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Can Fiscal, AI, or Monetary News Explain the Rise in r^*?

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Abstract

Following decades of secular decline, many estimates of r^*—the natural or steady-state short-term real interest rate—have risen roughly 1 percentage point since 2020 in the United States. The most prominent explanations attribute this reversal to heightened expectations of rising government debt and faster productivity growth from artificial intelligence (AI). However, a high-frequency event study finds that news about fiscal and AI developments does not explain this increase. Furthermore, contrary to earlier evidence that persistent shifts in longer-term yields occurred around monetary policy meetings, we find that monetary policy news does not account for the recent rise in r^*.

JEL Classification: C32, E43, E52, G12

Keywords: r-star, fiscal policy, artificial intelligence, monetary policy

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1 Introduction

The general level of interest rates gradually fell for several decades prior to the COVID-19 pandemic. In the 1980s and 1990s, a drop in inflation expectations was the primary driver of this decline, while in the 2000s and 2010s, falling interest rates generally reflected a decline in the natural or neutral real rate of interest, commonly labeled r_t^*—the short-term real rate of return that would prevail in the absence of transitory disturbances.[1] However, a surge in nominal and real interest rates during the first half of the 2020s has apparently reversed this trend. To help account for this reversal in yields, some economists have argued that r_t^* has moved higher in recent years as new factors—such as expectations of a significant expansion of projected fiscal deficits and AI-driven productivity growth—likely altered the underlying saving and investment motives.[2] Understanding the source of any such a change is crucial for assessing its broader implications. Indeed, the economic and financial importance of such a shift in the equilibrium real rate can hardly be overstated, as r_t^* provides a crucial benchmark for fiscal and monetary policymakers and for investors more generally. However, investigating a potential upturn in the natural rate since 2020 with conventional macroeconomic methods is very much constrained by the short sample that is available. Instead, this paper provides novel evidence on this issue using a high-frequency event study that assesses the relative importance of potential drivers of daily finance-based measures of r_t^* estimated from dynamic term structure models.

Much of the decades-long pre-pandemic decline in the equilibrium real interest rate is attributed to trending factors that have tended to increase savings or reduce desired investment, including lower productivity growth, aging demographics, declines in the price of capital goods, and strong precautionary saving flows from emerging market economies (e.g., Rachel and Smith (2015), Laubach and Williams (2016), and Del Negro et al. (2017)). In a comprehensive general equilibrium analysis that endogenizes global saving and investment flows, Rachel (2025) quantifies many of the structural changes that have gradually lowered r_t^* since 1990 including lower productivity and population growth and longer retirements. He also highlights two forces that may partially reverse this downtrend and act to push r_t^* higher in the current decade and beyond. The first of these is a worldwide surge in government debt levels relative to GDP that could raise longer-term real interest rates. Such a continuing surge may reflect an unwillingness in advanced economies to raise taxes to account for an aging demographic structure or higher military spending. A second factor identified by Rachel (2025) as potentially boosting the equilibrium interest rate is an AI-generated productivity boom, as a jump in productivity growth driven by exponential advances in AI significantly

[1] On the secular decline in real interest rates and r_t^*, see Rachel and Smith (2015), Laubach and Williams (2016), Christensen and Rudebusch (2019), Bauer and Rudebusch (2020), Obstfeld (2025), and many others.

[2] For example, Benigno et al. (2024), Rachel (2025), and others.

boosts capital demand.[3]

The extent to which any of these factors may be pushing the natural rate of interest higher has been much debated by financial investors and policymakers. For example, in a recent speech, Federal Reserve Governor Waller (2024) described how the natural rate reflects fiscal policy and other factors affecting the balance of aggregate saving and investment. He warned that the United States is on an unsustainable fiscal path and that large budget deficits will put upward pressure on r_t^*. By contrast, as a Federal Reserve Governor, Miran (2025a) argued that recent fiscal policy, such as increased tariffs, was putting strong downward pressure on the natural rate.

Similarly, the potential implications of AI for r_t^* and the level of interest rates more broadly have also been debated by Federal Reserve policymakers.[4] In a recent speech, Federal Reserve Governor Barr (2026) noted that AI was likely to give a long-lasting boost to productivity and the demand for capital, and as a result, r_t^* would increase:

> [D]emand for capital would rise because of the strong business investment required to take advantage of the [AI] technology, putting upward pressures on interest rates, and household savings could fall due to expectations of stronger real wage growth and thus higher lifetime earnings, also putting upward pressure on interest rates. All of this would imply a higher setting for the policy rate when the economy is at equilibrium, or what monetary economists call r*. Indeed, last year I raised my long-term estimate of r* modestly because of higher productivity.

This argument mirrors that of Rachel (2025) and other economists. A strikingly different perspective has been offered by Miran (2025b) and by Kevin Warsh, the current Fed Chair. Each contends that because AI is such a powerful productivity enhancer, it exerts downward pressure on production costs and inflation regardless of the level of aggregate demand. As Warsh described it, the AI technology would be "structurally disinflationary" (Smith and Casselman (2026)). In the Miran-Warsh view, the continuing vast expansion of the economy's productive capacity allows the Federal Reserve to maintain an easier stance of monetary policy with lower real interest rates for some time without risk of overheating, which effectively implies a lower longer-run r_t^* benchmark for real interest rates.

Because only six years have passed since interest rates started to reverse and move higher, it is very difficult to disentangle interest rate trend from cycle. The short sample of available macroeconomic data is too limited to obtain much certainty about shifts in quarterly estimates of the natural rate of interest from macroeconomic models. Across these models, there is always a wide range of r_t^* estimates as well as a high degree of uncertainty around any

[3] Chow, Halperin, Mazlish (2026) argue that whether advanced AI leads to rapid economic growth or poses a rogue existential risk to humanity, either possibility would increase long-term real interest rates through consumption smoothing.

[4] This issue has also been of interest to central bankers worldwide, for example, Bank for International Settlements (2026).

individual estimate (e.g., Benigno et al. (2024)). Instead, we use an event study to leverage high-frequency financial data, which incorporate forward-looking information from investors, to assess what can account for recent movements in r_t^*.

We examine the impact of AI and fiscal policy news on r_t^* by adopting a high-frequency identification approach similar to the event studies commonly used in empirical monetary economics to identify the effects of monetary policy on asset prices (e.g., Gürkaynak et al. (2005) and Bauer and Swanson (2023)). There are four important elements to implement our strategy: a set of fiscal policy news dates, a set of AI innovation dates, high-frequency estimates of r_t^*, and a cumulative-effect methodology that can uncover the importance of recent news as drivers of the rising equilibrium rate. To obtain these elements, we draw on four different strands of the research literature.

Regarding fiscal policy, various studies have applied the event-study logic to fiscal policy news. Most recently, Wiegand (2025) and Gomez-Cram, Kung, and Lustig (2025) construct deficit news measures from Congressional actions and use event studies to examine the transmission of fiscal shocks to Treasury yields and equity prices. We rely on this work to help identify the dates of events that convey new information to investors about future federal fiscal deficits, but we also include a larger set of news events—policy announcements, election results, etc.—as employed in many analyses of fiscal policy of a more narrative style (e.g., Romer and Romer (2010), Devries et al. (2011), Ramey and Zubairy (2018), and Bauer, Offner, and Rudebusch (2026)).

In a second strand of the literature, event studies have also been used to assess the response of financial market investors to news about the pace of AI innovation. For this purpose, we follow Andrews and Farboodi (2026) and Björkegren (2026), who show that U.S. bond yields fall around the release dates of updates to the most important generative AI models. We examine these release dates for the effect of AI news on finance-based measures of r_t^*.

A third strand of literature provides the high-frequency finance-based r_t^* measures that serve as the dependent variables in our analysis. The four measures employed for this purpose are constructed by Christensen, Lopez, and Rudebusch (2010), D'Amico, Kim, and Wei (2018), and Christensen and Rudebusch (2019), all of which use dynamic term structure models and daily data on prices of U.S. Treasury Inflation-Protected Securities (TIPS), which have coupon and principal payments that adjust for changes in the consumer price level. These dynamic term structure models estimate a market-based expected path of real short rates far into the future, purged of term—and in some cases also liquidity—premiums. The average expected real short rate 5-to-10-years ahead is used as a measure of r_t^*—the real rate consistent with the economy operating at potential once transitory economic shocks have abated. These approaches build on the broader arbitrage-free term structure literature and share the advantage of being available at daily frequency, enabling the high-frequency identification strategy pursued here. They differ substantially in model size and specification, including the treatment of expectations and liquidity premiums, so using all four of these measures provides a useful robustness check.

Finally, in terms of methodology, we follow Hillenbrand (2025) and investigate the cumulative effect of news on yields. Hillenbrand (2025) is focused on monetary policy news and shows that limiting attention to the yield movements during 3-day windows around the monetary policy meetings of the Federal Reserve's Federal Open Market Committee (FOMC) can capture essentially all of the secular decline in long-term interest rates before the pandemic. We use that same methodology of accumulating yield changes within 3-day event windows to assess whether fiscal policy and AI developments can account for an upward shift in r_t^* starting in 2020. This methodology differs from many earlier event studies that examine the impact of quantitatively estimated news shocks on bond yields. Our focus is not on the average effect of surprises on bond yields; instead, we assess the overall cumulative effect of news on r_t^* to determine whether fiscal and AI developments could account for the rise in the natural rate during the first half of this decade.

One potential caveat to these results is that Hillenbrand (2025) suggests that bond investors coordinate their response to new information so that yields respond to all news during the short windows around FOMC meetings. Given that the real economic effects of monetary policy do not appear to last long (i.e., long-run monetary neutrality), this is not a causal impact. However, Fed guidance about the long-run level of interest rates could lead investors to update their expectations of the future path of short rates as FOMC meetings focus investors' attention on longer-run trends that are caused by economic forces outside the Fed's control. If so, the responses of bond investors to fiscal and AI news could be concentrated around FOMC meetings rather than on the fiscal and AI news dates. We investigate this potential mechanism for information transmission by examining r_t^* movements during 3-day windows around FOMC meetings.[5]

Surprisingly, given that economists and policymakers have highlighted the potential effect of fiscal and AI developments on r_t^*, our empirical results provide no robust evidence that either of these factors account for much of the recent rise in the natural rate of interest in the United States. Indeed, the windows around AI news registered significant *declines* in the four estimates of r_t^* ranging from 23 to 35 basis points (bp) during the first half of this decade. Fiscal policy news had a small positive effect on the r_t^* estimates, accounting for about 20% of the overall increase so far in this decade (although given our generous fiscal event selection, this estimate is likely toward the upper end).

As for monetary policy, Hillenbrand (2025) found that FOMC windows can capture es-

[5]Thus, we differentiate the effects of fiscal policy and AI news, which can have causal long-term real economic effects, from monetary policy news, which arguably does not.

sentially all of the secular decline in long-term interest rates before the pandemic, and we provide new evidence that this result also holds true for all four estimates of r_t^* *before* 2020. Unfortunately, both of these empirical regularities fail in the 2020s. Cumulative interest rate changes around FOMC meetings post-2020 capture none of the overall movements in long-term yields or in the r_t^* estimates. Indeed, the FOMC event windows display a modest trend toward a lower r_t^*, which only deepens the mystery about the source of the recent rise in the natural rate.

In sum, the three event types—fiscal, AI, or monetary news—provide little support for the higher real interest rates evident in recent years. This null result may reflect empirical limitations, such as a short sample, event misclassification, or imprecise r_t^* measures. However, taken at face value, the results suggest that the rise in real interest rates, and particularly the natural rate of interest, in this decade is a puzzle. This is especially true given that some long-standing demographic and other secular forces appear to be continuing to weigh down on real interest rates.

The remainder of the paper is organized as follows. Section 2 describes the fall and rise of various measures of r_t^* over the past two decades. Section 3 gives the chronologies of fiscal policy and AI innovation events. Section 4 analyzes the cumulative change in yields during these events, while Section 5 provides a complementary investigation for FOMC meetings. Section 6 concludes.

2 The Fall and Rise of r_t^*

For fiscal policymakers, the natural rate of interest is a crucial input for understanding debt sustainability; for central bankers, it is a key benchmark that delineates expansionary from contractionary monetary policy; for investors, it is an anchor for future discount rates (e.g., Bauer and Rudebusch (2023)). This widespread importance has spurred much research employing a wide variety of methods to estimate r_t^*. This section provides an overview of the fall and recent rise in the natural rate based on professional forecaster and policymaker surveys as well as macroeconomic and term structure models. Figure 1 shows these estimates from 2007 to 2025—a sufficient sample to illustrate the recent change in direction of the trajectory of r_t^* estimates.[6]

The most straightforward assessments of r_t^* are available from surveys of economic forecasters and Federal Reserve policymakers. The blue line in Figure 1 is based on the semiannual Blue Chip survey of professional forecasters. This measure is constructed by simply subtracting the average projection for inflation in the consumer price index (CPI) from the projection for the federal funds rate for the five-year period about five years ahead. This survey mea-

[6]For a longer sample, see Del Negro, Elbarmi, and Pham (2026).

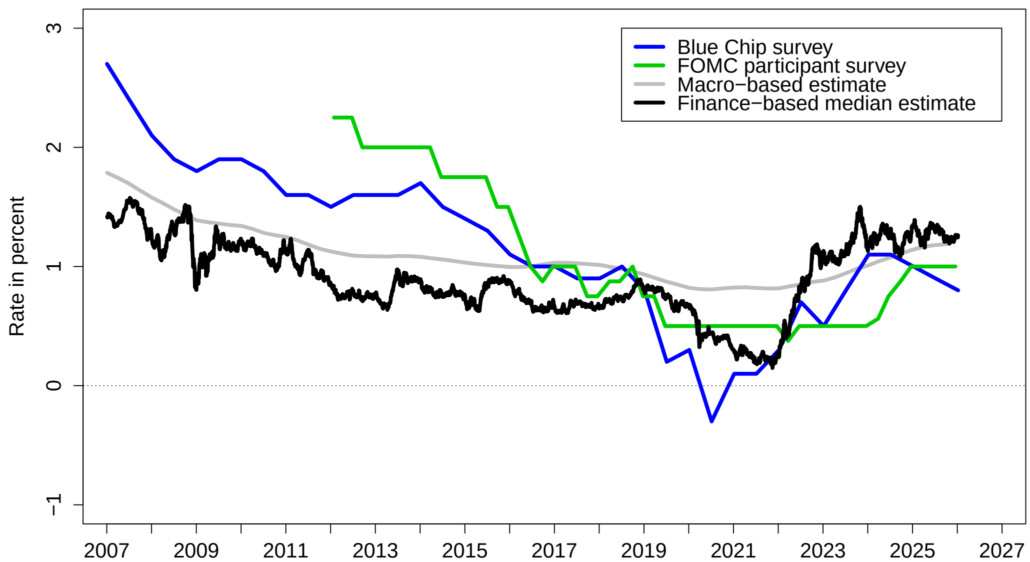


Figure 1: Fall and Rise of U.S. Estimates of r_t^*, 2007–2025
Estimates of r_t^* for the U.S. include the average from the Blue Chip professional forecaster survey, the median SEP assessment by FOMC participants, the macro model based estimate from Del Negro et al. (2017), and the median estimate across four finance models (CLR, DKW, CR-TO, and CR-TOL).

sure of r_t^* shows a long pre-pandemic decline of just over 2 percentage points followed by a 1 percentage point reversal from a 2020 trough through 2025. A very similar fall and rise is obtained from the median long-run forecasts provided in the Summary of Economic Projections (SEP) of FOMC participants. After the conclusion of about half of the policy meetings since January 2012, the FOMC has released longer-run forecasts for inflation and nominal short-term interest rates in an SEP, and differences in these forecasts are widely construed as an estimate of r_t^*. The path over time of the median such r_t^* estimate is shown as the green line in Figure 1. This FOMC estimate of the steady-state real interest rate fell before 2020, but in recent years, it has also risen decidedly.

To complement survey forecasts, many researchers have used macroeconomic models and data to obtain estimates of the natural rate of interest. As in Laubach and Williams (2016), these macro-based r_t^* estimates are typically defined as the level of the real interest rate expected to prevail, say, five to 10 years in the future, after the economy has emerged from any cyclical fluctuations. This perspective is employed in many studies and is consistent with the survey estimates and finance model estimates. For example, Del Negro et al. (2017) use a flexible vector autoregression (VAR) with common trends to extract the permanent component of the real interest rate from data on nominal bond returns, inflation, and long-run survey expectations. Their median r_t^* estimate (a two-sided filtered version) is shown as the gray line in Figure 1. The pre-pandemic decline and subsequent rise in this macro-based estimate of r_t^* is broadly similar to the survey estimates though less pronounced in its movements. Several other macro-based estimates show a similar fall and rise; however, there is considerable model uncertainty surrounding these measures regarding the specification of output and inflation dynamics, omitted variables, and structural shifts during the sample (e.g., Cho and Williams (2025)). It is challenging to infer the natural rate from simple models of output and inflation since 2020 given the recent sequence of supply shocks to prices and trade and other extraordinary conditions. However, Del Negro, Elbarmi, and Pham (2026) find that the recent rise in r_t^* in the U.S. of a little more than 1 percentage point is statistically significant.

A final method to estimate r_t^* uses term structure models and financial market data under the assumption that the longer-term expectations embedded in bond prices reflect financial market participants' views about the steady state of the economy, including the equilibrium interest rate. For an event study, such term structure-based measures have a crucial advantage relative to macro-based and survey estimates: they can produce r_t^* estimates on a daily basis. This characteristic is essential for assessing the importance of fiscal policy, AI, and monetary policy news in a high-frequency analysis of the impact of such new information. In addition, finance-based estimates naturally take a real-time perspective (as originally defined by Diebold and Rudebusch (1991)) by creating r_t^* estimates based on the information available at each point in time. The use of the available contemporaneous information sets is especially relevant for the types of financial market event studies considered below.[7]

Although the use of real yields—for example, the five-year five-year-forward real yield—provides a simple first approximation for measuring the steady-state real interest rate, their use is greatly complicated by the presence of time-varying term and liquidity premiums. Term structure models are able to mitigate these complications, and the resulting expected real short rate after accounting for term and potentially liquidity premiums—specifically, the average over a five-year period starting five years ahead—will be the finance model-based measure of the natural rate of interest. Of course, model uncertainty remains a serious challenge, and to help ensure the robustness of our results, we consider r_t^* estimates from four different arbitrage-free dynamic term structure models.

The oldest term structure specification we employ is taken from Christensen, Lopez, and Rudebusch (2010), henceforth CLR, who jointly model nominal and real Treasury yields and account for real term premiums but not any liquidity premiums. The resulting expected real short rate without term premiums is the CLR market-based measure of the natural rate of

[7]Macro-based analyses often use extensively revised output and inflation data to create equilibrium real rate estimates that would not have been available historically.

interest. The original CLR model was estimated on nominal yields from January 1995 and real TIPS yields from January 2003. We maintain the same model structure, but update the end of the estimation sample to the end of 2025.

The second source for daily estimates of r_t^* is the arbitrage-free dynamic term structure model of D'Amico et al. (2018), henceforth DKW (see also Kim, Walsh, and Wei (2019) for discussion and data). The DKW model estimation uses nominal and TIPS yields as well as monthly data on inflation and on expected inflation and short-term nominal interest rates from surveys of professional forecasters. The estimation sample starts in January 1983. Along with differences in scope of the data employed, the DKW model differs from the CLR model by accounting for both real term and liquidity premiums in its structure.

Importantly, the CLR and DKW joint specifications require specifying multiple pricing factors, an inflation risk premium, and inflation expectations, and these elements raise the risk of model misspecification. If the inflation components are misspecified, the entire dynamic term structure specification may be compromised. This concern is heightened during periods of structural change and transition, for example, during the pandemic and post-pandemic periods which encountered highly unusual inflationary shocks. The question of misspecification could also be an issue when the overnight federal funds rate was constrained by the zero lower bound as this led to asymmetric yield behaviors unaccounted for by the two models; see Christensen and Rudebusch (2016).

To try to overcome these empirical challenges, Christensen and Rudebusch (2019), henceforth CR, estimate r_t^* solely from the prices of TIPS using an arbitrage-free dynamic term structure model. By using only TIPS prices and not nominal bonds, this method can avoid many of the misspecification issues discussed above. CR estimate two versions of their model with and without a time-varying liquidity adjustment to TIPS prices. The specification without a liquidity adjustment, the TO (or TIPS-only) model accounts only for the real term premium in TIPS yields and has no additional structural assumptions about nominal yields or inflation. A more elaborate specification, referred to as the TOL (TIPS-only with liquidity adjustment) model, accounts for both real term and liquidity premiums in TIPS yields.[8]

The black line in Figure 1 shows the median of the four finance-based r_t^* estimates since 2007. Over the past 20 years, the median captures well the general contour of movements in these four measures, which show a similar trajectory of decline and subsequent rise. From 2007 to its low in 2021, the median fell more than 1 percentage point. Since then, it has risen by a bit more than a percentage point through the end of 2025.

[8] The estimation methodology of the TO and TOL models also differs substantially from the other two term structure models. The CLR and DKW models—like almost all such models—are estimated from synthetic yields obtained from interpolated zero-coupon yield curves, which may introduce measurement error (e.g., Andreasen, Christensen, and Rudebusch (2019)). Instead, the TO and TOL models are estimated directly from the prices of individual TIPS. (Up-to-date details on the estimation of the TO and TOL models are available from the authors in a supplemental appendix.)

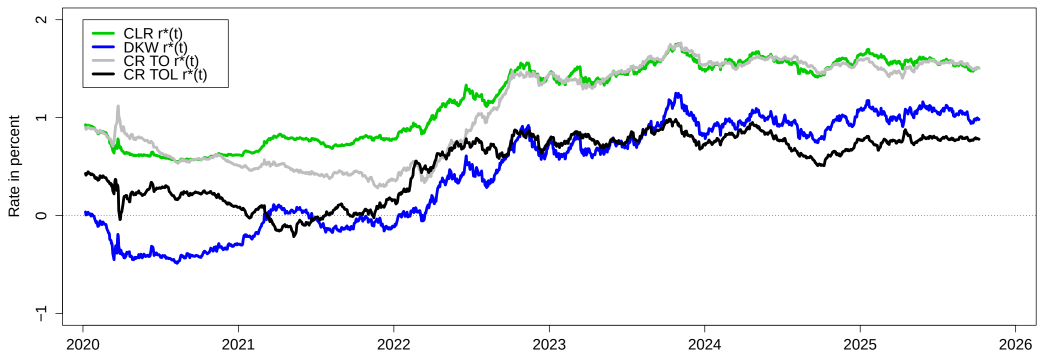


Figure 2: Four Finance Model r_t^* Estimates Since 2020
Estimates of r_t^* from four different arbitrage-free dynamic term structure models from January 2, 2020 to September 30, 2025.

Figure 2 provides recent detail on the individual estimates of r_t^* from the four finance models. The estimates are all obtained from underlying arbitrage-free dynamic term structure models, but differences across the specifications result in different levels and daily changes in the associated r_t^*. The estimates have a consistent range of dispersion of about a percentage point, and there are notable differences in the high-frequency fluctuations. However, there is general agreement regarding the overall trajectory. All four r_t^* estimates show about a percentage point increase from their lows in 2020 or 2021 to their levels in 2025.

In sum, a variety of estimates obtained from different methodologies show a long decline in r_t^* followed by a partial reversal in this decade. The finance-based estimates are consistent with macro and survey measures, which supports their use in the event study below.

3 Recent Fiscal and AI News Events

In this section, we provide chronologies of fiscal policy and AI innovation news. These dates will be used in the subsequent high-frequency event study of shifts in r_t^* since 2020.

3.1 Fiscal Policy Events

There is a rich literature assessing the financial market impacts of macroeconomic policy announcements. In the case of monetary policy, many researchers have exploited narrow windows around scheduled meetings to identify policy surprises, although these investigations have expanded to include central bank press conferences, speeches, and testimony (e.g., Bauer and Swanson (2023)). The analogous exercise for fiscal policy is more difficult given the convoluted gestation of most budgetary legislation. In the United States, major revenue and spending initiatives typically evolve over many months, passing through initial announcements, committee markups, floor amendments, conference negotiations, and executive action before becoming law.[9] At each step in this process—marked by both formal and impromptu news releases—financial market participants may acquire information about the probability and timing of enactment and the size of the fiscal effect.

To address the daunting challenge of identifying fiscal news events, we employ two complementary strategies in the literature. One strand of research has focused on identification of fiscal news from official releases of budget forecasts. For example, early on, Laubach (2009) used successive official federal budget projections to show that a one-percentage-point increase in the projected deficit-to-GDP ratio raises long-term real interest rates by roughly 25 bp. Similarly, Gomez-Cram, Kung, and Lustig (2025) identify fiscal news events on dates when the CBO releases formal cost estimates of proposed legislation, and Wiegand (2025) constructs a fiscal shock series using budget resolution and reconciliation markup dates. However, this identification strategy excludes fiscal events outside the standard legislative process. Notably, key political events can convey significant new information about future deficits and important fiscal news. For example, Bauer, Offner, and Rudebusch (2026) identify the impact on financial markets of two abrupt shifts in the likelihood of passage of the Inflation Reduction Act of 2022 (IRA) driven solely by press reports.[10] Similarly, Bhatt et al. (2026) estimate the effect of debt on interest rates based on the expected fiscal policy shifts driven by the January 5, 2021 Georgia Senate runoff. Therefore, to account for a larger set of fiscal events, we also include the dates of many political news releases—deal announcements, surprising floor votes, election results, and public statements by key legislative actors. This strategy is more in line with the many narrative analyses of fiscal policy (e.g., Romer and Romer (2010), Devries et al. (2011), and Ramey and Zubairy (2018)).

Selecting a set of fiscal policy events balances two risks. Including too many events raises the possibility of contamination by confounding contemporaneous news about other non-fiscal macroeconomic or financial developments. By contrast, a parsimonious selection may only partially capture the fiscal policy news conveyed to asset prices. Given our substantive focus on assessing the cumulative effect of fiscal news on finance-based measures of r_t^* over the whole post-pandemic period rather than estimating the average effect of fiscal surprises on the level of yields as in many earlier studies, we cast a fairly broad net for fiscal events. As a result, our estimates are unlikely to be conservative and may overestimate the total cumulative fiscal effect on interest rates during this period.

[9] For example, passage of the One Big Beautiful Bill Act (OBBBA) involved 140 Congressional actions including 47 House or Senate roll call votes: `https://www.congress.gov/bill/119th-congress/house-bill/1/all-actions`).

[10] The IRA represented the largest climate policy action ever undertaken in the United States. Although Senator Joe Manchin of West Virginia had earlier announced staunch opposition, late on July 27, 2022, news broke that he had reached a surprise agreement with Democratic leaders and passage was assured.

Table 1: **Chronology of Major U.S. Fiscal Policy Events, 2020–2025**

Date	**Event Description**
04/02/2020	CBO cost est.: Families First Act
04/16/2020	CBO cost est.: CARES Act
04/22/2020	CBO cost est.: PPP Act
06/01/2020	CBO cost est.: HEROES Act (H.R. 6800)
06/30/2020	CBO cost est.: Moving Forward Act
07/01/2020	CBO cost est.: NDAA FY2021 (Senate)
07/16/2020	CBO cost est.: Great American Outdoors & NDAA FY2021
07/17/2020	CBO cost est.: Child Care is Essential Act
10/16/2020	CBO cost est.: HEROES Act (H.R. 925)
10/21/2020	CBO cost est.: Delivering Immediate Relief Act
12/21/2020	FY2021 stimulus/budget text
12/22/2020	CBO cost est.: Appropriations Act (Division M)
01/05/2021	Georgia runoff confirms Democratic majority
01/14/2021	CBO cost est.: Appropriations Act (Divisions N–FF)
02/02/2021	House Budget Resolution Reported
02/20/2021	CBO cost est.: American Rescue Plan Act
08/05/2021	CBO cost est.: Infrastructure Investment Act
08/09/2021	Senate Budget Resolution Reported
10/08/2021	House Financial Services Reconciliation
10/19/2021	CBO cost est.: Reconciliation Health Insurance Provisions
10/26/2021	CBO cost est.: PACT Act (S. 3003)
11/15/2021	Build Back Better Act Reconciliation (Ag.&Financial Services)
11/17/2021	Build Back Better Act Reconciliation (Edu.&Natural Resources)
11/18/2021	CBO cost est.: Build Back Better Act
11/19/2021	House passes Build Back Better Act
12/07/2021	CBO cost est.: Medicare Sequestration & PACT Act
06/06/2022	CBO cost est.: PACT Act / FDA Amendments
07/28/2022	Manchin–Schumer IRA deal publicized
08/03/2022	CBO cost est.: Inflation Reduction Act
08/08/2022	Reconciliation Act Engrossed in Senate
08/09/2022	CHIPS and Science Act signed into law
09/07/2022	Reconciliation Act Final Cost Estimate
04/25/2023	CBO cost est.: Limit, Save, Grow Act
05/27/2023	Biden–McCarthy debt ceiling agreement
05/30/2023	CBO cost est.: Fiscal Responsibility Act
06/03/2023	Fiscal Responsibility Act signed
07/10/2023	CBO cost est.: NDAA FY2024
01/25/2024	CBO cost est.: Tax Relief for Families Act
06/27/2024	House budget resolution reported
11/06/2024	Republican sweep alters fiscal path
02/13/2025	Senate budget resolution referred to committee
02/25/2025	House passes FY2025 budget resolution
04/05/2025	Senate expands budget resolution
04/10/2025	House adopts Senate budget resolution
05/20/2025	Reconciliation Act Reported in House
05/22/2025	House passes One Big Beautiful Bill (OBBBA)
06/04/2025	CBO cost est.: OBBBA (initial release)
06/17/2025	CBO cost est.: OBBBA (revised estimate)
06/25/2025	OBBBA Senate agreement reached
06/28/2025	CBO cost est.: OBBBA (Senate revisions)
07/03/2025	OBBBA House passage and presented to President
07/21/2025	CBO cost est.: OBBBA (final)

Table 1 presents our chronology of 52 U.S. fiscal policy news events spanning January 2020 through September 2025.[11] For each event, the table reports the date on which financial market participants plausibly received new information about the future trajectory of the federal deficit and a brief description of the event. Many of the dates listed are for announcements and unexpected legislative breakthroughs rather than enactments, on the grounds that asset prices typically respond to the news releases rather than to formal institutional benchmarks that may already be largely anticipated. For events in which formal CBO cost estimates were released prior to or shortly after enactment, Table 1 includes the release dates of the estimates as separate events, since Gomez-Cram, Kung, and Lustig (2025) provide evidence that these releases contain information beyond what is captured in prior political announcements. In addition, consistent with the approach advocated by Wiegand (2025), the table includes key milestones in the congressional budget and reconciliation process as these dates mark the first formal quantification of planned fiscal actions.[12]

The preponderance of these events likely conveyed news that future federal deficits would be much larger than previously anticipated. The half-decade began with the largest emergency fiscal stimulus in modern U.S. history and ended with one of the largest deficit-increasing tax measures enacted in recent decades. The official net fiscal impact of the full set of events during this period is unambiguous: the cumulative CBO-scored impact of the legislation reflected in these events amounts to a historic expansion of the projected federal debt. Figure 3 shows the year-by-year long-run projections of federal debt that the CBO has produced since 1995. Each observation is the CBO's projection of federal debt held by the public 10 years ahead, expressed as a percentage of projected nominal GDP.[13] As a result of tax breaks and greater spending during the Great Recession, the pandemic, and beyond, federal debt is projected to soon surpass the size of the U.S. economy. This massive accumulation of debt illustrates the unsustainable fiscal burden that many have warned about, including, as noted above, Fed Governor Waller (2024). Moreover, as we investigate in the next section, the news during this period about further substantial upward revisions to the long-run U.S. fiscal deficit trajectory could reinforce market concerns about the long-run path of U.S. public debt and leave a sizable imprint on longer-run real interest rates (e.g., Rachel (2025)).

[11] Our sample end date avoids the chaotic government shutdown that started on October 1, 2025.

[12] We thank Roberto Gomez-Cram and Courtney Wiegand for guidance on fiscal events. We considered a few additional events for emergency pandemic appropriations enacted in March 2020 before CBO scoring. Though obscured by heightened bond market volatility early in the pandemic, these additional fiscal dates did not change our conclusions, consistent with the downward trends during early 2020 in all four measures of r_t^*.

[13] The CBO's debt projections, obtained from Plante et al. (2025), are required to be based on the tax and spending trajectories in law at the time of the forecast.

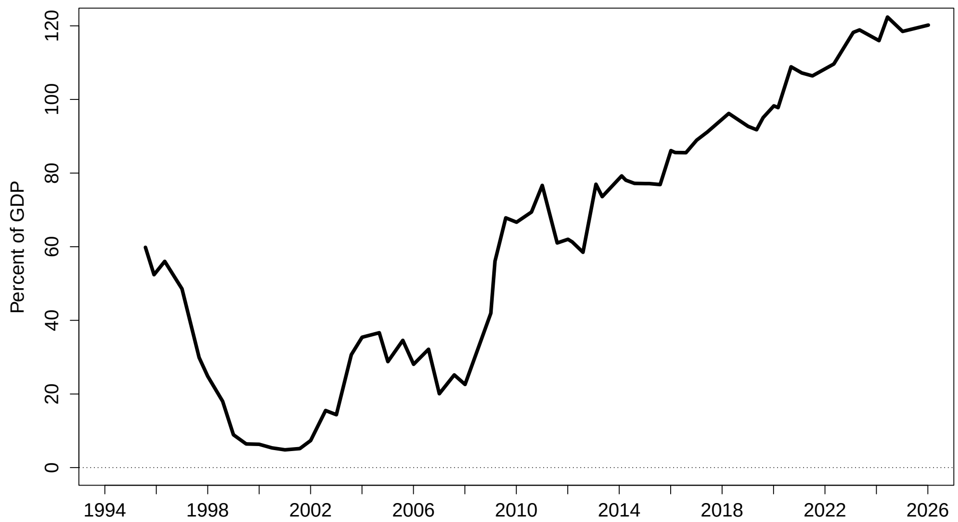


Figure 3: CBO Projections for Amount of U.S. Federal Debt 10 Years Ahead
The horizontal axis denotes the fiscal year in which the federal debt projection was made by the CBO.

3.2 AI Innovation Events

We now turn to a companion set of dates when financial market participants received important new information about the future evolution of AI technology. We follow Andrews and Farboodi (2026) by using the release dates of major updates to the flagship generative AI models developed by four leading AI laboratories: OpenAI, Google, Anthropic, and xAI. For each model, we use the first date on which it became broadly available to the public, as announced by the respective AI laboratory.[14] The resulting AI innovation news events are shown in Table 2.

An important characteristic of this chronology is the relatively late emergence of AI news. The first entry in Table 2 is the November 2022 launch of ChatGPT, which ignited public and investor interest in AI. The absence of earlier dates reflects the highly technical nature of AI research and model development before the ChatGPT launch. During that earlier period, AI laboratories typically disseminated advances in model capabilities via technical research papers. Publicly accessible products often did not appear until 12 to 18 months later, and even then, initial releases were narrowly distributed through gated waiting lists and other restrictions, attracting little attention outside the AI research community. The resulting lack of public interest in AI through late 2022, and its rapid growth thereafter, is illustrated in

[14]The release date of Gemini 2.0 Flash is corrected from 1/30/2025 to 12/11/2024, based on Google's official changelog: `https://ai.google.dev/gemini-api/docs/changelog#12-11-2024`.

Table 2: **Chronology of Major AI Model Updates, 2020–2025**

Date	Lab and AI model release
11/30/2022	OpenAI ChatGPT (GPT-3.5)
02/06/2023	Google Bard
03/14/2023	OpenAI GPT-4 / Anthropic Claude 1
07/11/2023	Anthropic Claude 2
11/03/2023	xAI Grok 1
11/21/2023	Anthropic Claude 2.1
12/06/2023	Google Gemini 1.0 Nano and Pro
02/15/2024	Google Gemini 1.5 Pro
03/04/2024	Anthropic Claude 3
05/13/2024	OpenAI GPT-4o
05/15/2024	xAI Grok 1.5
06/20/2024	Anthropic Claude 3.5 Sonnet
08/13/2024	xAI Grok 2
09/12/2024	OpenAI o1-preview
12/11/2024	Google Gemini 2.0 Flash
01/31/2025	OpenAI o3-mini
02/17/2025	xAI Grok 3
02/24/2025	Anthropic Claude 3.7 Sonnet
02/27/2025	OpenAI GPT-4.5
03/25/2025	Google Gemini 2.5 Pro
04/14/2025	OpenAI GPT-4.1
05/22/2025	Anthropic Claude 4
07/09/2025	xAI Grok 4
08/05/2025	Anthropic Claude Opus 4.1
08/07/2025	OpenAI GPT-5
09/29/2025	Anthropic Claude Sonnet 4.5

Event dates for official release dates of major updates to each lab's flagship AI model following Andrews and Farboodi (2026). On March 14, 2023, the OpenAI release of GPT-4 and the Anthropic release of Claude 1 are listed as a single AI news event.

Figure 4, which reports a normalized monthly index of the frequency of U.S. Google searches for the term "artificial intelligence" from 2018 through 2025. Search intensity remained low until the launch of ChatGPT, after which curiosity about and attention to AI developments increased rapidly.

Examining two pre-2023 AI announcements illustrates their limited reach and clarifies why such early innovation milestones are excluded from our event set. First, on May 18, 2021, Google unveiled LaMDA (Language Model for Dialogue Applications) during its annual developer conference. The announcement explicitly described LaMDA as an internal research effort, and the model was never made available as a standalone product. Although initially focused for the AI research community, LaMDA nonetheless eventually became the conversational backbone that powered the Bard chatbot, whose February 6, 2023 release does appear in the event set. As a second important AI research milestone, on April 5, 2022, Google published a research paper introducing a 540-billion-parameter model, PaLM

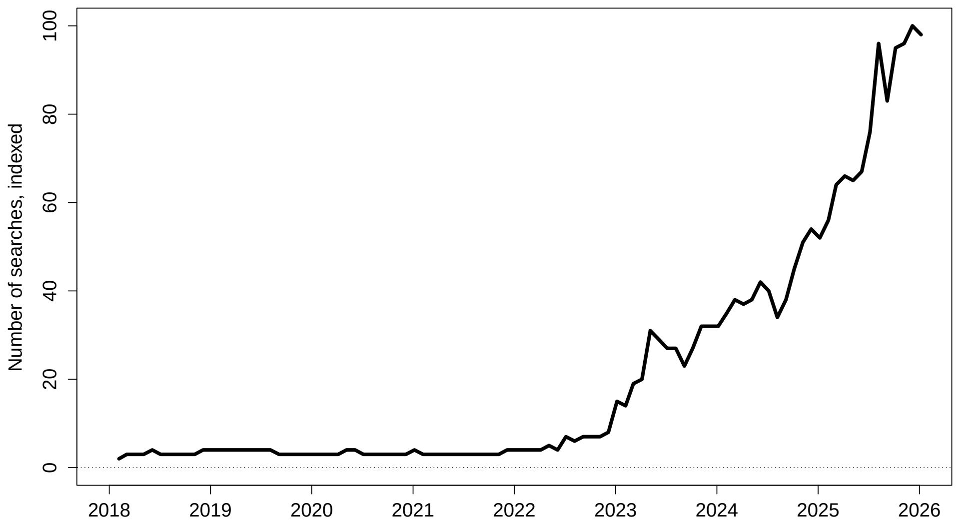


Figure 4: Google Search Interest for "Artificial Intelligence"
An index based on the number of monthly U.S. Google search queries for "Artificial Intelligence" where 100 represents the maximum monthly search frequency for the topic in the United States during the sample. Data retrieved from the Google Trends, www.google.com/trends, on March 15, 2026 for January 2018 to December 2025 for all categories.

(Pathways Language Model), which would ultimately serve as the foundation for later Bard iterations. However, the paper's description of an impressive research model contained no hints of public deployment, and this release generated no broad press coverage at the time.

Of course, Google search queries are not necessarily aligned with financial market investor interest. However, the November 30, 2022 launch of ChatGPT marks the first occasion on which many financial market participants were likely pushed to consider the significance of generative AI's near-term economic impact. Unlike its predecessors, ChatGPT was immediately free and open to the general public and reached an estimated one million users within five days of launch. It also generated widespread coverage in the mainstream financial press. Artificial intelligence appeared to plausibly move beyond simply a topic of research and attracted the attention of financial market participants, so November 30, 2022 is an obvious starting point for a financial markets event study of AI innovations.

4 Assessing Fiscal and AI Drivers of r_t^*

Hillenbrand (2025) introduced a simple metric to identify the longer-run movers of interest rates. He identified a set of relevant news releases and measured how much of the cumulative change in yields occurred during short windows surrounding those events. His focus was on monetary policy announcements and longer-term interest rates, and, quite surprisingly, he found that yield movements during 3-day event windows surrounding FOMC meetings accounted for most of the cumulative change in yields between June 1989 and June 2021. We use this same methodology to examine movements in the finance-based r_t^* estimates around the fiscal and AI news dates listed earlier and, in the next section, re-examine the importance of monetary policy news.

4.1 Did Fiscal Policy Push r_t^* Higher?

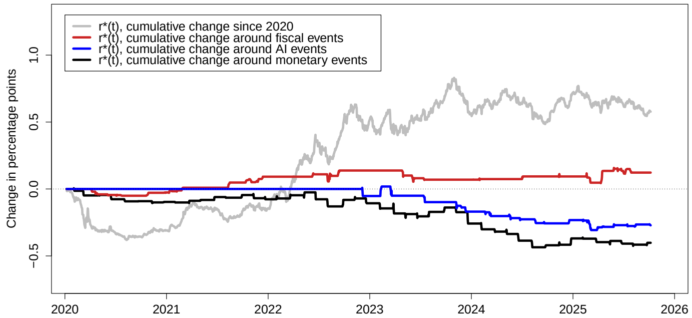
Figure 5 provides plots for the finance-based r_t^* estimates in the spirit of Hillenbrand (2025). In each panel, the gray line shows the cumulative change since January 2020 in one of the r_t^* estimates from the CLR, DKW, CR(TO), or CR(TOL) models. As noted earlier, from their lows reached in 2020 and 2021, these measures have all moved up by about a percentage point through the end of the sample with the gains concentrated in 2021 through 2023. The central question is whether the persistent rise in r_t^* estimates since 2020 can be traced to fiscal, AI, or monetary news events. Figure 5 considers all three types of news events, but in this subsection, we focus only on fiscal events.[15]

The red lines in each panel show the cumulative movements in the various r_t^* estimates during 3-day windows around the 52 fiscal events identified in Table 1. These paths account for the r_t^* changes realized during the 3-day fiscal event windows, but given some window overlap for a few adjacent dates, the 52 fiscal events result in 139 "event-window" days.[16] The red paths isolate the changes occurring during fiscal-event windows by setting changes to zero on all other days. The question of interest is whether the event-window red r_t^* paths can account for the secular increase in the gray r_t^* paths covering all days. Across the four r_t^* estimates, the cumulative increases on fiscal policy events from 2020 through 2025 average 18 bp. Fiscal policy news accounts for little of the overall increase in the finance-based r_t^* measures during this period.

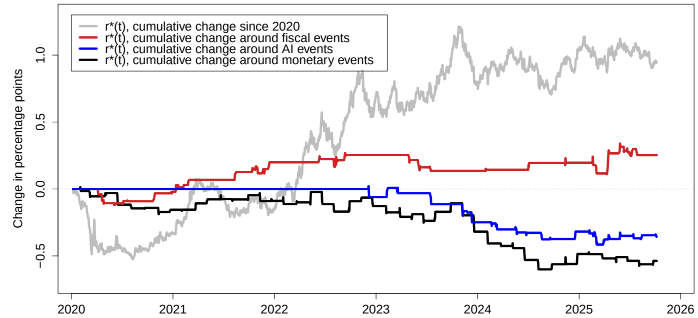
Table 3 provides a sharper quantification of the cumulative changes evident in the four panels of Figure 5 by focusing on changes since the low points in the r_t^*. For each r_t^* estimate, the date of its minimum value is given, and from this low point the cumulative change to September 30, 2025 is calculated in basis points. For example, while the CLR r_t^* rose 96 bp from its low point over all days, only 17 bp of this increase occurred in windows around the

[15]Following Hillenbrand (2025), we use 3-day windows running from the day before each event to the day after and distinguish between days that fall into the 3-day window and days that do not.

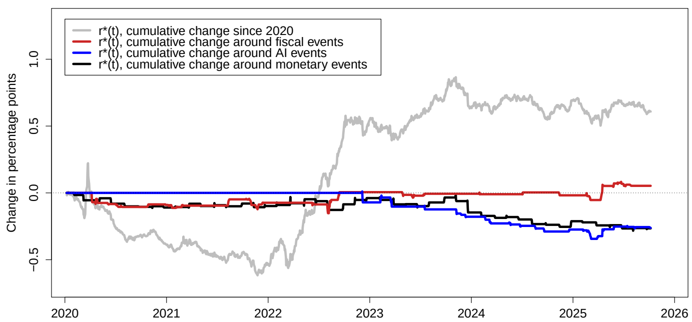
[16]A handful of fiscal policy and AI news events also occur on weekends or other days when the bond market is closed. In that case, we use the closest preceding or succeeding business day to center the event. For example, if an event occurred on a Saturday during a standard weekend, the associated 3-day window would include changes in bond yields on Thursday, Friday, and Monday (i.e., from Wednesday close of business to Monday close of business).



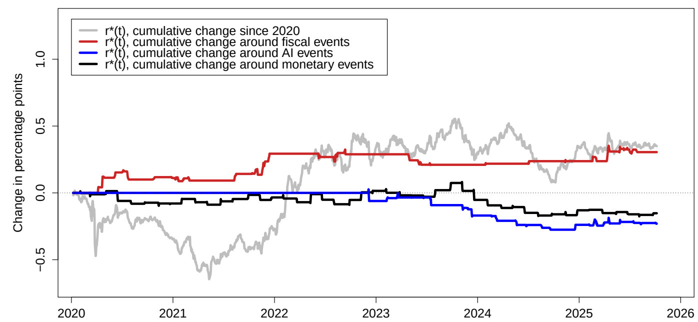
(a) CLR model



(b) DKW model



(c) CR (TO) model



(d) CR (TOL) model

Figure 5: **Changes in r_t^* around Fiscal, AI, and Monetary News Events**
In each panel, the gray lines show the cumulative change (in percentage points) in the listed r_t^* estimate from January 2, 2020, to September 30, 2025. Red, blue, and black lines show the cumulative changes in these r_t^* estimates only during 3-day windows around fiscal policy, AI, and monetary policy news events, respectively.

fiscal policy events. The other estimates tell a similar story with fiscal contributions ranging from 17 to 34 bp across the four models. On average, fiscal events account for about one-fifth of the overall increase in the natural rate.

To provide a broader investigation across interest rates and a statistical assessment, we compare the average daily interest rate changes within the three-day event windows with those outside the windows as in Hillenbrand (2025).[17] Panel A of Table 4 provides such comparisons for the fiscal policy events for the four finance-based r_t^* estimates, as well as for 5- and 10-year nominal Treasury yields and the 10-year TIPS yield and 5-year, 5-year-forward (5y5y) TIPS yield. For the r_t^* estimates, the results are consistent with Figure 5: the average daily changes during the fiscal event windows are positive though insignificantly different from zero.[18] A similar picture emerges for long-term nominal and real interest rates.

[17] Following Hillenbrand (2025), we use robust standard errors as in Bell and McCaffrey (2002).

[18] A total fiscal effect calculated from Table 4 by multiplying the mean daily change by the number of

Table 3: Cumulative Changes from Low Points in r_t^* Estimates (bp)

Estimate [Low Point]	All Days	Fiscal Events	AI Events	FOMC Events
CLR [08/04/2020]	96	17	-27	-31
DKW [08/04/2020]	147	34	-35	-39
CR(TO) [11/18/2021]	123	18	-26	-16
CR(TOL) [05/05/2021]	100	21	-23	-6
Average	116	23	-28	-23

Notes: Each entry reports the cumulative change in basis points from the date of the minimum estimated value of r_t^* through September 30, 2025. Changes are calculated across all sample days as well as within 3-day event windows surrounding fiscal, AI, and monetary policy announcements. Averages are calculated using unrounded estimates.

Average daily changes in these yields are statistically indistinguishable from zero during the fiscal policy news event windows with point estimates that are somewhat more positive than for the natural rate estimates. In sum, the fiscal policy news events in our sample do appear to have provided some modest support as a driving force behind recent r_t^* increases, but given the available sample, the estimated effect is not statistically significant.

Our results can be compared to a long empirical literature studying the relationship between government debt and interest rates. Gust and Skaperdas (2024) provide a useful survey showing that a fiscal policy news shock that persistently increases the deficit-to-GDP ratio by 1 percentage point raises the longer-run real yields by 1 to 6 bp—though the data sample employed typically ends before 2010. The two recent examples using high-frequency data—which were instrumental in developing our fiscal chronology—also estimate a similar average response of the term structure of nominal interest rates to the same standardized fiscal shock. Wiegand (2025) estimates that from 1980 to 2023 a 1 percentage point fiscal policy news shock raised the nominal 10-year yield by 2.3 bp, and Gomez-Cram, Kung, and Lustig (2025) estimate that from 1997 to 2022 a similar fiscal shock raised the 10-year yield by 6.75 bp. Relative to our analysis, this earlier research differs in methodology and sample. The event studies estimate the average response of yields to a standardized fiscal surprise, whereas we examine whether the realized sequence of fiscal news shocks since 2020 can account for the observed increase in r_t^*.[19]

For nominal yields, our results are broadly consistent with these average response estimates. From Table 4, the total change in the 10-year Treasury yield during the fiscal windows is 65 bp (= .47 x 139) during the first half of this decade. Over the same period, the projected federal debt to GDP ratio increased by about 20 percentage points as shown in Figure 3. Therefore, the cumulative effect of our fiscal events suggests an average response to a 1

event-window days (mean × N) is based on data since January 1, 2020, and will differ slightly from Table 3.

[19] Gomez-Cram, Kung, and Lustig (2024) do employ a Hillenbrand-style cumulative analysis of fiscal policy events from February 2020 to October 2023 and find 10-year TIPS yields rise about 1/2 percentage point.

Table 4: Daily Interest Rate Changes with Fiscal and AI Event Windows

	Within event windows			Outside event windows		
	Mean	t-stat	N	Mean	t-stat	N
Panel A: Fiscal policy events						
5y yield	0.37	(0.77)	139	0.12	(0.64)	1292
10y yield	0.47	(0.96)	139	0.12	(0.69)	1292
10y TIPS	0.19	(0.44)	139	0.10	(0.69)	1292
5y5y TIPS	0.50	(1.18)	139	0.10	(0.70)	1292
CLR r_t^*	0.09	(0.83)	139	0.03	(0.86)	1292
DKW r_t^*	0.18	(0.96)	139	0.05	(0.76)	1292
CR (TO) r_t^*	0.04	(0.34)	139	0.04	(1.06)	1292
CR (TOL) r_t^*	0.22	(1.55)	139	0.00	(0.05)	1292
Panel B: AI events						
5y yield	-1.65*	(-1.92)	75	0.24	(1.39)	1356
10y yield	-1.32*	(-1.87)	75	0.24	(1.38)	1356
10y TIPS	-1.29*	(-1.96)	75	0.19	(1.32)	1356
5y5y TIPS	-0.84	(-1.45)	75	0.19	(1.39)	1356
CLR r_t^*	-0.36*	(-1.93)	75	0.06	(1.62)	1356
DKW r_t^*	-0.47*	(-1.74)	75	0.09	(1.43)	1356
CR (TO) r_t^*	-0.35**	(-2.00)	75	0.06*	(1.65)	1356
CR (TOL) r_t^*	-0.31	(-1.63)	75	0.04	(0.91)	1356

The table shows mean daily yield and r_t^* changes for days within 3-day fiscal policy or AI windows and for days outside these windows from January 1, 2020 to September 30, 2025. The N columns report the number of days within and outside the event windows. Daily interest rate changes are reported in basis points, and t-statistics based on Bell-McCaffrey standard errors are shown in parentheses, with p-values annotated as $*p < .1$, $**p < .05$, and $***p < .01$.

percentage point shock of about 3 bp, which is in line with the literature. The response of real yields is much more muted. The change in r_t^* estimates during the fiscal windows implies r_t^* responses to a standardized shock of 0.3 to 1.5 bp.[20] As a result, even the sizable increase in the debt-to-GDP ratio during this period contributes little to the overall rise in the natural rate.

4.2 Did AI Push r_t^* Higher?

The responses of the finance-based r_t^* measures to the AI events are given by the blue lines in the four panels of Figure 5. These lines show cumulative movements during 3-day windows around the AI events identified in Table 2, with r_t^* changes set to zero on days outside these windows. Because the AI event days begin at the end of 2022, the blue lines are flat for the

[20]Based on interest rate fluctuations around the 2021 Georgia Senate runoff, Bhatt et al. (2026) estimate a similar response and find that a higher debt supply affects term premiums more than r_t^*.

first half of the sample.

The blue lines show net cumulative *declines* over the latter half of the sample. These are quantified in Table 3 and range from -23 to -35 bp, depending on the specific r_t^* estimate. The declines are fairly evenly distributed and are not concentrated around one or two dates. Statistical tests of daily changes in yields and r_t^* during the AI event windows, reported in Panel B of Table 4, confirm statistically significant negative effects across most series, including three of the four r_t^* estimates.[21] AI news, then, does not appear to be responsible for the increase in r_t^* during this period—if anything, it has worked in the opposite direction.

These empirical results are broadly consistent with Andrews and Farboodi (2026) and Björkegren (2026), who also document declines in long-term Treasury and TIPS yields following major AI releases. Our approach differs by relying on dynamic term structure models to separate r_t^* from bond risk premiums, which allows us to attribute part of the yield declines to falling expected long-run real rates net of term and liquidity premiums. Our use of 3-day AI event windows differs from the much longer ones used by Andrews and Farboodi (2026) who use 31- and 61-day windows. These extended windows are motivated by the view that the far-reaching economic and societal implications of AI adoption are much more complicated, say, than the consequences of fiscal or monetary policy news, so markets may need more time to fully register them. While we are sympathetic to this view, there are downsides to using such long event windows. The recorded yield reactions are at much greater risk of being contaminated by unrelated macroeconomic news, biasing the estimated effect in an unpredictable direction. Andrews and Farboodi (2026) do attempt to control for other interest-rate-relevant events during the long windows, but such controls may be incomplete. Narrower windows rest on the standard finance-based event-study premise that investors with money at stake have a strong incentive to quickly develop an informed view about the economic impact of any news they receive and devise trading strategies to exploit the acquired knowledge.

The source of the downward pressure on r_t^* from AI remains an open question. It may reflect Chair Warsh's view, cited earlier, that AI adoption is an overwhelming disinflationary force—which, if priced in by investors, could show up as a sustained markdown in expected future real rates. Alternatively, Rachel (2025) suggests that the uncertainty accompanying a technological revolution of this scale could raise precautionary saving and thereby lower the natural rate. Andrews and Farboodi (2026), however, use a consumption-based asset pricing model to show that changes in consumption growth uncertainty are unlikely, on their own, to explain the yield declines they document, and they raise a further possibility—that AI news lifts expectations of future tax revenue and lowers the credit risk premium on U.S. government debt.[22] Distinguishing among these channels is beyond the scope of this paper,

[21] Since all AI events occur after the r_t^* low points, the mean $\times N$ values from Table 4 provide the same range of declines.

[22] Kung, Lustig, and Paron (2026) suggest a similar channel for nominal yields through the term premium

but we note that the broader data—say, saving rates or surveys of inflation expectations by professional forecasters—do not offer corroborating evidence for any of these stories.

In sum, we find a systematic pattern of negative yield changes around the release of major generative AI model updates, part of which reflects a decline in the natural rate itself. There is no evidence in our sample that AI developments have pushed r_t^* higher this decade.

5 What about FOMC Events?

Hillenbrand (2025) documents a striking empirical regularity: the entire secular decline in longer-term U.S. Treasury yields since 1989 appears to occur during three-day windows around the eight or so Federal Open Market Committee (FOMC) meetings held each year. Yield movements outside these windows are minimal or transitory and account for little of the decline. Before the late 1990s, this result is not too puzzling as much of the decline in nominal yields reflected a fall in long-term inflation expectations, which was the result of increasing Federal Reserve credibility that was presumably established gradually FOMC meeting by FOMC meeting during this period (e.g., Bauer and Rudebusch (2020)). However, since the late 1990s, long-run inflation expectations have remained stable around the Fed's implicit (and more recently explicit) inflation target of 2 percent. It is this latter period that makes Hillenbrand's result genuinely puzzling: the continued decline in long-term nominal yields after the late 1990s reflected a fall in long-term real rates, yet it too was concentrated around FOMC meetings. This result is very much at odds with standard macroeconomic theory and evidence, both of which support long-run "monetary neutrality" whereby all of the long-run elements of the real economy, including r_t^*, are independent of monetary policy.[23]

To explain his result, Hillenbrand (2025) proposes that the policy action announcements, economic rationales, and Fed forecasts released at FOMC meetings provide crucial "Long-Run Fed Guidance" to bond investors that moves their views about the long-run level of nominal and real interest rates. Effectively, bond markets may be learning about macroeconomic fundamentals such as the underlying trend in r_t^* through Fed policy actions and communications.[24] Following this logic, bond investors could be incorporating information about fiscal policy and AI primarily during event windows around FOMC meetings rather than around the actual fiscal policy and AI news events. In that case, the lack of movement in bond yields during the fiscal policy and AI news events would reflect a sluggishness in the responses of investors, who require the Fed to focus or aggregate their attention, rather than

and convenience yield but not r_t^*.

[23]For example, long-run monetary neutrality is maintained by most macroeconomic models used to estimate r_t^*. An exception is Leiva-Leon, Sekkel, and Uzeda (2026), who estimate a Bayesian VAR that does allow for non-neutrality, but they find that monetary policy shocks accounted for none of the secular decline in r_t^*.

[24]Starting in February 1994, the FOMC released a statement if there was an adjustment of the policy interest rate, and in May 1999, the FOMC began releasing statements after every meeting (Acosta and Meade (2015)).

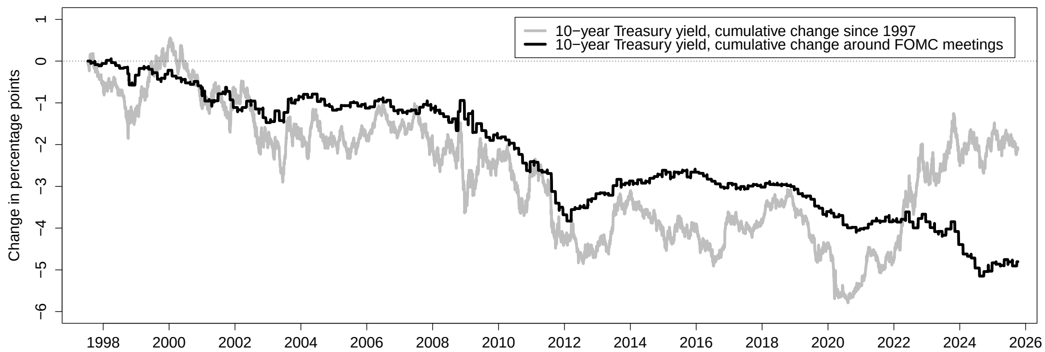


Figure 6: Cumulative Change in 10-Year Yield around FOMC Meetings
The gray line shows the cumulative change (in percentage points) of the 10-year U.S. Treasury yield during all business days since July 15, 1997. The black line shows the cumulative change in the yield during 3-day windows around FOMC meetings. The analysis includes all FOMC meetings from July 15, 1997 to September 30, 2025.

an insensitivity to that news. This interpretation reframes the results in the previous section in terms of when fiscal and AI information is processed rather than whether it matters.

To explore this possibility, Figure 6 replicates the key result in Hillenbrand (2025).[25] The gray line shows the cumulative change in the 10-year U.S. Treasury yield from July 15, 1997, to each subsequent day through September 30, 2025 (in percentage points). As noted above, longer-run inflation expectations were well anchored during this period, so ex ante real long-term yields closely follow this pattern. Following Hillenbrand (2025), the black line shows the cumulative change in the yield occurring within 3-day windows around FOMC meetings. This hypothetical time series is constructed by only including yield changes realized within these 3-day windows and setting all other daily changes to zero. Hillenbrand's (2025) sample ended in June 2021, and through that date, yield changes within the 3-day windows around FOMC meetings clearly account for most of the secular decline in long-term interest rates. However, Figure 6 extends the sample to September 2025, which reveals an important change in the pattern. Starting in 2020, the gray and black lines have trended in different directions. Indeed, recent changes in the 10-year yield around FOMC meetings have not captured the jump in bond yields in this decade at all. The recent breakdown in the Hillenbrand regularity suggests that bond investors are less reliant on the FOMC's guidance for an assessment of long-run yields.[26]

[25] Although nothing of substance changes, this replication uses 1997 as the starting normalization date, rather than 1989 as in Hillenbrand, because the pre-1997 period may be muddied by declining inflation expectations.

[26] Not surprisingly given the stability in long-term inflation expectations over this extended sample, a similar pattern emerges for the inflation-indexed yields, including the 10-year TIPS yield (e.g., Benigno et al. (2024)).

Table 5: Daily Interest Rate Changes with FOMC Event Windows

	Within event windows			Outside event windows		
	Mean	t-stat	N	Mean	t-stat	N
Panel A: FOMC events, Jul. 1997–Dec. 2019						
5y yield	-0.64**	(-2.23)	558	-0.02	(-0.20)	5055
10y yield	-0.65**	(-2.25)	558	-0.01	(-0.19)	5055
10y TIPS	-0.67***	(-3.08)	558	0.01	(0.12)	5055
5y5y TIPS	-0.61***	(-3.10)	558	0.00	(0.04)	5055
CLR r_t^*	-0.14*	(-1.85)	414	-0.00	(-0.05)	3832
DKW r_t^*	-0.26**	(-2.31)	558	-0.00	(-0.15)	5055
CR (TO) r_t^*	-0.17***	(-2.95)	558	-0.00	(-0.23)	5055
CR (TOL) r_t^*	-0.13*	(-1.96)	558	-0.01	(-0.39)	5055
Panel B: FOMC events, Jan. 2020–Sep. 2025						
5y yield	-1.22**	(-2.03)	138	0.29	(1.62)	1293
10y yield	-0.98*	(-1.78)	138	0.28	(1.58)	1293
10y TIPS	-0.85*	(-1.67)	138	0.21	(1.48)	1293
5y5y TIPS	-0.52	(-1.19)	138	0.21	(1.48)	1293
CLR r_t^*	-0.29**	(-2.19)	138	0.08*	(1.92)	1293
DKW r_t^*	-0.39*	(-1.82)	138	0.11*	(1.68)	1293
CR (TO) r_t^*	-0.19	(-1.43)	138	0.07*	(1.71)	1293
CR (TOL) r_t^*	-0.11	(-0.83)	138	0.04	(0.80)	1293

The table shows mean daily yield and r_t^* changes for days within 3-day FOMC event windows and for days outside these windows. Panel A analyzes all events and yield and r_t^* changes from July 16, 1997, to December 31, 2019, while Panel B analyzes all events and yield and r_t^* changes from January 2, 2020 to September 30, 2025. The N columns report the number of days within and outside the event windows. Daily yield changes are reported in basis points, and t-statistics based on Bell-McCaffrey standard errors are shown in parentheses, with p-values annotated as $^*p < .1$, $^{**}p < .05$, and $^{***}p < .01$. Note that the CLR r_t^* estimate is only available starting in January 2, 2003.

The black lines in Figure 5 show the cumulative changes (in percentage points) occurring within 3-day windows around FOMC meetings since 2020 in the four estimates of r_t^*. Over the first half of this decade, the FOMC window cumulative changes in these estimates show declines of around 25 bp.[27] That is, yield movements during the FOMC windows are accounting for none of the rise in r_t^* since 2020.[28]

In Table 5, the top panel A repeats Hillenbrand's (2025) main exercise using a pre-pandemic sample from July 16, 1997, to December 31, 2019. During that period, long-term

[27] The cumulative declines from the r_t^* minimums quantified in Table 3 range from -6 to -39 bp, while from the start of 2020, they range from -15 to -54 bp (Table 5, Panel B, mean × N).

[28] Even during 2024 when the FOMC's SEP reported several increases in the long-run level of the short-term interest rate (e.g., as shown in Figure 1), market-based r_t^* estimates continued to edge lower around monetary policy meetings.

interest rates fell significantly in the narrow windows around FOMC meetings. Moreover, based on the daily r_t^* estimates, we provide a new result that a portion of these yield declines reflected declines in the longer-run equilibrium real rate. These results suggest that investors systematically revised down their views about the steady state real rate in response to information received around FOMC meetings. Moreover, yield and r_t^* changes during all the non-FOMC windows are tiny on average and entirely insignificant. Thus, the declines are really concentrated around the FOMC windows as also apparent in Figure 6.

The bottom panel B in Table 5 reports the results of our update of Hillenbrand's (2025) main exercise using data and FOMC policy meetings covering the period from January 2, 2020 to September 30, 2025. The results show that long-term yields and our r_t^* estimates have continued to decline during 3-day windows around FOMC meetings, although now mostly insignificantly so. These findings reinforce our conclusion that the recent increases in long-term yields and the natural real rate have materialized despite some modest offsets recorded in 3-day windows around FOMC meetings.[29]

6 Conclusion

This paper examines whether this decade's rise in the natural rate of interest, r_t^*, can be attributed to the two explanations most frequently cited in recent research and policy discussions: a deteriorating fiscal outlook and expectations of AI-driven productivity gains. Using a high-frequency event study applied to finance-based measures of r_t^*, we find little support for these explanations. U.S. fiscal policy news shocks during the first half of this decade appear to have provided only a modest upward lift to the natural rate. At the same time, news surrounding major generative AI model releases is associated with an overall decline in measures of r_t^*. To supplement these results, we also considered whether the recent rise in r_t^* could be connected to monetary policy news releases; instead, long-term interest rates and finance-based estimates of r_t^* generally declined around FOMC meetings.

These findings point to several directions for future research. First, regarding fiscal and AI news, more work is needed to understand how investors incorporate new information into expectations about longer-run real interest rates. News headlines, official CBO cost estimates, and AI model releases may not be the most salient inputs that investors use to update their expectations. Unlike discrete monetary policy announcements, the fiscal and AI updates may shift expectations more diffusely through earnings calls, rumors, and gradual social adoption.[30] Still, taken at face value, the results suggest that the recent increase in r_t^*

[29] Cieslak, McMahon, and Pang (2026) analyze the dynamics of nominal interest rates in the post-2020 period and argue that uncertainty about the Fed's communications and policy actions induced important swings in risk premiums and nominal yields.

[30] Furthermore, the overlap and interaction between AI and fiscal developments should be assessed as in

reflects influences other than the fiscal, AI, and monetary news shocks identified here. Indeed, there appears to be a significant force pushing the natural rate higher *that more than offsets* the downward contributions from AI and monetary developments as well as demographic and other factors.

Given evidence that r_t^* appears to have risen in the 2020s in many countries (e.g., Brand, Lisack, and Mazelis (2025), Christensen, Rudebusch, and Shultz (2025)), a broader perspective on this issue would consider global forces rather than country-specific news. Changes in global saving and investment behavior or shifts in global risk preferences are compelling candidates. There has been a marked increase in frictions, fragmentation, and uncertainty in international trade and finance, and growing geopolitical tensions have partially reversed the decades-long path of liberalization and integration of global capital markets. In the theoretical analysis of Rachel (2025), such a "de-globalization" scenario, in which Asian exporters and oil producers reduce their holdings of Western assets, quickly results in a higher natural rate. Another possible global factor reflects fallout from the unexpected post-COVID surge in inflation that eroded the real value of nominal government debt. Rachel (2025) finds that an associated increase in inflation risk compensation and a narrowing of the safety premium can also push up the natural rate.[31] Finally, the increasing global investment required for a transition to a low-carbon economy may also lead to upward pressure on the neutral rate (e.g., Jonsson and Nilsson (2025)), although recent years have seen retrenchment as well as expansion on this front.

Translating these potential channels into event studies or other empirical analyses in order to provide a better understanding of the forces driving the recent increase in the natural rate of interest remains an important challenge for both economic researchers and policymakers.

Dynan, Elmendorf, and Sheiner (2026).

[31] Del Negro, Elbarmi, and Pham (2026), however, find that changes in investors' perceptions of the safety, liquidity, and convenience of advanced economies' government bonds account for little of the recent rise in r_t^*. Waller (2024) is also skeptical.

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