Phillips Curve across Space and Time*

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Abstract

In this paper, we examine the regional trade-off between inflation and unemployment using a state-level dataset. Our analysis delves into both the reduced-form correlation and the structural Phillips curve with a state-level panel dataset. By applying a data-driven classification method, we account for potential nonlinearities influenced by distinct features of the economy and explore unobserved heterogeneity in group patterns across states. Our findings underscore the presence of these nonlinearities and group patterns, highlighting that the flattening and return of the Phillips curve are regional and sporadical.

J.E.L. Codes: C33, C36, C38, E32, E52

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1 Introduction

There has been substantial evidence of disconnectedness between inflation and unemployment in the last decades. Concurrently, debates have intensified regarding whether the Phillips curve is dead. This has sparked heightened interest in deciphering its pattern, as seen in works such as Gagnon and Collins (2019), Del Negro et al. (2020), Ball et al. (2022), Hazell et al. (2022), among others. The primary challenge researchers face in estimating the structural Phillips curve is the issue of endogeneity. A large strand of literature employs aggregate-level time series data and estimates the Phillips curve as part of a structural macroeconomic model or by relying on instrumental variables. Both methods have further difficulties. Potential misspecification in any other part of the structural model might contaminate the Phillips curve estimate. The weak instruments problem exists pervasively in the aggregate level time series data – Mavroeidis, Plagborg-Møller and Stock (2014) claimed that "there simply isn't enough variation available in the aggregate data to separately identify the coefficients on unemployment and expected inflation." Given the difficulties associated with identifying the Phillips curve at an aggregate level, another strand of literature estimates the Phillips curve at a more disaggregated level. By focusing on deviations of regional inflation and unemployment, variation due to common factors determined at the aggregate level (e.g., aggregate level supply shocks, monetary policy) can be removed. We focus on this latter strand to use the disaggregate level data. By exploring the cross-sectional state-level information, we can further uncover potential heterogeneity pattern in the Phillips curve across space and time.

This paper investigates the trade-off between inflation and unemployment at a regional (state) level and tackles the following research questions: (1) Considering the unobserved heterogeneity across states in the U.S., is there still evidence of disconnectedness between inflation and unemployment? (2) How does the Phillips curve behave across different states? Is there a particular pattern? (3) Does the Phillips curve pattern alter significantly with features of the economy, and how? To answer these questions, we employ a state-level dataset of inflation and unemployment, constructed by Hazell et al. (2022), to look into both the reduced-form correlation and the structural Phillips curve, considering potential nonlinearities, in forms of state-dependence, governed by various features of the economy, as well as unobserved group pattern heterogeneity across states.

Our main findings follow the research questions posed above. Our analysis starts by examining the (reduced-form) state-level Phillips correlation and inflation forecasting relations, as defined in Stock and Watson (2020), and then moves on to estimating the structural Phillips curve, as discussed in Mavroeidis et al. (2014). Our finding reveals that, using various measures of slack economic and regional data, there has been a diminishing Phillips correlation over time, a marked instability in forecasting inflation using these candidate slack measures, and a notable flattening of the Phillips curve. These findings align with the prevalence of time variation in the existing literature.

Secondly, considering the potential disparities in the trade-off between inflation and unemployment across various states, we explore the unobserved heterogeneity across states in the Phillips curve. We find evidence of the existence of group patterns. The Phillips curve parameters remain the same within each group but vary between distinct groups. Importantly, we find the evolutions of the group-specific behaviors differ. We conclude that the flattening curve is a national phenomenon, while the disappearance of the Phillips curve is a regional phenomenon.

Thirdly, we investigate whether there are nonlinearities in the Phillips curve by considering its interaction with various feathers of the economy. We find evidence of nonlinearities resulting from the conventional and unconventional monetary policy, the expansionary and contractionary monetary policy, and the expansion and recession. (i) Comparing the regional Phillips curve patterns in conventional and unconventional times, we find substantial heterogeneity in the group-specific slopes during the latter. Some states (Alaska, Arkansas, California, Hawaii, Indiana, Louisiana, Maryland, Mississippi, New Jersey, North Carolina, Oklahoma, Oregon, Tennessee, Utah, and Virginia) have a steeper slope. In contrast, other states (Alabama, Colorado, Connecticut, District of Columbia, Florida, Georgia, Illinois, Kansas, Massachusetts, Michigan, Minnesota, Missouri, New York, Ohio, Pennsylvania, South Carolina, Texas, Washington, and Wisconsin) have an unusual positive slope estimate. Thus, we conclude that the unconventional monetary policy is more effective in these states. (ii) Comparing the regional Phillips curve patterns in expansionary and contractionary monetary policy regimes, we find evidence of lost information when ignoring the cross-sectional heterogeneity. Specifically, in the 'Contractionary' monetary policy regime, some states (Alabama, Alaska, Arkansas, Colorado, Connecticut, Florida, Georgia, Hawaii, Illinois, Indiana, Kansas, Louisiana, Maryland, Michigan, Missouri, North Carolina, Oklahoma, Oregon, Tennessee, Texas, Utah, Virginia, Washington) have a dead Phillips curve. In contrast, some other states (California, District of Columbia, Massachusetts, Minnesota, Mississippi, New Jersey, New York, Ohio, Pennsylvania, South Carolina, and Wisconsin) have a well and alive Phillips curve. (iii) Comparing the regional Phillips curve patterns during recession and expansion, we find that some states exhibit similar behavior during different times while other states exhibit very different patterns. Specifically, all the states examined have a flattening Phillips curve during the expansion. In contrast, some states (Alabama, Alaska, Arkansas, California, Colorado, Connecticut, District of Columbia, Illinois, Indiana, Kansas, Louisiana, Massachusetts, Minnesota, New Jersey, Oklahoma, Oregon, Tennessee, Utah, Virginia, and Wisconsin) have a dead Phillips curve during the expansion but a much steeper Phillips curve during a recession. This finding that the Phillips curve is well and alive during a recession is consistent with the conclusion in Blanchard (2016) as well as the findings that the Phillips curve is coming back in the recent pandemic recession periods in Inoue et al. (2023).

Compared with the literature, the main contribution of this paper is to introduce both nonlinearities and unobserved regional heterogeneity in the Phillips curve. To the best of our knowledge, the existing work in unobserved regional heterogeneity is at its early stage. A closely related paper is Smith et al. (2023), which applies a Bayesian panel method to estimate both the number and timing of breaks in the Phillips curve while determining the existence of disaggregate level clusters. We differ in the following perspectives. Regarding the form of time-variation, Smith et al. (2023) consider discrete shifts across time, while we consider time-variation that may depend on different features of the economy, which provides insights on what could be behind the change in the Phillips curve. Regarding the methodology, Smith et al. (2023) adopt a Bayesian method in detecting breaks in the group pattern of heterogeneity, while our break detection method, proposed in Huang, Sun and Wang (2023), is frequentist, which does not require priors for estimation. Besides, we further introduce a state-dependent group pattern, considering the potential interaction of the nonlinearities and the unobserved pattern of heterogeneity. Additionally, we consider instruments in identifying the Phillips curve and results across alternative specifications confirm the robustness of our findings, while Smith et al. (2023) do not use instruments and focus on the reduced-form estimation results. This paper is also closely related to Hazell et al. (2022), who estimate the slope of the Phillips curve in the cross-section of U.S. states. They find that the slope was small during the early 1980s and that there was no missing disinflation or reinflation over the past few business cycles. Compared with Hazell et al. (2022), we consider different forms of nonlinearities (state-dependence) that depend on features of the economy and allow for regional group patterns of heterogeneity. In addition, compared to the threshold panel Phillips curve in Doser et al. (2023), we allow for non-linearity in all Phillips curve's parameters instead of allowing for time variation in only the slope parameter.

The remainder of the paper is organized as follows. Section 2 examines the Phillips correlation, inflation forecasting relation, and structural Phillips curve using state-level inflation and unemployment data. Section 3 studies the group pattern of heterogeneity in the state-level Phillips curve. Section 4 looks into the Phillips curve in various states of the economy. Section 5 concludes.

2 Disconnectedness between inflation and unemployment

There is substantial empirical evidence of disconnectedness between inflation and unemployment in the recent US data, see Stock and Watson (2020). This section examines the Phillips correlation, inflation forecasting relation, and structural Phillips curve using state-level inflation and unemployment data, constructed in Hazell et al. (2022). Given the substantial evidence of the evident reduction in the cyclical correlation between inflation and real activity since the 1990s, see, e.g., Atkeson et al. (2001), Stock and Watson (2007), Stock and Watson (2008), and Stock and Watson (2020), we look into both the full sample and the pre/post-1990 subsamples throughout this section.

Our finding reveals that, using various measures of slack economic and regional data, there has been a diminishing Phillips correlation over time, a marked instability in forecasting inflation using these candidate slack measures, and a notable flattening of the Phillips curve.

2.1 State Level Phillip Correlation

We start by investigating the reduced-form relationship between inflation and the economic activity over time. We extend the Stock and Watson's (2020) time-series model into a panel version with state fixed effects, and focus on the estimated slope (β_1) in the following panel Phillips relation:

$$E_t \Delta_4 \pi_{i,t} = \beta_0 + \beta_1 x_{i,t}^4 + \mu_i, \tag{1}$$

where i refers to each state, $x_{i,t}^4$ is the four quarter moving average $x_{i,t}^4 = (\sum_{i=0}^{3} x_{i,t-l})/4$, $\Delta_4 = (1 - L^4)$ with L denoting the lag operator such that $Lx_{i,t} = x_{i,t-1}$, $\pi_{i,t}$ is the quarter-to-quarter CPI-inflation and $x_{i,t}$ is a measure of slack. The measure of slack is computed as the difference between an activity variable and the unobserved full utilization level of that variable. We choose the state-level unemployment rate and employment-population ratio as the activity variable. The slack is measured using five *ex-post* gaps and one real-time gap. The *ex-post* gaps are constructed as detrended unemployment and employment-population ratio with the underlying trend estimated from a linear or quadratic polynomial, a Hodrick–Prescott (HP) filter with a smoothing parameter of 1600 as Mavroeidis et al. (2014), a Baxter–King (BK) filter retaining cycles of duration between 6 and 32 quarters as Mavroeidis et al. (2014), or a Bi-weight filter with a bandwidth of 60 quarters as Stock and Watson (2020). The real-time gaps are computed through a one-sided exponentially-weighted moving average, with a weight of a half-life of 15 years, as Stock and Watson (2020). All the slack measures are standardized for comparison purposes.

Table 1 reports the correlation between $E_t \Delta_4 \pi_{\cdot,t}$ and $x_{\cdot,t}^4$ and the estimate of the slope β_1 in eq.(1) for various slack measures, based on the full sample and the pre-and post-1990 subsamples, respectively. Columns 2-5 display the average state-level Phillips correlation and the slope β_1, with clustered standard errors in the parentheses. Compared to the pre-1990 and post-1990 estimates, the state-level Phillips relation has dramatically flattened over time.

Additionally, we report the aggregate level time series estimation results in columns 6-9. Since the state level inflation is measured by core CPI excluding shelter, we use the aggregate level CPI for urban consumers excluding food, energy, and shelter (CPIU-xFES)[1] from Federal Reserve Economic Data (FRED). These aggregate level slack measures are similarly constructed as described above. We also consider the CBO unemployment gap and GDP gap as a supplement.

Overall, our results in Table 1 indicate that the US Phillips correlation, at both the aggregate and state levels, has been getting weaker. The results are robust across various slack measures. To complete this, we provide the results for the state-level Phillips relation assuming complete heterogeneity in Table A2 in the online Appendix. Similarly, the Phillips correlation of each state is decreasing over time.

INSERT TABLE 1 HERE

2.2 Inflation forecasting regression

Apart from the aforementioned contemporaneous Phillips relation, whether lagged values of economic slack can predict inflation is also essential to forecasters and reflects the Granger causality between inflation and economic slack. Stock and Watson (2020) investigate the aggregate level inflation forecasting regression using various gaps. They find that most gap measures worsen out-of-sample inflation forecasting performance, and there is substantial instability in this forecasting relation. In this section, we consider the panel version of Stock and Watson's (2020) prototypical Phillips curve forecasting regression:

$$\Delta_4\pi_{i,t} = \beta_0 + \beta_1 x_{i,t-4} + \beta_2\Delta_4\pi_{i,t-4} + \mu_i + e_{i,t}. \tag{2}$$

[1] Table A3 in the online appendix shows that the aggregate level result using different inflation measures have similar decreasing patterns. In particular, we consider CPI excluding food and energy (CPI-xFE), PCE excluding food and energy (PCE-xFE), CPI for urban consumers excluding food and energy (CPIU-xFE) or excluding shelters (CPIU-xS). Since food, energy, and shelter are all cyclically sensitive price components, the estimated slope of CPI-xFE, CPIU-xFE, and CPIU-xS are larger in absolute value as expected.

We investigate this panel forecasting relation instead of relying solely on time series data, as it has several advantages, including (i) exploiting information both across the state and across time, which may lead to more efficient and accurate estimates and help identify relationships that might not be apparent with purely time series inflation and slack data; (ii) incorporating individual heterogeneity and considering unobserved effects that remain constant over time.

Table 2 summarizes the results of the forecasting exercises for three forecasting models using various slack variables. We exclude the *ex-post* gaps for forecasting purposes and rely on the real-time gaps. The three blocks display the results using a panel data model with homogenous parameters, a panel data model with heterogenous parameters, and a time series model with aggregate-level data. The column labeled 'Sup-Wald test' reports the Sup-Wald test (Andrews (1993) and Hansen (1997)) results for testing instability in the parameter β_1 in eq.(2) based on the full sample estimates. The null hypothesis of stable coefficients in the forecasting regression is rejected at the 1% The column labeled 'Pseudo RMSFE ratio' reports the relative forecasting performances, measured by the ratio of the pseudo-out-of-sample root mean squared forecast errors (RMSFE) of the direct forecasting models discussed above, to the RMSFE for the corresponding restricted version without the slack variable. We consider the fixed, rolling, and recursive forecasting schemes. In line with Stock and Watson (2020), the first in-sample window is 1984Q1-2007Q1, and the out-of-sample four-quarter ahead forecasts range from 2008Q1 to 2018Q1, spanning the recession and recovery periods. Our results confirm that (i) there is evidence of instability in the forecasting relations and (ii) using gaps worsens out-of-sample performance in inflation forecasting, even when exploiting cross-sectional information. These findings are in line with the prevalence of time variation in the existing literature. The RMSFE ratio for each state when considering a complete heterogeneous panel model is provided in Table A4 in the online Appendix, which indicates similar results in most scenarios.

INSERT TABLE 2 HERE

To account for model instability in forecasting, we apply the Giacomini and Rossi (2010)'s Fluctuation test as a robustness check. This method compares the out-of-sample forecasting performance of our inflation-forecasting regression with and without the slack variable, in the presence of possible instabilities. It formally tests the null hypothesis of (1) the two models are equivalent; (2) the model with the slack variable outperforms the another; (3) the model without the slack variable outperforms the another. Similar to the previous setting, the in-sample window is 1984Q1-2007Q1, and the out-of-sample forecasts rang from 2008Q1 to 2018Q1. Table A5 in the online appendix reports the full result of Fluctuation test. The result indicates that either the adding slack variable as one of the predictor significantly worsen the forecasting performance, or the two models have no significant difference in performance. Therefore, this exercise further confirm that the forecasting relationship between the economic slack and the inflation rate experiences some nonlinearity around the Great Recession.

In addition, the time-series Fluctuation test of each state also points to the similar result. Take the recursive forecasting result as an example, the forecasting performance is significantly worse after adding the slack variable for around 30% of the states , while none of the states obtains significantly better performance. The remaining states have no significant difference within the two models. To save space, the full result is not shown in the text or appendix.

2.3 State Level Phillip Curve

Although we find the absence of a Phillips relation in Section 2, it doesn't mean that the structural Phillips curve has disappeared. The Phillips relation measures the (reduced-form) correlation between inflation and unemployment, while the Phillips curve measures the trade-off between inflation and unemployment due to supply shocks. A classic version of the Phillips curve is the hybrid New-Keynesian Phillips Curve (NKPC) by Galí and Gertler (1999):

$$\pi_t = \gamma_f E_t(\pi_{t+1}) + \gamma_b \pi_{t-1} + \lambda x_t + e_t, \tag{3}$$

where π_t denotes inflation, x_t measures the real marginal cost, $E_t(\cdot)$ denotes conditional expectations at time t, and u_t is an unobserved shock. This specification is also considered in Galí et al. (2005), Mavroeidis et al. (2014), and Barnichon and Mesters (2020), among others. As known in the literature, one of the main challenges in estimating the structural Phillips curve is the presence of endogeneity. Thus, the traditional ordinary least squares cannot consistently estimate the structural parameters, and instrument variables are required. Besides, as pointed out in the aggregate level Phillips curve literature, another challenge is the presence of weak instruments, which might cause high sampling and specification uncertainty; a minor change in the sample choice and specification might point to diverse results. Mavroeidis et al. (2014) conclude that “the literature has reached a limit on how much can be learned about the New Keynesian Phillips curve from aggregate macroeconomic time series. New identification approaches and new datasets are needed to reach an empirical consensus.” Considering there is not enough variation in the aggregate level time series data to identify the structural Phillips curve parameter, recent papers have introduced regional data to help overcome these challenges (McLeay and Tenreyro (2020), Kiley (2015), Babb and Detmeister (2017), Hooper et al. (2020), and Fitzgerald et al. (2020), Beraja et al. (2019)).

In what follows, we consider the state-level version of eq.(3) as follows:

$$\pi_{i,t} = \gamma_f \pi_{i,t+1} + \gamma_b \pi_{i,t-1} + \lambda \hat{x}_{i,t} + \mu_i + u_{i,t}, \tag{4}$$

where $\pi_{i,t}$ is the quarter-to-quarter inflation, $\hat{x}_{i,t}$ is an observable proxy for the forcing variable, and $u_{i,t} = e_{i,t} - \gamma_{i,f}(\pi_{i,t+1} - E_t(\pi_{i,t+1})) - \lambda(\hat{x}_{i,t} - x_{i,t})$ is the error term including unobserved shocks, μ_i is the state fixed effect, and $e_{i,t}$ is the measurement error. We estimate eq.(4) using instrumental variables. Our targets are the slope of the Phillips curve λ, which measures the degree to which real activity influences inflation dynamics, as well as the forward- and backward-looking parameters γ_f and γ_b, which concern the relative importance of forward- and backward-looking price setting behavior.

We focus on the specification where $x_{i,t}$ is computed through the one-sided exponentially-weighted moving average, following Stock and Watson (2020). The instruments considered are four lags of inflation and two lags of the slack variable. We focus on the specification where $x_{i,t}$ is computed through the one-sided exponentially-weighted moving average, following Stock and Watson (2020). The instruments considered are four lags of inflation and two lags of the slack

variable.

Table A6 in the online Appendix presents estimates of the first-stage regression for our IV estimates, indicating that the instruments are strong and that the panel instruments are stronger than those in the time-series setting.

We use the two-sample two-stage least squares (TS2SLS) estimation method, inspired by Hazell et al. (2022), to alleviate the effect of missing data during 1987-1988 as well as missing observations when using lags as instruments. Although both generalized instrumental variables (GIV) and two-stage least squares (2SLS) have been considered in the aggregate level Phillips curve literature, in this context, we mainly rely on TS2SLS instead of two-sample instrumental variables (TSIV), as the TS2SLS estimator is more asymptotically efficient than the TSIV estimator, see Inoue and Solon (2010). Additionally, the standard errors are clustered at the state level for panel data and adjusted to a TS2SLS version following Chodorow-Reich and Wieland (2020).

Table 3 reports the estimates of λ and γ_f in eq.(4) with a restriction $\gamma_f + \gamma_b = 1$, which is often imposed in empirical studies and is consistent with the existence of a vertical long-run Phillips curve, see Mavroeidis et al. (2014) and Barnichon and Mesters (2020). Considering potential time variation, we report the estimates based on the full sample (1979-2017), as well as the pre-and post-1990 subsamples, respectively. For comparison purposes, the estimates obtained from the corresponding time series regression in eq.(3) using aggregate level data are also reported. Figure 1 further compares the pre- and post-1990 state-level estimates. Panels (a) presents the point estimates of (λ, γ_f) together with the 68%, 90%, and 95% confidence regions. The pre-1990 results are presented in blue, and the post-1990 results in orange. Panels (b) presents the point estimates of various measures of slack, indicating that our results are robust.

Our results indicate a decrease in the slope of the structural Phillips curve λ, comparing the pre-1990 and post-1990 subsample estimates, which complies with the aggregate level time series estimates as well as the existing literature. The absolute value of the slope has decreased substantially from 0.218 to 0.015, which is statistically insignificantly different from zero. Also, in line with the regional Phillips curve literature, our state-level estimates are steeper than the slope estimated for the aggregate Phillips curve, no matter whether we look at the full sample or subsamples. Besides, our state-level estimation results reveal that the Phillips curve has become much more forward-looking after 1990, as the forward-looking component (γ_f) has increased from 0.133 to 0.531, implying that the importance of the backward-looking component in the Phillips curve has decreased.

INSERT TABLE 3 HERE

INSERT FIGURE 1 HERE

To complement this, we provide some robustness checks in the online Appendix. Table A7 reports the estimates obtained using an alternative estimation method, including the two-step GMM and continuously updated estimator (CUE) GMM with clustered error and the heteroscedastic and auto-correlated (HAC) robust error. Tables A9, A16 and Figure A5 report the results obtained without the restriction $\gamma_f + \gamma_b = 1$.

3 Group Pattern in State Level Phillips Curve

We have heretofore assumed homogeneity in the coefficients in eq.(4). Considering the potential disparities in the trade-off between inflation and unemployment across various states, we now assume the existence of a grouped pattern of heterogeneity. That is, the Phillips curve parameters remain the same within each group but vary between distinct groups. Identifying clusters that exhibit common patterns within Phillips curves can illuminate the underlying sources of these patterns. This phenomenon helps facilitate the analysis of factors affecting the trade-off between inflation and unemployment, exhibiting potential regional variations. Uncovering the underlying group patterns further assists in pinpointing the origins of the patterns of the Phillips curves.

Let β_i include the Phillips curve parameters in eq.(4) for state i, such that $\beta_i = (\lambda_i, \gamma_{f,i}, \gamma_{b,i})$, and it follows the group pattern:

$$\beta_i = \sum_{k=1}^{K} \theta_k 1\{i \in G_k\} \tag{5}$$

where $\theta_j \neq \theta_k$ for any $j \neq k$, $\cup_{k=1}^{K} G_k = \{1, 2, \cdots, N\}$, and $G_j \cap G_k = \varnothing$ for any $j \neq k$. Both the number of groups K and group membership G_k (i.e., the states assigned to group k) are unknown and to be determined by the data. Using the information criterion in Su et al. (2016), we find evidence of group patterns. The information criterion suggests the number of groups $\widehat{K} = 2$ across various choices of tuning parameters considering either full sample or subsamples; see detailed results in Table 4 and Figure A1 in the online Appendix.

INSERT TABLE 4 HERE

Table 5 presents the group-specific estimates of θ_k in eq.(5), using the Classifier-Lasso method proposed in Su et al. (2016) and considering two groups.[2] Given the evidence of time variation in the previous exercise, we report results for both the full sample and the pre-and post-1990 subsamples. The break date (1990Q4) is detected using the algorithm in Huang, Sun and Wang (2023). Figure 2 further compares the pre- and post-1990 group-specific state-level estimates. Panels (a) presents the group-specific point estimates of (λ, γ_f) together with the 68%, 90%, and 95% confidence regions. The pre-1990 results are presented in blue, and the post-1990 results in orange, with the hollow and filled circles denoting the two groups, respectively. Panels (b) presents the group-specific point estimates of various measures of slack, indicating that our results are robust.

Figure A2 and A3 in the online Appendix provide the group membership results using the real-time unemployment gap and averaged across twelve distinct slack measures, implying robustness in the group classification.

For each set of results, we report in a row 'Chow test' the Chow test statistics with the significance levels testing whether the group-specific estimates differ across groups, providing evidence of a significant difference in group-specific estimates. Our results indicate the following: (i) Comparing pre- and post-1990 results, a common pattern across two groups is a weakening of the slope of the Phillips curve across time. (ii) States in Group 1 have experienced a larger change

[2]Due to data limitation, there are 21 and 34 states before and after the year 1990, respectively. We refer to readers to Hazell et al. (2022) for a detailed discussion.

in the slope λ than those in Group 2. Although the Phillips curves of both groups become flatter after 1990, only the curve of Group 2 vanishes, which points to -0.002 and is indistinguishable from zero. Therefore, we conclude that the flattening curve is a national phenomenon, while the disappearance of the Phillips curve is only a regional phenomenon. (iii) Besides, in both pre-and post-1990 subsamples, Group 1 has a larger γ_f and thus smaller γ_b, indicating that states in Group 1 are more forward-looking and less backward-looking than those in Group 2.

INSERT TABLE 5 HERE

INSERT FIGURE 2 HERE

4 Does Phillips curve shift with features of the economy?

There is substantial evidence that features of the economy affect macroeconomic modeling and forecasting (Ng and Wright (2013)), the effectiveness of public policies (Tenreyro and Thwaites (2016), Ramey and Zubairy (2018), and Barnichon et al. (2022)), etc. Considering the potential interaction, the Phillips curve might also exhibit different patterns according to the features of the economy, and it would be essential for policymakers to uncover how different economic features shift the Phillips curve. In this section, we tackle this question by looking into the following state-dependent Phillips curve:

$$\begin{aligned}\pi_{i,t} = {} & I_{t-1}(\lambda_A x_{i,t} + \gamma_{f,A}\pi_{i,t+1} + \gamma_{b,A}\pi_{i,t-1} + \alpha_A) \\ & + (1 - I_{t-1})(\lambda_B x_{i,t} + \gamma_{f,B}\pi_{i,t+1} + \gamma_{b,B}\pi_{i,t-1} + \alpha_B) + \mu_i + u_{i,t},\end{aligned} \tag{6}$$

where I_{t-1} is a dummy variable that indicates the state of the economy, depending on the value of the state variable z at period $t-1$. $I_{t-1} = 1$ if a certain state variable is above a threshold $\bar{z}$ (i.e., if $z_{t-1} > \bar{z}$). Following Ramey and Zubairy (2018), all the state variables we use are lags. The subscripts A, B refer to different states. Following Ramey and Zubairy (2018), the instruments are the intersection of the state variables I_{t-1} and $(1 - I_{t-1})$, and the four inflation lags and two slack lags.

We investigate whether the Phillips curve parameters exhibit different patterns according to important features of the economy, including (1) whether interest rates are near ZLB, (2) monetary policy shocks of different kinds (contractionary or expansionary), and (3) whether the economy is in recession.[3] In each scenario, we further allow for unobserved group pattern of heterogeneity by letting β_i include the state-dependent Phillips curve parameters in eq.(6) for state i, such that $\beta_i = (\lambda_{A,i}, \gamma_{f,A,i}, \gamma_{b,A,i}, \lambda_{B,i}, \gamma_{f,B,i}, \gamma_{b,B,i}) = \theta_k$, which investigates whether and how the unobserved heterogeneity exhibits different patterns according to the aforementioned features of the economy.

4.1 Phillips curve during times of unconventional monetary policy

Researchers and policy makers have made multiple explanations for the apparent flattening of the Phillips curve, among which endogenous monetary policy actions could be an essential factor, see Haldane and Quah (1999), Roberts (2006), Williams (2006), Mishkin (2007), Carlstrom et al. (2009), and McLeay and Tenreyro (2020). When inflation rises, the Fed tightens monetary policy to stabilize inflation and anchor inflation expectations, causing unemployment to rise. This creates a positive link between inflation and the unemployment gap that biases the Phillips curve slope towards zero. However, in unconventional times (at the ZLB), the short-term interest rate cannot be lowered further to stimulate the economy, and the monetary policy transmission mechanism may also change.

In this subsection, we investigate whether the Phillips curve pattern changes in unconventional times when the interest rates are near the zero lower bound. Following Ramey and Zubairy (2018), we consider the 3-month t-bill treasury rate as the state variable. The 'ZLB state' is defined to be 2008Q4–2016Q4, during which the 3-month t-bill treasury rate is lower than 0.5%.

Table 6 presents the pool estimates as well as the group-specific estimates of the parameters in eq.(6). The column 'Pooled' in Table 6 reports the ZLB-dependent pool estimates when assuming cross-sectional homogeneity, with Figure 4 comparing the ZLB-dependent pool estimates with confidence sets. We also implement a Chow test testing whether the estimates differ across two

[3]See Figure 3 for all the state variables.

states. The test statistic is 114.701, which is significant at 1% level, providing evidence of the difference in the pattern of the Phillips curve during conventional and unconventional times. The estimates of the slope (λ) indicate that, in both non-ZLB and ZLB times, the slope is small but significant and that the slope in non-ZLB is steeper than that in ZLB, which to some degree, implies that the unconventional monetary policy is effective in stabilize inflation and anchor inflation expectations, causing the unemployment to rise. Besides, the estimates of the forward-looking component (γ_f) indicate that the forward-looking component is more important in the ZLB time than the non-ZLB.

The column 'C-Lasso' in Table 6 reports the ZLB-dependent group-specific estimates when assuming an unobserved group pattern of heterogeneity. We implement a Chow test to test whether the parameters are distinct across two groups. The test statistic is 17.798, which is significant at 1% significance level, providing evidence of a significant difference in group-specific estimates. Figure 5 further compares the ZLB-dependent group-specific estimates. Panels (a) presents the group-specific point estimates of (λ, γ_f) together with the 68%, 90%, and 95% confidence regions. The non-ZLB estimates are presented in blue and the ZLB estimates in orange, with the hollow and filled circles denoting the two groups, respectively. Panels (b) presents the point estimates of various measures of slack for robustness check. Figure 6 presents the group membership, identifying states with similar or differing patterns. Our results indicate the following: During the conventional time (non-ZLB), both groups have small but significant slopes (λ), and the group-specific estimates of λ are close in value, not exhibiting much heterogeneity. In contrast, the group-specific slopes (λ) exhibit more heterogeneity in unconventional times (ZLB). States in Group 2 (Alaska, Arkansas, California, Hawaii, Indiana, Louisiana, Maryland, Mississippi, New Jersey, North Carolina, Oklahoma, Oregon, Tennessee, Utah, Virginia) have a steeper slope, while states in Group 1 (Alabama, Colorado, Connecticut, District of Columbia, Florida, Georgia, Illinois, Kansas, Massachusetts, Michigan, Minnesota, Missouri, New York, Ohio, Pennsylvania, South Carolina, Texas, Washington, Wisconsin) have an unusual positive slope estimate. This might imply that the unconventional monetary policy is more effective in states in Group 1. Besides, the forward-looking component for states in both groups during ZLB is more important than during non-ZLB.

In addition, we report in Figure A4a in the online Appendix the group membership averaged across twelve distinct slack measures.

INSERT TABLE 6 HERE

INSERT FIGURE 4 HERE

INSERT FIGURE 5 HERE

INSERT FIGURE 6 HERE

4.2 Phillips curve in different monetary policy regimes

As is shown in the literature, see Tenreyro and Thwaites (2016), the response of the economy to monetary policy shocks may be nonlinear. Monetary policy shocks of different kinds (positive and negative shocks) may have different effects on the economy, which could lead to different patterns of the Phillips curve as responses of inflation and unemployment to a contractionary and an expansionary monetary policy shock may be different.

Considering this potential interaction, we investigate whether the Phillips curve pattern changes during different monetary policy regimes. Specifically, we define the 'Expansionary' state and the 'Contractionary' state according to the sign of the monetary policy shock. We use the monetary policy shock constructed by Romer and Romer (2004) and extended to 2007Q4 by Wieland and Yang (2020).

Table 7 presents the pool estimates as well as the group-specific estimates of parameters during different monetary policy regimes. The column 'Pooled' in Table 7 reports the (monetary policy) sign-dependent estimates when assuming across-sectional homogeneity, with Figure 7 comparing the sign-dependent pool estimates. We also implement a Chow test to test whether the estimates differ across the two regimes. The test statistic is 1.135, which is insignificant at 10% significance level, suggesting no significant difference in the estimates of the Phillips curve across the two regimes. The estimates indicate that, in both contractionary and expansionary monetary policy regimes, the slopes are small but significant and that the slopes in the two regimes are close in value. Also, the estimates of the forward-looking component (γ_f) indicate similar importance in the two regimes.

The column 'C-Lasso' in Table 7 reports the (monetary policy) sign-dependent group-specific estimates when assuming unobserved group pattern of heterogeneity. We implement a Chow test to test whether the parameters are distinct across two groups. The test statistic is 10.257, which is significant at 1% significance level, providing evidence of a significant difference in group-specific estimates. Figure 8 further compares the (monetary policy) sign-dependent group-specific estimates. Figure 9 presents the group membership, identifying states with similar or differing patterns. In addition, we report in Figure A4b in the online Appendix the group membership averaged across twelve distinct slack measures. Our results indicate the following: Useful information may be lost when ignoring the heterogeneity and using the pool estimates only. – In the 'Expansionary' monetary policy regime, there is not much heterogeneity, which is consistent with the pool estimates. However, in the 'Contractionary' monetary policy regime, there is great heterogeneity that has been unaccounted for. Specifically, in the 'Contractionary' monetary policy regime, states in Group 1 (Alabama, Alaska, Arkansas, Colorado, Connecticut, Florida, Georgia, Hawaii, Illinois, Indiana, Kansas, Louisiana, Maryland, Michigan, Missouri, North Carolina, Oklahoma, Oregon, Tennessee, Texas, Utah, Virginia, Washington) have a slope (λ) estimate of 0.004, which is insignificantly different from zero, implying disappearance of Phillips curve; while states in Group 2 (California, District of Columbia, Massachusetts, Minnesota, Mississippi, New Jersey, New York, Ohio, Pennsylvania, South Carolina, Wisconsin) have a slope (λ) estimate of -0.172, which implies a well and alive Phillips curve. Besides, after considering the group pattern of heterogeneity, the group-specific estimates in both groups exhibit great differences across the two regimes, although the pool estimates indicate the opposite. Specifically, states in Group 1 have a much more flattening curve in the 'Contractionary' regime than in the 'Expansionary' regime, while states in Group 2 have a much steeper curve in the 'Contractionary' regime than in the 'Expansionary' regime.

INSERT TABLE 7 HERE

INSERT FIGURE 7 HERE

INSERT FIGURE 8 HERE

INSERT FIGURE 9 HERE

4.3 Phillips curve during recession

There has been substantial empirical evidence of changes in macroeconomic dynamics during recessions. Take the Great Recession, for instance. In 2006-2007, the unemployment rate was below 5 percent. However, it surged to 10 percent by the end of 2009 before eventually dropping to below 4 percent again. While inflation has remained remarkably stable, with core inflation ranging between 1 and 2.5 percent most of the time. In occasional periods, it dipped below 1 percent. All this evidence implies different patterns in the inflation-unemployment trade-off during recessions, and it would be essential to statistically verify whether the Phillips curve pattern has significantly changed during recessions and figure out how. Due to data constraints, we lack state-level inflation and unemployment data during the recent pandemic. Nonetheless, insights from recession-dependent outcomes can offer a perspective on the potential behavior of the Phillips curve during the recent period, often considered a recession.

In what follows, we investigate whether the Phillips curve pattern has significantly changed during recessions and how. The 'recession state' is defined based on the NBER recession dates.[4]

Table 8 presents the pool estimates as well as the group-specific estimates of parameters during recessions and expansions, with two groups considered. The column 'Pooled' in Table 8 reports the recession-dependent estimates when assuming across-sectional homogeneity, with Figure 10 comparing the recession-dependent pool estimates. We also implement a Chow test to test whether the estimates differ between recession and expansion. The test statistic is 17.171, which is significant at 1% level, providing evidence of a difference in the pattern of the Phillips curve during recession and expansion. The estimates indicate that the slope (λ) during expansion is indistinguishable

[4]The dates are extracted from NBER public use date archive.

from zero, while it is significant during recession. Besides, the estimates of the forward-looking component (γ_f) during recession and expansion are close in value.

The column 'C-Lasso' in Table 8 reports the recession-dependent group-specific estimates when assuming unobserved group patterns of heterogeneity. We implement a Chow test testing whether the recession-dependent parameters are distinct across two groups. The test statistic is 10.225, which is significant at 1% significance level, providing evidence of a significant difference in group-specific estimates. Figure 11 further compares the recession-dependent group-specific estimates.

Figure 12 presents the group membership, identifying states with similar or differing patterns. Our results indicate the following: Group 1 has stable group-specific estimates of both the slope (λ) and the forward-looking component (γ_f). In both recession and expansion, states in Group 1 (Florida, Georgia, Hawaii, Maryland, Michigan, Mississippi, Missouri, New York, North Carolina, Ohio, Pennsylvania, South Carolina, Texas, and Washington) have a dead Phillips curve with insignificant slopes (λ). In contrast, states in Group 2 (Alabama, Alaska, Arkansas, California, Colorado, Connecticut, District of Columbia, Illinois, Indiana, Kansas, Louisiana, Massachusetts, Minnesota, New Jersey, Oklahoma, Oregon, Tennessee, Utah, Virginia, Wisconsin) exhibit very different patterns in recession and expansion – the slope (λ) is brought to 0.013 during expansion, which is insignificantly different from zero implying a dead Phillips curve; while the slope (λ) is brought to -0.258 during recession, which is much steeper. This finding implies that the Phillips curve is well and alive during the recession, which is consistent with the conclusion in Blanchard (2016) as well as the recent findings that the Phillips curve is coming back in the recent pandemic recession periods in Inoue et al. (2023). This finding is opposite to Smith et al. (2023) who find the price Phillips curve relatively steep when the economy is running hot.

Besides, the forward-looking component for states in Group 2 is more important than those in Group 1 during both recession and expansion.

In addition, we report in Figure A4c in the online Appendix the results based on twelve distinct slack measures.

INSERT TABLE 8 HERE

INSERT FIGURE 10 HERE

INSERT FIGURE 11 HERE

INSERT FIGURE 12 HERE

5 Conclusion

We contribute to the trade-off between unemployment and inflation by offering insights from a nonlinear panel approach. Our approach takes into account nonlinearities according to different features of the economy as well as unobserved heterogeneity across different states in the U.S. We find evidence of both nonlinearities and group patterns in the Phillips curve. Besides, we conclude that the disappearance of the Phillips curve is a regional and sporadical phenomenon. There are several interesting topics for further research. First, it may be interesting to investigate what characteristics are driving the group pattern, that is, the common behavior and the diverse behavior across states. Second, it may be interesting to introduce more flexible time-variation in the framework while considering the unobserved heterogeneity simultaneously. We leave these topics for future research.

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Figures and Tables

Table 1: **State and nation level Phillips relation.** The table shows the estimated correlation and slope in the Phillips relation: $E_t\Delta_4\pi_{i,t} = \beta_0 + \beta_1 x^4_{i,t} + \mu_i$, where $x^4_{i,t}$ is the four quarter moving average $x^4_{i,t} = (\sum_{i=0}^{3} x_{i,t-l})/4$ and $\Delta_4 = (1-L^4)$, L denotes the lag operator such that $Lx_{i,t} = x_{i,t-1}$. Inflation is measured by state CPI from Hazell et al. (2022) for panel data and CPIU-xFES for time series. x_{it} is various slacks, see Mavroeidis et al. (2014) and Stock and Watson (2020). Standard error is clustered at state level for panel data and adjusted by Newey and West (1987) using 8 lags for time series. The sample periods of full sample, pre- and post-1990 are 1979-2017, 1979-1990 and 1991-2017. There are 21 and 34 states in the pre- and post-1990 subsamples.

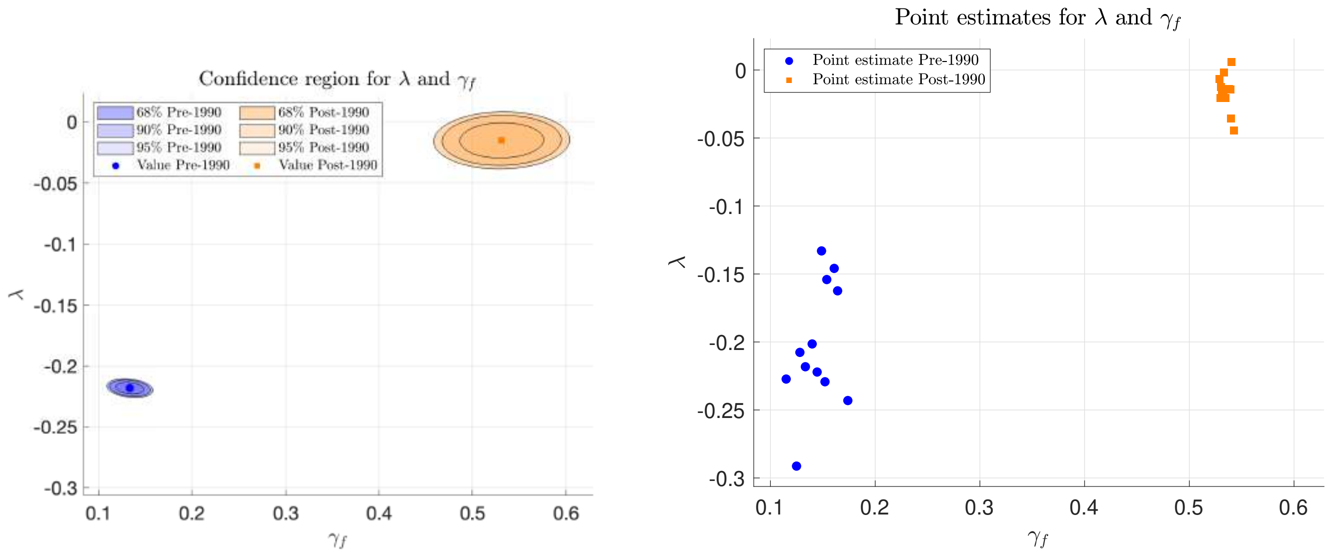
	Panel data: State-Level CPI						**Aggregate: CPIU-xFES**					
	Correlation			**Slope (SE)**			**Correlation**			**Slope (SE)**		
Slack	**Full sample**	**Pre-1990**	**Post-1990**	**Full sample**	**Pre-1990**	**Post-1990**	**Full sample**	**Pre-1990**	**Post-1990**	**Full sample**	**Pre-1990**	**Post-1990**
Unemployment rate	-0.139	-0.412	-0.072	-0.309	-0.791	-0.169	-0.455	-0.700	-0.255	-0.378	-0.774	-0.161
(Baxter-King filtered)				(0.044)	(0.089)	(0.045)				(0.164)	(0.133)	(0.087)
Unemployment rate	-0.136	-0.421	-0.068	-0.329	-0.890	-0.159	-0.457	-0.727	-0.250	-0.412	-0.868	-0.156
(Hodrick-Prescott filtered)				(0.063)	(0.183)	(0.044)				(0.157)	(0.090)	(0.079)
Unemployment rate	-0.122	-0.375	-0.060	-0.283	-1.090	-0.134	-0.325	-0.709	-0.106	-0.289	-0.993	-0.060
(Linear detrended)				(0.042)	(0.233)	(0.024)				(0.161)	(0.166)	(0.065)
Unemployment rate	-0.123	-0.393	-0.061	-0.293	-1.143	-0.135	-0.332	-0.729	-0.107	-0.297	-1.002	-0.061
(Quadratic detrended)				(0.044)	(0.239)	(0.025)				(0.165)	(0.150)	(0.065)
Unemployment rate	-0.138	-0.377	-0.071	-0.319	-0.967	-0.163	-0.370	-0.685	-0.157	-0.324	-0.875	-0.093
(Bi-weight filtered)				(0.045)	(0.211)	(0.030)				(0.163)	(0.178)	(0.076)
Unemployment rate	-0.111	-0.291	-0.055	-0.293	-1.188	-0.143	-0.307	-0.675	-0.078	-0.272	-0.928	-0.045
(Real time filtered)				(0.044)	(0.250)	(0.029)				(0.164)	(0.178)	(0.062)
Employment-population ratio	-0.095	-0.379	-0.032	-0.213	-0.769	-0.073	-0.457	-0.710	-0.237	-0.379	-0.766	-0.152
(Baxter-King filtered)				(0.055)	(0.177)	(0.045)				(0.151)	(0.151)	(0.080)
Employment-population ratio	-0.098	-0.385	-0.033	-0.227	-0.768	-0.077	-0.459	-0.733	-0.231	-0.422	-0.849	-0.149
(Hodrick-Prescott filtered)				(0.084)	(0.305)	(0.043)				(0.146)	(0.108)	(0.081)
Employment-population ratio	-0.079	-0.243	-0.025	-0.126	-0.698	-0.056	-0.214	-0.473	-0.068	-0.158	-0.638	-0.042
(Linear detrended)				(0.033)	(0.178)	(0.022)				(0.151)	(0.354)	(0.064)
Employment-population ratio	-0.089	-0.358	-0.033	-0.213	-1.101	-0.071	-0.317	-0.716	-0.092	-0.290	-1.016	-0.052
(Quadratic detrended)				(0.045)	(0.262)	(0.024)				(0.148)	(0.191)	(0.059)
Employment-population ratio	-0.091	-0.292	-0.031	-0.173	-0.749	-0.070	-0.284	-0.553	-0.110	-0.232	-0.730	-0.067
(Bi-weight filtered)				(0.033)	(0.230)	(0.024)				(0.144)	(0.306)	(0.064)
Employment-population ratio	-0.026	-0.260	-0.007	-0.092	-1.308	-0.019	-0.129	-0.550	0.027	-0.123	-1.097	0.015
(Real time filtered)				(0.028)	(0.270)	(0.022)				(0.089)	(0.443)	(0.059)
Unemployment gap (CBO)	/	/	/	/	/	/	-0.326	-0.712	-0.107	-0.290	-1.004	-0.061
				/	/	/				(0.163)	(0.162)	(0.065)
GDP gap (CBO)	/	/	/	/	/	/	-0.266	-0.719	-0.143	-0.250	-1.362	-0.077
				/	/	/				(0.131)	(0.190)	(0.063)

Table 2: **Forecasting annual changes in inflation.** The first column reports the Sup-Wald statistic (15% trimming) testing the null hypothesis that all three coefficients are stable in the four-quarter ahead direct forecasting regression $\Delta_4\pi_{i,t} = \beta_0 + \beta_1 x_{i,t-4} + \beta_2\Delta_4\pi_{i,t-4} + \mu_i + e_{i,t}$, when estimated over 1984Q1-2017Q4. **Rejects the null of constant coefficients at the 1% significance level. The remaining columns report the out-of-sample performance of the forecasting regression. It shows the pseudo out-of-sample RMSFE ratio, which is defined as the ratio of the pseudo out-of-sample root mean squared forecast errors of the direct forecasting regression above, to the RMSFE for the restricted version without the slack variable. The fixed estimation window is 1983Q1-2007Q1, and the RMSFEs are computed over 2008Q1-2017Q4. The rolling and recursive windows are modified from the fixed window. Inflation is measured by state CPI from Hazell et al. (2022) for panel data and CPIU-xFES for time series. The gap is computed through the one-sided exponentially-weighted moving average following Stock and Watson (2020).

Predictor slack variable	**Sup-Wald test**	**Pseudo RMSFE ratio**		
		Fixed	**Rolling**	**Recursive**
Panel data with homogeneity				
Unemployment rate	40.212**	1.068	1.031	1.060
Employment-population ratio	48.208**	1.157	1.028	1.085
Unemployment rate (real time gap)	48.505**	1.078	1.035	1.070
Employment-population ratio (real time gap)	38.140**	1.083	1.019	1.041
Panel data with heterogeneity				
Unemployment rate	/	1.094	1.105	1.123
Employment-population ratio	/	1.145	1.125	1.139
U. (real time gap)	/	1.111	1.117	1.138
E-p (real time gap)	/	1.155	1.128	1.143
Time series (aggregate level) data				
Unemployment rate	15.985**	1.222	0.996	1.128
Employment-population ratio	23.029**	1.251	1.001	1.114
Unemployment rate (real time gap)	18.502**	1.676	1.156	1.369
Employment-population ratio (real time gap)	29.479**	1.816	1.114	1.233

Table 3: **State and nation level Phillips curve given $\gamma_f + \gamma_b = 1$.** The table lists the coefficients of the structural Phillips curve $\pi_{i,t} = \lambda x_{i,t} + \gamma_f \pi_{i,t+1} + \gamma_b \pi_{i,t-1} + \mu_i + u_{i,t}$ given $\gamma_f + \gamma_b = 1$, estimated using TS2SLS. Inflation is measured by state CPI from Hazell et al. (2022) for panel data and CPIU-xFES for time series. The slack is unemployment gap obtained using the one-sided exponentially-weighted moving average following Stock and Watson (2020). The instruments include four inflation lags and two slack lags. Standard error is clustered at state level for panel data and adjusted to a TS2SLS version, following Chodorow-Reich and Wieland (2020). Adjusted R-squared is reported. The sample periods of full sample, pre- and post-1990 are 1979-2017, 1979-1990 and 1991-2017. There are 21 and 34 states in the pre- and post-1990 subsamples.

Slack: U. Gap (Real time)	**Panel data: State-level CPI**			**Aggregate: CPIU-xFES**		
	Full sample	**Pre-1990**	**Post-1990**	**Full sample**	**Pre-1990**	**Post-1990**
λ	-0.028	-0.218	-0.015	-0.014	-0.122	0.009
	(0.005)	(0.003)	(0.010)	(0.024)	(0.017)	(0.025)
γ_f	0.385	0.133	0.531	0.415	0.410	0.267
	(0.009)	(0.010)	(0.030)	(0.098)	(0.093)	(0.087)
Obs.	4395	672	3672	156	48	108
Adj. R-sq	0.080	0.052	0.102	0.092	0.246	0.007
State effects	✓	✓	✓	×	×	×



(a) Confidence region for λ and γ_f (b) Point estimates for λ and γ_f

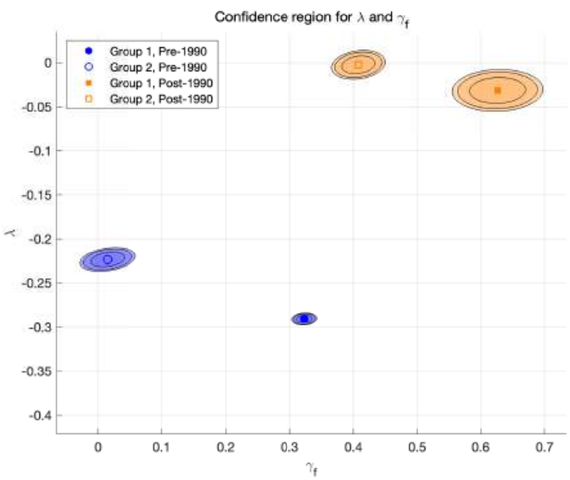
Figure 1: **State level Phillips curve given $\gamma_f + \gamma_b = 1$ before and after 1990.** This figures shows the coefficient estimates and confidence region of the structural Phillips curve $\pi_{i,t} = \lambda x_{i,t} + \gamma_f \pi_{i,t+1} + \gamma_b \pi_{i,t-1} + \mu_i + u_{i,t}$ given $\gamma_f + \gamma_b = 1$, estimated using TS2SLS. Inflation is measured by state CPI from Hazell et al. (2022). Panel (a) shows the estimated value (dot), 95%, 90%, and 68% confidence region (shadows) in the (λ, γ_f) space, where $x_{i,t}$ is unemployment gap obtained using the one-sided exponentially-weighted moving average following Stock and Watson (2020). Panel (b) shows the point estimates of various slacks from Stock and Watson (2020) and Mavroeidis et al. (2014) in the (λ, γ_f) space. The slacks include detrended series of unemployment rate and employment-population ratio using HP filter, BK filter, linear detrending, quadratic detrending, Bi-weight filter and one-sided exponentially weighted moving average. The instruments include four inflation lags and two slack lags. Standard error is clustered at state level for panel data and adjusted to a TS2SLS version, following Chodorow-Reich and Wieland (2020). The sample periods of pre- and post-1990 are 1979-1990 and 1991-2017. There are 21 and 34 states in the pre- and post-1990 subsamples.

Table 4: **Group selection of state level Phillips curve before and after 1990.** This table shows the information criterion $IC(K) = \ln \hat{\sigma}_K^2 + \rho_p K(NT)^{-1/2}$ of the group-specific Phillips curve $\pi_{i,t} = \lambda_i x_{i.t} + \gamma_{f,i}\pi_{i,t+1} + \gamma_{b,i}\pi_{i,t-1} + \mu_i + u_{i,t}$ given $\gamma_f + \gamma_b = 1$ where $\rho_p = \rho \cdot p$, $\beta_i = (\lambda_i, \gamma_{f,i})' = \theta_k$ if $i \in G_k, k = 1, .., K$ against the number of groups K. Inflation is measured by state CPI from Hazell et al. (2022). The slack is unemployment gap obtained using the one-sided exponentially-weighted moving average following Stock and Watson (2020). The instruments include four inflation lags and two slack lags. The model is estimated by C-Lasso and TS2SLS. The sample periods of full sample, pre- and post-1990 are 1979-2017, 1979-1990 and 1991-2017. There are 21 and 34 states in the pre- and post-1990 subsamples.

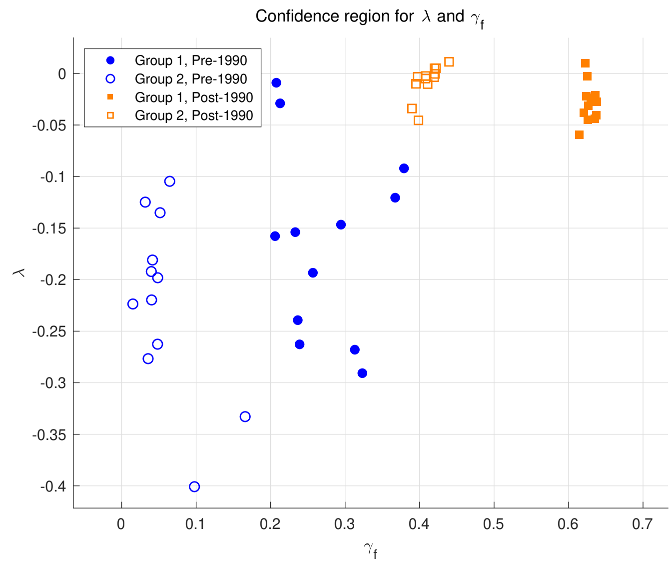
Slack: U. Gap	**Full sample**			**Pre-1990**			**Post-1990**		
(Real time)	ρ_p = **0.1**	**0.2**	**0.3**	**0.1**	**0.2**	**0.3**	**0.1**	**0.2**	**0.3**
$K = 1$	0.024	0.025	0.027	-0.131	-0.127	-0.123	0.028	0.030	0.032
$K = 2$	0.016	0.019	0.022	-0.152	-0.144	-0.137	0.025	0.029	0.032
$K = 3$	0.016	0.020	0.025	-0.154	-0.142	-0.131	0.025	0.030	0.035
$K = 4$	0.017	0.023	0.029	-0.150	-0.134	-0.119	0.029	0.036	0.042
$K = 5$	0.019	0.027	0.034	-0.141	-0.122	-0.102	0.030	0.039	0.047
Selected K	2	2	2	3	2	2	2	2	1

Table 5: **Group-specific Philips curve.** This table lists the coefficients of the group-specific structural Phillips curve $\pi_{i,t} = \lambda_i x_{i.t} + \gamma_{f,i}\pi_{i,t+1} + \gamma_{b,i}\pi_{i,t-1} + \mu_i + u_{i,t}$ given $\gamma_f + \gamma_b = 1$ where $\beta_i = (\lambda_i, \gamma_{f,i})' = \theta_k$ if $i \in G_k, k = 1, 2$, estimated using C-Lasso and TS2SLS. Inflation is measured by state CPI from Hazell et al. (2022) and slack is unemployment gap obtained using the one-sided exponentially-weighted moving average following Stock and Watson (2020). The instruments include four inflation lags and two slack lags. Standard error is clustered at state level for panel data and adjusted to a TS2SLS version, following Chodorow-Reich and Wieland (2020). The proportion of states in each group is reported as %G1. Adjusted R-squared is reported. Joint difference between vectors θ_1 and θ_2 is tested by Chow test. **Reject the null of constant coefficients at the 1% significance level. The sample periods of full sample, pre- and post-1990 are 1979-2017, 1979-1990 and 1991-2017. There are 21 and 34 states in the pre- and post-1990 subsamples.

Slack: U. Gap (Real time)	**Full sample**		**Pre-1990**		**Post-1990**	
	G1	**G2**	**G1**	**G2**	**G1**	**G2**
λ	-0.027	-0.046	-0.291	-0.224	-0.031	-0.002
	(0.008)	(0.005)	(0.003)	(0.002)	(0.010)	(0.007)
γ_f	0.508	0.249	0.323	0.015	0.626	0.408
	(0.023)	(0.012)	(0.008)	(0.003)	(0.029)	(0.017)
Obs.	2351	2044	288	384	2052	1620
Adj. R-sq	0.107	0.052	0.099	0.043	0.151	0.053
State effects	✓	✓	✓	✓	✓	✓
%G1	55.88%		42.86%		55.88%	
Chow test	3.419*		4.151*		34.000**	

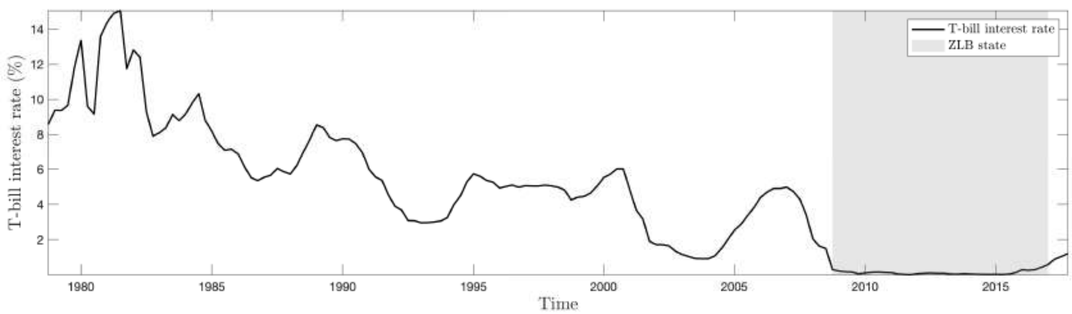


(a) Confidence region for λ and γ_f

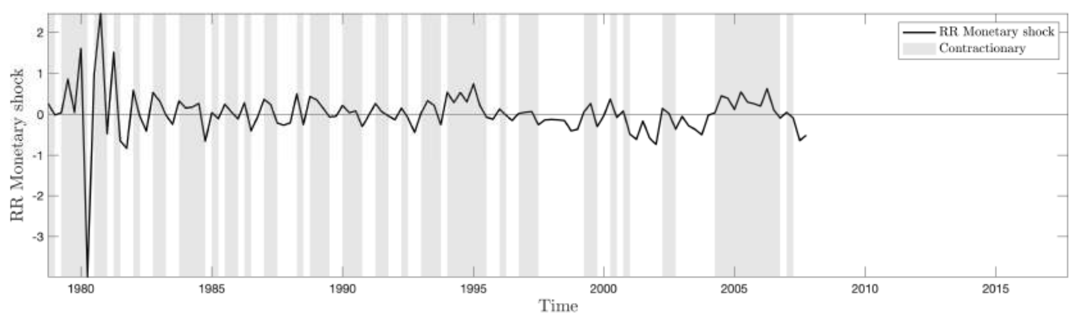


(b) Point estimates for λ and γ_f

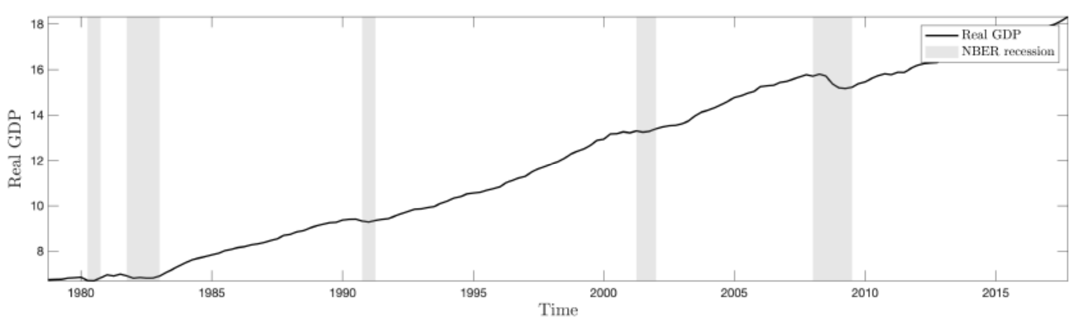
Figure 2: **Group-specific state level Phillips curve given $\gamma_f + \gamma_b = 1$ before and after 1990.** This figures shows the coefficient estimates and confidence region of the group-specific Phillips curve $\pi_{i,t} = \lambda_i x_{i.t} + \gamma_{f,i}\pi_{i,t+1} + \gamma_{b,i}\pi_{i,t-1} + \mu_i + u_{i,t}$ given $\gamma_{f,i} + \gamma_{b,i} = 1$ where $\beta_i = (\lambda_i, \gamma_{f,i})' = \theta_k$ if $i \in G_k, k = 1, 2$, estimated using C-Lasso and TS2SLS. Inflation is measured by state CPI from Hazell et al. (2022). The instruments include four inflation lags and two slack lags. Panel (a) shows the estimated value (dot), 95%, 90%, and 68% confidence region (shadows) in the (λ, γ_f) space, where $x_{i,t}$ is unemployment gap obtained using the one-sided exponentially-weighted moving average following Stock and Watson (2020). Panel (b) shows the point estimates of various slacks from Stock and Watson (2020) and Mavroeidis et al. (2014) in the (λ, γ_f) space. The slacks include detrended series of unemployment rate and employment-population ratio using HP filter, BK filter, linear detrending, quadratic detrending, Bi-weight filter and one-sided exponentially weighted moving average. The filled and hollow dots represent group 1 (larger γ_f) and 2. Standard error is clustered at state level for panel data and adjusted to a TS2SLS version, following Chodorow-Reich and Wieland (2020). The sample periods of pre- and post-1990 are 1979-1990 and 1991-2017. There are 21 and 34 states in the pre- and post-1990 subsamples.



(a) Zero lower bound



(b) Monetary shock sign

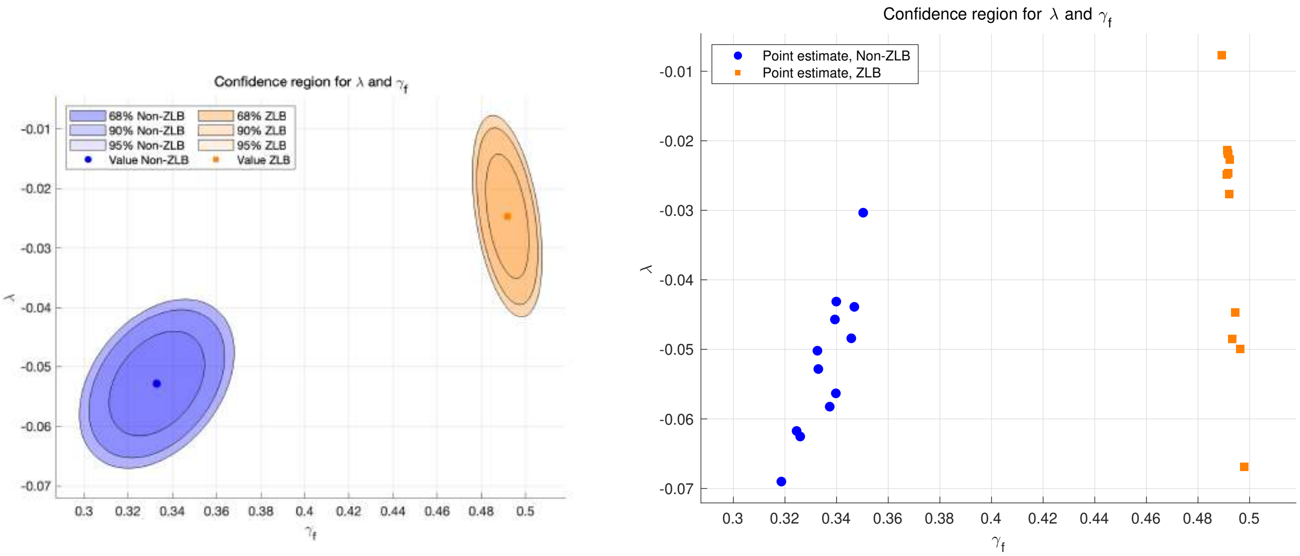


(c) NBER recession

Figure 3: **Features of economy.** This figure shows the definition of features of economy, including (1) 3-month t-bill interest rate near zero lower bound; (2) contractionary (positive) Romer and Romer's (2004) monetary shock; (3) NBER recession period. The grey shadow shows when $state = 1$, and otherwise $state = 0$. The state variable is available from 1979Q1 to 2017Q4, except that the monetary shock is only available till 2007Q4.

Table 6: **State level Phillips curve given $\gamma_f + \gamma_b = 1$ during times of unconventional monetary policy.** This table lists the coefficients of the state-dependent Phillips curve $\pi_{i,t} = I_{t-1}(\lambda_A x_{i,t} + \gamma_{f,A}\pi_{i,t+1} + \gamma_{b,A}\pi_{i,t-1} + \alpha_A) + (1 - I_{t-1})(\lambda_B x_{i,t} + \gamma_{f,B}\pi_{i,t+1} + \gamma_{b,B}\pi_{i,t-1} + \alpha_B) + \mu_i + u_{i,t}$ given $\gamma_{f,state} + \gamma_{b,state} = 1$ and the group-specific version under two groups estimated via C-Lasso. I is a dummy variable indicating the period of near zero lower bound. Inflation is measured by state CPI from Hazell et al. (2022) and slack is unemployment gap obtained using one-sided exponentially weighted moving average following Stock and Watson (2020). The instruments include the intersection of the two state variables (I_{t-1} and $1 - I_{t-1}$), and the four inflation lags and two slack lags. Standard error is clustered at state level. Adjusted R-squared is reported. Joint difference between the two states (in the pooled estimation) and the two groups (in the C-Lasso estimation) is tested by Chow test. **Reject the null of constant coefficients at the 1% significance level.

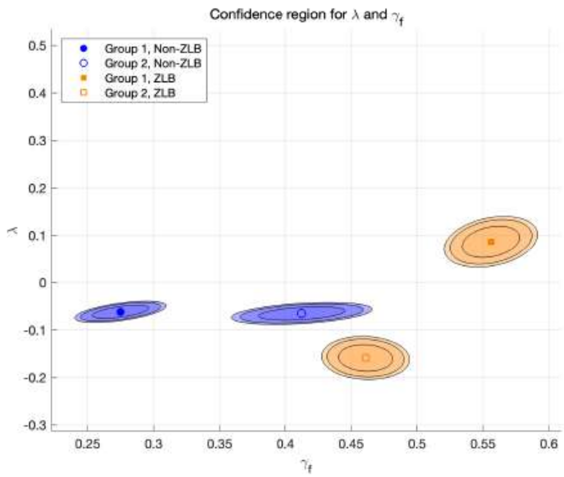
Slack: U. Gap (Real time)	**Pooled**		**C-Lasso**			
			Non-ZLB		**ZLB**	
	Non	**ZLB**	**G1**	**G2**	**G1**	**G2**
λ	-0.053	-0.025	-0.062	-0.065	0.086	-0.159
	(0.006)	(0.007)	(0.009)	(0.009)	(0.022)	(0.019)
γ_f	0.333	0.492	0.275	0.412	0.556	0.461
	(0.014)	(0.006)	(0.014)	(0.022)	(0.014)	(0.014)
Obs.	4340		2520	1875	2520	1875
Adj. R-sq	0.521		0.169	0.117	0.169	0.117
State effects	✓		✓	✓	✓	✓
Chow test	114.701**		17.798**			
%G1	/		55.88%			



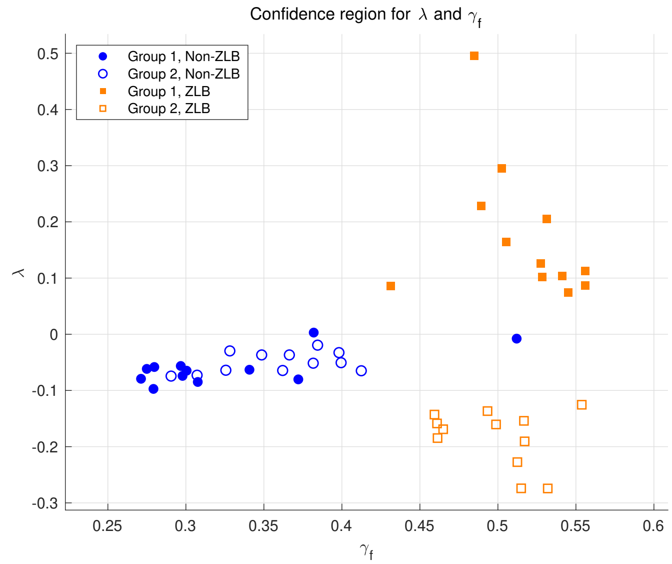
(a) Confidence region for λ and γ_f

(b) Point estimates for λ and γ_f

Figure 4: **State level Phillips curve given $\gamma_f + \gamma_b = 1$ during times of unconventional monetary policy.** This figure shows the coefficient estimates and confidence region of the state-dependent Phillips curve $\pi_{i,t} = I_{t-1}(\lambda_A x_{i,t} + \gamma_{f,A}\pi_{i,t+1} + \gamma_{b,A}\pi_{i,t-1} + \alpha_A) + (1 - I_{t-1})(\lambda_B x_{i,t} + \gamma_{f,B}\pi_{i,t+1} + \gamma_{b,B}\pi_{i,t-1} + \alpha_B) + \mu_i + u_{i,t}$ given $\gamma_{f,state} + \gamma_{b,state} = 1$, where I is the dummy variable indicating that interest rate is close to zero lower bound. Inflation is measured by state CPI from Hazell et al. (2022). The instruments include four inflation lags and two slack lags. Panel (a) shows the estimated value (dot), 95%, 90%, and 68% confidence region (shadows) in the (λ, γ_f) space, where $x_{i,t}$ is unemployment gap obtained using one-sided exponentially weighted moving average following Stock and Watson (2020). Blue circles and orange squares respectively represent the coefficients during non-ZLB and ZLB period. Panel (b) shows the point estimates of various slacks from Stock and Watson (2020) and Mavroeidis et al. (2014) in the (λ, γ_f) space. The slacks include detrended series of unemployment rate and employment-population ratio using HP filter, BK filter, linear detrending, quadratic detrending, Bi-weight filter and one-sided exponentially weighted moving average. Standard error is clustered at state level.

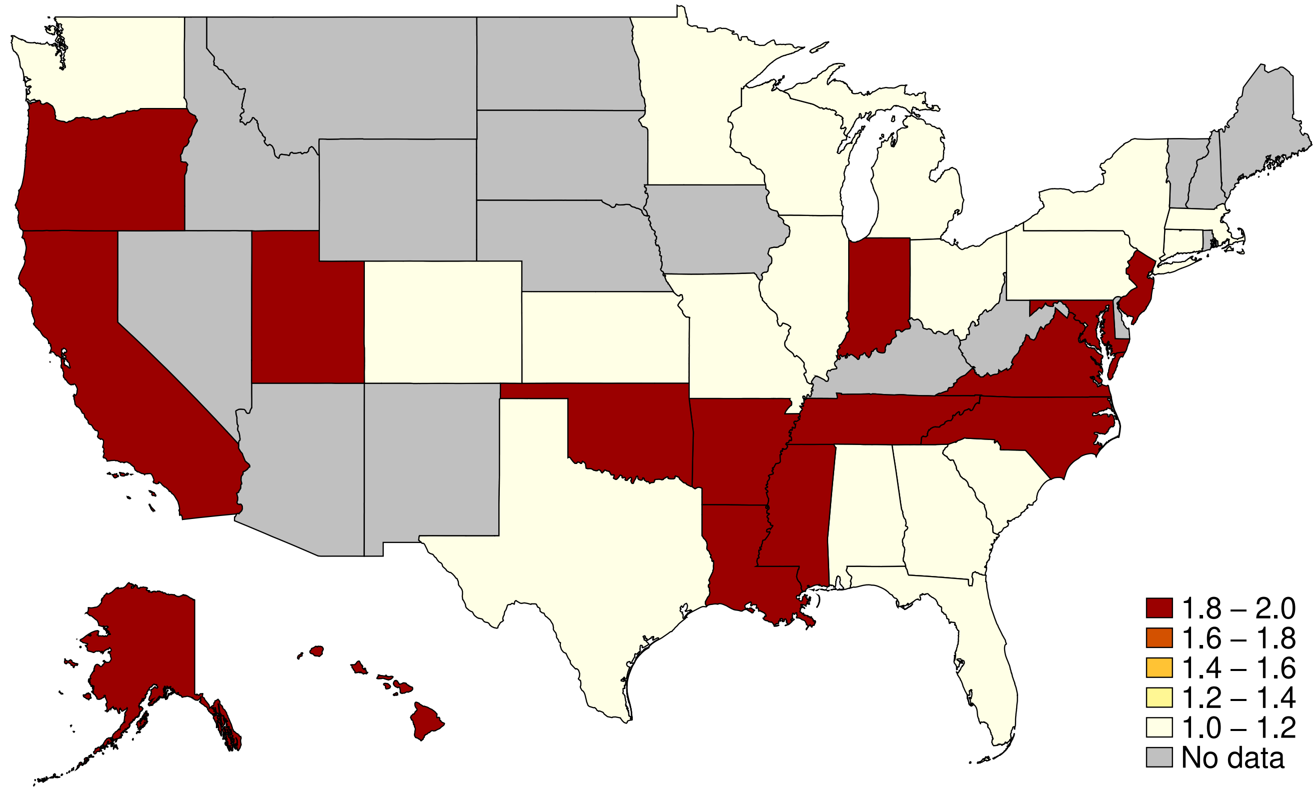


(a) Confidence region for λ and γ_f



(b) Point estimates for λ and γ_f

Figure 5: **Group-specific state level Phillips curve given $\gamma_f + \gamma_b = 1$ during times of unconventional monetary policy.** This figure shows the coefficient estimates and confidence region of the group-specific state-dependent Phillips curve $\pi_{i,t} = I_{t-1}(\lambda_{A,i}x_{i,t} + \gamma_{f,A,i}\pi_{i,t+1} + \gamma_{b,A,i}\pi_{i,t-1} + \alpha_{A,i}) + (1 - I_{t-1})(\lambda_{B,i}x_{i,t} + \gamma_{f,B,i}\pi_{i,t+1} + \gamma_{b,B,i}\pi_{i,t-1} + \alpha_{B,i}) + \mu_i + u_{i,t}$ given $\gamma_{f,state,i} + \gamma_{b,state,i} = 1$, where $\beta_i = (\lambda_{A,i}, \gamma_{f,A,i}, \alpha_{A,i}, \lambda_{B,i}, \gamma_{f,B,i}, \alpha_{B,i})' = \theta_k$ if $i \in G_k, k = 1, 2$. I is a dummy variable indicating the period of near zero lower bound. Panel (a) shows the estimated value (dot), 95%, 90%, and 68% confidence region (shadows) in the (λ, γ_f) space, where $x_{i,t}$ is unemployment gap obtained using one-sided exponentially weighted moving average following Stock and Watson (2020). Blue circles and orange squares respectively represent the coefficients during non-ZLB and ZLB period. The filled and hollow dots represent group 1 and 2. Panel (b) shows the point estimates of various slacks from Stock and Watson (2020) and Mavroeidis et al. (2014) in the (λ, γ_f) space. The slacks include detrended series of unemployment rate and employment-population ratio using HP filter, BK filter, linear detrending, quadratic detrending, Bi-weight filter and one-sided exponentially weighted moving average. Standard error is clustered at state level.

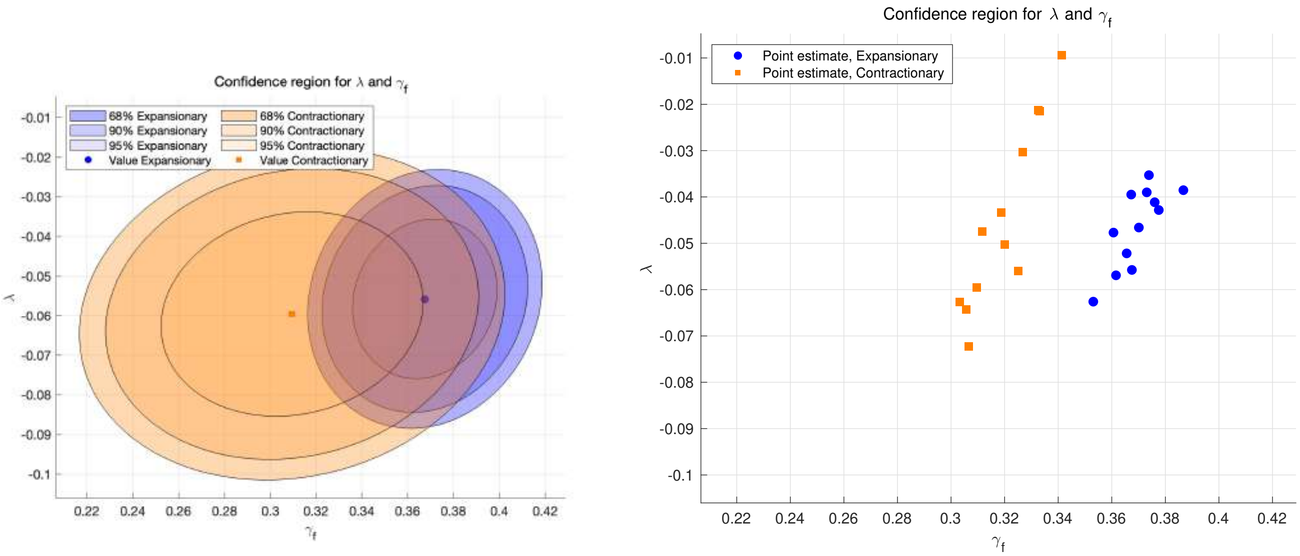


Group ID = 1: *Alabama, Colorado, Connecticut, District of Columbia, Florida, Georgia, Illinois, Kansas, Massachusetts, Michigan, Minnesota, Missouri, New York, Ohio, Pennsylvania, South Carolina, Texas, Washington, Wisconsin*
Group ID = 2: *Alaska, Arkansas, California, Hawaii, Indiana, Louisiana, Maryland, Mississippi, New Jersey, North Carolina, Oklahoma, Oregon, Tennessee, Utah, Virginia*

Figure 6: **Group membership of the state-dependent Phillips curve given $\gamma_f + \gamma_b = 1$ during times of unconventional monetary policy.** These maps show the classification of states in the group-specific state-dependent Phillips curve $\pi_{i,t} = I_{t-1}(\lambda_{A,i}x_{i,t} + \gamma_{f,A,i}\pi_{i,t+1} + \gamma_{b,A,i}\pi_{i,t-1} + \alpha_{A,i}) + (1 - I_{t-1})(\lambda_{B,i}x_{i,t} + \gamma_{f,B,i}\pi_{i,t+1} + \gamma_{b,B,i}\pi_{i,t-1} + \alpha_{B,i}) + \mu_i + u_{i,t}$ given $\gamma_{f,state,i} + \gamma_{b,state,i} = 1$, where $\beta_i = (\lambda_{A,i}, \gamma_{f,A,i}, \alpha_{A,i}, \lambda_{B,i}, \gamma_{f,B,i}, \alpha_{B,i})' = \theta_k$ if $i \in G_k, k = 1, 2$. I is a dummy variable indicating the period of near zero lower bound. Inflation is measured by state CPI from Hazell et al. (2022). $x_{i,t}$ is unemployment gap obtained using one-sided exponentially weighted moving average following Stock and Watson (2020).

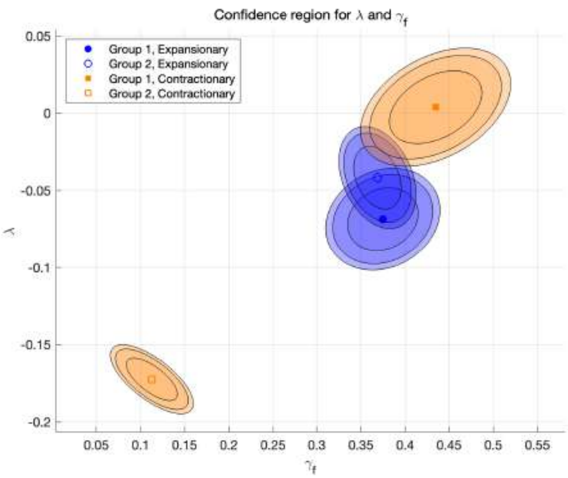
Table 7: **State level Phillips curve given $\gamma_f + \gamma_b = 1$ in different monetary policy regimes.** This table lists the coefficients of the state-dependent Phillips curve $\pi_{i,t} = I_{t-1}(\lambda_A x_{i,t} + \gamma_{f,A}\pi_{i,t+1} + \gamma_{b,A}\pi_{i,t-1} + \alpha_A) + (1 - I_{t-1})(\lambda_B x_{i,t} + \gamma_{f,B}\pi_{i,t+1} + \gamma_{b,B}\pi_{i,t-1} + \alpha_B) + \mu_i + u_{i,t}$ given $\gamma_{f,state} + \gamma_{b,state} = 1$ and the group-specific version under two groups estimated via C-Lasso. I is a dummy variable indicating contractionary monetary shock. Inflation is measured by state CPI from Hazell et al. (2022) and slack is unemployment gap obtained using one-sided exponentially weighted moving average following Stock and Watson (2020). The instruments include the intersection of the two state variables (I_{t-1} and $1 - I_{t-1}$), and the four inflation lags and two slack lags. Standard error is clustered at state level. Adjusted R-squared is reported. Joint difference between the two states (in the pooled estimation) and the two groups (in the C-Lasso estimation) is tested by Chow test. **Reject the null of constant coefficients at the 1% significance level.

Slack: U. Gap (Real time)	**Pooled**		**C-Lasso**			
			Expansionary		**Contractionary**	
	Exp.	**Con.**	**G1**	**G2**	**G1**	**G2**
λ	-0.056	-0.060	-0.069	-0.042	0.004	-0.172
	(0.013)	(0.017)	(0.014)	(0.013)	(0.016)	(0.009)
γ_f	0.368	0.310	0.375	0.369	0.435	0.113
	(0.021)	(0.038)	(0.026)	(0.018)	(0.035)	(0.019)
Obs.	3048		2014	1055	2014	1055
Adj. R-sq	0.468		0.063	0.058	0.063	0.058
State effects	✓		✓	✓	✓	✓
Chow test	1.135		10.257**			
%G1	/		67.65%			

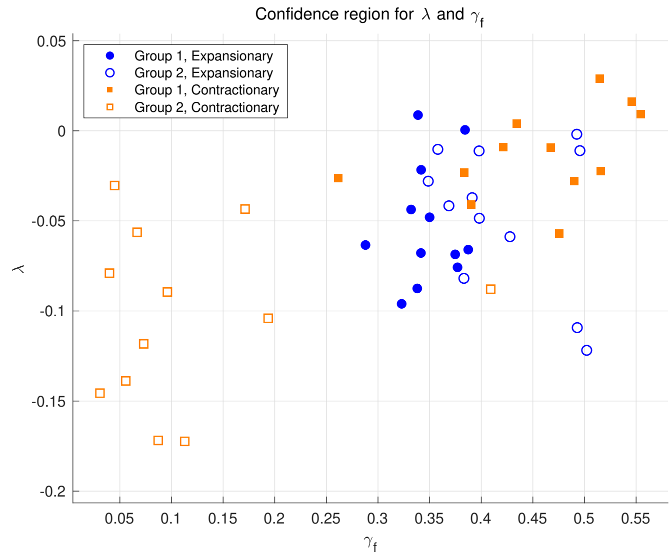


(a) Confidence region for λ and γ_f (b) Point estimates for λ and γ_f

Figure 7: **State level Phillips curve given $\gamma_f + \gamma_b = 1$ in different monetary policy regimes.** This figure shows the coefficient estimates and confidence region of the state-dependent Phillips curve $\pi_{i,t} = I_{t-1}(\lambda_A x_{i,t} + \gamma_{f,A}\pi_{i,t+1} + \gamma_{b,A}\pi_{i,t-1} + \alpha_A) + (1 - I_{t-1})(\lambda_B x_{i,t} + \gamma_{f,B}\pi_{i,t+1} + \gamma_{b,B}\pi_{i,t-1} + \alpha_B) + \mu_i + u_{i,t}$ given $\gamma_{f,state} + \gamma_{b,state} = 1$, where I is the dummy variable indicating contractionary monetary shock. Inflation is measured by state CPI from Hazell et al. (2022). The instruments include four inflation lags and two slack lags. Panel (a) shows the estimated value (dot), 95%, 90%, and 68% confidence region (shadows) in the (λ, γ_f) space, where $x_{i,t}$ is unemployment gap obtained using one-sided exponentially weighted moving average following Stock and Watson (2020). Blue circles and orange squares respectively represent the coefficients during expansionary and contractionary monetary policy shocks. Panel (b) shows the point estimates of various slacks from Stock and Watson (2020) and Mavroeidis et al. (2014) in the (λ, γ_f) space. The slacks include detrended series of unemployment rate and employment-population ratio using HP filter, BK filter, linear detrending, quadratic detrending, Bi-weight filter and one-sided exponentially weighted moving average. Standard error is clustered at state level.

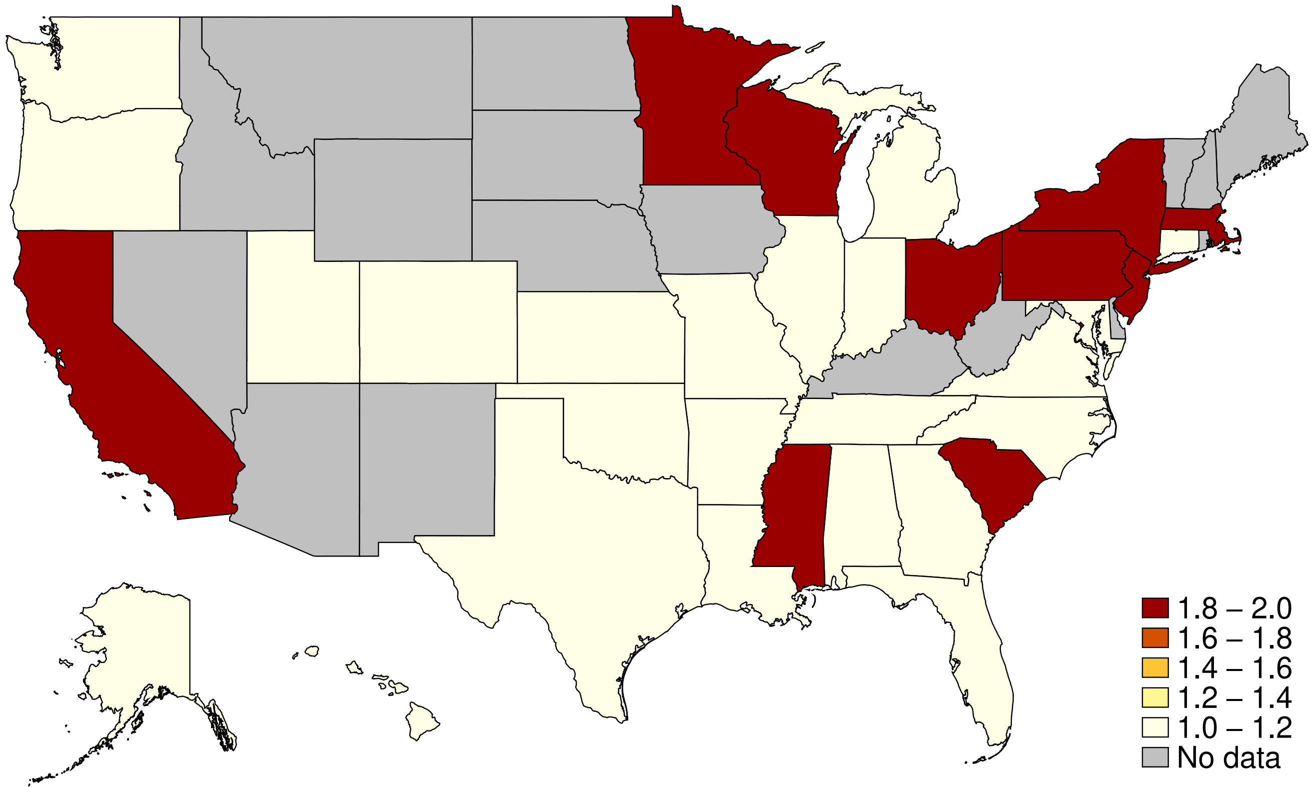


(a) Confidence region for λ and γ_f



(b) Point estimates for λ and γ_f

Figure 8: **Group-specific state level Phillips curve given $\gamma_f + \gamma_b = 1$ in different monetary policy regimes.** This figure shows the coefficient estimates and confidence region of the group-specific state-dependent Phillips curve $\pi_{i,t} = I_{t-1}(\lambda_{A,i}x_{i,t} + \gamma_{f,A,i}\pi_{i,t+1} + \gamma_{b,A,i}\pi_{i,t-1} + \alpha_{A,i}) + (1 - I_{t-1})(\lambda_{B,i}x_{i,t} + \gamma_{f,B,i}\pi_{i,t+1} + \gamma_{b,B,i}\pi_{i,t-1} + \alpha_{B,i}) + \mu_i + u_{i,t}$ given $\gamma_{f,state,i} + \gamma_{b,state,i} = 1$, where $\beta_i = (\lambda_{A,i}, \gamma_{f,A,i}, \alpha_{A,i}, \lambda_{B,i}, \gamma_{f,B,i}, \alpha_{B,i})' = \theta_k$ if $i \in G_k, k = 1, 2$. I is a dummy variable indicating contractionary monetary shock. Panel (a) shows the estimated value (dot), 95%, 90%, and 68% confidence region (shadows) in the (λ, γ_f) space, where $x_{i,t}$ is unemployment gap obtained using one-sided exponentially weighted moving average following Stock and Watson (2020). Blue circles and orange squares respectively represent the coefficients during expansionary and contractionary monetary policy shocks. The filled and hollow dots represent group 1 and 2. Panel (b) shows the point estimates of various slacks from Stock and Watson (2020) and Mavroeidis et al. (2014) in the (λ, γ_f) space. The slacks include detrended series of unemployment rate and employment-population ratio using HP filter, BK filter, linear detrending, quadratic detrending, Bi-weight filter and one-sided exponentially weighted moving average. Standard error is clustered at state level.

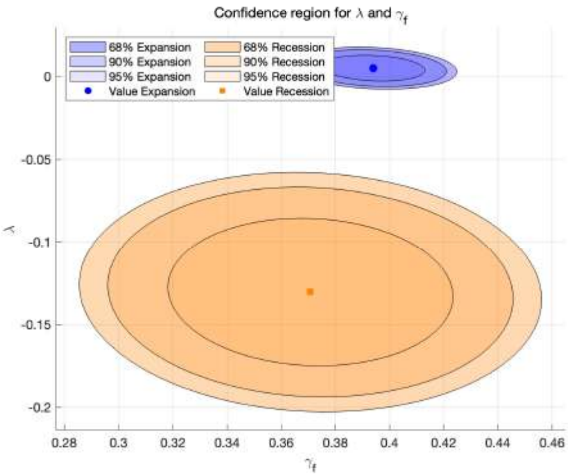


Group ID = 1: *Alabama, Alaska, Arkansas, Colorado, Connecticut, Florida, Georgia, Hawaii, Illinois, Indiana, Kansas, Louisiana, Maryland, Michigan, Missouri, North Carolina, Oklahoma, Oregon, Tennessee, Texas, Utah, Virginia, Washington*
Group ID = 2: *California, District of Columbia, Massachusetts, Minnesota, Mississippi, New Jersey, New York, Ohio, Pennsylvania, South Carolina, Wisconsin*

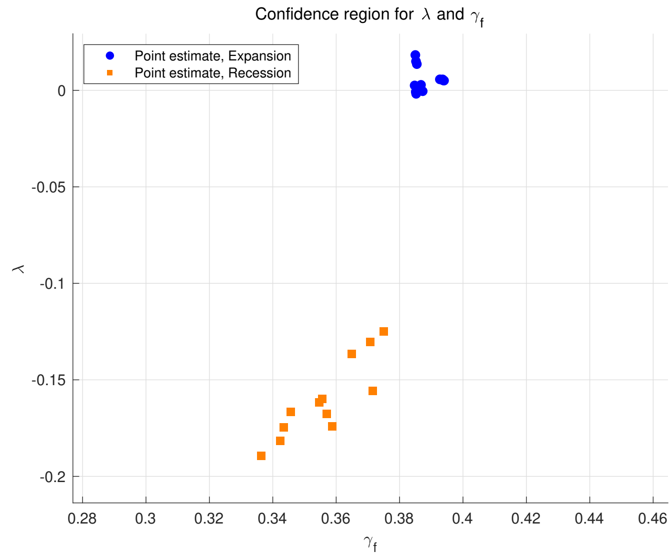
Figure 9: **Group membership of the state-dependent Phillips curve given $\gamma_f + \gamma_b = 1$ in different monetary policy regimes.** These maps show the classification of states in the group-specific state-dependent Phillips curve $\pi_{i,t} = I_{t-1}(\lambda_{A,i}x_{i,t} + \gamma_{f,A,i}\pi_{i,t+1} + \gamma_{b,A,i}\pi_{i,t-1} + \alpha_{A,i}) + (1 - I_{t-1})(\lambda_{B,i}x_{i,t} + \gamma_{f,B,i}\pi_{i,t+1} + \gamma_{b,B,i}\pi_{i,t-1} + \alpha_{B,i}) + \mu_i + u_{i,t}$ given $\gamma_{f,state,i} + \gamma_{b,state,i} = 1$, where $\beta_i = (\lambda_{A,i}, \gamma_{f,A,i}, \alpha_{A,i}, \lambda_{B,i}, \gamma_{f,B,i}, \alpha_{B,i})' = \theta_k$ if $i \in G_k, k = 1, 2$. I is a dummy variable indicating contractionary monetary shock. Inflation is measured by state CPI from Hazell et al. (2022). $x_{i,t}$ is unemployment gap obtained using one-sided exponentially weighted moving average following Stock and Watson (2020).

Table 8: **State level Phillips curve given $\gamma_f + \gamma_b = 1$ during NBER recession.** This table lists the coefficients of the state-dependent Phillips curve $\pi_{i,t} = I_{t-1}(\lambda_A x_{i,t} + \gamma_{f,A}\pi_{i,t+1} + \gamma_{b,A}\pi_{i,t-1} + \alpha_A) + (1 - I_{t-1})(\lambda_B x_{i,t} + \gamma_{f,B}\pi_{i,t+1} + \gamma_{b,B}\pi_{i,t-1} + \alpha_B) + \mu_i + u_{i,t}$ given $\gamma_{f,state} + \gamma_{b,state} = 1$ and the group-specific version under two groups estimated via C-Lasso. I is a dummy variable indicating NBER recession. Inflation is measured by state CPI from Hazell et al. (2022) and slack is unemployment gap obtained using one-sided exponentially weighted moving average following Stock and Watson (2020). The instruments include the intersection of the two state variables (I_{t-1} and $1 - I_{t-1}$), and the four inflation lags and two slack lags. Standard error is clustered at state level. Adjusted R-squared is reported. Joint difference between the two states (in the pooled estimation) and the two groups (in the C-Lasso estimation) is tested by Chow test. **Reject the null of constant coefficients at the 1% significance level.

Slack: U. Gap (Real time)	**Pooled**		**C-Lasso**			
			Expansion		**Recesion**	
	Exp.	**Rec.**	**G1**	**G2**	**G1**	**G2**
λ	0.005	-0.130	-0.011	0.013	-0.010	-0.258
	(0.005)	(0.030)	(0.005)	(0.009)	(0.015)	(0.028)
γ_f	0.394	0.371	0.278	0.472	0.200	0.502
	(0.013)	(0.035)	(0.014)	(0.020)	(0.032)	(0.037)
Obs.	4340		1876	2519	1876	2519
Adj. R-sq	0.534		0.082	0.127	0.082	0.127
State effects	✓		✓	✓	✓	✓
Chow test	17.171**		10.225**			
%G1	/		41.18%			

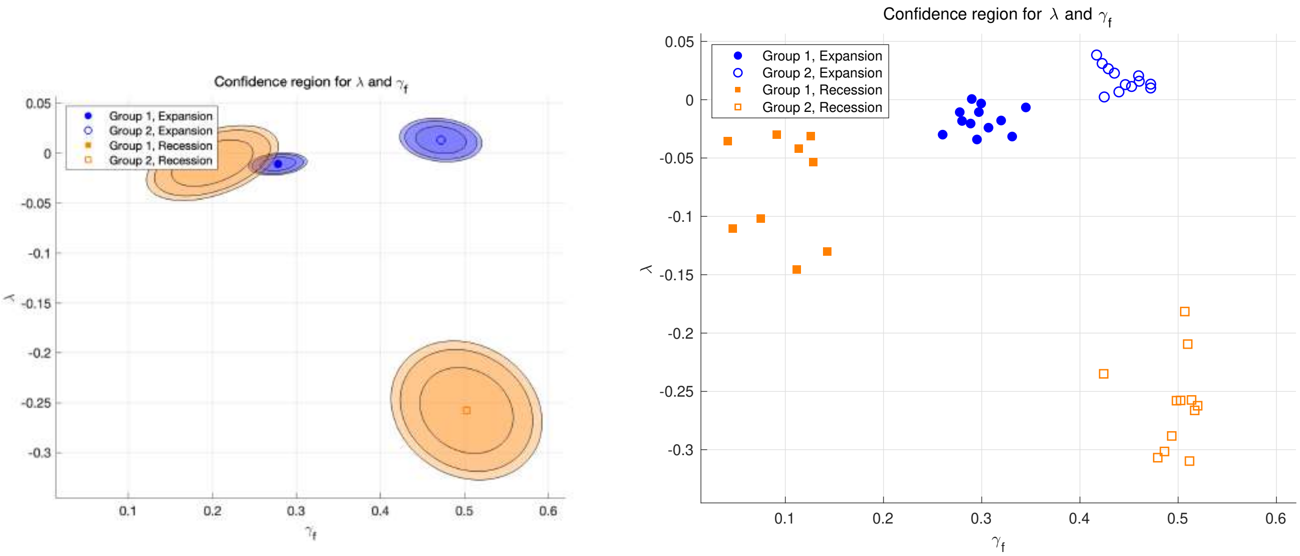


(a) Confidence region for λ and γ_f



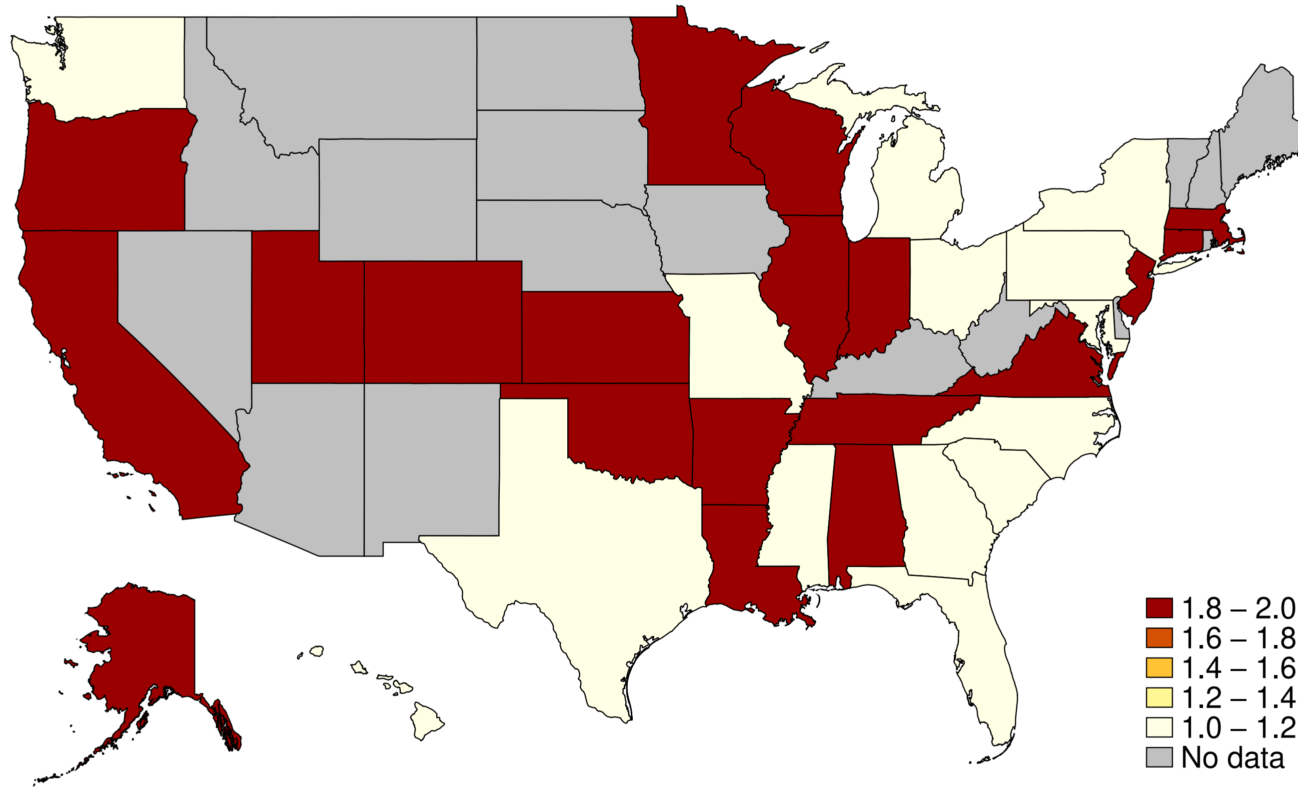
(b) Point estimates for λ and γ_f

Figure 10: **State level Phillips curve given $\gamma_f + \gamma_b = 1$ during NBER recession.** This figure shows the coefficient estimates and confidence region of the state-dependent Phillips curve $\pi_{i,t} = I_{t-1}(\lambda_A x_{i,t} + \gamma_{f,A}\pi_{i,t+1} + \gamma_{b,A}\pi_{i,t-1} + \alpha_A) + (1 - I_{t-1})(\lambda_B x_{i,t} + \gamma_{f,B}\pi_{i,t+1} + \gamma_{b,B}\pi_{i,t-1} + \alpha_B) + \mu_i + u_{i,t}$ given $\gamma_{f,state} + \gamma_{b,state} = 1$, where I is the dummy variable indicating NBER recession. Inflation is measured by state CPI from Hazell et al. (2022). The instruments include four inflation lags and two slack lags. Panel (a) shows the estimated value (dot), 95%, 90%, and 68% confidence region (shadows) in the (λ, γ_f) space, where $x_{i,t}$ is unemployment gap obtained using one-sided exponentially weighted moving average following Stock and Watson (2020). Blue circles and orange squares respectively represent the coefficients during normal and recession period. Panel (b) shows the point estimates of various slacks from Stock and Watson (2020) and Mavroeidis et al. (2014) in the (λ, γ_f) space. The slacks include detrended series of unemployment rate and employment-population ratio using HP filter, BK filter, linear detrending, quadratic detrending, Bi-weight filter and one-sided exponentially weighted moving average. Standard error is clustered at state level.



(a) Confidence region for λ and γ_f (b) Point estimates for λ and γ_f

Figure 11: **Group-specific state level Phillips curve given $\gamma_f + \gamma_b = 1$ during NBER recession.** This figure shows the coefficient estimates and confidence region of the group-specific state-dependent Phillips curve $\pi_{i,t} = I_{t-1}(\lambda_{A,i}x_{i,t} + \gamma_{f,A,i}\pi_{i,t+1} + \gamma_{b,A,i}\pi_{i,t-1} + \alpha_{A,i}) + (1 - I_{t-1})(\lambda_{B,i}x_{i,t} + \gamma_{f,B,i}\pi_{i,t+1} + \gamma_{b,B,i}\pi_{i,t-1} + \alpha_{B,i}) + \mu_i + u_{i,t}$ given $\gamma_{f,state,i} + \gamma_{b,state,i} = 1$, where $\beta_i = (\lambda_{A,i}, \gamma_{f,A,i}, \alpha_{A,i}, \lambda_{B,i}, \gamma_{f,B,i}, \alpha_{B,i})' = \theta_k$ if $i \in G_k, k = 1, 2$. I is a dummy variable indicating NBER recession. Panel (a) shows the estimated value (dot), 95%, 90%, and 68% confidence region (shadows) in the (λ, γ_f) space, where $x_{i,t}$ is unemployment gap obtained using one-sided exponentially weighted moving average following Stock and Watson (2020). Blue circles and orange squares respectively represent the coefficients during normal and recession period. The filled and hollow dots represent group 1 and 2. Panel (b) shows the point estimates of various slacks from Stock and Watson (2020) and Mavroeidis et al. (2014) in the (λ, γ_f) space. The slacks include detrended series of unemployment rate and employment-population ratio using HP filter, BK filter, linear detrending, quadratic detrending, Bi-weight filter and one-sided exponentially weighted moving average. Standard error is clustered at state level.



Group ID = 1: *Florida, Georgia, Hawaii, Maryland, Michigan, Mississippi, Missouri, New York, North Carolina, Ohio, Pennsylvania, South Carolina, Texas, Washington*
Group ID = 2: *Alabama, Alaska, Arkansas, California, Colorado, Connecticut, District of Columbia, Illinois, Indiana, Kansas, Louisiana, Massachusetts, Minnesota, New Jersey, Oklahoma, Oregon, Tennessee, Utah, Virginia, Wisconsin*

Figure 12: **Group membership of the state-dependent Phillips curve given $\gamma_f + \gamma_b = 1$ during NBER recession.** These maps show the classification of states in the group-specific state-dependent Phillips curve $\pi_{i,t} = I_{t-1}(\lambda_{A,i}x_{i,t} + \gamma_{f,A,i}\pi_{i,t+1} + \gamma_{b,A,i}\pi_{i,t-1} + \alpha_{A,i}) + (1 - I_{t-1})(\lambda_{B,i}x_{i,t} + \gamma_{f,B,i}\pi_{i,t+1} + \gamma_{b,B,i}\pi_{i,t-1} + \alpha_{B,i}) + \mu_i + u_{i,t}$ given $\gamma_{f,state,i} + \gamma_{b,state,i} = 1$, where $\beta_i = (\lambda_{A,i}, \gamma_{f,A,i}, \alpha_{A,i}, \lambda_{B,i}, \gamma_{f,B,i}, \alpha_{B,i})' = \theta_k$ if $i \in G_k, k = 1, 2$. I is a dummy variable indicating NBER recession. Inflation is measured by state CPI from Hazell et al. (2022). $x_{i,t}$ is unemployment gap obtained using one-sided exponentially weighted moving average following Stock and Watson (2020).