Heterogeneity in the Economic Impact of Temperature Shocks Across US States

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Abstract

This paper presents new empirical evidence on short- and medium-term heterogeneous temperature effects on real GDP growth and inflation at the US state level. The results reveal heterogeneity across states, seasons, and time horizons, with the sign of responses becoming synchronized seven quarters after temperature shocks. By examining the joint responses of output and prices, I explore whether temperature shocks resemble demand or supply shock at the state-level. The nature of shock varies by season and time horizon: cold season shock initially acts as positive demand and supply shock but transitions to negative supply (mostly in north-eastern states) and positive demand shock (mostly in southern states) as the time horizon extends, whereas warm season shock predominantly resembles negative supply shock after seven quarters (especially in southern states). Variations in state-level responses are explained by state attributes such as sectoral shares of manufacturing and services along with average temperature.

Keywords: temperature, heterogeneity, growth, inflation, US states
JEL codes: E23, E31, Q54, R11

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1 Introduction

How do temperature shocks impact real GDP growth and inflation at the US state-level? Is there substantial heterogeneity across states? How do these impacts vary across seasons? In this paper, I address these questions by examining heterogeneity in the economic impact of temperature shocks across US states at a quarterly frequency. In doing so, I depart from the related literature along two dimensions. First, while most related literature imposes extensive homogeneity assumptions across countries using panel regressions (e.g., Dell et al. (2012), Acevedo et al. (2020), Nath et al. (2024), among others), I conduct state-by-state local projections to fully capture potential heterogeneity effects.[1] Second, I focus on higher-frequency effects, whereas previous findings have mostly focused on annual frequency (e.g., Dell et al. (2012), Velasquez (2023), Berg et al. (2024), among others). Temperature effects on economic outcomes may differ across seasons and time horizons,[2] which can be masked in annual average effects.[3] As such, going to higher-frequency is important for revealing these subtle temperature effects.

By adopting the two dimensions, I extend the existing literature with two key contributions. First, by exploring sub-national effects at a higher frequency, I disentangle short-term and medium-term economic impacts and the underlying mechanisms driving these dynamics, which could provide useful information for policy makers to design more targeted and effective policies addressing climate risks at a disaggregated level. Second, by looking at the joint responses of quarterly state-level output and prices – variables that have not yet been studied in the related literature – I provide the first empirical exploration of whether state-level temperature shocks resemble supply- or demand-side shocks.

I first establish empirical evidence of heterogeneous economic effects. I use a nonlinear local projection for each state to estimate the causal impact of seasonal state-level tem-

[1] Similarly, a recent paper by Berg et al. (2024) conduct country-by-country analysis to uncover heterogeneity in cross-country responses. They find substantial dispersion between negative and positive impulse responses of real GDP per capita growth to positive temperature shocks. In this paper, I show such heterogeneity within a single country, the United States.

[2] A few recent studies emphasize this perspective. For example, Ciccarelli et al. (2023) document asymmetric seasonal effects of temperature shocks on inflation in the four largest euro area economies. In the US context, Colacito et al. (2019) highlight the varying effects of seasonal temperatures using *annual* state-level economic outcomes in a panel framework. Perhaps closest to my paper, Nguyen (2024) examines seasonal temperature effects in quarterly frequency at the US sub-national level. However, his target economic variable is *employment growth*, whereas I focus on real GDP growth and inflation.

[3] For example, opposite effects on economic activities from hot summer and mild winter could average out throughout the year.

perature shocks. The state-level temperature shocks are constructed in two steps. First, I calculate temperature anomaly (TA) for each state, capturing quarterly temperature deviations relative to historical average for that particular quarter. Second, I extract the portion of TA that is driven by common temperature fluctuations across states using Principal Component Analysis, which I denote as "common component of TA" (common TA). Focusing on the common TA (rather than TA itself) makes heterogeneous effects across states more comparable as it captures comprehensive effects affecting large regions.[4] Then, the seasonal state-level temperature shocks are defined as unexpected increase in the common TA during warm (spring and summer) and cold (fall and winter) seasons. For the state-level economic variables, I obtain quarterly real GDP (RGDP) growth from Baumeister et al. (2024) and inflation from Hazell et al. (2022).[5] Given the availability of the inflation data, the analysis covers the period from 1989 to 2017 for 31 states.

The results reveal heterogeneous effects across three dimensions: states, seasons, and time horizons. Cold season shocks initially have a positive short-term impact on RGDP growth, possibly due to favorable economic conditions, but lead to decline in some states – particularly in the eastern regions – after 7 quarters. Inflation responses to cold season shocks show a consistent increase across states, driven by increase in the responses of both tradeable and nontradeable goods prices in most states, with the increase in tradeable goods prices being more synchrnoized and pronounced.[6] In contrast, state responses to warm season shocks initially show varying effects on RGDP growth but eventually lead to uniform negative effects, with the largest contraction of around -0.6 p.p., particularly in southern states. Inflation responses to warm season shocks generally increase over time for most states, though exceptions exist with decreases observed in some West Coast states as the horizon extends. The effects on inflation are driven by a uniform and substantial increase in tradeable goods prices across most states, along with state-specific responses in

[4]Studying the *common* impacts is found in recent literature, although the specific temperature measures are defined differently. For example, Berg et al. (2024) decomposes country temperatures into global and idiosyncratic component and analyze the effects of shocks to each on country-level GDP, finding variations in responses across countries and across components. Similarly, Bilal and Känzig (2024) emphasizes that global temperature shocks have larger macroeconomic effects compared to local (i.e., within-country) temperature shocks as the global shocks are highly associated with extreme climatic events.

[5]In the US, the two variables in relation to weather shocks have been studied in different settings. For example, Colacito et al. (2019) study seasonal temperature effects for each of the four US regions using a panel regression with annual state GDP data. Kim et al. (2022) study the effects of severe weather shocks on the US macroeconomy, including national CPI inflation. Natoli (2023) examines effects of unfavorable temperature shocks on quarterly GDP and CPI but at the national level.

[6]Please see Section 2.2 for details on the tradeable and nontradeable inflation data.

nontradeable goods prices.

Building on the heterogeneous effects documented above, I explore whether state-level temperature shocks resemble demand- or supply-side shocks by examining the joint responses of RGDP and inflation. The shock types are identified by observing whether output and prices move in the same or opposite directions. The nature of temperature shocks depend on the season and time horizon. As observed in the impulse responses, in the short-term, cold season shocks are associated with positive demand and supply shocks, due to initial boost in RGDP growth. However, as the horizon extends, the shocks resemble negative supply-side (mainly for eastern states as they experience decline in RGDP growth) and positive demand shocks (mainly for southern states likely due to favorable conditions for leisure and hospitality). For warm season shocks, the uniform decrease in RGDP growth reveals predominantly negative supply-side effects after seven quarters, especially in southern states. This could be attributed to reduced labor productivity or higher energy prices, amplifying supply-side constraints. These results highlight the need for more nuanced modeling of temperature effects in structural models, as existing framework often assume a simple (negative) supply shock (for example, see Economides and Xepapadeas (2018)).

Based on the heterogeneous findings at quarterly frequency, I investigate the underlying mechanisms that explain variations in responses across states, seasons, and time horizons. The findings suggest that states with a higher concentration of non-durable goods, such as foods, beverages, rubber, and similar products are likely to have immediate spoilage, contribute to short-term negative impacts on RGDP growth following a warm season shock. In contrast, the share of durable goods has relatively limited role. States with a larger services sector exhibit a greater increase in inflation in response to warm season shocks. Moreover, consistent with existing findings, states with higher baseline temperature tend to experience greater decline in RGDP over longer horizons.

The rest of the paper is organized as follows: Section 2 provides details about the data. Section 3 outlines the econometric framework. Section 4 provides the results. Section 5 studies the underlying mechanisms that, in part, account for heterogeneity across states. Section 6 presents further discussions and robustness checks, and Section 7 concludes the paper.

2 Data

In this section, I describe how I build state-level temperature shocks. I also provide sources and details of the two state-level economic variables – RGDP growth and inflation – used in the analysis. The data span from 1989q2 to 2017q4.

2.1 Temperature Data

State-level temperature shocks are constructed in two steps. First, I calculate temperature anomalies for each state using monthly average temperatures (expressed in Fahrenheit) obtained from the National Oceanic and Atmospheric Administration (NOAA). The statewide temperature data is computed based on area-weights of climate divisions within each state, assigning larger weight to larger area of the climate divisions.[7] I also utilize a population weighting scheme as a robustness check, which I provide in Section 6.3.1. In order to match the frequency of state-level economic variables, which is explained in Section 2.2, the monthly temperature data is aggregated to quarterly frequency. I follow the conventional method of calculating temperature anomalies as follows:

$$TA_{s,q,y} = t_{s,q,y} - \bar{t}_{s,q}, \quad \text{where} \quad \bar{t}_{s,q} = \frac{1}{30} \sum_{i=1959q}^{1988q} t_{s,i}. \tag{1}$$

In Eq (1), $t_{s,q,y}$ denotes average temperature of state s at quarter q and year y, and $\bar{t}_{s,q}$ denotes the historical average temperature for quarter q calculated over a reference period of 30-years from 1959 to 1988.[8] The temperature anomalies measure by how much quarterly temperatures deviate from their historical (state-specific) averages. For example, positive (negative) values of TA in a given quarter indicate higher (lower) average temperatures relative to the historical average temperature for that specific quarter. By construction, the TA takes out average seasonal temperature variations and accounts for differing baseline

[7] To be specific, 5km × 5km grid-point estimates interpolated from station data are averaged up to state-level using area-weights of the climate divisions within each state. US climate divisions can be found at `https://psl.noaa.gov/data/usclimdivs/`. Detailed explanations about the statewide temperature data can be found in `https://www.ncei.noaa.gov/pub/data/cirs/climdiv/state-readme.txt`.

[8] I choose 30-year window as conventionally employed in climatological literature to calculate deviations from the historical averages. Although fixed reference period is commonly used in the related literature (for example, Faccia et al. (2021), Lucidi et al. (2024)), there could be a concern that using the fixed reference period disregards agents' updated temperature beliefs and could lead to overestimated positive values of temperature anomalies as discussed in Natoli (2023). As robustness analysis, in Section 6.3.2, I use 10-years rolling window instead of the fixed reference period and show the results are robust.

temperatures across states. Furthermore, measuring the short-run fluctuations (rather than level) of temperature alleviates concerns about endogeneity as these are less likely to be caused by economic factors.[9]

In the second step, I extract the portion of TA driven by common fluctuations across states, which I denote it as "common component of TA" (common TA). This approach captures comprehensive effects affecting large regions and allows potential heterogeneity effects across states to be comparable. Given the diverse geographical scope of the states, it is reasonable to expect that the degree to which each state is exposed to the common temperature fluctuations may vary. To identify the common temperature factors influencing multiple states and to quantify how each state is related to these factors, I conduct Principal Component Analysis (PCA). A factor model is formulated as:

$$TA_{s,t} = \lambda_s' f_t + \epsilon_{s,t} \tag{2}$$

where $TA_{s,t}$ is temperature anomaly of state s at time t as calculated in Eq (1) (subscripts for the specific quarter q and year y are abbreviated to t for simplicity), f_t and λ_s contains K-dimensional common factors and their corresponding loadings, respectively.[10] In Eq (2), the term $\lambda_s' f_t$ is referred to as the *common component*, and the term $\epsilon_{s,t}$ is referred to as the *idiosyncratic component*. The PCA is conducted for 48 states (excluding Alaska and Hawaii).[11]

[9]For each state, I demean the TA (subtracting the average over the sample period) as a simplified method to remove any long-term trend. This approach is often used in related-literature such as Velasquez (2023) and Lucidi et al. (2024). Throughout the rest of the paper, TA refers to demeaned temperature anomaly.

[10]The common factors represent unobserved variables that account for the largest variations across the temperature anomalies, and the loadings indicate the strength of association between each state and the k-th factor.

[11]Although only 31 states are used in the analysis due to the availability of state-level inflation data (details are provided in Section 2.2), I utilize 48 states for the PCA to capture a more comprehensive and accurate representation of the temperature dynamics across the US.

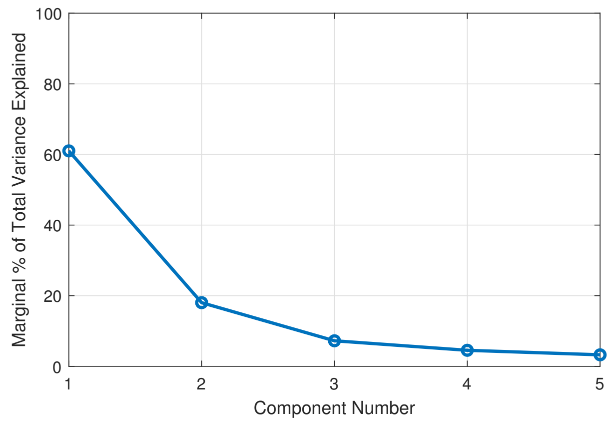


Figure 1: Scree plot showing the marginal power of the first five principal components (factors) in explaining the total variation of temperature anomalies across 48 states

Figure 1 shows a scree plot displaying the marginal amount of the total variation in the 48 temperature anomalies explained by the first five principal components (or factors). The first two components account for a substantial portion (around 80 percent) of the total variation, and the additional explanatory power of the third and higher components becomes negligible.[12] Thus, in Eq (2), I select the first two principal components ($K = 2$). In Figure 2, I plot a color-scaled US map where each state's color intensity reflects the contribution of each factor in explaining the variance of temperature anomalies. The darker the color, the more a specific state is associated with the factor. Interestingly, a clear distinction emerges in the role of the first and second principal component: the first principal component is strongly related to the non-West region[13] whereas the second principal component is highly associated with the West region.[14] This division between non-West and West region could be possibly due to a significant natural barrier, namely the Rocky Mountains, which blocks or changes the movement of air masses and contributes to different weather patterns between the western and eastern parts of the US.[15] The two distinct regional temperature

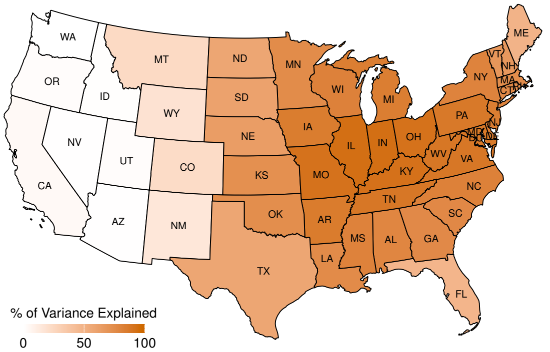
[12]As the two principal components account for majority of the variations in TA, the common component of TA closely mirrors the TA in most states.

[13]The non-West region refers to Midwest, South, and Northeast regions based on the classification of the US Census Regions. The regional map can be found in `https://www2.census.gov/geo/pdfs/maps-data/maps/reference/us_regdiv.pdf`.

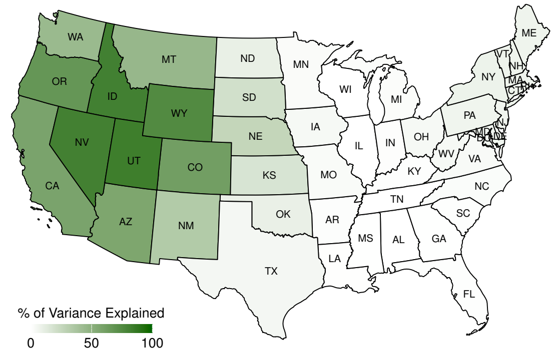
[14]These PCA results of temperature anomalies are also discussed in Velasquez (2023).

[15]For example, it is documented in Hauer et al. (1997) that the west side of the Rocky Mountains experiences a more moderate climate influenced by oceanic conditions, while regions east of the mountains, especially the Great Plains, experience greater temperature variability due to the dominance of continental

dynamics could potentially impact the regional economies in different ways.



(a) First Principal Component



(b) Second Principal Component

Figure 2: Contribution of each of the first two principal components in explaining the variations in temperature anomalies for each state. Darker colors indicate a stronger association between the state and the factor.

In Figure 3, I alternatively show the decomposed contributions of each component using a stacked bar for each state: the first principal component is shown in orange, the second in green, and the idiosyncratic component in gray. The states are ordered in descending order based on the contribution of the first principal component. The plot clearly illustrates that non-West states are predominantly influenced by the first principal component (capturing at least 50 percent to at most around 93 percent of the variance, except Maine and Florida), while West states are primarily influenced by the second principal component (ranging from at least 33 percent to at most around 83 percent).

Overall, the common TA for each state is interpreted as the portion of its temperature anomalies that is explained by the two principal components shared across states. It is useful to note that although the common TA shock is driven by the first two principal components, temperature fluctuations in non-West states are heavily influenced by the first principal component, wheres those in West states are mainly influenced by the second principal component. A shock to common TA may capture broad spillover effects across states, which may be missed when analyzing localized (state-specific) shocks.

air masses.

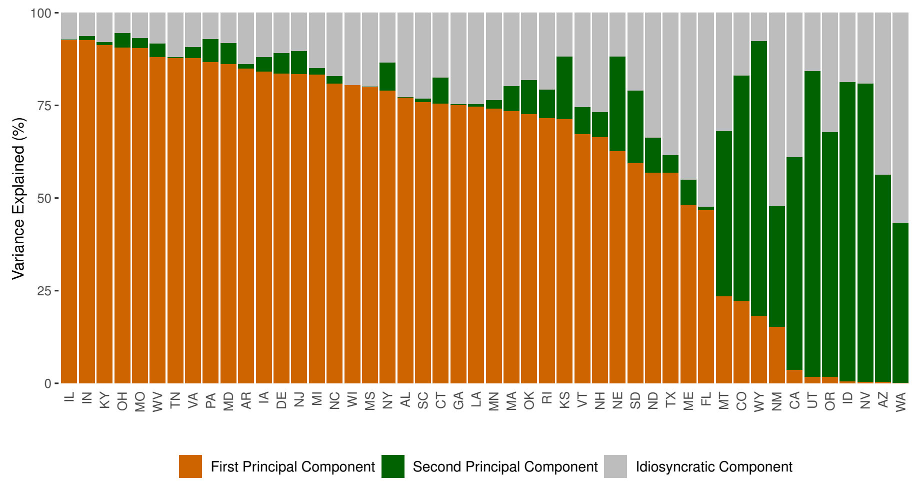


Figure 3: Plots the contribution of the first (orange) and second (green) principal components, along with the idiosyncratic component (gray) in explaining the variations in temperature anomalies for each state. The states on x-axis are ordered in descending order based on the contribution of the first principal component.

2.2 Economic Data

Compared to the availability of high-frequency national-level data, state-level macroeconomic data is less readily available. In the US, state-level output data is typically published at an annual frequency over longer periods, which has led previous studies (such as Colacito et al. (2019) and Velasquez (2023)) to examine the effects of temperature shocks on annual economic outcomes. In this paper, I employ state-level economic variables, specifically real GDP and inflation, in quarterly frequency sourced from Baumeister et al. (2024) and Hazell et al. (2022), respectively, for which I provide details below.

Baumeister et al. (2024) develop a novel dataset of weekly Economic Conditions Index (ECI) for US states using a mixed-frequency dynamic factor model.[16] The weekly ECI comprises various aspects of state-level economic indicators such as mobility, labor market, real activity, expectations, financial, and households, each consisting of several input series.[17] Among those series, my interest is the weekly estimates of the year-over-year growth rate of

[16]The dataset begins in April 1987 and is publicly available. It can be downloaded from `https://sites.google.com/view/weeklystateindexes/dashboard`

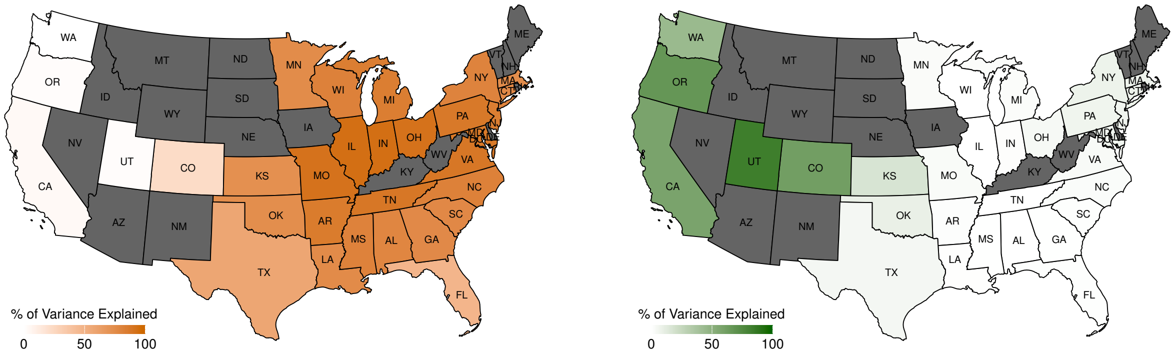
[17]See Baumeister et al. (2024) for detailed descriptions and construction of the index.

state-level real GDP, which is grouped under the real activity indicator.[18] I aggregate these weekly real GDP growth rates into quarterly frequency to match the quarterly state-level inflation data, which I describe below.

Hazell et al. (2022) construct quarterly state-level consumer price indices and publish the year-over-year growth rates for overall, tradeable, and nontradeable.[19] The data is available for 33 states and District of Columbia. For my analysis, I focus on 31 states by excluding Alaska and Hawaii due to their unique climates and economic structures. I revisit Figure 2 and 3, which display PCA results for 48 states, and show the same results focusing only on the 31 states in Figure 4 and 5 with the excluded states in gray color. The common period across the 31 states spans from 1989q2 to 2017q4, which determines the data period used in the empirical analysis. I use overall inflation as the benchmark specification and incorporate the two subcategories for in-depth inflation analysis.

[18] I take the series from the replication package of Baumeister et al. (2024) and adjust it for my purpose as follows: (i) The published state-level economic indicators are scaled to match the four-quarter growth rates of US real GDP to put state-level economic conditions into the national context. However, since I focus on state-by-state analysis rather than comparisons to the national context, I take the non-scaled estimates of the series to better capture state-specific effects. (ii) The non-scaled weekly estimates of the input series are expressed in standard deviations, as the series are standardized during the estimation process. I reverse the standardization process to convert the estimates back to their original units (i.e., growth rates). In this way, I obtain weekly estimates of real GDP growth rate for each state.

[19] For their research purpose, they define nontradeable based on their own categorization of items, which is similar to the Bureau of Labor Statistics (BLS) service aggregation but differs in two ways: (i) they include Entry Level Items (ELIs) in the Food Away from Home category, and (ii) exclude several ELIs in Transportation Services (mainly airline tickets), Utilities, and Truck Rentals. Tradeable is simply defined as the complement of nontradeable. The data is downloadable at `https://sites.google.com/view/jadhazell/state-consumer-price-index`. For the detailed construction method and categorizations, see the main text and Appendix B.4 of Hazell et al. (2022).



(a) First Principal Component

(b) Second Principal Component

Figure 4: Contribution of each of the first two principal components in explaining the variations in temperature anomalies for the 31 states used in the analysis. States not included in the sample are colored in gray. The darker the color, the more strongly a state is associated with the factor.

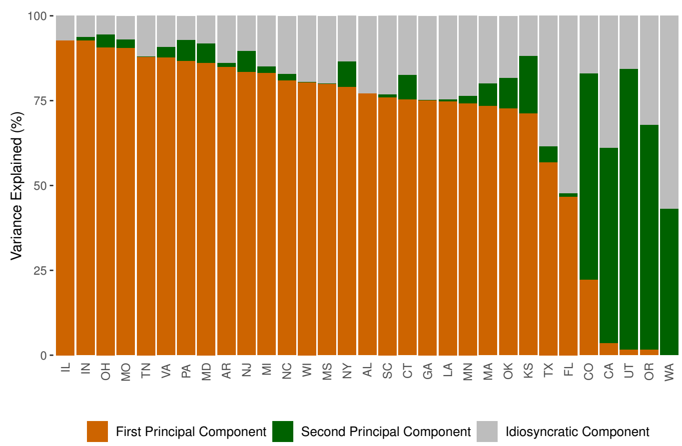


Figure 5: Plots the contribution of the first (orange) and second (green) principal components, along with the idiosyncratic component (gray) in explaining the variations in temperature anomalies for each of the 31 states used in the analysis. The states on x-axis are ordered in descending order by the contribution of the first principal component.

3 Empirical Specification: Nonlinear Local Projection

To fully uncover the existence of heterogeneous effects of the common component of temperature anomalies on state-level economies, I conduct a state-by-state analysis. Specifically, I employ a nonlinear LP by introducing an interaction term of the temperature shock and a seasonal dummy to investigate potential asymmetric effects across different seasons, which may be obscured in a linear model.

Several studies have found that temperature shocks can lead to varying economic outcomes depending on the season (for example, Colacito et al. (2019), Faccia et al. (2021), Ciccarelli et al. (2023), Nguyen (2024)). Recently, Lucidi et al. (2024) accommodated various types of nonlinearities to study the asymmetric effects of temperature anomalies on the European economy, especially focusing on energy transmission channels. As one of specifications, they find existence of asymmetries across seasons: a positive TA shock during spring-summer months leads to increase in different types of prices, whereas deflationary effects are observed during fall-winter months, with more compelling evidence for the latter.

Inspired by Jordà (2005) and Lucidi et al. (2024), I conduct seasonal dependence specification as:

$$y_{s,t+h} = \alpha_{s,h} + \beta_{s,h} commonTA_{s,t} + \tau_{s,h} Z_t * commonTA_{s,t} + \eta_{s,h} commonTA_{s,t-1} + \sum_{l=1}^{p} \gamma_{s,h,l} X_{s,t-l} + \varepsilon_{s,t+h}, \tag{3}$$

where $y_{s,t+h}$ denotes the economic variable of interest (quarterly RGDP growth or inflation rate) for state s at $t+h$, $commonTA_{s,t}$ denotes the common component of TA of state s at time t, and Z_t is a dummy variable taking the value of 1 during warm season, spring (Q2) and summer (Q3), and 0 during cold season, fall (Q4) and winter (Q1). The responses to a $1°F$ increase in common TA (i.e., an unexpected increase in common component of TA) are identified by the coefficients of $\beta_{s,h}$ and $\tau_{s,h}$, where the former reflects the baseline effect of the common TA when $Z_t = 0$ (in cold season) and the latter represents the additional effect of common TA in warm season ($Z_t = 1$).[20] A lag of common TA is included to control for the possible autocorrelation of common TA across 31 states.[21] I also control the two state-level macroeconomic variables, RGDP growth and inflation, in $X_{s,t-l}$ with lags up to 4 (i.e., p=4). To avoid any potential overfitting issues, I maintain a parsimonious set of

[20] A $1°F$ increase in common TA is equivalent to approximately $0.56°C$ increase.

[21] The common TA exhibits either no autocorrelation or, at most, autocorrelation up to lag 1 across the 31 states.

controls that are relevant as a benchmark specification.

Gonçalves et al. (2024) recently documented the validity of the LP estimator in nonlinear setting when the state is exogenous.[22] In my specification, the state (S_t in their notation) refers to the seasonal dummy, which is determined outside the economic system and is strictly exogenous with respect to the output and inflation variables. Thus, I interpret the impulse response estimators as capturing the causal effect of a temperature shock on the economic variables. I examine how the responses evolve over the two years following the shock ($h = 8$). The impulse response functions are performed with Newey-West standard errors (Newey and West, 1987).

4 Results

This section provides the main empirical results. I highlight three horizons for presenting the results: on impact, one year and 7 quarters after the shock. These horizons are selected to show the contemporaneous impacts of the shock, the period at which the state responses begin to synchronize, and the period when the effects and the synchronization reaches its peak, respectively. In the main text, I focus on the results based on 68% confidence intervals.[23]

4.1 Impulse Responses

I first show empirical evidence of heterogeneous economic effects observed across states, seasons, and time horizons. Figure 6 displays the seasonal responses of state-level RGDP growth to a positive common TA shock by horizon. The first two columns present the responses in a US map for each warm and cold season. In the map, positive effects are colored in red and negative effects in blue, with darker shades representing larger effects. The last column displays a scatter plot comparing the two seasonal responses, with filled dots indicating statistical significance.

In responses to an unexpected common increase in temperature across states during the cold season, there seems to be a short-term boost in nationwide economic activities (except Colorado and California), followed by a decline in most eastern states. On impact, the cold

[22]They show that the local projection estimator asymptotically recovers the population response regardless of the shock size when the state is exogenous.

[23]Results based on 90% confidence interval are provided in the Appendix A.5. Not surprisingly, the number of statistically significant states decrease. However, the overall implications remain the same.

season temperature shock mildly boosts output growth across states, although only around a third of the states are significant. A mild temperature increase during the cold season can improve conditions for economic activities, especially benefiting Louisiana by around 0.2 p.p. Additionally, it may be related to the positive effects of warmer winter on employment growth as found in Nguyen (2024).[24] However, the boost is short-lived with the output growth eventually turning negative mainly in eastern states.

During the warm season, the sign of responses varies initially but converges over time resulting in uniformly decreasing the output growth. Immediately following the shock, real output in eastern states is negatively affected, while some western states (such as Colorado, California, and Washington) and Oklahoma are positively affected.[25] This result confirms that the commonly identified negative impact of hotter temperature on annual economic outcomes could mask such short-term heterogeneity in the temperature effects on quarterly output, as the variations can be averaged out over the year. After 7 quarters, the responses show a synchronized decline in output growth for the majority of states, with southern states experiencing relatively stronger effects (more than -0.5 percentage points (p.p.) for states such as Mississippi, Louisiana, and Florida).[26] This may be attributed to the negative impact of an increase in the average summer temperature on the labor productivity growth (Colacito et al. (2019)) as well as employment growth (Nguyen (2024)).

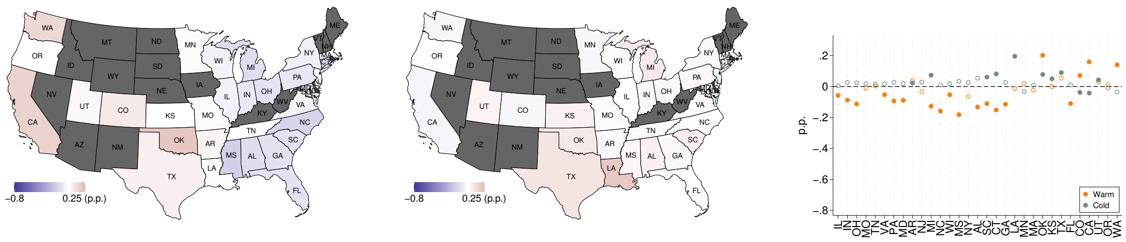
Some additional points are noteworthy. The overall dispersion of responses across states is larger for the warm season shock than for the cold season shock across all horizons. Also, the responses to the warm season shock are stronger and are more statistically significant than those to the cold season shock. Interestingly, after 4 quarters, Louisiana experiences the largest contraction among the states in response to both the warm and the cold season

[24] Nguyen (2024) documents that warmer winter temporarily increases employment growth (only significantly for the current winter). Moreover, he finds that hotter summer has persistent negative effects, and no significant results found in the milder fall and spring.

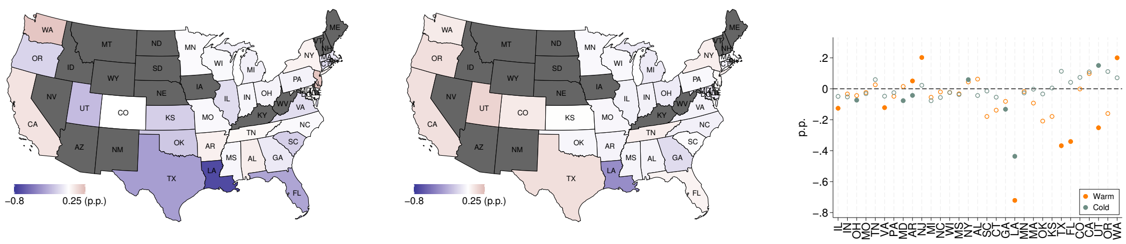
[25] These dispersed responses, with positive and negative signs across states, may offset each other, resulting in a non-significant impact on national-level RGDP during the spring and summer (up to horizon 4), as reported by Natoli (2023) in response to an increase in exceptionally hot days.

[26] This finding is broadly consistent with the US regional analysis in Colacito et al. (2019). They conduct a *regional* analysis on the contemporaneous effects of seasonal temperatures on gross state product (GSP) and particularly find statistically significant effects in southern states: negative effects of summer temperature and positive effects of fall temperature. Their approach differs from mine as the authors run panel regression of the *annual* growth rate of GSP on four seasonal temperatures for each of the four regions defined by the Census Bureau. Considering the warm season responses in my analysis as average effects of Spring and Summer in Colacito et al. (2019), the results are broadly consistent with my findings at the regional-level. However, it is important to note that the results are not directly comparable as my analysis provides state-level results using quarterly frequency.

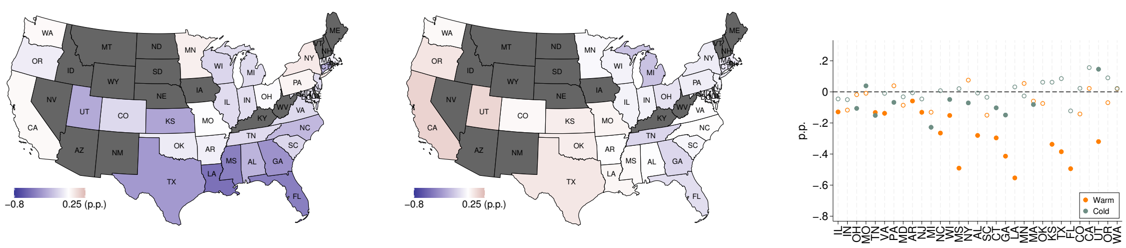
shock, with stronger effects during the warm season (exceeding -0.7 p.p.).



(a) h=0 (Warm) (b) h=0 (Cold) (c) h=0 (Warm & Cold)



(d) h=4 (Warm) (e) h=4 (Cold) (f) h=4 (Warm & Cold)



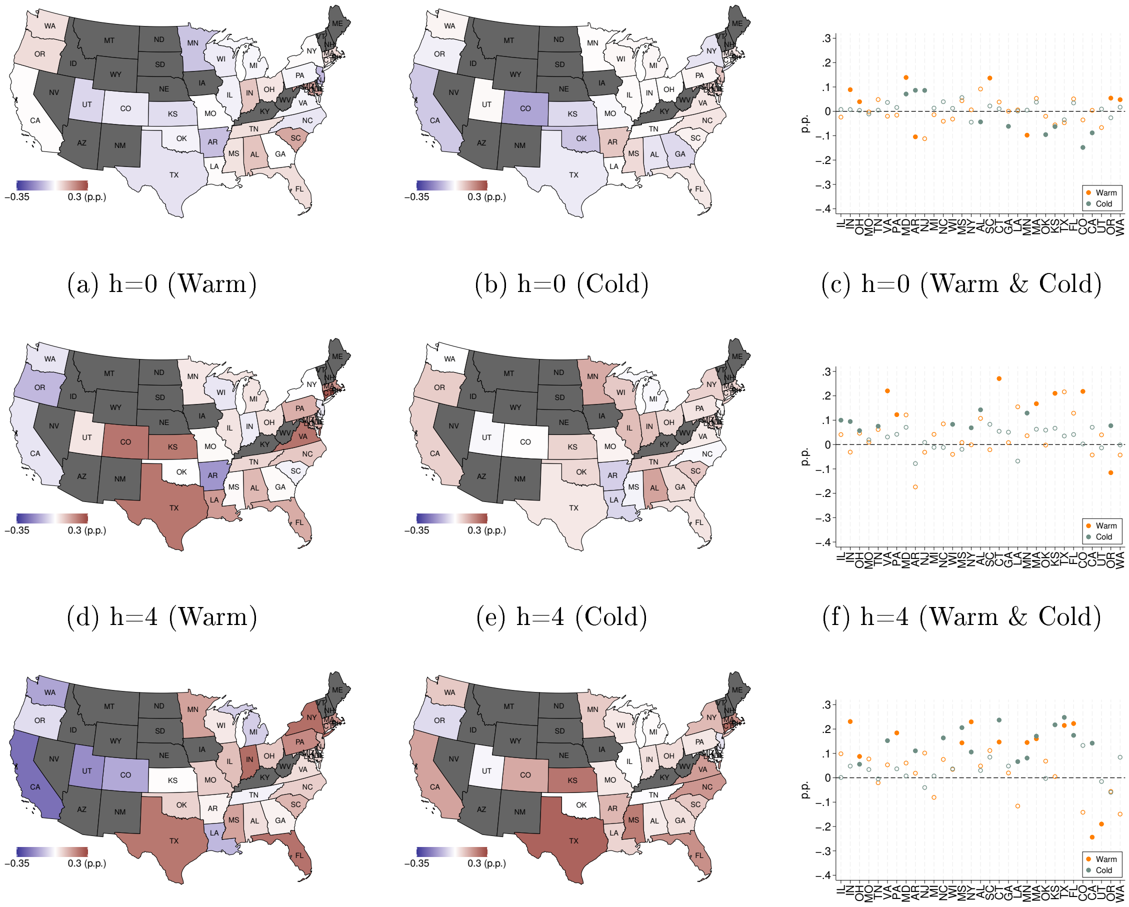
(g) h=7 (Warm) (h) h=7 (Cold) (i) h=7 (Warm & Cold)

Figure 6: Nonlinear LP results of state-level RGDP in response to a positive shock in the common TA for each season. The first and second columns display the responses for each warm and cold season in a US map, and the third column displays the two responses jointly in a scatter plot, with filled dots indicating statistical significance at 68% confidence interval. Each row corresponds to on impact, 4 and 7 quarters after the shock.

Figure 7 presents the state-level inflation responses by season and horizon, similarly highlighting heterogeneity effects. While the effects on RGDP growth are large to the warm season shock compared to the cold season shock, the seasonal asymmetric effects are less evident in the inflation responses. On impact, inflation responses are dispersed across states in both seasons, but over time, the direction of the responses become uniformly positive. Following a positive shock in the cold season, responses show a consistent increase across states, with the largest effects observed after 7 quarters. In states such as Texas, Kansas, and Mississippi, prices rise by more than 0.2 percentage points. In response to a positive warm season shock, inflation responses generally increase over time for most states, though exceptions exist, with decreases observed in Oregon, Utah, and California as the horizon extends.

Roughly aggregating these state-level inflation responses to the national-level, the results are broadly consistent with the seasonal responses of national CPI to US-wide heat shocks documented by Natoli (2023).[27] The author finds substantial variations in the sign of the national CPI responses across the four seasons, with positive values in winter and fall (corresponding to the cold season in my analysis) and slightly negative values, though not statistically different from zero up to horizon 8, across spring and summer (corresponding to the warm season in my analysis).

[27]Natoli (2023) defines the heat shock as fluctuations in the number of exceptionally hot days. My results are based on the overall fluctuations across different sizes of shocks rather than the extreme ones.



(a) h=0 (Warm) (b) h=0 (Cold) (c) h=0 (Warm & Cold)

(d) h=4 (Warm) (e) h=4 (Cold) (f) h=4 (Warm & Cold)

(g) h=7 (Warm) (h) h=7 (Cold) (i) h=7 (Warm & Cold)

Figure 7: Nonlinear LP results of state-level inflation in response to a positive shock in the common TA for each season. The first and second columns display the responses for each warm and cold season in a US map, and the third column displays the two responses jointly in a scatter plot, with filled dots indicating statistical significance at 68% confidence interval. Each row corresponds to on impact, 4 and 7 quarters after the shock.

4.2 Supply or Demand?

Building on the documented heterogeneous effects, I examine the joint response of RGDP growth and inflation to assess the nature of the temperature shock.[28] To be specific, for each

[28] A recent paper Ciccarelli and Marotta (2024) study the multifaceted macroeconomic effects (such as investment, output, and rices) of two categories of climate risk – physical and transition – using the OECD

season, I discuss whether the shock resembles either a demand or supply shock. I identify the shock types by observing whether output and prices move in the same or opposite directions.[29]

In Figure 8, each panel displays the responses of RGDP growth (horizontal axis) and inflation (vertical axis) for each state at a specific horizon and for particular season. The state names are colored in four ways based on statistical significance: green if only RGDP growth is significant, blue if only inflation is significant, red if both are significant, and black if neither response is significant. Based on the directions of responses, temperature shocks can be classified into four types, which are represented by the four sections divided by dashed lines. Each section corresponds to a specific shock type. The top-left represents a negative supply shock, the bottom-left a negative demand shock, the top-right a positive demand shock, and the bottom-right a positive supply shock.

As observed in impulse responses, a positive cold season shock initially benefits economic activities in several states, while the movements of inflation responses vary across states. This suggests that the cold season shock initially act as positive demand- or supply-side shocks, though exceptions exist from California and Colorado experiencing negative demand-side effects. After 7 quarters, however, the shock shifts toward negative supply-side and positive demand-side effects, as indicated by the overall increase in the state-level inflation and the positive and negative responses in output growth across states. States associated with negative supply-side effects are mainly located in the northern or mid-eastern regions, including Connecticut, Massachusetts, New York, and Ohio. Although warmer-than-usual cold seasons initially stimulate output, they may eventually disrupt sectors that rely on their colder climates. For example, crops that benefit from lower temperatures could yield lower outputs, which in turn drives up prices. On the other hand, states that experience positive demand-side effects are mainly related to the southern region, such as Texas, Louisiana, Mississippi, and Arkansas. One possible explanation is that warmer temperatures in these states, typically having mild cold season, could create favorable conditions for leisure and hospitality, thereby stimulating demand.

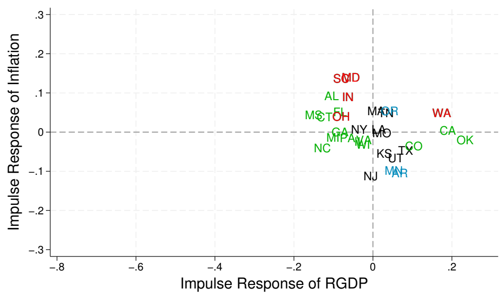
In contrast, warm season shocks are identified across all types of shocks but are par-

database and find that physical risks act as negative demand shocks, while transition risks act as downward supply movements. For the US economy, Natoli (2023) suggests that demand-side effects dominate supply-side ones by finding a slowdown in both *national* real GDP and CPI observed four to eight quarters after an increase in the number of unexpected extreme hot and cold days.

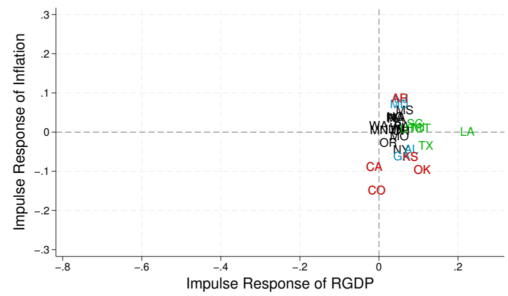
[29]A shock is identified as demand-side if output and prices move in the same direction, whereas it is identified as supply-side if the two variables move in the opposite direction.

ticularly concentrated in negative supply-side effects. As the detrimental effects on output growth become more prominent nationwide, the shock shifts toward negative supply-side effects for majority of states, especially in the South, after 7 quarters. This could be attributed to reduced labor productivity caused by higher temperatures. Moreover, heat shocks may increase energy demand and affect the stability of energy infrastructure, leading to higher energy prices. These factors result in higher production costs, which may amplify supply-side constraints and contribute to the transition toward negative supply-side shocks.

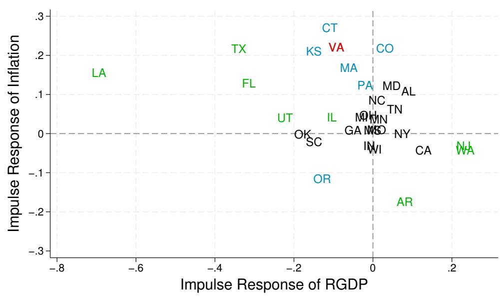
Overall, the nature of temperature shocks depend on the season and time horizon. These results highlight the need for more nuanced modeling of temperature effects in structural models, going beyond the simple assumption of a (negative) supply shock, as often done in existing frameworks (e.g., Economides and Xepapadeas (2018)).



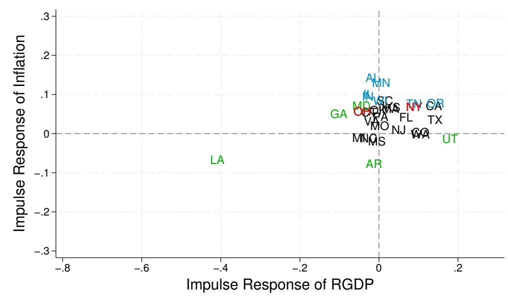
(a) h=0 (Warm)



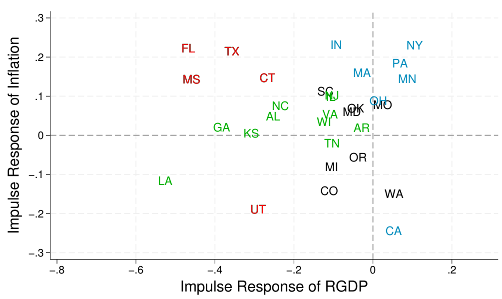
(b) h=0 (Cold)



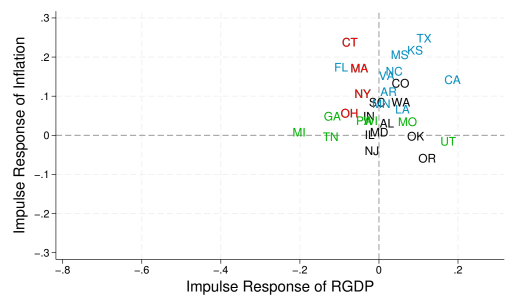
(c) h=4 (Warm)



(d) h=4 (Cold)



(e) h=7 (Warm)



(f) h=7 (Cold)

Figure 8: Nonlinear LP results of state-level RGDP (on x-axis) and inflation (on y-axis) to a positive shock in the common TA for each season. The first column displays the responses for the warm season and the second column displays the responses for the cold season. In each panel, state names are colored in four ways for indicating statistical significance at 68% confidence interval: red (both significant), green (only RGDP significant), blue (only inflation significant), black (neither significant). Each row corresponds to on impact, 4 and 7 quarters after the shock.

4.3 Inflation Analysis

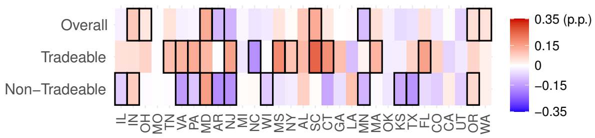
In this analysis, I use disaggregated state-level inflation data for tradeable and nontradeable goods from Hazell et al. (2022) to further study the overall inflation dynamics. I re-estimate the benchmark specification by replacing overall inflation with each component one at a time. Figure 9 visualizes the responses for each component in separate rows within a heatmap. Red color represents positive values and blue represents negative values with color intensity indicating the magnitudes. Statistically significant state-component cells are highlighted with square boxes.

Interestingly, but not surprisingly, tradeable goods prices exhibit more synchronized movements relative to nontradeable goods prices. The increase in the tradeable inflation becomes stronger and more statistically significant after 7 quarters, particularly in response to warm season shock with prices rising by more than 0.3 p.p. in Georgia, North Carolina, Florida, and New Jersey. This synchronization provides suggestive evidence of spillover effects of temperature fluctuations on tradeable goods, possibly through production networks (Velasquez (2023)).[30] Interestingly, opposite signs of synchronization in tradeable inflation responses is observed between non-West states and some western states, especially after 7 quarters. This may imply that tradeable prices are particularly sensitive to the two distinct regional temperature dynamics mentioned in Section 2.1: common temperature fluctuations in the non-West region appears to drive tradeable goods prices up, while the fluctuations in the West tends to lower the prices.

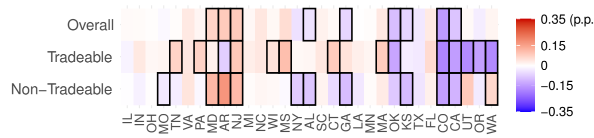
The responses of inflation in nontradeable goods are less synchronized across states, and this is even more evident in responses to the warm season shock. Since nontradeable goods consist of services consumed locally, their responses to temperature shocks are likely to depend on local economic conditions and consumers' behavioral effects.

A uniform increase in overall inflation in response to cold season shocks appears to be driven by rise in both tradeable and nontradeable goods prices, with the increase in tradeable goods prices being more pronounced.

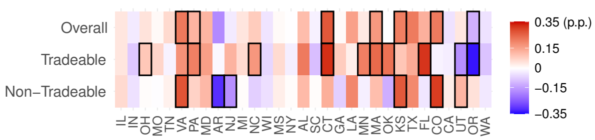
[30] In Velasquez (2023), the author documents that propagation of weather shocks from network linkages (which represents the spillover effect) implies that state-level outcomes are influenced by broader shocks that the whole economy faces simultaneously.



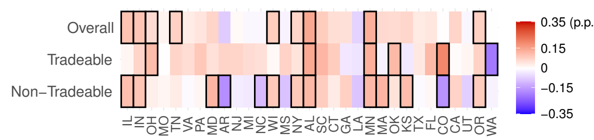
(a) h=0 (Warm)



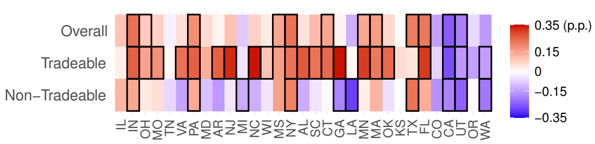
(b) h=0 (Cold)



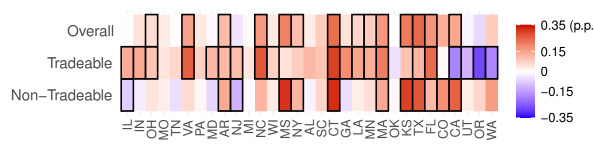
(c) h=4 (Warm)



(d) h=4 (Cold)



(e) h=7 (Warm)



(f) h=7 (Cold)

Figure 9: Nonlinear LP results of the inflation analysis for each season. The first column displays the responses for the warm season and the second column displays the responses for the cold season. Each panel shows a heatmap of impulse responses of overall, tradeable, and nontradeable inflation to a positive shock in common TA. Statistically significant state-component responses at 68% confidence interval are indicated by a square box line. Each row corresponds to on impact, 4 and 7 quarters after the shock.

5 Mechanisms

Some of the results have shown that geographical factors might matter for explaining the variations across states. To further study the possible underlying factors for the variations in state-level responses, I exploit a cross-sectional regression analysis.[31]

Several industries are significantly affected by increase in temperatures. Among those, I choose two key sectors, manufacturing and services. These sectors not only have relatively large shares of RGDP across states but are also frequently discussed in the literature as

[31] Cross-sectional analysis is employed in some literature to identify factors that explain heterogeneous responses of interest. For example, Berg et al. (2024) regresses local projection coefficients on country characteristics, and Liu and Williams (2019) regresses state tax responses on state tax structure and capital share.

mechanisms through which temperature shocks influence economic activities (e.g., Acevedo et al. (2020), Natoli (2023), Velasquez (2023)).[32] Manufacturing, as one of the largest industries across states, experiences considerable impacts from temperature fluctuations, which could have non-negligible contribution on state-level RGDP. The impact on manufacturing, however, may differ between its two subsectors: durable and non-durable goods. For example, states with a higher share of non-durable goods may be more immediately affected by temperature shocks. Non-durabale goods, such as food, beverage, rubber and similar products, are particularly vulnerable to temperature changes and are therefore likely to have immediate spoilage, leading to rapid negative impact on output. In the durable goods sector, increase in temperature may have significant effects through reduced labor productivity (Graff Zivin and Neidell (2014)) rather than the immediate destruction of goods. The services sector is also temperature-sensitive, as changes in temperature can influence consumer spending and behavior.

To examine these effects, I calculate the average share of durable goods, nondurable goods, and services as a proportion of total RGDP for each state, using data from the Bureau of Economic Analysis (BEA).[33] In addition to these sectoral shares, I also consider the average temperature of each state, as states with higher baseline temperature may be more affected by temperature shocks.[34]

It is important to note that agricultural share, which is emphasized as a direct channel for output damage from high temperatures (Deryugina and Hsiamg 2014, Deschenes and Greenstone 2007, among others), is not included in the analysis. This is because the top-ranked agricultural states (such as South Dakota, North Dakota, Nebraska, and Idaho) are not included in my sample, making it difficult to effectively study the importance of the agricultural channel.

[32] Given the number of states for cross-sectional analysis, which is 31 due to the availability of state-level inflation data, I focus on two relevant industries that account for a large portion of state-level RGDP, instead of including all industry categories to avoid any overfitting issue. On average, manufacturing contributes around 13% and services (corresponding to nontradeable) contribute about 33% to state-level RGDP.

[33] Specifically, I obtain annual real GDP and its sub-industries at the state-level from 1997 to 2017. I calculate the share of each industry by dividing the sum of its output across the periods by the total sum of all industries. The reason for obtaining the data from 1997 is to maintain consistency in industrial classification following the transition from the SIC system to NAICS. The BEA warns in their website about appending pre-1997 data with post-1997 data to obtain a single time series.

[34] Colacito et al. (2019) finds stronger temperature effects on state-level GDP in states with relatively higher summer temperatures. In a global context, Bilal and Känzig (2024) and Nath et al. (2024) document that the impact of global temperature shocks on country-level GDP is larger for countries with higher average temperature.

I run the following cross-sectional regression:

$$r_{s,h} = X_s' \delta_h + u_{s,h} \tag{4}$$

for horizons 0, 4, and 7. The dependent variable, $r_{s,h}$, is the estimated seasonal impulse responses of RGDP and inflation of state s at horizon h.[35] The aforementioned state attributes and a constant term are included in the vector X_s'.

Table 1 reports the results from the regression of the seasonal responses of RGDP and inflation at each horizon on the state attributes. The most notable relationship is observed in the positive and persistent impact of services sector on inflation to the warm season shock, suggesting that states with a higher share of services experience a greater increase in inflation responses. This inflationary pressure may be driven by a contraction in supply in industries such as food services and drinking places, professional and business services, and other services due to higher summer temperature (Colacito et al. (2019)). Additionally, the services share contributes to higher increase in inflation during the cold season, as shown in Figure 9, though only statistically significant at quarter 4. Its role in explaining RGDP responses, however, is relatively limited. States with an immediate decline in RGDP growth following a warm season shock tend to have a higher share of services. Similarly, the services share partially explains the decline in RGDP growth in response to cold season shocks after an initial boosting effect.

The role of non-durable goods is statistically associated with short-term effects, as these goods are assumed to have immediate impact by temperature changes. The higher the concentration of non-durable goods, the more negatively RGDP growth is affected immediately following a warm season shock. Moreover, the share of non-durable goods, in part, explain the observed short-term boost followed by decline in state-level RGDP to a cold season shock. The results imply that state economies with a substantial non-durable goods sector are particularly sensitive to temperature fluctuations, experiencing immediate effects. The share of durable goods has relatively limited role, except for its contribution to an initial increase in inflation during the warm season, likely due to production disruptions from heat shocks.

The results for average temperature in the warm season indicate that states with higher baseline temperatures experience greater decline in their RGDP responses over longer hori-

[35] This cross-sectional regression is free from the 'generated regressor' problem since the estimated responses, $r_{s,h}$, are used as the dependent variable (Berg et al. (2024)).

zon. This is evident in Figure 6(g), where southern states exhibit more pronounced decline in RGDP growth over time. It also contributes to higher inflation response immediately following a warm season shock.

		WARM				**COLD**			
	h	Dur.goods	Nondur.goods	Services	Avg.temp	Dur.goods	Nondur.goods	Services	Avg.temp
RGDP	0	-0.8598	-1.0884	-1.5074	-0.0015	0.0555	0.6164	0.1876	0.0016
		(0.5648)	(0.6228)*	(0.6893)**	(0.0025)	(0.3092)	(0.3672)*	(0.3207)	(0.0008)*
	4	0.6738	-1.1997	-0.1203	-0.0070	0.0936	-2.3163	-1.0162	-0.0003
		(1.2308)	(1.6507)	(1.2952)	(0.0043)*	(0.6095)	(0.7004)***	(0.6270)	(0.0016)
	7	-0.0422	-0.5555	0.1520	-0.0136	-1.0772	-0.5079	-1.9066	-0.0004
		(0.8099)	(0.9131)	(1.2295)	(0.0038)***	(0.5727)*	(0.3839)	(0.4834)***	(0.0020)
Inflation	0	1.0278	-0.0781	1.1321	0.0039	0.2124	0.4760	0.4808	0.0001
		(0.3643)***	(0.2612)	(0.4087)***	(0.0014)***	(0.3608)	(0.2759)*	(0.3535)	(0.0015)
	4	-0.4417	0.6827	1.6060	0.0006	0.4755	-0.1893	0.5908	-0.0001
		(0.6243)	(0.3981)*	(0.7127)**	(0.0023)	(0.3389)	(0.2779)	(0.2800)**	(0.0015)
	7	0.5199	0.7855	1.9640	0.0025	-0.0400	-0.0534	0.2395	0.0031
		(0.9956)	(1.0203)	(0.9555)**	(0.0037)	(0.5337)	(0.4221)	(0.7857)	(0.0020)

Table 1: Results from cross-sectional regression of each seasonal impulse responses of RGDP and inflation at horizons 0, 4, and 7 on state attributes. Within each warm and cold panel, columns denote the state attributes (industrial share of durable goods, non-durable goods, services, and average temperature). Standard errors are in parentheses. *, **, and *** indicate significance at 10%, 5%, and 1% levels, respectively.

To make the coefficients comparable across the regressors, the estimated coefficients are standardized by rescaling them based on the ratio of the volatility of dependent and independent variables, which are presented in Table 2.[36] In this way, the coefficients are interpreted as the number of standard deviation movements in the dependent variable to a one standard deviation movement in each regressor. For example, in the warm season, the standardized coefficient of services share in the regression of inflation responses at horizon 0 suggests that a one standard deviation increase in the services share leads to increase in on impact inflation responses by 0.54 of its standard deviation.

[36]For example, let coefficient of regressor 'Durable Goods' be $\delta_{DG,h}$ at horizon h. The coefficient is rescaled as $\delta_{DG,h} * \frac{S_{DG}}{S_{r_h}}$, where S_{DG} denotes cross-sectional standard deviation of durable goods share, and S_{r_h} denotes cross-sectional standard deviation of the impulse responses at horizon h.

	h	WARM Dur.goods	WARM Nondur.goods	WARM Services	WARM Avg.temp	COLD Dur.goods	COLD Nondur.goods	COLD Services	COLD Avg.temp
RGDP	0	-0.3147	-0.4221*	-0.4861**	-0.1260	0.0420	0.4945*	0.1252	0.2703*
	4	0.1318	-0.2486	-0.0207	-0.3044*	0.0313	-0.8203***	-0.2992	-0.0207
	7	-0.0085	-0.1179	0.0268	-0.6054***	-0.4314*	-0.2156	-0.6728***	-0.0365
Inflation	0	0.5600***	-0.0451	0.5434***	0.4667***	0.1393	0.3308*	0.2778	0.0192
	4	-0.1440	0.2358*	0.4612**	0.0402	0.3211	-0.1355	0.3515**	-0.0090
	7	0.1421	0.2276	0.4731**	0.1545	-0.0165	-0.0233	0.0869	0.2871

Table 2: Standardized coefficients from cross-sectional regression of each seasonal impulse responses of RGDP and inflation at horizons 0, 4, and 7 on state attributes. Within each warm and cold panel, columns denote the state attributes (industrial share of durable goods, non-durable goods, services, and average temperature). *, **, and *** indicate statistical significance results from Table 1.

6 Further Discussions and Robustness Checks

In this section, I show further analysis and various robustness checks. For the sake of brevity, I delegate the corresponding results to the Appendix.

6.1 Linear Local Projection

First, I show that significant and interesting heterogeneous effects of different seasons may be masked when applying linear approach. I conduct a linear LP using the same variables exploited in the benchmark specification.

The state-by-state linear LP is as follows:

$$y_{s,t+h} = \alpha_{s,h} + \beta_{s,h} commonTA_{s,t} + \eta_{s,h} commonTA_{s,t-1} + \sum_{l=1}^{p} \gamma_{s,h,l} X_{s,t-l} + \varepsilon_{s,t+h}. \quad (5)$$

Now, different from Eq (3), the interaction term is dropped while the remaining terms stay the same. The local projection coefficient $\beta_{s,h}$ represents the average effect across seasons to a positive common TA shock. Plagborg-Møller and Wolf (2021) show the asymptotic equivalence between local projection and vector autoregrssion (VAR) impulse response functions. More specifically, the local projection coefficients can be regarded as impulse responses from structural VAR imposing a recursive identification scheme by ordering the common TA first. It is reasonable to consider that the common TA is exogenous given that the economic activities are unlikely to affect the temperature fluctuations within a given quarter.[37] Thus, the impulse response coefficient in Eq (5) captures the causal effect of the common TA shock.

I report the impulse responses of the two main economic variables in Appendix A.1. The first column in Figure A.1 displays scatter plot of impulse responses of RGDP growth at each horizon from linear LP. For ease of comparison, I include the corresponding scatter plot from the nonlinear specification in the second column. The same applies for presenting the inflation in Figure A.2.

Overall, the results from the linear LP indicate that significant and opposing seasonal effects can be diluted when averaged across seasons. This dilution is particularly prominent in the immediate responses. Moreover, the magnitudes of the effects, particularly from the warm season shock, are underestimated in the linear approach. These findings highlight the importance of accounting for seasonal asymmetries when studying the impact of temperatures on the economy.

6.2 Idiosyncratic Component Analysis

While the common component of TA captures widespread temperature fluctuations across states, the idiosyncratic component of TA (hereafter idiosyncratic TA), which is $\epsilon_{s,t}$ in Eq (2), represents state-specific temperature variations not explained by the common factors. This idiosyncratic component is likely to reflect localized (extreme weather) events, such as cold air outbreaks, which can have disproportionately larger economic impacts compared to those from common TA shocks. In this section, I explore how the effects of common TA shock may differ from those of idiosyncratic TA shock.

To estimate the responses to idiosyncratic TA shocks, I rely on Eq (3), replacing the common TA with the idiosyncratic TA. The results are reported in Appendix A.2. Several points are noteworthy. First, the responses to the idiosyncratic TA shock show less synchronized directions across states, instead exhibiting substantial heterogeneity in both economic variables. Second, for some states, the magnitude of the impact of idiosyncratic shocks far exceeds that of the common TA shock. For example, during the cold season, the idiosyncratic shock results in more than 5 times larger negative impact on RGDP growth for Maryland (-0.45 p.p.) and New Jersey (-0.6 p.p.) after 4 quarters. Third, the signs of

[37] This identification assumption is used in many related studies such as Kim et al. (2022), Ciccarelli et al. (2023), and Ciccarelli and Marotta (2024)

the responses frequently go in opposite directions between the common TA and idiosyncratic TA shocks.[38] Not surprisingly, the observed synchronized responses in the tradeable inflation to common TA shock across states are not present in responses to idiosyncratic TA shocks. Instead, inflationary effects vary significantly across states for all types of inflation.

Overall, the results suggest that the localized shocks can have substantial economic implications at the state-level and often show opposite effects from the common TA shock. Although these idiosyncratic TA shocks can be quantitatively important, common TA shocks may be qualitatively more important having a larger aggregate impact due to their synchronized effects across states, affecting the national economy more broadly. While a thorough investigation of state-specific dynamics to idiosyncratic shocks lies beyond the scope of this paper, it could be a promising future work studying in-depth economic effects of this shock.

6.3 Alternative measures of Temperature Anomaly

6.3.1 Population-weighted Temperature Anomaly

Weighting weather observations by population, which assigns larger weights to more densely populated areas, is common in the related literature. The rationale behind this scheme is that the larger the population, the greater the economic exposure to temperature shocks. Thus, as an alternative weighting scheme, I use population-weighted temperature data sourced from Gortan et al. (2024).[39] They provide a unified, ready-to-use climate variables aggregated at national and sub-national levels with various weighting schemes.[40] The data I obtain is state-level monthly average temperature calculated as weighted average at the grid resolution of $0.5° \times 0.5°$, with weights based on population density measured in 2005. Using the population-weighted statewide temperature data, I re-construct the common component of temperature anomaly following the same procedure outlined in Section 2.1. Across the 31 states, the minimum correlation value between the original area-weighted common TA and the new population-weighted common TA is approximately 0.98, indicating that the two series are highly similar. In Appendix A.3, I show that the results are robust across

[38] Similarly, Berg et al. (2024) find that, in many cases, the effects of global and idiosyncratic (i.e., country temperature not explained by the global temperature) temperature shocks on real GDP per capita growth are opposite for a given country.

[39] The data is measured in Celsius. Thus, I convert it to Fahrenheit to ensure comparability with the benchmark results.

[40] They provide a user-friendly dashboard to explore the data, available in `https://weightedclimatedata.streamlit.app/`.

different weighting schemes, with the effects becoming even stronger for states like Texas and Florida when using the population-weighted series.

6.3.2 Rolling Window Reference Period

As discussed in Natoli (2023), using a fixed reference period of historical averages for calculating temperature anomaly implies that agents anchor their beliefs regarding temperatures and do not update them over time. This may result in overestimation of temperature anomalies, especially in more recent periods. Although I use fixed reference period, the constructed temperature anomalies in Section 2.1 may help mitigate the overestimation problem, as I demean the series to account for any long-term trends. As a robustness analysis, I construct an alternative measure of temperature anomalies using a rolling average of 10-year window for each quarter. To be specific, I calculate as

$$TA_{s,q,y} = t_{s,q,y} - \bar{t}_{s,q,y}, \quad \text{where} \quad \bar{t}_{s,q,y} = \frac{1}{10}\sum_{i=1}^{10} t_{s,q,y-i}. \tag{6}$$

The minimum correlation between the original common TA and the new rolling window-based common TA across the 31 states is around 0.87, suggesting that the original series may not suffer from the overestimation. The results reported in Appendix A.4 show that my findings are robust, indicating that the size of temperature fluctuations in the original series is not overestimated over time.

7 Conclusion

This paper presents new empirical evidence on short- and medium-term heterogeneous temperature effects on RGDP growth and inflation at the US state-level. I estimate the causal impact of the common component of TA, constructed for each state as state-level temperature fluctuations driven by common fluctuations across states, using a state-by-state nonlinear local projection. The results reveal heterogeneous effects across three dimensions: states, seasons (warm and cold), and time horizon. By jointly looking at the impulse responses of RGDP and inflation, I classify the nature of temperature shocks based on whether output and prices move in the same or opposite directions. I find that the shock types vary by season and time horizon. Cold season shocks initially act as positive demand and supply-side shocks but transition to negative supply and positive demand-side effects.

On the other hand, warm season shocks reveal predominantly negative supply-side effects, especially evident in southern states.

I also investigate state attributes that might explain variations in state-level RGDP growth and inflation responses. The results suggest that higher inflation responses to a warm season shock are strongly related to higher services share across time horizons. The share of nondurable goods is associated with short-term effects, likely due to immediate spoilage of these products from temperature changes. On the other hand, the share of durable goods has a limited role in explaining the effects. Consistent with existing findings, states with higher baseline temperature experience more pronounced decline in output growth to warm season shock over longer horizons.

These heterogeneous findings provide useful insights for policies addressing climate risks at a disaggregated level, such as by accounting for geographical factors and state-specific sectoral compositions. Additionally, the medium-term synchronized responses in RGDP growth and inflation imply a potential role for nationwide policies to mitigate these broad effects. A limitation of this paper is that the analysis is restricted to 31 states for which state-level inflation data is available. Higher availability of high-frequency economic variables at the state-level would allow future research to explore the full scope of heterogeneity effects in greater depth.

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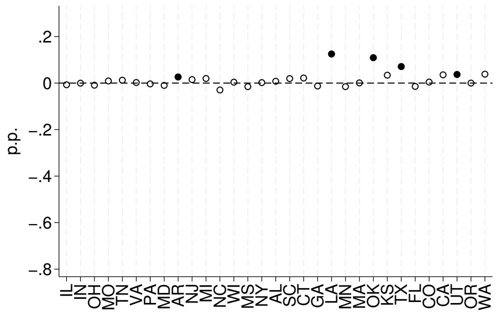
A Appendix

A.1 Linear Local Projection



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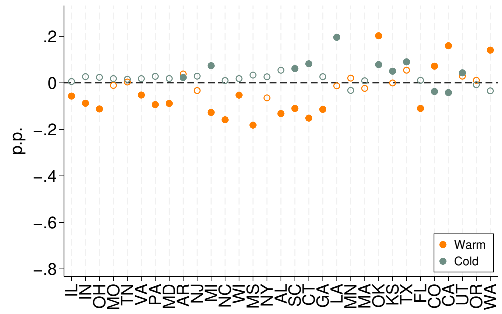

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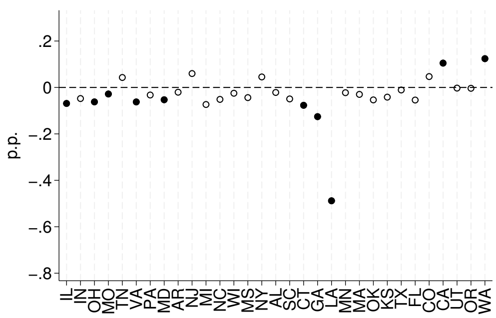
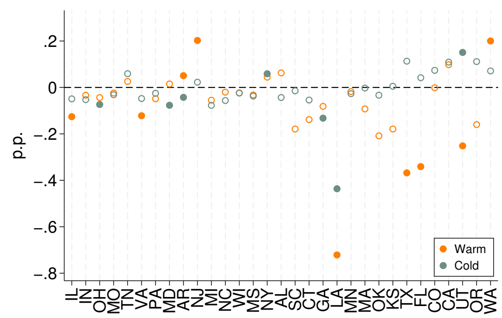


(c) h=4 (linear LP)



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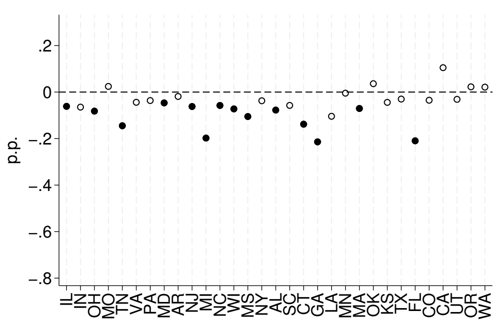
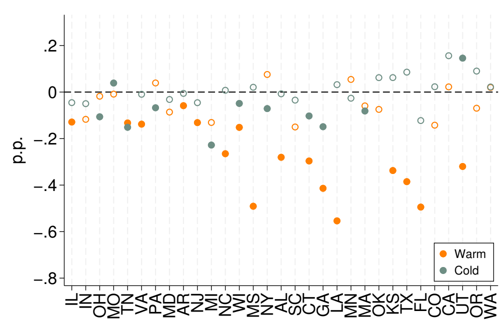
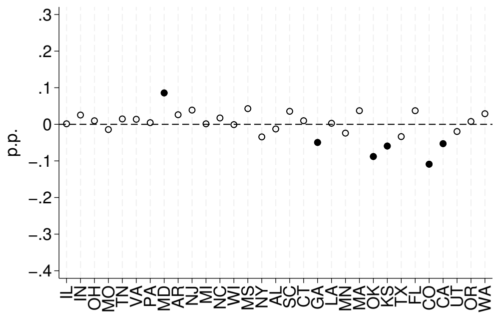


(e) h=7 (linear LP)

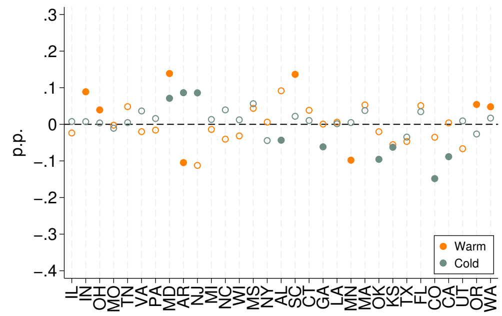


(f) h=7 (nonlinear LP)

Figure A.1: Linear LP (left column) and nonlinear LP (right column) results of state-level RGDP in response to a positive shock in the common TA. Dots are filled if statistically significant at 68% confidence interval. Each row corresponds to on impact, 4 and 7 quarters after the shock.



(a) h=0 (linear LP)



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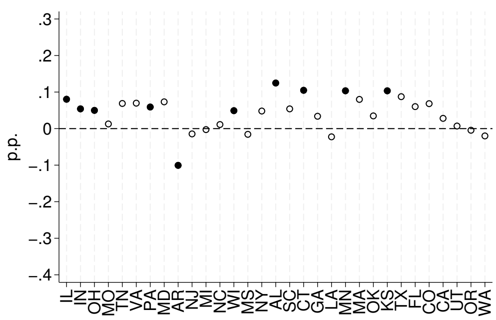

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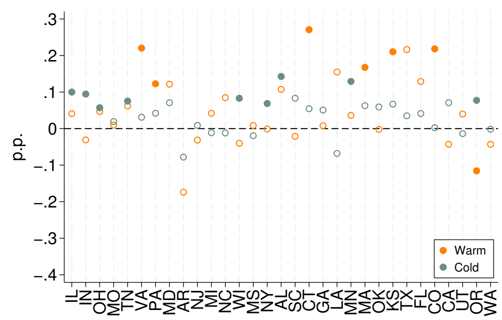

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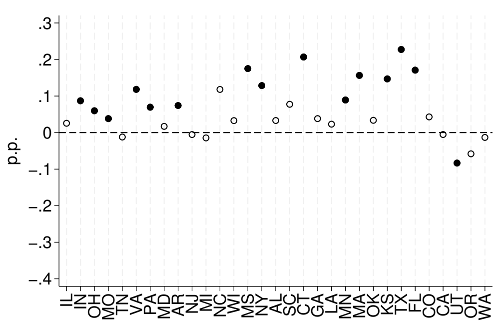

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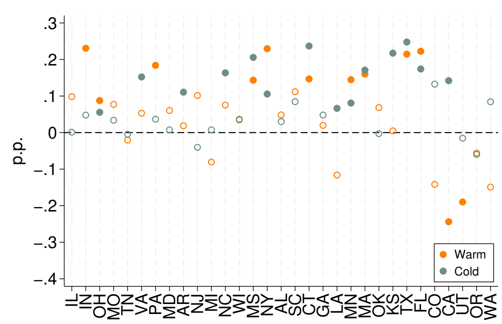
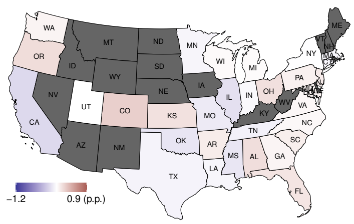


(f) h=7 (nonlinear LP)

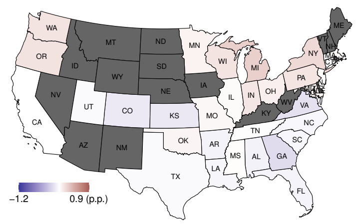
Figure A.2: Linear LP (left column) and nonlinear LP (right column) results of state-level inflation in response to a positive shock in the common TA. Dots are filled if statistically significant at 68% confidence interval. Each row corresponds to on impact, 4 and 7 quarters after the shock.

A.2 Idiosyncratic Component Analysis

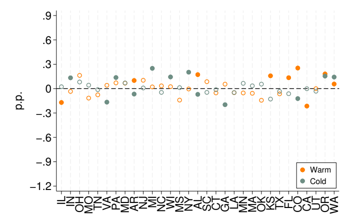
A.2.1 Impulse Responses



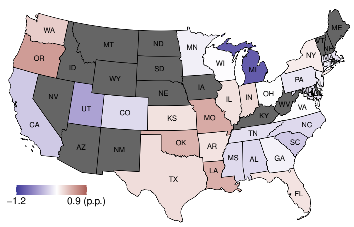
(a) h=0 (Warm)



(b) h=0 (Cold)



(c) h=0 (Warm & Cold)



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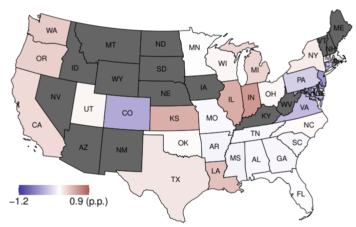

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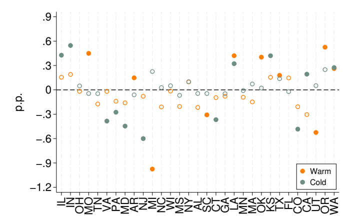
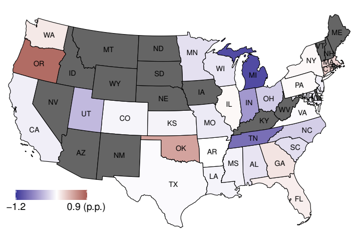
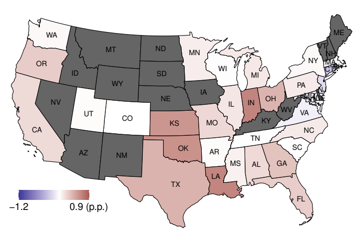


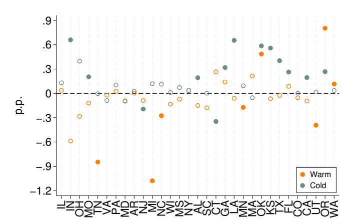
(f) h=4 (Warm & Cold)



(g) h=7 (Warm)

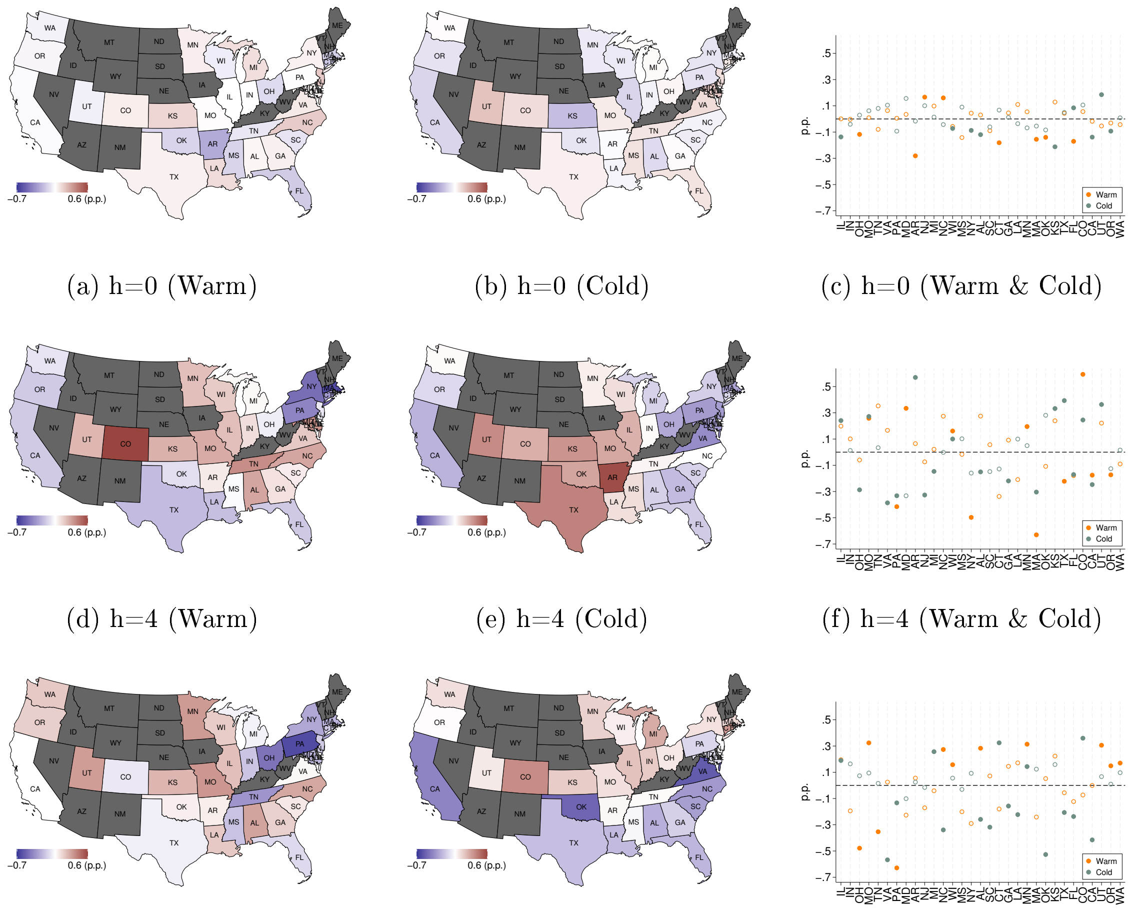


(h) h=7 (Cold)



(i) h=7 (Warm & Cold)

Figure A.3: Nonlinear LP results of state-level RGDP in response to a positive shock in the idiosyncratic TA for each season. The first and second columns display the responses for each warm and cold season in a US map, and the third column displays the two responses jointly in a scatter plot, with filled dots indicating statistical significance at 68% confidence interval. Each row corresponds to on impact, 4 and 7 quarters after the shock.



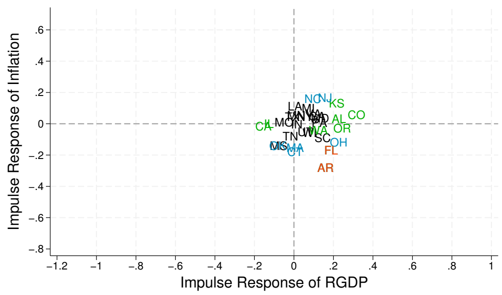
(a) h=0 (Warm) (b) h=0 (Cold) (c) h=0 (Warm & Cold)

(d) h=4 (Warm) (e) h=4 (Cold) (f) h=4 (Warm & Cold)

(g) h=7 (Warm) (h) h=7 (Cold) (i) h=7 (Warm & Cold)

Figure A.4: Nonlinear LP results of state-level inflation in response to a positive shock in the idiosyncratic TA for each season. The first and second columns display the responses for each warm and cold season in a US map, and the third column displays the two responses jointly in a scatter plot, with filled dots indicating statistical significance at 68% confidence interval. Each row corresponds to on impact, 4 and 7 quarters after the shock.

A.2.2 Supply or Demand?



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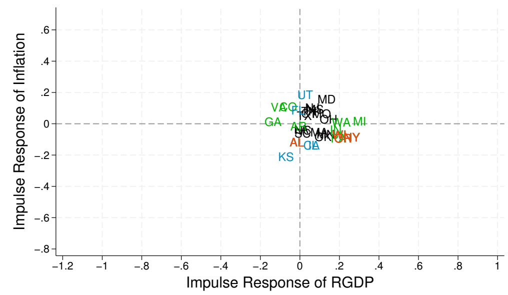

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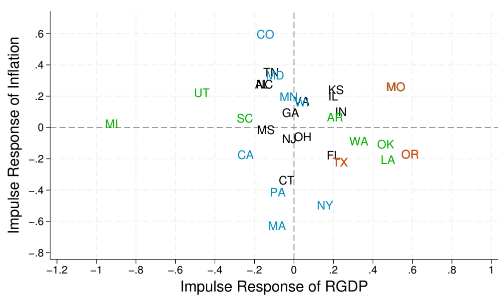

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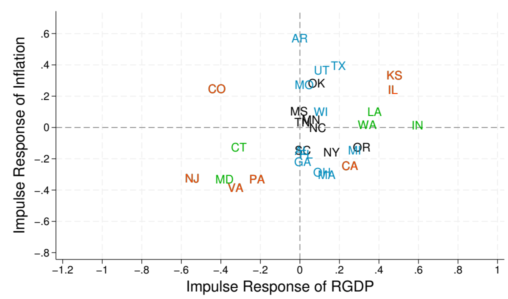
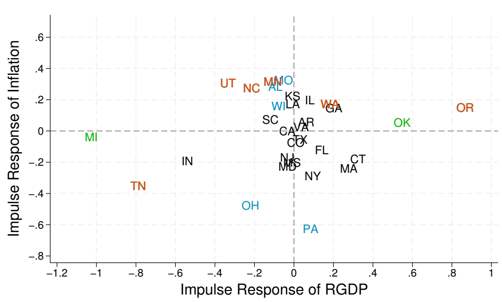
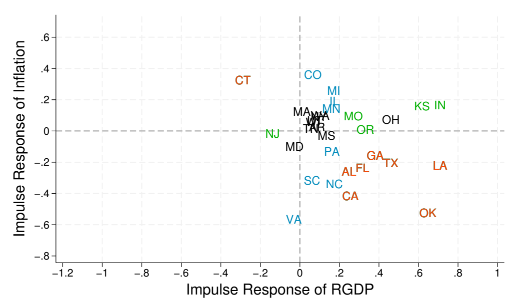


(d) h=4 (Cold)



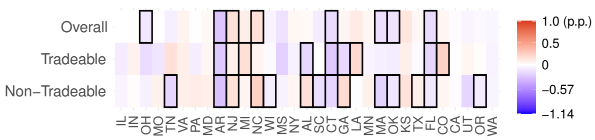
(e) h=7 (Warm)



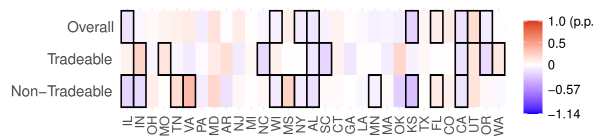
(f) h=7 (Cold)

Figure A.5: Nonlinear LP results of state-level RGDP (on x-axis) and inflation (on y-axis) to a positive shock in the idiosyncratic TA for each season. The first column displays the responses for the warm season and the second column displays the responses for the cold season. In each panel, state names are colored in four ways for indicating statistical significance at 68% confidence interval: red (both significant), green (only RGDP significant), blue (only inflation significant), black (neither significant). Each row corresponds to on impact, 4 and 7 quarters after the shock.

A.2.3 Inflation Analysis



(a) h=0 (Warm)



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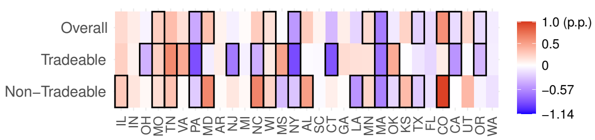
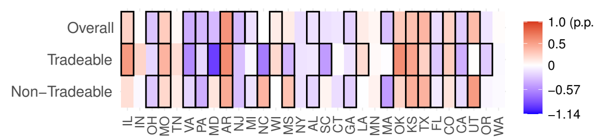


(c) h=4 (Warm)



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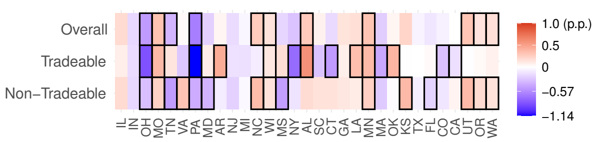

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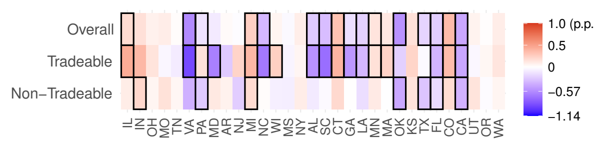
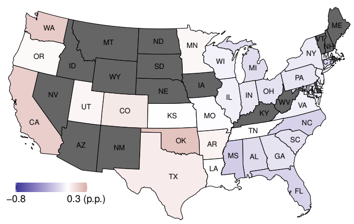


(f) h=7 (Cold)

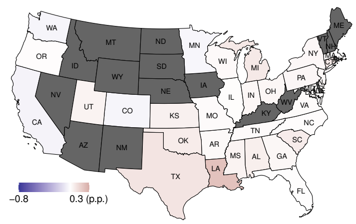
Figure A.6: Nonlinear LP results of the inflation analysis for each season. The first column displays the responses for the warm season and the second column displays the responses for the cold season. Each panel shows a heatmap of impulse responses of overall, tradeable, and nontradeable inflation to a positive shock in idiosyncratic TA. Statistically significant state-component responses at 68% confidence interval are indicated by a square box line. Each row corresponds to on impact, 4 and 7 quarters after the shock.

A.3 Population-weighted Temperature Anomaly

A.3.1 Impulse Responses



(a) h=0 (Warm)



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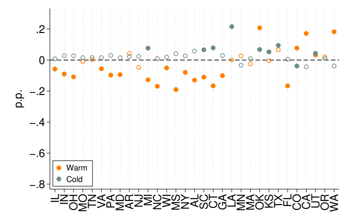
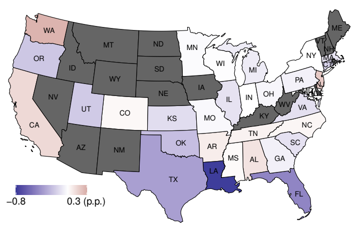
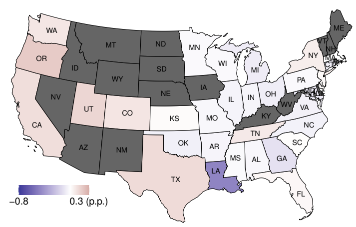


(c) h=0 (Warm & Cold)



(d) h=4 (Warm)



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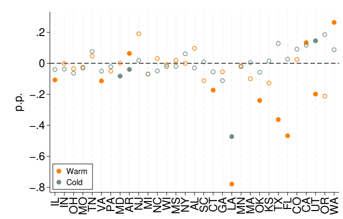
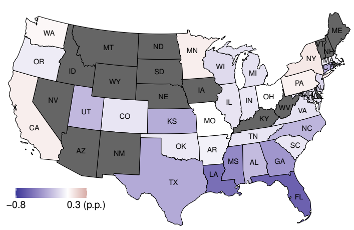
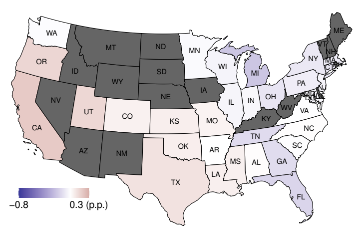


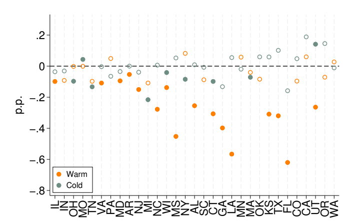
(f) h=4 (Warm & Cold)



(g) h=7 (Warm)

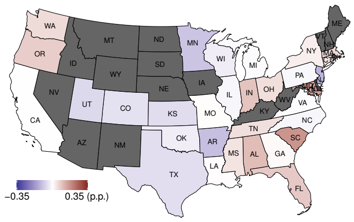


(h) h=7 (Cold)

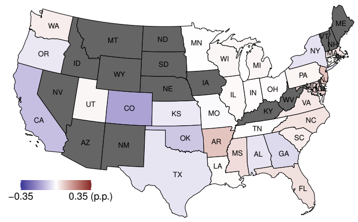


(i) h=7 (Warm & Cold)

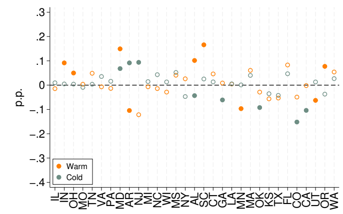
Figure A.7: Nonlinear LP results of state-level RGDP in response to a positive shock in the population-weighted common TA for each season. The first and second columns display the responses for each warm and cold season in a US map, and the third column displays the two responses jointly in a scatter plot, with filled dots indicating statistical significance at 68% confidence interval. Each row corresponds to on impact, 4 and 7 quarters after the shock.



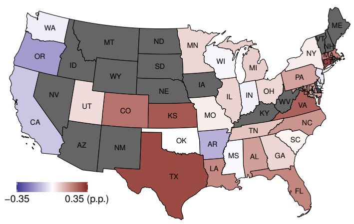
(a) h=0 (Warm)



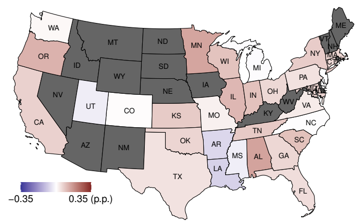
(b) h=0 (Cold)



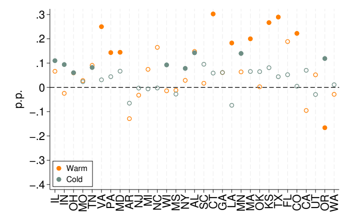
(c) h=0 (Warm & Cold)



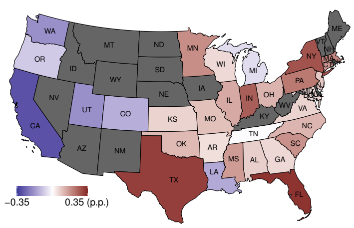
(d) h=4 (Warm)



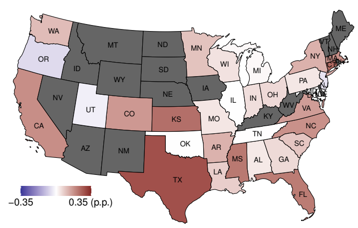
(e) h=4 (Cold)



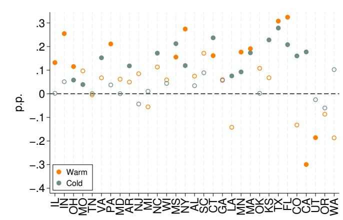
(f) h=4 (Warm & Cold)



(g) h=7 (Warm)



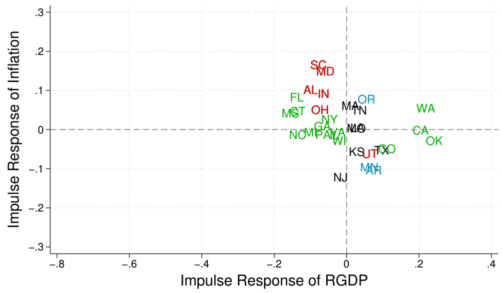
(h) h=7 (Cold)



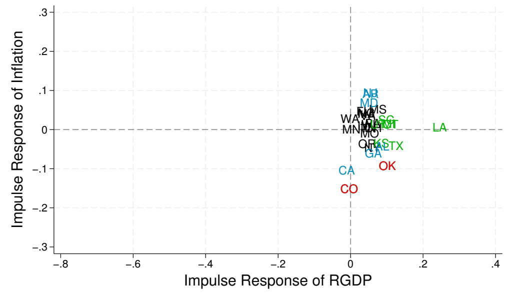
(i) h=7 (Warm & Cold)

Figure A.8: Nonlinear LP results of state-level inflation in response to a positive shock in the population-weighted common TA for each season. The first and second columns display the responses for each warm and cold season in a US map, and the third column displays the two responses jointly in a scatter plot, with filled dots indicating statistical significance at 68% confidence interval. Each row corresponds to on impact, 4 and 7 quarters after the shock.

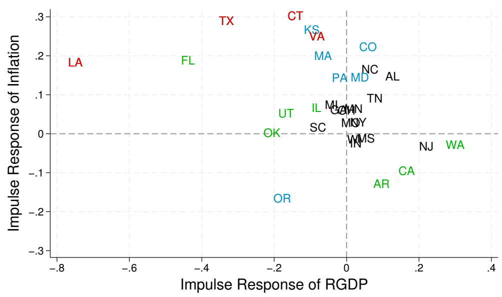
A.3.2 Supply or Demand?



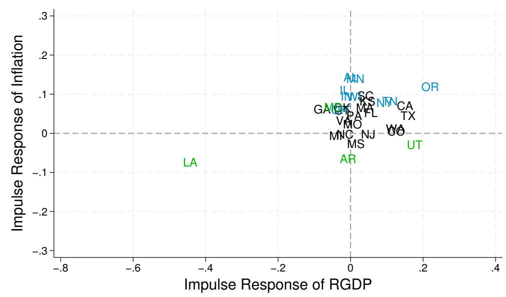
(a) h=0 (Warm)



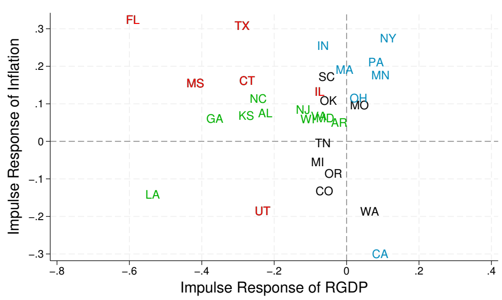
(b) h=0 (Cold)



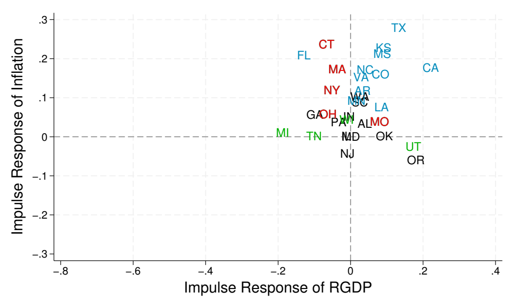
(c) h=4 (Warm)



(d) h=4 (Cold)



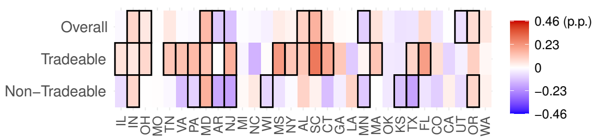
(e) h=7 (Warm)



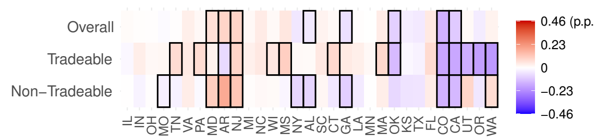
(f) h=7 (Cold)

Figure A.9: Nonlinear LP results of state-level RGDP (on x-axis) and inflation (on y-axis) to a positive shock in the population-weighted common TA for each season. The first column displays the responses for the warm season and the second column displays the responses for the cold season. In each panel, state names are colored in four ways for indicating statistical significance at 68% confidence interval: red (both significant), green (only RGDP significant), blue (only inflation significant), black (neither significant). Each row corresponds to on impact, 4 and 7 quarters after the shock.

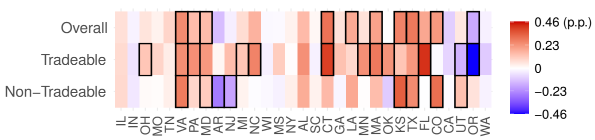
A.3.3 Inflation Analysis



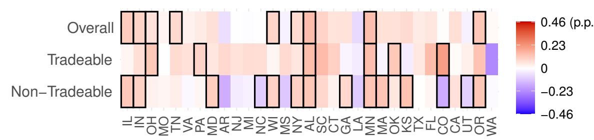
(a) h=0 (Warm)



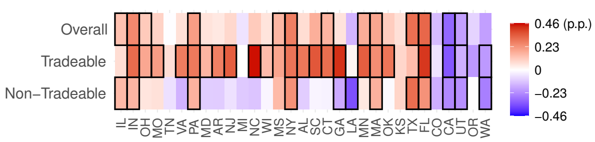
(b) h=0 (Cold)



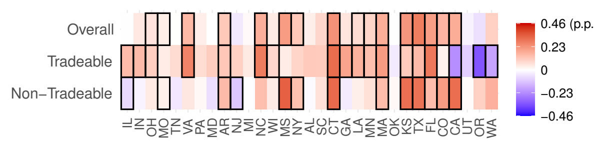
(c) h=4 (Warm)



(d) h=4 (Cold)



(e) h=7 (Warm)

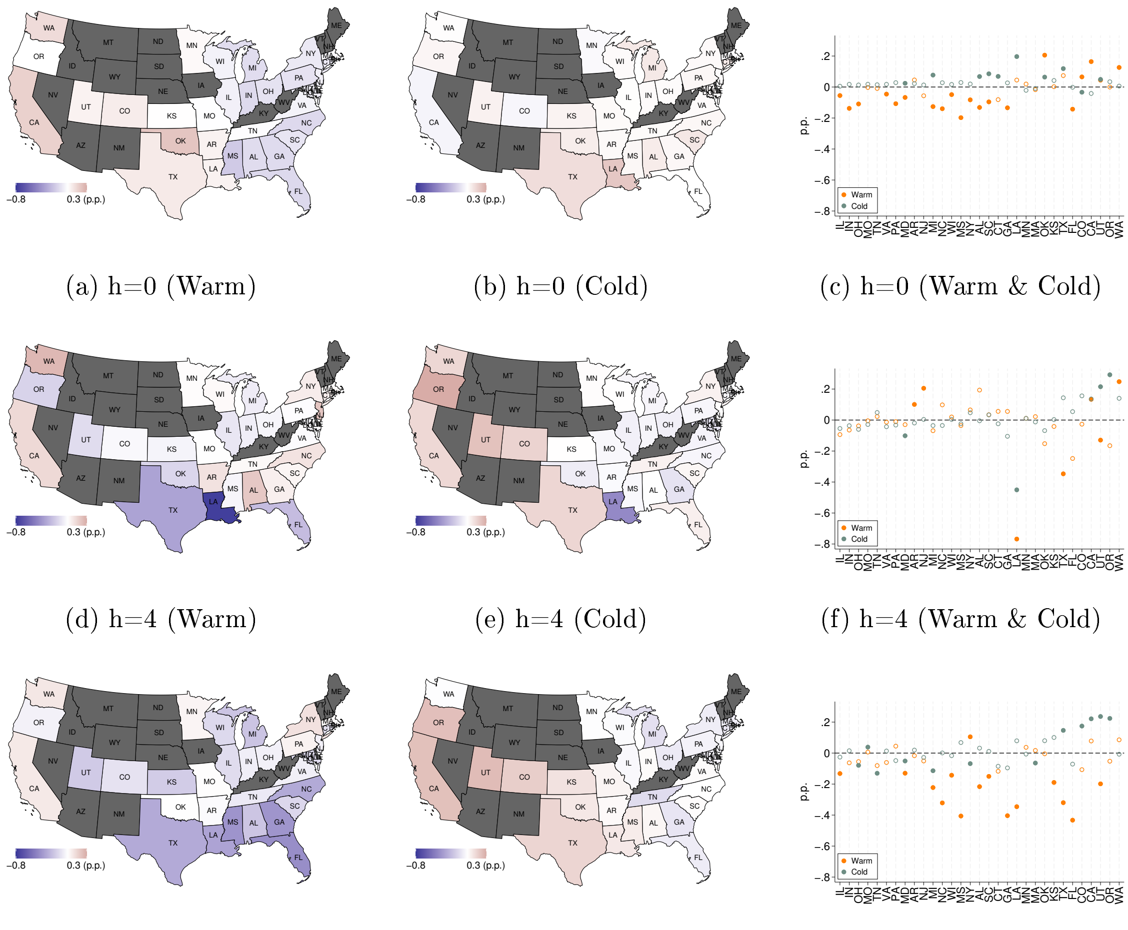


(f) h=7 (Cold)

Figure A.10: Nonlinear LP results of the inflation analysis for each season. The first column displays the responses for the warm season and the second column displays the responses for the cold season. Each panel shows a heatmap of impulse responses of overall, tradeable, and nontradeable inflation to a positive shock in population-weighted common TA. Statistically significant state-component responses at 68% confidence interval are indicated by a square box line. Each row corresponds to on impact, 4 and 7 quarters after the shock.

A.4 Rolling Window Reference Period

A.4.1 Impulse Responses

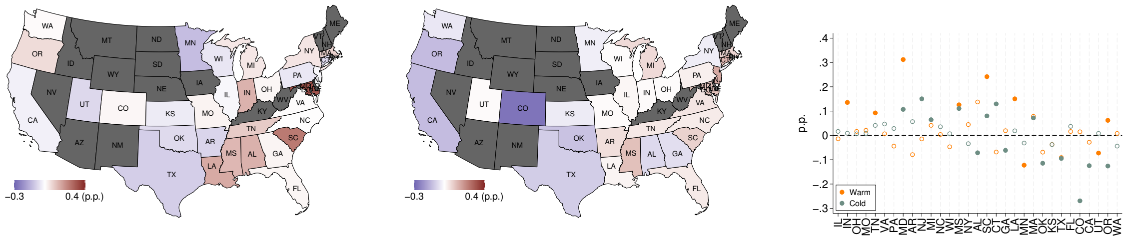


(a) h=0 (Warm) (b) h=0 (Cold) (c) h=0 (Warm & Cold)

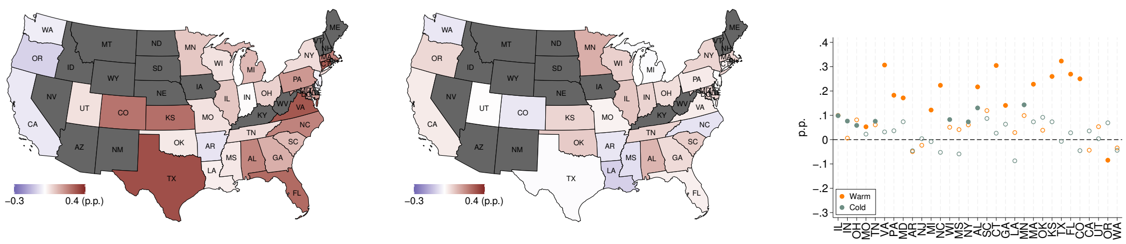
(d) h=4 (Warm) (e) h=4 (Cold) (f) h=4 (Warm & Cold)

(g) h=7 (Warm) (h) h=7 (Cold) (i) h=7 (Warm & Cold)

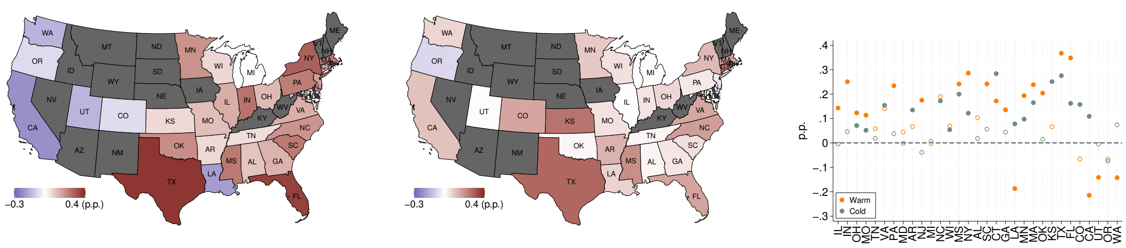
Figure A.11: Nonlinear LP results of state-level RGDP in response to a positive shock in the rolling-window-based common TA for each season. The first and second columns display the responses for each warm and cold season in a US map, and the third column displays the two responses jointly in a scatter plot, with filled dots indicating statistical significance at 68% confidence interval. Each row corresponds to on impact, 4 and 7 quarters after the shock.



(a) h=0 (Warm) (b) h=0 (Cold) (c) h=0 (Warm & Cold)



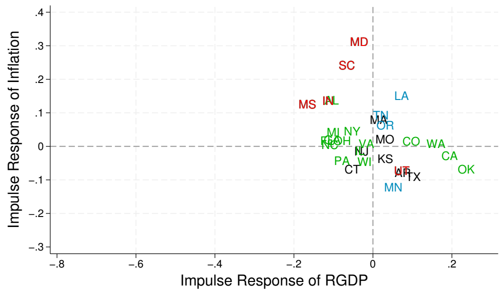
(d) h=4 (Warm) (e) h=4 (Cold) (f) h=4 (Warm & Cold)



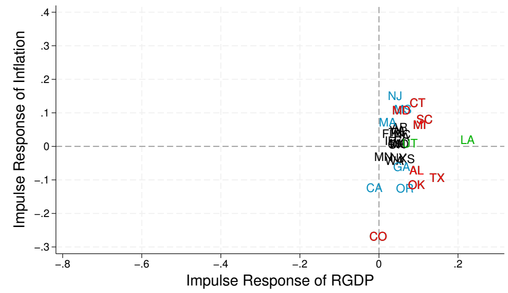
(g) h=7 (Warm) (h) h=7 (Cold) (i) h=7 (Warm & Cold)

Figure A.12: Nonlinear LP results of state-level inflation in response to a positive shock in the rolling-window-based common TA for each season. The first and second columns display the responses for each warm and cold season in a US map, and the third column displays the two responses jointly in a scatter plot, with filled dots indicating statistical significance at 68% confidence interval. Each row corresponds to on impact, 4 and 7 quarters after the shock.

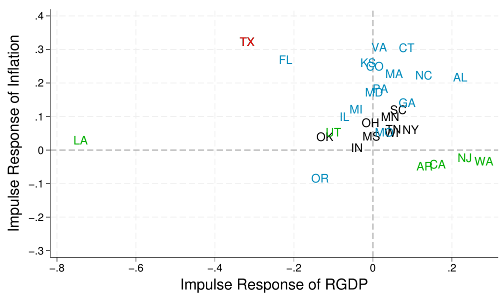
A.4.2 Supply or Demand?



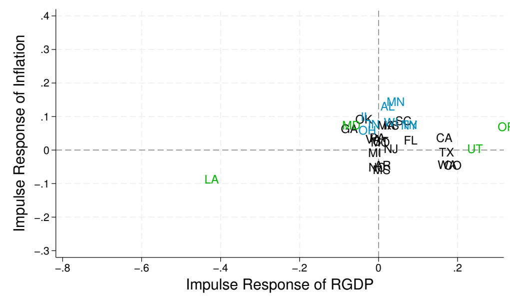
(a) h=0 (Warm)



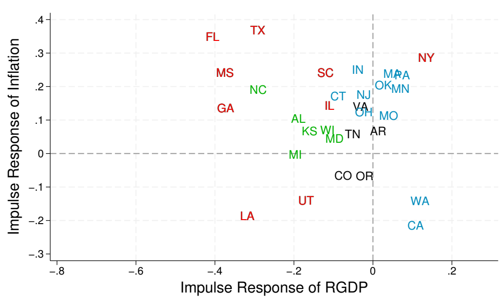
(b) h=0 (Cold)



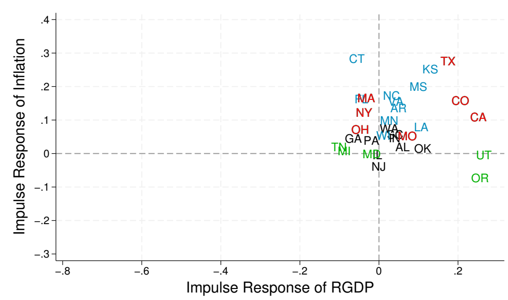
(c) h=4 (Warm)



(d) h=4 (Cold)



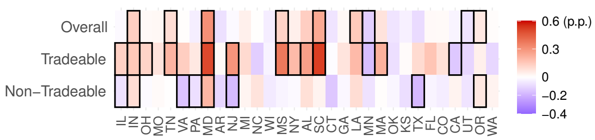
(e) h=7 (Warm)



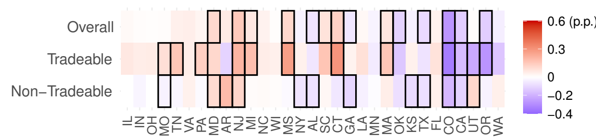
(f) h=7 (Cold)

Figure A.13: Nonlinear LP results of state-level RGDP (on x-axis) and inflation (on y-axis) to a positive shock in the rolling-window-based common TA for each season. The first column displays the responses for the warm season and the second column displays the responses for the cold season. In each panel, state names are colored in four ways for indicating statistical significance at 68% confidence interval: red (both significant), green (only RGDP significant), blue (only inflation significant), black (neither significant). Each row corresponds to on impact, 4 and 7 quarters after the shock.

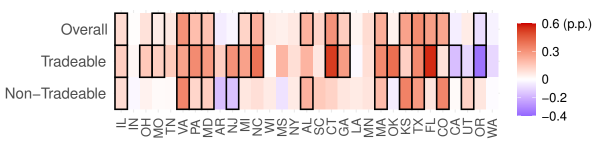
A.4.3 Inflation Analysis



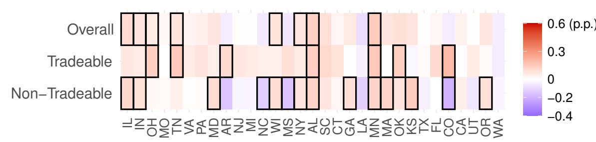
(a) h=0 (Warm)



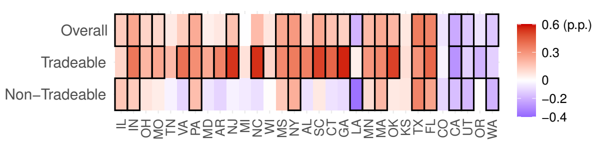
(b) h=0 (Cold)



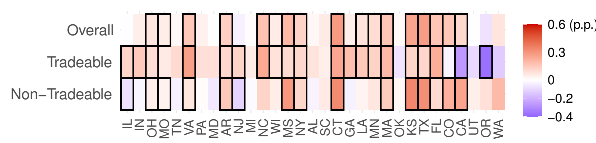
(c) h=4 (Warm)



(d) h=4 (Cold)



(e) h=7 (Warm)



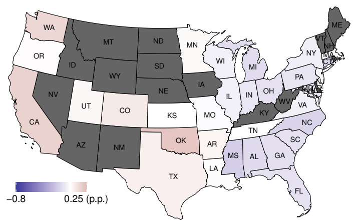
(f) h=7 (Cold)

Figure A.14: Nonlinear LP results of the inflation analysis for each season. The first column displays the responses for the warm season and the second column displays the responses for the cold season. Each panel shows a heatmap of impulse responses of overall, tradeable, and nontradeable inflation to a positive shock in rolling-window-based common TA. Statistically significant state-component responses at 68% confidence interval are indicated by a square box line. Each row corresponds to on impact, 4 and 7 quarters after the shock.

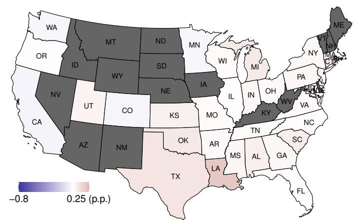
A.5 Results with 90% Confidence Intervals

In this section, I show the same results displayed in the main text with 90% confidence intervals. The US map figures are unchanged, as the impulse response coefficients remain the same across different confidence intervals. Although the number of statistically significant states decreases with the 90% confidence intervals, the overall implications remain the same.

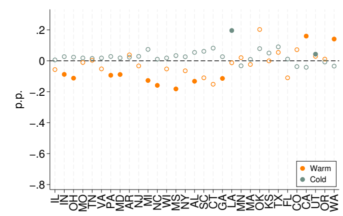
A.5.1 Impulse responses



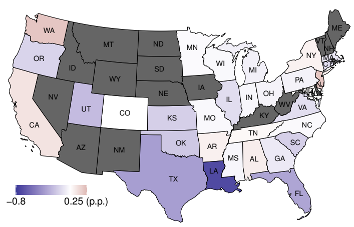
(a) h=0 (Warm)



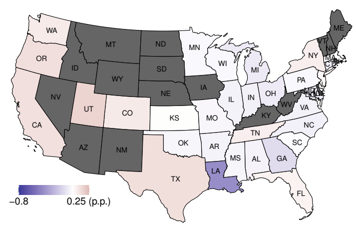
(b) h=0 (Cold)



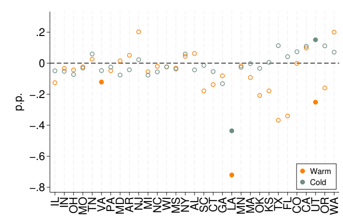
(c) h=0 (Warm & Cold)



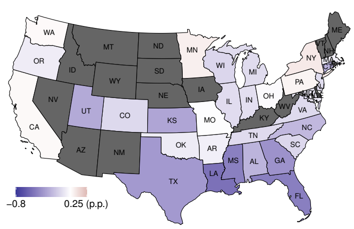
(d) h=4 (Warm)



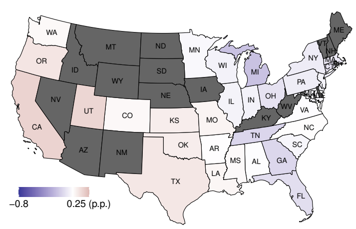
(e) h=4 (Cold)



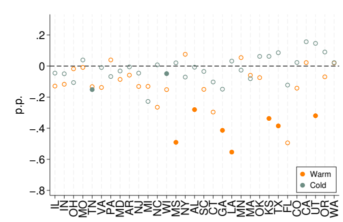
(f) h=4 (Warm & Cold)



(g) h=7 (Warm)

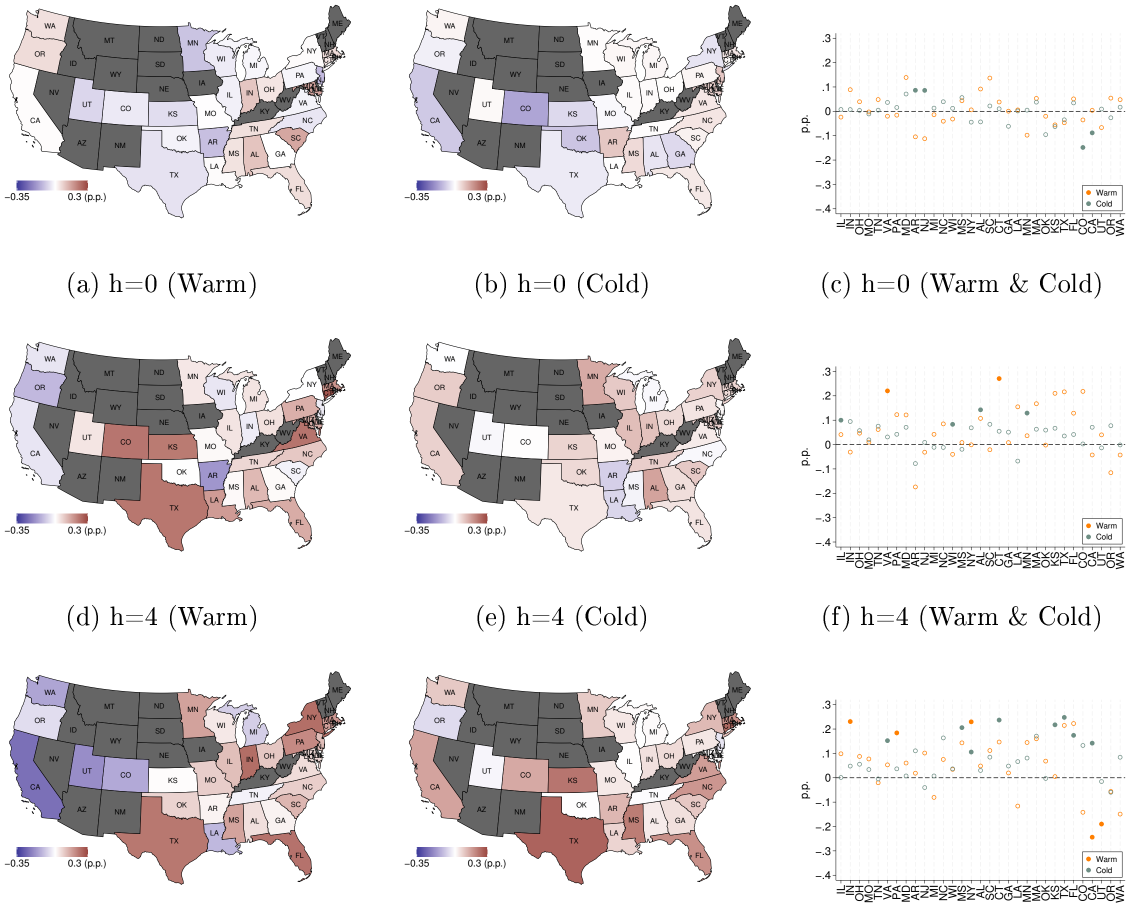


(h) h=7 (Cold)



(i) h=7 (Warm & Cold)

Figure A.15: Nonlinear LP results of state-level RGDP in response to a positive shock in the common TA for each season. The first and second columns display the responses for each warm and cold season in a US map, and the third column displays the two responses jointly in a scatter plot, with filled dots indicating statistical significance at 90% confidence interval. Each row corresponds to on impact, 4 and 7 quarters after the shock.



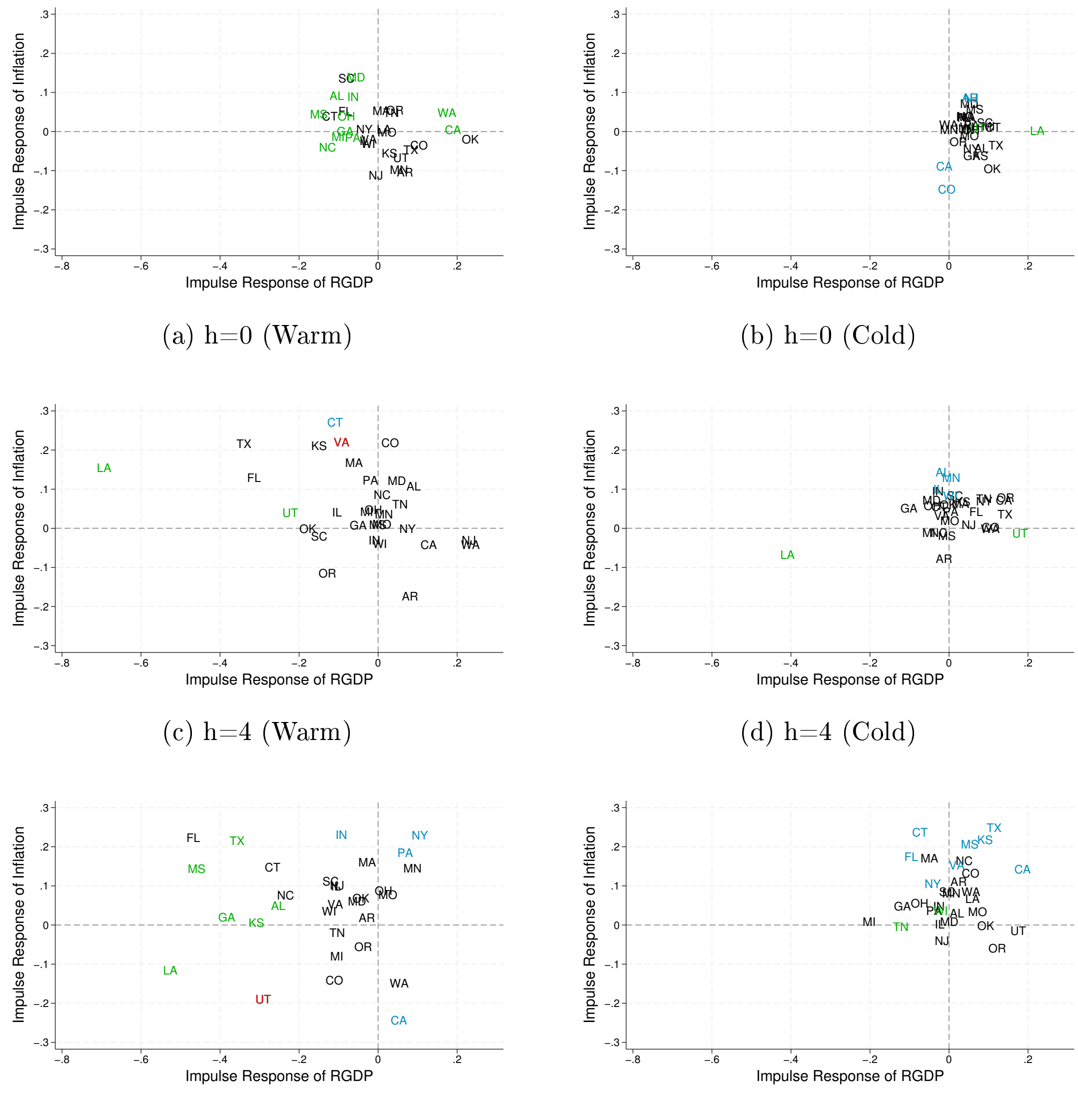
(a) h=0 (Warm) (b) h=0 (Cold) (c) h=0 (Warm & Cold)

(d) h=4 (Warm) (e) h=4 (Cold) (f) h=4 (Warm & Cold)

(g) h=7 (Warm) (h) h=7 (Cold) (i) h=7 (Warm & Cold)

Figure A.16: Nonlinear LP results of state-level inflation in response to a positive shock in the common TA for each season. The first and second columns display the responses for each warm and cold season in a US map, and the third column displays the two responses jointly in a scatter plot, with filled dots indicating statistical significance at 90% confidence interval. Each row corresponds to on impact, 4 and 7 quarters after the shock.

A.5.2 Supply or Demand?



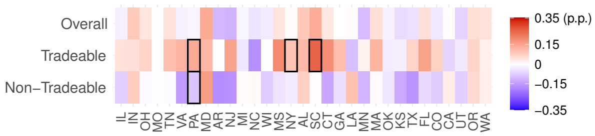
(a) h=0 (Warm) (b) h=0 (Cold)

(c) h=4 (Warm) (d) h=4 (Cold)

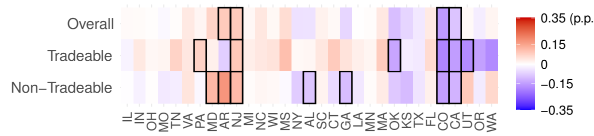
(e) h=7 (Warm) (f) h=7 (Cold)

Figure A.17: Nonlinear LP results of state-level RGDP (on x-axis) and inflation (on y-axis) to a positive shock in the common TA for each season. The first column displays the responses for the warm season and the second column displays the responses for the cold season. In each panel, state names are colored in four ways for indicating statistical significance at 90% confidence interval: red (both significant), green (only RGDP significant), blue (only inflation significant), black (neither significant). Each row corresponds to on impact, 4 and 7 quarters after the shock.

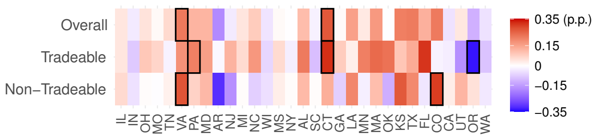
A.5.3 Inflation Analysis



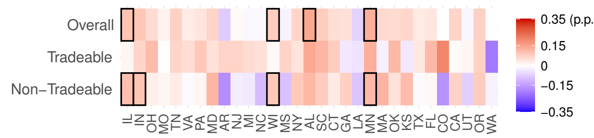
(a) h=0 (Warm)



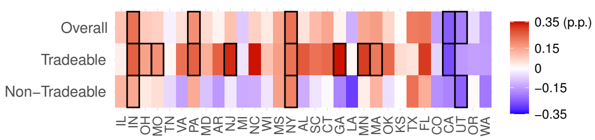
(b) h=0 (Cold)



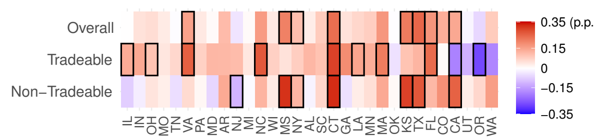
(c) h=4 (Warm)



(d) h=4 (Cold)



(e) h=7 (Warm)



(f) h=7 (Cold)

Figure A.18: Nonlinear LP results of the inflation analysis for each season. The first column displays the responses for the warm season and the second column displays the responses for the cold season. Each panel shows a heatmap of impulse responses of overall, tradeable, and nontradeable inflation to a positive shock in the common TA. Statistically significant state-component responses at 90% confidence interval are indicated by a square box line. Each row corresponds to on impact, 4 and 7 quarters after the shock.