Risk-Based Interest Rate Expectations

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Abstract

I develop a method to extract interest-rate expectations from options markets by connecting interest-rate risk premia to interest rate variance risk premia. This approach makes no assumptions on the stationarity or dynamics of interest-rate levels. I find first that historical excess bond returns mostly reflected anticipated risk premia, not forecast errors. Second, risk-based forecasts outperform surveys and traditional term-structure models, particularly during the zero-rate period. Third, the decline in rates around FOMC announcements may be driven by risk premia. Fourth, the positive stock-yield correlation of recent decades appears to be driven by expectations and not risk premia.

Keywords: term premium, term structure, bond risk premium, variance risk premium, return predictability, interest-rate risk, duration

JEL Classification: G12, G21

In January 2010 the yield curve sloped sharply upwards. A 1-year loan could be made at an interest rate of just 0.6%, but the same loan agreed to start in 1 year would pay 2%.[1] Were investors expecting inflation and interest rates to spike? Or was this just compensation for duration risk? Distinguishing between these possibilities and, more broadly, measuring interest-rate expectations is a critical task for central banks and investors.

The finance profession has many tools to measure expected interest rates, from simple bond return regressions to full-fledged dynamic term-structure models. What all of these approaches have in common is that they fit a historical relationship between a set of predictors and the next period's interest rate levels or, equivalently, bond returns

This paper proposes instead to measure the interest-rate risk premium and interest-rate expectations from options markets. I derive a no-arbitrage relationship that links the interest-rate risk premium to interest-rate variance and risk-neutral moments that are directly observable from options markets. I use this identity to create interest-rate forecasts that do not make any assumptions about the stationarity of the interest-rate level, circumventing the problems created by the secular decline of interest rates. The forecasts significantly outperform traditional stationary term-structure models out of sample. I use these forecasts to show that high historical bond returns have been driven by risk premium, not surprises, that bond risk premium is negatively correlated with stock returns, and that risk premium may account for much of the decline in long term rates around monetary policy announcements.

The key identity relates perceived risk to perceived return. If investors expect high returns on bonds, they will take on more interest-rate risk. A simple no-arbitrage identity tells us that the interest-rate risk premium RP_t perceived by an investor equals the investor's interest-rate risk "exposure" λ_t, multiplied by the risk-neutral variance σ_t^{*2}:

$$RP_t = \lambda_t \times \sigma_t^{*2}$$

[1]The 1-year LIBOR swap rate on January 1st was 0.6%, and the 1y-in-1y swap forward rate was 2%

The exposure, λ_t, is approximately equal to the investor's portfolio duration multiplied by risk aversion, if we assume a bond investor with CRRA utility. This approximation is exact in the log-utility special case..

To identify exposure, I use a parallel identity for squared interest-rate changes. The risk premium on contracts that pay off squared changes in interest rates ($RPSq_t$) approximately equals the level of interest-rate exposure multiplied by the risk-neutral third moment of interest-rate risk exposure:

$$RPSq_t \approx \lambda_t \text{ThirdMoment}_t^*$$

Intuitively, when the level of interest-rate risk exposure (λ_t) is high, the equilibrium price of "insuring against" large changes in interest rates ($RPSq$) should also be high. We can use the price of this insurance to learn about the level of risk exposure. If $\lambda_t > 0$, this relationship will be stronger and the insurance more valuable when the distribution is right-skewed and the third moment is high because large increases in rates will be more common than large declines.

Expected squared changes depend on variance, and so this identity allows us to back out the exposure and risk premium based on a variance forecast rather than a level forecast. This offers two advantages: first, the variance, unlike the level, is clearly stationary (see Figure 1). Second, variance can be learned quickly from daily data, and hence variance-forecasting models have a strong track record of empirical success (e.g. Bollerslev, 1986; Corsi, 2009).

The identity involves an additional unobservable term that captures the covariance between squared interest-rate changes and non-linear components of the investor's payoffs. I argue that this term is likely to be small. Observable proxies using common SDF specifications are an order of magnitude too small to explain the variance risk premium, and do not line up with the time series of variance risk premium. For my main analysis, I therefore set this value to zero. Under this assumption, the forecasts can be interpreted as the expectations that must be perceived by a log-utility investor who chooses to take a linear exposure to interest rates. Up to a modest approximation error, this same interpretation

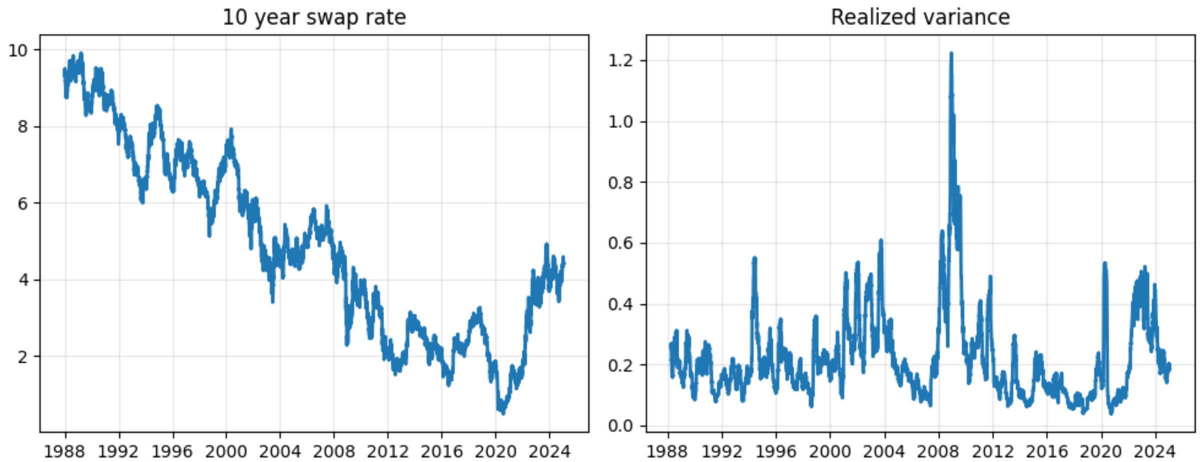

Figure 1: Stationarity of interest rate levels vs variance. The left-hand side plots the 10-year swap rate and the right-hand side plots the quarterly realized variance of the same rate, 1988-2025.

can be applied to an investor with power utility.

The forecasts that this approach generates are correlated with surveys and traditional risk premium measures, capturing well-known effects such as the association of slope with risk premium. However, they significantly outperform existing methods. At one-quarter horizons, the out-of-sample R2 improves on the Survey of Professional Forecasters by 28% and the popular Adrian, Crump, and Moench (2013) term-structure model by 10% (see Table 4). The predictions generate economically large trading profits with Sharpe ratios of 0.73 vs. -0.17 for traditional term-structure models.

Beyond forecasting performance, the risk-based approach provides new perspectives on three puzzles in fixed income markets. First, do the high returns on long-term bonds over the past 25 years represent an anticipated risk premium, or a series of surprises? Forward rates have tended to point upwards, while rates stayed low, leading to large returns for bond investors. The causes of these returns are of central interest to finance research — they can potentially account for the entire equity risk premium in this period (van Binsbergen, 2020).

Figure 2: Forward rates vs risk-based forecasts of the 10-year swap rate. The black line plots the 10-year swap rate from 2002 to 2023. The light gray lines each quarter plot the 1q and 1y forward rate. The red lines plot the 1q and 1y expected interest rates calculated using the methodology from this paper.

Standard approaches struggle to answer this question because of the secular decline in rates. Models with a stationary interest-rate process assume rates will return to the historical average, leading to low or negative risk premium in recent years. If one instead allows the long-term "end point" to shift, then a wide range of different risk premia are compatible with a reasonable set of priors (Farmer, Nakamura, and Steinsson, 2024).

My method gathers information instead from the variance of interest rates, which, in contrast, exhibits mean reversion with no obvious long-term trend, as shown in Figure 1. I find a highly significant variance risk premium ($t \approx 5$), that implies an interest-rate risk premium of 44 bp per year, similar to the realized premium of 34 bp. Figure 2 plots interest rate forwards versus my measure of expectations at each quarter from 2002-2023. When forward rates pointed upwards, as in 2002 or 2010, risk premia were large enough that expected rates stayed flat. The duration risk premium appears to have been expected risk compensation rather than forecasting errors.

Second, do investors learn their long-term interest-rate expectations from the Fed? Hillenbrand (2025) documents that the entire secular decline in long-term rates occurred during three-day FOMC windows, interpreting this as markets learning about long-run fundamentals from the Federal Reserve. Standard term-structure models are poorly suited to decompose these announcement effects into expectations versus risk premium. They either assume a constant long-run mean interest rate, ruling out learning about long-run levels, or they update long-run mean estimates at low frequencies.

My risk-based decomposition suggests an alternative explanation. Risk-neutral variance falls around FOMC meetings by amounts far exceeding mechanical effects from uncertainty resolution, and then reverses between meetings. This pattern is consistent with temporary risk premium compression. The implied declines in risk premium could potentially account for the entire FOMC-window rate puzzle. While I cannot rule out shifts in physical variance expectations, the transitory nature and magnitude of these moves point toward monetary policy systematically compressing risk premia.

Third, why are stocks now positively correlated with yields? The stock-yield correlation flipped from negative to positive in the late 1990s. Is this driven by correlated risk premia (e.g., flight-to-safety shocks) increasing stock risk premia while lowering bond risk premia (e.g. Antolin-Diaz, 2025) or correlated expectations about growth (e.g. Campbell, Sunderam, and Viceira, 2017)? Standard models show positive correlation of risk premium with equity returns, but this may result from the stationarity assumptions: growth news that raises long-run rate expectations could be misclassified as risk premium. Using the risk-based approach, I find interest-rate risk premium correlates negatively with equity returns, opposite to flight-to-safety predictions. The positive yield-stock correlation therefore appears to reflect correlation of stocks with expected future rates, not risk premium effects.

Related Literature

This paper extends techniques from the literature on option-based expected returns (Martin, 2017; Kremens and Martin, 2019; Chabi-Yo and Loudis, 2020; Tetlock, McCoy, and Shah, 2024). The existing literature has assumed that the SDF is a function of stock market returns. We cannot take a similar approach for interest rates because there is no liquid instrument that reveals the risk-neutral covariance of interest rates with equity returns. Nor is there an obvious theoretical benchmark for what exposure to interest rates a representative investor should have.

I therefore develop a new approach that instead takes the assumption that the investor's exposure to interest rates are not "too-nonlinear," and then uses the variance risk premium to find exposures and expected returns. In theory this approach could work for any asset class. My methodology is closely related Tetlock et al. (2024), who also calculate expected returns on equities using variance risk premium and risk-neutral third moment.

This paper also contributes to the extensive literature on interest-rate forecasting, term premium, and dynamic term-structure models. This paper presents an alternative way to forecast interest rates. The results can also be interpreted as supporting the use of shifting end-point models that allow for non-stationary interest rates e.g., Kozicki and Tinsley (2001); van Dijk, Koopman, van der Wel, and Wright (2014); Bauer and Rudebusch (2020), and as supporting evidence for models with unspanned stochastic volatility, e.g., Collin-Dufresne and Goldstein (2002); Collin-Dufresne, Goldstein, and Jones (2009).

The empirical findings of this paper are also related to Bauer and Chernov (2024), who find that risk-neutral skewness predicts treasury yields, Choi, Mueller, and Vedolin (2017), who document the interest-rate variance risk premium, and Trolle and Schwartz (2014), who measure risk-neutral yield moments from swaptions.

Organization of the paper

Section 1 derives the key relationship between variance risk premia and interest-rate risk premia. Section 2 describes the data and estimation of the model. Section 3 presents the the interest-rate expectations and evaluates their forecasting performance. Section 4 applies the estimator to measure the contribution of risk premium vs expectations to the stock-bond correlation and the decline in rates around FOMC announcement windows. Section 5 validates the key identifying assumption of the method: that the "residual coskew" is small.

Section 6 concludes. An appendix contains extensions to other maturities, robustness tests, and technical details.

1 Measuring expectations from risk

If investors are highly exposed to interest-rate risk, the equilibrium price to insure against variance in rates will be high. The price of that insurance can therefore inform us about their interest-rate exposure and the expected interest rate.

This section formalizes this intuition by deriving an identity relating the interest-rate risk premium to the variance risk premium and one unobservable quantity. I then discuss the key assumption needed to operationalize this relationship.

1.1 Defining interest rates and interest-rate risk premium

This paper aims to measure expectations of next period's interest rate:

$$E_t(y_{t+1})$$

y_{t+1} could represent any rate or yield. For empirical estimation, I will use swap rates, focusing on the 10-year swap rate one quarter or one year in the future.

Consider a one-period linear interest-rate forward. At time $t+1$ the buyer receives the level of the interest rate minus the pre-agreed forward price F_t. His payoff is equal to:

$$\Delta y_{t+1} = y_{t+1} - F_t$$

We can construct this interest rate forward price F_t from the observable yield curve.[2]

Using standard notation we can also describe the forward rate as the "risk-neutral expectation" of interest rates: $E_t^*(y_{t+1})$. If markets were priced by a risk-neutral agent, this would

[2]We do not exactly observe linear forward prices for most interest rates, but their value can be constructed with a minuscule convexity adjustment described in sections 2 and Appendix C.

be equal to the physical expectation. We call this hypothesis that $E_t^*(y_{t+1}) = E_t(y_{t+1})$ the "expectations hypothesis." In practice, we know that it is not true, and there are large gaps between the forward rates and interest-rate expectations (Fama and Bliss, 1987; Campbell and Shiller, 1991).

I will define the "interest-rate risk premium" as the difference between the forward rate (i.e. the risk-neutral expected rate) and the physical expected rate. This is equal to the the expected payoff from selling the linear interest-rate forward.

$$RP_t = F_t - E_t(y_{t+1}) = E_t^*(y_{t+1}) - E_t(y_{t+1}) = -E_t(\Delta y_{t+1})$$

If we can measure this interest-rate risk premium, then we know the expected interest rate next period.

The interest rate risk premium is closely linked to the bond risk premium. For example if we assume that y_{t+1} is the yield on a bond with maturity T, then expected excess return on a bond with maturity T+1 is approximately the bond's duration multiplied by the interest rate risk premium:[3]

$$E_t(R_{t+1} - R_{f,t+1}) \approx D(E_t(y_{t+1}) - F_t) = D \times RP_t$$

I use linear interest rate forwards instead of zero coupon bond returns as my basic unit of analysis for this paper, so that I can flexibly work with any type of yield. In practice we do not observe option prices for zero-coupon bonds.

1.2 Measuring the interest-rate risk premium without assumptions on the rate process

I will assume that there is no arbitrage and the fundamental theorem of asset pricing holds throughout this paper. In that case, the following result allows us to learn about

[3] To derive this, simply take a first-order approximation of the the bond price $P_{t+1}(y_{t+1})$ around $y_{t+1} = F_t$. Assume the bond forward approximately equal to the linear forward, so that $\frac{P_{t+1}(F_t)}{P_0} \approx R_{f,t+1}$

expectations without specifying an interest-rate process:

Proposition 1. *If no arbitrage holds, the expectation of any payoff X is given by:*

$$E_t^*(X) - E_t(X) = -\frac{1}{R_{f,t}} cov_t^* \left(\frac{1}{M_{t+1}}, X \right)$$

Where E^* represents risk-neutral expectations. From Martin and Wagner (2019); Chabi-Yo and Loudis (2020)[4].

Applying this identity to the interest rate y_{t+1} yields:

$$RP_t = -\frac{1}{R_{f,t}} cov_t^* \left(\frac{1}{M_{t+1}}, y_{t+1} \right)$$

The risk premium is revealed by the risk-neutral covariance of interest rates with the SDF. This result resembles the more familiar asset pricing identity that relates expected returns with the *physical* covariance with the SDF. However, it has the advantage of working with directly observable quantities. Risk-neutral covariances are potentially observable from asset prices.

Hence if we can make some assumptions about the nature of the SDF (i.e., what constitutes a good or bad state) and find the price of an asset whose payoffs are linked to interest rates but also this SDF, then we can calculate interest-rate expectations.

1.3 Projecting the SDF onto yields

The existing literature that uses proposition 1 to measure expectations has taken the perspective of an equity investor for whom $\frac{1}{M_{t+1}}$ is a function of stock market returns (Martin, 2017; Martin and Wagner, 2019; Kremens and Martin, 2019; Chabi-Yo and Loudis, 2020; Tetlock et al., 2024). In this case, expected returns are given by the risk-neutral covariance with stock market returns.

[4] The proposition can be proven simply by calculating the price of an asset with payoff $Z = \left(\frac{1}{M_{t+1}} - R_{f,t} \right) X$ using both SDF and risk-neutral pricing notation

This approach will not work for interest rates. We simply do not observe any liquid assets that reveal the risk-neutral covariance of interest rates with stocks Martin (2025). Additionally, even if such an asset were available, we might question whether equity returns are a reasonable proxy for fixed-income investor wealth. The efforts to find joint risk factors across stocks and bonds have not always been successful.

I therefore propose a new approach that does not rely on equity returns. Instead, I will consider the SDF as a function of interest rates and residual terms. Without loss of generality, we can consider the projection of any SDF onto interest rates (Δy_{t+1}) under the risk-neutral measure:

Definition 1. *Projection of the inverse SDF*

$$\frac{1}{M_{t+1}} = R_{f,t+1}\left(1 - \lambda_t \Delta y_{t+1} + \varepsilon_{t+1}\right)$$

where $E_t^*(\varepsilon_{t+1}) = cov_t^*(\varepsilon_{t+1}, \Delta y_{t+1}) = 0$

This is simply a linear projection under the risk-neutral arbitrage. The SDF can be written in this fashion for any model with no arbitrage. The intercept must be $R_{f,t+1}$ because $E_t^*\left(\frac{1}{M_{t+1}}\right) = R_{f,t+1}$ and $E_t^*(\Delta y_{t+1}) = 0$. In the case of a log investor who holds exactly linear exposures to the interest rate the inverse SDF is linear and $\varepsilon_{t+1} = 0$.

In general, I will refer to λ_t as the investor's "exposure" to interest rates, because it captures how much the investor suffers from a rise in interest rates. For a CRRA investor with linear interest-rate exposure and risk aversion coefficient γ:

$$\lambda_t \approx \gamma \times \text{duration}_t$$

For example, with a CRRA coefficient of 2 and a linear exposure of duration 20, $\lambda \approx 40$. In the special case of log utility where $\gamma = 1$, this approximation is exact and λ_t is the duration. More generally, there will be a small approximation error. Appendix B tests this approximation up to $\gamma = 4$ and shows it is accurate within 4% for the average risk-neutral distribution, and 8% on the most extreme day.

1.4 Risk premium as a function of exposure

Applying Proposition 1 to measure interest-rate expectations and plugging in the projection for $\frac{1}{M_{t+1}}$ yields an expression for interest-rate risk premium.

Proposition 2. *If no arbitrage holds, the interest rate risk premium is given by:*

$$RP_t = \lambda_t var_t^*(\Delta y_{t+1}) \equiv \lambda_t \sigma_t^{*2}$$

In words, Proposition 2 tells us the risk premium is equal to exposure times risk-neutral variance. Loosely speaking, this is because in equilibrium, the amount of risk agents take should tell us both the rewards to taking interest-rate risk and the price to insure against large changes in interest rates (the risk-neutral variance).

Now we have an expression for the interest-rate risk premium in terms of an observable variable. The risk-neutral variance represents the price of a contract that pays out squared interest-rate changes and can be easily measured from option prices, using the methodology described in Section 2. It is the interest rate equivalent of the $SVIX^2$ equity index from Martin (2017), and is highly correlated with the well-known VIX "fear index" for equity markets or the $MOVE$ index for bonds.

However, we still need to know our exposure term, λ_t before we know interest-rate expectations. Martin (2017) derives a similar expression for equities and posits that the exposure should be near 1. But for interest rates, the sign and magnitude of λ is not obvious. Is the marginal investor long or short duration, and by how much?

1.5 Exposure as a function of variance

We want to use the value of λ_t to measure expected payoffs on interest-rate forwards. But the same logic can be applied in reverse: if we can estimate any expected payoff, we can use it to learn about λ_t.

I will measure the expected payoff on a contract that pays out Δy_{t+1}^2 and use this expected payoff to learn about λ_t. This approach resembles the strategy that Tetlock et al. (2024) apply to equity markets.

Variance has three important characteristics that make it an attractive payoff to forecast. First, interest-rate variance does not display the same long-term non-stationary trend as the level (see Figure 1). Second, variance can be measured easily with high frequency data. For any function involving higher moments, this becomes more challenging due to volatility clustering.[5]. Third, there is a long track record of empirical success with simple variance forecasting models (e.g., Bollerslev, 1986; Corsi, 2009).

Applying Proposition 1 to the payoff Δy_{t+1}^2 yields an expression for the risk premium on squared interest rate contracts and variance risk premium.

Proposition 3. *The risk premium on squared interest rate contracts is given by:*

$$RPSq_t = \sigma_t^{*2} - E_t(\Delta y_{t+1}^2) = \lambda_t E_t^*(\Delta y_{t+1}^3) - cov_t^*(\Delta y_{t+1}^2, \varepsilon_{t+1}) \tag{1}$$

Or, restated in in terms of the "variance risk premium:"

$$VRP_t = \sigma_t^{*2} - \sigma_t^2 = \lambda_t E_t^*(\Delta y_{t+1}^3) + \sigma_t^{*4} \lambda_t^2 \tag{2}$$

To move from Equation (1) to (2), I have used the fact that the sum of squared changes is equal to the variance plus the expected change (i.e. risk premium) squared:

$$E_t(\Delta y_{t+1}^2) = \sigma_t^2 + RP_t^2 = \sigma_t^2 + \sigma_t^{*4} \lambda_t^2$$

The terminology of "variance risk premium" for the left-hand side of Equation (2) — the

[5] Intuitively, the daily autocorrelation of changes in rates should be low. Otherwise there would be large potential trading profits. But the daily autocorrelation of squared changes in rates, or the last period's change in rates with next period's squared change may be very high. Variance is persistent. Hence we cannot find a good estimate for third or higher moments by simply dividing up the sample into small pieces and calculating the moments of the short observations.

difference between the risk-neutral and physical variance — is consistent with the existing literature, e.g., Bollerslev, Tauchen, and Zhou (2009); Drechsler and Yaron (2011).

Proposition 3 tells us the expected profit from selling variance contracts is equal to exposure scaled by the risk-neutral third moment minus an unobservable term that I will call the "residual coskew." The risk-neutral third moment can be measured from option data in exactly the same way as the risk-neutral variance. So if we can make an assumption about the size of the residual coskew term, then a forecast of physical variance will yield a value for the exposure and interest-rate risk premium.

1.6 The residual coskew assumption

The residual term ε_{t+1} represents the portion of the inverse SDF that is uncorrelated with interest rates under the risk-neutral measure. The inverse SDF, loosely speaking, captures how "good" states are for the investor (1/ marginal utility). So the residual coskew term, $cov_t^*(\Delta y_{t+1}^2, \varepsilon_{t+1})$ represents the extent to which the investor tends to be better or worse off in states of the world with large interest-rate changes, regardless of their sign.

This quantity is unobservable. We do not observe ε, and even if we did, we would not observe the option prices that would reveal the relevant risk-neutral moment. Producing an estimate of the interest-rate risk premium therefore requires us to take an assumption on the size of this covariance. The simplest assumption that is most consistent with the existing literature is simply that the value is zero. This assumption will approximately hold, for example, in all standard dynamic term-structure models, because they assume that the log SDF is linear in interest-rate factors, making the inverse SDF nearly linear over short horizons.

Setting the residual coskew to zero amounts to an assumption that the risk premium on variance contracts reflects directional interest-rate risk by the investor (λ_t) rather than a non-linear exposure to rates. In other words, the reason why the investor does not choose to sell variance contracts despite their positive payoff is because of his level of interest-rate risk. This does not impose that other asset classes (e.g. equities) are not important to the investor, but only that the directional exposure of those assets to interest-rate risk is more important than exposure to squared changes.

I will take this as my main benchmark in developing a measure of interest-rate expectations. It turns out that despite the simplicity of this assumption, it produces forecasts that perform very well out of sample and lines up with the variables we expect to be associated with interest-rate risk premia (e.g. the slope of the yield curve), as shown in Section 3.

In Section 5 I will measure the closest observable data and argue the assumption is empirically reasonable. I calculate the physical covariance of ε with squared changes in rates under a few common specifications for the SDF and find they are an order of magnitude too small to explain the size variance risk premium. They also do not help to explain the time series of the variance risk premium compared to a simple no-residual-coskew model. I further demonstrate that if one assumes the investor has CRRA (power) utility with reasonable risk aversion parameters, the simple no-residual-coskew estimate will understate risk premium by approximately 25%, but retain a $> 99\%$ correlation with the true values.

1.7 Identifying the risk premium

Proposition 3 gives a relationship between physical variance σ_t^2, and the exposure λ_t. So an estimate of the physical variance will identify the value of λ_t. The risk-neutral third moment, $E_t^*(\Delta y_{t+1}^3)$, tells us how directional exposure translates into variance risk premium. If the distribution is highly right-skewed (i.e., the third moment is high), then the variance contract will mostly pay off in high-rate states of the world where the investor is poor and hence will be highly valuable. If, on the other hand, the risk-neutral third moment is very low, it will take a large amount of exposure to deliver much variance risk premium. The identification of λ_t will therefore be stronger in periods when the risk-neutral third moment is high.

2 Data and estimation

Section 1 shows how exposure, and hence interest-rate risk premium, can be identified by the physical variance, the risk-neutral variance, and the risk-neutral third moment of interest rates (Proposition 3).

This section describes how I operationalize this relationship to calculate interest-rate expectations. I first present the data sources that the paper employs. I then briefly describe how the risk-neutral variance and third moment are calculated, followed by the methodology for estimating physical variance. Finally I describe the functional form and estimation approach I use to solve for the exposure parameter.

2.1 Data

I measure realized variance from daily interest-rate swap rates obtained from Refinitiv, and risk-neutral moments from swaptions quotes obtained from Bloomberg. The sample covers USD LIBOR swaps from December 2001 to June 2023, when LIBOR ceased publication. I track six tenors (1, 2, 5, 10, 20, and 30 years) at three forecast horizons (3 months, 1 year, and 5 years). I construct swap forwards from swap rates and treasury yields using the procedure described in Appendix C.

The main results of this paper focus on the 10-year swap rate, the most liquid tenor. The methodology can be readily applied to other tenors of swap rate with similar results, although a few additional complications are introduced by the zero lower bound for short tenors. Appendix A shows the results from forecasts of the 1-, 2-, 5-, 20-, and 30-year interest-rate risk premium.

The results of this paper should be interpreted as risk premium on swap rates, rather than treasury rates. Arguably, this is the more relevant rate for many market participants who are more likely to borrow at rates linked to swap rates or hedge using swaps. The differences are unlikely to be large. The realized quarterly risk premium on 10-year swaps vs treasuries during my sample period differs by just 0.7 basis points. The spread between

10-year swaps and the equivalent (off the run) treasury yield averages just 12 basis points during the sample period and it explains only 3% of the variation of the 10-year yield. Since 2008, this spread has often been negative and is thought to be related to leverage constraints and capital requirements rather than bank credit risk (Boyarchenko, Gupta, Steele, and Yen, 2018).

I use swaptions to calculate risk-neutral interest-rate moments. A swaption is a contract that gives its holder the right to enter an interest-rate swap at a predetermined rate. Swaption markets represent the most liquid interest option market, with extensive participation of both buy-side and interdealer trading (ISDA, 2014; Barnes, 2024). While swaptions trade over-the-counter rather than on exchanges, collateralization through initial and variation margin is standard practice and limits counterparty credit risk.

Before 2011 only at-the-money swaption quotes are available. Out-of-the-money quotes are available for 10-year treasuries from CME and for closely-related LIBOR caps and floors from Bloomberg. I therefore estimate pre-2011 risk-neutral variance and skewness using the parameters from a regression on at-the-money variance, the 10-year treasury risk-neutral skewness (calculated by Bauer and Chernov, 2024), and the risk-neutral skewness of caps and floors. These regressions have an R2 of 0.99 for variance and 0.7 for skewness. Data before 2007 is only available on a weekly basis.

Treasury options data from CME offers an alternative source of interest-rate option data. While this data source has a longer history than swaptions, it covers fewer tenors, has lower trading volume, and trades as American options at a single, short and time-varying horizon of 1-3 months.

2.2 Constructing risk-neutral moments

I follow Carr and Madan (1998) and Martin (2017) to extract model-free measures of risk-neutral moments from option prices. The key insight is that a portfolio of options with strikes spanning all possible outcomes has a payoff equal to the squared change in rates vs the forward rate. The forward price of this portfolio therefore equals the risk-neutral variance. The third moment follows similarly. A portfolio of options weighted appropriately produces a payoff of cubed rate changes, and its forward price gives the risk-neutral third moment.

This result holds exactly when we can trade options on the underlying rate itself. However, swaptions are options on swap values rather than swap rates. The value of a swap depends on the price of an annuity, not just the swap rate. In Appendix C, I show that we can nevertheless derive the risk-neutral moments of the swap rate itself using a simple approximation. If we assume that changes in the 10-year annuity yield are the same as changes in the 10-year swap rate, then we can calculate the risk-neutral moments of the swap rate itself. Historical correlation of quarterly or annual changes in the swap rate with the annuity rate are $> 99.5\%$, so this is unlikely to introduce large approximation errors. Appendix C demonstrates this relationship and derives the relevant formulas. I can also use this strategy to calculate the risk neutral first moment of the interest rate, i.e. the risk neutral expectation. This is the the linear forward price discussed in section 1, which can theoretically differ from the ordinary swap or bond forward rate. In practice I find the differences are only a few basis points, and immaterial for the purpose of this paper.

Table 1 presents summary statistics for the second and third risk-neutral moments, and Figure 7 in Appendix D plots the time series. Variance is high during and after the financial crisis, during the 2022 inflation, and, more surprisingly, in 2002-4. The high option-implied interest-rate volatility of the early 2000s was noted at the time as puzzling by central banks (Fornari, 2005; ECB, 2005).

2.3 Measuring physical variance

2.3.1 Realized variance

The simplest way to estimate physical variance is to simply use realized variance measured over the subsequent period. Replacing the physical variance in Proposition 3 with the realized variance from daily data plus an error term yields:

$$\sigma_t^{*2} - RV_{t\to t+1} = \lambda_t E_t^*(\Delta y_{t+1}^3) + \sigma^{*4}\lambda_t^2 + \eta_{t+1}$$

Now all terms in this equation are observable except for λ_t and the error term η_t. If the conditional variance is equal to the conditional expectation of realized variance, then this error term should be uncorrelated with the other terms in the equation.

I use this approach to construct a simple test of the average size of λ_t, which I will discuss in Section 3.1. If we assume λ_t is constant then we can simply solve for the value of λ that minimizes the sum of squared errors $\sum \eta_t^2$ with no further assumptions.

2.3.2 Conditional variance forecasts

To develop conditional measures of time varying exposure (λ_t) for out-of-sample forecasting, we will want to use the latest information about variance available at time t. I therefore fit a simple variance forecasting model to produce estimates $\hat{\sigma}_t^2$.

I employ a simple linear regression estimator based on the heterogeneous autoregressive realized variance (HAR-RV) model of Corsi (2009), widely used in the variance risk premium literature (e.g., Bollerslev et al., 2009; Drechsler and Yaron, 2011). I estimate the model by regressing quarterly or annual realized variance onto the variance realized over the preceding week, month, and quarter:

$$RV_{t\to t+63d} = \beta_0 + \beta_1 RV_{t-5d\to t} + \beta_2 RV_{t-21d\to t} + \beta_3 RV_{t-63d\to t} + \varepsilon_{t+H}$$

where $RV_{t\to t+Hd}$ is the realized variance calculated from daily data from period t to $t+H$ business days. I assume 21 days in a month and 63 in a quarter. I use weekly, monthly, and quarterly lags rather than the standard daily, weekly, and monthly from Corsi (2009) to better suit the longer forecast horizons in my application, and because I do not have intra-day swap rate data.

Estimated conditional variance is then given by the regression coefficients multiplied by the latest realized variance:

$$\hat{\sigma}_t^2 = \hat{\beta}_0 + \hat{\beta}_1 RV_{t-5d\to t} + \hat{\beta}_2 RV_{t-21d\to t} + \hat{\beta}_3 RV_{t-63d\to t} \tag{3}$$

The model performs remarkably well out-of-sample, achieving R2 values exceeding 20% even at quarterly horizons, as shown in Table 2. This predictability confirms that it is easier to learn about variance than means, one of the key advantages of the risk-based forecasting approach. The time series of quarterly estimated variance risk premium is plotted in Figure 3. Results are robust to including interest-rate levels or allowing variance to depend on rate levels through a constant elasticity of variance specification.

2.4 Parameterizing exposure

The variance risk premium identity in Proposition 3 and the conditional variance forecasts from Section 2.3.2 allow us to solve for the exposure, λ_t, in each period. However, in periods where the risk-neutral third moment is low, the exposure will be poorly identified and highly sensitive to noise in the variance and skew estimates, as discussed in Section 1.7. To estimate exposure for the whole time series, I therefore assume that λ_t is a smooth function of state variables. This allows us to use the periods where the third moment is high to identify the plausible exposure when it is low. In Appendix E, I consider the alternative approach that estimates λ_t period-by-period without functional form assumptions. The results closely resemble the main results, indicating the choice of functional form is not critical.

I parameterize λ_t as a linear function of the first three principal components of the yield curve and the two risk-neutral moments used to construct my estimates (variance and skewness):

$$\lambda_t = \lambda_0 + \lambda_1 f_{1,t} + \lambda_2 f_{2,t} + \lambda_3 f_{3,t} + \lambda_4 \sigma_t^{*2} + \lambda_5 skew_t^* \tag{4}$$

where f_1, f_2, and f_3 are the first three principal components of yields, which capture the level, slope, and curvature of the yield curve. This can be interpreted as an assumption that investors choose their level of exposure depending on the shape of the yield curve and risk-neutral distribution of future yields, or that the shape of the yield curve responds to investor choices and exposure.

The first three principle components explain $> 99\%$ of variation in the shape of the yield curve and are empirically well known to be related to interest-rate risk premium. It has been standard practice in term-structure modeling since Duffee (2002) to assume that the price of risk is a function of yield curve factors.

I include the risk-neutral moments for the sake of completeness because they are used in construction of the estimator and because empirical work has suggested they contain additional information on interest-rate risk premium that is not included in the yield curve (Joslin and Konchitchki, 2018; Bauer and Chernov, 2024). Ultimately I find these are not significant explainers of the variance risk premium (shown in Table 6 in Section 3), but I allow my estimator to determine this rather than assuming this relationship a priori.

This paper's methodology is flexible, and more state variables could easily be added in the future to improve prediction or test theoretical predictions.

2.5 Estimation

Substituting the variance forecast (Equation 3) and the exposure parameterization (Equation 4) into Proposition 3 yields:

$$\sigma_t^{*2} - \hat{\sigma}_t^2 = \lambda_t E_t^*(\Delta y_{t+1}^3) + \lambda_t^2 \sigma_t^{*4} + \eta_t \tag{5}$$

where:

$$\lambda_t = \lambda_0 + \lambda_1 f_{1,t} + \lambda_2 f_{2,t} + \lambda_3 f_{3,t} + \lambda_4 \sigma_t^{*2} + \lambda_5 skew_t^*$$

The risk-neutral moments (σ_t^{*2} and $E_t^*(\Delta y_{t+1}^3)$) can be measured from options data. The estimated physical variance $\hat{\sigma}_t^2$ is measured from a variance forecasting regression.

The error term η_t captures three sources of error: (i) forecast errors in physical variance, (ii) time variation in λ_t orthogonal to the principal components, and (iii) the residual coskew term.

I estimate the parameters $\{\lambda_0, \lambda_1, \lambda_2, \lambda_3, \lambda_4, \lambda_5\}$ using nonlinear least squares. To address heteroskedasticity and reduce the influence of a few high-variance states, I weight observations by the inverse of risk-neutral variance. This is equivalent to dividing equation (5) through by σ_t^* and improves the stability of estimates, reducing the excess kurtosis of the left hand side variable from 4.2 to 0.1.

Where relevant, indicative standard errors are calculated using GMM with Newey-West corrections, using lags at least equal to the forecast horizon. Some caution is warranted in interpreting these standard errors as the appropriate autocorrelation structure for η_t depends on the relative importance of its three components. If variance forecasting errors are large and persistent, for example, the true error autocorrelation may be high. The main conclusions on the accuracy of these forecasts relies on out of sample prediction rather than in sample standard errors.

3 Risk-based interest-rate expectation results

This section reports the results and forecasting performance of the risk-based interest-rate expectation measure. I first show that the average interest-rate risk premium was large. I then show that conditional forecasts outperform existing measures out of sample and capture well-known relationships between the yield curve and risk premium. I close by showing evidence that equity betas and aggregate bond-market duration may drive some of the variance in investors' interest rate exposure.

3.1 A simple test of average rate risk premium

Proposition 1 tells us that the expectations hypothesis is equivalent to $\lambda_t = 0$ — i.e. there is only no risk-premium if there is no exposure. In Section 2.3.1 I describe a simple way to test this hypothesis by estimating the constant exposure parameter λ that best explains the variance risk premium, using realized variance to proxy for physical variance.

I find $\hat{\lambda} = 0.41$, with a standard error of 0.06, using monthly observations and GMM Newey West standard errors with 3 lags. This amounts to a very strong rejection of the expectations hypothesis with a t-statistic of over 5. The statistical significance is high enough that a simple difference in priors could not account for the apparent risk premium, as suggested by Farmer et al. (2024) for the level-based forecasts.

Multiplying this exposure by the risk-neutral variance yields an average interest-rate risk premium of 11 bp, or 44 bp annualized. This is similar to the 34 bp realized risk premium. Markets seem to have been demanding compensation for bearing interest-rate risk, rather than making systematic mistakes.

Since I denominate Δy_t in percentage points, this exposure estimate corresponds to a duration of 42 years for a log-utility fixed-income investor (with a confidence interval from 26 to 58). If we instead consider an investor with higher risk aversion, the implied duration would be lower. For example, in appendix F I show that with a CRRA risk aversion coefficient of 4, duration would be approximately 13. This high sensitivity to interest-rate changes could be consistent with models where leveraged intermediaries are the marginal investors in fixed-income markets. For example, Kekre, Lenel, and Mainardi (2024) suggest durations of 10 to 30 years for fixed-income arbitrageurs.

3.2 Forecasting performance

Moving beyond the average level of risk premium, Section 2 describes how we can create conditional estimates of time-varying risk premium, using conditional interest-rate forecasts. In this subsection I demonstrate that thee conditional forecasts successfully predict changes in interest rates out of sample.

I first show that the measured risk premium predict changes in interest rates. Table 3 reports regressions of out-of-sampe realized rate changes onto the conditional risk premium estimates at various horizons:

$$\Delta y_{t,t+h} = \alpha - \beta \times \widehat{\text{RP}}_{t,h} + \varepsilon_{t+h}$$

where $\widehat{\text{RP}}_{t,h}$ denotes the predicted risk premium from time t to $t+h$. For monthly horizons, I use the quarterly risk premium estimates divided by three. If the forecasts are perfect, we should expact that $\alpha = 0$ and $\beta = 1$.

The estimated β is highly significant at monthly (t-statistic 2.9), quarterly (t-statistic 2.9), and annual (t-statistic 2.4) horizons. More importantly, I cannot reject $\beta = 1$ or $\alpha = 0$ at any horizon. This suggests the measure captures risk premia accurately in levels, not just direction. The R2 values are high even at short horizons (4% monthly, and 6% quarterly), where term-structure models have traditionally struggled. The short-term performance allows for high trading profits as I will demonstrate in Section 3.2.1.

This predictive power is greater than that of professional forecasters or traditional term-structure models. Table 4 reports out-of-sample relative R2 statistics of the risk-based model vs these other models, calculated as $1 - \sum \varepsilon_t^2 / \sum \nu_t^2$, where ε_t is the error when the risk-based model is used to forecast changes in the yield and ν_t is the error when the alternative model is used. This represents the improvement in forecast accuracy from using the risk-based measure versus alternatives.

I compare my forecasts of the 10-year yield to the expectations hypothesis, the survey of professional forecasters (SPF), out of sample forecasts from the two most commonly used dynamic term-structure models (DTSMs) (Adrian et al., 2013; Kim and Wright, 2005), the Bauer and Rudebusch (2020) non-stationary "observed shifting endpoint" model and a simple forecast of no change in rates ("random walk"). The SPF and Bauer and Rudebusch (2020) data are produced quarterly, and Bauer and Rudebusch (2020) forecasts are only produced up to 2018. Details on the construction of the alternative benchmarks are included in the Appendix.

The risk-based interest-rate expectation measure delivers more accurate forecasts than all alternative benchmarks at all horizons. Improvements are highly statistically significant vs the expectations hypothesis and the stationary DTSMs at the 1 month and 1-year horizons. The improvements versus the Bauer and Rudebusch (2020) model are weaker (9% improvement in annual R2), and with just 18 years of data, the difference is not statistically significant.

The power of the risk-based forecasts comes from the use of theory to derive the level of interest-rate risk premium. If instead we were to take our predictor and regress it on changes in interest rates in each period, we would get a substantially worse out-of-sample performance, as the coefficient loadings swing around based on past performance. The last row of Table 4 compares the out-of-sample R2 from the risk based measure to a regression-based forecast constructed in this fashion. Using theory to derive the levels of the forecasts delivers a large (although only borderline significant) improvement in R2.

The random walk forecast (i.e., the current rate) remains surprisingly competitive, beating all benchmarks except for my risk-based forecast. This reminds us that assuming no mean reversion was, ex post, a successful strategy during this period. However, ex-ante it had no obvious justification.

3.2.1 Economic significance

To demonstrate that the R2 from the predictive regressions in Section 3.2 are large, Figure 6 shows cumulative returns from trading strategies based on different interest-rate risk premium estimates.

The strategy buys 10-year swap forwards to achieve a duration in each period equal to the estimated risk premium divided by double the risk neutral variance:

$$D_t = \frac{\widehat{RP}_t}{2\sigma_t^{*2}}$$

Positions are scaled up based on measured risk premium, and down based on risk neutral variance. Proposition 2 tells us this is the level of interest rate exposure of a CRRA investor with risk aversion coefficient 2 would choose if she believed in this risk premium estimate. In the case of my risk-based estimates, this is simply equal to $\lambda_t/2$.

The risk-based strategy generates a cumulative return of 20 over the sample period, with a Sharpe ratio of 0.75, compared to <\$1 using SPF forecasts or ACM. Much of the outperformance comes from 2013–2021, when stationary models consistently predicted rising rates that did not arrive. Sharpe ratios are the same using different levels of risk aversion coefficient, although the amount of leverage and cumuative returns will differ.

These results should be interpreted cautiously. The strategies exhibit high volatility, and transaction costs, though likely small in liquid swap markets, would reduce returns. Nevertheless, the magnitude of outperformance suggests that the statistical improvements in forecasting are economically meaningful.

3.3 Comparison with surveys and term-structure models

The time-series of interest rate forecasts resembles other surveys and models. Table 5 compares the forecast to various alternative benchmarks including the Survey of Professional Forecasters (SPF) and the widely used Adrian et al. (2013) (ACM) affine term-structure model, and Figure 4 plots the ACM series risk premium versus my estimates. The SPF and ACM forecasts both show $> 50\%$ correlation with the risk based estimate at the 1y horizon, despite the different underlying methods and sources of information.

The key difference lies in the behavior at low rates. The stationary assumption built into standard DTSMs meant that they always forecast rates to return to their long-term averages eventually. So when current and forward rates were low, as in 2016–2020, the ACM model forecast a very large negative risk premium. At their lowest, these forecasts implied investors were expecting to lose -1.5% on 10-year bonds in a single quarter.[6] In contrast, my estimates make no assumption about stationarity of interest-rate levels, and end up forecasting almost no interest-rate risk premium in this period. These forecasts are more in line with the suggestive evidence from surveys of institutional investors who

[6]Assuming duration of 8, and 10y-in-1q interest-rate risk premium of -0.2

mostly do not seem to report negative expected excess returns on bonds (Dahlquist and Ibert, 2024; Couts, Gonçalves, and Loudis, 2023).

3.4 Investor exposure to rates

Besides a risk premium estimate, the variance based approach delivers an estimate of λ_t: the exposure to interest-rate increases of the log investor who chooses a linear interest-rate exposure. Figure 5 shows the evolution of the estimated (in-sample) λ_t over time. The series shows a gradual decline from 0.8 to approximately 0 in 2020, followed by an increase to 0.35 in 2023.

To provide suggestive evidence on the economic determinants of investor exposure, I repeat the conditional risk premium estimation exercise (i.e., equation 5) allowing λ_t to be a function of economically-motivated variables instead of yield curve principal components. Table 6 reports coefficients from these alternative specifications. I find two significant relationships in Column (6).

First, λ_t increases 1:1 with the sensitivity of equity markets to interest-rate changes. The coefficient on equity beta (the sensitivity of stock returns to yield changes) is 0.97, significant at the 1% level. This relationship is consistent with a log investor fully invested in equities, as in Martin (2017).[7] Although most of the investor's interest rate exposure must come from non-equities sources since the lambda intercept remains large.

Second, λ_t appears to rise following increases in aggregate bond supply, although the statistical significance is weak. A 1% increase in aggregate bond duration (scaled by GDP) raises λ by 0.004, or approximately 1%. While the effect is only marginally significant, it aligns with models where slow-moving capital forces specialized arbitrageurs to absorb supply shocks, increasing their exposure and the compensation they demand. So the long-term decline in exposure could be related to the long-term growth of arbitrageur capital relative to the aggregate bond duration.

[7] It is also consistent with an arbitrageur whose equity value is correlated with the overall market (e.g. a bank). For example, the rolling sensitivity to interest-rate changes of stock returns of the primary dealers from the He, Kelly, and Manela (2017) closely resembles that of the overall market.

In general, economically-motivated variables do a poor job explaining the exposure variable λ relative to the simple principal components, with none adding more than 2 ppt of R2 over the constant-only model. The underlying causes of the reduction in sensitivity of investors to interest rates remains an open question.

4 Applications

This section considers two applications that traditional interest-rate forecasting methods are poorly suited to answer. I consider the average decline in long term rates around FOMC meetings and the positive stock-yield correlation of 2000–2021 and ask whether they are driven by interest-rate expectations or interest-rate risk premium. Both of these questions require measuring short-term changes in risk premium. I therefore start by developing a simple measure of daily or weekly changes in risk premium that loosens the exposure-parameterization assumptions from Section 2.

4.1 Measuring short-term changes in interest-rate risk premium

To measure short-term changes in conditional interest-rate risk premium, we could simply take the daily changes of the risk premium estimates from Section 3. However, we might be concerned that the functional form we have imposed for λ_t does not accurately capture small, high-frequency changes in the relationship between interest-rate risk premium and the yield curve, particularly around shocks such as FOMC announcements.

To find an alternative measure with looser functional form assumptions, we can combine propositions 1 and 2 to state interest-rate risk premium in terms of variance risk premium. Differentiating the relationship and then solving for dRP yields:

$$dRP_t \approx \frac{d\left(\sigma_t^{*2} - \sigma_t^2\right)}{\frac{E_t^*\left(\Delta y_{t+1}^3\right)}{\sigma_t^{*2}} + 2RP_t}$$

Change in interest-rate risk premium is revealed by change in variance risk premium, scaled by skewness and risk premium.[8]

This equation naturally suggests an estimator for short-term changes in risk premium. Simply plug in the fitted values for interest-rate risk premium ($\widehat{TP}_t$) and physical variance ($\Delta\hat{\sigma}_t^2$) from Section 3:

$$\widehat{\Delta RP}_t \approx \frac{\Delta\sigma_t^{*2} - \Delta\hat{\sigma}_t^2}{\frac{E_t^*\left(\Delta y_{t+1}^3\right)}{\sigma_t^{*2}} + 2\widehat{RP}_t}$$

This estimator no longer depends on short-term changes in exposure exactly aligning with changes in the interest-rate principal components used to parameterize λ_t. The functional form assumptions are still embedded in the risk premium estimates, $\widehat{RP}_t$, under the assumption that these are still a reasonable characterization of the level of exposure, even if they don't capture short-term changes well.

It is not possible in general to measure short-term changes in physical variance, $\Delta\hat{\sigma}_t^2$, around shocks with any accuracy. I therefore only consider long term averages and covariances of this change in risk premium measure, rather than considering specific days. In the case of FOMC announcement window results I will treat these results as indicative and check other indicators of the average change in physical variance.

4.2 Interest-rate risk premium during FOMC announcement windows

Hillenbrand (2025) documents an intriguing fact: the entire secular decline in long-term rates from the 1990s to 2020 occurred during three-day windows around FOMC meeting. This has been interpreted as evidence that markets primarily learn about long-run interest-rate levels from the Federal Reserve. I provide suggestive evidence that, instead, this FOMC-window decline may reflect falling risk premia.

Standard dynamic term-structure models are not very useful to decompose announcement effects. They either inherently assume constant long-term expectations (e.g. Adrian et al., 2013) or update long-run expectations at lower frequencies than daily (e.g. Bauer

[8] I omit a term involving changes in skewness, $-E_t(\Delta y_{t+1})d\frac{E_t^*(\Delta y_{t+1}^3)}{\sigma_t^{*2}}$, which is empirically negligible.

and Rudebusch, 2020).

In this section I first document that there is a large decline in risk-neutral variance around FOMC meetings that appears to be consistent with a change in risk premium. I then show that the size of the declines is large enough to be potentially consistent with full FOMC-window effect being driven by interest-rate risk premium rather than expectations. The fact that the FOMC-window declines match the magnitude of overall declines in rates could simply represent a coincidence.

4.2.1 The FOMC-window variance decline

Table 8 shows that risk-neutral variance of interest rates declines across tenors and maturities during FOMC windows. The proportional declines are similar whether we look at short or long tenors, 3-month or 1-year horizons. Even five-year variance—capturing uncertainty about rates far in the future—shows substantial FOMC-window declines.

This decline is much larger than the net change in physical or risk-neutral variance during the sample period. For example, over the full sample, five-year risk-neutral variance for the 10-year rate actually increased from 3.0 to 4.2 percentage points squared. Yet during FOMC windows alone, it declined by a cumulative 12.2 percentage points squared. For variance to end up higher despite falling dramatically during FOMC meetings requires an offsetting increase of 13.4 percentage points squared between meetings.

The evidence for the idea that the market primarily learns about the long term from the Federal reserve was the fact that the size FOMC-window and aggregate declines in long-term forward rates coincide. This is not the case for the declines in long-term risk-neutral variance. If there is information in the FOMC announcement windows about variance, it must be systematically countered by other information received outside the FOMC windows.

It seems likely that instead, these FOMC-window declines in risk-neutral variance are a result of declines in risk premia that reverse outside the windows. This would be consistent with demand-based mechanisms by which declines in short-term rates push down the risk premium on long-term rates. For example, reaching for yield (e.g. Hanson and Stein, 2015), improvements in intermediary capital (e.g. Kekre et al., 2024), or MBS or bank deposit duration hedging effects (e.g. Hanson, 2014; Rogers, 2024).

In Appendix G I show two further pieces of evidence to support the idea that these declines come from variance risk premium rather than physical variance. First, they are too large to be explained by simple "mechanical effects" from the high-variance FOMC window dropping out of the forecast period. Second, using the information from these changes does not improve on the regression-based forecast of interest-rate variance.

4.2.2 Measuring the implied risk premium decline

To understand how much interest-rate risk premium decline could be implied by the declines in variance risk premium, I will find the result if we assume there is no change in the physical variance during the estimation windows, i.e., $\Delta\sigma_t^2 = 0$. This is roughly what is implied by the regression-based variance stimates from Section 3.

From 2007–2018 (the end of the sample period from Hillenbrand, 2025), the average FOMC-window decline in the 10y-in-1y forward rate is 2.8 bp per meeting. The estimation procedure above yields a decline in 10y-in-1y risk premium of 3.4 bp, with a standard error of 1.2 bp, using daily data with standard errors clustered by meeting.

In other words, the entire FOMC-window decline in long-term rates could be attributable to declines in risk premia that are expected to be realized over the course of a year, with no change in long-term expectations at all. To the extent that physical variance declined during these windows as well, the decline in risk premium could be smaller. It is likely that the true decline involved some combination of risk premium and expectations.

In contrast, a traditional term-structure model that does not use the information from the risk-neutral variance will find a much smaller decline. For example, the Kim and Wright (2005) stationary DTSM provided by the Federal Reserve Board shows only a 0.4

bp decline in the 10-year term premium from 2007–2018.

4.3 Stock yield correlation

The correlation between stocks and long-term yields famously switched from negative to positive in the late 90s. A substantial literature seeks to explain the causes of the modern positive correlation.

By some explanations, the source is risk premium: when stocks go up, bond risk premium and yields go up. For example, Antolin-Diaz (2025) proposes flight to safety shocks move institutional investors out of stocks into long-term bonds.[9] By others, the covariance is expectations driven: news that leads to low stock returns lowers expected rates. For example, Campbell et al. (2017) propose inflation shocks now correlate with stock returns, or the framework from Gormsen and Lazarus (2025) implies positive long-term growth news will push stocks and yields in the same direction.

This paper lets us test between these explanations. Does the 1-year interest-rate risk premium correlate positively or negatively with stock returns? I show that the correlation is negative. Risk premium shocks cannot explain the positive stock-yield correlation 2002-2022. Table 9 shows the correlation of estimated changes in 10y-in-1y risk premium with stocks. I show results for daily, weekly, and monthly observation horizons, using the short-term change in risk premium measure developed in Section 4.1. All show a negative correlation, although the weekly figure is not significant. Risk-neutral variance tends to increase on days with bad stock returns more than the regression-estimated physical variance, suggesting risk premium rises.

In contrast, a traditional term-structure model finds the opposite. The second shows the correlation with changes in the Kim and Wright (2005) term-structure model, which are all positive. The model loads heavily on the level of interest rates due to the stationary structure, and hence interprets a portion of all increases in the level of interest rates to be

[9] The convenience yield covariance from Acharya and Laarits (2023) and the "hedging premium" shocks from Cieslak and Pang (2021) should also involve positive correlation of stock returns with bond risk premia.

due to risk premium, yielding a positive term-premium-yield correlation.

5 Validating the residual coskew assumption

The main theoretical result of this paper is that the interest-rate risk premium is a function of the variance risk premium and an unobservable term, the "residual coskew," that captures the correlation of squared rate changes with the inverse SDF (i.e., the investor's marginal utility). In Section 3 I show that if we assume this residual coskew term is 0, the implied interest-rate risk premium is a strong out-of-sample predictor of interest rates.

In this section I argue that this is a reasonable assumption based on the data that we can observe. I show first that for common models of the SDF, the equivalent *physical* moment, $cov_t(\Delta y_{t+1}^2, \varepsilon_{t+1})$, is an order of magnitude smaller than what would be needed to explain the observed variance risk premium. Where we can measure equity and interest-rate risk premia, they seem too small to make up this difference between the physical and risk-neutral covariance. Second, I show that in the time series the physical residual coskewness and other related measures do not help explain the variance risk premium versus term-premium-only model. Finally, I show that allowing for higher risk aversion levels cannot alone explain the variance risk premium. If we allow for CRRA utility with risk aversion coefficients up to 4, then my exposure and interest-rate risk premium estimates understate the true values by approximately 25%, but retain a 99% correlation.

In Appendix F, I further show that the levels of bond market convexity observed in the aggregate market are far too small to explain the variance risk premium.

5.1 Physical residual coskew under different SDF models

Measuring the residual coskew would require observing a set of options connecting interest rates with the parts of the SDF that are uncorrelated with interest rates. Since these options do not exist in reality, the best we can do is measure the physical covariance under various common models of the SDF.

I estimate the physical residual coskew under three models: the log-equity-investor model of Martin (2017), a linear Fama French three factor model, and a typical dynamic term-structure model. To calculate the coskew, I first regress daily observations of the SDF onto daily changes in the 10-year rate and collect the residuals: $\hat{\varepsilon}_t$. I then calculate quarterly covariance of $\hat{\varepsilon}_t$ with squared daily interest-rate changes[10] For the Fama French three factor model I use the price of risk coefficients that match the observed average returns on the three factors. For the dynamic term-structure model SDF, I calibrate the terms by fitting the 5 factor model of Adrian et al. (2013).

In all three cases this procedure yields an estimate of the residual covariance between -0.001 and -0.004 ppt squared. The average realized quarterly variance risk premium from Section 3.1 is 0.04 ppt squared. Hence the physical moments are approximately 10$\times$ too small to explain the observed variance risk premium. The results of each estimation are reported in Appendix F, Table 12.

Of course the risk-neutral moment may be larger in magnitude than the physical moment, but the risk premium we can observe on stocks and squared interest-rate changes does not appear large enough to make up the difference. From 2007-2023, the risk-neutral standard deviation Δy_{t+1}^2 is approximately 1.3$\times$ larger than the physical standard deviation.[11] Tetlock et al. (2024) estimate the risk-neutral standard deviation of R_m is about 1.3$\times$ the physical standard deviation. So if the physical and risk-neutral correlations were the same, we would only expect risk-neutral residual coskew to be roughly 2$\times$ as large as physical coskew, not the 10$\times$ needed to explain the variance risk premium.

5.2 Time series evidence

Proposition 3 tells us that the variance risk premium is a function of exposure multiplied by the risk-neutral third moment as well as the residual coskew. If the residual coskew

[10]Since there are 63 business days in the quarter, this is calculated as $63cov(\varepsilon_t, \Delta y_t^2) + \sum_{j=1}^{62}(63 - j)\left(cov(\varepsilon_{t-j}, \Delta y_t^2) + cov(\varepsilon_t, \Delta y_{t-j}^2)\right)$

[11]Variance calculated from moments of daily data, allowing for skewness and volatility clustering but assuming conditional mean of daily rate changes is 0.

plays an important role, then we should find that it helps explain the time series of variance risk premium. If it doesn't, then we should find the third moment alone explains the time series well.

In Section 3, I showed that the third moment explains a large share of the time series variance in estimated variance risk premium, even with a simplistic constant exposure assumption (see column 1 of Table 6). Do measures of residual coskew improve upon this fit? To answer this question I run simple regressions of VRP on the risk-neutral third moment alone, as well as the risk-neutral third moment plus variables that might plausibly be associated with residual coskew. This is a simplified version of the nonlinear estimation from Section 3, where we ignore the RP^2 term and assume λ_t is constant.

As variables that might be correlated with conditional coskew, I include rolling 1-year estimates of the physical residual coskew under the log equity investor ($M_t = \frac{1}{R_m}$) model[12], risk-neutral equity volatility ($SVIX$), aggregate bond market convexity (from the Bloomberg "Agg" index), and the He et al. (2017) intermediary capital ratio.

The results are reported in Table 7. In all cases the third moment is highly significant with a t-statistic of over 7, while the alternative explanatory variables are at most marginally significant. Most of the coefficients also have the wrong sign compared to what we would expect for a residual-covariance based explanation. For example, we would expect periods of negative residual coskew to be associated with high variance risk premium, but we find the opposite (although insignificant). Low intermediary capital ratios are also associated with lower variance risk premium, surprisingly. In short, measures of conditional residual coskewness do not improve on the simple zero-residual-coskew constant λ model at explaining the time series of variance risk premium.

[12] I do not include the Fama French 3 factor estimate because the two time series of coskewness is 99% correlated

5.3 Risk aversion

Another possible source of residual coskew is the convexity of the utility function itself, rather than the non-linearity of the payoffs. However, high risk aversion alone cannot explain the positive variance risk premium. In fact, the simple zero-residual-coskew estimate will tend to underestimate the risk premium if the investor is more risk averse than a log investor. In Appendix F I repeat the constant-λ estimation of risk premium from Section 3.1 allowing for CRRA coefficients (γ) of up to 4. I find that the zero-residual-coskew estimate would underestimate true risk premium by approximately 25%, but retain a $> 99\%$ correlation with the true estimates

6 Conclusion

This paper introduces a new approach to measuring interest-rate expectations and risk premia. By shifting focus from the non-stationary level of interest rates to their stationary variance, we can extract expectations from options data and test hypotheses about interest-rate dynamics in a new way.

The core theoretical result links the interest-rate risk premium perceived by an investor to the variance risk premium perceived by the same investor and an unobserved "residual coskew" quantity related to the non-linearity of the the his marginal utility with respect to interest rates. If we assume as a benchmark that this residual coskew term is 0, an assumption that does not appear unreasonable based on the data, then we can derive the exact perceived interest-rate risk pemium from the variance risk premium.

The empirical findings are fourfold. First, the historical interest-rate risk premium is large. The strong average bond returns over the past 25 years appear to be mostly due to risk premium rather than forecasting errors. Second, I construct a conditional measure of the interest-rate risk premium that outperforms standard dynamic term-structure models and survey-based measures in forecasting excess returns at short horizons, with a trading strategy based on the measure generating large economic profits. Third, I find that the secular decline in long-term rates concentrated in FOMC announcement windows may be better explained by a compression of risk premia than by learning about the long-run level of rates. Risk-neutral variance falls by a large amount during these windows, a pattern more consistent with temporary changes in risk appetite or exposure than with information updates. Finally, I show that the positive stock-yield correlation of the 2000s onward is not driven by bond risk premium. This suggests explanations based on inflation or growth expectations may have more promise that than explanations driven by investor flight to quality.

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Tables

Table 1: **Summary statistics**

The table reports summary means and standard deviations for the key model inputs and outputs. All statistics are quoted for January 2002 – June 2023 based on weekly data. Interest rates are reported in *ppt*, variances in ppt^2, and the third moment in ppt^3.

		Quarterly		Annual	
		Mean	Std Dev	Mean	Std Dev
Data	10 year rate (y_t)	3.18	1.36	3.18	1.36
	Change in 10y rate (Δy_{t+1})	-0.09	0.48	-0.33	0.94
	R.n variance (σ_t^{*2})	0.27	0.19	1.07	0.57
	R.n skewness ($skew_t^*$)	0.27	0.21	0.36	0.20
	R.n third moment ($E_t^*(\Delta y_{t+1}^3)$)	0.06	0.09	0.52	0.56
	Realized variance (RV_t)	0.23	0.18	0.92	0.59
Outputs	Conditional variance	0.22	0.10	0.89	0.29
	Variance risk premium	0.05	0.11	0.18	0.39
	Interest rate risk premium	0.13	0.13	0.25	0.23

Table 2: **Interest rate variance forecasting performance**

This table reports out-of-sample improvement in R2 for forecasts of realized variance of 10-year swap rates using the regression described in Section 3 compared to two benchmarks: risk-neutral variance calculated from swaptions, and lagged realized variance (random walk). Relative R2 is calculated as $1 - \sum \varepsilon_t^2 / \sum \nu_t^2$, where ε_t is the forecast error from the regression-based forecaster and ν_t is the forecast error from the alternative. Forecasts are calculated using an expanding window starting in 1988. Sample period is 2002–2023.

	Horizon		
Benchmark	Monthly	Quarterly	Annual
Risk Neutral Variance	0.22	0.30	0.26
Random Walk	0.29	0.17	0.33
# Non-Overlapping Observations	252	84	21

Table 3: **Interest-rate level forecasting regressions**

This table reports results from regressions of realized changes in 10-year swap rates on predicted risk premia: $\Delta y_{t,t+h} = \alpha - \beta \times \widehat{RP}_{t,h} + \varepsilon_{t+h}$, where $\widehat{RP}_{t,h}$ is the risk-based interest-rate risk premium estimate. Under the null hypothesis that the measure correctly captures risk premia, $\alpha = 0$ and $\beta = 1$. β is reported in the first row and α in the second. Sample period is March 2002– June 2023. Newey-West standard errors with lags equal to the forecast horizon.

	Monthly	Quarterly	Annual
Interest rate risk premium	1.8341***	0.9702***	1.4803**
	(0.64)	(0.34)	(0.61)
Intercept	0.0109	0.0362	0.0413
	(0.02)	(0.06)	(0.25)
R2	0.0414	0.0602	0.1439
Observations	1064.0	1064.0	244.0
Frequency	Weekly	Weekly	Monthly
NW lags	5	13	12

Table 4: **Interest rate level forecasting performance**

This table reports the improvement in $R2$ from using the risk-based interest-rate risk premium measure versus alternative models, 2002–2023. P-values from one-sided Diebold-Mariano tests for an improvement in forecast accuracy are included in square brackets. Relative $R2$ is calculated as $1 - \sum \varepsilon_t^2 / \sum \nu_t^2$, where ε_t is the forecast error from the risk-based model and ν_t is the forecast error from the alternative. Weekly or monthly frequencies are not available for the SPF or Bauer and Rudebusch (2020).

Benchmark	Monthly	Quarterly	Annual
Expectations Hypothesis	0.065**	0.081	0.230**
	[0.014]	[0.160]	[0.010]
Survey of Prof. Forecasters		0.275***	0.271**
		[0.005]	[0.015]
Adrian et al. (2013)	0.070***	0.095*	0.184
	[0.003]	[0.077]	[0.203]
Kim and Wright (2005)	0.100***	0.150*	0.497***
	[0.006]	[0.066]	[0.005]
Bauer and Rudebusch (2020)		0.045	0.087
		[0.406]	[0.311]
Random Walk	0.020*	0.022	0.043
	[0.073]	[0.347]	[0.287]
Regression-rescaled	0.049*	0.136	0.216*
	[0.096]	[0.100]	[0.091]
Observation frequency	Weekly	Weekly	Monthly

Note: Square brackets denote Diebold-Mariano p-values
*p<0.1; **p<0.05; ***p<0.01

Table 5: **Comparison of interest-rate risk premium estimates**

The table reports average risk premia from different models for 10-year swap rates, and their correlation with the risk-based estimates from this paper. The left two columns show the results for quarterly forecasts, and the right two columns for annual forecasts. "Realized" shows the ex post change in rates vs forward-implied rates. "Risk-based" uses the variance risk premium method developed in this paper. Other models are as described in Section 3.2. Monthly data from 2002–2023. Means are expressed in percentage points.

	Quarterly		Annual	
	Mean	Corr w/ risk-based	Mean	Corr w/ risk-based
Realized premium	0.08		0.34	
Risk-based estimate	0.13	1.00	0.26	1.00
Other forecasts:				
Survey of Prof Forecasters	-0.07	0.38	-0.12	0.60
Adrian et al. (2013)	0.02	0.65	0.06	0.74
Kim and Wright (2005)			-0.36	0.38
Bauer and Rudebusch (2020)	-0.06	-0.12	0.08	0.10
Random Walk	0.07	0.63	0.29	0.74

Table 6: **Determinants of marginal investor exposure**

This table reports coefficients from nonlinear least squares regressions where the exposure parameter λ_t is specified as a linear function of state variables. λ_t captures the marginal investor's sensitivity to interest-rate increases. PC1, PC2, and PC3 are the first three principal components of the yield curve. Skew is the risk-neutral quarterly skewness of the 10-year rate. ΔDur is log changes in aggregate bond duration (from the Bloomberg Agg index) to GDP. Equity beta is rolling estimates of sensitivity of S&P 500 returns to 10-year rate changes. Quarterly data from 2002–2023. Standard errors in parentheses calculated using GMM with Newey-West corrections with four lags.

	(1) Constant	(2) PCs only	(3) Main	(4) ΔAgg duration	(5) Equity β	(6) Δdur & Eq. β
Intercept	0.51^{***}	-0.06	-0.02	0.50^{***}	0.61^{***}	0.62^{***}
	(0.04)	(0.07)	(0.11)	(0.04)	(0.05)	(0.04)
PC 1		0.04^{***}	0.04^{***}			
		(0.01)	(0.01)			
PC 2		-0.06^{***}	-0.06^{***}			
		(0.01)	(0.02)			
PC 3		0.04	0.04			
		(0.03)	(0.03)			
Var			0.01			
			(0.09)			
Skew			-0.07			
			(0.25)			
ΔDur				0.22		0.42^{*}
				(0.26)		(0.24)
Equity β					-0.80^{***}	-0.97^{***}
					(0.28)	(0.31)
R2	0.54	0.65	0.65	0.54	0.56	0.57

Table 7: **Measures associated with residual coskew do not explain the variance risk premium well**

This table shows the results from regressing estimated conditional variance risk premium onto the risk-neutral third moment alone (column 1) or the risk-neutral third moment and other possible explanatory variables associated with non-linear interest rate risk (columns 2-6). The estimated physical residual coskew (column 2) uses the log-equity investor model calculated on a rolling 1y basis (see Section 5 for more detail). Risk-neutral equity vol uses the VIX index rescaled by a regression onto the $SVIX$ index from Martin (2017). Bond convexity is the convexity of the Bloomberg Barclays Aggregate Index. Intermediary capital is from He et al. (2017). Data is quarterly and standard errors in parentheses calculated using Newey-West with 4 lags. Sample period is 2002–2023.

	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	-0.010	-0.008	0.044	-0.008	-0.069**	-0.018
	(0.010)	(0.010)	(0.032)	(0.009)	(0.031)	(0.060)
3rd moment	0.893***	1.013***	0.968***	0.862***	0.941***	0.966***
	(0.094)	(0.148)	(0.098)	(0.095)	(0.089)	(0.117)
Phys. resid coskew		3.360				0.728
		(3.161)				(2.465)
Equity vol			-0.306*			-0.159
			(0.179)			(0.220)
Bond convexity				-5.859*		-4.388
				(3.016)		(3.280)
Int. capital					0.840**	0.538
					(0.402)	(0.477)
Observations	81	81	81	81	81	81
R2	0.677	0.689	0.700	0.697	0.709	0.726
Note:				*p<0.1; **p<0.05; ***p<0.01		

Table 8: **Declines in risk-neutral variance during FOMC announcement windows**

This table reports the average proportional decline in risk-neutral variance during 3-day windows around FOMC meetings for different swap rate tenors (rows) and swaption maturities (columns). Maturity refers to the time of expiry of the swaption, tenor refers to the maturity of the underlying swap. Changes are calculated from close on day $t-1$ to close on day $t+1$ where day t is the FOMC announcement. Sample period is 2007–2023. Standard errors in parentheses are clustered by FOMC announcement date.

	Option Maturity		
Swap Tenor	Quarter	Year	5 Year
1 year	-2.5%	-4.1%	-1.6%
	(3.4%)	(1.3%)	(0.6%)
2 year	-4.3%	-3.4%	-1.8%
	(1.7%)	(1.3%)	(0.5%)
5 year	-3.2%	-2.8%	-1.5%
	(1.3%)	(0.8%)	(0.6%)
10 year	-2.6%	-2.3%	-1.4%
	(1.0%)	(0.7%)	(0.6%)
20 year	-2.6%	-2.5%	-1.4%
	(1.1%)	(0.7%)	(0.6%)
30 year	-2.9%	-2.9%	-1.2%
	(1.0%)	(0.8%)	(0.6%)

Table 9: **Stock-risk-premium correlation under different models**

The first column calculates the correlation of market returns with changes in 10y-in-1y risk premium calculated using the methodology described in Section 4. The second column uses the 1-year instantaneous out-of-sample term premium from Kim and Wright (2005). The horizon for changes and market returns is given by the rows. Market returns are the CRSP value-weighted return. Sample period is 2002–2018 for weekly and monthly data, 2008–2018 for daily data. Newey-West standard errors in parentheses.

Horizon	Risk-based	Kim and Wright (2005)
Daily	-0.088***	0.29***
	(0.032)	(0.025)
Weekly	-0.052	0.2***
	(0.05)	(0.037)
Monthly	-0.22***	0.18***
	(0.075)	(0.052)

Figures

Figure 3: **Conditional variance risk premium**

This figure plots the difference between risk-neutral variance and forecasted physical variance for 10-year swap rate at a quarterly horizon, January 2002 – June 2023. Positive values indicate that investors are willing to pay a premium for protection against large changes in interest rates. Units are percentage point squared.

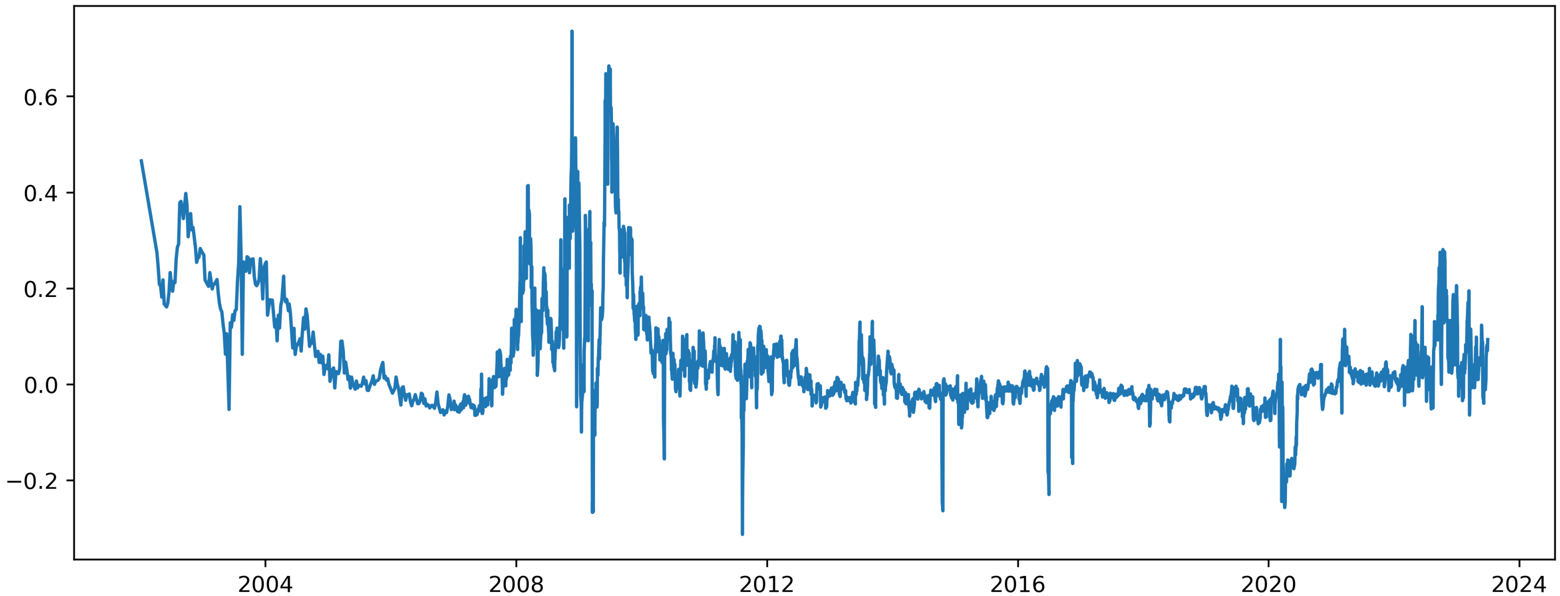


Figure 4: **Risk-based and term-structure-model risk premium estimates**

The blue line plots the risk-based out-of-sample 10y-in-1q interest-rate risk premium. The orange line plots the equivalent figure for the Adrian et al. (2013) dynamic term-structure model. Ppt, 2002–2023. Methodology is described in Section 3.

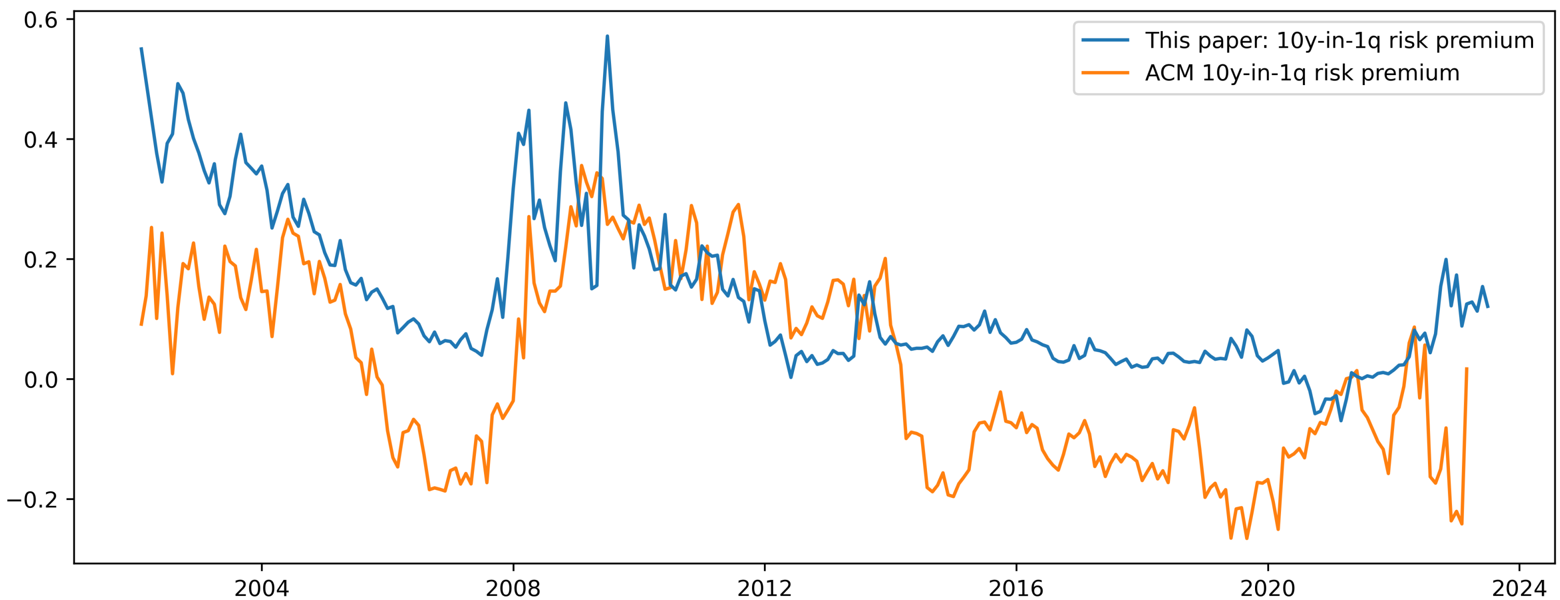


Figure 5: **Estimated investor exposure parameter,** λ_t

This figure plots the whole-sample estimates of exposure, λ_t, using the methodology described in Section 3. λ_t can be interpreted as the duration of the log-investor's portfolio divided by 100, or approximately, as the *duration* $\times \gamma/100$ for a CRRA investor with risk aversion γ.

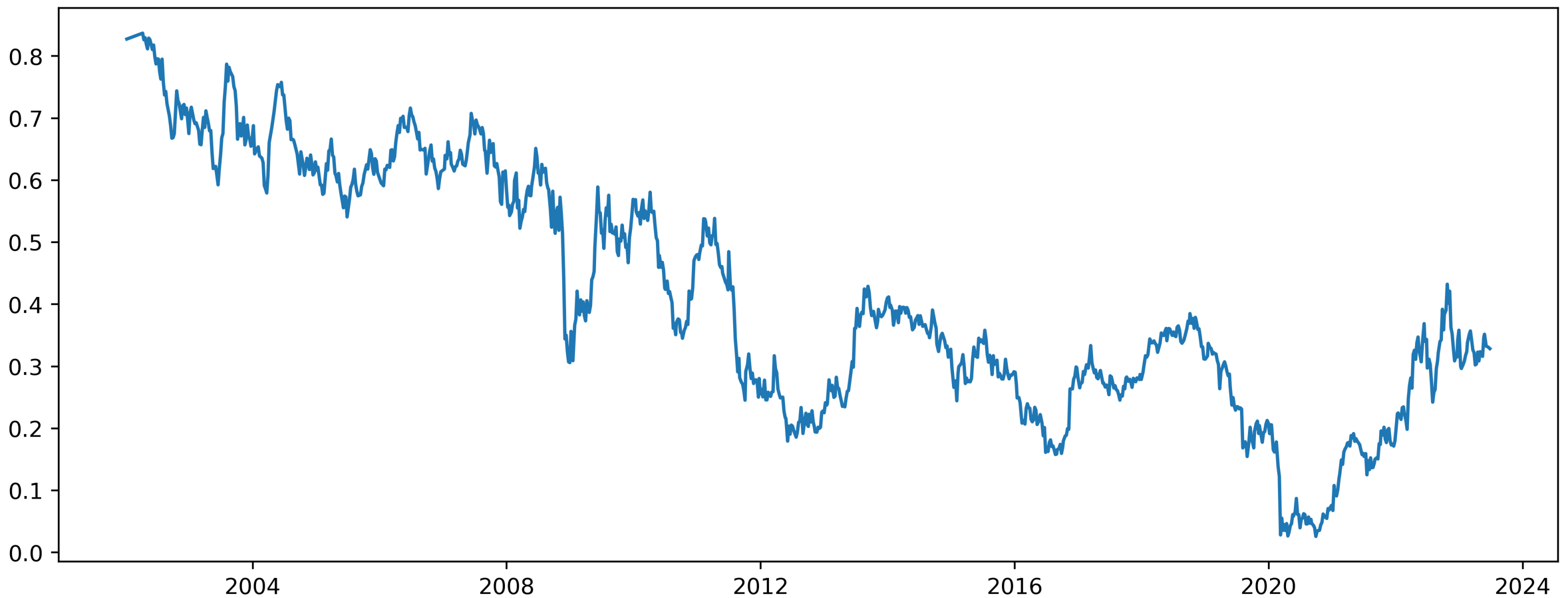
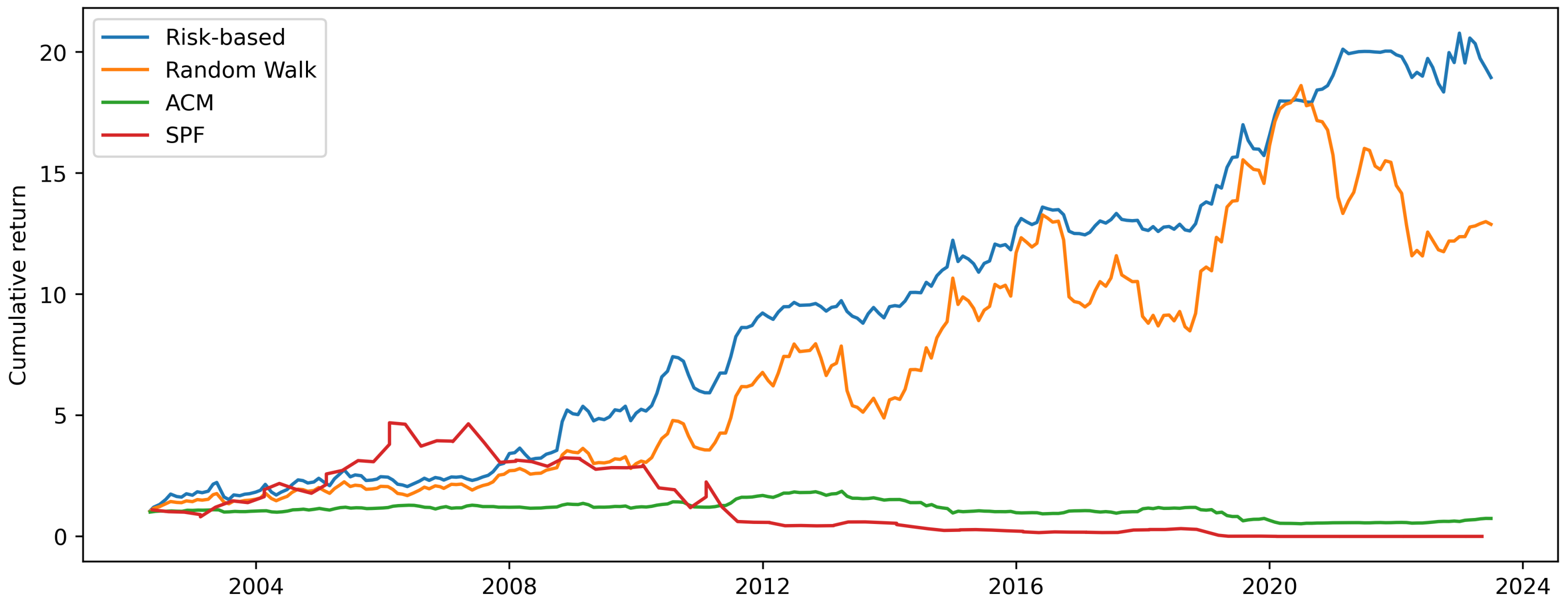


Figure 6: **Cumulative returns from interest-rate trading strategies**

This figure shows cumulative dollar returns from strategies that take positions in 1-month interest-rate swap forwards proportional to risk premia estimated from various models. Initial investment is normalized to \$1 in April 2002. Positions are scaled by $1/(2\sigma_t^{*2})$, in line with the implied portfolio of a CRRA investor with risk aversion coefficient $\gamma = 2$ who perceives the measured risk premium. Risk premium is estimated using this paper's risk-based measure, Survey of Professional Forecasters expectations, the Adrian et al. (2013) affine model, and a random walk assumption. Returns are calculated before transaction costs. The Survey of Professional Forecasters strategy uses quarterly forwards instead of monthly.



Appendices

A Forecasting other interest-rate tenors

Table 10 below reports the relative improvement in forecasting performance by applying this same methodology to the 1-year, 2-year, 5-year, 20-year, and 30-year swap yield. As a simple approximation I assume the value of λ_t for all tenors is the same as the values calculated in the main body of this paper.

Recalculating different values of λ_t for each tenor based on their respective variance risk premia can be done. However, there are some challenges in estimating physical variance for shorter tenors because the rates are at the zero lower bound for much of the sample and more subject to jumps around policy announcements.

Comparison model	Tenor	Monthly	Quarterly	Annual
Expectations Hypothesis	1	0.052	0.112	0.154
	2	0.063	0.119	0.185
	5	0.068	0.102	0.229
	10	0.065	0.081	0.230
	20	0.066	0.042	0.191
	30	0.072	0.022	0.174
Adrian et al. (2013)	1	0.126	0.228	0.153
	2	0.077	0.141	0.170
	5	0.060	0.096	0.162
	10	0.070	0.095	0.184

Table 10: Multi-tenor out-of-sample forecast performance. The table reports the improvement in R2 from risk-based interest-rate expectation measure versus the expectations hypothesis and the Adrian et al. (2013) DTSM. Improvement in R2 is defined as $1 - \sum \varepsilon_t^2 / \sum \nu_t^2$, where ε_t is the forecast error from the risk-based model and ν_t is the forecast error from the alternative. 2002-2023, monthly data.

B Duration and exposure for a CRRA fixed-income investor

CRRA utility with coefffficient γ implies:

$$\frac{1}{M} = (R_f(1 - D\Delta y))^{\gamma}$$

Where I will ignoring the time subscripts throughout in this subsection

D is here the "duration" of the CRRA investor's portfolio. Assume that γ is a positive integer. Since λ is the projection coefficient of the inverse SDF on yields, by binomial expansion we have:

$$\lambda = -\frac{1}{R_f} \frac{cov^*(\frac{1}{M}, \Delta y)}{\sigma^{*2}} = \sum_{k=1}^{\gamma} \binom{\gamma}{k} R_f^{k-1} D^k \frac{\mu_{k+1}^*}{\sigma^{*2}}$$

Where μ_k^* is the kth risk-neutral central moment of y.

The first term in this expansion is $\gamma R_f^{\gamma} D \approx \gamma D$. To demonstrate that the other terms are small, Table 11 calculates the duration implied by a λ of 0.4 under different values of γ using the time series average levels of the risk-free rate and the first four quarterly risk-neutral moments after 2011. Here I am using interest rates in percentage points terms, so a lambda of 0.4 is equivalent to a duration of 40 if $\gamma = 1$. The approximation $D \approx \frac{\lambda}{\gamma}$ is never off by more than 4%.

Repeating the exercise for every day from 2011 – 2023 gives a highest absolute approximation error of 8% for $\gamma = 4$.

CRRA Coefficient	Implied Duration	Approximation error	Note
1	0.400	0.0%	
2	0.196	2.0%	
3	0.129	3.1%	
4	0.096	3.7%	Assuming 5th moment is 0

Table 11: Accuracy of the Duration = $\frac{\lambda}{\gamma}$ approximation. Each row provides the duration that would deliver $\lambda = 0.4$ for a CRRA investor with various levels of risk aversion and with linear exposure to the interest rate y_t. The first 4 quarterly risk-neutral moments are taken as their time series average 2011-2023, and the 5th moment is assumed to be 0. Approximation error shows the percentage difference between the calculated duration and the simple approximation $D \approx \frac{\lambda}{\gamma}$

C Constructing risk-neutral interest-rate moments from swaptions

This section describes how I approximate the risk-neutral moments of swap yields from swaption data. Swaptions are not precisely options on the interest rate. I therefore need to employ a simple approximation. I assume that changes in the annuity yield are the same as changes in the swap yield. This approximation is unlikely to lead to substantive errors — changes in the 10-year annuity yield and swap yield are >99% correlated at the quarterly or annual horizon.

Swaps and swaption prices

By a standard result, we can write the value of a swap agreed at fixed rate K with tenor T as $(y - K)A$ where A is the price of the T-period annuity, and y is the swap rate (i.e., the rate that sets the value of the swap to 0).

The payoff of a swaption agreed at rate K is therefore

- Pay-fixed: $Max\left\{(y_{t+j} - K)\, A_{t+j}, 0\right\}$
- Receive-fixed: $Max\left\{(K - y_{t+j})\, A_{t+j}, 0\right\}$

And the forward price of the swaption can be written:

- Pay-fixed: $C\left(k\right) = E_t^*(Max\left\{\left(y_{t+j} - K\right)A_{t+j}, 0\right\})$
- Receive-fixed: $P\left(k\right) = E_t(Max\left\{\left(K - y_{t+j}\right)A_{t+j}, 0\right\})$

If we change measure to the T-tenor "annuity measure" we can write these swaption prices as options directly on the swap rate:

- Pay-fixed: $C\left(k\right) = E_t^A(Max\left\{\left(y_{t+j} - K\right), 0\right\})$
- Receive-fixed: $P\left(k\right) = E_t^A(Max\left\{\left(K - y_{t+j}\right), 0\right\})$

Applying Breeden & Litzenberger

Applying Breeden and Litzenberger (1978), we can write the expectation of any function of the swap rate under this annuity measure as:

$$E^A\left(g\left(y\right)\right) = \left(g\left(y^f\right) + \int_{-\infty}^{y^f} g''\left(y\right)P\left(k\right)dk + \int_{y^f}^{\infty} g''\left(y\right)C\left(k\right)dk\right)$$

Where y^f is the swap forward rate.

However, we want the moments under the risk-neutral measure, not the annuity measure. So I will assume that changes in the annuity yield vs its forward yield are always identical to changes in the swap yield vs its forward yield. The annuity price then becomes a function of the swap yield:

$$A = \sum_{t=1}^{4T} \frac{1}{(1+y)^{t/4}} = A(y)$$

Now we can find the risk-neutral expectation of any arbitrary function $f(y)$ by letting:

$$g(y) = \frac{E^*(A)}{A(y)} f(y)$$

.

The annuity measure is defined such that for any X:

$$E_t^A\left(\frac{E^*(A)}{A(y)}X\right) = E^*(X)$$

And hence we have

$$E^A(g(y)) = E^*(f(y))$$

Calculating the moments

For this paper I need to estimate $E^*(f(y))$ for $f(y) = y$, $f(y) = (y - E_t^*(y))^2$, and $f(y) = (y - E_t^*(y))^3$.

In each case, I need to first find the second derivative of the function:

$$g(y) = \frac{E^*(A)}{A(y)}f(y)$$

I then use my data on the forward prices of payer and receiver swaptions to calculate, using the standard:

$$E^*\left(f\left(y\right)\right) = \left(g\left(y^f\right) + \int_{-\infty}^{y^f} g''\left(y\right)P\left(k\right)dk + \int_{y^f}^{\infty} g''\left(y\right)C\left(k\right)dk\right)$$

For yields between the observed swaption strikes, I calculat the price using the Bachelier (normal) option pricing formula, as is standard in fixed-income markets.

D Risk-neutral moment time series

Figure 7 plots the time series of risk-neutral variance and skewness 2002-2023.

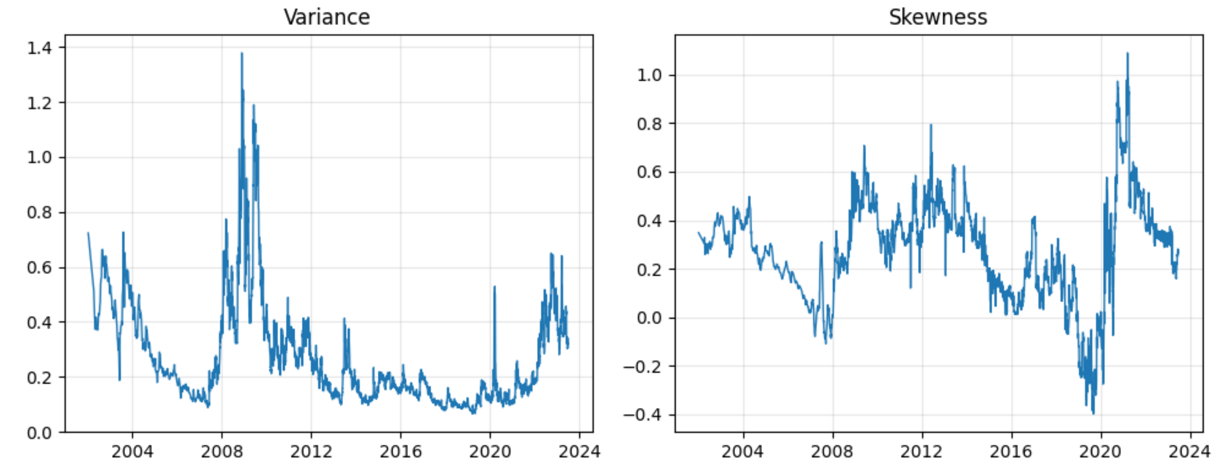


Figure 7: Quarterly risk-neutral variance (left) and skewness (right) of 10-year swap rates, 2002–2023. Variance and skewness are extracted from swaption prices, using the model free approach approach of Carr and Madan (1998). Variance is expressed in percentage points squared.

E Interest-rate risk premium with non-parametric form for λ_t

Figure 8 compares interest-rate risk premium estimated from the parametric specification for λ_t, described in Section 3, with interest-rate risk premium estimated by solving for λ separately each period, without a functional form. Since two roots are possible for lambda, I always choose the root with the minimum magnitude of the interest-rate risk premium. Confidence intervals are provided for each period for the non-parametric version. Where no value of λ_t was consistent with the measured variance risk premium, I take the closest value. If this implies a value for the variance risk premium that is outside of its 95% confidence interval of the variance-prediction regression, I plot this observation with a dotted line.

F Additional content on the residual coskew

In this Appendix I report the estimated physical residual coskew using three different SDFs, the estimated effect of risk aversion on residual coskew and term premium estimates, and

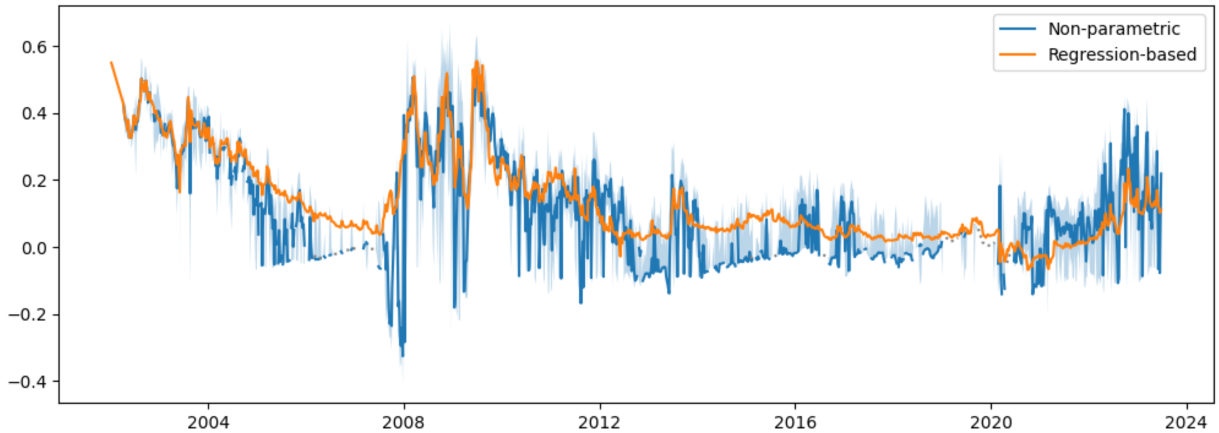


Figure 8: The left hand plot shows interest-rate risk premium estimated from the parametric specification for λ_t. The right hand plot shows interest-rate risk premium estimated by solving for λ separately each period. Quarterly forecasts in ppt, 2002-2023.

the estimated effects of bond market convexity on residual coskew.

F.1 Residual coskew estimation under different SDFs

Table 12 below reports the results from estimating the quarterly physical residual coskew using the three different SDF models described in section 5.

Model	Residual Physical Covariance
Log equity investor	-0.004
Fama-French 3 factor	-0.001
Dynamic term structure model	-0.001

Table 12: Estimations of average physical quarterly residual coskew under different models of the SDF. Residual coskew is the covariance of squared changes in yields with the residual portion of the inverse SDF left after regressing on changes in yields. See Section 5 for details.

F.2 Effects of risk aversion greater than 1

If the investor has CRRA utility, then we can write the inverse SDF as:

$$\frac{1}{M} = (R_f(1 - D\Delta y))^\gamma$$

where I will ignoring the time subscripts throughout in this subsection. D is here the "duration" of the CRRA investor's portfolio.

With a positive integer risk aversion coefficient (γ), applying the binomial expansion formula we can write the residual coskew as:

$$cov^*(\varepsilon, \Delta y^2) = cov^*(\frac{1}{M} - \lambda\Delta y, \Delta y^2) = \sum_{k=1}^{\gamma} \binom{\gamma}{k} R_f^{k-1} D^k \frac{\mu_{k+1}^*}{\sigma^{*2}}$$

In general, this term will be positive and lead us to underestimate the exposure and risk premium of a CRRA investor if we ignore it. A brief proof of this statement is provided at the end of this section.

To see how large an effect this term has on the estimated risk premium, I repeating the constant-λ estimation of risk premium from Section 3.1 for a CRRA investor. I estimate the constant duration that best explains the observed variance risk premium, allowing for the residual coskew above. I use the same non-linear least squares method as in the main body.

Table 13 shows the resulting duration and risk premium estimates for $\gamma = 1, 2, 3$, and 4. $\gamma = 1$ represents the log-investor case with no residual coskew. The risk premium for higher levels of risk aversion is higher, but 99% correlated with the zero-residual-coskew estimate. The zero-residual-coskew (i.e. $\gamma = 1$) estimate underestimates true values by roughly 25% for higher risk aversion parameters. For the $\gamma = 4$ calculation I have assumed the 5th moment is 0 (as in a normal distribution).

Intuitively, two investors can generate the same interest-rate risk premium through

CRRA coefficient	Est. duration	Est. risk prem	Corr w/ log case RP
1	0.413	0.444	1.000
2	0.274	0.607	1.000
3	0.183	0.625	0.999
4	0.134	0.621	0.998

Table 13: Estimated duration and risk premium for a linear-interest-rate-exposure investor with CRRA utility with different levels of risk aversion. The first column denotes the risk aversion coefficient. The second column shows the corresponding estimate of the constant duration that best explains the observed variance risk premium. The third column gives the annualized risk premium corresponding to that duration. The fourth column shows the correlation of the risk premium with the zero-residual-coskew (i.e. $\gamma = 1$) estimate.

different combinations of risk aversion and leverage. A less risk-averse investor needs high leverage (large D, small γ), while a more risk-averse investor needs less leverage (small D, large γ). But the highly levered investor fears far-away states more—a 5 percentage point rate move could wipe her out, while merely denting the un-leveraged investor's wealth. The levered investor therefore pays more for variance protection despite having the same directional exposure.

Proof. We need to show that $cov_t^*(\varepsilon_{t+1}, (\Delta y_{t+1})^2) > 0$ where $\varepsilon_{t+1} = \frac{1}{M_{t+1}} - \lambda_t \Delta y_{t+1}$, with $\frac{1}{M_{t+1}} = (R_{f,t+1} + D\Delta y_{t+1})^\gamma$ for $\gamma > 1$ and $E_t^*[\Delta y_{t+1}] = 0$.

First, expand $\frac{1}{M_{t+1}}$ around $\Delta y_{t+1} = 0$:

$$\begin{aligned}\frac{1}{M_{t+1}} =& R_{f,t+1} + \gamma R_{f,t+1}^{\gamma-1} D\Delta y_{t+1} + \frac{\gamma(\gamma-1)}{2} R_{f,t+1}^{\gamma-2} (D\Delta y_{t+1})^2 + \\ & \frac{\gamma(\gamma-1)(\gamma-2)}{6} R_{f,t+1}^{\gamma-2} (D\Delta y_{t+1})^3 + O((\Delta y_{t+1})^4)\end{aligned}$$

Since $E_t^*[\Delta y_{t+1}] = 0$ and $\lambda_t = \frac{cov_t^*\left(\frac{1}{M_{t+1}}, \Delta y_{t+1}\right)}{\sigma_t^{*2}}$, we have:

$$\lambda_t = \gamma R_{f,t+1}^{\gamma-1} D + \frac{\gamma(\gamma-1)}{2} R_{f,t+1}^{\gamma-2} D^2 \frac{E_t^*[\Delta y_{t+1}^3]}{\sigma_t^{*2}} + O(E_t^*[\Delta y_{t+1}^2])$$

The covariance of interest is:

$$cov_t^* \left(\varepsilon_{t+1}, \Delta y_{t+1}^2\right) = cov_t^* \left(\frac{1}{M_{t+1}}, \Delta y_{t+1}^2\right) - \lambda_t E_t^*[\Delta y_{t+1}^3]$$

Computing the first term using the Taylor expansion:

$$cov_t^* \left(\frac{1}{M_{t+1}}, \Delta y_{t+1}^2\right) = \gamma R_{f,t+1}^{\gamma-1} D E_t^*[\Delta y_{t+1}^3] + \frac{\gamma(\gamma-1)}{2} R_{f,t+1}^{\gamma-2} D^2 var_t^*[\Delta y_{t+1}^2] + O(E_t^*[\Delta y_{t+1}^4])$$

Substituting the expression for λ_t and simplifying, the leading-order term becomes:

$$cov_t^*(\varepsilon_{t+1}, (\Delta y_{t+1})^2) = \frac{\gamma(\gamma-1)}{2} R_{f,t+1}^{\gamma-2} D^2 \left(var_t^*[\Delta y_{t+1}^2] - \frac{(E_t^*[\Delta y_{t+1}^3])^2}{\sigma_t^{*2}}\right) + O(E_t^*[\Delta y_{t+1}^4]) \tag{6}$$

By the Cauchy-Schwarz inequality:

$$(E_t^*[\Delta y_{t+1}^3])^2 \leq \sigma_t^{*2} \cdot E_t^*[\Delta y_{t+1}^4] \tag{7}$$

Therefore, $var_t^*[\Delta y_{t+1}^2] - \frac{(E_t^*[\Delta y_{t+1}^3])^2}{\sigma_t^{*2}} > 0$ unless Δy_{t+1} is degenerate. Since $\gamma > 1$ implies $\gamma(\gamma-1) > 0$, we conclude that $cov_t^*(\varepsilon_{t+1}, \Delta y_{t+1}^2) > 0$. □

F.3 Effects of bond market convexity

Bonds with embedded options, particularly mortgage-backed securities, can exhibit negative convexity. When rates fall, prepayments accelerate and duration shrinks; when rates rise, prepayments slow and duration extends. Could this convexity explain the variance risk premium?

For a log investor holding a portfolio with duration D and convexity C, the inverse SDF becomes:

$$\frac{1}{M_{t+1}} = R_{f,t+1} - D\Delta y_{t+1} + \frac{1}{2}C(\Delta y_{t+1})^2$$

The residual covariance term equals:

$$E_t^*(\Delta y_{t+1}^2 \varepsilon_{t+1}) = \frac{1}{2} C \times \text{var}_t^*(\Delta y_{t+1}^2)$$

Using the relationship $\text{var}_t^*(\Delta y_{t+1}^2) = (\text{kurt}_t^*(\Delta y_{t+1}) - 1)\sigma_t^{*4}$, and noting that risk-neutral kurtosis averages 4.5 from 2011-2023 while quarterly risk-neutral variance squared averages 0.1, the convexity needed to generate the observed variance risk premium would be:

$$C = 2\frac{-E(\text{VRP})}{E((\text{kurt}^*(\Delta y) - 1)\sigma^{*4})} \approx 2\frac{-0.04}{3.5 \times 0.1} = -0.22$$

To put this in perspective, the Bloomberg Barclays Aggregate Bond Index recorded its most negative convexity at -0.005 in 2004 and most positive convexity at 0.006. A log investor would therefore need negative convexity equivalent to a 44-times levered position in the aggregate bond portfolio at its moment of peak negative convexity. This is implausible for a reasonable marginal investor.

G Testing for information effects in risk-neutral variance

While the magnitudes suggest risk premium changes, I conduct three tests to evaluate whether information effects could explain the patterns.

G.1 Mechanical variance effects

FOMC meetings are high-variance events. Once a meeting passes, forward-looking variance mechanically declines by removing this event from the forecast window. Could this explain the observed patterns?

The mechanical effect is far too small. Three-day FOMC-window variance for daily 10-year rate changes is 37% higher than non-FOMC periods. Passing through an FOMC window should therefore reduce:

- Quarterly variance by $0.37 \times \frac{3}{61} = 1.8\%$
- Annual variance by $0.37 \times \frac{3}{250} = 0.4\%$
- Five-year variance by less than 0.1%

I observe declines of 2.9% for annual variance—more than seven times the mechanical effect.

Moreover, the cross-sectional pattern contradicts the mechanical story. FOMC-day variance is twice as high for 1-year rates as for 10-year rates, yet the proportional variance declines are similar across tenors. The risk-neutral variance of rates five years forward falls substantially, which mechanical effects cannot explain.

G.2 Size of changes

For forward rates, the FOMC-window decline equals the total decline, consistent with gradual learning. But for variance, the cumulative FOMC effect dwarfs the total change.

For five-year risk-neutral variance on 10-year rates:

- Cumulative FOMC-window decline: -12.2 percentage points squared
- Net change 2007-2023: +1.2 percentage points squared
- Implied between-meeting increase: +13.4 percentage points squared

If markets were learning about future volatility, they would need to systematically "over-learn" during FOMC meetings that volatility will be low, then receive opposite information between every meeting. This asymmetric updating pattern seems implausible for rational learning but fits naturally with temporary risk premium compression.

G.3 Forecasting ability

If FOMC meetings reveal information about future volatility, then FOMC-window changes in risk-neutral variance should predict realized variance. I test:

$$\sigma^2_{RV,t} - \hat{\sigma}^2_{t-1} = \beta \Delta \sigma^{*2,\mathrm{FOMC}}_t + \varepsilon_t \tag{8}$$

where $\sigma^2_{RV,t}$ is subsequently realized variance and $\hat{\sigma}^2_{t-1}$ is the pre-FOMC forecast from Section 3.

Table 14 shows the results. The R2 is below 0.01 for both quarterly and annual horizons. The coefficient is insignificantly different from zero and, for annual horizons, significantly different from one. FOMC-window variance changes contain essentially no information about future realized variance.

	Quarterly	Yearly
const	0.013	0.070
	(0.021)	(0.124)
$\Delta\sigma^{*2}$	0.232	0.239
	(0.617)	(0.311)
R-squared	0.006	0.003
R-squared Adj.	-0.002	-0.004
N	137	137

Table 14: Information content of FOMC variance changes. The table reports regressions of realized variance forecast errors on FOMC-window changes in risk-neutral variance: $\sigma^2_{RV,t} - \hat{\sigma}^2_{t-1} = \alpha + \beta \Delta \sigma^{*2}_{FOMC,t} + \varepsilon_t$. If FOMC variance changes reflect information about future volatility, β should equal one. $\sigma^2_{RV,t}$ is subsequently realized variance, $\hat{\sigma}^2_{t-1}$ is the pre-FOMC HAR-RV forecast, and $\Delta\sigma^{*2}_{FOMC,t}$ is the change in risk-neutral variance during the FOMC window. Standard errors calculated using Newey-West with 2 lags (quarterly) and 8 lags (annual). Sample includes 137 FOMC meetings from 2007–2023.