Unemployment and the State-Dependent Effects of Monetary Policy

Eva F. Janssens[†] and Sean McCrary[‡]

February, 2025

Most Recent Version

Preliminary draft, please do not circulate without permission. Comments welcome!

Abstract

This paper provides evidence that time variation in the effects of monetary policy shocks arise from labor market frictions. We first demonstrate this analytically in a stylized New Keynesian model, motivating three empirical proxies for flow surplus: total factor productivity, marginal hiring costs, and corporate profits. Using these proxies, we provide model-free evidence that monetary policy shocks have stronger real effects when surplus is low. We estimate a quantitative model, solving it with local linear approximation methods that preserve this state dependence, and a novel filtering algorithm for nonlinear DSGE models. This framework allows us to construct time-varying impulse response functions and Phillips Multipliers. The model predicts that the Phillips Multiplier is twice as small following recessions as after expansions.

Keywords: numerical methods, Taylor projection, labor search

JEL classification codes: C63, C68, C32, E32, E52, J64

* Disclaimer: The views expressed in this paper are solely the responsibility of the authors and should not be interpreted as reflecting the views of the Board of Governors of the Federal Reserve System.

* Acknowledgements: We are grateful for Hilde Bjornland's discussion at Midwest Econometrics' mentoring meeting, and for the helpful comments of Ryan Michaels, Francesco Furlanetto, Rüdiger Bachmann, Yoosoon Chang, and conference participants at SEA, IAAE, Midwest Macro, Midwest Econometrics, and T2M. Any errors are our own.

Contact information:
† Eva F. Janssens: University of Michigan, Department of Economics. Email: `evafj@umich.edu`
‡ Sean McCrary: Ohio State University, Department of Economics. E-mail: `mccrary.65@osu.edu`

1 Introduction

Do the effects of monetary policy vary over the business cycle? If so, what drives this variation, and how can we empirically test the validity of the underlying mechanism? In models with labor market frictions, the propagation of shocks is scaled by the profitability of job creation, which itself is time varying. In this paper, we show this time-variability provides a theoretical foundation for state-dependence in the effects of monetary policy, supported by model-free empirical evidence and an estimated quantitative model.

For the first contribution of our paper, we set up a stylized New Keynesian model with Diamond-Mortensen-Pissarides[1] style labor market frictions, and show analytically how the propagation of monetary policy shocks is scaled by the flow profit of the firm.[2]. When the flow profit is low, monetary policy has large effects, and when the flow profit is large, the effects of monetary policy are small. The degree of price stickiness determines whether this state-dependence expresses itself mostly on the real or nominal side of the economy. Since the flow profit of the firm is a time-varying object, this generates state-dependence in the response to monetary policy shocks.

The extent to which this mechanism matters, however, is an empirical question, which brings us to our second contribution. Since surplus is unobserved, we use our stylized model to motivate three empirical proxies: the marginal cost of hiring, corporate profits, and total factor productivity (TFP). We provide model-free empirical evidence that the effects of monetary policy on real-side quantities—such as unemployment, market tightness, industrial production, and vacancies—are larger when surplus is low, consistent with the predictions of our theoretical model. This finding is robust across all three proxies, three different instruments for monetary policy shocks, and two distinct econometric frameworks. The empirical evidence for state dependence in prices is more mixed, suggesting that its magnitude may be small.

Since flow profit is unobserved and any proxy is necessarily imperfect, extrapolating from these empirical results would require strong assumptions. Instead, we develop a quantitative model with realistic labor market frictions, allowing us to filter the evolution of underlying economic states over time and assess their impact on shock propagation.

[1] Diamond (1982), Mortensen (1982), and Pissarides (1985)

[2] Holding the bargaining power of workers constant, this flow profit is one-to-one with notion of the *fundamental surplus* in Ljungqvist and Sargent (2017).

Solving the model nonlinearly is crucial, as a linear solution would fix flow profit at its steady-state value, failing to capture the interaction between flow surplus and shock propagation. To address this, we apply local linear model solution techniques, which solve the model at different points in the state space, precisely capturing the state dependence we aim to measure.

This relates to our third contribution, which is methodological. Building on local linear model solution techniques from Levintal (2018) and Mennuni, Rubio-Ramírez, and Stepanchuk (2024), we demonstrate that models solved using this approach can be mapped into a time-varying linear state-space representation and subsequently filtered with the time-varying Kalman filter. Through simulations, we show that this combination of solution methods and filtering techniques is both fast and accurate, outperforming global solution methods and particle filtering in finite samples in terms of both speed and accuracy. This framework allows us to filter the underlying economic states and compute impulse response functions (IRFs) at each point in time. Our results reveal substantial variation in IRFs, with periods where shocks have either minimal or large effects on the economy.

A key metric for policymakers is the cost of monetary policy, captured by the inflation-unemployment trade-off, commonly known as the Phillips Multiplier – which can be informally interpreted as the slope of the Phillips curve. Our model enables us to compute the Phillips Multiplier dynamically at each point in time and confirms a countercyclical pattern. Specifically, we find that in low-surplus periods (i.e, following recessions), the Phillips curve flattens, with the Phillips Multiplier close to zero (around -0.03 or -0.02). In high-surplus periods (i.e., following expansions), the Phillips curve steepens, and the Multiplier can double, reaching values as large as -0.07 – estimates well in line with existing studies such as Barnichon and Mesters (2021) and Hazell, Herreno, Nakamura, and Steinsson (2022). The range of time-variation in the Philips Multiplier we find aligns with the empirical findings of Gitti (2024) on differences in the slope of the Philips curve.

More broadly, by generating time-varying impulse response functions and Phillips Multipliers, our quantitative model and filtering technique offer a valuable framework for policymakers to assess how policy intervention effects evolve over time – a relevance underscored by the substantial time variation in monetary policy effectiveness that we document.

Related literature Our empirical results add to an existing literature studying state-dependence of impulse response functions as implied by Structural Vector Autoregressions (SVARs) or local projections, as in Barnichon, Debortoli, and Matthes (2022) and Ben Zeev, Ramey, and Zubairy (2023) for government spending shocks, and Ravn and Sola (2004), Angrist, Jordà, and Kuersteiner (2018), Tenreyro and Thwaites (2016), and Cloyne, Jordà, and Taylor (2023) for monetary policy. We focus on the role of flow surplus as the source of state dependence, which is a novel contribution. At first glance, our results may appear to contradict those of Tenreyro and Thwaites (2016), who argue that monetary policy is less effective during recessions. However, we contend that this discrepancy arises from differences in how economic states are classified. Their proxy for state dependence, a seven-quarter moving average of GDP growth, lags behind the business cycle. Consequently, when our surplus proxies are low, their state proxy is high. Periods classified as expansions in Tenreyro and Thwaites (2016) correspond to episodes in which we observe low TFP and other flow surplus proxies. We elaborate on this further in Section 3.

Our quantitative model builds on a long tradition of New Keynesian models and search-and-matching models à la Diamond (1982), Mortensen (1982), and Pissarides (1985). More recently, it connects to a literature that integrates both frameworks, as in Christiano, Eichenbaum, and Trabandt (2016) and Thomas (2011), with other significant contributions from Galí, Smets, and Wouters (2012), Blanchard and Galí (2010), Krause and Lubik (2007), and Gertler, Sala, and Trigari (2008). Our primary contribution to this literature is to demonstrate that the NKDMP model exhibits strong state dependence in the real response to a monetary policy surprise.

Our contribution to filtering and estimation is a novel framework for DSGE models. We show that models solved using local linear approximation methods, such as Levintal (2018) and Mennuni et al. (2024), can be mapped into time-varying linear state-space models and filtered using the time-varying Kalman filter, enabling fast and accurate estimation of nonlinear models. This relates to a broader literature on nonlinear DSGE estimation. A key benchmark is Fernández-Villaverde and Rubio-Ramírez (2007), who introduce the particle filter, though it suffers from high computational costs due to the curse of dimensionality, evident in Gust, Herbst, López-Salido, and Smith (2017) who estimate a globally solved model using the particle filter, needing many particles and parallel computing with many nodes. Similarly, Farmer (2021) employs a discretization filter for second-order perturbations, but discretizing the state space is computationally intensive and also suffers from the curse of dimensionality. In contrast, our proposed method is computationally efficient and feasible on a standard desktop computer. Other approaches, such as Borağan Aruoba, Cuba-Borda, and Schorfheide (2018) and Harding, Lindé, and Trabandt (2022), estimate a linearized DSGE model and evaluate it using a globally solved version. While computationally attractive, this method is unreliable when local perturbation deviates significantly from the global solution – a key issue in our model given the well-documented nonlinearities in labor search models (see, e.g., Petrosky-Nadeau and Zhang (2017)).

Finally, our paper relates to a long literature studying the Phillips (1958) curve, including its nonlinearities and time variation in its slope, as examined in Coibion and Gorodnichenko (2015), Smith, Timmermann, and Wright (2023), and others. Both Smith et al. (2023) (empirically) and Benigno and Eggertsson (2023) (model and empirics) argue that the Phillips curve is steeper at lower unemployment rates (i.e., in tighter labor markets), a finding consistent with our empirical and model-based results. Benigno and Eggertsson (2023) model this within a New Keynesian framework by introducing a kink in wage setting around a market tightness of one, which mechanically induces a kink in the Phillips curve. In contrast, we show that state dependence does not need to be imposed exogenously in a New Keynesian model; rather, it emerges endogenously from its nonlinear solution. An older literature suggests that nonlinearities and state dependence may arise from pricing setting frictions rather than labor market frictions, with contributions from Dotsey, King, and Wolman (1999), Gertler and Leahy (2008), and more recently, Harding et al. (2022) and Harding, Lindé, and Trabandt (2023). Instead, our focus is on labor market frictions as the primary source of state dependence. Finally, a recent study by Lahcen, Baughman, Rabinovich, and van Buggenum (2022) builds on the money search tradition of Berentsen, Menzio, and Wright (2011), showing that small-surplus calibrations imply state-dependent inflation costs. We view the money search literature as complementary, as it abstracts from the nominal rigidities central to New Keynesian frameworks and, consequently, from the role of active monetary policy, which is our primary focus.

Outline The rest of this paper is structured as follows. Section 2 presents a stylized New Keynesian model with labor market frictions. Section 3 presents empirical evidence on how the effect of monetary policy depends on these empirical proxies. Section 4 presents our solution approach and our proposed filtering framework. Section 5 presents our more elaborate model, and Section 6 presents results on the model-implied variation in the Philips Multipliers and IRFs. Section 7 concludes.

2 A Small New Keynesian Model with Search Frictions

In this section, we present a small New Keynesian (NK) model with search frictions, following the Diamond-Mortensen-Pissarides (DMP) framework. The model illustrates how the strength of monetary policy transmission depends on firms' flow surplus, leading to state-dependent effects of monetary policy. We demonstrate this analytically by log-linearizing the model around two distinct steady states: one characterized by low surplus and the other by high surplus. Additionally, the model provides theoretically grounded proxies for firm surplus, which we employ in our empirical analysis to test for the presence of such state dependence in the data. Furthermore, this model serves as the foundation for the more comprehensive NK-DMP framework developed in Sections 5 and 6.

2.1 Key Model Ingredients

Overview The economy consists of households that consume and supply labor, intermediate good producers that set prices and hire labor in a frictional labor market where workers seek to match with jobs, and final good producers that aggregate intermediate goods while taking prices as given. Wages are determined through Nash bargaining between workers and intermediate goods firms. The government sets the nominal interest rate according to an inertial Taylor rule.

Timing The timing of the model is designed to be compatible with low-frequency (quarterly) data. In particular, we assume that workers who lose their jobs at the beginning of period t can be re-employed within the same period.[3] Each model period consists of four sub-periods: (i) separations, (ii) search and matching, (iii) bargaining, and (iv) production and consumption/saving.

Households Households are composed of a continuum of members $i \in [0, 1]$ who derive utility from consumption $c_t(i)$, and supply one unit of labor $n_t(i) \in \{0, 1\}$ if employed and none if unemployed. The members of the household perfectly insure each other against variations in income due to unemployment. Hence, defining $C_t := \int c_t(i)di$, and

[3] This assumption reflects the fact that most unemployment spells are shorter than a quarter, allowing us to use quarterly data without requiring higher-frequency modeling. According to the estimate of Ahn and Hamilton (2022), two-thirds of workers exit unemployment within the first quarter of an unemployment spell.

$N_t := \int n_t(i)di$, households maximize:

$$\mathbb{E}_0\left[\sum_{t=0}^{\infty}\beta^t \frac{C_t^{1-\tau}-1}{1-\tau}\right],$$

subject to the budget constraint

$$P_tC_t + B_t = P_tW_tN_t + P_t(1-N_t)\nu + R_{t-1}B_{t-1} + T_t,$$

and the law of motion for employment

$$N_t = (1-\delta)N_{t-1} + q_tV_t$$

Here β is the discount factor, $1/\tau$ is the intertemporal elasticity of substitution, P_t is the price of the final good, B_t denotes one-period risk-free bonds with gross return R_t, and T_t denotes lump sum taxes net of profits transferred from firms. W_t are real wages, ν is the resources provided by the unemployed (e.g., unemployment benefits and home production). The law of motion for employment depends on the exogenous separation rate δ and the number of new hires q_tV_t made by firms which the household takes as given, with V_t the number of vacancies and q_t the vacancy filling rate

Defining the surplus to the household of employment S_t^h using the envelope condition, we obtain:

$$S_t^h = W_t - \nu + (1-\delta)E_t\left[Q_{t,t+1}S_{t+1}^h\right].$$

which denotes the present value of a marginal employed household member.

Search and Matching The number of aggregates matches is determined by a constant return to scale matching function $M_t = M(V_t, S_t)$ where V_t is aggregate vacancies and S_t is the number of unmatched workers searching for jobs. Given the timing assumption, the mass of unmatched workers in the search stage is given by $S_t = 1 - N_{t-1} + \delta N_{t-1} = 1-(1-\delta)N_{t-1}$, that is the workers who were not matched at the end of the previous production stage plus those who incurred an involuntary separation at the beginning of the period. The probability a vacancy contacts workers can be summarized by the market tightness $\theta_t = V_t/S_t$ as $q_t = M_t/V_t = M\left(1, \theta_t^{-1}\right)$.

Final Goods Producers The finals good producer aggregates intermediate goods $Y_t(j)$, $j \in [0,1]$, using the technology:

$$Y_t = \left(\int_0^1 Y_t(j)^{1-\gamma} dj \right)^{\frac{1}{1-\gamma}}.$$

The representative firm maximizes profits

$$P_t Y_t - \int_0^1 P_t(j) Y_t(j) dj,$$

taking input prices $P_t(j)$ and output prices P_t as given. Profit maximization implies that the demand for input j is given by:

$$Y_t(j) = \left(\frac{P_t(j)}{P_t} \right)^{-\frac{1}{\gamma}} Y_t.$$

Intermediate Goods Producers There is a continuum $j \in [0,1]$ of identical monopolistic intermediate goods producers, with production technology

$$Y_t(j) = Z_t N_t(j)$$

where Z_t is a neutral technology shock, and $N_t(j)$ is the quantity of labor. These firms are monopolists in the product market and hire in frictional labor markets. Price adjustments are subject to a Rotemberg (1982) quadratic adjustment cost given by

$$AC_t(j) = \frac{\phi}{2} \left(\frac{P_t(j)}{P_{t-1}(j)} - \bar{\Pi} \right)^2 Y_t,$$

where $\bar{\Pi}$ is long-run, i.e., target, inflation and ϕ determines the price stickiness in equilibrium.

Firms hire labor in a frictional labor market by posting vacancies at a fixed cost κ. Hence, the firm's problem is to choose employment $N_t(j)$, vacancies $V_t(j)$, and prices $P_t(j)$ to maximize the present value of real profits discounted by $Q_{0,t}$:

$$\Pi_0(j) = \mathbb{E}_0 \sum_{t=0}^{\infty} Q_{0,t} \left\{ \left(\frac{P_t(j)}{P_t} Z_t - W_t \right) N_t(j) - \kappa V_t(j) - AC_t(j) \right\}.$$

subject to

$$Z_t N_t(j) = \left(\frac{P_t(j)}{P_t} \right)^{-\frac{1}{\gamma}} Y_t, \qquad [\omega_t]$$
$$N_t(j) = (1-\delta) N_{t-1}(j) + q_t V_t(j). \quad [\mu_t]$$

where the first constraint implies that the choice of output $Y_t(j) = Z_t N_t(j)$ and prices $P_t(j)$ are constrained to lie on the firms' product demand curves. The multiplier on this constraint is given by ω_t. This leads to both an explicit cost of labor the real wage W_t and an implicit cost ω_t as hiring a marginal worker– all else equal–leads to a reduction in prices. The second constraint is the law of motion for employment at the firm and the multiplier μ_t represents the value of a marginal worker to the firm.

Wage Bargaining The wage is determined by the Nash sharing rule

$$\eta \mu_t = (1-\eta) S_t^h.$$

where η is the workers' bargaining weight. This leads to the following expression for the real wage

$$W_t = \eta Z_t (1 - \omega_t) + (1-\eta)\nu$$

where ν is the flow value of non-employment and ω_t is the implicit marginal cost of hiring.

Government Monetary policy is determined by a Taylor Rule for the nominal interest rate:

$$\frac{R_t}{\bar{R}} = \left[\left(\frac{\Pi_t}{\bar{\Pi}} \right)^{\psi_1} \left(\frac{Y_t}{Y_{t-1}} \right)^{\psi_2} \right]^{1-\rho_R} \left(\frac{R_{t-1}}{\bar{R}} \right)^{\rho_R} e^{\epsilon_{R,t}}$$

where R_t is the nominal interest rate. The systematic component of monetary policy reacts to the state of the economy, $\Pi_t = P_t / P_{t-1}$ is inflation, Y_t is output, and $\epsilon_{R,t}$ is the shock. The government levies lump-sum taxes (or provides a subsidy) to run a balanced budget every period.

Equilibrium Conditions We assume vacancy costs and adjustment costs are paid in lump-sum fashion to households, so market clearing implies $C_t = Y_t$. This leads to the following Euler equation

$$1 = \beta \mathbb{E}_t \left[\left(\frac{Y_{t+1}}{Y_t} \right)^{-\tau} \frac{R_t}{\Pi_{t+1}} \right].$$

In a symmetric equilibrium all firms set the same prices $P_t = P_t(j)$ and choose the same level of employment $N_t(j) = N_t$ and vacancies $V_t(j) = V_t$ leading to the following pricing equation

$$\frac{\omega_t}{\gamma} = 1 - \phi(\Pi_t - \bar{\Pi})\Pi_t + \phi\beta\mathbb{E}_t \left[\left(\frac{Y_{t+1}}{Y_t} \right)^{1-\tau} (\Pi_{t+1} - \bar{\Pi})\Pi_{t+1} \right].$$

Similarly, optimal vacancy posting and the expression for the Nash wage leads to the following job-creation condition

$$\frac{\kappa}{q_t} = (1-\eta)\left[(1-\omega_t)Z_t - \nu\right] + \beta(1-\delta)\mathbb{E}_t \left[\left(\frac{Y_{t+1}}{Y_t} \right)^{-\tau} \frac{\kappa}{q_{t+1}} \right]$$

To close the model, the interest rate rule and law of motion for employment are given by

$$\frac{R_t}{\bar{R}} = \left[\left(\frac{\Pi_t}{\bar{\Pi}} \right)^{\psi_1} \left(\frac{Y_t}{Y_{t-1}} \right)^{\psi_2} \right]^{1-\rho_R} \left(\frac{R_{t-1}}{\bar{R}} \right)^{\rho_R} e^{\epsilon_{R,t}}$$

$$N_t = (1-\delta)N_{t-1} + \underbrace{q_t\theta_t\left[1-(1-\delta)N_{t-1}\right]}_{=\, q_t V_t}$$

2.2 State-Dependence

We use the system of log-linearized conditions to think about the deterministic response of the system to a one-time monetary shock $\epsilon_{R,t}$, that is, the perfect foresight path. Details on the equilibrium conditions and the derivation of the log-linear system are provided in Appendix D. In this framework, total factor productivity is at steady state, hence $\hat{z}_t = 0$, where the $\hat{\cdot}$ notation denotes a variable in log-deviation from the steady state. This gives us a reduced system of equations (where we omit expectation operators as this is the perfect foresight response):

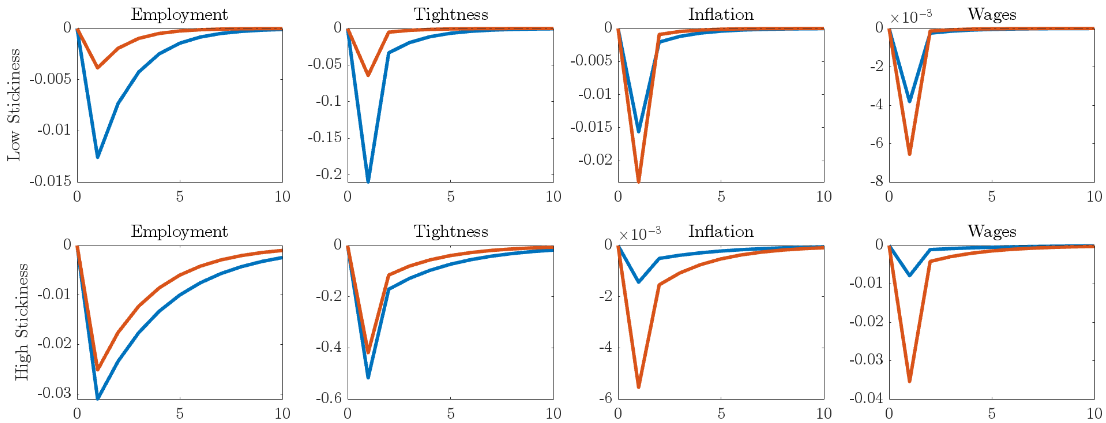
$$
\begin{aligned}
\text{Euler/IS: } & \hat{n}_{t+1} = \hat{n}_t + \frac{1}{\tau}\left[\hat{r}_t - \hat{\pi}_{t+1}\right] \\
\text{Pricing/NK-Phillips: } & \hat{\pi}_t = \beta \hat{\pi}_{t+1} - \frac{1}{\phi}\hat{\omega}_t \\
\text{Job-Creation: } & \hat{q}_t = \frac{\gamma(1-\beta(1-\delta))}{(1-\eta)(1-\gamma-\nu)}\hat{\omega}_t + (1-\delta)\beta\left[\hat{q}_{t+1} + \hat{r}_t - \hat{\pi}_{t+1}\right] \\
\text{Taylor Rule: } & \hat{r}_t = (1-\rho_R)\left[\psi_1\hat{\pi}_t + \psi_2(\hat{n}_t - \hat{n}_{t-1})\right] + \rho_R\hat{r}_{t-1} + \epsilon_{R,t} \\
\text{LOM: } & \hat{n}_t = (1-\delta)\hat{n}_{t-1} + \delta\left(\hat{q}_t + \hat{v}_t\right)
\end{aligned}
$$

As evident from the log-linearized job creation condition, the sensitivity of q_t to ω_t scales inversely with $(1-\eta)(1-\gamma-\nu)$, which represents the steady-state flow profit of the firm. This is closely related to the *fundamental surplus* concept in Ljungqvist and Sargent (2017). When the flow profit is small, shocks propagate more strongly to the vacancy-filling rate q_t, and vice versa. Since q_t determines market tightness, the same mechanism governs the propagation of shocks to market tightness and, consequently, employment and output. Given that inflation depends on $\hat{\omega}_t$ through the New Keynesian Phillips curve, this mechanism also drives state dependence in inflation. The strength of inflation's response to a monetary shock is influenced by the degree of price stickiness ϕ, as specified in the Rotemberg (1982) adjustment cost framework.

In a log-linearized NK-DMP model, the propagation mechanisms depend on steady-state profit $(1-\eta)(1-\gamma-\nu)$ for real variables and on price stickiness ϕ for inflation. However, these elasticities remain constant across different economic states. To accurately capture state dependence, we require a solution method that allows these elasticities to vary with the state of the economy. As we will demonstrate in Section 6, the nonlinear model solution exhibits significant state dependence.

Even in our log-linearized solution, however, we can illustrate this intuition by computing perfect foresight paths for a monetary policy shock around four different steady states: one economy with a low steady-state profit and another with a high steady-state profit, and then examining how these economies differ under varying levels of price stickiness. We visualize this in Figure 1. When prices are flexible, the model reveals strong state dependence in real variables (employment and market tightness), whereas price variables

Figure 1: Perfect foresight paths to a monetary policy shock in a low and high surplus steady state and a low and high price stickiness economy



(inflation and real wages) exhibit weaker state dependence. Increasing the degree of price stickiness reduces state dependence in real quantities while amplifying it in prices.

To summarize, an economy with a small surplus steady state exhibits larger responses to a monetary shock than one with a large surplus steady state. However, whether this state dependence primarily affects quantities or prices depends on the degree of price stickiness.

2.3 Model-Implied Proxies for Surplus

The simple NK-DMP model implies that the propagation of monetary shocks depends on the profitability of job creation. The job-creation condition equates the marginal cost of hiring, κ/q_t, to the present value of profits from a marginal hire. Following this logic, we identify three proxies for the state of the economy, which we examine in the empirical section.

1. **Marginal Cost of Hiring:** In the model, the marginal cost of hiring is given by κ/q_t, but in the data, q_t is not directly observed. However, assuming a constant returns to scale matching function, $f_t = \theta_t q_t$, where f_t is the job-finding rate and θ_t represents market tightness—both of which are observable. This relationship implies that the marginal cost of hiring is proportional to θ_t/f_t, which we use as our first proxy.

2. **Corporate Profits:** The value of job creation corresponds to the present value of profits obtained from a marginal hire. While this present value is not directly observable in the data, corporate profits are. In the data, we measure profits as the ratio of total profits (value added net of employee compensation) to value added in the corporate sector.

3. **Total Factor Productivity (TFP):** In the model, when total factor productivity Z_t increases, the rigidity in real wages implied by the Nash bargaining rule causes wages to rise by less than one-to-one with the marginal product. This results in procyclical profits and procyclical job creation. A natural candidate for capturing the state of the economy is TFP. However, TFP is not directly observable and must be inferred from aggregate accounting exercises.

Taken in isolation, each of these proxies has predictive power for state dependence if (i) the NK-DMP model is the data-generating process and (ii) the proxies are well measured. However, (i) is not strictly true, as any model is only an approximation of reality, and (ii) relies on the assumptions that vacancy costs are linear, that flow profit and the present value of profit are related, and that TFP can be reliably measured. To mitigate potential limitations associated with any single proxy, we examine the effects of monetary policy shocks by comparing results across all three proxies. To the extent that our empirical findings are consistent across all three proxies, we consider our results robust.

3 Empirical Evidence

Building on the theoretical framework established in the previous section, which analytically demonstrates that in a New Keynesian model with labor market frictions, the transmission of monetary policy shocks depends on the surplus of the firm, this section presents empirical evidence that aligns with this theory. We show robustness by looking at two different methodologies, three different proxies for surplus, and three different monetary policy shock instruments.

3.1 Data Description

Outcome Variables The empirical analysis focuses on the effects of monetary policy shocks on the following real-side variables: the Industrial Production Index (IPI), the unemployment rate, vacancies (measured using the Help-Wanted Index from Barnichon (2010), divided by the active labor force participation rate), and market tightness (the ratio of vacancies to unemployment). In addition to these real-side variables, we consider two price variables: the Consumer Price Index (CPI) and real wages, where real wages are calculated as the log of average hourly earnings divided by the CPI. Detailed descriptions of the data sources and transformations are provided in Appendix A.

Controls In the local projection instrumental variable framework, we follow the approach of Ramey (2016) by including controls for the CPI, the unemployment rate, the Producer Price Index (PPI), and lags of the monetary policy variable and the dependent variable. Following the recommendations of Bauer and Swanson (2023), the LP-IV framework includes 12 monthly lags. For the STLP analysis, we adopt the same controls, number of lags, time period, and specifications as in Tenreyro and Thwaites (2016).

State Variables The empirical analysis in this section uses three proxies of firm surplus as were motivated in the previous section to examine state-dependent monetary policy transmission:

1. Corporate Profits: Corporate profits are measured as the ratio of profits to the sum of profits and compensation, as reported in the National Income and Product Accounts (NIPA), Table 1.10.

2. Marginal Cost of Hiring: Marginal hiring costs in our model scale with the log of market tightness minus the log of the job finding rate. For the job finding rate, we follow Shimer (2005).

3. Total Factor Productivity (TFP): We use the quarterly TFP growth proxy constructed by Fernald (2014). From this measure, we create a TFP index, which is detrended using the Hamilton (2018) filter to obtain a proxy for TFP levels.

We acknowledge that a causal interpretation of this framework relies on the exogeneity of the monetary policy shocks with respect to both state and outcome variables at all horizons (Gonçalves, Herrera, Kilian, and Pesavento, 2023) — a condition that may not be satisfied for all proxies. Our aim in this section is more modest: to document correlations indicative of state dependence that are consistent with the theoretical model.

Instruments and Policy Variables For the LP-IV framework, we employ three commonly used instruments:

1. The monetary policy shocks from Romer and Romer (2004), extended by Wieland and Yang (2020) to 2007, used to instrument the Federal Funds Rate (FFR).
2. The high-frequency identification approach of Bauer and Swanson (2023), starting in 1989, and we use the data up until 2019, used to instrument the two-year U.S. Treasury yield.
3. The language-processing approach of Aruoba and Drechsel (2024), spanning 1982-2008, used to instrument the two-year U.S. Treasury yield.

In the STLP framework, we follow Tenreyro and Thwaites (2016) and use the extended Romer and Romer (2004) series as the identified monetary policy instrument.

3.2 Empirical Framework

State-Dependent Local Projections Consider the framework of Local Projections, as introduced by Jordà (2005):

$$y_{t+h} = \alpha_h + \beta_h s_t + w_t \gamma_h + \varepsilon_t, \quad \text{for } h = 0, \ldots, H \text{ and } t = 1, \ldots, T, \tag{1}$$

where s_t denotes an exogenous shock, y_{t+h} is the outcome of interest, and w_t is a set of control variables, typically including lagged values of the shock s_t and the outcome variable y_t. Under standard assumptions, the coefficients β_h, $h = 0, \ldots, H$, trace out the *Impulse Response Function* (IRF) of y_{t+h} to s_t.

Following Cloyne et al. (2023), we extend this framework to allow for state-dependent impulse responses by incorporating a term motivated by the Kitagawa-Blinder-Oaxaca (KBO) decomposition. Specifically, consider a *state variable* x_t. The state-dependent local projection framework is given by:

$$y_{t+h} = \alpha_h + \beta_h s_t + \beta_h^x s_t (x_t - \bar{x}) + w_t \gamma_h + \varepsilon_t, \quad \text{for } h = 0, \ldots, H \text{ and } t = 1, \ldots, T, \tag{2}$$

where w_t is now augmented with $(x_t - \bar{x})$, representing deviations of the state variable from its steady-state level $\bar{x}$. Relative to Equation (1), this specification introduces the term

$\beta_h^x s_t(x_t - \bar{x})$, which captures the interaction between the shock s_t and the state variable x_t. The state-dependent impulse response function is then given by the sum of the direct effect of the shock, $\hat{\beta}_h$, and the state-dependent effect, $\hat{\beta}_h^x(x_t - \bar{x})$. To aid inference, we impose the restriction that the response for each month in a quarter is the same, reducing the number of parameters to be estimated and shortening confidence intervals.

As is standard in the literature, we extend the local projections framework by incorporating an instrumental variable (IV) approach, where the shock s_t is replaced by a policy variable, such as the Federal Funds Rate (FFR) or two-year Treasury yield, which is instrumented in a first stage using an exogenous shock series. When the model includes an interaction term, as in Equation (2), the instrument set is extended by the interaction between the exogenous shock and the deviation of the state variable from its steady-state level.

Smooth Transition Local Projections A second way to incorporate state dependence in local projections is through the smooth transition local projection (STLP) approach, as in Tenreyro and Thwaites (2016). This approach allows for nonlinear state dependence by modeling the transition between regimes as a smooth function of the underlying state variable. Specifically, the model assumes that the economy can be in different states, such as in the case of Tenreyro and Thwaites (2016) an expansion or a recession regime as measured by GDP growth, and that the effects of monetary policy shocks vary continuously depending on the level of the state variable. This is achieved by augmenting the local projections framework with a transition function $g(x_t)$, which smoothly varies between 0 and 1 depending on the state variable x_t. The STLP specification can be written as:

$$y_{t+h} = (\alpha_h + \beta_h s_t + w_t \gamma_h)\left[1 - g(x_t)\right] + (\alpha_h^g + \beta_h^g s_t + w_t \gamma_h^g) g(x_t) + \varepsilon_t. \tag{3}$$

A common choice for the transition function is the logistic function $g(x_t) = [1+\exp(-\theta(x_t - c))]^{-1}$, where θ determines the speed of transition between regimes and c is the threshold level of the state variable. The coefficients β_h and β_h^g capture the responses of y_{t+h} to the shock s_t in the low and high regimes, respectively. The IRF at any point in time is given by a weighted average of these responses, with the weights determined by $g(x_t)$.

3.3 Empirical evidence on surplus-dependence

Quantities We first focus our attention on the state-dependent effects on quantities: the unemployment rate, IPI, vacancies, and market tightness. Figure 2 visualizes the estimated interaction terms between three different surplus proxies and the Federal Funds Rate (FFR), as specified in Equation (2). The FFR is instrumented using the monetary policy shocks identified by Romer and Romer (2004). The figure shows that the interaction effects are statistically significant at the 90% confidence level or higher, and the estimated effects on real variables are broadly consistent across all three surplus proxies.

To understand the interpretation of this interaction term, it is important to keep in mind the baseline responses of the outcome variables to a monetary policy shock. For instance, following an increase in the FFR, the Industrial Production Index, market tightness, and vacancies decrease. The positive interaction terms suggest that during periods of below-average surplus (i.e., low surplus), these variables exhibit even larger declines, indicating heightened sensitivity to monetary policy under such conditions. Conversely, the unemployment rate increases in response to a monetary policy shock. The negative interaction term implies that lower surplus levels further amplify the rise in unemployment. Figure 3 visualizes the results for the Corporate Profits proxy, aiding interpretation by computing the implied impulse response function for a low profit (one standard deviation below the mean) and high profit (one std. above the mean) state.

We also find evidence for surplus-dependence in quantities using the two other monetary policy instruments, that is, those of Bauer and Swanson (2023) and Aruoba and Drechsel (2024). We present these results in the Appendix in Figure B1. Overall, these results consistently show that the responsiveness of the unemployment rate, IPI, vacancies, and market tightness to monetary policy shocks is greater during periods of low surplus, regardless of the proxy used.

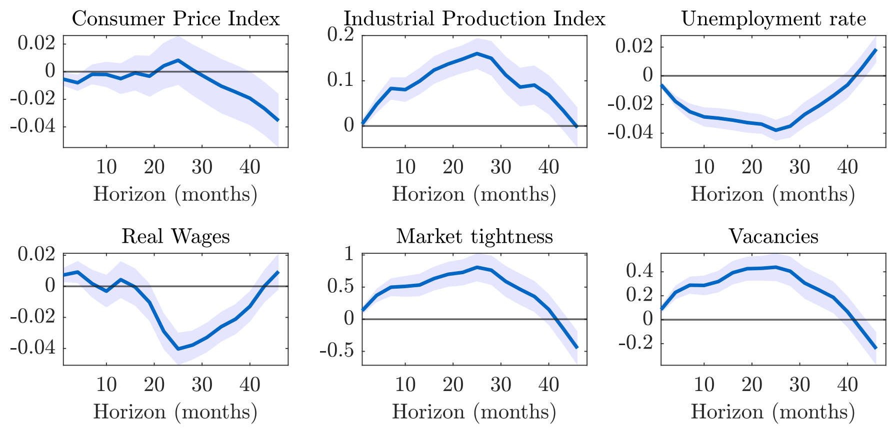
The results above are confirmed using the smooth transition local projection, presented in Figure 4 for the marginal hiring cost proxy, and in Appendix Figures B2 and B3 for the other two proxies.

Prices and Wages The results regarding state dependence in price variables are more ambiguous, with different methodologies yielding inconsistent signs. However, it is well recognized that in local projections, price responses can be affected by the so-called price puzzle (see, e.g., the discussion in Ramey (2016)). Therefore, we do not emphasize the sign of state dependence but rather focus on its magnitude. As shown in Figures 3 and 4, the differences in inflation and wage responses between high- and low-surplus states are not economically meaningful.

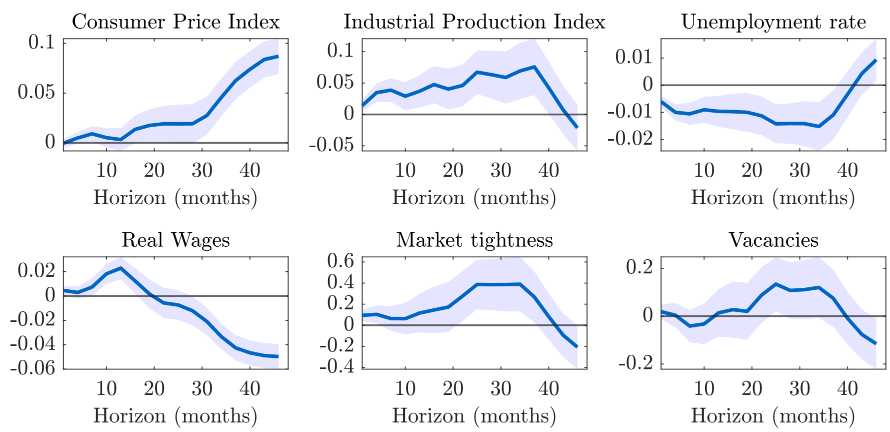
Comparison with results in Tenreyro and Thwaites (2016) Tenreyro and Thwaites (2016) find that monetary policy has larger effects during expansions than during recessions. At first glance, this may seem to contradict our findings, as one may think that expansions are high surplus periods, and our results instead suggest that monetary policy has smaller real-side effects when surplus is high. However, to understand how our results can co-exist with those of Tenreyro and Thwaites (2016), one has to revisit the definition of expansions and recessions in Tenreyro and Thwaites (2016). In particular, their state variable is defined as a seven-quarter moving average of GDP growth. We show in Appendix C that this seven-quarter moving average roughly coincides with the cycle-component of the Hamilton filter of GDP, hence we believe their state indicator is best interpreted as an indicator of whether GDP is above or below trend. Furthermore, we show in Appendix Section C that our surplus proxies are negatively correlated with this state variables. For example, our indicator for TFP tends to be low when GDP is above trend, as is the marginal cost of hiring. This explains why we find evidence that the effect of monetary policy shocks is larger during times of low surplus, which coincides with periods in time when GDP is above trend.

Figure 2: Interaction Term of Surplus and Federal Funds Rate (as in Eq. (2)*), instrumented using the Romer and Romer (2004) shocks.*

(a) Corporate Profits as a surplus proxy



(b) Marginal Cost of Hiring as a surplus proxy



(c) Total Factor Productivity as a surplus proxy

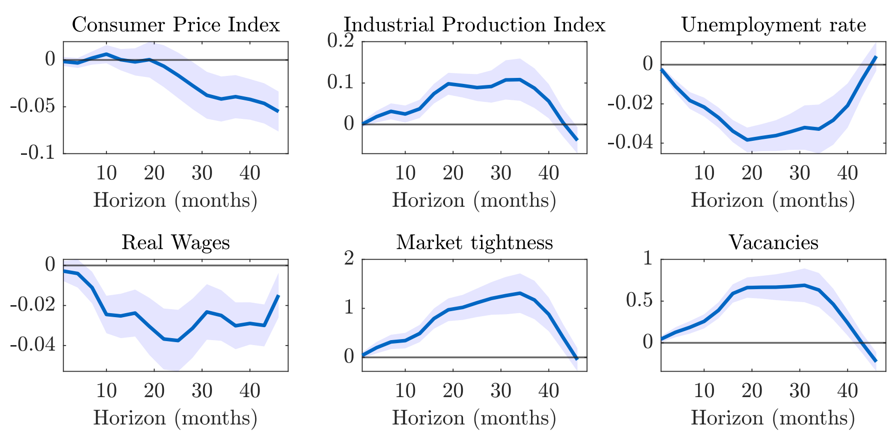


Figure 3: State-Dependent Local Projections (State Proxy: Corporate Profits), with the state ± 1 standard deviation above and below the mean, using the Romer and Romer (2004) shocks as instrument.

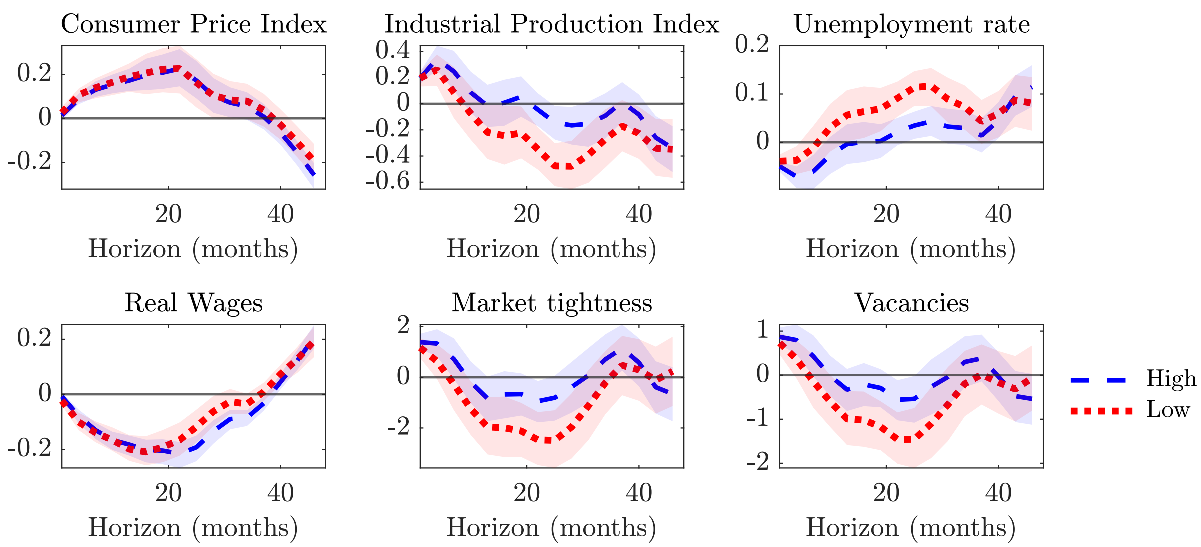
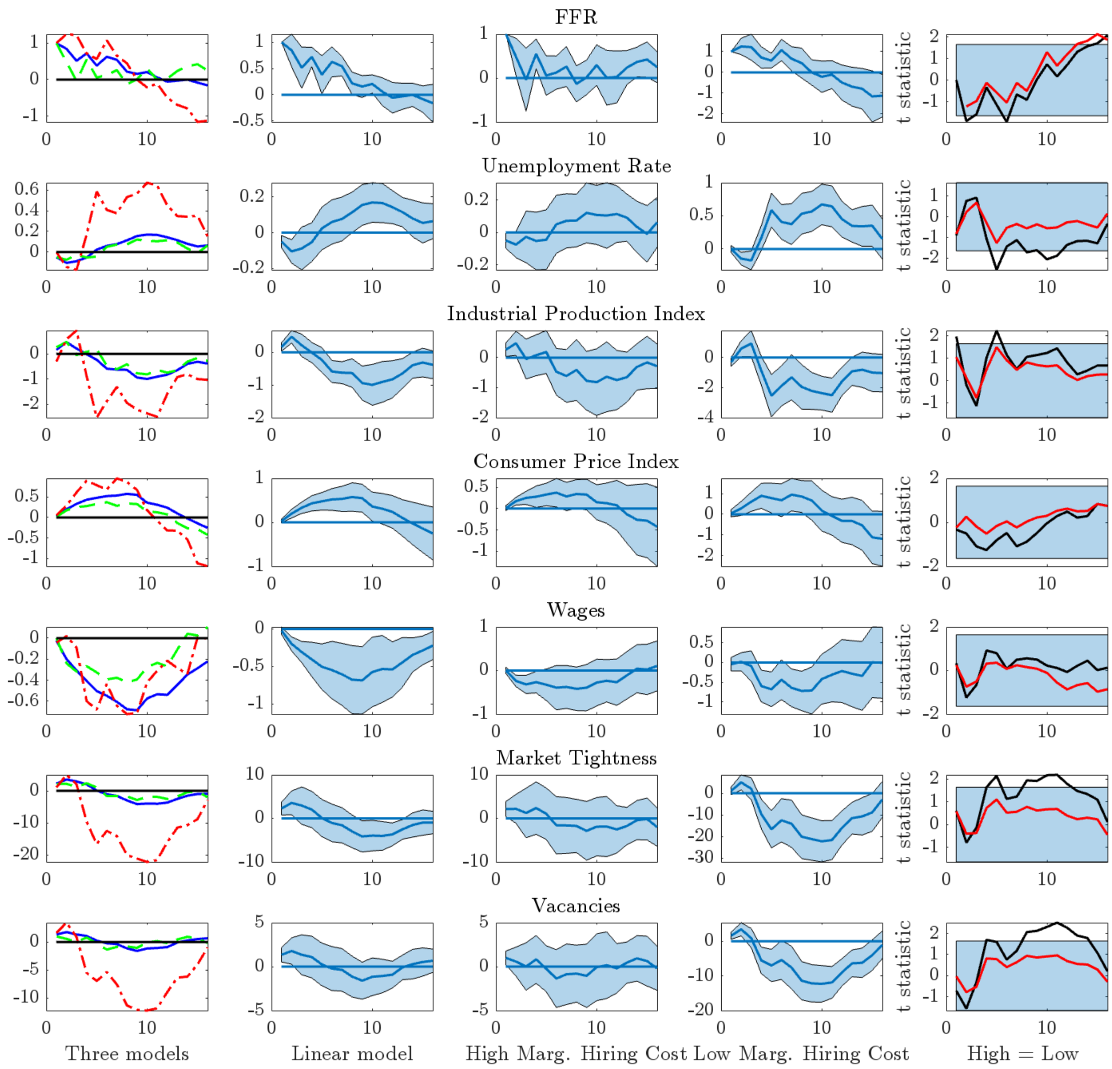


Figure 4: Smooth Transition Local Projections Using Marginal Hiring Costs as a Proxy for Surplus



Note: The first four columns show the response of the outcome variable to a 1 percentage point change in the FFR on impact across 16 horizons (quarters). In the first column, the average response (solid), the high-surplus (dashed) and the low-surplus (dash-dot) are shown on the same axis. The next three columns show the average response, high-surplus and low-surplus response respectively, with 90% confidence intervals. The last column tests the hypothesis that the coefficients in the high and low surplus regime are equal, where the red line is computed using a Bootstrap, and the black line using the Driscoll-Kraay method, and shaded area is ± 1.65. For details we refer to Tenreyro and Thwaites (2016).

4 Local Linear Approximations and Time-Varying Kalman Filtering

In this section, we discuss how to solve DSGE models using local linear approximations. We then propose a filtering framework based on these approximations, enabling us to filter nonlinear models both accurately and efficiently.

The motivation for focusing on local linear approximation methods is threefold. First, novel work by Levintal (2018), Fernández-Villaverde and Levintal (2018), and Mennuni et al. (2024) demonstrates that local linear approximations are both fast and accurate, with Euler errors often comparable to those of global model solution approaches.

Second, we are primarily interested in state dependence, and our small NK-DMP model shows that the choice of the state around which the model is locally approximated can significantly affect shock propagation, impulse response functions, and overall dynamics. A key advantage of local perturbation methods is that, while they restrict policies to be linear in the state variables, the coefficients are allowed to vary with the current state. This implies that the elasticities of economic variables to shocks will vary with the state of the economy, which is essential for the model to generate state-dependent responses to monetary shocks. This stands in contrast to traditional log-linearization, which imposes constant elasticities and, therefore, precludes any state-dependent effects.

Third, local linear approximation methods facilitate the implementation of the filtering framework we propose below. This last point represents the key novelty of our approach. Existing nonlinear solution methods typically rely on Monte Carlo (i.e., simulation-based) filters such as the particle filter for likelihood-based estimation. By taking a locally linear approximation of the model at different points in the state space, we retain the nonlinear model dynamics, but exploit its local linearity enabling filtering and likelihood evaluation using a Time-Varying Kalman filter. To our knowledge, we are the first to integrate these novel perturbation methods within a full-information estimation routine. Moreover, the computational advantages of this approach extend beyond the specific model studied in this paper and generalize to a broader class of models.

We center our discussion on our preferred computational algorithm, Taylor projections (Fernández-Villaverde and Levintal, 2018; Levintal, 2018), as we find it to be computationally more efficient than alternative methods. However, the filtering approach outlined below is more general and can be applied to other local linearization techniques, such as Dynamic Perturbation, as proposed by Mennuni et al. (2024).

4.1 Local Linear Approximation Methods

A standard Dynamic Stochastic General Equilibrium (DSGE) model can be represented as follows:

$$\mathbb{E}_t \left[f(y_{t+1}, y_t, x_{t+1}, x_t, \varepsilon_{t+1}) \right] = 0, \tag{4}$$

where the state variables evolve according to the known law of motion:

$$x_{t+1} = \Phi(x_t, y_t, \varepsilon_{t+1}), \tag{5}$$

and the policy function, the object we wish to solve for, satisfies:

$$y_t = g(x_t). \tag{6}$$

Here, x_t represents the state variables, y_t represents the control variables, ε_{t+1} represents the independent and identically distributed (i.i.d.) shocks. The function Φ is known and governs the evolution of the state variables, while g is the unknown policy function that we aim to solve for.

Taylor Projection (Levintal, 2018) The Taylor projection method consists of four main steps. In this exposition, we focus on the first-order Taylor projection.

In the first step, we approximate the policy function $g(x_t)$ using a linear function:

$$\tilde{g}(x_t; \Theta) = \Theta_1 + \Theta_2 x_t. \tag{7}$$

In step two, we define the residual function $R(x_t, \Theta)$ by substituting $y = \tilde{g}(x_t; \Theta)$ into the equilibrium conditions:

$$R(x_t, \Theta) \approx 0. \tag{8}$$

Our objective is to find Θ such that this residual function is minimized.

To do so, in step three, we perform a Taylor series expansion of the residual function around a specific point x_0, retaining terms up to first order:

$$R(x_t, \Theta) \approx R(x_0, \Theta) + \left.\frac{\partial R(x, \Theta)}{\partial x}\right|_{x=x_0} (x - x_0). \tag{9}$$

At last, in step four, we solve for the optimal Θ^* such that the Taylor series satisfies:

$$\begin{aligned} &R(x_0, \Theta) = 0, \\ &\left.\frac{\partial}{\partial x} R(x, \Theta)\right|_{x=x_0} = 0. \end{aligned}$$

Since x may consist of multiple state variables, the first-order derivatives capture all partial derivatives. Solving this system gives a set of state-dependent parameters $\Theta^* = \Theta(x_0)$, yielding an approximate solution $\tilde{g}(x, \Theta^*)$ around x_0.

4.2 Time-Varying Kalman Filter

Consider a standard linear state space model:

$$y_t = Z_t x_t + d_t + \varepsilon_t \tag{10}$$

$$x_{t+1} = T_t x_t + c_t + R_t \eta_t \tag{11}$$

with ε_t i.i.d. with variance-covariance matrix H_t, and η_t i.i.d. with variance-covariance Q_t. y_t is the set of observed variables, x_t are the states, which are assumed unobserved. It should be noted that these y's may or may not overlap with y in the previous subsection, in the sense that we may have only a subset of observed controls, but we may also observe direct proxies for the state variables. It is well-known that a linearized DSGE model can be mapped into a linear state space model, and hence, its parameters can be estimated using standard Kalman filtering approaches. For a textbook treatment, consider Herbst and Schorfheide (2016). For a model that is log-linearized around the steady state, the matrices Z_t, d_t, H_t, Q_t, T_t, c_t and R_t depend on structural model parameters, but are constant and do not depend on time.

Our novel approach uses the fact that when a model is solved using a local linear approximation method such as Levintal (2018)'s Taylor Projection method outlined above, the local linear model solution can be mapped into a time-varying state space model, and the model's states can be filtered using a time-varying Kalman Filter.

Assume that we solved our model using a local approximation method such as Taylor Projection in some state $x = x_0$. First, note that the law of motion of the state variables in Equation (5) is typically linear, or, else, can be approximated using a local linear Taylor approximation just like the policy function g. In that case, our model becomes:

$$y_t = Z_x x_t + d_x + \varepsilon_t \tag{12}$$

$$x_{t+1} = T_x x_t + c_x + R\eta_t \tag{13}$$

where Z_x will contain elements of Θ_2 of the local approximation of the policy function as in Equation (7), and d_x will contain elements from Θ_1. The elements of T_x and c_x follow from Equation (5). H and Q typically do not have state-dependence when using this solution method, so we suppress their subscripts.

The Kalman filter is still valid and optimal when the system matrices are time-varying, as long as this time-dependence is fully known when conditioning on the information set $\mathcal{Y}_{t-1} = \{y_{t-1}, y_{t-2}, ...\}$. This follows from the recursive definition of the Kalman filter.[4] This allows us to replace the subscript x in Equations (12)-(13) by $\hat{x}_{t|t-1}$, our prediction for x_t using all information up to and including time $t-1$, and implies the filtering procedure outlined in Algorithm 1.

Computational Cost A potential concern with Algorithm 1 is its computational cost, as it requires solving the model T times, which can be time-consuming. However, in our experience – and as we will illustrate below – the Taylor Projection method is highly efficient. Even for our extended model in Section 5, solving the model approximately $T = 250$ times takes only a few seconds. In the following subsection, we compare this computational cost to that of particle filtering and standard log-linearization with Kalman filtering.

Comparison to Extended Kalman Filter The filtering framework we propose above is closely related to the Extended Kalman Filter (EKF), as both involve local linearization of a nonlinear system. However, a key distinction lies in how this linearization is constructed.

[4] This is a well-established result; see, for example, Durbin and Koopman (2012).

Algorithm 1 Time-Varying Kalman Filtering with Taylor Projections

Initialize: Set $t = 0$, start x_0 in the steady state, and initialize covariance $P_{0|0}$.
while $t \leq T$ **do**

Taylor Projection Step:
Solve the model using Taylor Projections at $x_{t|t-1}$, obtaining the time-varying system:

$$y_t = Z_{x_{t|t-1}} x_t + d_{x_{t|t-1}} + \varepsilon_t, \quad \varepsilon_t \sim \mathcal{N}(0, H) \tag{14}$$

$$x_{t+1} = T_{x_{t|t-1}} x_t + c_{x_{t|t-1}} + R\eta_t, \quad \eta_t \sim \mathcal{N}(0, Q) \tag{15}$$

Update Step:
Compute the Kalman gain:

$$K_t = P_{t|t-1} Z'_{x_{t|t-1}} \left(Z_{x_{t|t-1}} P_{t|t-1} Z'_{x_{t|t-1}} + H \right)^{-1} \tag{16}$$

Update the state estimate using the new observation y_t:

$$\hat{x}_{t|t} = \hat{x}_{t|t-1} + K_t \left(y_t - Z_{x_{t|t-1}} \hat{x}_{t|t-1} - d_{x_{t|t-1}} \right) \tag{17}$$

Update the covariance:

$$P_{t|t} = (I - K_t Z_{x_{t|t-1}}) P_{t|t-1} \tag{18}$$

Prediction step:
Compute the predicted state estimate:

$$\hat{x}_{t+1|t} = T_{x_{t|t-1}} \hat{x}_{t|t} + c_{x_{t|t-1}} \tag{19}$$

Compute the predicted covariance:

$$P_{t+1|t} = T_{x_{t|t-1}} P_{t|t} T'_{x_{t|t-1}} + RQR' \tag{20}$$

Advance time: Set $t \leftarrow t + 1$ and repeat.
end while

The Taylor Projection solution combined with the filter computes the optimal linear policy at state $x_{t|t-1}$, which is accurate by construction. The EKF on the other hand computes a linear approximation to the true policy around a state $x_{t|t-1}$, which may no longer be an optimal policy itself, and can be a potentially poor approximation.

4.3 Monte Carlo: Filtering the DMP model with Taylor Projection-based Filter

We now consider a simulation experiment based on 1,000 simulated datasets for three different lengths: $T = 250$, which is comparable to the data we use when we filter the extended NKDMP model, and $T = 1000$ and $T = 2000$ to get a sense of asymptotic behavior. The experiment is conducted using the DMP model, which is a subset of the NKDMP model presented in Section 2 without nominal rigidities[5]. Importantly, the DMP model is highly nonlinear (see, e.g., Petrosky-Nadeau and Zhang (2017)). The only unobserved state in the DMP model is TFP, and we assume we observe market tightness and wages with measurement error which has variance equal to 20% of the variance of the true underlying variable.

To conduct the experiment, we first solve the DMP model using a global solution method and generate simulated data from this solution. We then apply three different solution plus filtering approaches:

1. Linear perturbation with a standard Kalman filter (KF).
2. Global solution method with a particle filter (PF).
3. Taylor Projection (TP) with the time-varying Kalman filter (TV-KF) in Algorithm 1.

We fix the structural model parameters to their true values, and our goal is to assess how well each method recovers the unobserved states from the simulated data. We evaluate performance by comparing the R-squared (R^2) of the filtered states with the true states, along with the mean squared error (MSE) and mean absolute error (MAE). Additionally, we report computation time for each approach.

The results show that TP+TV-KF is about three times slower than Linear+KF, while Global+PF is several orders of magnitude slower than TP+TV-KF.[6] In terms of accuracy, TP+TV-KF consistently outperforms both other methods across all choices of T, across all three metrics. For larger T, Global+PF with a sufficient number of particles does improve and approaches the accuracy of TP+TV-KF. For all sample sizes, Linear+KF performs significantly worse than the other methods. We conclude that the combination of Tay-

[5] Letting the adjustment cost $\phi = 0$ implies zero response to monetary shocks.

[6] This holds even after vectorizing the code to efficiently evaluate particles.

lor Projections and the Time-Varying Kalman Filter is an accurate and computationally efficient solution and filtering approach.

Table 1: Comparing Solution and Filtering Methods for the DMP model

	Linear + KF	Global + PF			TP + TV-KF
Particles:		200	2,000	20,000	
T = 200					
R^2 Market Tightness	0.981	0.975	0.976	0.976	0.985
R^2 TFP	0.983	0.975	0.976	0.976	0.985
MSE Market Tightness	0.174	0.087	0.086	0.085	0.057
1e4 × MSE TFP	0.174	0.087	0.086	0.085	0.057
MAE Market Tightness	0.295	0.194	0.191	0.191	0.185
100 × MAE TFP	0.222	0.169	0.165	0.165	0.159
Computation time (sec)	0.004	0.118	0.783	6.239	0.010
T = 1,000					
R^2 Market Tightness	0.979	0.985	0.985	0.986	0.987
R^2 TFP	0.981	0.985	0.985	0.985	0.987
MSE Market Tightness	0.213	0.092	0.090	0.089	0.082
1e4 × MSE TFP	0.127	0.069	0.066	0.066	0.061
MAE Market Tightness	0.333	0.232	0.228	0.228	0.226
100 × MAE TFP	0.259	0.200	0.196	0.195	0.194
Computation time (sec)	0.013	0.327	3.024	24.84	0.035
T = 2,000					
R^2 Market Tightness	0.978	0.986	0.987	0.987	0.987
R^2 TFP	0.980	0.986	0.987	0.987	0.987
MSE Market Tightness	0.224	0.095	0.092	0.092	0.089
1e4 × MSE TFP	0.138	0.071	0.068	0.068	0.065
MAE Market Tightness	0.344	0.240	0.237	0.236	0.236
100 × MAE TFP	0.269	0.208	0.203	0.203	0.202
Computation time (sec)	0.024	0.604	6.000	49.48	0.067

5 Quantitative Model

This section extends the simple NK-DMP model from Section 2 to include (i) a set of exogenous shocks, (ii) a zero lower bound for the nominal interest rate, and (iii) habit preferences. These extensions allow us to estimate the model using full-information methods on postwar U.S. data. Since the firms and wage bargaining protocol are identical to that in Section 2, we focus on the household and government sectors and refer interested readers to the previous section for details on the production side.

Households The economy is populated by a continuum of identical households $i \in [0, 1]$ who derive utility from consumption, and supply one unit of labor inelastically to the labor market. The preferences of the representative household are an equally weighted average of its members.

The welfare of household i is given by

$$\mathbb{E}_0 \left[\sum_{t=0}^{\infty} \beta^t D_t \frac{(C_{it} - bC_{t-1})^{1-\tau} - 1}{1 - \tau} \right],$$

where b is a measure of external habits, β is the discount factor, D_t is a shock to intertemporal preferences, and $1/\tau$ is the intertemporal elasticity of substitution.

Members of the household perfectly insure each other against variations in income due to unemployment, which implies consumption is identical for all members. This leads to the representative household budget constraint

$$P_t C_t + B_t = P_t W_t N_t + P_t (1 - N_t)\nu + R_{t-1} B_{t-1} + T_t,$$

and the law of motion for employment

$$N_t = (1 - \delta) N_{t-1} + q_t V_t.$$

Here, N_t represents the mass of household members employed at the production stage, P_t is the price of the final good, B_t denotes one-period risk-free bonds with a gross return of R_t, and T_t captures all remaining income, including firm dividends net of lump-sum taxes. The law of motion for employment depends on the exogenous separation rate δ and the total hires made by firms, $q_t V_t$, which the household takes as given.

The first-order condition with respect to consumption implies

$$\lambda_t = D_t \left(C_{it} - bC_{t-1}\right)^{-\tau},$$

where λ_t is the marginal utility of consumption. We define the stochastic discount factor used by firms as

$$Q_{t,t+1} = \beta \frac{\lambda_{t+1}}{\lambda_t}.$$

Government Monetary policy is determined by a Taylor Rule for the nominal interest rate subject to a ZLB constraint:

$$R_t = \max\left\{1, \tilde{R}_t e^{m_t}\right\},$$

where $\tilde{R}_t$ is the systematic component of monetary policy that reacts to the state of the economy, and m_t is the shock. We consider the following Taylor rule:

$$\tilde{R}_t = R \left(\frac{\Pi_t}{\bar{\Pi}}\right)^{\psi_\pi} \left(\frac{Y_t}{Y_{t-1}}\right)^{\psi_y}$$

The central bank responds to deviations in inflation and output from their targeted values, $\bar{\Pi}$, as well as to the growth rate of output. Note that the nominal interest rate is almost everywhere differentiable, except at the kink where the ZLB begins to bind. The local perturbation method we employ assumes that the equilibrium conditions of the model are differentiable in the state variables. To accommodate the ZLB, we smooth the kink using the softmax function

$$R_t = \zeta \log\left(e^{1/\zeta} + e^{\tilde{R}_t e^{m_t}/\zeta}\right),$$

where the parameter ζ determines how smooth the approximation is and has the property

$$\lim_{\zeta \to 0} R_t = \max\left\{1, \tilde{R}_t e^{m_t}\right\}.$$

Exogenous States The model is perturbed by three exogenous states which evolve according to

$$\begin{aligned}
\ln D_t &= \rho_d \ln D_{t-1} + \sigma_d \epsilon_t^d. \\
\ln Z_t &= \rho_z \ln Z_{t-1} + \sigma_z \epsilon_t^z. \\
m_t &= \sigma_m \epsilon_t^m.
\end{aligned}$$

Both the discount factor D_t and TFP Z_t are assumed to be AR(1) in logs, while the monetary shock m_t is assumed to be serially uncorrelated.

Equilibrium Conditions The first-order condition for bonds leads to the following Euler equation

$$1 = \beta \mathbb{E}_t \left[\left(\frac{\lambda_{t+1}}{\lambda_t} \right)^{-\tau} \frac{R_t}{\Pi_{t+1}} \right].$$

Optimal price setting and vacancy posting gives the following pricing equation

$$\frac{\omega_t}{\gamma} = 1 - \phi(\Pi_t - \bar{\Pi})\Pi_t + \phi\beta\mathbb{E}_t \left[\left(\frac{\lambda_{t+1}}{\lambda_t} \right)^{-\tau} \left(\frac{Y_{t+1}}{Y_t} \right) (\Pi_{t+1} - \bar{\Pi})\Pi_{t+1} \right].$$

and the expression for the Nash wage leads to the following job-creation condition

$$\frac{\kappa}{q_t} = (1-\eta)\left[(1-\omega_t)Z_t - \nu\right] + \beta(1-\delta)\mathbb{E}_t \left[\left(\frac{\lambda_{t+1}}{\lambda_t} \right)^{-\tau} \frac{\kappa}{q_{t+1}} \right]$$

To close the model, the interest rate rule and law of motion for employment are given by

$$\begin{aligned}
R_t &= \zeta \log\left(e^{1/\zeta} + e^{\tilde{R}_t e^{m_t}/\zeta} \right) \\
\tilde{R}_t &= R \left(\frac{\Pi_t}{\bar{\Pi}} \right)^{\psi_\pi} \left(\frac{Y_t}{Y_{t-1}} \right)^{\psi_y} \\
N_t &= (1-\delta)N_{t-1} + \underbrace{q_t \theta_t \left[1 - (1-\delta)N_{t-1}\right]}_{= q_t V_t}
\end{aligned}$$

A minimum state variable representation of the model has five states $\mathbb{S}_t = \{N_{t-1}, Z_t, m_t, Z_{t-1}, D_t\}$ and three policies $\{\Pi(\mathbb{S}_t), \omega(\mathbb{S}_t), \theta(\mathbb{S}_t)\}$.

5.1 Data

The data used for estimation are summarized in Table A2 in the Appendix. This table also details the data transformations applied. Our three key variables of interest are market tightness, the federal funds rate, and inflation. We analyze data spanning the period from 1967 to 2019 at a quarterly frequency.

6 Model Results

We now present results from our quantitative model, which is solved using Taylor projections and our Time-Varying Kalman Filter to infer the underlying states of the economy. This approach enables us to compute implied impulse response functions over time, as well as other objects of interest to policymakers, and to quantify the extent of state dependence in the U.S. economy.

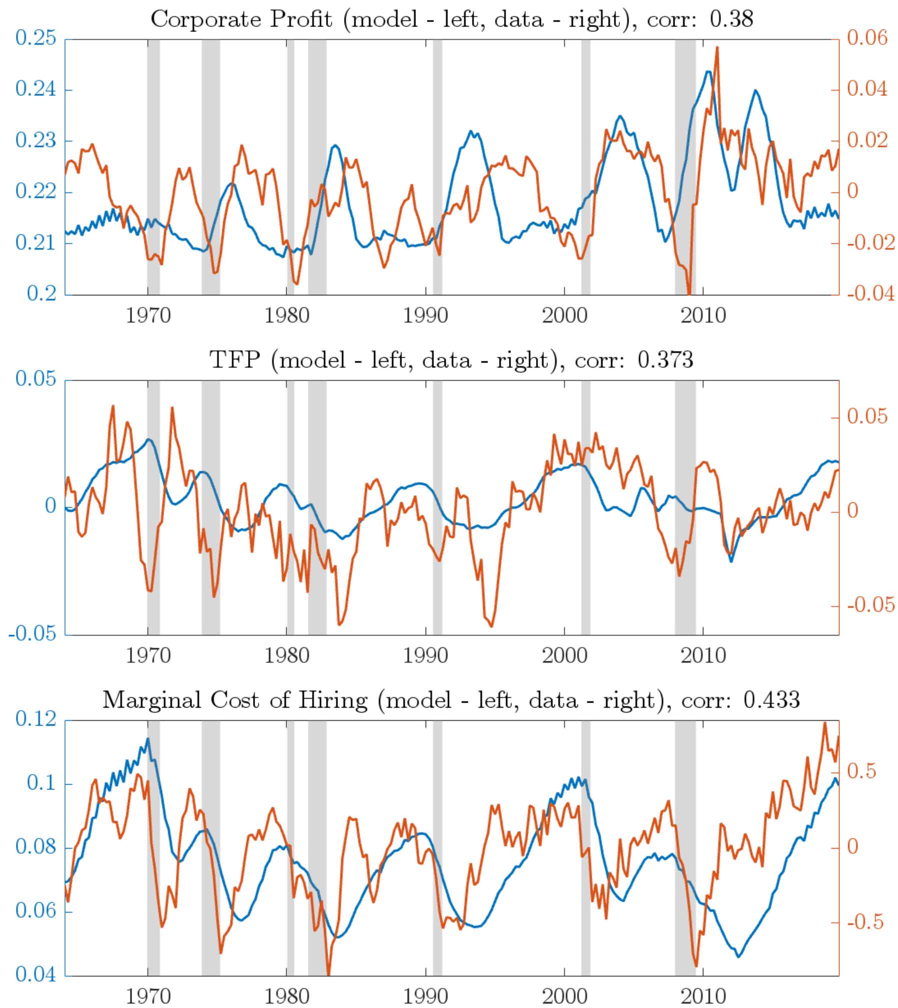
6.1 External validation: assessing our state proxies

After filtering the states, we compute the surplus proxies implied by our model and compare them with the proxies used in the empirical section. This serves as an external validity check. As shown in Figure 5 all three model-implied proxies are positively correlated with the data proxies, none of which are directly used to estimate the model. This suggests the empirical evidence used to motivate the quantitative model is broadly consistent with the model implied states.

6.2 Philips Multiplier

A key concern for policymakers is the unemployment-inflation trade-off, which captures the nominal effects relative to the real effects of a monetary shock. However, state dependence in impulse responses alone does not necessarily imply variation in the unemployment-inflation trade-off; this depends on whether the real versus nominal effects differ in relative magnitude across states. To illustrate that the unemployment-inflation trade-off is state dependent, we use the concept of the Phillips multiplier, as in Barnichon and Mesters (2021), motivated by Mankiw (2001). The Phillips multiplier quantifies this trade-off by measuring the average change in inflation caused by an interest

Figure 5: Proxies for Surplus in Data and Through the Lens of the Model



rate change that reduces the unemployment rate by one percentage point over h periods:

$$T_h = \frac{\partial \bar{\Pi}_{t:t+h}}{\partial R_t}\bigg|_{\varepsilon_t} \bigg/ \frac{\partial \bar{U}_{t:t+h}}{\partial R_t}\bigg|_{\varepsilon_t}$$

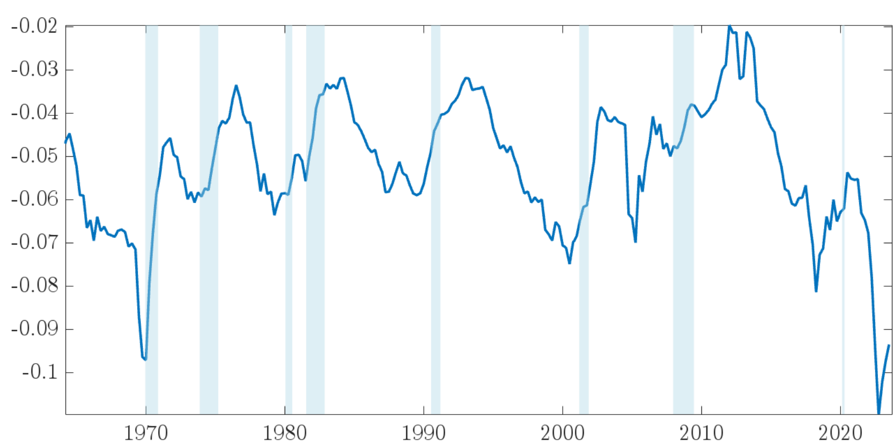
Here $\bar{\pi}_{t:t+h}$ is the average over variable Π over h time periods, and ε_t is the exogenous change in the interest rates. The statistical counterpart of T_h is the so-called Philips multiplier (Barnichon and Mesters, 2021):

$$\mathcal{P}_h = \mathcal{R}_h^{\bar{\Pi}} / \mathcal{R}_h^{\bar{U}}, \quad h = 0, 1, 2, ...,$$

that is, the ratio of the cumulative impulse response function (up to horizon h) of inflation over unemployment. The Philips Multiplier can loosely be interpreted as the slope of the Philips curve. In the case of state-dependent impulse response functions, the Philips Multiplier is also state-dependent when the magnitude of the effect of a monetary shock on inflation relative to unemployment depends on the state of the economy.

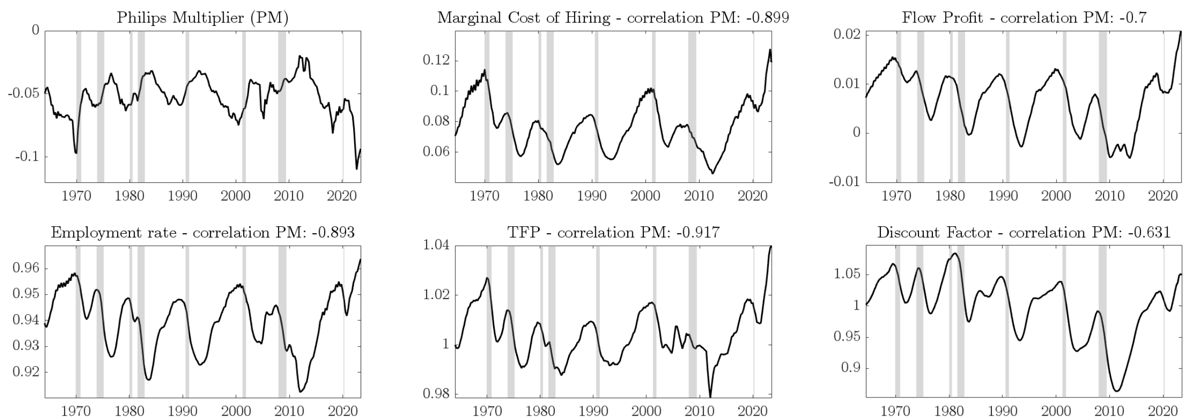
Using the model to filter the latent states –employment, TFP, discount factor shock, monetary shock, and lagged TFP – we compute the implied impulse response of a 40 basis point monetary policy shock at each point in time. These impulse responses, evaluated at each filtered state, allow us to compute the Phillips Multiplier over a six-year horizon, after which the cumulative impulse responses stabilize as the effects dissipate. We visualize this filtered series in Figure 6. As shown, the Phillips Multiplier is generally countercyclical, tending to rise during recessions. Several periods stand out where the Phillips curve was particularly flat, typically following a recession. Note, the Phillips Multiplier can be loosely interpreted as the slope of the Phillips curve. One period of particular interest is the post-2010 era when the zero lower bound (ZLB) was binding. Conversely, two periods where the Phillips curve was particularly steep occurred around 1970 and 2022. More recently, we observe a steepening trend in the Phillips curve following the departure from the ZLB in the latter part of the sample.

Figure 6: Philips Multiplier (Filtered)



The fluctuations in the Phillips Multiplier can be explained and interpreted through the mechanisms outlined in this paper. To illustrate this, Figure 7 visualizes the Phillips Multiplier alongside relevant proxies and state variables, with their respective correlations noted. For example, the correlation between the model-implied marginal cost of hiring and the Phillips Multiplier across filtered states is -0.899, while its correlation with TFP is -0.917. Flow profit exhibits a slightly correlation of -0.7 with the Phillips Multiplier, as this are also strongly influenced by the discount factor in this model in the latter part of the sample.

Figure 7: Philips Multiplier alongside Surplus Proxies and Model States



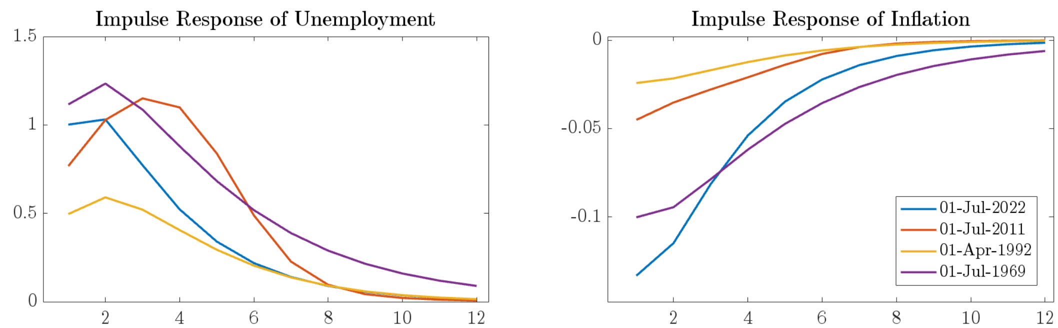
Comparison with other empirical evidence on the Philips Multiplier Looking at the existing literature, our Philips Multiplier estimates are consistent with Barnichon and Mesters (2021) post-1990's estimate, and the estimates of Hazell et al. (2022). The range of our estimates is comparable to Gitti (2024), who posits that the Philips curve is nonlinear in market tightness,[7] and finds a multiplier of -0.03 when markets are slack, versus -0.08 when markets are tight.

6.3 Time-Varying Impulse Responses

To provide further insights into the state-dependent effects of monetary policy, Figure 8 visualizes impulse response functions for unemployment and inflation at four different points in time, computed based on our filtered states. We consider two periods with a flat Phillips curve, as indicated by our Phillips Multiplier estimates in Figure 6: the zero lower bound (ZLB) period (2011Q3) and 1992Q2. Additionally, we examine two periods with a steep Phillips curve, 2022Q3 and 1969Q3.

[7] By assuming there is a kink in the Philips curve at market tightness $\theta = 1$

Figure 8: Impulse Response Functions over Time



During the two visualized periods of low absolute Phillips Multiplier (PM) values, 2011Q3 and 1992Q2, the inflation response is small. However, the unemployment rate responses differ significantly due to the lower model-implied TFP in 2011Q3, which leads to a larger response compared to 1992Q2, when TFP was near its steady-state value. Conversely, in periods with high absolute PM values, such as 2022Q3 and 1969Q3, we find that the effects of a monetary policy shock on prices are twice as large as in low-PM states, while the cumulative effect on unemployment falls between the values observed in low-PM states. Overall, we conclude that the presence of nonlinearities introduced by labor search frictions leads to significant time variation in the unemployment-inflation trade-off. This variation is driven by both time-varying responses of unemployment and time-varying responses of prices.

7 Conclusion

This paper establishes a link between time variation in the effects of monetary policy due to search frictions in the labor market. We first demonstrate this analytically in a stylized New Keynesian model with labor market frictions, motivating empirical proxies for flow surplus - the key determinate of propagation in this class of models. Using these proxies, we provide model-free evidence that monetary policy shocks have stronger real effects when flow profit is low.

To further explore this mechanism, we develop a quantitative model, solve it using local linear approximation techniques, and introduce a novel filtering algorithm for nonlinear DSGE models. Our framework enables the estimation of time-varying impulse response functions and Phillips Multipliers, revealing substantial variation in monetary policy effectiveness over the business cycle. Notably, we find that the Phillips Multiplier is twice as small during recessions as it is during expansions.

State dependence in the effects of monetary policy and the slope of the Phillips curve are critical considerations for policymakers. Our framework allows them to filter the underlying state of the economy and compute the implied impulse response functions and Phillips Multiplier in real time, ensuring that policy decisions are informed by current economic conditions rather than historical averages. More broadly, our modeling and filtering approach offers a generalizable framework for analyzing time-varying macroeconomic relationships. This methodology can be extended to study other forms of state dependence in policy transmission.

References

Ahn, H. J., and Hamilton, J. D. (2022). "Measuring labor-force participation and the incidence and duration of unemployment". *Review of Economic Dynamics*, *44*, 1-32.

Angrist, J. D., Jordà, Ò., and Kuersteiner, G. M. (2018). "Semiparametric Estimates of Monetary Policy Effects: String Theory Revisited". *Journal of Business & Economic Statistics*, *36*(3), 371–387.

Aruoba, S. B., and Drechsel, T. (2024). *"Identifying Monetary Policy Shocks: A Natural Language Approach"* (Tech. Rep.). National Bureau of Economic Research.

Barnichon, R. (2010). "Building a Composite Help-Wanted Index". *Economics Letters*, *109*(3), 175–178.

Barnichon, R., Debortoli, D., and Matthes, C. (2022). "Understanding the Size of the Government Spending Multiplier: It's in the Sign". *The Review of Economic Studies*, *89*(1), 87–117.

Barnichon, R., and Mesters, G. (2021). "The Phillips Multiplier". *Journal of Monetary Economics*, *117*, 689–705.

Bauer, M. D., and Swanson, E. T. (2023). "A Reassessment of Monetary Policy Surprises and High-Frequency Identification". *NBER Macroeconomics Annual*, *37*(1), 87–155.

Benigno, P., and Eggertsson, G. B. (2023). *"It's baaack: The Surge in Inflation in the 2020s and The return of the Non-Linear Phillips Curve"* (Tech. Rep.). National Bureau of Economic Research.

Ben Zeev, N., Ramey, V. A., and Zubairy, S. (2023). "Do Government Spending Multipliers Depend on the Sign of the Shock?". In *AEA Papers and Proceedings* (Vol. 113, pp. 382–387).

Berentsen, A., Menzio, G., and Wright, R. (2011). Inflation and unemployment in the long run. *American Economic Review*, *101*(1), 371–398.

Blanchard, O., and Galí, J. (2010). "Labor markets and monetary policy: A new keynesian model with unemployment". *American economic journal: macroeconomics*, *2*(2), 1–30.

Borağan Aruoba, S., Cuba-Borda, P., and Schorfheide, F. (2018). "Macroeconomic Dynamics near the ZLB: A Tale of Two Countries". *The Review of Economic Studies*, *85*(1), 87–118.

Christiano, L. J., Eichenbaum, M. S., and Trabandt, M. (2016). "Unemployment and Business Cycles". *Econometrica*, *84*(4), 1523–1569.

Cloyne, J., Jordà, Ò., and Taylor, A. M. (2023). *"State-Dependent Local Projections: Understanding Impulse Response Heterogeneity"* (Tech. Rep.). National Bureau of Economic Research.

Coibion, O., and Gorodnichenko, Y. (2015). "Is the Phillips Curve Alive and Well After All? Inflation Expectations and the Missing Disinflation". *American Economic Journal: Macroeconomics*, *7*(1), 197–232.

Diamond, P. A. (1982). "Wage Determination and Efficiency in Search Equilibrium". *The Review of Economic Studies*, *49*(2), 217–227.

Dotsey, M., King, R. G., and Wolman, A. L. (1999). "State-Dependent Pricing and the General Equilibrium Dynamics of Money and Output". *The Quarterly Journal of Economics*, *114*(2), 655–690.

Durbin, J., and Koopman, S. J. (2012). *"Time Series Analysis by State Space Methods"* (Vol. 38). OUP Oxford.

Farmer, L. E. (2021). "The Discretization Filter: A Simple Way to Estimate Nonlinear State Space Models". *Quantitative Economics*, *12*(1), 41–76.

Fernald, J. (2014). "A Quarterly, Utilization-Adjusted Series on Total Factor Productivity"..

Fernández-Villaverde, J., and Levintal, O. (2018). "Solution Methods for Models with Rare Disasters". *Quantitative Economics*, *9*(2), 903–944. Retrieved from https://www.sas.upenn.edu/~jesusfv/rare_disasters.pdf doi: 10.3982/QE895

Fernández-Villaverde, J., and Rubio-Ramírez, J. F. (2007). "Estimating Macroeconomic Models: A Likelihood Approach". *The Review of Economic Studies*, *74*(4), 1059–1087.

Galí, J., Smets, F., and Wouters, R. (2012). "Unemployment in an estimated New Keynesian model". *NBER macroeconomics annual*, *26*(1), 329–360.

Gertler, M., and Leahy, J. (2008). "A Phillips Curve with an Ss Foundation". *Journal of Political Economy*, *116*(3), 533–572.

Gertler, M., Sala, L., and Trigari, A. (2008). "An Estimated Monetary DSGE Model with Unemployment and Staggered Nominal Wage Bargaining'. *Journal of Money, Credit and Banking*, *40*(8), 1713–1764.

Gitti, G. (2024). "Nonlinearities in the Regional Phillips Curve with Labor Market Tightness".

Gonçalves, S., Herrera, A. M., Kilian, L., and Pesavento, E. (2023). "State-Dependent Local Projections".

Gust, C., Herbst, E., López-Salido, D., and Smith, M. E. (2017). "The Empirical Implications of the Interest-rate Lower Bound". *American Economic Review*, *107*(7), 1971–2006.

Hamilton, J. D. (2018). "Why You Should Never Use the Hodrick-Prescott Filter". *Review of Economics and Statistics*, *100*(5), 831–843.

Harding, M., Lindé, J., and Trabandt, M. (2022). "Resolving the Missing Deflation Puzzle". *Journal of Monetary Economics*, *126*, 15–34.

Harding, M., Lindé, J., and Trabandt, M. (2023). "Understanding Post-Covid Inflation Dynamics". *Journal of Monetary Economics*.

Hazell, J., Herreno, J., Nakamura, E., and Steinsson, J. (2022). "The Slope of the Phillips Curve: Evidence from US States". *The Quarterly Journal of Economics*, *137*(3), 1299–1344.

Herbst, E. P., and Schorfheide, F. (2016). *"Bayesian Estimation of DSGE Models"*. Princeton University Press.

Jordà, Ò. (2005). "Estimation and Inference of Impulse Responses by Local Projections". *American Economic Review*, *95*(1), 161–182.

Krause, M. U., and Lubik, T. A. (2007). "The (ir) relevance of real wage rigidity in the New Keynesian model with search frictions". *Journal of Monetary Economics*, *54*(3), 706–727.

Lahcen, M. A., Baughman, G., Rabinovich, S., and van Buggenum, H. (2022). "Nonlinear Unemployment Effects of the Inflation Tax". *European Economic Review*, *148*, 104247.

Levintal, O. (2018). "Taylor Projection: A New Solution Method for Dynamic General Equilibrium Models". *International Economic Review*, *59*(3), 1345–1373. Retrieved from https://doi.org/10.1111/iere.12306 doi: 10.1111/iere.12306

Ljungqvist, L., and Sargent, T. J. (2017). "The Fundamental Surplus". *American Economic Review*, *107*(9), 2630–2665.

Mankiw, N. G. (2001). "The Inexorable and Mysterious Tradeoff Between Inflation and Unemployment". *The Economic Journal*, *111*(471), 45–61.

Mennuni, A., Rubio-Ramírez, J. F., and Stepanchuk, S. (2024, April). "Dynamic Perturbation". *The Review of Economic Studies*. Retrieved from https://academic.oup.com/restud/advance-article/doi/10.1093/restud/rdae037/7642916 (Advance online publication) doi: 10.1093/restud/rdae037

Mortensen, D. T. (1982). "Property Rights and Efficiency in Mating, Racing, and Related Games". *The American Economic Review*, *72*(5), 968–979.

Petrosky-Nadeau, N., and Zhang, L. (2017). "Solving the Diamond–Mortensen–Pissarides Model Accurately". *Quantitative Economics*, *8*(2), 611–650.

Phillips, A. W. (1958). "The Relation between Unemployment and the Rate of Change of Money Wage Rates in the United Kingdom, 1861-1957". *Economica*, *25*(100), 283–299.

Pissarides, C. A. (1985). "Short-run Equilibrium Dynamics of Unemployment, Vacancies, and Real Wages". *American Economic Review*, *75*(4), 676–690.

Ramey, V. A. (2016). "Macroeconomic Shocks and Their Propagation". *Handbook of Macroeconomics*, *2*, 71–162.

Ravn, M. O., and Sola, M. (2004). "Asymmetric Effects of Monetary Policy in the United States". *Review-Federal Reserve Bank of Saint Louis*, *86*, 41–58.

Romer, C. D., and Romer, D. H. (2004). "A New Measure of Monetary Shocks: Derivation and Implications". *American Economic Review*, *94*(4), 1055–1084.

Rotemberg, J. J. (1982). "Sticky prices in the United States". *Journal of Political economy*, *90*(6), 1187–1211.

Shimer, R. (2005, March). "The Cyclical Behavior of Equilibrium Unemployment and Vacancies". *American Economic Review*, *95*(1), 25–49. Retrieved from https://www.aeaweb.org/articles?id=10.1257/0002828053828572 doi: 10.1257/0002828053828572

Smith, S., Timmermann, A., and Wright, J. H. (2023). *"Breaks in the Phillips Curve: Evidence from Panel Data"* (Tech. Rep.). National Bureau of Economic Research.

Tenreyro, S., and Thwaites, G. (2016). "Pushing on a String: US Monetary Policy is Less Powerful in Recessions". *American Economic Journal: Macroeconomics*, *8*(4), 43–74.

Thomas, C. (2011). "Search frictions, real rigidities, and inflation dynamics". *Journal of Money, Credit and Banking*, *43*(6), 1131–1164.

Wieland, J. F., and Yang, M.-J. (2020). "Financial Dampening". *Journal of Money, Credit and Banking*, *52*(1), 79–113.

Supplementary Appendix to “Unemployment and the State-Dependent Effects of Monetary Policy”

Eva F. Janssens & Sean McCrary

February, 2025

A Data

Table A1: Data details: Outcome Variables, Controls and State Proxies for Local Projections, Obtained January 9th, 2025.

Variable	Details	Transformation	Source
Unemployment Rate	Percent, Monthly, Seasonally Adjusted	None	LNS14000000
Real Wages	Average Hourly Earnings of Production and Nonsupervisory Employees, Total Private, Dollars per Hour, Monthly, Seasonally Adjusted	$100 \times \log(W/CPI)$	CES0500000008
Federal Funds Rate	Percent, Monthly, Not Seasonally Adjusted	None	DFF
Market tightness	Vacancy over unemployments	$100 \times \log$	Barnicon (2010) & FRED
Job finding rate		$100 \times \log$	Shimer (2005)
CPI	Consumer Price Index for All Urban Consumers: All Items in U.S. City Average, Index 1982-1984=100, Monthly, Seasonally Adjusted	$100 \times \log$	CPIAUCSL
PPI	Producer Price Index by Commodity: All Commodities, Index 1982=100, Monthly, Not Seasonally Adjusted	$100 \times \log$	PPIACO
IPI	Industrial Production: Total Index, Index 2017=100, Monthly, Seasonally Adjusted	$100 \times \log$	IP.B50001.S
HWI	Help-Wanted-Index from Barnicon (2010), JOLTS post 2001	$100 \times \log$	Barnicon (2010)
TFP	1 quarter moving average of TFP growth	Made into Index, Log, Hamilton Filter	Fernald (2014)
Corporate Profits	(Profit/Profit+Compensation)	log, Hamilton Filter	NIPA Table 1.10

Table A2: Data details: estimation and filtering

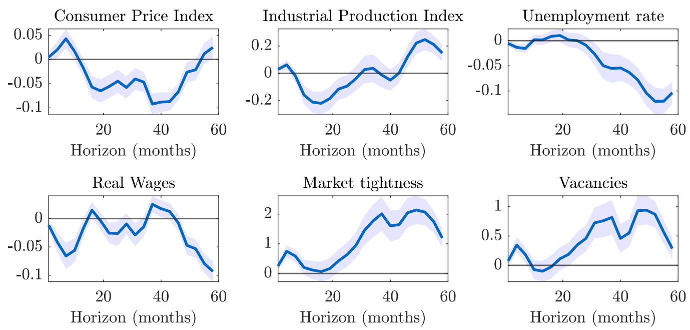
Variable	Details	Transformation	Source
Unemployment Rate	Percent, Quarterly, Seasonally Adjusted	Detrended*	UNRATE (FRED)
Average Weekly Earnings of Production and Nonsupervisory Employees Total Private	Dollars per Week, Quarterly, Seasonally Adjusted	Detrended* & demeaned	CES0500000030 (FRED)
Nonfarm Business Sector: Output per Worker	Index 2017=100 Quarterly Seasonally Adjusted	Detrended* & demeaned	PRS85006163
Market tightness	Vacancy over unemployments	Detrended*	Barnicon (2010) & FRED
Federal Funds Effective Rate	Percent	Quarterly**	DFF
CPI	Consumer Price Index for All Urban Consumers: All Items in U.S. City Average Index 1982-1984=100, Monthly, Seasonally Adjusted	Quarter-to-quarter % ch., detrended*	CPIAUCSL

Notes: (*) We use the Hamilton filter to remove long-run trends (Hamilton, 2018). (**) DFF converted to a quarterly interest rate ($100 * ((1 + DFF/100)^{(1/4)} - 1)$).

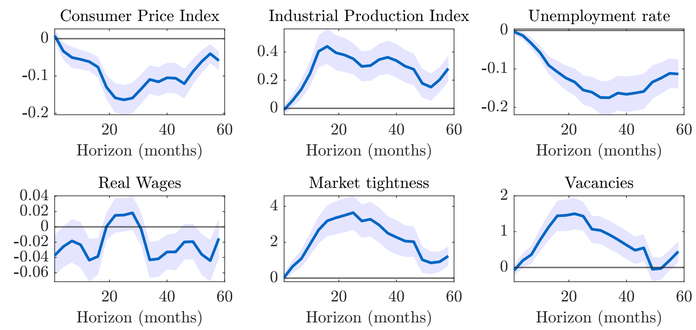
B Additional Results for the Local Projections

Figure B1: Interaction Term of Surplus Proxy and Policy Variable (as in Eq. (2)*).*

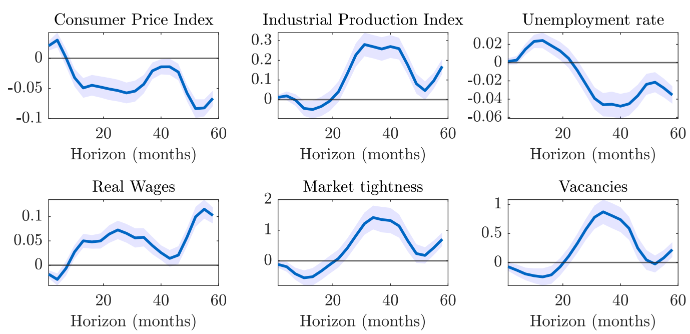
(a) Interaction of Two-Year Treasury Yield and Total Factor Productivity, using the Bauer and Swanson (2023) Instrument



(b) Interaction of Two-Year Treasury Yield and Profit, using the Bauer and Swanson (2023) Instrument



(c) Interaction of Two-Year Treasury Yield and Profit, using the Aruoba and Drechsel (2024) Instrument



(d) Interaction of Two-Year Treasury Yield and Marginal Hiring Cost, using the Aruoba and Drechsel (2024) Instrument

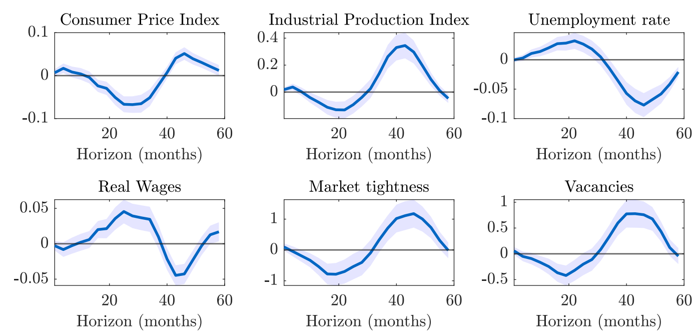
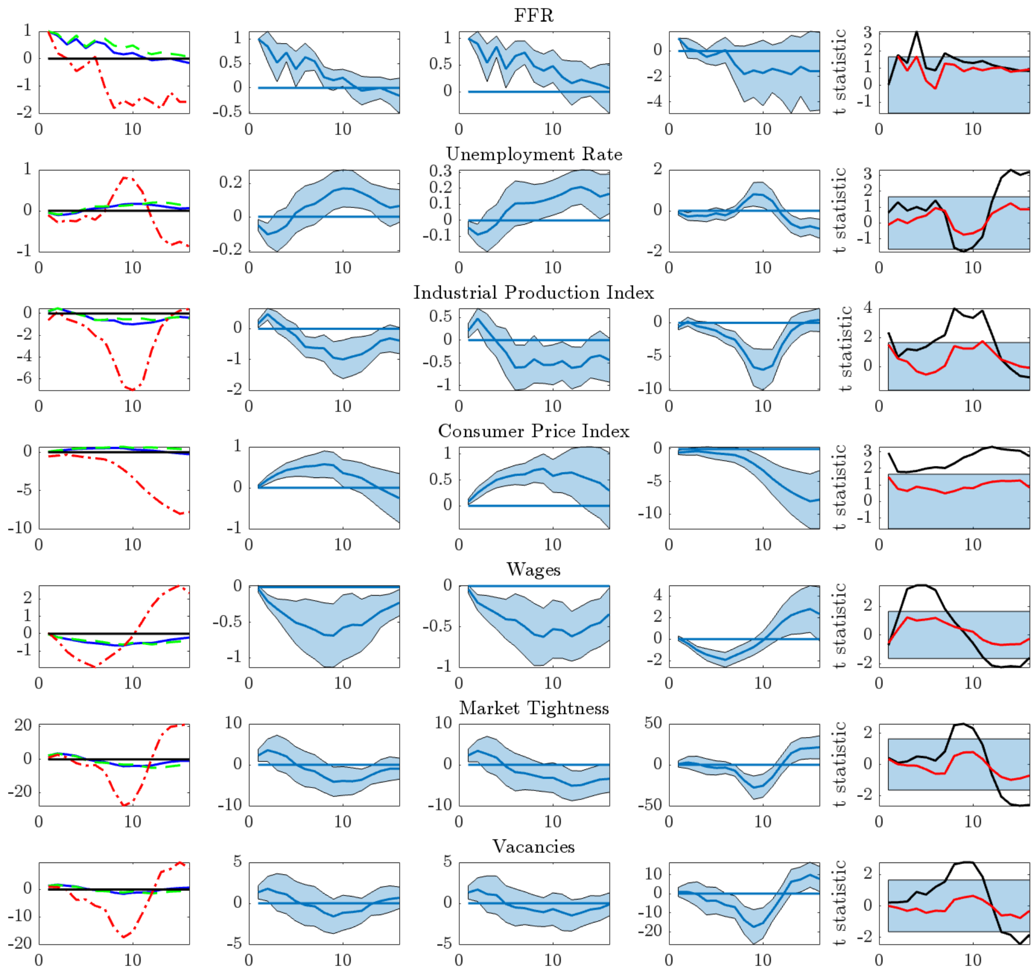
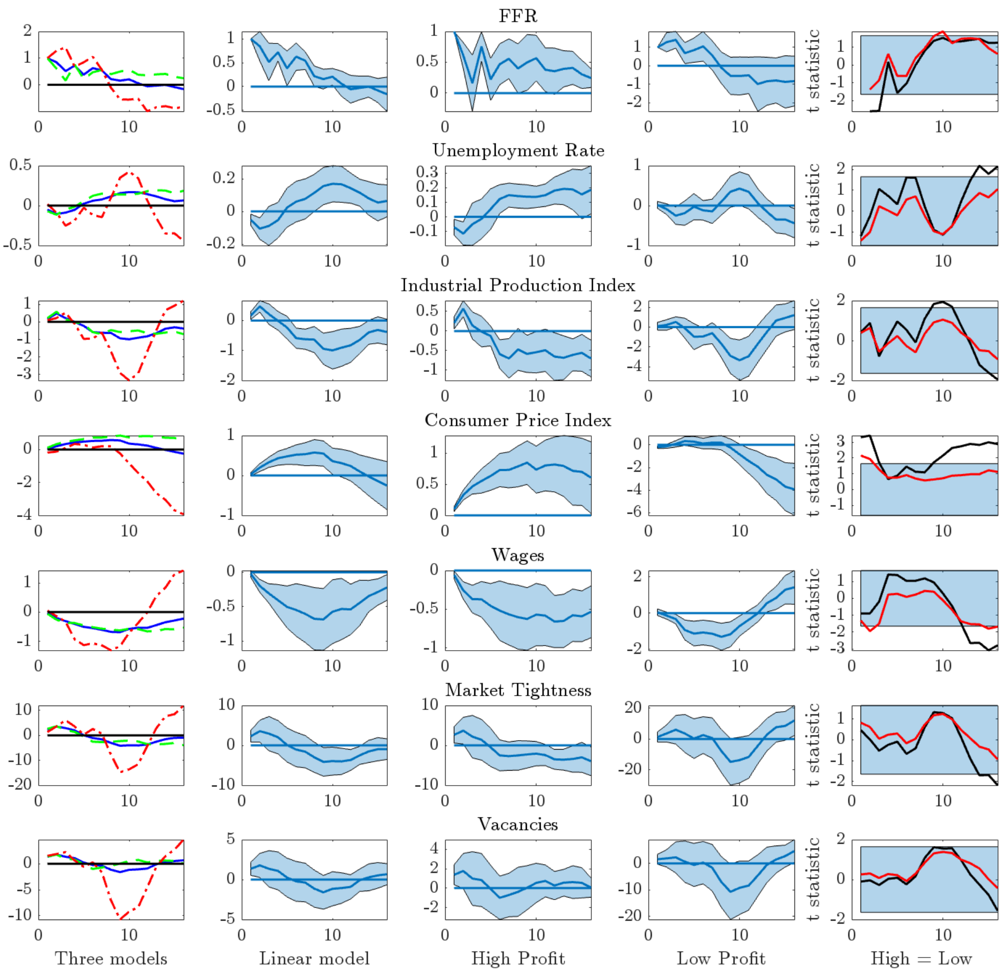


Figure B2: Smooth Transition Local Projections Using Total Factor Productivity as a Proxy for Surplus



Note: The first four columns show the response of the outcome variable to a 1 percentage point change in the FFR on impact across 16 horizons (quarters). In the first column, the average response (solid), the high-surplus (dashed) and the low-surplus (dash-dot) are shown on the same axis. The next three columns show the average response, high-surplus and low-surplus response respectively, with 90% confidence intervals. The last column tests the hypothesis that the coefficients in the high and low surplus regime are equal, where the red line is computed using a Bootstrap, and the black line using the Driscoll-Kraay method, and shaded area is ± 1.65. For details we refer to Tenreyro and Thwaites (2016).

Figure B3: Smooth Transition Local Projections Using Profit as a Proxy for Surplus

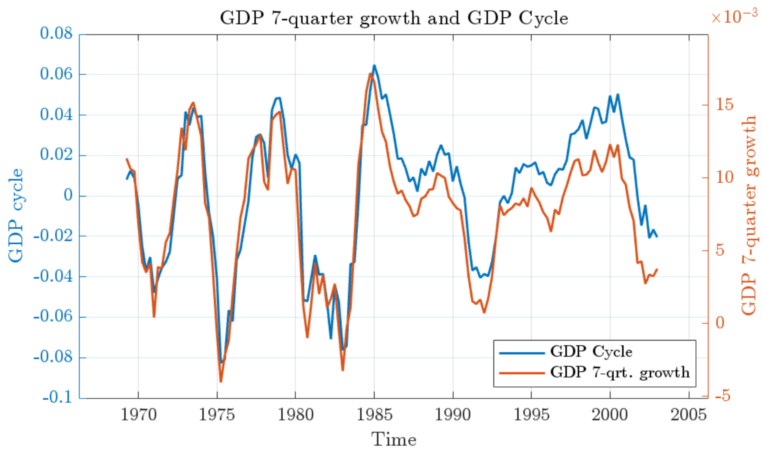


Note: The first four columns show the response of the outcome variable to a 1 percentage point change in the FFR on impact across 16 horizons (quarters). In the first column, the average response (solid), the high-surplus (dashed) and the low-surplus (dash-dot) are shown on the same axis. The next three columns show the average response, high-surplus and low-surplus response respectively, with 90% confidence intervals. The last column tests the hypothesis that the coefficients in the high and low surplus regime are equal, where the red line is computed using a Bootstrap, and the black line using the Driscoll-Kraay method, and shaded area is ± 1.65. For details we refer to Tenreyro and Thwaites (2016).

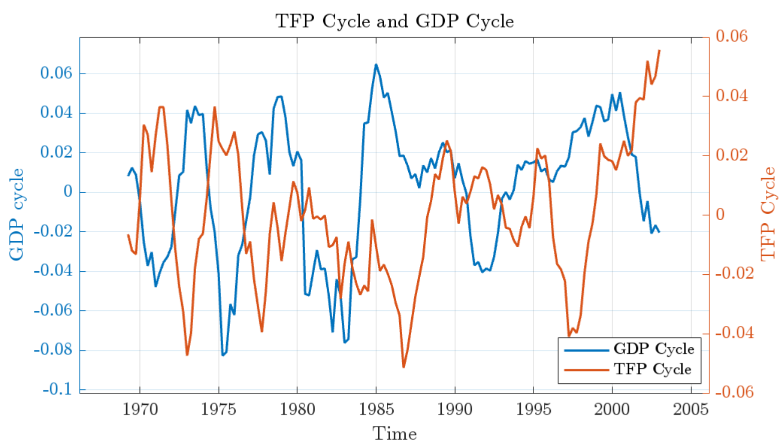
C Comparison to Tenreyro and Thwaites (2016)

Figure C1: Time Series over the Tenreyro and Thwaites (2016) Sample.

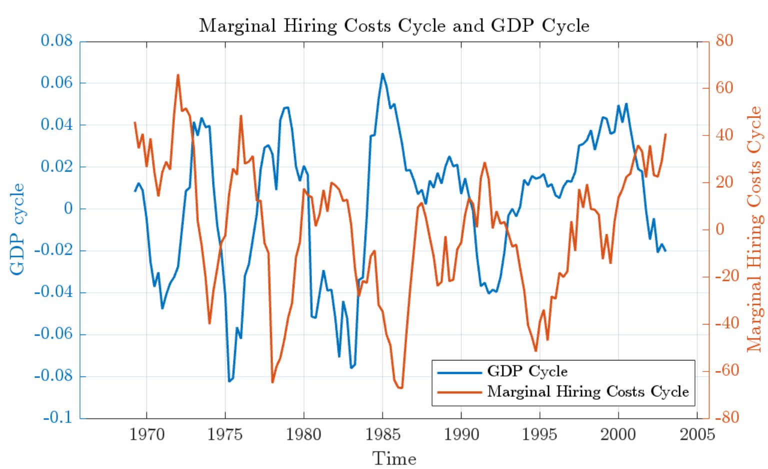
(a) GDP Cycle (Hamilton Filter) and 7-quarter Average of GDP growth.



(b) GDP Cycle (Hamilton Filter) and TFP (Cycle).



(c) GDP Cycle (Hamilton Filter) and Marginal Hiring Cost (Cycle).



D Analytical log-linearization

D.1 Smaller version of the model

In the first part of this Appendix section, we consider a smaller version of the model, for which we analytically derive a set of log-linearized first-order conditions. Compared to the main model in the text, this model leaves out the following elements: (i) discount factor shocks, (ii) zero lower bound (ZLB), (iii) external habits in the utility function of the households.

D.1.1 Equilibrium Conditions

$$1 = \beta E_t \left[\frac{R_t}{\Pi_{t+1}} \left(\frac{C_{t+1}}{C_t} \right)^{-\tau} \right] \tag{D.1}$$

$$\frac{\omega_t}{\gamma} - 1 = -\phi(\Pi_t - \Pi)\Pi_t + \phi \mathbb{E}_t \left[Q_{t,t+1}(\Pi_{t+1} - \Pi)\Pi_{t+1} \frac{Y_{t+1}}{Y_t} \right] \tag{D.2}$$

$$C_t = Y_t = Z_t N_t \tag{D.3}$$

$$N_t = (1-\delta)N_{t-1} + q_t V_t \tag{D.4}$$

$$\ln Z_{t+1} = \rho_z \ln Z_t + \epsilon_{z,t+1} \tag{D.5}$$

$$q_t = \chi \left(1 + \theta_t^{\iota}\right)^{\frac{-1}{\iota}} \tag{D.6}$$

$$\theta_t = \frac{V_t + X_t}{1 - (1-\delta)N_{t-1}} \tag{D.7}$$

$$\frac{\kappa}{q_t} = (1-\omega_t)Z_t - w_t + (1-\delta)E_t \left[Q_{t,t+1} \frac{\kappa}{q_{t+1}} \right] \tag{D.8}$$

$$w_t = \eta(1-\omega_t)Z_t + (1-\eta)\nu + \eta(1-\delta)\kappa E_t \left[Q_{t,t+1}\theta_{t+1} \right] \tag{D.9}$$

$$\frac{R_t}{\bar{R}} = \left[\left(\frac{\Pi_t}{\bar{\Pi}} \right)^{\psi_1} \left(\frac{Y_t}{\bar{Y}} \right)^{\psi_2} \right]^{1-\rho_R} \left(\frac{R_{t-1}}{\bar{R}} \right)^{\rho_R} e^{\epsilon_{R,t}} \tag{D.10}$$

D.1.2 Steady State

We consider a steady state with $\Pi = 1$.

$$\pi = 1 \tag{D.11}$$

$$R = \beta^{-1} \tag{D.12}$$

$$\omega = \gamma \tag{D.13}$$

$$Z = 1 \tag{D.14}$$

$$C = Y = N \tag{D.15}$$

$$\delta N = qV \tag{D.16}$$

$$\theta = \frac{V}{1 - (1 - \delta)N} \tag{D.17}$$

$$q\left(\theta\right) = \chi\left(1 + \theta^{\iota}\right)^{\frac{-1}{\iota}} \tag{D.18}$$

$$w = \eta\left[1 - \gamma + (1 - \delta)\beta\kappa\theta\right] + (1 - \eta)\nu \tag{D.19}$$

$$w = 1 - \gamma - \frac{\kappa}{q\left(\theta\right)}\left[1 - (1 - \delta)\beta\right] \tag{D.20}$$

D.1.3 Log-Linear Solution

$$E_t\left[\hat{y}_{t+1}\right] = \hat{y}_t + \frac{1}{\tau} E_t\left[\hat{r}_t - \hat{\pi}_{t+1}\right] \tag{D.21}$$

$$\hat{c}_t = \hat{y}_t = \hat{z}_t + \hat{n}_t \tag{D.22}$$

$$\hat{n}_t = (1-\delta)\hat{n}_{t-1} + \delta\left(\hat{q}_t + \hat{v}_t\right) \tag{D.23}$$

$$\hat{z}_t = \rho_z \hat{z}_{t-1} + \epsilon_{z,t} \tag{D.24}$$

$$\hat{r}_t = (1-\rho_R)\left[\psi_1 \hat{\pi}_t + \psi_2 \hat{y}_t\right] + \rho_R \hat{r}_{t-1} + \epsilon_{R,t} \tag{D.25}$$

$$\hat{\pi}_t = \beta E_t\left[\hat{\pi}_{t+1}\right] - \frac{1}{\phi}\hat{\omega}_t \tag{D.26}$$

$$\hat{w}_t = \frac{(1-\gamma)\hat{z}_t - \gamma\hat{\omega}_t + (1-\delta)\kappa\beta\theta E_t\left[\hat{\pi}_{t+1} - \hat{r}_t + \hat{\theta}_{t+1}\right]}{1-\gamma+\frac{1-\eta}{\eta}\nu + (1-\delta)\kappa\beta\theta} \tag{D.27}$$

$$\hat{q}_t = \frac{-1}{1+\theta^{\iota}}\hat{\theta}_t \tag{D.28}$$

$$\hat{\theta}_t = \hat{v}_t + \frac{(1-\delta)N}{1-(1-\delta)N}\hat{n}_{t-1} \tag{D.29}$$

$$\begin{aligned}\hat{q}_t = {} & \frac{\gamma(1-\beta(1-\delta))}{1-\gamma-w}\hat{\omega}_t + \frac{(\gamma-1)(1-\beta(1-\delta))}{1-\gamma-w}\hat{z}_t + \frac{w(1-\beta(1-\delta))}{1-\gamma-w}\hat{w}_t \ldots \\ & + (1-\delta)\beta E_t[\hat{q}_{t+1} + \hat{r}_t - \hat{\pi}_{t+1}]\end{aligned} \tag{D.30}$$

These ten equations determine the dynamics of the ten variables $\left\{\hat{y}_t, \hat{r}_t, \hat{\pi}_t, \hat{z}_t, \hat{n}_t, \hat{q}_t, \hat{v}_t, \hat{w}_t, \hat{\omega}_t, \hat{\theta}_t\right\}$.