Measuring Weather Impacts Using Panel Data

Robert Mendelsohn*

Yale School of Forestry and Environmental Studies

December 29, 2016

Abstract

This essay develops a theoretical model to measure weather across different climates using panel methods. The model reveals that the effect of weather should vary across climates. Most panel models are also not estimated correctly. Because weather models are nonlinear, fixed effects do not properly control for time-invariant variables. The panel literature must demean variables before they are transformed in order to estimate unbiased weather effects. Current panel models also assume weather effects are the same across climates. Intertemporal panel studies need to include an interaction between weather and climate if they wish to measure weather effects accurately across space.

Keywords: weather studies, panel analysis, climate change

JEL: Q51, Q54

*I want to thank Namrata Kala for her insights on estimation errors in panel models.

Introduction

There are two major econometric approaches to measure the impacts of temperature and precipitation: cross sectional and intertemporal. Cross sectional methods compare outcomes across space and evaluate how these outcomes vary with climate (Mendelsohn, Nordhaus, and Shaw 1994; Mendelsohn 2007). The cross sectional approach could be biased if there are missing time-invariant variables that are correlated with both climate and impacts (Deschenes and Greenstone 2007). In order to avoid this problem, Deschenes and Greenstone recommended using the weather variation in panels across time to estimate the climate sensitivity of economic outcomes. From this suggestion, an extensive intertemporal weather literature has developed that relies on panels to estimate weather effects (see review by Dell, Jones, and Olken 2014). Intertemporal panel studies have been used to study crop yields (Schlenker and Roberts 2009), farm net revenue (Deschenes and Greenstone 2007), conflict (Hsiang, Meng, Cane 2011; Hsiang, Burke, Miguel 2013), health (Deschenes and Greenstone 2011), labor (Graff Zivin and Neidell 2014), and GDP growth rates (Dell, Jones, Olken 2009; 2012; Burke, Hsiang, Miguel 2015). The advantage of the weather studies is that they depend solely on random weather variation and therefore should be immune to missing time-invariant variable bias.

This paper develops a theoretical model that explains both climate and weather impacts. The paper argues that the response to weather should be more concave than the response to climate. Nevertheless, the two functions should be tangent when weather and climate are the same (when the actual weather happens to be equal to the long term average weather). Because the marginal effect of climate varies with climate, the marginal effect of weather should vary across climate.

Unfortunately, most intertemporal studies of weather have confused weather effects and climate effects. They fail to measure the impact of either weather or climate correctly. They have made two fundamental mistakes. First, although the models are nonlinear, they have relied on fixed effects to remove time-invariant effects. Because the resulting coefficients include an interaction term with climate, this error also makes the estimates vulnerable to missing time-invariant variables. Second, the studies have not explicitly modeled the interaction between weather and climate. The models have assumed that the marginal effect of weather is the same across climates. These two mistakes together imply that most studies have biased estimates of both the marginal and nonmarginal effects of weather.

We begin the paper with a theoretical model that includes both weather and climate effects together. The model distinguishes between the consequence of weather deviations around a climate and changes in climate. Empirical and laboratory evidence strongly suggests that both weather effects and climate effects are nonlinear with a concave shape. The weather panel literature consequently allows weather variables to enter in a nonlinear fashion with either higher order polynomials or non-parametric approaches (bins).

In theory, weather effects could be the same regardless of the underlying climate. That is, weather could be independent of climate. However, this assumption also implies that the response of systems to weather would tell researchers nothing about climate responses. But weather and climate are likely to be related to each other. The response of crops or people to an unusually warm day is likely to be very different in a cold versus hot climate. For example, if one added 5°C (9°F) to a day that was normally 10°C (50°F), the resulting 15C (59°F) might seem quite pleasant. In contrast, if one added 5°C (9°F) to a day that is normally 25°C (86°F), the resulting 30C (95°F) might seem quite hot. The models therefore need to include an explicit interaction between climate and weather to capture weather effects properly across space.

We then develop an econometric model to estimate weather effects. We show that fixed effects do not accurately estimate weather effects with nonlinear models. Fixed effects would remove time-invariant variables only if the underlying models were linear. The fixed effects estimates are biased by an interaction between weather and climate that comes from the nonlinear shape of both the weather and climate impacts. The fixed effects inadvertently include an interaction term in the weather coefficient. The resulting model does not capture interactions or weather correctly. The interaction term is also vulnerable to missing time-invariant variables that are correlated with climate.

The third section develops a new model to estimate weather effects correctly using panel data. Two changes need to be made. First, the dependent and independent variables must be demeaned before they are transformed (see Moore and Lobell 2014). For example, instead of including observed daily temperature which is a combination of the climate of a location and the weather that day, the researcher should include the deviation in the weather that day. For example, if the underlying climate was 25C and the observed temperature that day was 30C, the researcher should include the +5C weather deviation, not the observed 30C. It is the deviation that measures weather. It is this deviation that is time-variant. A similar principle would apply to bins. The correct bin to place this observation in is +5C, not 30C.

Of course, this makes quite clear why climate-weather interactions are likely important. The +5C bin could well have a different effect if the underlying climate is 25C rather than 10C. So in addition to the pure weather, the researcher should also include an explicit interaction between the weather and the climate.

But if missing time-invariant variables are correlated with climate, they will be correlated with the sum of climate and weather. One needs to strip climate of undesired variation. One could regress climate variables (temperature and precipitation) on other climate variables (solar radiation, clouds, atmospheric pressure, month) and undesired time-invariant variables (such as soils, population density) and use the climate coefficients to predict climate. The predicted climate would then be entered in the interaction term.

The paper then explores a few empirical examples to demonstrate that these changes make a difference. However, it is up to the literature to review each past panel study and re-estimate the results.

I. Theoretical Model

We begin the theory section by defining climate and weather. The technical definition of the climatology of temperature (t) and rainfall (r) is the probability distribution f(t, r) of both variables. In this paper, we will use the word "climate" to mean the expected value of this distribution. The expected value of temperature we label as T and the expected value of rainfall is R.

$$E[f(t)]=T \qquad\qquad E[(f(p)]=R \qquad\qquad (1)$$

For the moment, we ignore that both variables also vary over the months of the year. We will return to this within year variation problem later.

We ignore throughout the paper the fact that climate, the probability distribution of weather, has many moments. We begin by focusing only on the first moment of the distribution, the expected value of weather. However, the literature has shown that the variance (second moment) of the climate distribution are important (Mendelsohn, Nordhaus and Shaw 1999; Mendelsohn et al. 2007).

Weather is the realization of the climate distribution at each moment in time (i). So at each moment in time (i), one can observe (t(i), r(i)). Weather is the observed deviation from the expected value of weather, the first moment (T, R) of the climate distribution:

$$t_i = T - t(i) \quad \text{and} \quad r_i = R - r(i)$$

Given this definition, the expected value of weather is zero:

$$E[t_i]=0 \qquad \text{and} \quad E[r_i]=0$$

We now explore the impact of weather (intertemporal deviations) and climate (mean climate) on a net benefit function, $V_j\,(T, R, K, t_i, r_i)$ to an actor (j) where K reflects a vector of capital that can be adjusted in the long term but not the short term. We define V so that higher levels are generally welfare improving (preferred). Weather and climate damages lead to a reduction in V. We assume that each sector has a unique function. For example, V could reflect an increase in yields, an increase in net revenue, a decrease in the energy required for interior comfort, an increase in health, or an increase in ecosystem productivity.

Because the actor chooses K, we assume the actor chooses the value of K that leads to the highest V. That is, dV/dK=0. The resulting K* maximizes V given what is known in advance about T, R, and the probability distribution of weather. However, the value of K must be chosen without knowing the realization of weather each year. The value of K is optimized for the climate but not the weather. Actors in each different consequently choose a unique K*. K* changes as climate changes. However, K* does not change with each realization of weather. The overall shape of V with respect to climate therefore cannot be the same as the overall shape of V to weather. The only exception is when the realized weather is like the climate, that is when $t_i=r_i=0$. In this sole circumstance, K* is optimized and the responmse to weather and climate can be the same.

What do we know about $V(T, R, K, t_i, r_i)$? The cross sectional climate change and intertemporal weather literature suggests that V(T, R, K, t, r) is nonlinear and concave with respect to each of its arguments (Mendelsohn and Schlesinger 1999; Mendelsohn and Dinar 2009; Dell Jones and Olken 2014):

$$dV/dT(0)>0 \quad dV^2/dT^2<0 \qquad dV/dR(0)>0 \quad dV^2/dr^2<0 \tag{2}$$

$$dV^2/dt_i^2<0 \qquad dV/dr_i^2<0$$

Economic outcomes (V) are curtailed at cold temperatures and at hot temperatures. Economic activity is also curtailed in desert conditions and extreme wet conditions. But the optimal temperature and rainfall in the long run and the short run is different for different economic sectors. The only feature that is somewhat ubiquitous is that the overall relationship is concave.

One simple result that follows from (2) is that the marginal effect of a change in the expected temperature, T, depends on the level of that temperature:

$$d(V(T_j,R)/dT_j \neq d(V(T_k, R)/dT_k \quad \text{for } j\neq k \tag{3}$$

In fact, concavity implies that the marginal value consistently declines with T and with R:

$$d(V(T_j,R)/dT_j<d(V(T_k,R)/dT_k \quad \text{for } T_j>T_k \tag{4}$$

$$d(V(T,R_j)/dR_j<d(V(T,R_k)/dR_k \quad \text{for } R_j>R_k \tag{5}$$

What does V tell us about the interaction between impacts from weather versus impacts from climate?

A. Independence Between Weather and Climate

One possibility is that there is no interaction between weather and climate in $V(T, R, t_i, r_i)$ in which case.

$$V(T, R, t_i, r_i)= F(T, R) + G(t_i, r_i) \tag{6}$$

The effect of weather, holding climate constant, is the same at every observed climate. In this case, weather effects $G(t_i, r_i)$ provide no information about climate effects F(T, R). The impact of (t, r) in G(t, r) depends solely on the values of (t,r). The value of (T, R) play no role in G(t,r). This is the implicit theoretical assumption of most intertemporal weather studies. They use fixed effects to remove climate from each observation and then assume that the resulting estimated function applies to every site regardless of its climate. More formally, G_j (t, r) is the same for all sites (j) no matter what the value of (T_j, R_j). For example, the marginal value of dG(0,0)/dt and dG(0,0)/dr are the same for every observation no matter what the value of (T, R). By assuming weather impacts are independent of climate impacts, one is also assuming there is no interaction between climate and weather impacts. Weather has nothing to do with climate.

Given this assumption, the marginal value of dF(T, R)/dT and dF(T, R)/dR are not revealed by estimating the marginal value of dG(0,0)/dt or dG(0,0)/dr even though both measures are being taken at the same place. Given the assumption of independence, the marginal value of weather provides no information about the marginal value of climate. Nor does it provide any information about the shape of F(T, R). By assumption, it provides no information about climate effects at all, just a uniform weather effect.

B. Weather and Climate Interact

An alternative hypothesis about V is that weather and climate interact. In this case, the marginal effect of weather changes with climate. The first derivative of dV/dt_i (T) or dV/dr_i (R) would be a function of T and/or R. For example, one could include an interaction term between T and t_i:

$$V(T, t_i) = B_{0+} B_1T + B_2T^2 + B_3t_i + B_4t_i^2 + B_5T{*}t_i \qquad (7)$$

The marginal weather impact is:

$$dV/dt_i = B_3 + 2B_4t_i + B_5T$$

The derivative of weather would vary with the underlying climate. If $B_5<0$, there would be more damage from an unusually hot day if the climate was hot rather than if the climate was cold. Symmetrically, there would be more harm from an unusually cold day if the climate was cold rather than hot.

When is the marginal value of weather and climate the same? Theory tells us when the weather deviation is zero V(T, R, t=0, r=0), these two functions could be tangent. Taking the derivative of (7) when t=0 and r=0 leads to the following two marginal measures:

$$dV/dT = B_1 + 2B_2T$$

$$dV/dt_i = B_3 + B_5T$$

For the marginal weather impact to be equal to the marginal climate impact:

$$dV(T,0)/dT = B_1 + 2B_2T = dV(T,0)/dt_i = B_3 + B_5T$$

For the marginal impact of weather and the marginal impact of climate to be the same in this model, there are two conditions. $B_1 = B_3$ and $2B_2 = B_5$. The marginal effect of weather (t=0, r=0) must depend on the value of climate (T, R). In order for a weather study to measure marginal climate impacts, it must include an interaction between weather and climate.

III. Estimating Panel Weather Models

Existing intertemporal panel studies looking at temperature estimate the following model:

$$V(T+t_i, R+r_i) = \Sigma B_k(T+t_i)^k + \theta X + \varepsilon \qquad (8)$$

where B and θ are coefficients and X includes control variables. Using fixed effects, they subtract the mean of each moment from the dependent and independent variables:

$$V = B_1 [T+t-T] + B_2 [(T+t)^2-E[(T+t)]^2] + B_3 [(T+t)^3-E[(T+t)]^3] + \ldots + \theta X + \varepsilon$$

$$V = B_1 [t] + B_2[T^2+2Tt + t^2 - T^2] + B_3[T^3+3T^2t+3Tt^2+t^3-T^3] + \ldots + \theta X + \varepsilon$$

$$V = B_1t + B_2[2Tt+t^2] + B_3[3T^2t+3Tt^2+t^3] + \ldots + \theta X + \varepsilon \qquad (9)$$

In contrast, the model that is consistent with the theory is:

$$V = B_1t + B_2[t^2] + B_3[t^3] + \ldots + \theta X + \varepsilon \qquad (10)$$

Fixed effects cannot remove the influence of time invariant variables if the models are nonlinear (McIntosh and Schlenker 2006). It is evident that (9) and (10) are the same only if the panel model is linear. Nonlinear models of (T+t) (9) whether they be polynomials, loglinear, or nonparametric will not estimate the desired model (10). The coefficients of the nonlinear terms will invariably be biased by interaction terms between t (time variant) and T (time invariant) variables. Any missing time invariant variable that is correlated with the dependent variable and T will also influence the coefficients. As estimated, the panel weather studies are also vulnerable to the same omitted time invariant variable problem as cross sectional studies.

This particular problem is relatively easy to reverse. Instead of using (T+t) as the independent variable, researchers can simply use (t) and estimate equation (10) as in (Moore and Lobell 2014). Weather temperature could be introduced as the deviation from the mean. This applies to nonparametric approaches as well. The temperature bins could be defined in terms of (t) instead of (T+t).

Once the weather model is properly estimated as in (10), it makes clear that there is an additional problem. The model does not include an interaction term between weather and climate. The underlying assumption in this model is that weather effects are the same at all climates. The second change that must happen in weather models for them to even capture marginal climate effects is that they must allow an interaction between weather and climate. Of course, this explicitly introduces the problem that omitted time invariant variables could be correlated with both climate and V. The interaction term will be biased unless the omitted variable problem can be controlled.

One simple approach to this problem is to find some instrumental variables, Z, that might control for these unwanted time invariant variables. One could first regress climate on these instrumental variables:

$$T= f(Z)+\delta \tag{11}$$

The resulting predicted value of climate, $\hat{T}$, could then be used to create interaction terms with t_i in (10):

$$V=B_1t + B_2[t^2] +B_3[t^3] + \ldots + \gamma_1 [\hat{T} x\ t] + \theta X + \varepsilon \tag{12}$$

III. Empirical Example

It is helpful to see whether the concerns raised in this paper are trivial and would lead to almost identical results as in the literature. It is not the intent of this paper to review the entire panel literature. It is expected that each author can make the relevant changes in their study on their own and re-estimate their paper. The intent of this section is merely to examine an important case to see whether estimating these models correctly might matter.

We use Deschenes and Greenstone (2007) because this was the first paper to suggest using intertemporal weather variation instead of cross-sectional variation. We rely on the data in Deschenes and Greenstone (2012) rather than the original paper because of errors in the original data set. Using the data and programs on farm incomes in US counties by Deschenes and Greenstone (2012), we first estimate the following equation:

$$V(DD+dd_i, R+r_i) = \Sigma B_k(DD+dd_i)^k + \Sigma\gamma_k(R+r_i)^k +\theta X +\varepsilon \tag{13}$$

using just US counties with dryland farms east of the 100^{th} meridian. V is farm income, DD is long run degree days, dd is the deviation of monthly degree days that year, R is long run rainfall, r is the deviation in monthly rainfall that year, X are control variables including year dummies, β, γ, and θ are coefficients, and ε is an error term. DD+dd is the sum of observed degree days that year and R+r is the sum of observed rainfall that year. We examine both a linear and quadratic term for weather.

We contrast this with a model that relies on monthly deviations:

$$V(dd_i, r_i) = \Sigma B_k(dd_i)^k + \Sigma\gamma_k(r_i)^k + \theta X + \varepsilon \tag{14}$$

This model is also a quadratic where dd and r is the sum of monthly deviations that year. We also add an interaction term between weather and climate:

$$V(dd_i, r_i) = \Sigma B_k(dd_i)^k + \Sigma\gamma_k(r_i)^k + \delta_1(dd_i x DD) + \delta_2(r_i x R) + \theta X + \varepsilon \tag{15}$$

The results for all three models are reported in Table 1. The estimation of (13) suggests that the coefficients of degree days and precipitation are not significant. Nonetheless, the marginal effect of a degree day is significant and reduces income by $1.20. The marginal effect of precipitation is also significant and reduces income by $.57 per mm/month. When the model is estimated using just weather deviations, however, the coefficients of degree days and precipitation are significant. The marginal harm of a degree day falls to $1.02 and the marginal harm of precipitation falls to $.50. When the interaction term with climate is introduced into the model, the only coefficient that loses significance is the linear degree day term. The interaction term for degree days is negative though not significant and the interaction term for precipitation is positive and significant. The sign of the temperature and precipitation effects are as expected. An especially warm month is more harmful in a warm climate or season. An especially dry month is especially harmful in a dry climate or season. The marginal effect of degree days becomes $.95 and the marginal effect of precipitation becomes -$.88. Both marginal values using (15) are significantly different from the original marginal estimates using (13).

Variable	Original D&G	Weather Deviation	Weather Deviation and Interaction
Degree Days	-0.0140 (2.87)	-0.0102 (5.25)	-.0038 (.95)
Degree Days Sq	.022e-5 (0.31)	2.7e-5 (6.85)	2.6e-5 (6.63)
Degree Days Interaction	….	….	-0.19e-5 (1.62)
Precipitation	-0.705 (1.24)	-0.499 (4.74)	-1.611 (4.44)
Precipitation Sq	4.86e-3 (0.36)	-62.5e-3 (3.35)	61.4e-3 (3.29)
Precipitation Interaction	…	…	55.2e-3 (2.91)
F test	28.3	41.7	36.0
Root MSE	33.0	28.6	28.5
Marginal Degree Day	-1.27 (5.15)	-1.02 (5.23)	-0.95 (5.16)
Marginal Precipitation	-0.57 (2.43)	-0.50 (4.75)	-0.88 (6.24)

Table 1 Impact of Weather on Farm Income for Dryland Farms

(Data and original regression Deschenes and Greenstone 2012- county clustered and weighted regression)

We now examine the same data using bins. We import temperature and precipitation data from NARR to match with the economic data in Deschenes and Greenstone. We start by creating bins that reflect the range of temperature and precipitation in the data set and estimate the following bin model:

$$V(T+t, R+r) = \Sigma B_k(T+t)_k + \Sigma\gamma_k(R+r)_k + \theta X + \varepsilon \qquad (16)$$

Where each $(T+t)_k$ represents a bin of observed temperature with a 3C range. For example, the reference bin that is omitted is a bin from 16.5C-19.5C. Each $(R+r)_k$ bin represents a bin of observed precipitation with a range of 20mm/mo. The reference bin that is omitted is a bin from 60-80mm/mo. Both reference bins were chosen to include the median temperature and precipitation.

The second bin model (17) uses measurements of the monthly deviation that year from the long term value for that month. Each temperature deviation is then included in a bin of 1C range. The omitted reference bin is a bin from -.5C to +.5C. The precipitation bins are generally 20mm/mo wide and the omitted bin is from -20 to 0 mm/mo. The second bin model examines bins of all of these deviations:

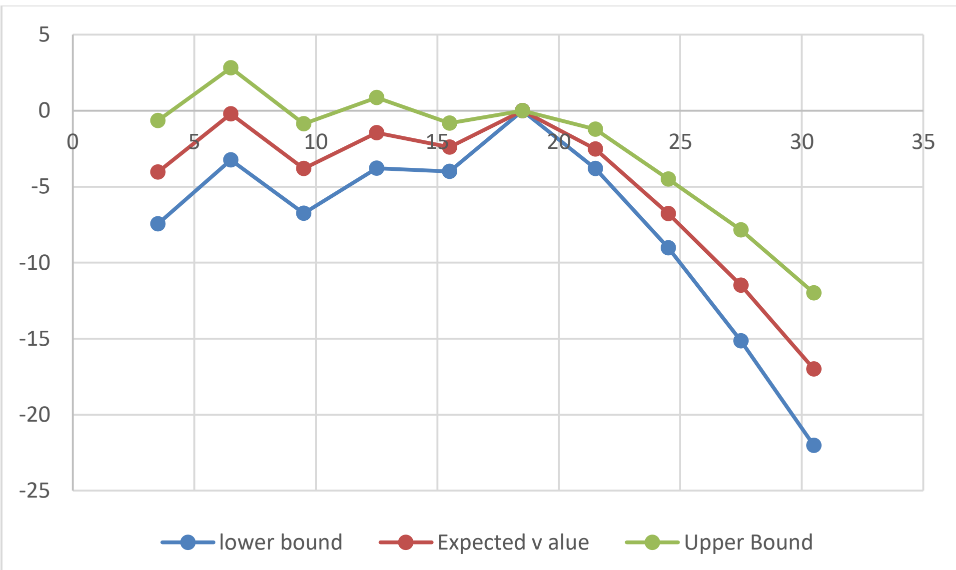
$$V(t, r) = \Sigma B_k(t)_k + \Sigma\gamma_k(r)_k + \theta X + \varepsilon \qquad (17)$$

The third bin model (18) includes bins of deviations and interaction terms. The temperature interaction term is between the underlying climate (T) and the reference bin temperature. It measures the marginal effect of weather at the reference bin across climates. The model also includes a parallel interaction term for precipitation.

$$V(t, r) = \Sigma B_k(t)_k + \Sigma\gamma_k(r)_k + \gamma_1 [T x \text{ t}] + \gamma_2 [P x \text{ p}] + \theta X + \varepsilon \qquad (18)$$

The temperature results for the standard panel approach are shown in Figure 2. The figure describes how farm income changes depending on observed temperatures each month. The results look very similar to the agricultural results reported in the literature (for example, Schlenker and Roberts 2009), with cool months having indecisive effects and warm months beyond 20C looking increasingly harmful.

Figure 2: Farm Income by Temperature



In contrast, when the bin model is estimated using temperature deviations, the results change to Figure 3. The unusually cool months remain indecisive but unusually warm months are only harmful for a short range and then become beneficial. Why they become beneficial when counties experience an extraordinary high temperature for a month is not clear.

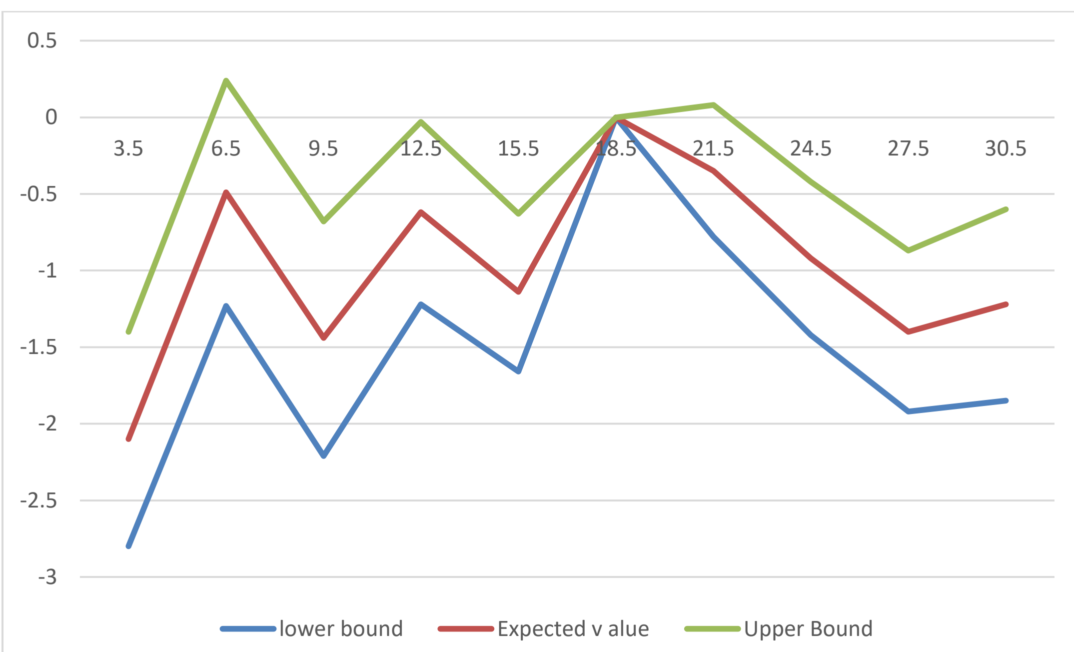
Figure 3: Farm Income Change by Temperature Change

(Weather deviations)

Finally, the temperature interaction term is added to the model and shown in Figure 4. Figure 4 implies that the marginal effect of weather varies with climate. The marginal effect is harmful for both cooler counties and warmer counties. This interaction effect is from cross sectional variation and is not yet controlled in Figure 4 for omitted variables. However, one interesting feature of this cross sectional variation is that it explains the warm effects found in Figure 2 using the standard panel estimation approach. However, Figure 4 also implies that there are harmful effects associated with cool temperatures that are not visible in Figure 2.

Figure 4: Marginal Weather Effects by Long Term Temperature

(Evaluated at reference weather deviation)



IV. Conclusion

This paper set out to develop a general theory explaining both climate and weather impacts. There is both a response to climate (long term weather) and to the immediate weather. The theory suggests that actors adapt their stock of capital to the climate (long run weather) but not to immediate weather realizations. The two response functions are consequently generally not the same. The weather response function should be more concave than the climate response function. However, when the immediate weather is similar to the average long term climate, the two response functions should be tangent, suggesting a similar marginal response.

Unfortunately, intertemporal models have done a poor job of measuring weather effects. They have over relied on fixed effects to control for time invariant variation. Fixed effects cannot completely remove the influence of time invariant factors when models are nonlinear. All weather models are nonlinear. Most of the panel weather models that have been estimated to date are mispecified. The coefficients are biased as they include interaction terms between climate and weather deviations.

The correct way to estimate these models is to use demeaned weather variables. The weather should measure the deviation of weather from the climate (expected weather). These demeaned variables can then be transformed or used in bin models.

However, the theoretical model suggests that there is a second problem with the intertemporal studies if they wish to use the resulting weather effects to study climate. A weather model can estimate marginal effects at a single location. However, theory suggests that the marginal effect of climate varies with climate. The marginal effect of weather in a panel must also vary with climate if the model wishes to capture climate effects. The estimated panel models must include an explicit interaction with climate to capture the effect of weather at each climate.

Of course, it is difficult to include an explicit interaction term with climate because that means the model is vulnerable to omitted time-invariant variables that are correlated with climate. The panel method consequently cannot avoid the omitted variable problem associated with cross sectional models.

Using data from Deschenes and Greenstone (2012), the paper reveals that there is a big difference between using actual weather versus using the deviation in weather each year. The mispecification is not a trivial matter. Specifically, the marginal effects change.

The interaction between weather and climate suggests that the marginal effect of weather may indeed vary across climates. Unless, the panel weather model begins to include this effect, it cannot even argue that it gets the marginal effects correct.

Although the paper suggests a deep problem with the existing literature, it also suggests a path to correct these errors. All the weather panel studies can be re-estimated with weather deviations. They all can begin to model the interaction between weather and climate. It will be very interesting to see how the panel weather literature changes as authors return to their original studies and correct these mistakes.

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