Abstract—The downtrend in U.S. interest rates over the past two decades may partly reflect a decline in the longer-run equilibrium real rate of interest. We examine this issue using dynamic term structure models that account for time-varying term and liquidity risk premiums and are estimated directly from prices of individual inflation-indexed bonds. Our finance-based approach avoids two potential pitfalls of previous macroeconomic analyses: structural breaks at the zero lower bound and misspecification of output and inflation dynamics. We estimate that the longer-run equilibrium real rate has fallen about 2 percentage points and appears unlikely to rise quickly.

I. Introduction

The general level of U.S. interest rates has gradually but steadily declined over the past few decades. In the 1980s and 1990s, falling inflation was the major impetus for this decline. But more recently, while yields have continued to trend lower, actual inflation, as well as survey-based measures of longer-run inflation expectations, have stabilized close to 2%. Some have argued that the continuing decline in interest rates since 2000 reflects a variety of persistent real-side factors. These real factors, such as slower productivity growth and an aging population, affect global saving and investment and can push down nominal and real yield curves by lowering the steady-state level of the safe short-term real interest rate. This steady-state real rate is often called the equilibrium or natural rate of interest and is commonly defined as the short-term real rate of return that would prevail in the absence of transitory disturbances. Other observers, however, have dismissed the evidence for a new lower equilibrium real rate. They downplay the role of persistent real-side factors, and argue that yields have been held down recently by temporary factors, such as the cyclical headwinds from credit deleveraging in the aftermath of the financial crisis. So far, this ongoing debate about a possible lower new normal for interest rates has focused on estimates drawn from macroeconomic models and data. In this paper, we use financial models and data to provide an alternative perspective on this issue.

The question of whether the equilibrium real rate has shifted lower is of widespread importance. For investors, the steady-state level of the real short rate serves as an anchor for projections of the future discount rates used in valuing financial assets (Clarida, 2014; Bauer & Rudebusch, 2017). For central bankers and economists, the equilibrium or natural rate of interest is a policy lodestar that provides a neutral benchmark to calibrate the stance of monetary policy: Monetary policy is expansionary if the short-term real interest rate lies below the natural rate and contractionsary if it lies above. In particular, a good estimate of the equilibrium real rate is necessary to operationalize popular monetary policy rules such as the Taylor rule.

Given the significance of the equilibrium real interest rate, many researchers have used macroeconomic models and data to try to pin it down. The best known of these—Laubach and Williams (2003, 2016)—infers the equilibrium real short rate by using the Kalman filter to distinguish the real interest rate trend and cycle within a model of the above definition of the neutral stance of monetary policy. Laubach and Williams (2016, p. 57) define the natural rate of interest as based on “a longer-run perspective, in that it refers to 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 and is expanding at its trend rate.” This is precisely the perspective that we will take in this paper, and it is the definition of the natural rate that we will employ, albeit using finance models and data.

There are several different conceptual definitions of the equilibrium real rate in the literature. Some researchers focus on a short-run equilibrium rate, which represents the current value of the real rate that would be consistent with the economy at full employment and stable inflation. Others consider a very long-run empirical equilibrium rate defined as the real rate that would prevail in the infinite future, as calculated, for example, from a statistical trend-cycle decomposition of real rates. In practice, these different definitions appear to be closely related (e.g., Del Negro et al., 2017). As already noted, we focus on an intermediate-term or longer-run definition, namely, the level of the short rate that is expected to prevail after the cyclical imbalances in the economy are expected to work themselves out. Our five- to ten-year horizon

On the role of the natural rate in monetary policy, see Rudebusch (2001), Orphanides and Williams (2002), Eggertsson et al. (2016), and Hamilton et al. (2016), among others.

Cúrdia et al. (2015) uses a dynamic stochastic general equilibrium (DSGE) model to estimate such a short-run equilibrium rate defined as the real rate that would prevail in a perfectly competitive counterfactual economy with flexible prices and no monopoly power.
is much shorter than the infinite-horizon steady state but in
our view is of particular interest. First, our data sample, like
most finite ones, is likely too short to accurately calculate
an infinitely distant steady state. Furthermore, there is am-
plicable evidence that the five- to ten-year horizon is particularly
relevant for current monetary policy discussions. For exam-
ple, in the Federal Reserve Board’s recent Monetary Policy
Report to Congress (2018), a similar forecast horizon un-
derlies the estimated neutral real interest rate used in various
monetary policy rules. More broadly, during the past decade
or so, longer-run definitions of a normal interest rate, like
ours, have been at the center of key policy debates about the
bond market conundrum, the global saving glut, and secular
stagnation.

To construct their macro-based measure of the equilib-
rium rate, Laubach and Williams (2003, 2016) use the model
of Rudebusch and Svensson (1999) and data on a nominal
short-term interest rate, consumer price inflation, and the
output gap. Johannsen and Mertens (2016) and Lubick and
Matthes (2015) provide closely related equilibrium rate es-
timates from a similar filtering of the macroeconomic data,
while other macroeconomic researchers, such as Cúrdia et al.
(2015), take a more structural approach. However, these and
other macro-based approaches for identifying a new lower
equilibrium real rate have several potential shortcomings.
First, Kiley (2015), Taylor and Wieland (2016), and Lewis
and Vazquez-Grande (2017) note that the macro-based esti-
mates of the natural rate can be distorted by model misspec-
ifications, especially in the assumed output and inflation dy-
namics. Such model misspecifications could also arise from
omitted variables or from structural or regime shifts during
the sample. The latter concern may be important in the af-
termath of the Great Recession when nominal interest rates
were constrained by the lower bound near zero, a nonlinearity
that likely affects the dynamic correlations between nominal
interest rates and output. Furthermore, Kiley (2015) argues
that the key intertemporal IS curve/Euler equation correla-
tion between real interest rates and output, which is crucial
for pinning down macro-based estimates of the natural rate,
is a weak empirical foundation for this analysis. Finally, as
Clark and Kozicki (2005) noted, a macro-based approach may
face a number of problems from the standpoint of a real-time
analysis. For example, macro-based analyses often use exten-
sively revised output and inflation data to create equilibrium
real rate estimates that would not have been available his-
itorically. In addition, a one-sided macro-based filtering that
could be applied in real time is completely backward looking
and may face difficulties in distinguishing persistent shifts
from cyclical and transitory fluctuations.

Given these potential pitfalls of a macro-based estimation,
we turn to financial models and data to provide an alterna-
tive approach to estimate the equilibrium real rate of interest.
We use the prices of inflation-indexed debt, namely, U.S.
Treasury Inflation-Protected Securities (TIPS). These secu-
rities have coupon and principal payments that adjust for
changes in the Consumer Price Index (CPI) and thus com-
penate investors for the erosion of purchasing power due to
inflation. The prices of these securities can provide a fairly
direct reading on real yields since 1997 when the TIPS pro-
gram was launched. We assume that the longer-term expecta-
tions embedded in TIPS prices reflect financial market partic-
ipants’ views about the steady state of the economy, including
the equilibrium interest rate. Our finance-based measure of
the natural rate has several potential advantages relative to
the macro-based estimates. Most notable, our measure of the
equilibrium interest rate does not depend on obtaining a correct spec-
fication of the output and inflation dynamics—unlike previ-
ous estimates that rely on a specific macroeconomic represen-
tation. Furthermore, our measure can be obtained in real time
at the same high frequency as the underlying bond price data,
and it is based on financial market data and so is naturally
forward looking.

Still, the use of TIPS for measuring the steady-state short-
term real interest rate poses its own empirical challenges.
One difficulty is that inflation-indexed bond prices include
a real term premium. Given the generally upward slope of the
TIPS yield curve, the real term premium appears positive on
average, but its variability is unknown. In addition, despite
the fairly large notional amount of outstanding TIPS, these
securities arguably face appreciable liquidity risk. For exam-
ple, Fleming and Krishnan (2012) report that TIPS usually
have a smaller trading volume and wider bid-ask spreads than
nominal Treasury bonds. Presumably investors require a pre-
mium for bearing the liquidity risk associated with holding
TIPS, but the size and variability of this liquidity premium are
also hard to pin down.

To estimate the equilibrium rate of interest in the presence
of liquidity and real term premiums, we use arbitrage-free
dynamic term structure models of real yields. The theoretical
arbitrage-free formulation of the models provides identifica-
tion of a time-varying real term premium in the pricing of
TIPS. In addition, our models are estimated using the prices
of individual bonds rather than the more usual input of yields
from fitted synthetic curves. Our methodology contrasts with
previous term structure models, which are almost universally
estimated on synthetic zero-coupon yields obtained from
fitted yield curves. However, the use of interpolated yield
curves in term structure analysis can introduce unnecessary

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5For recent monetary policy discussions using a longer-run neutral or
equilibrium rate of interest, see Yellen (2015), Fischer (2016), and Nechio
and Rudebusch (2016).

6See Greenspan (2005), Bernanke (2005), and Summers (2015), respect-
ively.

7See Bomfim (2001) for an early model-free discussion of this issue. Also,
Joyce, Kaminska, and Lildholdt (2012) use dynamic term structure
models of U.K. index-linked government yields to study long-term real rate
expectations.

8See Sack and Elsasser (2004), Campbell, Shiller, and Viceira (2009),
Giürkaynak, Sack, and Wright (2010), Fleckenstein, Longstaff, and Lustig
(2014), Driessen, Nijman, and Simon (2016), and Pfueger and Viceira
(2016).
measurement error. Avoiding interpolated bond yields appears particularly useful for analyzing situations with only a limited sample of bonds, as is often the case for inflation-indexed debt.

For robustness, we consider two different dynamic term structure models. One is more standard, with no separate explicit treatment of the liquidity premium; term and liquidity risks are implicitly modeled together. The second model is augmented with an explicit liquidity risk factor. This model identifies an overall TIPS liquidity factor and each individual bond’s loading on that factor from the cross section of TIPS prices over time—with each security possessing a different time since issuance and time to maturity. The identification of the overall liquidity risk factor comes from its unique loading for each individual TIPS as in Andreasen, Christensen, and Riddell (2018, henceforth ACR). This loading assumes that over time, an increasing proportion of the outstanding inventory is locked up in buy-and-hold portfolios. Given forward-looking investor behavior, this lock-up effect implies that a particular bond’s sensitivity to the market-wide liquidity factor will vary depending on how seasoned the bond is and how close to maturity it is. Fontaine and Garcia (2012) provide empirical support for such an approach as they uncover a pervasive liquidity factor that affects nominal Treasury prices with loadings that vary with the maturity and age of each bond.

Our two models complement each other. The first is a parsimonious representation of TIPS prices, while the second is a highly parameterized specification that can provide sharper inference—if the underlying assumed structure is appropriate. After using these models to identify the relevant bond premiums, we can estimate the underlying real rate term structure and the natural rate of interest, which we define as the average expected real short rate over a five-year period starting five years ahead—consistent with the Laubach and Williams (2016) longer-run perspective noted above. Our preferred measure of the natural rate of interest, \( r^* \), is shown in figure 1 along with ten-year nominal and real Treasury yields. This measure is an average of the estimates from the two models. Both nominal and real long-term yields have trended down together over the past two decades, and this concurrence suggests little net change in inflation expectations or the inflation risk premium. The estimated equilibrium real rate has fallen from just over 2% to near 0% during this period. Accordingly, our results show that about half of the 4 percentage point decline in longer-term Treasury yields over the past two decades represents a reduction in the natural rate of interest. Our model estimates also suggest that this situation is unlikely to reverse quickly in the years ahead.

Our focus on a TIPS-only analysis contrasts with past TIPS research that jointly modeled both the real and nominal yield curves, as in Christensen, Lopez, and Rudebusch (2010), Abrahams et al. (2016, henceforth AACMY), and D’Amico, Kim, and Wei (2018). Such joint specifications can also be used to estimate the steady-state real rate, although this earlier work has emphasized only the measurement of inflation expectations and the inflation risk premium. The earlier investigations that include both real and nominal yields have advantages and disadvantages relative to our procedure of using only TIPS. A joint modeling approach is able to estimate a model on a much longer and larger sample of bond yields. It also can be used to explore whether the estimated linkages among real and nominal interest rates, inflation expectations, and risk premiums have counterfactual model implications for these variables. However, a joint specification also requires additional modeling structure, including specifying more pricing factors, an inflation risk premium, and inflation expectations. The greater number of modeling elements, along with the requirement that this more elaborate structure
remains stable over the sample, raise the risk of model mis-
 specification, which can contaminate estimates of the natural rate and model inference more generally. In particular, if the inflation components are misspecified, the whole dynamic system may be compromised. Furthermore, during the period from 2009 to 2015, when the Federal Reserve kept the overnight federal funds rate at its effective zero lower bound, the dynamic interactions of short- and medium-term nominal Treasury yields were affected. The zero lower bound is difficult to incorporate in an empirical term structure model of nominal yields (see Christensen & Rudebusch, 2015). By relying solely on real TIPS yields, we minimize the implications of this constraint. Still, for completeness, we do compare our TIPS-only estimates to the natural rate estimates from existing joint representations of the real and nominal yield curves.

The paper is organized as follows. Section II describes our theoretical framework. Section III contains a description of the TIPS data, while section IV discusses econometric identification and model estimates. Section V compares our TIPS-based measures of the natural rate to previous estimates. Section VI concludes. Online appendixes contain additional technical details.

II. Identifying the Natural Rate of Interest with TIPS

In this section, we first describe how real bond yields can be decomposed into the underlying real rate expectations component and a residual real term premium in a world without any trading frictions. We then describe a potential wedge between the theoretical frictionless real yields and the observed TIPS yields caused by imperfect bond market liquidity.

A. Decomposing Real Yields with Frictionless Affine Models

Assume a world with no trading frictions, so any financial claim can be traded in arbitrarily small or large amounts without affecting its price. As a consequence, financial market prices contain no liquidity premiums, and real yields vary either because fundamental factors in the economy have changed or because investors have altered their perceptions of, or aversions to, the risks that those economic fundamentals represent. Assessing the variation in real yields caused by time-varying real term premiums requires an accurate model of expectations for the instantaneous risk-free real rate $r_t$ and the term premium. For simplicity, we focus on decomposing $P_t(\tau)$, the price of a zero-coupon real bond at time $t$ that has a single payoff, namely, one consumption unit, at maturity $t+\tau$. Under standard assumptions, this price is given by

$$ P_t(\tau) = E_t^P \left[ \frac{M_{t+\tau}}{M_t} \right], $$

where the stochastic discount factor, $M_t$, denotes the value at time $t_0$ of a real claim (one measured in consumption units) at a future date $t$, and the superscript $P$ refers to the actual, or real-world, probability measure underlying the dynamics of $M_t$.

Our working definition of the equilibrium rate of interest $r_t^*$ is

$$ r_t^* = \frac{1}{5} \int_{t+5}^{t+10} E_t^P [r_{t+s}] ds, \tag{1} $$

that is, the average expected real short rate over a five-year period starting five years ahead (5yr5yr) where the expectation is with respect to the objective $P$-probability measure. Such a medium-run horizon is of particular interest to policymakers. The 5yr5yr forward average expected real short rate is a long enough horizon to be little affected by short-term transitory shocks but a short enough one to be plausibly pinned down by the available evidence. Alternatively, $r_t^*$ could be defined as the expected real short rate at an infinite horizon (i.e., as $E_t^P [r_{t+\infty}]$ as in Johannsen & Mertens, 2016, and Lubeck & Matthes, 2015). However, quantifying this end point is arguably quite difficult as it depends crucially on whether the factor dynamics are assumed to exhibit a unit root. Our model follows the finance literature and adopts a stationary structure, so strictly speaking, our infinite-horizon, steady-state expected real rate is constant. In general, we do not view our data sample as having sufficient information in the ten-year to infinite-horizon range to definitively pin down the steady state, so we prefer our definition that uses a medium-to longer-run horizon.11

In the empirical analysis, we rely on the market prices of TIPS to construct this market-based measure of the natural rate. In doing so, it is important to acknowledge that financial market prices do not reflect objective $P$-expectations as in equation (1). Instead, they reflect expectations adjusted with the premiums investors demand for being exposed to the underlying risks. We follow the usual empirical finance approach that models bond prices with latent factors, here denoted as $X_t$, and the assumption of no residual arbitrage opportunities.12 We assume that $X_t$ follows an affine Gaussian process with constant volatility, with dynamics in continuous time given by the solution to the following stochastic differential equation (SDE): $dX_t = K^P(\theta^P - X_t) + \Sigma dW_t^P$, where $K^P$ is an $n \times n$ mean-reversion matrix, $\theta^P$ is an $n \times 1$ vector of mean levels, $\Sigma$ is an $n \times n$ volatility matrix, and $W_t^P$ is an $n$-dimensional Brownian motion. The dynamics of the stochastic discount function are given by $dM_t = r_t M_t dt + \Gamma_t M_t dW_t^P$, and the instantaneous risk-free real rate, $r_t$, is assumed affine in the state variables $r_t = \delta_0 + \delta_1 X_t$, where

10. The online appendix shows our results are robust to alternative horizons to define $r_t^*$.

11. Available time series data do not distinguish strongly between highly persistent stationary processes and nonstationary ones (Rudebusch, 1993). The online appendix shows that our results are robust to assuming a unit root in the factor dynamics.

12. Ultimately, of course, the behavior of the stochastic discount factor is determined by the preferences of the agents in the economy, as in, for example, Rudebusch and Swanson (2011).
\[ \delta_0 \in \mathbb{R} \text{ and } \delta_1 \in \mathbb{R}^n. \] The risk premiums, \( \Gamma_t \), are also affine: 
\[ \Gamma_t = \gamma_0 + \gamma_1 X_t, \] where \( \gamma_0 \in \mathbb{R}^n \) and \( \gamma_1 \in \mathbb{R}^{n \times n}. \)

Duffie and Kan (1996) show that these assumptions imply that zero-coupon real yields are also affine in \( X_t \):
\[ y_t(\tau) = \frac{1}{\tau} A(\tau) - \frac{1}{\tau} B(\tau) X_t, \]
where \( A(\tau) \) and \( B(\tau) \) are solutions to the system of ordinary differential equations:
\[ \begin{align*}
\frac{dB(\tau)}{d\tau} &= -\delta_1 - (K^P + \Sigma \gamma_1) B(\tau), \quad B(0) = 0, \\
\frac{dA(\tau)}{d\tau} &= -\delta_0 + B(\tau)'(K^P \theta^P - \Sigma \gamma_0) \\
&\quad + \frac{1}{2} \sum_{j=1}^n (\Sigma' B(\tau) B(\tau)' \Sigma)_{j,j}, \quad A(0) = 0.
\end{align*} \]

Thus, the \( A(\tau) \) and \( B(\tau) \) functions are calculated as if the dynamics of the state variables had a constant drift term equal to \( K^P \theta^P - \Sigma \gamma_0 \) instead of the actual \( K^P \theta^P \) and a mean-reversion matrix equal to \( K^P + \Sigma \gamma_1 \) as opposed to the actual \( K^P \).\(^{13}\) The difference is determined by the risk premium \( \Gamma_t \) and reflects investors’ aversion to the risks embodied in \( X_t \).

Finally, we define the real term premium as
\[ TP_t(\tau) = y_t(\tau) - \frac{1}{\tau} \int_{\tau}^{\tau+\tau} E_t^-[r_s] ds. \quad (2) \]
That is, the real term premium is the difference in expected real return between a buy-and-hold strategy for a \( \tau \)-year real bond and an instantaneous rollover strategy at the risk-free real rate \( r_t \). This model thus decomposes yields into a real term premium and real short rate expectations component, which can then be used to obtain the natural rate via equation (1).\(^{14}\)

### B. A Frictionless Arbitrage-Free Model of Real Yields

To model the frictionless real yield curve, we focus on the tractable affine dynamic term structure model introduced in Christensen, Diebold, and Rudubusch (2011). Although the model is not formulated using the canonical form of affine term structure models introduced by Dai and Singleton (2000), it can be viewed as a restricted version of the canonical Gaussian model. In this arbitrage-free Nelson-Siegel (AFNS) model, the state vector is denoted by \( X_t = (L_t, S_t, C_t) \), where \( L_t \) is a level factor, \( S_t \) is a slope factor, and \( C_t \) is a curvature factor. The instantaneous risk-free real rate is defined as \( r_t = L_t + S_t \).

The risk-neutral (or \( Q^- \)) dynamics of the state variables are given by
\[ \begin{align*}
\left( \begin{array}{c}
dL_t \\
dS_t \\
dC_t \end{array} \right) &= \left( \begin{array}{ccc}
k_{11}^P & k_{12}^P & k_{13}^P \\
k_{21}^P & k_{22}^P & k_{23}^P \\
k_{31}^P & k_{32}^P & k_{33}^P \end{array} \right) \left( \begin{array}{c}
\theta_1^P \\
\theta_2^P \\
\theta_3^P \end{array} \right) - \left( \begin{array}{c}
L_t \\
S_t \\
C_t \end{array} \right) dt + \Sigma \left( \begin{array}{c}
dW^L_t \\
dW^S_t \\
dW^C_t \end{array} \right),
\end{align*} \quad (3) \]
where \( \Sigma \) is the constant covariance (or volatility) matrix.\(^{14}\)

Based on this specification of the \( Q^- \)-dynamics, zero-coupon real bond yields preserve the Nelson-Siegel factor loading structure:
\[ y_t(\tau) = L_t + \left( \frac{1 - e^{-\lambda \tau}}{\lambda \tau} \right) S_t + \left( \frac{1 - e^{-\gamma \tau}}{\gamma \tau} - e^{-\gamma \tau} \right) C_t \]
\[ - \frac{A(\tau)}{\tau}, \quad (4) \]
where the yield-adjustment term is given by
\[ A(\tau) = \frac{\sigma^2_1}{6} \tau^2 + \sigma^2_2 \left[ \frac{1}{2\lambda^2} \frac{1 - e^{-\lambda \tau}}{\lambda \tau} + \frac{1}{4\lambda^3} \frac{1 - e^{-2\lambda \tau}}{\tau} \right] \]
\[ + \sigma^2_3 \left[ \frac{1}{2\lambda^2} + \frac{1}{4\lambda} \frac{1 - e^{-\gamma \tau}}{\gamma \tau} - \frac{3}{4\lambda^2} \frac{1 - e^{-2\gamma \tau}}{2\gamma \tau} \right] \]
\[ + \frac{5}{8\lambda^3} \frac{1 - e^{-2\gamma \tau}}{\gamma \tau} - \frac{2}{\lambda^3} \frac{1 - e^{-\gamma \tau}}{\gamma \tau}. \]

Finally, we specify the risk premiums that connect these \( Q^- \)-measure factor dynamics to the real-world \( P^- \)-measure dynamics. There are no restrictions on the latter beyond the requirement of constant volatility. To facilitate empirical implementation, we use the essentially affine risk premium specification introduced in Duffee (2002). In the Gaussian framework, this specification implies that the risk premiums, \( \Gamma_t \), depend on the state variables, that is, \( \Gamma_t = \gamma^0 + \gamma^1 X_t \), where \( \gamma^0 \in \mathbb{R}^3 \) and \( \gamma^1 \in \mathbb{R}^{3 \times 3} \) contain unrestricted parameters. Thus, the resulting unrestricted three-factor AFNS model has \( P^- \)-dynamics given by
\[ \begin{align*}
\left( \begin{array}{c}
dL_t \\
dS_t \\
dC_t \end{array} \right) &= \left( \begin{array}{ccc}
k_{11}^P & k_{12}^P & k_{13}^P \\
k_{21}^P & k_{22}^P & k_{23}^P \\
k_{31}^P & k_{32}^P & k_{33}^P \end{array} \right) \left( \begin{array}{c}
\theta_1^P \\
\theta_2^P \\
\theta_3^P \end{array} \right) - \left( \begin{array}{c}
L_t \\
S_t \\
C_t \end{array} \right) dt + \Sigma \left( \begin{array}{c}
dW^L_t \\
dW^S_t \\
dW^C_t \end{array} \right), \quad (3) \]
where \( \Sigma \) is diagonal and \( \theta^Q \) is 0 without loss of generality. Also, with a unit root in the level factor, the model is not arbitrage free with an unbounded horizon, so we impose an arbitrary maximum horizon.
This is the transition equation in the Kalman filter estimation. We will denote this representation as the TIPS-only (T-O) model.

C. An Arbitrage-Free Model of Real Yields with Liquidity Risk

As common in the literature, the T-O model implicitly models term and liquidity risk premiums together. This section augments the T-O model to explicitly account for liquidity risk. By adjusting the TIPS prices for liquidity effects, we obtain alternative estimates of the real yield decomposition in equation (2) and alternative readings on the natural rate as in equation (1). A very narrow interpretation of liquidity risk focuses on the uncertain cost of quickly selling a bond. More broadly, liquidity risk is a catch-all term to account for the transactional frictions that lead to deviations from the law of one price. In this regard, Fontaine and Garcia (2012) highlight the funding requirements faced by bond arbitrageurs and the variation over time in the cost of funding liquidity, say, via the repo market.

If TIPS yields are sensitive to liquidity pressures, the discounting of their future cash flows is not performed with the frictionless real discount function described in section IIA, but, rather, with a discount function that accounts for liquidity risk. Thus, we follow ACR and assume a single liquidity risk factor denoted \( X_{t}^{liq} \). Furthermore, the ACR approach assumes liquidity risk is security specific in nature. Indeed, we use a unique function to discount the cash flow of each TIPS indexed \( i \),

\[
\bar{r}_{t} = r_{t} + \beta^{i}(1 - e^{-\lambda L_{t}(t-t_{0})})X_{t}^{liq},
\]

where \( r_{t} \) is the frictionless instantaneous real rate, \( t_{0}^{i} \) denotes the date of issuance of the security, \( \beta^{i} \) is its sensitivity to the variation in the liquidity risk factor, and \( \lambda L_{t} \) is a decay parameter. We allow the \( \beta^{i} \) sensitivities and decay parameters \( \lambda L_{t} \) to vary across individual securities. The \( \beta^{i} \) and \( \lambda L_{t} \) are identified econometrically through the nonlinear bond pricing formula below. The inclusion of the issuance date \( t_{0}^{i} \) in the pricing formula captures the effect that as time passes, an increasing fraction of a given security is held by buy-and-hold investors. This limits the amount of the security available for trading and affects its sensitivity to the liquidity factor. Rational, forward-looking investors will take this dynamic pattern into consideration when they determine what they are willing to pay for the security at any given point in time between the date of issuance and the maturity of the bond. This dynamic pattern is built into the model structure. In short, the measurement and identification of the TIPS liquidity pricing effects depend on the assumption that liquidity deteriorates over the lifetime of each bond (broadly consistent with Fontaine & Garcia, 2012). However, the individual form of that deterioration is determined by a very flexible structure that can vary substantially from bond to bond.

To augment the T-O model to account for TIPS liquidity risk, let \( X_{t} = (L_{t}, S_{t}, C_{t}, X_{t}^{liq}) \) denote the state vector of the TIPS-only with liquidity adjustment (T-O-L) model. Again, we define the frictionless instantaneous real risk-free rate as \( r_{t} = L_{t} + S_{t} \), while the risk-neutral dynamics of the state variables used for pricing are given by

\[
\begin{pmatrix}
    dL_{t} \\
    dS_{t} \\
    dC_{t} \\
    dX_{t}^{liq}
\end{pmatrix} =
\begin{pmatrix}
    0 & 0 & 0 & 0 \\
    0 & \lambda & -\lambda & 0 \\
    0 & 0 & \lambda & 0 \\
    0 & 0 & 0 & \lambda X_{t}^{liq}
\end{pmatrix}
\begin{pmatrix}
    0 & 0 & 0 & 0 \\
    S_{t} \\
    C_{t} \\
    X_{t}^{liq}
\end{pmatrix} dt + \\
\sum \begin{pmatrix}
    dW_{t}^{L} \\
    dW_{t}^{S} \\
    dW_{t}^{C} \\
    dW_{t}^{X_{t}^{liq}}
\end{pmatrix},
\]

where \( \Sigma \) continues to be a diagonal matrix.

It follows from these \( Q \)-dynamics that TIPS yields are sensitive to liquidity risk. In particular, pricing of TIPS is not performed with the frictionless real discount function, but rather with the discount function that accounts for the liquidity risk as detailed earlier:

\[
\bar{r}_{t} = r_{t} + \beta^{i}(1 - e^{-\lambda L_{t}(t-t_{0})})X_{t}^{liq} = L_{t} + S_{t} + \beta^{i}(1 - e^{-\lambda L_{t}(t-t_{0})})X_{t}^{liq}.
\]

In the online supplementary appendix, we show that the net present value of one unit of consumption paid by TIPS at \( t + \tau \) has the following exponential-affine form

\[
P_{t}(t_{0}^{i}, \tau) = E_{t}^{Q} \left[ e^{-\int_{t_{0}^{i}}^{\tau} r_{s}(s, t_{0}^{i}) ds} \right] = \exp \left( B_{1}(\tau)L_{t} + B_{2}(\tau)S_{t} + B_{3}(\tau)C_{t} + B_{4}(t, t_{0}^{i}, \tau)L_{t}^{liq} + A(t, t_{0}^{i}, \tau) \right).
\]

This result implies that the model belongs to the class of Gaussian affine term structure models, but unlike standard Gaussian models, \( P_{t}(t_{0}^{i}, \tau) \) is not time homogeneous. Note also that by fixing \( \beta^{i} = 0 \) for all \( i \), we recover the T-O model.

Now consider the whole value of the TIPS issued at time \( t_{0}^{i} \) with maturity at \( t + \tau \) that pays an annual coupon \( C_{t} \) semi-annually. At time \( t \), this value is given by the sum of the

\[\text{Downloaded from http://www.mitpressjournals.org/doi/pdf/10.1162/rest_a_00821 by guest on 06 May 2021}\]
next (prorated) coupon payment, subsequent coupons, and the principal—all appropriately discounted:

\[ P_t(t_0, t, C) = C(t_1 - t)E_t^Q \left[ e^{-\int_{t_0}^t \rho^i(s,t_0) ds} \right] + \sum_{j=2}^N C_j \frac{1}{2} E_t^Q \left[ e^{-\int_{t_0}^t \rho^i(s,t_j) ds} \right] + E_t^Q \left[ e^{-\int_{t_0}^t \rho^{liq}(s,t_0) ds} \right]. \] (7)

Specifically, when a TIPS is purchased at time \( t \), the investor pays for a prorated share of the next coupon payment—the portion that has yet to accrue from \( t \) to \( t_1 \). Subsequently, the investor receives \( C/2 \) every six months as reflected in the price. The special treatment of the first coupon to be paid after time \( t \) maps directly to our use of “clean” TIPS + \( r \).

The maturity distribution of all TIPS issued is shown by solid black lines. Thick gray lines highlight overlapping pairs of recent ten-year and seasoned twenty-year TIPS with identical maturity dates.

The data are available at http://www.treasurydirect.gov.

IV. Estimation of TIPS-Only Term Structure Models

This section describes the restrictions imposed to achieve econometric identification of the real term structure models and model estimates with and without a liquidity adjustment.

A. Econometric Identification

Due to the nonlinearity of the TIPS pricing formula, the models cannot be estimated with the standard Kalman filter. Instead, we use the extended Kalman filter detailed in the online appendix. To make the fitted errors comparable across TIPS of different maturities, we scale each TIPS price by outstanding with a face value of $1.2 trillion or about 9% of all marketable Treasury debt.\(^{17}\) As Gürkaynak et al. (2010) noted, near maturity, the indexation lag in TIPS payouts can distort prices. Therefore, we censor TIPS from our sample when they have less than one year to maturity, which, as described in the online appendix, only modestly reduces the sample. The U.S. Treasury has issued ten-year TIPS on a regular basis and five-, twenty-, and thirty-year TIPS more sporadically. The maturity distribution of all 62 TIPS that have been issued since the inception of the indexed-debt program through the end of 2016 is shown in figure 2. Each TIPS that has been issued is represented by a single downward-sloping line that plots its remaining years to maturity for each date. For the five- to ten-year maturities of particular interest for our analysis, the universe of TIPS provides fairly good coverage.

The data are available at http://www.treasurydirect.gov.
its duration. Thus, the measurement equation for the TIPS prices is

\[ \frac{P_i(t_i^0, τ^i, C^i)}{D_i(τ^i, C^i)} = \frac{\hat{P}_i(t_i^0, τ^i, C^i)}{D_i(τ^i, C^i)} + \varepsilon_i, \]

where \( \hat{P}_i(t_i^0, τ^i, C^i) \) is the model-implied price of TIPS \( i \); \( D_i(τ^i, C^i) \) is its duration, which is fixed and calculated before estimation; and all TIPS measurement errors are normal i.i.d. with zero mean and standard deviation \( \sigma_\varepsilon \). (See Andreasen et al., 2019, for supporting evidence.) Initial identification of the three or four factors of the two models requires at least three or four TIPS securities, respectively, so the estimation samples start in January for the T-O model and April 1998 for the T-O-L model. The level of the latent liquidity factor is not identified without additional restrictions, so we let the level factor, is a volatile but quickly mean-reverting factor, while the slope and curvature factor are less volatile and much more volatile. Thus, the measurement equation for the TIPS prices is

\[ \frac{P_i(t_i^0, τ^i, C^i)}{D_i(τ^i, C^i)} = \frac{\hat{P}_i(t_i^0, τ^i, C^i)}{D_i(τ^i, C^i)} + \varepsilon_i, \]

where \( \hat{P}_i(t_i^0, τ^i, C^i) \) is the model-implied price of TIPS \( i \); \( D_i(τ^i, C^i) \) is its duration, which is fixed and calculated before estimation; and all TIPS measurement errors are normal i.i.d. with zero mean and standard deviation \( \sigma_\varepsilon \). (See Andreasen et al., 2019, for supporting evidence.) Initial identification of the three or four factors of the two models requires at least three or four TIPS securities, respectively, so the estimation samples start in January for the T-O model and April 1998 for the T-O-L model. The level of the latent liquidity factor is not identified without additional restrictions, so we let the level factor.

### B. Model Estimates

The estimated parameters of the T-O and T-O-L models are reported in tables 1 and 2. In both models, the usual pattern holds that the level factor is the most persistent and least volatile factor, while the slope and curvature factor are less persistent and much more volatile. Also, both estimates of \( \lambda \) are about 0.4, which is typical of previous estimates for this parameter using nominal U.S. Treasury data. Thus, in terms of dynamic characteristics for the frictionless factors in the models, the results are very similar to what other studies have reported for nominal Treasury yields using standard Gaussian AFNS models.

The estimated paths of the level, slope, and curvature factors from the two models are shown in figure 3. The two models’ level and curvature factors are fairly close to each other during the entire sample, but there is a notable difference between the two estimated slope factors in the years following the financial crisis. Accordingly, the main impact of accounting for TIPS liquidity premiums is on the slope of the frictionless real yield curve, which affects the models’ longer-run projections of real rates and, hence, the estimates of the natural rate. The fourth factor in the T-O-L model, the liquidity factor, is a volatile but quickly mean-reverting factor with an estimated mean of \( -0.0036 \), which is only slightly below the average of its filtered path shown in figure 3. The liquidity factor notably jumps during the 2008–2009 financial crisis, which is consistent with the extensive financial market dislocations of that period. It is also elevated during the first several years after the introduction of TIPS, when there was some uncertainty about whether the U.S. Treasury was committed to continuing to issue TIPS on an ongoing basis.

The estimated liquidity sensitivity parameters \( (\beta^i_1, \lambda^L_1) \) for each TIPS in the sample are reported in the online appendix, together with summary statistics for the fit of each TIPS implied by both the T-O model and the T-O-L model (which have 17 and 151 estimated parameters, respectively). Fitted yield errors are calculated by converting the fitted TIPS prices from the model estimation into fitted yields to maturity that are deducted from the midmarket yields to maturity downloaded from Bloomberg. For all TIPS yields combined, the RMSE is 8.65 basis points for the T-O model and 4.34 basis points for the T-O-L model. Consistent with Andreasen et al. (2019), there appears to be no material loss in model performance from using all available TIPS bond prices rather than just a few interpolated synthetic zero-coupon yields.

Figure 4 shows the estimated TIPS liquidity premium averaged across all available TIPS at each point in time. With the exception of the financial crisis, this average liquidity premium has been relatively stable over the sample, so it cannot account for the persistent downturn in real yields. The mean of this average liquidity premium, which is 34 basis points, and the time series pattern of variation are similar to the TIPS liquidity premiums reflect expectations under the risk-neutral Q-measure. Given its positive mean under that measure, even a negative value of the liquidity risk factor will not necessarily imply a negative liquidity premium for most of the TIPS in our sample. However, a negative liquidity premium is feasible in the model and occasionally occurs, signaling a security so desirable that investors are willing to pay a premium to hold it.

---

**Table 1. T-O Model Estimates**

<table>
<thead>
<tr>
<th>( K^{p^1}_1 )</th>
<th>( K^{p^2}_2 )</th>
<th>( K^{p^3}_3 )</th>
<th>( \theta^p_1 )</th>
<th>( \Sigma )</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.2163</td>
<td>-0.0671</td>
<td>-0.5000</td>
<td>0.0349</td>
<td>0.0045</td>
</tr>
<tr>
<td>(0.1642)</td>
<td>(0.0539)</td>
<td>(0.0496)</td>
<td>(0.0082)</td>
<td>(0.0001)</td>
</tr>
<tr>
<td>( K^{p^2}_2 )</td>
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<td>0.0919</td>
<td>-0.0561</td>
<td>-0.0236</td>
</tr>
<tr>
<td>(1.0284)</td>
<td>(0.3836)</td>
<td>(0.4015)</td>
<td>(0.0076)</td>
<td>(0.0010)</td>
</tr>
<tr>
<td>( K^{p^3}_3 )</td>
<td>-1.7790</td>
<td>0.4520</td>
<td>1.0854</td>
<td>-0.0183</td>
</tr>
<tr>
<td>(1.1688)</td>
<td>(0.4941)</td>
<td>(0.4772)</td>
<td>(0.0162)</td>
<td>(0.0018)</td>
</tr>
</tbody>
</table>

The table shows the estimated parameters of the \( K^{p^1}_1 \), \( K^{p^2}_2 \), and \( K^{p^3}_3 \) vector, and diagonal \( \Sigma \) matrix in the T-O model. The estimated value of \( \lambda \) is 0.3849 (0.0032). The maximum log-likelihood value is 25,852.69. The numbers in parentheses are the estimated parameter standard deviations.

**Table 2. T-O-L Model Estimates**

<table>
<thead>
<tr>
<th>( K^{p^1}_1 )</th>
<th>( K^{p^2}_2 )</th>
<th>( K^{p^3}_3 )</th>
<th>( \theta^p_1 )</th>
<th>( \Sigma )</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.4200</td>
<td>0.0079</td>
<td>-0.0361</td>
<td>0.2901</td>
<td>0.0369</td>
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<td>(0.2860)</td>
<td>(0.1112)</td>
<td>(0.0850)</td>
<td>(0.2529)</td>
<td>(0.0136)</td>
</tr>
<tr>
<td>( K^{p^2}_2 )</td>
<td>0.9204</td>
<td>1.1853</td>
<td>-0.0653</td>
<td>2.4599</td>
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<tr>
<td>(0.7894)</td>
<td>(0.4612)</td>
<td>(0.4112)</td>
<td>(0.7317)</td>
<td>(0.0257)</td>
</tr>
<tr>
<td>( K^{p^3}_3 )</td>
<td>-1.0592</td>
<td>0.2050</td>
<td>0.8798</td>
<td>-0.3331</td>
</tr>
<tr>
<td>(0.7653)</td>
<td>(0.4669)</td>
<td>(0.4406)</td>
<td>(0.7149)</td>
<td>(0.0233)</td>
</tr>
<tr>
<td>( \theta^p_1 )</td>
<td>1.2109</td>
<td>0.3911</td>
<td>-0.4036</td>
<td>1.7962</td>
</tr>
<tr>
<td>(0.8638)</td>
<td>(0.5426)</td>
<td>(0.5572)</td>
<td>(0.7388)</td>
<td>(0.0158)</td>
</tr>
</tbody>
</table>

The table shows the estimated parameters of the \( K^{p^1}_1 \), \( K^{p^2}_2 \), and \( K^{p^3}_3 \) vector, and diagonal \( \Sigma \) matrix in the T-O-L model. The estimated value of \( \lambda \) is 0.3902 (0.0084), while \( \sigma_{\varepsilon}^2 = 1.0457 (0.0923) \) and \( \sigma_{\varepsilon}^2 = 0.0018 (0.0004) \). The maximum log-likelihood value is 25,852.69. The numbers in parentheses are the estimated parameter standard deviations.
estimate reported by ACR, although their data are weekly and for a shorter sample. Figure 4 also shows an average measure of fit to a smoothed yield curve of individual TIPS at each point in time as an observable proxy for liquidity. Specifically, this measure is the mean absolute deviation of all TIPS yield curve fitting errors following Gürkaynak et al. (2010, henceforth GSW). This series represents the degree to which TIPS prices are outliers or unusually different from their near-maturity neighbors at any time. Hu et al. (2013) argue that such deviations measure time variation in the availability of arbitrage capital and therefore constitute useful proxies for illiquidity, and this measure is highly positively correlated (87%) with our estimated average TIPS liquidity premium series.

V. A Lower New Normal for Interest Rates?

In this section, we compare TIPS-only measures of the equilibrium real rate to alternative market-based and macro-based estimates and consider the persistence of lower real rates.

A. TIPS-Only Estimates of the Natural Rate

Our finance- or market-based measure of the natural rate is the average expected real short rate over a five-year period starting five years ahead. This 5yr5yr forward average expected real short rate should be little affected by short-term transitory shocks and well positioned to capture the persistent
The average estimated TIPS liquidity premium across all TIPS available in each month as implied by the T-O-L model estimated with monthly data from April 1998 to December 2016. A TIPS liquidity premium is measured as the estimated yield difference between the fitted yield to the maturity of an individual TIPS and the corresponding frictionless yield to maturity with the liquidity risk components zoned out. Also shown are the TIPS mean absolute fitting errors from Gürkaynak et al. (2010, henceforth GSW). This series represents deviations in the prices of TIPS from a fitted yield curve and has been scaled up by a factor of ten for comparability.

**Figure 5.** Comparison of $r^*$ estimates from T-O and T-O-L models

Figure 5 compares the estimates of $r^*$ from the T-O-L and T-O models, that is, with and without an explicit adjustment for time-varying liquidity effects in TIPS prices. Accounting for the liquidity premiums in the T-O-L model leads to some differences, with the T-O-L model $r^*$ displaying more cyclical variation in the first half of the sample. In addition, the T-O-L model estimate has notable volatility during the financial crisis. Still, the general magnitude and timing of the overall downtrend in the estimates of the equilibrium interest rate are similar across the two specifications. The estimates gradually decline from around 2% to 3% in 2000 to near 0% by the end of the sample. Figure 5 also provides evidence regarding the statistical significance of the $r^*$ estimates by including a confidence interval for the T-O model estimate based on a Monte Carlo analysis.

These simulation-based confidence intervals indicate considerable uncertainty, with a 1 standard deviation of the $r^*$ estimate of roughly 1 percentage point. Clearly, there is no statistical basis to differentiate between the two estimates, and for robustness, we will focus on the average of the T-O and T-O-L model $r^*$ estimates for our analysis. As noted, each specification has pros and cons: the T-O model is a parsimonious representation, while the T-O-L model is a highly parameterized specification that can provide sharper inference—if the underlying assumed structure is appropriate. We simply average the two estimates for a composite measure that smooths out some of the model idiosyncrasies. In the online appendix, we further explore the robustness of the $r^*$ estimates to the choice of dynamic specification and sample.

19Occasional negative T-O-L values of $r^*$ may seem unusual, but they could reflect short-run imbalances between global savings and available safe investment opportunities.

20As detailed in the online appendix, we used the T-O model estimates to simulate data samples for the three state variables, converted these to bond price samples, added measurement error, and reestimated the T-O model and an associated $r^*$ path for each sample—an infeasible procedure for the T-O-L model due to its large number of parameters.

21This range of uncertainty is not necessarily lower than that surrounding the macro-based estimates. However, the two very different approaches—macro and finance—likely have largely orthogonal confidence intervals.
As noted in section I, real-time macro-based estimates of $r^*_t$ can be quite different from later estimates that look back in time. Finance-based estimates should be less subject to this criticism as they are based on data, namely, the observed bond prices, that are available in real time and never revised. However, finance-based $r^*_t$ estimates could still be subject to revision as the model parameter estimates vary as the sample increases. To evaluate such concerns, we repeatedly estimate the T-O model with varying sample end points from January 2012 through December 2016. Figure 6 compares these expanding-sample estimates, which are effectively equivalent to real-time estimates of $r^*_t$, to the corresponding full-sample, “look-back” estimates. The average difference between these real-time and full-sample estimates is 0.35 percentage point, so that in real time, the equilibrium rate would have been estimated to be a bit higher than what the data at the end of 2016 indicate. Going forward, with a larger historical estimation sample, we would expect smaller revisions between real-time and final estimates.

Finally, estimates of the term premium from the T-O and T-O-L models provide another dimension for model comparison. Figure 7 shows the 5yr5yr real term premium estimates from each model and a confidence interval for the T-O model estimate based on the same Monte Carlo analysis described above. The real term premium estimates from the two models show little if any downtrend and broadly similar countercyclical dynamics—although the T-O-L model displays somewhat greater volatility. The elevated level of the forward real-term premium during economic recessions is consistent with theory. The very low estimated risk premiums after 2010 may reflect the increase in TIPS purchases by the Federal Reserve as part of its large-scale asset purchases (or quantitative easing), which started in November 2010 (see Christensen & Gillan, 2018, for details). The two model estimates do not differ much, so below, we focus on their average risk premium estimate.

B. Comparison with Other Estimates of the Natural Rate

There are several other estimates of the equilibrium or natural interest rate in the literature to compare with our TIPS-only estimates. To start, we consider two other estimates that are also based on only financial models and bond market data. Specifically, we consider the joint models of nominal
and real yields developed by AACMY and ACR, which also adjust for term and liquidity premiums in TIPS yields. All three market-based estimates of $r^*_t$ are shown in figure 8. The ACR model is a five-factor structure that imposes restrictions between the slope and curvature of the nominal yield curve and those of the real yield curve that were first detailed in Christensen et al. (2010). The ACR model provides $r^*_t$ estimates that are slightly lower on average and more cyclically variable than our composite CR $r^*_t$ estimate. By contrast, the AACMY model has a negative $r^*_t$ estimate for almost the entire sample, which is at odds with other estimates. AACMY use a very flexible six-factor model of nominal and real yields with two separate TIPS-specific factors, which provides very tight in-sample fit to the observed yields but potentially less accurate estimates of the factor $\mathbb{P}$-dynamics. Since those dynamics are critical to the model-implied estimates of $r^*_t$, as evident in equation (1), this may explain the unusually low AACMY estimates of $r^*_t$.

Estimates of the term premium from these arbitrage-free models provide another dimension for comparison. Figure 9 shows the 5yr5yr real term premium estimates from AACMY, ACR, and our CR estimate (the average of the T-O-L and T-O models). The CR and ACR real term premium estimates show similar countercyclical fluctuations. The CR estimate has little, if any, downward trend, while the ACR estimate has only slightly more. The real-term premium from AACMY drifts notably lower over the sample, which could reflect insufficiently persistent factor dynamics from finite-sample bias, as discussed in Bauer, Rudebusch, and Wu (2012).

Now we turn to the crucial comparison of our finance-based estimate of $r^*_t$ with the estimates based on macroeconomic models and data. Figure 10 shows the CR average $r^*_t$ estimate together with a composite macro-based measure of $r^*$. The specific macro-based series shown (the gray line) is a summary measure that averages across three fairly similar macro-based estimates. The black line shows...
The CR estimate is the average of the T-O and T-O-L model estimates.

our TIPS-only estimate of $r^*_t$—an average of the T-O and T-O-L models. The macro-based estimate shown in the figure starts in 1980—almost twenty years earlier than the start of the TIPS sample. However, in the 1980s and 1990s, the macro-based estimate changed little and generally remained between 2% and $2^{1/2}\%$. This is consistent with the received wisdom of that era in monetary economics that viewed the natural rate as effectively constant—for example, as assumed in the large Taylor rule literature. It is only just after 2000 that a decided downtrend begins in the macro-based $r^*_t$ measure. This decline started shortly after the introduction of TIPS, a fortuitous coincidence of timing for our investigation. Accordingly, even though our estimation sample is limited to the past two decades, the evidence suggests that this is the very sample of most relevance for discerning shifts in the equilibrium real rate.

During their shared sample, the macro- and finance-based estimates exhibit a similar general trend—starting from just above 2% in the late 1990s and ending the sample near 0%—and tell a similar story despite the differences in their volatility. Importantly, in terms of the levels of the natural rate estimates, both methodologies imply that $r^*_t$ is currently near its historical low. However, it should be noted that the TIPS-based natural rate estimates use the CPI as the price index, and the macro-based estimates use an alternative price deflator for personal consumption expenditures (PCEPI). Due to technical differences, the PCEPI, on average, reports a bit lower inflation than the CPI. One forward-looking measure of this discrepancy is the difference between the ten-year-ahead forecasts for PCEPI and CPI inflation reported by the Survey of Professional Forecasters. Over the sample from 2007:Q1 to 2017:Q1, the average difference between these two forecasts is 23 basis points. Therefore, on PCEPI basis, our finance-based estimate of the $r^*_t$ would be modestly higher—by about a quarter percentage point—than the version shown in figure 10.

There are also differences between the two estimates with regard to the timing of the decline in $r^*_t$. The macro-based estimate of the natural rate shows a fairly modest decline from the late 1990s until the financial crisis and the start of the Great Recession. Then it drops precipitously to less than 1% and edges only slightly lower thereafter. Arguably, this path leaves open the possibility that the Great Recession and the associated financial crisis played a key role in the decline in $r^*_t$ during the past decade. Such an interpretation suggests that the drop in $r^*_t$ could be at least partly reversed by a cyclical boom. In contrast, the drop in the finance-based $r^*_t$ estimate does not coincide with the Great Recession. The TIPS-only estimate instead declines in the early 2000s, stabilizes, and then declines a bit more starting in 2012. Therefore, the finance-based version suggests that the path of the equilibrium rate has secular, more persistent drivers.

C. Whither the Natural Rate?

In light of the intense debate among researchers, investors, and policymakers about a possible lower new normal for interest rates, we end our analysis by presenting the outlook for the natural rate based on estimated model projections, as well as discussing some of the potential drivers of a lower real rate. We follow the approach of Christensen, Lopez, and Rudebusch (2015) and simulate 10,000 factor paths over a ten-year horizon conditioned on the shape of the TIPS yield curve and investors’ embedded forward-looking expectations as of the end of our sample (that is, using estimated state variables and factor dynamics as of December 30, 2016). The simulated factor paths are then converted into forecasts of $r^*_t$. Figure 11 shows the median projection and the 5th and 95th
percentile values for the simulated natural rate, which delineate the distribution of all simulation outcomes at a given point in time. The median \( r^* \) projection shows only a very gradual partial reversal of the declines over the past two decades and only reaches 1% after 2025. Like most estimates of persistent dynamics, the T-O model will likely suffer from some finite-sample bias in the estimated parameters of its mean-reversion matrix \( K^F \), which would imply that it does not exhibit sufficient persistence—as discussed in Bauer et al. (2012). In turn, this would suggest (all else equal) that the outcomes below the median are more likely than a straight read of the simulated probabilities indicate. As a consequence, it seems even more likely that the natural rate will remain below 1% for some time.

Although our analysis has focused on measuring the dynamic path of the equilibrium real rate, it is also of interest to relate these dynamics to macroeconomic developments. In particular, the past and future path of our TIPS-based estimate of \( r^* \) is relevant to the debate about the source of the decline in the equilibrium real rate. Although our measure of the real rate fluctuated at the start of the global financial crisis, our average \( r^* \) estimate in 2010 is not much different than in 2007. This relative stability before and after the financial crisis suggests that flight-to-safety and safety premium explanations of the lower equilibrium real rate are unlikely to be key drivers of the downtrend in Treasury rates (as proposed by Hall, 2016, and Del Negro et al., 2017, among others). Instead, our estimates appear more broadly consistent with many of the explanations that attribute the decline in the natural rate to real-side fundamentals. To shed some light on these potential macroeconomic drivers, we first consider the connection between economic growth projections and bond market participants’ perceptions of the equilibrium rate.

Based on standard economic theories, such as the intertemporal consumption Euler equation, which connects the short real rate to consumption growth, longer-run economic growth is widely viewed as a key driver of the equilibrium rate. To examine this relationship with our \( r^* \) estimate, we regress monthly changes in \( r^* \) on monthly revisions to the growth projections of private forecasters:

\[
\Delta r^*_t = -1.16 + 0.24 \Delta g^{BC}_t + \epsilon_t, \quad n_{obs} = 224, \quad R^2 = 0.14, (0.98) (0.04)
\]

where \( g^{BC}_t \) is the forecast for real gross domestic product (GDP) growth over the next four quarters from the Blue Chip Economic Indicator’s monthly survey of business economists (and both series are measured in percentage points). This regression suggests that a 1 percentage point increase (decrease) in the four-quarter-ahead GDP forecast tends to be associated with a 0.24 percentage point increase (decrease) in \( r^* \). This result is also statistically significant (standard errors are given below each coefficient in parentheses). In direction, the evidence is consistent with the theoretical benchmark connecting growth and real rates with a positive sign. In terms of magnitude, the slope coefficient is much less than the usual estimate of unity employed in, for example, Laubach and Williams (2003, 2016) and Fisher (2016). However, the monthly private sector real GDP forecasts that are available are not for projections of longer-run trend or potential growth but are for growth over the next four quarters, which would certainly be more variable and require a smaller coefficient. A more serious caveat is that the results are largely driven by the observations during the great recession when a few very large downward and upward GDP growth forecast revisions coincided with similar changes in \( r^* \). Given the very few business cycles in our data sample, it is difficult to know whether to consider this episode as particularly informative of the correlation between \( r^* \) and growth or more as a spurious outlier.

\[24\]The Blue Chip survey is generally conducted on the first two working days of each month and released on the tenth of each month, and our \( r^* \) estimate is determined on the last business day of each month. Thus, the regression suggests that TIPS investors change their views partly in response to the information received during the month as reflected or released in the Blue Chip survey.
Although we take our regression evidence as broad confirmation that our finance-based measure of \( r^* \) responds in a sensible way to economic news, a cautious interpretation of our results is warranted in light of recent quite negative empirical findings based on much longer spans of data. Notably, Hamilton et al. (2016) have correlated real interest rates and output growth rates in twenty countries in samples going back as far as 1800. They find little support for the view that long-run economic growth drives changes in the equilibrium interest rate. Similarly, Lumsford and West (2017) and Leduc and Rudebusch (2014) do not find a reliable correlation between these two variables.

Instead, examinations of the historical record generally find that demographic variables have the most reliable connection with real interest rates. For example, over long samples, the fraction of the total population of working age and life expectancy appear to co-move with the real rate in ways consistent with models of aggregate saving and investment. Not surprisingly, then, the link between the changing demographic structure of global economies and real interest rates has been the recent focus of much additional theoretical and empirical work (Carvalho, Ferrero, & Nechio, 2016; Favero, Gozlukul, & Yang, 2016; Ferrero, Gross, & Neri, 2017). In an interesting theoretical contribution, Gagnon et al. (2016, denoted GJLS) calibrate an overlapping-generations model to observed and projected changes in U.S. population, family composition, and life expectancy. They assess the effects of these changes on saving and investment and real interest rates, and their resulting calculation of the contribution of demographic factors to a lower equilibrium real interest rate is shown as the gray line in figure 11. This contribution—from a calibrated theoretical model—can account for almost half of the decline in our estimated \( r^* \), and shows a similar timing of the broad decline over the past two decades. In closely related work, Lisack, Sajedi, and Thwaites (2017) also calibrate an overlapping generations model to show that demographic changes alone could account for just over a 100 basis point of the broad decline over the past two decades. In closely related work, Lisack, Sajedi, and Thwaites (2017) also calibrate an overlapping generations model to show that demographic changes alone could account for just over a 100 basis point downward trend in the U.S. equilibrium real rate from 2000 to 2015, which is broadly in line with the GJLS results.

VI. Conclusion

Using macroeconomic models and data, many researchers have investigated the contribution to the downtrend in yields in recent decades from a falling equilibrium real interest rate. However, uncertainty about the correct macroeconomic specification has led some to question the validity of the resulting macro-based estimates of the natural rate. We sidestep this debate by introducing a finance-based measure of the equilibrium real rate that is obtained solely from dynamic term structure models estimated using the prices of inflation-indexed bonds. By adjusting for both TIPS liquidity premiums and real-term premiums, we uncover investors’ expectations for the underlying frictionless real short rate for the five-year period starting five years ahead. Our resulting measure of the natural rate of interest exhibits a gradual decline over the past two decades to a level of essentially 0. Furthermore, model projections suggest that the natural rate is likely to remain quite low for some time.

We view our finance-based equilibrium rate analysis as a complement to previous macro-based ones. Like the macro-based estimates, a finance-based estimate is also subject to critiques about model specification and the information content of the available data. In light of such critiques, the range of uncertainty attached to a finance-based estimate does not appear to be necessarily smaller than that surrounding the macro-based estimates. However, the underlying models and data in the two approaches are so different that the confidence intervals are also likely largely uncorrelated, which does suggest substantial value from constructing and comparing both finance- and macro-based estimates. Of course, a joint approach that combines macroeconomic and financial market data would appear to be particularly promising for future research. Indeed, our measure could be incorporated into an expanded joint macroeconomic and finance analysis, particularly with an eye toward further understanding the determinants of the lower new normal for interest rates. In this regard, Bauer and Rudebusch (2017) show that accounting for fluctuations in the natural rate substantially improves long-range interest rate forecasts and helps predict excess bond returns. In addition, future research could also be expanded along an international dimension (as in Holston, Laubach, & Williams, 2017). With a significant degree of capital mobility, the natural rate will depend on global saving and investment, so the joint modeling of inflation-indexed bonds in several countries could be informative. Finally, the issue investigated in this paper depends crucially on inference about the \( P^* \)-dynamics of interest rates, which is perhaps the Achilles’ heel of dynamic term structure modeling. We have taken a standard approach, but other possibilities would be to incorporate survey forecast information, restrict the prices of risk, or bias-adjust or shrink the dynamic parameters toward nonstationarity.

REFERENCES


