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Extreme weather shocks and state-level inflation of the United States☆

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ABSTRACT

This study investigates the impact of a metric of extreme weather shocks on 32 state-level inflation rates of the United States (US) over the quarterly period of 1989:01 to 2017:04. In this regard, we first utilize a dynamic factor model with stochastic volatility (DFM-SV) to filter out the national factor from the local components of overall, non-tradable and tradable inflation rates, to ensure that the effect of regional climate risks is not underestimated, given the derived sizeable common component. Second, using impulse responses derived from linear and nonlinear local projections models, we find statistically significant increases in the state (and national) factor of overall inflation rates, with the aggregate effect being driven by the tradable sector relative to the non-tradable one, particularly across the agricultural states in comparison to the non (less)-agricultural ones. Our findings have important policy implications.

1. Introduction

Theoretically speaking, extreme weather conditions, resulting from global warming and climate change, can impact inflation of a country through changes in both aggregate demand and aggregate supply conditions (Kabundi et al., 2022; Cevik and Jalles, 2023). On one hand, negative supply shocks, which operate through lower agricultural production and increases in food prices, dampened economic activity and reduced labor productivity, and destruction of transportation infrastructure and increase in associated distribution costs, are likely to cause an inflationary impact. On the other hand, adverse demand shocks, which tend to raise the risk aversion of economic agents and reduce consumption and investment even after fiscal support and reconstruction, are expected to translate into a reduction in inflation. Understandably, the final effect on inflation is contingent on the strength of these two shocks and firmly remains an empirical issue.

Against this backdrop, the objective of our paper is to analyze the effect of extreme weather shocks on a panel of (32) state-level aggregate, non-tradable, and tradable inflation rates of the United States (US) over the quarterly period of 1989:01 to 2017:04. To achieve our objective econometrically, we undertake a two-step approach. In the first stage, realizing the possibility of the importance of a common (national) factor in explaining a large proportion of the total variability in state-level inflation rates, we first estimate a time series-based Dynamic Factor Model with Stochastic Volatility (DFM-SV), as in Bhatt et al. (2017), one each separately for the state-level aggregate, non-tradable, and tradable inflation rates. The DFM-SV allows us to separate out the influence of the national factor before determining the effect of extreme local weather shocks on the local or state factors, which, in turn, prevents us from underestimating the predictive effect of regional climate risks on state-level inflation rates. In the second step, we utilize the linear local projections (LP) method of Jordà (2005), in the context of a panel data-setting, to obtain Impulse Response Functions (IRFs) for the local factors of the aggregate, non-tradable and tradable inflation rates following climate risk shocks, after controlling for standard drivers of inflation rates (i.e., unemployment rate, monetary policy and oil price). As an additional analysis, we also utilize the nonlinear LP approach of Ahmed and Cassou (2016) to derive regime-specific IRFs associated with

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weather shocks on the local factors of the aggregate inflation rate, with the states now categorized as agricultural and non-agricultural. The decision to use the LPs method, instead of a Vector Autoregressive (VAR) model, is motivated by the fact that the former is simple, provides appropriate inference, and is robust to misspecification as it does not require the specification and estimation of the unknown data generating process as required while generating IRFs from a VAR, aptly handles persistence in data series because of lag augmentation, and easily accommodates nonlinear specifications (Jordà, 2005).

At this stage, it is important to highlight two pertinent issues: First, the choice of the US as our case study was an obvious one due to the free availability of reliable and detailed disaggregated state-level inflation rates constructed recently by the work of Hazell et al. (2022). Second, we need to look at regional inflation rates rather than an aggregate one at the country level, which is in fact derived from a weighted average of prices from urban areas, emanates from the recent line of work by Colacito et al. (2019), Sheng et al. (2022a, 2022b), and Cepni et al. (2023a). These authors stress the need to look at state-level data to derive reliable inferences while studying the impact of climate-related risks on economic activity and uncertainty profile of the US, especially in light of the dissimilarity in terms of the underlying time series properties of the regional metrics of risks involving climate change, as highlighted by Gil-Alana et al. (2022).

To the best of our knowledge, this is the first paper to provide an in-depth state-level analysis of the impact of regional weather shocks on local factors of aggregate, non-tradable and tradable inflation rates, derived from DFM-SV, using linear and nonlinear panel LP methods. Since we are also able to extract corresponding national factors for the three inflation rates under study, we also implement a time series-based LP approach to study the impact of the extreme weather shocks of the overall US economy on the common factors of aggregate, non-tradable and tradable inflation rates. As we separate out the influence of the national and local factors in the state-level inflation rates, we, in the process, are able to provide an accurate picture of the impact of climate risks on price-level dynamics, and possibly resolve the mixed results obtained in this context for the aggregate inflation rate of the US.[1] For instance, while Cashin et al. (2017) and Sheng et al. (forthcoming) note an increase in inflation following climate shocks, Natoli (2023) suggests a decline, with Laosuthi and Selover (2007) earlier, and Kim et al. (2022), even reporting no impact in terms of statistical significance, especially when one considers core inflation (i.e., excluding energy and food prices).[2]

Damages due to the physical risks of climate change have become more apparent in terms of magnitude, more severe, and more frequent in the US and globally (Stott, 2016), and such trends are expected to continue (Fifth National Climate Assessment (NCA5)[3]). Understandably, our analysis involving the effects of extreme weather shock on inflation, has monetary policy implications for the Federal Reserve to achieve its objective of maintaining low inflation rates, especially if we do detect a positive impact of climate-related risks on the national factor of inflation.

The remainder of the paper is organized as follows: Section 2 discusses the data, while Section 3 presents the basics of the DFM-SV, and linear and nonlinear LPs methods. These approaches are then used to obtain national and local factors of the state-level inflation rates, as well as the standard and regime-specific IRFs for the relevant inflation-related variables following climate risk shocks in the empirical results segment contained in Section 4. Finally, Section 5 concludes the paper.

2. Data

Data for inflation are derived from the new state-level consumer price indexes for the US constructed by Hazell et al. (2022), which are categorized into overall, non-tradable, and tradable inflation rates.[4] Based on data availability to construct a balanced panel, required for the implementation of the DFM-SV, over the quarterly period of 1989:01 to 2017:04, we consider 32 states (the names of which have been explicitly mentioned in Table 1 discussed in the next segment).

For capturing climate risks,[5] we rely on a recently developed meteorological time series, i.e., the (seasonally-adjusted) Actuaries Climate Index (ACI) for severe weather.[6] The ACI, as developed by actuary associations of Canada and the US, is an aggregate indicator of the frequency of severe weather (high and low temperatures, heavy rainfall, drought (consecutive dry days), and high wind, with all based on gridded data at the resolution of 2.5 by 2.5° latitude and longitude), and the extent of sea level rise (using tidal gauge station data). ACI data is not available at the state level, but for seven regions of the US: Alaska, Central East Atlantic, Central West Pacific, Midwest, Southeast Atlantic, Southern Plains, and Southwest Pacific. We categorize the 32 states as per the relevant region,[7] and hence, the ACI for that region is repeated for those specific states while deriving our linear and nonlinear IRFs.

In line with Sheng et al. (2023), outlining the role of oil shocks in the specification of a state-level Phillips-curve, the additional controls used are state-level unemployment rates, available from the Local Area Unemployment (LAU) Databases on the website of the US Bureau of Labor Statistics,[8] as well as log-returns of the West Texas Intermediate (WTI) oil price, and the Federal Funds Effective Rate, with the latter two variables obtained from the FRED database of the Federal Reserve Bank of St. Louis.

3. Methodologies

Our DFM-SV framework follows Del Negro and Otrok (2008) and Bhatt et al. (2017) and decomposes overall, non-tradable and tradable inflation rates for each state into a common national factor and an idiosyncratic (local) factor as follows:

We construct the following DFM-SV to extract the national factor for the inflation rates.

$$\pi_{i,t} = \lambda_i f_t + e_{i,t} \tag{1}$$

where $\pi_{i,t}$ is the overall, non-tradable, and tradable inflation rate for the i-th state at time period t; f_t is the national inflation factor at time period t, which captures the co-movement of different states; λ_i is the

[1] The reader is referred to Faccia et al. (2021), Kabundi et al. (2022), and Cevik and Jalles (2023) for reviews of the international literature on the effect of climate risks on inflation rates based on cross-country data, which in turn, also tend to highlight the importance of country-specific characteristics in explaining the range of possible effects.

[2] Kim et al. (2022) also highlighted the likelihood of overall inflation going up or down depending on whether one considers higher or lower regime-specific extreme weather shocks.

[3] See: https://nca2023.globalchange.gov/.

[4] The data is available for download from the research-segment of the website of Professor Emi Nakamura at: https://eml.berkeley.edu/~enakamura/papers.html.

[5] The risks associated with climate change can be typically categorised into two groups. The first group comprises physical risks arising due to, for example, rising temperatures, higher sea levels, more destructive storms, and floods or wildfires. The second group comprises the so-called transition risks. Transition risks result from the gradual switchover to a low-carbon economy and include risks due to climate-policy changes, the emergence of competitive green technologies, and shifts in consumer preferences. Understandably, we consider only the physical component of climate change in this paper.

[6] The data is downloadable from: https://actuariesclimateindex.org/data/.

[7] The reader is referred to: https://actuariesclimateindex.org/data/region-definitions/ for getting a map-based understanding of the categorization.

[8] See: https://www.bls.gov/lau/data.htm.

corresponding factor loading, and $e_{i,t}$ is the idiosyncratic state factor. We assume that both the national inflation factor and the idiosyncratic factors follow AR(2) process with stochastic volatilities as follows:

$$f_t = \alpha_1 f_{t-1} + \alpha_2 f_{t-2} + \sqrt{exph_t^f}\epsilon_t, \epsilon_t \sim i.i.d.N(0, Q_f) \tag{2}$$

$$e_{i,t} = \beta_1^i e_{i,t-1} + \beta_2^i e_{i,t-2} + \sqrt{exph_t^i}\eta_t^i, \eta_t^i \sim i.i.d.N(0, Q_i) \tag{3}$$

To deal with the stochastic volatilities, we assume random walk processes given by:

$$h_t^f = h_{t-1}^f + \sigma_h^f v_t^f, v_t^f \sim i.i.d.N(0,1) \tag{4}$$

$$h_t^i = h_{t-1}^i + \sigma_h^i v_t^i, v_t^i \sim i.i.d.N(0,1) \tag{5}$$

Following Del Negro and Otrok (2008), we assume the initial value of the stochastic volatilities to be equal to 0.

Once we have the national and state-level factors for the three inflation rates under consideration for each state, we first utilize the LPs method of Jordà (2005). The linear panel data-based model for computing the IRFs of the local factors of the overall, non-tradable, and tradable inflation rates for a unit shock to ACI is specified as follows:

$$\pi_{i,t+s} = \alpha_{i,s} + \beta_{i,s} ACI_t + \sum_{j=0}^{j=1} \gamma_{i,s} Z_{t-j} + \epsilon_{i,\ t+s},\ \text{for } s = 0, 1, 2,\ \ldots H \tag{6}$$

where s is the forecast horizons,[9] $\alpha_{i,s}$ measures the fixed effect for the panel dataset, and β_s captures the responses of the state-level factor at time $t+s$ to a shock to ACI at time t. The IRFs are calculated as a series of β_s which are estimated separately at each horizon (s).[10] $\sum_{j=0}^{j=1}\gamma_{i,s}Z_{t-j}$ control for the contemporaneous and lagged effects of the three control variables, i.e., the state-level unemployment rate, the oil price returns, and the monetary policy interest rate.

For the regime-specific IRFs, based on whether a state is agricultural or non (less)-agricultural, we rely on the approach of Ahmed and Cassou (2016). In this case, we utilize the threshold model to investigate the nonlinear effects of a unit ACI shock on the state-level factors of the overall, non-tradable, and tradable inflation rates of agricultural and non-agricultural US states. The formal specification is given as follows:

$$\pi_{i,t+s} = (1 - DM)\left[\alpha_{i,s}^{Non\ (less)-Agricultural} + \beta_{i,s}^{Non\ (less)-Agricultural} ACI_t + \sum_{j=0}^{j=1} \gamma_{j,s}^{Non\ (less)-Agricultural} Z_{t-j}\right] + DM\left[\alpha_{i,s}^{Agricultural} + \beta_{i,s}^{Agricultural} ACI_t + \sum_{j=0}^{j=1} \gamma_{j,s}^{Agricultural} Z_{t-j}\right] + \epsilon_{i,\ t+s},\ \text{for } s = 0, 1, 2,\ \ldots H \tag{7}$$

where DM is a threshold dummy variable that indicates whether US state i is heavily dependent on agriculture, with the variable taking a value of 1 if US state i is an agricultural state and 0 otherwise (non (less)-agricultural), whereby, more specifically, we assign the dummy value of 1 to the top 16 agricultural states in our sample, as per the information provided by the US Department of Agriculture (USDA) on the state ranking of cash receipts from all agricultural commodities for the year 2022.[11]

[9] The maximum length of the forecast horizons, H, is set to 20 quarters in this study.

[10] The technically minded reader is referred to Jordà (2005) for detailed discussions about the LPs method.

[11] See: https://data.ers.usda.gov/reports.aspx?ID=17844.

Table 1
Variance of state-level inflation rates explained by the common factor.

States	Non-Tradable	Tradable	Overall
Alabama	35.98 %	73.07 %	65.46 %
Alaska	3.64 %	61.42 %	33.00 %
Arkansas	20.73 %	59.41 %	48.72 %
California	49.39 %	76.46 %	61.93 %
Colorado	33.84 %	74.19 %	60.76 %
Connecticut	38.56 %	61.77 %	61.97 %
Florida	68.09 %	87.68 %	81.57 %
Georgia	44.48 %	79.47 %	66.47 %
Illinois	31.76 %	92.46 %	62.04 %
Indiana	39.98 %	77.28 %	66.26 %
Kansas	59.30 %	74.28 %	75.41 %
Louisiana	12.78 %	69.31 %	36.14 %
Maryland	37.38 %	81.62 %	69.94 %
Massachusetts	75.35 %	89.38 %	82.41 %
Michigan	15.61 %	80.50 %	44.48 %
Minnesota	36.90 %	61.31 %	56.91 %
Mississippi	22.20 %	55.24 %	40.97 %
Missouri	43.13 %	83.77 %	59.01 %
New Jersey	23.60 %	80.05 %	48.09 %
New York	66.03 %	92.44 %	81.63 %
North Carolina	40.86 %	70.38 %	57.83 %
Ohio	57.13 %	93.21 %	81.87 %
Oklahoma	12.91 %	72.91 %	36.70 %
Oregon	31.74 %	69.48 %	53.20 %
Pennsylvania	66.29 %	92.98 %	79.98 %
South Carolina	47.67 %	73.37 %	63.82 %
Tennessee	21.83 %	74.52 %	45.68 %
Texas	66.34 %	92.97 %	83.22 %
Utah	3.06 %	61.78 %	19.28 %
Virginia	25.37 %	82.61 %	64.86 %
Washington	40.58 %	77.30 %	61.14 %
Wisconsin	31.75 %	78.62 %	66.41 %
Average	37.63 %	76.60 %	59.91 %

4. Empirical findings

We start off by reporting in Table 1 the variances in percentages of the state-level inflation rates as explained by the national factor extracted from the DFM-SV for the non-tradable, tradable and overall inflation rates. On average, the common factor explains 76.60 % of the state-level tradable inflation rates, while this number drops down to 37.63 % for the non-tradable sector inflation rate, with the corresponding number for the overall inflation rate being 59.91 %. In sum, the role of the national factor, especially for the variabilities of the tradable sector and general inflation rates is indeed sizeable, and surely not negligible for the non-tradable inflation rate either. These findings provide us with the motivation to decompose the inflation rates into common and idiosyncratic (local) factors to obtain an accurate inference of the effects of the ACI shock, which we turn to next.

In Fig. 1, we provide the panel data-based IRF from the linear model for the state-level local factors of the overall inflation rate due to a one-unit shock to the ACI. Over the horizon of 20 quarters considered, the effect is in general positive and significant, barring the interval of quarters 11 to 16, with the strongest effect of slightly over one unit (1.08) at around the 5th-quarter-ahead horizon following the extreme weather shock. In other words, we find evidence of a virtually one-to-one maximum increase in the local factors of the overall inflation

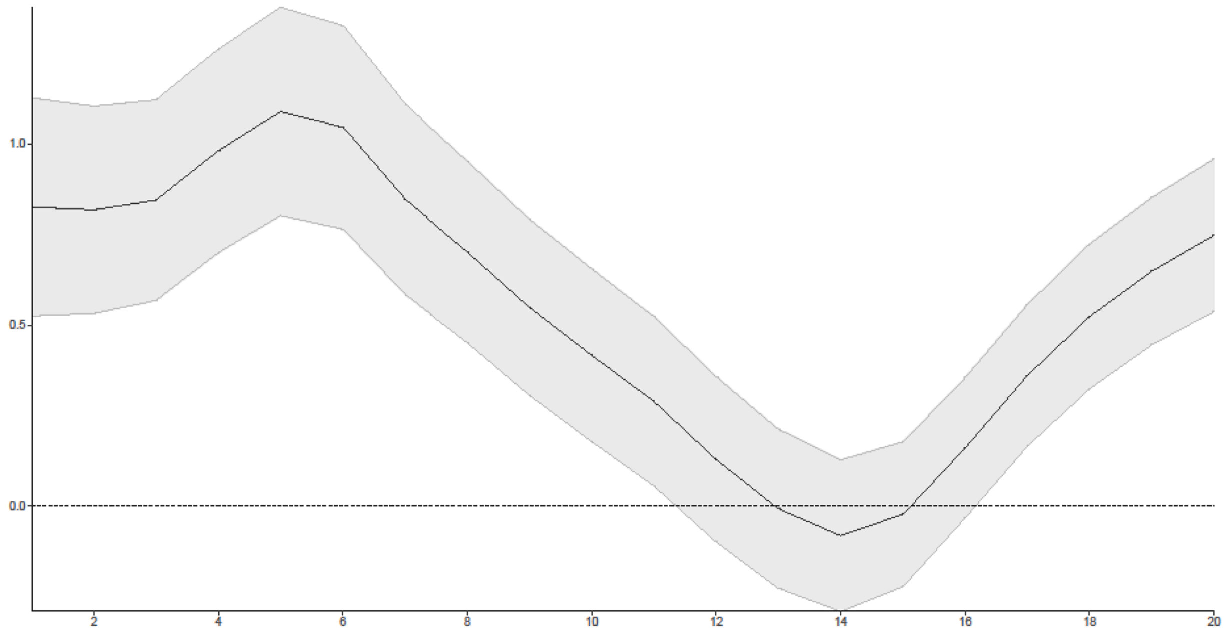

Fig. 1. Linear IRF of the local-factors of overall inflation rate to a one unit ACI shock.
Note: The grey area represents a one standard deviation error band.

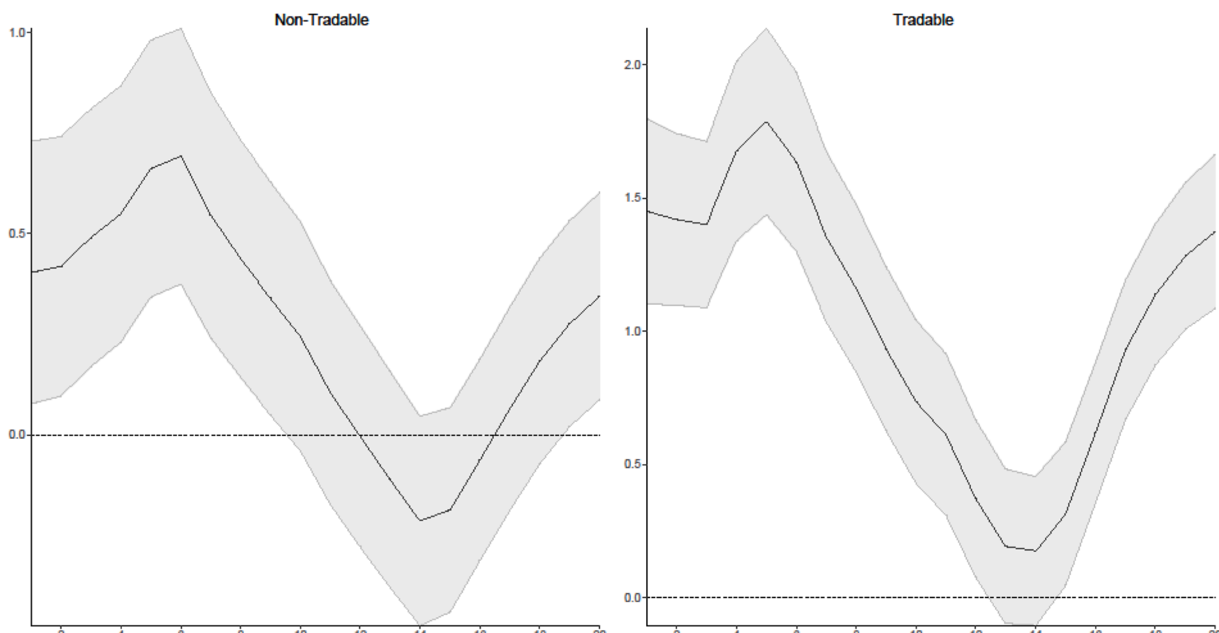

Fig. 2. Linear IRF of the local-factors of non-tradable and tradable inflation rates to a one unit ACI shock.
Note: The grey area represents a one standard deviation error band.

rates in the wake of a climate risks shock, suggesting the dominance of the supply-side channel.[12]

When we repeat the above analysis in Fig. 2 for non-tradable and tradable inflation rates-based local factors, we observe a similar pattern in the respective IRFs as for the case of the overall inflation rate, but unsurprisingly, the positive effect is relatively dominant, both in terms of magnitude (maximum impact being 1.79 units versus 0.69 unit) and time-length of significance, for the tradable sector than the non-tradable one, keeping in mind that the former includes food commodities. Understandably then, the nonlinear IRFs reported in Fig. 3, align with observations made in Fig. 2, in terms of the stronger strength of the initial effects (1.08 units versus 0.38 units) and the time length of significance of the agricultural states compared to the non (less)-agricultural ones, though the maximum impacts (1.36 units against 1.18) are only slightly higher in magnitude. Interestingly, the non (less)-

[12] Based on the suggestion of any anonymous referee, we present in Fig A1, the IRF using a panel LPs model of monthly year-on-year inflation based on regional (North East, North Central, South and West) CPI data available at: https://download.bls.gov/pub/time.series/cu/, following a shock to the corresponding regional ACIs. As can be seen, as in Fig 1, the effect is positive, and stays significant till the 11th month following the shock, thus confirming the dominance of aggregate supply over aggregate demand when shaping the effect of climate risks on inflation.

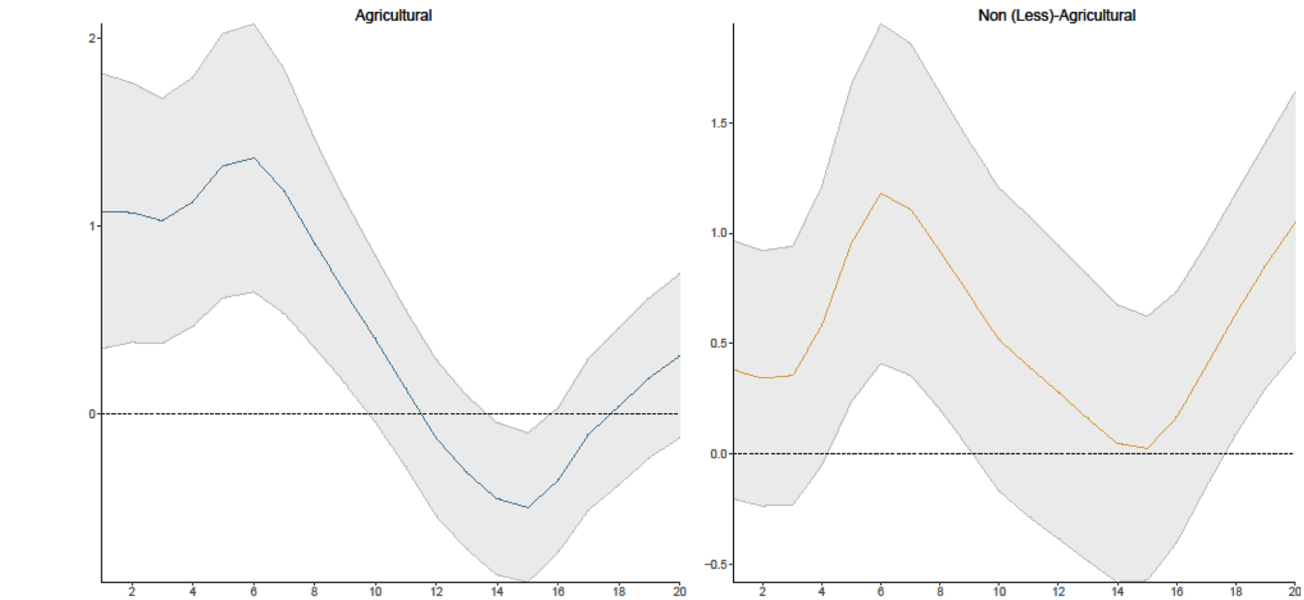

Fig. 3. Nonlinear IRFs of the local-factors of overall inflation rate to a one unit ACI shock in agricultural and non-agricultural US states.
Note: The grey area represents a one standard deviation error band.

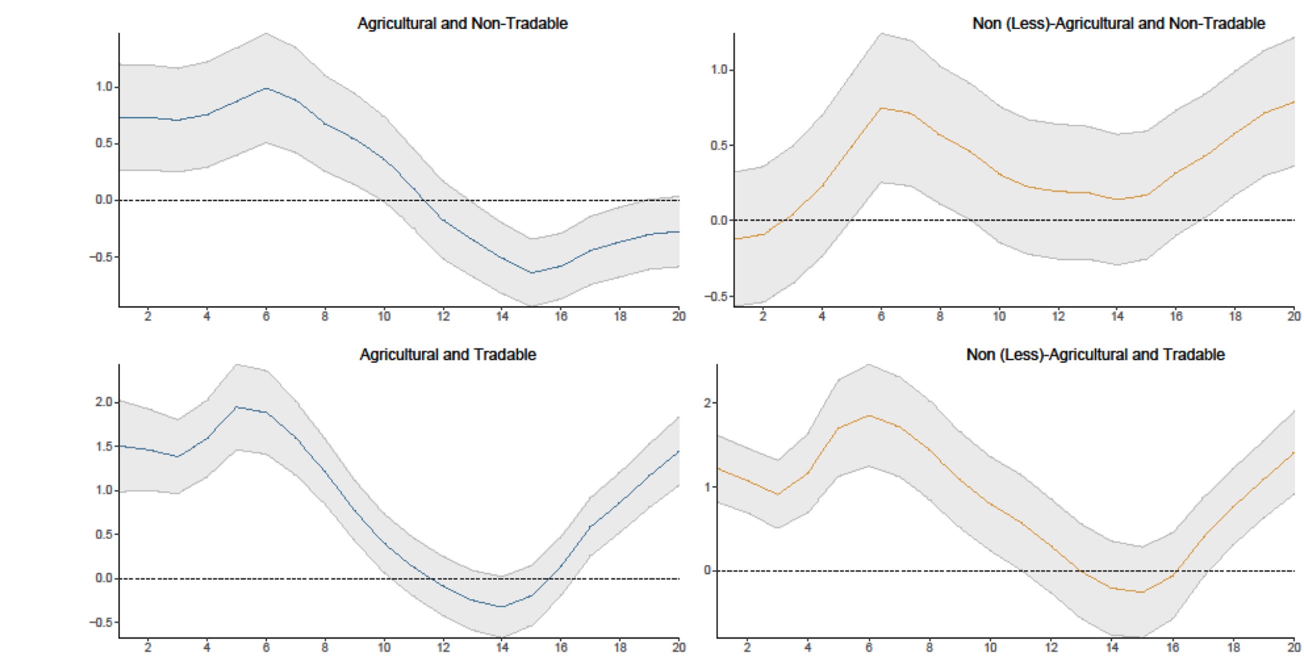

Fig. 4. Nonlinear IRFs of the local-factors of non-tradable and tradable inflation rates agricultural and non-agricultural US states.
Note: The grey area represents a one standard deviation error band.

agricultural states tend to have a positive and significant long-term effect, unlike the agricultural states. In addition, as expected, the positive effects of extreme weather shocks within the categories of non-tradables and tradables across agricultural and non (less)-agricultural states tend to paint a similar picture to the case of the aggregate inflation rate, when we look at the nonlinear IRFs in Fig. 4. In other words, the maximum effects across the regimes are quite similar in magnitudes, i.e., 1.94 units versus 1.85 units for tradables and 0.87 units against 0.75 units for non-tradables. But, at the same time, looking at it from the perspective of within the nature of the states and across the sectors, the maximum effects more than double, for the tradable compared to the non-tradable inflation rates factors. In other words, the results from the linear IRFs involving overall, non-tradable and tradable state-level inflation factors, are robust to the distinction of the states into agricultural or not in a nonlinear set-up.

Finally, in Fig. 5, we present the IRFs of the national factors of overall, non-tradable and tradable inflation rates following a one unit aggregate US ACI shock, derived from the modification of the panel-based LPs model in Eq. (6) to suit the set-up for our time series data in these cases.[13] The initial positive impacts are the highest for the common inflation factor of tradable inflation, followed by that of the overall inflation, and then comes the non-tradable sector, with maximum effects to the order of over 6.00 units (i.e., 6.11), over 4.30 units (i.e., 4.39), and nearly 3.50 units (specifically, 3.47), respectively. Interestingly,

[13] Essentially, the formal representation in the context of a time series is exactly the same, barring the suffix i in equation (6).

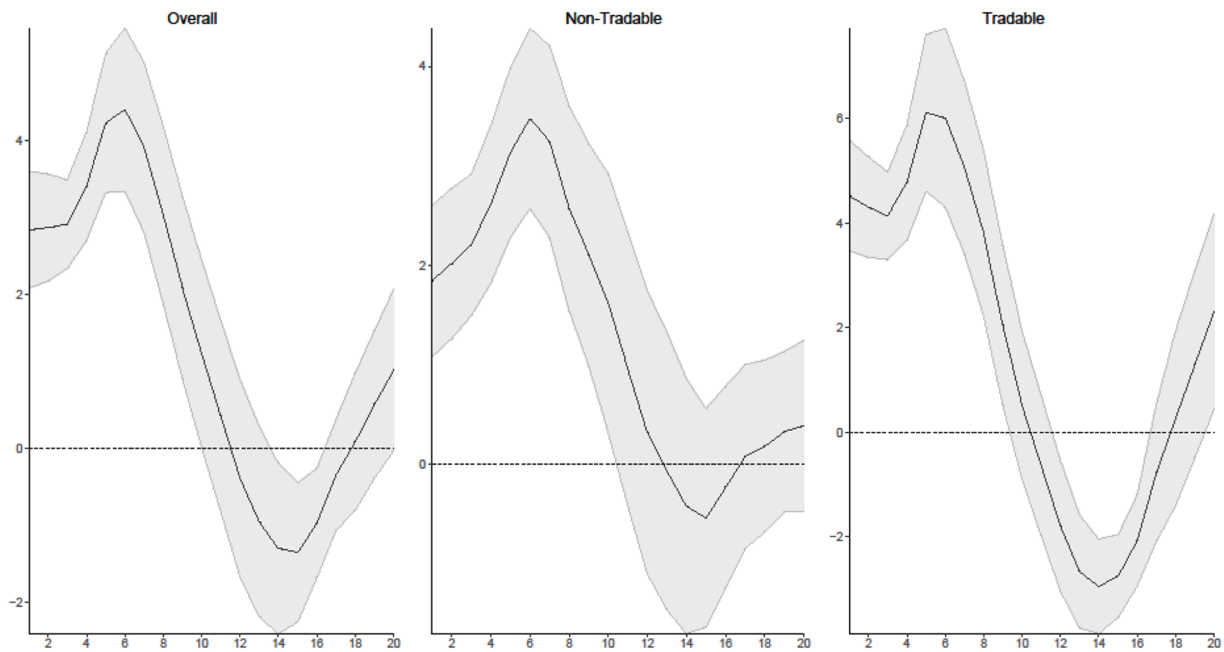

Fig. 5. Linear IRFs of the national factors of overall, nontradable and tradable inflation rates to a one unit ACI shock.
Note: The grey area represents a one standard deviation error band.

negative and significant effects are also observed around the medium-term (12 to 16-quarter-ahead) horizons, especially for the overall and tradable sector national inflation factors, suggesting a dominant adverse aggregate demand-side effect, before returning to the positive influence in the long run, driven by a relatively stronger negative aggregate supply-side influence.

While it is not possible to draw a one-to-one correspondence of our findings with the existing literature involving aggregate US inflation rates, given the regional and disaggregated approach we undertake, we can confirm with certainty that extreme weather shocks are indeed inflationary for the US economy in line with the observations of Cashin et al. (2017), Sheng et al. (forthcoming), and to some extent with that of Kim et al. (2022).

5. Concluding remarks

This paper examines the role of regional extreme weather shocks in driving overall, non-tradable, and tradable inflation rates for a panel of 32 US states over the quarterly period of 1989:01to 2017:04. To prevent an underestimation of the predictive impact in line with the importance of a national factor in driving local inflation, we utilize a DFM-SV model to decompose the three inflation rates into their respective common factors and idiosyncratic state-factors, with the former and latter groups used to evaluate the national and local effects of climate risks. Our results, based on impulse responses from linear panel and time series-based frameworks, reveal statistically significant increases in the state and national factors of overall inflation rates, with the aggregate effect driven by the tradable sector relative to the non-tradable one. In addition, when a nonlinear model was used to capture regime-specific impacts, with the states categorized as agricultural and non (less)-agricultural, the comparatively important role of the tradable inflation rates over the non-tradable sector continued to hold, with corresponding effects for both these sectors being relatively dominant for the agricultural states.

The main implication of our findings is that the Federal Reserve, in its effort to maintain low inflation rates, would require to increase the Federal Funds Effective Rate following extreme weather shocks. But since the effect inflationary is stronger in agricultural than non (less)-agricultural regions, the role of state-specific contractionary fiscal policy cannot be ignored either. But, the trade-offs for such policy decisions are likely to amplify the recessionary effects of climate change (Cepni et al., 2023b; Gupta et al., 2023), and hence would require a general effort by the government to undertake environment-friendly policies that are aimed directly at reducing the risks associated with global warming. Academically, our results imply the need to distinguish and publish data on non-tradable and tradable inflation rates (Johnson, 2017) regularly, when studying the impact of climate risks on overall inflation rates of the US, given the dominant role of the latter over the former. This, in turn, would also assist from the policy perspective.

Our current work can be extended in at least two directions. In this paper, we only consider the physical risk component of climate change, and completely ignore the transition risk aspect. Note that the transition to a net zero carbon emission world may imply sharp increases in the price of carbon, in turn affecting consumer prices directly through higher electricity, gas and petrol prices, and indirectly through increased costs of production for firms across a broad range of sectors (Faccia et al., 2021). Hence, a similar analysis to the current one involving transition risk is indeed a question we need to delve into in the future, especially in terms of its importance in causing inflation relative to physical risk. While structural analysis of the impact of climate risk on inflation is important, the Federal Reserve would ideally require real-time forecasts of inflation rates for the appropriate design of monetary policy. In this regard, the role of physical and transition risks in forecasting regional and aggregate inflation, along the lines of Yeganegi et al. (2023), over and above the traditional predictors, particularly based on time-varying models,[14] forms an interesting area of future research.

Data availability

Data will be made available on request.

Appendix

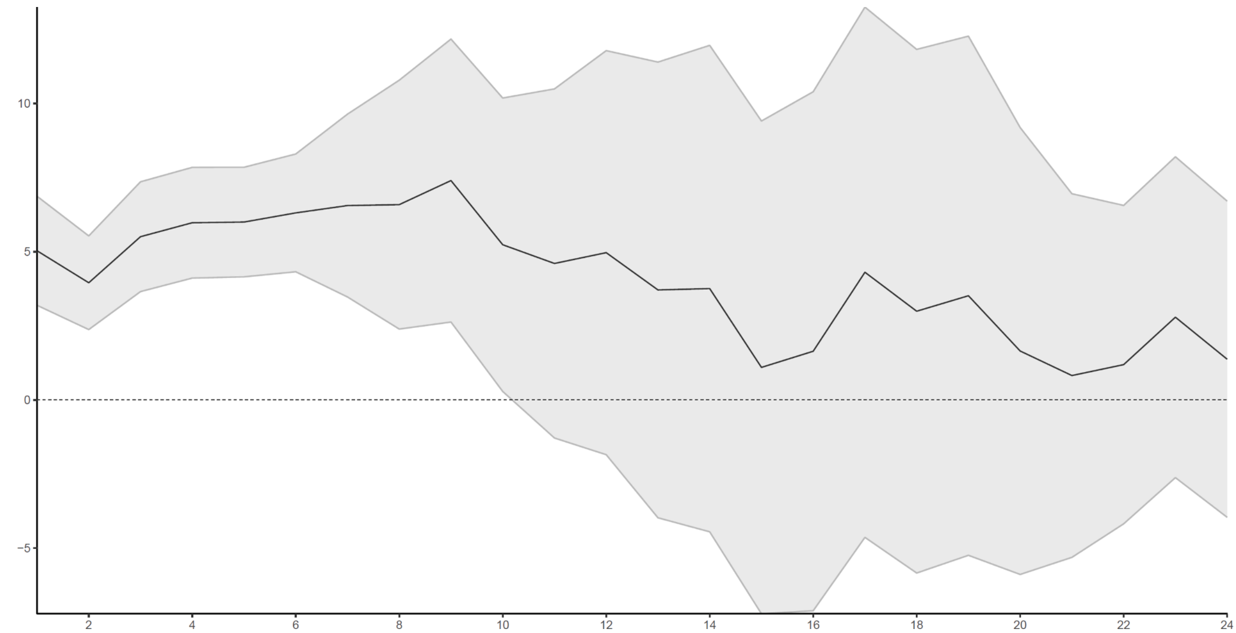

Fig. A1. Linear IRF of monthly regional (North East, North Central, South and West) inflation rates to a one unit ACI shock.

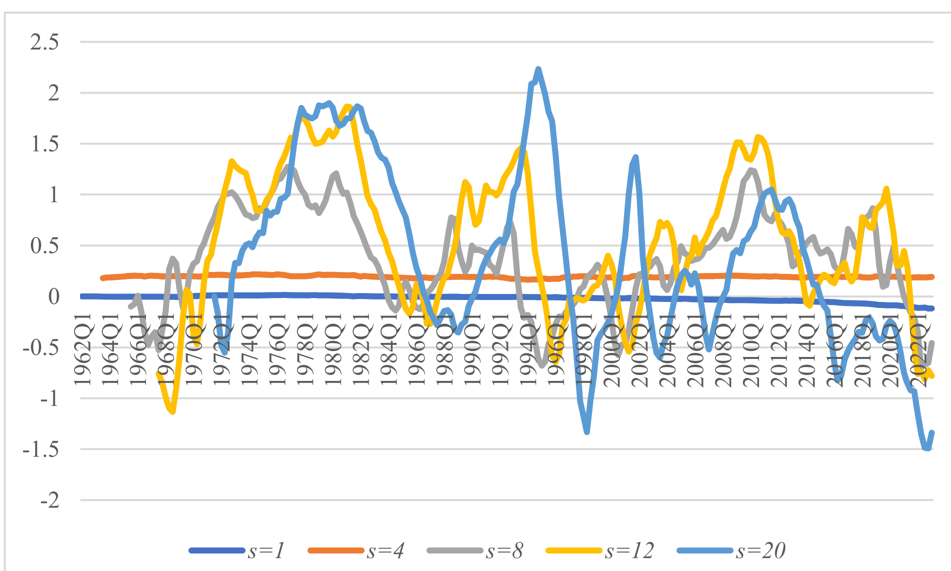

Fig. A2. Time-varying response of the aggregate US inflation rate to ACI.

[14] This claim, as depicted in Fig A2 in the Appendix, is motivated by the horizon-specific (s = 1, 4, 8, 12, and 20) time-varying responses of the aggregate US CPI inflation to (changes) in the ACI, required to ensure stationarity, over the quarterly period of 1961:02 to 2023:01, as obtained from the fast and flexible Bayesian Time-Varying Parameter (TVP) regression model of Hauzenberger et al. (2022). Note that, the results are produced from the Time-Varying-Parameter-Random Walk-Forward-Filtering Backward-Sampling-Factors (TVP-RW-FFBS-FAC), as it (based on 50 predictors: 49 associated with a generalized Phillips curve plus first-difference of US-level ACI) could be estimated with the shortest computational time of 1.37 minutes, compared to 6.27, 5.94, and 10.04 under the alternative models of Time-Varying-Parameter-White Noise-Singular Value Decomposition (TVP-WN-SVD), Time-Varying-Parameter-Random Walk-Singular Value Decomposition (TVP-RW-SVD), Time-Varying-Parameter-Random Walk-Forward-Filtering Backward-Sampling (TVP-RW-FFBS), respectively. Further details are available upon request from the authors.

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