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Estimating National Weather Effects from the Ground Up*

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Abstract

Understanding the effects of weather on macroeconomic data is critically important, but it is hampered by limited time series observations. Utilizing geographically granular panel data leverages greater observations but introduces a "missing intercept" problem: "global" (e.g., nationwide spillovers and GE) effects are absorbed by time fixed effects. Standard solutions are infeasible when the number of global regressors is large. To overcome these problems and estimate granular, global, and total weather effects, we implement a two-step approach utilizing machine learning techniques. We apply this approach to estimate weather effects on U.S. monthly employment growth, obtaining several novel findings: (1) weather, and especially its lags, has substantial explanatory power for local employment growth, (2) shocks to both granular and global weather have significant immediate impacts on a broad set of macroeconomic outcomes, (3) responses to granular shocks are short-lived while those to global shocks are more persistent, (4) favorable weather shocks are often more impactful than unfavorable shocks, and (5) responses of most macroeconomic outcomes to weather shocks have been stable over time but the consumption response has fallen.

JEL codes: Q52, Q54, R11

Keywords: Weather, Macroeconomic Fluctuations, Employment Growth, Granular Shocks

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1 Introduction

Understanding both the micro and macroeconomic effects of weather is critically important for at least three reasons. First, certain weather events, such as severe storms or natural disasters, can have substantial impacts that policymakers and the public should be aware of for planning purposes. Second, researchers, policymakers, financial market participants, and other economic agents may want to filter out transitory weather-driven fluctuations from macroeconomic data series – just as we do with seasonal fluctuations – to accurately measure the underlying strength of the economy (Boldin & Wright (2015)).Third, understanding exactly how weather fluctuations affect the macroeconomy is crucial for researchers studying the economic implications of longer-run changes in weather and weather volatility.

Yet, estimating the aggregate, macroeconomic effects of weather is hampered by the small-T problem: there are a relatively small number of observations available in time series data, which leads to low statistical power and the potential for overfitting. Estimating the effects of weather on economic outcomes using granular (e.g., geographically disaggregated) panel data leverages the larger number of observations, NT, to achieve greater statistical power and out-of-sample predictive accuracy. However, the panel approach is subject to the "missing intercept" problem the plagues analyses of macroeconomic effects of micro shocks in many contexts, not just weather. Specifically, the time fixed effects typically included in panel regressions absorb cross-sectional spillovers (either related to distance or to supply chains), aggregate policy responses, and general equilibrium effects that cause a wedge between the true aggregate effects and the aggregated local effects.

In this paper, we develop a two-step approach for separately estimating the granular, global, and combined effects of local shocks on aggregate outcomes. This methodology can be useful in a variety of contexts. We apply it to estimating the granular, global, and combined effects of local weather on national monthly employment growth in the U.S.

The first step involves estimating the local effects using the conventional two-way fixed effects panel estimator. We do this using a rich county-level panel data set that we constructed covering the past roughly 45 years. The data set combines administrative employment counts (Census of Employment and Wages) with several dozen weather variables related to temperature, precipitation, and extreme events such as natural disasters. These variables are adjusted for local, time-varying seasonality so as to measure deviations from normal/expected values (i.e., "shocks"). We estimate a number of alternative, candidate specifications that vary in their degree of effect heterogeneity. From each of these panel estimations, we retain the predicted local weather effects (i.e., the fitted values excluding the fixed effects) and the estimated time fixed effects. We aggregate these predicted local effects to the national level and refer to the resulting time series as the "granular effects" of weather, following the terminology of Gabaix (2011).

In the second step, we regress the estimated time fixed effects on aggregated (i.e., national) weather variables. Because there are a large number of weather variables relative to the number of observations in this time series regression, we employ machine learning techniques – specifically, regularized regression, cross-validation, and recursive out-of-sample evaluation – to mitigate potential overfitting. This step yields predicted national weather effects that capture the cross-sectional spillovers, aggregate policy responses, and general equilibrium effects of weather fluctuations around the country. We refer to this time series as "global effects" following the terminology of Giroud et al. (2024).[1]

The results of this application reveal four sets of important, novel findings. The first set involves the results from the local panel estimation, revealing the mechanisms by which weather affects *local* employment – results that would be unattainable with an aggregate time series approach. We find that variables associated with temperature, precipitation, temperature-precipitation interactions, and extreme events all have significant explanatory power for predicting local employment growth. Surprisingly, the results also show that lagged weather has greater explanatory power than the contemporaneous weather, highlighting the importance of accounting for dynamics. Analyzing the effects of selected weather variables, we find that the effects are often non-linear and that the lagged effects typically offset the contemporaneous effects, leading to near-zero cumulative effects after 3 to 4 months.

Our second set of results quantify the role of weather in explaining fluctuations in national employment growth. Given that our two-step estimation approach yields separate estimates of the granular and global weather effects, we can quantify the separate role of each as well as their combined role. We find that weather explains roughly 7% of the monthly variation in national payroll employment growth from May 1981 through April 2024, with both the granular and global effects having statistically significant impacts.

Third, we investigate the extent to which these weather effects, though targeted on employment, might also explain some of the variation in other macroeconomic and financial time series. The weather effects are found to have surprisingly large explanatory power across an array of outcomes. In particular, the weather effects have a statistically significant association with labor force participation, hires, separations, vacancies, industrial production, the Chicago Fed national activity index, and retail sales. The weather effects are especially strongly correlated with retail and food sales, suggesting that weather has important demand-side effects (i.e., favorable weather stimulates retail activity in the short-run). Supporting the validity of our estimated effects, we also show they are strongly correlated with household-reported absences from work due to weather. In addition, the weather effects are strongly predictive of payroll employment *surprises* – the difference between realized payroll employment growth and consensus pre-report expectations, suggesting that the influence of weather on each month's employment report is largely unobserved by market participants in real time, at least historically. Moreover, likely because surprises are positively associated with

[1] Giroud et al. (2024) estimates both the granular (originating at local plants) and global (nationwide via knowledge spillovers within multi-plant, multi-region firms) productivity effects stemming from plant openings spread across the U.S.

changes in Treasury yields on employment report release days, the estimated weather effects are also predictive of those Treasury yield responses to employment reports.

Fourth and lastly, using the Jordà (2005) Local Projections estimator, we provide estimates of the dynamic responses of key macroeconomic outcomes to shocks in the granular, global, and combined weather effects. We find that a combined weather shock leads to a short-lived increase in employment growth but a long-lasting (up to at least 36 months) increase in the level of employment. It also increases personal consumption expenditures (PCE) and industrial production, though widening confidence intervals make these responses statistically insignificant after roughly 12 months. We find near-zero impacts on inflation and the fed funds rate. We find the responses are similar for granular versus global weather shocks except that the longer-run employment response to granular shocks is larger and more statistically significant for the response to global shocks. Finally, similar to Kim et al. (2025) and Baleyte et al. (2024), we examine whether the dynamic macroeconomic responses to total weather shocks have changed over time. Contrary to the former study but consistent with the latter, we find that weather shocks in the first half of our sample (1981-2001) generally have larger and more significant effects than do shocks in the second half of the sample. Specifically, early-sample shocks lead to long-lasting significant responses of employment, total PCE, goods PCE, and services PCE, while late-sample shocks have no significant effects. These results suggest that firms, and the economy more generally, have become better adapted to dealing with weather shocks over time, perhaps due to improvement in inventory and supply chain management. It is also possible that the structural change in the U.S. economy away from more weather-sensitive goods production toward less weather-sensitive services has led the aggregate economy to be less weather-sensitive.[2]

The contributions of this paper are four-fold. First, we provide a methodology for separately estimating the local, aggregate, and combined effects of granular shocks on aggregate outcomes. While we apply this methodology to estimating weather effects, which is natural given that weather is highly localized yet can still have aggregate effects, the approach likely is applicable for many other types of granular or place-based shocks.[3] Second, we provide a full characterization of the relationship between various types of weather and current and subsequent months' employment growth. Third, we demonstrate that weather plays a significantly larger role in explaining fluctuations in U.S. employment growth, as well as other macroeconomic outcomes, than previously known. Fourth and finally, the weather effect estimates generated by the methodology in this paper can be subtracted from official seasonally-adjusted employment growth to measure seasonally and weather adjusted (SWA) employment growth, which should provide a better measure of the true strength of the labor market.[4]

[2]In future research, the methodology developed in this paper could be employed at the industry level to distinguish between these two mechanisms.

[3]As discussed below, Matthes et al. (2024) propose an alternative, Bayesian approach to estimating aggregate effects that utilize micro panel estimates to inform priors and apply the approach to estimating the fiscal multiplier.

[4]see Boldin & Wright (2015) for purely time series approach to integrating weather adjustment with seasonal

2 Related Literature

This paper relates to and draws from prior work in four main literatures. The first is the literature on "granular effects." Dating at least as far back as Long Jr & Plosser (1983), macroeconomists have been interested in the potential for disaggregate shocks – i.e., shocks originating at the level of plants, firms, counties, states, etc. – to propagate and amplify macroeconomic business cycles. Gabaix (2011)'s influential paper demonstrated that "granular" economic shocks – which he conceptualized as firm-level productivity shocks – need not average out in the aggregate if the firm size distribution is fat-tailed. In that case, the economy-wide aggregate of firm productivity shocks aggregated to the economy-wide level – which he called the "granular residual" – will be non-zero. Along with standard macroeconomic shocks such as wars, monetary policy shocks, and fiscal policy shocks, these granular effects can impact economy-wide output. Gabaix found empirically that the granular effects explain around one-third of the variation in both total GDP growth and total productivity in the U.S. over 1952–2008. Our paper applies analogous logic to argue that local-level weather shocks aggregate to produce non-zero economy-wide "granular" shocks that can affect the macroeconomy. However, one conceptual difference in our analysis of weather shocks is that we seek to identify *both* granular and aggregate shocks, and to assess their separate and combined effects on the macroeconomy. In this sense our analysis shares some similarities to the those of Giroud et al. (2024) and Barrot & Sauvagnat (2016). Giroud et al. (2024) estimates the national productivity effects of local plant openings that generate both granular shocks (at the local plant-level) and "global" (national) shocks, where the latter stems from knowledge spillovers within multi-plant, multi-region firms. Barrot & Sauvagnat (2016) study the economy-wide spillover from county-level natural disaster shocks via input-output linkages. Unlike these studies, our paper does not explicitly model the various local-to-national propagation mechanisms, be they production network, general equilibrium, or other. Rather, we estimate the reduced-form result of all propagation channels by estimating a common time effect and relating it to the aggregated local shocks (national weather shocks in our application).

Another related paper is that of Matthes et al. (2024), which develops a Bayesian approach to estimating the aggregate effects of shocks originating at a disaggregate level. In their approach, microeconomic panel data estimates are used to inform priors used in the Bayesian estimation of the economy-wide effects. This approach differs from ours both in the use of the Bayesian approach and in their assumption that local effects, unlike in Gabaix (2011), cancel out in the aggregate. That is, the approach by assumption rules out any granular effect, making it inapplicable in settings such as our application in which some local weather shocks, such as major disasters or shocks occurring in very populous counties, are likely to have nationwide effects.

The second related literature is the econometrics literature on panel fixed effects. That literature, which we discuss in more detail in the next section, has derived many alternative estimators for panel data that allow for both local (time- and unit-varying) slope effects and time-varying effects common

adjustment for national macroeconomic data.

to all panel units. These estimators generally differ in the identification assumptions required. Our approach is most closely related to the two-way Hausman-Taylor (Hausman & Taylor (1981)) estimator developed by Wyhowski (1994) and Baltagi (2023). Hausman & Taylor (1981)'s estimator allowed for the inclusion of both unit fixed effects and time-invariant regressors. The two-way Hausman-Taylor estimator simply extends the estimator to also allow for time fixed effects and time-varying regressors. Hausman & Taylor (1981) show their one-way estimator can be implemented using either a two-step approach or an IV approach.[5] In this paper, we implement an analogous two-step approach for analyzing the time fixed effects as opposed to the unit fixed effects. In our context, following the two-step approach rather than the IV has a key advantage. Because we have a large number of aggregate weather variables (unit-invariant regressors) relative to T, overfitting becomes a serious concern. By separating out the estimation of the coefficients of the aggregate weather variables into this second step, we can apply machine learning techniques designed to avoid overfitting.

Our paper thus also relates to a third literature, that of machine learning techniques in time series forecasting. Stock & Watson (2002)'s seminal paper was one of the first to address the challenge of time series forecasting when the number of candidate predictor series is large relative to the number of time series observations. They propose using principal component analysis (PCA) to reduce the dimension of the predictor space to a smaller number of dynamic factors. This method has become standard in time series forecasting, though it has been critiqued on the grounds that the dynamic factors from PCA are optimized to maximally explain the common variation of the underlying predictor series, not their explanatory power for predicting the targeted outcome (see, e.g., Bai & Ng (2008)). Huang et al. (2022) propose a simple modification of the PCA method, which they call "scaled-PCA," that replaces the raw values of each underlying predictor in the PCA with its values scaled by the coefficient obtained from regressing the target series on the predictor. Scaled-PCA thus "assigns more weights to those predictors with stronger forecasting power" (Huang et al. (2022)).

In our application, we alternately use scaled-PCA factor-augmented regression in addition to, or instead of, machine learning estimators that utilize the full set of variables. The latter approach was followed in a recent paper by Dunn et al. (2025), who used payroll processing data to estimate "nowcasts" (i.e., contemporaneous forecasts) of local employment growth in the U.S. This application shares some similarities to our first step, whereby we use of local weather data, rather than local payroll processing data, to predict contemporaneous local employment growth. However, Dunn et al.'s objective stops at the local level, seeking to obtain the best local nowcasts. Our objectives, on the other hand, are to produce the best *national* nowcast (or at least the best nowcast based solely on weather), along with decomposing that into the granular and global effects. That said, we utilize similar ML techniques – specifically, out-of-sample cross-validation – to evaluate and compare the

[5]The asymptotic equivalance of the two approaches is shown in Hausman & Taylor (1981)'s Appendix B and discussed in more detail in Hansen (2022).

performance of alternative models.[6]

Fourth and most obviously, this paper relates to the growing literature on the macroeconomic effects of weather and climate shocks. The seminal paper of Deschênes & Greenstone (2007), which estimated the effects of annual weather fluctuations on county-level crop yields in the U.S., was one of the first studies in the climate literature to utilize panel data variation with the two-way fixed effects (TWFE) estimator. Numerous subsequent studies have since followed this same approach. In particular, many studies have employed the TWFE estimator with cross-country panel data to examine the effects of nationwide temperature shocks on annual GDP and GDP growth. Dell et al. (2012) was a pioneering study in this area and found that high temperatures have long-lasting negative effects on both the level and growth of GDP, especially among developing countries. More recently, Nath et al. (2024) found that temperature shocks have persistent but not permanent effects of GDP growth, with the persistence driven largely by the persistence of the temperature shocks themselves.[7] Baleyte et al. (2024) investigates the macroeconomic effects of high temperature shocks using monthly panel data across 14 EU countries, finding high temperature shocks lower GDP growth and raise inflation, consistent with their acting as supply shocks. Akyapı et al. (2025) also study the dynamic response of GDP growth with cross-county annual panel data but they consider a much broader set of weather variables than prior studies. Like in our application utilizing a large set of weather variables, they use Elastic Net and other machine learning techniques to allow for the large number of potential regressors. They find that shocks to drought, extreme heat, and non-mild temperatures have transitory negative effects on GDP growth and permanent effects on GDP levels.

A number of studies have similarly used TWFE models but with subnational, instead of cross-country, panel data. Colacito et al. (2019) study the impacts of temperature on GDP growth in the U.S. They find insignificant effects in time series regressions, which they attribute to low statistical power due to the small number of annual observations, but significant negative effects of summer temperature shocks using the TWFE estimator with state panel data. Wilson (2019), Roth Tran & Wilson (forthcoming) use U.S. county-by-month panel data, as in our paper, to estimate the local economic effects of weather and natural disasters, respectively.[8] Roth Tran & Wilson (forthcoming) used a panel TWFE local projections estimator and found that natural disaster shocks have a positive and long-lasting impact on local income per capita and short-lived positive effect on the level of employment. As in our paper, Wilson (2019) aggregates estimated local weather effects to obtain a national time series measure of weather effects – corresponding to what we call granular effects in this paper – and finds the granular effects have significant explanatory power for national

[6] Dunn et al estimate LASSO and Random Forest ML models, while we focus on the Elastic Net, which nests LASSO and Ridge regressions.

[7] Other examples of cross-country panel studies estimating the effects of temperature (and sometimes precipitation) shocks on GDP and other macroeconomic outcomes include Kahn et al. (2021), Burke et al. (2015), Newell et al. (2021)

[8] See also the TWFE studies of Coronese et al. (2025), which estimates the local income and wage effects of storms in the U.S., and Leduc & Wilson (2023), which examines the longer-run effects of changes in extreme temperatures and precipitation on local population, employment, wages, and house prices.

employment growth as well as financial market price responses to employment reports. Thus, our paper expands on Wilson (2019) in several dimensions. First, we estimate not only granular effects but also global effects. Second, we include many additional weather variables in the analysis. Third, we study the dynamic macroeconomic responses to granular and global weather shocks.

Several recent papers have focused on time series analyses of weather and climate effects, motivated by the missing intercept concern inherent to the TWFE panel data analyses. Bilal & Känzig (2024) provides an important example and quantification of the missing intercept. They estimate the dynamic response of global GDP to worldwide temperature shocks using long historical time series data and compare it to the dynamic response estimated from the cross-country panel TWFE approach. They find much larger effects at the global level and provide evidence suggesting "local" (country) temperature shocks have worldwide spillovers (via country-level shocks leading to extreme events throughout the world). Kim et al. (2025) use a VAR approach to estimate the responses of several macroeconomic outcomes to "severe weather" shocks. They rely on U.S. national time series data (aggregating a county-level measure of severe weather) rather than subnational panel data, arguing that the panel TWFE approach "can better identify the effects of local weather shocks on the local economy," but "will miss out on general equilibrium and spillover effects, which get soaked up in time fixed effects" (pp.323-324).[9] Thus, our approach can be seen as marrying the panel approach with the time series approach, allowing for estimation of both granular and nationwide/global effects, in addition to allowing for detailed analyses of local effects.

3 Methods

This section describes our methodology for estimating the granular, global, and combined total effects of disaggregate shocks on an aggregate outcome. In our specific application, the disaggregate shocks are county-level weather shocks and the aggregate outcome is national monthly employment growth. But the methodology is general and can be applied to any context involving disaggregate shocks – for example, plant-level or firm-level productivity shocks (as in Gabaix (2011) and Giroud et al. (2024)), state-level fiscal shocks (as in Nakamura & Steinsson (2014), Leduc & Wilson (2013), and Dupor et al. (2023)), and country-level climate shocks (as in Nath et al. (2024) and Akyapı et al. (2025)).

3.1 General Approach

Let us start by defining terms. An aggregate outcome is, by definition, an aggregate of disaggregate outcomes. For level variables, the aggregate outcome is simply the sum of disaggregate levels. For growth rates, it is the weighted mean of disaggregate growth rates, weighting by disaggregate

[9] See also Natoli (2024), which constructs aggregate (U.S. national) heat and cold temperature shocks from county-level weather shocks and use these shocks in time series analyses.

levels. For instance, national employment L_t is the sum of local employment across all subnational units, $L_t \equiv \sum_i L_{it}$, and its growth rate is an employment-weighted mean of local employment growth rates:

$$\frac{L_t - L_{t-1}}{L_{t-1}} \equiv \sum_i \eta_{i,t-1} \frac{L_{it} - L_{i,t-1}}{L_{i,t-1}} \approx \sum_i n_{i,t-1} \Delta\ell_{it}, \tag{1}$$

where i indexes local units, $n_{i,t-1} = \frac{L_{i,t-1}}{L_{t-1}}$, and $\ell_{it} \equiv log(L_{it})$.

Now suppose that local growth rates $\Delta\ell_{it}$ are determined as follows:

$$\Delta\ell_{it} = \alpha_i + \alpha_t + \mathbf{w}_{it}'\boldsymbol{\beta} + \mathbf{w}_t'\boldsymbol{\gamma} + \mathbf{x}_t'\boldsymbol{\psi} + \epsilon_{it}, \tag{2}$$

where α_i are unit (local) fixed effects, α_t are time fixed effects, and ϵ_{it} is an i.i.d. error term.[10] Let $\mathbf{w}_{it}'$ represent a vector of local weather variables and $\mathbf{w}_t' \equiv \sum_i n_{i,t-1}\mathbf{w}_{it}'$ be a vector of national weather variables. Note that $\mathbf{w}_{it}'$ can include both contemporaneous and lagged weather variables. The vector $\mathbf{x}_t'$ represents other observable aggregate variables affecting employment growth nationwide. (For instance, in our application we include recession dummies in $\mathbf{x}_t'$.) The coefficient vector $\boldsymbol{\beta}$ represents the marginal effects of *local* weather. The $\boldsymbol{\gamma}$ vector of coefficients represents the marginal effects of aggregated weather common to all localities. Following the terminology of Gabaix (2011), we refer to the aggregate of $\mathbf{w}_{it}'\boldsymbol{\beta}$ (i.e., $\sum_i n_{i,t-1}\mathbf{w}_{it}'\boldsymbol{\beta}$) as the "granular" effects of weather. Following the terminology of Giroud et al. (2024), we refer to the aggregate of $\mathbf{w}_t'\boldsymbol{\gamma}$, which of course is simply $\mathbf{w}_t'\boldsymbol{\gamma}$, as the "global" effects of weather. We refer to the combined granular and global effects as the "combined" or "total" effect.

Aggregated weather ($\mathbf{w}_t'$) could affect local outcomes either directly via nationwide spillovers (e.g., holding own-county weather fixed, bad weather nationwide causes more tourism in locality i) or indirectly via general equilibrium (GE) effects.[11] For example, a major natural disaster in one locality could raise demand and prices for construction materials nationwide, having an impact on the economic outcome of interest in all localities. It could also induce a national policy response, such as disaster relief spending funded by current or future taxes, which in turn could affect economic activity in all localities.

The obvious challenge with estimating equation (2) is that the time fixed effects will fully absorb aggregated weather, leaving $\boldsymbol{\gamma}$ unidentified. The existing literature on the effects of weather and climate on macroeconomic outcomes generally follows one of two approaches. The first approach

[10] Note this would be exactly the same specification considered in Hausman & Taylor (1981) if one replaced $\mathbf{w}_t'$ and $\mathbf{x}_t'$ with $\mathbf{w}_i'$ and $\mathbf{x}_i'$.

[11] A richer model could allow for more localized spillovers by adding a spatial lag of weather (as in, for example, Albert et al. (2021) and Roth Tran & Wilson (forthcoming)). We omit spatial lags in this paper because they would greatly increase the number of regressors such that estimating the models would become computationally infeasible.

essentially aggregates equation (2) and estimates the resulting time series model:

$$\Delta \ell_t \equiv \sum_i n_{i,t-1} \Delta \ell_{it} = \alpha + \mathbf{w}_t' \boldsymbol{\phi} + \mathbf{x}_t' \boldsymbol{\psi} + e_t, \tag{3}$$

where $\boldsymbol{\phi} = \boldsymbol{\beta} + \boldsymbol{\gamma}$ and $e_t = \alpha_t + \sum_i n_{i,t-1}\epsilon_{it}$. See, for example, Boldin & Wright (2015) and Kim et al. (2025) in the context of U.S. national outcomes and Bilal & Känzig (2024) in the context of global GDP growth. The vector $\boldsymbol{\phi}$ will capture the combined granular and global weather effects under the identification assumption that aggregated weather $\mathbf{w}_t'$ is orthogonal to e_t, which captures all unobserved time series shocks affecting $\Delta \ell_t$ (i.e., α_t). That is, e_t must be modeled as "random effects." While such an identification assumption would be unrealistic in many settings, it is arguably more reasonable in the case of weather shocks (especially if controls for other observed macroeconomic shocks, $\mathbf{x}_t'$, are included).

Yet, there are two key drawbacks to this approach. First, while it estimates the combined effect, $\mathbf{w}_t'(\boldsymbol{\beta} + \boldsymbol{\gamma})$, it does not separately estimate the granular and global effects, which are often of interest to researchers and policymakers. Second, there may be a large number of potentially relevant weather regressors relative to the number of observations, leading to low statistical power and overfitting concerns.

The second approach seeks to overcome these limitations by estimating the two-way fixed effects (TWFE) panel model formed by dropping $\mathbf{w}_t'\boldsymbol{\gamma}$ and $\mathbf{x}_t'\boldsymbol{\psi}$ from equation (2). See, for example, Deschênes & Greenstone (2007), Dell et al. (2012), Wilson (2019), Colacito et al. (2019), Roth Tran & Wilson (2021), and Nath et al. (2024). The appeal of the TWFE approach is two-fold. First, it does not require the unobserved time effects to be random; they can instead be modeled as fixed effects and can be correlated with $\mathbf{w}_{it}'\boldsymbol{\beta}$. Second, this approach leverages the potentially much larger number of observations available in panel data (NT) than is available in time series data (T), affording much greater precision in estimating $\boldsymbol{\beta}$.

Yet, dropping $\mathbf{w}_t'\boldsymbol{\gamma}$ introduces two concerns. First, aggregating $\mathbf{w}_{it}'\boldsymbol{\beta}$ to the national level will not capture the total effects of weather because it omits $\mathbf{w}_t'\boldsymbol{\gamma}$. This is an example of the so-called "missing intercept" problem that hampers the ability to infer aggregate effects from aggregating estimated local effects and motivates many of the time series studies (e.g., Kim et al. (2025) and Bilal & Känzig (2024)). Second, if one wants to project employment growth for time periods in which weather data is available but employment growth data is not (yet), this cannot be done without having to assume the values of the time fixed effects for those periods.

Conceptually, equation (2) can be estimated via three alternative estimators, that differ in the identification assumptions required. The first estimator is a two-way effects model with unit fixed effects and time *random* effects – that is, a model that assumes α_t is random. This estimator requires all unobserved aggregate time effects to be orthogonal to both $\mathbf{w}_{it}'$ and $\mathbf{w}_t'$, which is violated if there are any unobserved weather variables. The second estimator is the Mundlak (1978) Correlated Random Effects (CRE) model, which assumes *all* time effects are absorbed by means of the unit-and time-varying regressors (here, $\mathbf{w}'_{it}$). This assumption is almost certainly violated in our context where local and national employment growth are impacted by many time-varying shocks beyond weather (e.g., labor strikes, wars, policy shocks, productivity shocks, etc.).

The third estimator, which we employ, is the two-way Hausman-Taylor estimator. The original Hausman-Taylor (Hausman & Taylor (1981)) estimator was developed to estimate the effects of time-invariant unit characteristics while also allowing for unit fixed effects. This estimator has since been extended to the TWFE context (see Wyhowski (1994) and Baltagi (2023)). As discussed in Hausman & Taylor (1981) (see their Appendix B) and in more detail in Hansen (2022), the Hausman-Taylor estimator can be implement using either an IV approach or via a two-step approach, where the first step estimates the marginal effects of the time-and-unit-varying regressors (our $\mathbf{w}'_{it}$) and the unit fixed effects. The second step regresses the estimated unit fixed effects on the time-invariant regressors.

This same approach can be applied in the time dimension. Specifically, in the first step, one estimates the standard two-way fixed effects model (equation 2 omitting $\mathbf{w}'_t\boldsymbol{\gamma}$ and $\mathbf{x}'_t\boldsymbol{\psi}$):

$$\Delta\ell_{it} = \alpha_i + \alpha_t + \mathbf{w}'_{it}\boldsymbol{\beta} + \epsilon_{it}, \tag{4}$$

retaining $\hat{\boldsymbol{\beta}}$ and $\hat{\alpha}_t$.

In the second step, one regresses the time fixed effects, $\hat{\alpha}_t$, on the aggregated weather variables, in addition to the control vector $\mathbf{x}_t$, in order to estimate $\boldsymbol{\gamma}$:

$$\hat{\alpha}_t = \delta + \mathbf{w}'_t\boldsymbol{\gamma} + \mathbf{x}'_t\boldsymbol{\psi} + \varepsilon_t. \tag{5}$$

Using the two-step approach rather than the IV approach has a key advantage in our application. Because we have a large number of aggregate weather variables (unit-invariant regressors) relative to T, overfitting becomes a serious concern. By estimating the coefficients of the aggregate weather variables in a separate step, we can apply dimension reduction and machine learning techniques designed to mitigate overfitting.

3.2 Dimension Reduction and Machine Learning

The dimension of $\mathbf{w}'_t$ could be quite large. Indeed, in some applications, the number of aggregate regressors, K, could even exceed the number of time series observations, T. In our application, we have 160 aggregate weather variables – 40 contemporaneous variables plus 3 lags of each – and T of roughly 500 months between 1981 and 2024.[12] (We also include dummies for recession and pandemic lockdown (March–December 2020) months in $\mathbf{x}'_t$, further reducing degrees of freedom.) This high dimensionality concern is exacerbated if one is interested, as we are, in using subsamples to evaluate

[12]In some specifications, we include a much larger set of weather variables in $\mathbf{w}'_{it}$ because, as discussed in Section 5, we add interactions between some of these 40 weather variables and their climatic region. To facilitate dimension reduction, we do not include aggregates of those interacted variables in $\mathbf{w}'_t$.

how weather effects may have changed over time or in interacting the weather variables with various characteristics, such as allowing for heterogeneity in the effects of favorable and unfavorable weather shocks. Having a large K relative to T leads to both imprecision (wide confidence intervals) and overfitting concerns. The latter is particularly relevant in our setting, where a key objective is estimating the global weather effects. Overfitting is the problem that estimating the coefficient vector that maximizes in-sample fit tends to yield poor out-of-sample fit when K is large relative to T. In our context, this means that spurious in-sample correlations between aggregate employment growth and aggregate weather events would be misidentified as global weather effects.

We turn to methods from the literatures on time series forecasting and machine learning to address these concerns. In particular, we employ the scaled-PCA dimension reduction approach discussed in Section 2 and the Elastic Net (EN) machine learning operator. We use the scaled-PCA approach to reduce the dimension of our set of aggregate weather variables down to four interpretable factors, plus their lags. Specifically, for each of the following categories – temperature, precipitation, their interactions, and extreme events – we use the first principal component from the scaled versions of the variables within that category (see categorizations in Section 4). These four factors, plus their lags, become the set of aggregate weather regressors used in the second step described in the previous subsection.

While this initial dimension reduction should help mitigate overfitting, it may not entirely eliminate the concern. Recent advances in time series forecasting have turned to machine learning techniques, either in addition to or instead of factor-augmentation. For instance, Dunn et al. (2025) use LASSO and Random Forest machine learning models to predict county employment growth using a large set of predictors coming from payroll processing data. Akyapı et al. (2025) use LASSO to estimate the national GDP and fiscal effects of national climate shocks using cross-country panel data. Bianchi et al. (2022) combine scaled-PCA with the Elastic Net (EN) in their exercise of estimating "machine-efficient" macroeconomic forecasts. EN is a regularized regression technique that nests LASSO regression, which applies an L1-norm penalty to potentially reduce the number of variables in the model, and Ridge regression, which applies an L2-norm penalty to shrink some or all coefficients toward zero (Zou & Hastie (2005), Hastie et al. (2009)).

We consider three variants of the above techniques in our application. The first uses EN with all 40 aggregate weather variables, plus their lags, as potential predictors. The second uses the OLS estimator with the four scaled-PCA factors, plus their lags, as regressors. The third combines the two techniques, using the EN estimator with the four scaled-PCA factors, plus their lags as potential predictors. We treat $\mathbf{x}'_t$ the same in all three variants by first residualizing the dependent variable, $\hat{\alpha}_t$, with respect $\mathbf{x}'_t$.

EN estimation requires selecting two hyper-parameters, the penalty parameter and the mixing parameter governing the balance between LASSO and Ridge. Following standard practice in the literature, we use K-fold cross-validation with $K = 5$ and folds clustered by year (12-month) blocks of observations to select these hyper-parameters. Specifically, we set up a grid search across 100 candidate values for the L1 (LASSO) penalty parameter and 4 values for the mixing parameter, including the values corresponding to pure ridge and pure LASSO. For each pair of hyper-parameters, the EN operator randomly partitions the full sample into 5 equal-sized folds (subsamples). One fold is set aside as the hold-out sample while the other 4 folds are used to estimate the model (i.e., equation (5)). Out-of-sample prediction errors are then generated for observations in the hold-out sample and the mean squared error is calculated. The process is repeated, where each of the folds is used once as the hold-out sample while the other 4 are used as the estimation/training sample. The selected hyper-parameters are those that yield the lowest MSE across all folds.

3.3 Model Evaluation and Comparison

It is difficult to know *a priori* what combination of variable measurements, dimension reduction technique, and machine learning technique is "best." To evaluate and compare the performance of alternative combinations ("models"), one must first select a performance criteria. In our application, because our primary objective is to predict the effects of weather on national payroll employment growth, we use the R^2 from regressing national payroll employment growth on the combined effects as our performance metric. Given the overfitting concerns, it is standard in the ML literature to judge performance based on one-step-ahead or multi-step-ahead *out-of-sample* fit. See, for example, Dunn et al. (2025) which evaluates performance using one-step-ahead mean absolute errors.

We follow this general approach in our application using expanding-window rolling samples. Specifically, for each expanding rolling sample formed by the start-month of January 1980 and an end-month that varies from April 2010 to April 2024, we use our two-step approach to estimate granular and global weather effects.[13] For each end-month, E, we generate the 8-month ahead predicted value using the actual weather data up to $E + 8$. We refer to this predicted value as a nowcast because it mimics the weather effect estimates that an analyst could produce in real-time given that county weather data is available in real-time but the QCEW county employment data becomes available only with a 6 to 8 month lag. Hence, we evaluate models' performance based on how well they could "nowcast" national employment growth, meaning predicting current national employment growth using current weather data and a model estimated with county employment and weather data covering all months up to 8 months ago.

4 Data and Stylized Facts

4.1 Data on Employment

We use data on employment by county, industry, and month from the Bureau of Labor Statistics (BLS) Census of Employment and Wages (CEW). These data represent counts of employees on

[13] Note that the elastic net hyper-parameters are allowed to vary across the rolling samples. They are estimated for each sample using the K-fold cross-validation procedure described above.

payroll based on state Unemployment Insurance administrative records. They are not seasonally adjusted. Employment covers "all full- and part-time workers who worked during or received pay (subject to Unemployment Insurance wages) for the pay period which includes the 12th day of the month." Note that this is the same definition of employment used for the BLS Current Employment Statistics (CES) payroll survey which underlies the monthly national employment report (i.e., the "Employment Situation" report). We use data for total nonfarm private industry from January 1980 onward.[14]

4.2 Data on Weather and Natural Disasters

We pull daily county-level data on weather and natural disasters from several sources. See Appendix A for details on variable definition and sources. We first construct weekly variables from these daily data. Distinguishing between the weeks of the months is potentially important given the timing aspects of the employment data. Specifically, as noted above, both the CEW county employment data and the national CES payroll employment report are based on the number of workers "who worked during or received pay...for the pay period which includes the 12th day of the month." Pay periods can be weekly, biweekly or monthly. For weekly pay periods, this timing suggests that weather during the second week of the month should matter more than during other weeks of the month. For biweekly, pay periods, the first two weeks should matter more. And for monthly pay periods, all weeks may matter similarly.[15]

We generate 40 variables, which can be grouped into four categories:

1. (T) Temperature: mean cooling degree days (CDD), mean heating degree days (HDD), number of days with Heat Index (HI) above 80 but less than equal to 90, number of days with HI above 90, number of days with minimum temperature below 32, number of days with Wind Chill below 20. For CDD and HDD, we also include their interactions with season indicators.[16]

2. (P) Precipitation: a cubic in mean daily precipitation, a cubic in mean daily snowfall, and the Palmer Drought Severity Index (PDSI, "drought"). For mean precipitation, we also include its interactions with season indicators.

3. (I) Interactions: CDD and HDD each interacted with a cubic in precipitation, PDSI interacted with mean precipitation, PDSI interacted with CDD, and PDSI interacted with HDD.

[14]We exclude agriculture, ranching, fishing, and hunting employment to match the industry coverage of the CES payroll survey. These subsectors represent a very small fraction of total CEW employment.

[15]The likely importance of accounting for the weekly distribution of weather within months is illustrated in Appendix Figure B1. This heatmap visualizes the signs and magnitudes of the coefficients from simple bivariate TWFE regressions of county employment on each weather variable, separately for each week of the month. Stars indicate the level of statistical significance. As expected given the timing structure of the CEW, week 2 weather has the largest marginal effects, followed by week 1 and week 3 weather with similar magnitudes. Week 4 weather has the weakest relationship with CEW measured employment growth.

[16]Seasons are defined as follows: Winter = December–February, Spring = March–May, Summer = June–August, and Fall = September–November.

4. (E) Extreme events: FEMA disasters by type (6 major types) and a cubic in wind speed.

These are the raw weekly variables used as the inputs into our model estimations. To aggregate to the monthly frequency – the frequency of the employment data – we use either unweighted or weighted averages across the weeks (and compare the resulting models' performance). For constructing weighted averages, we weight using the coefficients from an initial TWFE regression of county monthly employment growth on all weekly weather variables. This regression includes the same fixed effects described below to account for seasonality and trends.

4.3 Seasonal Adjustment and Detrending

Because our objective is to model and predict current *seasonally-adjusted* employment growth (both locally and nationally), and because weather has strong seasonal patterns, we must first seasonally adjust the weather data. We also must seasonally adjust county-level employment growth because the CEW data is available only non-seasonally adjusted. In addition, employment growth and some weather variables may be non-stationary, at least for some counties. Hence, prior to estimating the effects of weather on employment growth, we also want to remove any trends in the series.

To remove both seasonality and trends, we residualize employment growth and each weather variable with respect to county-specific calendar month fixed effects and those fixed effects interacted with a quartic time trend.[17] We also include in these regressions dummy variables for each sample month from March 2020 through December 2020 to absorb the enormous nationwide swings in employment growth during the Covid-19 lockdown period so as not to misattribute these swings to calendar-month effects (i.e., seasonal factors).

4.4 Stylized Facts

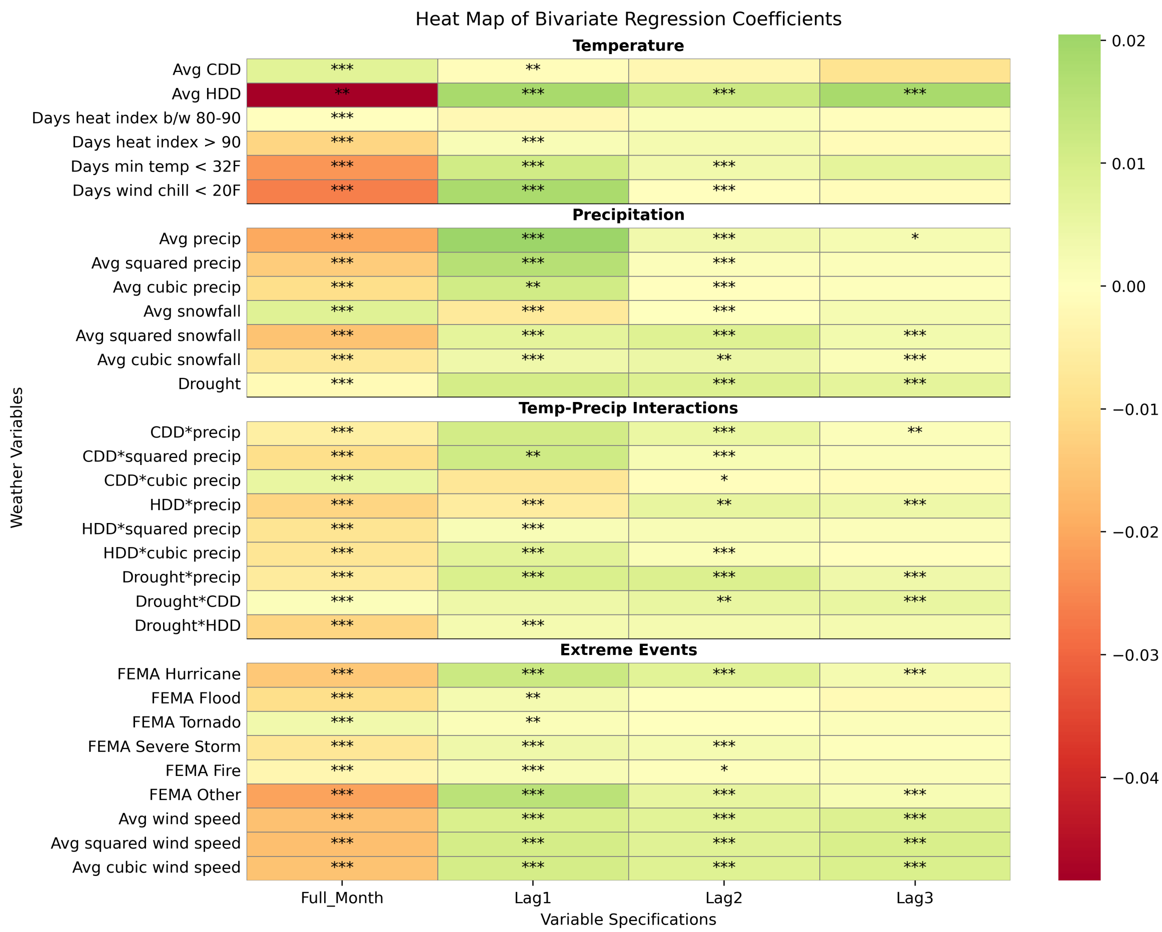
Before proceeding with applying our two-step approach to estimating granular and global weather effects, we start with a brief descriptive analysis. Figure 1 provides a heat map where each cell represents the estimated coefficient from a bivariate TWFE regression of county employment growth on the (week-weighted) monthly weather variable indicated in the row heading. The weather variables have all been standardized to be in standard deviation units. The first column uses the contemporaneous value of the weather variable, while the 2nd, 3rd, and 4th columns use the value lagged 1, 2, and 3 months, respectively. Color intensities indicate how positive (green) or negative (red) is the estimated coefficient; stars indicate statistical significance.

With a few exceptions, the monthly weather variables have the contemporaneous correlations with employment growth that one would expect. One exception is that snowfall is positively correlated with employment growth, though snowfall squared and cubed have negative correlations.

[17]Specifically, the fixed effects consist of county-by-calendar month indicators by themselves and interacted with time (sample month), time squared, time cubed, and time to the 4th power.

Another exception is that tornado disasters have a small positive correlation. Figure 1 also reveals a clear dynamic pattern: correlations with lagged weather variables generally have the opposite sign of the contemporaneous correlations. This hints at the possibility that contemporaneous weather effects may be unwound over the subsequent few months.

Figure 1 : Correlations between Employment Growth and Weather Variables



Notes: Each cell corresponds to a bivariate regression of county employment growth on the weather variable indicated in the row heading. The regression also accounts for time (sample-month) and county fixed effects. As discussed in the text, employment growth and all weather variables are seasonally-adjusted and detrended. Cell color intensities indicate how positive (green) or negative (red) is the estimated slope coefficient. Stars indicate statistical significance: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Of course, these bivariate correlations do not necessarily represent the direct effect of each weather variable because many of the weather variables are correlated with each other. Accounting for these correlations, Figure 2 presents a heat map in which the cells in the first four columns represent coefficients from a single "full" TWFE regression containing all 40 variables shown in Figure 1 plus three lags of each. This regression corresponds to the TWFE panel estimation (step 1) using the first ("Model B") of the candidate predictive models evaluated in the next section. The rightmost column shows the implied cumulative effect of each variable (i.e., the sum of the contemporaneous and lagged effects). For precipitation, snowfall, and wind speed, we show the implied effect of the cubic polynomial (as opposed to the separate coefficients on the linear, squared, and cubed terms).

Figure 2 documents a number of interesting results. First, fewer weather variables have statistically significant effects compared with their bivariate correlations in Figure 1, which indicates multicollinearity among the variables. Second, the general pattern of lagged effects offsetting contemporaneous effects continues to hold, though there are some exceptions. Third, variables in all four categories are found to have statistically significant effects on both contemporaneous and cumulative employment growth. For temperature, the results point to non-linear contemporaneous effects. Specifically, increases in temperature above 65° F, which is the base value for the definition of cooling degree days (CDD), have generally positive effects but temperature above 80° F, and especially above 90° F, have negative effects. In addition, decreases below 60° F, which represent increases in heating degree days (CDDs), have negative marginal effects. The negative effects of cold become larger when minimum daily temperatures fall below freezing and further still when the wind chill factor falls below 20°F. A more complete characterization of the non-linear relationship between temperature and employment growth is provided in Section 6. Lastly, we note that a few weather variables, which recall are deviations from county-specific trends, have lasting cumulative effects.

Figure 2 : Estimated Effects of Weather on Employment Growth

Notes: Each cell of the first four columns represent coefficients from a single multivariate regression containing all 40 variables listed in Section 4 plus three lags of each. The rightmost column shows the implied cumulative effect of each variable (i.e., the sum of the contemporaneous and lagged effects). For precipitation, snowfall, and wind speed, we show the implied effect of the cubic polynomial (as opposed to the separate coefficients on the linear, squared, and cubed terms). The regression also accounts for time (sample-month) and county fixed effects. As discussed in the text, employment growth and all weather variables are seasonally-adjusted and detrended. Cell color intensities indicate how positive (green) or negative (red) is the estimated slope coefficient. Stars indicate statistical significance: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

5 Results: Model Evaluation and Selection

In this section, we compare the performance of a number of alternative "models" for estimating the combined granular and global effects of weather on U.S. national employment growth. These models vary along two dimensions. The first involves the set of local weather variables, $\mathbf{w}'_{it}$, included in the first step regression of the two-step approach. The second dimension is the *method* used to mitigate overfitting in step 2. As discussed in Section 3.2, we alternatively employ Elastic Net (EN), Scaled-PCA, and a combination of the two.

As a benchmark, we start by estimating a very simple model that includes only average daily precipitation and average daily maximum temperature, plus their three lags, as the weather measures in the first and second step regressions. Given the use of so few variables, overfitting should not be a major concern, and so we simply use OLS (as opposed to Elastic Net or Scaled-PCA) in the second step regression. This model, which we refer to as *Model A*, is similar to models used in some past studies that rely only on time series data (e.g., Boldin & Wright (2015)).

We then estimate a model that includes the 40 contemporaneous variables in the T, P, I and E categories described in Section 4. We also include three lags of each variable, yielding a total of 160 variables. We refer to this baseline model as *Model B*. For *Model B*, we measure the monthly variables using weighted averages of the variables' weekly values, as discussed in Section 4.2. We also estimate an alternative version of *Model B*, which we will refer to as *Model B-UW*, that weights weeks equally.

Next, we estimate two extensions of *Model B*. These extensions allow for local heterogeneity in the marginal effects of weather, as estimated in the step 1 regression. The step 2 regression specification for these extensions includes the same 160 variables as in *Model B*. The first extension, which we refer to as *Model B+Q*, allows the marginal effects of weather, excluding seasonal interactions and extreme events, to vary by the typical climate of the local area. Recall that a weather shock is defined as a deviation from a cubic time trend in the expected value of that weather variable for that county in that calendar month. It is possible, for example, that a positive June temperature shock in Anchorage, Alaska has a positive effect on employment growth while a positive June temperature shock in Phoenix, Arizona has a negative effect. We allow for such heterogeneity by interacting each temperature, precipitation, and interaction variable (excluding seasonal interactions) with indicators for each quartile (Q) of that variable's 1980-2024 mean (using the raw, non-seasonally adjusted data) across all counties. In other words, for each temperature, precipitation, and interaction variable, counties are sorted into four "climatic regions" based on the cross-county distribution of that variable's local climate normal (as measured by its historical average for each county). This extension results in a total of 424 variables. Our second extension, *Model B+SQ*, allows the seasonal (S) interaction variables to also be interacted with their "climatic region" quartile (Q) indicators, yielding a total of 532 variables.

Note that while these rich first-step regression specifications each contain a large number of regressors, the number is small compared to the 800,000 to 1.5 million county-month observations (depending on sample end-month). Thus, overfitting is unlikely to be a major concern for estimating the granular weather effects in our application.[18] Nonetheless, we also estimate a version of our baseline using Elastic Net.[19] However, we find this model performs substantially worse in terms of

[18] In applications involving smaller numbers of geographic units, lower frequency time series, or both, one could apply machine learning techniques in this first step as well. For example, Akyapı et al. (2025) employ LASSO in their estimation of "local" climate effects using cross-country annual panel data.

[19] We estimate the Elastic Net (EN) hyper-parameters using cross-sectional K-fold cross-validation. Specifically, we first cluster observations by county so that all observations for a given county are always kept when selecting sample subsets (folds). We then set up a grid search across 100 candidate values for the L1 (LASSO) penalty parameter and 4 values for the mixing parameters, including the values corresponding to pure ridge and pure LASSO. For each pair of hyper-parameters, the EN estimator randomly partitions the full sample into 10 equal-sized folds. Since

Table 1 : Model Evaluation

R^2's Based on 8-Step-Ahead Out-of-Sample Predicted Weather Effects

Dependent Variable: National Private Sector Employment Growth (CES)

	(1) Model A†	(2) Model B-UW	(3) Model B	(4) Model B+Q	(5) Model B+SQ	(6) Model B+SQ(noPDSI)
Elastic Net (EN)	.024	.043	.041	.044	.043	248
Scaled PCA	.024	.026	.053	.056	.056	248
Scaled PCA + EN	.024	.043	.074	.079	.084	248

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: † For Model A, because it uses only 2 variables (average daily precipitation and average daily maximum temperature), the step 2 regression is a standard OLS regression and does not use Elastic Net or Scaled-PCA. Column (1) reports the R^2 from that regression.

predictive accuracy compared with the models using OLS in the first step.

We evaluate each of the alternative model's accuracy in terms of predicting contemporaneous national employment growth, as measured by the official seasonally-adjusted data on private-sector employment growth from the BLS Current Employment Statistics (CES) series.

To compare model performance across various alternatives, we compute the R^2 from regressing national predicted employment growth on rolling out-of-sample nowcasts of the granular and global weather effects. The results are shown in Table 1.[20] Each cell is the R^2 from this regression based on alternative sets of nowcast estimates. Nowcasts are derived from alternative *specifications* – those discussed above and labeled in the column headings – and alternative dimension reduction and machine learning *methods* (labeled in the row headings).

We first see that a simple, parsimonious model using only average daily precipitation and average daily maximum temperature, and their lags, explains 2.4% of the variation monthly employment growth outside of recessions. Incorporating the full set of weather variables, as in Model *Model B-UW*, increases this explanatory power to between 2.6 and 4.3%, with the highest R^2 coming from using either just EN or EN in addition to scaled-PCA.

Next, comparing columns 2 and 3, we see that weighting different weeks of the month differently in the construction of the monthly weather variables results in notable improvement in explanatory power. Comparing across columns 3 through 5, we find that allowing for heterogeneity in local

there are around 3,100 counties, each fold consists of roughly 310 counties. One fold is set aside as the hold-out sample while the other 9 folds are used to estimate the model (i.e., the coefficients on each weather predictor). Out-of-sample forecast errors are then generated for the hold-out sample and the mean squared error is calculated. The process is repeated, where each of the 10 folds is used once as the hold-out sample while the other 9 are used as the estimation/training sample. The selected hyper-parameters are those that yield the lowest MSE across all folds.

[20] As noted earlier, the step 2 regressions exclude recession and pandemic lockdown (March–December 2020) months. Hence, the same months are excluded in the regressions underlying Table 1.

weather effects based on climatic region leads to modest improvements to model performance. Comparing across the rows, we see clear performance differences across the dimension reduction and machine learning techniques. In particular, the R^2's are generally higher using scaled-PCA compared to Elastic Net with the full set of weather variables, and the combination of the two techniques yields the highest R^2's. Using the EN and scaled-PCA combination, the model with climatic-region interactions of all variables including the seasonal interactions – that is, *Model B+SQ* – yields the highest R^2. Specifically, the nowcast weather effects from this model explain 8.4% of the (non-recession) variation in U.S. private sector employment growth over January 2011 to December 2024.

Based on these results, we use this model – i.e., *Model B-SQ* using scaled-PCA and Elastic Net – as the preferred model for the remainder of the paper. We use this model to estimate granular and global weather effects, using the two-step approach laid out in Section 3, for the full sample period of January 1981 to April 2024 (latest available month of county-level employment data). In the following two sections, we first "unpack" the mechanisms underlying these weather effects and then analyze their static and dynamic impacts on the aggregate macroeconomy.

6 Results: Unpacking Weather Effects

6.1 Understanding Granular Weather Effects

Because of the large number of weather variables in our analysis, standard regression outputs, such as tables of coefficient estimates, are of limited usefulness. Here, we present the first-step, TWFE results in two ways. First, we perform a Relative Weights Analysis (RWA) following Tonidandel & LeBreton (2011). RWA is a method for decomposing the total variance explained by a model into the contributions from each predictor. Because RWA contributions are additive, we can calculate what share each category of weather contributes to explaining the variation in predicted employment growth. Second, we use non-parametric techniques to plot the non-linear relationships between selected weather variables and predicted local employment growth.

We present results here based on the full-sample estimation of *Model B*. As shown in the previous section, this model yields the highest predictive accuracy in terms of step-ahead out-of-sample fit.

6.1.1 Contributions of Weather Variables to Predicted County Employment Growth

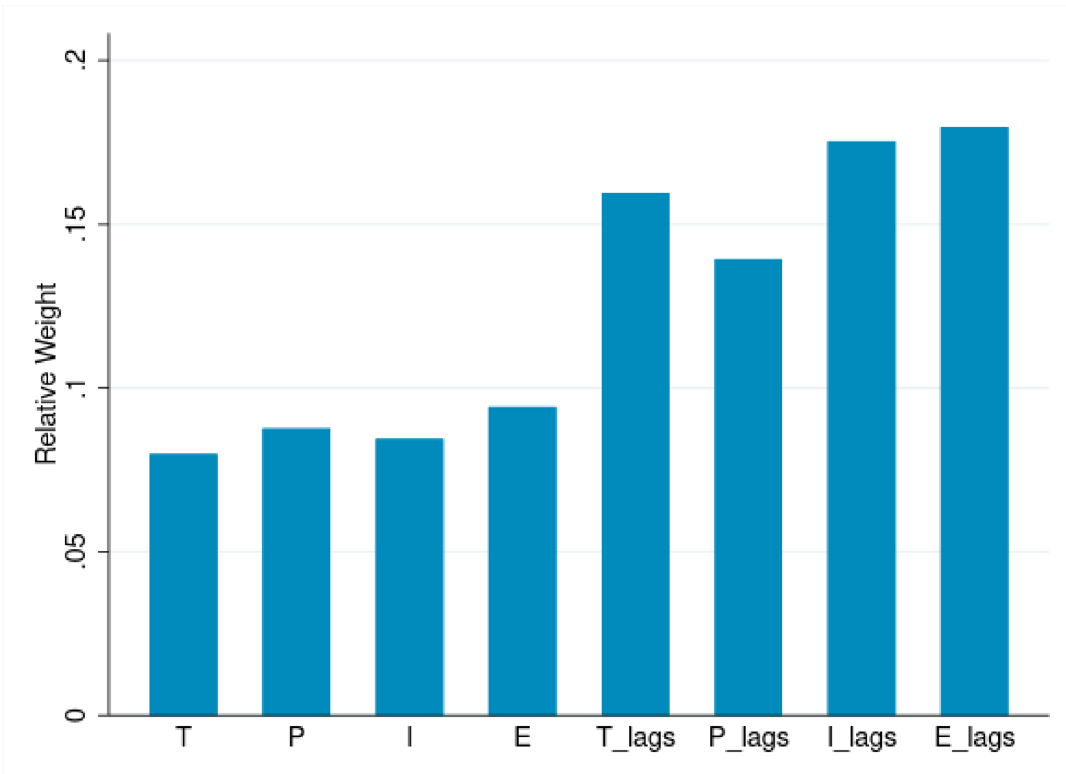
Here we report the contributions of particular groupings of the weather variables to the explained variation of the preferred model. We follow the RWA approach of Tonidandel & LeBreton (2011).[21] The relative weight of a predictor variable measures its contribution to the total variation in a model's predicted values. The relative weights are calculated using a three step process. First, the

[21] An alternative approach is Shapley decomposition. Shapley decomposition is very computationally intensive for large data sets and hence is infeasible with our data.

predictors are orthogonalized using PCA. Second, the target variable (here, county employment growth) is regressed on the orthogonalized predictors to obtain standardized coefficients and the total explained variance. Third, the relative weight for each predictor is calculated as the product of the squared standardized coefficient and the squared orthogonalized predictor, divided by the total explained variance.

We report the sum of the contributions across the variables within each of the four categories: temperature (T), precipitation (P), temperature-precipitation interactions (I), and extreme events (E). We do this separately for each category's contemporaneous values and its lagged values (that is, summing the contributions of each lag for a given weather variable across the lags and then summing those sums across all variables in the category).

Figure 3 : Contributions of Weather Groupings to Model's Explanatory Power



Notes: Each bar in this graph shows the contributions (relative weights) of the indicated category of weather variables in explaining the explained variance of the preferred model (i.e., the variance of predicted employment growth). T, P, I, and E refer to categories of variables related to temperature, precipitation, temperature-precipitation interactions, and extreme events, respectively. See Section 4 for the list of variables contained within each category. Groupings with "_lags" in their name consist of all lags of the variables in the indicated category.

The results, shown in Figure 3, reveal two important findings. First, we find that the extreme events category contributes the most to the model's explanatory power. That said, all four categories contribute substantially to the overall explanatory power. Second, we see that the lags collectively explain more of the variance in predicted employment growth than the contemporaneous values. For a given category, the lags explain roughly 1.5 to 2 times as much variation in predicted employment growth as the contemporaneous values. In other words, knowing the past few months of weather turns out to be more valuable for predicting current employment growth than knowing the current month's weather. This suggests that a model similar to those estimated above could be useful not only for predicting contemporaneous employment growth – i.e., *now*casting – but also for *fore*casting employment growth one or more months out of sample. Thus, in addition to the main results based on *Model B-SQ*, in Section 7 we also report results from a model equivalent to *Model B-SQ* but where only lagged values of weather are used in the step 1 and step 2 regressions. Prior months' weather may influence current employment growth through a variety of channels including intertemporal substitution in household consumption (e.g., delaying retail shopping and leisure activity when the weather is unfavorable) and in construction activity.

6.1.2 Relationships Between Weather and Predicted County Employment Growth

To understand *how* weather affects local employment growth according to any given predictive model, it is useful to visualize the (potentially non-linear) relationships between the model's predicted employment growth and key weather variables using non-parametric plots. Specifically, we use bin scatter plots over 100 quantile bins to visualize how predicted local employment growth varies with any given weather variable. These plots characterize the empirical relationship between the weather variable and predicted employment growth according to the model. The plots can be generated even for variables that were not used in estimating the model. For example, we can plot the relationship between predicted employment growth from our preferred model against average maximum daily temperature even though the latter was technically not used to estimate the model. There is still an empirical relationship between the two variables because average maximum daily temperature is correlated with heating degree days, cooling degree days, and other variables that are included in the model.

An alternative approach known as Partial Dependency Plots (PDPs) is suggested by Friedman (2001) and Cook et al. (2024). PDPs show the relationship between the predicted values and a model-included weather variable *holding fixed* (at sample average values) all other input variables. PDPs are useful for estimating the marginal effect of a variable x independent of the effects of other variables correlated with x. However, they can be difficult to interpret in models containing many correlated variables. For example, suppose we are interested in the relationship between hurricanes (number of days in the months with a FEMA-declared hurricane) and predicted employment growth. As hurricanes are highly correlated with wind speed, temperature, and precipitation, a PDP may show that FEMA hurricane days have little or no effect on predicted employment growth because the overall effect of hurricanes works largely through the effects of wind speed, temperature, and precipitation. Instead, a non-parametric plot of predicted employment against hurricane days reveals the empirical relationship between the two, regardless of the channels within the estimated model that mediate how hurricanes affect predicted employment growth. The latter typically would be of more relevance to analysts and policymakers wanting to predict what will happen to employment growth if there is a hurricane.

Figure 4 shows these non-parametric plots for six selected variables: average daily maximum temperature, average heating degree days (HDDs), average cooling degree days (CDDs), average daily precipitation, average daily snowfall, and the (weekly average in the month) of the number of days with a wildfire disaster. In each panel, we plot the bin scatter for the contemporaneous values and each of the three lags.

Starting with panel (a), we find a striking bimodal pattern: predicted employment growth increases with contemporaneous average daily temperature, but only up to around 62°F (17 ≈°C). Predicted employment growth falls with further temperature increases until around 80°F (27°C). Surprisingly, predicted employment growth is found to increase with temperatures above the mid-80s up to at least 100°F (38°C). These patterns are consistent with the patterns shown for contemporaneous values of CDDs and HDDs (panels (b) and (c)). Specifically, increases in CDDs, which is a measure of temperature increases above 65 degrees Fahrenheit, have slightly negative marginal effects at lower values but rise sharply above around 15. Increases in HDDs, which is a measure of temperature decreases from 60, have a slightly positive relationship with predicted employment growth at low values and then have an increasingly negative relationship for values above around 30.

Panels (d)-(f) illustrate how, for many weather variables, lagged effects offset contemporaneous effects. Specifically, we see that predicted employment growth falls near-linearly with contemporaneous precipitation, snowfall, and wildfire days, but growth increases with lagged values. In each case, the sum of the lagged effects is close to the contemporaneous effect, suggesting no lasting effects of these weather shocks on the level of employment after 4 months.

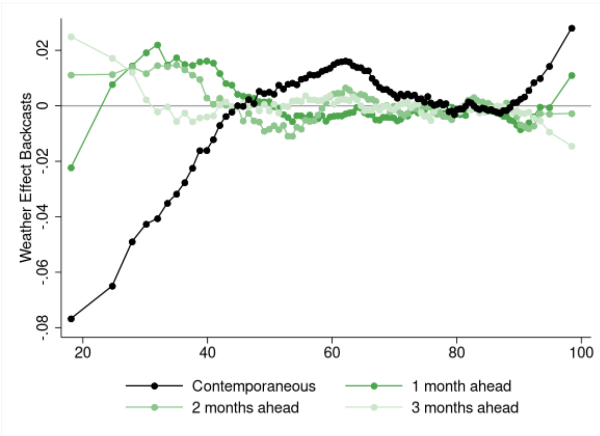
6.2 Understanding Global Weather Effects

Here we present the results of the second step of our two-step estimation approach. Recall that the second step entails regressing the time fixed effects ($\hat{\alpha}_t$), estimated in the first step, on aggregated, national weather variables ($\mathbf{w}_t'$). As discussed in Section 3, we use scaled-PCA to reduce the dimension of $\mathbf{w}_t'$ down to four factors and their lags, where the factors represent temperature, precipitation, temperature-precipitation interactions, and extreme events. We then use Elastic Net (EN) penalized regression, which nests LASSO and Ridge regressions. LASSO includes a L1-norm penalty, which can result in setting some coefficients to zero. Ridge regressions includes an L2-norm penalty, which generally results in the shrinkage of coefficients toward zero. The predicted values from this EN regression are used in Section 7 to measure the "global" effects of weather on U.S. national employment growth.

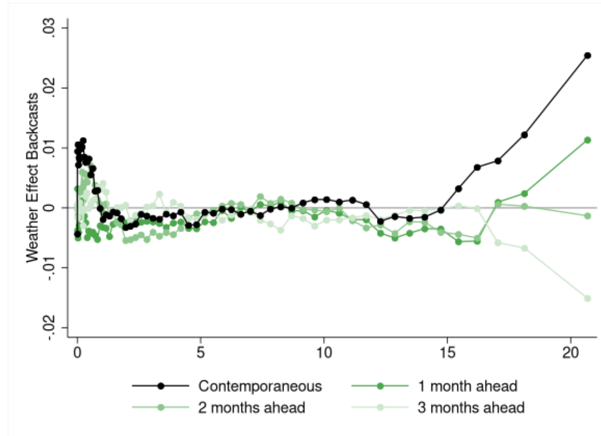
The estimated EN penalized coefficients are shown in Table 2. Also shown, at the bottom of the table, is the EN mixing hyper-parameter that balances LASSO and Ridge. This hyper-parameter is

Figure 4 : Non-linear Relationship Between Selected Variable and County Employment Growth

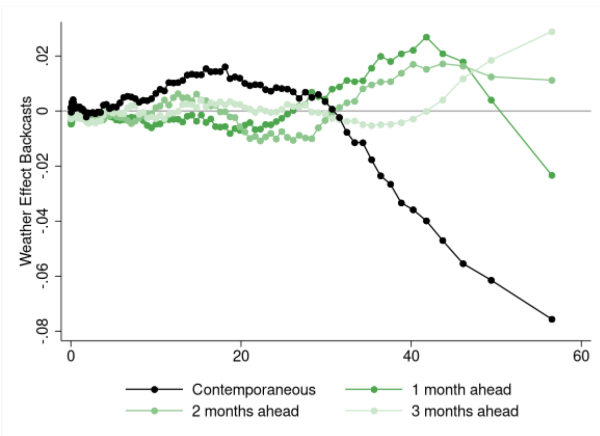
(a) Average Daily Maximum Temperature



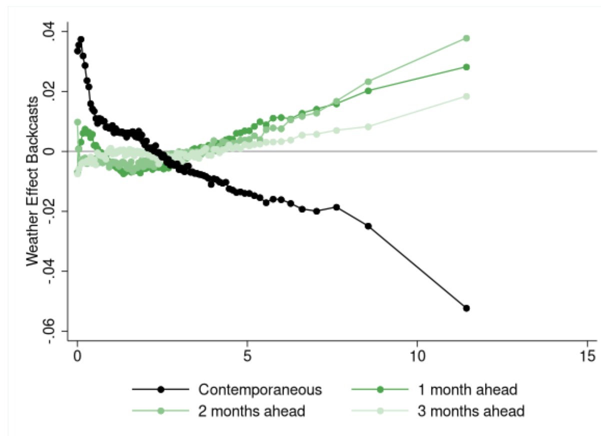
(b) Average CDDs



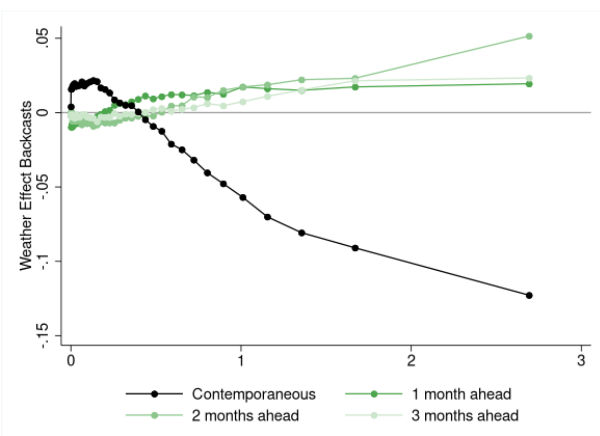
(c) Average HDDs



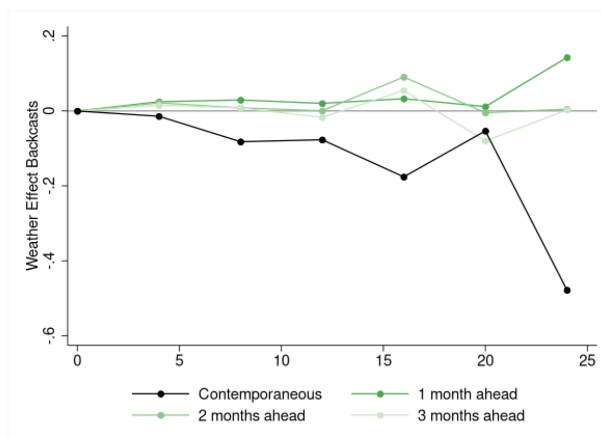
(d) Average Daily Precipitation



(e) Average Daily Snowfall



(f) Wildfire Days



Notes: Each panel displays a bin-scatter plot of predicted employment growth (y-axis) against the indicated weather variable (x-axis). Predicted employment growth is demeaned (relative to mean of predicted local employment growth over all county-month observations).

selected, as described in Section 3.2, via K-fold cross-validation.[22] We obtain a value of zero, which

[22]The EN mixing hyper-parameter is estimated to be zero in the full sample but is often non-zero in the rolling,

corresponds to putting full weight on the Ridge regression and zero weight on LASSO. As such, no variables are dropped from the regression. Because there is no general asymptotic formula for penalized coefficient standard errors, we also report the unpenalized coefficients and their standard errors obtained from a post-EN, OLS regression. In addition, we show the implied cumulative effects of each factor in the table.

The contemporaneous and lagged coefficients are generally small and statistically insignificant. The cumulative effects are near zero with the exception of the temperature-precipitation interactions, which have a positive and significant cumulative effect. Overall, we find the aggregate weather factors can explain 4.5% of the variation in the estimated time fixed effects. This explanatory power indicates that weather affects national employment growth not only due to aggregated local (granular) effects but also due to nationwide (global) weather effects. As discussed earlier, these nationwide effects could stem from local shocks having cross-geographical spillovers, national policy responses, or general equilibrium effects.

expanding-window samples used to evaluate model performance in Section 5.

Table 2 : Regression of Time Fixed Effects on Aggregate Weather Factors

	(1) Temperature	(2) Precipitation	(3) Interactions	(4) Extreme Events
Contemporaneous				
Penalized Coef.	.001	0	.001	.002
Unpenalized Coef.	.007	-.004	-.001	.008
Standard Error	(.005)	(.006)	(.007)	(.006)
1-Month Lag				
Penalized Coef.	-.001	.001	.002	0
Unpenalized Coef.	-.006	.005	.01	-.002
Standard Error	(.005)	(.006)	(.007)	(.006)
2-Month Lag				
Penalized Coef.	0	-.001	.002	0
Unpenalized Coef.	.002	-.009	.01	-.005
Standard Error	(.005)	(.006)	(.007)	(.006)
3-Month Lag				
Penalized Coef.	0	.002	.001	-.001
Unpenalized Coef.	-.002	.006	0	-.007
Standard Error	(.005)	(.006)	(.006)	(.006)
Cumulative Effect				
Penalized Coef.	0	.002	.006	0
Unpenalized Coef.	.001	-.003	.02**	-.006
Standard Error	(.009)	(.011)	(.01)	(.011)
EN Mixing Parameter	0			
R-Squared	.045			
Number of Obs.	457			

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: Table shows the results from a single regression of the time fixed effects estimated from the panel data (step 1) on the scaled-PCA factors representing aggregate weather. These factors are the first principal components of the scaled weather variables within each of the four categories shown in the row headings. The "Cumulative Effect" row shows the sum of the coefficients across the contemporaneous and three lags (and its implied standard error).

7 Results: Macroeconomic Effects of Weather

In this section, we quantify the role of weather in explaining U.S. macroeconomic fluctuations. While our estimated weather effects are targeted on explaining employment growth, we also examine their explanatory power for other macroeconomic time series. In the first subsection below, we use a standard static regression analysis to estimate how much variation, as measured by R^2, in employment growth and other macroeconomic time series can be explained by the combined granular and global effects of weather (which reflect weather in the current and past three months).[23] We then turn to local projections analysis in the second subsection to identify the dynamic responses of macroeconomic outcomes to shocks in the weather effects series.

[23]As noted earlier, the step 2 regressions include dummies for recession and pandemic lockdown (March–December 2020) months in $\mathbf{x}_t'$. Therefore, we exclude these months from the sample used for the regressions in this section.

7.1 Static Analysis

Table 3 shows the results of regressing national private-sector employment growth on alternative weather effect backcasts. Employment growth is measured using the official (current-vintage), seasonally-adjusted data from the BLS Current Employment Statistics (CES). This corresponds most closely to the county-level data we use in estimating the model, which comes from the CEW and also correspond to the private sector. Note that the CES data are benchmarked annually (each March) to the aggregate CEW data.[24] We find that weather explains roughly 6% of the monthly variation in national private-sector nonfarm employment growth from May 1981 through April 2024, with both the granular and global effects having statistically significant effects. Columns (2) and (3) show the results of including only the granular component and only the global component, respectively. Individually, the granular component can explain much more of the variation in private employment growth, with an R^2 of .044% compared to just 0.008% for the global component.

Table 3 : Predictability of Weather Backcasts for National Private-Sector Employment Growth

April 1981 – April 2024

	(1) Model B-SQ	(2) Model B-SQ	(3) Model B-SQ	(4) Model B-SQ Lags	(5) Model A	(6) Model A-Time Series
Granular Effects	.716***	.644***		1.040***	.495***	
	(.142)	(.141)		(.244)	(.147)	
Global Effects	.532 ***		.362*	.408 *	.154	.609***
	(.188)		(.19)	(.221)	(.178)	(.197)
R^2	.061	.044	.008	.052	.024	.021
N	457	457	457	457	457	457

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: Data for employment growth are from the BLS Current Employment Statistics series.

The results in 6.1.1 and Figure 3 suggested that more of the explanatory power of weather for employment growth actually comes from lagged, rather than contemporaneous, weather. Hence, in column (4) we report results of a modified version of *Model B-SQ* in which we omit the contemporaneous weather variables from both the step 1 and step 2 regressions. Consistent with the earlier findings, we find only a modest decline in explanatory power, with the R^2 falling only to 0.052 and both the granular and global components remaining statistically significant at at least the 10% level.[25]

[24]We do not uses the monthly aggregate CEW data in this exercise because it is not seasonally adjusted. The aggregate CEW data is also less useful for policy analysis because it is only available with a 6 to 8 month lag.

[25]In Tables B1, B4, and B6, we provide results from this *Model B-SQ Lags* for all of the outcomes examined below in Tables 4-6.

In column (5), we show the results from the simple model including only average daily temperature and average daily precipitation, *Model A*. As expected, the R^2 is much lower, less than half of that for *Model B-SQ*, and only the granular component is statistically significant. Column (6) shows the results of a simple time series model in which aggregated private employment growth is regressed on national (county employment weighted) average daily temperature and average daily precipitation. This is similar to the time series model used in Boldin & Wright (2015). The explanatory power is roughly one-third of that from *Model B-SQ*, indicating that exploiting the rich set of weather variables and allowing for heterogeneity across counties leads to significant improvement.

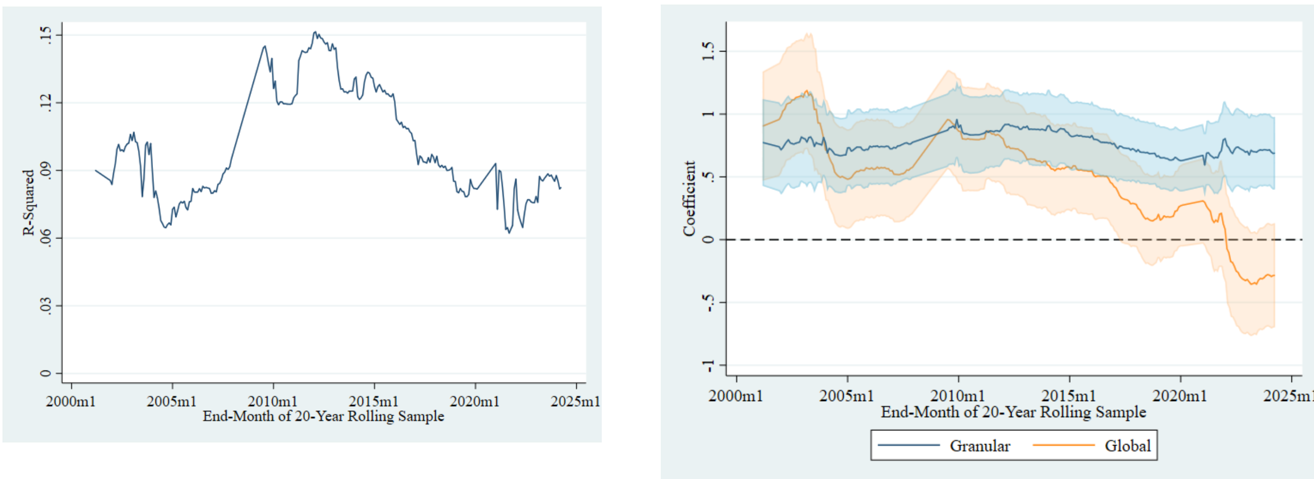
Before examining other labor market outcomes, we assess whether the explanatory power of the granular and global weather effects for employment growth have changed over time. To do this, we repeat the regression of private nonfarm employment growth on the granular and global weather effects for 20-year rolling samples with end-months ranging from July 2001 through April 2024. We report the resulting R^2's and slope coefficients in panels (a) and (b), respectively, of Figure 5. The R^2's vary over time, from a low of around 0.06 to a high of around 0.15, with no clear trend. The slope coefficient for the granular effects is quite stable, staying with a fairly tight range between 0.7 and 0.9. The slope coefficient for the global effects is more variable and exhibits a downward trend, from around 1 for the earliest samples to roughly zero, and statistically insignificant, by the latest sample. These results suggest that the global effects of weather on employment growth have fallen over time, but the overall explanatory power of weather – stemming from the combined granular and global effects – shows no clear trend. The declining role of global weather effects – that is, general equilibrium and nationwide spillover effects – could reflect technological improvements in supply chain management or structural changes making geographic regions more economically independent. For instance, Foschi et al. (2025) find that differences in industry compositions across U.S. states have declined over time.

Table 4 shows the results of regressing each of several different labor market outcomes on our measures of granular and global weather effects.[26] We also redisplay in the top row the results for private-sector employment growth from Table 3 to facilitate comparison. We see in the second row that the explanatory power of weather for *total*, including government, employment growth is somewhat lower than for private sector growth, presumably because government employment is less weather sensitive than private sector employment. The next seven rows provide results for employment growth by selected major sectors. We see that the granular and global weather effects are especially predictive of employment growth in the construction sector, jointly explaining approximately 23% of its non-recessionary variation since 1981. Note that this strong relationship is particularly striking given that these weather effects come from a model trained on predicting all private-sector employment growth, not the construction sector specifically. A model trained on construction employment growth could potentially explain much more of this variation. We also see

[26]For completeness, results using the weather effect nowcasts and backcasts for the January 2011 through April 2024 sample period are provided in Appendix Tables B2 and B3.

Figure 5 : Results from 20-Year Rolling-Sample Regressions

(a) R^2 **(b)** Estimated Slope Coefficients



Notes: Panel (a) shows the R^2's, and Panel (b) the estimated slope coefficients, from 20-year rolling-sample regressions of national private-sector nonfarm employment growth on the granular and global weather effect estimates. The shaded areas in Panel (b) correspond to 90% confidence intervals. The rolling samples have end-months ranging from July 2001 through April 2024.

notable impacts of the weather effects on employment growth in leisure & hospitality, retail trade, manufacturing, and transportation. We find essentially no impacts for the utilities and natural resources & mining sectors.

It is striking that for retail and leisure & hospitality employment, the impact of granular weather is much larger than the impact of global weather, while the opposite is true for employment in manufacturing and in transportation. Input-output linkages provide a natural explanation: favorable (unfavorable) weather in a local area has little impact on local manufacturing and transportation but significantly boosts (decreases) local retail and hospitality demand.[27] The increase (decrease) in local retail sales induces higher (lower) demand from the manufacturers throughout the country that produce those retail goods and the transportation businesses that deliver those goods. Local construction activity may also contribute to higher demand from manufacturers and transporters across the country.

Next, we see in Table 4 that the weather effects explain a small amount of the variation in the unemployment rate, with the global weather effects having a statistically significant negative impact. The granular weather effects have a statistically significant impact on the labor force participation rate, the hires rate, the separations rate, and the vacancy rate. They have no significant impact on the job finding rate. We also find strong, statistically significant associations for both the granular and global effects with the weather absences rate, which is the share of employed households that report, in the BLS household survey, being absent from work during the month due to weather.

[27]Prior research using cellphone mobility data has documented very strong positive links between retail shopping activity and favorable weather.

Table 4 : Predictability of Weather Backcasts for Labor Market Outcomes

Slope Coefficients and R^2 from Regressions on Weather Effects

	(1) Granular	(2) Global	(3) R^2	(4) N
Employment Growth - Private	.716***	.532***	.061	457
	(.142)	(.188)		
Employment Growth - Total	.624***	.382**	.055	457
	(.126)	(.167)		
Employment Growth - Constr.	4.952***	1.236**	.229	457
	(.427)	(.565)		
Employment Growth - Leis.&Hosp.	.737**	.297	.01	457
	(.341)	(.452)		
Employment Growth - Retail	.693***	-.1	.027	457
	(.205)	(.271)		
Employment Growth - Mfg.	.331	.954***	.027	457
	(.212)	(.281)		
Employment Growth - Transp.	.632	1.428***	.017	457
	(.412)	(.545)		
Employment Growth - Utilities	-.091	-.706**	.009	457
	(.263)	(.348)		
Employment Growth - Nat. Res.	1.422	1.888	.006	457
	(1.118)	(1.482)		
Unemployment Rate	-.112	-.37**	.01	457
	(.136)	(.181)		
Labor Force Participation Rate	.003**	-.001	.013	457
	(.001)	(.002)		
Hires Rate	.462***	-.256	.036	244
	(.176)	(.246)		
Quits Rate	-.019	-.199	.005	244
	(.133)	(.186)		
Separations Rate	-.445**	-.368	.032	244
	(.174)	(.243)		
Vacancy Rate	.649**	-.047	.026	244
	(.26)	(.364)		
Job Finding Rate	.016	.021	.005	366
	(.016)	(.021)		
Weather Absences Rate	-.012***	-.005***	.156	457
	(.001)	(.002)		

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: All non-growth rate outcomes are measured as changes from prior month. Data for employment growth, unemployment rate, and labor force participation rate are from the BLS Current Employment Statistics series. Data for hires, quits, separations, and vacancies come from the BLS JOLTS survey and start in December 2000; rates are calculated by dividing by establishment-survey total nonfarm employment. The job finding rate is defined as the monthly flow of individuals from unemployed to employed status, divided by initial employment. The weather absences rate is the share of employed individuals that report being employed but not at work during the reference period due to “bad weather.” Data for the job finding rate and weather absences rate come from the BLS Household Survey, with data starting in February 1990 for the job finding rate and data starting in January 1980 for the weather absences rate.

This association supports the validity of our estimated effects.

In Table 5, we consider the extent to which the estimated weather effects are predictive of other, non-labor market macroeconomic outcomes.[28] In the first row, we see that both the granular and global effects are statistically significantly related to the Chicago Fed national activity index, together explaining 11% of its monthly time series variation (outside of recessions). Next, consistent with the results above on retail employment, we find that the granular weather effects, but not the global effects, have a strong, significant impact on retail and food sales, suggesting that local weather has important demand-side effects, with favorable (unfavorable) local weather stimulating (weakening) local retail activity. The next three rows show the impacts of the weather effects on total industrial production (IP), manufacturing IP, and utilities IP. We find statistically significant impact from both global and granular weather effects on total IP. For manufacturing IP, both granular and global weather have significant positive impacts, and jointly explain nearly 11% of its variation. For utilities IP, granular weather has a very large negative impact, reflecting that favorable weather reduces demand for heating and cooling (which is provided by local utilities). More surprisingly, global weather has a large positive impact on utilities IP. As with sectoral employment growth, input-output linkages may explain this result. As positive global weather effects boost manufacturing activity, this stimulus may spillover to higher electricity demand. Taken together, the granular and global weather effects explain 31% of the variation in utilities IP.

The final four rows show the results for total personal consumption expenditures (PCE), PCE on goods, PCE on services, and housing starts. Granular, but not global, weather effects are associated with higher total PCE, explaining a minor fraction of total PCE's variation. The granular weather effects explain a higher share of the variation separately for goods PCE (around 5%) and services PCE (nearly 3%). The impact on goods PCE is found to be positive, consistent with our results on retail activity, while the impact on services PCE is negative. The negative impact could stem from general equilibrium effects (e.g., favorable weather boosting demand for goods, pushing up overall inflation and thus reducing spending on services) or from the negative demand for utility services, as seen in the IP results. Lastly, we find that a considerable amount of the variation in national housing starts can be explained by the granular weather effects, presumably reflecting that local weather conditions help determine the optimal timing for local builders to begin residential construction projects.

Table 6 shows the analogous results for a number of key financial market outcomes.[29] In the first row, we show results where the dependent variable is employment report "surprises." Surprises are measured as the difference between realized (as first reported) total employment growth and expected total employment growth just prior to the employment report release. The latter is based on the median response from the Money Market Services (MMS) survey of financial market

[28]Results using the weather effect nowcasts and backcasts for the January 2011 through April 2024 sample period are provided in Appendix Table B5.

[29]Results using the weather effect nowcasts and backcasts for the January 2011 through April 2024 sample period are provided in Appendix Table B7.

Table 5 : Predictability of Weather Backcasts for Other Macro Variables

Slope Coefficients and R^2 from Regressions on Weather Effects

	(1) Granular	(2) Global	(3) R^2	(4) N
FRB-Chicago National Activity Index	2.506***	1.903***	.108	457
	(.364)	(.482)		
Retail & Food Sales	6.676***	.93	.087	457
	(1.017)	(1.347)		
Industrial Production (IP)	1.333***	1.363**	.027	457
	(.439)	(.581)		
IP Manufacturing	3.514***	.785	.108	457
	(.474)	(.628)		
IP Utilities	-22.134***	6.917***	.314	457
	(1.666)	(2.207)		
Personal Consumption Expenditures (PCE)	1.136***	.835	.017	457
	(.434)	(.575)		
PCE Goods	4.573***	1.276	.046	457
	(.982)	(1.301)		
PCE Services	-.847***	.508	.032	457
	(.261)	(.346)		
Housing Starts	.612***	.124	.083	457
	(.095)	(.126)		

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: Retail sales and PCE variables are month-over-month growth rates. IP and housing starts are monthly changes. Data cover April 1981 to April 2024. Sources: Federal Reserve Board (IP); Census Bureau (retail & food sales and housing starts); and Bureau of Economic Analysis (PCE).

participants conducted over several days leading up to the release and has been used in many prior studies (see, e.g., Gürkaynak et al. (2005) and Wilson (2019)). We find that the weather effects explain roughly 7% of the variation in the employment report surprises and that only the granular effects are statistically significant. The significant effects of the granular component suggests that market participants, at least historically, did not account for local weather effects spread across the country when formulating their expectations for employment growth. This could be either because they did not have information on local weather or because they did not recognize its importance for national employment. Using a smaller set of weather variables, all of which were available in real-time back to at least 1980, Wilson (2019) found that local employment growth nowcasts based on these real-time weather data, aggregated to the national level, were significantly associated with employment growth surprises, suggesting that at least part of the effect we find here is due to the latter explanation – market participants not fully recognizing weather's importance for national employment growth. We do not conduct such a real-time exercise here because some of the sources for weather data we use in constructing the weather effects were not available in the past. It is also worth noting that the global weather effects have no significant relationship with the surprises, suggesting that nationwide weather effects are fully "priced" into expectations for employment growth.

Table 6 : Predictability of Weather Backcasts for Financial Market Reactions

Slope Coefficients and R^2 from Regressions on Weather Effects

	(1) Granular	(2) Global	(3) R^2	(4) Payroll surprise	(5) R^2	(6) N
Total Employment Growth Surprise	.48***	.035	.069			428
	(.086)	(.118)				
1-year Treasury Bond daily change	.224***	.064	.016	.483***	.258	447
	(.082)	(.108)		(.04)		
2-year Treasury Bond daily change	.255***	.036	.016	.567***	.268	447
	(.094)	(.123)		(.046)		
5-year Treasury Bond daily change	.213**	.006	.011	.553***	.243	447
	(.096)	(.127)		(.048)		
10-year Treasury Bond daily change	.152*	-.036	.008	.428***	.187	447
	(.085)	(.112)		(.044)		
30-year Treasury Bond daily change	.095	-.05	.005	.326***	.15	447
	(.073)	(.096)		(.038)		

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The relationship between the weather effects and employment report surprises is important because such surprises have large effects on financial market asset prices. In particular, as is well-known in the asset pricing literature, positive (negative) surprises lead to significant increases (decreases) in Treasury bond yields on the days of employment reports. This relationship is shown in columns 4 and 5 of Table 6. Each row displays the slope coefficient and R^2 from a regression of the yield change on employment report days, for the indicated Treasury bond, on the employment report surprise. This measure of employment report surprises explains around one-quarter of the variation in the Treasury bond yield changes on employment report days. The relationship is strongest for the shorter maturity Treasuries. The positive relationship between payroll surprises and Treasury bond yields likely derives from two standard channels. First, positive labor market news increases expectations concerning current and future aggregate income and consumer spending, increasing expectations for corporate earnings and causing investors to substitute away from Treasury bonds in favor of stocks. Second, such news also raises expectations of the central bank increasing short-term interest rates, which pushes up Treasury bond yields (while potentially reducing stock returns by increasing the discount rate underlying the present discounted value of future earnings).

Columns 1-3 of the same rows show the results from regressing the release-day Treasury bond yield changes on the granular and global weather effects. Consistent with the estimated impact of the granular weather effects on payroll surprises, and the estimated impact of surprises on yield changes, we find a statistically significant relationship between the granular weather effects and the Treasury bond yield changes, with the strongest relationship for the shorter-maturity bonds. For instance, the granular weather effects can explain 1.6% of the variation over time in the 2-year Treasury bond's yield change on employment report days.

7.2 Dynamic Analysis

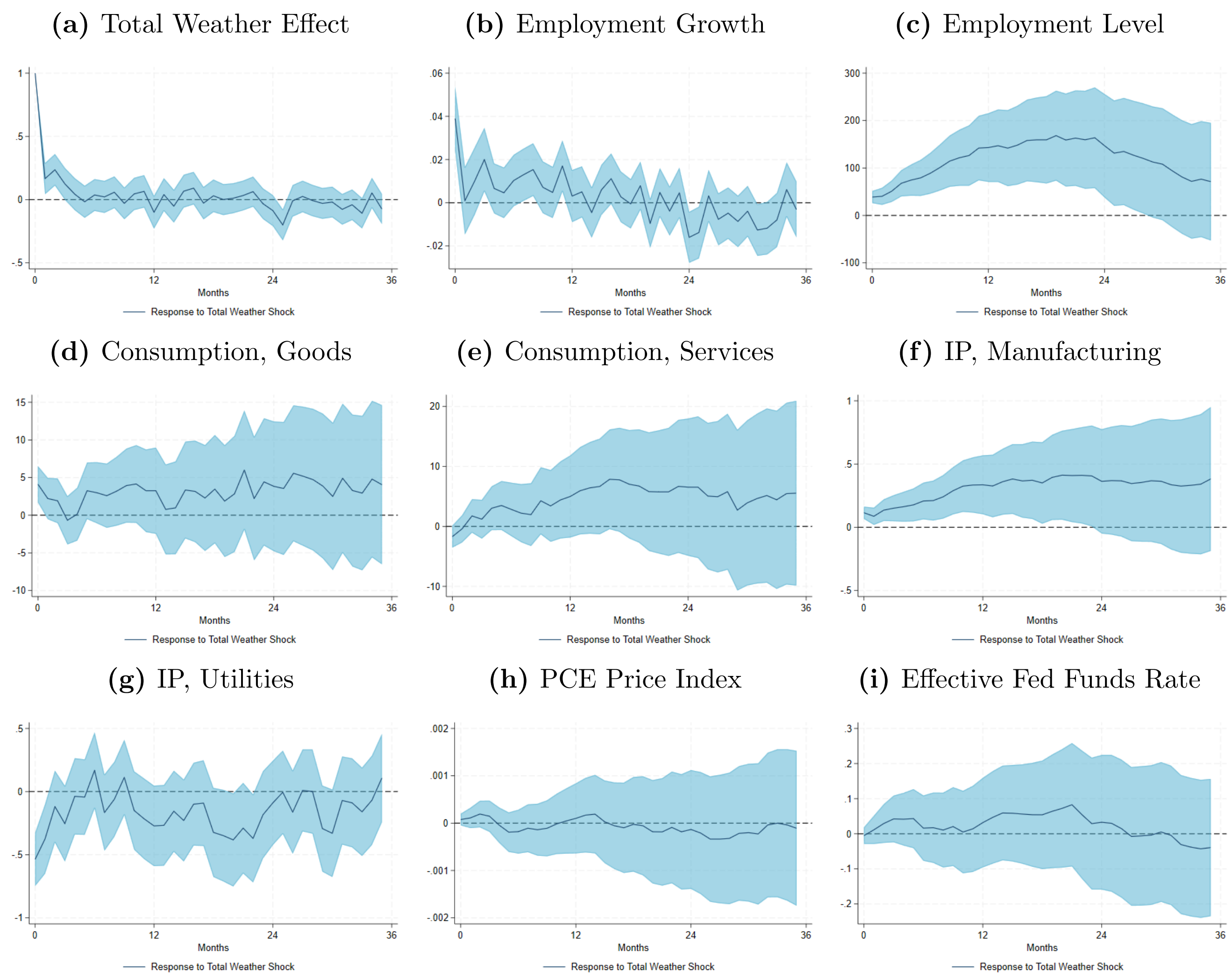
In our final empirical exercise, we employ the Jordà (2005) local projections (LP) estimator to estimate the dynamic responses of key macroeconomic outcomes to shocks in the granular, global, and combined weather effects. We first examine responses to shocks to the combined/total weather effects. We measure total weather effects, ω_t, using the predicted value from regressing national private nonfarm employment growth on the granular and global weather effects (i.e., the regression underlying row 1 of Table 4). We implement a standard LP estimation by estimating the following specification for horizons h from 0 to 36 months ahead:

$$y_{t+h} = a + b^h \omega_t + \mathbf{\Gamma X_t} + e_t, \tag{6}$$

where $\mathbf{X_t}$ is a vector of control variables consisting of six monthly lags of both the dependent variable and ω_t. The estimates b^h for $h = 0$ to $h = 36$ trace out the impulse response function (IRF) for the outcome y_t. We examine the following monthly outcomes: employment (level and growth rate), personal consumption expenditures (PCE)(separately for goods and services), industrial production (separately for manufacturing and utilities), the PCE price index, and the effective federal funds rate. We also estimate the response of total weather effects to its own shocks in order to assess their persistence.

The estimated IRFs, along with their 90% confidence intervals, are shown in Figure 6. The IRF's show the responses to a one standard deviation shock to the total weather effects. We first note that the shocks are quite transitory, having a small positive impact on total weather effects up to 3 months ahead and near-zero effects thereafter. Note that the non-permanence of the shocks is as expected given that the county-level weather variables used in the estimation are detrended. We next find that a weather shock leads to a short-lived increase in the growth rate of employment, but a longer lasting – up to around 30 months ahead – increase in the level of employment. Turning to consumption, we see that the goods consumption response is positive and significant on impact but generally insignificant thereafter. The services consumption response is actually negative on impact before becoming near-zero and statistically insignificant thereafter. For industrial production, we find a positive and statistically significant impact for manufacturing lasting around 24 months, and a short-lived negative and significant impact for utilities. Lastly, we find near-zero impacts on inflation and the fed funds rate. A key take-away from these findings is that, while macroeconomic effects of transitory weather shocks are surprisingly gradual, they are not permanent for any of the outcomes we look at. We find no evidence of significant effects beyond three years. The transitory nature of weather's macroeconomic effects implies that underlying macroeconomic trends should be unaffected by weather. Hence, analysts and policymakers may wish to filter out estimated weather effects from macro time series in order to better guage underlying macroeconomic conditions.

Figure 6 : Impulse Responses to Total Weather Effect Shock



(a) Total Weather Effect **(b)** Employment Growth **(c)** Employment Level

(d) Consumption, Goods **(e)** Consumption, Services **(f)** IP, Manufacturing

(g) IP, Utilities **(h)** PCE Price Index **(i)** Effective Fed Funds Rate

Notes: Impulse responses of macro variables (columns 2 to 5) to a one standard deviation shock to the Total Weather Effect (column 1). Shaded areas represent 90 percent confidence bands. Horizontal axis: Months after the Total Weather Effect shock.

Next, we estimate the IRFs from separate shocks to the granular and global weather effects. We do this by replacing ω_t in equation 6 with the separate granular and global weather components and replacing in $\mathbf{X_t}$ the lags of the total weather effects with the lags of the two separate components. The results are shown in Figure 7. In panel (a), we see that the two series respond differently to their own shocks. After an initial shock, the granular weather effects respond in the opposite direction for the following two months. This is consistent with our results in Section 6 showing that for many local weather variables, the lagged effects generally go in the opposite direction from the contemporaneous effects. For global weather effects, though, there is more positive auto-correlation, with an initial shock having a persistent positive effect up to around six months later.

Overall, the two types of shocks often have rather different dynamic effects on the macroeconomic outcomes. For employment, the granular shock has a larger initial impact but near-zero effects after the first few months. By contrast, the global shock's initial impact is small but then grows and is generally positive and statistically significant up to around 24 months from the initial shock. For goods consumption, granular weather shocks have a positive but very transitory impact, while global weather shocks have no significant effect at all horizons. For services consumption, the global weather shocks have a persistent positive and significant impact, similar to that on employment. Global weather shocks also have a persistent positive effect on manufacturing IP. These results suggest that, while local weather shocks have only short-lived impacts on local economic activity, they have longer lasting, but not permanent, impacts in national economic activity, perhaps through delayed geographical and input-output network spillovers. Lastly, we see in the final panel, that granular and global weather shocks tend to have offsetting impacts on the effective federal funds rate, though the impacts are statistically insignificant at most horizons.

7.3 Asymmetric Effects of Favorable vs. Unfavorable Weather

Most prior studies of the macroeconomic effects of weather and climate shocks have focused solely on adverse/unfavorable weather, such as severe storms or natural disasters. Our rich weather data allow us to estimate the effects of both favorable and unfavorable weather. Hence, in this subsection, we investigate whether macroeconomic responses to weather shocks are asymmetric, differing for positive (favorable) and negative (unfavorable) shocks. We do this by interacting our total weather effects variable (ω_t) with a positive-value (zero otherwise) indicator and similarly with a negative-value indicator. We then replace ω_t in equation 6 with the separate positive and negative components and replace in $\mathbf{X_t}$ the lags of the total weather effects with the lags of the two separate components.

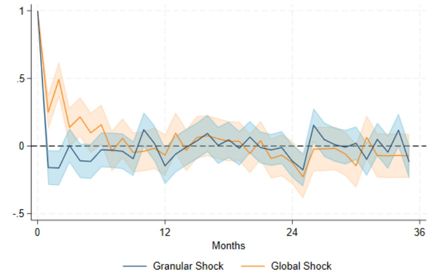
The results are shown in Figure 8. Note that we invert the IRFs for the negative shocks such that an unfavorable shock *reduces* the total weather effects by one standard deviation. There are a few notable cases of asymmetric effects. First, we see that favorable weather shocks have somewhat larger and more significant effects on employment than do unfavorable weather shocks, though both shocks have near-zero effects in the long run. The pattern is similar for manufacturing IP. Second, there is a near opposite pattern for services consumption, with unfavorable shocks have a larger and more significant medium-run effect. Third, as expected, favorable and unfavorable shocks have symmetric and short-lived effects on utilities IP. Neither type of shock have significant effects on either inflation or the fed funds rate.

7.4 How has the Role of Weather Changed Over Time

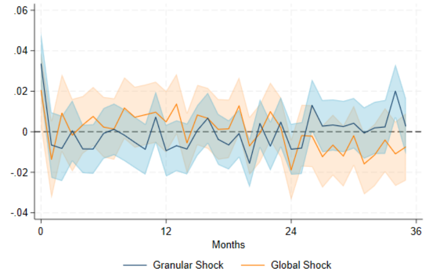
Finally, following Kim et al. (2025) and Baleyte et al. (2024), we examine whether the dynamic macroeconomic responses to total weather shocks have changed over time. To do this, we interact

Figure 7 : Impulse Responses to Granular and Global Weather Effect Shocks

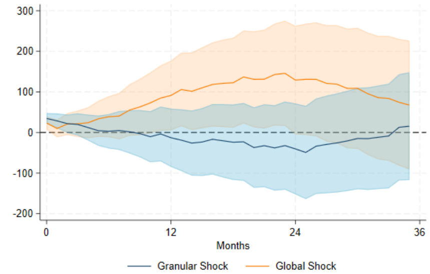
(a) Weather Effects



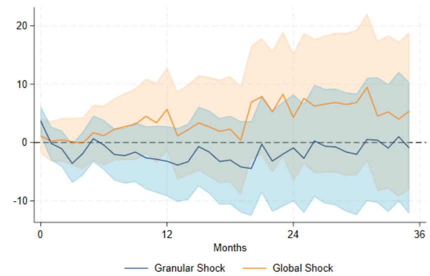
(b) Employment Growth



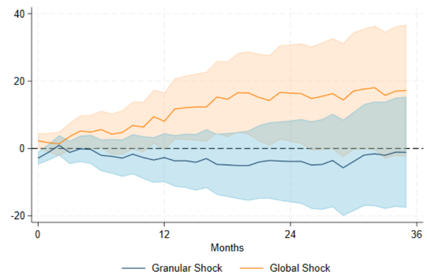
(c) Employment Level



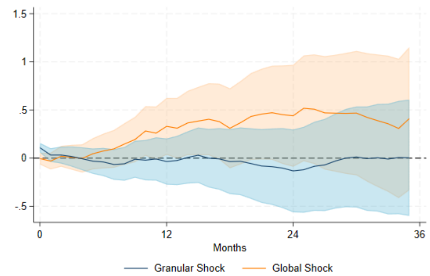
(d) Consumption, Goods



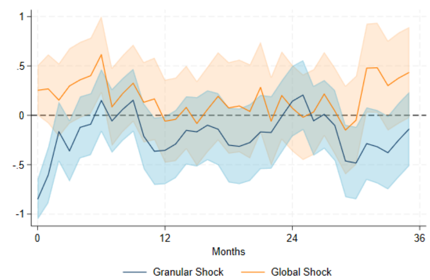
(e) Consumption, Services



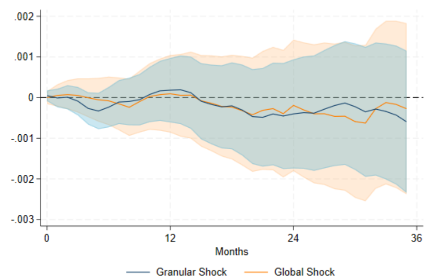
(f) IP, Manufacturing



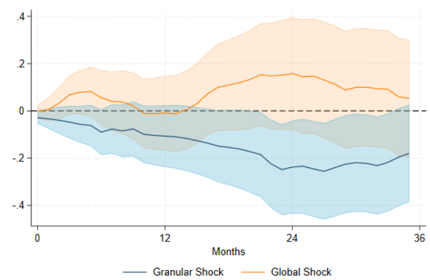
(g) IP, Utilities



(h) PCE Price Index



(i) Effective Fed Funds Rate



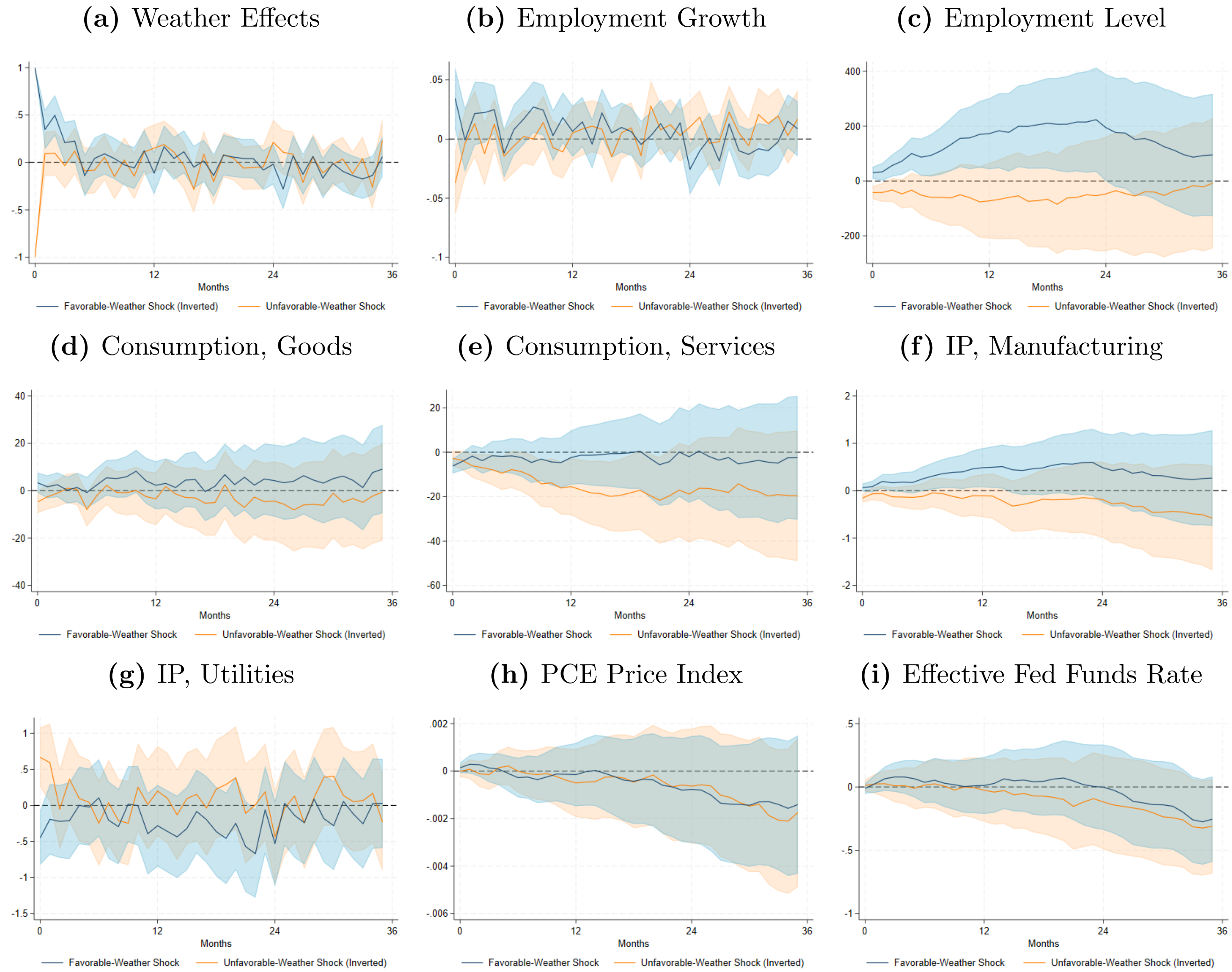
Notes: Impulse responses of macro variables (columns 2 to 5) to a one standard deviation shock to the Total Weather Effect (column 1). Shaded areas represent 90 percent confidence bands. Horizontal axis: Months after the Total Weather Effect shock.

our total weather effects variable (ω_t) with an early-sample (zero otherwise) indicator and similarly with a late-sample indicator. We define early sample as all months prior to January 2001 and late sample as all months thereafter. We then replace ω_t in equation 6 with the separate early- and late-sample components and replace in $\mathbf{X_t}$ the lags of the total weather effects with the lags of the two separate components.

The results are shown in Figure 9. Contrary to Kim et al. (2025) but consistent with Baleyte et al. (2024), we find that weather shocks in the early part of our sample generally have larger and more significant effects than do shocks in the second half of the sample.[30] In particular, early-sample

[30]Baleyte et al. (2024) investigates the macroeconomic effects of high temperature shocks using monthly panel data across 14 EU countries. They find that the marginal effects of these shocks have fallen over time, consistent with our evidence that the macroeconomic effects of weather shocks in the U.S. have fallen over time. Kim et al. (2025), on the other hand, find that the marginal effects of severe weather shocks have increased over time.

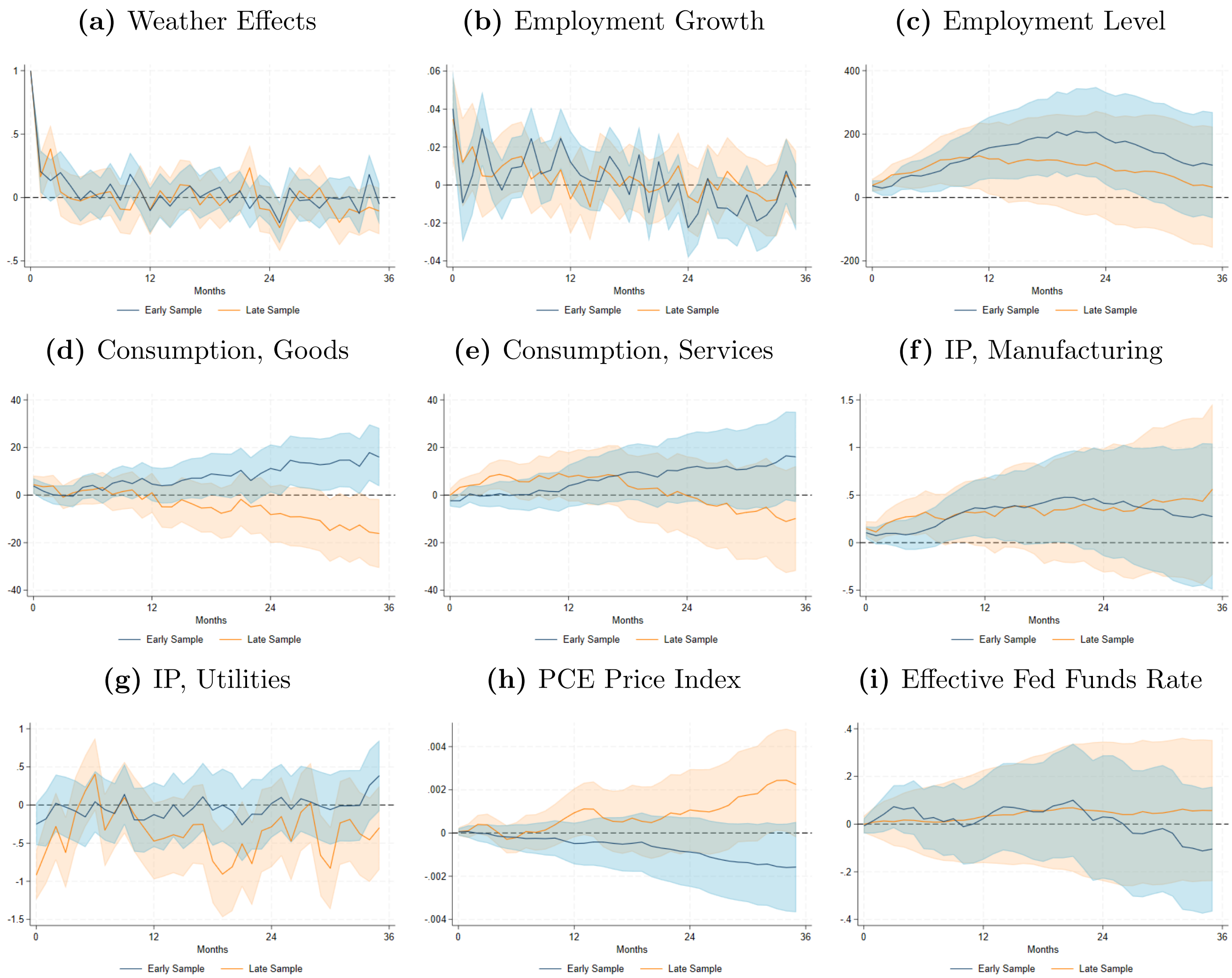
Figure 8 : Impulse Responses to Favorable vs. Unfavorable Total Weather Effect Shocks



Notes: Impulse responses of macro variables (columns 2 to 5) to a one standard deviation shock to the Total Weather Effect (column 1). Shaded areas represent 90 percent confidence bands. Horizontal axis: Months after the Total Weather Effect shock.

shocks are associated with long-lasting significant responses of employment, total PCE, goods PCE, and services PCE. The late-sample shocks have no statistically significant effects. One interpretation of these results is that firms and households have become better adapted to dealing with weather shocks over time, perhaps due to improvements in inventory management, supply chain management, and contingency resilience on the part of firms and due to better planning (perhaps facilitated by better weather forecasting services) on the part of households. Another, complementary explanation is that structural change away from more weather-sensitive goods production toward less weather-sensitive services has led the aggregate U.S. economy to be less weather-sensitive.

Figure 9 : Impulse Responses to Total Weather Effect Shock, Early vs. Late Subsamples



Notes: Impulse responses of macro variables (columns 2 to 5) to a one standard deviation shock to the Total Weather Effect (column 1). Shaded areas represent 90 percent confidence bands. Horizontal axis: Months after the Total Weather Effect shock.

8 Conclusion

This paper introduces a novel two-step methodology for estimating the macroeconomic effects of high-dimensional weather shocks by leveraging granular panel data and machine learning techniques. The approach entails estimating granular weather effects with a standard two-way fixed effects model and then using the estimated time fixed effects to estimate economy-wide weather effects. As such, the methodology combines the separate identification of local (granular) and economy-wide (global) weather effects—a decomposition that is not feasible under conventional panel or time series frameworks alone. Applying this methodology to U.S. monthly employment growth over the past four decades, we document several key findings.

First, we find that combining dimension reduction and machine learning techniques in the second step results in a model with the strongest step-ahead out-of-sample predictive accuracy. These step-ahead predicted values from the best-performing model explain nearly 10% of the time series variance in national private nonfarm employment growth over the evaluation sample period (January 2011 to December 2024). Second, using the specification of the best-performing model, we find that temperature, precipation, their interactions, and extreme events all have substantial explanatory power for local employment growth and that lags of local weather have greater explanatory power than contemporaneous weather. Third, we find that these weather-induced fluctuations also have predictive power for a wide array of other macroeconomic indicators, including consumption, labor force flows, and financial market surprises. Fourth, using the Local Projections estimator, we find that shocks to both granular and global weather effects have significant immediate impacts on macroeconomic outcomes such as employment, consumption, and industrial production. Fifth, favorable weather shocks are often more impactful than unfavorable/severe weather shocks. Sixth, the responses of employment and consumption to weather shocks has weakened over time, suggesting a degree of adaptation or structural economic change.

The methodology in this paper can also be used to build on the efforts of Boldin & Wright (2015) and Wilson (2019) toward weather-adjusting national employment growth and potentially other macroeconomic time series. As argued by Boldin & Wright (2015), "weather adjustment can be a useful supplement [to seasonal adjustment] to measure underlying economic momentum."

Lastly, we note that our approach is broadly applicable beyond weather: it offers a framework for estimating the macroeconomic effects of any granular shock—whether environmental, fiscal, or productivity-related—that may have both local and aggregate dimensions. In future work, this method could be extended to firm-level or international settings to further illuminate how localized shocks propagate across space and time to influence aggregate outcomes.

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ONLINE APPENDICES – NOT FOR PUBLICATION

A Data Sources and Definitions

We construct the following weekly (or monthly if indicated) variables:
From NOAA's GHCN-Daily data set[31]:

- Daily snowfall. We construct county-area averages of daily snowfall using the weather station-level data on snowfall from GHCN-Daily.

From NOAA's nClimDiv data set[32] (which provides county-area averages of weather station-level data from GHCN-Daily):

- Temperature distribution over the month: number of days in each 10-degree bin.
- Cooling Degree Days (CDDs) and Heating Degree Days (HDDs).
- Daily precipitation.
- Palmer drought severity index (PDSI) (available only at a monthly frequency).

FEMA disaster declarations[33]:

- Indicators of the occurrence of a natural disaster (of various types) in the county.

GridMet[34]:

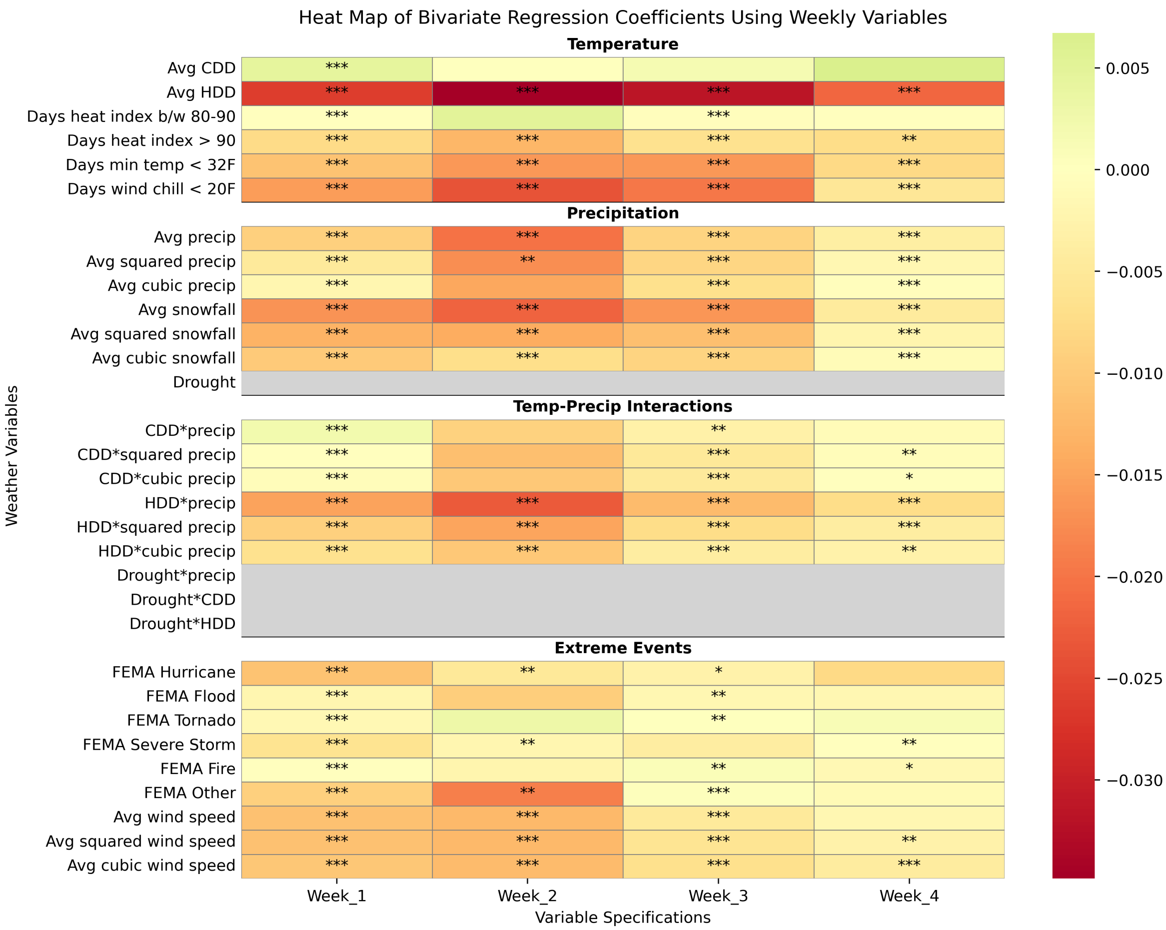
- Humidity and Heat Index
- Wind speed

[31] `https://www1.ncdc.noaa.gov/pub/data/ghcn/daily/`
[32] `https://www.ncei.noaa.gov/pub/data/cirs/climdiv`
[33] `https://www.fema.gov/api/open/v2/DisasterDeclarationsSummaries.csv`
[34] GridMet data are available here: `www.climatologylab.org/gridmet.html`. GridMet data are constructed from daily weather estimates from PRISM, which in turn are based on readings from an extensive network of weather stations, and regional reanalysis data from NLDAS-2.

B Additional Results

B.1 Employment Growth and Week-of-Month Weather

Figure B1 : Bivariate Relationships Between Employment Growth and Week-of-Month Weather



Notes: Each cell corresponds to a bivariate regression of county monthly employment growth on the contemporaneous weather variable indicated in the row heading. The first (resp. second, third, fourth) column uses the first (resp. second, third, fourth) week of the month to measure that contemporaneous weather variable. The regression also accounts for time (sample-month) and county fixed effects. As discussed in the text, employment growth and all weather variables are seasonally-adjusted and detrended. Cell color intensities indicate how positive (green) or negative (red) is the estimated slope coefficient. Stars indicate statistical significance: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

B.2 Additional Results from Static Analysis

B.2.1 Labor Market

Table B1 : Predictability of Weather Backcasts for Labor Market Outcomes
Slope Coefficients and R^2 from Regressions on Weather Effects
Weather Effects Based on only lagged terms of *Model B-SQ*

	(1) Granular	(2) Global	(3) R^2	(4) N
Employment Growth - Private	1.04***	.408*	.052	457
	(.244)	(.221)		
Employment Growth - Total	.859***	.289	.043	457
	(.217)	(.196)		
Employment Growth - Constr.	5.36***	.739	.101	457
	(.789)	(.715)		
Employment Growth - Leis.&Hosp.	1.531***	.116	.016	457
	(.582)	(.528)		
Employment Growth - Retail	1.195***	-.411	.026	457
	(.35)	(.318)		
Employment Growth - Mfg.	.37	.986***	.024	457
	(.363)	(.329)		
Employment Growth - Transp.	.784	1.284**	.013	457
	(.706)	(.64)		
Employment Growth - Utilities	-.563	-.569	.009	457
	(.45)	(.408)		
Employment Growth - Nat. Res.	3.266*	.176	.007	457
	(1.914)	(1.735)		
Unemployment Rate	-.31	-.295	.01	457
	(.234)	(.212)		
Labor Force Participation Rate	.003	-.002	.004	457
	(.002)	(.002)		
Hires Rate	.736**	-.482*	.032	244
	(.295)	(.286)		
Quits Rate	.072	-.17	.003	244
	(.223)	(.216)		
Separations Rate	-.181	-.422	.012	244
	(.295)	(.285)		
Vacancy Rate	1.074**	-.043	.025	244
	(.436)	(.422)		
Job Finding Rate	.011	.032	.006	366
	(.026)	(.025)		
Weather Absences Rate	-.011***	-.004*	.06	457
	(.002)	(.002)		

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: All non-growth rate outcomes are measured as changes from prior month. Data for employment growth, unemployment rate, and labor force participation rate are from the BLS Current Employment Statistics series. Data for hires, quits, separations, and vacancies come from the BLS JOLTS survey and start in December 2000; rates are calculated by dividing by establishment-survey total nonfarm employment. The job finding rate is defined as the monthly flow of individuals from unemployed to employed status, divided by initial employment. The weather absences rate is the share of employed individuals that report being employed but not at work during the reference period due to "bad weather." Data for the job finding rate and weather absences rate come from the BLS Household Survey, with data starting in February 1990 for the job finding rate and data starting in January 1980 for the weather absences rate.

Table B2 : Predictability of Weather *Nowcasts* for Labor Market Outcomes

Slope Coefficients and R^2 from Regressions on Weather Effects; Sample: 2011m1 - 2024m4

	(1) Granular	(2) Global	(3) R^2	(4) N
Employment Growth - Private	.773***	-1.021***	.084	248
	(.249)	(.286)		
Employment Growth - Total	.699***	-.921***	.082	248
	(.227)	(.261)		
Employment Growth - Constr.	3.949***	.342	.09	248
	(.806)	(.928)		
Employment Growth - Leis.&Hosp.	.468	-2.439***	.036	248
	(.719)	(.828)		
Employment Growth - Retail	.249	-.731*	.014	248
	(.359)	(.414)		
Employment Growth - Mfg.	.631	-1.43***	.043	248
	(.42)	(.484)		
Employment Growth - Transp.	1.884***	-1.132	.041	248
	(.658)	(.757)		
Employment Growth - Utilities	0	-1.234**	.018	248
	(.504)	(.58)		
Employment Growth - Nat. Res.	1.656	-5.608***	.039	248
	(1.627)	(1.874)		
Unemployment Rate	-.111	-.133	.001	248
	(.266)	(.307)		
Labor Force Participation Rate	-.001	0	.001	248
	(.003)	(.003)		
Hires Rate	.157	.006	.002	248
	(.255)	(.293)		
Quits Rate	.162	-.234	.008	248
	(.186)	(.215)		
Separations Rate	-.569**	.044	.023	248
	(.235)	(.271)		
Vacancy Rate	.936**	-.439	.029	248
	(.373)	(.429)		
Job Finding Rate	.015	.008	.001	248
	(.027)	(.031)		
Weather Absences Rate	-.015***	-.001	.125	248
	(.003)	(.003)		

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: All non-growth rate outcomes are measured as changes from prior month. Data for employment growth, unemployment rate, and labor force participation rate are from the BLS Current Employment Statistics series. Rates are calculated by dividing by establishment-survey total nonfarm employment. The job finding rate is defined as the monthly flow of individuals from unemployed to employed status, divided by initial employment. The weather absences rate is the share of employed individuals that report being employed but not at work during the reference period due to "bad weather." Data for the job finding rate and weather absences rate come from the BLS Household Survey.

Table B3 : Predictability of Weather *Backcasts* for Labor Market Outcomes

Slope Coefficients and R^2 from Regressions on Weather Effects; Sample: 2011m1 - 2024m4

	(1) Granular	(2) Global	(3) R^2	(4) N
Employment Growth - Private	.735***	-.031	.069	240
	(.178)	(.252)		
Employment Growth - Total	.637***	-.029	.062	240
	(.164)	(.231)		
Employment Growth - Constr.	3.974***	.424	.183	240
	(.547)	(.773)		
Employment Growth - Leis.&Hosp.	.534	-.725	.01	240
	(.52)	(.736)		
Employment Growth - Retail	.377	-.094	.01	240
	(.256)	(.362)		
Employment Growth - Mfg.	.424	.202	.009	240
	(.303)	(.428)		
Employment Growth - Transp.	1.652***	.394	.05	240
	(.466)	(.659)		
Employment Growth - Utilities	.138	-.322	.003	240
	(.36)	(.508)		
Employment Growth - Nat. Res.	2.74**	.44	.023	240
	(1.171)	(1.655)		
Unemployment Rate	.091	-.147	.003	240
	(.189)	(.267)		
Labor Force Participation Rate	.003	-.002	.012	240
	(.002)	(.003)		
Hires Rate	.525***	-.251	.047	240
	(.171)	(.242)		
Quits Rate	-.009	-.113	.002	240
	(.13)	(.183)		
Separations Rate	-.37**	-.313	.026	240
	(.163)	(.231)		
Vacancy Rate	.636**	-.023	.025	240
	(.262)	(.37)		
Job Finding Rate	.015	-.007	.004	240
	(.018)	(.026)		
Weather Absences Rate	-.012***	-.004	.169	240
	(.002)	(.002)		

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: All non-growth rate outcomes are measured as changes from prior month. Data for employment growth, unemployment rate, and labor force participation rate are from the BLS Current Employment Statistics series. Rates are calculated by dividing by establishment-survey total nonfarm employment. The job finding rate is defined as the monthly flow of individuals from unemployed to employed status, divided by initial employment. The weather absences rate is the share of employed individuals that report being employed but not at work during the reference period due to "bad weather." Data for the job finding rate and weather absences rate come from the BLS Household Survey.

B.2.2 Other Macro Variables

Table B4 : Predictability of Weather Backcasts for Other Macro Variables
Slope Coefficients and R^2 from Regressions on Weather Effects
Weather Effects Based on only lagged terms of *Model B-SQ*

	(1) Granular	(2) Global	(3) R^2	(4) N
FRB-Chicago National Activity Index	2.323***	1.936***	.06	457
	(.64)	(.58)		
Retail & Food Sales	6.957***	-.209	.033	457
	(1.792)	(1.624)		
Industrial Production (IP)	.795	1.219*	.011	457
	(.757)	(.686)		
IP Manufacturing	2.471***	1.122	.027	457
	(.848)	(.768)		
IP Utilities	-18.701***	4.194	.065	457
	(3.33)	(3.017)		
Personal Consumption Expenditures (PCE)	1.101	.632	.008	457
	(.746)	(.676)		
PCE Goods	4.593***	.799	.018	457
	(1.706)	(1.546)		
PCE Services	-.981**	.532	.012	457
	(.452)	(.41)		
Housing Starts	.446***	.174	.021	457
	(.169)	(.153)		

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: Retail sales and PCE variables are month-over-month growth rates. IP and housing starts are monthly changes. Data cover April 1981 to April 2024. Sources: Federal Reserve Board (IP); Census Bureau (retail & food sales and housing starts); and Bureau of Economic Analysis (PCE).

Table B5 : Predictability of Weather Effects for Other Macro Variables

Slope Coefficients and R^2 from Regressions on Weather Effects

Panel A: Nowcasts: 2011m1 - 2024m4

	(1) Granular	(2) Global	(3) R^2	(4) N
FRB-Chicago National Activity Index	3.982***	-1.298*	.138	248
	(.662)	(.762)		
Retail & Food Sales	10.479***	-1.646	.109	248
	(1.929)	(2.221)		
Industrial Production (IP)	3.101***	-1.013	.035	248
	(1.077)	(1.241)		
IP Manufacturing	6.929***	-2.313*	.144	248
	(1.124)	(1.294)		
IP Utilities	-38.007***	11.014**	.244	248
	(4.402)	(5.069)		
Personal Consumption Expenditures (PCE)	3.507***	.159	.082	248
	(.752)	(.866)		
PCE Goods	7.941***	1.47	.076	248
	(1.792)	(2.063)		
PCE Services	1.19**	-.507	.028	248
	(.474)	(.546)		
Housing Starts	.606***	-.205	.039	248
	(.201)	(.232)		

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Panel B: Backcasts: 2011m1 - 2024m4

	(1) Granular	(2) Global	(3) R^2	(4) N
FRB-Chicago National Activity Index	2.821***	.563	.131	240
	(.472)	(.667)		
Retail & Food Sales	8.683***	-.852	.156	240
	(1.343)	(1.898)		
Industrial Production (IP)	1.663**	1.22	.022	240
	(.764)	(1.079)		
IP Manufacturing	4.874***	-.053	.138	240
	(.8)	(1.131)		
IP Utilities	-33.234***	12.165***	.421	240
	(2.73)	(3.859)		
Personal Consumption Expenditures (PCE)	2.255***	-.066	.07	240
	(.54)	(.763)		
PCE Goods	6.241***	-.085	.096	240
	(1.26)	(1.782)		
PCE Services	.161	-.094	.001	240
	(.344)	(.487)		
Housing Starts	.478***	.092	.046	240
	(.142)	(.2)		

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: Retail sales and PCE variables are month-over-month growth rates. IP and housing starts are monthly changes. Data cover April 1981 to April 2024. Sources: Federal Reserve Board (IP); Census Bureau (retail & food sales and housing starts); and Bureau of Economic Analysis (PCE).

B.2.3 Financial Markets

Table B6 : Predictability of Weather Backcasts for Financial Market Reactions
Slope Coefficients and R^2 from Regressions on Weather Effects
Weather Effects Based on only lagged terms of *Model B-SQ*

	(1) Granular	(2) Global	(3) R^2	(4) Payroll surprise	(5) R^2	(6) N
Total Employment Growth Surprise	.527***	-.085	.029			428
	(.148)	(.142)				
1-year Treasury Bond daily change	.269*	-.019	.008	.483***	.258	447
	(.143)	(.128)		(.04)		
2-year Treasury Bond daily change	.293*	-.044	.007	.567***	.268	447
	(.163)	(.146)		(.046)		
5-year Treasury Bond daily change	.323*	-.08	.008	.553***	.243	447
	(.167)	(.15)		(.048)		
10-year Treasury Bond daily change	.328**	-.13	.012	.428***	.187	447
	(.147)	(.132)		(.044)		
30-year Treasury Bond daily change	.252**	-.135	.01	.326***	.15	447
	(.126)	(.113)		(.038)		

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table B7 : Predictability of Weather Effects for Financial Market Reactions

Slope Coefficients and R^2 from Regressions on Weather Effects

Panel A: Nowcasts: 2011m1 - 2024m12

	(1) Granular	(2) Global	(3) R^2	(4) Payroll surprise	(5) R^2	(6) N
Total Employment Growth Surprise	.269*	-.095	.016			248
	(.141)	(.162)				
1-year Treasury Bond daily change	.09	-.019	.003	.275***	.124	244
	(.112)	(.131)		(.047)		
2-year Treasury Bond daily change	.129	-.096	.004	.455***	.164	244
	(.161)	(.188)		(.066)		
5-year Treasury Bond daily change	.18	-.077	.005	.53***	.189	244
	(.174)	(.203)		(.071)		
10-year Treasury Bond daily change	.128	-.026	.003	.401***	.14	244
	(.154)	(.179)		(.064)		
30-year Treasury Bond daily change	.129	-.035	.004	.261***	.083	244
	(.13)	(.151)		(.056)		

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Panel B: Backcasts: 2011m1 - 2024m12

	(1) Granular	(2) Global	(3) R^2	(4) Payroll surprise	(5) R^2	(6) N
Total Employment Growth Surprise	.282***	.005	.033			240
	(.099)	(.141)				
1-year Treasury Bond daily change	.069	.032	.004	.254***	.127	237
	(.073)	(.103)		(.044)		
2-year Treasury Bond daily change	.116	-.012	.005	.433***	.163	237
	(.109)	(.155)		(.064)		
5-year Treasury Bond daily change	.155	-.073	.009	.512***	.187	237
	(.121)	(.171)		(.07)		
10-year Treasury Bond daily change	.111	-.102	.007	.389***	.137	237
	(.107)	(.151)		(.064)		
30-year Treasury Bond daily change	.068	-.103	.006	.253***	.081	237
	(.091)	(.129)		(.056)		

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$