FCI-star

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Abstract

Central banks rely on r^*—the neutral interest rate—to assess policy stance. However, monetary policy affects activity through broad financial conditions, not only the short-term rate. We propose FCI^*, the neutral level of a financial conditions index consistent with output at potential. Unlike r^*, FCI^* is insulated from financial fluctuations: when asset prices move, FCI captures their estimated effect on output, leaving FCI^* to reflect only what the macroeconomy requires. In U.S. data, r^* co-moves with the equity premium; FCI^* does not. FCI gaps provide useful real-time guidance on policy stance, especially when financial conditions diverge from the policy rate.

JEL Codes: E52, E58, E43, E44, C32

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1. Introduction

> "Financial conditions matter to us because... financial conditions are the main channel to the real economy through which our policy has its effect."— Jerome Powell, Federal Reserve Chair, Press Conference, March 19, 2025

Central banks rely on estimates of r^*—the rate consistent with output at potential—to assess policy stance. Estimates of r^* declined persistently after the Global Financial Crisis (GFC), shaping narratives around secular stagnation and the zero lower bound. Yet as of late 2025, policy rates remain well above pre-COVID-19 levels even as inflation has normalized, and r^* estimates have drifted upward. What explains these fluctuations? Monetary policy transmits to the real economy primarily through broad financial conditions—long-term interest rates,

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equity prices, house prices, and exchange rates—rather than through the policy rate alone. To stabilize output, policy must offset movements in these volatile asset prices. This forces r^* to absorb financial fluctuations—falling when asset prices collapsed after the GFC, rising alongside the asset price boom since COVID-19. Moreover, an r^* driven by volatile financial variables is difficult to estimate in real time. This complicates policy stance assessment when financial conditions diverge from the policy rate.

We propose an alternative measure of neutral monetary conditions that addresses these limitations. Financial conditions indices (FCIs) quantify the effect of asset prices and rates on output. We introduce, characterize, and estimate FCI^*, the neutral level of financial conditions consistent with output at potential. By working in FCI space, we leverage the extensive empirical research underlying FCI construction. Since FCIs already incorporate the demand effects of asset prices, these effects need not be absorbed by the neutral benchmark. Our theory formalizes this intuition, showing that FCI^* is insulated from financial market fluctuations and driven primarily by macroeconomic forces. Our empirical analysis confirms this. We further demonstrate that deviations of FCI from FCI^* provide useful real-time information on the effective policy stance.

We work with the FCI-G index introduced by Ajello et al. (2023), which uses the Federal Reserve's quantitative models to estimate the effect of recent asset price and interest rate changes on expected output growth. This index connects naturally to the output-asset price relation from Caballero and Simsek (2022), where asset prices and demand shocks drive economic activity with inertia (the conceptual analog of the IS relation expressed in terms of financial conditions). We exploit this connection to describe output growth in terms of FCI and demand shocks. This reformulation enables us to define FCI^* as the neutral level of financial conditions that balances expected output with potential a few quarters ahead.

Our framework reveals that FCI^* primarily reflects macroeconomic forces rather than financial market developments. In particular, FCI^* is determined by demand shocks, as well as expected potential output growth. In contrast, we demonstrate that the (neutral) r^* is influenced by financial markets as well as macroeconomic factors. For instance, consider a decline in stock and house prices driven by a shift in risk premiums or sentiment. All else equal, this reduces r^* but leaves FCI^* unchanged. Intuitively, since a decrease in asset prices reduces aggregate demand, the central bank is forced to set lower interest rates to provide support—and vice versa when asset prices rise. However, since these effects are already accounted for in the FCI construction, FCI^* remains unaffected. When asset prices move, FCI moves accordingly, leaving FCI^* to reflect only what the macroeconomy requires.

Our model further demonstrates that FCI gaps—the deviations between actual FCI and FCI^*—drive output gaps (along with unanticipated shocks). This relationship forms the basis of our empirical analysis as it allows us to infer FCI^* from estimated output gaps. Negative output gaps indicate that observed FCI is too tight relative to FCI^*, while positive output gaps suggest the opposite.

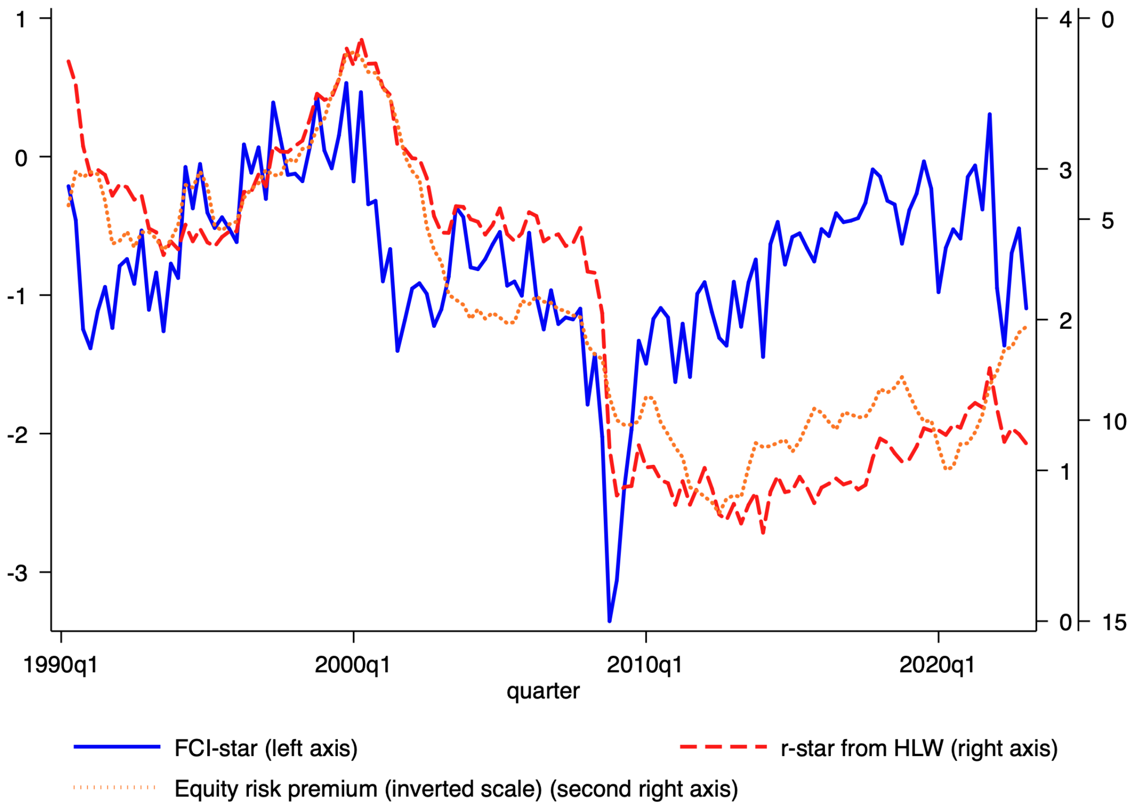

Figure 1: This figure plots r^* as estimated in Holston et al. (2023) alongside our estimate of FCI^*. The equity risk premium measure is from Duarte and Rosa (2015) and is available through 2023Q1.

Our estimation approach follows closely the approach in Laubach and Williams (2003) for estimating r^*: we develop and estimate a two-equation macroeconometric model. The first equation links output gaps to FCI gaps rather than interest rate gaps. The second equation is a backward-looking Phillips curve; we adopt the same specification as in Laubach and Williams (2003) to facilitate comparisons. We estimate this model using quarterly data spanning from 1990Q2 to 2024Q4, incorporating adjustments for the COVID-19 period through the Oxford COVID-19 Stringency Index (Holston et al., 2023). We employ a combination of calibrated parameters and maximum likelihood estimation via the Kalman filter. This approach provides a tractable way of estimating the latent FCI^* state and makes it directly comparable with prevailing estimates of r^*.

Our empirical findings confirm the theoretical predictions. The Holston-Laubach-Williams r^* strongly correlates with the equity risk premium, but FCI^* does not once we control for macroeconomic conditions. Figure 1 illustrates this divergence. The figure suggests some co-movement between FCI^* and the risk premium, but this reflects periods when financial booms and busts drove the business cycle—such as during the late 1990s and early 2000s. In multivariate regressions controlling for output gaps, the equity risk premium has no independent relationship with FCI^*. In contrast, r^* remains strongly correlated with the risk premium even after controlling for output gaps.

While FCI^* is insulated from financial shocks by construction, observed FCI is not—creating FCI gaps in the data. These gaps are especially large during financial recessions such as the GFC, where observed FCI tightens with market distress while FCI^* loosens to reflect the degree of stimulus required by the economy. Such gaps might emerge from frictions the central bank faces in practice: the zero lower bound, policy gradualism, transmission lags, or cost-push shocks.

Two additional findings support our conclusion that FCI^* is a useful measure of monetary policy stance, especially when financial conditions diverge from the policy rate. First, in recent decades the IS curve fits better with FCI than with interest rates, reflecting the broader channels of monetary policy transmission that FCI captures. Since the IS curve is central to the estimation—we infer the neutral level from the relationship between financial conditions and output gaps—this stronger fit results in more stable estimates of FCI^* than comparable estimates of r^*. Second, FCI gaps accurately reflect shifts in the effective policy stance. After the GFC, FCI remained tighter than FCI^*, suggesting policy was effectively tight and demand was weak throughout the recovery. The Laubach and Williams (2003) framework, in contrast, implies policy was accommodative and attributes the weakness to declining potential output. FCI gaps also offer real-time advantages. In 2022, they captured the rapid tightening at a time when interest rate gaps still suggested accommodation—asset prices and long-term rates moved well ahead of policy rates.

Related Literature. This paper relates to the theoretical literature on r^* and its usefulness for monetary policy (Wicksell, 1936; Woodford, 2003). We contribute by introducing a new concept, FCI^*. This paper also relates to the empirical literature that estimates r^*. Within this literature, the approaches range from flexible econometric models that impose no theoretical structure (Lubik and Matthes, 2015, 2023), to semistructural models with some connection to theory (Laubach and Williams, 2003; Holston et al., 2017, 2023), to fully structural DSGE models (Negro et al., 2013; Barsky et al., 2014). We build on the semistructural approach of Laubach and Williams (2003). Our estimates differ from theirs in several ways, as we described above. In addition, since we explicitly incorporate cyclical demand shocks, our FCI^* is a *neutral* measure relevant over shorter horizons, whereas Laubach-Williams estimates a *natural* rate intended for 5 to 10 years ahead.

In terms of the underlying theory, our paper builds upon our earlier work that investigates the connections between financial markets and monetary policy (see Caballero and Farhi (2018); Caballero and Simsek (2020, 2021, 2022, 2024b,a); Caballero et al. (2024); Caballero and Simsek (2025)). The most closely related paper is Caballero and Simsek (2022), which develops a New-Keynesian model where monetary policy transmits through asset prices. In that paper, we theoretically investigate the gap-minimizing asset price, which we refer to as p^*, and show that it is determined by macroeconomic needs rather than financial market forces. The current paper is an empirical complement to Caballero and Simsek (2022): we connect the asset price in the model to measures of FCI, and we use this connection to estimate FCI^* and empirically investigate its properties. In Caballero et al. (2024), we use VAR counterfactuals to construct an optimal financial conditions target that a central bank might set under realistic frictions. Despite their completely different construction procedures, the optimal target and FCI^* move closely together outside the GFC, suggesting that FCI^* serves as a reliable guide for practical policy evaluation (see Online Appendix D.6). Beyond our own work, this paper is part of a large literature on New Keynesian models with risk and asset prices (Pflueger et al., 2020; Kekre and Lenel, 2022; Kekre et al., 2023; Beaudry et al., 2024; Adrian and Duarte, 2018; Adrian et al., 2020).

Finally, our paper relates to an empirical literature that documents the predictive power of financial conditions, particularly regarding the likelihood of tail events (Adrian et al., 2019, 2022; Ajello et al., 2024). We emphasize the usefulness of FCIs not only for predicting tail outcomes but also for assessing the monetary policy stance during normal periods.

2. Theoretical Framework

2.1. How is the FCI constructed?

We use the Financial Conditions Impulse on Growth index (FCI-G) constructed by Ajello et al. (2023). Two features of FCI-G make it particularly suited to our analysis. First, FCI-G is constructed from the estimated causal effects of asset prices and interest rates on output, using the Federal Reserve Board's FRB/US model and other structural models. These models incorporate the various channels by which financial markets affect economic activity: borrowing and investment effects of interest rates, wealth effects of stock and house prices, and expenditure switching effects of exchange rates. Second, FCI-G aggregates changes in financial variables rather than levels, which maps directly into our theoretical framework without modification. Other well-known indices—such the Chicago Fed's NFCI or the Goldman Sachs FCI (Hatzius and Stehn, 2018)—differ in one or both of these dimensions.[1]

Formally, FCI-G measures changes in seven financial variables indexed by j: three asset prices (stock prices, house prices, and the US dollar exchange rate) and four interest rates (the Fed Funds rate, 10-year Treasury yield, 30-year fixed mortgage rate, and BBB bond yield). For asset prices, changes are calculated as log price differences. For interest rates, changes are calculated as differences in yields. To simplify the notation and link the analysis to our theoretical model, we use the uniform notation Δp_t^j for all assets, with the convention that $\Delta p_t^j < 0$ corresponds to

[1] The NFCI uses statistical weights to summarize co-movement among financial variables, not estimated causal effects on output—a fundamentally different approach. The Goldman Sachs FCI captures estimated asset price effects but in levels rather than changes; our framework could be adapted to such indices.

a tightening of financial conditions (higher rates or lower asset prices).[2] For each asset j, FCI-G constructs an asset-specific index as a weighted sum of current and past price changes

$$FCI_t^j = \sum_{\ell=0}^{T-1} \omega_\ell^j \left(-\Delta p_{t-\ell}^j \right). \tag{1}$$

The weights ω_ℓ^j capture the estimated causal effect of asset price changes on output growth over the next year. They are constructed from model-implied dynamic impulse responses to an unanticipated shock to the price of asset j, holding other price changes constant.[3] The summation extends over $T = 12$ quarters since financial variables affect activity with long lags. The aggregate FCI is then $FCI_t = \sum_j FCI_t^j$. By construction, a reading of 1 implies that recent financial conditions will reduce next-year's GDP growth by approximately 1 percentage point.

Figure 2 illustrates the index and the contribution of each financial variable over 1990Q1-2024Q2. The stock market is the main driver of the index followed by the exchange rate. The housing market is an important driver during the buildup of the GFC and COVID recovery. Risky asset prices drive the index fluctuations not because their weights are large but because they are more volatile than bond prices.

2.2. How does this FCI map to a model?

We next map the FCI to a stylized structural model. Consider the aggregate demand block in Caballero and Simsek (2022). The baseline setup features an output-asset price relation:

$$y_t = m + p_t + \delta_t.$$

Here, y_t is log output, p_t is the log price of the market portfolio, δ_t is a demand shock, and m is a constant. This relation captures the various mechanisms by which asset prices affect aggregate demand and output. We think of p_t as an average of the asset prices in FCI-G weighted by their impact on output.

We generalize this to include realistic inertial dynamics:[4]

$$y_t = \eta y_{t-1} + (1 - \eta)(m + p_{t-1}) + \delta_t. \tag{2}$$

Here, the parameter η controls the degree of inertia in aggregate demand. Taking first differences

[2] For a bond with duration n, $\Delta p \simeq -n\Delta i$, so yield changes are approximately proportional to log price changes.

[3] Specifically, the Fed's models are used to estimate the impact of a price decline $-\Delta p_{t-\ell}^j$ on current log output ($\beta_{0,\ell}^j$) and on log output one year ahead ($\beta_{4,\ell}^j$). The weight is the difference: $\omega_\ell^j = \beta_{4,\ell}^j - \beta_{0,\ell}^j$.

[4] See Caballero and Simsek (2022, 2023, 2024b) for similar formulations. Caballero and Simsek (2024b) provides a microfoundation based on infrequent adjustment of spending and portfolio decisions.

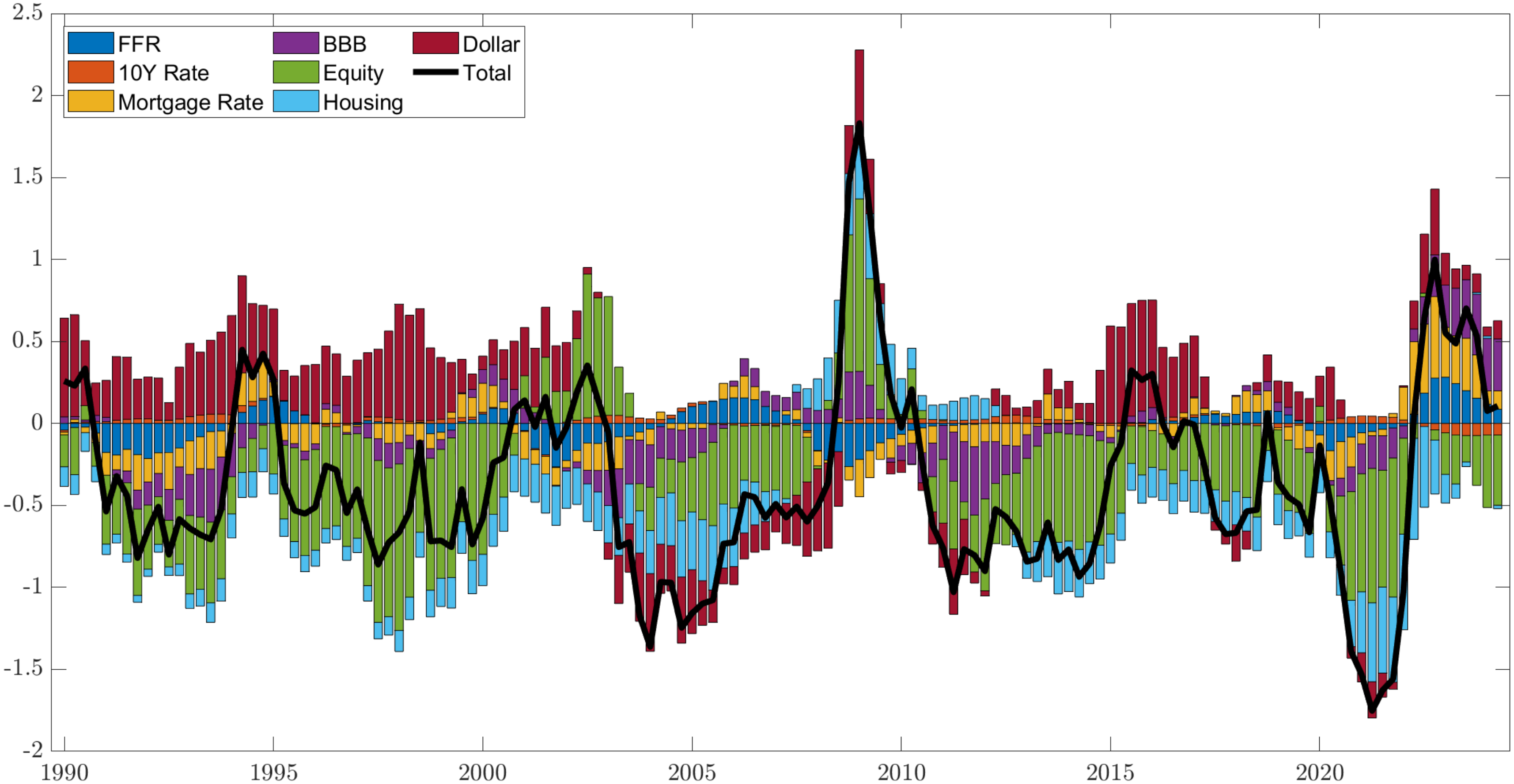

Figure 2: The FCI-G index (baseline measure with a three-year lookback) and its drivers over 1990Q1-2024Q2. Positive values imply a decrease in GDP growth in the next year. Source: Ajello et al. (2023)

and iterating, we obtain

$$\Delta y_t = (1-\eta)\sum_{\ell=0}^{\infty}\eta^{\ell}\Delta p_{t-1-\ell} + \sum_{\ell=0}^{\infty}\eta^{\ell}\Delta\delta_{t-\ell}.$$

The first term captures the total effect of past asset price changes on current quarter output growth—similar to the FCI-G construction. In fact, considering the cumulative effect over the next year, $(1-\eta)(1+\eta+\eta^2+\eta^3) = 1-\eta^4$, we get the model equivalent of FCI:

$$FCI_{t-1} = -(1-\eta^4)\sum_{\ell=0}^{\infty}\eta^{\ell}\Delta p_{t-1-\ell}. \tag{3}$$

The minus sign reflects the sign convention that higher FCI indicates tighter conditions. We can then write current quarter output growth as:

$$\begin{aligned} \Delta y_t &= -a(\eta)FCI_{t-1} + \sum_{\ell=0}^{\infty}\eta^{\ell}\Delta\delta_{t-\ell}, \qquad (4)\\ \text{with } a(\eta) &= \frac{1-\eta}{1-\eta^4} = \frac{1}{1+\eta+\eta^2+\eta^3}. \end{aligned}$$

A tightening of FCI reduces output growth in the next quarter, with a magnitude that depends on aggregate demand inertia.

2.3. From FCI to FCI^*

We next develop the model further to construct FCI^*. Suppose the economy is subject to three sources of exogenous disturbances:

$$y_t^n = y_{t-1}^n + g_{t-1} + \epsilon_t^{y^n} \tag{5}$$

$$g_t = g_{t-1} + \epsilon_t^g \tag{6}$$

$$\delta_t = \rho_\delta \delta_{t-1} + \epsilon_t^\delta \tag{7}$$

Potential output y_t^n follows a random walk with growth rate g_t, which itself follows a random walk. This specification follows Laubach and Williams (2003) and is the same we use in Section 3. Supply-side innovations capture both permanent supply shocks ($\epsilon_t^{y^n}$), as well as news that permanently shift the expected growth rate (ϵ_t^g). Demand shocks have persistence ρ_δ, with $|\rho_\delta| < 1$. They capture non-financial forces that affect aggregate spending, e.g., a consumer sentiment shock or a fiscal policy shock. All innovations are mutually and serially uncorrelated.

We define FCI^* as the FCI in a counterfactual economy where the central bank closes expected output gaps: $E_t[y_{t+1}] = E_t[y_{t+1}^n]$ for all t. Given transmission lags, closing gaps exactly each period is infeasible; closing them in expectation is achievable. We denote variables in this economy with a star superscript. Given equation (2), the only variable that can affect output directly at t is a surprise aggregate demand shock. Thus, output in the star economy satisfies:

$$y_t^* = E_{t-1}[y_t^n] + \epsilon_t^\delta = y_{t-1}^n + g_{t-1} + \epsilon_t^\delta. \tag{8}$$

Here, we used $E_{t-1}[y_t^*] = E_{t-1}[y_t^n]$.

After evaluating equation (4) at $t+1$, taking expectations, using (8), and rearranging, we obtain an expression for FCI_t^*:

$$FCI_t^* = a(\eta)^{-1}\left(-g_t - \epsilon_t^{y^n} + (E_t[\delta_{t+1}] - E_{t-1}[\delta_t]) + \eta\left[\sum_{\ell=0}^{\infty} \eta^\ell \Delta\delta_{t-\ell}\right]\right). \tag{9}$$

FCI^* is driven by macroeconomic developments. Equation (9) reveals that FCI^* reflects *macroeconomic* forces—aggregate supply and demand—rather than financial market valuations.

First, FCI^* depends negatively on expected growth g_t. Faster potential growth requires looser financial conditions so that demand growth keeps up with supply growth.

Second, FCI^* depends negatively on supply shocks $\epsilon_t^{y^n}$. A positive shock raises potential output permanently, so financial conditions should loosen for demand to increase with supply. Notice that only the current value of the shock $\epsilon_t^{y^n}$ appears in FCI^*: permanent supply shocks generate short-term fluctuations in FCI^* because they require a one-time adjustment in demand.

Third, FCI^* depends on demand shocks—both the current forecast update $E_t[\delta_{t+1}]-E_{t-1}[\delta_t]$ and all past demand changes. Past demand shocks affect current activity due to the inertia in equation (2). Higher expected activity requires tighter conditions. Thus, demand shocks generate persistent (but not long-run) fluctuations in FCI^*.

Notably absent from equation (9) are financial market variables such as risk premia or asset valuations. The FCI construction already incorporates the demand effects of asset prices, so financial variables do not enter equation (4) once we control for FCI. This implies FCI^* does not depend on financial fluctuations.

r^* is influenced by financial developments. In contrast to FCI^*, r^* depends on financial market variables. To characterize r^*, we must specify the financial market block that determines asset prices p_t for a given path of interest rates r_t. There are many different ways of specifying the financial market block. This richness already hints that r^* depends on the details of the financial market structure. We consider the setup in Caballero and Simsek (2022) where r^* that closes expected output gaps is given by (see Online Appendix A for details):

$$\begin{aligned} r_t^* &= \rho + g + \frac{\eta}{1-\eta}\left(\epsilon_t^\delta - \epsilon_t^{y^n}\right) + \frac{\beta}{1-\eta}s_t - \frac{1}{2}\overline{rp} \qquad (10) \\ \text{where } \overline{rp} &= \left(\frac{\beta}{1-\eta}\right)^2 \sigma_{y^n}^2 + \left(\frac{1-\eta-\beta}{1-\eta}\right)^2 \sigma_\delta^2 \\ \text{and } s_t &= \rho_s s_{t-1} + \epsilon_t^s. \end{aligned}$$

Here, $\rho = -\log\beta$ is the discount rate, g is the expected growth rate, $\overline{rp}$ denotes the average risk premium. In this model, average risk premium is related to the volatility of supply and demand shocks. The variable s_t represents financial market "sentiment": excessive optimism or pessimism about future cash flows that shifts asset valuations. We assume sentiment follows an AR(1) process.

Equation (10) shows r^* depends on sentiment in addition to macroeconomic factors. A negative sentiment shock reduces the asset price p_t, tightening FCI and reducing future output. To prevent this, r^* must fall—absorbing financial fluctuations that are orthogonal to fundamentals.

The same logic applies to any force that shifts asset valuations without changing macroeconomic fundamentals. A large finance literature documents that asset prices exhibit "excess volatility"—fluctuating considerably due to sentiment (e.g., Shiller (2014)), time-varying risk premiums (e.g., Cochrane (2011)), or noise in inelastic markets (e.g., De Long et al. (1990); Gabaix and Koijen (2021)). In our previous work, we have shown that r^* fluctuates with such forces (Caballero and Simsek, 2020; Caballero et al., 2024). The broad point is that r^* carries the burden of responding to financial fluctuations, whereas FCI^* is insulated from them.

Remark 1 (Relation between FCI^* and neutral vs natural r^*)**.** *Since FCI^* depends on short-term factors (such as transitory supply and demand shocks) as well as long-run factors (long-run GDP growth), it is conceptually closer to estimates of the* neutral *interest rate that provides a benchmark over shorter horizons. A related object, which following Obstfeld (2023) we refer as the natural interest rate, corresponds to the long-run interest rate that would hold after the effects of transitory demand and supply shocks have dissipated. See Reis (2025) for a discussion on different concepts that are all referred to as r^*.*

2.4. From FCI gaps to output gaps

The final step links FCI gaps—deviations between observed FCI and FCI^*—to output gaps. Let $\tilde{y}_t = y_t - y_t^*$ be the output gap.[5] Subtracting equation (4) from its counterpart in the star economy, yields:

$$\Delta\tilde{y}_t = -a(\eta)(FCI_{t-1} - FCI^*_{t-1}). \tag{11}$$

This equation is key to our empirical strategy: a positive output gap implies a negative FCI gap. Thus, the FCI gap plays the role of the real rate gap $r_t - r_t^*$ in a standard New Keynesian setup.

The drivers of FCI gaps. What drives FCI away from FCI^*? First, FCI is directly influenced by monetary policy (Caballero and Simsek, 2022; Caballero et al., 2024). Therefore, the same reasons that may drive the policy rate away from r^* apply here: (i) cost-push shocks,

[5]We define output gaps as relative to the output in the star economy y_t^* as opposed to potential output y_t^n. This simplifies the expressions and only has a small effect on our estimates since the two measures are identical up to contemporaneous supply and demand shocks $y_t^* = y_t^n - \epsilon_t^{y^n} + \epsilon_t^{\delta}$ (see (5) and (8)).

which the central bank might fight optimally by inducing negative output gaps, (ii) gradualism, which induces the central bank to adjust interest rates and influence financial conditions at a slower pace, (iii) imperfect information about the exact value of FCI_t^*. Second, unlike the policy interest rate, the Fed does not directly control FCI. Therefore, financial market shocks that affect FCI directly and that might not be quickly stabilized by the central bank can also induce FCI gaps. This creates ample scope for FCI gaps because, as our analysis shows, FCI^* depends *only* on macroeconomic factors.

3. Empirical Framework to Estimate FCI^*

We now turn to the estimation of FCI^*. Our basic approach follows Laubach and Williams (2003): We build a simple macroeconometric model where FCI^* is an unobserved state variable, and estimate it using the Kalman filter. Given that FCI^* is a relatively novel theoretical concept, we prefer to use a small, transparent model that has a direct connection to the theory outlined in Section 2.

3.1. Model Overview

Our empirical model has the following two observation equations:

$$\tilde{y}_t = \tilde{y}_{t-1} - a(\eta)\widetilde{FCI}_{t-1} + \epsilon_{\tilde{y},t} \tag{12}$$

$$\pi_t = b_\pi \pi_{t-1} + (1 - b_\pi)\pi_{t-2:4} + b_y \tilde{y}_{t-1} + \epsilon_{\pi,t}, \tag{13}$$

where $\tilde{y}_t$ represents the output gap, $\widetilde{FCI}_{t-1}$ represents the gap in financial conditions, π_t is inflation, $\pi_{t-2:4} = (\pi_{t-2} + \pi_{t-3} + \pi_{t-4})/3$ is a moving average of inflation in the past 2 to 4 quarters.

Equation (12) is the empirical analog of equation (11)—we have simply added an error term. This equation is our key departure from Laubach and Williams (2003): our specification emphasizes that the main variable governing aggregate demand is financial conditions instead of the real interest rate. The rest follows Laubach and Williams (2003). Equation (13) is a backward-looking Phillips curve. The shocks $\epsilon_{\tilde{y},t}, \epsilon_{\pi,t}$ are assumed to be mutually and serially uncorrelated. They account for short-term movements in the data that are unrelated to the core macroeconomic forces that we attempt to uncover.

In order to find the law of motion of FCI_t^*, multiply both sides of equation (9) by $(1 - \eta L)$ where L is the lag operator, and rearrange to obtain:

$$\begin{aligned} FCI_t^* = \; & \eta FCI_{t-1}^* + [a_f(\eta)]^{-1} \left(-\epsilon_{y^n,t} - \epsilon_{g,t} + \epsilon_{\delta,t}(\eta + \rho_\delta) - (1-\eta)g_{t-1} + \right. \\ & \left. \eta(y_{t-1}^n - (y_{t-2}^n + g_{t-2})) - (\eta + (1-\rho_\delta)\rho_\delta)\delta_{t-1} + \eta\rho_\delta\delta_{t-2})\right). \end{aligned} \tag{14}$$

Thus, equations (5), (6), (7) and (14) constitute our state evolution equations. We assume that

$\epsilon_{y^n}, \epsilon_{g,t}, \epsilon_{\delta,t}$ are all mutually and serially uncorrelated.

Noting that $y_t^* = y_{t-1}^n + g_{t-1} + \delta_t - \rho_\delta \delta_{t-1}$, we can write equations (12)-(13) as a function of observables and underlying states. These are the observation equations of our system. Online Appendix C collects all equations and explicitly writes down the matrix representation following the notation in Hamilton (1994).

3.2. Implementation Details

We cover the main implementation choices in this subsection, with additional details relegated to Online Appendix B. We inspect the robustness to several of these choices in Online Appendix D.

Data. We use quarterly data; our main sample is 1990Q2–2024Q4. For estimation, we measure output y_t as the log of real GDP, inflation π_t as (annualized) quarter-on-quarter PCE core inflation, and FCI using the FCI-G index. To inspect correlations with financial variables, we use the equity risk premium measure from Duarte and Rosa (2015), updated to 2023Q1. Finally, for comparison, an alternative estimate of the output gap is $\tilde{y}^{CBO} = 100 \times (y_t - y_t^{p,CBO})$, where $y_t^{p,CBO}$ is potential output estimated by CBO (in logs).

COVID-19 adjustments. We address COVID-19 data issues following the procedure in Holston et al. (2023). First, we allow the variance of innovations during Q2 through Q4 of 2020 to scale by a factor κ_{2020}, which is estimated as a free parameter (Lenza and Primiceri, 2022).

Second, we deal with the supply-side effects of COVID-19 by assuming that potential output is:

$$y^*_{t,COVID-19-adj.} = y_t^* + \frac{\phi}{100} d_t. \tag{15}$$

Here, d_t is the quarterly COVID-19 Stringency Index for the U.S. and ϕ is a parameter to be estimated. Since the data for the index finishes at 2022Q4, we set its value to 0 from 2023Q1 onwards.

Parameter estimation. We use a mix of calibration and estimation to obtain parameters. We fix the parameters of the Phillips curve to $(b_\pi, b_{\tilde{y}}) = (0.689, 0.08)$, the point estimates of Holston et al. (2023). We do this for two reasons. First, for comparability with Holston et al. (2023): since we are using exactly the same Phillips curve, any differences in the inferred states must be due to the different specification of the demand block. Second, estimates of a structural Phillips curve are sensitive to the exact specification and estimation method (Mavroeidis et al., 2014). We sidestep this issue by externally calibrating the parameters. We also fix the ratio of variances of innovations in y^n and g_t to the point estimate in Holston et al. (2023), $\lambda_g = \frac{\sigma_g}{\sigma_{y^n}} = 0.0667$ for econometric reasons, see Stock and Watson (1998); Laubach and Williams (2003). Assuming all shocks are normally distributed, the remaining parameters are estimated by maximum likelihood.

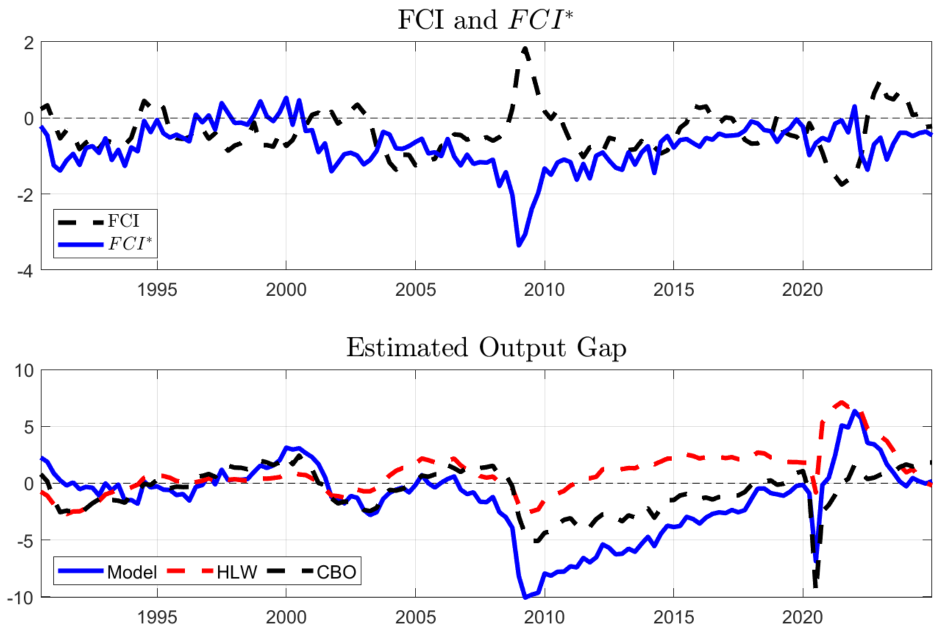

Figure 3: Top: FCI (black) and FCI^* (blue). Bottom: estimates from current model (blue), Holston et al. (2023) (red) and CBO (black). All estimates are one-sided. Online Appendix D presents additional results for two sided estimates.

4. Estimation Results

4.1. Estimated FCI^* and Output Gap

The top panel of Figure 3 shows the estimated FCI^* along with the measured FCI. The bottom panel shows the one-sided estimated value of the output gap (in blue). For comparison, we also include the output gap from the Holston et al. (2023) model (in red) and the CBO output gap (black).

The estimated value of FCI^* has some short-run volatility but does not closely track the observed FCI. Sizeable gaps open up in several moments, most notably during the GFC. Intuitively, since FCI is a weighted average of asset price changes, it naturally imports the excess volatility of asset prices emphasized by the finance literature. On the other hand, by construction FCI^* depends on macroeconomic rather than financial factors. Therefore, large asset price shocks naturally induce FCI gaps.

Our estimated output gap is close to zero during much of the 1990s, turns positive around 2000 during the dot-com bubble, becomes negative during the early 2000s recession, and turns positive again during the run-up to the GFC. The gap drops sharply during the GFC and does not turn positive again until COVID-19, when we estimate a large positive output gap. The large output gaps during COVID-19 are driven by a fall in potential output, consistent with pandemic lockdowns meaningfully reducing aggregate supply.

	Dependent variable	
	FCI^*	r^*
ERP	0.017	-0.292^{***}
	(0.016)	(0.011)
Output Gap	0.17^{***}	0.028
	(0.026)	(0.018)
R^2	0.347	0.883
Observations	132	132

Table 1: Regression Results. "ERP" is the equity risk premium measure by Duarte and Rosa (2015). The output gap is the one measured by the CBO. Sample: 1990Q2-2023Q1. Standard errors in parentheses.$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$

Our estimated output gap is similar to the HLW and CBO output gaps until right before the GFC. Around the GFC, all three estimates decline, but ours falls much more sharply. The key difference emerges in the aftermath: our estimate, like the CBO's, remains negative for almost a decade, whereas the HLW estimate recovers quickly—turning positive by 2011 and reaching peaks similar to those before the GFC.

This divergence reflects how each framework interprets the same data. HLW observe that interest rates were low after the GFC and inflation did not fall dramatically. In their framework, low rates imply loose policy, and the absence of disinflation implies output gaps cannot be too negative. They reconcile weak output and low interest rates with small output gaps by inferring a decline in potential output and in r^*

We use exactly the same Phillips curve but reach a different conclusion. While interest rates were low, FCI was not particularly loose in this period—credit spreads remained elevated, equity valuations were depressed, and risk premia were high. Given the strong link between FCI and output that we estimate, our framework implies persistently negative output gaps. We attribute the lack of large disinflation to the Phillips curve error term. This interpretation aligns with the literature on the "missing disinflation" puzzle (see Ball and Mazumder (2011); Coibion and Gorodnichenko (2015)) and with the conventional narrative of a prolonged demand-driven slump.

4.2. Correlations with Financial Fluctuations

Our theoretical framework predicts that FCI^* is driven by macroeconomic fundamentals while r^* also responds to financial fluctuations. Our estimates support this prediction. Figure 1, introduced earlier, shows that r^* is highly correlated with the risk premium throughout the sample, while FCI^* is only mildly correlated with the risk premium earlier in the sample—a correlation that breaks down after the GFC.

While this figure is suggestive, a multivariate analysis is necessary since financial fluctuations and macroeconomic outcomes are correlated. We therefore regress both FCI^* and r^* on the equity risk premium and the CBO output gap. The equity risk premium proxies for financial fluctuations while the CBO output gap proxies for macroeconomic conditions.

Table 1 reports the results. When we regress FCI^* on both variables, only the output gap enters significantly; the equity risk premium has no independent relationship with FCI^*. In particular, the mild correlation between the risk premium and FCI^* in Figure 1 reflects the correlation between the output gap and the risk premium. In contrast, when we regress r^* on the same variables, the equity risk premium remains strongly significant. These regressions confirm that FCI^* is driven by macroeconomic fundamentals, whereas r^* is significantly influenced by financial valuations. Online Appendix D.4 shows that these results are robust to alternative measures of expected excess returns.

4.3. Comparing IS curves estimated with FCI versus r

The IS curve (12) is the core of our estimation: we invert estimated output gaps to infer FCI gaps, just as Laubach-Williams invert output gaps to infer interest rate gaps. The strength of this relationship determines how robustly the Kalman filter can extract the latent neutral benchmark. We now compare IS curves estimated with FCI versus interest rates.

In our baseline specification, aggregate demand inertia is high, with $\eta = 0.994$. This implies that the impact of FCI on next quarter output growth is $a(\eta) = 0.252$ (standard error: 0.002): since aggregate demand is very persistent, the effect of asset price innovations is spread roughly equally over the next four quarters. Online Appendix D.1 reports additional results.

Our empirical approach effectively constrains the $a(\eta)$ coefficient in the IS curve (12) to be positive. We also estimated an alternative version in which $a(\eta)$ is a free parameter. The estimate is still positive and statistically significant—$a(\eta) = 0.29$ (standard error of 0.003).

In contrast, when we re-estimated the Holston et al. (2023) equations in our sample period with the same parameter constraints they imposed, we found that the slope of the IS curve is estimated to be at the constraint—which is essentially zero. As a result, the estimated r^* features implausibly large swings, going from a maximum of 24.5% in 2000, to a minimum of -71.6% at the heights of the GFC.

The IS curve fits better with FCI than with interest rates. This is unsurprising: monetary policy transmits through broad financial conditions, not just the policy rate, and FCI directly measures these conditions and their calibrated impact on activity. The policy rate is one step removed—it affects aggregate demand only by first changing financial conditions. Moreover, financial conditions are volatile and only loosely related to the policy rate, so using the policy rate in place of FCI introduces additional noise in the IS curve (which makes it harder to estimate). Our estimates suggest this problem became more severe in recent decades, possibly reflecting greater financial deepening and the increased importance of market-based finance.

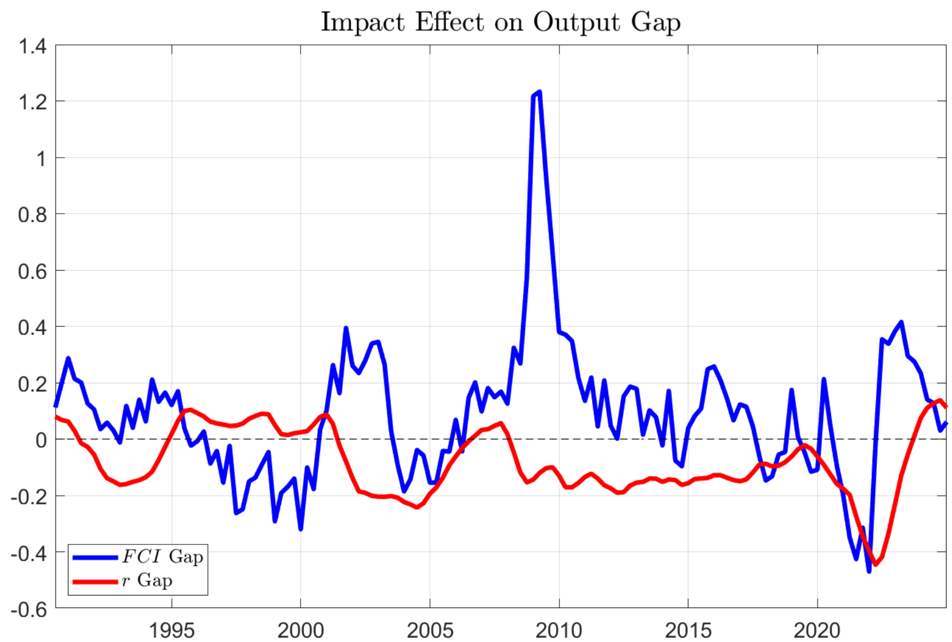

Figure 4: Direct effect of FCI (blue) and real rate (red) gaps on output gaps, normalized such that a positive value implies lower output gaps. Red is computed as $-a_r\tilde{r}_t$, where a_r is the slope of the IS curve and $\tilde{r}_t$ is the real rate gap estimated in Holston et al. (2023).

4.4. Effective Monetary Policy Stance According to FCI^* vs. r^*

We next analyze FCI gaps as a measure of the effective policy stance. From equation (11), the term $a(\eta)(FCI_t - FCI_t^*)$ captures the effect of current financial conditions on output gaps relative to a neutral benchmark. We compare this measure with an analogous measure constructed from HLW's estimate for r^*: the real rate gap. Figure 4 plots both measures over time. The two differ in sign for long periods, with large discrepancies during the GFC and COVID cycles.

During the GFC recovery, the real rate gap suggests highly accommodative policy throughout 2010–2020, with rates well below r^*. Yet, as we documented above, output gaps remained persistently negative. The FCI gap resolves this tension: despite low policy rates, financial conditions remained neutral or slightly tight during much of this period. Given high risk premia and low asset prices, low rates did not translate into loose financial conditions.

The COVID-19 cycle highlights a further dimension of this divergence. Both measures signal pronounced accommodation through 2021, but they separate markedly thereafter. The FCI gap turns contractionary in early 2022, reflecting the rapid tightening in broader financial conditions as long-term yields rose and equity prices fell. By contrast, the real-rate gap remains accommodative well into 2023: elevated inflation expectations kept ex ante real rates low even as the Federal Reserve raised nominal policy rates. From 2023 onward, the measures diverge again. The FCI gap indicates a loosening of financial conditions driven by the equity-market rally, even as interest rates stayed persistently high through 2023 and 2024. Overall, the FCI-based measure more closely matches the widespread perception of a sharp policy pivot in 2022 and captures the subsequent easing in conditions associated with the stock-market rebound. Online Appendix D.5 shows that these conclusions are robust to our COVID-era adjustments.

5. Conclusion

Building on the observation that monetary policy operates through financial conditions, we introduce FCI^*, the neutral level of financial conditions that closes expected output gaps. Our approach leverages the empirical research embedded in FCIs, which quantify how asset prices affect aggregate demand. We work with the FCI-G index by Ajello et al. (2023), which uses the Federal Reserve's models to estimate the impact of recent changes in financial variables on output growth. We link this index with a theoretical framework to characterize FCI^* and its drivers. Our framework reveals that FCI^* is insulated from financial fluctuations by construction and is driven by macroeconomic fluctuations; in contrast, r^* is influenced by financial shocks. Our framework also links output gaps to FCI gaps, enabling us to estimate the latent FCI^* using a two-equation model similar to Laubach and Williams (2003) and Holston et al. (2023).

Empirically, we confirm that FCI^* does not correlate with the risk premium once we control for macroeconomic conditions; in contrast, the standard measures of r^* do. We also find that the IS curve fits better with FCI than with interest rates, reflecting the broader channels of monetary policy transmission. This results in more stable estimates of FCI^* compared to r^*. Finally, we find that there are frequent FCI gaps in the data, and these gaps provide a useful description of the policy stance, especially in episodes where financial conditions diverge from interest rates. This was the case during the post-GFC recovery where tight FCI relative to FCI^* indicated tight policy, whereas low interest rates relative to standard estimates of r^* implied loose policy. It was also the case throughout 2022 when FCI gaps captured the rapid tightening of policy whereas interest rate gaps still suggested accommodation.

Our main goal is to introduce FCI^*—a benchmark insulated from financial fluctuations—as a potentially useful alternative measure for monetary policy stance. We have therefore deliberately kept our framework close to prevailing methods in the r^* literature to facilitate comparisons. Future research may refine this model further using more elaborate time-series methods or more structural models to capture additional frictions (see, e.g., Caballero et al. (2024)).

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Online Appendix: Not for Publication

A. Financial market block and r^*

In the main text, we considered a theoretical model in which log output is driven by (2)

$$y_t = \eta y_{t-1} + (1-\eta) p_{t-1} + m(1-\eta) + \delta_t.$$

and aggregate supply and demand shocks evolve according to $(5-7)$

$$\begin{aligned} y_t^n &= y_{t-1}^n + g_{t-1} + \epsilon_t^{y^n} \\ g_t &= g_{t-1} + \epsilon_t^g \\ \delta_t &= \rho_\delta \delta_{t-1} + \epsilon_t^\delta. \end{aligned}$$

We have deliberately left the financial market block that determines p_t and thus FCI unspecified, because this block does not affect FCI^* and is not necessary for our estimation. In this appendix, we specify a financial market block and complete the theoretical characterization, solving in particular for the r^*. We use this solution in Section 2.3 to compare FCI^* with r^*.

Financial markets. The financial market block follows our earlier work in Caballero and Simsek (2022). We briefly describe the setup and refer the reader to those papers for additional details. There are two assets: a risk-free asset in zero net supply and a market portfolio. The market portfolio is a claim on firms' profits αY_t (the firms' share of output). We let P_t denote the ex-dividend price of the market portfolio (which we also refer to as "the aggregate asset price"). The gross return of the market portfolio is $R_{t+1}^m = \frac{\alpha Y_{t+1} + P_{t+1}}{P_t}$. Log-linearizing this expression, we obtain

$$r_{t+1}^m = \kappa + (1-\beta)\, y_{t+1} + \beta p_{t+1} - p_t. \tag{A.1}$$

Here, $r_{t+1}^m = \log R_{t+1}^m$ is the log return, $\frac{1-\beta}{\beta}$ is the steady-state dividend to price ratio, and $\kappa \equiv -\beta \log \beta - (1-\beta)\log\left(\frac{1-\beta}{\alpha}\right)$.

The households make a portfolio choice between the market portfolio and the risk-free asset in zero net supply, whose return R_t is set by the Fed. We assume households delegate their portfolio choice to portfolio managers (the market), who invest on their behalf. The managers make a portfolio allocation to maximize expected log household *wealth*

$$\max_{\omega_t} E_t^M \left[\log\left(W_t \left(R_t + \omega_t \left(R_{t+1}^m - R_t\right)\right)\right)\right].$$

Here, the superscript M denotes the market's belief which can in general be different than the central bank's belief or the objective belief. In equilibrium, the approximate log-linearized optimality condition is

$$\omega_t \sigma_t^M \left[r_{t+1}^m\right] = \frac{E_t^M\left[r_{t+1}^m\right] + \frac{Var_t^M\left[r_{t+1}^m\right]}{2} - r_t}{\sigma_t^M\left[r_{t+1}^m\right]}.$$

Here, $r_t = \log R_t$ denotes the log risk-free interest rate. Managers invest in the market portfolio until their *perceived* portfolio risk (the left-hand side) is equal to their *perceived* Sharpe ratio from the market portfolio (the right-hand side).

Market clearing requires $\omega_t = 1$: in equilibrium, portfolios are reinvested in the market portfolio. Combining this with the optimality condition, we obtain a relation between the expected return on the market portfolio and the risk-free rate

$$E_t^M \left[r_{t+1}^m \right] = r_t + \frac{Var_t^M \left[r_{t+1}^m \right]}{2}. \tag{A.2}$$

The equilibrium expected return (or the discount rate) is equal to the risk-free rate plus a risk premium, which in this model depends on the variance of the return on the market portfolio. Combining this with $(A.1)$ provides a solution for the equilibrium asset price

$$p_t = \kappa + (1-\beta) E_t^M [y_{t+1}] + \beta E_t^M [p_{t+1}] - \left(r_t + \frac{1}{2} Var_t^M \left[r_{t+1}^m \right] \right). \tag{A.3}$$

The price of the market portfolio depends on the expected future output (through cash flows), the expected future asset prices (since it is a long-lived asset) and inversely on the risk-free rate and the risk premium.

Characterizing p^* and r^*. We next characterize p^*—the asset price counterpart to FCI^*—which we use to solve r^*. Conceptually, p^* is the asset price that obtains in an economy in which the central bank closes the output gap in expectation. Therefore, to calculate p^*, we need to specify the central bank's beliefs along with the market's beliefs. For tractability, we focus on a special case of $(5-7)$ where the expected growth is constant, $g_t = g$, demand shocks are i.i.d. $\rho_\delta = 0$. That is, the objective driving processes are given by

$$\begin{aligned} y_{t+1}^n &= y_t^n + g + \epsilon_{t+1}^{y^n} \\ \delta_{t+1} &= \epsilon_{t+1}^{\delta} \\ \text{where } \epsilon_{t+1}^{\delta} &\sim N\left(0, \sigma_\delta^2\right) \text{ and } \epsilon_{t+1}^{y^n} \sim N\left(0, \sigma_{y^n}^2\right). \end{aligned} \tag{A.4}$$

We assume that the central bank knows these processes and has no other signals, so these equations also describe the central bank's beliefs. The market's beliefs about demand shocks are also the same, $\epsilon_{t+1}^{\delta} \sim^M N\left(0, \sigma_\delta^2\right)$. However, the market's beliefs for the supply shock are different and given by

$$\begin{aligned} \epsilon_{t+1}^{y^n} &\sim {}^M N\left(s_t, \sigma_{y^n}^2\right) \\ \text{where } s_{t+1} &= \rho_s s_t + \epsilon_{t+1}^s \text{ and } \epsilon_{t+1}^s \sim N\left(0, \sigma_s^2\right). \end{aligned} \tag{A.5}$$

Here, s_t denotes a sentiment shock: when $s_t > 0$, the market thinks future supply will be higher than usual (and vice versa for $s_t < 0$) even though the actual expected supply is unchanged. This is a modeling device to capture a variety of forces that might generate asset price fluctuations without changes in fundamentals, including time-varying sentiment, time-varying risk premium, or noisy demand shocks. We assume the belief shocks follow an AR(1) process that is known to both the Fed and the market.

We next use (2) to solve for p^*,

$$p_t^* = \frac{E_t \left[y_{t+1}^n \right]}{1-\eta} - \frac{\eta}{1-\eta} y_t^* - \frac{E_t \left[\delta_{t+1} \right]}{1-\eta} - m.$$

Recall also that in the star economy we have $y_t^* = E_{t-1}[y_t^n] + \epsilon_t^\delta$ (see 8). Note also that the processes in $(A.4)$ imply $E_t[\delta_{t+1}] = 0$ and $E_t\left[y_{t+1}^n\right] = y_t^n + g = E_{t-1}[y_t^n] + \epsilon_t^{y^n} + g$. After substituting these observations, we obtain

$$
\begin{aligned}
p_t^* &= \frac{E_{t-1}[y_t^n] + \epsilon_t^{y^n} + g}{1-\eta} - \frac{\eta}{1-\eta}\left(E_{t-1}[y_t^n] + \epsilon_t^\delta\right) - m \\
&= y_{t-1}^n + g + \frac{g}{1-\eta} + \frac{\epsilon_t^{y^n}}{1-\eta} - \frac{\eta}{1-\eta}\epsilon_t^\delta - m.
\end{aligned}
$$

In the star economy, the asset price is determined by the expected potential output, potential output shocks, demand shocks, and the expected demand shifter in the next period. Note that this expression is the analogue of FCI^* from the main text; it describes the financial conditions that close the output gaps in terms of the asset price level rather than the FCI (see (9)).

Next, we substitute the expressions for p^* and y* into $(A.1)$ to describe the return process in the star economy

$$
\begin{aligned}
r_{t+1}^{m,*} &= \kappa + (1-\beta)\, y_{t+1}^* + \beta p_{t+1}^* - p_t^* \\
&= \kappa + (1-\beta)\left(E_t\left[y_{t+1}^n\right] + \epsilon_{t+1}^\delta\right) \\
&\quad + \beta\left(E_t[y_{t+1}^n] + \frac{1}{1-\eta}\epsilon_{t+1}^{y^n} - \frac{\eta}{1-\eta}\epsilon_{t+1}^\delta - m\right) \\
&\quad - \left(E_{t-1}[y_t^n] + \frac{1}{1-\eta}\epsilon_t^{y^n} - \frac{\eta}{1-\eta}\epsilon_t^\delta - m\right) \\
&= \rho + E_t[y_{t+1}^n] - E_{t-1}[y_t^n] + \frac{\beta}{1-\eta}\epsilon_{t+1}^{y^n} - \frac{1}{1-\eta}\epsilon_t^{y^n} \\
&\quad + \frac{1-\eta-\beta}{1-\eta}\epsilon_{t+1}^\delta + \frac{\eta}{1-\eta}\epsilon_t^\delta \\
&= \rho + g + \frac{\eta}{1-\eta}\left(\epsilon_t^\delta - \epsilon_t^{y^n}\right) + \frac{\beta}{1-\eta}\epsilon_{t+1}^{y^n} + \frac{1-\eta-\beta}{1-\eta}\epsilon_{t+1}^\delta. \qquad \text{(A.6)}
\end{aligned}
$$

Here, the third equality simplifies the constant terms to obtain the intercept $\rho = -\log\beta$. The last equality substitutes $E_t[y_{t+1}^n] - E_{t-1}[y_t^n] = g + \epsilon_t^{y^n}$ in view of $(A.4)$ and simplifies the expression.

Finally, note from $(A.2)$ that the interest rate in the star economy satisfies

$$r_t^* = E_t^M\left[r_{t+1}^{m,*}\right] - \frac{1}{2}Var_t^M\left[r_{t+1}^{m,*}\right].$$

We combine this expression with the return in $(A.6)$ and the market's beliefs in $(A.5)$ to solve for r^*

$$
\begin{aligned}
r_t^* &= \rho + g + \frac{\beta}{1-\eta}s_t + \frac{\eta}{1-\eta}\left(\epsilon_t^\delta - \epsilon_t^{y^n}\right) - \frac{1}{2}\overline{rp} \\
\text{where } \overline{rp} &= \left(\frac{\beta}{1-\eta}\right)^2\sigma_{y^n}^2 + \left(\frac{1-\eta-\beta}{1-\eta}\right)^2\sigma_\delta^2.
\end{aligned}
$$

This proves (10) that we use in the main text.

Aside from demand and supply shocks, r^* also depends on the average risk premium $\overline{rp}$ and on sentiment shock s_t. In this model, the risk premium remains constant over time (for simplicity). However, sentiment shocks fluctuate according to the AR(1) process in $(A.5)$. We view these shocks as a stand-in for asset price fluctuations that are orthogonal to expected cash flows, including those driven by time-varying risk premiums, time-varying noisy demand, or time-varying sentiment. Absent a central bank reaction, these fluctuations would shift asset prices, the FCI, and therefore also the future economic activity. Since these shocks are orthogonal to actual macroeconomic fundamentals (by assumption), the central bank optimally raises the interest rate to insulate the FCI and economic activity from them.

B. Additional Implementation Details

B.1. Data

We use quarterly data; our main sample is 1990Q2–2024Q4. We start at 1990Q2 due to the availability of the FCI index. We measure the output gap as $\tilde{y}_t = 100(y_t - (y_t^* + \frac{\phi}{100}d_t))$, where y_t is the log of real GDP and $y_t^* + \frac{\phi}{100}d_t$ is the COVID-19-adjusted potential (log) output, a latent variable to be estimated. We measure the financial conditions gap as $\widetilde{FCI}_t = FCI_t - FCI_t^*$, where FCI_t is the financial conditions index from Ajello et al. (2023) and FCI_t^* is our measure of neutral financial conditions, which is a latent variable. Inflation π_t is annualized quarter-on-quarter PCE core inflation. To inspect correlations with financial fluctuations, we use the equity risk premium measure from Duarte and Rosa (2015), this series is available through 2023Q1. Finally, in some cases we compare our results to those of Holston et al. (2023), and to the CBO output gap. We use the 2024Q4 vintage of Holston et al. (2023), and the CBO output gap is obtained as $\tilde{y}^{CBO} = 100 \times (y_t - y_t^{p,CBO})$, where $y_t^{p,CBO}$ is the logarithm of potential output estimated by CBO.

B.2. COVID-19 adjustments

We address COVID-19 data issues following the procedure in Holston et al. (2023). First, as suggested by Lenza and Primiceri (2022), we assume that the volatility of $(\epsilon_{\tilde{y},t}, \epsilon_{\pi,t})$ can be larger during the COVID-19 period. We parametrize this by assuming that the standard deviation of the shocks is given by $(\kappa_t\sigma_{\tilde{y}}, \kappa_t\sigma_\pi)$, where:

$$\kappa_t = \begin{cases} \kappa_{2020} & 2020:\text{Q2} \leq t \leq 2020:\text{Q4} \\ 1 & \text{otherwise.} \end{cases} \tag{B.1}$$

The value of κ_{2020} is estimated as a free parameter. Second, we deal with the supply-side effects of COVID-19 by assuming that potential output is:

$$y^*_{t,COVID-19-adj.} = y_t^* + \frac{\phi}{100}d_t. \tag{B.2}$$

Here, d_t is the quarterly COVID-19 Stringency Index from the Oxford COVID-19 Government Response Tracker (OxCGRT) for the U.S. Since the data for the index finishes at 2022Q4, we set its value to 0 from 2023Q1 onwards.

Our implementation of COVID-19-related adjustments differs from Holston et al. (2023) in two ways: first, whereas they extrapolate the COVID-19 stringency index for 2023 and 2024, we set it to zero; second, they allow for potentially higher variances in 2021 and 2022 as well. We adopt this different specification because we want estimated FCI^* to better reflect short- and medium-run macroeconomic factors during the COVID-19 period, rather than the long-run factors emphasized by Holston et al. (2023). Appendix D.5 presents results using their exact specification for comparison.

B.3. Parameter estimation

In order to evaluate the model, we need to obtain parameters $\theta = (b_\pi, b_{\tilde{y}}, \sigma_{\tilde{y}}, \sigma_\pi, \sigma_{y^n}, \sigma_g, \sigma_\delta, \phi, \kappa_{2020}, \rho_\delta, \eta)$. We use a mix of calibration and estimation.

We fix the parameters of the Phillips curve to $(b_\pi, b_{\tilde{y}}) = (0.689, 0.08)$. These are the point estimates of Holston et al. (2023). We do this for two reasons. First, for comparability with Holston et al. (2023): since we are using exactly the same Phillips curve, any differences in the inferred states must be due to the different specification of the demand block. Second, estimates of a structural Phillips curve are sensitive to the exact specification and estimation method (Mavroeidis et al., 2014). We sidestep this issue (which is orthogonal to our main focus) by externally calibrating the parameters. Appendix D shows robustness to different values for the slope of the Phillips curve.

We further fix the ratio of variances of innovations in y^n and g_t to the point estimate in Holston et al. (2023), $\lambda_g = \frac{\sigma_g}{\sigma_{y^n}} = 0.0667$. We do this to address econometric issues that arise when trying to estimate the variance of a time-varying parameter, see Stock and Watson (1998); Laubach and Williams (2003). Estimating this parameter in a previous step as done in Holston et al. (2023) yields very similar values.

B.4. Initializing the filter

Given that several latent variables have unit roots, we set the prior distribution of $\xi_1 \sim N(\xi_{1|0}, P_{1|0})$ as follows. For the means, we follow (Holston et al., 2023) and initialize y_t^* and its lags using the trend component of real GDP that comes out of applying the Hodrick-Prescott filter with $\lambda = 36000$. We initialize g_t as the first differences of the mentioned trend. We initialize (FCI_t^*, δ_t) and its respective lags at 0. Given that the observed value FCI_t is also close to zero, this encodes that a priori financial conditions are neither boosting nor restraining GDP from their potential level. Regarding prior uncertainty, we follow the same two step procedure as in (Holston et al., 2023). Initially, we assume that all states are a priori uncorrelated. We assume that the prior standard deviation for potential output and its lags is one percentage point, whereas the prior standard deviation for all other states is 0.5 percentage points. In the first step, we estimate the model with this prior. We then run the Kalman Filter with the estimated parameters, we update the prior variance matrix $P_{1|0}$ to $P_{2|1}$. We then use the updated variance matrix as initial values for the actual estimation.

C. State Space Representation

Collecting the equations, the state space system is:

$$
\begin{aligned}
y_t &= (y^n_{t-1} + g_{t-1} + \delta_t - \rho_\delta \delta_{t-1} + \phi d_t) + (y_{t-1} - (y^n_{t-2} + g_{t-2} + \delta_{t-1} - \rho_\delta \delta_{t-2} + \phi d_{t-1})) \\
&\quad - a(\eta)(FCI_{t-1} - FCI^*_{t-1}) + \epsilon_{\tilde{y},t} \\
\pi_t &= b_\pi \pi_{t-1} + (1 - b_\pi)\pi_{t-2:4} + b_y(y_{t-1} - (y^n_{t-2} + g_{t-2} + \delta_{t-1} - \rho_\delta \delta_{t-2} + \phi d_{t-1})) + \epsilon_{\pi,t} \\
y^n_{t+1} &= y^n_t + g_t + \epsilon_{y^n,t+1} \\
g_{t+1} &= g_t + \epsilon_{g,t+1} \\
\delta_{t+1} &= \rho_\delta \delta_t + \epsilon_{\delta,t+1} \\
FCI^*_{t+1} &= \eta FCI^*_t - a(\eta)^{-1}\left(\epsilon_{y^n,t+1} + (1-\eta)g_t + \epsilon_{g,t+1} - \epsilon_{\delta,t+1}(\eta + \rho_\delta)\right. \\
&\quad \left. - \eta(y^n_t - (y^n_{t-1} + g_{t-1})) + (\eta + (1-\rho_\delta)\rho_\delta)\delta_t - \eta\rho_\delta\delta_{t-1})\right)
\end{aligned}
$$

Following the Hamilton (1994) notation we can generally write the state space system as:

$$
\begin{aligned}
\boldsymbol{\xi}_{t+1} &= \mathbf{F}\boldsymbol{\xi}_t + \mathbf{v}_{t+1} \\
\mathbf{y}_t &= \mathbf{A}'\mathbf{x}_t + \mathbf{H}'\boldsymbol{\xi}_t + \mathbf{w}_{t+1} \\
E_{t-1}(\mathbf{v}_t\mathbf{v}'_t) &= \kappa^2_t \mathbf{Q} \\
E_{t-1}(\mathbf{w}_t\mathbf{w}'_t) &= \kappa^2_t \mathbf{R}
\end{aligned}
$$

where the only difference is that the variance of the shocks is scaled by κ_t in order to account for the large COVID-19 innovations.

In our case, signals, exogenous variables and states are given by:

$$
\begin{aligned}
\mathbf{y}_t &= [y_t, \pi_t]' \\
\mathbf{x}_t &= [y_{t-1}, FCI^m_{t-1}, \pi_{t-1}, \pi_{t-2:4}, d_t, d_{t-1}]' \\
\boldsymbol{\xi}_t &= [y^*_t, y^*_{t-1}, y^*_{t-2}, g_t, g_{t-1}, g_{t-2}, FCI^*_t, FCI^*_{t-1}, \delta_t, \delta_{t-1}, \delta_{t-2}]'
\end{aligned}
$$

with matrices:

$$
\mathbf{F} = \begin{bmatrix}
1 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\
a(\eta)^{-1}\eta & -a(\eta)^{-1}\eta & 0 & -a(\eta)^{-1}(1-\eta) & -a(\eta)^{-1}\eta & 0 & \eta & 0 & -a(\eta)^{-1}(\eta + (1-\rho_\delta)\rho_\delta) & a(\eta)^{-1}\eta\rho_\delta & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \rho_\delta & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0
\end{bmatrix}
$$

$$\mathbf{Q} = \begin{bmatrix} \sigma^2_{y*} & 0 & 0 & 0 & 0 & 0 & -a(\eta)^{-1}\sigma^2_{y*} & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & (\lambda_g \sigma_{y*})^2 & 0 & 0 & -a(\eta)^{-1}(\lambda_g \sigma_{y*})^2 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ -a(\eta)^{-1}\sigma^2_{y*} & 0 & 0 & -a(\eta)^{-1}(\lambda_g \sigma_{y*})^2 & 0 & 0 & a(\eta)^{-2}(((1+\lambda_g)\sigma_{y*})^2 + (\eta+\rho_\delta)^2\sigma^2_\delta) & 0 & a(\eta)^{-1}(\eta+\rho_\delta)\sigma^2_\delta & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & a(\eta)^{-1}(\eta+\rho_\delta)\sigma^2_\delta & 0 & \sigma^2_\delta & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

$$\mathbf{H}' = \begin{bmatrix} 0 & 1 & -1 & 0 & 1 & -1 & a(\eta) & 0 & 1 & -(1+\rho_\delta) & \rho_\delta \\ 0 & 0 & -b_y & 0 & 0 & b_y & 0 & 0 & 0 & -b_y & \rho_\delta b_y \end{bmatrix}$$

$$\mathbf{A}' = \begin{bmatrix} 1 & -a(\eta) & 0 & 0 & \phi & -\phi \\ b_y & 0 & b_\pi & 1-b_\pi & 0 & -\phi b_y \end{bmatrix} \quad \mathbf{R} = \begin{bmatrix} \sigma^2_{\tilde{y}} & 0 \\ 0 & \sigma^2_\pi \end{bmatrix}$$

D. Additional Empirical Results

Figure 7 presents the estimated natural output alongside the realized output.

D.1. Parameter Estimates

Table 2 shows the estimated parameters. The estimated degree of aggregate demand inertia (η) is quite high. This implies that the impact of FCI on the next quarter output growth is $a(\eta) = 0.252$: since aggregate demand is very persistent, the effect of asset price innovations is spread roughly equally over the next four quarters.

The bottom part of Table 2 shows that uncertainty about the estimated states is high.[6] This primarily reflects that the informational content of the two equations is limited relative to the magnitude of the shocks. This finding is standard in the literature (Lubik and Matthes, 2015; Holston et al., 2023).[7]

D.2. Two Sided Estimates

Figure 5 compares FCI^* and output gap estimates using the information up to time t (i.e., a one sided estimate, $\boldsymbol{\xi}_{t|t} = E[\boldsymbol{\xi}_t | y_s, x_s{}_{t=0}^{s}])$ or the using all information in the sample (i.e., the two-sided or smoothed estimate, $\boldsymbol{\xi}_{t|T} = E[\boldsymbol{\xi}_t | y_s, x_s{}_{t=0}^{T}])$. It also shows 90 percent confidence bands based on the Kalman Filter contemporaneous variance covariance matrix for the states, $P_{t|t} = E_t[(\boldsymbol{\xi}_t - \boldsymbol{\xi}_{t|t})(\boldsymbol{\xi}_t - \boldsymbol{\xi}_{t|t})'])$. As we can see the one and two sided estimates of FCI^* are quite close, with the main difference appearing during the GFC: the two-sided estimate shows a less sharp decline than the one sided. Turning to the output gap, we see larger differences, with the two sided estimate of the output gap being above the one sided estimate for a large part of the sample.

[6] We use the procedure in Hamilton (1986) that accounts for both parameter and filter uncertainty. This is the same procedure used in Laubach and Williams (2003)

[7] Our estimates for uncertainty in FCI^* and y^* are lower than the uncertainty in r^* and y^* reported in (Holston et al., 2023). However, since we are fixing the coefficient of the Phillips Curve, we are assuming away an important source of uncertainty, so the estimates are not directly comparable.

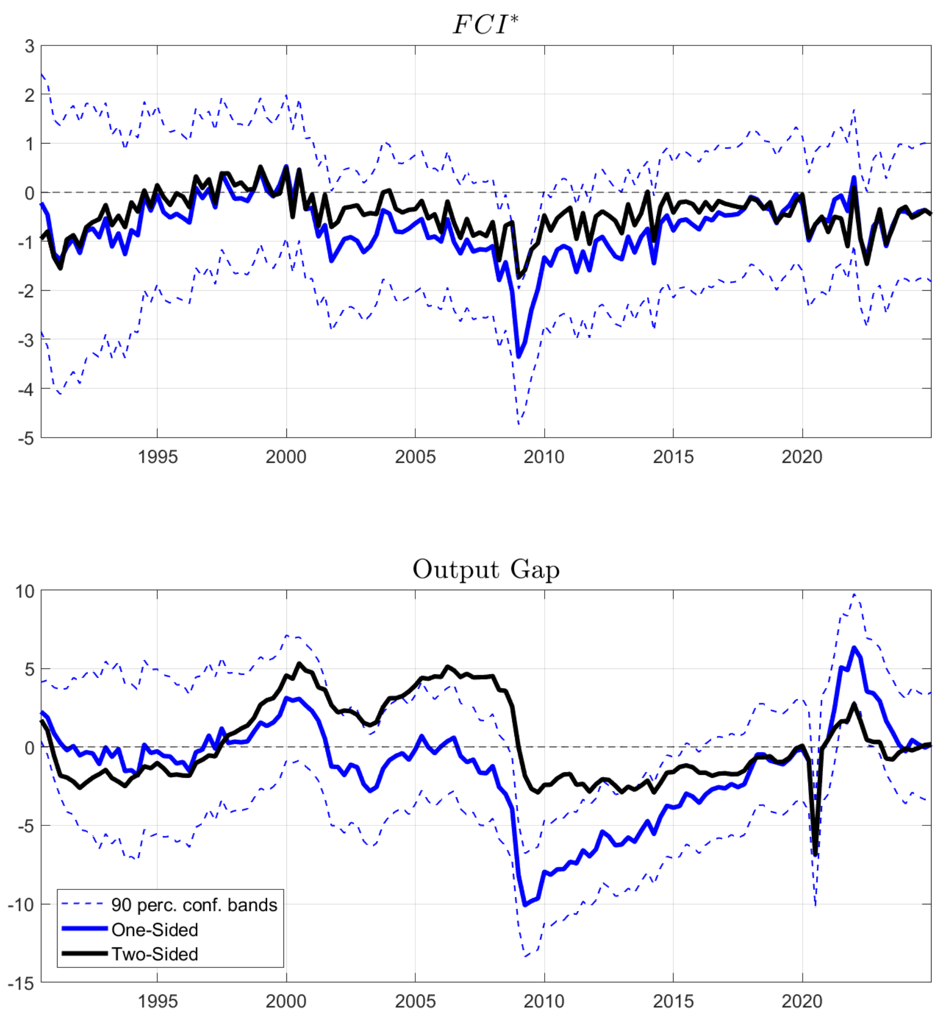

Figure 5: 90 Percent confidence bands use the contemporaneous variance-covariance matrix $P_{t|t} = E_t[(\boldsymbol{\xi}_t - \boldsymbol{\xi}_{t|t})(\boldsymbol{\xi}_t - \boldsymbol{\xi}_{t|t})']$.

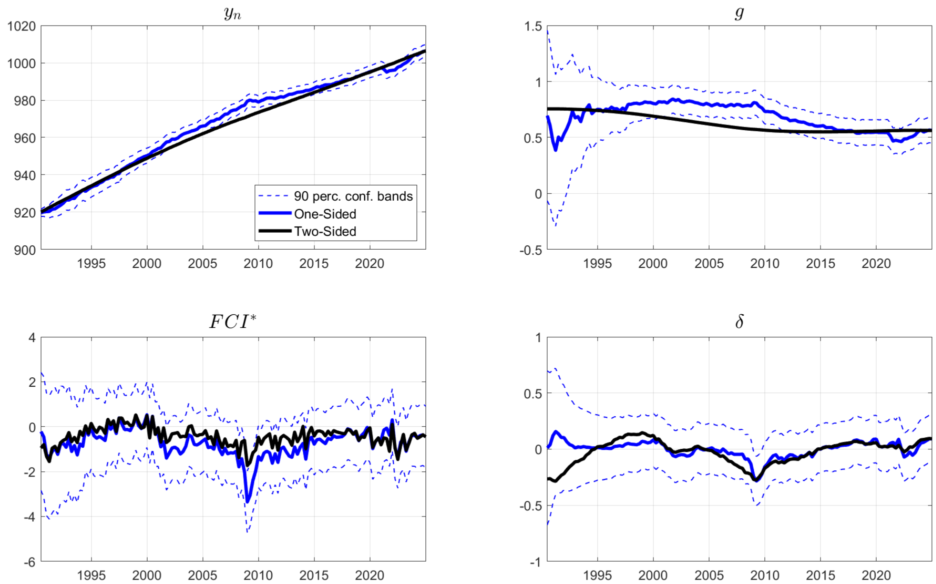

Figure 6: One sided and two sided estimates for latent states. Confidence bands use the contemporaneous variance-covariance matrix $P_{t|t} = E_t[(\boldsymbol{\xi}_t - \boldsymbol{\xi}_{t|t})(\boldsymbol{\xi}_t - \boldsymbol{\xi}_{t|t})']$.

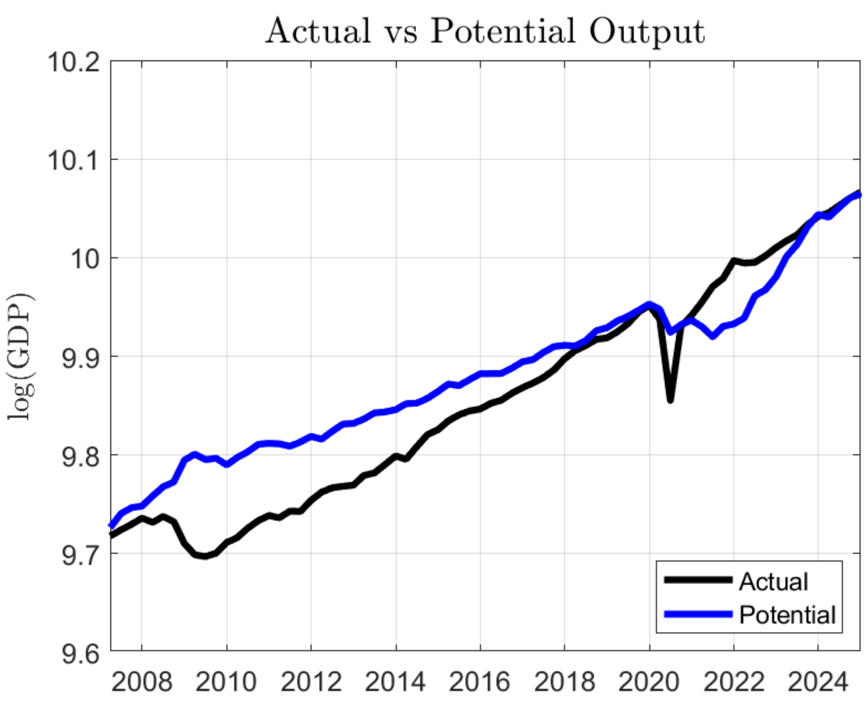

Figure 7: Estimate of Potential Output $(y_t^n + \phi d_t)$ is one-sided.

Parameter	Estimate	Standard Error
λ_g	0.067	Fixed
b_π	0.689	Fixed
b_y	0.080	Fixed
η	0.994	0.006
$a(\eta)$	0.252	0.002
$\sigma_{\tilde{y}}$	0.509	0.065
σ_π	0.677	0.034
σ_{y^*}	0.155	0.043
σ_δ	0.056	0.054
ϕ	-0.053	0.011
κ_{2020}	7.606	3.162
ρ_δ	0.928	0.104
Log-likelihood	-285.368	
S.E (sample avg.)		
FCI^*	0.847	
g (annualized)	0.185	
y^*	1.230	
S.E (Final Obs.)		
FCI^*	0.899	
g (annualized)	0.281	
y^*	2.157	

Table 2: Estimated Parameters and standard errors. The variance-covariance matrix of parameters is computed using the Outer Product of Gradients of the likelihood. The SE of $a(\eta)$ is obtained from the SE of η using the Delta method.

Figure 6 compares the one and two sided estimates of all latent states. Regarding y_t^n, we see that the two sided estimate of potential output is substantially lower during the 2000-2015 period. This is what drives the positive output gaps discussed before. As we can see, apart from some discrepancy in the beginning, the estimates of g and δ are close for both construction procedures.

D.3. Alternative Phillips Curve Calibration

Given the large uncertainty regarding the slope of the Phillips Curve, in Figure 8 we report the estimated FCI^* and output gaps that correspond to alternative calibrations of this parameter. We keep the same lag structure as the baseline, since we found the effects of changing b_π to be minimal. We consider two alternative estimates that lie at opposite ends of the spectrum: i) a flatter slope using the estimates provided by Hazell et al. (2022); ii) a steeper slope using estimates from Barnichon and Mesters (2020). This amounts to setting $b_y = 0.0248$ and $b_y = 0.28$ respectively.[8] In each case, we fully re-estimate all model parameters reported in Table 2 under the new calibration for the Phillips Curve.

Prior to the GFC all three series are quite close, for both FCI^* and the output gap. After the GFC

[8]The parameter reported in Hazell et al. (2022) corresponds to a Phillips curve with quarter-on-quarter inflation, not annualized. Thus we multiply their estimate by 4. The specification in Barnichon and Mesters (2020) is estimated in annualized terms so it does not require conversion.

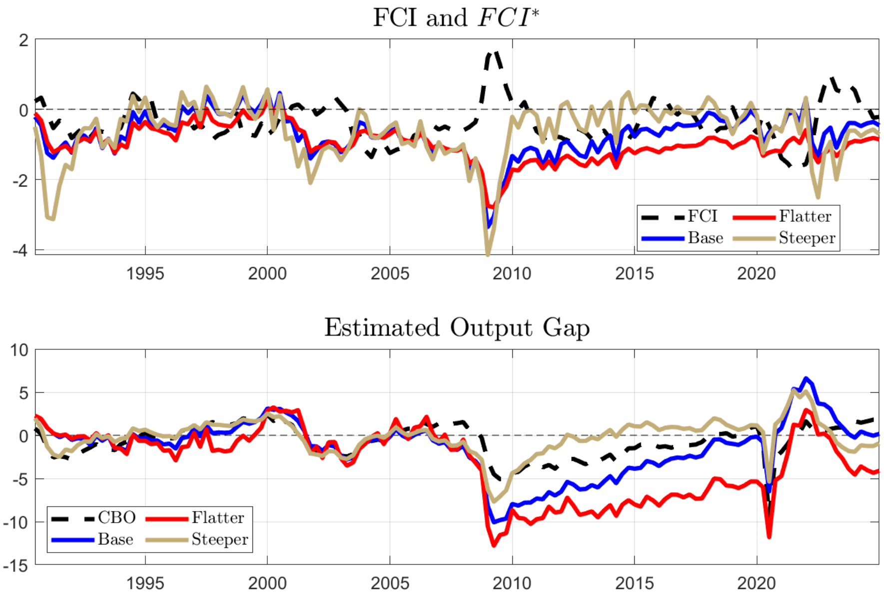

Figure 8: Results for different Phillips Curve slopes. Top: FCI (black dashed) and FCI^* with: baseline (blue), a flatter slope (Hazell et al., 2022) (red) and a steeper slope (Barnichon and Mesters, 2020). Bottom: Output gap estimated by the CBO (black, dashed), and the three mentioned parametrizations. Each model is fully reestimated taking the corresponding Phillips Curve as fixed.

a gap appears on the three measures of FCI^*, that lasts until before COVID-19. The steeper Phillips Curve parametrization shows a tighter FCI^*, whereas the flatter Phillips Curve version infers a looser FCI^*. Finally, all three measures become close again after the COVID-19 shock. Besides this discrepancy in the levels between the GFC and the COVID-19 period, the overall trends of FCI^* are similar for all three measures.

The obtained FCI^* with a steeper Phillips curve is noisier than the baseline. This is because, under a steeper Phillips Curve, the same observed fluctuations in inflation are interpreted to be more informative of the underlying states, and thus more of the noise in inflation leaks to the estimates of the states. For the same reason, the estimates are smoother under a flat Phillips Curve.

Turning to the inferred output gap, we see sizable differences after the GFC, with a steeper Phillips Curve inferring a faster recovery and the flatter Phillips Curve inferring a much lower level of output gap after the GFC. Intuitively, a flatter Phillips Curve implies i) much larger movements in output gaps for given movements in inflation, ii) slower updating of the natural output, since the signal (inflation) is less informative of the unobserved state. This explains the significantly larger drop in output gaps during the GFC for the flatter calibration, as well as the slower return back to zero afterwards. In unreported results, we find a similar sensitivity in post-GFC output gap estimates for the HLW model, so these issues seem to be unrelated to exact specification of the demand block.

Overall, the assumed slope of the Phillips Curve is an important determinant of inferred output gaps after the GFC, whereas it plays a more limited role in the exact inferred path for FCI^*.

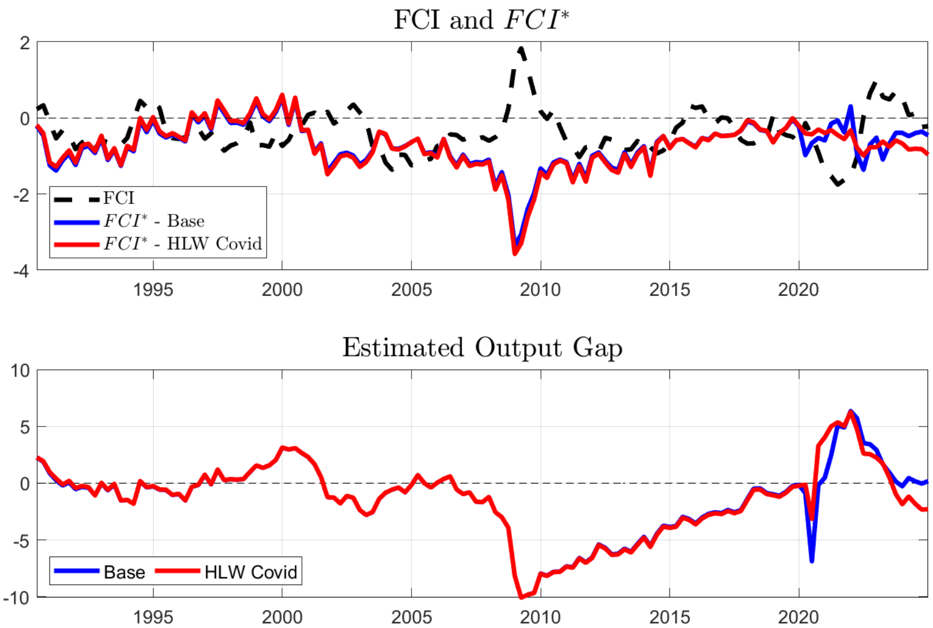

Figure 9: Base results from Figure 3 (blue) and results with alternative treatment of the COVID-19 period, following Holston et al. (2023) exactly (red). Black dashed line in the top panel corresponds to the observed FCI.

D.4. Regression Results for alternative measures of risk premium

Table 3 shows multivariate regression results when we substitute the equity risk premium measure by Shiller's Excess CAPE Yield measure. We maintain the 1990Q2-2023Q1 sample for comparability with the results in the main text. Results are similar with the following differences: i) the Excess CAPE Yield is now significant in the FCI^* equation, but the output gap remains significant; ii) In the r^*, the output gap now turns significant at the 10% level, but it has the wrong sign. The overall picture remains: FCI^* correlates more strongly with macro variables, whereas r^* is more driven by financial variables.

D.5. Alternative Adjustments for COVID-19

In this subsection, we present results following Holston et al. (2023) exactly for handling COVID-19 data issues. As in the main text, we allow the volatility of $(\epsilon_{\tilde{y},t}, \epsilon_{\pi,t})$ to be larger during the COVID-19 period, parametrized exactly as in Holston et al. (2023): we assume that the standard deviation of the shocks is $(\kappa_t \sigma_{\tilde{y}}, \kappa_t \sigma_{\pi})$, where:

$$\kappa_t = \begin{cases} \kappa_{2020} & 2020:\text{Q2} \leq t \leq 2020:\text{Q4} \\ \kappa_{2021} & 2021:\text{Q1} \leq t \leq 2021:\text{Q4} \\ \kappa_{2022} & 2022:\text{Q1} \leq t \leq 2022:\text{Q4} \\ 1 & \text{otherwise.} \end{cases} \tag{D.1}$$

The values of $\kappa_{2020}, \kappa_{2021}, \kappa_{2022}$ are estimated as free parameters. Second, instead of setting d_t to zero after 2023Q1, we extrapolate it with a constant geometric decay from 2023Q1 until reaching 0 in 2024Q4,

	Dependent variable	
	FCI^*	r^*
Excess CAPE Yield	-0.147^{***}	-0.582^{***}
	(0.037)	(0.044)
Output Gap	0.103^{***}	-0.061^{*}
	(0.03)	(0.036)
R^2	0.411	0.694
Observations	132	132

Table 3: Regression Results. "Excess CAPE Yield" obtained from the Shiller database. The output gap is the one measured by the CBO. Sample: 1990Q2-2023Q1. Standard errors in parentheses.$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$

as in Holston et al. (2023).

Figure 9 compares the results. The only difference appears during the COVID-19 period, which is unsurprising given that estimated parameters change very little. Under HLW's COVID-19 treatment, the estimated FCI^* series is smoother. This is intuitive: since the estimated variance of the innovations in equations (12) and (13) is larger, the Kalman Filter perceives more noise in that period, and thus updates the estimated values of the states by less. Thus, allowing smoother d_t dynamics and higher variances leads to smoother inferred series for the states, which might be preferable if one is focusing on long-run factors, as in Holston et al. (2023), but less preferable if one wants the inferred FCI^* to also reflect short and medium-run considerations, as in our case.

D.6. Comparison with the Optimal FCI Target from Caballero et al. (2024)

As explained in Section 2, there are several reasons why setting $FCI_t = FCI_t^*$ exactly in all periods is neither feasible nor desirable. Thus, a key question is: how far is FCI_t^* from the level of FCI that a planner would like to target under empirically relevant frictions, such as a desire for policy gradualism, realistic transmission lags, and cost-push shocks? In Caballero et al. (2024), we present an answer to that question. We give a short summary below; readers are referred to that paper for additional details.

Constructing the optimal FCI target. Using the tools developed in McKay and Wolf (2023) and Caravello et al. (2024), we can compute the historical evolution of any variable of interest under a counterfactual policy rule. The policy rule is the solution to a minimization problem with loss:

$$\mathcal{L} = \sum_{t=0}^{T} \beta^t [\pi_t^2 + \tilde{y}_t^2 + \lambda_{\Delta i}(i_t - i_{t-1})^2 + \psi(FCI_t - \overline{FCI}_t)^2] \tag{D.2}$$

where i_t is the nominal interest rate, and $\overline{FCI}_t$ is a target that is announced one period in advance. As explained in Caballero et al. (2024), committing to maintain financial conditions around a preannounced target helps lower financial market volatility, which in turn reduces the amount by which noise affects financial conditions. This beneficial effect reduces *macroeconomic* volatility even further, since as we empirically show in Caballero et al. (2024), financial noise meaningfully affects macroeconomic outcomes.

In order to compute the counterfactual evolution of the economy under alternative rules, it is sufficient to have a set of forecasts of all the variables of interest at each date, as well as an estimate of the dynamic

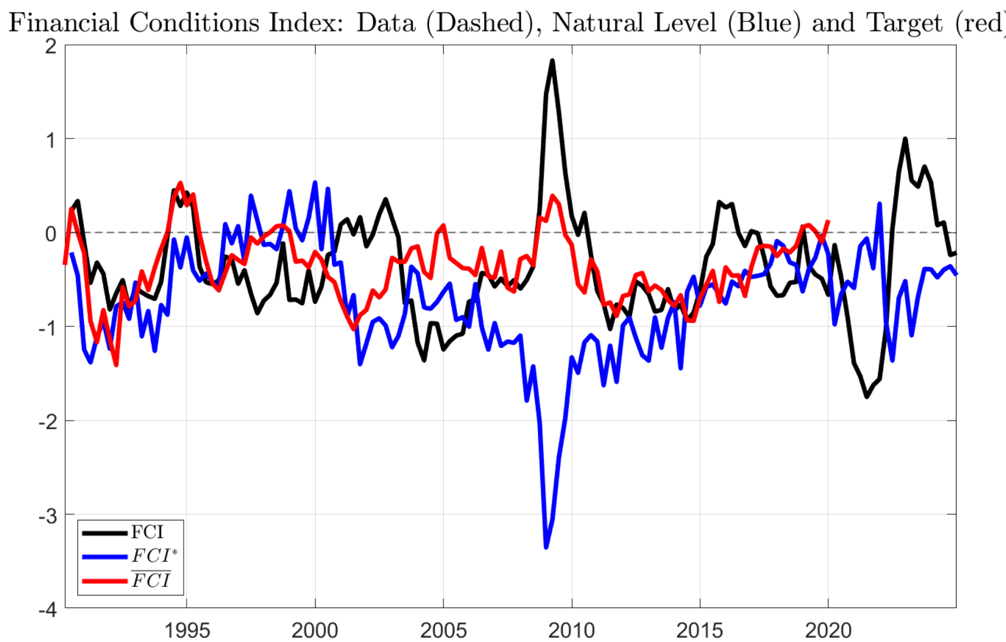

Figure 10: FCI^* and optimal FCI target ($\overline{FCI}$) constructed in Caballero et al. (2024).

causal effects of monetary policy shocks at several horizons (Caravello et al., 2024). We estimate both objects directly from the data.[9]

It is important to note that although FCI^* and $\overline{FCI}$ are conceptually related, the construction procedure of each series is completely different. In order to estimate FCI^*, we use a simple macroeconometric model to infer it as a latent variable from observed output, inflation, and financial conditions. The advantage of this construction is that the estimation is transparent. However, a disadvantage is that this simple model potentially misses many important aspects that are relevant for actual policy implementation. On the other hand, the procedure to construct $\overline{FCI}$ incorporates realistic frictions faced by a policymaker, but it is more complex and might appear less transparent.

FCI^* vs. $\overline{FCI}$. Figure **??** compares our estimate of FCI^* with the optimal FCI target that minimizes the loss (D.2), which we denote by $\overline{FCI}$. Except for the GFC, both series generally move quite closely. At the beginning of the 1990s, both series track the behavior of the actual FCI. Moving on to the late 1990s, both series are above the observed FCI, indicating that financial conditions were too loose from a macroeconomic perspective. After the crash of the dotcom bubble, both FCI^* and $\overline{FCI}$ move significantly into negative territory due to the recession. Starting in late 2001, both series move up again and stay above the observed FCI. A divergence between both series starts in mid 2006: $\overline{FCI}$ remains close to zero whereas FCI^* dives deeper into negative territory. This divergence reaches a maximum at the height of the financial crisis, where $\overline{FCI}$ is initially tighter, while FCI^* has a sharp drop. After the

[9]For the counterfactual to be exact, we would need to estimate the effects of monetary policy shocks at *each point in the yield curve*. Given that empirical estimates of this are not available, we approximate the counterfactual using the monetary policy shocks from Romer and Romer (2004) and Aruoba and Drechsel (2024). Caravello et al. (2024) show that this two shock approximation is good as long as the counterfactual does not involve significant changes at the long end of the yield curve, which is what we find in our context.

GFC, both series reunite again around 2011, and move quite closely together for the rest of the sample.[10]

The divergence between FCI^* and $\overline{FCI}$ during the GFC can be explained by a combination of factors. First, prior to the crisis, inflation was running persistently above target. In this context, the planner finds it optimal to tighten financial conditions to fight inflation, even if this generates an expected recession. Second, given that the planner has a preference for gradualism (since it penalizes interest rate changes), a large part of the rise in $\overline{FCI}$ during the GFC is committed well in advance, as part of the fight against inflation. Given that the planner is gradualist, once the crisis hits, it only gradually adjusts down the optimal $\overline{FCI}$. Finally, inflation during the crisis bounces back to levels close to 2 percent relatively quickly—the so called "*missing disinflation puzzle*". Thus, the planner perceives that giving additional stimulus during this period will cause higher inflation, so it refrains from doing it. All of this explains why $\overline{FCI}$ remains relatively high. Regarding the sharp drop in FCI^*, this is a consequence of what happens with output. Given that potential output moves slowly, if we observe such a large decline in output, it must be that a large negative output gap opened up. Since equation (12) links output gaps with FCI gaps, if a large negative output gap opened, it must be the case that there is a large FCI gap. Even if the observed FCI_t did go up, the increase is not large enough to justify the drop in output according to equation (12). The inferred FCI^* goes down accordingly.

In summary, apart from a discrepancy around the GFC, both series move quite closely in the rest of the sample. This is remarkable given that, as we mentioned earlier, the construction procedure for both series is completely different. We see this as a validation exercise on the usefulness of FCI^* as a guide for practical policy evaluation: even when one considers a quantitatively relevant optimal policy problem, most of the time the planner does not want to meaningfully deviate from the FCI^* estimated with a simple two equation model.

[10]The series for $\overline{FCI}$ stops in 2019Q4 since the main sample in that paper is pre-COVID.