Nonlinear Effects of Inflation on Market Work: A State-Dependent Bayesian Local Projections Approach

Jalal Bagherzadeh *

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Abstract

This paper studies how phases of unemployment, inflation, inflation expectations, government spending, monetary policy, and uncertainty cycles shape the transmission of inflationary shocks to market work hours. A Bayesian state-dependent local projection framework is developed to identify nonlinear responses of market labor supply to inflationary shocks, using aggregated microdata from the Current Population Survey to proxy individual working hours. The empirical findings reveal pronounced state dependence: the effect of inflationary shocks on market work is stronger during periods of high unemployment, elevated government spending, and tight monetary policy, while the response is attenuated when inflation and inflation expectations are high. To address endogeneity and estimation instability common in local projections, a two-stage instrumental-variable local projection approach within a Bayesian framework is implemented, which removes contemporaneous feedback from inflation to macroeconomic controls and regularizes horizon-by-horizon regressions through informative priors. Overall, the findings highlight substantial nonlinearities in labor supply responses to inflationary disturbances across macroeconomic states.

Keywords: Inflationary Shocks, Market Work Hours, Bayesian Local Projection, Stat Dependence

1 Introduction

The macroeconomic literature increasingly recognizes that the responses of key macroeconomic indicators are not constant across all economic conditions, instead, the effects frequently depend on the underlying state of the economy. This paper investigates whether the transmission of inflationary shocks to market work hours is affected by the states of the economy. The states of economy are proxied based on unemployment, inflation,

*Texas Tech University, Department Of Economics, 41014, Lubbock, TX, 79409. E-mail: jalal.bagherzade@ttu.edu. Website: https://jalal-bagherzadeh.github.io.

inflation expectation, fiscal policy, monetary policy, and uncertainty, thereby nonlinearity of individuals' responses to inflationary shocks by their working hours in the market is studied.

In the first part of the paper, a two-stage local projection (LP) model is presented to capture the responses of market work hours to inflationary shocks while addressing the inherent endogeneity of inflation. The LP regression model is allowed for state-dependence to detect possible nonlinearities and asymmetries in the transmission of inflationary shock to working hours. To sharpen the inference for the impulse responses across different states, a Bayesian Local Projection (BLP) technique introduced by Ferreira et al. (2025) is employed to regularize informative priors. The results highlight the larger effect of inflationary shocks on working hours when unemployment and government spending is higher and the lower effect when inflation, inflation expectations are higher, and monetary policy is tighter.

Rendering linear, state-invariant models is empirically inadequate and potentially misleading for both inference and policy design due to inherent asymmetric, nonlinearity, and contingency relationships amongst macroeconomic indicators. The state-dependent empirical framework represents a departure from linear models that assume stability of parameter relationships over time. A vast body of empirical macroeconomic research has demonstrated that the transmission mechanisms of shocks—whether fiscal, monetary, financial, or uncertainty-related—vary systematically across expansions and recessions, high- and low-slack environments, and periods of financial stress versus tranquility. Consequently, analyzing macroeconomic indicators through a state-contingent lens is essential not only for accurate measurement of causal effects but also for aligning empirical evidence with theoretical predictions and for designing countercyclical policies that are effective, credible, and welfare-enhancing across the full spectrum of economic conditions.

This paper apply the LP method, introduced by Jordà (2005), to estimate impulse responses of working hours to inflation. This technique seeks to estimate the dynamic causal effects of macroeconomic shocks on aggregate outcomes by running a sequence of horizon-specific regressions. The future value of an outcome variable is directly projected onto a contemporaneous shock along with a set of predetermined controls, thereby tracing impulse responses without relying on the full specification of a multivariate dynamic system as in vector autoregression (VARs) model. Formally, for each horizon h, a separate regression of y_{t+h} on the shock of interest and a set of predetermined controls is framed, allowing the dynamic response to be traced out horizon by horizon without imposing cross-equation or cross-horizon restrictions. Because each horizon is estimated separately, errors in modeling short-run dynamics do not mechanically contaminate responses at longer horizons, in contrast to vector autoregressions (VARs), where impulse responses are recovered through repeated iteration of a single estimated system. The LP method trades lower bias for higher variance, whereas VAR models generate impulse response estimates with relatively low variance at the cost of potentially substantial bias. LPs are also highly adaptable in practice, as nonlinearities, state dependence, time variation, interactions, or instrument identification can be incorporated transparently by modifying the horizon-specific regressions rather than restructuring the entire model.

State-dependent LPs extend the standard LP framework by allowing the dynamic response of macroeconomic variables to shocks to vary systematically with the state of the economy, thereby relaxing the implicit assumption of linear and time-invariant impulse responses. In practice, this is achieved by interacting the shock of interest with an indicator or continuous measure of the state —such as the business cycle, financial conditions, inflation expectations, or unemployment —so that separate impulse responses are estimated conditional on different regimes or economic environments. This approach preserves the core appeal of LPs while providing a flexible and easier way to implement to capture nonlinear transmission mechanisms. At the same time, the method comes with important limitations: splitting the sample by states reduces the effective sample size sharply, which can lead to imprecise estimates at long horizons, and inference can be sensitive to how the state variable is defined or thresholded. Bayesian methods can partially mitigate this problem by sharing information across states, horizons, and parameters in a disciplined probabilistic way. Instead of estimating two completely independent sets of coefficients—one for each state—the coefficients are modeled as deviations from a common latent response. Conceptually, the state-specific impulse responses are allowed to differ, but large differences must be supported by the data. When the number of observations in a state is small, the posterior automatically shrinks the state-specific response toward the common component, reducing variance without forcing equality. This directly mitigates the "double small-sample" problem that arises when both horizons and states fragment the data.

BLPs embed the LP regressions in a Bayesian environment, replacing classical standard-error-based inference with posterior distributions for impulse responses and allowing to incorporate prior information. This is particularly valuable because classical LPs, while robust, are statistically inefficient when samples are small or horizons are long, which often results in wide confidence intervals. In addition, absence of any cross-horizon discipline leads to noisy and unstable IRFs. The BLP framework addresses these issues by regularizing LP regressions through informative, horizon-specific Bayesian priors, while preserving the non-parametric spirit of LPs. The distinction between classical and BLP is therefore not conceptual but inferential: both estimate the same horizon-by-horizon objects, but BLPs explicitly acknowledge parameter uncertainty and allow priors to discipline estimation. At the same time, both approaches share limitations: LPs can become noisy at long horizons, are sensitive to weak identification of the underlying shock, and may overfit when many lags or states are included, while BLPs introduce sensitivity to prior choices and greater computational complexity, especially in high-dimensional or state-dependent settings.

This paper adopts the technique introduced by Ferreira et al. (2025) to estimate the BLP. The key methodological aspect of this paper centers around how informative priors are constructed and disciplined across horizons in local projections, and how their tightness is endogenously chosen. The procedure can be broken down into the following steps. This technique reinterprets each horizon-h local projection as an auxiliary (misspecified) Gaussian likelihood. Rather than attempting to model the true data generating process, inference is conducted on the pseudo-true coefficients of the h-step-ahead predictive regression. This provides a likelihood object to which Bayesian priors can be attached, even though LP residuals are serially correlated and heteroskedastic. LP coefficients are centered on iterated VAR responses estimated on the sample. This embeds the belief that short-horizon dynamics are well approximated by VARs, while still allowing LP flexibility at longer horizons. The paper introduce hierarchical hyperpriors for prior tightness that prior informativeness is not fixed ex ante. Instead, the tightness parameter governing shrinkage at each horizon is treated as an unknown hyperparameter. The hyperprior is assigned to follow the Maximum Likelihood Type-II (ML-II), ensuring that the Type-II marginal likelihood criterion selects the degree of shrinkage relevant for impulse response inference. This method allows prior tightness to vary systematically with the horizon. The variance of the hyper-prior is designed to increase with the forecast horizon, reflecting the idea that stylized VARs become less reliable at long horizons. This is implemented via a shifted logistic (sigmoid) function.

***Related Literature*—.** Understanding macroeconomic dynamics in a nonlinear, state-dependent setting has become a central pursuit in empirical macroeconomics. A core insight from this literature is that macroeconomic relationships—particularly the effects of fiscal and monetary policy—vary systematically with the economic environment, rendering linear, time-invariant models insufficient for capturing critical heterogeneity in shocks, responses, and policy effectiveness. Early theoretical work on regime shifts and occasionally binding constraints laid the conceptual foundation for empirical investigations that explicitly condition responses on macroeconomic states.

A seminal strand of research demonstrates that fiscal policy multipliers are state dependent, with significantly larger effects during downturns than expansions. Auerbach and Gorodnichenko (2012) and Auerbach and Gorodnichenko (2013) pioneered this literature by asking whether the impact of government spending on output is uniform across the business cycle. Using regime-dependent procedures that allow macro responses to differ between expansions and recessions, they find that fiscal multipliers are substantially larger in recessions, often by an order of magnitude, relative to expansions. The state of the economy is defined through business cycle indicators such as negative output gaps or recession dating, and responses are estimated via local projections conditioned on these regimes. Their results imply that average multiplier estimates obscure meaningful heterogeneity and that expansionary fiscal policy may be most potent when slack is high and monetary policy constraints are binding.

Building on this framework, Fazzari et al. (2015) employ threshold vector autoregressions (TVAR) to examine fiscal multipliers across regimes defined by labor market slack. The threshold variable—typically unemployment or an output gap—separates states of high and low slack. They find that in high-slack states (loosely corresponding to deep recessions), fiscal multipliers are several times larger than in low-slack states. This threshold approach reinforces nonlinear fiscal responses, confirming that standard linear VARs can understate multipliers in downturns by conflating regimes. Both studies underscore that state definitions tied to observable macro slack measures yield robust evidence of nonlinear fiscal effects.

This paper contributes to the large empirical literature on state-dependent macroeconomic variables, notably studies such as Auerbach and Gorodnichenko (2012), Ramey and Zubairy (2018)

A closely related literature examines how monetary policy transmission varies with macroeconomic and financial conditions. Alpanda et al. (2021) ask whether the effects of monetary policy differ not only across business cycle states but also along dimensions of credit and interest rate cycles. They define state variables using cyclical indicators—business cycle slack, credit growth, and the level of interest rates relative to historical norms—to create three separate state definitions. Estimating state-dependent local projections, they find that the output and inflation responses to monetary tightening are muted during recessions and periods of low credit or high interest rates. Such evidence challenges the assumption of uniform monetary transmission and highlights the importance of multiple interacting state dimensions in shaping policy effectiveness.

The empirical literature on state dependence has advanced not only substantive findings but also econometric methods. Cloyne et al. (2023) develop a state-dependent local projection (SDLP) framework that flexibly conditions impulse responses on continuous or discrete state indicators. Their research question centers on how to decompose heterogeneous impulse responses into contributions from state variables and interactions with other macro conditions. Unlike binary regime splits, the SDLP approach accommodates smooth transitions and multiple conditioning variables, revealing that fiscal multipliers can vary continuously with macro conditions such as slack and monetary policy stance. Their findings underscore the statistical importance of allowing state definitions to interact rather than imposing rigid dichotomies, thereby revealing richer nonlinearity in macro responses.

Markov-switching models represent another major methodological contribution. These frameworks treat economic states as latent regimes that evolve endogenously via a Markov process, with parameters that shift across regimes. For example, Markov-switching dynamic factor models (MS-DFMs) classify periods into latent states such as expansions, normal recessions, and severe recessions, allowing for distinct dynamics in each regime. Papers employing this approach consistently find that volatility, persistence, and impulse response functions differ across latent regimes, offering nuanced evidence of state-dependent macroeconomic behavior that is not captured by observable indicators alone.

The rest of the paper is organized as follows: Section 2 presents the econometric methodology, identification strategy and instrumental variable, the Bayesian framework and ruling priors, Section 3 describe data and definition of states, Section 4 summarizes the empirical results, and Section 5 concludes.

2 Econometric Methodology

To understand the effects of inflation on market work, I conduct a comprehensive analysis of both average and state-dependent effects of inflationary shocks. I employ local projections Jordà (2005) to assess both the average and state-dependent.

2.1 State-Dependent Local Projection Model

The regression model (1) remove contemporaneous influence of other macroeconomic variables on inflation by estimating inflation using lagged values of inflation expectations and the output gap, arguing that the lagged variables contain only past shocks, not current innovations. In other words, lagged inflation expectations and output gap are unaffected by the current-quarter inflationary shock but remain correlated with current-quarter inflation. This ensures they do not capture other shocks correlated with ϵ_{t+h}, thereby satisfying the instrumental variable conditions.

The first stage model is specified in (1) and regression table is provided in Appendix **??** Table 8. The F-statistic of 16.13 with a p-value close to zero suggests that variables in the first-stage have explanatory power for the dependent variable.

$$\pi_t = \delta + \sum_{i=1}^{l} \phi_i^{\pi} E_{t-i}\pi_{t+1} + \sum_{i=1}^{l} \phi_i^{u} \Delta u_{t-i} + \sum_{i=1}^{l} \phi_i^{p} \Delta \pi_{t-i}^{p} + \mu_t^{\pi} \tag{1}$$

where, π_t denotes inflation, $E_t\pi_{t+1}$ is the next period's inflation expectation, Δu_t represents percentage deviation of unemployment from natural rate of unemployment, $\Delta\pi^p$ represents the inflation of the producer's price, and μ_t^{π} is the residual term.

After fitting inflation using the first-stage regression model in (1), the local projection model in (2) is applied to estimate responses of time use categories following a one-standard deviation inflationary shock. For identification, the predicted inflation $\widetilde{\pi}_t$ from the first stage is used as an instrument, rather than the observed inflation directly from data. The local projection specification is given by (2):

$$H_{t+\kappa} - H_{t-1} = I_{t-1}\left[\alpha_{\kappa}^{A} + \beta_{\kappa}^{A}\widetilde{\pi}_t + \sum_{i=1}^{l}\gamma_{i,\pi}^{A}\pi_{t-i} + \sum_{i=1}^{l}\gamma_{i,h^j}^{A}\log H_{t-i}\right] \tag{2}$$

$$+ (1 - I_{t-1})\left[\alpha_{\kappa}^{B} + \beta_{\kappa}^{B}\widetilde{\pi}_t + \sum_{i=1}^{l}\gamma_{i,\pi}^{B}\pi_{t-i} + \sum_{i=1}^{l}\gamma_{i,h^j}^{B}\log H_{t-i}\right] + \varepsilon_{t+\kappa}^{j} \tag{3}$$

where κ stands for horizon (set to 12 quarters), $\widetilde{\pi}_t$ is the instrumented inflation from equation (1), and H_t corresponds to market work. $\log H_{t-i}$ denotes the first difference of time use categories added as control variables to the model. Following CGH, number of lags is set to three. The left-hand side of the regression (2) measures the first difference in time use. Accordingly, β_{κ}^{A} and β_{κ}^{B} identify the state-conditional average responses to the macroeconomic variable of interest, accounting for the possibility that the economy transitions between states over the projection horizon.

2.2 Bayesian Local Projection Model

Based on the paper, the horizon-specific prior tightness parameter λ_h is constructed as a deterministic function of the forecast horizon in order to discipline the estimation of local-projection impulse responses while preserving smooth dynamics across horizons. The starting point is the specification of a Gaussian prior for the local-projection coefficient at horizon h, denoted β_h, with mean anchored to an external benchmark—typically the impulse response from a reduced-form VAR—and variance that varies systematically with h. Formally, the prior is written as

$$\beta_h|\lambda_h \sim \mathcal{N}(\mu_h^{\text{prior}}, \sigma^2_{\lambda(h)}) \tag{4}$$

$$Var(\beta^h_{BLP}) = (Global\ Tightness) \times (Horizon\ Decay) \times (Lag\ Decay) \times (Scale\ Normalization) \tag{5}$$

$$\sigma^2_{\lambda(h)} = \frac{\lambda(h)^2}{\ell^\gamma} \frac{\sum^{(h)}_{\epsilon,ij}}{(\omega^{(h)}_{0,ij})^2} \tag{6}$$

$$\lambda^* = \underset{\lambda \in \Lambda}{arg\,max} \log p(y \mid \lambda) \tag{7}$$

$$\lambda(h) = \lambda^* g(h), \quad g(h) = \kappa_0 + \frac{\alpha}{1 + \exp(-\theta(h - h_0))} \tag{8}$$

where $\lambda(h)^2$ is horizon-specific prior tightness, ℓ^γ is lag-order shrinkage (Minnesota-style decay), ensuring higher-order lags are more tightly regularized, $\sum^{(h)}_{\epsilon,ij}$ is scale normalization using the innovation variance of the shocks. where μ_h^{prior} is the VAR-based prior mean and λ_h is the horizon-specific prior standard deviation. Rather than estimating a separate λ_h for each horizon, the paper imposes a parsimonious structure by expressing λ_h as the product of a global scale parameter and a smooth, horizon-dependent weighting function. Specifically,

Type-II ML selects λ^* (global scale),

where λ^* is a global scale parameter governing the overall tightness of the prior for local-projection coefficients and $g(h)$ is a deterministic, horizon-dependent logistic function. Thus, λ^* scales the entire sequence of horizon-specific prior standard deviations, while $g(h)$ controls how this tightness decays with the horizon.

Consequently, the λ-grid must span values that range from very tight priors (strong shrinkage toward the VAR) to very loose priors (essentially noninformative). Small λ^* values correspond to the belief that the VAR provides a highly informative benchmark and that LP coefficients should deviate from it only modestly while large λ^* values correspond to the belief that the VAR is uninformative and that the LP should be driven almost entirely by the data. The admissible λ-range must therefore include both regimes so that the data can select the appropriate balance.

In this formulation, $\lambda > 0$ governs the overall level of prior tightness common to all horizons, h_0 denotes the midpoint of the transition —defined by the equality $g(h_0) = 1/2$ —and $\kappa > 0$ controls the smoothness of the decay in prior informativeness as the horizon increases. By construction, $g(h)$ is a monotone decreasing logistic function satisfying $g(0) \approx 1$ and $\lim_{h\to\infty} g(h) = 0$, implying that short-horizon coefficients are tightly shrunk toward their prior means, while long-horizon coefficients are increasingly data-driven. This structure ensures that the prior variance λ_h^2 evolves smoothly with h, thereby preventing erratic or kinked impulse responses that often arise in classical local projections. The paper also presents an equivalent parameterization that embeds the same idea directly in the horizon-dependent standard deviation

where κ_0 represents a baseline level of dispersion, α determines the amplitude of the horizon-dependent component, and θ governs the slope of the logistic transition. This expression is algebraically distinct but conceptually equivalent to $\lambda_h = \lambda g(h)$, as both encode the same restriction that prior tightness should decline smoothly with the forecast horizon. Taken together, these steps define λ_h as a low-dimensional, horizon-dependent prior scale that regularizes local-projection estimates, pools information across horizons, and improves finite-sample precision without imposing sharp breaks or horizon-specific tuning.

The λ-grid is chosen to span values ranging from strong shrinkage toward the VAR prior to effectively noninformative priors, ensuring that the horizon-dependent regularization encompasses both VAR-like and classical local-projection behavior.

By construction, $g(h)$ is a monotone decreasing logistic function. short-horizon coefficients are tightly shrunk toward their prior means, while long-horizon coefficients are increasingly data-driven.

as the product of a global scale parameter and a smooth, horizon-dependent weighting function. Specifically, The parameters h_0 and κ govern the horizon at which prior information becomes dominant and the smoothness of that transition. They shape the distribution of posterior uncertainty across horizons without affecting overall prior tightness, which is selected endogenously. In the Bayesian local projection framework, priors are required for all regression coefficients. Following the paper, horizon-dependent shrinkage governed by the global tightness parameter is applied exclusively to the shock coefficients that define the impulse response. Control variables are treated as nuisance parameters and assigned simpler, horizon-invariant Gaussian priors with relatively tight variance. This separation stabilizes estimation, avoids overfitting at long horizons, and ensures that the Type-II marginal likelihood criterion selects the degree of shrinkage relevant for impulse response inference rather than for auxiliary dynamics.

shrink LP coefficients toward plausible dynamics without imposing causal structure.

3 Definition of States

3.1 Data Set

This study draws on two main datasets: the ATUS, which measures the amount of time individuals allocate to activities such as market work, home production, and leisure, and the Survey of Professional Forecasters (SPF) from the Federal Reserve Bank of Philadelphia, used here as a proxy for aggregate inflation expectations. ATUS has been collected since 2003, making it relatively recent, whereas SPF data extend back to 1981 (Q3). Given the shorter time span of ATUS, the analysis in this paper is limited to the 2003–2024 period. Data is discussed in the next section.

3.1.1 Micro-level Data

Estimated impulse responses of market work to one percent increase in the inflation rate, using the median level of next-quarter inflation expectations. The series "AHRSWORKT: the total number of hours worked over all jobs in the last week" downloaded from IPUMS and aggregated by the author. Shaded areas indicate 68-percent confidence interval around estimate. Data from 1989:Q1–2024:Q4.

3.1.2 Aggregated-level Data

To specify inflation, a time series regression model is developed that combines the lagged inflation expectations from the SPF with the output gap. The SPF began in 1968 (Q4), originally conducted by the American Statistical Association (ASA) and the National Bureau of Economic Research (NBER), was eventually handed over to the Philadelphia Fed in 1990(Q2). However, quarterly CPI inflation expectations from professional forecasters have only been available since 1981(Q3). In this survey, forecasters provide quarterly estimates for the next five quarters, along with annual projections for the current and following year. Since the time series variables are considered quarterly, next-quarter CPI inflation expectations—at the mean[1], median[2], 25th percentile, and 75th percentile levels[3]—are selected for the first-stage time series regression model, with the median used as the baseline. Projections are reported as annualized quarter-over-quarter percent changes in the quarterly average price index. Figure **??** in Appendix **??** presents inflation expectations alongside actual inflation since 1981(Q3). Other macroeconomic variables used in this paper include

[1]The data can be downloaded directly from the Philadelphia Federal Reserve's website https://www.philadelphiafed.org/surveys-and-data/real-time-data-research/mean-forecasts

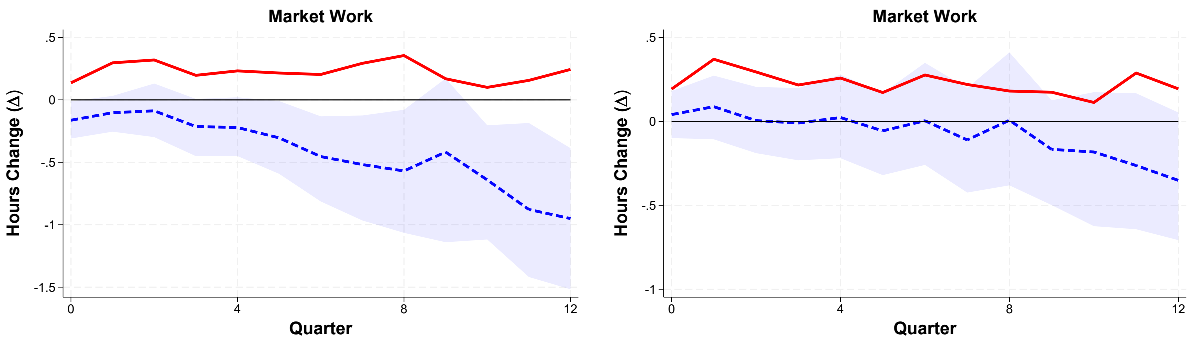
[2]The data can be downloaded directly from the Philadelphia Federal Reserve's website https://www.philadelphiafed.org/surveys-and-data/real-time-data-research/median-forecasts

[3]The data can be downloaded directly from the Philadelphia Federal Reserve's website https://www.philadelphiafed.org/surveys-and-data/real-time-data-research/dispersion-forecasts

quarterly CPI inflation, real GDP, and potential real GDP, all obtained from the Federal Reserve Bank of St. Louis (Fred) database. Aggregated data preparation is provided in Appendix **??**.

4 State-Dependent Effects of Inflationary Shocks

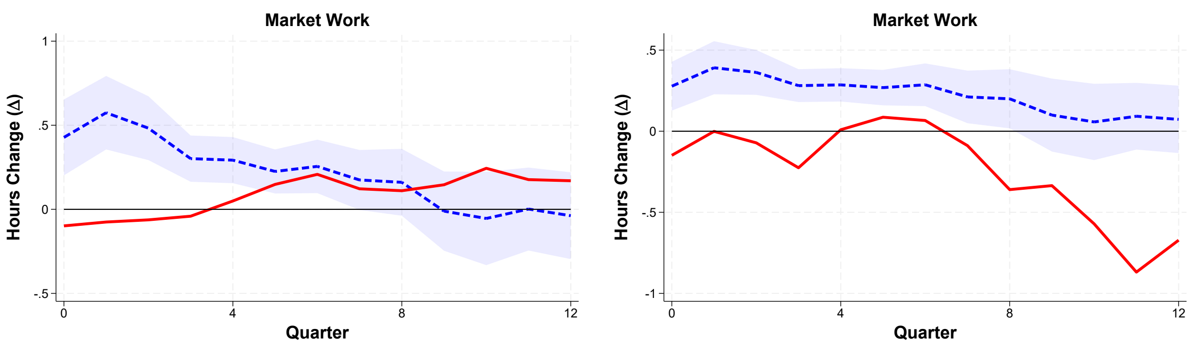
4.1 Unemployment



(a) (b)

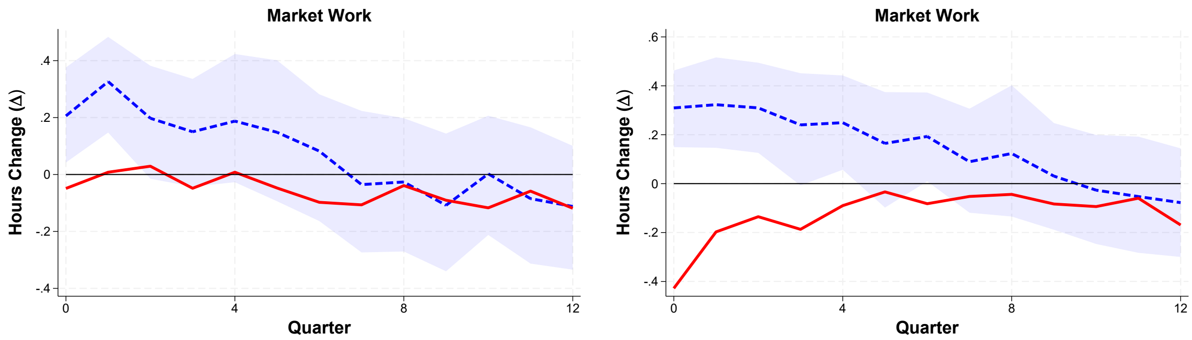
Figure 1: State-dependent IRFs to a one percent inflation shock. Low-unemployment states are shown by the blue dashed line and high-unemployment states by the red solid line. Shaded areas indicate one standard error confidence interval around estimate.

4.2 Inflation and Inflation Expectation



(a) (b)

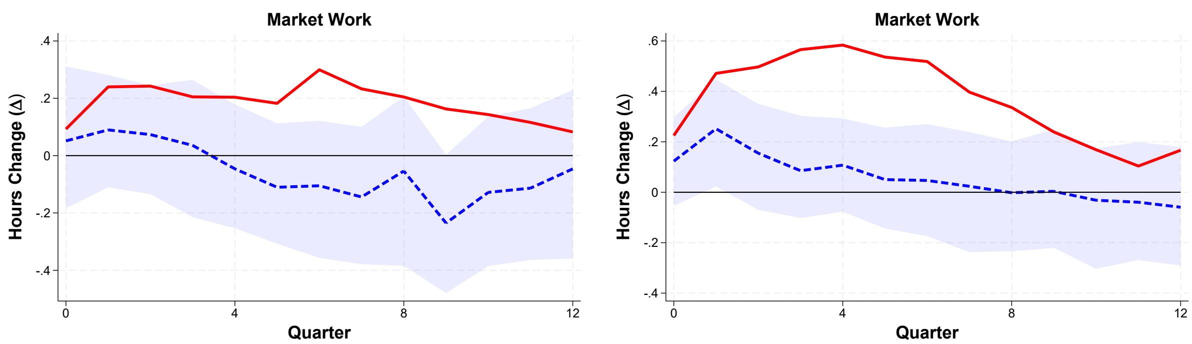
Figure 2: State-dependent IRFs to a one percent inflation shock. Low-inflation states are shown by the blue dashed line and high-inflation states by the red solid line. Shaded areas indicate one standard error confidence interval around estimate.



(a) (b)

Figure 3: State-dependent IRFs to a one percent inflation shock. Low inflation expectation states are shown by the blue dashed line and high inflation expectation states by the red solid line. Shaded areas indicate one standard error confidence interval around estimate.

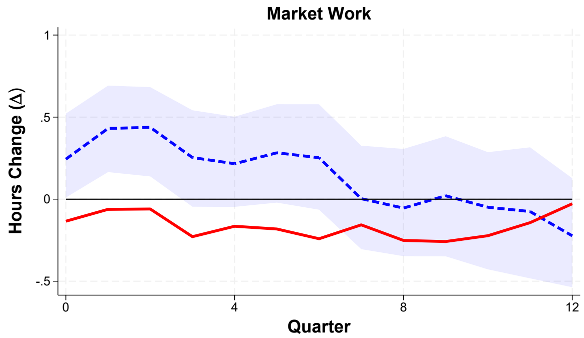
4.3 Government Spending



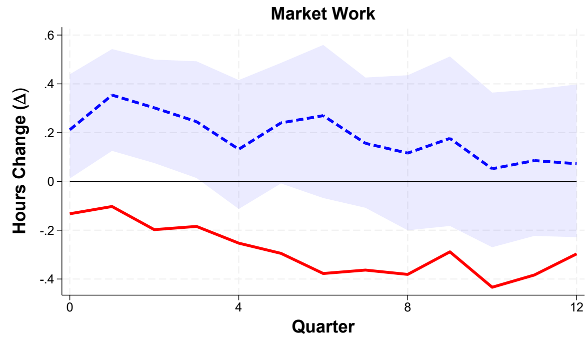
(a) (b)

Figure 4: State-dependent IRFs to a one percent inflation shock. Low fiscal multipliers states are shown by the blue dashed line and high fiscal multipliers states by the red solid line. Shaded areas indicate one standard error confidence interval around estimate.

4.4 Monetary Policy

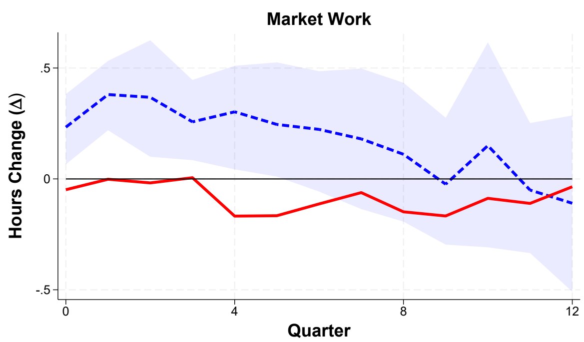


(a)

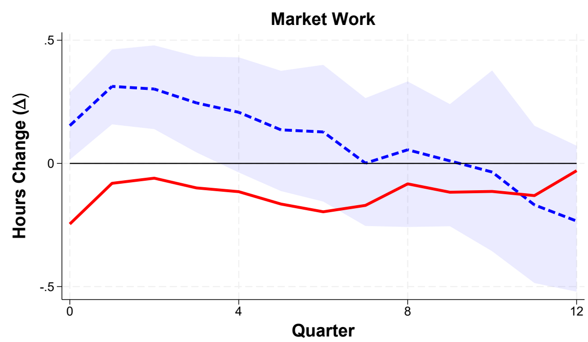


(b)

Figure 5: State-dependent IRFs to a one percent inflation shock. Low interest rate states, federal funds rate, are shown by the blue dashed line and high interest rate states by the red solid line. Shaded areas indicate one standard error confidence interval around estimate.

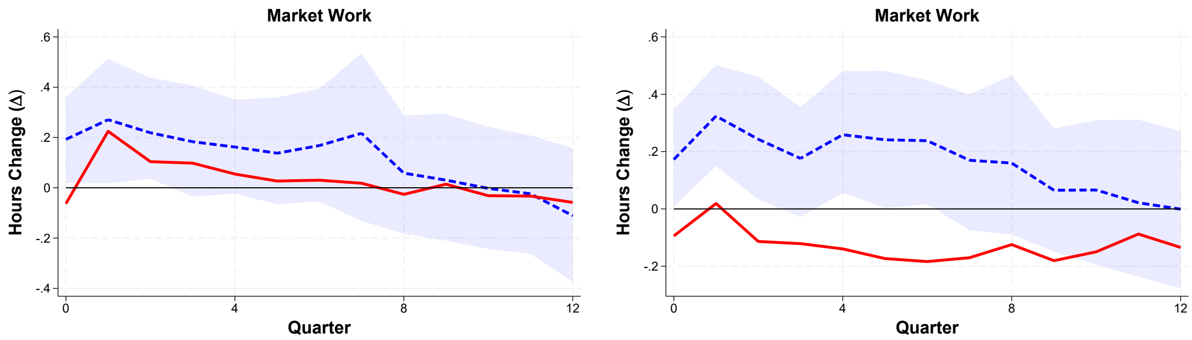


(a)



(b)

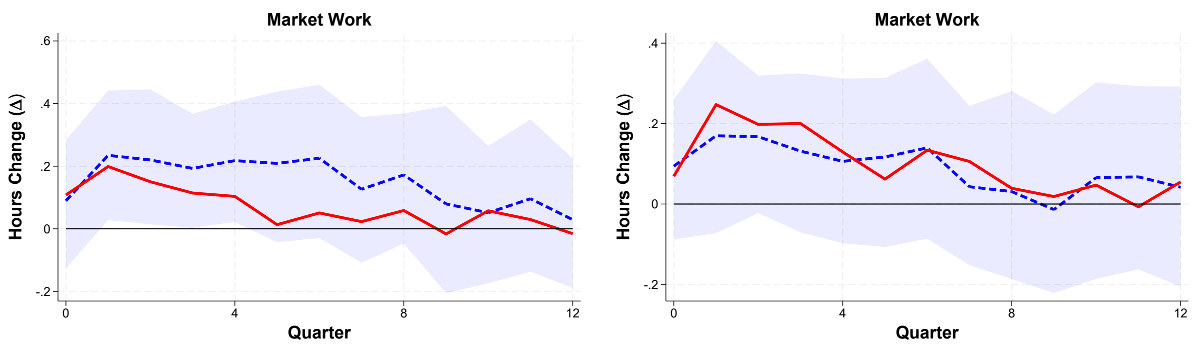
Figure 6: State-dependent IRFs to a one percent inflation shock. Low interest rate, 10-years treasury bill, states are shown by the blue dashed line and high interest rate states by the red solid line. Shaded areas indicate one standard error confidence interval around estimate.



(a) (b)

Figure 7: State-dependent IRFs to a one percent inflation shock. Low interest rate, real interest rate, states are shown by the blue dashed line and high interest rate states by the red solid line. Shaded areas indicate one standard error confidence interval around estimate.

4.5 Uncertainty



(a) (b)

Figure 8: State-dependent IRFs to a one percent inflation shock. Low-uncertainty states are shown by the blue dashed line and high-uncertainty states by the red solid line. Shaded areas indicate one standard error confidence interval around estimate.

5 Conclusion

In this paper, regimes are manually defined; however, data-driven methods, for instance Goulet Coulombe and Klieber (2025) can be introduced for this purpose.

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Online Appendix

"The State-Dependent Effects of Inflation on Market Work Hours: A Bayesian Local Projection Approach"

Jalal Bagherzadeh

A Data Description

- **Slack Variable:** $Unemployment\ gap = UNRATE - NROU$

  UNRATE: Unemployment Rate, Percent, Quarterly, Seasonally Adjusted.

  NROU: Noncyclical Rate of Unemployment, Percent, Quarterly, Seasonally Adjusted

- **Inflation Expectation**

  Mean forecasts for the headline CPI inflation rate: Next-quarter forecasts for annualized quarter-over-quarter percent changes of the quarterly average price index level, Percent, Quarterly, Seasonally adjusted, Annual rate.

- **Inflation** $= (\log(CPIAUCSL_t) - \log(CPIAUCSL_{t-4}) * 100$

  CPIAUCSL: Consumer Price Index (CPI) for All Urban Consumers: All Items in U.S. City Average, Index 1982-1984=100, Quarterly, Seasonally Adjusted.

- **Market Work**

  AHRSWORKT: Total number of hours the respondent was at work during the previous week. For employers and the self-employed, this includes all hours spent attending to their operation(s) or enterprise(s). For employees, it is the number of hours they spent at work. For unpaid family workers, it is the number of hours spent doing work directly related to the family business or farm (not including housework)

- **Producer Price Inflation** $= (\log(WPUID61_t) - \log(WPUID61_{t-1}) * 100$

  WPUID61: Producer Price Index by Commodity: Intermediate Demand by Commodity Type: Processed Goods for Intermediate Demand, Index 1982=100, Quarterly, Not Seasonally Adjusted.

- **Fiscal Multipliers** $= \frac{FGEXPND}{GDP}$

  FGEXPND: Federal Government: Current Expenditures, Billions of Dollars, Quarterly Seasonally Adjusted, Annual Rate.

  GDP: Gross Domestic Product, Billions of Dollars, Quarterly, Seasonally Adjusted, Annual Rate.

- **Monetary Policy**

  FEDFUNDS: Federal Funds Effective Rate, Percent, Quarterly, Not Seasonally Adjusted.

DGS10: Market Yield on U.S. Treasury Securities at 10-Year Constant Maturity, Quoted on an Investment Basis, Percent, Quarterly, Not Seasonally Adjusted.

$Ex-ante\ Real\ Interest\ Rate = FEDFUNDS - Inflation\ Expectation$

$Ex-post\ Real\ Interest\ Rate = FEDFUNDS - Inflation$

- **Uncertainty**

  VIXCLS: CBOE Volatility Index, Index, Quarterly, Not Seasonally Adjusted.

B Micro-level Evidence

Table 1: Market Work Across States of Unemployment (Z) and Inflation (π)

	(1)	(2)	(3)
$\mathbb{1}(Z > q_{0.75})$	-0.551***	-0.873***	-0.904***
	(0.013)	(0.035)	(0.034)
$\mathbb{1}(\pi > q_{0.75})$	0.029**	-0.458***	-0.453***
	(0.012)	(0.041)	(0.040)
$\mathbb{1}(Z > q_{0.75}) \times \mathbb{1}(\pi > q_{0.75})$	0.204***	1.010***	1.021***
	(0.027)	(0.064)	(0.062)
Observations	24,449,620	3,722,567	3,722,567
Clusters (individual)	5,260,185	574,171	574,171

(1): All population

(2): Sample restricted to individuals observed in both states

(3): Sample restricted to individuals observed in both states. Controls for age and sex

Robust standard errors clustered at the individual level in parentheses.

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table 2: Market Work Across States of (π)

	(1)	(2)	(3)
$\mathbb{1}(\pi > q_{0.75})$	0.14***	0.13***	0.16***
	(0.01)	(0.01)	(0.01)
Observations	24,449,620	7,779,653	7,779,653
Clusters (individual)	5,260,185	1,235,411	1,235,411

(1): All population

(2): Sample restricted to individuals observed in both states

(3): Sample restricted to individuals observed in both states. Controls for age and sex

Robust standard errors clustered at the individual level in parentheses.

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table 3: Market Work Across States of Inflation Expectation (Z) and Inflation (π)

	(1)	(2)	(3)
$\mathbb{1}(Z > q_{0.75})$	-0.06***	0.14***	0.21***
	(0.02)	(0.03)	(0.03)
$\mathbb{1}(\pi > q_{0.75})$	0.17***	0.07**	0.12***
	(0.01)	(0.03)	(0.03)
$\mathbb{1}(Z > q_{0.75}) \times \mathbb{1}(\pi > q_{0.75})$	-0.01	-0.18***	-0.26***
	(0.02)	(0.04)	(0.04)
Observations	24,449,620	2,838,945	2,838,945
Clusters (individual)	5,260,185	466,650	466,650

(1): All population

(2): Sample restricted to individuals observed in both states

(3): Sample restricted to individuals observed in both states. Controls for age and sex

Robust standard errors clustered at the individual level in parentheses.

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table 4: Market Work Across States of Government Spending (Z) and Inflation (π)

	(1)	(2)	(3)
$\mathbb{1}(Z > q_{0.75})$	-0.56***	-0.49***	-0.51***
	(0.01)	(0.02)	(0.02)
$\mathbb{1}(\pi > q_{0.75})$	0.07***	0.03	0.05
	(0.01)	(0.03)	(0.03)
$\mathbb{1}(Z > q_{0.75}) \times \mathbb{1}(\pi > q_{0.75})$	0.40***	0.46***	0.47***
	(0.02)	(0.05)	(0.05)
Observations	24,449,620	3,654,026	3,654,026
Clusters (individual)	5,260,185	558,287	558,287

(1): All population

(2): Sample restricted to individuals observed in both states

(3): Sample restricted to individuals observed in both states. Controls for age and sex

Robust standard errors clustered at the individual level in parentheses.

${}^{*}p < 0.10$, ${}^{**}p < 0.05$, ${}^{***}p < 0.01$

Table 5: Market Work Across States of Monetary Policy —Federal Funds Rate (Z) —and Inflation (π)

	(1)	(2)	(3)
$\mathbb{1}(Z > q_{0.75})$	0.21***	0.09***	0.08***
	(0.01)	(0.02)	(0.02)
$\mathbb{1}(\pi > q_{0.75})$	0.16***	0.28***	0.16***
	(0.01)	(0.03)	(0.03)
$\mathbb{1}(Z > q_{0.75}) \times \mathbb{1}(\pi > q_{0.75})$	-0.16***	-0.12***	-0.00
	(0.02)	(0.04)	(0.04)
Observations	24,449,620	6,269,574	6,269,574
Clusters (individual)	5,260,185	1,014,960	1,014,960

(1): All population

(2): Sample restricted to individuals observed in both states

(3): Sample restricted to individuals observed in both states. Controls for age and sex

Robust standard errors clustered at the individual level in parentheses.

${}^{*}p < 0.10$, ${}^{**}p < 0.05$, ${}^{***}p < 0.01$

Table 6: Market Work Across States of Monetary Policy —10-years Treasury Bill (Z) —and Inflation (π)

	(1)	(2)	(3)
$\mathbb{1}(Z > q_{0.75})$	0.21***	0.26***	0.25***
	(0.02)	(0.02)	(0.02)
$\mathbb{1}(\pi > q_{0.75})$	0.18***	0.11**	0.08*
	(0.01)	(0.05)	(0.04)
$\mathbb{1}(Z > q_{0.75}) \times \mathbb{1}(\pi > q_{0.75})$	-0.20***	-0.12**	-0.08
	(0.02)	(0.05)	(0.05)
Observations	24,449,620	3,523,240	3,523,240
Clusters (individual)	5,260,185	559,404	559,404

(1): All population

(2): Sample restricted to individuals observed in both states

(3): Sample restricted to individuals observed in both states. Controls for age and sex

Robust standard errors clustered at the individual level in parentheses.

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table 7: Market Work Across States of Uncertainty (Z) and Inflation (π)

	(1)	(2)	(3)
$\mathbb{1}(Z > q_{0.75})$	-0.19***	-0.30***	-0.25***
	(0.01)	(0.01)	(0.01)
$\mathbb{1}(\pi > q_{0.75})$	0.18***	0.05***	0.10***
	(0.01)	(0.02)	(0.02)
$\mathbb{1}(Z > q_{0.75}) \times \mathbb{1}(\pi > q_{0.75})$	0.01	0.14***	0.10***
	(0.02)	(0.02)	(0.02)
Observations	24,449,620	10,604,203	10,604,203
Clusters (individual)	5,260,185	1,696,283	1,696,283

(1): All population

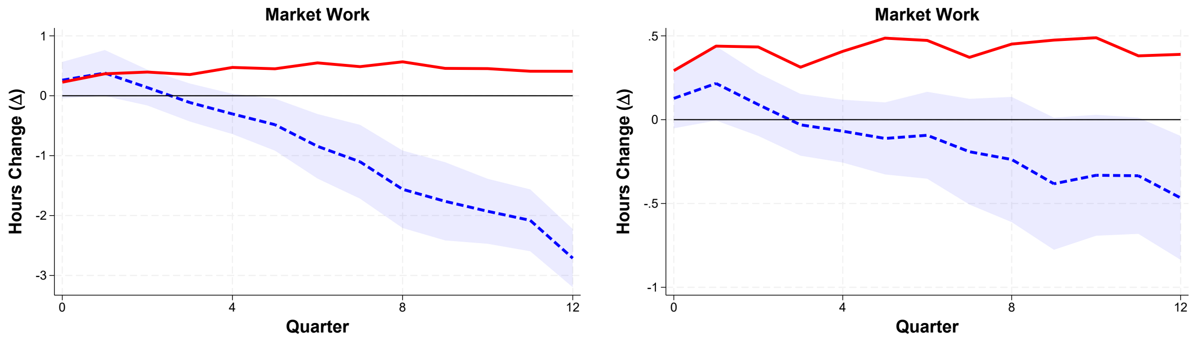
(2): Sample restricted to individuals observed in both states

(3): Sample restricted to individuals observed in both states. Controls for age and sex

Robust standard errors clustered at the individual level in parentheses.

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

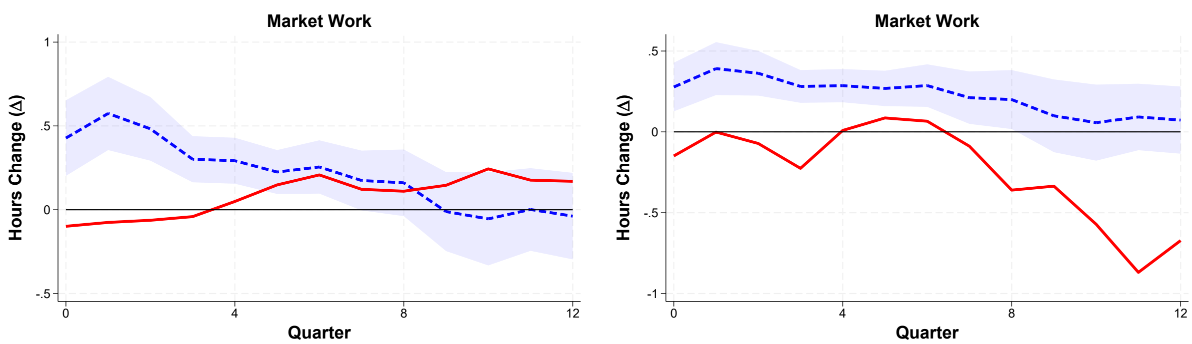
C Frequentist Approach



(a)

(b)

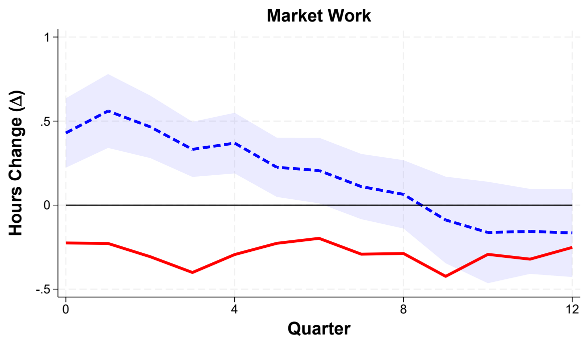
Figure 9: State-dependent IRFs to a one percent inflation shock. Low-unemployment states are shown by the blue dashed line and high-unemployment states by the red solid line. Shaded areas indicate one standard error confidence interval around estimate.



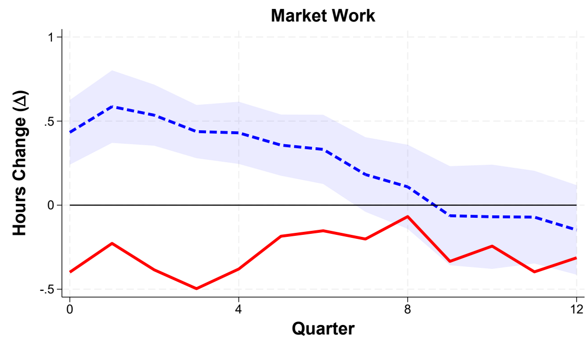
(a)

(b)

Figure 10: State-dependent IRFs to a one percent inflation shock. Low-inflation states are shown by the blue dashed line and high-inflation states by the red solid line. Shaded areas indicate one standard error confidence interval around estimate.

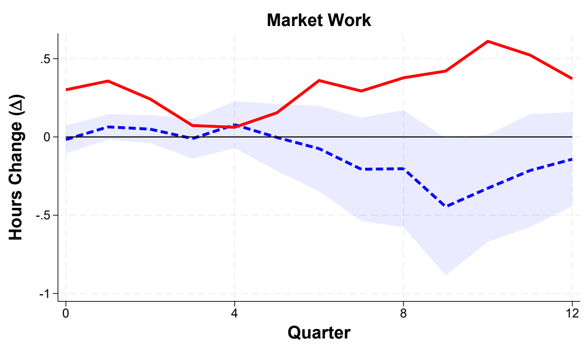


(a)

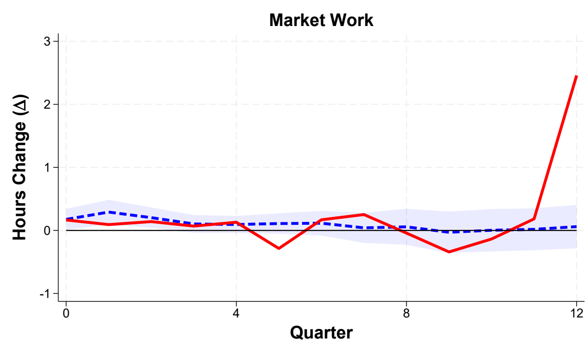


(b)

Figure 11: State-dependent IRFs to a one percent inflation shock. Low inflation expectation states are shown by the blue dashed line and high inflation expectation states by the red solid line. Shaded areas indicate one standard error confidence interval around estimate.

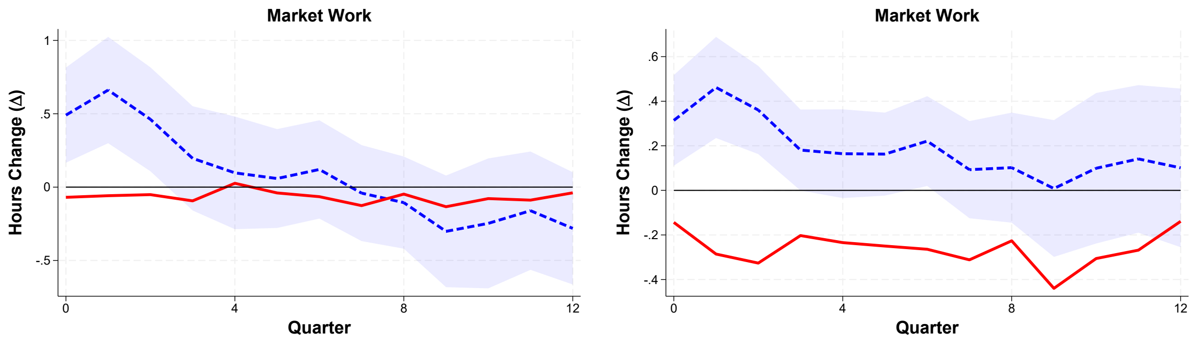


(a)



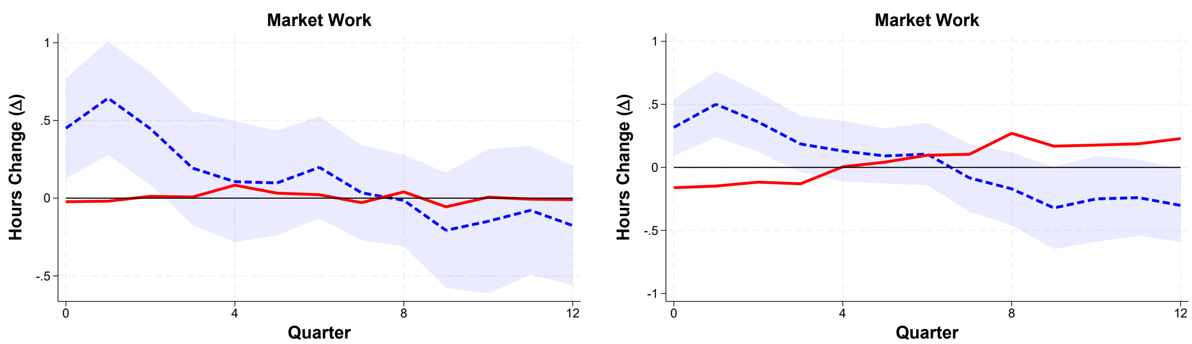
(b)

Figure 12: State-dependent IRFs to a one percent inflation shock. Low fiscal multipliers states are shown by the blue dashed line and high fiscal multipliers states by the red solid line. Shaded areas indicate one standard error confidence interval around estimate.



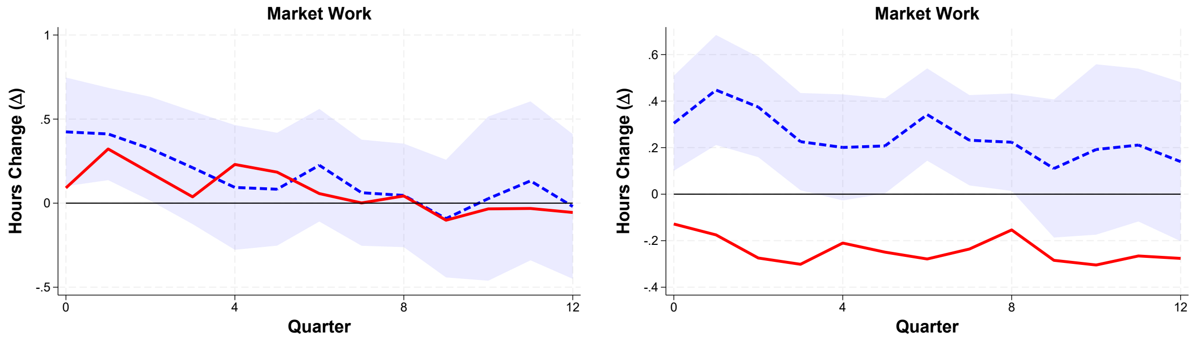
(a) (b)

Figure 13: State-dependent IRFs to a one percent inflation shock. Low interest rate states are shown by the blue dashed line and high interest rate states by the red solid line. Shaded areas indicate one standard error confidence interval around estimate.



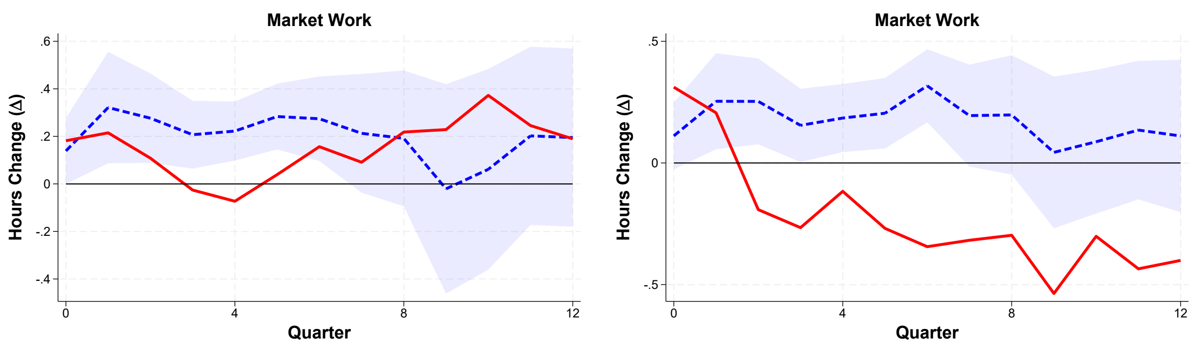
(a) (b)

Figure 14: State-dependent IRFs to a one percent inflation shock. Low interest rate, 10-years treasury bill, states are shown by the blue dashed line and high interest rate states by the red solid line. Shaded areas indicate one standard error confidence interval around estimate.



(a) (b)

Figure 15: State-dependent IRFs to a one percent inflation shock. Low interest rate, 10-years treasury bill, states are shown by the blue dashed line and high interest rate states by the red solid line. Shaded areas indicate one standard error confidence interval around estimate.



(a) (b)

Figure 16: State-dependent IRFs to a one percent inflation shock. Low-uncertainty states are shown by the blue dashed line and high-uncertainty states by the red solid line. Shaded areas indicate one standard error confidence interval around estimate.

Table 8: 1-Stage Regression Result

	$\widetilde{\pi}$
L.$E_t\pi_{t+1}$	0.586**
	(0.228)
L2.$E_t\pi_{t+1}$	0.278
	(0.226)
L3.$E_t\pi_{t+1}$	0.314
	(0.191)
L.Δu_t	0.043
	(0.079)
L2.Δu_t	-0.124*
	(0.072)
L3.Δu_t	0.055
	(0.064)
L.$\Delta\pi_t^p$	0.292***
	(0.043)
L2.$\Delta\pi_t^p$	0.093**
	(0.045)
L3.$\Delta\pi_t^p$	0.228***
	(0.040)
Constant	-0.599***
	(0.229)
Observations	140
R^2	0.796
F-statistics	38.82
Prob > F	0.0000

$*p < 0.10$, $**p < 0.05$, $***p < 0.01$