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A unifying approach to measuring climate change impacts and adaptation

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ABSTRACT

We develop a unifying approach to estimating climate impacts and adaptation, and apply it to study the impact of climate change on local air pollution. Economic agents are usually constrained when responding to daily weather shocks, but may adjust to long-run climatic changes. By *simultaneously* exploiting variation in weather and climate, we identify both the short- and long-run impacts on economic outcomes, and measure adaptation *directly* as the difference between those responses. As a result, we identify adaptation without making extrapolations of weather responses over time or space, and overcome omitted variable bias concerns from prior approaches.

1. Introduction

Failure to achieve climate mitigation goals puts increasing pressure on climate adaptation strategies.[2] Therefore, it is crucial to develop methods to measure climate impacts and adaptation. Inspired by the macroeconomic literature on the effects of unanticipated versus anticipated shocks on the economy (e.g., Lucas, 1972), the labor literature on the importance of distinguishing transitory versus permanent income shocks (e.g., Solon, 1992), and the properties of the Frisch–Waugh–Lovell theorem (Frisch and Waugh, 1933; Lovell, 1963), we develop a unifying approach to measuring climate impacts and adaptation. The proposed approach is then applied to examine the impact of climate change on ambient "bad" ozone concentration in U.S. counties over the period 1980–2013. Ozone is not emitted directly into the air, but rather formed by a Leontief-like production function of Nitrogen Oxides

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2 According to the Sixth Assessment Report from the Intergovernmental Panel on Climate Change (IPCC, 2022), the warming of the climate system is unequivocal, and global temperatures are likely to rise from 1.5 to 4.5 degree Celsius over the 21st century, depending on the emissions scenario.

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(NOx) and Volatile Organic Compounds (VOCs) in the presence of sunlight and warm temperatures; hence, affected by climate change (e.g., Jacob and Winner, 2009).

Our unifying approach overcomes key challenges of the literature by decomposing meteorological conditions into climatic variation and weather shocks, and estimating climate and weather effects in the *same* panel fixed-effects equation. The pioneer cross-sectional approach to estimate the impact of climate change on economic outcomes (Mendelsohn et al., 1994) has relied on permanent, anticipated components behind meteorological conditions, but may suffer from omitted variable bias. In contrast, the panel fixed-effects approach (Deschenes and Greenstone, 2007) exploits transitory, unanticipated weather shocks, and deals with that bias, but identification of climate effects using weather variation is not trivial. Current hybrid approaches combining cross-sectional and panel data variation also face challenges (see a recent review by Kolstad and Moore, 2020). The partitioning variation approach also decomposes meteorological conditions and estimates climate and weather effects jointly, but typically does not include spatially-disaggregated fixed effects leaving it susceptible to omitted variable bias (e.g., Kelly et al., 2005; Moore and Lobell, 2014; Merel and Gammans, 2021).[3] Our unifying approach combines the strengths of the prior methods while addressing their shortcomings by relying on the properties of the Frisch–Waugh–Lovell theorem.

Influential studies have proposed measuring adaptation as the difference between the estimates of impacts in fixed-effects and cross-sectional approaches (Dell et al., 2012, 2014). Estimates of climate impacts based on cross-sectional analysis are usually inclusive of adaptation, whereas those from fixed-effects are typically not. Our unifying approach estimates the short- and long-run impacts in the same equation. As a result, our approach enables a straightforward test for the statistical significance of the measure of adaptation and addresses two other shortcomings from existing approaches. First, it recovers a measure of adaptation *directly* from the jointly estimated impacts of weather and climate. In contrast, a common approach in the literature tackles adaptation *indirectly*, by flexibly estimating economic damages due to weather shocks, then assessing climate damages by using shifts in the future weather distribution predicted by climate models (e.g., Deschenes and Greenstone, 2011). Second, and analogous to the Lucas Critique (Lucas, 1976), our approach overcomes the challenges of identifying adaptation by comparing the profiles of weather responses across time and space, under the assumption that preferences are constant across those dimensions (Barreca et al., 2016; Heutel et al., 2021; Carleton et al., 2022).[4] Instead, we identify adaptation by comparing how economic agents in the *same* season and location respond to weather shocks – which, by definition, limit opportunities to adapt – with their own response to climatic changes, which should incorporate adaptive behavior.

We apply our unifying approach to the context of daily temperature and ambient ozone concentration across the continental United States. In our analysis, we merge location-by-day ozone concentration data with temperature data across the United States for the period 1980–2013. In a typical climate impact setting, the outcome of interest is (i) affected by temperature, (ii) something of value to the agent, and (iii) responsive to adaptive behavior that dampens the temperature effect. By definition, adaptation involves adjusting to or coping with climatic change with the goal of reducing vulnerability to its harmful effects.[5] In our setting, for agents to be adapting to rising temperatures in a way that changes atmospheric ozone levels, one needs all of the following: (i) agents must be worried about ozone's detrimental impacts, (ii) agents have some knowledge of the process of ozone formation such that they are aware not only of temperature's role but also the impact of an agent's emissions, and (iii) agents believe their actions can sufficiently alter ozone concentrations. There is evidence that on high ozone days, individuals may avoid outdoor exposure (e.g., Neidell, 2009) and buy medicines to remediate exposure (e.g., Deschenes et al., 2017). Also, they may drive less and use public transit in smog alert days (e.g., Cutter and Neidell, 2009). Indeed, the alerts educate the public on the impact of temperature and the agents' actions on ambient ozone levels. Hence, it not unreasonable to assume that our research setting satisfies the three conditions for adaptation enumerated above.

Our approach has two key features. The first is the decomposition of meteorological variables into "climate" and "weather". The second is identifying responses to weather shocks and longer-term climatic changes in the *same* estimating equation. As noted, the difference between those short- and long-run responses is what the literature refers to as adaptation.[6] Indeed, ozone, as with most climate-related outcomes of interest, responds to realized temperature — regardless of how that temperature may be decomposed into "weather" or "climate". It is only agents, by virtue of being able to adjust to long-run climate, that may affect the ozone response to climatic changes. In the absence of any adaptive behavior, the ozone response to equivalent changes in weather or climate would be the same.

For the first feature of our approach, the daily temperature variable is used to construct two variables. The first, $Temp^C$, is operationalized as a 30-year moving average of month-specific average temperatures (e.g., take the average of June daily

[3] The long differences approach is a special case of partitioning variation which leverages panel data variation in weather over a range of timescales (e.g., annual, decadal, and multi-decadal) to identify climate impacts, but does not estimate climate and weather effects jointly (e.g., Dell et al., 2012; Moore and Lobell, 2015; Burke and Emerick, 2016).

[4] One way to address this issue is to use experimental or quasi-experimental variation in those attributes in order to causally capture the extent to which they offset weather effects. One example is Garg et al. (2020), who leverage quasi-experimental variation in eligibility to a cash transfer program in Mexico to identify how income may mitigate the temperature-homicide relationship.

[5] The IPCC defines adaptation as "the process of adjustment to actual or expected climate and its effects in order to moderate harm or take advantage of beneficial opportunities", and further states that "[a]daptation plays a key role in reducing exposure and vulnerability to climate change. (…) In human systems, adaptation can be anticipatory or reactive, as well as incremental and/or transformational". IPCC (2022).

[6] Although we focus on adaptive behavior, we are agnostic about the true impacts. There may be adaptation or intensification effects (Dell et al., 2014).

temperatures for each year and location and then apply a 30-year moving average). This is what we interpret as "climate".[7] The second temperature variable, $Temp^W$, is daily temperature with $Temp^C$ subtracted, interpreted as "weather".

For the second feature of our approach, both variables enter in our estimating equation along with a set of location-by-season-by-year fixed effects, ϕ_{is} (e.g., Chicago-Spring 1990, Chicago-Summer 1990, etc.). Because we create the variable "weather" as a first step, the Frisch–Waugh–Lovell theorem guarantees we do not need to include granular time fixed effects to identify weather effects (Lovell, 1963, Theorem 4.1, p.1001).[8] On the other hand, the inclusion of ϕ_{is} allows us to leverage two sources of climatic variation to identify climate impacts. Conditional on location-by-season fixed effects, the first source of variation comes from adding the most recent year's monthly weather information and dropping the oldest portion from the 30-year moving average. The underlying idea is similar to filtering different frequencies of temperature, as has been done in the time series literature (e.g., Baxter and King, 1999; Christiano and Fitzgerald, 2003). In other words, we identify the agents' response to their new climate expectation. The second source of variation arises from demeaning $Temp^C$ from a location-specific season-by-year fixed effect.[9] Take, for example, days in April, May, and June in Chicago, all within the spring season of the same year. After demeaning from a spring fixed effect, the average April moving-average measure of climate will likely be a negative value and the average June climate a positive value.

Our methodology contributes to the estimation of climate damage functions and the costs of climate change (e.g., Auffhammer, 2018; Tol, 2018). Our unifying approach to uncover climate impacts and adaptation should be of interest to a broad set of applications due to its simplicity. Our novel application to the impact of climate change on ambient ozone adds an overlooked force behind determinants of ozone pollution (e.g., Salvo and Wang, 2017).

This paper proceeds as follows: Section 2 provides an overview of the previous methodological approaches used to identify climate impacts and proposes our unifying approach and the resulting measure of adaptation. Section 3 provides a conceptual framework of an agent's adaptation decision-making, describes our data, and presents our empirical strategy. Section 4 reports our main findings, examines the robustness of our estimates, generalizes our approach to nonlinear settings, and explores heterogeneity in adaptive responses. Finally, Section 5 concludes.

2. Prior methods and our unifying approach to measuring climate change impacts and adaptation

2.1. Prior methods

Prior literature on estimating climate impacts and adaptation has usually relied on two approaches. The first is the cross-sectional approach (e.g., Mendelsohn et al., 1994; Schlenker et al., 2005), which exploits permanent, anticipated components behind meteorological conditions, leveraging climate variation across locations to estimate climate impacts *inclusive* of adaptation, but may suffer from omitted variable bias. The other is the panel fixed-effects approach (e.g., Deschenes and Greenstone, 2007; Schlenker and Roberts, 2009), which deals with that bias but identifies the effect of transitory, unanticipated weather shocks, most likely *exclusive* of adaptation, making the transition to estimated climate effects nontrivial.[10] By using either the short- or long-run variation behind meteorological conditions to identifying climate impacts, those research designs trade off key assumptions. More recent literature (e.g., Dell et al., 2012, 2014) has proposed various hybrid approaches for combining these two strands of the literature, but face issues of their own (Kolstad and Moore, 2020).

The cross-sectional (CS) approach estimates the following equation:

$$y_i = \alpha + \beta_{CS} x_i + (\mu_i + \nu_i) = \alpha + \beta_{CS} x_i + e_i, \tag{1}$$

where y_i is an outcome variable measured at location i, and is affected by the climatological variable of interest, x_i – typically taken as temperature. μ_i represents the vector of all time-invariant unobserved covariates that may be correlated to x_i, while ν_i reflects the standard idiosyncratic error term. Thus, if μ_i is non-empty and $cov(x_i, \mu_i) \neq 0$, $\hat{\beta}_{CS}$ suffers from omitted variable bias (OVB).

The panel fixed-effects (FE) approach instead estimates the following equation:

$$y_{it} = \alpha + \beta_{FE} x_{it} + \mu_i + \lambda_t + \nu_{it}, \tag{2}$$

where the outcome variable, y_{it}, and climatic variable of interest, x_{it}, are now additionally measured at some recurring time interval t. By averaging each variable in Eq. (2) for each unit i over time, we obtain:

$$\bar{y}_i = \alpha + \beta_{FE} \bar{x}_i + \mu_i + \bar{\nu}_i, \tag{3}$$

[7] Climate normals are, by definition, 30-year averages of weather variables such as temperature (WMO, 2017). The *monthly* frequency for the moving averages in our empirical decomposition is without loss of generality. All we need is a time frame that economic agents can easily remember information from the past. Our robustness checks using *daily* moving averages provide nearly identical results.

[8] Intuitively, by decomposing observed temperature into its moving average "climate" component and daily "weather" component as the difference from this average, the Frisch–Waugh–Lovell theorem shows that the "weather" variable is already de-meaned as if we had included location-by-month-by-year fixed-effects in the final estimating equation.

[9] Note that we use "location" here in the general sense as the spatial unit of analysis. For example, in our empirical setting location is taken as an individual ozone monitor.

[10] Only in certain conditions does weather variation exactly identify the effects of climate (e.g., Hsiang, 2016; Lemoine, 2020).

where $\bar{y}_i \equiv 1/T \sum_{t=1}^{T} y_{it}$, and the other variables are defined similarly.[11] Subtracting Eq. (3) from Eq. (2), we highlight the source of variation in the identification of β_{FE}:

$$(y_{it} - \bar{y}_i) = \beta_{FE}(x_{it} - \bar{x}_i) + \lambda_t + (v_{it} - \bar{v}_i). \tag{4}$$

Because $(x_{it} - \bar{x}_i)$ is the deviation of observed temperature from its local long-run value, β_{FE} is clearly identified from temperature shocks. Thus, in this approach, although most OVB problems are resolved by the μ_i term, $\hat{\beta}_{FE}$ now identifies the impact of meteorological, rather than climatological, phenomena.

Recently, focus has expanded from simply estimating climate impacts to estimating adaptation to climate change. Some authors have noted that β_{CS} identifies climate impacts *inclusive* of any adaptation, while β_{FE}, by its nature, identifies meteorological impacts which can be taken as an approximation of climate impacts *exclusive* of any adaptation (e.g., Dell et al., 2012, 2014). Thus, they propose measuring adaptation as the difference between $\hat{\beta}_{FE}$ and $\hat{\beta}_{CS}$. Although this principle to recovering a measure of adaptation is accurate, the approach faces two empirical challenges. First, to the extent that OVB may impact $\hat{\beta}_{CS}$ in the cross-sectional model, this will translate directly into bias in the estimate of climate adaptation. Second, even if an unbiased estimate of β_{CS} could be obtained, $\hat{\beta}_{CS}$ and $\hat{\beta}_{FE}$ arise from two different estimating equations. While OLS, equation by equation, allows us to easily test hypotheses about the coefficients within an equation, it does not provide a convenient way for testing hypotheses involving coefficients from different equations. Thus, in practice, one must resort to seemingly unrelated regression (SUR) models to explicitly test whether the measure of adaptation is statistically distinguishable from zero.[12] Aside from SUR, it would be possible to statistically test the difference between coefficients recovered via the CS and FE models using re-sampling methods – i.e., block bootstrap or Bayesian bootstrap with random weights assigned at the block-level. However, while these methods may solve the hypothesis testing issue for inferring the significance of adaptation, they would not address the issue of potential bias in the underlying estimating equations, making it difficult to interpret the magnitude of adaptation.

2.2. Our unifying approach

Our unifying approach nests both of those strands of the climate-economy literature in the *same* estimating equation. It simultaneously identifies long-run climatological impacts and short-run effects of meteorological shocks, and thus allows for an explicitly testable measure of adaptation in the spirit of prior comparisons between short- and long-run effects (e.g., Dell et al., 2012, 2014). Specifically, we begin by posing the ideal estimating equation, although infeasible:

$$y_{it} = \alpha + \beta_W(x_{it} - \bar{x}_i) + \beta_C \bar{x}_i + \mu_i + \lambda_t + v_{it}. \tag{5}$$

If this infeasible equation were estimable, β_W – the effect of weather shocks – would exactly identify β_{FE} by the Frisch–Waugh–Lovell theorem. On the other hand, β_C – the effect of changes in climate – would identify β_{CS} minus *OVB* due to the inclusion of fixed effects. Unfortunately, β_C cannot be identified because $\bar{x}_i$ is perfectly collinear with μ_i.

Notice that emerging hybrid approaches have also relied on such "partitioning variation" (e.g., Kelly et al., 2005; Moore and Lobell, 2014; Merel and Gammans, 2021). They have attempted to address this collinearity issue by dropping the unit fixed-effect, μ_i, instead including a set of location controls, c_i, in their estimating equation, taking the general form of $y_{it} = f(x_{it} - \bar{x}_i) + g(\bar{x}_i) + c_i\gamma + \epsilon_{it}$, where $f(.)$ and $g(.)$ can take flexible functional forms. While this approach can include spatially-aggregate and time fixed-effects, identification would still ultimately rely on cross-sectional variation within the spatially-aggregate region, and thus may suffer from similar OVB concerns as the CS model.

We therefore propose the following feasible approximation of the ideal Equation (5), which allows for the inclusion of unit fixed-effects by letting the measure of climate vary across time within the sample[13]:

$$y_{it} = \alpha + \beta_W(x_{it} - \bar{x}_{i\bar{p}}) + \beta_C \bar{x}_{i\bar{p}} + \mu_i + \lambda_s + v_{it}. \tag{6}$$

As time can be aggregated into multiple subset levels – day, month, season, year, decade, etc. – we first define a time period, p, as a weakly larger aggregation of t. Agents, however, may observe and react to the slow evolution of climate. Thus, we define $\bar{p}$ to incorporate data from the same time period p in the past. Furthermore, agents may need time to adjust, so we additionally restrict $\bar{p}$ to exclude contemporaneous data. We also replace λ_t with λ_s – where s is a one-level higher aggregation in time than p – in order to retain relevant variation in $\bar{x}_{i\bar{p}}$.[14] Depending on the study context, μ_i and λ_s may be interacted to flexibly control for unit-level effects that may vary over time.

[11] Note that via the inclusion of the intercept, the λ_t and μ_i fixed effects are both relative to the same baseline, α, and thus the λ_t term drops out when averaging over time by the restriction that $\sum_t \lambda_t = 0$.

[12] As is well known, a SUR system is a generalization of a linear regression model that consists of several regression equations – each having its own dependent variable and potentially different sets of exogenous explanatory variables – that has cross-equation error correlation, that is, the error terms in the regression equations are correlated. Also recall that all equations in a SUR system are estimated jointly, but that such estimation usually requires feasible generalized least squares with a specific assumption on the form of the variance–covariance matrix regarding the structure of the correlation among the error terms. Hence, further structural assumptions are needed for statistical inference of the measure of adaptation.

[13] Observe that for simplicity, and to keep the comparison with the prior CS and FE strands of the literature as clear as possible, our unifying approach uses a linear specification, which should also capture the first-order effects of potentially nonlinear responses. Later, in Section 4.4, we show how this approach can be easily extended to include higher order nonlinear effects.

[14] Note that just as t, by convention, represents a specific time-step *of the sample*, e.g. day-of-the-sample, we take s as similarly representing a more aggregate time-step *of the sample*, e.g. season-of-the-sample.

Defined in this way, variation in $\bar{x}_{i\bar{p}}$ comes from two separate sources. First, although more aggregate than t, $\bar{p}$ still varies across time within the higher level time period s. Second, $\bar{p}$ is defined to include historical data, and thus "updates" its value from year to year. Following the same steps as with the fixed-effects model and averaging each variable in Eq. (6) for each cross-sectional unit i over time, we obtain:

$$\bar{y}_i = \alpha + \beta_W(\bar{x}_i - \bar{x}_i) + \beta_C\bar{x}_i + \mu_i + \bar{v}_i = \alpha + \beta_C\bar{x}_i + \mu_i + \bar{v}_i, \tag{7}$$

where, once again, $\bar{y}_i \equiv 1/T\sum_{t=1}^{T} y_{it}$, and the other variables are defined similarly.[15] Subtracting Eq. (7) from Eq. (6), we highlight the source of variation that allows for the identification of both β_W and β_C:

$$(y_{it} - \bar{y}_i) = \beta_W(x_{it} - \bar{x}_{i\bar{p}}) + \beta_C(\bar{x}_{i\bar{p}} - \bar{x}_i) + \lambda_s + (v_{it} - \bar{v}_i). \tag{8}$$

In Eq. (8) we can observe that $\hat{\beta}_W$ is identified from temperature shocks, therefore approximately equivalent to $\hat{\beta}_{FE}$, whereas $\hat{\beta}_C$ is identified from climatic changes, approximately equivalent to $\hat{\beta}_{CS}$, though now critically free from a number of OVB concerns. We thus naturally define adaptation as the difference $\hat{\beta}_W - \hat{\beta}_C$. Because both coefficients of interest are estimated in a single equation, statistical inference on the measure of adaptation is straightforward. Furthermore, observe that while our method does require the researcher to take a stance on the temporal granularity of the climate variable, $\bar{x}_{i\bar{p}}$, and time fixed-effects, λ_s, the recovered measure of adaptation leverages the behavioral responses of the *same* economic agents to both weather shocks and climatic changes via the inclusion of unit fixed effects, μ_i.

2.3. Decomposition of meteorological variables: Climate norms vs. Weather shocks

As mentioned above and seen in Eq. (6), implementing our approach requires that we first decompose x_{it} into its long-run component, $\bar{x}_{i\bar{p}}$, and its short-run deviation from this value, $(x_{it} - \bar{x}_{i\bar{p}})$. Econometrically, from the Frisch–Waugh–Lovell theorem, we can decompose x_{it} into its longer term seasonal component and a contemporaneous de-seasonalized component. For example, as weather varies day-to-day, t, and local climate varies both seasonally (e.g., month-to-month within a year) and over time (e.g., year-to-year), we could take "month-of-the-sample", my, as representing the seasonal component and pose the following first-stage regression:

$$x_{it} = \gamma_{imy} + \epsilon_{it}, \tag{9}$$

such that temperature in location i on day t (of month m in year y) is regressed on a set of location-by-month-by-year fixed effects. In this case, the matrix of coefficients $\hat{\gamma}_{imy}$ would constitute the matrix of monthly average temperature values $\bar{x}_{imy}$, while the estimated residuals $(x_{it} - \bar{x}_{imy})$ $(\equiv \hat{\epsilon}_{it})$ would reflect the de-seasonalized daily local deviations of temperature. Because this regression simply de-means x_{it} over the my period in the time-series dimension for each individual location i, we could instead recover the $x_{it} - \bar{x}_{imy}$ values in Eq. (9) arithmetically via the following:

$$\underbrace{Temp}_{x_{it}} = \underbrace{Temp^C}_{\bar{x}_{imy}} + \underbrace{Temp^W}_{(x_{it}-\bar{x}_{imy})}, \tag{10}$$

such that $Temp^C$ $(\equiv \bar{x}_{imy})$ represents climate patterns, and $Temp^W$ $(\equiv x_{it} - \bar{x}_{imy})$ deviations from those longer-run patterns. Notice that although the above example uses daily temperatures, de-seasonalized at the monthly level, the choice of timing can be selected to match the study context. To use the example of agriculture, a common focus in the climate literature, it may be that a year, or the growing seasons within a year, would be better suited to the analysis than the months of the year example illustrated in Eqs. (9) and (10).

Economically, however, this presents a potential problem. As mentioned in the previous section, agents may need time to adapt, and prior information sets likely inform agents' beliefs. Thus, $\bar{x}_{imy}$ is not strictly equivalent to $\bar{x}_{i\bar{p}}$ as defined in Eq. (6). To address this, we propose, as a first step, replacing $\bar{x}_{imy}$ with a lagged function of its historical values:

$$\bar{x}_{i\bar{p}} \equiv \frac{1}{J}\sum_{j=1}^{J<y} \omega_j \bar{x}_{imj} \approx \bar{x}_{imy}, \tag{11}$$

where ω_j represents a scalar weighting of $\bar{x}_{imj}$, such that the function defining $\bar{x}_{i\bar{p}}$ can be generalized to fit various contexts.[16] Returning to the agriculture example, it is possible that farmers need more than a single year to adjust production processes or change crop choice, in which case the $(\omega_{y-k}, \dots, \omega_{y-1})$ weighting scalars of Eq. (11) could all simply be set to zero, with $k > 1$. Furthermore, the functional form of Eq. (11) itself can be chosen to best suit the application by changing the specific values of ω_j. Myopic and Bounded agents may simply assume that contemporaneous monthly temperature will be equal to what it was in the

[15] Note that in Eq. (7) the $\bar{x}_i$ derived from the $\bar{x}_{i\bar{p}}$ term would rely on a longer time-series of information than the $\bar{x}_i$ derived from the x_{it} term. Still, they are approximately equivalent, with correlation between these two terms above 0.95 in our empirical application.

[16] These weights, ω_j, can be defined by values derived from other literatures, such as climatology, which defines a climate normal as the average temperature over the last 30 years: "*The 30 year interval was selected by international agreement, based on the recommendations of the International Meteorological Conference in Warsaw in 1933. The 30 year interval is sufficiently long to filter out many of the short-term interannual fluctuations and anomalies, but sufficiently short so as to be used to reflect longer term climatic trends*" (Climatology Office, 2003). Alternative filtering techniques could also be implemented (e.g., Baxter and King, 1999; Christiano and Fitzgerald, 2003), and would implicitly follow from this expression by varying the values of ω_j.

previous year, that is, ω_j simply evaluates to zero for all $j \in \{1, \ldots, y-2\}$. Other agents may flexibly fit values of ω_j to the historical data in an attempt to predict $\bar{x}_{i\bar{p}}$ through statistical means. A similar idea has been used in macroeconomics to measure business cycles,[17] and in the literature of intergenerational mobility following Solon's (1992) seminal work.[18] Note that $\bar{x}_{i\bar{p}}$ can be calculated from a longer time-series of x to take into account historical information beyond the sample period of the outcome variable.

We then return to Eq. (10), substituting $\bar{x}_{i\bar{p}}$ for $\bar{x}_{imy}$ in representing $Temp^C$, and recovering $x_{it} - \bar{x}_{i\bar{p}}$ ($\approx x_{it} - \bar{x}_{imy}$) for $Temp^W$, giving us all the components necessary for estimating Eq. (6).[19] Notice that by the properties of the Frisch–Waugh–Lovell theorem (specifically, point 4 of Lovell (1963, Theorem 4.1, p.1001)) it is unnecessary to de-seasonalize the outcome variable y_{it} in the same way as $(x_{it} - \bar{x}_{i\bar{p}})$, which allows us to estimate both effects of interest in the same equation.[20]

This decomposition highlights the two sources of variation that have been used in the climate-economy literature. $Temp^C$ and $Temp^W$ in the decomposition above are associated with different sets of information. On the one hand, $Temp^C$ includes climate patterns that economic agents can only gather by experiencing weather realizations over a long period of time, and can be thought of as the "climate normal" temperature. On the other hand, $Temp^W$ represents weather shocks, which by definition are revealed to economic agents virtually at the time of the weather realization. Usually one adjusts to something they happen to know by experience. Therefore, adaptation can be measured as the difference between responses to changes in $Temp^C$ relative to effects of weather shocks $Temp^W$. This is analogous to Lucas' powerful insight that economic agents respond differently depending on the set of information that is available to them. Lucas (1977), for instance, provides an example of a producer that makes no changes in production or works less hard when facing a *permanent* increase in the output price, but works harder when the price increase is *transitory*.[21]

It is also important to emphasize that this decomposition does not make any assumption on how individuals and firms process and use the information from the past. Rational agents would respond optimally to all information at hand when deciding the degree of adaptation, while myopic and inattentive agents (e.g., Gabaix and Laibson, 2006; Reis, 2006), on the other hand, may find it costly to absorb and process all the information at all times, and may respond only to partial information or only sporadically. Our measure of adaptation is agnostic to either type of behavior; the goal of our approach is to empirically assess the economic and statistical significance of adaptation, regardless of how economic agents make decisions on whether to adapt, or the extent of adaptation.

Finally, notice that this decomposition represents a first-order Taylor approximation of a potentially nonlinear relationship between climate and realized temperature. Two types of variation are often associated with a changing climate: changes in averages, and changes in the frequency of extreme weather events (IPCC, 2022). For simplicity, and to keep the comparison with prior approaches as clear as possible, our temperature decomposition focuses on increases in averages, not on variability. In fact, in the following section we show that our weather data, comprised of the comprehensive set of national weather monitors, suggests a gradual increase in average temperature, but that the magnitude of temperature shocks, defined as deviations from the 30-year moving averages, are relatively stable over time, and narrowly bounded. Therefore, in our approach, dispersion shows up only implicitly in the sense that long-run norms take into account the frequency and intensity of daily temperature extremes.

3. Empirical application: Climate impacts on ambient ozone

We apply our unifying approach to measure climate impacts on ambient ozone concentration, and adaptation to climate change in this context, and examine the heterogeneity in adaptive behavior. This application is ideal for three reasons. First, ozone is not emitted directly into the air, but rather rapidly formed by Leontief-like chemical reactions between nitrogen oxides (NOx) and volatile organic compounds (VOCs) in the presence of sunlight and warm temperatures.[22] Hence, meteorological conditions do matter in determining surface ozone levels, and climate change may increase ozone concentration in the near future (e.g., Jacob and Winner, 2009). Furthermore, ozone is rapidly destroyed during the night; thus, correlation between ambient concentrations across two consecutive days is limited. Second, nationwide high-frequency data on ambient ozone and meteorological conditions are publicly available for a long period of time in the United States: we use daily measurements for the typical ozone season from 1980–2013.[23] Third, this is a highly policy-relevant issue. The so-called "climate penalty" on ozone means that climate change might deteriorate air quality in the near future, with important implications for public health and labor productivity.[24]

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[17] See, for example, Baxter and King (1999), Christiano and Fitzgerald (2003) and Hsiang (2016).

[18] In Solon's context, observed income is noisy: it includes a permanent and a transitory component. To establish a relationship between permanent income of sons and fathers, Solon proposes averaging fathers' income for a number of years to reduce the errors-in-variables bias.

[19] In our preferred decomposition detailed in the following section, $Cor(\bar{x}_{i\bar{p}}, \bar{x}_{imy}) > 0.95$ and $Cor((x_{it} - \bar{x}_{i\bar{p}}), (x_{it} - \bar{x}_{imy})) > 0.90$.

[20] "*Theorem 4.1: Consider the following alternative regression equations, where the subscript α indicates that the data have been adjusted by the least squares procedure with D as the matrix of explanatory variables: 1.* $Y = Xb_1 + D_{\alpha 1} + e_1$ *2.* $Y_\alpha = X_\alpha b_2 + e_2$ *3.* $Y = Xb_3 + e_3$ *4.* $Y = X_\alpha b_4 + e_4$*... The identity* $b_2 = b_4$ *reveals that it is immaterial whether the dependent variable is adjusted or not, provided the explanatory variables have been seasonally corrected*" (Lovell, 1963).

[21] Notably, in our context the behavior would be reversed. Due to the contemporaneous nature of *transitory* weather shocks, little to no change in production is possible, while the producer would be able to change behavior in response to *permanent* changes in climate.

[22] See Appendix A.1 for further details.

[23] The ozone season varies by state and usually consists of only six months (typically April–September), but concerns are mounting that longer spring and fall would expand the ozone season in some states (e.g., Zhang and Wang, 2016).

[24] Exposure to ambient ozone has been causally linked to asthma hospitalization, pharmaceutical expenditures, mortality, and labor productivity (e.g., Neidell, 2009; Moretti and Neidell, 2011; Graff Zivin and Neidell, 2012; Deschenes et al., 2017).

3.1. Conceptual framework

In the context of ozone, economic agents could be polluting firms, households engaging in consumption that produces precursor pollutants, or local regulators concerned with pollution and public health. For example, households may respond to an ozone alert day by mowing their lawns or refueling their cars earlier or later in the day – or on a different day altogether – to avoid VOC emissions, taking public transit, carpooling, or working from home to reduce emissions altogether, or purchasing hybrid or electric vehicles to reduce local emissions. On the other hand, firms may (i) reshuffle their production activities within the day to avoid VOC emissions in peak hours, such as painting in construction sites, or even between different months, increasing emissions during colder months in order to reduce emissions during hotter months; (ii) install pollution abatement technologies, or otherwise change their production function, for instance by electrifying emissions-intensive production processes such as switching from oil or gas furnaces to electric. Additionally, local regulators may provide ground-level ozone information to at-risk populations to avoid intense ozone exposure on hot days, e.g., by issuing an ozone alert when a heat wave is forecasted, and coordinating local actions with households and firms to reduce permanently or shift emissions-intensive activities within the day or across days, weeks, or months. Importantly, these agents could be reacting to either the realized or anticipated outcome of climate change, and could be undertaking small or large actions — adjusting behaviors within a day might be a small action that adds up across many agents, for example, while the switch to alternative commuting or production methods may be more transformational.[25]

For simplicity of exposition, consider the case of a polluting firm. The agent minimizes cost by selecting the optimal production schedule for the given input costs, climate, and other local factors faced by the agent. But, ambient ozone itself can impose an additional shadow price on the agent's chosen production schedule, implied by, e.g., public or regulatory pressures. Specifically, for the agent engaging in dirty production, the emission of ozone precursor pollutants (VOCs and NOx) are *de facto* "inputs" into the agent's production schedule.[26] Any shadow price on ozone faced by the agent would thus translate into an implicit shadow price on the emission of either of these precursors as inputs in their production process, conditional on local climate and atmospheric composition.[27] Ceteris paribus, the agent would thus minimize costs taking into account the implicit shadow prices on these precursors.[28] In practice, the optimizing decisions are often over changes in input mix or timing of production (Henderson, 1996). In other words, the agent is implicitly considering ozone levels whenever they choose the cost-minimizing inputs for production of goods and services.[29]

To better understand why agents may adapt to climatic changes in ways that reduce ambient ozone, compare the ozone context to a standard agricultural setting. As has been shown in that context (e.g., Mendelsohn et al., 1994; Schlenker et al., 2005; Deschenes and Greenstone, 2007; Schlenker and Roberts, 2009), the agent maximizes profit by optimizing over their choice of crop and other inputs such as irrigation, conditional on anticipated or realized climate, controlling for other local factors such as soil quality. Restated, the agent minimizes cost by selecting the optimal production schedule for the given set of input costs, climate, and other local factors faced by the agent.

Fig. 1 illustrates this "cost-minimizing" optimization decision agents face with respect to ozone and its precursors, depicting the envelope of minimum-cost production schedules, conditional on realized climate, in the spirit of Deschenes and Greenstone (2007). Cost of production is on the left y-axis, associated ozone concentration is on the right y-axis, and temperature is on the x-axis.[30] For simplicity in illustration, we assume that factors such as precipitation and other exogenous determinants have been adjusted for. The production schedule 1 and 2 cost functions reveal the relationship between cost and temperature, as well as ozone and temperature, when these production schedules are chosen. It is evident that schedule specific costs, and associated ozone concentrations, vary with temperature. Further, the cost-minimizing production schedule varies with temperature. For example, production schedule 1 minimizes cost between T_1 and T_2; the agent would be indifferent between the two at T_2 where the cost functions cross (i.e., point B); and production schedule 2 minimizes cost between T_2 and T_3. The long-run equilibrium is denoted by the dashed gray line and represents the long-run optimum when the agent can freely adjust their production schedule in response to changes in temperature.

Consider first an agent that is initially faced with a climate normal temperature of T_1. Their optimal choice would thus be to minimize cost under production schedule 1, at point A. Now consider two alternative scenarios: one in which the agent is faced with a transitory temperature shock of T_3, and a second in which the agent is faced with a permanent change to a new climate

[25] Observe that some local regulators are making a direct case for reducing precursor pollutants to control climate change driven increases in ozone (e.g., Baaqmd, 2017), and that the EPA also acknowledges the role of climate change in worsening ozone concentrations, stating that "[i]n addition to being affected by changing emissions, future O3 concentrations may also be affected by climate change" (USEPA, 2015).

[26] That is, they are emitted in proportion to the choice, and quantity used, of actual production inputs.

[27] Naturally, there may also be regulatory pressures for the precursors themselves, therefore explicitly defining (shadow) prices for them as well (Auffhammer and Kellogg, 2011; Deschenes et al., 2017). In the robustness checks, however, we provide evidence that these regulations do not seem to play an important role in agents' adaptation measures regarding climatic changes. This is not surprising, given that it is ozone formation, not the precursors, that primarily depends on climate.

[28] Unlike in the agriculture setting, a common focus of prior studies, where markets exist for most inputs, in our context markets for ozone precursors (*de facto* inputs in production) existed only in some areas and in specific periods of time. Notwithstanding, the implicit shadow prices – reflecting social valuation of ambient ozone reductions – may provide incentives for producers similar to those provided by market prices.

[29] Of course there are other factors that may affect ambient ozone concentrations, climate being the obvious one, but precursor emissions are the only source that is controllable by the agent. While this could lead to measurement error in the direct relationship between agents' decisions and ozone concentration, ozone – in this context – is the outcome variable, and any measurement error in ozone would simply be absorbed by the error term in a reduced form model.

[30] Notice that from the cost minimization problem, we observe a derived demand function for VOCs and NOx, conditional on the agent's chosen level of output. In turn, that demand for precursors maps into resultant ambient ozone levels, conditional on the temperature.

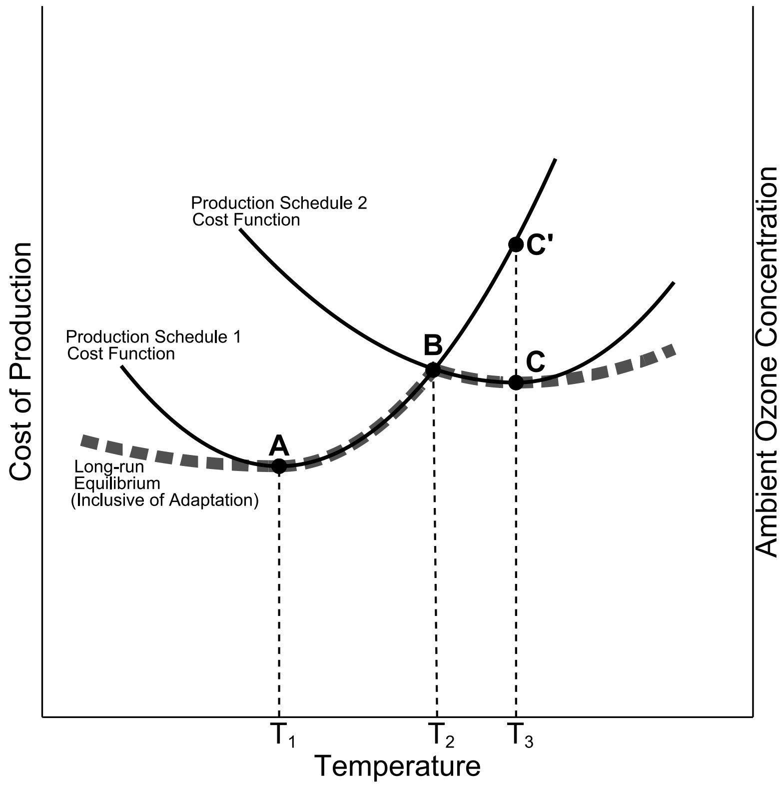

Fig. 1. Theoretical relationship between marginal cost of dirty production and temperature. *Notes*: This figure illustrates a stylized example of how changes in temperature could affect the cost of production through the shadow price on ozone, and thus the implicit shadow prices on VOCs or NOx that are emitted under the chosen production schedule. The profit-maximizing firm minimizes cost — the amounts inputs used in production multiplied by their respective prices, as well as the quantity of VOCs and NOx produced under the chosen production schedule multiplied by the shadow prices of these ozone precursor pollutants implied by the local shadow price on ozone and conditions of the local atmosphere. While in many cases firms may not face an observable market price for their emissions of VOCs or NOx, they may face a shadow price for doing so based on, for example, public or regulatory pressures. As depicted, at a temperature of T_1, production schedule one dominates schedule two, and the firm minimizes cost at point A, with associated daily maximum ozone concentration. At a temperature of T_2 the firm is indifferent between either production schedule one or two at point B. At a temperature of T_3, however, production schedule two now dominates schedule one, and the firm minimizes cost at point C. A firm may not, however, be capable of adjusting their production schedule on a day-to-day basis. Thus, a firm facing a *climate normal* temperature of T_1 may opt to produce at point A, but end up producing at point C', and a much higher ozone concentration, when faced with a *temperature shock* of T_3. A firm that experiences many such shocks would thus update their beliefs about the underlying climate norm and shift their production schedule towards schedule two.

normal temperature of T_3. Under the first scenario, the agent would be unable, or unwilling,[31] to adapt to the temperature shock and would temporarily produce at point C', with higher associated ozone concentration and higher cost of production. Under the second scenario, the agent would adjust to this permanent change in the climate normal temperature and change to production schedule 2, now producing at point C rather than C'. Notice, however, that while point C is lower cost than point C', it still implies a higher cost of production and associated ozone concentration than point A. This is to be expected. Adaptation is typically not costless (e.g., Kelly et al., 2005; Carleton et al., 2022) – as production schedule 1 was cost-minimizing under the original climate norm of T_1, this implies that schedule 2 must be (weakly) more costly to implement in the absence of any climatic changes.

Finally, notice that our unifying approach estimates *simultaneously* both of these reduced form relationships between ambient ozone concentration and temperature, accounting for agents' differential responses to temperature shocks versus changes in the climate norm. The recovered estimate for temperature shocks – β_W in Eq. (6) – reflects the difference between the ozone concentrations associated with points C' and A, while the recovered estimate for changes in the climate norm – β_C in Eq. (6) – reflects the difference between points C and A, and thus adaptation can be clearly taken as the difference between C' and C.

[31] From a purely mechanical standpoint, the agent may be technologically unable to adjust their production schedule on such short notice – i.e., daily. From an economic standpoint, even if such adjustments were technologically feasible, they may not be economically sound, as such adjustments would likely incur greater costs than could be saved by avoiding the additional cost associated with transitory sub-optimal production.

3.2. Data

Weather Data — For meteorological data, we use daily measurements of maximum temperature as well as total precipitation from the National Oceanic and Atmospheric Administration's Global Historical Climatology Network database (NOAA, 2014). This dataset provides detailed weather measurements at over 20,000 weather stations across the country for the period 1950–2013. Figure A1, in Appendix A, presents the yearly temperature fluctuations and overall climate trend in the US as measured by these weather stations, relative to a 1950–1979 baseline average temperature, while Figure A2 illustrates the geographical location of the complete sample of weather stations from 1950–2013. Fig. 2, by comparison, depicts the variation and trend of our decomposed temperature variables, $Temp^C$ and $Temp^W$, between 1980 and 2013 for the comprehensive set of national weather stations, indicating that while average temperature has been gradually increasing, temperature variability has remained relatively stable.[32] These weather stations are typically not located adjacent to the ozone monitors. Hence, we develop an algorithm to obtain a weather observation at each ozone monitor in our sample.[33] Our preferred matching algorithm uses information from the two closest weather stations within 30 km of each ozone monitor, as these stations are likely to better reflect the local environment than stations that are further away. The final sample under this matching algorithm includes 97.25% of all daily ozone observations (97.91% of all ozone monitors). However, we also expand the matching algorithm to include the closest five weather stations within 80 km, for a final sample that includes over 99.99% of all daily ozone observations (100% of all ozone monitors). Table A1, in Appendix A, reports the summary statistics for daily temperature and our decomposed variables, for each year in our sample from 1980–2013.

Ozone Data — For ground-level ozone concentrations, we use daily readings from the nationwide network of the EPA's air quality monitoring stations. In our preferred specification we use an unbalanced panel of ozone monitors.[34] Appendix A Figure A5 illustrates the evolution of ambient ozone concentrations over our sample period for both the full unbalanced panel of monitors, as well as a smaller balanced panel. Figure A6 depicts the evolution of our sample of ozone monitors over the three decades in our data, and illustrates the expansion of the network over time. Table A2 describes some features of the sample of ozone monitors used in our analysis, for every year between 1980 and 2013.

Consolidating information from the above sources, we reach our final unbalanced sample of ozone monitors over the period 1980–2013.[35] Figure A7 illustrates the proximity of our final sample of ozone monitors to the matched weather stations.

We carry out the analysis focusing on the effect of daily maximum temperature on daily maximum ozone concentration since 1980. We choose this relationship because increases in temperature are expected to be the principal factor driving increases in ambient ozone concentrations (Jacob and Winner, 2009). Indeed, data on ozone and temperature from our sample, plotted in Appendix A Figure A8, highlights the close correlation between these two variables. Interestingly, we see that not only does contemporaneous temperature have an effect on ambient ozone, but the long-term climate normal temperature also seems to be affecting it, although perhaps to a lesser extent. We leverage both relationships in the empirical framework we now describe.

3.3. Empirical strategy

Decomposition of Meteorological Variables: An Empirical Counterpart — Focusing on temperature ($Temp$), our primary variable of interest, we express it around ozone monitor i in day t of month m and year y, and decompose it into $Temp^C$ ($\equiv \bar{x}_{i\bar{p}}$) and $Temp^W$ ($\equiv x_{it} - \bar{x}_{i\bar{p}}$) as in Section 2. For our application, we define:

$$\bar{x}_{i\bar{p}} = \frac{1}{30} \sum_{j=y-30}^{y-1} \bar{x}_{imj}, \tag{12}$$

Implicitly defining ω_j as equal one for all $j \in \{y-30, \dots, y-1\}$ – where y denotes the contemporaneous year – and zero otherwise, such that $Temp^C$ ($\equiv \bar{x}_{i\bar{p}}$) is equal to the 30-year monthly moving average (MA) of past temperatures.[36]

We choose a one-year lag to make this variable part of the information set held by economic agents at the time that the outcome of interest is measured. At the same time, we average temperature over 30 years because it is how climatologists usually define climate normals, and because we wanted individuals and firms to be able to observe climate patterns for a long period of time, enough to potentially make adjustments.[37] For example, the 30-year MA associated with May 1982 is the average of May temperatures for all years in the period 1952–1981. Therefore, economic agents should have had at least one year to respond to unexpected changes in climate normals at the time ambient ozone is measured. We use monthly MAs, rather than daily or seasonal, because it is likely that

[32] Figures A3 and A4 in Appendix A present similar patterns using a semi-balanced sample of weather stations, and our final sample of weather stations once matched to ozone monitors.

[33] We detail the steps taken in Appendix A.2 as well as conduct robustness checks on the sensitivity of our results to changes in the algorithm in Appendix B.1.

[34] We discuss the reasoning for this approach as well as our results using a balanced panel in Appendix B.1.

[35] For further details regarding the construction of the final dataset for our analysis, see Appendix A.2.

[36] Our decomposition of meteorological variables into a 30-year moving average (norms) and deviations from it (shocks), as discussed in Section 2, is a data filtering technique to separate the "signal" from the "noise". This should not be confused with (a special case of) an autoregressive integrated *moving average* (ARIMA) model of climate change.

[37] It is possible, however, that agents form beliefs regarding expected climate over much shorter and more recent time windows (e.g., Kaufmann et al., 2017), or that organizational inertia slows the rate at which firms adapt to a changing climate. In our robustness checks we provide similar estimates using 3-, 5-, 10-, and 20-year moving averages, as well as longer lag lengths between the contemporaneous weather shock and the defined climate normal.

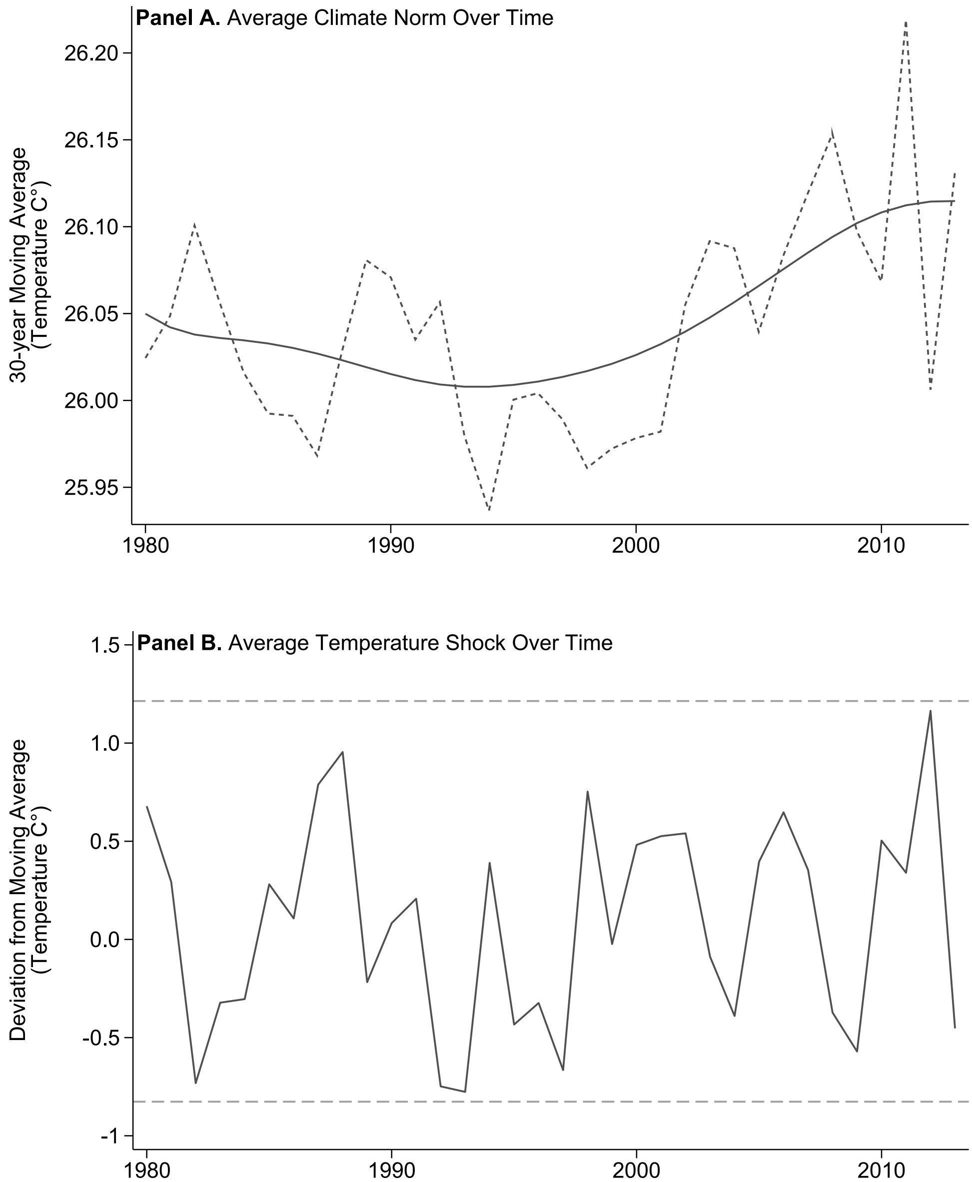

Fig. 2. Climate norms and shocks. *Notes*: This figure depicts US temperature over the years in our sample (1980–2013), decomposed into their climate norm and temperature shock components. The climate norm (Panel A) and temperature shocks (Panel B) are constructed from a complete, unbalanced panel of weather stations across the US from 1950 to 2013, restricting the months over which measurements were gathered to specifically match the ozone season of April–September, the typical ozone season in the US (see Appendix A Table A3 for a complete list of ozone seasons by state). Recall that the climate norm represents the 30-year monthly moving average of the maximum temperature, lagged by one year, while the temperature shock represents the difference between this value and the contemporaneous maximum temperature. The solid line in Panel A smooths out the annual averages of the 30-year moving averages, and the horizontal dashed lines in Panel B highlights that temperature shocks are bounded in our period of analysis. Appendix A Figure A3 depicts these same norms and shocks when restricting the dataset to include only a semi-balanced panel of weather stations, while Appendix A Figure A4 depicts these when the dataset is restricted to only those weather stations that are matched to an ambient ozone monitor for our main estimation sample.

individuals recall climate patterns by month, not by day of the year. Indeed, meteorologists on TV and social media often talk about how a month has been the coldest or warmest in the past 10, 20, or 30 years, but not how a particular day of the year has deviated from the norm for that specific day.[38] Taking this approach, $Temp^W$ represents weather shocks and is defined as the deviation of the daily temperature from the lagged 30-year monthly MA.

[38] There may be a concern that because temperature can have a within-month trend, defining temperature as a monthly average (climate norm) with daily (weather) shocks could mechanically lead to a stronger relationship between ozone and weather than between ozone and climate. As another robustness check,

By definition, these shocks are revealed to economic agents only at the time ambient ozone is being measured. Thus, in this case agents may have had only a few hours to adjust, limiting their ability to respond to unexpected temperatures.[39] Fig. 3 provides an illustrative example of our preferred decomposition in Panel A, compared to a traditional fixed-effects decomposition in Panel B, using data for Los Angeles in 2013.[40]

Econometric Model — Given the decomposition of meteorological variables into two sources of variation, our parsimonious econometric specification to estimate the impact of temperature on ambient ozone is the following:

$$Ozone_{it} = \beta_W Temp^W_{it} + \beta_C Temp^C_{i\bar{p}} + X'_{it}\delta + \phi_{is} + \epsilon_{it}, \tag{13}$$

where i represents an ozone monitor, t stands for day, and s for *season-of-the-sample* (Spring or Summer, in each year). As mentioned in the prior section, our analysis focuses on the most common ozone season in the U.S. – April to September – in the period 1980–2013.[41] The dependent variable $Ozone$ captures daily maximum ambient ozone concentration. $Temp$'s represent the two components of the decomposition proposed for meteorological variables.[42] The matrix of additional control covariates X_{it} contains a similar decomposition of precipitation.[43] Finally, we replace the monitor fixed effects, μ_i, and time fixed effects, λ_s, from the generalized model presented in Eq. (6) with ϕ_{is} – fixed effects for monitor-by-season-by-year, and include ϵ_{it}, an idiosyncratic term.[44] From a theoretical standpoint this change is not necessary — and in fact the empirical results are qualitatively similar in our context when implemented using μ_i and λ_s as separate fixed effects. We nevertheless combine them to more flexibly control for local factors that may have changed across seasons and years, allowing us to more closely approximate the ideal experiment.[45]

Analogous to Isen et al. (2017), notice that by including fixed effects for monitor-by-season-by-year, it is as if we regressed our main specification monitor by monitor, individually, for each season of the sample, and then took the weighted average of all recovered coefficients. Conceptually, consider the following thought experiment that we observe in our data many thousands of times for both daily temperature shocks and monthly climate norms: Take two days (months) in the same location, same season, and same year. Now, suppose that one of the days (months) experiences a larger temperature shock (hotter climate norm) than the other. Our estimation strategy quantifies the extent to which this difference in temperature shock (climate norm) affected the ozone concentration observed on that day (month). Therefore, this approach controls for a number of potential time-invariant and time-varying confounding factors that one may be concerned with, such as the composition of the local atmosphere, regulatory burden, and technological progress.

Measuring Adaptation — Once we credibly estimate the impact of the two components of temperature – daily shocks and within-season changes in climate normals – on ambient ozone concentration, we uncover our measure of adaptation. The average adaptation across all monitored locations in our sample is the difference between the coefficients $\hat{\beta}_W$ and $\hat{\beta}_C$ estimated in Eq. (13). If economic agents engaged in full adaptive behavior, $\hat{\beta}_C$ would be zero, and the magnitude of the average adaptation would be equal to the size of the weather shock effect on ambient ozone concentration.[46] As previously discussed, agents would react to "permanent" increases in temperature by reducing ozone precursor emissions to offset potential increases in ozone concentration.

In our preferred econometric specification, behavioral responses are allowed to occur only in the year after the change in temperature norm is observed. Those adjustments, however, might be related to innovations in temperature happening both in the previous year and 30 years before. Indeed, the "moving" feature of the 30-year MA is, by definition, associated with the removal of the earliest observation included in the average – 31 years before, and the inclusion of the most recent observation – one year before. Nevertheless, in the robustness checks we consider cases where economic agents can take a decade or two to adjust.

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we redefine $\bar{x}_{i\bar{p}}$ in Eq. (12) to the special case in which $p = t$, using *daily* instead of *monthly* moving averages, discussed further in the following subsection. Economic agents, however, may still associate a day with its corresponding month when making adjustment decisions.

[39] Because precise weather forecasts are made available only a few hours before its realization, economic agents may have limited time to adjust prior to the ozone measurement. This might be true even during Ozone Action Days (OAD). An OAD is declared when weather conditions are likely to combine with pollution emissions to form high levels of ozone near the ground that may cause harmful health effects. Individuals and firms are urged to take action to reduce emissions of ozone-causing pollutants, but usually only a day in advance or in the same day. Unlike what happens in a few developing countries, however, neither production nor driving is forced to stop in those days, limiting the impact of short-run adjustments. In the robustness checks, we find no evidence of any additional adaptation occurring due to OAD announcements. That is, short-run adjustments, if any, do not seem large enough to be comparable to what happens in the long run.

[40] Figure A9, in Appendix A, illustrates this same concept but over the entire 34-year sample period.

[41] Table A3 in Appendix A lists the official ozone season by state.

[42] We further explore the nonlinear effects of temperature on ozone in Section 4.4, providing two alternative approaches for extending the linear model to allow for nonlinearities in the response function of ozone to weather shocks and climate norms.

[43] Although Dawson et al. (2007) find it to be less important than temperature, Jacob and Winner (2009) point out that higher water vapor in the future climate may decrease ground-level ozone concentration. Our estimates are in line with those authors' assessment, and are available upon request.

[44] Appendix C details how both sources of monitor-level variation in $\bar{x}_{i\bar{p}}$, within-season and across-year, are still leveraged within this monitor-by-season-by-year fixed-effects structure.

[45] One may be concerned that we do not include fixed effects for "predictable" within-season variation such as the "ozone weekend effect". As a robustness check we re-estimated Eq. (13) after further extending our monitor-by-season-by-year fixed effects, ϕ_{is}, to monitor-by-season-by-year-by-weekday/end. Our results were quantitatively unchanged to the third decimal digit.

[46] This outcome is unlikely because, as noted previously, adaptation is typically not costless and thus the costs of engaging in 'full adaptive behavior' likely outweigh the benefits (Kelly et al., 2005; Carleton et al., 2022).

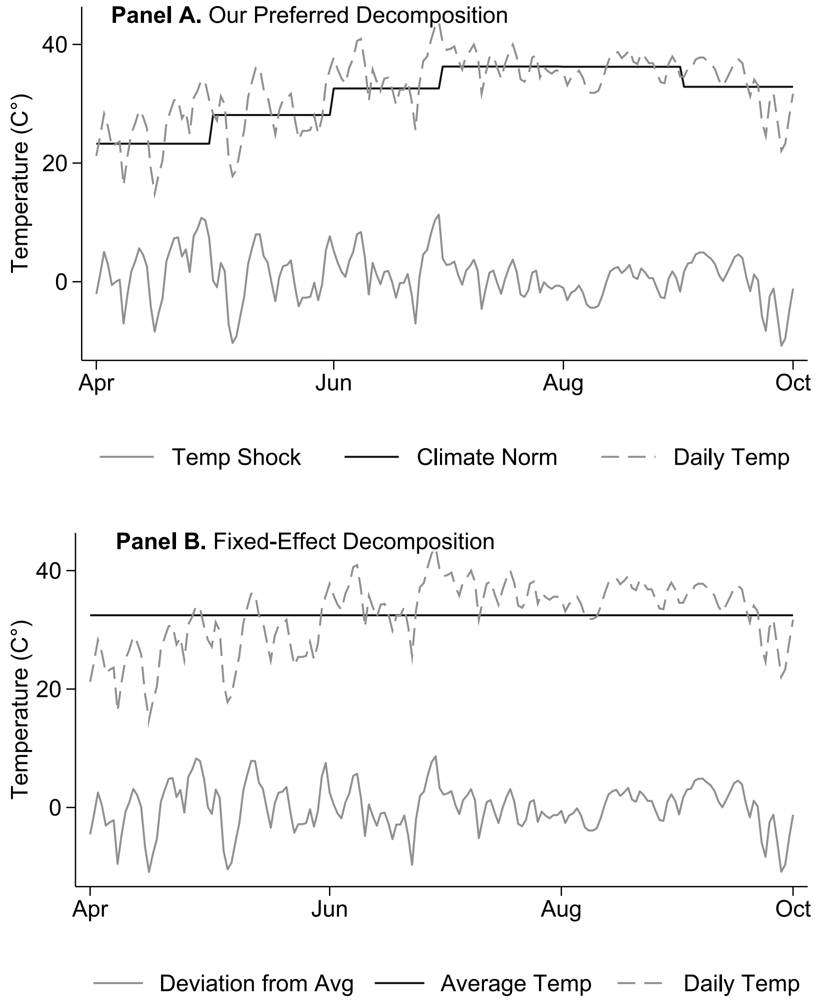

Fig. 3. Decomposition of temperature norms & shocks – Illustration (Los Angeles, 2013). *Notes*: This figure compares our preferred temperature decomposition method with a standard fixed-effects approach using data from the 2013 Los Angeles ozone season, illustrating the benefit of our unifying approach as outlined in Eq. (6) relative to the standard fixed-effects approach outlined in Eq. (2). Specifically, Panel A depicts the daily measure of temperature, as well as its decomposition into climate norm and temperature shock. By contrast, Panel B depicts the same daily measure of temperature, but instead decomposed into a typical fixed-effect average temperature and the deviations from this constant value after additionally controlling for monthly fixed effects. The dashed line at the top of each panel indicates observed daily maximum temperature while the black solid line represents long-run norms. The gray solid line at the bottom of each panel indicates temperature shocks. Notice that the temperature shocks in our preferred decomposition are nearly identical to the deviations in the fixed-effects decomposition, as would be expected from the Frisch–Waugh–Lovell theorem, and illustrate the source of variation used for identifying β_W and β_{FE} respectively. Additionally, Panel A highlights the source of variation in climate used to identify β_C in our proposed approach, while the fixed-effects decomposition lacks any such variation in the measure of climate, as the LA fixed effect is collinear with average temperature. Recall that for our proposed approach the climate norm represents the 30-year monthly moving average of the maximum temperature, lagged by one year, while the temperature shock represents the difference between this value and the contemporaneous maximum temperature.

4. Results

4.1. Impacts of temperature on ambient ozone concentration

Column (1) of Table 1 presents the effects on ambient ozone of the two components of observed temperature: climate norm, represented by the *lagged* 30-year monthly MA, and temperature shock, represented by the deviation from that long-run norm.[47] Although the effects are uncovered by estimating Eq. (13), columns (2) and (3), respectively, benchmark them against effects that

[47] As mentioned before, even though we use monthly moving averages in our main analysis, as a robustness check we also estimate our preferred specifications using daily moving averages. The results are virtually identical, and are reported in Appendix B.1 Table B4.

Table 1
Climate impacts and adaptation — our unifying approach vs. Prior approaches.

	Daily max ozone levels (ppb)		
	Unifying (1)	Fixed-Effects (2)	Cross-Section (3)
Temperature shock	1.678*** (0.063)		
Climate norm	1.164*** (0.051)		
Max temperature		1.659*** (0.063)	
Average max temperature			1.166*** (0.106)
Implied adaptation	0.514*** (0.041)		0.493** (0.225)
Fixed effects:			
Monitor-by-Season-by-Year	Yes		
Monitor-by-Month-by-Year		Yes	
State			Yes
Precipitation controls	Yes	Yes	Yes
Latitude & Longitude			Yes
Non-attainment control			Yes
Observations	5,139,523	5,139,523	2712
R^2	0.481	0.542	0.352

Notes: This table reports the weather and climate impacts on ambient ozone concentrations, estimated by different methodologies. Column (1) reports the estimates of our unifying approach, in which we decompose daily maximum temperature into climate norms and weather shocks, and exploit variation in both components in the same estimating equation — our Eq. (13). Recall that the climate norm represents the 30-year monthly moving average of the maximum temperature, lagged by one year to allow for economic agents to potentially adapt, while the temperature shock represents the difference between this value and the contemporaneous maximum temperature. Column (2) reports the effect of daily maximum temperature on ambient ozone from the panel fixed-effects approach, exploiting day-to-day variation in temperature, hence capturing the effect of a change in weather. Column (3) reports cross-sectional estimates using average maximum temperature and ambient ozone concentrations for each ozone monitor in the sample. Having averaged the variables over all the years from 1980–2013, this estimate captures the effect of a change in climate. Note that while estimates in column (3) must additionally control for whether a county is in violation of the CAA ozone standards, this is implicitly controlled for via the fixed-effects in columns (1) and (2). Combining our estimates in column (1) with climate projections from the U.S. Fourth National Climate Assessment (Vose et al., 2017) under the business-as-usual scenario (RCP 8.5) – 1.6 °C temperature increase by 2050, and 4.8 °C by 2100 – ambient ozone concentrations would rise by 1.9 and 5.6 ppb, respectively. This should be the so-called "climate penalty" – the response of economic agents to longer-term climatic changes, which is *inclusive* of adaptation. Wrongly using the response to temperature shocks as the penalty, which is *exclusive* of adaptation, those numbers would be larger: 2.7 and 8 ppb, respectively. For a comparison, modeling studies find increases in summertime ambient ozone concentrations by 1–10 ppb (for a review, see Jacob and Winner, 2009). Standard errors are clustered at the county level in columns (1) and (2), while column (3) uses standard heteroskedastic robust errors. ***, **, and * represent significance at 1%, 5% and 10%, respectively.

would have been found if one had exploited either only the panel (e.g., Deschenes and Greenstone, 2007; Schlenker and Roberts, 2009) or only the cross-sectional (e.g., Mendelsohn et al., 1994; Schlenker et al., 2005) structure of the data.

Column (2) reports the effect of temperature on ozone identified by exploiting within-monitor daily variation in maximum temperature after controlling for monitor-by-month-by-year fixed effects. The coefficient indicates that a 1 °C increase in maximum temperature leads to a 1.66 parts per billion (ppb) increase in maximum ambient ozone concentration. Column (3) reports results from a cross-sectional estimation of daily maximum ozone concentration on daily maximum temperature around each monitor, averaged over the entire period of analysis 1980–2013. These variables capture information for all the years in our sample and are good proxies for the average pollution and climate around each monitor. The estimate suggests that a 1 °C increase in average maximum temperature is associated with an increase of 1.17 ppb in ozone concentration, approximately. When we decompose daily maximum temperature into our two components in column (1), as expected the estimated effect of temperature shocks on ambient ozone is statistically the same as the fixed-effects approach in column (2). Coincidentally, the effect for the lagged 30-year MA climate norm is also statistically the same as its counterpart in column (3). Specifically, a 1 °C temperature shock increases ozone concentration by 1.68 ppb, and a 1 °C change in climate norm increases ozone concentration by 1.16 ppb. To be clear, this does not imply that the cross-sectional approach is free of omitted variable bias concerns. In this specific context there may simply be both upward and downward bias simultaneously affecting the estimate as in Griliches (1977).[48] In fact, when we re-estimate our model on a more balanced sample of monitors as a robustness check the bias in the cross-sectional approach becomes much more evident, leading to an over-estimation of the implied measure of adaptation by more than 100 percent.[49]

[48] More generally, in contexts where one is able to control for all key covariates (e.g., in an agricultural setting with measurements of soil quality, storage, irrigation, and other relevant variables), then the fixed effects would be capturing much of the same content. But there are likely to be many contexts where the crucial controls are omitted – e.g., in analyses of mortality and health outcomes, several confounding factors may be unobserved such as genetic traits, defensive investments, and lifestyle choices such as smoking, drinking, and exercising.

[49] See estimates in Appendix B.1 Table B2.

It is widely recognized that the cross-sectional approach is plagued with omitted variable bias. In our context, if more informed/concerned local monitoring agencies inspect heavy emitters of ozone precursors more often when average temperature rises, and more intense enforcement of environmental regulations induces reductions in ozone concentration, then this unobserved behavior might lead to underestimation of the long-run impact of temperature. On the other hand, as emphasized in the conceptual framework, estimates from the standard panel data fixed-effects methodology and our approach should be statistically the same due to the properties of the Frisch–Waugh–Lovell theorem. The deseasonalization embedded in the fixed-effects model is approximately equivalent to the use of deviations from 30-year norms in our regression model.

Our estimates imply a so-called "climate penalty" on ozone on the lower end of the ranges found in the literature. Indeed, Jacob and Winner (2009), in their review of the effects of climate change on air quality, find that climate change alone may lead to a rise in summertime surface ozone concentrations by 1–10 ppb – a wide interval partly driven by the different regional focuses of the studies they review. The U.S. EPA, in its 2009 Interim Assessment, claims that "*the amount of increase in summertime average … O3 concentrations across all the modeling studies tends to fall in the range 2–8 ppb*" (USEPA, 2009, p.25). Combining our estimates in column (1) with climate projections from the U.S. Fourth National Climate Assessment (Vose et al., 2017) under a business-as-usual scenario (RCP 8.5), one would predict an increase in ambient ozone concentrations by the mid and end of the century in the range of 1.9–5.6 ppb, approximately.[50] To be clear, "climate penalty" in our setting is the response of economic agents to longer-term climatic changes, which is *inclusive* of adaptation, as it will be discussed below. If one would wrongly use the response to temperature shocks as the penalty, which is *exclusive* of adaptation, the range would be 2.7–8 ppb, a nontrivial shift to the right. In fact, this may be one of the reasons why our estimate of the penalty is on the lower ranges of the values produced by simulation studies (again, for a review, see Jacob and Winner, 2009); they usually do not take into account behavioral responses. To put those values in perspective, each of the last few times EPA revised the air quality standards for ambient ozone, they decreased it by 5 ppb.

4.2. Measuring adaptation to climate change

Our results indicate that short-run temperature shocks have a larger impact on ozone levels compared to long-run temperature norms. The comparison between the short- and long-run effects of temperature may provide a measure of adaptive responses by economic agents (Dell et al., 2012, 2014). Our measure of adaptation – also a comparison between the impact of changes in the long-run climate normal temperature (lagged 30-year MA) and the effect of the temperature shock (deviation from the MA) – is 0.51 ppb, suggesting that economic agents may be adapting to climate change. In the case of polluting firms, for example, they might be making adjustments to their production processes so that whenever average temperature rises, the emissions of ozone precursors reduce to keep ambient ozone at controllable levels. Such adjustments might be driven by public and regulatory pressures and/or technological innovation.

If we ignored such adaptive responses by economic agents, then we would be overestimating the "climate penalty" on ozone by more than 44 percent. Again, we would be making the mistake of taking the effect of weather shocks as the penalty, when we should be looking at the impact of climatic changes, which incorporates adaptive responses by economic agents. Using the climate projections from the U.S. Fourth National Climate Assessment under the business-as-usual scenario (RCP 8.5), we would overestimate the climate penalty by 0.82 ppb by mid-century, and 2.47 ppb by the end of the century.

4.3. Robustness checks

Measurement Error & Agents' Expectations — A concern regarding our decomposition of meteorological variables in Eq. (10) might be measurement error. Because both components are intrinsically unobserved, we define the long-run climate norm as the 30-year MA, and weather shocks as deviations from that moving average. If there is classical measurement error, the estimates of the coefficients of interest in Eq. (13) will suffer from attenuation bias. Moreover, the bias will be magnified in fixed-effect regressions.

To investigate the robustness of our results to measurement error, we carry out analyses using moving averages of different length. We start by using a 3-year MA, then 5-, 10-, and 20-year MAs, relative to our preferred specification using 30 years. As argued seminally by Solon (1992), as we increase the time window of a moving average, the permanent component of a variable that also includes a transitory component will be less mismeasured. If this is the case, we should observe the coefficients of interest increasing as longer windows are used for the moving averages. Our estimates in columns (1) through (4) of Table 2 remain remarkably stable over the different lengths of the moving averages, but if anything they get slightly larger until the 20-year moving average.

As pointed out by Blanc and Schlenker (2017), a fixed-effects regression with variables under classical measurement error is plagued by larger attenuation bias. The identifying variation in a standard panel analysis comes from deviations from the cross-sectional averages in the panel structure. Once the variables of interest are demeaned, the share of measurement error variation is magnified, and the coefficients of interest will be even more attenuated. Again, our estimates in Table 2 remain largely unchanged over the different lengths of the moving averages, with a slight attenuation of the coefficient of the moving average when we

[50] To be clear, while our estimate of adaptation does not rely on extrapolation, any prediction of the *future* "climate penalty" must do so by construction. In that sense, the "climate penalty" implied by our estimates may still be an upper bound. As we will discuss later in Section 4.5, although our measure of adaptation has remained relatively constant over time, the impact of the climate norm on ozone has decreased. This could imply that long-run changes in the economic or regulatory landscape, driven, e.g., by technological advancement or shifting preferences, could lead to further decreases in this impact in the future. At the same time, we also find non-linear and increasing effects of temperature on ozone formation, indicating that there may be counter-acting intensification effects.

Table 2
Key robustness checks.

	Alternative lengths of climate norm				Adaptation responses		
	3-year MA	5-year MA	10-year MA	20-year MA	Long run 10-year Lag	Long run 20-year Lag	Short-run *2004–2013 only*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Temperature shock	1.669***	1.670***	1.670***	1.673***	1.681***	1.685***	1.179***
	(0.063)	(0.062)	(0.062)	(0.062)	(0.063)	(0.063)	(0.029)
Climate norm	1.158***	1.166***	1.176***	1.175***	1.155***	1.143***	0.581***
	(0.049)	(0.050)	(0.051)	(0.051)	(0.050)	(0.049)	(0.034)
Implied adaptation	0.511***	0.504***	0.495***	0.499***	0.527***	0.542***	0.597***
	(0.040)	(0.040)	(0.041)	(0.041)	(0.041)	(0.041)	(0.029)
Shock × Action day							0.068
							(0.188)
All controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,139,523	5,139,523	5,139,523	5,139,523	5,131,943	5,127,886	1,879,041
R^2	0.481	0.481	0.481	0.481	0.481	0.481	0.444

Notes: This table reports the results for key robustness checks investigating sensitivity to alternative definitions for the climate norm, as well as allowing more or less time for economic agents to engage in adaptive behavior. Columns (1) through (4) report estimates when we adjust the length of the constructed climate norm (moving averages of temperature) using different time windows. Recall that the 3- to 30-yr moving average is lagged by 1 year, while the temperature shock represents the difference between this value and the contemporaneous maximum temperature. The estimates in columns (5) and (6) are obtained by Eq. (13), but using 10- and 20-year lags between the moving average and contemporaneous temperature, rather than 1-year lag. Column (7) continues using the 1-year lag of the main specification, but adds an additional interaction term on temperature shock using clean air action day announcements (days in which the relevant air quality authority observes, or expects to observe, unhealthy levels of pollution on the Air Quality Index and releases a public service announcement to this effect) at the county-level to estimate short-run adaptive behavior. Note that although action day policies first began in the 1990's, EPA data only begins from 2004 onwards, leading to a restricted overall sample (approximately 35% of our full sample). The full list of controls are the same as in the main model, depicted in column (1) of Table 1. Standard errors are clustered at the county level. ***, ** and * represent significance at the 1%, 5% and 10%, respectively.

move from the 20- to the 30-year moving average. This latter result suggests that the widely used climate normals are close to the "optimal" long-run norms. The improvements from reducing measurement error might be offset by the panel-driven attenuation bias between 20- and 30-year time windows.

At the same time, it is possible that agents form climate expectations in a way that exhibits recency weighting (e.g., Kaufmann et al., 2017). This presents a second trade-off. Longer, 20- to 30-year MAs, guided by climatology, appear "optimal" in our setting for navigating the first trade-off between potential measurement error and fixed effect induced attenuation bias for the purposes of estimating a long-run climate impact. Shorter, 3- to 5-year MAs, however, may better reflect agents' internalized information set with regards to forming expectations over the current climate conditions and thus better capture medium-run adaptive behavior (Moore et al., 2019). It is plausible, therefore, that the observed increases, however slight, in the coefficient on climate norm as we move from a 3- to a 20-year MA are, at least in part, due to agents' stronger adaptive response to recent events than to longer-run trends in the climate norm.

Lagged & Short-run Adaptive Responses — Another potential concern with our preferred specification might be the fact that we have used the 1-year lagged 30-year moving average to capture the long-term climate norm, implying that agents adapt within one year. Hence, we check the sensitivity of our results when agents have 10 or 20 years to adapt, instead of just one. In columns (5) and (6) of Table 2, we provide estimates from our preferred specification but using respectively 20-year moving averages of temperature *lagged by 10 years*, and 10-year moving averages *lagged by 20 years*. By doing so, we are providing agents more time to potentially adjust to climate change. Even though we would expect that the effects of the weather shocks to be similar, we anticipate the effects of the climate norm to be slightly smaller than before, as agents should now be able to adapt more than before. This is what we find from our estimates reported in Table 2, although the magnitude of the coefficients is remarkably close to that of our main results.

Alternatively, one might be concerned that agents are in fact able to respond rapidly and adapt to weather shocks, in which case the coefficient on temperature deviations would be inclusive of any such adaptive responses, and thus our estimate of adaptation would be biased downwards. In column (7) we make use of a widespread policy of "Ozone Action Day" (OAD) alerts, where a local air pollution authority would issue an alert, usually a day in advance, that meteorological conditions are expected to be more conducive to a high concentration of ambient ozone in the following day. If agents are adapting to contemporaneous weather shocks, these "action days" would be the days we would be most likely to observe an adaptive response. Indeed, individuals are urged to take *voluntary* action to reduce emissions of ozone precursors such as working from home, carpooling to work, or using public transportation; combining auto trips while running errands; and reducing home landscaping projects. Firms are also urged to provide work schedule flexibility, reduce refueling of the corporate fleet during daytime, and save AC-related energy usage by adjusting indoor temperature (USEPA, 1997). Interacting an indicator variable for days in which OAD alerts were issued for a given county with our other covariates, we find that such alerts have a negligible and statistically insignificant impact on the effect of a 1 °C change in the contemporaneous temperature shock.[51] Although previous studies have provided evidence of some decline in driving and increases in the use of public transportation in a few locations (e.g., Cutter and Neidell, 2009; Sexton, 2012), we find little indication that agents engage in meaningful short-run adaptive responses across the country.

Further Robustness Checks — We conduct additional robustness checks regarding features in the construction of the data, selection of the estimating sample, and alternative econometric specifications in Appendix B.1 Tables B1, B2, B3, and B4. Specifically, Table B1 examines the sensitivity of our results to our algorithm for matching ozone and temperature monitoring stations. Table B2 restricts our sample of ozone monitors to a semi-balanced panel, including only monitors with data for every year of our sample; however, as pointed out by Muller and Ruud (2018), our preferred unbalanced panel is likely more nationally representative. Table B3 examines the sensitivity of our results to the exclusion of regions that had implemented policies aimed at reducing ambient ozone concentrations by specifically targetting ozone precursors.

Table B4 contains four additional robustness checks: (i) implementing a *daily* MA rather than *monthly*; (ii) purposefully aggregating our data to the monthly level to simulate our methodology with lower frequency data; (iii) controlling for wind speed and sunlight with the subset of data for which that information is available; and (iv) examining the sensitivity of our results to inter-regional NOx transport by restricting the estimating sample to exclude, or conversely, only include, the states designated by the EPA as part of the "ozone transport region" (OTR). Across all of these models results remain qualitatively similar to our central findings. Finally, Appendix B.1 Table B5 provides bootstrapped standard errors for our main estimates, finding little difference relative to the standard errors clustered at the county level. In addition, that table presents standard errors clustered at the state level. Although they double in magnitude, they do not change the statistical significance of the results.

4.4. Estimating nonlinear effects of temperature

In many empirical settings there has been a focus in the economics literature on allowing for nonlinear effects of temperature or climate on the outcome of interest. Thus, while our central model adopts a linear specification for simplicity in interpretation and comparison with prior methods, we note that our proposed approach is easily extendable to any nonlinear setting with nth order polynomial effects by simply including higher-order polynomial terms for both the weather shock, $(x_{it} - \bar{x}_{i\bar{p}})$, and climate norm, $\bar{x}_{i\bar{p}}$. The following equation presents the quadratic model:

$$y_{it} = \alpha + \beta_W(x_{it} - \bar{x}_{i\bar{p}}) + \beta_C\bar{x}_{i\bar{p}} + \beta_{W2}(x_{it} - \bar{x}_{i\bar{p}})^2 + \beta_{C2}\bar{x}_{i\bar{p}}^2 + \mu_i + \lambda_s + \nu_{it}, \tag{14}$$

while a cubic model would add the terms $\beta_{W3}(x_{it} - \bar{x}_{i\bar{p}})^3$ and $\beta_{C3}\bar{x}_{i\bar{p}}^3$. Adaptation could then be inferred for the quadratic model as:

$$Adaptation = (\beta_W - \beta_C) + 2(\beta_{W2}(x_{it} - \bar{x}_{i\bar{p}}) - \beta_{C2}(\bar{x}_{i\bar{p}})), \tag{15}$$

while adaptation for a cubic model would add the term $3(\beta_{W3}(x_{it} - \bar{x}_{i\bar{p}})^2 - \beta_{C3}(\bar{x}_{i\bar{p}})^2)$. Notably, for a marginal deviation of the daily temperature from the climate norm, i.e., $x_{it} - \bar{x}_{i\bar{p}} \approx 0$, Eq. (15) simplifies to:

$$Adaptation = \beta_W - \beta_C - 2\beta_{C2}(\bar{x}_{i\bar{p}}), \tag{16}$$

with marginal adaptation in the cubic model additionally including the term $-3\beta_{C3}(\bar{x}_{i\bar{p}})^2$.

Note that estimating the impacts of climate and weather in a setting with nonlinear effects will also inherently include the interaction of these two channels of temperature response, as discussed by Mendelsohn (2016), because the marginal impact of weather will vary with the underlying climate norm from which it is deviating.[52]

As an alternative to including nonlinear terms, one could construct a set of indicator variables denoting whether realized temperature at location i on day t fell within a certain temperature bin. By interacting these indicators with the shock, norm, and control variables in a linear model, the response function of the outcome variable to both weather and climate would be allowed to flexibly adjust across the temperature distribution in a piece-wise linear fashion.[53] Allowing for a more flexible response function may be especially desirable in settings where the underlying functional form is unknown. Furthermore, by estimating a (locally) linear relationship within each bin, the specification allows for intuitive and easily interpretable measures of weather and climate impacts and implied measure of adaptation.

The exact functional form of the ozone-temperature relationship is unknown because ozone formation may be intensified with higher temperatures, but also exhibits a shorter half-life (McClurkin et al., 2013). We thus examine the nonlinear effects of weather shocks and climate norms on ambient ozone concentrations across the temperature distribution using quadratic and cubic versions of Eq. (13) by including the additional terms outlined in Eq. (14). We also estimate a "binned" specification as described above

[51] Although the recovered coefficients of temperature shock, climate norm, and implied adaptation are quantitatively different for column (7) than columns (5) and (6), this is due to a difference in the underlying sample. EPA data on "action day" alerts were only provided from 2004 onwards, leading to a restricted overall sample (approximately 36% of our full sample).

[52] To see this mathematically, one need only expand the higher order weather terms to see that they include the interaction effects. For example, the expansion of $(x_{it} - \bar{x}_{i\bar{p}})^2$ includes the term $-2x_{it}\bar{x}_{i\bar{p}}$.

[53] In this way, the *marginal* effect of a 1 °C change in either component of temperature is constrained to be constant within its respective temperature bin, but is allowed to vary across each bin.

by creating indicator variables denoting whether the contemporaneous daily maximum temperature at a given ozone monitor falls within a certain 5 °C temperature bin.[54]

Fig. 4 depicts the ozone relationship and marginal response to climate and weather, as well as marginal adaptation, across the temperature distribution for the linear, quadratic, cubic, and binned specifications.[55] The linear specification appears to provide an adequate first-order approximation of the nonlinearities captured by the cubic and binned specifications, while the quadratic model appears to mis-specify the ozone-weather relationship compared to the other models. Although both the cubic and binned specifications find similar ozone and adaptation responses across the majority of the temperature distribution, due to the functional form restrictions of the cubic it also implies a large, and rather unintuitive, level of adaptation at lower temperatures.

With this in mind, our preferred approach for capturing potential nonlinearities in our empirical context is the binned specification. Table B6, column (1), in Appendix B presents the results of our preferred specification when interacting each of the independent variables with the 5 °C temperature bin indicators. The implied measure of adaptation is then presented in column (2).[56] Similar to Fig. 4, we find that the ozone/temperature response is increasing at an increasing rate at lower temperature ranges, but increases at a decreasing rate at higher temperatures, particularly for increases in the climate norm. These results suggest that agents may be making extra effort to reduce ozone precursor emissions when temperatures are the highest and could otherwise lead to greater ozone formation.

4.5. Exploring heterogeneity

Earlier studies have inferred adaptation *indirectly*, by flexibly estimating economic damages due to weather shocks, then assessing climate damages through shifts in the future weather distribution. We have pointed out the shortcomings of that time/space extrapolation approach in the spirit of the Lucas Critique (Lucas, 1976). Importantly, once we have recovered a measure of adaptation from responses to weather shocks and longer-term climatic changes by the *same* economic agents, then we are able to explore the heterogeneity in their degree of adaptation. In Appendix B.2 we report results of heterogeneity analyses examining adaptive behavior over time in Figure B1 and Table B8, across varying measures of belief in climate change in Tables B9–B11. Table B12 then examines how the effect of temperature on ozone may be attenuated if the local atmosphere is limited in one ozone precursor (NOx or VOCs) relative to the other.

5. Concluding remarks

We have developed a unifying approach to measuring climate change impacts and adaptation that considers both responses to weather shocks and longer-term climatic changes in the *same* estimating equation. By bridging the two earlier strands of the climate-economy literature – cross-sectional studies that relied on permanent, anticipated components behind meteorological conditions (e.g., Mendelsohn et al., 1994; Schlenker et al., 2005), and panel fixed effects that exploit transitory, unanticipated weather shocks (e.g., Deschenes and Greenstone, 2007; Schlenker and Roberts, 2009) – we have overcome identification concerns from earlier cross-sectional studies, improved on the measurement of adaptation, and provided a test for the statistical significance of this measure. Our approach rests on two rather simple but powerful ideas. First, the decomposition of meteorological variables into long-run climate norms and contemporaneous weather shocks. Second, the properties of the Frisch–Waugh–Lovell theorem, which enables the simultaneous identification of these two short- and long-run impacts.

In the spirit of Dell et al. (2012, 2014), we recovered a measure of adaptation defined as the difference between those short- and long-run responses. Unlike previous studies, however, this measure was derived *directly* from coefficients estimated in the same fixed-effects model; hence, less susceptible to omitted variable biases from cross-sectional estimates. In addition, it compares the responses of the *same* economic agents, overcoming the challenges of identifying adaptation by comparing the profiles of weather responses across time and space (e.g., Deschenes and Greenstone, 2011; Barreca et al., 2016; Heutel et al., 2021), which requires that preferences be constant across those dimensions.

We applied our unifying approach to study the impact of climate change on ambient "bad" ozone in U.S. counties over the period 1980–2013. Others have relied on atmospheric-sciences simulation models to study the so-called "climate penalty" on ozone (see a review in Jacob and Winner, 2009). By ignoring the adaptive behavior of economic agents, they may have substantially overestimated the magnitude of this penalty — in our study setting, disregarding adaptation overestimates the climate penalty by approximately 44 percent. When considering the impacts of climate change on air pollution, the application of our unifying methodology led to four main findings.

First, a changing climate appears to be affecting ambient ozone concentrations in two ways. A 1 °C shock in temperature increases ozone levels by 1.68 parts per billion (ppb) on average, which is expectedly what would have been found in the standard fixed-effects approach. A change of similar magnitude in the 30-year moving average increases ozone concentration by 1.16 ppb. *Second*, we found strong evidence of adaptive behavior. For a 1 °C change in temperature, our measure of adaptation in terms of ozone concentration

[54] The lowest bin is below 20 °C (just over the 10th percentile of our temperature distribution), and the highest bin is above 35 °C (90th percentile of our temperature distribution), with the middle bin, 25–30 °C, approximately centered around the temperature distribution median (27.8 °C) and mean (27.1 °C).

[55] Recall that the effects of climate and weather under higher order models depend on the level of the other variable. For graphing the climate norm effects we assume a weather shock of zero — approximately the sample average as the shocks are constructed as deviations from the norm. For graphing the weather shock effects we assume the sample average climate norm of approximately 27.5 °C.

[56] Table B7 additionally compares the implied level of adaptation under the linear, binned, quadratic, and cubic specifications.

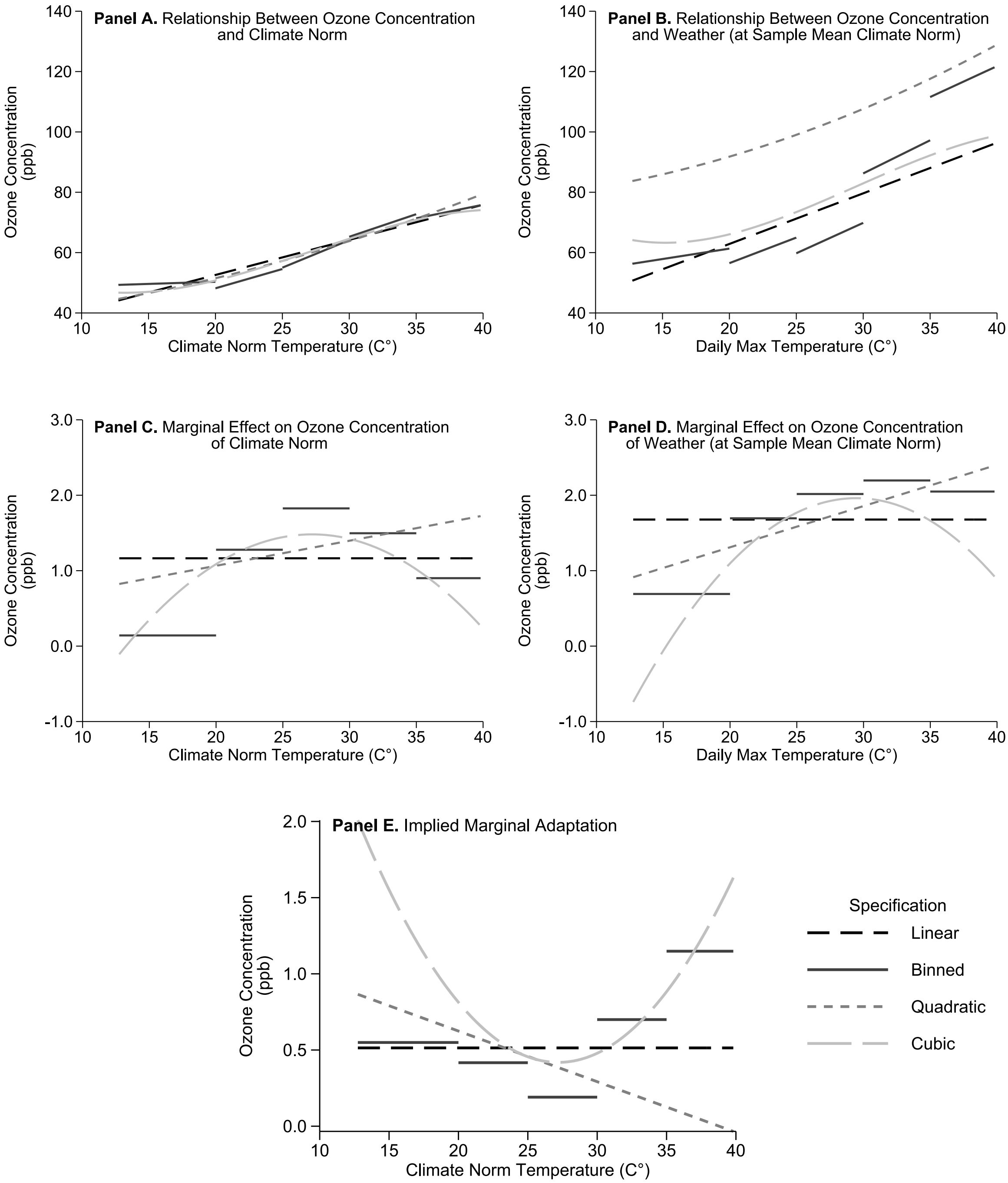

Fig. 4. Comparing linear, binned, and nonlinear specifications. *Notes*: This figure compares our central linear specification with a 5 °C binned linear specification, as well as quadratic and cubic specifications following Eq. (14). For clarity in the figures, we trim the top and bottom one-percent of the temperature distribution. Panels A and B depict the relationship between ozone and either climate or weather, respectively, across the temperature distribution. While both relationships exhibit some nonlinearity, the linear specification appears to capture the first-order relationship. Panels C and D depict the marginal impacts of climate and weather on ozone concentration, with both the flexible binned specification and the cubic reflecting an "inverted u" shape, suggesting that while ozone increases with temperature, above a certain temperature it begins to increase at a decreasing rate. Finally, Panel E shows marginal adaptation, wherein both the binned and cubic specifications exhibit a "normal u" shape, suggesting that adaptation is larger when temperature is hotter and could lead to higher ozone formation.

is 0.51 ppb, which is statistically and economically significant. *Third*, by extending our central model to flexibly recover estimates accounting for the nonlinear relationship between ozone and temperature, we found that agents – perhaps unsurprisingly – tend to focus their adaptive efforts on the hottest days, which would *ex ante* be likely to lead to higher levels of ambient ozone. *Finally*, we provided evidence of nontrivial heterogeneity in the degree of temperature response and adaptation across time and space, which highlights the potential biases of existing approaches in assigning weather responses or adaptation from one period and/or location to other periods and locations, consistent with insights by Olmstead and Rhode (2011) and Bleakley and Hong (2017).

Notably, although we made use of high frequency data in this study, our unifying framework is generalizable to any empirical setting where one can obtain short-term variation in weather associated with limited opportunities to adapt, and long-term climatological variation allowing for adaptation. Settings in which opportunities to adapt are limited at the daily level, but may exist at the monthly or seasonal level are reliant on temporally disaggregated data, while those in which such opportunities are limited even at the monthly or seasonal level may be able to use more aggregate data.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

The appendix for this article can be found online at https://doi.org/10.1016/j.jeem.2023.102843. Replication materials can be found online at https://doi.org/10.3886/E192708V1.

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