Risk and Return in Government Bonds*

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Abstract

As the risks of government bonds change over time, does the compensation that investors require for holding them change? While realized excess returns show little relation to bond risk, we find that subjective expected excess returns constructed from professional forecasts of future long-term yields are tightly linked to bonds' stock market betas, consistent with a CAPM-style relation. In a U.S. month-by-maturity panel from 1988–2024, the correlation of subjective excess returns with rolling bond–stock betas is 66%. The estimated market price of risk is comparable to the equity premium and stable when controlling for time and maturity fixed effects. Realized excess returns are predicted by subjective excess returns, but this predictability is driven by higher-frequency variation and not by betas. Similar results hold in an international panel of developed countries from 1989–2024. The change in betas from positive to negative accounts for half of the decline in long-term U.S. Treasury yields from the 1980s to the 2010s and implies a negative term premium as early as 2001. During quantitative easing episodes, the price of bond risk declines, suggesting an increased investor willingness to bear risk.

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1. Introduction

Long-term government bonds are often viewed as safe assets, yet even in the absence of default risk, they can expose investors to substantial interest-rate and inflation risk. In the United States in the 1970s and 1980s, government bonds were risky in the sense that they exhibited strong comovement with stocks. By contrast, in the 2000s, they were largely hedges, negatively correlated with stocks. Bond returns have again recently become more positively correlated with stock returns in the U.S. and other advanced economies. These shifts raise a natural question: How do changes in bond risk translate into the returns investors require for holding long-term government bonds?

We provide new evidence on the link between expected excess returns on government bonds and their underlying risk exposures. In the classic capital asset pricing model (CAPM) of Sharpe (1964) and Lintner (1965), expected excess returns are proportional to an asset's beta with respect to the market portfolio. We show new evidence that expected excess returns on government bonds are well described by a CAPM-style relation once subjective interest rate expectations are incorporated. Using forecasts of government bond yields made by professional forecasters, we construct one-year expected bond excess returns purged of interest-rate surprises. We find that these subjective expected excess returns are tightly related to bond–stock betas, with an implied price of risk close to the equity premium. The relationship holds over time and across maturities in U.S. data, as well as in an international panel of developed countries spanning nearly four decades.

Figure 1 illustrates the importance of using subjective expected bond excess returns to uncover this result for the U.S. Panel A plots realized one-year bond excess returns on the y-axis against bond-stock betas on the x-axis. Each dot corresponds to a month-by-bond maturity combination.[1] The risks of Treasury bonds have varied substantially over time. In broad strokes, Treasury bonds turned from being risky with positive betas before 2000, to being hedges with negative bond-stock betas after 2000, though there is also substantial higher-frequency variation.[2] According to the CAPM, one would expect a positive relationship between bond excess returns and the risk of bonds, but no such relationship is visible in Panel A.

By contrast, we see a strongly positive relationship in Panel B, where excess returns are cleansed from the effects of yield surprises using professional survey forecasts of future bond yields. When bond-stock betas were negative in the 2000s, forecasters expected negative

[1] Betas are estimated over five-year rolling windows from daily bond and stock excess returns. We use three, six, and eleven-year par bond excess returns and the corresponding betas to match the bond maturities available in the Blue Chip Financial Forecasts (BCFF).

[2] See Campbell et al. (2026) for a review of variation in bond-stock betas and their economic drivers.

excess returns on government bonds. Conversely, when betas were positive and bonds were risky, forecasters expected positive excess returns. The slope of the relationship in Panel B is 11% annualized with a raw correlation of 66%.

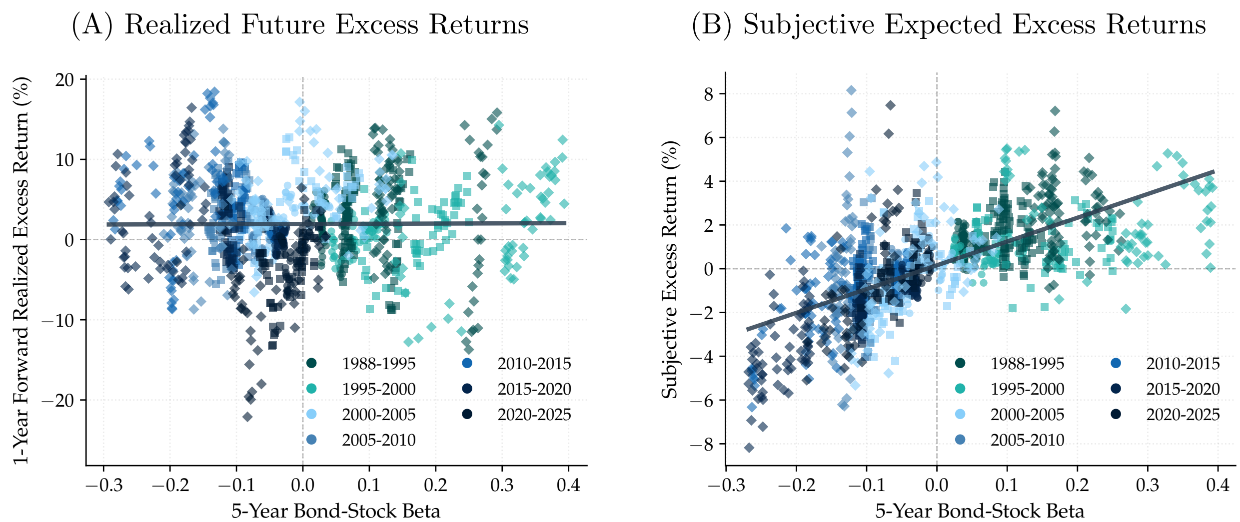
We start by developing a stylized term-structure model that can account for our empirical results. The aim of the model is to characterize conditions under which subjective expected excess returns are well explained by bond–stock betas, while realized excess returns are not. In the model, the short rate and bond-stock betas both follow AR(1) processes. We allow both market and forecaster expectations to deviate from rational expectations. In particular, markets and forecasters may form expectations about future short rates and bond–stock betas using persistence parameters that differ from the true data-generating process. We then derive the loading of subjective expected excess returns on bond–stock betas, and compare it to the corresponding loading for realized excess returns.

Two key lessons emerge. First, subjective expected excess returns can load on bond–stock betas even if forecasters do not explicitly use the CAPM when forming yield forecasts. As long as market yields adjust to betas more than forecasters' expected future yields do, subjective expected excess returns will be strongly related to betas. Second, noise and biased expectations can weaken the relationship between realized excess returns and bond–stock betas. In particular, if markets underestimate the persistence of bond–stock betas, the loading of realized excess returns on betas is attenuated. Guided by the model, we then document a number of empirical facts.

First, we document the empirical relationship between subjective expected bond excess returns and rolling bond–stock betas in the U.S. We use a bond maturity-by-month panel from January 1988 through March 2024. Subjective expected excess returns are constructed using the average four-quarter-ahead forecast of 2-, 5-, and 10-year Treasury yields from Blue Chip Financial Forecasters (BCFF). Following Piazzesi et al. (2015) and Nagel and Xu (2023), we compute expected one-year bond excess returns analogously to realized one-year excess returns, replacing the realized bond yield one year ahead with its survey forecast. Bond–stock betas are computed from daily bond and stock excess returns using a five-year backward-looking rolling windows. We find substantial variation in both subjective expected excess returns and bond–stock betas.

In a panel regression of U.S. subjective expected excess returns onto betas, we find an economically and statistically significantly positive relationship, consistent with the evidence in Figure 1 Panel B. The magnitude and significance of the relationship are unchanged when we control for a time trend, maturity and time fixed effects, the term spread, or the principal components of yields. The relationship is also similar for each bond maturity, with or without controlling for a time trend. A higher bond return variance is also associated with higher

Figure 1: Bond Excess Returns and Bond-Stock Betas



Note: Panel A plots realized excess returns on U.S. Treasury bonds—computed over the subsequent one-year period—against their five-year stock-market betas for different maturities. Panel B plots subjective expected excess returns against the corresponding five-year stock-market betas. Maturities are distinguished by marker shape: three-year bonds (circles), six-year bonds (squares), and eleven-year bonds (diamonds). The sample spans January 1988 to March 2024.

subjective excess returns, but leaves the coefficient on bond-stock betas unchanged and offers only limited additional explanatory power.

We next decompose subjective expected excess returns into the current-yield component and the forecasted-yield component. Since subjective expected excess returns depend positively on current market yields and negatively on forecasted future yields, they load on bond–stock betas when current yields are more sensitive to betas than forecasted yields are. This is what we find. The result is consistent with our model. What matters for subjective expected excess returns is that market yields price bond–stock betas. If forecasted future yields respond less strongly to current bond–stock betas than market yields do, this only strengthens the relationship between subjective expected returns and betas.

We then show that this relationship is not explained by inflation or by simple forecasting rules. The loading on bond–stock betas remains after controlling for inflation uncertainty and long-run expected inflation. Since Shue et al. (2025) shows that forecasts of long-term yields are strongly related to forecasts of short-term rates, we control for expected changes in the federal funds rate. The loading on bond–stock betas is largely unchanged. The result is also robust to controlling for pseudo expected excess returns based on autoregressive forecasts, moving-average forecasts, and the slow-learning model of Farmer et al. (2024). In other words, simple forecasting rules for long-term yields do not generate expected returns that are strongly correlated with betas.

Next, we document that subjective excess returns predict future realized excess returns, even though betas do not. In other words, the component of subjective expected returns orthogonal to betas strongly predicts future realized returns with a coefficient not statistically distinguishable from the full information rational expectations (FIRE) benchmark. In our sample period, the slow-moving component associated with bond-stock betas does not predict realized excess returns, but the higher-frequency residual in expected bond excess returns does. This suggests that professional forecasters have information about the bond market, but our sample may be too short to detect a significant relationship between realized bond excess returns and slow-moving betas.

We show that these new facts carry over to an international panel of twelve developed economies from September 1989 to December 2024, where subjective expected excess returns for non-U.S. countries are constructed using 12-month forecasts of 10-year government bond yields from Consensus Economics. The international panel adds important new time variation, with some countries, such as Japan, already experiencing negative bond-stock betas in the mid-1990s, when U.S. betas were still positive. Matching this different pattern in betas, subjective bond excess returns turned negative earlier in Japan than in the U.S.

In a panel regression for the twelve developed countries, we estimate a strong and positive relationship between betas and subjective expected excess returns. A unit increase in beta is associated with an 8 percentage point higher expected excess return. This strong positive relationship holds when controlling for a time trend or country and time fixed effects, and the term spread, long-term, and short-term interest rates. Bond return variance enters positively but not significantly for the international panel. The estimated relationship between subjective excess returns and betas is positive and indistinguishable from the U.S. coefficient for all countries in our sample, and is generally precisely estimated.[3] Similarly to the U.S., subjective excess returns in the international panel have predictive power for realized bond excess returns, so forecasters appear to be informed. The relationship between bond-stock betas and realized bond excess returns is positive but imprecisely estimated, consistent with the idea that realized bond excess returns are too noisy over our sample to detect a relationship with slow-moving betas.

We use our findings to provide a simple decomposition of long-term Treasury yields into risk-neutral and term premium components. The decline in U.S. Treasury yields since the 1980s has generated an active debate over the extent to which the natural rate—i.e., the

[3]Only a small number of countries with substantial credit risk, Italy and Spain, and some countries with shorter samples, such as Norway and Switzerland, have insignificant relationships between betas and expected bond excess returns.

real rate absent cyclical fluctuations—has fallen. Declining natural rates could be driven by a secular decline in economic growth and lower inflation (Laubach and Williams, 2016). Our estimates suggest that about half the decline in 10-year Treasury yields from 1986 to 2016–the end of the first zero-lower-bound period–and half of their increase since 2016 can be attributed to term premia due to changing bond risks. The increasing risk of real (i.e., inflation-indexed) bonds accounts for the majority of the recent increase. While our estimated peak-to-trough change in term premia is similar to conventional term premium estimates (Adrian et al., 2013; Kim and Wright, 2011; Bauer and Rudebusch, 2020), the timing is different. We estimate an earlier switch to negative term premia, well before the global financial crisis. This matters for monetary policy. For example, if monetary policy should optimally lower the policy rate in response to a decline in the natural rate but not in response to negative term premia, understanding that term premia were negative could have led to higher policy rates.

We then use our international panel and framework as an application to study the channels through which quantitative easing (QE) operates. Over the last 25 years, central banks around the world have engaged in large-scale asset purchases with the purpose of lowering long-term bond yields when traditional short-term policy rates were constrained by the zero lower bound. We find that during QE periods, the price of risk that investors require for holding bonds declines, broadly consistent with the "portfolio balance channel" (Tobin, 1958, 1969; Vayanos and Vila, 2021). During QE, the loadings of subjective expected bond excess returns onto betas and bond return volatility both weaken. We also show some evidence that the magnitude of bond-stock betas declines during QE periods, with both negative and positive bond-stock betas narrowing towards zero, suggestive of state-contingent promises of future QE (Haddad et al. (2025)). Overall, these results suggest that the effects of QE on bond risk premia are heterogeneous, with QE lowering bond risk premia more strongly in countries where bonds are risky and bond-stock betas are positive.

While the strong relationship between bond-stock betas and subjective expected bond excess returns is suggestive of an integrated market between bonds and stocks, understanding QE typically requires segmented bond markets. We show that our empirical results can be reconciled with QE in a simple two-period model, where bond market investors have stock-like background risk. Arbitrageurs are assumed to choose their bond market exposure optimally while having to absorb overall bond supply, similar to Vayanos and Vila (2021). Different from them, but similar to standard representative agent models, we assume that bond market arbitrageurs have background risk, such as business risk or risk of losing credit access, that is correlated with the stock market. The bond market investors' first-order condition implies that beta and bond return variance are both priced. The price of beta is large if bond market investors' risk aversion and stock-like background risk are high. In this model, QE flattens the slope of bond risk premia with respect to both bond return volatility and bond-stock betas. The intuition is that by absorbing some of the bond supply, the central bank makes arbitrageurs wealthier, in turn lowering the price of risk for both bond return variance and bond comovement with background risk. Hence, quantities matter, and QE affects bond yields, while bond risk premia closely resemble a CAPM-style relation most of the time, consistent with our empirical results.

1.1 Literature Review

This paper speaks to the long-standing question in asset pricing on what constitutes risk and should be priced in the cross-section of financial assets, providing new evidence on the integration of bond and stock markets. The classic capital asset pricing model (CAPM) of Sharpe (1964) and Lintner (1965) predicts that the market portfolio is the unique systematic factor and that expected excess returns are proportional to market beta. Ross (1976)'s arbitrage pricing theory generalizes this intuition by allowing a small number of priced factors rather than a single market factor. Empirically, the literature—focused largely on U.S. equities—finds mixed support. Early tests by Black et al. (1972) and Fama and MacBeth (1973) document a positive but too-flat relation between beta and returns, while later work identifies substantial cross-sectional deviations (see Fama and French (2004); Frazzini and Pedersen (2014)). Beyond equities, Fama and French (1993) shows that bond and stock returns load on distinct term and default factors.

We also contribute to the literature on the term structure of interest rates. While the expectations hypothesis of interest rates states that expected bond excess returns are constant and long-term bond yields reflect only expected future short-term rates (Cochrane, 2005, Ch. 19), there is substantial evidence that bond risk premia vary strongly over time (Fama and Bliss, 1987; Campbell and Shiller, 1991; Cochrane and Piazzesi, 2005; Adrian et al., 2013, e.g.). Affine term structure models, building on Vasicek (1977) and Cox et al. (1985), allow for time-varying bond risk premia driven by a small set of state variables—typically bond yields themselves—but are largely silent on links to the stock market. Extensions incorporating macroeconomic risks, such as Ang and Piazzesi (2003) and Ang et al. (2006), take steps toward integrating bond markets with the broader economy. In contrast, segmented-markets approaches, such as Vayanos and Vila (2021), attribute bond risk premia to arbitrageur constraints and maturity-specific demand rather than full market integration. We provide new evidence and a reconciliation of these views.

More recently, a growing literature emphasizes that bond risks—as measured by bond–stock betas—vary substantially over time. While U.S. Treasury bonds comoved positively with the stock market in earlier decades, their comovement turned negative around the turn of the millennium, with bonds acting as hedges against equity risk (Baele et al. (2010), Campbell et al. (2017)). Building on this evidence, Campbell et al. (2020) show that bond–stock betas are linked to inflation cyclicality, with time-varying risk premia providing a quantitatively important amplification mechanism. Pflueger (2025) shows that turning bonds into risky assets, as they were in the 1980s, requires both: (a) volatile supply-type shocks; and (b) an aggressive Federal Reserve response that prioritizes fighting inflation over supporting employment. Neither element alone is sufficient. In standard consumption-based models where the stock market approximates the maximum Sharpe ratio portfolio, time-varying bond–stock betas are tightly connected to term premia (Campbell et al., 2026). Despite this strong theoretical link, tests based on realized bond excess returns find little relation between betas and returns. We contribute by providing new evidence that betas are an important determinant of professional forecasts of expected bond excess returns.

In our use of survey expectations, we build on tools from the recent literature investigating the role of expectations in asset prices. Following Piazzesi et al. (2015) and Nagel and Xu (2023), we define subjective expected excess returns as those that would obtain if professional forecasts of bond yields at a one-year horizon were realized. While in an infinite sample with rational expectations, the gap between subjective expectation and realized bond excess returns would merely be noise, several authors have pointed out that it can be substantial and systematic in practice (Cieslak, 2018). Such errors may arise from slow but rational learning (Farmer et al., 2024) or behavioral biases (Shue et al., 2025). Our measure of subjective expected bond excess returns automatically adjusts for expectations errors due to small samples and behavioral biases, allowing us to study how bond risks relate to subjective expected bond risk premia.

Beyond bonds, a large literature shows that survey expectations contain useful information about asset prices across markets. In equities, earnings expectations are priced (Bordalo et al., 2024; Delao and Myers, 2021). In foreign exchange, survey forecasts predict long-horizon currency returns (Kremens et al., 2025). Couts et al. (2026) show that institutional investors' long-run return expectations are consistent with their expectations for covariance, with a median forecast horizon of ten years. Different from them, we consider actual bond-stock betas and show that they are linked to one-year subjective excess returns. Within fixed income, Pesch et al. (2024) links bond return volatility to subjective excess returns, while Rogers (2026) uses derivatives to construct short-horizon expectations, and Molavi et al. (2025b) finds little evidence of time-varying term premia for short-term bonds. We contribute by studying longer-horizon risk premia for long-term bonds and find that betas matter for subjective bond risk premia.

2. Simple Model of Bond Risks and Expectations

This section presents a highly stylized term structure model. The aim of the model is to understand conditions under which subjective expected excess returns are well-explained by bond-stock betas, but realized excess returns are not. Two key lessons emerge. First, subjective excess returns can depend on betas even if forecasters do not explicitly use the CAPM. So long as the market adjusts bond yields to betas, and forecasters adjust their forecasts weakly less than the market, there will be a strong relationship between subjective expected excess returns and bond-stock betas. Second, both noise and behavioral biases can weaken the relationship between realized excess returns and betas.

We start with a simple single-factor model of the term structure. Letting t denote time in months, we assume that the one-year nominal yield is driven by a single factor, f_t:

$$y_{1,t} \quad = \quad f_t, \qquad f_{t+12} = \rho_f f_t + \varepsilon_{t+12}. \tag{1}$$

The residual ε_{t+12} is assumed to be uncorrelated with time-t variables. f_t can represent the short-term interest rate. Alternatively, it can also be interpreted as longer-run variables like perceptions of the central bank's inflation target or the natural rate of interest, as in shifting end-point models (e.g., Kozicki and Tinsley, 2001).

We allow both market and forecaster expectations to deviate from rational expectations. We denote rational expectations by $\mathbb{E}$, forecaster expectations by $\widetilde{\mathbb{E}}$ and market expectations by $\widehat{\mathbb{E}}$. Associated perceived parameters are defined analogously. Forecasters are assumed to be sophisticated, i.e., they understand that their beliefs may differ from the market's.

Letting n denote the bond maturity in years, the n-year zero-coupon bond-stock beta is assumed to follow:

$$\beta_{n,t+12} \quad = \quad \rho_\beta \beta_{n,t} + \eta_{t+12}, \tag{2}$$

where η_{t+12} is uncorrelated with time-t variables but may be correlated with ε_{t+12}. In order to price bonds as they roll down the maturity structure, we make the additional auxiliary assumption that bond-stock betas are proportional to maturity: $\beta_{i,t} = \frac{i}{n}\beta_{n,t}$.

The main assumption in our model is that comovement with the stock market is priced proportionally to the perceived beta persistence.[4]

[4]We do not specify a stochastic discount factor and instead directly model the relationship between markets' expected bond excess returns and bond-stock betas, which allows us to focus on the implications for bond yields and subjective expected excess returns. In Appendix E we provide a stylized general equilibrium model, where a relationship between bond-stock betas and market expected excess returns arises from bond investors' background exposure to the stock market.

Assumption 1. *Expected bond excess returns are proportional to perceived betas with a price of risk* $\lambda > 0$*:* $\widehat{\mathbb{E}}_t xr_{n,t+12} = \lambda \widehat{\mathbb{E}}_t \beta_{n,t+12} = \lambda \hat{\rho}_\beta \times \beta_{n,t}$ *and* $\widetilde{\mathbb{E}}_t xr_{n,t+12} = \lambda \widetilde{\mathbb{E}}_t \beta_{n,t+12} = \lambda \tilde{\rho}_\beta \times \beta_{n,t}$.

If $\hat{\rho}_\beta = 0$ or $\tilde{\rho}_\beta = 0$ the market or forecasters pay no attention to betas. For simplicity, we do not allow for separate λ for the market and forecasters, which would act similarly to different perceived beta persistence but complicate the analytic expressions.

Realized log bond excess returns, market expected excess returns, and the subjective expected excess returns of forecasters are defined as:

$$xr_{n,t+12} = ny_{n,t} - (n-1)y_{n-1,t+12} - y_{1,t} \tag{3}$$

$$\widehat{\mathbb{E}}_t xr_{n,t+12} = ny_{n,t} - (n-1)\widehat{\mathbb{E}}_t y_{n-1,t+12} - y_{1,t} \tag{4}$$

$$\widetilde{\mathbb{E}}_t xr_{n,t+12} = ny_{n,t} - (n-1)\widetilde{\mathbb{E}}_t y_{n-1,t+12} - y_{1,t} \tag{5}$$

Here, $y_{n,t}$ denotes the actual market yield on an n-year zero coupon bond at time t. Expression (3) is the model counterpart to the realized bond excess returns shown in Figure 1 Panel A, while expression (5) is the model counterpart for the subjective expected excess returns in Figure 1 Panel B.

The long-term bond yield $y_{n,t}$ depends on market expectations of f_t and $\beta_{n,t}$:

$$y_{n,t} = \frac{1}{n}\widehat{\mathbb{E}}_t \sum_{i=0}^{n-1} y_{1,t+12i} + \frac{\lambda}{n}\widehat{\mathbb{E}}_t \sum_{i=1}^{n-1} \beta_{n-i+1,t+12i} = \underbrace{\frac{1-\widehat{\rho}_f^{\,n}}{1-\widehat{\rho}_f}\frac{1}{n} f_t}_{\text{risk neutral}} + \underbrace{\lambda \left(\sum_{i=1}^{n-1} \widehat{\rho}_\beta^{\,i} \frac{n-i+1}{n^2} \right) \beta_{n,t}}_{\text{term premium}}. \tag{6}$$

Expression (6) shows that actual market bond yields rise with bond-stock betas, provided that the market prices beta ($\widehat{\rho}_\beta > 0$, $\lambda > 0$). Conversely, when markets perceive no persistence in betas ($\hat{\rho}_\beta = 0$), beta has no influence on market bond yields.

The following proposition describes realized and subjective expected bond excess returns.

Proposition 1. (Realized and subjective expected excess returns:) *There exists a function* $\Lambda_n(\hat{\rho}_\beta, \rho_\beta)$, $\frac{\partial \Lambda_n}{\partial \hat{\rho}_\beta} > 0$, $\frac{\partial \Lambda_n}{\partial \rho_\beta} < 0$, $\Lambda_n(0, \rho_\beta) = 0$, $\Lambda_n(\hat{\rho}_\beta, \hat{\rho}_\beta) = \hat{\rho}_\beta$ *such that:*[5]

i) Realized excess returns equal: $xr_{n,t+12} = \lambda \Lambda_n(\hat{\rho}_\beta, \rho_\beta)\beta_{n,t} + \frac{(\hat{\rho}_f - \rho_f)(1-\hat{\rho}_f^{\,n-1})}{1-\hat{\rho}_f} f_t + u_{t+12}$, *where* u_{t+12} *is a residual uncorrelated with time-*t *variables.*

ii) Subjective expected excess returns equal: $\widetilde{\mathbb{E}}_t xr_{n,t+12} = \lambda \Lambda_n(\hat{\rho}_\beta, \tilde{\rho}_\beta)\beta_{n,t} + (\hat{\rho}_f - \tilde{\rho}_f)\frac{1-\hat{\rho}_f^{\,n-1}}{1-\hat{\rho}_f} f_t$

[5] The function is $\Lambda_n(\hat{\rho}_\beta, \rho_\beta) = \hat{\rho}_\beta + (\hat{\rho}_\beta - \rho_\beta)\frac{1}{n}\sum_{i=1}^{n-2}(n-i)\hat{\rho}_\beta^{\,i}$. See Appendix A.

The proposition says that the loading of realized returns on $\beta_{n,t}$ depends on the actual persistence of betas (ρ_β) versus the market's perception ($\widehat{\rho}_\beta$). When betas are less persistent than the market's perception ($\rho_\beta < \hat{\rho}_\beta$), realized excess returns load more strongly onto $\beta_{n,t}$. When betas are positive, the market is surprised by how much betas fall, and yields fall more at $t + 1$ than expected, generating a larger bond return, particularly for high-beta assets.

The loading of subjective excess returns on $\beta_{n,t}$ depends on the market's versus forecasters' perceived beta persistence. When forecasters perceive betas to be less persistent than the market ($\widetilde{\rho}_\beta < \widehat{\rho}_\beta$), the loading of subjective expected excess returns on $\beta_{n,t}$ is larger: the current market yield has a more positive relationship with beta than forecasters' forecasted yields, and hence their duration-weighted difference in expression (5) also has a strongly positive loading on beta. Full proofs are provided in Appendix A.

We next make an additional assumption on the perceived persistence of betas.

Assumption 2. *Forecasters perceive bond-stock betas to be weakly less persistent than the market, which perceives positive persistence:* $\widehat{\rho}_\beta > 0$ *and* $\widetilde{\rho}_\beta \leq \widehat{\rho}_\beta$.

We then obtain the following Corollary.

Corollary 1. *Under Assumption 2, the loading of subjective excess returns onto bond-stock betas is positive and weakly greater than the market price of beta:* $\lambda\Lambda_n\left(\widehat{\rho}_\beta, \widetilde{\rho}_\beta\right) \geq \lambda\widehat{\rho}_\beta > 0$.

Corollary 1 says that subjective expected excess returns load on betas, so long as the market prices beta, and forecasters put weakly less weight on beta than the market. Neither forecaster nor market rationality are required for Corollary 1, though full rationality is nested as a simple special case. Assumption 2 is intuitively plausible and consistent with anecdotal evidence about forecasters. In our data, forecasters are predominantly macroeconomic forecasters, with titles such as "Chief Economist." In major financial institutions, these tend to be upstream of portfolio allocation and fixed income trading functions, and tend to place greater weight on fundamental valuations, and less weight on explicit term-premium considerations. Anecdotally, throughout our sample macroeconomic forecasters predominantly use "fair value" models, which relate bond yields to long-term fundamentals, such as long-term inflation expectations.[6] In the limiting case in which forecasters do not incorporate the persistence of bond–stock betas into their yield forecasts, $\widetilde{\rho}_\beta = 0$, Corollary 1 shows that subjective excess returns still load on bond–stock betas, as long as those betas are priced by the market.[7] Thus, the positive loading of subjective excess returns on betas does not

[6] See e.g. the "Sudoku" model used by Goldman Sachs since 2007 http://www.verstyuk.net/papers/GlobalViewpoint.07-24.pdf. We are grateful to Cary Leahey for confirming that this class of models has been used by major forecasters since the 1980s.

[7] Allowing forecasters to have a lower market price of risk than the market ($\tilde{\lambda} < \hat{\lambda}$) would act similarly, further strengthening the loading of subjective expected excess returns onto betas.

require forecasters to explicitly account for market betas when forming their yield forecasts.

We next assume two additional deviations from full rationality.

Assumption 3. *(i) Markets underestimate the persistence of beta:* $\widehat{\rho}_\beta < \rho_\beta$*.*

(ii) Markets and forecasters share a non-zero bias about the persistence of f_t*:* $\widetilde{\rho}_f = \widehat{\rho}_f \neq \rho_f$*.*

We then obtain the following Corollary:

Corollary 2. *Under Assumptions 2 and 3, realized bond excess returns have a smaller loading on beta than subjective excess returns, but a larger loading (in absolute value) on* f_t*.*

Corollary 2 says that, beyond finite-sample noise, there are systematic reasons that subjective expected excess returns should be more strongly related to bond-stock betas than realized bond excess returns. Unlike Corollary 1, Corollary 2 requires deviations from full information rationality, captured by Assumption 3.

If markets underestimate the persistence of bond-stock betas, ex-post bond return surprises tend to be negatively correlated with lagged beta, lowering the realized bond excess return loading on beta: negative beta tends to be followed by negative beta surprises (from the market's point of view), lower-than-expected yields, and higher-than-expected bond returns.[8] Under the plausible assumption that markets find it difficult to estimate the actual persistence of bond-stock betas, the model hence delivers a downward-bias for the loading of realized bond excess returns onto bond-stock betas.

Finally, if markets and forecasters have biased expectations about f_t, but roughly share the same bias, realized excess returns will load on f_t, whereas subjective expected excess returns will not. Intuitively, realized returns compare today's market yield to the realized future yield, so errors in the market's belief about the persistence of f_t show up as ex-post return surprises. By contrast, in the construction of subjective expected excess returns, the common bias affects both the market yield and the forecaster's expected future yield in the same direction, so it cancels out. Thus, incorrect expectations can contribute noise and potentially even bias to a regression of realized bond excess returns onto bond-stock betas, which can be mitigated by using subjective expected excess returns. In a sample like ours with persistent downward trends in interest rates and long-term inflation, incorrect expectations are plausible. Moreover, the assumption that forecasters and markets make biased forecasts about how long-term inflation expectations and short-term monetary policy affect bond yields is in line with a growing literature on expectational biases in bond yields (Cieslak, 2018; Bauer et al., 2024; Farmer et al., 2024; Shue et al., 2025).

[8] The mechanism is similar when markets do not fully understand the persistence of the short rate (e.g., Farmer et al., 2024) for the term premium rather than the risk-neutral component of yields.

Overall, the model clarifies under what conditions both empirical relationships in Figure 1 hold. A positive relationship between subjective expected excess returns and bond-stock betas arises as long as the *market* prices betas. Forecaster rationality is not required, though also not ruled out. By contrast, deviations from full rationality are required to rationalize the weak empirical relationship between realized bond excess returns and bond-stock betas. In this case, subjective expected bond excess returns are particularly useful to test whether the market prices bond-stock betas.

3. U.S. Panel Evidence

This section presents the main results for the U.S. We describe and plot data for expected excess returns and bond-stock betas, and estimate their relationship in a month-by-maturity panel regression. Realized bond excess returns are regressed onto expected bond excess returns, decomposed into the fitted component from bond-stock beta and a residual. Implications for U.S. term premia are presented at the end of the section.

3.1 U.S. Data and Summary Statistics

The data for our U.S. sample come from three main sources. First, we obtain forecasts of future long-term bond yields from the Blue Chip Financial Forecasts (BCFF). The survey asks for forecasts of interest rates, including the federal funds rate and Treasury yields of several maturities. Participating institutions include large investment banks and other financial institutions, with between 30 and 50 institutions participating in each survey. Our sample is monthly, starting in January 1988, when a consistent set of Treasury yield forecasts becomes available. Our second main source of data is nominal Treasury par yields from Gürkaynak et al. (2007). We use par yields to match the object that BCFF participants forecast.

Subjective Expected Excess Returns on Bonds Following the data construction of Piazzesi et al. (2015) and Nagel and Xu (2023), we compute the subjective expected bond excess return or risk premium for an n-year coupon bond by combining the current market yield on the n-year bond with the forecasters' one-year-ahead expectation of the $n-1$-year yield. Specifically, we substitute forecasters' expectations of future bond yields from Blue Chip into the standard expression for a coupon bond return:

$$\tilde{E}_t xr_{n,t\to t+12} \quad = \quad dur_{n,t} y^{par}_{n,t} - (dur_{n,t} - 1) \times \tilde{E}_t y^{par}_{n-1,t+12} - y_{1,t}. \tag{7}$$

This is the analogue of model equation (5) for a coupon bond. The yield $y^{par}_{n,t}$ denotes the current n-year government bond yield, $\tilde{E}_t y^{par}_{n-1,t+12}$ denotes the forecast for the $(n-1)$-year yield in 12 months, and $y_{1,t}$ is the one-year zero-coupon yield.[9] All yields are in annualized percent, so the expected excess return is also in annualized percentage units. Because the forecasts are made for coupon Treasury bonds and Treasury bonds tend to sell close to par, we approximate the duration of the n-year bond selling at par (Campbell, 2017, pp. 236–237): $dur_{n,t} = \left(1 - (1 + y^{par}_{n,t})^{(-n)}\right) / \left(1 - (1 + y^{par}_{n,t})^{(-1)}\right)$. Since Blue Chip contains forecasts for the two-, 5-, and 10-year bond yields, we can construct subjective expected excess returns for the 3-, 6-, and 11-year government bonds. We proxy for the 12-month ahead forecast with 4-quarter forecasts, averaged across forecasters. Blue Chip forecasters are required to submit their responses at the end of the previous month. To make sure the information sets are consistent, the March survey is paired with the realized par yield at the end of February in expression (7). We average the realized par yield over the last week of each month to reduce day-to-day noise. Appendix Figure F.3 plots the realized 10-year yield together with the survey forecast of the 10-year yield.

This procedure gives us a monthly series for U.S. expected bond excess returns over a sample from January 1988 through March 2024. Because we have monthly data and three different bond maturities ($n = 3, 6, 11$), this leaves us with roughly 1300 observations, though of course we must account for joint variation across maturities and time in our regressions. To reduce month-to-month noise, we also construct a smoothed series by taking the average expected excess returns over the preceding twelve months.[10] Subjective expected excess returns are plotted in Figure 2. While there is substantial variation month-to-month, the moving average shows clear patterns over time and across bond maturities.

Realized Bond Excess Returns We construct realized twelve-month bond excess returns for an n-year par bond:

$$xr_{n,t\to t+12} = dur_{n,t}\, y^{par}_{n,t} - (dur_{n,t} - 1)\, y^{par}_{n-1,t+12} - y_{1,t}. \tag{8}$$

Realized bond excess returns on n-year zero-coupon bonds are computed analogously, using zero-coupon bond yields from Gürkaynak et al. (2007) and setting the bond duration equal to the bond maturity.

Summary statistics in Table I, Panel A, show that, in contrast to realized bond excess returns, subjective expected excess returns on average were close to zero over our sample, but

[9]For the one-year risk-free rate we use the market yield on U.S. Treasury Securities at one year constant maturity downloaded from Fred (ticker `DGS1`).

[10]Higher-frequency fluctuations in expected bond excess returns could arise, for example, if forecasters update their forecasts incompletely month-to-month while actual bond yields fluctuate. Because we use expected excess returns primarily as the dependent variable in our regressions, this should simply act as white noise. In Tables VI and F8, where expected excess returns are on the right-hand side, we use the twelve-month moving average to mitigate attenuation bias.

they exhibited substantial variation over time. The 12-month moving average of subjective expected excess returns on the three-year bond ranges from -1.2% to 1.5%, with a standard deviation of 0.7%. The moving average of subjective expected excess returns on the eleven-year bond exhibits more variation, ranging from -5.5% to 4.7%, with a standard deviation of 2.7%.

One might wonder whether our measures of subjective expected bond excess returns are affected by forecaster incentives or institutional constraints. However, a simple split by forecaster type suggests that this is not a first-order concern. We classify forecasters in the Blue Chip data into three groups: dealers (e.g. Goldman Sachs), buy-side firms (e.g. Swiss Re), and research firms (e.g. Oxford Economics). Despite their opposite positions in long-term bonds, different customer bases, and different incentives, the average yield forecasts for the three subgroups are highly correlated Across any two of these forecaster types, the pairwise corelation for the 11-year subjective expected bond excess return is at least 0.89 or higher.[11]

Bond Betas The CAPM-beta of Treasury bonds with respect to the stock market is estimated using daily data. Daily U.S. stock market excess returns are obtained from Ken French's website. The Treasury bond excess return from day d to $d+1$ is computed using nominal Treasury par yields from Gürkaynak et al. (2007) as

$$xr_{n,d+1} = dur_{n,d} y^{par}_{n,d} - \left(dur_{n,d} - \frac{1}{252} \right) y^{par}_{n,d+1} - y_{rfr,d}, \tag{9}$$

where the daily risk-free rate $y_{rfr,d}$ is from Ken French's website, and the duration of the n-year par bond on day d is computed assuming that bonds sell at par.[12]

The beta of a bond with maturity n in month t is estimated by regressing Treasury bond excess returns on stock market excess returns using daily data:

$$xr_{n,d} = a_{n,t} + \beta^{w}_{n,t} xr^{eq}_{d} + \varepsilon_d, \tag{10}$$

where d denotes the trading day and runs from the first trading day of month $t-w$ to the last trading day of month t. Our baseline estimate of $\beta^{w}_{n,t}$ uses a rolling window of $w = 60$ months (a five-year rolling beta) but we also report estimates based on a shorter window of $w = 12$ months (a one-year rolling beta).

The monthly series of estimated betas are shown in Figure 3, and summary statistics

[11]Appendix Table F1 reports the full set of pairwise forecaster-type correlations across bond maturities. See also Appendix Figures F.4 and F.5.

[12]Par yields are in annualized percent, the risk-free rate is the daily T-Bill return in percent, and duration is measured in years.

are provided in Panel B of Table I. Across maturities, the overall time-series patterns are broadly similar, although there are notable cross-sectional differences. During periods of positive betas—such as at the beginning of the sample—the eleven-year bond exhibits a substantially larger beta than the shorter maturities. At its peak, the five-year rolling beta for the eleven-year bond reaches 0.4, compared with a peak of 0.1 for the three-year bond.

Combined, Figures 2 and 3 show a clear association between bond-stock betas and subjective expected returns, both over time and across maturities. Subjective expected excess returns were positive until the turn of the millennium, then turned negative after 2000. They fluctuated around zero during the global financial crisis and its aftermath. Several more years of negative expected bond excess returns during the 2010s and early 2020s were then followed by a return to positive expected bond excess returns in 2023 and early 2024. There is also substantial variation across bond maturities, with expected excess returns on eleven-year bonds more positive during the 1980s and 1990s, but also more negative during the 2000s.

The parallels to bond-stock betas in Figure 3 are visually apparent. Betas were positive before the turn of the millennium, but then became negative thereafter. The change in bond stock betas is most apparent in the eleven-year bond, but still visible in the smoother beta for three-year maturity bonds. The parallels also extend to the increase in subjective expected returns in recent years. Betas turned positive around the same time as subjective expected excess returns, with both patterns more pronounced in long-maturity bonds than shorter-maturity bonds. These figures provide a first hint that the rise in bond risks may help to understand the substantial increase in long-term bond yields during the post-pandemic period.

In our regressions below, these rolling betas are technically generated regressors. However, as Panel B of Table I shows, they are very precisely estimated, so any concerns about statistical inference with generated regressors should be minimal.[13] The five-year rolling beta is somewhat more precisely estimated than the one-year, so we use it as the baseline in discussing our results, but we report all of our main results for both betas. The 12-month autocorrelation of the baseline five-year rolling betas is 0.96. This matters for our analysis, because as long as market expectations for beta persistence are not too far from reality, the predicted lower bound for the loading of subjective expected bond excess returns onto betas in Corollary 1 ($\lambda\hat{\rho}_\beta$) is basically the market price of risk (λ).

[13] For betas computed over five-year rolling windows, the average Huber-White robust standard errors are 0.008 for the three-year Treasury bond, 0.014 for the 6-year Treasury bond, and 0.022 for the 11-year Treasury bond. For comparison, the bond-stock betas exhibit quite large variation over time. The standard deviations of the point estimates of these betas are 0.05 for the three-year Treasury bond, 0.11 for the 6-year Treasury bond, and 0.19 for the 11-year Treasury bond.

Table I: Summary Statistics: U.S. Panel

Panel (A): Subjective Expected Excess Returns and Realized Excess Returns

	Subjective XR			Subjective XR (MA)			Realized XR		
	3Y	6Y	11Y	3Y	6Y	11Y	3Y	6Y	11Y
Average	0.09	-0.03	-0.05	0.08	-0.05	-0.10	1.02	2.08	2.84
Std	0.84	1.76	3.11	0.71	1.46	2.70	2.43	4.75	7.24
Min	-2.03	-4.23	-8.18	-1.21	-3.17	-5.53	-7.05	-13.21	-22.11
Max	2.17	4.42	8.16	1.55	3.06	4.67	6.75	12.77	18.42

Panel (B): Bond-Stock Betas

	5-y rolling β			1-y rolling β		
	3Y	6Y	11Y	3Y	6Y	11Y
Average	-0.01	-0.01	-0.02	-0.00	-0.00	-0.01
Std	0.05	0.11	0.19	0.07	0.14	0.23
Min	-0.09	-0.13	-0.27	-0.14	-0.22	-0.36
Max	0.13	0.25	0.39	0.21	0.42	0.67
Average S.E.	0.008	0.014	0.022	0.013	0.025	0.039

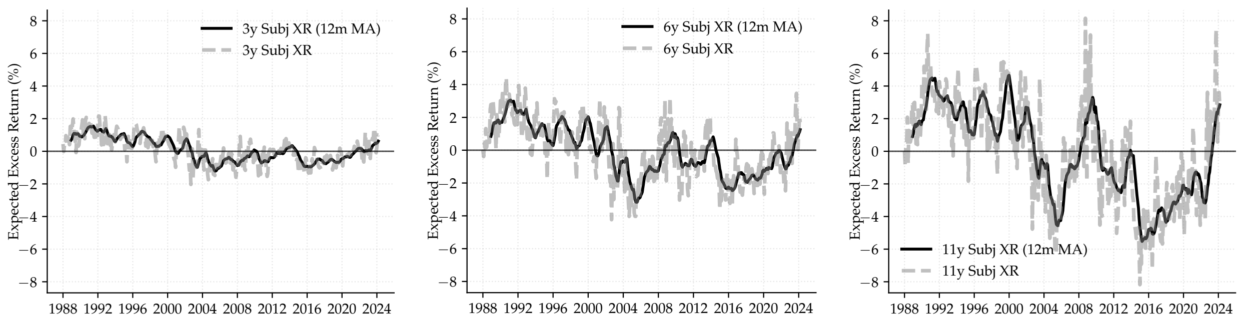
Note: Panel A reports the summary statistics for the expected excess returns (columns (1) to (3)), 12-month moving average (MA) expected excess returns (columns (4) to (6)), and realized excess returns (columns (7) to (9)) for bonds with three-, 6-, and 11-year maturities. Subjective expected bond excess returns are computed according to Equation 7. We use 4-quarter par bond yield forecasts from BCFF. Panel B reports the summary statistics for the rolling estimates of Treasury bond–stock betas for par bonds with three-year, 6-, and 11-year maturities. Bond–stock betas are computed as the regression coefficient of daily par bond excess returns on stock excess returns over a backward-looking rolling window, as defined in Equation 10. We use either 60-month rolling windows (five-year rolling β) or 12-month rolling windows (one-year rolling β). We resample the data to a monthly frequency by taking the estimate from the last trading day of each month. The table reports the average estimate, standard deviation, minimum and maximum values, and the average HW-robust standard errors. The sample runs from January 1988 to March 2024.

Alternative Beta Estimates Our baseline bond–stock beta is estimated using daily returns over a five-year rolling window. In addition to this baseline measure and the alternative specification based on a one-year rolling window, we also consider several alternative estimates of bond–stock betas. First, we estimate rolling regressions using daily data and apply the Dimson (1979) adjustment to account for non-synchronous trading. The Dimson beta is obtained by including two lags and two leads of the market return in the regression and summing the corresponding coefficients.[14] Second, we estimate the five-year rolling betas using monthly rather than daily returns. Finally, we construct bond–stock betas using exponentially decaying weights with a half-life of three years. The resulting beta estimates are shown in Appendix Figure F.2.

[14]Specifically, we estimate $xr_{n,d} = \alpha_n + \sum_{k=-2}^{2} \beta_{n,k}\, xr_{d+k}^{mkt} + \varepsilon_{n,d}$, and define the Dimson beta as $\beta_n^{Dimson} = \sum_{k=-2}^{2} \beta_{n,k}$.

Figure 2: Subjective Expected Excess Returns: U.S. Treasury Bonds

(A) 3-Year Treasury Bond (B) 6-Year Treasury Bond (C) 11-Year Treasury Bond



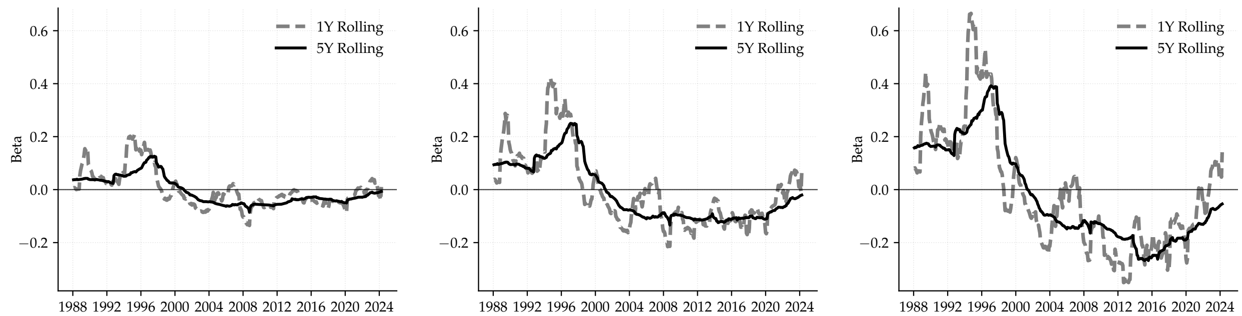
Note: This figure plots one-year subjective expected excess return for U.S. Treasury par bonds of three- (Panel A), 6- (Panel B), and 11-year (Panel C) maturities. Subjective expected excess returns are computed according to equation (7). We use 4-quarter par bond yield forecasts from the Blue Chip Financial Forecasts. The dashed gray line shows monthly subjective expected excess returns, and the black line shows the 12-month moving average. The sample is monthly from January 1988 to March 2024.

Other Predictors We also include additional predictors of bond excess returns. In particular, we construct a measure of bond return variance using the rolling variance of daily bond excess returns, computed over either a 60-month or a 12-month window. We further include controls for the shape of the yield curve. Specifically, we compute the level, slope, and curvature factors as the first three principal components of zero-coupon nominal bond yields with maturities of one, two, 5, 7, 10, 15, and 20 years. Next, we define the term spread as the difference between the n-year par yield and the one-year zero-coupon yield. The term spread is a traditional predictor of bond excess returns (Campbell and Shiller, 1991), though its influence has been found to be weaker for subjective expected excess returns than for realized ex-post bond excess returns (Nagel and Xu, 2023). In our specification, we use the maturity-specific term spread: for the n year expected excess return, we use the n-year term spread.

Long-Term Forecasts. We use long-term forecasts of CPI inflation and the Treasury bill rate from the Survey of Professional Forecasters (SPF). The SPF is a quarterly survey conducted in the middle month of each quarter. So, for example, the Q1 SPF long-term forecasts are matched to the March BCFF, collected at the end of February. The survey provides forecasts of the average CPI inflation rate over the next ten years, available at a quarterly frequency, and forecasts of the average U.S. Treasury bill rate over the next ten years, available at an annual frequency.

Figure 3: Estimated Stock Market Betas for U.S. Treasury Bonds

(A) 3-Year Treasury Bond (B) 6-Year Treasury Bond (C) 11-Year Treasury Bond



Note: This figure plots rolling estimates of stock market betas for par Treasury bonds of three- (Panel A), 6- (Panel B), and 11-year (Panel C) maturities. Betas are computed by regressing daily par bond excess returns onto stock market excess returns over a backward-looking rolling window according to equation (10). The dashed gray line uses 12-month rolling windows, and the black line uses 60-month rolling windows. We resample the data to a monthly frequency by taking the estimate from the last trading day of each month. The sample runs from January 1988 to March 2024.

3.2 U.S. Expected Excess Returns vs. Betas

Our stylized model predicts that subjective expected excess returns increase with bond-stock betas, provided that the market prices bond-stock betas and that forecasters put weakly less weight on betas than the market (Proposition 1). We now provide evidence for this prediction using our monthly U.S. panel, estimating the following panel regression:

$$\tilde{E}_t xr_{n,t\to t+12} = \alpha + \lambda\beta^w_{n,t} + X'_{n,t}\delta + \eta_{n,t}, \tag{11}$$

where $\beta^w_{n,t}$ denotes the estimated rolling beta available at time t, and $X_{n,t}$ is a vector of control variables. We estimate regression (11) both in a stacked panel, including bonds of all three available maturities, and separately for each maturity using only time series variation. According to the CAPM, the slope λ is predicted to be positive and equal to the equity premium, and the intercept α is predicted to equal zero.

We are careful that the betas and other yield curve-based controls are known at the time when forecasts are made. For concreteness, consider the March observation of $\tilde{E}_t xr_{n,t\to t+12}$. This measure is constructed using the *March* Blue Chip survey, which forecasters submit at the end of February. Hence, we use bond betas and other predictors at the end of February.

Table II shows the results for the stacked panel, where the unit of observation is bond maturity $n \in \{3, 6, 11\}$ by month t. We use our baseline betas estimated over five-year rolling backward-looking windows. Throughout the paper, we use Driscoll–Kraay standard errors for panel regressions and Newey–West standard errors for time-series regressions. We use 27 lags, following the truncation rule suggested by Lazarus et al. (2018), and evaluate statistical significance using fixed-b critical values (Kiefer and Vogelsang, 2002, 2005).

Column (1) in Table II shows our baseline result. A unit increase in beta is associated with an increase in subjective expected excess returns of 10.9 percentage points per year. This magnitude is large and statistically indistinguishable from conventional estimates of the equity premium, which range from 6 to 8 percent per year. The R^2 of the regression is high at 43%, corresponding to a correlation coefficient of 66%. In addition, the constant, or the expected alpha, in Column (1) is close to zero and statistically insignificant, indicating that forecasters did not expect bonds to earn a premium above and beyond compensation for exposure to the stock market. As a simple back-of-the-envelope calculation, the peak-to-trough decline in the beta of the eleven-year bond from roughly 0.39 to -0.27 can explain a decline in the expected bond excess return from $0.39 \times 10.9\% = 4.26\%$ to $-0.27 \times 10.9\% = -2.91\%$. For comparison, the moving average of expected excess returns in Figure 2 Panel C declined from roughly 4.7% to -5.5%.

We next show that the relationship between betas and subjective expected excess returns is unchanged economically and statistically when we include a host of controls. Given that both subjective expected return and betas drift downward over our sample, it is important to control for a time trend. Column (2) shows that this leaves our baseline result unchanged. Column (3) includes maturity fixed effects to allow for the possibility that some bond maturities may persistently have higher or lower expected excess returns, for example, due to different liquidity. Column (4) allows for maturity-specific time trends, constructed by interacting a linear time trend with maturity indicators; maturity fixed effects are included separately to absorb level differences.

Column (5) adds bonds' return variance, estimated as the variance of daily bond excess returns over a rolling five-year window. The estimated coefficient on the beta in this specification remains similar, and the R-squared increases slightly. The coefficient on bond variance, equal to 0.0, is also positive and statistically significant. This result is consistent with the idea that investors require higher expected excess returns during periods of elevated bond return volatility, though the relationship with betas remains unchanged.

Column (6) adds the term spread, defined as the difference between the bond yield at the relevant maturity (3, 6, or 11 years) and the one-year par bond yield. Column (7) controls for the first three principal components of the yield curve: level, slope, and curvature. Throughout the table, the R^2 only increases modestly from column (1) to column (7), emphasizing the substantial explanatory power of betas for subjective expected excess

Table II: Expected Excess Returns and Stock Market Betas: U.S. Panel

Dependent Variable: Expected Excess Returns								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Bond-Stock Beta 5YR	10.87***	10.12***	10.87***	9.65***	11.24***	11.09***	8.38***	11.69***
	(1.84)	(2.41)	(1.84)	(3.22)	(1.80)	(1.75)	(1.87)	(1.89)
Bond Variance					0.02**			
					(0.01)			
Term Spread						0.32		
						(0.24)		
Level							0.47***	
							(0.18)	
Slope							-0.26	
							(0.17)	
Curvature							0.14	
							(0.17)	
Constant	0.16							
	(0.20)							
Time Trend		✓						
Maturity FE			✓	✓	✓	✓	✓	✓
Time Trend × Maturity FE				✓				
Time FE								✓
R-squared	0.43	0.43	0.43	0.43	0.44	0.44	0.47	0.86
Observations	1305	1305	1305	1305	1305	1305	1305	1305

Note: The table reports estimates from regressions of expected excess returns on bond-stock betas and controls, as in Equation (11):

$$\tilde{E}_t xr_{n,t\to t+12} = \alpha + \lambda\beta^w_{n,t} + X'_{n,t}\delta + \eta_{n,t}.$$

We use the bond-stock beta estimated over a 5-year rolling window. Driscoll–Kraay standard errors with 27 lags are reported in parentheses. Stars denote significance at the 10, 5, and 1 percent levels based on Kiefer–Vogelsang fixed-b critical values. The sample consists of monthly data from January 1988 to March 2024.

returns.[15]

Column (8) flexibly controls for both time-series patterns and maturity-specific characteristics by including time and maturity fixed effects. Because time fixed effects absorb aggregate variation common to all maturities, this specification exploits only cross-maturity variation within a given month. The estimated coefficient in Column (8), equal to 11.7, remains statistically significant and similar in magnitude to those reported in the other columns. This finding indicates that the relationship between bond–stock betas and subjective expected excess returns holds both over time and across maturities.

Robustness We show additional robustness results in the Appendix. Table F2 shows analogous results for the noisier but faster-updating one-year rolling beta. We find that the one-year rolling beta has similarly high explanatory power for expected bond excess

[15] In unreported results, we find that controlling for the Cochrane and Piazzesi (2005) tent-shaped factor similarly leaves the magnitude and significance of bond-stock betas unaffected.

returns, though the coefficients and R^2s are somewhat attenuated. This is what one would expect if using the shorter one-year rolling window leads to measurement error and hence attenuation bias. Appendix Table F4 shows robustness to more alternative measures of bond–stock betas. In Column (3), we use betas estimated from daily returns over a five-year rolling window with the Dimson (1979) correction for non-synchronous trading, while Column (5) uses betas estimated from monthly returns over a five-year window. In both cases, the estimated coefficients and the R^2 are broadly unchanged relative to the baseline specification. In Column (6), we construct betas using monthly data with exponentially decaying weights with a half-life of three years. In this case, the estimated coefficient is larger (12.48), and the explanatory power of the regression increases, with the R^2 rising to 48%. Table F5 in the Appendix reports results from specifications that control for a range of alternative variables, including realized bond return volatility and realized stock return volatility estimated over different rolling windows, as well as the VIX.

Table F3 runs results separately for each bond maturity, and shows that the relationship between the bond–stock beta and subjective expected returns is both statistically and economically significant for every maturity.

Overall, our results point to a robust relationship between subjective expected excess returns and bond–stock betas. This relationship holds both over time and across maturities, and remains stable across a wide range of controls and fixed effects. In the next sections, we examine the nature of this relationship in more detail.

3.2.1 Expected Return Decomposition

So far, we have documented a strong empirical relationship between subjective expected excess returns and bond-stock betas in U.S. panel data. To understand the source of this relationship, we next decompose the subjective expected excess return in Equation (7) into its main components. We test whether betas are priced in market yields, in forecasts or both. This decomposition maps into the model-analogue of subjective expected excess returns in Section 2, where we saw that subjective expected excess returns should be related to bond-stock betas as long as betas are priced by market yields, and forecasts load equally or less onto bond-stock betas. The model hence predicts that market yields load positively onto bond-stock betas, and that the loading is higher for market yields than for yield forecasts.

Before turning to the decomposition, it is useful to define $\widetilde{i}_t^n$ as the forecaster-implied expected average Treasury bill rate over the next n years:

$$\widetilde{i}_t^n = \widetilde{E}_t \left[\frac{1}{n} \sum_{j=0}^{n-1} i_{t+12j} \right],$$

where we maintain our convention that t is measured in months. We can then rewrite the expected excess return in Equation (7) as

$$\widetilde{E}_t xr_{n,t\to t+12} = dur_{n,t}\left(y_{n,t} - \widetilde{i}_t^n\right) - (dur_{n,t} - 1)\left(\widetilde{E}_t y_{n-1,t+12} - \widetilde{i}_t^n\right) + \left(\widetilde{i}_t^n - y_{1,t}\right). \tag{12}$$

Expressing yields relative to the expected Treasury bill rate offers two main advantages. First, it removes the common low-frequency component in interest rates: because the level of interest rates has trended downward over the past several decades, subtracting the expected average Treasury bill rate from both observed and forecasted bond yields allows us to focus on variation in spreads rather than levels. Second, the difference between an observed or forecasted long-term yield and the expected average Treasury bill rate provides a proxy for the term premium, that is, the average risk premium over the life of the bond. This exercise therefore complements the results in Table II, which focus on the one-year holding-period risk premium.

We measure $\widetilde{i}_t^{10}$ using data from the SPF, which reports forecasts of the average Treasury bill rate over the next ten years. These forecasts are available only at the annual frequency. Because this forecast is the expected average short rate over the next ten years, it is naturally matched to the 10-year yield forecast, and hence to the risk premium on the 11-year bond.[16] These data limitations unfortunately imply a smaller sample than for our baseline results, with 33 observations for the 11-year bond and 99 observations for the U.S. panel.

We proceed in three steps. First, we regress the spread between the observed 11-year yield and the expected average Treasury bill rate, $y_{11,t} - \widetilde{i}_t^{10}$, on the 11-year bond–stock beta. Second, we regress the spread between the forecasted 10-year yield and the expected average Treasury bill rate, $\widetilde{E}_t y_{10,t+12} - \widetilde{i}_t^{10}$, on the same beta. Finally, we regress the difference between observed and forecasted yields, $y_{11,t} - \widetilde{E}_t y_{10,t+12}$, on the beta.

Panel (A) of Table III reports the results. This panel uses only the 11-year bond because this maturity maps most cleanly into the long-term T-bill forecast reported by the SPF. Column (1) uses as the dependent variable the spread between the current 11-year bond yield and the expected average Treasury bill rate over the next ten years. The coefficient is equal to 4.1 and is statistically significant. Hence, actual market yields load positively onto bond-stock betas, as predicted by the model. Column (2) shows that a similar relationship holds when controlling for a time trend.

Columns (3) and (4) find a positive but weaker relationship for forecasted yields, as

[16] In this exercise, we combine bond yield forecasts from Blue Chip with Treasury bill rate forecasts from the SPF. We find that bond yield forecasts from the two surveys are extremely close to each other. It is therefore reasonable to use the expected Treasury bill rate from the SPF and assume that Blue Chip forecasters have similar expectations.

predicted by the model. The forecasted yield minus the expected average Treasury bill rate loads positively onto bond-stock betas, but the loading is smaller in magnitude than for actual market yields, and not always significant. Columns (5) and (6) shows that the difference is statistically significant, i.e. market yields have a significantly more positive relationship with bond-stock betas than yield forecasts, as predicted by the model. This holds with or without controlling for a time trend. Note also that the difference in columns (5) and (6) does not use data on long-term T-bill rate forecasts, so the difference in loadings is not an artifice of the long-term T-bill forecast data.

Panel (B) shows that the decomposition results for the 11-year maturity carry through to the full panel. The SPF only asks for the average expected T-bill rate over the next 10 years, and we use this long-term forecast for all bond maturities in Panel B. Subjective expected excess returns are a duration-weighted difference between the actual market yield and the yield forecast, so the difference in loadings onto bond-stock betas is further amplified for subjective expected excess returns, as shown in Appendix Table F6.

Overall, the decomposition of subjective expected excess returns shows that the relationship between bond-stock betas and subjective expected excess returns is driven by the term premium in actual market yields rather than by the term premium predicted by forecasters, consistent with the predictions of Corollary 1.

3.2.2 Relation to inflation uncertainty and inflation expectations

In this section, we analyze the role of inflation in the relation between bond–stock betas and subjective expected excess returns. We use inflation-related information in two ways. First, because the level of inflation is well-known to be correlated with inflation risk (Taylor (1981)), one might be concerned that bond-stock betas just pick up on the trend in inflation over our sample period. If inflation or inflation uncertainty are correlated with bond-stock betas but bond-stock betas are the true driver of bond risk premia, we would expect our results to hold up when controlling for them. Second, we use inflation forecasts to construct an alternative forecast of long-term bond yields that is free of term premia, and feed this alternative yield forecast into subjective expected excess returns. This approach provides us with another way to show that the relationship between bond-stock betas and subjective expected excess returns does not depend on forecasters thinking about the term premium, consistent with our model.

Column (2) in Table IV shows that inflation volatility, measured as the standard deviation of CPI inflation over a 5-year rolling window, is not significantly related to subjective expected bond excess returns on its own. Column (3) shows that the estimated beta loading is unchanged when controlling for inflation volatility. Inflation volatility now enters

Table III: Market Yield, Forecasted Yield and Bond-Stock Beta

Panel (A): 10-Year Yield

Dependent Variable:	$y - \tilde{E}i^{10y}$		$\tilde{E}y - \tilde{E}i^{10y}$		$y - \tilde{E}y$	
	(1)	(2)	(3)	(4)	(5)	(6)
Beta 5YR	4.09***	3.24**	2.69***	1.03	1.44***	1.85***
	(0.80)	(1.34)	(0.83)	(0.97)	(0.22)	(0.51)
Time trend		✓		✓		✓
R-squared	0.66	0.68	0.42	0.52	0.43	0.45
Observations	33	33	33	33	435	435

Panel (B): Panel of All Maturities

Dependent Variable:	$y - \tilde{E}i^{10y}$		$\tilde{E}y - \tilde{E}i^{10y}$		$y - \tilde{E}y$	
	(1)	(2)	(3)	(4)	(5)	(6)
Beta 5YR	5.70***	5.60***	3.97***	2.76**	1.83***	2.48***
	(0.90)	(1.73)	(0.94)	(1.38)	(0.28)	(0.66)
Time trend × Maturity FE		✓		✓		✓
Maturity FE	✓	✓	✓	✓	✓	✓
R-squared	0.51	0.55	0.43	0.49	0.31	0.34
Observations	99	99	99	99	1305	1305

Note: The table compares how strongly observed and forecasted bond yields load on the bond–stock beta. Yields are expressed relative to $\tilde{i}_t^{10}$, the SPF forecast of the average Treasury bill rate over the next ten years. Each column regresses one of three objects on the five-year rolling bond–stock beta: the observed-yield spread $y_{11,t} - \tilde{i}_t^{10}$ (Columns 1–2), the forecasted-yield spread $\tilde{E}_t y_{10,t+12} - \tilde{i}_t^{10}$ (Columns 3–4), and the gap between observed and forecasted yields $y_{11,t} - \tilde{E}_t y_{10,t+12}$ (Columns 5–6). The even columns add a linear time trend (maturity-specific in Panel (B)). Panel (A) uses the eleven-year bond alone (Newey–West standard errors); Panel (B) pools the three-, six-, and eleven-year bonds with maturity fixed effects (Driscoll–Kraay standard errors). Because $\tilde{i}_t^{10}$ is observed annually, Columns 1–4 are estimated at the annual frequency with 4 lags, while Columns 5–6 use the full monthly sample with 27 lags. Standard errors in parentheses; stars denote significance at the 10, 5, and 1 percent levels based on Kiefer–Vogelsang fixed-b critical values. Sample: January 1988 to March 2024.

positively and significantly, but the R-squared is only slightly higher than in the baseline specification in column (1). Inflation uncertainty might enter, for example, if the marginal bond market investor holds a non-zero position in bonds, and uncertainty about nominal bond returns is priced in addition to bond-stock comovements. In terms of magnitude, the inflation standard deviation ranges from 0.23% to 2.69%, so moving from its minimum to its maximum is associated with a 1.95 percentage point increase in expected excess returns, when controlling for beta. The result shows that the inflation standard deviation is positively related to expected excess returns, but does not reduce the loading on the bond–stock beta.

We then relate subjective expected excess returns to long-term inflation expectations. We use the SPF expected inflation over the next ten years, which can also be thought of as a natural measure for perceived shifting end-points (Kozicki and Tinsley, 2001) and is available at quarterly frequency.[17] In Column (4), we find a positive relationship between expected inflation and expected excess returns: a 1 percentage point increase in expected inflation is associated with a 2.07 percentage point increase in expected excess returns. The R-squared is 0.18, which is substantially smaller than the baseline explanatory power of bond–stock betas of 0.43, reported in Column (1). Column (5) shows that the loading on expected inflation is driven out by bond-stock betas. Here, the loading on long-term expected inflation becomes small and statistically insignificant, while the loading on beta is similar to the baseline and highly statistically significant. This is what we would expect if bond-stock betas exhibit some joint movement with inflation expectations over our sample, but markets price bond-stock betas.

Having shown that inflation-related controls do not subsume the relationship between bond–stock betas and subjective expected excess returns, we next use inflation forecasts in a different way. Rather than using inflation as a control, we use long-run inflation expectations to construct an alternative proxy for subjective expected excess returns that is immune to concerns that we might merely capture the term premium perceptions of a particular forecasting model. Starting from Equation (7), we replace the forecasted future bond yield, $\widetilde{E}_t y_{n-1,t+12}$, with the expected average inflation rate over the next ten years. This gives a *pseudo* expected excess return based only on the current yield, the short rate, and long-run expected inflation. To make the magnitudes comparable to our baseline measure, we rescale this pseudo expected excess return separately by maturity. For each maturity, we regress the baseline subjective expected excess return on $\widetilde{E}_t^{\pi} xr_{n,t\to t+12}$, and use the fitted value as the rescaled pseudo expected excess return. See Appendix C for further details.

We then regress the rescaled pseudo expected excess returns on bond–stock betas and report the results in Column (6) of Table IV. The coefficient is positive, statistically significant, and comparable to the equity premium. The R-squared rises to 0.56. The magnitude of the coefficient is similar to the equity premium, though somewhat harder to interpret due to the scaling.[18] This finding is what we would expect based on Corollary 1, where the positive relation between bond–stock betas and subjective expected excess returns is not driven by forecasters' attempts to predict bond term premia and even strengthens when viewing forecasts as a simple fair-value model of long-term inflation. This result hence further reiterates that our baseline empirical result likely reflects the market's pricing of bond-stock betas, and forecasts serve as a fair-value benchmark that absorbs trends in small samples

[17]We use a very long-term measure of expected inflation to give inflation expectations the greatest possible chance. We find similar or weaker relationships between subjective expected excess returns and a broad range of shorter-horizon inflation expectations in unreported results.

[18]We also find a positive and statistically significant relationship when we use the unscaled pseudo expected excess returns. In that case, the magnitude of the coefficient becomes large and is hard to interpret.

Table IV: Expected Excess Returns, Bond–Stock Betas, and Inflation: U.S. Panel

Dependent Variable:	Expected Excess Returns					XR CPI 10Y
	(1)	(2)	(3)	(4)	(5)	(6)
Beta 5YR	10.87***		11.75***		9.40***	27.56***
	(1.84)		(1.64)		(2.17)	(8.26)
CPI Std		0.04	0.79***			
		(0.45)	(0.25)			
CPI 10Y				2.07***	0.27	
				(0.34)	(0.48)	
Maturity FE	✓	✓	✓	✓	✓	✓
R-squared	0.43	0.00	0.46	0.18	0.38	0.27
Observations	1305	1305	1305	390	390	390

Note: The table reports estimates from regressions of expected excess returns on bond–stock betas and inflation-related controls, as in Equation (11):

$$\tilde{E}_t xr_{n,t\to t+12} = \alpha + \lambda\beta^w_{n,t} + X'_{n,t}\delta + \eta_{n,t}.$$

Column (1) reports the baseline specification with the bond–stock beta alone. Columns (2) and (3) add the five-year rolling standard deviation of CPI inflation (CPI Std), first on its own and then jointly with the beta. Columns (4) and (5) instead use long-run expected inflation from the SPF (CPI 10Y), defined as the expected average CPI inflation over the next ten years. In column (6) the dependent variable is the pseudo expected excess return constructed from long-run inflation expectations (XR CPI 10Y), regressed on the bond–stock beta. Columns (1)–(3) use monthly data, while columns (4)–(6) use quarterly data, since the SPF inflation expectations are observed once per quarter. Driscoll–Kraay standard errors are reported in parentheses, using 27 lags for the monthly specifications and 15 lags for the quarterly specifications. Stars denote significance at the 10, 5, and 1 percent levels based on Kiefer–Vogelsang fixed-b critical values. The sample period is January 1988 to March 2024.

and potentially biased term structure expectations.

3.2.3 Controlling for Forecaster Biases

So far, we have found that bond–stock betas are an important factor in explaining subjective expected bond excess returns. This is consis Our measure of subjective expected excess returns uses professional forecasters' predictions of medium- and long-maturity interest rates. However, Shue et al. (2025) show that expected future changes in short-term interest rates predict corresponding expected changes in long-term interest rates. It is therefore natural to test whether the expected change in the federal funds rate can explain subjective expected bond excess returns, and whether the relation between bond–stock betas and expected excess returns disappears once we control for this expected short-rate change.

We construct the expected change in the federal funds rate using Blue Chip forecasts. Specifically, we use the expected change in the federal funds rate four quarters ahead. This horizon matches our construction of subjective expected excess returns, which uses four-quarter-ahead forecasts of bond yields. In fact, Shue et al. (2025) show that forecasters predict similar paths for short- and long-term interest rates over the next several quarters, making the four-quarter-ahead expected change in the federal funds rate the natural control in our setting.

In Column (2) of Table V, we regress subjective expected excess returns on bond–stock betas and the expected change in the federal funds rate. The coefficient on the expected change in the federal funds rate is negative, equal to -0.61, and statistically different from zero. This sign is expected: when forecasters expect the federal funds rate to increase, they also expect long-term rates to increase, which reduces expected excess returns on long-term bonds because the forecasted future yield enters negatively in Equation (7). However, controlling for the expected change in the federal funds rate has little effect on the coefficient on bond–stock betas, which remains close to the baseline estimate reported in Column (1).

In Column (3), we interact the expected change in the federal funds rate with bond maturity. The estimated effects are stronger for longer-maturity bonds, consistent with the mechanics of Equation (7). Intuitively, if expected changes in the federal funds rate translate into similar expected changes in long-term yields across maturities, their effect on expected excess returns is larger for longer-maturity bonds because the forecasted future yield is multiplied by $dur_{n,t} - 1$.

In Columns (4) and (5), we control for pseudo expected excess returns constructed under the assumption that forecasters form yield expectations using an autoregressive (AR) model. This exercise tests whether forecasters simply predict mean reversion in bond yields, and whether such a forecasting rule can account for our findings. Appendix C describes the construction of these forecasts in detail. At each date, the forecast uses only information available up to that point: we estimate the AR model recursively using the preceding fifteen years of monthly yield data and then compute the implied expected excess return.

Controlling for this AR-based pseudo expected excess return slightly strengthens the relationship between bond–stock betas and subjective expected excess returns, with a coefficient of 12.03 in Column (5).[19]

Columns (6) and (7) instead use pseudo expected excess returns constructed from a moving-average model, in which forecasters predict the yield twelve months ahead using the average yield observed over the preceding five years. The coefficient on bond–stock betas is again essentially unchanged.

Finally, we show that our results are distinct from, and incremental to, expected excess returns implied by biased interest rate forecasts. Specifically, we control for the expected excess return implied by the slow-learning model of Farmer et al. (2024), which has been

[19]The results are virtually unchanged if we use expanding windows or different rolling windows.

Table V: Short-Term Rate Forecasts and Statistical Forecasts

Dependent Variable: Expected Excess Returns									
Control Variable:		$\tilde{E}_t[\Delta FF]$		AR Roll		MA 60		FNS	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Beta 5YR	10.87***	10.12***	9.91***	11.90***	12.03***	11.21***	11.30***	11.61***	11.67***
	(1.84)	(1.73)	(1.73)	(2.01)	(2.03)	(2.00)	(1.99)	(2.16)	(2.18)
Control		-0.61***		0.26**		0.08***		-0.04	
		(0.18)		(0.12)		(0.03)		(0.23)	
Control × Mat. 3			-0.20**		-0.00		-0.00		-0.22**
			(0.10)		(0.07)		(0.03)		(0.11)
Control × Mat. 6			-0.58***		0.19		0.04		0.00
			(0.18)		(0.13)		(0.03)		(0.23)
Control × Mat. 11			-1.06***		0.43**		0.12***		0.07
			(0.31)		(0.18)		(0.03)		(0.38)
Maturity FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
R-squared	0.43	0.46	0.47	0.45	0.46	0.46	0.46	0.47	0.47
Observations	1305	1305	1305	1305	1305	1305	1305	435	435

Note: The table reports estimates from regressions of expected excess returns on bond–stock betas and inflation-related controls, as in Equation (11):

$$\tilde{E}_t xr_{n,t\to t+12} = \alpha + \lambda\beta^w_{n,t} + X'_{n,t}\delta + \eta_{n,t}.$$

In each pair of columns the control enters first with a single (common) loading (the "Control" row) and then with maturity-specific loadings (the "Control × Mat. 3/6/11" rows). Column (1) is the baseline specification with the bond–stock beta alone. Columns (2)–(3) control for the Blue Chip forecast of the change in the federal funds rate over the next four quarters, $\tilde{E}_t[\Delta FF]$. Columns (4)–(9) control for pseudo expected excess returns, constructed by replacing the survey yield forecast in our baseline measure with a purely statistical forecast of future bond yields: a rolling AR(1) forecast estimated over a fifteen-year window (AR, Columns (4)–(5)), a five-year (60-month) trailing moving-average forecast (MA, Columns (6)–(7)), and the FNS forecast (FNS, Columns (8)–(9)). The construction of each pseudo expected excess return is detailed in Appendix C. Columns (1)–(7) use monthly data, while Columns (8)–(9) use quarterly data, since the FNS measure is observed once per quarter. Driscoll–Kraay standard errors are reported in parentheses, using 27 lags for the monthly specifications and 15 lags for the quarterly specifications. Stars denote significance at the 10, 5, and 1 percent levels based on Kiefer–Vogelsang fixed-b critical values. The sample period is January 1988 to March 2024.

shown to account for a large share of forecast errors in policy rate expectations in recent decades, including forecasters' failure to anticipate the timing of liftoff from the zero lower bound. The estimated coefficient on bond–stock betas is virtually unchanged when we control for these additional pseudo expected excess returns in Columns (8) and (9). Appendix B describes the construction of the Farmer et al. (2024) forecasts, and Appendix C describes how we convert them into pseudo expected excess returns.

3.3 U.S. Realized Excess Return Predictability

One might wonder whether the relationship between betas and expected bond excess returns carries over to realized excess returns. Under the full information rational expectations

(FIRE) benchmark, betas should have the same relationship with subjective expected returns and realized returns in a sufficiently long sample. In practice, however, our sample is finite, and interest rate forecasts may be biased due to behavioral biases (Bordalo et al., 2020; Shue et al., 2025; Molavi et al., 2025a) or imperfect knowledge of the parameters describing the interest rate process (Farmer et al., 2024; Molavi et al., 2024; Bauer et al., 2024).

We estimate predictive regressions of the form:

$$xr^{par}_{n,t\to t+12} = b_0 + b_1\, \tilde{E}xr_{n,t\to t+12} + b_2\,(\hat{\lambda} \times \hat{\beta}^w_{n,t}) + X'_{n,t}\delta + \varepsilon_{n,t+12}. \tag{13}$$

Here, $\hat{\beta}^w_{n,t}$ denotes the fitted value from the regression of expected excess returns on bond–stock betas, as specified in equation (11). We use the fitted value solely to ensure that the magnitude of the coefficient is directly comparable to that of subjective expected excess returns.

Under the FIRE benchmark, we would expect to find that the subjective expected excess return $\tilde{E}xr_{n,t\to t+12}$ and the scaled beta $(\hat{\lambda} \times \hat{\beta}^w_{n,t})$ should both individually enter with unit coefficients, i.e. $b_1 = b_2 = 1$. However, if forecasters have no information above and beyond the CAPM, the beta should be the only driver of expected bond excess returns, the regressors would be collinear, and b_1 and b_2 might not be identified in a multivariate regression. We hence first introduce the regressors individually and then combine them in a multivariate regression.

Table VI reports the results. To increase power, we again stack the different bond maturities in a panel, where the unit of observation is bond maturity $n \in \{3, 6, 11\}$ by month t. We use the smoother version of subjective expected excess returns, computed as the twelve-month moving average. Appendix Table F7 reports the corresponding results using the unsmoothed series. Column (1) reports a univariate regression of realized excess returns onto subjective expected returns, finding a coefficient of 0.82. This coefficient is statistically significantly different from zero, but not significantly different from one. Expected bond excess returns hence predict realized bond excess returns with a large magnitude that does not reject that expected bond excess returns are roughly rational. While the R-squared in these columns may appear small at roughly 8%, recall that this is similar to the R-squared in typical stock return predictability regressions and can lead to a substantial improvement in investor Sharpe ratios (Campbell and Thompson, 2008). Hence, forecasters appear to have some useful information, but realized returns are at best a very noisy measure of ex-ante expected returns.

We next examine whether subjective expected returns are predictive due to their correlation with betas or due to the part of subjective expected return that is orthogonal to beta.

Table VI: Realized and Expected Excess Returns: U.S. Panel

Dependent Variable: Future Realized Excess Return							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Subj. Excess Returns (MA)	0.82***	0.84***		1.85***	1.80***	1.55***	1.18***
	(0.30)	(0.28)		(0.33)	(0.32)	(0.35)	(0.33)
$\lambda\times$ Beta			0.19	-1.69***	-1.59***	-1.32**	-2.00***
			(0.38)	(0.45)	(0.53)	(0.59)	(0.73)
Bond Variance					6.98		
					(18.62)		
Term Spread						0.85	
						(0.74)	
Level							2.08**
							(0.91)
Slope							-0.74
							(0.67)
Curvature							0.57
							(0.56)
Constant	2.09***						
	(0.71)						
Maturity FE		✓	✓	✓	✓	✓	✓
R-squared	0.08	0.10	0.02	0.18	0.18	0.19	0.26
Observations	1236	1236	1269	1236	1236	1236	1236

Note: The table reports the estimates of equation (13):

$$xr^{par}_{n,t\to t+12} = b_0 + b_1\,\tilde{E}xr_{n,t\to t+12} + b_2\,(\hat{\lambda}\times\hat{\beta}^w_{n,t}) + X'_{n,t}\delta + \varepsilon_{n,t+12}.$$

All independent variables are lagged by twelve months. $\lambda\times$ *Beta* is the fitted value from a regression of expected excess returns on five-year betas, as specified in equation (11). The beta is thus rescaled so that its magnitude is comparable to the expected excess return. The table uses 12-month moving average of expected excess returns. Driscoll–Kraay standard errors with 27 lags are reported in parentheses. Stars denote significance at the 10, 5, and 1 percent levels based on Kiefer–Vogelsang fixed-b critical values. The sample consists of monthly data from January 1988 to March 2024.

In column (3), we regress realized excess returns on the beta. Consistent with Figure 1 in the introduction, the coefficient b_2 (in column (3)) is equal to 0.19 and is not statistically different from zero. However, the standard error is large. Hence, while forecasts are informative about future bond excess returns, the picture looks quite different for the component driven by betas. This could simply be due to noise in short samples, if realized bond yields have a substantial volatility relative to expectations, and bond-stock betas move slowly. If interest rate expectations further contain systematic bias, the empirical relationship between realized excess returns and betas could be further weakened relative to ex ante expectations. Either way, the results in Table VI reiterate the usefulness of using subjective expected excess returns to uncover the relationship with betas.

When we include both subjective expected returns and scaled betas in column (4), the two predictors enter with opposite signs, and the coefficient on expected bond excess returns strengthens further to 0.95. Controlling for the risk of Treasury bonds, a one percentage point increase in expected bond excess returns predicts a 185 bps increase in the realized bond excess return, i.e., almost one-for-one. The R^2 of the regression strengthens to 18.1%. A potential explanation for this result is that forecasters have higher-frequency information about bond returns, e.g., information about unconventional monetary policy or supply-and-demand imbalances, while betas are lower-frequency drivers of excess returns. Within our sample, subjective expected returns appear to better predict the first, higher-frequency component.

Column (5) includes the variance of bond returns, which enters with a positive coefficient, although it is not statistically significant. The inclusion of this control has little effect on the estimated coefficient on expected excess returns. The coefficient on the scaled beta remains of similar magnitude but is estimated less precisely.

The remaining columns of Table VI introduce term-structure controls and show that the predictive power of expected bond excess returns remains economically and statistically significant when both subjective expected returns and the bond–stock beta are included (columns (6) and (7)). This suggests that survey forecasts contain information about future bond excess returns that is not fully captured by the term structure, highlighting the benefits of using survey forecasts directly rather than relying on term-structure models in which expected returns and yields are typically driven by a limited number of factors.

Table F7 repeats the analysis using the raw, unsmoothed subjective expected returns. The main conclusions carry over to this unsmoothed specification. The estimates of b_1 are somewhat smaller across all models, and the R^2 also declines, reflecting the higher noise in the subjective expected excess returns. Taken together, the findings suggest that the predictability of future realized excess returns is driven mainly by the component of expected excess returns that is orthogonal to beta.

Table F8 reports results from regressions estimated separately by maturity. The table confirms the findings from the panel regression. Panel (A), column (1), (5), and (9), report coefficients from a simple predictive regression of future realized bond excess returns on subjective expected returns. The estimated coefficient is approximately 0.6 for the 3-, 6-, and 11-year maturities. When using the smoothed moving-average measure, the estimated coefficient increases to approximately 0.9, and the explanatory power rises substantially. When we use jointly the expected excess returns and the bond-stock betas, the R^2 equals 14% for the three-year maturity, 17% for the six-year maturity, and 17% for the eleven-year maturity, indicating that subjective expected returns contain substantial predictive power for future realized bond excess returns.

Consistent with the results from the panel regression, the beta is not statistically significant when included on its own, but it enters with a negative and statistically significant coefficient when included jointly with expected excess returns. Finally, when we include term structure controls, the coefficient on expected excess returns remains broadly unchanged relative to the baseline specification without controls, although it is estimated with lower precision and is not statistically significant in most specifications.

3.4 Implications for the Decline in Long-Term Yields

Our findings have implications for the decomposition of long-term bond yields into term premium and expected future short rates, thereby shedding light on the decades-long decline in U.S. long-term bond yields. Define the risk-neutral n-year zero-coupon yield as the yield that would hold under the expectations hypothesis (EH)

$$y_{n,t}^{rn} = \frac{1}{n}\tilde{E}_t \sum_{i=0}^{n-1} y_{1,t+12\times i}. \tag{14}$$

This is the long-term bond yield that should prevail if investors simply price the expected path of future short rates. We make the simplifying assumption that the one-year zero-coupon yield does not contain a risk premium, which is likely to be a good approximation.

We define the term premium component of the n-year zero-coupon bond yield as the difference between the actual yield and its risk-neutral counterpart. This can be written in terms of the average expected excess return over the lifetime of the bond:

$$y_{n,t}^{rp} \equiv y_{n,t} - y_{n,t}^{rn} = \frac{1}{n}\sum_{i=0}^{n-1} \tilde{E}_t xr_{n-i,t+12\times(i+1)}. \tag{15}$$

Plugging in our baseline estimate gives the following estimate for the n-year zero-coupon term premium:

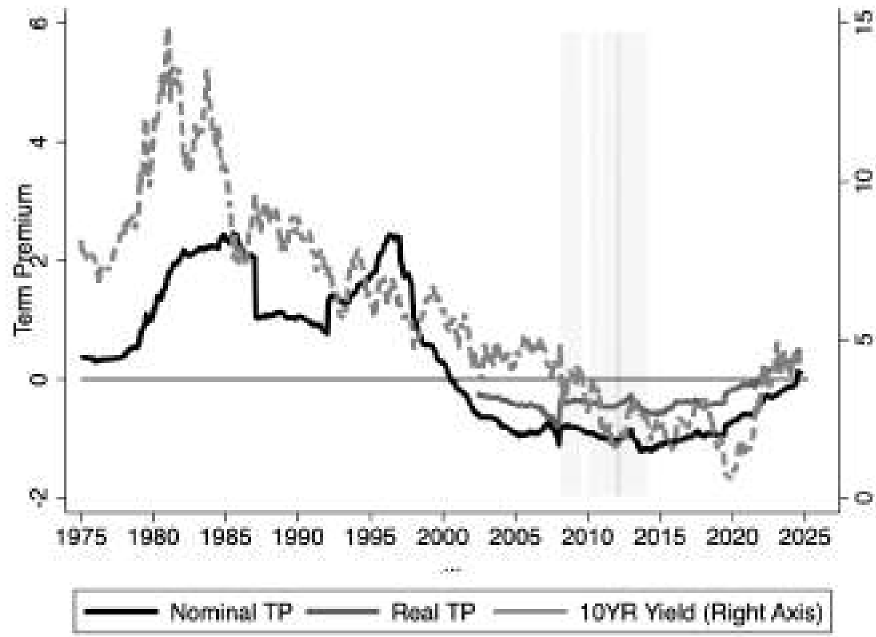
$$\hat{y}_{n,t}^{rp} = \frac{\hat{\lambda}}{n}\sum_{i=0}^{n-1} \rho_\beta^i \beta_{n-i,t+i\times 12}. \tag{16}$$

We next construct forecasts of bond-stock betas at different horizons. We use a simple econometric procedure that exploits their empirical persistence. Realized betas for n-year zero-coupon bonds are estimated from daily bond and stock returns over five-year rolling windows, analogously to the par bond-stock betas used in our main analysis. We then estimate the persistence of these betas through a panel regression of the form:

$$\beta_{n,t+12} = b + \rho_\beta \beta_{n,t} + \varepsilon_{t+12}, \tag{17}$$

using a monthly panel of bond-stock betas with bond maturities $n = 1, 2, ..., 10$. The

Figure 4: Implied U.S. Ten-Year Term Premium



Note: This figure reports the estimated zero-coupon nominal Treasury bond term premia estimated via equation (16) for U.S. ten-year nominal and real bonds from January 1975, when five-year rolling bond-stock betas become available, to June 2025. The ten-year nominal par yield from Gürkaynak et al. (2007) is shown for comparison on the right y-axis. Quantitative Easing program dates for QE1, QE2, Operation Twist (MEP), QE3 are shaded in gray.

regression yields an autoregressive coefficient of $\hat{\rho} = 0.96$ with a Driscoll-Kraay standard error with 27 lags of 0.05 and a constant of $\hat{b} = -0.002$ with a standard error of 0.005. Because the constant is tiny and not statistically different from zero, we set it to zero going forward. The expression for the risk premium on a real or inflation-indexed bond is constructed analogously, by using inflation-indexed bond-stock betas and re-estimating (17). To obtain an estimate of the order of magnitude of term premia, we use the econometrically estimated value for ρ_β in this section, analogous to the assumption that markets and forecasters are rational about beta persistence in the model.

Figure 4 shows estimated nominal and real term premia against the 10-year nominal zero-coupon yield from Gürkaynak et al. (2007). The figure starts in January 1975, when nominal five-year rolling window betas required for (16) become available. Our estimates imply a peak nominal term premium of 2.46% in March 1986 and a trough of -1.21% in August 2016, after the end of the first zero-lower-bound, for a total peak-to-trough decline in the term premium of 3.67 percentage points. For comparison, over the same time period, the 10-year nominal zero-coupon yield declined by 5.88 percentage points from 7.51% to

1.63%, so the estimated term premium accounts for more than half the decline in the 10-year yield over these three decades. Since then, the decline in long-term yields has reversed, along with the estimated term premium, which accounts for roughly half of this increase. Inflation-indexed (TIPS) bond yields also increased by almost as much as nominal yields from roughly 0% to 2% over the past ten years. Figure 4 shows that these level shifts in nominal and inflation-indexed bond yields are mirrored by our estimated term premia, which attribute most of the recent increase in term premia to their real component.

While our estimated overall decline in the 10-year term premium is similar or smaller than conventional estimates by Kim and Wright (2011) or Adrian et al. (2013), the timing is different. According to our estimates, nominal 10-year term premia turned negative as early as 2001, whereas the estimated term premia by Kim and Wright (2011) and Adrian et al. (2013) remain positive until 2011 and 2015, respectively. This matters for the interpretation of monetary policy before the Global Financial Crisis. During this period, low long-term yields were sometimes interpreted as a downward trend in the natural rate or r-star (Laubach and Williams, 2016), or as the result of a "savings glut" from international investors (Caballero et al., 2008). While our term premium estimates do not explain the full decline, they suggest that U.S. Treasury bonds' improved hedging properties played a substantial role in driving down long-term Treasury yields prior to the financial crisis. This matters for monetary policy because – different from a low natural rate – a negative term premium does not necessarily call for lower short-term policy rates (Caballero and Farhi, 2018).

4. International Panel Evidence

We now present the data and evidence for the international panel of twelve developed countries: Canada, France, Germany, Italy, Japan, the Netherlands, Norway, Spain, Sweden, Switzerland, the U.K., and the U.S. We also use this international panel to estimate how the subjective expected bond risk premia and bond-stock betas changed during QE periods.

4.1 International Data

We estimate subjective expected excess returns following equation (7). To obtain bond yield forecasts for the international panel, we turn to Consensus Economics. For each month, we use the average forecast of the ten-year yield twelve months ahead. This is the only bond maturity consistently reported across countries in Consensus Economics, giving a month-by-country panel. Consensus Economics reports the exact survey date, which typically falls on the second or third Monday of each month.[20] The Consensus Economics sample begins in September 1989 and ends in December 2024. For some countries, Consensus Economics forecasts become available at later dates. Coverage starts in 1994 for the Netherlands, Spain, and Sweden, and in 1998 for Norway and Switzerland.

We obtain month-end ten-year realized government bond yields, one-year government bond yields, T-bill rates, and total stock return indexes from the Global Financial Database (GFD).[21] For all countries except the U.S., we use the 10-year bond yield as a substitute for the 11-year bond yield in equation (7). For the U.S., we use the 11-year government par bond yield from Gürkaynak et al. (2007), as in our baseline U.S. analysis.[22] To proxy the risk-free rate in equation (7), we use the one-year government bond yield. For a small subset of countries, the one-year government bond yield is not available over the full sample. In those cases, we instead use the three-month T-bill rate.[23]

We construct bond–stock betas in the international panel using monthly realized excess returns on 10-year government bonds and monthly excess returns on the domestic stock market, with both stock returns and the risk-free rate in local currency. We compute realized returns on the ten-year government bond using equation (9), based on one-month holding-period returns rather than daily returns due to data availability in the international sample. To compute monthly excess returns in the beta estimation, we use the T-bill rate as the risk-free rate. We then estimate equation (10) separately for each country. As only monthly data are available, bond–stock betas are estimated using a five-year rolling window (60 months), since shorter rolling windows would lead to substantial estimation noise. As an alternative specification, we also compute bond–stock betas using returns on the U.S. stock market in excess of the U.S. T-bill, which corresponds to currency-hedged excess returns on the U.S. stock market for local currency investors up to second-order hedging approximation error.[24]

International expected bond excess returns and rolling betas are plotted in Figure 5, and summary statistics are reported in Appendix Table F9. In each panel of Figure 5, the

[20]The definition of the Consensus Economics forecasts is largely comparable to that of the Blue Chip forecasts described above. Consistent with this, for the U.S. the two series are strongly correlated, with a correlation of 0.99 (see Appendix Figure F.8). Minor differences may arise because: (i) Consensus Economics elicits forecasts of the yield twelve months ahead, whereas Blue Chip reports forecasts of the average yield in the quarter four quarters ahead; (ii) survey dates may differ slightly within the month; and (iii) the sets of surveyed economists do not perfectly overlap.

[21]For Italy, the series of the total return index from GFD stops in 2019. We supplement this series with the total return index for the Italian market downloaded from Datastream.

[22]For the U.S., we average daily bond yields over the last week of each month to reduce the volatility of outliers and use the average BCFF forecast of 10-year Treasury yields. These choices ensure consistency with the U.S. analysis but are not crucial for the results.

[23]The one-year rate is not available for Canada until 2007, for the Netherlands until 1999, and for Norway until 2003.

[24]Summary statistics for betas with respect to U.S. stock excess returns are in Appendix Table **??**.

dashed gray line (left-hand y-axis) represents subjective expected excess returns, while the solid black line (right-hand y-axis) represents the beta for a specific country. The figure illustrates the usefulness of bringing in data from other countries. First, a close correlation between expected bond excess returns is visible consistently across countries. For example, the univariate correlation equals 84% for Canada and 68% for Germany. Second, cross-country differences in betas are also mirrored in expected bond excess returns. One case in point is Japan, which experienced negative bond-stock betas substantially earlier than most other countries, and this was matched by a correspondingly earlier switch to negative expected bond excess returns.

4.2 International Expected Excess Returns vs. Betas

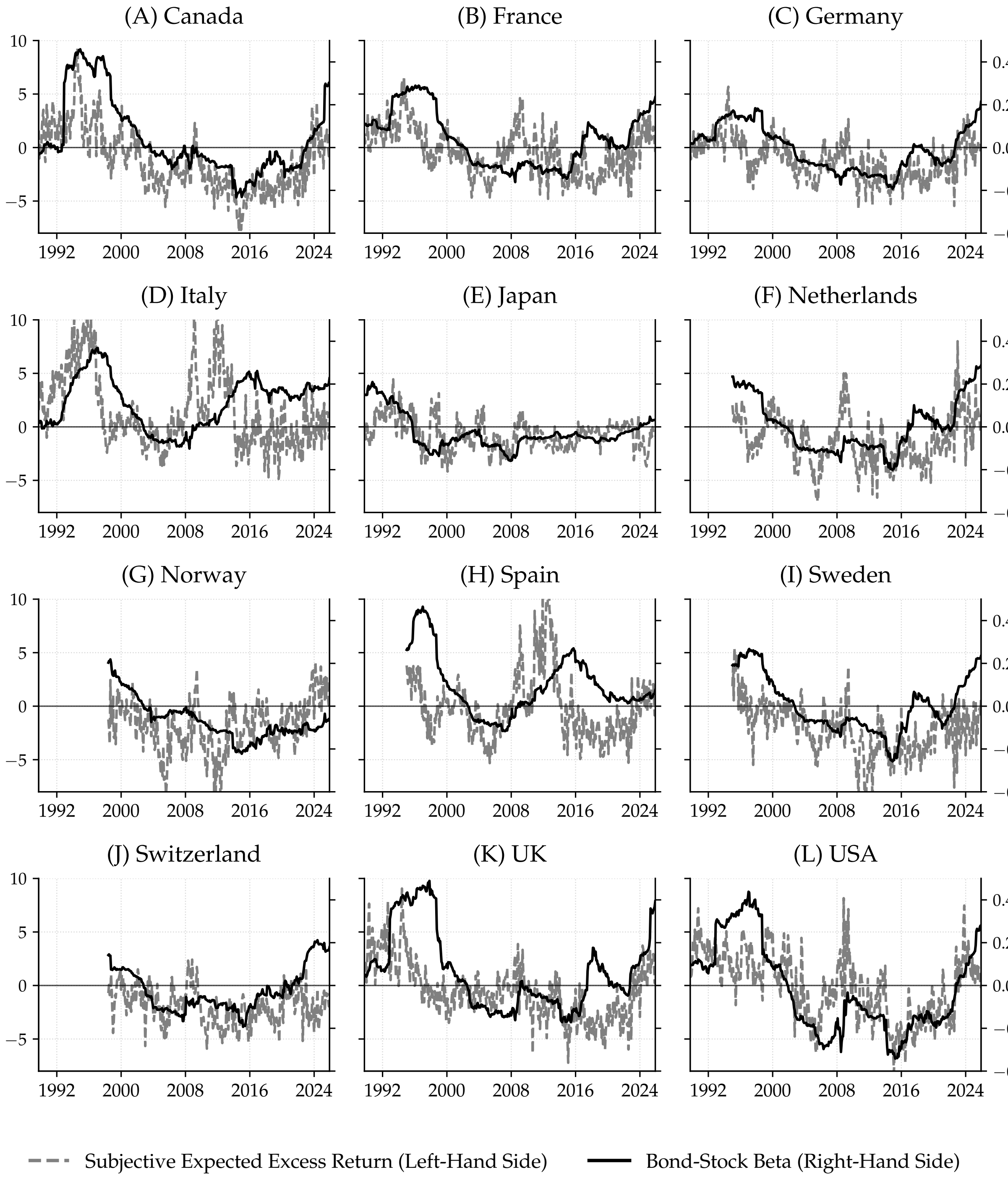
We next estimate the relationship between subjective expected excess returns and betas across countries and over time via the following international panel regression:

$$\tilde{E}_t xr_{c,t\to t+12} = \alpha + \lambda\beta_{c,t} + X'_{c,t}\delta + \eta_{c,t}, \tag{18}$$

where c indexes countries, $E_t xr_{c,t\to t+12}$ denotes subjective expected excess return for the eleven-year bond in country c over a twelve-month forecast horizon, $\beta_{c,t}$ is the five-year rolling beta estimated using information available at time t, and $X_{c,t}$ is a vector of control variables. The specification mirrors equation (11), with the cross-sectional dimension given by countries rather than maturities. As before, the CAPM predicts a positive coefficient λ equal to the equity premium, and a zero intercept α.

Table VII shows that the estimated relationship between bond-stock betas and expected bond excess returns is indeed significantly positive and economically meaningful for the international panel. Column (1) starts with the univariate regression without controls or fixed effects, finding an estimated coefficient 8.4. Its magnitude is comparable to the U.S. results reported in Table II and on the order of the equity premium. The standard deviation of beta in the sample is 0.15, while the standard deviation of subjective expected excess returns is 2.70. A one-standard-deviation increase in the beta is associated with a $1.24 = 0.15 \times 8.4$ percentage point increase in the subjective expected excess return. The estimated constant in column (1) is statistically significantly negative, different from what the CAPM predicts. However, we need to keep in mind that in the international panel, we approximate the 11-year yield in the expected excess return equation (7) by a 10-year yield. For example, if the actual par yield $y^{par}_{n,t}$ is under-estimated by 10 bps and the bond duration equals roughly 9 years, this could explain the estimated -90 bps constant merely through measurement bias due to the unavailability of complete yield curves for the international sample, even when

Figure 5: Expected Excess Returns and Betas by Country



Note: The figure reports estimated subjective expected excess returns and betas for each country. The sample runs from September 1989 through December 2024. We compute subjective expected bond excess returns using survey forecasts from Consensus Economics and financial data from Global Financial Database. The only exception is the U.S., where we use our baseline subjective expected excess returns based on the BCFF. Bond-stock betas are estimated using monthly bond and stock excess returns from the Global Financial Database. We use a five-year (60 months) rolling window. Consensus Economics data are not available since the start of the sample for a number of countries: the Netherlands, Norway, Spain, Sweden, and Switzerland. We use the same x-axis and y-axis for all panels.

the actual CAPM alpha equals zero.[25]

The relationship between expected bond excess returns and betas in the international panel is robust to a wide range of controls and fixed effects. In Column (2), we include a linear time trend, which has little effect on the results, yielding a slightly smaller coefficient of 7.1. In Column (3), we additionally include country fixed effects, which absorb time–invariant country–specific characteristics, such as persistent differences in risk premia. The estimated coefficient is slightly smaller and equal to 7.8. With country fixed effects, identification comes from within–country variation over time, indicating that changes in beta within a country are associated with changes in subjective expected excess returns. In Column (4) we allow for the time trend to differ across country, by interacting the time trend with the country fixed effect. The coefficient in this specification is equal to 6.5.

In Column (5), we add the rolling variance of bond excess returns as a control, where the variance is estimated over the same window and using the same data frequency as bond-stock betas. One might expect that higher bond return variance goes along with higher bond risk premia if the marginal bond investor is primarily invested in bonds. In the international panel, we again find a positive coefficient on the bond return variance, similar to the U.S. regression in Table II, though it is smaller and not statistically distinguishable from zero in the international panel. The coefficient on bond-stock betas and the R-squared are again little changed.

Columns (6) and (7) add term structure controls, showing that this again leaves the coefficient on betas unchanged. In Column (6), we add the term spread. Column (7) separately controls for the one-year and ten-year bond yields, since level, slope, and curvature are not available for our international panel. The coefficient on beta remains unchanged, while the coefficient on the term spread is close to zero. This suggests that the term spread does not contain information beyond the beta in explaining subjective expected excess returns. A likely reason why the term spread does not explain expected bond excess returns controlling for bond-stock betas is that variation in the term spread conflates the expected path of interest rates with compensation for risk.[26] By contrast, subjective expected bond excess returns adjust for the expected path of interest rates, providing a more direct measure of bond risk premia than the term spread.

Columns (8) and (9) add increasingly restrictive fixed effects. Column (8) controls for

[25]On average, the U.S. 11-year par yield exceeds the U.S. 10-year par yield by 7 bps in Gürkaynak et al. (2007) data.

[26]A long literature has found that the term spread's ability to predict bond excess returns is not as strong internationally as in the U.S. The term spread appears to predict bond excess returns better in countries and time periods when interest rates are better approximated by a random walk, which would lead the expected path component to drop out of the term spread (Mankiw et al., 1987; Hardouvelis, 1994).

time fixed effects, thereby exploiting only cross-country variation. The coefficient on bond-stock betas declines somewhat in magnitude, but remains statistically significant and on the order of the equity premium. The time fixed effects absorb common time-series variation across countries. The fact that the coefficient remains large and significant indicates that, while countries comove over time, countries that tend to have more positive bond-stock betas also tend to have higher subjective expected excess returns. Only when we include both time and country fixed effects in Column (9) does the estimated coefficient on beta become smaller in magnitude; however, it remains highly statistically significant and approximately half as large as the equity premium. In this specification, a large share of the variation is absorbed by fixed effects, so it is not surprising that results change somewhat, even though the slope remains statistically significant and large.

So far, the results use betas constructed using domestic stock market returns. However, if investors are primarily exposed to the U.S. equity market, the relevant beta may instead be the one computed with respect to U.S. stock returns. For this reason, we replicate the same set of regressions using betas of bond returns with respect to the U.S. stock market. The results are reported in Appendix Table F10 and are very similar to the baseline results. A natural explanation is that stock market returns are highly correlated across countries, so the choice between domestic and U.S. stock returns has little effect on the international panel regression results.

Individual Countries We next show that the relationship between expected bond excess returns and betas is consistently present for all countries, and not driven by a small number of countries. For this, we estimate equation (18) separately for each country using betas computed with respect to the domestic stock market, thereby only exploiting time series variation. The consistent results across countries are visible in Figure 6, which reports the estimated coefficient $\hat{\lambda}_c$ together with its 95% confidence interval for each country. The figure shows that the estimated coefficient is positive for all countries. The magnitude of the coefficient varies across countries: it is the largest in Canada, Germany, and the United States, where it exceeds 10; it lies between 5 and 10 for France, Japan, the Netherlands, Sweden, and the United Kingdom; and it is smaller in Italy, Norway, Spain, and Switzerland, where it remains positive but is not always statistically significant.

Differences in magnitude partly reflect differences in sample length and spikes in expected bond excess returns during the European debt crisis. Italy and Spain, most exposed to the European debt crisis, exhibit substantial volatility in both beta and subjective expected returns, as can be seen in Figure 5. For both countries, betas and subjective expected excess returns display a very strong comovement from 1990 to 2014. After 2014, this relationship weakens: the beta remains positive, while subjective expected excess returns turn negative.

Table VII: Expected Excess Returns and Stock Market Betas: International Panel

Dependent Variable: Expected Excess Returns	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Bond-Stock Beta	8.39***	7.09***	7.77***	6.54***	6.68***	7.81***	3.92***	5.79***	3.81***
	(1.67)	(1.69)	(1.59)	(2.00)	(1.62)	(1.57)	(1.49)	(1.92)	(1.16)
Bond Variance					0.15				
					(0.11)				
Term Spread						0.18			
						(0.17)			
10-Year Rate							0.70***		
							(0.21)		
1-Year Rate							-0.20		
							(0.18)		
Constant	-0.90***								
	(0.26)								
Time Trend		✓							
Country FE			✓	✓	✓	✓	✓		✓
Time Trend × Country FE				✓					
Time FE								✓	✓
R-squared	0.21	0.25	0.28	0.36	0.29	0.29	0.45	0.55	0.62
Observations	4798	4798	4798	4798	4798	4798	4798	4798	4798

Note: The table reports the results of equation (18):

$$\tilde{E}_t xr_{c,t\to t+12} = \alpha + \lambda \beta^w_{c,t} + X'_{c,t}\delta + \eta_{c,t},$$

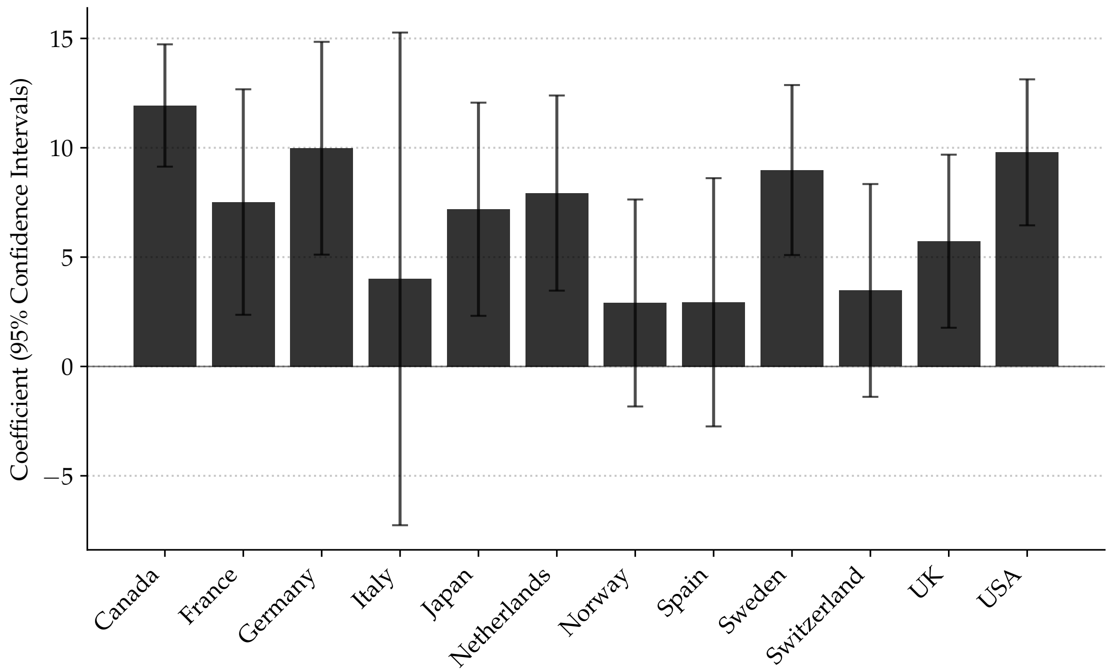
estimated using our international panel. The bond-stock beta is estimated using monthly data over a five-year rolling window (60 months) and using domestic stock market excess returns. Expected yields are from Consensus Economics, while bond yields, T-bill rates, and stock returns are from the Global Financial Database (GFD). The term spread is the difference between the ten-year government bond yield and the one-year government bond yield. Driscoll-Kraay standard errors with 27 lags are reported in parentheses. Stars denote significance at the 10, 5, and 1 percent levels based on Kiefer–Vogelsang fixed-b critical values. The data are monthly and span September 1989 to December 2024.

This break coincides with the launch of the ECB's quantitative easing (QE) program in January 2015, through the Public Sector Purchase Programme. One interpretation is that QE substantially lowered sovereign spreads and term premia in these countries, leading to persistently low expected returns. We explore the relationship between expected excess returns and QE further in Section 4.4.

In contrast, Norway and Switzerland display a weaker relationship between expected bond excess returns and bond-stock betas simply because their data start in 1998, when betas were already zero. Lacking any positive betas over their shorter samples, it is unsurprising that the relationship is estimated to be weaker for those two countries.

Figure F.10 presents the corresponding country-by-country regressions when bond-stock betas are computed with respect to U.S. stock excess returns. Overall, the results are robust and very similar. However, the estimated coefficients are somewhat smaller in magnitude

Figure 6: Country-by-Country Expected Excess Returns onto Beta



Note: The figure plots the estimated coefficient from regression (18), estimated separately for each country. The figure also reports 95% confidence intervals constructed using Newey–West standard errors with 27 lags. The data are monthly, and for most countries, the sample spans September 1989 to December 2024. A few countries use shorter samples, as detailed in Table F9.

relative to the baseline results, with the difference being particularly pronounced for Italy and Spain. This may suggest that the domestic stock market is the relevant market portfolio for investors in the local bond market, particularly for those two countries.

4.3 International Realized Excess Return Predictability

Having established a robust relationship between the beta and subjective expected excess returns in the international context, we now extend the analysis of Section 3.3 to the international setting. We examine whether the relationship between the beta and expectations also translates into predictability for realized excess returns. To this end, we estimate predictive regressions of the following form:

$$xr^{par}_{c,t\to t+12} = b_0 + b_1\, \tilde{E}_t xr_{c,t\to t+12} + b_2\, (\hat{\lambda} \times \hat{\beta}^w_{c,t}) + X'_{c,t}\delta + \varepsilon_{c,t+12}. \tag{19}$$

Here, $\hat{\beta}^w_{c,t}$ denotes the fitted value from the regression of subjective expected excess returns on betas, as specified in equation (18). The regression is estimated in a panel setting with countries as the cross-sectional dimension.

Table VIII reports the results, using the twelve-month moving average of subjective expected excess returns. Table F7 shows the results using the unsmoothed series. Columns (1) and (2) report a simple predictive regression of realized excess returns on subjective expected excess returns, without and with country fixed effects, respectively. The estimated univariate coefficient is statistically significant in both cases, equal to 0.72 without country fixed effects and 0.81 with them. In the case with country fixed effects, the estimated coefficient is statistically different from zero, but not statistically different from one, as one would expect under FIRE. While the point estimate is somewhat smaller than one would expect under FIRE, we cannot necessarily reject FIRE with statistical significance. Overall, it appears that surveys are informed about international realized bond excess returns.

The next few columns decompose expected bond excess returns into a component due to bond-stock betas and the remaining variation in expected bond excess returns. In Column (3), we replace subjective expected excess returns with the scaled beta. The estimated coefficient equals 0.77, but is not precisely estimated, and we cannot reject the null that it is equal to zero. Nevertheless, the magnitude of the coefficient is similar to that obtained when using subjective expected excess returns directly, suggesting that there may be a positive relationship, though the data on realized international bond excess returns is too noisy to reliably estimate this relationship.

In Column (4), we estimate a regression that includes both subjective expected excess returns and the scaled bond–stock beta. If expected bond excess returns were fully driven by bond-stock betas, the two regressors in this specification would be collinear, and the coefficients could not be estimated. We find that the coefficient on subjective expected excess returns remains very similar to the univariate regression in Column (1), while the coefficient on the bond–stock beta declines further and remains statistically insignificant. In Column (5), we further control for the term spread, which enters positively and significantly as in Campbell and Shiller (1991), but leaves the other coefficients unchanged.

Appendix Table F11 reports the corresponding results using the unsmoothed subjective expected excess returns as regressors. The qualitative results are broadly unchanged, although the coefficient on subjective expected excess returns is slightly smaller.

Overall, international surveys are informative for future bond excess returns, and we cannot reject that forecasters are rational. However, the most significant predictability of realized bond excess returns arises from the component in expected bond excess returns that is orthogonal to betas. Similar to the U.S., one possible interpretation is that forecasters have information about international bond returns, but because betas move at low frequency, the sample is too short to detect a significant relationship between betas and necessarily noisy realized bond excess returns. Alternatively, if bond yield expectations contain systematic

Table VIII: Realized Returns, Expected Excess Returns, and Betas: International Evidence

Dependent Variable: Future Realized Excess Return					
	(1)	(2)	(3)	(4)	(5)
Subj. Excess Returns (MA)	0.72***	0.81***		0.85***	0.69**
	(0.26)	(0.28)		(0.28)	(0.29)
$\lambda\times$ Beta			0.77	-0.16	0.05
			(0.64)	(0.67)	(0.61)
Term Spread					1.78***
					(0.41)
Constant	2.68***				
	(0.90)				
Country FE		✓	✓	✓	✓
R-squared	0.064	0.073	0.021	0.074	0.140
Observations	4653	4653	4653	4653	4653

Note: The table reports the results of equation (19) estimated using our international panel:

$$xr^{par}_{c,t\to t+12} = b_0 + b_1\,\tilde{E}_t xr_{c,t\to t+12} + b_2\,(\hat{\lambda}\times\hat{\beta}^{w}_{c,t}) + X'_{c,t}\delta + \varepsilon_{c,t+12},$$

All independent variables are lagged by twelve months. $\lambda \times Beta$ is the fitted value from a regression of the expected excess return on the five-year bond-stock beta, as specified in equation (11). The beta is therefore rescaled so that its magnitude is comparable to the expected excess return. The table uses moving average expected excess returns. The moving average expected excess return is the average expected excess return over the past year. Driscoll-Kraay standard errors with 27 lags are reported in parentheses. Stars denote significance at the 10, 5, and 1 percent levels based on Kiefer–Vogelsang fixed-b critical values. The sample consists of monthly data from September 1989 to December 2024.

bias, this may further weaken the relationship between betas and realized excess returns. Either way, our measure of subjective expected excess returns automatically adjusts for both sources of contamination.

4.4 Quantitative Easing in the International Panel

So far, we have shown that bond risk premia are closely linked to bonds' betas with respect to the aggregate stock market. In this section, we apply our framework to study the implications of quantitative easing for this relationship.

While QE is now a standard tool of central banks, its transmission mechanisms remain debated (Tenreyro and Wazzi, 2025). First, under the signaling channel, QE may act by credibly committing the central bank to lower future short rates. In that case, long-term yields fall through the expectations hypothesis, with no effect on risk premia. Second, the portfolio balance channel predicts that by removing duration risk from private investors' balance sheets, QE lowers the price of bond risk and thus the compensation investors require to hold long-duration bonds, especially when bond returns are more volatile (Tobin, 1958, 1969; Vayanos and Vila, 2021). Under a broader interpretation of this channel, QE may also reduce the price of bond–stock beta risk by raising investor wealth and lowering aggregate risk aversion, as in intermediary-based models (Kekre et al., 2024) and similar to habit-based frameworks (Campbell et al., 2020). Third, QE may affect bond market liquidity, thereby lowering bond yields and risk premia by reducing market stress. Finally, QE may be perceived as state-contingent if investors expect similar interventions in future crises (Haddad et al., 2025). Under this channel, QE should affect bond betas themselves and, through this effect, bond risk premia. Against this backdrop, we study whether the relationship between bond–stock betas and subjective expected excess returns differs during QE periods relative to non-QE periods.

The international panel is advantageous because different countries initiated QE at different times, providing more variation than the time series of a single country. Nonetheless, our analysis is naturally limited because each country had at most one or two programs over our sample. Moreover, the onset of QE is endogenous and potentially confounded with other policy changes, so our results are not necessarily causal.

We construct an indicator variable $\text{QE}_{c,t}$ that equals one during periods in which QE is active in country c at time t. QE was implemented in Italy, France, Germany, the Netherlands, Spain, the U.S., the U.K., Japan, Canada, and Sweden. The remaining countries, Norway and Switzerland, are included in the panel with their QE dummies set to zero.[27]

We test for a relationship between QE, expected bond excess returns, and the price of risk through panel regressions of the form:

$$\tilde{E}_t xr_{c,t\to t+12} = \alpha + \alpha_{QE}\text{QE}_{c,t} + \lambda\beta_{c,t} + \lambda_{QE}\left(\text{QE}_{c,t} \times \beta_{c,t}\right) + \mu\hat{\sigma}^2_{c,t} + \mu_{QE}\left(\text{QE}_{c,t} \times \hat{\sigma}^2_{c,t}\right) + \eta_{c,t}, \tag{20}$$

where c indexes countries, and $\hat{\sigma}^2_{c,t}$ is the rolling bond return variance over a five-year moving window. As before, $\beta_{c,t}$ denotes the five-year rolling bond–stock beta.

The results are displayed in Table IX. For all specifications, we use the twelve-month moving average of subjective expected returns to reduce noise.[28] In column (1), we regress expected excess returns on the QE dummy and obtain a negative and statistically significant coefficient of -1.2. However, this result may simply reflect the fact that QE was enacted

[27]While the Swiss National Bank had a program purchasing foreign currency, it did not have a program purchasing Swiss government bonds. We therefore set the Switzerland QE dummy to zero. We define QE periods based on central bank announcement dates. Specifically, the start date corresponds to the initial QE announcement, while the end date is given by the announcement that QE would be terminated or that quantitative tightening (QT) would begin. If multiple programs overlap, we consider QE to be active as long as at least one program remains in place. For example, the ECB's Asset Purchase Programme (APP) and Pandemic Emergency Purchase Programme (PEPP).

[28]Results using raw subjective expected returns are similar and are reported in Appendix Table F13.

in a period of generally low bond risk premia. This is visible in the small and insignificant dummy coefficient in Column (2), which includes country and time fixed effects. The evidence whether QE leads to a level shift in bond risk premia is hence somewhat ambiguous in our data.

However, we find that QE is associated with a change in the price of risk. In Column (3), we extend the regression to include beta and its interaction with the QE dummy. The base coefficient on beta, λ, is similarly large and significant as in our baseline regressions at 9.5. In addition, Column (3) shows a large and negative interaction coefficient between bond–stock betas and the QE dummy. This implies that the loading of subjective expected excess returns on bond–stock betas declines during QE periods. To assess whether this relationship effectively disappears, we test whether the implied slope during QE, $\lambda + \lambda_{QE}$, is equal to zero using a Wald test of the linear restriction $\lambda + \lambda_{QE} = 0$. We find that we cannot reject this hypothesis (p-value= 0.758), implying that the pricing of beta is statistically indistinguishable from zero during QE periods. The results for λ and λ_{QE} in Column (3) carry over to Column (4), which additionally includes country and time fixed effects. Overall, we find a lower price of risk for bond-stock betas during QE periods, consistent with the broader portfolio balance channel.

Next, we study how the price of bond return variance changes during QE. Column (5) shows that an increase in bond return volatility is associated with higher expected bond excess returns. The coefficient μ is equal to 0.6 and is statistically significant. In addition, the interaction coefficient between bond return variance and the QE dummy is strongly negative and significant, fully offsetting the positive effect of bond return variance during non-QE periods. Consistent with this pattern, we cannot reject that the implied slope during QE is equal to zero (p-value=0.911). Column (6) adds country and time fixed effects and finds similar results.

Column (7) provides our full and preferred specification, including beta, bond return variance, and their interactions with QE. The price of bond-stock beta risk during non-QE periods remains statistically significant and economically large at 7.1, and the coefficient on bond return variance is also positive and highly statistically significant. The interaction coefficients, on the other hand, are both negative and similar in magnitude to the baseline coefficients, indicating a substantial decline in the price of bond-stock beta risk and bond return variance risk during QE periods. The coefficient on the QE dummy, α_{QE}, is small and statistically indistinguishable from zero, as one would expect if a combination of changing prices and quantities of risk explains QE's effect on bond risk premia.

Column (8) reports results for the same specification with both country and time fixed effects. The estimates for the prices of risk and their interactions are qualitatively and quan-

Table IX: Quantitative Easing: International Panel

Dependent Variable: Expected Excess Returns	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
QE	-1.17***	0.16	-0.92***	-0.33	1.17**	1.92***	0.19	1.36***
	(0.39)	(0.32)	(0.21)	(0.40)	(0.52)	(0.39)	(0.53)	(0.47)
Beta			9.48***	5.92***			7.12***	4.51***
			(1.62)	(1.75)			(1.54)	(1.43)
QE × Beta			-8.91***	-6.93***			-6.48***	-3.21
			(2.23)	(2.66)			(2.37)	(2.79)
Bond Variance					0.58***	0.31***	0.28***	0.23***
					(0.11)	(0.11)	(0.09)	(0.09)
QE × Bond Variance					-0.58***	-0.49***	-0.29**	-0.42***
					(0.13)	(0.14)	(0.13)	(0.11)
Constant	-0.53		-0.77***		-2.89***		-1.86***	
	(0.39)		(0.23)		(0.53)		(0.45)	
Country FE		✓		✓		✓		✓
Time FE		✓		✓		✓		✓
R-squared	0.03	0.62	0.35	0.66	0.27	0.66	0.39	0.68
Observations	4798	4798	4798	4798	4798	4798	4798	4798

Note: The table reports the results of equation (20) estimated using our international panel:

$$\tilde{E}_t xr_{c,t\to t+12} = \alpha + \alpha_{QE}\text{QE}_{c,t} + \lambda\beta_{c,t} + \lambda_{QE}\left(\text{QE}_{c,t} \times \beta_{c,t}\right) + \mu\hat{\sigma}^2_{c,t} + \mu_{QE}\left(\text{QE}_{c,t} \times \hat{\sigma}^2_{c,t}\right) + \eta_{c,t}$$

The beta is estimated using monthly data over a five-year rolling window (60 months), based on excess returns on the domestic stock market. Similarly, bond variance is estimated as the rolling variance of monthly bond excess returns over the same five-year window. Expected yields are from Consensus Economics, while bond yields, T-bill rates, and stock returns are from the Global Financial Database (GFD). The term spread is the difference between the ten-year government bond yield and the one-year government bond yield. Driscoll-Kraay standard errors with 27 lags are reported in parentheses. Stars denote significance at the 10, 5, and 1 percent levels based on Kiefer–Vogelsang fixed-b critical values. The data are monthly and span September 1989 to December 2024.

titatively similar. [29] Overall, our results suggest that a combination of a changing price of risk–as predicted by the portfolio balance channel–and changing quantities of risk–as predicted by the state-contingent policy channel–may help to explain movements in subjective expected bond excess returns during international QE periods.

It is important to note that our results capture the correlation between QE periods and the relationship between bond–stock betas and subjective expected excess returns. They should therefore not be interpreted as causal. With this caveat in mind, the results provide a useful perspective on how the pricing of bond–stock risk differs during QE periods.

The model in Appendix E provides a natural setting to interpret the results. In the model, bond-market arbitrageurs bear stock-like background risk and absorb the supply of

[29]The only discrepancy is that the direct QE dummy now enters positively and significantly. One possibility is that in this relatively rich specification with bond-stock betas and bond return variances, the difference in timing of QE across countries leaves little variation to identify α_{QE}.

long-term bonds, requiring compensation that rises with a bond's bond–stock beta and its return variance at a price of risk that increases with the supply they hold. By absorbing bond supply, quantitative easing lowers this price of risk. The model therefore predicts not a uniform level shift but a *flattening* of the sensitivity of expected excess returns to both the bond–stock beta and bond return variance. This matches Table IX: the QE×Beta and QE×Bond Variance interactions are negative, while the stand-alone QE dummy is small and insignificant once country and time fixed effects are included.

Before the start of euro-area asset purchases in 2015, core countries such as Germany, France, and the Netherlands had negative bond–stock betas, while peripheral countries such as Italy and Spain had positive bond–stock betas. Following the launch of the Public Sector Purchase Programme in 2015, these betas began to converge: core-country betas increased toward zero, while peripheral-country betas declined toward zero. The evidence for the U.S., UK, and Japan is more mixed and harder to detect.

Overall, the appendix provides suggestive evidence that QE is associated with a compression of bond–stock betas toward zero. However, the empirical setting offers limited independent variation around QE episodes, so we cannot rule out confounding factors or draw firm causal conclusions.

5. Conclusion

We show that bond risks, measured by bond–stock betas, are a central determinant of subjective bond risk premia. Using survey forecasts to isolate ex ante expectations, we document a strong and stable relationship between bond–stock betas and subjective expected bond excess returns in U.S. data and in an international panel of developed economies. In both settings, the estimated market price of risk is economically large and comparable to the equity premium, consistent with a CAPM-style pricing relation for bonds. We also find a positive relationship between expected bond excess returns and bond return volatility, although this relationship is not uniformly statistically significant.

Subjective expected excess returns are informative, predicting realized excess returns with a coefficient that is indistinguishable from full information rational expectations (FIRE). In contrast, the relationship between realized bond excess returns and betas is weak. This weak relationship may reflect both small-sample issues and biases in expectation formation, that are absorbed by the construction of subjective expected excess returns, highlighting the advantage of using subjective expected excess returns.

Our findings provide a new perspective on the secular decline, and more recent increase, in long-term yields. Our estimated link between bond risk premia and bond-stock betas attributes roughly half of the secular decline in interest rates since the 1980s to the improved hedging properties of bonds. Moreover, rising bond risk can account for about half the increase in 10-year Treasury rates between 2016 and 2025, with the majority driven by the risks of real bonds. In contrast to standard estimates, our results suggest that term premia turned negative already in the early 2000s, prior to the global financial crisis.

Finally, we apply our findings to quantitative easing episodes in our international panel. We find that the prices of beta and of bond return volatility both decline substantially during QE episodes. We jointly rationalize our baseline and QE empirical findings in a simple two-period model, where bond market arbitrageurs have non-zero exposure to the bond market. Different from most segmented market models, bond market arbitrageurs in our model are required to have substantial stock-like background risk. But different from a standard representative agent model, bond market investors in our model are also required to hold positive bond market exposure.

This paper opens up avenues for future research. Government bond markets are a cornerstone for financial markets. Our finding that subjective bond risk premia increase with bond risks is likely to have implications for financial investors, optimal portfolio choice, and fiscal and monetary policy.

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A. Proofs of Model in Section 2

Proof. **Proof of Proposition 1:** The zero-coupon bond yield satisfies

$$\begin{aligned}
y_{n,t} &= \underbrace{\frac{1}{n}\widehat{\mathbb{E}}_t\sum_{i=0}^{n-1} f_{t+12i}}_{\text{risk-neutral component}} + \underbrace{\frac{1}{n}\sum_{i=1}^{n-1}\widehat{\mathbb{E}}_t xr_{n-i+1,t+12i}}_{\text{term-premium component}} \\
&= \frac{1}{n}\widehat{\mathbb{E}}_t\sum_{i=0}^{n-1} f_{t+12i} + \frac{\lambda}{n}\sum_{i=1}^{n-1}\widehat{\mathbb{E}}_t\beta_{n-i+1,t+12i} \\
&= \frac{1}{n}\widehat{\mathbb{E}}_t\sum_{i=0}^{n-1} f_{t+12i} + \frac{\lambda}{n}\sum_{i=1}^{n-1}\frac{n-i+1}{n}\widehat{\mathbb{E}}_t\beta_{n,t+12i} \\
&= \frac{1}{n}\sum_{i=0}^{n-1}\hat{\rho}_f^i f_t + \frac{\lambda}{n}\sum_{i=1}^{n-1}\frac{n-i+1}{n}\hat{\rho}_\beta^i\beta_{n,t} \\
&= \frac{1-\hat{\rho}_f^n}{1-\hat{\rho}_f}\frac{1}{n}f_t + \lambda S_n(\hat{\rho}_\beta)\beta_{n,t}, \qquad (21)
\end{aligned}$$

where

$$S_n(\rho_\beta) \equiv \frac{1}{n^2}\sum_{i=1}^{n-1}(n-i+1)\rho_\beta^i. \qquad (22)$$

S_n satisfies the telescoping property:

$$n^2 S_n(\rho_\beta) - \rho_\beta(n-1)^2 S_{n-1}(\rho_\beta) = n\rho_\beta, \qquad S_1(\rho_\beta) = 0. \qquad (23)$$

For part i), realized bond excess returns satisfy

$$xr_{n,t+12} = ny_{n,t} - (n-1)y_{n-1,t+12} - y_{1,t}. \qquad (24)$$

Substituting the expression for the actual yield into the excess-return identity and using $y_{1,t} = f_t$ gives

$$\begin{aligned}
xr_{n,t+12} &= \lambda n S_n(\hat{\rho}_\beta)\beta_{n,t} - \lambda(n-1)S_{n-1}(\hat{\rho}_\beta)\beta_{n-1,t+12} \\
&\quad + \left[\frac{1-\hat{\rho}_f^n}{1-\hat{\rho}_f}f_t - \frac{1-\hat{\rho}_f^{n-1}}{1-\hat{\rho}_f}f_{t+12} - f_t\right]. \qquad (25)
\end{aligned}$$

Actual state dynamics imply

$$f_{t+12} = \rho_f f_t + \varepsilon_{t+12}, \qquad \beta_{n-1,t+12} = \frac{n-1}{n}\beta_{n,t+12} = \frac{n-1}{n}\left(\rho_\beta\beta_{n,t} + \eta_{t+12}\right).$$

Therefore,

$$xr_{n,t+12} = \lambda\left[nS_n(\hat{\rho}_\beta) - \frac{(n-1)^2}{n}\rho_\beta S_{n-1}(\hat{\rho}_\beta)\right]\beta_{n,t} + \left[\frac{1-\hat{\rho}_f^n}{1-\hat{\rho}_f} - \rho_f\frac{1-\hat{\rho}_f^{n-1}}{1-\hat{\rho}_f} - 1\right]f_t + u_{t+12}, \tag{26}$$

where

$$u_{t+12} \equiv -\frac{1-\hat{\rho}_f^{n-1}}{1-\hat{\rho}_f}\varepsilon_{t+12} - \lambda\frac{(n-1)^2}{n}S_{n-1}(\hat{\rho}_\beta)\eta_{t+12}. \tag{27}$$

Since

$$\frac{1-\hat{\rho}_f^n}{1-\hat{\rho}_f} - 1 = \hat{\rho}_f\frac{1-\hat{\rho}_f^{n-1}}{1-\hat{\rho}_f},$$

the loading on f_t is

$$(\hat{\rho}_f - \rho_f)\frac{1-\hat{\rho}_f^{n-1}}{1-\hat{\rho}_f}.$$

Define

$$\Lambda_n(\hat{\rho}_\beta, \rho_\beta) = \hat{\rho}_\beta + \frac{(n-1)^2}{n}(\hat{\rho}_\beta - \rho_\beta)S_{n-1}(\hat{\rho}_\beta). \tag{28}$$

By the telescoping property of S_n then

$$xr_{n,t+12} = \lambda\Lambda_n(\hat{\rho}_\beta, \rho_\beta)\beta_{n,t} + (\hat{\rho}_f - \rho_f)\frac{1-\hat{\rho}_f^{n-1}}{1-\hat{\rho}_f}f_t + u_{t+12}, \tag{29}$$

as claimed. The properties for Λ_n follow from the definition (28), and $S_n(0) = 0$, and $S_n' > 0$.

For part ii), note that under forecasters' beliefs, the expected $n-1$-period yield in 12 months is given by

$$\widetilde{\mathbb{E}}_t y_{n-1,t+12} = \frac{1-\hat{\rho}_f^{n-1}}{1-\hat{\rho}_f}\frac{\tilde{\rho}_f}{n-1}f_t + \lambda S_{n-1}(\hat{\rho}_\beta)\tilde{\rho}_\beta\frac{n-1}{n}\beta_{n,t}, \tag{30}$$

where the last equality uses the maturity-proportionality assumption $\beta_{n-1,t} = \frac{n-1}{n}\beta_{n,t}$. The rest of the proof is analogous to part i). This proves the Proposition. □

B. Farmer Nakamura Steinsson Excess Returns

We collect data from Farmer et al. (2024) (FNS). We use the model with structural break that is used to plot Figure 9 in their paper, which the authors note is their best model to fit the yield curve data. We use the full term structure of forecasts for the 3-months T-bill. Consistently with their equation (10), we compute the model implied yield for an n-year maturity bond as:

$$y_{n,t}^{FNS} = c_n^{FNS} + \frac{1}{4n}\sum_{h=0}^{4n-1} \mathbb{E}_t y_{t+h}^{FNS}$$

where n is the number of years, y_{t+h}^{FNS} is the expected quarterly T-bill h quarters ahead. c_n^{FNS} is the constant term premium for the bond with maturity n. As y_{t+h}^{FNS} is quarterly, to compute the n year bonds we use the average over the subsequent $4n$ quarters.

We then estimate c_n by equating the sample average of $y_{n,t}^{FNS}$ to the sample average of the observed n-year par yields over our main sample 1988–2024. Let

$$\hat{y}_{n,t}^{FNS} \equiv y_{n,t}^{FNS} - c_n^{FNS} = \frac{1}{4n}\sum_{h=0}^{4n-1} \mathbb{E}_t\, y_{t+h}^{FNS}$$

denote the expectations-hypothesis (risk-neutral) component of the model yield, i.e. the model yield stripped of its term premium. Applying the model one year ahead and using the law of iterated expectations, we compute the one-year-ahead expected $(n-1)$-year yield as:

$$\tilde{E}_t^{FNS} y_{n-1,t+12}^{par} = \frac{n\,\hat{y}_{n,t}^{FNS} - \hat{y}_{1,t}^{FNS}}{n-1} + c_{n-1}^{FNS}. \tag{31}$$

Because the term premium c_m^{FNS} is maturity-specific, the premium added back in Equation 31 is the one for the $(n-1)$-year bond being forecast, c_{n-1}^{FNS}, rather than the n-year premium; expressing the forecast through the risk-neutral yields $\hat{y}^{FNS}$ ensures that the n- and one-year term premia do not enter. We then use these expected rates, duration as in Equation **??** and the observed par-yield to compute the implied expected excess returns on a bond of n-year maturity over the twelve months:

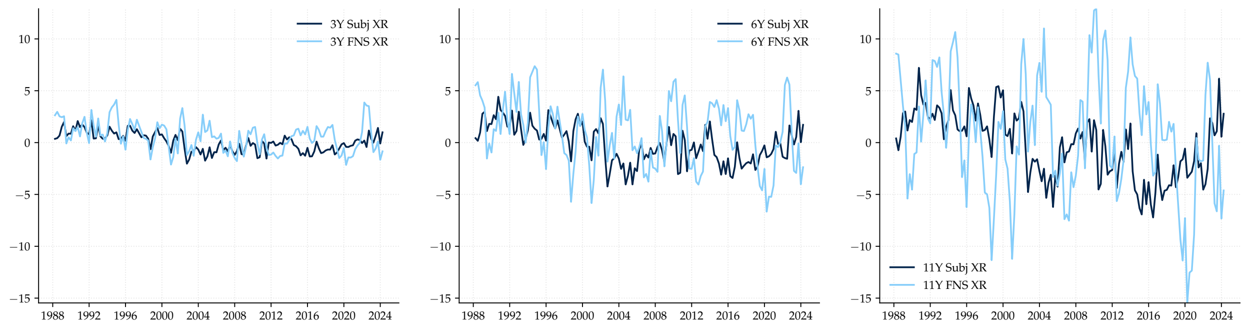
$$\tilde{E}_t^{FNS} xr_{n,t\to t+12} = dur_{n,t} y_{n,t}^{par} - (dur_{n,t} - 1) \times \tilde{E}_t^{FNS} y_{n-1,t+12}^{par} - y_{1,t}. \tag{32}$$

Figure B.1 compares the subjective expected excess returns implied by the Blue Chip forecasts with the expected excess returns obtained from the FNS model using Equation 32.

Figure B.2 presents the observed par yield for a bond of maturity n together with the corresponding FNS–based forecast, constructed using Equation 31.

Figure B.1: FNS Subjective Expected Excess Returns

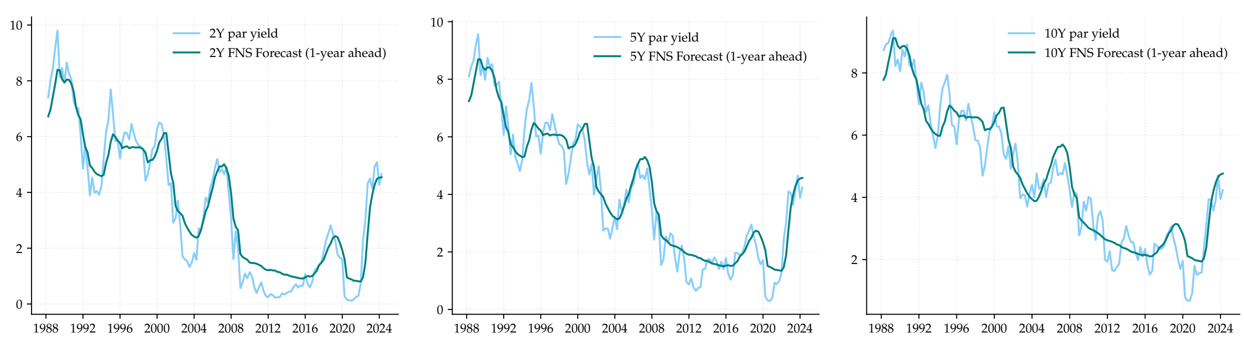
(A) 3-Year Treasury Bond Maturity (B) 6-Year Treasury Bond Maturity (C) 11-Year Treasury Bond Maturity



Note: This figure plots 1-year FNS subjective expected excess return for US Treasury par bonds of three-year (Panel (A)), six-year (Panel (B)), and eleven-year (Panel (C)) maturities based on Farmer et al. (2024). Subjective expected bond excess returns are computed according to equation (32). The sample is quarterly from January 1988 to March 2024.

Figure B.2: Actual Yields and FNS–Implied Forecasts

(A) 2-Year Treasury Bond Maturity (B) 5-Year Treasury Bond Maturity (C) 10-Year Treasury Bond Maturity



Note: This figure plots the actual observed par yield for the n-year maturity bond and the FNS expected yield for the n-year maturity bond one year ahead. We show the two-year (Panel (A)), five-year (Panel (B)), and ten-year (Panel (C)) maturities based on Farmer et al. (2024). The FNS one-year-ahead forecast of the $(n-1)$-year yield is computed according to equation (31). The sample is quarterly from January 1988 to March 2024.

C. Pseudo Expected Excess Returns

In the paper, we construct pseudo measures of subjective expected excess returns by replacing the forecasted future bond yield with alternative proxies. According to Equation (7), our baseline measure of subjective expected excess returns is

$$\widetilde{E}_t xr_{n,t\to t+12} = dur_{n,t} y^{par}_{n,t} - (dur_{n,t}-1)\,\widetilde{E}_t y^{par}_{n-1,t+12} - y_{1,t}.$$

We then replace $\widetilde{E}_t y^{par}_{n-1,t+12}$ with alternative measures that do not directly rely on forecasts of future bond yields.

Expected Inflation. We first replace the forecasted future bond yield, $\widetilde{E}_t y^{par}_{n-1,t+12}$, with the expected average CPI inflation rate over the next ten years. We use the corresponding long-term inflation forecast from the SPF. This procedure gives an inflation-based pseudo measure of subjective expected excess returns that depends only on the current bond yield, the short rate, and long-run expected inflation.

Specifically, denote the expected average CPI inflation rate over the next ten years by

$$\widetilde{\pi}_t^{10} = \widetilde{E}_t \left[\frac{1}{10} \sum_{j=0}^{9} \pi_{t+12j} \right].$$

For each maturity n, we construct the inflation-based pseudo expected excess return as

$$\widetilde{E}_t^{\pi} xr_{n,t\to t+12} = dur_{n,t} y^{par}_{n,t} - (dur_{n,t} - 1)\, \widetilde{\pi}_t^{10} - y_{1,t}.$$

We use the same ten-year expected inflation forecast for all maturities, including the three- and six-year bonds, because this is the only long-horizon inflation forecast available. To make the magnitudes comparable to our baseline measure, we rescale the inflation-based pseudo expected excess return separately by maturity. Specifically, for each maturity, we regress the baseline subjective expected excess return, which uses bond yield forecasts, on $\widetilde{E}_t^{\pi} xr_{n,t\to t+12}$, and use the fitted value as the rescaled pseudo expected excess return.

Autoregressive (AR) Forecast. At each date, we assume forecasters predict future bond yields with a first-order autoregressive (AR(1)) model estimated in real time. For each of the two-, five-, and ten-year par yields—the maturities relevant for the three-, six-, and eleven-year bonds—we estimate

$$y^{par}_{m,s} = c_t + \rho_t\, y^{par}_{m,s-1} + \varepsilon_{m,s}$$

by OLS on monthly data over the trailing fifteen-year (180-month) window ending at date t. The implied twelve-month-ahead forecast of the $(n-1)$-year yield is

$$\widehat{E}_t^{AR} y^{par}_{n-1,t+12} = \mu_t + \rho_t^{12} \left(y^{par}_{n-1,t} - \mu_t \right), \qquad \mu_t = \frac{c_t}{1-\rho_t},$$

where μ_t is the long-run mean implied by the rolling AR(1). Because the regression uses only data available through date t, the forecast is formed in real time. The AR-based pseudo expected excess return replaces $\widetilde{E}_t y^{par}_{n-1,t+12}$ in Equation (7) with this forecast:

$$\widehat{E}_t^{AR} xr_{n,t\to t+12} = dur_{n,t}\, y^{par}_{n,t} - (dur_{n,t} - 1)\, \widehat{E}_t^{AR} y^{par}_{n-1,t+12} - y_{1,t}.$$

Moving-Average (MA) Forecast. As a second purely statistical benchmark, we forecast the future yield with a trailing moving average. The MA forecast of the $(n-1)$-year yield is its average over the preceding w months,

$$\widehat{E}_t^{MA} y_{n-1,t+12}^{par} = \frac{1}{w} \sum_{j=0}^{w-1} y_{n-1,t-j}^{par}.$$

In the paper we use a sixty-month window ($w = 60$, i.e. five years). The MA-based pseudo expected excess return is constructed exactly as the AR one, replacing $\widetilde{E}_t y_{n-1,t+12}^{par}$ by $\widehat{E}_t^{MA} y_{n-1,t+12}^{par}$ in Equation (7).

Farmer–Nakamura–Steinsson (FNS) Forecast. Finally, we use the yields implied by the term-structure model of Farmer et al. (2024), described in Appendix B. The measure entering the predictability table is computed entirely within the FNS model: we replace *both* the current and the forecasted yield in Equation (7) with their FNS counterparts. For the three-, six-, and eleven-year bonds, we use the FNS model-implied current yield $y_{n,t}^{FNS}$ and the FNS one-year-ahead forecast of the $(n-1)$-year yield, $\tilde{E}_t^{FNS} y_{n-1,t+12}^{FNS}$ (Equation (31)):

$$\widehat{E}_t^{FNS} xr_{n,t\to t+12} = dur_{n,t}\, y_{n,t}^{FNS} - (dur_{n,t} - 1)\, \tilde{E}_t^{FNS} y_{n-1,t+12}^{FNS} - y_{1,t}.$$

Because both the level and the forecast come from the FNS model, this isolates the expected excess return implied by the model, purged of the observed market yield. The alternative measure that keeps the observed current par yield, $y_{n,t}^{par}$, and replaces only the forecast is given in Equation (32). Since the FNS forecasts are available at the quarterly frequency, the measure is observed once per quarter.

Unlike the inflation-based measure, the AR, MA, and FNS forecasts are themselves forecasts of the bond yield, so they enter Equation (7) in the same units as the baseline measure and therefore require no rescaling.

D. QE and Betas

The results in Section 4.4 suggest that QE may weaken the relationship between bond–stock betas (and bond return variance) and subjective excess bond returns. A natural question is whether QE also affects the bond–stock betas themselves. In this subsection, we provide exploratory evidence on the evolution of betas during QE periods. Broadly, we find that bond-stock betas changed substantially during QE periods, with both negative and positive bond-stock betas compressed towards zero. Combined with the reduction in the price of risk documented in the previous subsection, this implies that QE is associated with stronger reductions in bond risk premia for risky countries with positive bond-stock betas.

Figure D.1 visualizes bond–stock betas for the main countries that have experienced QE, with QE periods indicated by shaded areas. In what follows, we place particular emphasis on the first QE announcement, which–consistent with the findings of Haddad et al. (2025)– appears to be associated with the most pronounced movements in financial markets.

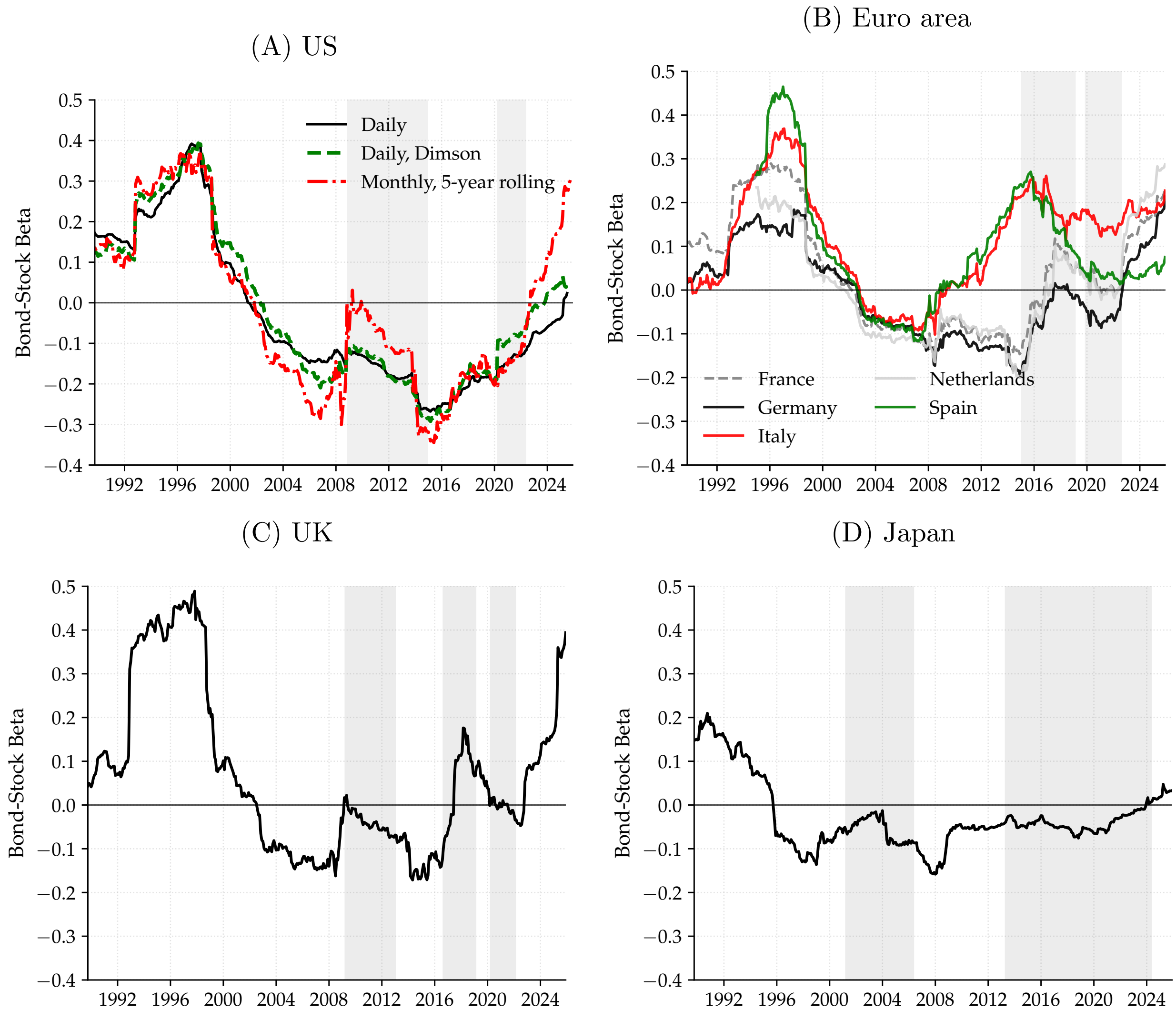
Panel A of Figure D.1 plots the U.S. bond–stock beta. We report three estimates based on 5-year rolling windows: one constructed using daily returns (black line), one using daily returns with the Dimson (1979) correction (green), and one based on monthly returns (red). All three series display an increase around the QE announcement, though the magnitude differs somewhat across measures. The change appears particularly pronounced for the beta estimated using monthly returns, while the beta based on daily returns shows only a modest increase. The Dimson-corrected beta lies between these two. These patterns suggest that returns during QE were more positively correlated across asset classes than normally, which could occur if QE news raises equity and bond prices simultaneously.

We now turn to the Euro area in Panel B. The figure plots bond–stock betas for the five Euro area countries in our sample: Spain (green) and Italy (red) exhibit markedly higher betas than France (dashed), the Netherlands (gray), and Germany (black). In the 1990s, there was substantial cross-country heterogeneity in bond-stock betas. However, as the introduction of the euro approached in the late 1990s, these differences narrowed, and betas converged. By the early 2000s, bond–stock betas are virtually identical across countries. This convergence in Euro area betas reversed sharply following the global financial crisis. Starting in 2008, betas began to diverge, with the divergence intensifying during the sovereign debt crisis. Over this period, the bond–stock betas of core countries (Germany, the Netherlands, and France) become increasingly negative, reaching values around -0.2 by the end of 2014. In contrast, the betas of peripheral countries (Italy and Spain) turn positive, rising to approximately 0.3 over the same period. The divergence is consistent with flight-to-safety dynamics. During periods of equity market declines or adverse macroeconomic news, investors reallocated away from peripheral bonds toward core sovereign debt. ECB unconventional policies—including the Long-Term Refinancing Operations (LTROs), the Securities Markets Programme (SMP), and the "whatever it takes" speech associated with the Outright Monetary Transactions (OMT) framework—did not materially alter this divergence in betas, even though they did affect the *levels* of bond yields.

A sharp reversal in Euro area bond-stock betas occurred in 2015, following the announcement of the Public Sector Purchase Programme (PSPP). At this point, peripheral bond–stock betas began to decline, while core betas increased. In other words, the ECB's QE announcement was associated with a reversal in the divergence in bond–stock betas. This pattern is consistent with the interpretation in Haddad et al. (2025), whereby central bank purchases provide support to bond prices in adverse states of the world. It is also consistent with Leombroni et al. (2021), who document that between 2009 and 2014 the response of sovereign yields to ECB policy was highly heterogeneous across countries, while the announcement of QE restored a more uniform transmission mechanism. While the precise channel driving bond-stock betas is not crucial for our core results, one potential transmission mechanism is that ECB QE entailed fiscal redistribution across euro-area countries (Chien et al., 2025).

Panels (C) and (D) report results for the U.K. and Japan, showing patterns consistent with the U.S. For the U.K., the bond–stock beta increased sharply at the onset of QE in March 2009. For Japan, the compression of the bond–stock beta to zero during QE is more gradual, but still visible. Moreover, QE in Japan partly took the form of yield curve control, which mechanically dampens bond yield fluctuations and, in turn, tends to compress the bond–stock beta toward zero. We complement the descriptive evidence with a more formal panel analysis relating bond–stock betas to QE episodes. The results are displayed in Appendix Table D1. Consistent with the patterns discussed above, QE is associated with a compression of bond–stock betas toward zero. Overall, to the extent that policy affects bond-stock betas in either direction, the findings on changing bond-stock betas during QE illustrate the importance of understanding the link between bond-stock betas and bond risk premia, as shown in our benchmark results.

Figure D.1: Bond-Stock Betas and QE



Note: The figures plot the bond-stock betas for different countries, with the shaded area representing QE Periods. Bond-stock betas are estimated using monthly bond and stock excess returns from the Global Financial Database. We use a five-year (60 months) rolling window. The sample runs from 1989 to 2024. For the U.S., in Panel A, we show three estimates based on 5-year rolling windows: one constructed using daily returns (black line), one using daily returns with the Dimson (1979) correction (green), and one based on monthly returns (red). Panel B plots the bond-stock betas for the five Euro area countries in our sample: Spain (green) and Italy (red) exhibit markedly higher betas than France (dashed), the Netherlands (gray), and Germany (black). Panel C shows the bond-stock beta for the U.K., and Panel D for Japan.

Table D1: QE and Bond-Stock Beta

	$\tilde{\beta}$	$\tilde{\beta}$	$\lvert\tilde{\beta}\rvert$	$\lvert\tilde{\rho}\rvert$	$\tilde{\sigma}_{bond}$	$\tilde{\sigma}_{mkt}$
	(1)	(2)	(3)	(4)	(5)	(6)
QE	0.03	-0.10	-0.14***	-0.10**	-0.15	0.08
	(0.08)	(0.14)	(0.05)	(0.05)	(0.10)	(0.13)
QE × ($\tilde{\beta} < 0$)		0.25**				
		(0.12)				
$\tilde{\beta} < 0$		-0.66***				
		(0.13)				
Constant	0.01	0.37***	0.23***	0.26***	0.18*	0.57***
	(0.07)	(0.11)	(0.06)	(0.07)	(0.09)	(0.21)
Lagged Value	✓	✓	✓	✓	✓	✓
R-squared	0.84	0.87	0.63	0.58	0.93	0.77
Observations	4677	4677	4677	4677	4677	4677

Note: Table D1 reports the results from the following regression:

$$Y_{c,t} = \alpha + b_1 \text{QE}_{c,t} + b_2 Y_{c,t-12} + \eta_{c,t}, \tag{33}$$

where $Y_{c,t}$ denotes a set of dependent variables, and $Y_{c,t-12}$ is the corresponding value lagged by 12 months. Controlling for the lagged dependent variable is important, as it allows us to isolate the effect of QE from slow-moving dynamics in bond–stock betas. For instance, betas are on average negative in the post-2000 period but were positive on average prior to 2000; failing to control for persistence would confound these low-frequency trends with the effect of QE.

Column (1) regresses the level of $\tilde{\beta}$ on the QE indicator, where the tilde denotes that the variable is standardized (i.e., divided by its standard deviation). Column (2) allows the effect of QE to differ depending on whether the beta is positive or negative. Column (3) instead uses the absolute value of $\tilde{\beta}$. Finally, Columns (4) to (6) examine the effects of QE on the absolute value of the correlation, $\tilde{\rho}$, and on the standard deviations of bond and equity returns.

E. Preferred Habitat Model with Background Risk

This section develops a simple two-period model to jointly explain the following empirical findings: 1) Bond-stock betas are linked to expected bond excess returns with a positive coefficient close to the equity premium; 2) QE is associated with a lower price of bond return volatility; 3) QE is associated with a lower price of beta. While the first finding is reminiscent of a classical representative agent, the second and third findings challenge this notion. The second finding – along with bond volatility being priced during non-QE periods – is typical of segmented market models, where the key priced factor is duration risk held by bond market investors (Vayanos and Vila, 2021). However, the third finding is new and requires a reconciliation between the representative agent and segmented market views.

E.1 Model Setup

We assume there are 2 periods $t = 1, 2$. In the first period, arbitrageurs pick their wealth share in long-term bonds α_1^{bond} to maximize:

$$\max_{\alpha_1^{bond}} \frac{E_1 W_2^{1-\gamma}}{1-\gamma}. \tag{34}$$

Here, γ is the arbitrageur's risk aversion, and W_t is the arbitrageur's wealth in period t. We assume CRRA utility, which Kekre et al. (2024) show gives rise to wealth effects. Period 1 wealth is assumed to be exogenous, but period 2 wealth is endogenous. In addition, in period $t = 1$ arbitrageurs have exogenous equity exposure, S_1^{eq}, which can be thought of as business background risk, such as exposure to general macroeconomic conditions, labor contracts, real estate exposure, etc. Arbitrageurs also have access to a risk-free asset. Each arbitrageur is atomistic and optimizes over their bond market holdings. In equilibrium, bond market arbitrageurs must absorb total bond supply S_1^{bond}, so the portfolio shares are given by $\alpha_1^{bond} = \frac{S_1^{bond}}{W_1}$ and $\alpha_1^{eq} = \frac{S_1^{eq}}{W_1}$.

In order to build the most parsimonious two-period model that can jointly explain our main empirical findings, we take bond market volatility and beta as given. Specifically, log stock returns are assumed to follow an exogenous process:

$$r_2^{eq} - r_1 + \frac{1}{2}\sigma_{eq}^2 \quad = \quad EP + \varepsilon_{eq,2}, \tag{35}$$

where r_t is the real risk-free rate at time t, $\varepsilon_{eq,t}$ is i.i.d. with variance σ_{eq}^2, and the equity premium EP is exogenous.

The log risk-free rate is assumed to follow an exogenous process with mean zero that is correlated with stock returns:

$$r_t \quad = \quad -\beta\varepsilon_{eq,t} - \varepsilon_{r,t}, \tag{36}$$

where $\varepsilon_{r,t}$ is i.i.d. with variance σ_r^2, uncorrelated with $\varepsilon_{eq,t}$. The assumption of mean-zero interest rates is without loss of generality. Because the two-period bond at time 1 becomes a one-period bond at time 2 the unexpected bond return from period 1 to period 2 equals

$r_2^{bond} - E_1 r_2^{bond} = -r_2$, the bond-stock beta equals β, and the bond return variance equals $\sigma^2_{bond} = \sigma^2_r + \beta^2 \sigma^2_{eq}$.

E.2 Equilibrium

We first solve for the bond risk premium from the arbitrageur's first-order condition. Using the standard Campbell and Viceira (2002) log-linear solution for optimal portfolio choice:

$$E_1 r_2^{bond} - r_1 + \frac{1}{2}\sigma^2_{bond} \quad = \quad \gamma\beta\sigma^2_{eq}\alpha_1^{eq} + \gamma\sigma^2_{bond}\alpha_1^{bond}. \tag{37}$$

The last term on the left-hand side is a Jensen's inequality adjustment. This leads to:

Proposition E2. *Expected bond excess returns have the following properties:*

(a) They are positively related to bond-stock betas, provided that arbitrageurs' exogenous stock market exposure is positive.

(b) The relationship between expected excess returns and betas has a slope equal to the equity premium if i) arbitrageurs' risk aversion γ equals stock market investors' risk aversion; and ii) bond market investors have substantial stock-like background risk, i.e. $\alpha_1^{eq} \approx 1$.

(c) The relationship between expected excess returns and bond return volatility is positive, provided that bond market arbitrageurs have positive exposure to the bond market.

Here, we have also assumed that stock market investors hold zero net bonds. Part (a) of the Proposition says that the bond market investors' first-order condition rationalizes a positive relationship between expected bond excess returns and bond-stock betas (Fact 1). A positive relationship, as we find in the data, obtains under fairly general conditions, provided that bond market investors have at least some stock-like background risk. Whether the marginal investors in the bond market are large financial institutions, pension funds, part of an investment bank, or hedge funds whose financing conditions depend on investment banks, positive stock-like background risk seems plausible.

Part (b) of the proposition provides sufficient conditions under which the relationship between expected bond excess returns and beta is close to the equity premium. Bond market and stock market investors must have similar preferences, and bond market investors' exposure to the stock market must be large. The assumption of CRRA preferences is not restrictive here, as a similar relationship between beta and the equity premium would hold quite generally, e.g. under Epstein-Zin preferences or habit formation preferences. Note that we do not need to assume that bond and stock markets are fully integrated, as they would be if bond market investors were also marginal in the stock market, though the Proposition would continue to hold under those stronger conditions.

Part (c) says that bond return variance is also priced. This prediction is common in segmented markets models, but different from a typical representative agent model with net-zero bond market exposure. It is in line with our empirical results in Table II and the international QE regressions in Table IX.[30] Overall, interpreting our empirical findings through the lens of this simple segmented markets model suggests that bond market arbitrageurs' exposure to the bond market is positive, but also that their background exposure to stock-like risk is large.

E.3 QE in the Model

Our empirical Facts 2 and 3 are about how the pricing of beta and bond return volatility changes with QE. We introduce QE by allowing an unexpected change (an MIT shock) in arbitrageurs' bond share. That is, immediately after portfolio shares have been chosen and prices have been formed in period 1, the central bank comes in unexpectedly and absorbs some of the bond supply. Formally, we assume that the arbitrageurs' bond share falls to $\alpha_1^{bond,*} < \alpha_1^{bond}$ to absorb the new supply.[31]

To understand the new equilibrium, we again use the Campbell and Viceira (2002) log-linear portfolio return, giving the change in log arbitrageur wealth as

$$w_1^* - w_1 \quad = \quad \alpha_1^{bond} \left(E_1 r_2^{bond} - E_1^* r_2^{bond} \right). \tag{38}$$

Here, we have used the approximation with zero volatility because the shock was unanticipated. The new bond risk premium is again determined by (37) at the new portfolio shares $\alpha_1^{bond,*}$ and $\alpha_1^{eq,*}$. While the new bond portfolio share $\alpha_1^{bond,*}$ is exogenous, the new equity share $\alpha_1^{eq,*}$ is endogenous. This is because while the total stock-like risk is fixed, the share that this represents of total arbitrageur wealth changes endogenously with wealth. This leads us to:

Proposition E3. *Around an unanticipated decline in bond supply $\alpha_1^{bond,*} < \alpha_1^{bond}$:*

(a) The slope of the relationship between expected bond excess returns and beta decreases.

(b) The slope of the relationship between expected bond excess returns and bond return variance decreases.

The intuition for part (a) relies on a wealth effect when the central bank purchases bonds unexpectedly. By purchasing bonds, the central bank reduces duration risk held by bond market arbitrageurs. This, in turn, reduces the bond risk premium that investors require and raises bond prices through (37). As bond prices rise, background stock exposure becomes a smaller share of overall wealth, driving down the equity share $\alpha_1^{eq,*} < \alpha_1^{eq}$. Part b) follows directly from the bond risk premium (37) and the assumption that $\alpha_1^{bond,*} < \alpha_1^{bond}$. Overall, because bond arbitrageurs are less exposed to bonds *and* stocks, the equilibrium prices of beta and bond volatility *both* fall.

It is informative to consider under which conditions part (a) of Proposition E3 fails. This happens when either bond return volatility is zero, arbitrageurs' pre-QE bond share is

[30] Note, however, that the international regression that averages across QE and non-QE periods in Table VII finds a positive but insignificant coefficient on bond return volatility.

[31] The direct assumption on the bond portfolio share is merely a simplification to provide intuitive algebraic expressions. All predictions would continue to hold if instead we assume that the new bond supply declines, i.e. $S_1^{bond,*} < S_1^{bond}$ and derive the new bond portfolio share endogenously.

zero, or arbitrageurs' pre-QE stock market exposure is zero. The reason is that bond prices only respond to bond quantities if bond return volatility – or duration – is priced in the first place. If arbitrageurs have net zero bond market exposure or bond return volatility is zero, arbitrageurs have no bond market risk, so their wealth is unaffected when the central bank absorbs bond market risk through QE. Naturally, if arbitrageurs have no stock market exposure to start with, the wealth effect on this exposure also disappears. Proofs are collected in Appendix E.4.

The declines in the prices of beta and variance could be amplified if QE raises output and consumption relative to a slow-moving average, thereby reducing risk aversion similar to a standard monetary policy easing shock to the short rate (Pflueger and Rinaldi (2022)). However, in a pure representative agent model, with or without time-varying risk aversion, it is not clear how bond quantities would affect the macroeconomy in the first place. Layering time-varying risk aversion on top of the simple model of bond quantities presented here would presumably amplify the declines in the prices of risk for both beta and variance and could be useful for a quantitative analysis. We do not pursue this avenue here to preserve clarity of the analytical insights.

Overall, our empirical results can be generated by a simple two-period model of bond market investors with non-zero exposure to bonds and stocks. In this model, QE lowers both the prices of beta and bond return volatility by affecting the wealth of bond arbitrageurs.

E.4 Proof of Proposition E3

We define the bond risk premium including the Jensen's inequality term as

$$\mu_1^{bond} - r_1 \quad = \quad E_1 r_2^{bond} - r_1 + \frac{1}{2}\sigma_{bond}^2 \tag{39}$$

Bond and stock returns around the instantaneous interval of the MIT shock are given by:

$$\frac{P_1^{bond,*}}{P_1^{bond}} \quad = \quad \exp\left(-\mu_1^{bond,*} + \mu_1^{bond}\right), \tag{40}$$

$$\frac{P_1^{eq,*}}{P_1^{eq}} \quad = \quad 1 \tag{41}$$

The log wealth change over the same instantaneous interval then equals approximately

$$w_1^* - w_1 \quad = \quad \alpha_1^{bond}\left(\mu_1^{bond} - \mu_1^{bond,*}\right) \tag{42}$$

The new equity portfolio share satisfies:

$$\alpha_1^{eq,*} \quad = \quad \alpha_1^{eq}\frac{W_1}{W_1^*} \tag{43}$$

Then the change in the equity share can be approximated log-linearly:

$$\alpha_1^{eq,*} - \alpha_1^{eq} = \alpha_1^{eq} \left(\exp(-(w_1^* - w_1)) - 1\right) \tag{44}$$

$$= -\alpha_1^{eq}\alpha_1^{bond} \left(\gamma\beta\sigma_{eq}^2 \left(\alpha_1^{eq} - \alpha_1^{eq,*}\right) + \gamma\sigma_{bond}^2 \left(\alpha_1^{bond} - \alpha_1^{bond,*}\right)\right) \tag{45}$$

Solving for the change in the equity share gives

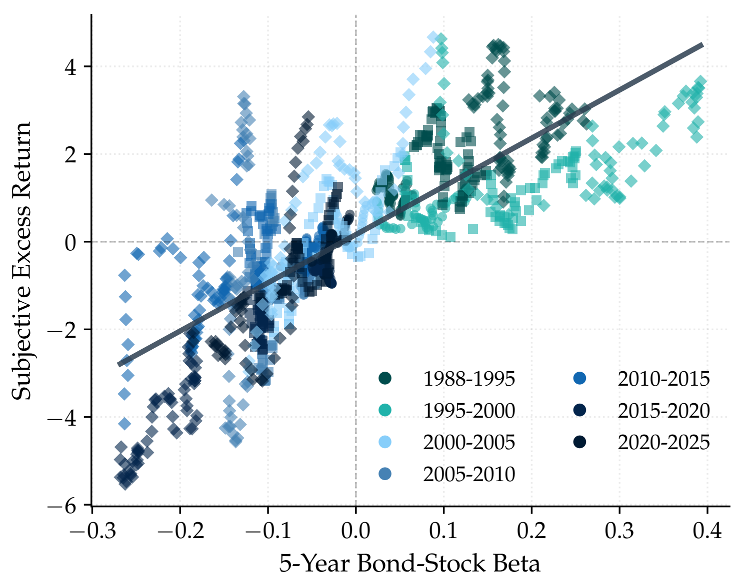
$$\alpha_1^{eq,*} - \alpha_1^{eq} = \frac{\alpha_1^{eq}\alpha_1^{bond}\gamma\sigma_{bond}^2}{1 - \alpha_1^{eq}\alpha_1^{bond}\gamma\beta\sigma_{eq}^2} \left(\alpha_1^{bond,*} - \alpha_1^{bond}\right). \tag{46}$$

The denominator $1-\alpha_1^{eq}\alpha_1^{bond}\gamma\beta\sigma_{eq}^2$ could in principle be negative when $\beta > 0$ and $\alpha_1^{eq}\alpha_1^{bond}\gamma\beta\sigma_{eq}^2 > 1$. However, since $\alpha_1^{eq}\alpha_1^{bond}$ are portfolio shares (small numbers) and $\gamma\beta\sigma_{eq}^2$ is also typically small on the order of the equity premium, the denominator is close to 1 in practice.

Typically, the slope coefficient in (46) is then positive, provided that $\alpha_1^{eq} > 0$, $\alpha_1^{bond} > 0$, and $\sigma_{bond}^2 > 0$. That is, the investor must have a non-zero exposure to the stock market and have a non-atomic position in bonds. If $\alpha_1^{eq} = 0$, a change in wealth does not affect the share exposed to the stock market. If $\alpha_1^{bond} = 0$ or $\sigma_{bond}^2 = 0$, removing quantity from the bond market does not affect investors' overall portfolio volatility and hence wealth. This completes the proof.

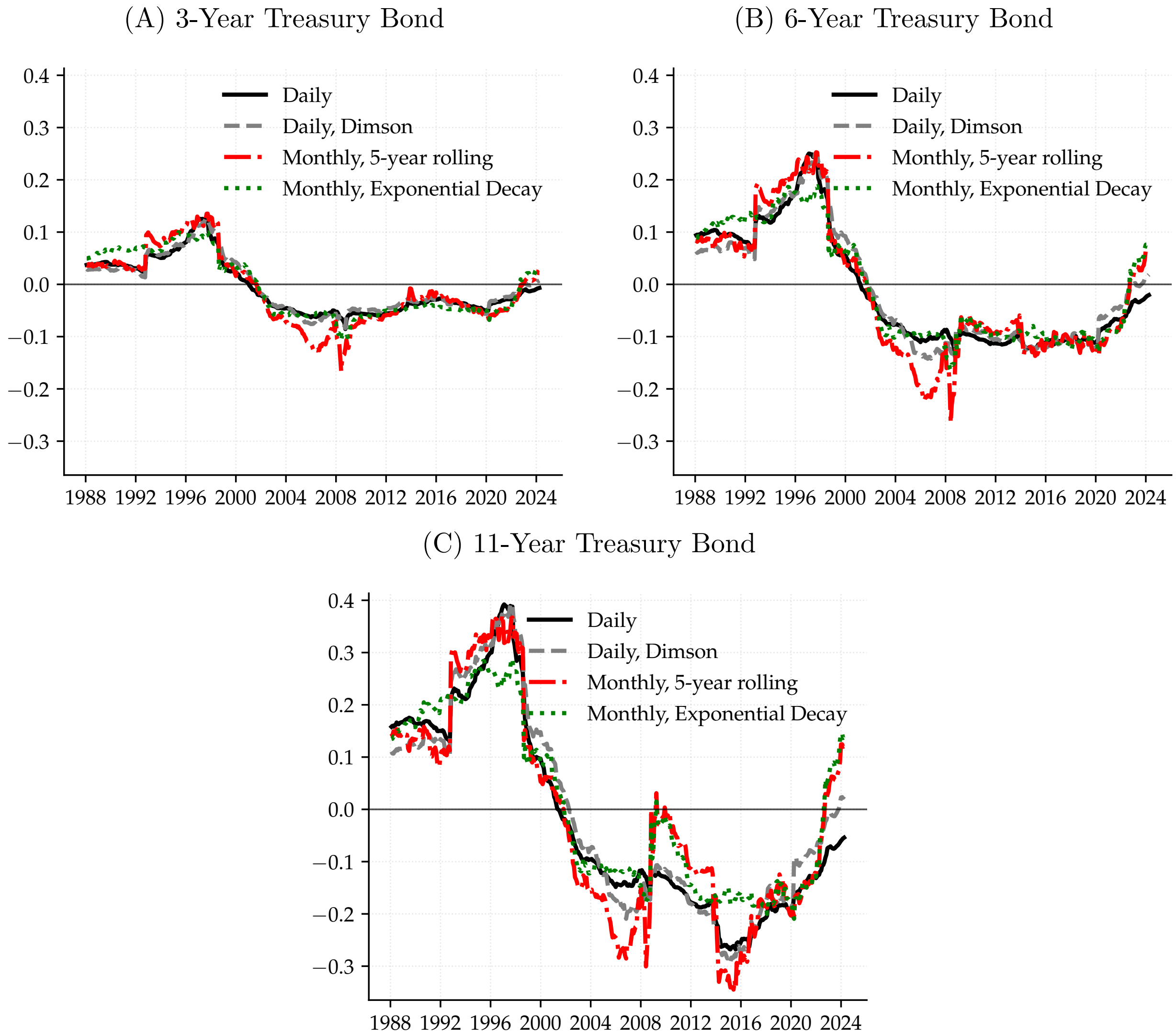
F. Additional Tables and Figures

Figure F.1: Subjective Excess Returns (MA) and Stock Market Betas



Note: This figure plots subjective excess returns on U.S. Treasury bonds (12 months moving average) against their five-year stock-market betas. The figure pools bonds of different maturities, which are distinguished by marker shape: three-year maturities (circles), six-year maturities (squares), and eleven-year maturities (diamonds). The sample spans January 1988 to March 2024.

Figure F.2: Estimated Betas



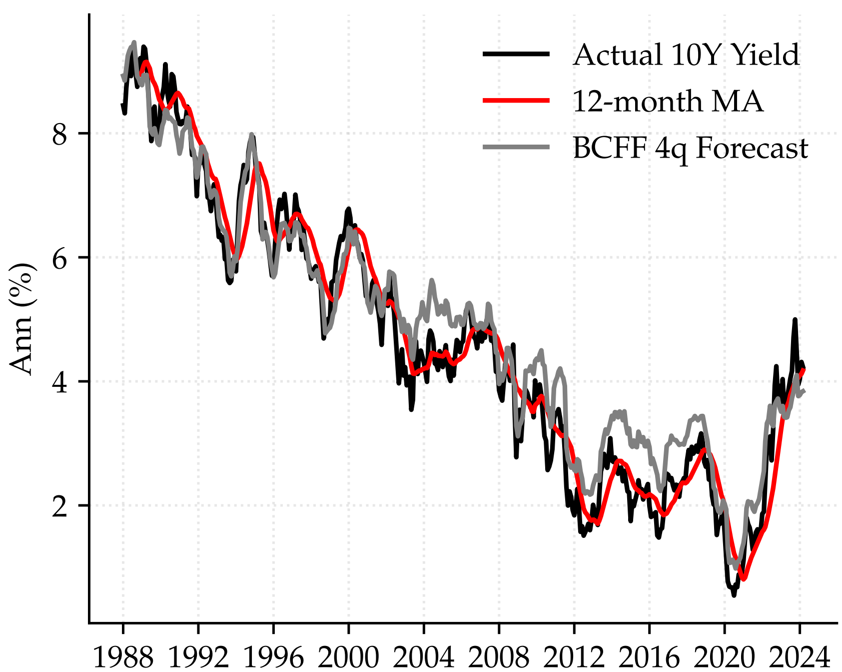
Note: This figure plots alternative estimates of stock market betas for par Treasury bonds of three-year (Panel A), six-year (Panel B), and eleven-year (Panel C) maturities. Our baseline estimate (black line) uses five-year rolling regressions of daily par bond excess returns on stock market excess returns. The dashed gray line reports betas estimated using daily data with the Dimson (1979) adjustment, which includes two lags and two leads of the market return. The red dash–dot line reports betas estimated from five-year rolling regressions using monthly returns instead of daily returns. The green dotted line reports betas estimated using exponentially decaying weights with a half-life of three years. Par bond excess returns are computed from Gürkaynak et al. (2007) nominal Treasury bond par yields. Stock market excess returns are from Ken French's website. We resample the estimates to a monthly frequency by taking the estimate from the last trading day of each month. The sample runs from January 1988 to March 2024.

Table F1: Correlation in Expected Excess Returns Across Groups

	3Y			6Y			11Y		
	Dealer	Buy-side	Research	Dealer	Buy-side	Research	Dealer	Buy-side	Research
Dealer	1.00	0.89	0.92	1.00	0.87	0.92	1.00	0.89	0.92
Buy-side	0.89	1.00	0.88	0.87	1.00	0.87	0.89	1.00	0.90
Research	0.92	0.88	1.00	0.92	0.87	1.00	0.92	0.90	1.00

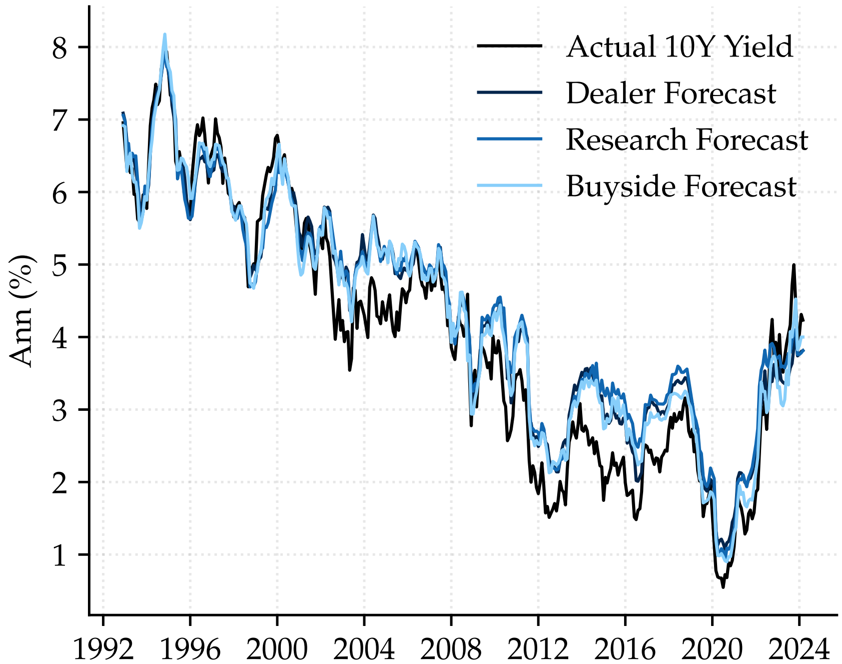
Note: The table reports correlations in expected bond excess returns across different groups of forecasters. Using information from Blue Chip on the firm associated with each forecaster, we classify forecasters into three groups: dealers, buy-side firms, and research institutes. Based on their forecasts, we compute group-level expected excess returns as in Equation 7.

Figure F.3: 10 Year Forecasts



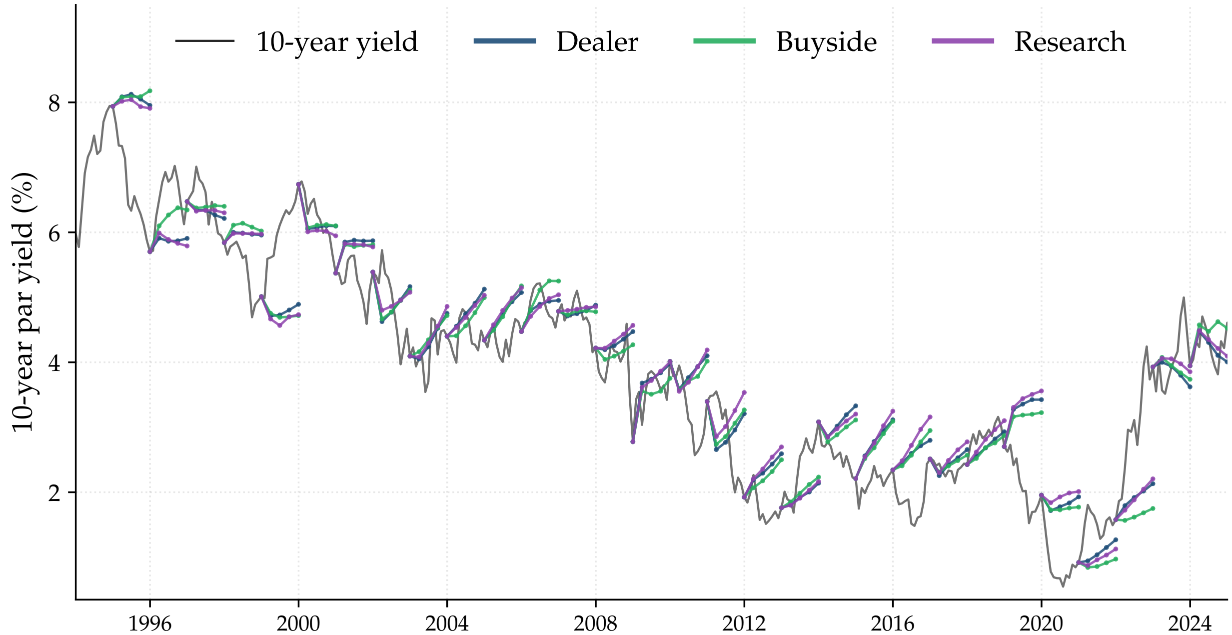
Note: The figure plots the actual 10-year yield, its trailing 12-month moving average, and the Blue Chip consensus forecast of the 10-year yield four quarters ahead. The consensus forecast averages across all forecasters. The series are shown over the months for which the Blue Chip 10-year forecast is available; the sample runs from 1988 to 2024.

Figure F.4: 10-Year Forecasts by Forecaster Type



Note: The figure plots the actual 10-year yield together with the Blue Chip consensus forecast of the 10-year yield four quarters ahead, computed separately by forecaster type. Using information from Blue Chip on the firm associated with each forecaster, we classify forecasters into three groups: dealers, buy-side firms, and research institutes, and average their forecasts within each group. The actual yield is shown over the months for which the grouped forecasts are available; the sample runs from 1992 to 2024.

Figure F.5: 10-year bond yield forecasts by group



Note: The figure plots forecasts of the 10-year yield, from one-quarter-ahead to five-quarters-ahead horizons, by forecaster group. Using information from Blue Chip on the firm associated with each forecaster, we classify forecasters into three groups: dealers, buy-side firms, and research institutes. Based on their individual forecasts, we compute group-level forecasts of the 10-year yield. The figure reports forecasts made in December of each year in the sample for which individual forecasts are available. The sample runs from 1995 to 2024.

Table F2: Expected Excess Returns and One-Year Rolling Bond-Stock Betas: U.S. Panel

Dependent Variable: Expected Excess Returns	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Bond-Stock Beta 1YR	7.14***	5.11***	7.13***	4.20**	7.42***	7.76***	4.20***	7.78***
	(1.55)	(1.61)	(1.53)	(1.86)	(1.56)	(1.67)	(1.40)	(1.71)
Bond Variance					5.27***			
					(1.95)			
Term Spread						0.49**		
						(0.23)		
Level							0.81***	
							(0.19)	
Slope							-0.33*	
							(0.17)	
Curvature							0.07	
							(0.16)	
Constant	0.02							
	(0.25)							
Time Trend		✓						
Maturity FE			✓	✓	✓	✓	✓	✓
Time Trend × Maturity FE				✓				
Time FE								✓
R-squared	0.29	0.34	0.29	0.37	0.34	0.33	0.41	0.82
Observations	1305	1305	1305	1305	1305	1305	1305	1305

Note: The table reports the estimates for the regression of expected excess returns on bond-stock beta as in equation (11):

$$\tilde{E}_t xr_{n,t\to t+12} = \alpha + \lambda\hat{\beta}^w_{n,t} + X'_{n,t}\delta + \eta_{n,t}.$$

We use the 1-year rolling bond-stock beta. Driscoll–Kraay standard errors with 27 lags are reported in parentheses. Stars denote significance at the 10, 5, and 1 percent levels based on Kiefer–Vogelsang fixed-b critical values. The sample consists of monthly data from January 1988 to March 2024.

Table F3: Expected Excess Returns and Stock Market Betas: U.S., Individual Maturities

Panel (A): Five-Year Rolling Beta

	3-year			6-year			11-year		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Beta 5YR	10.99***	9.23***	7.31***	9.89***	8.40***	5.89**	11.20***	10.22***	6.08***
	(1.89)	(2.42)	(2.10)	(1.94)	(3.06)	(2.54)	(1.86)	(3.53)	(2.22)
Level			0.28**			0.59**			1.16***
			(0.12)			(0.29)			(0.43)
Slope			-0.07			-0.26			-0.39
			(0.07)			(0.17)			(0.30)
Curvature			0.10			0.18			0.07
			(0.08)			(0.16)			(0.31)
Constant	0.17*	0.39*	0.15*	0.11	0.46	0.05	0.18	0.55	0.07
	(0.09)	(0.23)	(0.08)	(0.20)	(0.60)	(0.17)	(0.34)	(1.06)	(0.30)
Time Trend		✓			✓			✓	
R-squared	0.44	0.45	0.52	0.38	0.38	0.46	0.44	0.45	0.50
Observations	435	435	435	435	435	435	435	435	435

Panel (B): One-Year Rolling Beta

	3-year			6-year			11-year		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Beta 1YR	7.07***	5.05***	4.12***	6.51***	4.08**	2.85*	7.37***	4.15**	1.76
	(1.30)	(1.42)	(1.44)	(1.49)	(1.63)	(1.59)	(1.60)	(2.09)	(1.72)
Level			0.37***			0.82***			1.80***
			(0.10)			(0.24)			(0.51)
Slope			-0.08			-0.30*			-0.45
			(0.08)			(0.17)			(0.31)
Curvature			0.11			0.14			-0.05
			(0.07)			(0.15)			(0.30)
Constant	0.09	0.55**	0.09	-0.01	0.97**	-0.02	-0.01	1.96**	-0.04
	(0.11)	(0.23)	(0.09)	(0.24)	(0.49)	(0.20)	(0.44)	(0.94)	(0.35)
Time Trend		✓			✓			✓	
R-squared	0.34	0.41	0.50	0.27	0.34	0.44	0.30	0.37	0.47
Observations	435	435	435	435	435	435	435	435	435

Note: The table reports the regression estimates for equation (11) estimated maturity by maturity:

$$\tilde{E}_t xr_{n,t\to t+12} = \alpha + \lambda\hat{\beta}^w_{n,t} + X'_{n,t}\delta + \eta_{n,t}.$$

Panel (A) presents the results for five-year betas, while Panel (B) reports the results for one-year betas. Columns (2), (5), and (8) include a time trend. Newey—West standard errors with 27 lags are reported in parentheses. Stars denote significance at the 10, 5, and 1 percent levels based on Kiefer–Vogelsang fixed-b critical values. The sample consists of monthly data from January 1988 to March 2024.

Table F4: Subjective Excess Returns and Stock Market Betas, Alternative Betas

Dependent Variable: Expected Excess Returns	(1)	(2)	(3)	(4)	(5)	(6)
Beta 5YR	10.87***					
	(1.84)					
Beta 1YR		7.13***				
		(1.53)				
Beta 5YR (Dimson)			10.58***			
			(1.80)			
Beta 1YR (Dimson)				7.13***		
				(1.23)		
Beta 5YR (Monthly)					9.98***	
					(1.61)	
Beta HL 3Y (Monthly)						12.48***
						(1.67)
Constant	0.17*	0.09	0.15*	0.09	0.20**	0.16**
	(0.09)	(0.11)	(0.09)	(0.10)	(0.10)	(0.07)
Maturity FE	✓	✓	✓	✓	✓	✓
R-squared	0.43	0.29	0.42	0.34	0.44	0.48
Observations	1305	1305	1305	1305	1305	1305

Note: The table reports regression estimates of Equation (11) using alternative measures of beta. The dependent variable is the subjective excess return. Columns (1) and (2) use betas estimated from daily returns over five-year and one-year rolling windows, respectively. Columns (3) and (4) use the corresponding Dimson betas, which account for non-synchronous trading by including two leads and two lags of the market return and summing the associated coefficients. Column (5) uses a five-year rolling beta estimated from monthly returns. Column (6) uses a beta constructed with exponentially decaying weights with a half-life of three years, estimated using monthly data. Driscoll–Kraay standard errors with 27 lags are reported in parentheses. The sample consists of monthly observations from January 1988 to March 2024.

Table F5: Subjective Excess Returns and Stock Market Betas, Controlling for Volatility

Panel (A): Five-Year Rolling Beta

Dependent Variable: Expected Excess Returns	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Beta 5YR	10.87***	10.98***	11.12***	11.58***	12.91***	11.07***	12.95***	9.70***
	(1.84)	(1.76)	(1.77)	(1.71)	(1.68)	(1.96)	(1.95)	(2.32)
Vol Bond 1Y		4.47**					2.25	1.47
		(1.88)					(2.45)	(2.57)
Vol Bond 5Y			5.13**				0.96	-2.36
			(2.21)				(3.25)	(4.73)
Vol Mkt 1Y				0.86***			0.68*	0.88**
				(0.31)			(0.38)	(0.41)
Vol Mkt 5Y					1.75***		0.95	1.57**
					(0.50)		(0.73)	(0.76)
VIX						0.03	-0.01	-0.02
						(0.02)	(0.02)	(0.02)
Level								0.76***
								(0.26)
Slope								-0.07
								(0.16)
Curvature								0.20
								(0.14)
Constant	0.17*	-0.55	-0.68*	-0.72*	-1.72***	-0.48	-1.80***	-1.89***
	(0.09)	(0.36)	(0.35)	(0.37)	(0.51)	(0.45)	(0.57)	(0.72)
Maturity FE	✓	✓	✓	✓	✓	✓	✓	✓
R-squared	0.43	0.46	0.44	0.46	0.47	0.44	0.50	0.55
Observations	1305	1305	1305	1305	1305	1233	1233	1233

Panel (B): One-Year Rolling Beta

Dependent Variable: Expected Excess Returns	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Beta 1YR	7.13***	7.30***	7.39***	8.34***	7.93***	7.87***	8.54***	4.34***
	(1.53)	(1.56)	(1.47)	(1.45)	(1.79)	(1.56)	(1.81)	(1.55)
Vol Bond 1Y		4.75**					0.55	0.60
		(1.87)					(2.75)	(2.95)
Vol Bond 5Y			5.27*				6.26	-5.03
			(2.73)				(4.12)	(5.16)
Vol Mkt 1Y				1.16***			1.00**	1.17**
				(0.35)			(0.46)	(0.48)
Vol Mkt 5Y					0.92		-0.51	0.71
					(0.69)		(0.79)	(0.79)
VIX						0.06***	0.02	0.00
						(0.02)	(0.02)	(0.02)
Level								1.22***
								(0.20)
Slope								-0.24
								(0.17)
Curvature								-0.03
								(0.14)
Constant	0.09	-0.67*	-0.78*	-1.13***	-0.92	-1.14**	-1.94***	-1.11
	(0.11)	(0.37)	(0.44)	(0.41)	(0.77)	(0.46)	(0.69)	(0.72)
Maturity FE	✓	✓	✓	✓	✓	✓	✓	✓
R-squared	0.29	0.33	0.31	0.35	0.30	0.33	0.37	0.49
Observations	1305	1305	1305	1305	1305	1233	1233	1233

Note: The table reports regression estimates for Equation 11. Column (2) controls for bond-market realized volatility, estimated over a one-year rolling window. Column (3) controls for bond-market realized volatility, estimated over a five-year rolling window. Column (4) controls for stock-market realized volatility, estimated over a one-year rolling window. Column (5) controls for stock-market realized volatility, estimated over a five-year rolling window. Column (6) controls for the VIX. Column (7) includes all volatility controls jointly. Column (8) additionally controls for the principal components of the yield curve. Panel A presents the results for 5-year betas, while Panel B reports the results for 1-year betas. Driscoll–Kraay standard errors with 27 lags are reported in parentheses. The sample consists of monthly data from January 1988 to March 2024.

Table F6: Decomposition of Risk Premium

Dependent Variable:	$\tilde{E}_t xr_{n,t}$		$dur_{n,t}\, y_{n,t}$		$(dur_{n,t}-1)\, \tilde{E}_t y_{n-1,t+12}$		$y_{1,t}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Beta 5YR	10.87***	9.65***	73.98***	27.41*	49.59***	7.93	13.53***	9.84**
	(1.84)	(3.22)	(12.67)	(14.68)	(9.44)	(8.95)	(2.43)	(4.05)
Time trend x Maturity FE		✓		✓		✓		✓
R-squared	0.43	0.43	0.83	0.91	0.86	0.94	0.46	0.59
Observations	1305	1305	1305	1305	1305	1305	1305	1305

Note: The table reports regressions of the subjective expected bond excess return and each of its components on the bond–stock beta. The expected excess return decomposes as

$$\tilde{E}_t xr_{n,t\to t+12} = dur_{n,t}\, y_{n,t} - (dur_{n,t}-1)\, \tilde{E}_t y_{n-1,t+12} - y_{1,t},$$

where $dur_{n,t}$ is the bond's duration, $y_{n,t}$ the current par yield, $\tilde{E}_t y_{n-1,t+12}$ the Blue Chip forecast of next year's yield, and $y_{1,t}$ the one-year rate. Each pair of columns uses one of these four objects as the dependent variable—the expected excess return in Columns (1)–(2), $dur_{n,t} y_{n,t}$ in (3)–(4), $(dur_{n,t}-1)\tilde{E}_t y_{n-1,t+12}$ in (5)–(6), and $y_{1,t}$ in (7)–(8)—regressed on the five-year rolling bond–stock beta. The second column of each pair adds a maturity-specific linear time trend (one drift per maturity), and all specifications include maturity fixed effects. Driscoll–Kraay standard errors with 27 lags are reported in parentheses; stars denote significance at the 10, 5, and 1 percent levels based on Kiefer–Vogelsang fixed-b critical values. The sample period is January 1988 to March 2024.

Table F7: Realized and Expected Excess Returns: U.S. Panel, Unsmoothed Expected Excess Returns

Dependent Variable: Future Realized Excess Return							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Subjective Excess Returns	0.59**	0.61***		0.95***	0.91***	0.74***	0.53**
	(0.24)	(0.23)		(0.22)	(0.21)	(0.22)	(0.23)
$\lambda\times$ Beta			0.19	-0.77**	-0.67	-0.46	-1.30**
			(0.38)	(0.36)	(0.42)	(0.46)	(0.63)
Bond Variance					11.68		
					(18.33)		
Term Spread						1.45**	
						(0.74)	
Level							1.99**
							(0.84)
Slope							-1.10*
							(0.65)
Curvature							0.73
							(0.57)
Constant	2.06***						
	(0.71)						
Maturity FE		✓	✓	✓	✓	✓	✓
R-squared	0.06	0.08	0.02	0.10	0.11	0.15	0.22
Observations	1269	1269	1269	1269	1269	1269	1269

Note: The table reports the estimates of equation (13):

$$xr_{n,t\to t+12} = b_0 + b_1\,\tilde{E}xr_{n,t\to t+12} + b_2\,(\hat{\lambda}\times\hat{\beta}^{w}_{n,t}) + X'_{n,t}\delta + \varepsilon_{n,t+12}.$$

All independent variables are lagged by twelve months. $\lambda \times Beta$ is the fitted value from a regression of expected excess returns on five-year betas, as specified in equation (11). The beta is thus rescaled so that its magnitude is comparable to the expected excess return. The table uses unsmoothed expected excess returns. Driscoll–Kraay standard errors with 27 lags are reported in parentheses. Stars denote significance at the 10, 5, and 1 percent levels based on Kiefer–Vogelsang fixed-b critical values. The sample consists of monthly data from January 1988 to March 2024.

Table F8: Realized and Expected Excess Returns: U.S., Individual Maturities

Panel (A): Realized and Expected Excess Returns

	3-year				6-year				11-year			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Subjective XR	0.64*		0.99**	0.29	0.67***		1.01***	0.37	0.58**		0.92***	0.34
	(0.37)		(0.43)	(0.49)	(0.25)		(0.26)	(0.36)	(0.24)		(0.23)	(0.25)
$\lambda\times$ Beta		0.23	-0.77	-1.76**		0.14	-0.88*	-2.18*		0.20	-0.74**	-1.72*
		(0.50)	(0.54)	(0.85)		(0.47)	(0.49)	(1.15)		(0.35)	(0.34)	(1.03)
Level				1.38**				2.81**				4.15**
				(0.65)				(1.35)				(2.02)
Slope				-0.22				-0.94				-2.17**
				(0.31)				(0.64)				(1.02)
Curvature				0.31				0.77				0.97
				(0.26)				(0.56)				(0.91)
Constant	0.99**	1.02**	1.04**	1.16***	2.17***	2.13***	2.18***	2.03***	3.02***	2.95***	3.04***	2.77***
	(0.42)	(0.45)	(0.43)	(0.39)	(0.74)	(0.77)	(0.71)	(0.64)	(1.03)	(1.07)	(0.98)	(0.93)
R-squared	0.05	0.00	0.07	0.23	0.06	0.00	0.09	0.26	0.06	0.00	0.08	0.26
Observations	423	423	423	423	423	423	423	423	423	423	423	423

Panel (B): Realized and Expected Excess Returns (MA)

	3-year				6-year				11-year			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Subjective XR (MA)	0.93**		2.19***	0.85	0.96***		2.03***	0.93	0.79***		1.77***	0.72**
	(0.45)		(0.63)	(1.04)	(0.31)		(0.40)	(0.75)	(0.29)		(0.34)	(0.36)
$\lambda\times$ Beta		0.23	-1.96**	-2.38**		0.14	-1.90***	-2.84**		0.20	-1.61***	-2.14**
		(0.50)	(0.82)	(0.96)		(0.47)	(0.65)	(1.24)		(0.35)	(0.42)	(1.07)
Level				1.49**				3.03**				4.33*
				(0.73)				(1.46)				(2.27)
Slope				-0.15				-0.66				-1.80
				(0.38)				(0.80)				(1.10)
Curvature				0.26				0.60				0.80
				(0.24)				(0.52)				(0.90)
Constant	1.01**	1.02**	1.08***	1.26***	2.23***	2.13***	2.21***	2.18***	3.04***	2.95***	3.04***	2.92***
	(0.43)	(0.45)	(0.42)	(0.38)	(0.75)	(0.77)	(0.68)	(0.63)	(1.03)	(1.07)	(0.92)	(0.92)
R-squared	0.07	0.00	0.14	0.28	0.09	0.00	0.17	0.30	0.09	0.00	0.17	0.29
Observations	412	423	412	412	412	423	412	412	412	423	412	412

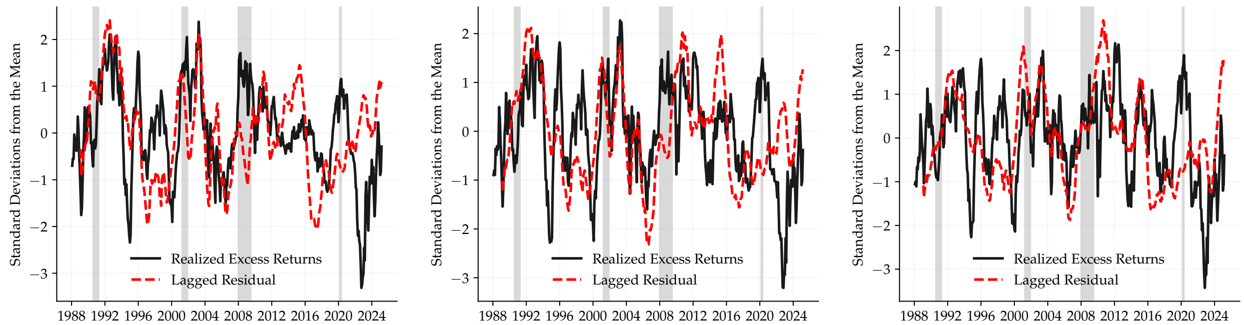
Note: The table reports the estimates of equation (13):

$$xr_{n,t\to t+12} = b_0 + b_1\,\tilde{E}xr_{n,t\to t+12} + b_2\,(\hat{\lambda}\times\hat{\beta}^{w}_{n,t}) + X'_{n,t}\delta + \varepsilon_{n,t+12},$$

estimated maturity by maturity. All independent variables are lagged by twelve months. $\lambda \times Beta$ is the fitted value from a regression of the expected excess return on the five-year bond-stock beta, as specified in equation (11). The beta is therefore rescaled so that its magnitude is comparable to the expected excess return. Panel A uses expected excess returns, while Panel B uses moving average expected excess returns. The moving average expected excess return is the average expected excess return over the past year. The sample consists of monthly data from January 1988 to March 2024. Driscoll-Kraay standard errors with 27 lags are reported in parentheses.

Figure F.6: Realized Excess Returns and Lagged Residual Expected Excess Returns

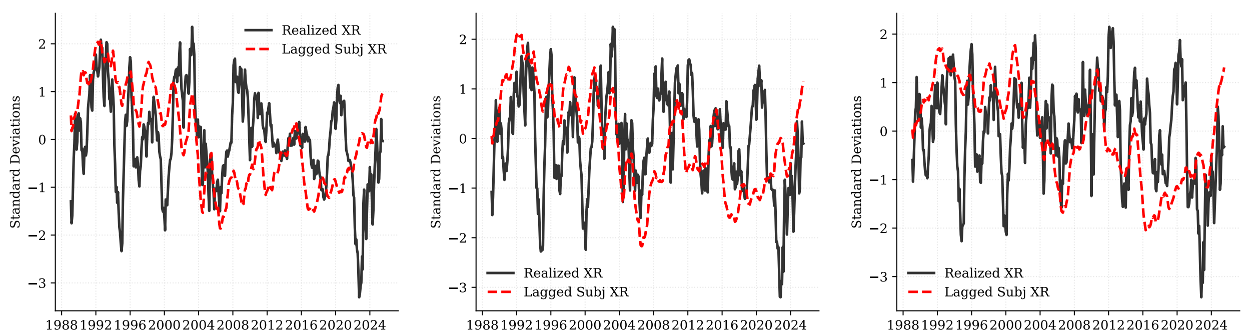
(A) 3-Year Treasury Bond (B) 6-Year Treasury Bond (C) 11-Year Treasury Bond



Note: The figure plots realized excess returns together with the lagged, residualized expected excess returns from equation (11), where expected excess returns are smoothed using a 12-month moving average. Both series are standardized to facilitate comparison within and across panels. Realized excess returns are shown in black, while the residualized expected excess returns are shown in dashed red. Shaded regions indicate NBER recession periods. The sample spans January 1988 to March 2024.

Figure F.7: Realized Excess Returns and Lagged Subjective Excess Returns

(A) 3-Year Treasury Bond Maturity (B) 6-Year Treasury Bond Maturity (C) 11-Year Treasury Bond Maturity



Note: The figure plots realized excess returns together with the lagged, residualized subjective excess returns from Equation 11, where subjective excess returns are smoothed using a 12-month moving average. Both series are standardized to facilitate comparison within and across panels. Realized excess returns are shown in blue, while the residualized subjective excess returns are shown in teal. Shaded regions indicate NBER recession periods. The sample spans January 1988 to March 2024.

Table F9: Summary Statistics: International Panel

Panel (A): Subjective Expected Excess Returns

	Pooled	Canada	France	Germany	Italy	Japan	Netherlands	Norway	Spain	Sweden	Switzerland	UK	USA
Average	-0.73	-1.23	-0.30	-1.10	1.50	-0.67	-1.21	-1.76	-0.07	-2.14	-1.89	-0.51	-0.04
Std	2.70	2.92	2.21	1.86	3.40	1.43	2.36	2.36	3.06	2.35	1.68	2.62	3.12
Min	-9.73	-8.50	-4.80	-5.71	-4.87	-4.17	-6.96	-9.24	-5.32	-9.73	-5.90	-7.22	-8.18
Max	13.03	9.37	6.63	5.68	11.80	4.44	8.00	4.15	13.03	5.44	2.42	9.06	8.16
N	4823	435	435	435	435	435	372	331	372	372	331	435	435
First Year	1989	1989	1989	1989	1989	1989	1994	1998	1994	1994	1998	1989	1989

Panel (B): Subjective Expected Excess Returns (Moving Average)

	Pooled	Canada	France	Germany	Italy	Japan	Netherlands	Norway	Spain	Sweden	Switzerland	UK	USA
Average	-0.72	-1.22	-0.30	-1.10	1.53	-0.67	-1.21	-1.80	-0.04	-2.09	-1.88	-0.51	-0.03
Std	2.35	2.61	1.82	1.51	3.00	1.10	1.92	1.80	2.69	1.95	1.21	2.27	2.71
Min	-6.49	-6.49	-3.60	-3.87	-2.81	-2.75	-5.30	-6.20	-4.19	-6.21	-4.44	-4.33	-5.53
Max	8.83	6.53	4.60	3.02	8.83	2.10	2.97	2.10	8.81	3.53	0.97	5.19	4.67

Panel (C): Realized Excess Returns

	Pooled	Canada	France	Germany	Italy	Japan	Netherlands	Norway	Spain	Sweden	Switzerland	UK	USA
Average	1.94	2.06	1.90	1.67	2.62	1.61	2.06	0.95	2.74	2.42	1.67	1.54	1.91
Std	6.95	6.30	6.82	6.55	9.68	4.88	6.63	5.89	8.45	7.36	5.07	7.17	6.76
Min	-29.99	-15.75	-25.17	-24.22	-29.99	-21.48	-25.66	-16.51	-25.61	-26.94	-15.61	-25.52	-19.87
Max	24.44	15.62	16.77	15.24	24.44	14.92	14.83	13.82	21.90	18.16	12.78	16.42	15.54

Panel (D): Bond-Stock Betas

	Pooled	Canada	France	Germany	Italy	Japan	Netherlands	Norway	Spain	Sweden	Switzerland	UK	USA
Average	0.02	0.04	0.04	-0.01	0.12	-0.03	0.00	-0.07	0.09	0.00	-0.02	0.07	-0.02
Std	0.15	0.18	0.13	0.10	0.12	0.08	0.12	0.09	0.14	0.13	0.10	0.18	0.21
Min	-0.34	-0.23	-0.16	-0.19	-0.10	-0.16	-0.20	-0.22	-0.12	-0.26	-0.19	-0.17	-0.34
Max	0.49	0.46	0.29	0.21	0.37	0.21	0.29	0.22	0.46	0.27	0.21	0.49	0.44
Average S.E.	0.05	0.07	0.05	0.04	0.05	0.04	0.05	0.05	0.05	0.05	0.05	0.07	0.08

Panel (E): β w.r.t. US Stock Returns

	Pooled	Canada	France	Germany	Italy	Japan	Netherlands	Norway	Spain	Sweden	Switzerland	UK	USA
Average	0.02	0.04	0.03	-0.01	0.10	0.02	-0.01	-0.03	0.10	0.00	-0.03	0.02	-0.02
Std	0.15	0.17	0.13	0.13	0.13	0.09	0.13	0.13	0.16	0.19	0.10	0.16	0.21
Min	-0.34	-0.22	-0.22	-0.26	-0.17	-0.12	-0.28	-0.27	-0.18	-0.33	-0.21	-0.23	-0.34
Max	0.55	0.49	0.32	0.27	0.39	0.31	0.32	0.29	0.55	0.45	0.22	0.39	0.44
Average S.E.	0.06	0.07	0.07	0.06	0.08	0.04	0.06	0.06	0.07	0.07	0.05	0.08	0.08

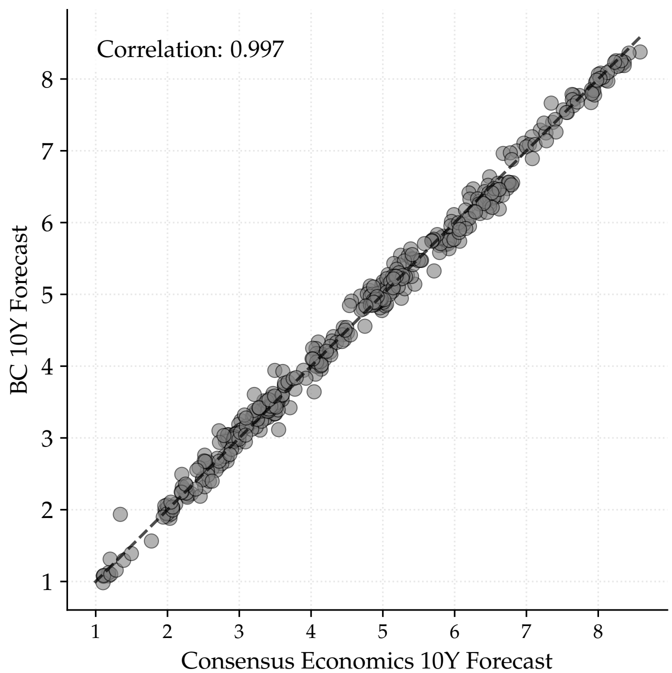
Note: The table reports summary statistics for expected excess returns (Panel A), the one-year moving average of expected excess returns (Panel B), one-year holding period realized excess returns (Panel C), bond-stock betas using local equity (Panel D) and bond-stock betas using US equity (Panel E) for different countries. Subjective expected bond excess returns are computed according to Equation 7. We use four-quarter par bond yield forecasts from Consensus Economics. Bond yields, T-bill rates, and stock returns are obtained from GFD. Bond–stock betas are computed as the regression coefficient of monthly par bond excess returns on stock excess returns over a backward-looking rolling window, as defined in Equation 10. We use 60-month rolling windows (five-year rolling β). Par bond excess returns are constructed using ten-year par yields, and stock market excess returns are computed using domestic stock market index returns. The table reports the average estimate, standard deviation, minimum and maximum values, the average HW-robust standard errors, and the number of observations. The sample is monthly and spans September 1989 to December 2024.

Table F10: Subjective Excess Returns and Bond-Stock (US) Market Betas: International Panel

Dependent Variable: Expected Excess Returns									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Beta 5YR (US)	8.04***	6.80***	7.37***	6.26***	6.32***	7.44***	3.73**	6.01***	3.59**
	(1.61)	(1.68)	(1.48)	(1.86)	(1.39)	(1.49)	(1.56)	(2.28)	(1.54)
Bond Variance					0.17				
					(0.11)				
Term Spread						0.20			
						(0.16)			
10-Year Rate							0.71***		
							(0.21)		
1-Year Rate							-0.21		
							(0.17)		
Constant	-0.88***								
	(0.25)								
Time Trend		✓							
Country FE			✓	✓	✓	✓	✓		✓
Time Trend × Country FE				✓					
Time FE								✓	✓
R-squared	0.21	0.25	0.29	0.37	0.30	0.29	0.46	0.55	0.62
Observations	4798	4798	4798	4798	4798	4798	4798	4798	4798

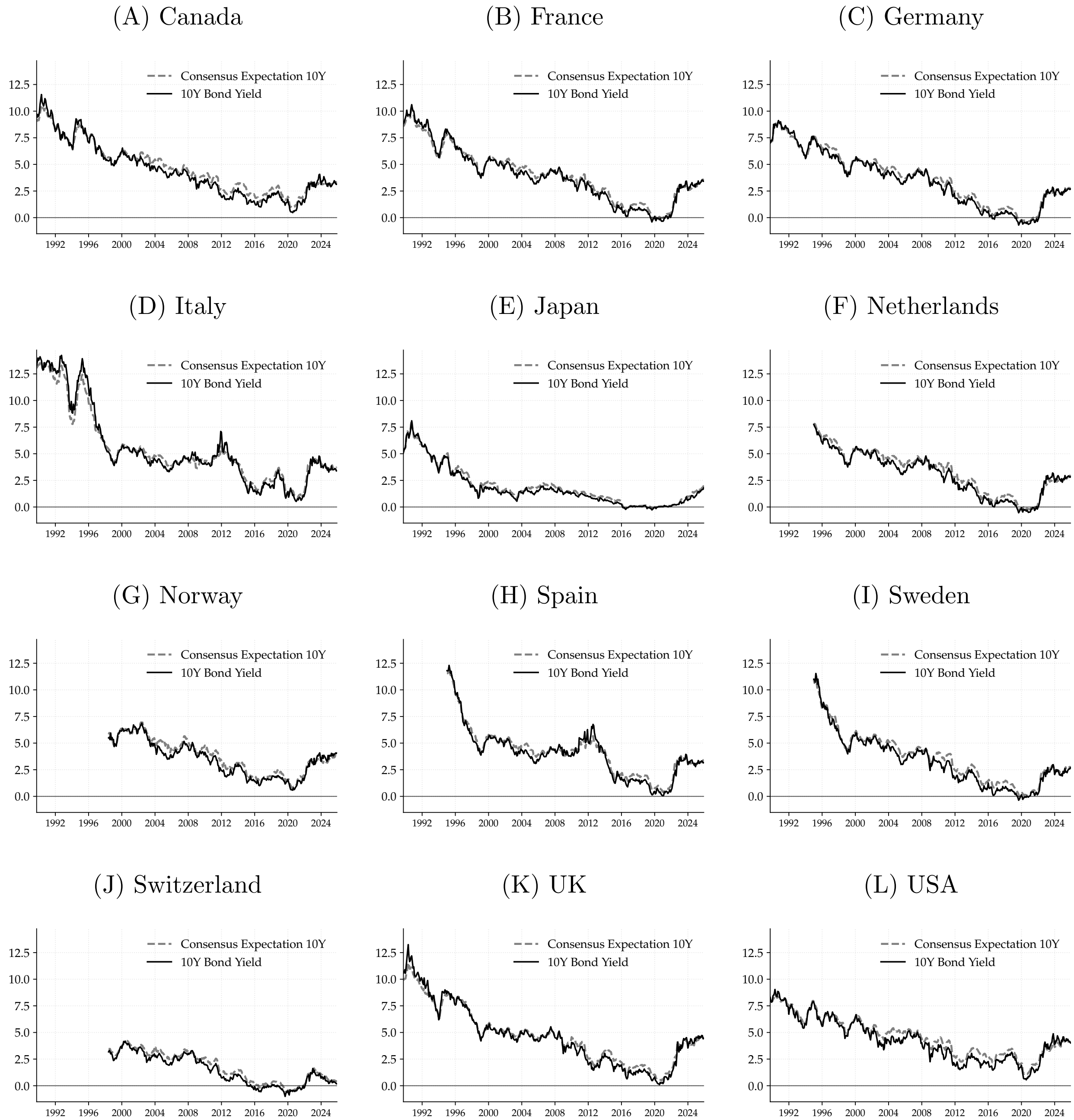
Note: This table is analogous to Table VII in the main paper, but it uses bond betas with respect to U.S. stock excess returns rather than domestic stock excess returns. The data are monthly and span September 1989 to December 2024.

Figure F.8: Consensus Economics vs Blue Chip for the US



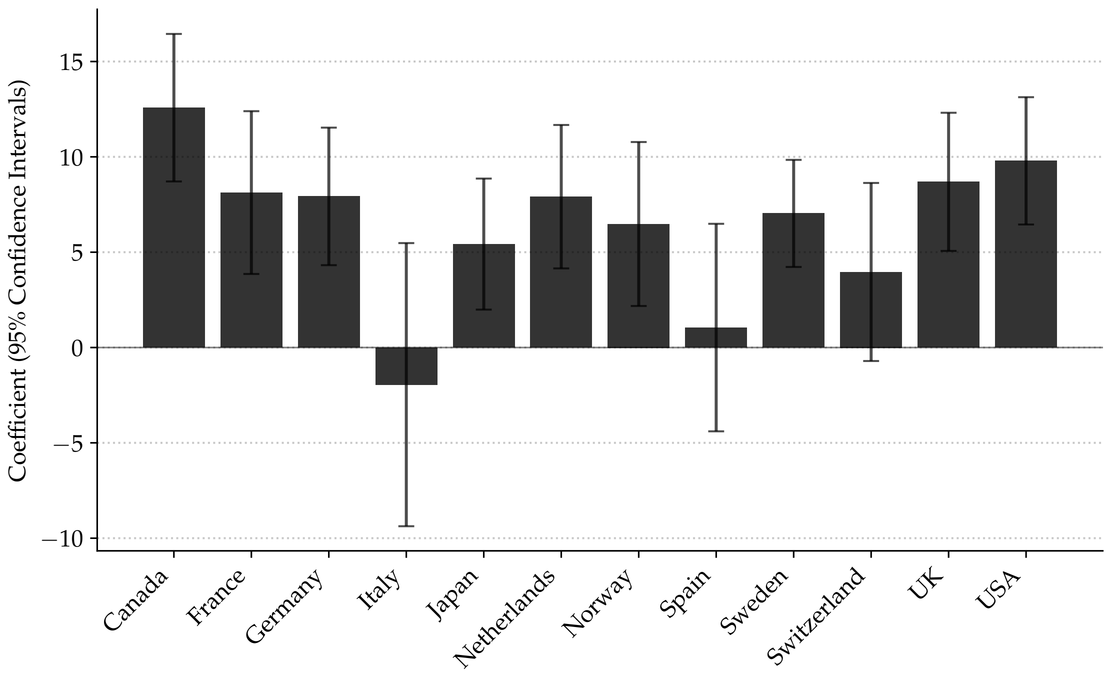
Note: The figure plots Consensus Economics forecasts of the 10-year government bond yield on the x-axis and the corresponding Blue Chip forecasts on the y-axis. Sample: September 1989 to June 2024.

Figure F.9: Consensus Economic Forecasts and Actual 10-year Yield



Note: The figure plots the realized 10-year government bond yield for each country together with the consensus economists' average forecast of the 10-year yield one year ahead. The realized yield is measured on the survey date, that is, at the time the forecasts are collected.

Figure F.10: Subjective Returns on Beta, using US stock returns



Note: The figure plots the estimated coefficient from regression (18), estimated separately for each country. This figure is analogous to Figure 6 in the main paper but uses bond betas with respect to U.S. stock excess returns instead of bond betas with respect to domestic market stock excess returns.

Table F11: Realized Returns, Expected Excess Returns, and Betas: International Evidence, Unsmoothed

Dependent Variable: Future Realized Excess Return					
	(1)	(2)	(3)	(4)	(5)
Subjective Excess Returns	0.53***	0.57***		0.53***	0.46**
	(0.20)	(0.21)		(0.18)	(0.19)
$\lambda\times$ Beta			0.77	0.24	0.33
			(0.64)	(0.64)	(0.57)
Term Spread					1.90***
					(0.43)
Constant	2.54***				
	(0.93)				
Country FE		✓	✓	✓	✓
R-squared	0.046	0.052	0.021	0.053	0.131
Observations	4653	4653	4653	4653	4653

Note: The table reports the results of equation (19) estimated using our international panel:

$$xr_{c,t\to t+12} = b_0 + b_1\, \tilde{E}_t xr_{c,t\to t+12} + b_2\,(\hat{\lambda}\times\hat{\beta}^{w}_{c,t}) + X'_{c,t}\delta + \varepsilon_{c,t+12},$$

All independent variables are lagged by twelve months. $\lambda\times$ *Beta* is the fitted value from a regression of the expected excess return on the five-year bond-stock beta, as specified in equation (11). The beta is therefore rescaled so that its magnitude is comparable to the expected excess return. The table uses *unsmoothed* expected excess returns. Driscoll-Kraay standard errors with 27 lags are reported in parentheses. Stars denote significance at the 10, 5, and 1 percent levels based on Kiefer–Vogelsang fixed-b critical values. The sample consists of monthly data from September 1989 to December 2024.

Table F12: Quantitative Easing (QE) Policy Periods Across Central Banks

Country	Central Bank	Regime	Start	End	Links
Italy	ECB	QE (APP)	2015–01–15	2018–12–19	Start – End
Italy	ECB	QE (Restart)	2019–11–01	2022–06–30	Start – End
Italy	ECB	QE (PEPP)	2020–03–26	2022–03–31	Start – End
France	ECB	QE (APP)	2015–01–15	2018–12–19	Start – End
France	ECB	QE (Restart)	2019–11–01	2022–06–30	Start – End
France	ECB	QE (PEPP)	2020–03–26	2022–03–31	Start – End
Germany	ECB	QE (APP)	2015–01–15	2018–12–19	Start – End
Germany	ECB	QE (Restart)	2019–11–01	2022–06–30	Start – End
Germany	ECB	QE (PEPP)	2020–03–26	2022–03–31	Start – End
Spain	ECB	QE (APP)	2015–01–15	2018–12–19	Start – End
Spain	ECB	QE (Restart)	2019–11–01	2022–06–30	Start – End
Spain	ECB	QE (PEPP)	2020–03–26	2022–03–31	Start – End
USA	Federal Reserve	QE1–QE3	2008–11–25	2014–10–29	Start – End
USA	Federal Reserve	QE (COVID)	2020–03–15	2022–03–15	Start – End
UK	Bank of England	QE	2009–03–05	2012–11–01	Start – End
UK	Bank of England	QE (Brexit)	2016–08–04	2018–12–01	Start – End
UK	Bank of England	QE (COVID)	2020–03–19	2021–12–01	Start – End
Japan	Bank of Japan	QE	2001–03–19	2006–03–09	Start – End
Japan	Bank of Japan	QQE	2013–04–04	2024–03–19	Start – End
Canada	Bank of Canada	QE	2020–04–01	2021–10–27	Start – End
Sweden	Riksbank	QE	2015–02–12	2021–11–01	Start – End

Notes: The table reports QE programme periods across major central banks. Hyperlinks point to official policy decision announcements. Norway is excluded as it did not implement QE.

Table F13: International and QE, Unsmoothed Subjective Excess Returns

Dependent Variable: Expected Excess Returns								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
QE	-1.17***	0.15	-0.93***	¿-0.25	0.99*	1.82***	0.14	1.43***
	(0.39)	(0.34)	(0.25)	¿(0.25)	(0.42)	(0.43)	(0.53)	(0.50)
Beta			8.86***	¿4.69***			6.71***	3.56**
			(1.90)	¿(1.70)			(1.86)	(1.50)
QE × Beta			-7.56***	¿-5.80**			-5.19**	-2.02
			(2.45)	¿(2.78)			(2.44)	(2.87)
Bond Variance				¿0.54***		0.24**	0.26***	0.18**
				¿ (0.11)		(0.10)	(0.10)	(0.09)
QE × Bond Variance				¿-0.53***		-0.45***	-0.28**	-0.41***
				¿ (0.14)		(0.13)	(0.13)	(0.11)
Constant	-0.53		-0.76***	¿-2.73***			-1.75***	
	(0.40)		(0.25)	¿ (0.55)			(0.46)	
Country FE		✓		¿✓		✓		✓
Time FE		✓		¿✓		✓		✓
R-squared	0.03	0.49	0.24	¿0.50	0.18	0.51	0.26	0.52
Observations	4798	4798	4798	¿4798	4798	4798	4798	4798

Note: The table reports the results of equation (20) estimated using our international panel:

$$\tilde{E}_t xr_{c,t\to t+12} = \alpha + \alpha_{QE}\text{QE}_{c,t} + \lambda\hat{\beta}_{c,t} + \lambda_{QE}\left(\text{QE}_{c,t} \times \hat{\beta}_{c,t}\right) + \mu\hat{\sigma}^2_{c,t} + \mu_{QE}\left(\text{QE}_{c,t} \times \hat{\sigma}^2_{c,t}\right) + \eta_{c,t}.$$

The bond–stock beta is estimated using monthly data over a five-year rolling window (60 months), based on excess returns on the domestic stock market. Similarly, bond variance is estimated as the rolling variance of monthly bond excess returns over the same five-year window. Expected yields are from Consensus Economics, while bond yields, T-bill rates, and stock returns are from the Global Financial Database (GFD). The term-spread is the difference between the 10-year government bond yield and the 1-year government bond yield. Driscoll-Kraay standard errors with 27 lags are reported in parentheses. Stars denote significance at the 10, 5, and 1 percent levels based on Kiefer–Vogelsang fixed-b critical values. The data are monthly and span September 1989 to December 2024.