stock market returns and volatility shocks. This is because volatility shocks affect cash flow through their relation to both current consumption and future consumption growth. The standard precautionary savings motive implies a stable negative relationship between current consumption and volatility.

However, when CGP is positive, positive volatility shocks are also likely to be associated with a decrease in expected future consumption growth, which causes stock returns to react more to the same volatility shock. In contrast, when CGP is negative, stock returns will react less to volatility shocks, thereby decreasing the magnitude of the leverage effect.

The last two panels of Figure 1 show the relationship between CGP and stock market leverage, which is defined as the slope coefficient of the regression of market returns on variance shocks. For this figure, we use the exact formulas that are provided in the appendix. Results for the consumption-only model and our full specification are provided in Panels (c) and (d), respectively. For comparison, we again include flat lines indicating the values obtained under the baseline model, which produces a leverage effect that is negative and constant.

The figure shows that stock market leverage is negatively related to CGP. This relationship is essentially linear, and it implies a perfect correlation between the leverage effect and ρ_t, as we report in Panel B of Table II. The figure also shows that the leverage effect is sensitive to the value chosen for the precautionary savings parameter ϱ_{ps}, as the intuition above suggests.

The three models display large differences in the average level of the leverage effect. Panel B of Table I shows estimates of the leverage effect that are obtained from simulating each model. These are estimates of the unconditional leverage effect, but they are close to the average of the conditional values. The table also shows the value estimated in the data using a procedure we describe in Section 1. In comparing the model-implied values with an estimate from the data, we can see that the baseline and consumption-only models drastically overstate the size of the leverage effect. The full model, which introduces a dividend process with its own error term, reduces the average of the leverage beta. The calibrated value is only moderately larger than the one estimated from the data.

5. Conditional moments of consumption growth

The key assumption of our generalized model is that consumption growth shocks have time-varying persistence. In this section, we address how this assumption affects the conditional distribution of consumption growth for different values of ρ_t in order to formulate empirical predictions.

While greater CGP will clearly increase the serial correlation in consumption growth, it is difficult to assess the strength of this and other relations analytically. We simulate 10 million months of data from our full model and compute approximate conditional moments by separating the simulated sample into narrow bins (e.g., [-0.05, 0), [0, 0.05), [0.05, 0.1), etc.) according to the value of ρ_t. We then compute the variable of interest (e.g., first-order autocorrelation) using all the observations in each bin. Our model simulation is monthly, but to facilitate comparison with later empirical results, we aggregate to the quarterly level by adding three consecutive realizations of the consumption growth process.

Panel (a) of Figure 2 shows the relationship between consumption growth and contemporaneous shocks to expected future consumption growth. As assumed in our model, there is a positive relationship between the two, and the plot serves only to quantify the effect. For example, our figure suggests that when ρ_t is at the first quintile (-0.17), one standard deviation shock to x_t implies a -0.1% consumption growth shock. Panel (b) shows how the first-order serial correlation of consumption growth relates to CGP. Similar to panel (a), the consumption growth process is aggregated to the quarterly level, and we examine serial correlation in quarterly growth rates. As expected, serial correlation is positive on average, due to the presence of the LRR process, and rises with ρ_t. It is notable that even very negative values of ρ_t nevertheless imply conditionally positive serial correlation.

Because we have assumed that the correlation between expected consumption growth and volatility shocks is equal to $\rho_t \varrho_{ps}$, our model implies that this correlation will be more negative when CGP is high. Panel (c) of Figure 2 shows that the same relation also holds in levels. The level of expected future consumption growth is more negatively related to the level of consumption variance when CGP is high, where we measure the relation by the slope coefficient of the regression of x_t on σ_t^2. We examine levels here to be consistent with our empirical analysis, where first differences in observable proxies for x_t on σ_t^2 are likely to be dominated by measurement error.

6. Stock return predictability of bond yields

Most consumption-based asset pricing models imply that bond yields should negatively predict future stock returns. This prediction results from stock risk premia increasing in consumption volatility, which will also lower bond yields due to precautionary savings. These relationships imply that when bond yields are lower, the equity risk premium should be higher.

However, there is, at best weak empirical evidence for such a relationship. While several studies starting with Fama and Schwert (1977) find a negative relation between stock returns on lagged bond yields, the negative relationship appears sample-dependent. Also, as evidenced by Welch and Goyal (2008) the statistical significance is well below that of other predictors such as the aggregate dividend yield.

The final implication of the model is that the strength of this form of stock market return predictability depends on the relationship between current and expected future consumption growth. Bond yields are the inverse of the expected marginal utility of the investors, which is closely related to the level of the expected consumption growth. Meanwhile, the stock risk premium is higher when volatility is higher. Therefore, when expected consumption growth is more negatively related to volatility, the relationship between bond yields and stock risk premia should become more strongly negative.

Given that the SB correlation and the stock market leverage betas are increasing in CGP, we expect a more negative predictive relationship between future stock returns and bond yields when either of those correlations is low.

Using the simulations described earlier, we first examine the regression of stock risk premia on lagged bond yields. As with other results, we examine how the slope coefficient of this regression depends on the lagged value of ρ_t. In this analysis, we use the exact formula for the market risk premium, which is an increasing function of uncertainty and the current/expected consumption growth covariance (δ), as shown in the appendix. Results based on realized excess returns would be identical except for some increase in simulation error.

Panel (d) of Figure 2 shows that for values of ρ_t that are greater than -0.5, we see a negative relationship between bond yields and the market risk premium, as implied by many other asset pricing models. But whereas other models imply that the degree of predictability is constant, our model suggests that it is highly time-varying. This figure suggests that bond yields should be better predictors of future stock returns when CGP is high. Given that CGP can be proxied by either the SB correlation or the stock market leverage beta, where each relation is negative, the degree of conditional predictability should be inversely related to either of these two measures.

A more intuitive explanation of this result starts with the idea that highly correlated assets are likely exposed to the same systematic risk factors. If the compensation for factor risk increases, both assets should see higher expected returns. For bonds, the yield to maturity is the return that the investor would obtain if the bond is held until maturity, albeit with specific assumptions on the returns to reinvestment. For stocks, no single variable encapsulates future returns in the same way, but if bond and stock returns are highly correlated, then we should be able to infer something about the expected return on bonds by looking at expected returns on bonds, as proxied by yields.

III. Data

Quarterly consumption data is obtained from the national income and product accounts (NIPA) provided by the Bureau of Economic Analysis. We measure consumption at the quarterly frequency as the sum of the real personal consumption expenditure on non-durables and services. We take the quantity index of NIPA Table 2.3.3 and divide it by the total population obtained from NIPA Table 7.1. Consumption growth is defined as the first log difference and is computed from 1962 to 2019.

Bond yields are obtained from the website of the Federal Reserve Bank of St. Louis and are available from 1962 to 2019. We use the 10-year yield, though changing the maturity does not affect our results qualitatively. Real bond yields are calculated by subtracting the expected inflation rate from the nominal yield. Expected inflation is estimated on an out-of-sample basis using a first order AR(1) process applied to quarterly seasonally-adjusted first differences in the Consumer Price Index (CPI), where we use a 10-year rolling window for the estimation.[5] The CPI data is obtained from the Bureau of Labor Statistics. Excess market returns are from Ken French's data library.

We measure macroeconomic uncertainty in three different ways. First, we use the 12-month macro uncertainty measure from Jurado, Ludvigson, and Ng (2015), which is obtained from Sydney Ludvigson's website and is available from 1961 to 2019. These data are available on a monthly basis, and we convert to quarterly by choosing the last value of each quarter. Second, we use the monetary policy uncertainty from Baker, Bloom, and Davis (2016). This uncertainty index is estimated using textual analysis of newspaper articles and is substantially different from those estimated from macroeconomic aggregates. The data covers the period from 1985 to 2019 and can be downloaded at the authors' Economic Policy Uncertainty website. Third, we use the volatility estimate of expected consumption growth estimated using the long-run risk model of Schorfheide, Song, and Yaron (2018). That series, which was provided by the authors of the paper, is available from 1962 to 2014.

We also use several different measures of stock market volatility. The first is a monthly measure, the so-called "realized variance" computed as the squared daily excess market returns. The second volatility measure is the VXO index of the Chicago Board Options Exchange (CBOE). VXO is the predecessor of the VIX and measures the implied volatility of options on the S&P 100 Index (as opposed to the VIX, which is the model-free implied volatility of S&P 500 Index options). We choose it because it is available going back

[5]Ang, Bekaert, and Wei (2007) show that an ARMA or even an AR model performs relatively well in forecasting future inflation rates.

to 1986, while the VIX starts in 1990. Finally, we estimate measure of equity market volatility using the two-factor EGARCH model of Brandt and Jones (2006), which is closely related to the model of Engle and Lee (1999). Specifically, we use the long-run factor from the most general specification of Brandt and Jones, which we fit using daily market returns from 1950 to 2019. By focusing on the long-run factor, we are excluding volatility fluctuations with very low persistence, which we believe are less relevant for explaining macroeconomic dynamics at horizons of one quarter or more.

IV. Empirical Results

1. Empirical proxies for CGP

Direct measurement of time variation in the relationship between current and expected consumption growth shocks is hampered by the difficulty in measuring the latent expected consumption growth process (e.g., Schorfheide, Song, and Yaron 2018) and the relatively low frequency of consumption growth data. The direct measurement of CGP is unlikely to be successful if it varies through time.

Therefore, we examine CGP using an indirect approach using high-frequency asset price data. The stock/bond return correlation is estimated as the negative correlation between the first-order difference in bond yields and stock returns. This estimate approximates the true stock/bond return correlation, as it ignores the effect of convexity, but it is extremely accurate. As a baseline, the correlations are estimated using a rolling basis using daily observations of the past 365 calendar days. Since the stock/bond correlations can be measured for bond maturity, we can compute several such correlation series. In this paper, we report the results of the ten-year constant maturity bonds, though using other maturities produces very similar results.

As an alternative, we calculate the negative correlation between stock returns and the first-order difference of real yields using the past 60 monthly observations. While we expect larger measurement errors in this procedure, both due to the estimation of real yields and from using fewer observations, this measure is less likely to be contaminated by any correlations between stock returns and inflation rates (e.g., Boons, Duarte, de Roon, and Szymanowska 2017).

We estimate the leverage effect from the monthly regression

$$R_{m,t} = \beta_0 + \beta_v(\hat{\sigma}_t - \hat{\sigma}_{t-1}) + \epsilon_t, \tag{11}$$

where $R_{m,t}$ is the excess market return in month t. $\hat{\sigma}_t$ is the long-run volatility forecast of stock returns from the two-factor EGARCH model of Brandt and Jones (2006), measured at the end of month t and scaled to a monthly value. The regression is estimated using a 60-month rolling window. We call the beta estimate of this regression the stock market leverage effect and denote it by Lev_t.

As an additional measure, we estimate the daily regression using the daily changes in the VXO Index as the independent variable. We estimate this regression using a rolling-window of 365 calendar days.

There are benefits and drawbacks of using this alternative volatility measure. One benefit is that we can either reduce the standard errors of the estimates or use a shorter sample period. This is especially useful when the beta estimates are time-varying. One drawback is that VXO is a measure of risk-neutral volatility, which means that it contains a component driven by the volatility risk premium. A second drawback is that such measures can only be constructed starting in 1986.

2. Serial correlation of consumption growth

The first implication of the model is that the persistence of consumption growth shocks should be reflected in the level of the stock/bond correlation or the leverage beta. Establishing this relationship is critical because it justifies using the SB correlation (or the leverage beta) as an empirical proxy for the latent CGP process.

In interpreting these results, it is important to note that short-run autocorrelations from consumption growth data are likely high due to time-aggregation effects absent from our theoretical model. As shown both by Breeden, Gibbons, and Litzenberger (1989) and Heaton (1993), if investors make consumption decisions more frequently than the interval over which consumption is measured, then autocorrelation in growth rates will be high, perhaps 0.25 in quarterly data. Our model suggests that serial correlation will be larger during periods when the SB correlation or the stock market leverage beta is more negative.

To test the hypothesis, we first estimate a predictive regression of quarterly consumption growth on its own lag. We test whether this relationship is stronger or weaker during high or low SB correlation or stock market leverage periods by adding an interactive term. The regression we estimate is

$$\Delta c_{t+1} = \alpha_0 + \alpha_1 \Delta c_t + \alpha_2 R_t \times \Delta c_t + \alpha_3 R_t + \epsilon_{t+1},$$

where Δc_t is quarterly consumption growth and where R_t is either the SB correlation or the stock market leverage beta. If, as implied by our model, the serial correlation is stronger during periods when the SB correlation or the stock market leverage is negative, we expect to see $\alpha_2 < 0$.

Panel A of Table III summarizes the results. The simple regression of using only lagged consumption growth in the first column shows that past consumption growth predicts future consumption growth. As mentioned above, this is likely due to time aggregation, at least in part. Long-run risk in consumption growth also naturally leads to a positive autocorrelation in consumption growth. The R^2 of 0.233 is comparable to numbers reported by previous studies, for example, Savov (2011).

Our primary interest is to test the sign and the significance of the interactive coefficient, α_2. The panel shows that, consistent with the model's predictions, the interactive coefficient is negative across all four measures considered. Three out of four are statistically significant.

We also vary the forecast horizon, replacing the one quarter-ahead dependent variable with one that is between two and ten quarters ahead. These dependent variables are non-cumulative and, hence, non-overlapping. Figure 3 shows, for various horizons, the regression slope coefficients on the interactive regressor $R_t \times \Delta c_t$. Across all four measures, the figures show that our findings are not just restricted to the one quarter-ahead forecast. Using the daily SB correlation as our interactive variable, predictability is observed as far as eight quarters ahead.

An alternative test exploits the high correlation implied by our model between bond yields (y_t) and expected consumption growth (x_t). This directly suggests that higher CGP will be reflected in a higher contemporaneous correlation between consumption growth and changes in yields. Given the negative relation between CGP and the SB correlation, the model, therefore, predicts that the α_2 coefficient in the regression

$$\Delta c_t = \alpha_0 + \alpha_1 \Delta y_t + \alpha_2 R_t \times \Delta y_t + \alpha_3 R_t + \epsilon_{2,t}$$

to be negative. The results of this analysis are reported in Panel B.

These regressions are much different from those in Panel A. The 0.043 R^2 of the simple regression, consumption growth regressed on the contemporaneous first-order difference in bond yields, is much smaller due to these regressions being unaffected by time aggregation. Nevertheless, we find that bond yield changes are unconditionally positively related to consumption growth. Our model implies a stronger relationship when SB correlations or the stock market leverage betas are negative. By examining the interactive coefficient α_2, we find consistent results with our theoretical prediction. All specifications show a negative coefficient, with two that are highly significant.

A potential concern is that a significant fraction of the variation in nominal yields may be driven by inflation, which is outside our model. Using the methodology outlined in Appendix III, we attempt to remove the expected inflation component from nominal yields. We then repeat the previous analysis using real yield changes instead of nominal. The results are shown in Panel C, where we observe patterns similar to those based on nominal yields, though with lower statistical significance.

3. Stock/bond correlation and stock market leverage

Given the results in Table III, a natural question is whether the two proxies for CGP, namely the SB correlation and the stock market leverage beta, are themselves related. Testing the relationship between the two series is challenging, as both of them must be estimated from rolling samples. If these samples are too short, estimation errors will dominate the observed variation. If the samples are too long, we will induce artificial persistence that could lead to the spurious regression problem of Granger and Newbold (1974).

We strike a balance between these concerns using a rolling window length that is shorter than that used in Table III, in which the spurious regression problem was not a concern. For measures based on daily data, we either use one month or 12 months of data.[6] For measures based on monthly data, we use one or five years.

We evaluate the relationship between the two series using a time-series regression. For measures estimated with just a single month of data, the regression is monthly. For those estimated with 12 months of data, we use annual end-of-year values to eliminate issues of using overlapping data. Similarly, for measures estimated with 60 months of data, we only use the values every five years (i.e., December of 1965, 1970, etc.). We further calculate the standard errors using Newey-West adjustment.

Table IV summarizes the results of the regression where SB correlations are regressed on stock market leverage betas. We choose to control for the level of stock market volatility because several studies (e.g., Baele, Bekaert, and Inghelbrecht 2010) show that SB correlation is empirically negatively related to the level of volatility, possibly due to the 'flight-to-quality' phenomenon. Using daily estimates, we find that SB correlations are positively related to stock market leverage betas. This remains so even after controlling for the level of market volatility and is consistent for different measures of correlations.

[6] Pyun (2019) shows that stock market leverage betas can be estimated with reasonable accuracy using just one month of daily data. For a more accurate measure we also consider 12-month estimates.

4. Stock market variance

As shown in (10), our model implies that the market variance should be related to macroeconomic uncertainty and the covariance between shocks to current and future expected consumption growth. The latter effect, which relates to the stock/bond return correlation, suggests a link to the "flight-to-quality" hypothesis. In this view, the stock/bond correlations become negative in high volatility times as investors shift their portfolios from more risky stocks to safer bonds in periods of heightened uncertainty. On the other hand, our model suggests that both the SB correlation and stock market volatility depends on CGP.

In this section, we test whether our empirical proxies are negatively related to future stock market realized variance in the manner our model predicts. In particular, since the proxies represent the correlation between shocks to current and expected future consumption growth, not the covariance, the SB correlation should have an effect that is interactive with macroeconomic uncertainty. This suggests the predictive regression

$$RV_{t+1} = \beta_0 + \beta_1 UNC_t + \beta_2 UNC_t \times R_t + \beta_3 RV_t \epsilon_{t+1}, \tag{12}$$

where RV_t is the realized variance , UNC_t is either macroeconomic uncertainty of Jurado, Ludvigson, and Ng (2015), monetary policy uncertainty of Baker, Bloom, and Davis (2016), and consumption volatility from Schorfheide, Song, and Yaron (2018) as defined as in the data appendix, and where R_t is either the SB correlation or the stock market leverage beta. Our primary interest is in the interactive coefficient β_2, which we expect to be negative.

The results of these regressions are summarized in Table V. Panels A, B, and C show the results using macroeconomic uncertainty, monetary policy uncertainty, and consumption volatility, respectively. Overall, the results are consistent with our model. We find strong statistical significance of the β_2 coefficient across three uncertainty measures using the daily SB correlation as our CGP proxy. The results for monthly measures are weaker, likely in part due to estimation errors in expected inflation. For the stock market leverage betas, in contrast, we find stronger results for the monthly measures, possibly for the reasons mentioned in the previous section

Overall, the result suggests that economic uncertainty predicts stock market variance with a higher slope when SB correlations are negative, and when stock market leverage betas are negative.

5. Expected consumption growth and volatility

Our model implies that the correlation between shocks to expected consumption growth and consumption volatility also varies with CGP. This is a critical implication because this correlation links CGP to the equity risk premia. Because shocks to expected consumption growth and consumption volatility are difficult to measure, we instead examine the relationship in levels. This is justified by the results in panel (c) of Figure 2, which showed that our model implies a higher correlation between x_t and σ_t when ρ_t is low. Equivalently, the correlation between x_t and σ_t will be higher when the SB correlation or the stock market leverage beta is high.

Because Δc_{t+1} is equal to x_t in expectation, we test this hypothesis using full and restricted versions of the predictive regression

$$\Delta c_{t+1} = \beta_0 + \beta_1 UNC_t + \beta_2 R_t \times UNC_t + \beta_3 R_t + \beta_4 \Delta c_t + \epsilon_{t+1}, \tag{13}$$

where R_t is either the SB correlation or the stock market leverage beta and UNC_t is one of the uncertainty measures. We also add an estimate of stock market volatility from the two-component model of Brandt and Jones (2006). If R_t is closely (negatively) related to CGP, we should obtain positive estimates for the β_2 parameter.

Table VI summarizes the results of these regressions, where each of the four panels represents the results of using different proxies for R_t. We include regressions with and without the controls R_t and Δc_t. Overall, the table provides reasonably strong support for our hypothesis. A positive β_2 is found in each regression and is statistically significant (at the 10 percent level) in most cases. Results are strongest in Panel A, which uses the daily SB correlation to proxy for CGP. Other panels use CGP proxies based on lower frequency data (Panels B and C) or are available only over a shorter sample (Panel D).

6. Stock return predictability

One final implication of the model is the time-varying negative relationship between bond yields and future stock returns. The relationship between bond yields and stock market returns has been studied in a number of papers. Fama and Schwert (1977) estimate a simple predictive regression of future stock returns on lagged bond yields and find a negative slope, which they interpret as the result of stocks being inflation hedges. Breen, Glosten, and Jagannathan (1989) further confirm the economic significance of this predictability. More recently, Ang and Bekaert (2007) find that short-term Treasury yields, along with dividend yields, jointly predict stock returns in many international markets. They argue that the yields represent a component of the discount rate used by investors to value equities. Campbell and Thompson (2008) also document statistically significant in-sample predictability and but Welch and Goyal (2008) report weak in and out-of-sample performance.

Our model suggests that the extent to which bond yield predict stock returns depends on the CGP. Specifically, a higher CGP is associated with a stronger, more negative predictive slope between bond yields and future returns. We test this hypothesis in the monthly regression

$$R^e_{S,t,t+\tau} = \beta_0 + \beta_1 y_t + \beta_2 y_t \times R_t + \epsilon_{t+1}, \tag{14}$$

where $R^e_{S,t,t+\tau}$ is the τ-month excess market return, y is the one-year constant maturity Treasury yield, and R_t is the estimated SB correlation or the stock market leverage beta. We show the result for one, three, six, and 12-month forecast horizons (τ) and across our four proxies for CGP.

Table VII summarizes the results of these regressions. Panel A shows the results of simple predictive regressions, in which only the lagged bond yield is used to predict excess stock returns. Although the regression coefficients are all negative, they are only marginally statistically significant for the one-month horizon. This is qualitatively consistent with but notably weaker than the results of early studies by Fama and Schwert (1977) and Breen, Glosten, and Jagannathan (1989).

The novel implication of our model is that the slope should be more negative when the SB correlation or the stock market leverage is lower, implying $\beta_2 > 0$. In Panel B, we test for this effect using the SB correlations as the proxy for CGP, while Panel C uses the stock market leverage beta in place of R_t. We find evidence of this hypothesis in both panels of the table, as evidenced by the consistently positive coefficients on the $y_{j,t} \times R_t$ terms. The evidence is more substantial for SB correlations and daily stock market leverage betas. The relatively weaker result for monthly SB correlations and daily leverage betas is partly expected from previous tables, as they tend to be more noisy measures of CGP.

To understand the degree to which return predictability varies, consider forecasts based on one-year Treasury yields. If the SB correlation were 0.4, the conditional slope of one-month market excess returns on yields would be a paltry -0.037 $(-0.271 + 0.585 \times 0.4)$, implying that yields have essentially no predictive power for future returns. Similar conclusions hold for longer investment horizons as well. However, were the return correlation instead -0.5, a 1% increase in the one-year Treasury yield would be associated with a 0.6% decline in monthly stock returns, a 1.7% decline in three-month returns, 2.0% decline in six-month returns, and 4.7% decline in 12-month returns. Economic magnitudes are similar when based on the stock market leverage betas.

In Panel D and E, we repeat the exercise with our estimated real yields rather than nominal yields. Overall, we see similar results, albeit slightly weaker results for short-term predictability. The six-month and 12-month interactive coefficients are all highly statistically significant. In terms of economic magnitude, the results are similar to those using nominal yields, but results using real yields are statistically weaker.

Many asset pricing models imply a negative relationship between bond yields and stock risk premium, as high uncertainty both means lower bond yields and higher risk premium. Therefore, it is puzzling why the empirical relationship is so weak. Our results show that the predictive relationship is stronger than it appears, but only during periods when proxies indicate that CGP is high.

V. Conclusion

While the exogenous consumption process examined by Bansal and Yaron (2004) is highly successful in replicating key moments of asset returns, its assumption of independent shocks is inconsistent both with macroeconomic theory and with consumption data. In particular, the model does not account for the relationship between shocks to current consumption growth and expected future consumption growth, which we term consumption shock persistence (CGP). In theory, this relationship may be positive or negative, depending on whether permanent or transient shocks to income or productivity are more prevalent. The model also does not account for the negative correlation between shocks to consumption growth and consumption volatility, which likely arises from the precautionary savings motive.

Because of these assumptions, the model cannot match several well-documented features of financial markets. The correlation between stocks and bonds is highly time-varying in the data and appears to vary with the level of stock market volatility. These effects are absent in the model of Bansal and Yaron, which features a constant stock/bond correlation. The model also implies a constant stock market leverage effect, which is inconsistent with the evidence showing time-variation in the leverage effect

We propose a model that allows for a significantly more realistic dependence structure. Shocks to current and expected future consumption growth are stochastically correlated, which we view as a reduced form approach to modeling the relative importance of transitory and permanent shocks. Shocks to current consumption and consumption growth are negatively correlated at a fixed value, which maintains parsimony and reflects the likely importance of the precautionary savings motive.

The model implies that the correlation between stock and bond returns is decreasing in CGP. So is the stock market leverage beta. Empirically, we see that consumption growth tends to become more serially correlated during periods of more negative stock/bond correlations or leverage betas. This result provides evidence of time variation in CGP, and it also links it to correlations that are readily estimable from high-frequency asset price data. We also see strong evidence that the SB correlation and the market leverage beta are positively related, which is implied by our model and new to this paper.

Our model also predicts the negative relation between stock market volatility and the SB correlation that has been observed in prior studies, such as Connolly, Stivers, and Sun (2005) or Baele, Bekaert, and Inghelbrecht (2010). This is because high consumption persistence makes cash flows and discount rates negatively correlated, which amplifies the effects of these shocks. Empirically, we find strong evidence for this relation.

We also find evidence of a time-varying relation between current uncertainty and future consumption growth. Nakamura, Sergeyev, and Steinsson (2017) show that this relation is generally negative, particularly during economic contractions. Our model implies that the correlation should be more negative when CGP is high or equivalently when the SB correlation or the stock market leverage beta is negative, which we confirm in the data.

Finally, the model implies that the slope coefficient of the predictive relationship between current bond yields and future stock returns also varies as a function of CGP. Using our CGP proxies, we confirm this prediction in the data. Stock returns are strongly related to lagged bond yields, but only in environments where the SB correlation or leverage beta is negative. We also show that the source of this predictability is the real yield rather than the inflation component.

Thus, consumption shock persistence accounts for various stylized facts that are typically not linked together and whose explanations are still not fully understood. Furthermore, it uses an intuitive and relatively modest generalization of the standard LRR framework. As researchers examine the conditional implications of LRR more closely, it seems natural that time-varying correlations should play an important role.

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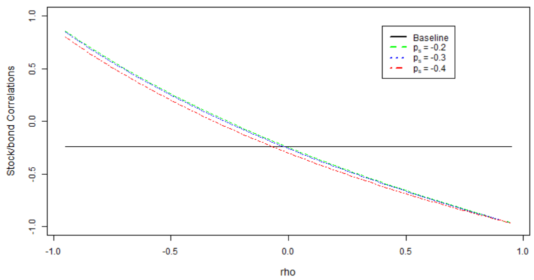
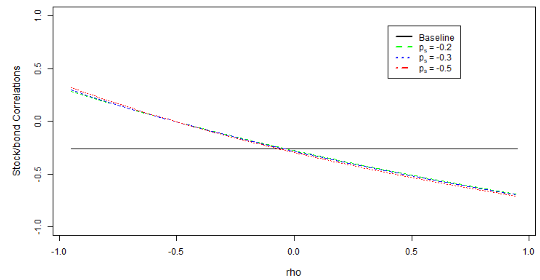
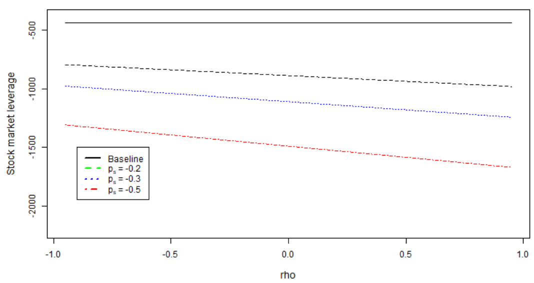


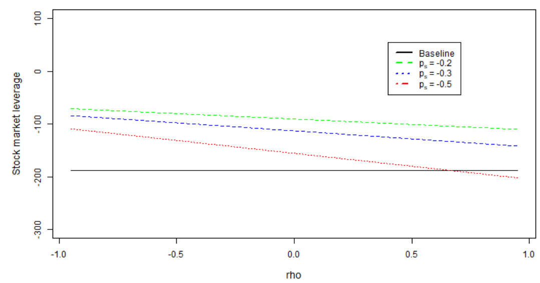
(a) Consumption-Only (Stock/bond)



(b) Full Model (Stock/bond)



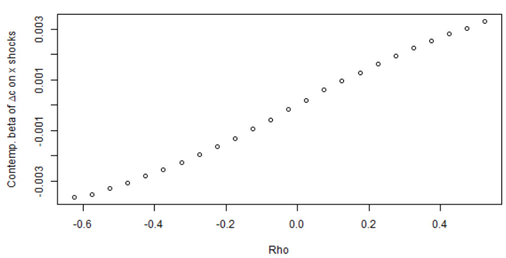
(c) Consumption-Only (Leverage Beta)



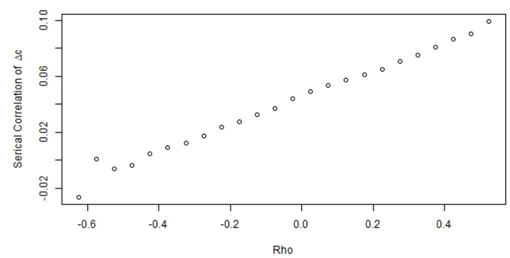
(d) Full Model (Leverage Beta)

Figure 1. Consumption Persistence and Model-based Correlations

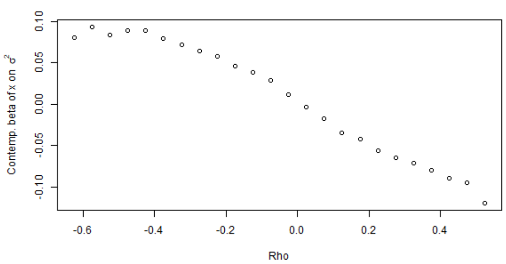
This figure shows the relationships between CGP and either the stock/bond return correlations or the stock market leverage betas under the consumption and dividend dynamics provided in the main text.



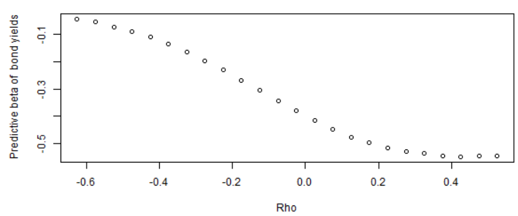
(a) Regression of Δc_t on x_t shocks



(b) Regression of Δc_{t+1} on Δc_t



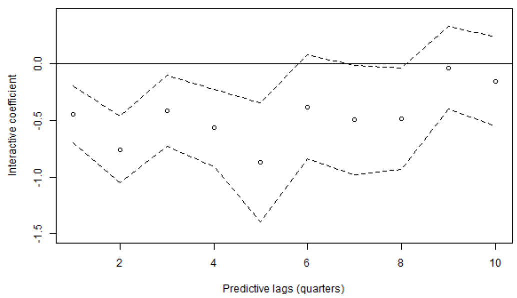
(c) Regression of x_t on σ_t^2



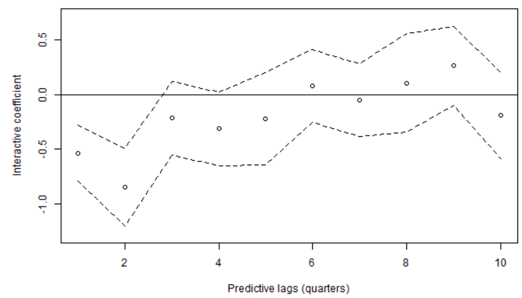
(d) Regression of MRP_t on y_t

Figure 2. Simulation-based Regression Betas Conditional on Consumption Growth Leverage

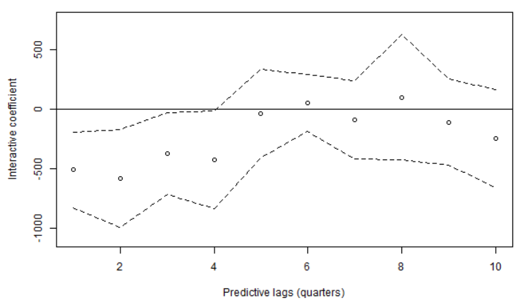
This figure describes the relationship between the slope coefficients of various simple linear regressions and CGP. MRP_t denotes the market risk premium at time t.



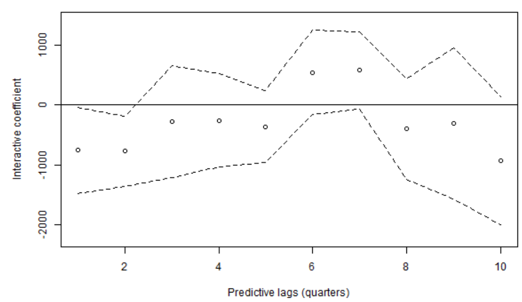
(a) Stock/bond correlations (daily)



(b) Stock/bond correlations (monthly)



(c) Stock market leverage (monthly)



(d) Stock market leverage (daily)

Figure 3. Interactive Beta of Consumption Growth Regressions For Multiple Lags
This figure plots the slope estimates ($\hat{\alpha}_{3,k}$) of the interactive regressions

$$\Delta c_{t+k} = \alpha_{0,k} + \alpha_{1,k}\Delta c_t + \alpha_{2,k} R_t \times \Delta c_t + \alpha_{3,k} R_t + \epsilon_{t+k},$$

for different values of the interval (k), where R_t is the stock/bond return correlation or the stock market leverage beta estimated using daily or monthly observations. The dotted lines show 90% confidence intervals.

Table I
Model Calibration

This table summarizes the parameters that describe the representative investor's preference and the dynamics of consumption and dividend growth, volatility, and covariance processes used as the main specification as well as asset pricing moments implied by these parameters. Panel A shows the values of the parameters, and Panel B shows the moments obtained via simulating the dynamics. y denotes bond yields, $R_{TW/m}$ is the return of the wealth (consumption only) or the market portfolio (full model), σ is the volatility of the wealth/market portfolio, SB Corr denotes the stock/bond return correlation, and Lev is the beta of market/wealth portfolio returns regressed on the first difference of market volatility. Values in Panel B are scaled to the annual level.

Panel A. Parameters

	Parameters		Parameters
Preference Parameters		Consumption Parameters	
γ	10	μ	0.0015
ψ	1.75	p_x	0.947
β	0.998	ϕ_x	0.044
Correlation Parameters		Variance Parameters	
ω_0	0	s_0	1.04×10^{7}
ω_1	0.947	s_1	0.991
σ_p	5.0×10^{-4}	σ_v	3.47×10^{-4}
Dividend Parameters		Precautionary Savings	
μ_d	0.0015	ϱ_{ps}	-0.3
ϕ_d	2.5		
φ_{cd}	3.0		
φ_d	4.5		

Panel B. Simulated Moments

	Baseline Model	Consumption-Only	Full Model	Data (1962-2019)
$E[R_{TW/m}]$	3.77%	3.79%	6.31%	6.86%
y (10-year real yields)	2.75%	2.88%	2.72%	2.67%
$\sigma_{TW/m}$	2.84%	2.92%	15.70%	15.24%
$SD(y)$	3.12%	3.20%	3.12%	2.77%
SB Corr	-0.25	-0.27	-0.28	-0.27
Lev	-188.39	-670.03	-112.94	-77.17
SV Corr	-0.07	-0.32	-0.26	-0.22

Table II
Relationships Between Simulated Values

This table summarizes the correlation between macroeconomic and asset pricing variables based on the simulation. Panel A shows the relationship between Δc_{t+1}, the shocks to x_{t+1}, σ_{t+1}, and the first-order difference in bond yields (y_{t+1}), returns of the total wealth/market portfolio ($R_{TW/m}$), and the first-order difference in the variance of the wealth/market portfolio ($\sigma_{TW/m,t+1}$). Panel B shows the relationship between CGP (ρ_t) and the model-based stock/bond correlations (SB Corr) or the stock market leverage (Lev). The simulations are based on 1,000,000 observations, where the first 100,000 are dropped when calculating the correlations. Model (1) is the baseline, (2) is the consumption only, and (3) is the full model.

Panel A. Relationships between simulated variables

	Model	Δy_{t+1}	$R_{TW/m,t+1}$	$\Delta\sigma^2_{TW/m,t+1}$
Δc_{t+1}	Baseline	-0.021	0.964	-0.001
	Consumption	0.015	0.965	-0.251
	Full Model	0.015	0.552	-0.279
$x_{t+1} - E_t[x_{t+1}]$	Baseline	0.976	0.251	0.000
	Consumption	0.971	0.244	0.000
	Full Model	0.971	0.250	0.000
$\sigma^2_{t+1} - E_t[\sigma^2_{t+1}]$	Baseline	-0.074	-0.142	0.997
	Consumption	-0.121	-0.361	0.843
	Full Model	-0.124	-0.263	0.935

Panel B. Correlation between ρ_t and proxies

Model	SB Corr	Lev
Consumption	-0.991	-1.000
Full Model	-0.996	-1.000

Table III
Predictability of Consumption Growth (I)

This table summarizes the slopes and the Newey-West adjusted t-statistics of quarterly regressions that examine the relationship between CGP and asset correlations. Panel A summarizes the results of

$$\Delta c_{t+1} = \alpha_0 + \alpha_1 \Delta c_t + \alpha_2 R_t \times \Delta c_t + \alpha_3 R_t + \epsilon_{1,t+1},$$

where R is either the stock/bond return correlation (SB Cor) or the stock market leverage beta divided by 100 (Lev). Panel B shows the results of the contemporaneous regression

$$\Delta c_t = \alpha_0' + \alpha_1' \Delta y_t + \alpha_2' R_t \times \Delta y_t + \alpha_3' R_t + \epsilon_{2,t},$$

where y_t is the nominal 10-year bond yield. In Panel C, we replace the nominal yield with the real yield (r_t).

Panel A. Serial Correlation of Consumption Growth

	Dependent Variable: Δc_{t+1}				
		SB Cor (D)	SB Cor (M)	Lev (D)	Lev (M)
Δc_t	0.486	0.489	0.411	−0.144	0.389
	(7.17)	(11.16)	(6.24)	(−0.35)	(5.35)
$\Delta c_t \times R_t$		−0.446	−0.381	−7.507	−3.218
		(−2.91)	(−1.75)	(−1.72)	(−1.90)
R_t		0.003	0.005	0.055	0.035
		(2.97)	(2.65)	(2.10)	(2.72)
Adj-R^2	0.233	0.255	0.238	0.240	0.288

Panel B. Consumption Growth and Bond Yield Innovations

	Dependent Variable: Δc_t				
		SB Cor (D)	SB Cor (M)	Lev (D)	Lev (M)
Δy_t	0.096	0.178	0.173	0.082	0.168
	(3.83)	(3.76)	(5.38)	(0.80)	(6.88)
$\Delta y_t \times R_t$		−0.401	−0.324	−9.911	−3.119
		(−3.18)	(−2.61)	(−1.79)	(−3.67)
R_t		0.003	0.004	0.131	0.034
		(1.41)	(1.89)	(1.65)	(2.20)
Adj-R^2	0.043	0.101	0.166	0.148	0.141

Panel C. Consumption Growth and Real Bond Yield Innovations

	Dependent Variable: Δc_t				
		SB Cor (D)	SB Cor (M)	Lev (D)	Lev (M)
Δr_t	0.112	0.165	0.150	−0.025	0.143
	(4.50)	(3.99)	(4.33)	(−0.21)	(4.97)
$\Delta r_t \times R_t$		−0.288	−0.199	−7.086	−1.786
		(−2.29)	(−1.56)	(−1.32)	(−1.84)
R_t		0.003	0.004	0.124	0.036
		(1.44)	(1.85)	(1.50)	(2.24)
Adj-R^2	0.073	0.081	0.175	0.105	0.189

Table IV
Stock/Bond Return Correlations and the Stock Market Leverage Effect

This table summarizes the slopes and Newey-West adjusted standard errors of contemporaneous regressions of realized stock/bond correlations on stock market leverage betas (Lev), with or without controlling for market volatility ($\hat{\sigma}_t$). Daily measures use daily data on stock and bond returns to compute the SB correlation and daily data on stock returns and VXO changes to compute the leverage beta and are estimated using 1-month and 12-month non-overlapping windows. Monthly measures use monthly data for returns and compute volatility changes using the long-run volatility estimate ($\hat{\sigma}_t$) from the Brandt and Jones (2006) two-factor EGARCH model and are estimated using non-overlapping 12-month and 60-month windows.

	Stock/Bond Correlation							
	Daily Measures				Monthly Measures			
	1M Estimation		12M Estimation		12 M Estimation		60 M Estimation	
$\hat{\sigma}_t$		−7.850		−8.047		−9.555		−0.031
		(−3.82)		(−3.50)		(−3.82)		(−0.01)
Lev_t	0.026	0.017	0.049	0.037	1.890	1.526	3.408	3.408
	(4.00)	(3.14)	(2.80)	(2.59)	(2.55)	(2.16)	(3.09)	(3.10)
Adj-R^2	0.058	0.147	0.122	0.062	0.053	0.201	0.189	0.293

Table V
Market Variance Predictability

This table summarizes the relationship between stock/bond correlations, the stock market leverage effect, and the market variance. In all regressions, the dependent variable is the realized variance of stock returns (RV_{t+1}) estimated using the sum of daily squared returns in the following month. Independent variables include the macro uncertainty measure of Jurado, Ludvigson, and Ng (2015), the monetary policy uncertainty measure of Baker, Bloom, and Davis (2016), and the consumption growth volatility estimate of Schorfheide, Song, and Yaron (2018). Uncertainty measures are interacted with either the monthly or daily measure of stock/bond return correlation or the stock market leverage beta.

Panel A. Uncertainty is Macro Uncertainty

	Dependent Variable: RV_{t+1}							
RV_t					0.439	0.463	0.461	0.370
					(3.11)	(3.07)	(3.14)	(2.62)
Uncertainty_t	0.016	0.017	0.018	0.051	0.008	0.008	0.009	0.030
	(2.62)	(2.33)	(2.45)	(2.93)	(2.79)	(2.50)	(2.74)	(2.59)
Uncertainty_t ×								
SB Cor_t(D)	−0.005				−0.003			
	(−2.59)				(−2.76)			
SB Cor_t(M)		−0.004				−0.002		
		(−1.85)				(−2.36)		
Lev_t(M)			−0.034				−0.016	
			(−2.43)				(−2.78)	
Lev_t(D)				0.000				−0.009
				(−0.28)				(−1.10)
Adj-R^2	0.158	0.112	0.125	0.225	0.312	0.304	0.303	0.326

Panel B. Uncertainty is Monetary Policy Uncertainty

	Dependent Variable: RV_{t+1}							
RV_t					0.443	0.454	0.484	0.500
					(3.21)	(3.14)	(3.07)	(3.37)
Uncertainty_t	0.067	0.125	0.085	0.067	−0.064	0.013	−0.019	−0.187
	(1.17)	(1.80)	(1.77)	(1.17)	(−1.80)	(0.31)	(−0.50)	(−2.38)
Uncertainty_t ×								
SB Cor_t(D)	−0.584				−0.374			
	(−2.11)				(−2.21)			
SB Cor_t(M)		−0.506				−0.306		
		(−1.49)				(−1.83)		
Lev_t(M)			−3.697				−1.648	
			(−1.98)				(−2.34)	
Lev_t(D)				−0.123				−2.832
				(−1.61)				(−2.06)
Adj-R^2	0.143	0.105	0.073	0.084	0.300	0.289	0.272	0.284

Panel C. Uncertainty is Consumption Growth Volatility

	Dependent Variable: RV_{t+1}							
RV_t					0.441	0.474	0.484	0.457
					(3.05)	(3.00)	(3.04)	(2.77)
Uncertainty_t	0.004	0.003	0.004	0.004	0.002	0.002	0.002	0.002
	(2.79)	(2.30)	(2.49)	(2.48)	(2.49)	(2.16)	(2.38)	(1.17)
Uncertainty_t ×								
SB Cor_t(D)	−0.006				−0.003			
	(−2.40)				(−2.40)			
SB Cor_t(M)		−0.004				−0.002		
		(−1.65)				(−2.23)		
Lev_t(M)			−0.026				−0.011	
			(−2.19)				(−2.38)	
Lev_t(D)				−0.002				−0.032
				(−1.83)				(−2.19)
Adj-R^2	0.157	0.078	0.090	0.109	0.313	0.303	0.297	0.300

Table VI
Predictability of Consumption Growth (II)

This table summarizes the results of the predictive regression

$$\Delta c_{t+1} = \beta_0 + \beta_1 UNC_t + \beta_2 R_t \times UNC_t + \beta_3 R_t + \beta_4 \Delta c_t + \epsilon_{t+1},$$

where R is either the stock/bond correlation or the stock market leverage beta, and the proxies of uncertainty (UNC) are defined as in previous tables.

Panel A. Stock/Bond Return Correlation (Daily)

	Dependent Variable: Δc_{t+1}											
	UNC = MU			UNC = MPU			UNC= HX			UNC= $\hat{\sigma}_{m,t}$		
UNC_t	−0.025	−0.016	−0.028	0.016	0.039	0.020	−0.004	−0.002	−0.005	−0.083	−0.034	−0.077
	(−5.51)	(−4.16)	(−7.03)	(0.20)	(0.70)	(0.26)	(−2.19)	(−1.37)	(−2.62)	(−2.14)	(−1.33)	(−1.87)
$\text{UNC}_t \times R_t$	0.005	0.003	0.030	0.361	0.242	0.393	0.005	0.000	0.011	0.057	0.043	0.140
	(3.05)	(2.65)	(1.90)	(1.76)	(2.26)	(1.87)	(2.27)	(2.11)	(1.65)	(1.18)	(1.47)	(1.31)
R_t			−0.024			0.000			−0.007			−0.004
			(−1.54)			(−0.17)			(−0.95)			(−0.98)
Δc_t		0.342			0.419			0.437			0.419	
		(5.44)			(4.90)			(8.61)			(8.67)	
Adj-R^2	0.216	0.305	0.224	0.093	0.252	0.087	0.079	0.259	0.104	0.115	0.259	0.116

Panel B. Stock/Bond Return Correlation (Monthly)

	Dependent Variable: Δc_{t+1}											
	UNC = MU			UNC = MPU			UNC= HX			UNC= $\hat{\sigma}_{m,t}$		
UNC_t	−0.013	−0.013	−0.023	−0.034	−0.009	−0.049	−0.003	−0.001	−0.003	−0.024	−0.003	−0.004
	(−0.24)	(−3.04)	(−5.14)	(−0.73)	(−0.24)	(−1.14)	(−1.40)	(−0.90)	(−1.57)	(−0.68)	(−0.01)	(−0.11)
$\text{UNC}_t \times R_t$	0.505	0.004	0.031	0.505	0.296	0.297	0.006	0.004	0.009	0.121	0.084	0.288
	(2.62)	(3.06)	(1.85)	(3.11)	(2.90)	(1.61)	(2.35)	(2.47)	(1.24)	(2.42)	(2.58)	(2.79)
R_t			−0.024			0.003			−0.004			−0.008
			(−1.46)			(1.05)			(−0.62)			(−1.95)
Δc_t		0.307			0.369			0.389			0.362	
		(3.81)			(4.18)			(5.48)			(5.73)	
Adj-R^2	0.113	0.251	0.215	0.154	0.260	0.154	0.120	0.246	0.118	0.139	0.247	0.154

Panel C. Stock Market Leverage (Daily)

	Dependent Variable: Δc_{t+1}											
	UNC = MU			UNC = MPU			UNC= HX			UNC= $\hat{\sigma}_{m,t}$		
UNC_t	−0.030	−0.025	0.005	0.099	0.089	0.070	−0.002	−0.006	0.007	−0.003	0.101	0.152
	(−3.01)	(−0.38)	(0.15)	(0.94)	(1.03)	(0.54)	(−0.63)	(−0.38)	(0.01)	(−0.01)	(0.48)	(1.30)
$\text{UNC}_t \times R_t$	0.020	0.013	0.447	2.584	1.638	2.215	0.049	0.028	0.172	0.650	0.481	2.512
	(0.95)	(0.91)	(1.20)	(2.09)	(1.69)	(1.25)	(2.01)	(1.84)	(1.50)	(1.47)	(1.64)	(1.65)
R_t			−0.389			0.005			−0.127			−0.004
			(−1.18)			(0.23)			(−1.12)			(−1.44)
Δc_t		0.360			0.437			0.400			0.429	
		(3.56)			(4.04)			(3.79)			(4.27)	
Adj-R^2	0.178	0.283	0.179	0.065	0.231	0.058	0.143	0.266	0.159	0.080	0.234	0.089

Panel D. Stock Market Leverage (Monthly)

	Dependent Variable: Δc_{t+1}											
	UNC = MU			UNC = MPU			UNC= HX			UNC= $\hat{\sigma}_{m,t}$		
UNC_t	−0.024	−0.015	−0.025	0.040	0.042	0.029	−0.003	−0.001	−0.003	−0.025	−0.005	0.005
	(−5.06)	(−3.91)	(−6.56)	(0.81)	(0.99)	(0.47)	(−1.50)	(−0.99)	(−1.58)	(−0.63)	(−0.27)	(0.02)
$\text{UNC}_t \times R_t$	0.054	0.039	0.270	3.930	2.374	3.499	0.042	0.024	0.090	0.888	0.572	2.336
	(4.10)	(3.74)	(2.03)	(3.09)	(3.05)	(1.72)	(2.84)	(2.47)	(1.37)	(2.27)	(2.19)	(1.96)
R_t			−0.201			0.005			−0.056			−0.062
			(−1.62)			(0.20)			(−0.81)			(−1.39)
Δc_t		0.266			0.398			0.376			0.372	
		(3.24)			(3.97)			(4.63)			(5.40)	
Adj-R^2	0.242	0.292	0.251	0.119	0.254	0.113	0.130	0.241	0.159	0.119	0.232	0.129

Table VII
Market Return Predictability

This table summarizes the results of the regression

$$R^e_{S,t+1} = \beta_0 + \beta_1 \text{Yield}_t + \beta_2 \text{Yield}_t \times R_t + \epsilon_{t+1},$$

where R^e_S and Yield are the value-weighted market excess return and the nominal (y_t) or estimated real yields (r_t) of the one-year constant maturity Treasury, respectively. R_t is either the estimated correlation between stock and bond returns (SB Corr) or the slope of the market returns regressed on the first-order difference in market volatility divided by 100 (Lev). The correlations and the leverage betas are estimated using daily (columns "Daily") or monthly (columns "Monthly") observations. The t-statistics are adjusted for heteroscedasticity and autocorrelation using Newey-West standard errors.

Panel A. Simple predictive regressions

	One-month	Three-month	Six-month	Twelve-month
y_t	−0.088	−0.201	−0.339	−0.621
	(−1.64)	(−1.56)	(−1.28)	(−1.29)
Adj-R^2	0.003	0.006	0.009	0.008

Panel B. Interactive predictive regressions using stock/bond return correlations

	One-month		Three-month		Six-month		Twelve-month	
	Daily	Monthly	Daily	Monthly	Daily	Monthly	Daily	Monthly
y_t	−0.271	−0.170	−0.781	−0.411	−1.410	−0.771	−2.120	−1.398
	(−3.21)	(−2.69)	(−3.61)	(−2.78)	(−3.60)	(−2.69)	(−2.82)	(−2.52)
$y_t \times$ SB Corr_t	0.585	0.291	1.757	0.765	3.420	1.632	5.099	3.389
	(2.47)	(1.87)	(2.91)	(1.93)	(3.07)	(2.16)	(2.39)	(2.19)
Adj-R^2	0.014	0.005	0.040	0.014	0.072	0.027	0.080	0.050

Panel C. Interactive predictive regressions using stock market leverage betas

	One-month		Three-month		Six-month		Twelve-month	
	Daily	Monthly	Daily	Monthly	Daily	Monthly	Daily	Monthly
y_t	0.123	−0.150	0.443	−0.373	0.997	−0.640	2.088	−0.997
	(0.73)	(−2.43)	(1.32)	(−2.48)	(1.63)	(−2.06)	(2.16)	(−1.78)
$y_t \times \text{Lev}_t$	0.287	0.024	1.022	0.061	2.281	0.112	4.763	0.184
	(1.25)	(2.07)	(2.15)	(2.15)	(2.55)	(2.05)	(2.16)	(1.99)
Adj-R^2	0.001	0.009	0.015	0.021	0.044	0.033	0.096	0.042

Panel D. Interactive predictive regressions using stock/bond return correlations

	One-month		Three-month		Six-month		Twelve-month	
	Daily	Monthly	Daily	Monthly	Daily	Monthly	Daily	Monthly
r_t	−0.190	−0.218	−0.514	−0.508	−1.035	−0.940	−1.853	−1.712
	(−2.25)	(−2.79)	(−2.47)	(−2.60)	(−2.84)	(−2.63)	(−2.82)	(−2.94)
$r_t \times$ SB Corr_t	0.101	0.372	1.765	1.022	3.306	2.938	7.131	6.959
	(0.28)	(1.18)	(1.08)	(1.34)	(2.32)	(2.17)	(2.50)	(2.70)
Adj-R^2	0.005	0.005	0.015	0.020	0.040	0.032	0.078	0.067

Panel E. Interactive predictive regressions using stock market leverage betas

	One-month		Three-month		Six-month		Twelve-month	
	Daily	Monthly	Daily	Monthly	Daily	Monthly	Daily	Monthly
r_t	0.241	−0.171	0.791	−0.397	2.307	−0.621	5.426	−0.956
	(0.68)	(−2.21)	(1.13)	(−2.13)	(1.77)	(−1.78)	(2.63)	(−1.60)
$r_t \times \text{Lev}_t$	0.451	0.025	1.452	0.080	3.871	0.199	8.914	0.400
	(1.01)	(1.10)	(1.65)	(1.48)	(2.24)	(2.06)	(3.05)	(2.24)
Adj-R^2	0.000	0.000	0.010	0.010	0.039	0.034	0.099	0.056

A. Technical appendix

1. The wealth-consumption ratio

Following the Campbell-Shiller decomposition, the returns to total wealth portfolio can be represented by

$$R_{TW,t+1} = \kappa_0 + \Delta c_{t+1} + A_0(\kappa_1 - 1) + A_1(\kappa_1 x_{t+1} - x_t) + A_2(\kappa_1 \sigma_{t+1}^2 - \sigma_t^2) + A_3(\kappa_1 p_{t+1} - p_t).$$

The intertemporal marginal rate of substitution (IMRS) is

$$\begin{aligned} m_{t+1} = \theta \log\beta - \gamma\Delta c_{t+1} + (\theta - 1)\big[\kappa_0 + A_0(\kappa_1 - 1) + A_1(\kappa_1 x_{t+1} - x_t) \\ + A_2(\kappa_1 \sigma_{t+1}^2 - \sigma_t^2) + A_3(\kappa_1 p_{t+1} - p_t)\big]. \end{aligned}$$

The unexpected component of the IMRS is represented by

$$m_{t+1} - \mathrm{E}_t[m_{t+1}] = \lambda_c \sigma_t \epsilon_{c,t+1} + \lambda_x \sigma_t \epsilon_{x,t+1} + \lambda_v \sigma_t \epsilon_{v,t+1} + \lambda_\delta \sigma_t \epsilon_{p,t+1},$$

where $\lambda_c = -\gamma$, $\lambda_x = (\theta - 1)\kappa_1 A_1 \phi_x$, $\lambda_v = (\theta - 1)\kappa_1 A_2 \sigma_v$, and $\lambda_\delta = (\theta - 1)\kappa_1 A_3 \sigma_p$.

We solve for A_0, A_1, A_2, and A_3 using equation using the Euler equation $\mathrm{E}_t[m_{t+1} + R_{TW,t+1}] + \mathrm{Var}_t[m_{t+1} + R_{TW,t+1}] = 0$. For A_1, we collect all terms associated with x_t:

$$A_1 = \frac{1 - \frac{1}{\psi}}{1 - \kappa_1 p_1}.$$

Collecting the terms from the Euler equation that are functions of σ_t^2 and p_t, it can be seen that A_2 and A_3 must jointly satisfy the conditions

$$2A_2(\kappa_1 s_1 - 1) + \theta\Big((A_1\kappa_1\varphi_x)^2 + (A_2\kappa_1\sigma_v)^2 + (A_3\kappa_1\sigma_p)^2 + (1 - \frac{1}{\psi})^2\Big) + 2(1-\gamma)\kappa_1 A_2 \sigma_v \varrho_{ps} = 0$$

$$A_3 = A_{30} + A_{32} A_2,$$

where $A_{30} = \frac{(1-\gamma)\kappa_1 A_1 \varphi_x}{1-\kappa_1\omega_1} < 0$ and $A_{32} = \frac{\theta \varrho_{ps} \kappa_1^2 A_1 \varphi_x \sigma_v}{1-\kappa_1\omega_1} > 0$.

A_2 can be obtained by solving a quadratic equation after plugging the second equation into the first. It can also be shown that $A_2 < 0$ when $\gamma > 1$ and $\psi > 1$ by evaluating the characteristics of the quadratic equation. We obtain two values for A_2. We choose the value that is closer to the baseline model. The second value generates unrealistic moments of asset returns. The negative sign of A_2 also implies $A_3 < 0$.

Finally, A_0 satisfies $A_0 = \frac{1}{1-\kappa_1}\Big[\log\beta + \kappa_0 + (1-\frac{1}{\psi})\mu + k_1(A_2 s_0 + A_3\omega_0)\Big]$.

2. The price-dividend ratio

Similar to the wealth-consumption ratio, market returns can be expressed as

$$R_{m,t+1} = \kappa_0 + \Delta d_{t+1} + A_{m,0}(\kappa_1 - 1) + A_{m,1}(\kappa_1 x_{t+1} - x_t) + A_{m,2}(\kappa_1\sigma^2_{t+1} - \sigma^2_t) + A_{m,3}(\kappa_1 p_{t+1} - p_t).$$

We again solve for the coefficients using the Euler equation $E_t[m_{t+1} + R_{m,t+1}] + 0.5Var_t[m_{t+1} + R_{m,t+1}] = 0$. Collecting the terms associated with x_t, σ^2_t, and p_t, we can solve for $A_{m,0}, A_{m,1}, A_{m,2}$, and $A_{m,3}$. First, we have

$$A_{m,1} = \frac{\phi_d - \frac{1}{\psi}}{1 - \kappa_1 p_1}.$$

As in the wealth-consumption ratio, $A_{m,2}$, and $A_{m,3}$ must jointly satisfy the conditions

$$\begin{aligned}
&2A_{m,2}(\kappa_1 s_1 - 1) + 2(\theta-1)(\kappa_1 s_1 - 1)A_2 + 2(\varphi_{cd} + \lambda_c)(\kappa_1 A_{m,2}\sigma_v + \lambda_v)\varrho_{ps} \\
&\qquad + (\kappa_1 A_{m,1}\varphi_x + \lambda_x)^2 + (\kappa_1 A_{m,2}\sigma_v + \lambda_v)^2 + (\kappa_1 A_{m,3}\sigma_p + \lambda_\delta)^2 + (\varphi_{cd} + \lambda_c)^2 + \varphi_d^2 = 0 \\
&A_{m,3} = A_{m,30} + A_{m,32}A_{m,2},
\end{aligned}$$

where $A_{m,30} = \frac{1}{1-\kappa_1\omega_1}\big((\varphi_{cd}+\lambda_c)(\kappa_1 A_{m,1}\varphi_x + \lambda_x) + (\theta-1)(\kappa_1\omega_1 - 1)A_3 + \lambda_v(\kappa_1 A_{m,1}\varphi_x + \lambda_x)\varrho_{ps}\big)$ and $A_{m,32} = \frac{1}{1-\kappa_1\omega_1}\kappa_1\sigma_v(\kappa_1 A_{m,1}\varphi_x + \lambda_x)\varrho_{ps}$. Evaluating the characteristics of the quadratic function, similar to the earlier case, $A_{m,2} < 0$ when $\gamma > \varphi_{cd} > 1$, which is consistent with a general long-run risk specification. Also, one can show that $A_{m,30} <$ and $A_{m,32} > 0$, under the condition of $\gamma > \phi_d$ and $\varphi_{cd} > 1$, which implies $A_{m,3} < 0$.

Finally, $A_{m,0}$ satisfies

$$\begin{aligned}
A_{m,0} = \frac{1}{1-\kappa_1}\big(&\theta\log\beta + \theta\kappa_0 + (1-\gamma)\mu \\
&+ \kappa_1 s_0(A_2(\theta-1) + A_{m,2}) + \kappa_1\omega_0(A_3(\theta-1) + A_{m,3}) + (\theta-1)(\kappa-1)A_0\big).
\end{aligned}$$

3. The stock/bond correlation

The interest rate on a riskless bond is derived by solving

$$\mathrm{E}_t[m_{t+1}] + 0.5\mathrm{Var}_t[m_{t+1}] = 0.$$

It can be shown that the yield of the bond is represented by

$$y_t = Y_0 + Y_1 x_t + Y_2 \sigma_t^2 + Y_3 p_t,$$

where

$$\begin{aligned}
Y_0 &= -\theta \log \beta + \gamma\mu - (\theta - 1)\left(\kappa_0 + (\kappa_1 - 1)A_0 + \kappa_1 s_0 A_2 + \kappa_1 \omega_0 A_3\right) \\
Y_1 &= \frac{1}{\psi} \\
Y_2 &= -(\theta - 1)(\kappa_1 s_1 - 1)A_2 - \frac{1}{2}\left(\lambda_c^2 + \lambda_x^2 + \lambda_v^2 + \lambda_\delta^2\right) - \lambda_c \lambda_v \varrho_{ps} \\
Y_3 &= -(\theta - 1)(\kappa_1 \omega_1 - 1)A_3 - \lambda_x \lambda_v \varrho_{ps} - \lambda_c \lambda_x.
\end{aligned}$$

The unexpected return of the total wealth portfolio and the market return are derived using the Campbell-Shiller decomposition:

$$\begin{aligned}
R_{TW,t+1} - E_t[R_{TW,t+1}] &= \kappa_1 \phi_x A_1 \sigma_t \epsilon_{x,t+1} + \kappa_1 \sigma_v A_2 \sigma_t \epsilon_{v,t+1} + \kappa_1 \sigma_p A_3 \epsilon_{p,t+1} + \sigma_t \epsilon_{c,t+1} \\
R_{m,t+1} - E_t[R_{m,t+1}] &= \kappa_1 \phi_x A_{m,1} \sigma_t \epsilon_{x,t+1} + \kappa_1 \sigma_v A_{m,2} \sigma_t \epsilon_{v,t+1} + \kappa_1 \sigma_p A_{m,3} \epsilon_{p,t+1} + \varphi_{cd} \sigma_t \epsilon_{c,t+1} + \varphi_d \sigma_t \epsilon_{d,t+1}
\end{aligned}$$

We represent the above relationship by:

$$S_{j,1} \sigma_t \epsilon_{x,t+1} + S_{j,2} \sigma_t \epsilon_{v,t+1} + S_{j,3} \sigma_t \epsilon_{p,t+1} + S_{j,c} \sigma_t \epsilon_{c,t+1} + S_{j,d} \sigma_t \epsilon_{d,t+1},$$

where j is either TW for the wealth portfolio or m for the market portfolio. From the above equation, we can derive the stock/bond return correlation by taking the negative of conditional correlation between wealth portfolio/market returns and bond yields.

The conditional covariance can be expressed as

$$\begin{aligned}
\mathrm{Cov}_t(R_{j,t+1}, y_{t+1}) &= \left(Y_1 S_{j,1} \varphi_x + Y_2 S_{j,2} \sigma_v + Y_3 S_{j,3} \sigma_p + Y_2 S_{j,c} \sigma_v \varrho_{ps}\right) \sigma_t^2 \\
&\quad + \left((Y_1 \varphi_x S_{j,2} + Y_2 S_{j,1} \sigma_v) \varrho_{ps} + Y_1 S_{j,c} \varphi_x\right) p_t.
\end{aligned}$$

The conditional variance of the bond yield is

$$\mathrm{Var}_t(y_{t+1}) = \left((Y_1 \varphi_x)^2 + (Y_2 \sigma_v)^2 + (Y_3 \sigma_p)^2\right) + 2 Y_1 Y_2 \varphi_x \sigma_v p_t.$$

Similarly, the conditional variance of the wealth portfolio/market returns is

$$\sigma_{j,t+1}^2 = (V_{j,2} + V_{j,3} \rho_t) \sigma_t^2$$

for $j = \{TW, m\}$, where $V_{j,2} = \sum_{k=1}^{3} (S_{j,k}^2 + S_{j,c}^2 + S_{j,d}^2) + 2 S_{j,c} S_{j,2} \varrho_{ps}$ and $V_{j,3} = 2 S_{j,1} S_{j,2} \varrho_{ps} + 2 S_{j,c} S_{j,1}$.

4. The stock market leverage effect

The leverage correlation is the conditional covariance between the returns and variance shocks of the wealth portfolio divided by the conditional standard deviations of each. The covariance can be represented by

$$\mathrm{Cov}_t(R_{j,t+1}, \sigma^2_{j,t+1}) = \left[(S_2 + S_c\varrho_{ps})V_2\sigma_v + S_3V_3\sigma_p + S_1V_2\sigma_v\varrho_{ps}\rho_t\right]\sigma_t^2,$$

for $j = \{TW, m\}$. Dividing the above by the variance of variance shocks yields the stock market leverage effect. The variance of the market variance shocks is

$$\big((V_2\sigma_v)^2 + (V_3\sigma_p)^2\big)\sigma_t^2.$$

5. The market risk premium

The risk premium of the wealth/market portfolio can be expressed as

$$\mathrm{Cov}_t(-m_{t+1}, R_{j,t+1}) = \big(-\lambda_c(S_{j,c} + S_{j,2}\varrho_{ps}) - \lambda_x S_{j,1} - \lambda_v S_{j,2} - \lambda_\delta S_{j,3} - S_{j,c}\lambda_v\varrho_{ps}\big)\sigma_t^2$$
$$(-\lambda_x S_{j,2}\varrho_{ps} - \lambda_v S_{j,1}\varrho_{ps} - \lambda_c S_{j,1} - \lambda_x S_{j,c})p_t$$

for $j = \{TW, m\}$.