Working Paper Series
Congressional Budget Office
Washington, D.C.

Effects of Fiscal Policy on Inflation: Implications of Supply Disruptions and Economic Slack

U. Devrim Demirel
Congressional Budget Office
devrim.demirel@cbo.gov

Matthew Wilson
Congressional Budget Office
matthew.wilson@cbo.gov

Working Paper 2023-05

April 2023

To enhance the transparency of the work of the Congressional Budget Office and to encourage external review of that work, CBO's working paper series includes papers that provide technical descriptions of official CBO analyses as well as papers that represent independent research by CBO analysts. Papers in this series are available at https://go.usa.gov/xUzd7.

The authors are grateful to Laurence M. Ball of Johns Hopkins University, Joseph E. Gagnon of the Peterson Institute for International Economics, and Emi Nakamura of the University of California, Berkeley, for valuable comments. The authors also benefited greatly from comments by Richard DeKaser, Mark Doms, Jeffrey Kling, Mark Lasky, Junghoon Lee, Jeffrey Werling (formerly of CBO), and other members of CBO's staff. The authors gratefully acknowledge the editorial assistance provided by Christine Browne.

Abstract

Fiscal policy provided substantial support to economic growth in 2020 and 2021 amid disruptions to supply in product and labor markets, adding to the inflationary pressures that emerged during the strong rebound from the pandemic-induced recession. In this paper, we investigate the implications of supply disruptions and economic slack for the inflationary effects of fiscal policy. We propose and estimate a nonlinear Phillips curve, whereby the sensitivity of inflation to changes in demand varies with supply conditions and the amount of slack in the economy. Our results suggest that supply disruptions, low economic slack, and the interaction of restrained supply with low slack each amplify the effects of expansionary fiscal policies on inflation.

Keywords: nonlinear Phillips curve, fiscal policy, supply disruptions, economic slack

JEL Classification: E31, E37, E62

Contents

1 Introduction

After remaining below the Federal Reserve's long-term goal of 2 percent during much of the past 15 years, consumer price inflation in the United States surged in 2021 and early 2022. The seasonally adjusted consumer price index (CPI) rose 8.9 percent between June 2021 and June 2022, reaching its fastest pace in more than four decades. Inflation accelerated in 2021 amid supply-chain disruptions and labor shortages, expansionary fiscal and accommodative monetary policies, and rising overall demand for goods and services. A rapidly growing body of research has examined the role of restrained supply (see, for example, Barnichon and Shapiro, 2022; Shapiro, 2022) and rising demand (see Furman, 2022; Jordà et al., 2022) in recent developments and reached different conclusions about which factors were central. Most studies, however, have been based on the assumption that supply and demand factors have distinct and separately identifiable effects on inflation. The abrupt surge in prices in early 2021, beyond what most researchers predicted from the sum of the estimated effects of individual supply and demand factors, raises questions about whether different factors interact and reinforce one another. Do supply disruptions amplify the inflationary pressure from heightened demand? How does economic slack (that is, the amount of unused production capacity) affect the relationship between supply disruptions and inflation? The answers provide important insights into the drivers of inflation dynamics and have key implications for the effects of fiscal policy.

In this paper, we evaluate how interactions of supply conditions and slack shape inflation outcomes and develop an approach to estimating the effects of fiscal policy changes on inflation in the presence of supply disruptions. We find that changes in overall demand (arising from policy or nonpolicy factors) have larger effects on inflation in periods of restrained supply. Moreover, low economic slack amplifies the inflationary pressure from supply disruptions and heightened demand. Those findings suggest that the combination of restrained supply and low slack caused the inflationary effects of pandemic-related fiscal policies to be larger than they would have been otherwise.

Our analysis builds on the standard framework for modeling aggregate inflation dynamics, known as the Phillips curve. The Phillips curve formalizes the idea that inflation tends to increase as economic slack diminishes and puts upward pressure on wages and prices. In the commonly adopted linear version of the Phillips curve, the effect of economic slack on inflation is represented by a constant (that is, time-invariant) slope parameter. We modify that standard specification in two ways. First, we introduce a state-dependent relationship between economic slack and inflation by allowing the slope parameter to vary with supply conditions. That enables us to capture the interactions of demand-driven inflationary pressures with supply disruptions. Second, we consider a convex, rather than linear, relationship between inflation and economic slack, allowing the slope to vary across periods of high and low slack. Using an estimated version of our modified Phillips curve, we examine how the slope parameter changed over time. We find evidence that the slope increased markedly in 2020 and 2021 because of supply disruptions and, more recently, as a result of diminishing slack.

We then assess the predictive performance of the modified Phillips curve relative to that of the standard linear specification by evaluating the out-of-sample forecast errors of the two models in the post-2010 period. We consider alternative measures of economic slack, including the unemployment rate gap (that is, the difference between the unemployment rate and the Congressional Budget Office's estimate of the noncyclical rate of unemployment), the ratio of job openings to unemployed, and the employment gap (the percentage difference between employment and CBO's estimate of potential, or maximum sustainable, employment). The root mean square errors (RMSE) for one-quarter-ahead inflation predictions of the modified Phillips curve are smaller than those produced by the standard Phillips curve under all considered measures of slack and in both the full evaluation period and the prepandemic subperiod. We find that no single measure of slack is clearly superior to the others in terms of predictive accuracy under all specifications and in both the prepandemic and full evaluation periods. Crucially, however, the null hypothesis of no state dependence in the slope term (that is, no effect on the slope from supply disruptions) is rejected under all specifications.

We provide further evidence for the effects of supply disruptions on the slope of the Phillips curve by examining regional data. We augment a linear regional Phillips curve (formulated as in McLeay and Tenreyro, 2019) by introducing a state-dependent slope parameter and estimate that specification by using regional unemployment, gross domestic product (GDP), and price data from the Commodity Flow Survey (CFS) conducted by the U.S. Census Bureau. Adopting an instrumental variable (IV) approach, we find suggestive evidence that regional exposure to supply disruptions steepens the slope of the regional Phillips curve.

To quantitatively assess the implications of supply conditions and slack for the inflationary effects of fiscal policy, we embed the modified Phillips curve into a simple (and otherwise standard) New Keynesian model and evaluate an illustrative policy increasing government purchases by 1 percent of potential GDP starting in the second quarter of 2023. Using a calibrated version of the model, we find that the policy causes inflation to be about 15 basis points higher in the second quarter of 2023 under a baseline path in which supply disruptions remain at their historical average value in 2023 and 2024. If, instead, supply disruptions in 2023 become as severe as they were in 2021, the policy's boost to inflation in the second quarter of 2023 is nearly five times as large as the amount under the baseline path. Under a different (counterfactual) path in which the unemployment rate in the second quarter of 2023 is 7 percent (or about 3.2 percentage points greater than in the baseline path), the increase in inflation is roughly 87 percent smaller, and elevated supply disruptions amplify the policy's inflationary effects by a smaller amount. Those results suggest that supply pressures, low economic slack, and the interaction of supply pressures with low slack each increase the inflationary pressures that result from expansionary fiscal policies.

This paper augments the existing research in two ways. First, we provide evidence that supply disruptions exacerbate the inflationary pressures from heightened demand by steepening the Phillips curve (in addition to directly boosting inflation). The slope of the Phillips curve and how it has changed over time is the subject of a large body of research. That research has primarily focused on the role of changing inflation expectations and their contribution to inflation dynamics (see, for example, Pfajfar and Roberts, 2022; Hazell et al., 2021; Hooper et al., 2020; Ng et al., 2018; Ball and Mazumder, 2011; Bernanke, 2007; Mishkin, 2007) and downward nominal wage rigidities (see Daly and Hobijn, 2014) as key factors underpinning the estimated slope of the Phillips curve. Our analysis adds to that literature by exploring the role of supply conditions as a direct determinant of the slope and its evolution over time.

Second, we assess the recent forecasting performance of the state-dependent nonlinear Phillips curve by considering an alternative functional form that allows the slope to increase as economic slack decreases. Recent research has found evidence for a nonlinear Phillips curve that steepens when unemployment is low or the economy is operating above its sustainable capacity (see, for example, Forbes et al., 2021; Hooper et al., 2020; Doser et al., 2017; Barnes and Olivei, 2003). We provide further support for nonlinearities by showing that allowing the slope term to vary with supply conditions improves the out-of-sample predictive accuracy of the Phillips curve under all considered measures of slack. Incorporating a convex relationship between inflation and slack (in addition to state-dependent slope) further improves the predictive accuracy of the Phillips curve, albeit by a small amount, when the measure of slack is the unemployment rate gap.

2 Analytical Framework

Our framework is based on the well-known New Keynesian Phillips curve (NKPC). In this section, we briefly discuss the standard NKPC and describe how we modify it to capture the interactions of supply conditions with economic slack and the nonlinear relationship between inflation pressures and slack.

2.1 The New Keynesian Phillips Curve

The standard NKPC is described by the following equation:

$$\pi_t = -\kappa(u_t - u_t^n) + \beta E_t \pi_{t+1} + \xi_t \tag{1}$$

The variable π_t denotes the inflation rate, u_t stands for the unemployment rate, u_t^n stands for the noncyclical rate of unemployment, $E_t\pi_{t+1}$ denotes expected period $t+1$ inflation, the term ξ_t captures cost-push factors, and β is a discount factor. Equation (1) can be derived from a linear approximation to the optimal pricing decision of profit-maximizing firms in a standard New Keynesian model with sticky prices (of the type proposed by Calvo, 1983, or Rotemberg, 1982).

The Phillips curve is based on the idea that a decrease in the unemployment rate increases competition among firms for workers, thereby boosting real wages and causing firms to increase prices. The parameter κ is the slope of the Phillips curve: It measures the responsiveness of inflation to changes in the amount of slack (measured by the unemployment rate gap). The slope parameter is central to fiscal policy analysis because it governs the size of the effects of demand-driven changes in economic activity on inflation. The composite variable ξ_t represents cost-push factors, including supply-chain disruptions: Changes in those factors result in shifts in the Phillips curve (rather than movements along the curve) on the inflation–unemployment plane.

2.2 A Nonlinear Phillips Curve With State-Dependent Slope

In the standard NKPC, changes in economic slack affect inflation through changes in the unemployment rate gap and expectations of future inflation. Cost-push factors (some of which arise from supply-chain disruptions) are specified as an exogenous process, and the relationship between inflation and economic slack is linear. Exogeneity of cost-push factors, paired with that linear specification, renders the effects of slack on inflation insensitive to supply disruptions and other cost-push shocks. In addition, the sensitivity of inflation to changes in slack does not vary with the amount of existing slack in the economy, or with any other economic variable. As a result, a given change in the unemployment rate gap has the same effect on inflation when the economy is in a deep recession and when it is operating above its sustainable capacity.

To allow the effects of slack on inflation to vary with supply conditions and with the amount of existing slack in the economy, we modify the standard NKPC as follows:

$$\begin{aligned} \pi_t &= -\kappa_t \widehat{u}_t + \beta E_t \pi_{t+1} + \xi_t \\ \kappa_t &= \overline{\kappa} + a \cdot I_t(s_t > 0) \cdot s_t \\ \xi_t &= b s_t + \theta' W_t + \varepsilon_t \\ \widehat{u}_t &= \log \frac{u_t}{u_t^n} \end{aligned} \quad (2)$$

where $\overline{\kappa}$, a, and b are constant scalars and θ is a vector of constants. The variable s_t is an index that measures the severity of supply-chain disruptions, defined as standard deviations from their average value. The vector W_t collects a set of variables that control for some cost-push factors. The variable

ε_t represents the remaining unobserved cost-push factors. The indicator function $I_t(s_t > 0)$ equals one if supply-chain stress is above its mean value and equals zero otherwise.

For the purposes of fiscal policy analysis, there are two key differences between Equations (1) and (2). The first is related to the state-dependent slope term κ_t and the parameter a: By allowing the slope to vary with supply disruptions, Equation (2) accounts for the interactions between the effects of policy changes and supply conditions. In the case $a > 0$, a larger value for s_t (increased supply-chain stress) means a larger effect on inflation from a given change in the unemployment rate. This reflects the intuition that increased overall demand would put more stress on an already strained supply chain and exacerbate the upward pressure on prices. As a result, stimulative fiscal policies become more inflationary in the presence of supply disruptions.

The second difference is the nonlinear relationship between unemployment and inflation. In Equation (2), the unemployment rate gap is defined as the log difference between the actual and noncyclical rates of unemployment (rather than as a level difference). Under that specification, the Phillips curve is convex: A given decrease in the unemployment rate causes a larger increase in inflation when unemployment is lower. That is consistent with the idea that the inflationary pressures from increased overall demand are stronger when the labor market is tight because firms must offer larger wage increases to attract or retain workers. Therefore, if $\overline{\kappa} > 0$ and $a > 0$, increased supply-chain stress and lower unemployment both cause the Phillips curve to become steeper.

Under the assumptions that expectations are model-consistent (that is, agents form their expectations with the knowledge that inflation is governed by Equation 2) and the rule of iterated expectations ($E_t E_{t+1} ... E_{t+i} \pi_{t+1+i} = E_t \pi_{t+1+i}$ for all $i > 0$) holds, the modified Phillips curve can be solved forward to express inflation as

$$\pi_t = E_t \sum_{i=0}^{T} \beta^i [-\overline{\kappa} \widehat{u}_{t+i} - a I_{t+i}(s_{t+i} > 0) s_{t+i} \widehat{u}_{t+i} + \xi_{t+i}] + \beta^{T+1} E_t \pi_{t+T+1}. \tag{3}$$

Equation (3) defines inflation as a function of the current and expected future values of the unemployment rate gap, $\widehat{u}_{t+i}$, and supply disruptions, s_{t+i}. The equation illustrates how the inflationary effects of demand changes depend on the entire future path of supply pressures and slack in the economy.

3 Empirical Approach

Here we describe the methods we use to estimate the modified Phillips curve. First, we discuss our IV approach to estimating the parameters of the state-dependent slope term. Then, we present our benchmark estimates and assess the sensitivity of our results to alternative measures of economic slack.

3.1 Estimation

Estimating the slope of the Phillips curve (state dependent or otherwise) is challenging. First, it is difficult to disentangle the effect of the unemployment rate (or other measures of economic slack) on inflation from the effect of expected future inflation. That is because changes in the unemployment rate alter inflation expectations, which then feed back to the unemployment rate by affecting the real interest rate and overall demand. Second, the unemployment rate is an endogenous variable: It is correlated with cost-push shocks. To the extent that those shocks affect unemployment, estimates of the slope based on standard ordinary least squares regressions will be biased.

To separate the effects of demand-driven changes in unemployment from those of changing inflation expectations (and address the first issue), we first incorporate the definitions of κ_t and ξ_t into Equation (2) and rearrange the terms, to have

$$\pi_t - \beta E_t \pi_{t+1} = -\overline{\kappa}\widehat{u}_t - aI_t(s_t > 0)s_t\widehat{u}_t + bs_t + \theta' W_t + \varepsilon_t. \tag{4}$$

Then, we define the variable $y_{t+1} = \pi_t - \beta\pi_{t+1}$ and rewrite Equation (4) as

$$y_{t+1} = -\overline{\kappa}\widehat{u}_t - aI_t(s_t > 0)s_t\widehat{u}_t + bs_t + \theta' W_t + v_{t+1} \tag{5}$$

with

$$v_{t+1} = \varepsilon_t + \eta_{t+1}$$

where the expectation error $\eta_{t+1} = \beta(E_t\pi_{t+1} - \pi_{t+1})$ is orthogonal to the information set in period t. We also compare our results with the estimates of Hazell, Herreño, Nakamura, and Steinsson (2021). Hazell et al. addressed "the problem of shifting values of [long-term inflation expectations] confounding the estimation of the slope" by estimating regional (state-level) Phillips curves.

To address the problem of endogeneity, we use the shocks to U.S. monetary policy identified by Bu, Rogers, and Wu (2021) to instrument for the unemployment rate. Monetary policy surprises are a viable instrument because they are orthogonal to the cost-push factors and the expectation error included in the residual term v_{t+1}, but they affect unemployment by altering overall demand. Using externally identified monetary shocks as an instrument has a key advantage over the more traditional approach of using lagged values of unemployment, inflation, or other macroeconomic variables as instruments: Although lagged variables should be orthogonal to the expectation error, η_{t+1}, if the cost-push factors represented by the term ε_t are serially correlated, they will also correlate with the residual term, v_{t+1}, thereby violating the exogeneity condition for instrument validity. Because monetary surprises are unexpected deviations from systematic monetary policy, they should be exogenous to all leads and lags of v_{t+1}.

The parameter a is of key interest—as is the time-invariant component of the slope, $\overline{\kappa}$—because it determines the extent to which the effects of economic slack on inflation vary with supply conditions. One approach to implementing the IV estimation of a and $\overline{\kappa}$ is to use the current and all of the past monetary policy shocks to instrument for the endogenous regressors $\widehat{u}_t$ and $s_t\widehat{u}_t$ in Equation (5). That approach, however, involves using many instruments, and when the number of instruments is large relative to the sample size, inference based on standard IV (and generalized-method-of-moments) estimates becomes less reliable (see Andrews and Stock, 2007). To mitigate that problem, we follow Barnichon and Mesters (2020) in assuming that the responses of the endogenous variables to monetary shocks at different horizons are smooth functions of time and can be approximated by a second-order polynomial of the form $x_h = a_0 + a_1 h + a_2 h^2$, where x_h denotes the h-quarter-ahead response of $\widehat{u}_t$ or $s_t\widehat{u}_t$ to a monetary policy shock and $a_0, a_1,$ and a_2 are constant parameters. That specification reduces the number of instruments to three; those instruments are denoted $z_{1t}, z_{2t},$ and z_{3t} and defined as

$$z_{1t} = \sum_{i=N_1}^{N_2} m_{t-i},\ z_{2t} = \sum_{i=N_1}^{N_2} i \times m_{t-i},\ z_{3t} = \sum_{i=N_1}^{N_2} i^2 \times m_{t-i}$$

where m_{t-i} denotes the monetary shock in quarter $t - i$. Because monetary policy shocks affect the economy with a lag, we set N_1 to 1 (rather than 0). We set N_2 to 15—roughly the midpoint of the range recommended by Barnichon and Mesters (2020). We do not estimate the discount factor β. Instead, we set it to 0.99, which is within the standard range of values used in calibrated macroeconomic models.

3.2 Data

The measure of supply conditions, s_t, is the global supply chain pressure index (GSCPI) constructed by the staff of the Federal Reserve Bank of New York (see Figure 1 and Benigno et al., 2022). The GSCPI measures the supply-side drivers of domestic and international transportation costs as well as "the extent to which supply-chain delays in the economy impact producers—a variable that may be viewed as identifying a purely supply-side constraint; 'backlogs,' which quantifies the volume of orders that firms have received but have yet to either start working on or complete; and, finally, 'purchased stocks,' which measures the extent of inventory accumulation by firms in the economy" (Benigno et al., 2022). The GSCPI, therefore, is a useful summary of many economic conditions affecting the supply curve. Figure 1 plots the path of this measure along with inflation over the course of the sample period, showing a strong historical relationship between the two, especially in the time since the COVID-19 pandemic.

The measure of inflation, π_t, is the percentage change in the core personal consumption expenditures price index over the previous 12 months; the unemployment rate, u_t, is the number of unemployed people as a percentage of the civilian labor force; and the noncyclical rate of unemployment, u_t^n, is CBO's published measure. The control vector, W_t, includes the percentage change in oil and nonenergy import prices over the previous 12 months. The sample period runs from the fourth quarter of 1997 to the third quarter of 2021.

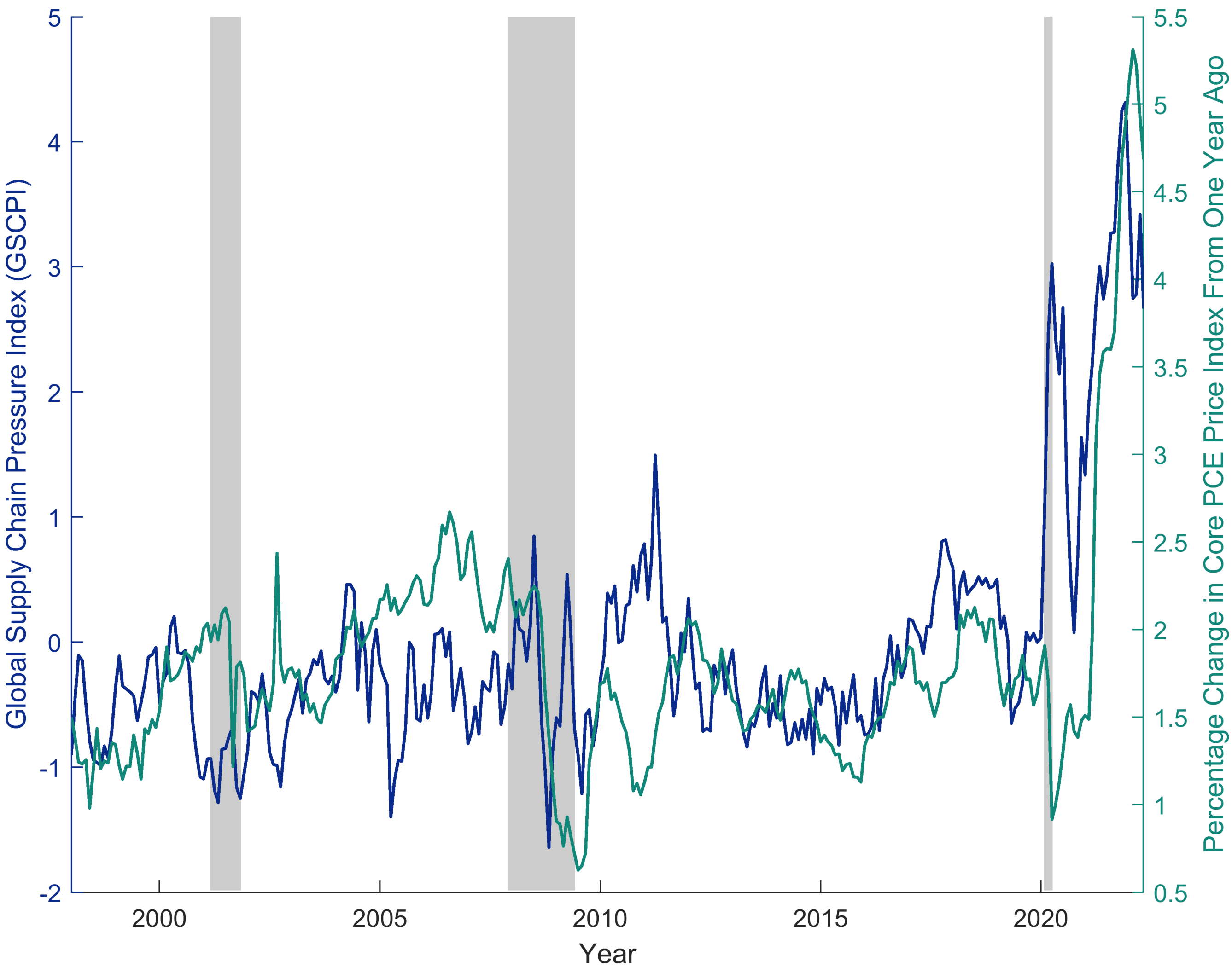
3.3 Benchmark Results

Table 1 reports the estimated values of $\overline{\kappa}$ and a, the corresponding *p*-values for the nulls $\overline{\kappa} = 0$ and $a = 0$, and the averages of the state-dependent slope parameter for different periods. Standard *F* statistics from the first-stage IV regressions indicate that monetary policy shocks are weak instruments. For that reason, we conduct inference using Anderson–Rubin statistics, which are robust to weak instruments (see Stock et al., 2002). The estimated values of the parameters $\overline{\kappa}$ and a are positive and significantly different from zero. Those results indicate that increased supply-chain stress steepens the Phillips curve and exacerbates the inflationary effects of stimulative fiscal policies.

Because the slack measure in our modified Phillips curve is logarithmic in the unemployment rate, the time-invariant component of the slope term, $\overline{\kappa}$, does not exactly correspond to the constant slope parameter in the standard NKPC. The parameter $\overline{\kappa}$ is the semi-elasticity of the inflation rate with respect to $\log(u_t/u_t^n)$. When the unemployment rate, u_t, is low, the slope of the modified Phillips curve (that is, the partial derivative $d\pi_t/du_t$ in Equation 2$)$ is steep, suggesting a larger effect on inflation from changes in economic slack when labor markets are tight. (For example, a decrease in the unemployment rate from 4 percent to 3 percent is much more inflationary than a decrease from 8 percent to 7 percent.) As a result, the relationship between inflation and the unemployment rate is stronger under tight labor market conditions such as those that prevailed in late 2021 and early 2022.

The estimated average of the slope in the full sample period (1997 to 2021) is 0.026. That value is greater than the recent estimate of Hazell et al. (2021), which was 0.0055 for the nonhousing nontradable sector in the 1990–2018 period, but well within the range of values reported in the recent literature (see Crump et al., 2022; Jørgensen and Lansing, 2021; McLeay and Tenreyro, 2019). The sample period used by Hazell et al. (2021) ended in 2018, and the full-sample average that we estimate is heavily influenced by the historically high levels of supply-chain stress in 2020 and 2021. Dropping the last three years to facilitate a better comparison, we find that the average slope in the 1997–2018 period is 0.014. That value is closer to the weighted average of the slope estimates for the nonhousing nontradable sector and housing services reported by Hazell et al.

Figure 1. A Measure of Supply Disruptions



Note: The global supply chain pressure index is produced by the Applied Macroeconomics and Econometrics Center at the Federal Reserve Bank of New York (see www.newyorkfed.org/research/policy/gscpi#/overview). It is expressed as standard deviations from average values. The core personal consumption expenditures (PCE) price index excludes food and energy prices. Data are monthly from January 1998 to May 2022. Shaded areas indicate business-cycle recessions, as determined by the National Bureau of Economic Research.

Table 1. Estimated Parameters and the Time-Variant Slope of the Phillips Curve

Parameters		*p*-Values		Average Slope		
$\overline{\kappa}$	a	$\overline{\kappa}=0$	$a=0$	1997-2021	1997-2018	2011-2021
0.038	0.338	0.172	0.005	0.026	0.014	0.049

Note: Reported *p*-values are based on weak-instrument-robust Anderson–Rubin statistics.

Table 2. Comparison of Phillips Curve Specifications

Specification	Full-Sample Estimates		*p*-Values		Root Mean Square Error	
	$\overline{\kappa}$	a	$\overline{\kappa}=0$	$a=0$	2010-2019	2010-2021
Linear	0.024	—	0.704	—	0.157	0.285
Linear, State-Dependent Slope	0.018	0.027	0.030	0.011	0.141	0.278
Convex, State-Dependent Slope	0.038	0.338	0.172	0.005	0.140	0.273

Note: This table shows the estimated values of the parameters and one-period-ahead root mean square errors for three versions of Equation (5). “Linear” corresponds to the standard New Keynesian Phillips curve in Equation (1). “Linear, State-Dependent Slope” replaces the time-invariant slope parameter in Equation (1) with the state-dependent version in Equation (2). “Convex, State-Dependent Slope” corresponds to the full modified specification in Equation (2). The reported *p*-values are based on weak-instrument-robust Anderson–Rubin statistics.

(2021), though on the low end of the range of estimates reported by Crump, Eusepi, Giannoni, and Şahin (2022).

The results shown in Table 1 suggest that state-dependent slope is an whether the state-dependent Phillips curve has better forecasting properties than the standard linear NKPC. To answer that question, we produce out-of-sample inflation forecasts using different specifications of the Phillips curve and calculate the RMSE for one-quarter-ahead predictions. Specifically, we estimate the parameters of each model using data available through quarter T, where T goes from the first quarter of 2010 to the third quarter of 2021 (that is, the forecast evaluation period), and use the estimated models to forecast inflation in quarter $T + 1$.

Table 2 compares the forecasting performance of three alternative specifications of the Phillips curve: the standard linear NKPC with no state dependence, a linear specification with state-dependent slope, and the full modified specification with state-dependent slope and a convex relationship between the unemployment rate and inflation. In both the full evaluation period and the prepandemic subperiod, the introduction of a state-dependent slope increases the model’s forecasting performance, suggesting a relevant role for supply disruptions in inflation dynamics as a determinant of the slope term even before the COVID-19 pandemic. The convex specification also yields a slightly lower RMSE when included together with state-dependent slope in both samples. But the marginal improvement generated by that feature is small, especially in the prepandemic period.

3.4 Alternative Measures of Slack

The Phillips curve specification we have discussed so far describes inflation as a function of the unemployment rate gap. The unemployment rate, however, is an imperfect measure of labor market slack, and alternative measures of such slack—in particular, those that incorporate information about job openings and individuals' search activity—may provide a better measure of inflationary pressures that result from changes in labor market conditions (see Furman and Powell, 2021). Therefore, we consider three additional measures: the ratio of job openings to unemployed (V/U), the quits rate, and the employment gap. Furman and Powell (2021) argued that the first two measures predict core CPI inflation better than the unemployment rate does in the 2001–2019 period, and the employment gap (defined as the difference between the actual level of employment and CBO's estimate of the potential level) is another comprehensive measure of labor market slack.

Along with the three alternative measures of slack, we report an alternative measure of supply conditions, s_t: the Institute for Supply Management's Backlog of Orders Index for the manufacturing sector. That index is intended to capture whether goods supply backups are increasing or decreasing and is similar to the backlogs measure used by Ball, Leigh, and Mishra (2022), but for goods only. For comparison with the coefficients on the GSCPI in the other specifications, we standardize this index such that the units are standard deviations from the mean value over the sample period.

In addition to the alternative slack and supply measures, we investigate two alternative methods for incorporating inflation expectations. In Equation (2), expectations that drive inflation dynamics are entirely forward-looking, and expectation errors are assumed to be orthogonal to the information available at the time when expectations are formed. To evaluate a case in which inflation expectations also depend on lagged inflation, we first consider a "hybrid" specification of the form

$$\pi_t = -\kappa_t \widehat{u}_t + \gamma \pi_{t-1} + (\beta - \gamma) E_t \pi_{t+1} + \xi_t,$$

where all variables are defined as in Equation (2). The hybrid case can be motivated by the possibility that some businesses index their prices to past inflation or have backward-looking expectations. We estimate the parameters of the hybrid specification by including the variable $y_{2,t+1} = \pi_{t-1} - \pi_{t+1}$ as an endogenous regressor in Equation (5).[1] That variable captures relevant information if expectation errors in period t are correlated with inflation in period $t-1$. Second, we consider a survey-based measure of inflation expectations. Specifically, we estimate the form

$$\pi_t = -\kappa_t \widehat{u}_t + \gamma_1 \pi_{t-1} + \gamma_2 \widehat{E}_t \pi_{t+1} + \xi_t,$$

[1] In this case, the expectation error captured in the residual term in Equation (5) is defined as $\eta_{t+1} = (\beta - \gamma)(E_t \pi_{t+1} - \pi_{t+1})$.

where $\widehat{E}_t\pi_{t+1}$ represents the median expectations of one-year-ahead inflation as measured by the University of Michigan's Surveys of Consumers.

Table 3 shows the estimated parameters and the RMSE of out-of-sample forecasts under alternative specifications in both the prepandemic period and the full evaluation period. Allowing the slope parameter to vary with supply conditions produces lower RMSEs across the board (that is, under all considered specifications and measures of slack, and in both samples). Introducing convexity in addition to state dependence delivers mixed results: It yields lower RMSEs under some of the specifications but produces higher RMSEs in others. But, as in the benchmark case, the effect on RMSEs is small relative to the improvement achieved by the state-dependent slope term.

Comparison of different slack measures also offers a mixed picture, though the evidence supports that alternative measures are appropriate for use in the Phillips curve. The ratio of job openings to unemployed produces the lowest RMSE in the prepandemic period and outperforms the unemployment rate gap under most of the specifications in the prepandemic and full samples.[2] However, the quits rate performs best in the full sample. The employment gap performs at least as well as the unemployment rate gap (used in the benchmark specification) in both samples. The hybrid model with lagged inflation exhibits the worst performance, probably because of the additional uncertainty arising from the estimation of the lagged inflation coefficient. Those findings suggest that, although the slack measures that are based on labor market indicators (such as the job-openings-to-unemployment ratio or the quits rate) perform better than the unemployment rate gap under most of the specifications, no single measure of slack is clearly superior to the others under all specifications and in both the prepandemic and full evaluation periods.[3]

3.5 The Effect of Supply-Chain Conditions on the Phillips Curve: Regional Evidence

So far, we have presented evidence that a nonlinear Phillips curve with a state-dependent slope term exhibits better predictive performance than a standard Phillips curve. In this section, we augment that evidence by using regional inflation and supply-chain information, defining a region as a group of counties included in the CFS. We find suggestive evidence that interactions of supply conditions and slack are a relevant determinant of inflation dynamics at the regional level, as they are at the

[2] This result is consistent with the findings of Furman and Powell (2022) and Barnichon and Shapiro (2022). By comparing the adjusted R^2 statistics from linear Phillips curve regressions that used different measures of slack, Furman and Powell concluded that the ratio of unemployed workers to job openings was the best predictor of core CPI inflation in the 2001–2019 period. Barnichon and Shapiro compared nine alternative measures of slack and found that the ratio of vacancies (or job openings) to unemployment exhibited the best out-of-sample forecasting performance.

[3] We also evaluated a model using a quadratic specification to capture nonlinearities in the unemployment gap, finding RMSEs of 1.542 and 1.654 in the full and shortened sample, respectively. Though the in-sample fit is good under this specification, out-of-sample forecast errors are large, suggesting that this model may suffer from overfitting.

Table 3. Estimated Values of the Parameters and Root Mean Square Errors Under Different Measures of Slack and Alternative Specifications of the Phillips Curve

	Full-Sample Estimates		*p*-Values		Root Mean Square Error	
Specification	$\overline{\kappa}$	a	$\overline{\kappa} = 0$	$a = 0$	2010-2019	2010-2021
Job-Openings-to-Unemployed Ratio						
Linear	0.072	—	0.679	—	0.182	0.283
Linear, State-Dependent Slope	0.027	0.244	0.106	0.014	0.156	0.262
Convex, State-Dependent Slope	-0.062	-0.092	0.045	0.062	0.134	0.278
Quits Rate						
Linear	0.051	—	0.679	—	0.167	0.278
Linear, State-Dependent Slope	-0.003	0.146	0.362	0.008	0.143	0.219
Convex, State-Dependent Slope	0.026	0.340	0.247	0.017	0.149	0.212
Employment Gap						
Linear	-0.008	—	0.704	—	0.154	0.280
Linear, State-Dependent Slope	0.002	0.020	0.164	0.005	0.136	0.259
Convex, State-Dependent Slope	0.245	2.958	0.167	0.004	0.136	0.260
Hybrid Case With Lagged Inflation						
Linear	0.018	—	0.780	—	0.197	0.332
Linear, State-Dependent Slope	-0.006	0.033	0.648	0.030	0.192	0.371
Convex, State-Dependent Slope	-0.050	0.272	0.724	0.016	0.196	0.350
Backward-Looking						
Linear	0.176	—	3e-5	—	1.592	1.868
Linear, State-Dependent Slope	0.014	0.036	0.200	0.021	0.251	0.562
Convex, State-Dependent Slope	0.042	0.262	0.089	0.013	0.247	0.558
Order Backlogs						
Linear, State-Dependent Slope	0.022	0.066	0.025	0.019	0.163	0.303
Convex, State-Dependent Slope	0.056	0.646	0.111	0.017	0.163	0.295

Note: This table reports the estimated values of the parameters and one-period-ahead root mean square errors for different specifications of Equation (5) under alternative measures of labor market slack. "Linear" corresponds to the standard New Keynesian Phillips curve in Equation (1). "Linear, State-Dependent Slope" replaces the time-invariant slope parameter in Equation (1) with the state-dependent version in Equation (2). "Convex, State-Dependent Slope" corresponds to the full modified specification in Equation (2). The reported *p*-values are based on weak-instrument-robust Anderson–Rubin statistics.

national level.

3.5.1 A Time-Varying Regional Phillips Curve

McLeay and Tenreyro (2019) showed that if inflation and the output gap can be written as weighted averages of regional inflation and output gaps, and the Phillips curve relationship is the same in every region, then Equation (1) can be written as

$$\pi_t^i = \beta E_t \pi_{t+1}^i + \kappa^x x_t^i + \varepsilon_t^i, \tag{6}$$

where x_t^i denotes the output gap in region i. Assuming that the relationship between output and unemployment gaps is similar across regions and subtracting each region's inflation and unemployment gap from national averages, we can rewrite Equation (6) as

$$\bar{\pi}_t^i = \beta E_t \bar{\pi}_{t+1}^i - \kappa^u \bar{u}_t^i + \bar{\varepsilon}_t^i, \tag{7}$$

where the variables with bars denote differences from national averages. To introduce supply-chain-induced time variation in the slope parameter as in Equation (2), we modify Equation (7) as

$$\bar{\pi}_t^i = \beta E_t \bar{\pi}_{t+1}^i - (\kappa^u + a_1 s_t + a_2 s_i + a_3 s_t s_i)\bar{u}_t^i + v_t^i, \tag{8}$$

where

$$v_t^i = b_1 s_t + b_2 s_i + b_3 s_t s_i + \bar{\varepsilon}_t^i.$$

In Equation (8), the effects of supply disruptions on the slope parameter are represented by three separate terms: the supply-chain disruption index, s_t; a measure of region i's exposure to supply disruptions, s_i; and the interaction of supply disruptions and regional exposure, $s_t s_i$.[4] The aggregate supply measure s_t is the GSCPI measure from the Federal Reserve Bank of New York. We construct the exposure variable s_i by measuring the magnitude of each region's trade within the United States. Specifically, we use data from the most recent CFS to calculate the total value of shipments to establishments in a CFS subregion.[5] We then divide that value by the sum of the GDPs of the counties included in that region, thereby obtaining a measure of local trade activity that is defined relative to the size of the economy in that locality. Intuitively, the subregions in which the value of shipments is greater relative to the size of the economy are likely to be more exposed to supply-chain issues, especially in times of global shortages. Indeed, Figure 2 shows a positive

[4] This method of measuring exposure to supply-chain issues is similar to the method employed by Santacreu and LaBelle (2022) to evaluate supply disruptions at the industry level.

[5] The most recent CFS was conducted in 2017. A CFS subregion is a group of counties within a state. A subregion is associated with one or more metropolitan statistical areas (MSAs) or with some large portion of a state not associated with a large MSA. We consider only subregions that are explicitly linked to at least one MSA.

relationship between exposure to trade, as measured by the value of shipments to establishments in a region divided by that region's GDP, and local inflation in 2021.

We calculate inflation for each subregion by using implicit price deflators at the metropolitan statistical area (MSA) level, which are available at annual frequency from the Bureau of Economic Analysis (BEA).[6] We then match MSA-level inflation to counties linked to subregions in the CFS data that are located in MSAs. For the subregions that include more than one MSA, we use the average inflation across counties. We construct annual unemployment rates by averaging monthly rates from the Bureau of Labor Statistics at the county level and then averaging those annual rates across counties within a subregion. Measures of noncyclical unemployment are not readily available at the local level. For that reason, we use the unemployment rate in place of $\bar{u}_t^i$. In a robustness check, we construct an alternative unemployment gap measure by assuming that the gap was zero in 2016 in all regions and the local noncyclical rate has a constant difference from the national noncyclical rate.[7] We call this the "synthetic" unemployment gap.

Estimating regional Phillips curves by using cross-sectional data also helps alleviate the endogeneity problem. That is because monetary policy cannot respond to regional demand shocks by using a single interest rate or other policy tools that operate at the national level. As a result, those shocks are expected to play a more important role in driving the variation that is used to identify the slope of the Phillips curve. Using regional data, however, does not fully address the issue of endogeneity. Thus, we use an IV approach as described in the previous section. A key concern with using the past values of externally identified monetary policy shocks (that is, the instrument we used to estimate the national Phillips curve) is that, at annual frequency, past values of monetary shocks are extremely weak instruments for regional unemployment rates. For that reason, we follow the more commonly adopted approach of using lagged values of regional GDP growth as instruments. Specifically, we use the two-period lagged value of regional GDP growth to instrument for the regional unemployment gap.

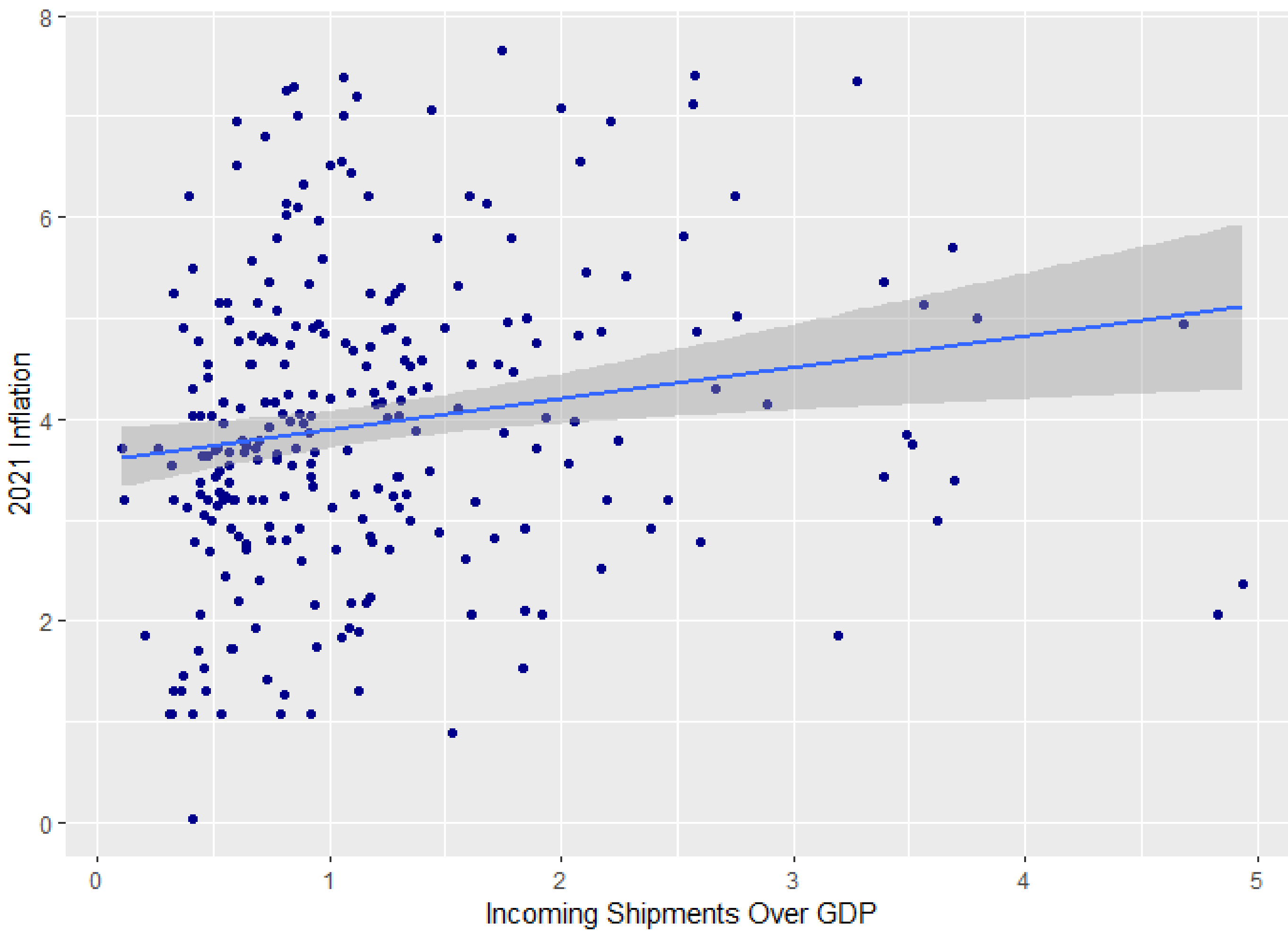
3.5.2 Results

Table 4 presents the results under six alternative specifications that differ by the estimation sample, whether the log specification is used for unemployment, and whether the indicator function for $s_t > 0$ is included in Equation (8) by using the variable $I_t(s_t > 0) \times s_t$ in place of s_t. All specifications incorporate backward-looking inflation expectations because, with annual data, using forward-looking expectations results in the most recent observation (for the year 2021) being dropped

[6] Those price deflators are published along with BEA's regional price parities and allow the construction of MSA-level inflation rates at the annual frequency.

[7] In CBO's estimation, the national unemployment gap crosses from positive to negative between the fourth quarter of 2016 and the first quarter of 2017. Therefore, the gap is estimated to be zero by the end of 2016.

Figure 2: Local Area Supply Chains and Inflation, 2021



Note: Outliers, defined as the regions that have interregional shipments more than five times greater than their gross domestic product (GDP), have been dropped. Shipments as a percentage of GDP are calculated at the Commodity Flow Survey subarea level in 2017.

Table 4. Estimated Parameters of the Regional Phillips Curve

	(1)	(2)	(3)	(4)	(5)	(6)
κ^u	0.354**	0.377**	0.477	2.329**	2.47**	2.037
	(0.166)	(0.178)	(0.739)	(1.135)	(1.23)	(3.217)
a_1	-0.107	-0.107	-0.448	-0.621	-0.628	-1.852
	(0.101)	(0.104)	(0.307)	(0.596)	(0.614)	(1.251)
a_2	-0.038	-0.054	-0.125	-0.330	-0.409	-0.475
	(0.103)	(0.127)	(0.269)	(0.520)	(0.629)	(1.164)
a_3	0.128***	0.104**	0.176*	0.644**	0.544**	0.820**
	(0.053)	(0.045)	(0.091)	(0.275)	(0.238)	(0.412)
Measure of $\bar{u}_t^i$	Linear	Linear	Linear	Log	Log	Log
Indicator	No	Yes	No	No	Yes	No
Sample	2011-2021	2011-2021	2017-2021	2011-2021	2011-2021	2017-2021

Note: This table reports results for various estimation specifications for Equation (9). All regressions include state and year fixed effects. Standard errors clustered at the state level are presented in parentheses. The sample comprises Commodity Flow Survey subareas from 2011 to 2021. *p < 0.10, **p < 0.05, ***p < 0.01.

from the estimation sample. Preserving that data point is important for keeping a key observation of supply disruptions and inflation in the sample. All specifications include state and time fixed effects, and standard errors are clustered at the state level.

The results shown in Table 4 suggest that the state-dependent Phillips curve is empirically relevant at the regional level, as it is at the national level. The estimated values of the coefficient a_3—the parameter measuring the time-varying effect of the regional exposure to supply disruptions on the slope of the Phillips curve—is positive and statistically significant under all specifications. Therefore, economywide supply disruptions steepen the Phillips curve more in regions that are more exposed to such disruptions. A rough glance at the estimates under different specifications reveals that, when shipments equal local GDP (that is, $s_i = 1$) and the economywide supply disruptions are 1 standard deviation above the long-run average ($s_t = 1$), the slope of the Phillips curve increases by about a third. The results also indicate that the time-invariant component of the Phillips curve slope is positive under all specifications and statistically significant under most of them. These findings are consistent with our earlier results, which were based on national data.

Table 5 presents the results under an alternative specification of regional economic slack. When the variable $\bar{u}_t^i$ in Equation (8) represents the previously discussed synthetic unemployment gap (rather than the actual rate of unemployment in region i), the coefficient a_3 remains positive and statistically significant in the full sample regardless of whether the indicator function for $s_t > 0$ is included in Equation (8). When we restrict our attention to the much shorter subsample for the 2017–2021 period, the estimate for a_3 is no longer significant (as one might expect).

Because limitations on the availability of regional data compel us to use a short sample period,

Table 5. Regional Phillips Curve Parameters Under the Synthetic Unemployment Gap

	(1)	(2)	(3)
κ^u	0.847**	0.875	0.114
	(0.424)	(0.641)	(4.244)
a_1	-0.186	-0.203	-1.716
	(0.309)	(0.382)	(1.723)
a_2	-0.251	-0.135	-0.778
	(1.437)	(2.672)	(2.587)
a_3	0.139**	0.123*	0.588
	(0.062)	(0.066)	(0.514)
Indicator	No	Yes	No
Sample	2011-2021	2011-2021	2017-2021

Note: All regressions include state and year fixed effects. Standard errors clustered at the state level are presented in parentheses. The sample comprises Commodity Flow Survey subareas from 2011 to 2021. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

we interpret our regional results as suggestive rather than definitive evidence of the effect of supply disruptions on the slope of regional Phillips curves. On the basis of that suggestive evidence, we conclude that Phillips curves may be heterogeneous across regions and that this heterogeneity is related in part to measures of exposure to supply-chain disruptions. We take these regional results as generally supportive of our previous conclusions about the effects of economywide supply disruptions on the slope of the Phillips curve. Our results also highlight the need for further research on local supply conditions and how they are related to regional inflation outcomes.

4 Effects of Government Spending on Inflation

In this section, we quantitatively assess the implications of supply conditions and economic slack on the inflationary effects of fiscal policy. To that end, we analyze an illustrative policy that would boost overall demand by increasing government spending. Under that policy, government purchases would increase by 1 percent of potential GDP over four consecutive quarters, and the additional spending would be financed by increased borrowing (rather than increased taxes or reduced transfers).

4.1 Characterization of the Demand Side and Monetary Policy

The Phillips curve we have examined thus far describes the effects of overall demand (as captured by the unemployment rate gap or other measures of economic slack) on inflation. To fully evaluate those effects, however, one must account for the response of monetary policy to inflationary or deflationary pressures that result from changes in demand and how that response, in turn, affects inflation. Therefore, the effects of fiscal policy on inflation are best analyzed in a general equilibrium framework that captures the response of monetary policy to inflation and the effect of inflation expectations on overall demand (in addition to the effect of overall demand on inflation described by the Phillips curve).

4.1.1 The Response of Monetary Policy to Inflation

In response to inflationary pressures, the central bank raises short-term nominal interest rates to prevent inflation from deviating from a target rate in the long term. That response can be described by a standard Taylor-type feedback rule of the form

$$i_t = \max\{0, (1 - \lambda_r)i_{t-1} + \lambda_r(i_t^* + \lambda_\pi \pi_t + \lambda_y y_t)\}, \tag{9}$$

where i_t denotes the short-term nominal interest rate controlled by the central bank and y_t denotes the output gap, defined as the difference between the logs of actual and potential levels of output. Parameters λ_π and λ_y measure the responsiveness of the nominal rate to inflation and output gap fluctuations, respectively. Parameter λ_r measures the degree of monetary policy inertia (or smoothing), and i_t^* denotes the central bank's target interest rate. Equation (9) rules out negative values for the nominal rate by incorporating an effective lower bound for i_t at zero.

4.1.2 The Effect of Inflation Expectations on Overall Demand

In a broad class of general equilibrium models, including the standard New Keynesian framework, inflation expectations affect overall demand by altering the real interest rate, defined as the difference between the nominal rate and expected inflation, $i_t - E_t\pi_{t+1}$. An increase in the real rate causes private saving to be higher (and spending lower) by making current consumption more expensive in terms of future consumption, thereby reducing overall demand; a decrease does the reverse. That relationship can be captured by an equation of the form

$$y_t = -\frac{1}{\sigma}(i_t - E_t\pi_{t+1}) + E_t y_{t+1} + \gamma_t, \tag{10}$$

where the composite term γ_t represents external factors that affect overall demand, such as purchases of goods and services by the government.

Equation (10) is based on the intertemporal allocation of private spending that households implement in a class of models in which households' decisions about consumption and saving are forward-looking and rational, and it is obtained by linearizing the first-order optimality condition

Table 6. Parameter Values

Parameter	Value	Description
σ	3	Inverse of intertemporal substitution elasticity
α	-0.5	Okun's law coefficient
$\overline{\kappa}$	0.038	Invariant slope parameter
a	0.338	Responsiveness of the slope to supply disruptions
λ_π	1.5	Monetary policy response to inflation
λ_y	0.5	Monetary policy response to output gap
λ_r	0.6	Monetary policy inertia parameter

Note: This table shows the calibrated values of the parameters. The values of the time-invariant slope parameter and the responsiveness of the slope term to supply disruptions correspond to the estimated values reported in Table 1.

governing households' consumption expenditure (that is, the consumption Euler equation).[8] The parameter $\sigma > 0$ is the inverse of the elasticity of intertemporal substitution and determines the responsiveness of demand to changes in the real interest rate.

The Phillips curve Equation (2) describes inflation as a function of the unemployment rate gap (rather than the output gap). To complete the model, we specify the relationship between the unemployment rate and output gaps as $u_t - u_t^n = \alpha y_t$, where α is a constant. That relationship and Equations (2), (9), and (10) fully characterize the dynamics of the inflation rate, the output gap, the unemployment rate gap, and the interest rate as functions of the exogenous variables ξ_t, i_t^*, and γ_t.

4.2 Calibration

To quantitatively evaluate the effects of the illustrative policy on inflation, we next assign values to the parameters of the model described by Equations (2), (9), and (10). Each period in the model represents one quarter. We set the inverse of the elasticity of intertemporal substitution, σ, to 3, which is within the range used in the literature and consistent with the value used in CBO's overlapping generations model (see Nishiyama and Reichling, 2015, and Table 6). We set the monetary policy parameters λ_r, λ_π, and λ_y to 0.6, 1.5, and 0.2, respectively; those values are also fairly standard in the literature (see, for example, Orchard et al., 2022; Christiano et al., 2011). We assign the value -0.5 to the constant α, which is consistent with the relationship commonly known as Okun's law. Finally, we assign the estimated values 0.038 and 0.338 to the slope parameters $\overline{\kappa}$ and a, respectively.

We analyze the effects of the illustrative policy on inflation in two steps. In the first step, we calibrate the model's exogenous processes to replicate CBO's baseline projections over the next three decades. Specifically, we set the values of ξ_t, i_t^*, and γ_t in quarters $t = 1, 2, ...120$ so that

[8] For more detailed discussions, see Woodford (2003) and McCallum and Nelson (1999).

the inflation rate, the unemployment rate gap, and the interest rate sequences produced by the model match CBO's baseline projections for the 2023–2053 period on a quarterly basis. Replicating CBO's baseline projections in the first step ensures that, in the absence of the policy change, the model produces outcomes that are consistent with the existing outlook for unemployment, inflation, and supply conditions. That consistency is important for accurately assessing the effects of policy changes, because convexity of the Phillips curve and state dependence of the slope render the inflationary effects of fiscal policy sensitive to the unemployment rate and supply conditions that prevail in the absence of the policy change.

In the second step, we evaluate the effects of the illustrative policy by increasing the exogenous component of overall demand, γ_t, by 1 percentage point in quarters $t = 1, 2, 3,$ and 4. That value measures the size of the initial shock to the output gap from the boost in government purchases before the monetary policy response and other general equilibrium effects are taken into account (and corresponds to roughly $260 billion in the second quarter of 2023). We then solve Equations (2), (9), and (10) by using that alternative path for γ_t (while using the baseline paths for ξ_t and i_t^* produced in the first step). We examine the effects of the policy by calculating the difference between the inflation paths produced in the first and second steps.

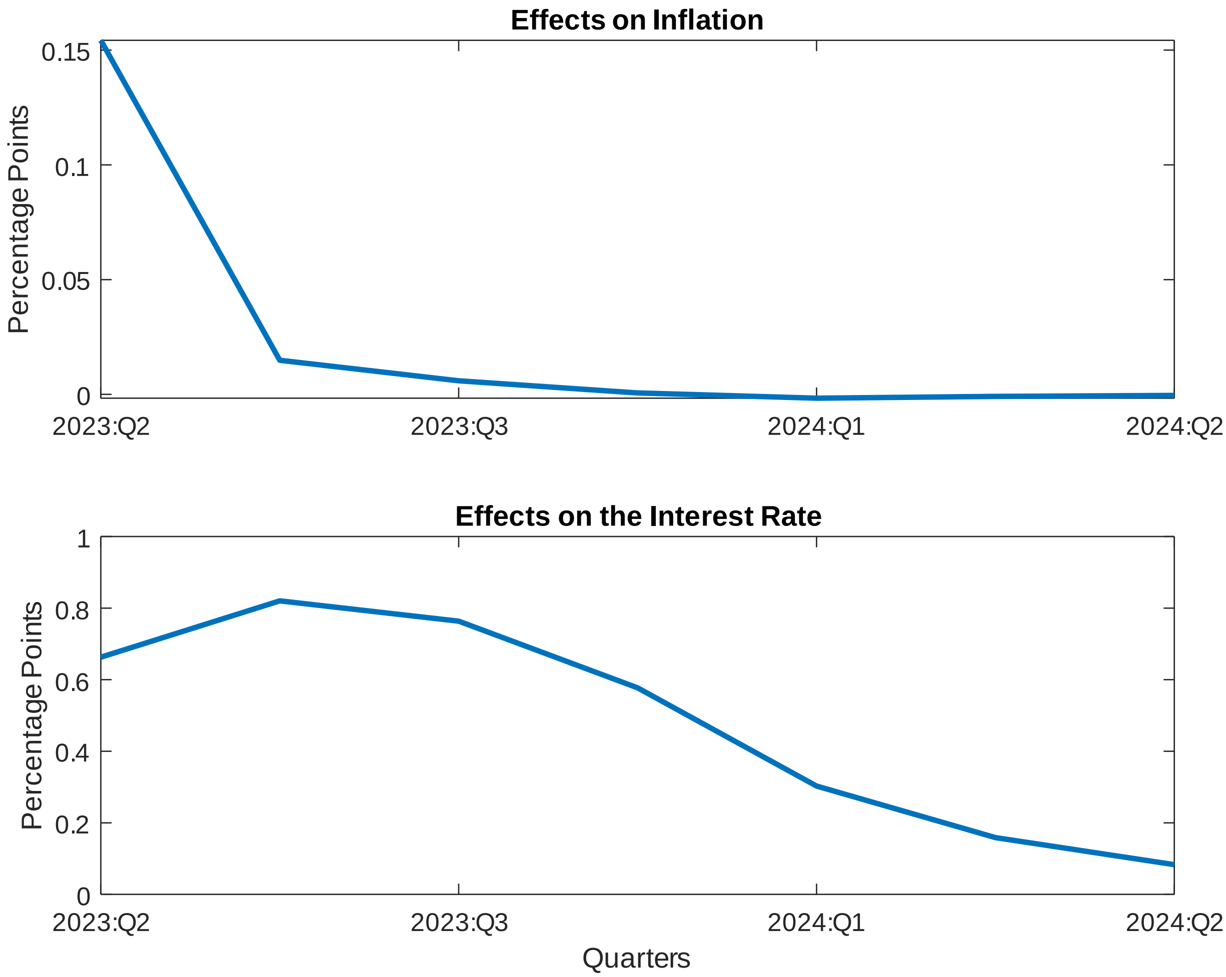
4.3 Results

Figure 3 shows the responses of inflation and the interest rate to the increase in government purchases under the baseline calibration shown in Table 6. The boost in demand causes inflation to increase by 15 basis points in the first quarter. The central bank responds by raising the short-term interest rate, which reduces the upward pressure on prices by dampening demand. The response of inflation diminishes monotonically over the subsequent quarters and disappears by the end of the fourth quarter as the fiscal stimulus fades. The increase in the interest rate, however, continues beyond the fourth quarter because of monetary policy inertia—that is, the central bank's commitment to keeping the interest rates high for an extended period of time to quell inflation pressures. That commitment has a stabilizing effect on inflation expectations, which helps reduce the persistence of the effects on inflation.

4.3.1 The Role of Supply Disruptions

The results shown in Figure 3 are based on the assumption that the disruption index, s_t, remains at its average value of zero after the second quarter of 2023. To examine how the response of inflation changes with supply pressures, we evaluate the policy under an alternative scenario, called Scenario 1, in which disruptions in the second, third, and fourth quarters of 2023 are as severe as those that occurred in 2021. Under that scenario, the increase in inflation in the second quarter of

Figure 3. Effects of the Illustrative Policy on Inflation and the Interest Rate



Note: This figure shows the effects of the illustrative policy on core personal consumption expenditures inflation and the short-term interest rate in the calibrated model.

2023 is nearly five times as large as the increase under the baseline path, and the average increase in 2023 is nearly seven times as large (see Figure 4).

4.3.2 The Role of Slack

To evaluate how the amount of slack, as measured by the rate of unemployment, affects the response of inflation to the boost in government purchases, we next examine what would happen if the policy change occurred in a state of high unemployment (that is, starting from a position of slack) rather than a state of low unemployment and tight labor markets. We consider a counterfactual scenario, called Scenario 2, in which the unemployment rate in the first quarter of the policy change is 7 percent (that is, about 3.2 percent greater than the baseline value) and remains elevated over the next four quarters, averaging 6 percent, before returning to CBO's baseline path by the end of 2024. Under that scenario, the increase in inflation in the second quarter of 2023 is 87 percent smaller than the increase under the baseline specification, and the average increase in 2023 is about 80 percent smaller.

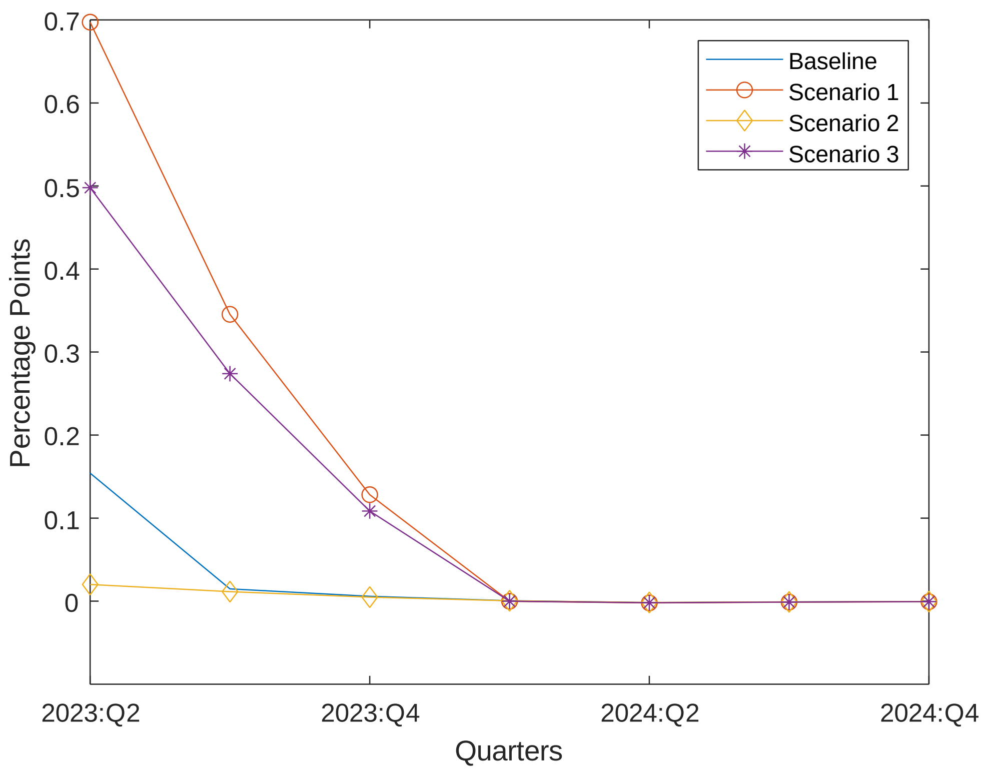
4.3.3 Interaction of Supply Disruptions With Slack

Our results indicate that supply conditions and slack both matter for the effects of policy changes on inflation. Higher supply-chain stress and lower slack amplify policies' inflationary pressures; lower supply-chain stress and higher slack do the reverse. Another key finding is that lower slack magnifies and higher slack reduces the impact of supply disruptions on the inflationary pressure from expansionary policies. To assess that relationship, we evaluate a counterfactual scenario, called Scenario 3, in which supply disruptions remain elevated (as specified in Scenario 1) and the economy starts from a position of slack (as specified in Scenario 2). Under that scenario, the increase in inflation is roughly 29 percent smaller in the second quarter of 2023 than the increase under Scenario 1 (in which the economy initially has low slack), and the average increase in 2022 and 2023 is about 25 percent smaller (see Figure 4). Those results suggest that the combined effect of increased supply-chain stress and reduced slack exceeds the sum of the individual effects from those changes and, therefore, that the interaction of supply conditions and slack plays an important role in inflation dynamics.

5 Conclusion

This paper proposes and estimates a new Phillips curve with two important differences from the standard specification. First, the slope parameter depends on the prevailing supply conditions. We find that state-dependent slope, one that steepens in times of restrained supply, is an empirically

Figure 4. Responses of Inflation to The Policy Change Under Alternative Scenarios



Note: This figure shows the effects of the illustrative policy on core personal consumption expenditures inflation under alternative paths for supply disruptions and economic slack. Scenarios 1, 2, and 3 represent paths in which supply disruptions in 2023 are as severe as they were in 2021 (Scenario 1), the unemployment rate in the first quarter of the policy change is 3.2 percentage points greater than the value in the baseline specification (Scenario 2), and supply disruptions remain as elevated as in Scenario 1 and the economy starts from a position of slack as in Scenario 2 (Scenario 3).

relevant feature of the Phillips curve and a helpful predictor of next-period inflation. Those findings suggest that supply disruptions, such as those recently encountered in the United States and elsewhere, affect both the level and the slope of the Phillips curve. Second, the relationship between inflation and economic slack is nonlinear—changes in slack have larger effects on inflation when unemployment is low and labor markets are tight. We identify the parameters of the proposed Phillips curve by adopting an IV approach, whereby we use externally identified monetary policy shocks to construct valid instruments. We also investigate the predictive performance of the proposed curve by using three alternative measures of slack: the ratio of job openings to unemployed, the quits rate, and the employment gap. The state-dependent specification produces more accurate out-of-sample inflation predictions in the post-2010 period than its linear counterpart under all considered measures of slack.

The state-dependent slope and the nonlinear relationship between inflation and economic slack suggest that the effects of fiscal policy on inflation depend on economic conditions, including supply conditions and the amount of slack. We conduct quantitative analysis by incorporating the proposed Phillips curve into an otherwise standard New Keynesian model and evaluating the effects of an illustrative policy increasing government purchases. We find that, under a plausible set of parameter values, continued supply disruptions, low slack, and the interaction of supply disruptions with low slack each amplify the inflationary effect of increased government purchases. Our results suggest that fiscal policies implemented over the past couple of years would have had a smaller effect on inflation if disruptions to supply in product and labor markets had not occurred.

References

Andrews, Donald W. K., and James H. Stock. 2007. "Testing With Many Weak Instruments." *Journal of Econometrics* 138 (1): 24–46.

Ball, Laurence M., Daniel Leigh, and Prachi Mishra. 2022. "Understanding U.S. Inflation During the COVID Era." NBER Working Paper 30613.

Ball, Laurence M., and Sandeep Mazumder. 2011. "Inflation Dynamics and the Great Recession." NBER Working Paper 17044.

Barnes, Michelle L., and Giovanni P. Olivei. 2003. "Inside and Outside Bounds: Threshold Estimates of the Phillips Curve." *New England Economic Review* 2003: 3–18.

Barnichon, Regis, and Geert Mesters. 2020. "Identifying Modern Macro Equations With Old Shocks." *Quarterly Journal of Economics* 135 (4): 2255–98.

Barnichon, Regis, and Adam Hale Shapiro. 2022. "What's the Best Measure of Economic Slack?" FRBSF Economic Letter 2022-04.

Benigno, Gianluca, Julian di Giovanni, Jan J. J. Groen, and Adam I. Noble. 2022. "A New Barometer of Global Supply Chain Pressures." *Liberty Street Economics*, January 4. https://libertystreeteconomics.newyorkfed.org/2022/01/a-new-barometer-of-global-supply-chain-pressures.

Bernanke, Ben S. 2007. "Inflation Expectations and Inflation Forecasting." Speech delivered at the National Bureau of Economic Research Summer Institute, Cambridge, Massachusetts, July 10. www.federalreserve.gov/newsevents/speech/bernanke20070710a.htm.

Bu, Chunya, John Rogers, and Wenbin Wu. 2019. "A Unified Measure of Fed Monetary Policy Shocks." Finance and Economics Discussion Series 2019-043. Washington: Board of Governors of the Federal Reserve System.

Calvo, Guillermo A. 1983. "Staggered Prices in a Utility-Maximizing Framework." *Journal of Monetary Economics* 12 (3), 383–98.

Christiano, Lawrence, Martin Eichenbaum, and Sergio Rebelo. 2011. "When Is the Government Spending Multiplier Large?" *Journal of Political Economy* 119 (1): 78–121.

Crump, Richard K., Stefano Eusepi, Marc Giannoni, and Ayşegül Şahin. 2022. "The Unemployment-Inflation Trade-off Revisited: The Phillips Curve in COVID Times." NBER Working Paper 29785.

Daly, Mary C., and Bart Hobijn. 2014. “Downward Nominal Wage Rigidities Bend the Phillips Curve.” *Journal of Money, Credit and Banking* 46 (52): 51–93.

Doser, Alexander, Ricardo Nunes, Nikhil Rao, and Viacheslav Sheremirov. 2017. “Inflation Expectations and Nonlinearities in the Phillips Curve.” Federal Reserve Bank of Boston Working Paper 17-11.

Forbes, Kristin, Joseph Gagnon, and Christopher G. Collins. 2021. “Low Inflation Bends the Phillips Curve Around the World.” NBER Working Paper 29323.

Furman, Jason. 2022. “This Inflation Is Demand-Driven and Persistent.” *Project Syndicate*, April 20. www.project-syndicate.org/commentary/inflation-demand-driven-persistent-by-jason-furman-2022-04.

Furman, Jason, and Wilson Powell. 2021. “What Is the Best Measure of Labor Market Tightness?” *Realtime Economics*, November 22. www.piie.com/blogs/realtime-economic-issues-watch/what-best-measure-labor-market-tightness.

Hazell, Jonathon, Juan Herreño, Emi Nakamura, and Jón Steinsson. 2021. “The Slope of the Phillips Curve: Evidence From U.S. States.” NBER Working Paper 28005.

Hooper, Peter, Frederic S. Mishkin, and Amir Sufi. 2020. “Prospects for Inflation in a High Pressure Economy: Is the Phillips Curve Dead or Is It Just Hibernating?” *Research in Economics* 74 (1): 26–62.

Jordà, Òscar, Celeste Liu, Fernanda Nechio, and Fabián Rivera-Reyes. 2022. “Why Is U.S. Inflation Higher Than in Other Countries?” FRBSF Economic Letter 2022-07.

Jørgensen, Peter Lihn, and Kevin J. Lansing. 2021. “Anchored Inflation Expectations and the Slope of the Phillips Curve.” Federal Reserve Bank of San Francisco Working Paper 2019-27.

McCallum, Bennett T., and Edward Nelson. 1999. “An Optimizing IS-LM Specification for Monetary Policy and Business Cycle Analysis.” *Journal of Money, Credit and Banking* 31 (3): 296–316.

McLeay, Michael, and Silvana Tenreyro. 2019. “Optimal Inflation and the Identification of the Phillips Curve.” NBER Working Paper 25892.

Mishkin, Frederic S. 2007. “Inflation Dynamics.” *International Finance* 10 (3): 317–34.

Ng, Michael, David Wessel, and Louise Sheiner. 2018. “The Hutchins Center Explains: The Phillips Curve.” *Brookings: Up Front*, August 21. www.brookings.edu/blog/up-front/2018/08/21/the-hutchins-center-explains-the-phillips-curve.

Nishiyama, Shinichi, and Felix Reichling. 2015. “The Costs to Different Generations of Policies That Close the Fiscal Gap.” CBO Working Paper 2015-10.

Orchard, Jacob, Valerie A. Ramey, and Johannes F. Wieland. 2022. “Micro MPCs and Macro Counterfactuals: The Case of the 2008 Rebates.” Unpublished.

Pfajfar, Damjan, and John M. Roberts. 2022. “The Role of Expectations in Changed Inflation Dynamics.” *International Journal of Central Banking* 18: 199–238.

Rotemberg, Julio J. 1982. “Sticky Prices in the United States.” *Journal of Political Economy* 90 (6): 1187–211.

Santacreu, Ana Maria, and Jesse LaBelle. 2022. “Global Supply Chain Disruptions and Inflation During the COVID-19 Pandemic.” Federal Reserve Bank of St. Louis *Review.* 104 (2): 78–91.

Shapiro, Adam Hale. 2022. “How Much Do Supply and Demand Drive Inflation?” FRBSF Economic Letter 2022-015.

Stock, James H., Jonathan H. Wright, and Motohiro Yogo. 2002. “A Survey of Weak Instruments and Weak Identification in Generalized Method of Moments.” *Journal of Business & Economic Statistics* 20 (4): 518–29.

Woodford, Michael. 2003. *Interest and Prices: Foundations of a Theory of Monetary Policy*. Princeton University Press.