Estimating the Term Premium: Sample Periods Matter

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July 2026

Abstract

Estimated risk-neutral rates from canonical affine term structure models are highly sensitive to sample periods. For example, the 5-5 forward risk-neutral rate for September 1981 can differ by 4.6 percentage points (98%) depending on whether the sample starts in 1961 or 1981. Additionally, the estimated response of this rate to high-frequency monetary policy shocks varies severalfold, even within the same sample for monetary policy transmission regressions. We propose that a shifting endpoint model can mitigate these issues and provide new estimates of the effects of monetary policy shocks on long-term risk-neutral rates.

Keywords: Yield curve, term premium, monetary policy.

JEL Codes: E43, E52, F42

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I. Introduction

Long-term yields play a crucial role in monetary policy transmission because they are closely tied to the interest rates and asset prices that households and firms encounter, such as mortgage and corporate borrowing rates. According to the expectations hypothesis, the dynamics of long-term yields are determined entirely by fluctuations in expected interest rates.[1] In standard New Keynesian theories, the expectations hypothesis is central to how monetary policy impacts long-term yields. Given its theoretical significance, it is empirically important to estimate the expectations hypothesis component of long-term yields and their responses to monetary policy shocks. Understanding this relationship can provide insights into the effectiveness of monetary policy in influencing economic conditions through long-term interest rates.

A standard approach to estimating the expectations hypothesis component of long-term yields, i.e., the risk-neutral yields, involves estimating a dynamic term structure model and computing the model-implied interest rate expectations. These dynamic term structure models adhere to no-arbitrage restrictions and fit observed yields with high accuracy, making them valuable tools for understanding yield dynamics. As a result, many central banks utilize these models to estimate risk-neutral yields and term premia. For instance, the Federal Reserve Bank of New York employs the Adrian, Crump, and Moench (2013) (ACM) model to estimate daily

[1] The hypothesis stipulates that the long-term yield equals the average expected short-term yields between t and the maturity date: $y_t^{(n)} = \frac{1}{n}\mathbf{E}_t\left[y_t^{(1)} + \cdots + y_{t+n-1}^{(1)}\right] + \theta^{(n)}$, where $y_t^{(n)}$ is the log n-period zero coupon yield, and $\theta^{(n)}$ is a constant that only depends on maturity. The expectations hypothesis component is also called the "risk-neutral yield", and the residual between the actual yield and the risk-neutral yield is the term premium. Therefore, estimations of the risk-neutral yield and term premium are equivalent.

Treasury term premia and post the regularly updated results on its website.[2] This method allows policymakers to gain insights into the expected future interest rates and the risks associated with holding long-term securities, thereby enhancing the effectiveness of monetary policy.

In this paper, we demonstrate that the risk-neutral rates estimated for a given day are highly sensitive to the choice of sample periods. For instance, the risk-neutral 5-5 forward rate estimated for September 1981 can vary by 4.6 percentage points based on the chosen sample period for estimation. Additionally, the responses of the model-implied risk-neutral rates to a specific monetary policy shock also vary significantly depending on the sample period used for estimating these rates. These findings pose challenges for empirical exercises that rely on risk-neutral rates derived from canonical dynamic term structure models. We show that a shifting endpoint term structure model produces risk-neutral rates that are much more robust to variations in the estimation sample period. Furthermore, we provide new estimates of the responses of risk-neutral rates to monetary policy shocks, suggesting that the role of the expectations hypothesis in monetary policy transmission is stronger than typically implied by canonical models.

To proceed, we start by estimating a canonical affine term structure model. The state variable follows a stationary VAR(1) process with Gaussian shocks. The log stochastic discount factor is affine in the state variables, and the market prices of risk take the essentially affine form (Duffee (2002)). We estimate the model to match the Gürkaynak, Sack, and Wright (2007) zero coupon yields. Importantly, we repeat the estimation using different samples and compare the model-implied risk-neutral rates across the overlapping periods of these samples. In principle, the

[2] https://www.newyorkfed.org/research/data_indicators/term-premia-tabs#/interactive

risk-neutral rates should coincide during the overlapping periods as they are implied by the same model; however, our results reveal significant discrepancies, highlighting the sensitivity of these estimates to the choice of sample periods.

The risk-neutral rates estimated from different samples exhibit not only discrepancies in levels but also in their loadings on state variables, making impulse response analyses of the risk-neutral yields and term premia unreliable. Following Adrian et al. (2013), we define the state vector as the first five principal components (PCs) of the yield curve. We observe an interesting dichotomy regarding which state variables contribute to discrepancies in levels and loadings. Specifically, the discrepancies in levels are mainly driven by the variations in the yield curve level and slope, while the differences in loadings on the state variables are mainly due to the fluctuations in the curvature and higher-order PCs. The level and slope factors demonstrate significantly different mean values across samples. The time paths of yields display high persistence with an inverted V shape, peaking in the early 1980s; thus, the closer the sample period is to this peak, the larger the level factor becomes. On the other hand, the loadings on the state variables depend on the persistence of the state vector. The first two principal components maintain similar degrees of persistence across sample periods, while the persistence of the third principal component (the curvature factor) and higher-order PCs varies considerably across samples.

An important consequence of the sample dependence is the variation in the estimated effects of a given monetary policy shock on risk-neutral yields. Focusing on the 1995-2011 sample (the intersection of all sample periods we consider) for the regression analysis, the responses of the risk-neutral rates implied by the canonical model are highly sensitive to the samples used to estimate the risk-neutral rates. The response of the risk-neutral component estimated using the 1961-2020 sample constitutes 95% of the 10-year yield's response to the Gürkaynak, Sack, and Swanson (2005) path factor, but the response of the same rate estimated using the post-1981 or post-1990 sample only constitutes 45% of the 10-year yield's response. The former estimation result is twice as much as the latter one, although, in principle, they should coincide. The former risk-neutral rates are off-the-shelf from the Federal Reserve Bank of New York's website, and the latter ones are closer to what the researchers would get if they estimated the risk-neutral rates using the same sample as the regression analysis. Theoretically, it is unclear which risk-neutral rate should be adopted, but these empirical results underscore the need for unification.

In another exercise, we investigate the contribution of the risk-neutral component to the cumulative changes in long-term yields during FOMC announcement windows. Hillenbrand (2025) documents that three-day windows bracketing FOMC announcements can explain almost the entire downward trend of U.S. Treasury yields. We demonstrate that the contribution of the risk-neutral component to this pattern is, again, highly sensitive to the sample period for estimating the risk-neutral yield. When using the risk-neutral yields from the Federal Reserve Bank of New York's website (estimated using the post-1961 sample), the risk-neutral component explains 87% of the cumulative changes in the 10-year yield during FOMC announcement windows between 1990 and 2020. In contrast, if the risk-neutral yields were estimated using the same sample as the exercise (1990-2020), the risk-neutral component accounts for only 14%.

We demonstrate that a shifting endpoint model can effectively address the discrepancies in estimated risk-neutral rates across sample periods. The model is based on Bauer and Rudebusch (2020). The state vector is the same as in the canonical model but contains a unit root component. Compared with the canonical model, the shifting endpoint model implies that the risk-neutral rates load less on the principal components. The unit root component of the state vector plays a more significant role in determining the risk-neutral rates, with coefficients that are robust to varying sample periods. Compared with the fixed endpoint model, the risk-neutral yield parameters from the shifting endpoint models are more stable. Therefore, the risk-neutral rates implied by the shifting endpoint model are highly consistent with each other across sample periods, thus solving the inconsistency problem.

We propose a new estimate of the effects of monetary policy shocks on risk-neutral rates motivated by the consistency of the shifting endpoint risk-neutral rates across sample periods. Using the high-frequency regression approach, we find that the expected short-term rates are more important than the term premia in transmitting monetary policy shocks to long-term yields. Moreover, the estimation results based on the canonical model using the post-1961 sample are the closest to our new estimate. Regarding the Hillenbrand (2025) exercise, we find that over 90% of the cumulative changes in long-term yields during FOMC announcement windows can be attributed to the risk-neutral component. This underscores the pivotal role of risk-neutral rates in understanding the dynamics of long-term yields in response to monetary policy actions.

Our high-frequency regressions utilize the risk-neutral rates estimated using the OSE method of Bauer and Rudebusch (2020). A contribution is that we employ a trend proxy that is available daily and easy to construct. Consequently, the original OSE model, which can only be estimated quarterly, can now be used to estimate daily risk-neutral rates and term premia. Our trend proxy is motivated by Hillenbrand (2025), who demonstrates that three-day windows around FOMC announcements almost perfectly account for the persistent variations in the U.S. Treasury yields. Accordingly, our trend proxy is the first principal component of the sum of daily changes in the yield curve during FOMC windows.

Our findings can be generalized to international sovereign yields. We focus on G10 countries because of the availability of long yield curve samples, which date back to the early 1990s. Although the sample periods are much shorter than the U.S. sample, we still find substantial variations in the canonical model-implied risk-neutral rates estimated for a given date using different sample periods. Moreover, the shifting endpoint model alleviates the sampling uncertainty.

Related Literature The paper is related to the literature that uses affine term structure models to estimate expected short-term rates and term premia. For example, Duffee (2002), Wright (2011), Adrian et al. (2013), and Abrahams, Adrian, Crump, Moench, and Yu (2016) estimate an affine term structure model with a stationary VAR(1) process for the state vector, and attribute the bulk of the dynamics of long-term yields to the term premia. Bauer, Rudebusch, and Wu (2012) and Bauer, Rudebusch, and Wu (2014) demonstrate that the small-sample bias makes the OLS underestimate the persistence of the state variables, and correcting the bias makes the model attribute more variations in the long-term yields to expected short-term rates. Bauer and Rudebusch (2020) incorporate a random walk component in the state vector and find that the expectations component explains the trend behavior of long-term yields. We demonstrate that the risk-neutral rates implied by stationary models, whether bias-corrected or not, are sensitive to sample periods.

Our paper is closely related to Li, Meldrum, and Rodriguez (2017), which also points out the instability of term premium estimation across different samples. We extend their analysis by exploring the implications for monetary policy transmission studies and proposing a remedy.

Another strand of literature estimates term premia from micro-founded DSGE models.

For example, Rudebusch and Swanson (2008), Rudebusch and Swanson (2012), Gourio and Ngo (2020), Pflueger and Rinaldi (2022), Amisano and Tristani (2023) estimate term premia from new Keynesian DSGE models, and Amisano and Tristani (2023) refer to the ACM term premia as a benchmark. Term premia estimated from affine term structure models can serve as important references for the DSGE models because both methods derive interest rates as the expected stochastic discount factor. Our paper suggests that when referencing the term premia implied by affine term structure models, the researchers should pay attention to the sample period for estimating the affine model.

This paper is also related to the literature on monetary policy transmission. There is accumulating empirical evidence that monetary policy shocks significantly affect long-term rates, see, for example, Bernanke and Kuttner (2005), Gertler and Karadi (2015), Hanson and Stein (2015), Abrahams et al. (2016), Nakamura and Steinsson (2018), Hanson, Lucca, and Wright (2021), Hillenbrand (2025). Nagel and Xu (2024) argues that the stock price reaction to monetary policy shocks is mainly explained by changes in the yield curve. In light of the significance of the yield curve response, an open question is how important the risk-neutral yields and term premia are. Albagli, Ceballos, Claro, and Romero (2019) regress the risk-neutral yields and term premia implied by the Adrian et al. (2013) model on monetary policy shocks and conclude that U.S. monetary policy shocks affect developed economy long-term yields mainly through the expectations channel. While we qualitatively confirm their findings, we find the risk-neutral yields quantitatively more important in the monetary policy transmission.

Road map The rest of the paper is organized as follows. Section II lays out the canonical dynamic term structure model for estimating risk-neutral rates. Section III describes the data and

estimation procedures. Section IV presents the baseline results that the risk-neutral rates estimated for a given time period can be very sensitive to the sample periods. Section V investigates how the estimated responses of risk-neutral rates to monetary policy shocks depend on the sample period for estimating the risk-neutral rates. Section VI shows that a shifting endpoint model can produce much more robust estimates of the risk-neutral rates. Section VII shows that the effects of monetary policy shocks on risk-neutral rates implied by the shifting endpoint model are not sensitive to the sample periods for estimating the term structure model. Section VIII investigates the mechanisms for the sensitivity of estimated risk-neutral rates to the sample periods.
Section IX generalizes the U.S. results to international yields. Section X concludes.

II. The Canonical Term Structure Model

Affine term structure models have become enormously popular in the literature. We consider the standard form, which is also adopted by Gürkaynak and Wright (2012) and Adrian et al. (2013).

The yield curve is determined by a $K \times 1$ vector of state variables X_t following a vector autoregression (VAR) process:

$$X_{t+1} = \boldsymbol{\mu} + \Phi X_t + U_{t+1}. \tag{1}$$

Since the X_t process is stationary, $X_t^* \equiv \lim_{s\to\infty} \mathbf{E}_t[X_{t+s}] = (I - \Phi)^{-1}\boldsymbol{\mu}$ is constant. So, we refer to the model as the "fixed endpoint (FE) model". The shocks U_{t+1} are conditionally normal:

(2) $$U_{t+1}|\{X_s\}_{s=0}^{t} \sim \mathcal{N}(\mathbf{0}, \Omega).$$

Let $P_t^{(n)}$ denote the zero coupon bond price with maturity n periods at period t. The no-arbitrage condition implies

(3) $$P_t^{(n)} = \mathbf{E}_t \left[M_{t,t+1} P_{t+1}^{(n-1)} \right],$$

where $M_{t,t+1}$ is the stochastic discount factor (SDF). The SDF is exponentially affine:

(4) $$\ln M_{t,t+1} = -\delta_0 - \boldsymbol{\delta}_1^\top X_t - \frac{1}{2}\Lambda_t^\top \Lambda_t - \Lambda_t^\top \Sigma^{-1} U_{t+1},$$

where $\Sigma\Sigma^\top = \Omega$. The market prices of risk are of the essentially affine form:

(5) $$\Lambda_t = \Sigma^{-1}(\Lambda_0 + \Lambda_1 X_t).$$

The no-arbitrage condition (3) implies

(6) $$\ln P_t^{(n)} = \mathcal{A}_n + \mathcal{B}_n^\top X_t,$$

and the coefficients $\mathcal{A}_n, \mathcal{B}_n$ satisfy the following recursions:

$$\mathcal{A}_n = \mathcal{A}_{n-1} - \delta_0 + \mathcal{B}_{n-1}^\top(\boldsymbol{\mu} - \Lambda_0) + \frac{1}{2}\mathcal{B}_{n-1}^\top \Omega \mathcal{B}_{n-1}, \quad \mathcal{A}_1 = -\delta_0, \tag{7}$$

$$\mathcal{B}_n^\top = \mathcal{B}_{n-1}^\top(\Phi - \Lambda_1) - \boldsymbol{\delta}_1^\top, \quad \mathcal{B}_1 = -\boldsymbol{\delta}_1. \tag{8}$$

The risk-neutral bond prices satisfy

$$P_t^{(n)rn} = \mathbf{E}_t\left[e^{-y_t^{(1)}} P_{t+1}^{(n-1)rn}\right], \tag{9}$$

where $y_t^{(1)} = \ln P_t^{(1)}$ is the log short-term interest rate. The risk-neutral bond prices are also affine in X_t:

$$\ln P_t^{(n)rn} = \mathcal{A}_n^{rn} + \mathcal{B}_n^{rn\top} X_t \tag{10}$$

with

$$\mathcal{A}_n^{rn} = \mathcal{A}_{n-1}^{rn} - \delta_0 + \mathcal{B}_{n-1}^{rn\top}\boldsymbol{\mu} + \frac{1}{2}\mathcal{B}_{n-1}^{rn\top}\Omega\mathcal{B}_{n-1}^{rn}, \quad \mathcal{A}_1^{rn} = -\delta_0, \tag{11}$$

$$\mathcal{B}_n^{rn\top} = \mathcal{B}_{n-1}^{rn\top}\Phi - \boldsymbol{\delta}_1^\top, \quad \mathcal{B}_1^{rn} = -\boldsymbol{\delta}_1. \tag{12}$$

III. Data and Estimation

A. Data

We estimate the U.S. term structure models using the zero coupon yield data constructed by Gürkaynak et al. (2007) (GSW), available for download at the Federal Reserve Board's website. The dataset provides Nelson-Siegel-Svensson parameters. We use these parameters to back out the yields for maturities from 3 months to 10 years with a monthly increment. The data coverage goes back to June 14, 1961, which is the earliest starting point for the samples we study, matching the starting date of the ACM 10-year term premium provided by the Federal Reserve Bank of New York's website.[3]

We also estimate international yield curves using the updated Du, Im, and Schreger (2018) data, which is originally from Bloomberg. The Bloomberg sample periods differ across countries, but all start after 1990. For Canada and the U.K., the respective central banks provide longer yield curve data than Bloomberg, so we adopt the central banks' data.

B. Estimation

We use the regression method of Adrian et al. (2013) (ACM) to estimate both models. The method assumes that the state vector is observable and proceeds in two steps:

1. Let X_t be the first five principal components of the yield curve. Estimate $\boldsymbol{\mu}, \Phi, \Omega$ from Equation (1) using OLS.

[3]GSW do not provide data for the 8-, 9-, and 10-year yields before Aug 16, 1971, but we back out the yields using the Nelson-Siegel-Svensson parameters provided by the dataset.

2. Estimate Λ_0, Λ_1 from the excess bond return regression.

The regression is based on excess monthly holding period returns for maturities from 6 months to 5 years with a half-year increment, 7 years, and 10 years. The estimation of the fixed endpoint model exactly follows the procedures in ACM.

For the fixed endpoint model, the excess holding period return over one period is

$$rx_{t+1}^{(n)} = \mathcal{B}_{n-1}^{\top}(\Lambda_0 - \boldsymbol{\mu}) - \frac{1}{2}\mathcal{B}_{n-1}^{\top}\Omega\mathcal{B}_{n-1} + \mathcal{B}_{n-1}^{\top}(\Lambda_1 - \Phi)X_t + \mathcal{B}_{n-1}^{\top}X_{t+1}. \tag{13}$$

We add pricing errors to the excess bond returns as in ACM. The coefficients Λ_0 and Λ_1 can be backed out from regression coefficients of Equation (13), which is estimated by regressing $rx_{t+1}^{(n)}$ on X_t and X_{t+1}.

IV. Sample Periods and Risk-Neutral Rates

This section demonstrates that the risk-neutral rates at a given time estimated by the same model using different sample periods can differ substantially. We consider five sample periods to estimate the term structure model.

- 1961-2020. The sample starts at the earliest available date of the GSW dataset. The ACM term premium data posted on the Federal Reserve Bank of New York's website also starts from 1961.
- 1987-2011. This is the sample period for the published version of ACM.

- 1981-2011. The U.S. Treasury yields in the GSW dataset peaked in 1981. So, we extend the published ACM sample backward to start from the peak.

- 1987-2020. This updates the ACM sample to 2020.

- 1981-2020. This sample runs from the peak to the trough of the GSW data.

A. Summary Statistics

Interest rates are highly persistent. Since 1961, U.S. Treasury yields have increased steadily until 1981 and then declined almost monotonically until 2020. Between 1961 and 1981, Treasury yields rose by ten percentage points, while from 1981 to 2020, they declined by more than ten percentage points. The substantial changes in the yields make statistical analyses during this period highly sensitive to the choice of subsamples.

Table 1 presents the mean values ($\bar{y}$), minimum and maximum values, persistence and standard deviations of the 3-month yield, 10-year yield, 5-5 forward rate, and the first principal component 1 (PC1) of the monthly yield curve across various subsamples. Given that observed Treasury yields exhibit a single peak in 1981 during the 1961-2020 period, the average subsample yield tends to be higher when the subsample is closer to 1981. For instance, the average value of PC1 is 5.11 percent for the Adrian et al. (2013) sample (1987-2011) but increases by nearly one percentage point to 6.06 percent when the starting date extends back to 1981. Another important statistic for the term structure model is the AR(1) coefficient, governing the rate of decay for the loading on X_t in Equation (12). Treasury yields across all maturities are highly persistent, with AR(1) coefficients estimated across all subsamples being indistinguishable from 1. This indicates that the persistence of yield levels does not significantly contribute to the differences in estimated risk-neutral rates.

TABLE 1

Summary statistics of Treasury yields.

$\bar{y}$: sample average of the yield. sd(y): sample standard deviation of the yield. AR1(y): slope coefficient from $y_t = \mu + \rho y_{t-1} + u_t$. sd($u$): standard deviation of the AR(1) residual. sd($\tilde{y}$): standard deviation of the Beveridge-Nelson cyclical component. AR1($\tilde{y}$): the AR1 coefficient of the cyclical component. sd($\tilde{u}$): standard deviation of the AR1 residual of the cyclical component. The data are month-end observations of the GSW yields in annualized percentage points.

Sample	$\bar{y}$	min	max	sd(y)	AR1(y)	sd(u)	sd($\tilde{y}$)	AR1($\tilde{y}$)	sd($\tilde{u}$)
	3-Month Yield								
1961-2020	4.76	0.03	16.49	3.32	0.99	0.58	0.82	0.77	0.53
1987-2011	4.06	0.03	9.22	2.36	1.00	0.24	0.48	0.92	0.19
1981-2011	4.92	0.03	14.96	3.00	0.98	0.41	0.66	0.81	0.37
1987-2020	3.20	0.03	9.22	2.51	1.00	0.22	0.47	0.92	0.18
1981-2020	3.98	0.03	14.96	3.17	0.98	0.36	0.63	0.83	0.34
	10-Year Yield								
1961-2020	6.04	0.55	14.89	2.83	1.00	0.31	0.46	0.79	0.28
1987-2011	5.89	1.98	9.64	1.76	0.99	0.28	0.37	0.73	0.25
1981-2011	6.79	1.98	14.89	2.65	0.98	0.33	0.45	0.74	0.30
1987-2020	4.90	0.55	9.64	2.26	1.00	0.26	0.36	0.75	0.24
1981-2020	5.73	0.55	14.89	3.05	0.99	0.31	0.43	0.76	0.28
	5-5 Forward Rate								
1961-2020	6.47	0.86	14.61	2.67	0.99	0.33	0.44	0.75	0.29
1987-2011	6.57	3.09	10.12	1.55	0.99	0.31	0.37	0.68	0.27
1981-2011	7.41	3.09	14.61	2.40	0.98	0.35	0.45	0.71	0.31
1987-2020	5.56	0.86	10.12	2.18	0.99	0.29	0.37	0.71	0.26
1981-2020	6.34	0.86	14.61	2.90	0.99	0.33	0.44	0.73	0.30
	PC1								
1961-2020	5.52	0.27	15.25	3.05	1.00	0.34	0.54	0.82	0.31
1987-2011	5.11	0.90	9.33	2.06	1.00	0.28	0.41	0.80	0.24
1981-2011	6.06	0.90	15.25	2.92	0.98	0.34	0.50	0.78	0.30
1987-2020	4.14	0.27	9.33	2.41	1.00	0.25	0.40	0.82	0.22
1981-2020	5.01	0.27	15.25	3.23	0.99	0.31	0.48	0.80	0.28

B. Estimated Risk-Neutral Rates

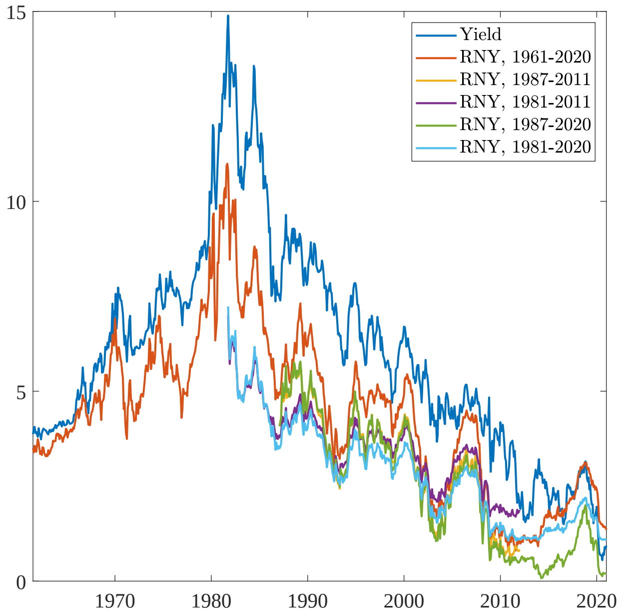
Figure 1 presents the time series of the 10-year yield and the 5-5 forward rates together with their risk-neutral components estimated using different sample periods. A striking feature is that the estimated risk-neutral rates do not coincide during the overlapping sample periods, although they should. For instance, the 10-year risk-neutral rate for January 1990 is estimated at 6.46% using the 1961-2020 sample, 4.89% using the 1987-2011 sample, and 4.23% using the 1981-2020 sample. This variation in estimates illustrates a substantial change of 52% ((6.46-4.23)/4.23). The discrepancy is even more pronounced for the 5-5 forward rate. For September 1981, the estimated risk-neutral rate is 9.29% using the 1961-2020 sample, compared to 4.70% using the 1981-2011 sample. This results in a difference of 4.6 percentage points, or an astounding 98% ((9.29-4.70)/4.70)!

The risk-neutral rates estimated using different sample periods do not merely differ by constants, i.e., they are not parallel shifts of each other. For instance, the risk-neutral rates estimated using the 1981-2020 sample are flatter than those from other sample periods and exhibit less cyclical fluctuation. This indicates that the loadings of the risk-neutral rates on the state variables, $\mathcal{B}_n^{rn}$ from Equation (10), are highly sensitive to the choice of sample periods. As a result, the estimated responses of risk-neutral rates to shocks can be unreliable and strongly influenced by the sample period chosen for estimating the risk-neutral rates, even when the sample for estimating impulse responses is fixed. In Section V, we present an example demonstrating that the responses of risk-neutral rates to monetary policy shocks can differ by more than fourfold, depending on whether the risk-neutral rates are estimated using the post-1961 or the post-1987 sample.

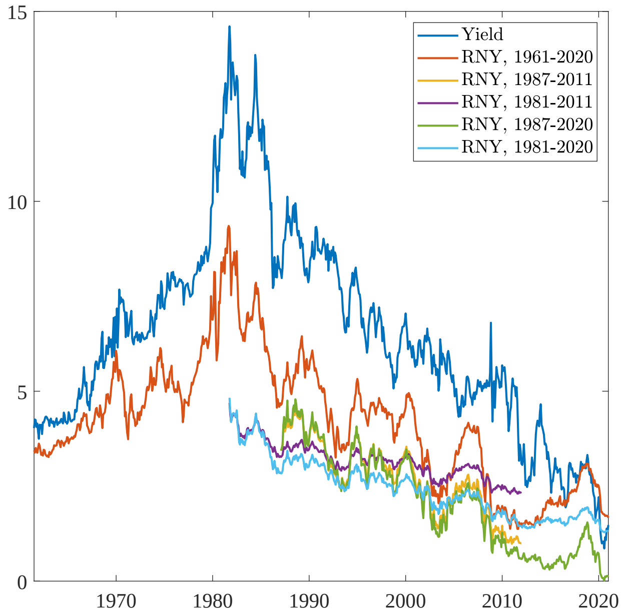
FIGURE 1

ACM risk-neutral yields estimated on different samples.

The risk-neutral yields are estimated from the canonical Adrian et al. (2013) model using different sample periods.



(a) **10-year yield.**



(b) **5-5 forward rate.**

To quantify the differences in the risk-neutral rates illustrated in the figure, we compute the maximum difference between the risk-neutral rates estimated using pairs of sample periods. According to Table 2, the 10-year risk-neutral rates estimated for a given date can differ by as much as 3.81 percentage points. Similarly, the 5-5 risk-neutral forward rate can vary by 4.60 percentage points. In relative terms, this difference represents at least 29% of the lower estimate for the 10-year risk-neutral rate and 41% for the 5-5 risk-neutral forward rate.

C. Bias Correction

A potential issue in estimating the term structure model is that the OLS estimator may underestimate the persistence of the state vector X_t in the first step of the ACM algorithm. This problem is particularly severe when the sample size is small. Since the loadings of the risk-neutral rates on X_t depend on the persistence matrix Φ, this bias could contribute to the inconsistencies observed in this section. Bauer et al. (2012) (BRW) propose a bias-correction method based on simulations to make the estimated $\hat{\Phi}$ more persistent than the OLS result.

In Step 1, we estimate $\boldsymbol{\mu}, \Phi, \Omega$ using the bias correction method instead of the standard OLS method. Given the estimated $\boldsymbol{\mu}, \Phi, \Omega$, we proceed to Step 2 as in Section B.

Figure 2 presents the bias-corrected ACM risk-neutral rates estimated from different sample periods. Compared with the uncorrected estimates in Figure 1, the risk-neutral rates appear to be higher, especially for those estimated using post-1981 samples. The risk-neutral rates estimated using the post-1981 samples are closer to those estimated using the 1961-2020 sample. However, there are still substantial inconsistencies in the 1980s, early 2000s, and 2010s.

TABLE 2

Maximum difference in risk-neutral rates estimated from different samples.

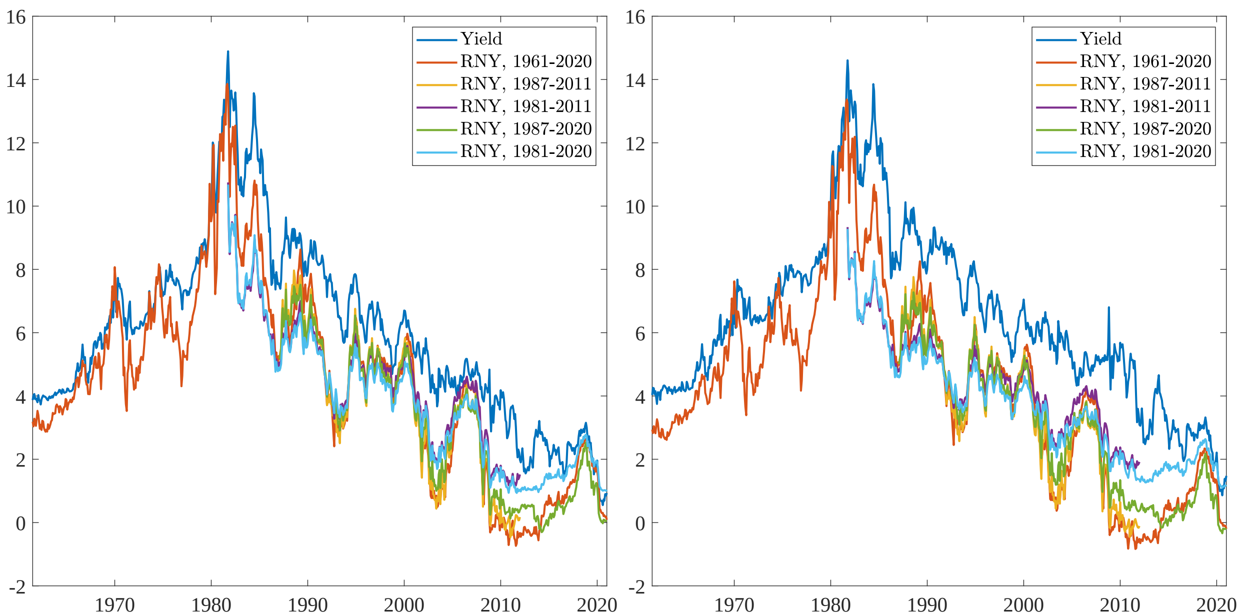
The first column reports the date that the monthly FE risk-neutral rates estimated using Sample_i and Sample_j differ the most. RNY_i and RNY_j denote the values of the risk-neutral rate estimated using the respective sample on the maximum difference date. $\Delta_{ij} = RNY_i - RNY_j$, $\min_{i,j} = \min\{RNY_i, RNY_j\}$.

Date	RNY_i	RNY_j	$\lvert\Delta_{ij}\rvert$	$\lvert\Delta_{ij}\rvert / \min_{i,j}$ (%)	Sample_i	Sample_j
			10-Year Yield			
1989/10	6.24	4.47	1.76	39.41	1961-2020	1987-2011
1981/9	10.81	7.00	3.81	54.51	1961-2020	1981-2011
1989/10	6.24	4.52	1.72	38.08	1961-2020	1987-2020
1982/3	10.03	6.43	3.60	55.94	1961-2020	1981-2020
1988/7	5.77	4.47	1.29	28.87	1987-2011	1981-2011
2011/8	0.88	0.55	0.34	61.43	1987-2011	1987-2020
1988/7	5.77	4.33	1.44	33.18	1987-2011	1981-2020
2011/12	1.87	0.52	1.35	260.63	1981-2011	1987-2020
2011/12	1.87	1.12	0.75	67.05	1981-2011	1981-2020
1988/7	5.75	4.33	1.42	32.88	1987-2020	1981-2020
			5-5 Forward Rate			
1989/9	5.85	3.82	2.03	53.22	1961-2020	1987-2011
1981/9	9.29	4.70	4.60	97.89	1961-2020	1981-2011
1989/9	5.85	3.82	2.03	52.98	1961-2020	1987-2020
1981/9	9.29	4.83	4.46	92.45	1961-2020	1981-2020
2010/12	0.98	2.38	1.40	142.66	1987-2011	1981-2011
2011/12	1.00	0.58	0.42	72.48	1987-2011	1987-2020
1988/7	4.66	3.31	1.36	41.08	1987-2011	1981-2020
2011/12	2.35	0.58	1.77	304.74	1981-2011	1987-2020
2011/12	2.35	1.44	0.91	62.76	1981-2011	1981-2020
1988/7	4.79	3.31	1.48	44.88	1987-2020	1981-2020

FIGURE 2

ACM bias-corrected risk-neutral yields estimated on different samples.

The risk-neutral yields are estimated from the canonical Adrian et al. (2013) model, where the VAR parameters are bias-corrected using the method of Bauer et al. (2012).



(a) **10-year yield.**

(b) **5-5 forward rate.**

V. Monetary Policy Transmission

In this section, we show that the estimated responses of risk-neutral rates to monetary policy shocks are highly sensitive to the sample period for estimating the risk-neutral rates. First, we estimate the contemporaneous responses of risk-neutral yields to high-frequency monetary policy shocks. Second, we estimate the contribution of the risk-neutral component to the cumulative changes in long-term yields during monetary policy announcement windows.

A. High-Frequency Regressions

A standard approach to estimating the effects of monetary policy shocks involves regressing the dependent variable on the shock. We estimate the following equation:

$$\Delta y_t = \beta_0 + \beta_1 x_t + \varepsilon_t, \tag{14}$$

where each t corresponds to an FOMC monetary policy announcement. Here, Δy_t is the daily change in a Treasury yield or its risk-neutral component on the announcement day, and x_t denotes a measure of the monetary policy shock. A standard measure of the monetary policy shock is the change in the Eurodollar futures rates, with maturities ranging from the current quarter to a year ahead, during 30-minute event windows bracketing monetary policy announcements. We summarize the Eurodollar shocks with the first principal component, denoted as MPS_t. Furthermore, Bauer and Swanson (2022,0) argue that MPS_t contains a component that responds to macroeconomic news and is not fully exogenous to information before the FOMC meeting. They extract a component MPS_t^o from MPS_t that is orthogonal to macroeconomic news, which we also consider in our regression. FOMC announcements not only set the current target for the federal funds rate but also convey information about its future path. The latter is especially relevant for long-maturity yields because the expected path of the short-term interest rate (risk-neutral yield) is an important component of long-maturity yields. Following Gürkaynak et al. (2005), we use their target and path factors to measure shocks to the current federal funds rate target and the expected policy rates, respectively.

Table 3 reports the estimated responses of the 10-year yield and the 5-5 forward rate and their risk-neutral components to various measures of the monetary policy shock. We estimate the ACM risk-neutral rate parameters using the sample periods considered in Figure 1. Then, we combine the respective monthly model parameters with daily yield curve PCs to compute daily risk-neutral rates for the regression analysis. The regression sample period is from 1995 to 2011, which is the maximal intersection among all monetary policy shock data and the risk-neutral rate estimation samples.

Monetary policy shocks significantly affect long-maturity yields. For example, when MPS_t decreases by 1 percentage point, the 10-year yield decreases by 33 basis points. The path factor has much stronger effects on long-maturity yields than the target factor, which is intuitive. How much of the effects are due to the responses of expected short-term rates? According to the ACM model estimated using 1961-2020 data, the risk-neutral rates respond much more strongly than the term premia to monetary policy shocks.[4] However, the same model estimated using post-1981 data suggests that the expectations hypothesis component of the 10-year yield is less

[4]The difference between the yield's response and the risk-neutral rate's response is the term premium's response.

than half as responsive to monetary policy shocks as the model using 1961-2020 data suggests.

More starkly, the 5-5 forward rate results differ by a factor of more than three.

TABLE 3

Contemporaneous effects of monetary policy shocks.

The table reports the slope coefficient from $\Delta y_t = \beta_0 + \beta_1 x_t + \varepsilon_t$, where Δy_t denotes the daily change in the yield or its risk-neutral component on the FOMC announcement date, and x_t denotes one of the monetary policy shocks. MPS is the first principal component of ED1-ED4, MPS^o is the orthogonalized MPS from Bauer and Swanson (2022), "target" and "path" are the target and path factors from Gürkaynak et al. (2005), and updated by Acosta (2023). The column label denotes the method and sample period for estimating the risk-neutral rate. The sample period for estimating β_1 is 1995-2011 for all columns.

	Yield	OSE	FE 1961-2020	FE 1987-2011	FE 1981-2011	FE 1987-2020	FE 1981-2020
	10-Year Yield						
MPS	0.31**	0.44***	0.38***	0.17*	0.18***	0.22**	0.18***
	(0.09)	(0.09)	(0.07)	(0.08)	(0.04)	(0.08)	(0.04)
MPS^o	0.36***	0.48***	0.42***	0.19*	0.20***	0.25**	0.21***
	(0.11)	(0.10)	(0.08)	(0.09)	(0.04)	(0.09)	(0.05)
target	0.15	0.35**	0.33**	0.20	0.16**	0.21	0.16**
	(0.12)	(0.12)	(0.11)	(0.11)	(0.06)	(0.11)	(0.06)
path	0.42***	0.52***	0.40***	0.19*	0.19***	0.25***	0.21***
	(0.08)	(0.06)	(0.04)	(0.08)	(0.02)	(0.07)	(0.03)
	5-5 Forward Rate						
MPS	0.12	0.36***	0.29***	0.06	0.07***	0.08	0.07**
	(0.10)	(0.09)	(0.06)	(0.05)	(0.02)	(0.06)	(0.02)
MPS^o	0.15	0.38***	0.32***	0.07	0.08***	0.10	0.08**
	(0.10)	(0.10)	(0.07)	(0.07)	(0.02)	(0.07)	(0.03)
target	-0.03	0.27*	0.23**	0.08	0.05	0.08	0.05
	(0.15)	(0.11)	(0.09)	(0.08)	(0.03)	(0.08)	(0.03)
path	0.25*	0.45***	0.32***	0.11	0.09***	0.14*	0.10***
	(0.10)	(0.07)	(0.04)	(0.05)	(0.01)	(0.06)	(0.02)

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

B. Bias-Corrected Risk-Neutral Rates

To examine whether bias correction alleviates the inconsistency problem in high-frequency regressions, we re-estimate Equation (14) using BRW bias-corrected risk-neutral yields as the dependent variable. Albagli et al. (2019) use a similar method to estimate the risk-neutral yields and study the effects of U.S. monetary policy shocks on world long-term yields.

Table 4 reports the estimated effects of high-frequency monetary policy shocks on bias-corrected risk-neutral yields, where the risk-neutral yields are estimated using the same sample periods as in Table 3 and the regressions are estimated using the 1995-2011 sample. Compared with the results in Table 3, the bias-corrected risk-neutral yields are more responsive to monetary policy shocks regardless of the sample periods for estimating the term structure model. However, the bias correction does not make the estimated $\hat{\beta}_1$ more consistent across sample periods. For example, the 10-year risk-neutral yield estimated from the 1961-2020 sample is twice as responsive to monetary policy shocks as the one estimated from the 1987-2011 sample.

VI. A Remedy

A shifting endpoint model can solve the discrepancy problem. Our model is based on Bauer and Rudebusch (2020) but estimated using the ACM method.

TABLE 4

Contemporaneous effects of monetary policy shocks: bias-corrected risk-neutral rates.

The table reports the slope coefficient from $\Delta y_t = \beta_0 + \beta_1 x_t + \varepsilon_t$, where Δy_t denotes the daily change in the yield or its risk-neutral component on the FOMC announcement date, and x_t denotes the monetary policy shock. The FE risk-neutral rates are bias-corrected using the method of Bauer et al. (2012). MPS is the first principal component of ED1-ED4, MPS^{o} is the orthogonalized MPS from Bauer and Swanson (2022), "target" and "path" are the target and path factors from Gürkaynak et al. (2005), and updated by Acosta (2023). The column label denotes the method and sample period for estimating the risk-neutral rate. The sample period for estimating β_1 is 1995-2011 for all columns.

	Yield	OSE	FE 1961-2020	FE 1987-2011	FE 1981-2011	FE 1987-2020	FE 1981-2020
				10-Year Yield			
MPS	0.31^{**}	0.44^{***}	0.53^{***}	0.25^{*}	0.31^{***}	0.31^{**}	0.30^{***}
	(0.09)	(0.09)	(0.10)	(0.12)	(0.07)	(0.11)	(0.06)
MPS^{o}	0.36^{***}	0.48^{***}	0.59^{***}	0.28^{*}	0.35^{***}	0.36^{**}	0.33^{***}
	(0.11)	(0.10)	(0.12)	(0.14)	(0.07)	(0.12)	(0.07)
target	0.15	0.35^{**}	0.45^{**}	0.31	0.29^{**}	0.31	0.25^{**}
	(0.12)	(0.12)	(0.16)	(0.17)	(0.10)	(0.16)	(0.09)
path	0.42^{***}	0.52^{***}	0.57^{***}	0.27^{*}	0.33^{***}	0.35^{***}	0.33^{***}
	(0.08)	(0.06)	(0.06)	(0.12)	(0.04)	(0.10)	(0.04)
				5-5 Forward Rate			
MPS	0.12	0.36^{***}	0.50^{***}	0.14	0.22^{***}	0.18	0.19^{***}
	(0.10)	(0.09)	(0.10)	(0.11)	(0.05)	(0.09)	(0.05)
MPS^{o}	0.15	0.38^{***}	0.56^{***}	0.17	0.25^{***}	0.22	0.22^{***}
	(0.10)	(0.10)	(0.11)	(0.13)	(0.06)	(0.11)	(0.06)
target	-0.03	0.27^{*}	0.40^{**}	0.19	0.18^{*}	0.18	0.14
	(0.15)	(0.11)	(0.15)	(0.16)	(0.08)	(0.14)	(0.07)
path	0.25^{*}	0.45^{***}	0.56^{***}	0.21	0.27^{***}	0.25^{**}	0.25^{***}
	(0.10)	(0.07)	(0.06)	(0.12)	(0.03)	(0.09)	(0.03)

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

A. A Shifting Endpoint Model

The same state vector X_t as in the fixed endpoint model determines the yield curve. However, we now assume that X_t contains a random walk component

$$
\begin{aligned}
X_t =& \boldsymbol{\mu} + \Gamma \boldsymbol{\tau}_t + \tilde{X}_t, \\
\boldsymbol{\tau}_t =& \boldsymbol{\tau}_{t-1} + \boldsymbol{\eta}_t, \quad \boldsymbol{\eta}_t \sim \mathcal{N}(0, \Omega_\eta) \\
\tilde{X}_t =& \Phi \tilde{X}_{t-1} + \tilde{U}_t, \quad \tilde{U}_t \sim \mathcal{N}(0, \tilde{\Omega}),
\end{aligned} \tag{15}
$$

where $\boldsymbol{\tau}_t$ is a $K_\tau \times 1$ random walk and $\tilde{X}_t$ is a $K \times 1$ stationary VAR(1). The shocks are i.i.d over time and $\boldsymbol{\eta}_t \perp \tilde{U}_t$. Define

$$
Z_t \equiv \begin{bmatrix} \boldsymbol{\tau}_t^\top & X_t^\top \end{bmatrix}^\top, U_t \equiv \Gamma \boldsymbol{\eta}_t + \tilde{U}_t, \Omega \equiv \mathbf{E}[U_t U_t^\top] = \Gamma \Omega_\eta \Gamma^\top + \tilde{\Omega}.
$$

The SDF is exponentially affine:

$$
\ln M_{t,t+1} = -\delta_0 - \boldsymbol{\delta}_1^\top X_t - \frac{1}{2} \Lambda_t^\top \Lambda_t - \Lambda_t^\top \Omega^{-\frac{1}{2}} U_{t+1}. \tag{16}
$$

The price of risk is an affine function of Z_t:

$$
\Lambda_t = \Sigma^{-1}(\Lambda_0 + \Lambda_1 Z_t), \tag{17}
$$

where $\Sigma\Sigma^\top = \Omega$.

Note that the log SDF is affine in X_t, but the market prices of risk are affine in Z_t. The shock U_{t+1} is a $K \times 1$ dimensional vector with the same dimension as X_t, but is a combination of shocks to $\boldsymbol{\tau}_t$ and $\tilde{X}_t$. We assume that Λ_1 satisfies

$$\Lambda_1 = \Big[(I - \Phi)\Gamma, \Lambda_{12}\Big], \tag{18}$$

i.e., the first K_τ column of Λ_1 (the loading on $\boldsymbol{\tau}_t$) equals $(I - \Phi)\Gamma$ and the remaining K columns is an unrestricted $K \times K$ matrix Λ_{12}. This implies that the log bond prices are still affine in X_t, taking the same form as Equation (6). Although the trend $\boldsymbol{\tau_t}$ does not directly affect the observed yields, it affects term premia by affecting the price of risk, so the risk-neutral bond prices are

$$\ln P_t^{(n)rn} = \mathcal{A}_n^{rn} + \mathcal{B}_n^{rn\top} X_t + \mathcal{C}_n^{rn\top} \boldsymbol{\tau}_t. \tag{19}$$

The risk-neutral parameters solve the following recursions:

$$\begin{aligned}
\mathcal{A}_n^{rn} =& \mathcal{A}_{n-1}^{rn} - \delta_0 + \mathcal{B}_{n-1}^{rn\top}(I - \Phi)\boldsymbol{\mu} + \frac{1}{2}\mathcal{B}_{n-1}^{rn\top}\Omega\mathcal{B}_{n-1}^{rn}, \\
&+ \frac{1}{2}\left(\mathcal{B}_{n-1}^{rn\top}\Gamma\Omega_\eta\mathcal{C}_{n-1}^{rn} + \mathcal{C}_{n-1}^{rn\top}\Omega_\eta\Gamma^\top\mathcal{B}_{n-1}\right) + \frac{1}{2}\mathcal{C}_{n-1}^{rn\top}\Omega_\eta\mathcal{C}_{n-1}^{rn}, \quad \mathcal{A}_1 = -\delta_0, \qquad (20)\\
\mathcal{B}_n^{rn\top} =& \mathcal{B}_{n-1}^{rn\top}\Phi - \boldsymbol{\delta}_1^\top, \quad \mathcal{B}_1 = -\boldsymbol{\delta}_1, \qquad (21)\\
\mathcal{C}_n^{rn\top} =& \mathcal{B}_{n-1}^{rn\top}(I - \Phi)\Gamma + \mathcal{C}_{n-1}^{rn\top}, \quad \mathcal{C}_1 = \mathbf{0}. \qquad (22)
\end{aligned}$$

B. Estimation

We follow similar estimation procedures as the fixed endpoint model. The excess holding period return over one period for the shifting endpoint model is

$$rx_{t+1}^{(n)} = \mathcal{B}_{n-1}^{\top}(\Lambda_0 - (I-\Phi)\boldsymbol{\mu}) - \frac{1}{2}\mathcal{B}_{n-1}^{\top}\Omega\mathcal{B}_{n-1} + \mathcal{B}_{n-1}^{\top}(\Lambda_{12} - \Phi)X_t + \mathcal{B}_{n-1}^{\top}X_{t+1}. \tag{23}$$

Note that Φ here refers to the persistence parameter of the cyclical component $\tilde{X}_t$ of the state vector, whereas the Φ in Equation (13) refers to the persistence parameter of the state vector X_t. This is the main reason that the two models produce different estimates of the risk-neutral rates.

A prerequisite for estimating the risk-neutral rates is to obtain a τ_t series. For the monthly model, we estimate τ_t as the Beveridge-Nelson trend of the first principal component of the yield curve using the method of Kamber, Morley, and Wong (2018) and Kamber, Morley, and Wong (2024). Alternatively, we can estimate Equation (15) using the Bayesian method as in Bauer and Rudebusch (2020) and Del Negro, Giannone, Giannoni, and Tambalotti (2017). The two methods produce virtually identical results, but our method is much faster.[5] Since τ_t is estimated, we refer to this method as the "estimated shifting endpoint" (ESE) model, following Bauer and Rudebusch (2020). The state variables X_t, τ_t and the model parameters $\mathcal{A}, \mathcal{B}, \mathcal{A}^{rn}, \mathcal{B}^{rn}, \mathcal{C}^{rn}$ are estimated using data from each subsample. At the daily frequency, the estimation of τ_t becomes unreliable. Instead, we proxy τ_t with the first principal component of the sum of daily changes in Treasury yields during three-day windows bracketing FOMC announcements. Hillenbrand (2025) shows that the series explains the persistent variations in Treasury yields almost perfectly, making it a

[5] Section A compares the results implied by the Beveridge-Nelson decomposition and the Bayesian method.

suitable proxy for τ_t in the shifting endpoint model. We denote this method as the "observed shifting endpoint" (OSE) model.[6]

C. ESE Risk-Neutral Rates

Figure 3 presents the monthly 10-year yield and the 5-5 forward rate alongside their ESE risk-neutral components, estimated using the same sample periods as in Figure 1. Notably, the risk-neutral components for a given yield estimated with different samples almost coincide, effectively addressing the discrepancy problem associated with the fixed endpoint (FE) model. Furthermore, the risk-neutral rates implied by the ESE model are higher than those implied by the FE model and are more parallel to the observed yields.

VII. Monetary Policy Transmission Revisited

A. Contemporaneous Effects

We revisit the high-frequency regression Equation (14) using OSE risk-neutral yields. Since the empirical proxy for τ_t is only available after 1989, we consider two sample periods for estimating the term structure model: 1989-2011 and 1989-2020. The sample period for estimating Equation (14) is 1995-2011.

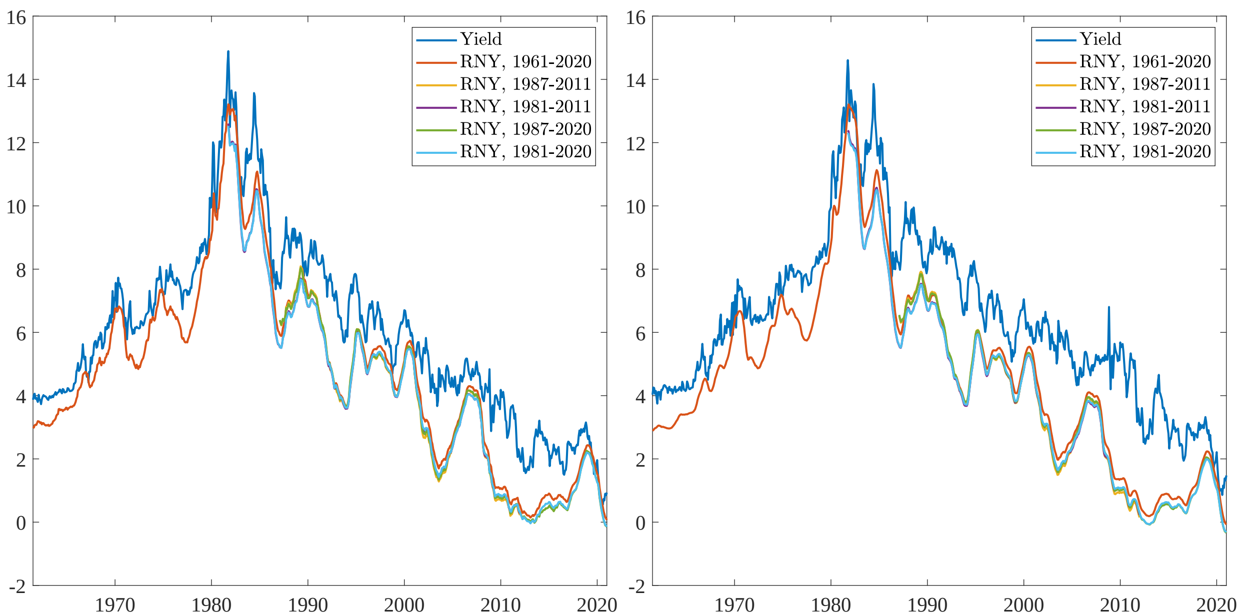
Table 5 reports the effects of high-frequency monetary policy shocks on OSE risk-neutral yields. To facilitate comparison, we reproduce the ACM FE risk-neutral yields using the

[6]The OSE model only applies to post-1989 data because of the availability of FOMC announcement dates. Refer to Hillenbrand (2025) for details.

FIGURE 3

ESE risk-neutral yields estimated on different samples.

The risk-neutral yields are estimated from the ESE model.



(a) **10-year yield.** (b) **5-5 forward rate.**

1989-2011 and 1989-2020 sample periods. The estimated $\hat{\beta}_1$ is much more stable across sample periods for the OSE risk-neutral yields than for the FE ones.

Interestingly, the OSE results are similar to the FE results estimated from the 1961-2020 sample, and the differences in $\hat{\beta}_1$ between the FE, 1961-2020 column and the FE, 1989- columns are much larger than the difference between the FE, 1989- columns. This further indicates that the high-frequency regression results are highly sensitive to the sample periods for estimating the FE term structure model, and the OSE method significantly stabilizes the estimation results.

B. Cumulative Effects of Monetary Policy Announcements

In an intriguing paper, Hillenbrand (2025) demonstrates that three-day windows around FOMC announcements can almost perfectly explain the persistent variations in long-maturity Treasury yields since 1989. How much of this phenomenon is attributable to the expectations hypothesis component? We show that the answer to this question, according to the fixed endpoint model, highly depends on the sample period used to estimate the risk-neutral rates.

To quantify the fraction of total variations in the FOMC-window changes explained by the expectations hypothesis component, we define the adjusted R-squared $\tilde{R}^2$ as follows:

$$\tilde{R}^2 = 1 - \frac{\sum_t \left(y_t^{FOMC} - y_t^{rn,FOMC}\right)^2}{\sum_t \left(y_t^{FOMC} - y_t^{rn,FOMC}\right)^2 + \sum_t \left(y_t^{FOMC} - y_t^{tp,FOMC}\right)^2}. \quad (24)$$

In this equation, y_t^{FOMC} denotes the cumulative change in y_t during FOMC windows up to t, while $y_t^{rn,FOMC}$ and $y_t^{tp,FOMC}$ denote the cumulative changes in the risk-neutral and term premium components of y_t during FOMC windows up to t. Note that

TABLE 5

Contemporaneous effects of monetary policy shocks.

The table reports the slope coefficient from $\Delta y_t = \beta_0 + \beta_1 x_t + \varepsilon_t$, where Δy_t denotes the daily change in the yield or its risk-neutral component on the FOMC announcement date, and x_t denotes one of the monetary policy shocks. MPS is the first principal component of ED1-ED4, MPS^o is the orthogonalized MPS from Bauer and Swanson (2022), "target" and "path" are the target and path factors from Gürkaynak et al. (2005), and updated by Acosta (2023). The column label denotes the method and sample period for estimating the risk-neutral rate. The sample period for estimating β_1 is 1995-2011 for all columns.

	Yield	OSE 1989-2011	OSE 1989-2020	FE 1961-2020	FE 1989-2011	FE 1989-2020
			10-Year Yield			
MPS	0.31^{**}	0.44^{***}	0.44^{***}	0.38^{***}	0.21^{**}	0.17^{*}
	(0.09)	(0.09)	(0.09)	(0.07)	(0.07)	(0.07)
MPS^o	0.36^{***}	0.47^{***}	0.48^{***}	0.42^{***}	0.25^{**}	0.19^{*}
	(0.11)	(0.10)	(0.10)	(0.08)	(0.08)	(0.08)
target	0.15	0.34^{**}	0.35^{**}	0.33^{**}	0.21^{*}	0.20
	(0.12)	(0.12)	(0.12)	(0.11)	(0.11)	(0.11)
path	0.42^{***}	0.52^{***}	0.52^{***}	0.40^{***}	0.25^{***}	0.18^{**}
	(0.08)	(0.07)	(0.06)	(0.04)	(0.06)	(0.07)
			5-5 Forward Rate			
MPS	0.12	0.38^{***}	0.36^{***}	0.29^{***}	0.09	0.06
	(0.10)	(0.10)	(0.09)	(0.06)	(0.05)	(0.05)
MPS^o	0.15	0.41^{***}	0.38^{***}	0.32^{***}	0.11	0.07
	(0.10)	(0.11)	(0.10)	(0.07)	(0.06)	(0.05)
target	-0.03	0.29^{*}	0.27^{*}	0.23^{**}	0.09	0.08
	(0.15)	(0.13)	(0.11)	(0.09)	(0.07)	(0.07)
path	0.25^{*}	0.49^{***}	0.45^{***}	0.32^{***}	0.14^{**}	0.10^{*}
	(0.10)	(0.08)	(0.07)	(0.04)	(0.05)	(0.04)

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

$y_t^{rn,FOMC} + y_t^{tp,FOMC} = y_t^{FOMC}$, and $\tilde{R}^2 \in [0,1]$. A bigger $\tilde{R}^2$ indicates that the risk-neutral component explains a larger fraction of the total variations in y_t^{FOMC}.

In Figure 4, we present the actual 10-year yield and the 5-5 forward rate, along with their cumulative changes during FOMC windows and the cumulative changes in their risk-neutral components during these windows. When risk-neutral rates are estimated using the 1961-2020 sample or directly sourced from the Federal Reserve Bank of New York's website, the expectations hypothesis explains 87% of the cumulative change in the 10-year yield and 76% of that in the 5-5 forward rate during the FOMC windows. In contrast, when risk-neutral rates are estimated using sample periods closely aligned with the FOMC sample, such as the 1987-2020 sample, the expectations hypothesis results in a significantly lower $\tilde{R}^2$ of only 14% for the 10-year yield and 6% for the 5-5 forward rate. However, utilizing the post-1989 sample with the observed shifting endpoint (OSE) method indicates that the expectations hypothesis explains nearly all of the yield dynamics during the FOMC windows. The $\tilde{R}^2$ for this case is strikingly high at 99% for the 10-year yield and 83% for the 5-5 forward rate.

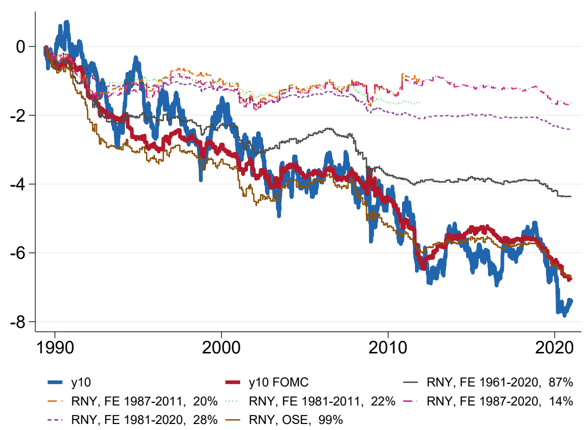
VIII. Inspecting the Mechanism

We start by investigating the fit of the models estimated using different samples. Figure 5 presents the observed data of the 10-year yield and the 5-5 forward rate against the fitted values from the fixed endpoint model. Although the risk-neutral rates estimated from different subsamples differ substantially, the model-implied yields are highly consistent with each other and indistinguishable from the data. Therefore, the discrepancy in risk-neutral rates generated by the fixed endpoint model is not caused by the failure to match observed yields on any subsample.

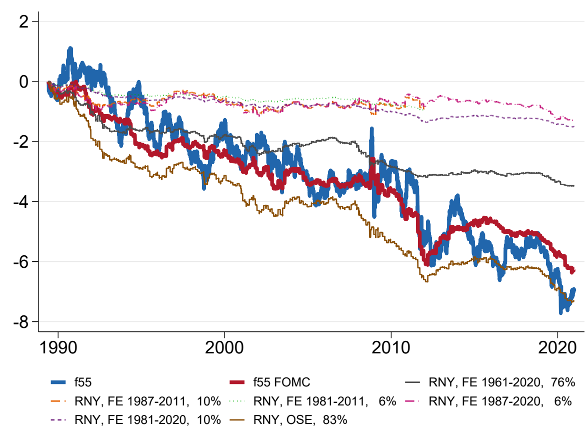
FIGURE 4

Cumulative change in the risk-neutral rates during FOMC windows.

The series `y10` and `f55` are the observed 10-year Treasury yield and 5-5 forward rate relative to their initial values, `y10FOMC` and `f55FOMC` are the sums of daily changes in `y10` and `f55` during FOMC windows, and the remaining series are cumulative changes in the risk-neutral rates from the OSE or FE model estimated on different samples. The percentage number indicates the fraction of total variation in `y10FOMC` or `f55FOMC` explained by the respective risk-neutral rate.



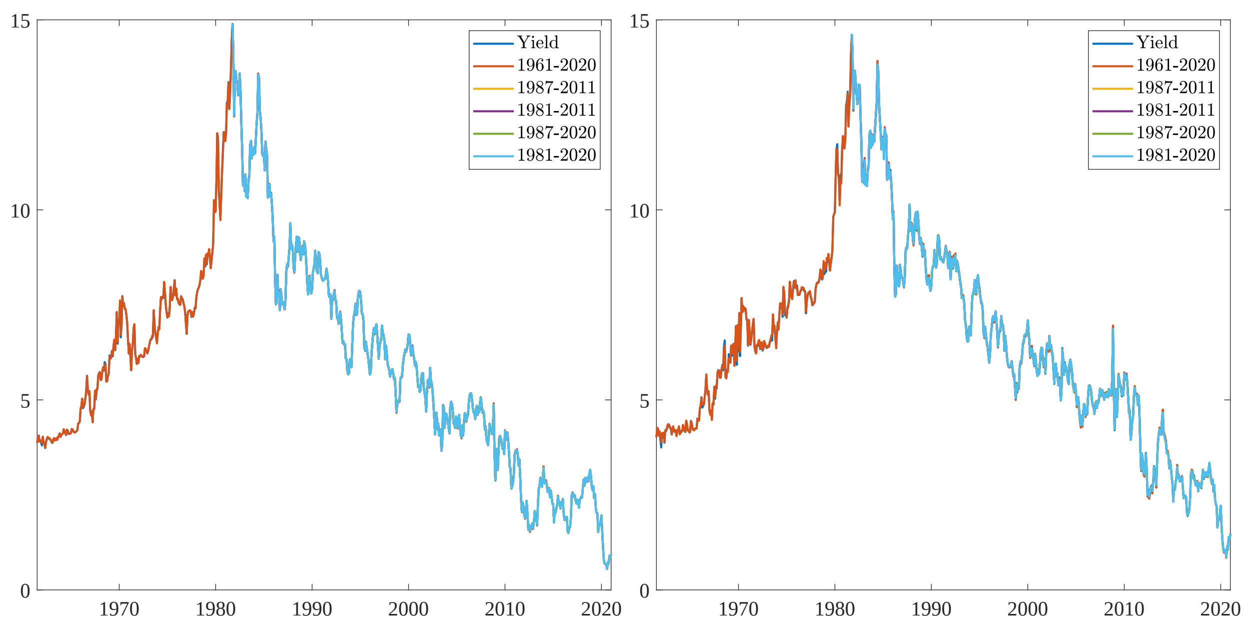
(a) **10-year yield.**



(b) **5-5 forward rate.**

FIGURE 5

Fitted yields from the ACM fixed endpoint model.



(a) **10-year yield.** (b) **5-5 forward rate.**

A. Consistency of Parameters

Why are the risk-neutral rates estimated from the fixed endpoint model highly sensitive to sample periods? Table 1 suggests that the average yields differ substantially over time, so the estimate of $\boldsymbol{\mu}$ is sensitive to the choice of sample periods. According to Equation (11), differences in $\boldsymbol{\mu}$ lead to differences in $\mathcal{A}_n^{rn}$, the intercept for risk-neutral rates. Consequently, the levels of risk-neutral rates estimated from different subsamples are different.

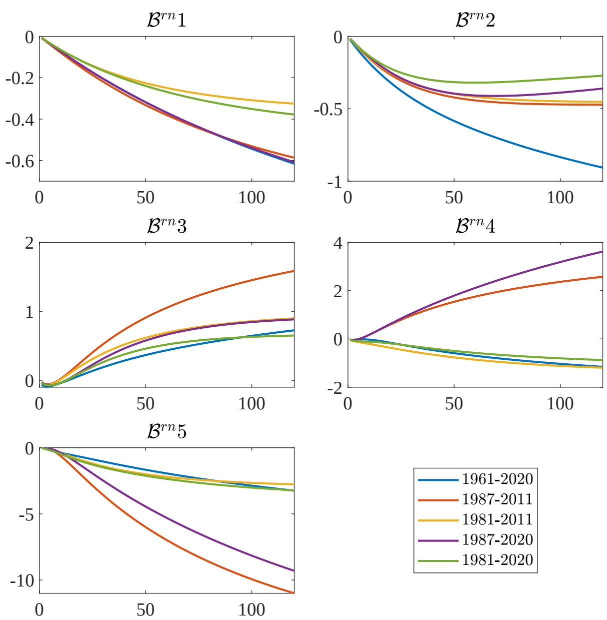
More interestingly, the risk-neutral rates estimated from different sample periods also exhibit different slopes and volatility of cyclical fluctuations, indicating differences in $\mathcal{B}_n^{rn}$. Figure 6a plots the FE model's $\mathcal{B}_n^{rn}$ against maturity n. Each panel of Figure 6a plots the coefficient on an element of X_t. For example, the point with a horizontal coordinate 50 in panel $\mathcal{B}^{rn}1$ corresponds to the loading of the 50-month log risk-neutral bond price on the first element of X_t, i.e., the first principal component of the yield curve. The curves coincide at maturity 1, indicating that all sample periods yield identical estimates of $\boldsymbol{\delta}_1$ (ref. Equation (12)), but the values estimated from different sample periods diverge at longer maturities.

According to Equation (12), the value of $\mathcal{B}_n^{rn}$ depends on $\boldsymbol{\delta}_1$ and the persistence parameter Φ of the yield curve principal components. Since $\boldsymbol{\delta}_1$ is identical across sample periods, Φ must be different. Table 6 reports the AR(1) coefficients of the first five yield curve principal components estimated from different samples. To isolate the variation in estimated parameters from the principal components, we fix the latter to be estimated from the full sample, ranging from 1961 to 2020. The average yield (PC1) is highly persistent, with the AR(1) coefficient close to 1 across all sample periods. Similarly, the slope factor (PC2) also shows consistent degrees of persistence throughout the different periods. In contrast, the curvature factor (PC3) has an AR(1) coefficient

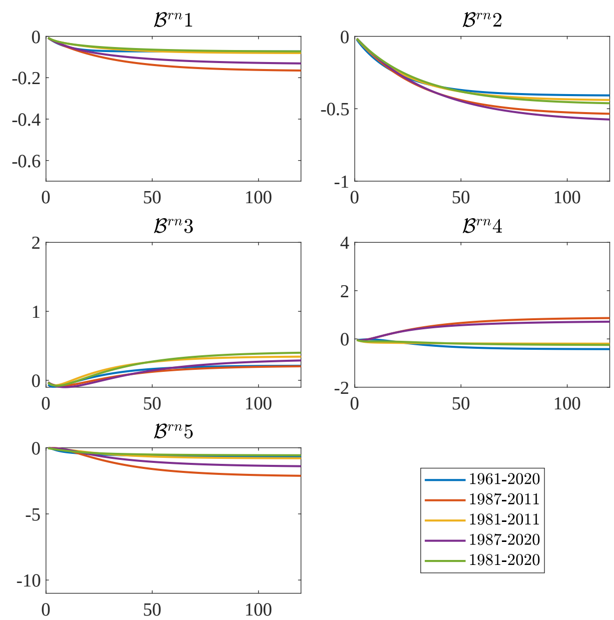
FIGURE 6

Slope parameters of risk-neutral bond prices from the FE and ESE models.

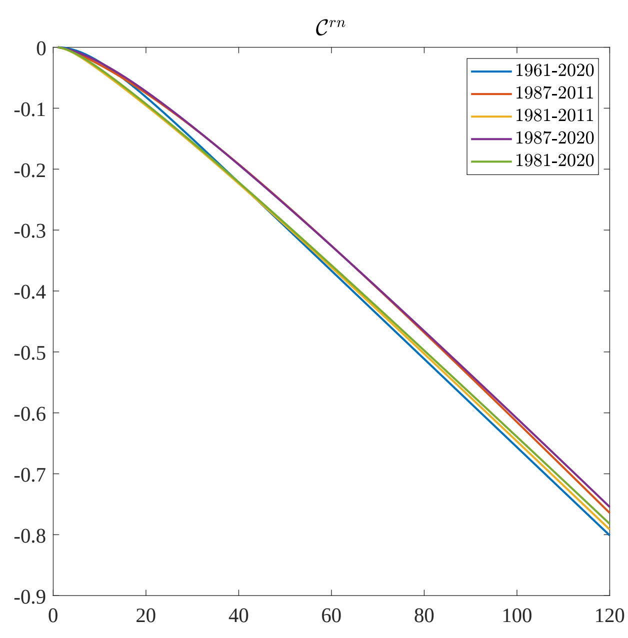
For the fixed endpoint model, the risk-neutral bond price is $\ln P_t^{(n)rn} = \mathcal{A}_n + \mathcal{B}_n^{rn\top} X_t$; for the shifting endpoint model, the risk-neutral bond price is $\ln P_t^{(n)rn} = \mathcal{A}_n + \mathcal{B}_n^{rn\top} X_t + \mathcal{C}_n^{rn} \tau_t$. X_t is the first five yield curve principal components. Each panel of the $\mathcal{B}^{rn}$ figure presents the coefficient on the respective principal component. The horizontal axis denotes maturity (months).



(a) **Fixed endpoint.**



(b) **Shifting endpoint**



(c) **Shifting endpoint**

of 0.56 over the 1961-2020 sample, but this coefficient ranges from 0.83 to 0.89 across other subsamples. Beyond the third principal component, higher-order principal components also exhibit significantly different degrees of persistence across subsamples. Therefore, the primary reason for the discrepancies in $\mathcal{B}_n^{rn}$ is that the high-order principal components of the yield curve exhibit different degrees of persistence across sample periods.

Why does the shifting endpoint model produce highly consistent risk-neutral rates from different sample periods? Recall that the risk-neutral bond price is $\ln P_t^{(n)rn} = \mathcal{A}_n + \mathcal{B}_n^{rn\top} X_t + \mathcal{C}_n^{rn} \tau_t$. As shown in Figure 6b, the magnitudes of $\mathcal{B}_n^{rn}$ from the shifting endpoint model are smaller than those from the fixed endpoint model, and the discrepancies in $\mathcal{B}_n^{rn}$ across sample periods are also reduced. This reduction in variability can be attributed to the fact that Φ in the recursion Equation (21) is the persistence parameter of the cyclical component $\tilde{X}_t$, and Table 1 suggests that the cyclical yields are much less persistent than the actual yields. Additionally, Figure 6c shows that $\mathcal{C}_n^{rn}$ remains very similar across samples. Note that τ_t is the Beveridge-Nelson trend of the first principal component of the yield curve, and the two series have similar degrees of variations. The magnitude of $\mathcal{C}^{rn}$ in Figure 6c is larger than that of $\mathcal{B}^{rn}1$ in Figure 6b, suggesting that the variations of the risk-neutral rates from the ESE model are mainly driven by fluctuations in τ_t. The consistency of $\mathcal{C}^{rn}$ across estimation samples implies that the estimated risk-neutral rates are robust across sample periods.

B. Estimated States vs. Parameters

Note that the state variables X_t, τ_t are estimated from observed yields, so the parameters producing them may also vary across sample periods. To examine the contributions of the state

TABLE 6

Summary statistics of the yield curve principal components.

The principal components are computed using the full sample–from 1961 to 2020–and fixed when computing subsample statistics. $\bar{y}$: sample average of the PC. sd(y): sample standard deviation of the PC. AR1(y): slope coefficient from $y_t = \mu + \rho y_{t-1} + u_t$. sd($u$): standard deviation of the AR(1) residual. sd($\tilde{y}$): standard deviation of the Beveridge-Nelson cyclical component. AR1($\tilde{y}$): the AR1 coefficient of the cyclical component. sd($\tilde{u}$): standard deviation of the AR1 residual of the cyclical component. The data are month-end observations of the principal components of GSW yields in annualized percentage points.

Sample	$\bar{y}$	min	max	sd(y)	AR1(y)	sd(u)	sd($\tilde{y}$)	AR1($\tilde{y}$)	sd($\tilde{u}$)
	PC1								
1961-2020	5.52	0.27	15.25	3.05	1.00	0.34	0.54	0.82	0.31
1987-2011	5.11	0.90	9.33	2.06	1.00	0.28	0.41	0.80	0.24
1981-2011	6.06	0.90	15.25	2.92	0.98	0.34	0.50	0.78	0.30
1987-2020	4.14	0.27	9.33	2.41	1.00	0.25	0.40	0.82	0.22
1981-2020	5.01	0.27	15.25	3.23	0.99	0.31	0.48	0.80	0.28
	PC2								
1961-2020	-0.60	-1.50	0.72	0.39	0.95	0.13	0.17	0.74	0.11
1987-2011	-0.74	-1.50	-0.02	0.38	0.98	0.08	0.13	0.84	0.07
1981-2011	-0.78	-1.50	-0.02	0.37	0.97	0.10	0.14	0.81	0.09
1987-2020	-0.67	-1.50	0.07	0.38	0.98	0.08	0.13	0.84	0.07
1981-2020	-0.71	-1.50	0.07	0.38	0.97	0.09	0.14	0.82	0.08
	PC3								
1961-2020	0.17	-0.78	0.98	0.14	0.56	0.11	0.12	0.38	0.11
1987-2011	0.19	-0.18	0.49	0.09	0.87	0.04	0.05	0.58	0.04
1981-2011	0.18	-0.35	0.49	0.09	0.83	0.05	0.06	0.62	0.05
1987-2020	0.17	-0.18	0.49	0.09	0.89	0.04	0.04	0.62	0.03
1981-2020	0.17	-0.35	0.49	0.09	0.86	0.05	0.05	0.65	0.04
	PC4								
1961-2020	-0.08	-0.51	0.35	0.09	0.75	0.06	0.06	0.43	0.05
1987-2011	-0.11	-0.35	0.03	0.06	0.87	0.03	0.04	0.66	0.03
1981-2011	-0.10	-0.35	0.03	0.06	0.86	0.03	0.04	0.63	0.03
1987-2020	-0.10	-0.35	0.03	0.06	0.89	0.03	0.03	0.69	0.02
1981-2020	-0.10	-0.35	0.03	0.06	0.88	0.03	0.03	0.66	0.03
	PC5								
1961-2020	-0.02	-0.16	0.13	0.03	0.68	0.02	0.02	0.52	0.02
1987-2011	-0.03	-0.08	0.03	0.02	0.80	0.01	0.01	0.52	0.01
1981-2011	-0.03	-0.13	0.03	0.02	0.73	0.01	0.02	0.51	0.01
1987-2020	-0.02	-0.08	0.05	0.02	0.87	0.01	0.01	0.58	0.01
1981-2020	-0.02	-0.13	0.05	0.02	0.81	0.01	0.02	0.55	0.01

variables and the yield curve parameters $\mathcal{A}^{rn}, \mathcal{B}^{rn}, \mathcal{C}^{rn}$ to the (in)stability of estimated risk-neutral yields, we conduct two exercises.

Fixed parameters. The parameters $\mathcal{A}^{rn}, \mathcal{B}^{rn}, \mathcal{C}^{rn}$ are estimated from the 1961-2020 sample. For each subsample, we only reestimate X_t and τ_t, and combine them with the fixed $\mathcal{A}^{rn}, \mathcal{B}^{rn}, \mathcal{C}^{rn}$ to produce risk-neutral yields.

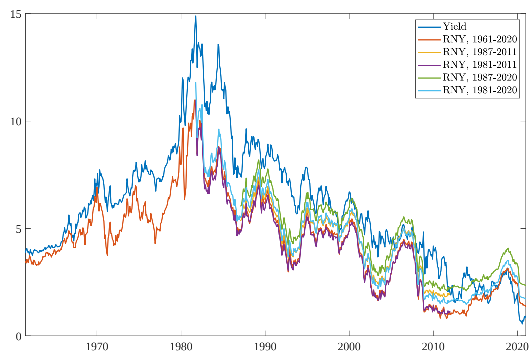
Fixed states. The state variables X_t, τ_t are estimated from the 1961-2020 sample. For each subsample, the respective X_t, τ_t are extracted from the fixed full sample. Then, we estimate $\mathcal{A}^{rn}, \mathcal{B}^{rn}, \mathcal{C}^{rn}$ and combine with the state variables to produce risk-neutral yields.

Figure 7 presents the 10-year risk-neutral yields implied by the ACM, BRW, and ESE models. For all models, the fixed parameters exercise produces unstable risk-neutral yields across subsamples. This reflects the fact that the state variables X_t and τ_t are estimated and are thus unstable across subsamples. Notice that the shifting-endpoint model does not make the state estimation more stable. On the other hand, the fixed states exercise forces the state variables to be consistent across subsamples. The variations in the risk-neutral yields across subsamples are solely due to inconsistencies in $\mathcal{A}^{rn}, \mathcal{B}^{rn}, \mathcal{C}^{rn}$. The BRW bias correction makes the yield curve parameters more stable than those implied by the canonical ACM method, but there are still substantial discrepancies in the risk-neutral yields in the 1980s and 2010s. In contrast, the risk-neutral yields implied by the ESE method almost coincide, suggesting more consistent estimates of the yield curve parameters.

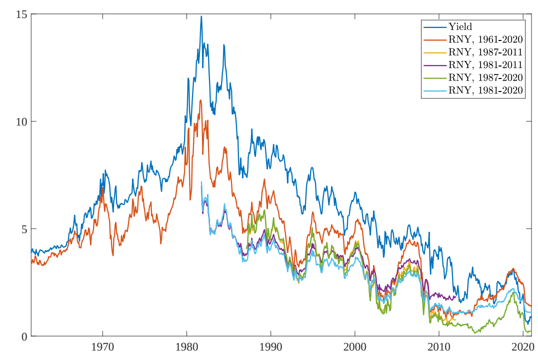
FIGURE 7

Fixed parameters or states, 10-year risk-neutral yield.

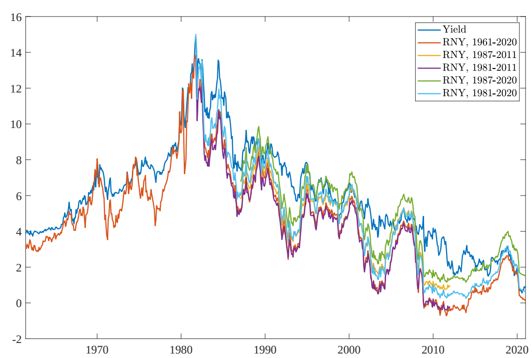
ACM: Adrian et al. (2013) fixed-endpoint model. BRW: the ACM fixed endpoint model adopting the Bauer et al. (2012) correction. ESE: shifting-endpoint model with an estimated trend. Fixed parameters: all subsamples use the parameters $\mathcal{A}^{rn}, \mathcal{B}^{rn}, \mathcal{C}^{rn}$ estimated from the 1961-2020 sample. The state variables are estimated separately for each subsample. Fixed states: compute the principal components and τ_t using the 1961-2020 sample, then take the snapshot according to the subsample periods; the yield curve parameters $\mathcal{A}^{rn}, \mathcal{B}^{rn}, \mathcal{C}^{rn}$ are estimated using each snapshot.



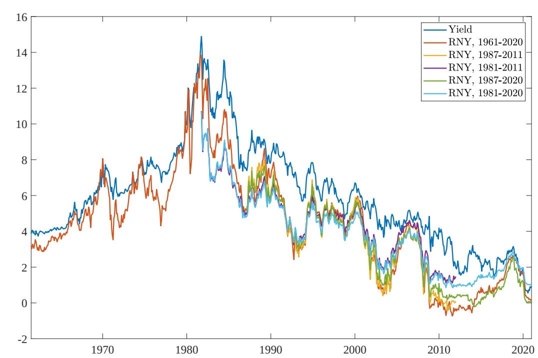
(a) **ACM, fixed parameters.**



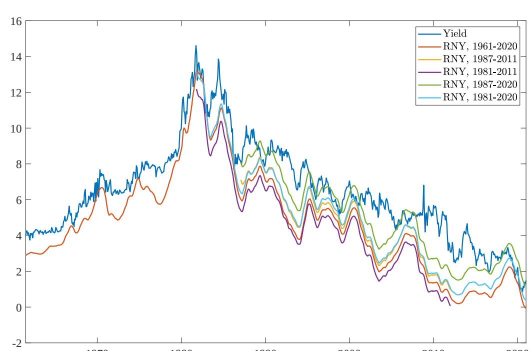
(b) **ACM, fixed states.**



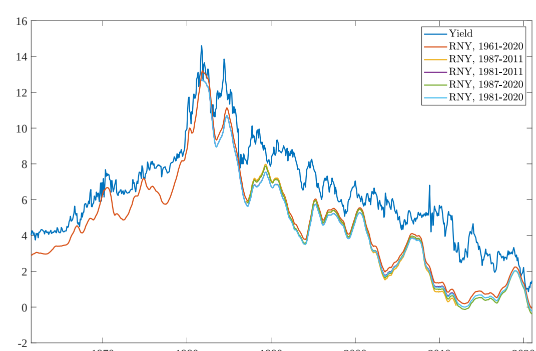
(c) **BRW, fixed parameters.**



(d) **BRW, fixed states.**



(e) **ESE, fixed parameters.**



(f) **ESE, fixed states.**

C. Monetary Policy Transmission

Finally, we investigate why the estimated effects of monetary policy shocks on FE risk-neutral yields are sensitive to the sample periods for estimating the risk-neutral yields and why the results for the OSE risk-neutral yields are more stable.

The FE model implies that the risk-neutral yields are

$$y_t^{(n)rn} = A_n^{rn} + B_n^{rn\top} X_t, \tag{25}$$

and the OSE model implies

$$y_t^{(n)rn} = A_n^{rn} + B_n^{rn\top} X_t + C_n^{rn} \tau_t, \tag{26}$$

with $A_n^{rn} = -\frac{1}{n}\mathcal{A}_n^{rn}$, $B_n^{rn} = -\frac{1}{n}\mathcal{B}_n^{rn}$, and $C_n^{rn} = -\frac{1}{n}\mathcal{C}_n^{rn}$. We investigate how the responses of X_t, τ_t and $B_{n,i}^{rn} X_{i,t}, C_n^{rn}\tau_t$ depend on the sample periods. Since the "fixed states" exercise mechanically generates identical responses of the state variables across sample periods, we jointly estimate the state variables and model parameters on each subsample, and then regress the model-implied risk-neutral yields on the high-frequency monetary policy shocks.

Table 7 reports the response of the estimated 10-year risk-neutral yield to MPS^o, the first principal component of Eurodollar shocks. Among the state variables, the level (PC1) and slope (PC2) factors are the most responsive to the monetary policy shock, and the response of the slope factor is the most sensitive to sample periods in absolute terms. In the FE model, the variation in B_n^{rn} amplifies the sensitivity of the estimated risk-neutral yields' responses to sample periods. According to the FE model, the response of $B_{10,2}^{rn} \times PC2_t$ varies by more than 100% across sample periods, and the higher order principal components times the respective B_n^{rn} vary by even more percentages. The responses of the $B_n^{rn}PC_t$ components in the OSE model are also sensitive to the sample periods, but are orders of magnitude smaller than in the FE model. Instead, the response of $C_n^{rn}\tau_t$ is large and stable, significantly reducing the variation in the risk-neutral yield across sample periods.

This decomposition clarifies why the shifting-endpoint model's results merit greater confidence: its primary driver of responses to policy shocks — the τ_t term — is stable across sample periods, ensuring robustness of the estimated policy channel. By contrast, FE's reliance on unstable PCs amplifies sample-period sensitivity, making its estimates far less reliable when long historical data are unavailable.

TABLE 7

Decomposing the 10-year RNY response to MPS^o.

The 10-year risk-neutral yield is decomposed as $y_t^{(10)rn} = A_{10}^{rn} + B_{10}^{rn} PC_t$ (FE) or $y_t^{(10)rn} = A_{10}^{rn} + B_{10}^{rn} PC_t + C_{10}^{rn} \tau_t$ (OSE). Panel I reports the responses of each PC or τ to the monetary policy shock MPS^o. Panel II reports the responses of each $B_{10}^{rn} PC_t$ or $C_{10}^{rn} \tau_t$ to MPS^o. The column label indicates the method and sample period for estimating PC, τ, A_{10}^{rn}, B_{10}^{rn} and C_{10}^{rn}. The sample period for the MPS^o regression is 1995-2011 for all columns.

	OSE 1989-2011	OSE 1989-2020	FE 1961-2020	FE 1989-2011	FE 1989-2020
	I: $\Delta PC_t = \beta_0 + \beta_1 \times MPS_t^o + \varepsilon_t$				
PC1	5.521***	5.785***	5.473***	5.521***	5.785***
se	(1.712)	(1.711)	(1.708)	(1.712)	(1.711)
PC2	3.254***	2.714***	3.358***	3.254***	2.714***
se	(0.579)	(0.586)	(0.583)	(0.579)	(0.586)
PC3	-1.574***	-1.605***	-1.483***	-1.574***	-1.605***
se	(0.383)	(0.388)	(0.388)	(0.383)	(0.388)
PC4	-0.030	-0.508**	-0.486**	-0.030	-0.508**
se	(0.194)	(0.166)	(0.174)	(0.194)	(0.166)
PC5	-0.363**	-0.155	0.005	-0.363**	-0.155
se	(0.134)	(0.150)	(0.142)	(0.134)	(0.150)
τ	0.290***	0.290**			
se	(0.084)	(0.084)			
	II: $\Delta(B^{rn} \times PC_t) = \beta_0 + \beta_1 \times MPS_t^o + \varepsilon_t$				
$B_{10,1}^{rn} \times$ PC1	0.095***	0.079***	0.203***	0.185***	0.210***
se	(0.019)	(0.016)	(0.063)	(0.057)	(0.062)
$B_{10,2}^{rn} \times$ PC2	0.005	0.042	0.259***	0.150***	0.125***
se	(0.027)	(0.028)	(0.045)	(0.027)	(0.027)
$B_{10,3}^{rn} \times$ PC3	0.062***	0.073***	-0.079***	-0.188***	-0.234***
se	(0.013)	(0.016)	(0.021)	(0.046)	(0.057)
$B_{10,4}^{rn} \times$ PC4	0.006	0.007	0.037**	0.002	0.045**
se	(0.009)	(0.005)	(0.013)	(0.011)	(0.015)
$B_{10,5}^{rn} \times$ PC5	-0.021	-0.006	0.000	0.098**	0.041
se	(0.014)	(0.006)	(0.004)	(0.036)	(0.039)
$C_{10}^{rn} \times \tau$	0.327***	0.287***			
se	(0.095)	(0.083)			

IX. International Evidence

World long-term interest rates declined steadily between 1990 and 2020. How much of the dynamics of world long-term yields can be attributed to the expectations hypothesis component? Internationally, we demonstrate that the answer to this question based on the fixed endpoint model can be sensitive to the specification of sample periods, and the shifting endpoint model can yield a much more robust answer.

A. Time Series of Risk-Neutral Rates

We focus on the domestic currency nominal sovereign yields of the G10 countries: Australia (AUD), Canada (CAD), Switzerland (CHF), Denmark (DKK), the Eurozone/Germany (EUR), the U.K. (GBP), Japan (JPY), Norway (NOK), New Zealand (NZD), and Sweden (SEK). The sovereign yield data are updated from Du et al. (2018). For most countries, the sample starts in the early 1990s. For Norway, the sample starts in 1998. For Canada and the U.K., we obtain the yield curve data from the respective central bank's website, which start earlier than the Bloomberg data. The Canadian yield curve starts in January 1986, and the U.K. yield curve starts in January 1979.

We consider the following three specifications of sample periods:

- Earliest observation - 2020.
- Earliest observation - 2011. The sample stops at the end of the Adrian et al. (2013) sample.
- 2001-2020. The sample has roughly the same length as the previous one but covers the later part of the full sample.

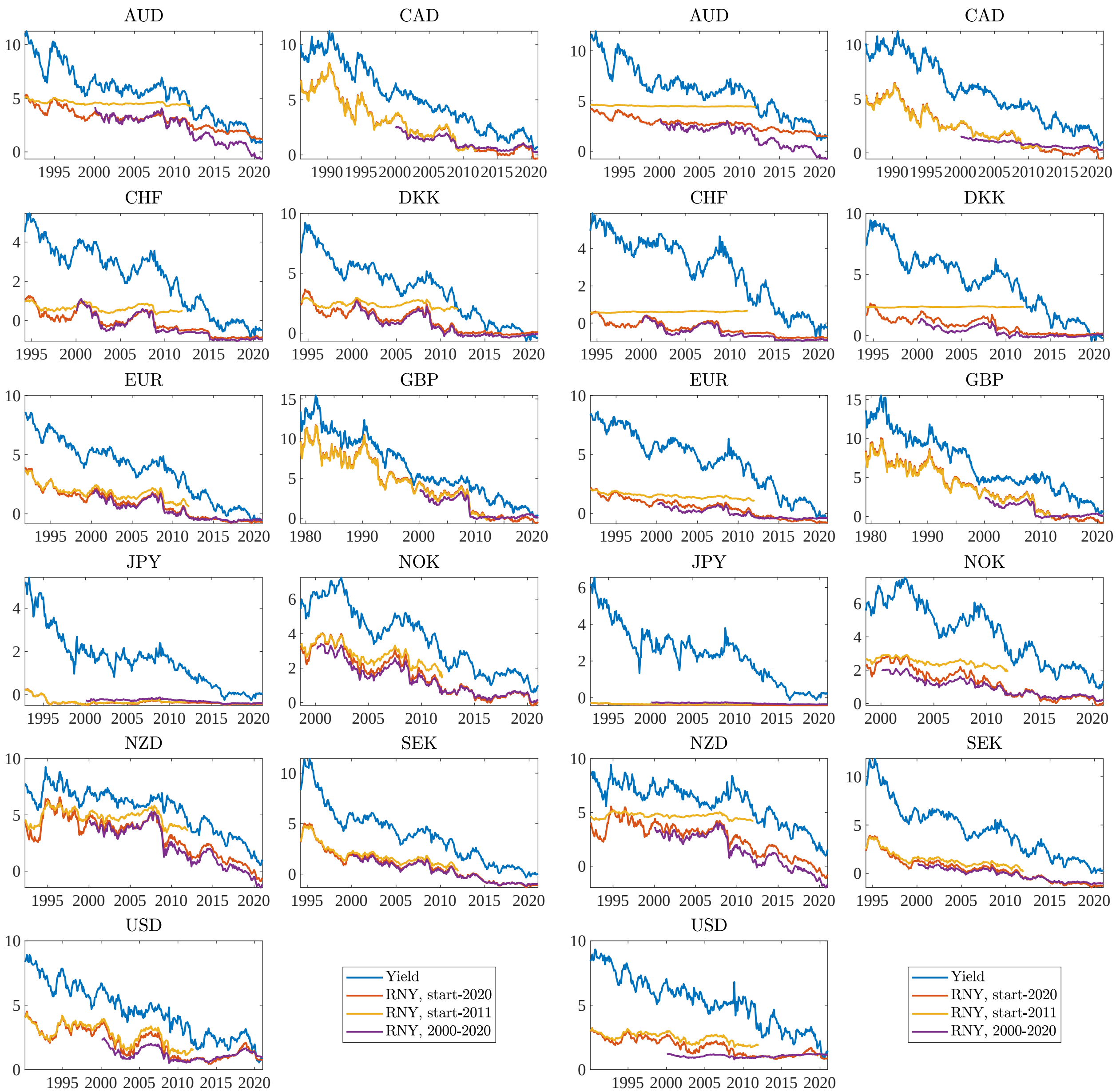
We begin by estimating the fixed endpoint model for each G10 country individually. Figure 8 presents the observed yields alongside their risk-neutral components, estimated from the fixed endpoint model using different samples. The risk-neutral rates for some countries show significantly larger discrepancies than those observed for the U.S. during the post-1990 period. For instance, the 10-year risk-neutral rates of Australia, Switzerland, and Denmark appear essentially flat when estimated using the start-2011 sample. However, when estimated using the start-2020 sample, these rates exhibit much stronger downward trends and cyclical fluctuations. The discrepancies in the 5-5 risk-neutral forward rates are even more pronounced. For example, in September 2011, the 5-5 risk-neutral forward rates estimated from the start-2011 sample and the 2000-2020 sample differ by 1.42 percentage points, which represents 266% of the latter's value. In several countries—including Australia, Switzerland, Denmark, the Eurozone, Norway, New Zealand, and Sweden—the maximum vertical difference in the 5-5 risk-neutral forward rates, when estimated using these two samples, exceeds 100% of the value derived from the 2000-2020 sample. Notably, Sweden experiences a staggering 2676% difference. In absolute terms, New Zealand has the maximum difference of 3.86 percentage points, which was recorded in December 2011.

Next, we estimate the ESE model on a country-by-country basis. Figure 9 displays the risk-neutral 10-year yield and the 5-5 forward rates estimated from different sample periods. While the ESE risk-neutral rates do not coincide perfectly across samples, they demonstrate significantly greater robustness to the specification of sample periods than the FE risk-neutral rates. Additionally, the ESE risk-neutral rates reveal stronger downward trends than their FE counterparts. In this international context, our findings align with those of Bauer and Rudebusch

FIGURE 8

FE risk-neutral yields estimated on different samples.

The risk-neutral yields are estimated country-by-country from the FE model.



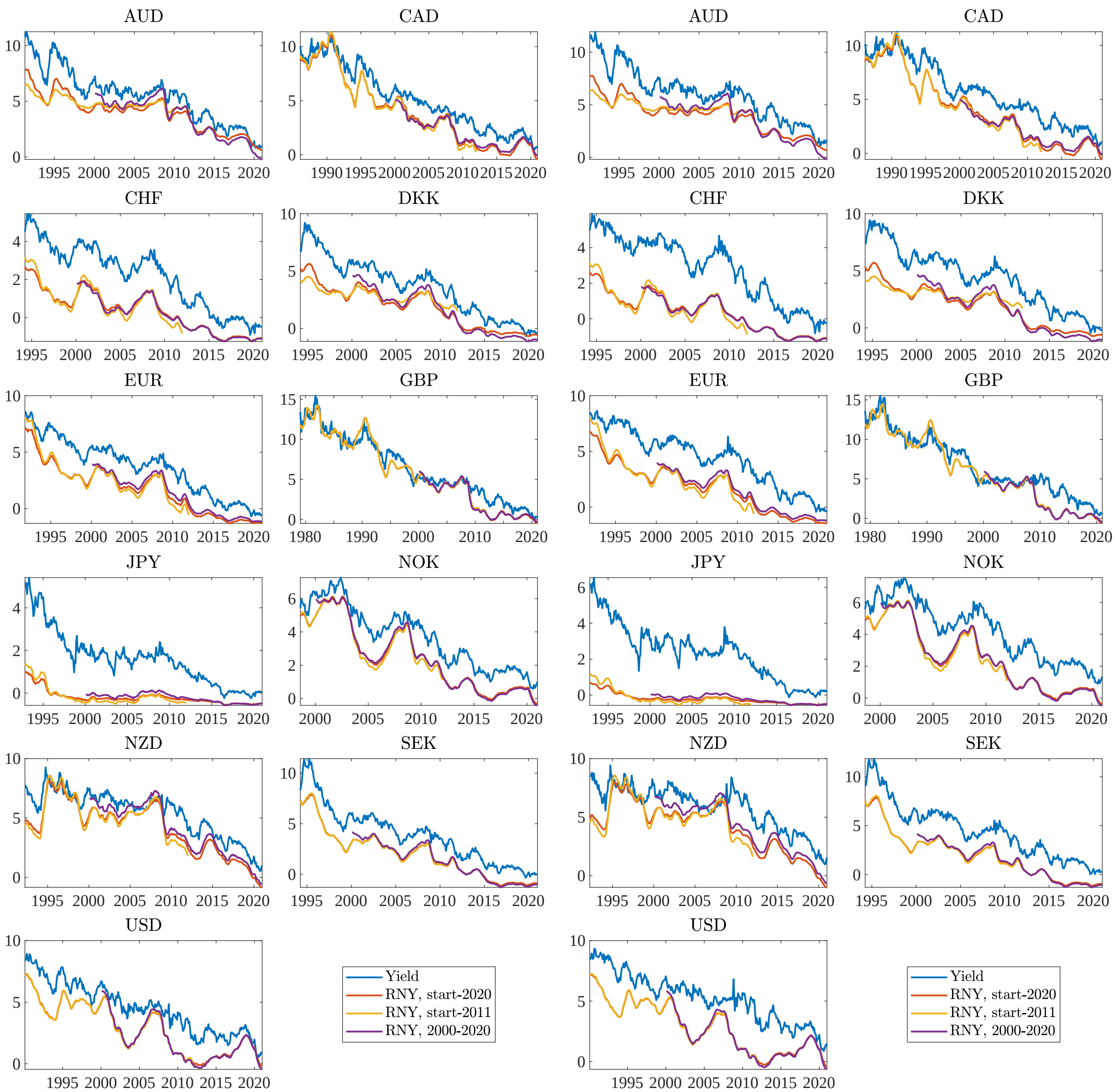
(a) **10-year yield.** (b) **5-5 forward rate.**

(2020), indicating that the shifting endpoint model attributes a larger fraction of the observed decline in long-term yields to the expectations component than the fixed endpoint model does.

FIGURE 9

ESE risk-neutral yields estimated on different samples.

The risk-neutral yields are estimated country-by-country from the ESE model.



(a) **10-year yield.** (b) **5-5 forward rate.**

B. U.S. Monetary Policy Spillover

The global financial cycle literature documents that U.S. monetary policy shocks significantly affect international long-term yields. How much of the spillover effect is attributable to interest rate expectations? We estimate the regression

$$\Delta y_{i,t} = \beta_0 + \beta_1 MPS_t^o + \varepsilon_t \tag{27}$$

for each country, where $\Delta y_{i,t}$ the daily change in a long-term yield or its risk-neutral component of country i on the FOMC announcement date, and MPS_t^o is the orthogonalized monetary policy shock from Bauer and Swanson (2022). The sample for estimating Equation (27) is 1990-2011, and we consider two alternative sample periods for estimating the FE risk-neutral rates: 1990-2020 and 1990-2011. In Section B, we present the spillover effects of other high-frequency measures of U.S. monetary policy shocks.

Table 8 reports the estimation results for the slope coefficient. We focus on the 10-year yield and the 5-5 forward rate. For each yield, the first column uses the daily change in the yield as the dependent variable, and the other columns use the daily change in the risk-neutral rate as the dependent variable. U.S. monetary policy shocks significantly affect G10 countries' 10-year yields, but the effects on the 5-5 forward rates are smaller and insignificant. The estimated responses of international FE risk-neutral rates to U.S. monetary policy shocks are not robust to the choice of sample periods, although the sample periods for estimating risk-neutral rates only differ by 9 years. For example, the estimated values of $\hat{\beta}_1$ for Switzerland and Denmark's 10-year FE risk-neutral rates differ by more than two times across the sample periods. The contrasts for the 5-5 risk-neutral forward rates are stronger, but the estimates of $\hat{\beta}_1$ are noisier.

TABLE 8

International transmission of U.S. monetary policy shock.

The table reports the slope coefficient from $\Delta y_t = \beta_0 + \beta_1 MPS_t^o + \varepsilon_t$, where Δy_t denotes the daily change in the yield or its risk-neutral component on the FOMC announcement date, and MPS_t^o denotes the orthogonalized monetary policy shock from Bauer and Swanson (2022). The regression is estimated separately for each country, and all columns are estimated on the 1990-2011 sample. The column label denotes the method and sample period for estimating the risk-neutral rate.

	10-Year Yield				5-5 Forward Rate			
	Yield	OSE	FE (1990-2020)	FE (1990-2011)	Yield	OSE	FE (1990-2020)	FE (1990-2011)
AUD	0.38***	0.53***	0.20***	0.08***	0.16	0.52***	0.08	0.01
	(0.09)	(0.10)	(0.05)	(0.02)	(0.09)	(0.10)	(0.04)	(0.01)
CAD	0.38***	0.63***	0.24***	0.23***	0.16	0.56***	0.09*	0.08**
	(0.09)	(0.11)	(0.06)	(0.05)	(0.09)	(0.10)	(0.04)	(0.03)
CHF	0.40***	0.35***	0.28***	0.12**	0.18	0.35***	0.20***	-0.00
	(0.11)	(0.08)	(0.08)	(0.04)	(0.11)	(0.07)	(0.05)	(0.01)
DKK	0.40***	0.55***	0.44***	0.17***	0.18	0.43**	0.29***	0.01
	(0.11)	(0.15)	(0.10)	(0.04)	(0.11)	(0.15)	(0.07)	(0.01)
EUR	0.38***	0.76***	0.42***	0.34***	0.16	0.64***	0.19**	0.09**
	(0.09)	(0.16)	(0.09)	(0.07)	(0.10)	(0.15)	(0.06)	(0.03)
GBP	0.38***	1.00***	0.48***	0.41***	0.16	1.03***	0.30***	0.20***
	(0.09)	(0.24)	(0.10)	(0.09)	(0.09)	(0.24)	(0.07)	(0.05)
JPY	0.42***	0.12***	0.16***	0.16***	0.22*	-0.05	0.02***	0.02***
	(0.11)	(0.03)	(0.04)	(0.04)	(0.11)	(0.03)	(0.00)	(0.00)
NOK	0.33**	0.41	0.43*	0.32*	0.13	0.33	0.26	0.12
	(0.12)	(0.28)	(0.20)	(0.15)	(0.12)	(0.30)	(0.14)	(0.06)
NZD	0.35***	1.29***	0.72***	0.43***	0.13	1.29***	0.58***	0.17***
	(0.10)	(0.36)	(0.18)	(0.11)	(0.10)	(0.37)	(0.15)	(0.04)
SEK	0.40***	0.62***	0.31**	0.23*	0.18	0.58***	0.18	0.11
	(0.11)	(0.17)	(0.11)	(0.09)	(0.11)	(0.16)	(0.10)	(0.08)

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

X. Conclusion

Risk-neutral rates estimated from canonical term structure models are not robust to the choice of sample periods. For instance, the U.S. 5-5 forward risk-neutral rate at a given date can differ by as much as 98% depending on the sample period utilized for estimation. This lack of robustness extends internationally, where canonical term structure models also produce risk-neutral rate estimates that are highly sensitive to the specified sample periods. As a result, estimates of the monetary policy transmission mechanism become unreliable.

The varying sample periods may lead monetary policy regressions using a given regression sample to different conclusions about the effects of monetary policy shocks on long-maturity yields, attributing the majority of these effects either to the responses of expected short-term rates or to changes in the term premium, depending on the chosen time period for estimating the risk-neutral rates and term premia.

The discrepancies in the estimated risk-neutral rates primarily arise from the time-varying means of the yield curve's level and slope and the persistence of the curvature and higher-order principal components. By employing a shifting endpoint term structure model that minimizes the influence of these principal components, we can mitigate this issue. Our findings using the shifting endpoint model indicate that monetary policy shocks predominantly affect long-term yields through the expectations hypothesis component. Because this conclusion is robust to the sample period used for estimation, and because the shifting-endpoint model reproduces the canonical FE(1961–2020) benchmark under ideal conditions, it provides a credible basis for inference even when researchers must work with shorter or period-specific data. This stability stems from assigning yield variation to a trend component estimated consistently across samples, rather than to sample-sensitive changes in persistent principal components.

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A. Comparing ESE Models

In the main text, the ESE method estimates the trend state τ_t using the Beveridge-Nelson decomposition. An alternative is to estimate τ_t using the Bayesian Monte Carlo method as in Bauer and Rudebusch (2020) and Del Negro et al. (2017). In this section, we show that the two methods yield similar results.

In Figure A1, we present the risk-neutral 10-year yield and 5-5 forward rate implied by the Bayesian Monte Carlo ESE model using different subsamples. The state variables and the model parameters are estimated together using data from each subsample. Like in the main text, the risk-neutral yields are consistent across subsamples. Table A1 reports the correlation between the risk-neutral yields estimated using the two methods. In all sample periods, the correlation is close to 1.

TABLE A1

Correlation between MC and BN.

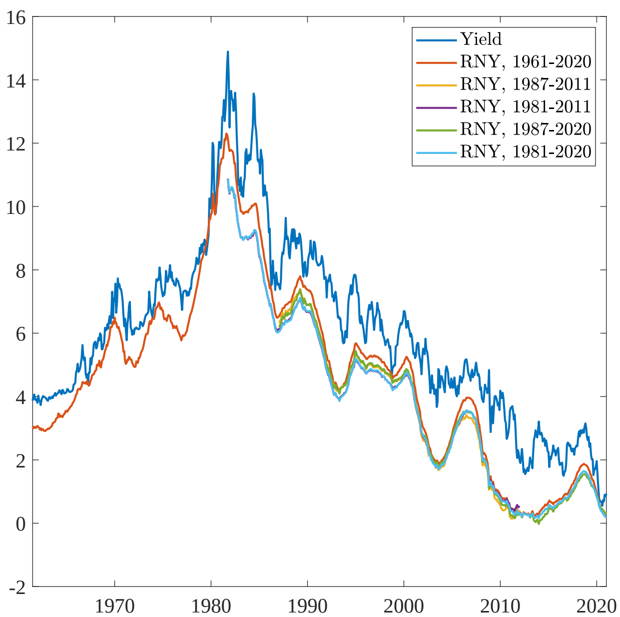
The table reports the correlation between the ESE risk-neutral yields, where the τ_t is estimated using either the Bayesian method or the Beveridge-Nelson decomposition.

	1961-2020	1987-2011	1981-2011	1987-2020	1981-2020
10-Year	0.99	0.98	0.99	0.99	0.99
5-5 Forward	0.99	0.98	0.99	0.99	0.99

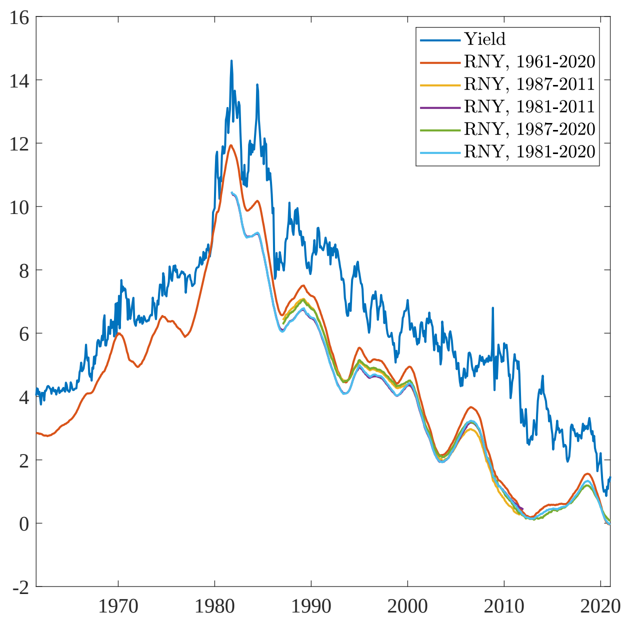
FIGURE A1

ESE risk-neutral yields estimated on different samples.

The trend τ_t is estimated using the Bayesian Monte Carlo method.



(a) **10-year yield.**



(b) **5-5 forward rate.**

B. High-Frequency Responses of G10 Yields to Other Monetary Policy Shocks

In the main text, we reported the spillover effects of MPS_t^o, the orthogonalized monetary policy shock. In this section, we report the responses of G10 yields to other high-frequency measures of U.S. monetary policy shocks. Table A2 reports the spillover effects of MPS_t, the first principal component of ED1-ED4 shocks. The regression sample period is 1990-2011. Additionally, Table A3 and Table A4 report the spillover effects of the target and path factors from Gürkaynak et al. (2005). These shocks are updated by Acosta (2023). Due to data availability, the regression sample for the target and path factor is 1995-2011.

TABLE A2

International transmission of U.S. monetary policy shock: MPS.

The table reports the slope coefficient from $\Delta y_t = \beta_0 + \beta_1 MPS_t + \varepsilon_t$, where Δy_t denotes the daily change in the yield or its risk-neutral component on the FOMC announcement date, and MPS_t denotes the first principal component of ED1-ED4 shocks. The regression is estimated separately for each country, and all columns are estimated on the 1990-2011 sample. The column label denotes the method and sample period for estimating the risk-neutral rate.

	10-Year Yield				5-5 Forward Rate			
	Yield	OSE	FE (1990-2020)	FE (1990-2011)	Yield	OSE	FE (1990-2020)	FE (1990-2011)
AUD	0.32***	0.51***	0.19***	0.08***	0.13	0.50***	0.08*	0.01
	(0.08)	(0.09)	(0.04)	(0.01)	(0.08)	(0.09)	(0.04)	(0.00)
CAD	0.33***	0.59***	0.22***	0.21***	0.13	0.52***	0.09**	0.08**
	(0.08)	(0.09)	(0.05)	(0.04)	(0.08)	(0.08)	(0.03)	(0.02)
CHF	0.33***	0.31***	0.25***	0.10*	0.14	0.32***	0.17***	-0.00
	(0.10)	(0.07)	(0.07)	(0.04)	(0.10)	(0.06)	(0.05)	(0.01)
DKK	0.33***	0.50***	0.37***	0.14***	0.14	0.40**	0.25***	0.01
	(0.10)	(0.13)	(0.09)	(0.04)	(0.10)	(0.13)	(0.06)	(0.00)
EUR	0.32***	0.70***	0.37***	0.30***	0.13	0.59***	0.17**	0.07***
	(0.08)	(0.13)	(0.07)	(0.06)	(0.09)	(0.13)	(0.05)	(0.02)
GBP	0.32***	0.93***	0.44***	0.38***	0.13	0.95***	0.27***	0.18***
	(0.08)	(0.20)	(0.08)	(0.07)	(0.08)	(0.21)	(0.06)	(0.04)
JPY	0.34***	0.10***	0.14***	0.14***	0.16	-0.05	0.02***	0.02***
	(0.10)	(0.03)	(0.04)	(0.04)	(0.10)	(0.03)	(0.00)	(0.00)
NOK	0.28**	0.46	0.43*	0.32*	0.10	0.40	0.28*	0.12*
	(0.11)	(0.24)	(0.17)	(0.13)	(0.11)	(0.26)	(0.12)	(0.05)
NZD	0.31***	1.29***	0.71***	0.42***	0.10	1.29***	0.57***	0.17***
	(0.09)	(0.31)	(0.15)	(0.09)	(0.10)	(0.32)	(0.12)	(0.04)
SEK	0.33***	0.60***	0.27*	0.20*	0.14	0.58***	0.15	0.09
	(0.10)	(0.15)	(0.10)	(0.09)	(0.10)	(0.14)	(0.09)	(0.08)

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

TABLE A3

International transmission of U.S. monetary policy shock: target factor.

The table reports the slope coefficient from $\Delta y_t = \beta_0 + \beta_1 target_t + \varepsilon_t$, where Δy_t denotes the daily change in the yield or its risk-neutral component on the FOMC announcement date, and $target_t$ denotes the Gürkaynak et al. (2005) target factor, updated by Acosta (2023). The regression is estimated separately for each country, and all columns are estimated on the 1995-2011 sample. The column label denotes the method and sample period for estimating the risk-neutral rate.

	10-Year Yield				5-5 Forward Rate			
	Yield	OSE	FE (1990-2020)	FE (1990-2011)	Yield	OSE	FE (1990-2020)	FE (1990-2011)
AUD	0.15	0.27	0.03	0.05*	-0.03	0.25	-0.06	-0.01
	(0.12)	(0.19)	(0.11)	(0.03)	(0.15)	(0.19)	(0.09)	(0.01)
CAD	0.15	0.45***	0.12	0.12	-0.03	0.38**	0.03	0.03
	(0.12)	(0.13)	(0.09)	(0.07)	(0.15)	(0.12)	(0.06)	(0.04)
CHF	0.15	0.30***	0.19*	0.13**	-0.03	0.25***	0.12	0.01
	(0.12)	(0.07)	(0.09)	(0.05)	(0.15)	(0.07)	(0.06)	(0.01)
DKK	0.15	0.30	0.33**	0.15**	-0.03	0.14	0.18*	0.01
	(0.12)	(0.24)	(0.11)	(0.04)	(0.15)	(0.23)	(0.08)	(0.01)
EUR	0.15	0.49	0.16	0.14	-0.03	0.37	-0.01	-0.01
	(0.12)	(0.27)	(0.13)	(0.09)	(0.15)	(0.28)	(0.10)	(0.04)
GBP	0.15	0.61	0.19	0.17	-0.03	0.59	0.05	0.03
	(0.12)	(0.40)	(0.16)	(0.14)	(0.15)	(0.42)	(0.12)	(0.08)
JPY	0.16	0.16***	0.16***	0.17***	0.00	0.02	0.01	0.01*
	(0.12)	(0.03)	(0.04)	(0.04)	(0.15)	(0.05)	(0.01)	(0.00)
NOK	0.06	0.06	-0.11	-0.07	-0.09	-0.04	-0.15	-0.07
	(0.15)	(0.44)	(0.32)	(0.23)	(0.18)	(0.48)	(0.23)	(0.10)
NZD	0.15	0.59	0.36	0.31**	-0.03	0.53	0.19	0.09*
	(0.12)	(0.47)	(0.20)	(0.09)	(0.15)	(0.50)	(0.19)	(0.04)
SEK	0.15	0.34	-0.01	-0.03	-0.03	0.33	-0.11	-0.11
	(0.12)	(0.26)	(0.16)	(0.13)	(0.15)	(0.25)	(0.14)	(0.11)

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

TABLE A4

International transmission of U.S. monetary policy shock: path factor.

The table reports the slope coefficient from $\Delta y_t = \beta_0 + \beta_1 path_t + \varepsilon_t$, where Δy_t denotes the daily change in the yield or its risk-neutral component on the FOMC announcement date, and $path_t$ denotes the Gürkaynak et al. (2005) path factor, updated by Acosta (2023). The regression is estimated separately for each country, and all columns are estimated on the 1995-2011 sample. The column label denotes the method and sample period for estimating the risk-neutral rate.

	10-Year Yield				5-5 Forward Rate			
	Yield	OSE	FE (1990-2020)	FE (1990-2011)	Yield	OSE	FE (1990-2020)	FE (1990-2011)
AUD	0.42***	0.62***	0.25***	0.09***	0.25*	0.63***	0.13**	0.01
	(0.08)	(0.11)	(0.06)	(0.02)	(0.10)	(0.11)	(0.05)	(0.01)
CAD	0.42***	0.64***	0.34***	0.30***	0.25*	0.56***	0.16***	0.13***
	(0.08)	(0.07)	(0.05)	(0.04)	(0.10)	(0.07)	(0.03)	(0.02)
CHF	0.42***	0.33***	0.31***	0.11***	0.25*	0.35***	0.21***	-0.01
	(0.08)	(0.05)	(0.05)	(0.03)	(0.10)	(0.04)	(0.03)	(0.01)
DKK	0.42***	0.72***	0.47***	0.17***	0.25*	0.60***	0.32***	0.01*
	(0.08)	(0.14)	(0.07)	(0.03)	(0.10)	(0.13)	(0.05)	(0.01)
EUR	0.42***	0.83***	0.44***	0.33***	0.25*	0.78***	0.26***	0.11***
	(0.08)	(0.14)	(0.07)	(0.05)	(0.10)	(0.15)	(0.05)	(0.02)
GBP	0.42***	1.28***	0.55***	0.45***	0.25*	1.34***	0.36***	0.23***
	(0.08)	(0.21)	(0.09)	(0.07)	(0.10)	(0.23)	(0.07)	(0.04)
JPY	0.42***	0.08***	0.14***	0.14***	0.23*	-0.12***	0.02***	0.02***
	(0.09)	(0.02)	(0.02)	(0.02)	(0.10)	(0.03)	(0.00)	(0.00)
NOK	0.42***	0.63**	0.71***	0.53***	0.25*	0.61**	0.50***	0.22***
	(0.09)	(0.21)	(0.15)	(0.11)	(0.11)	(0.23)	(0.11)	(0.05)
NZD	0.42***	1.45***	0.74***	0.40***	0.25*	1.49***	0.64***	0.17***
	(0.08)	(0.28)	(0.12)	(0.06)	(0.10)	(0.29)	(0.11)	(0.02)
SEK	0.42***	0.78***	0.41***	0.32***	0.25*	0.74***	0.28***	0.19**
	(0.08)	(0.14)	(0.09)	(0.08)	(0.10)	(0.14)	(0.08)	(0.07)

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$