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Quasi-experimental estimates of the transient climate response using observational data

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Abstract
The transient climate response (TCR) is the change in global mean temperature at the time of an exogenous doubling in atmospheric CO_2 concentration increasing at a rate of 1% per year. A problem with estimating the TCR using observational data is that observed CO_2 concentrations depend in turn on temperature. Therefore, the observed concentration data are endogenous, potentially leading to simultaneous causation bias of regression estimates of the TCR. We address this problem by employing instrumental variables regression, which uses changes in radiative forcing external to earth systems to provide quasi-experiments that can be used to estimate the TCR. Because the modern instrumental record is short, we focus on decadal fluctuations (up to 30-year changes), which also mitigate some statistical issues associated with highly persistent temperature and concentration data. Our estimates of the TCR for these shorter horizons, normalized to be comparable to the traditional 70-year TCR, fall within the range in the IPCC-AR5 and provide new observational confirmation of model-based estimates.

Keywords TCR · Endogeneity · Instrumental variables · Radiative forcing

1 Introduction

The transient climate response (TCR) has traditionally been defined as the change in global mean temperature at the time of a doubling of atmospheric CO_2 concentration increasing at a

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rate of 1% per year, which takes approximately 70 years (Collins et al. (2013), Box 12.2). Empirical estimates of the TCR based on the historical record constrain climate models. They also provide a simple, data-based way to communicate the effects of anthropogenic emissions to audiences on a human timescale without invoking complex climate models.

As Fig. 1 shows, there is a strong correlation between the mean global temperature anomaly (T) and radiative forcing from CO_2 (RF^{CO2}). However, the bivariate relation between T and RF^{CO2} omits other sources of radiative forcing, which could be correlated with RF^{CO2} and thus invalidate regression estimates. This concern is readily (and conventionally) handled by aggregating radiative forcings from multiple sources (Bruns et al. (2020), Kaufmann et al. (2006a), Myhre et al. (2013), Pretis (2020)). A regression of T on aggregate radiative forcing, however, has two more substantial limitations. First, because both temperature and CO_2 concentrations have increasing trends, there is the possibility that the estimated relationship is spurious, a well-known problem in the analysis of time series data with trends (Kaufmann and Stern (2002), Granger and Newbold (1974)). Second, because the earth system has multiple and complex feedbacks from temperature to CO_2 concentrations, CO_2 concentrations are simultaneously determined with temperature (i.e., endogenous), resulting in simultaneity bias in the regression estimates (Stern and Kaufmann (2014), Stock and Watson (2018, Ch. 12), Wooldridge (2009, Ch. 16)).

One approach to these two challenges – trends and simultaneous causality – is to adopt time series methods developed for modeling highly persistent data. Some papers have taken this avenue (Bruns et al. (2020), Kaufmann and Stern (2002), Kaufmann et al. (2006a, b), Phillips et al. (2020), Pretis (2020)). While this is an important line of work, the appropriate modeling framework for the trends is a matter of debate, and how the trends are modeled matters for the empirical results (Bruns et al. (2020), Kaufmann and Stern (1997, 2000), Kaufmann et al. (2006a)).

This paper therefore takes a different, quasi-experimental approach to estimating the TCR from historical data. The starting point is the thought experiment of an idealized randomized experiment in which radiative forcings are chosen randomly, the earth is "treated" for h years, and the h-year change in temperature is recorded; after enough repetitions, the resulting data

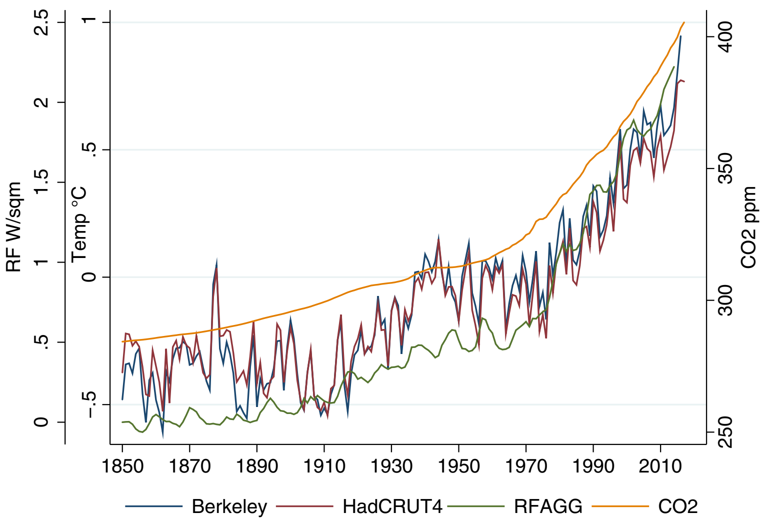


Fig. 1 Temperature, CO_2 concentrations and aggregate radiative forcing

could be used to estimate an h-year treatment effect, which (after normalization) is the h-year TCR. While this experiment is infeasible, there have in fact been many quasi-experiments that can be used to estimate the response of global temperature to radiative forcing. For example, the reductions in chlorofluorocarbons (CFCs) because of the Montreal protocol provide exogenous sources of variation in radiative forcing.

Specifically, we exploit five such sources of as-if random variation in radiative forcing: variation in solar radiative forcing arising from solar cycles, from motor vehicle emissions of CO_2, from total anthropogenic CO_2 emissions, from CFCs; and from anthropogenic emissions of sulfur oxides (SO_x). We use these five sources of as-if random variation to construct instrumental variables to estimate the effect of radiative forcing on temperature. The main methodological virtue of these quasi-experimental estimates is that they stick closely to the data, they use credible sources of exogenous variation, and they do not require modeling time series trends. Because the resulting estimates do not rely on climate science beyond the use of well-established methods for constructing radiative forcings, they provide external checks on climate model output and can be used to communicate anthropogenic warming effects without invoking climate models.

Using this approach, we estimate h-year TCRs for $5 \leq h \leq 30$. (Because our data from 1850–2014 contain only two non-overlapping 70-year periods, we do not estimate a 70-year TCR.) As we discuss in more detail below, our estimates are in line with estimates of the longer-run temperature response using time series methods (Kaufmann et al. (2006a), Phillips et al. (2020), Pretis et al. (2020), Bruns et al. (2020)), once one takes into account the short response horizon that is our focus. The shorter horizons are of independent interest because they align with recent human memory and with the short time frames relevant to policy-makers.

2 The quasi-experimental approach to estimating the h-year TCR

Radiative forcing measures the imposed change in the balance between the absorption of solar radiation and the emission of infrared radiation to space (Myhre et al. (2013), Section 8.1.1). Using the standard linear approximation (e.g., Ramaswamy et al. (2001)), over the long run, the global temperature is proportional to global radiative forcing. Because there is dynamic adjustment toward this long-run relationship through earth system responses, the temperature change arising from a sustained increase in radiative forcing depends on the horizon. Over an h-year horizon, under this linear approximation, the change in temperature (*Temp*) is proportional to the change in radiative forcing (*RF*):

$$\Delta_h Temp_t = \beta_h \Delta_h RF_t + u_t \tag{1}$$

where $\Delta_h X_t = X_t - X_{t-h}$ for variable X, t is time, measured in years, and u_t is an error term representing other factors affecting temperature. Our measure of radiative forcing is the sum of the contributions of insolation, tropospheric sulfur dioxide (SO_2) and the greenhouse gases carbon dioxide (CO_2), methane (CH_4), nitrous oxide (N_2O), and chlorofluorocarbons:

$$RF_t = RF_t^{Solar} + RF_t^{CO_2} + RF_t^{CH_4} + RF_t^{N_2O} + RF_t^{SO_2} + RF_t^{CFCs} \tag{2}$$

In (1), β_h is the causal effect of a unit increase in radiative forcing occurring over h years on temperature over those h years. The radiative forcing arising from an increase in CO_2, relative to a base year, is approximated by $RF_t^{CO_2} = 5.35\ln\left(CO_{2,t}/CO_{2,base}\right)$ (Myhre et al. 2013).

Thus, if atmospheric CO_2 concentrations increase by 1% per year for h years, the causal effect on temperature over those h years would be $5.35h\ \ln(1.01)\beta_h$. For $h = 69.99 \approx 70$, $h\ln(1.01) = \ln(2)$, and this effect is the standard definition of the TCR. For purposes of comparability across horizons, we define the (normalized) h-year TCR to be $TCR_h = 5.35\ \ln(2)\beta_h$.

If $\Delta_h RF_t$ were randomly assigned in the historical record, then β_h could be estimated from observational data by estimating (1) using ordinary least squares (OLS). But because radiative forcing is not randomly assigned, ordinary least squares estimation can, and in general does, lead to biased estimation of the regression coefficient and thus of the TCR.

This bias, referred to as simultaneity bias, arises because of feedbacks in the earth climate system. Specifically, suppose that an increase in concentrations results in an increase in temperature, but that increase in temperature in turn results in a decrease in concentrations (through, say, increased plant uptake). Then the observed temperature increase associated with a given concentration increase – the relation estimated by OLS – will understate the initial impact effect which is the causal effect of a concentration increase on temperature. If the decrease in ocean uptake outweighs plant uptake, then concentrations will go up instead of down, and the bias has the opposite sign. In general, the sign of the bias cannot be discerned from an OLS regression coefficient or from data on concentrations and temperature alone. Rather, additional information must be brought to bear.

This problem arises in a more complicated way when there are trends in the variables, as is the case in concentrations and temperature. In that case, in large samples, there are conditions under which trend analysis, specifically cointegration methods that use the level, not difference, of temperature and radiative forcing, can circumvent this simultaneity bias, e.g., Kaufmann et al. (2006a). Implementing those methods, however, requires making specific assumptions about the trend models, and those assumptions are often difficult to verify. Moreover, trend assumptions that are difficult to distinguish empirically can lead to substantially different inferences (Elliott (1998), Müller and Watson (2017)). Thus, the absence of random assignment of radiative forcing leads to biased estimation of the TCR, a situation further complicated by the trends in the data.

We therefore adopt a different approach, which is new to this literature, that exploits the as-if random assignment of certain components of radiative forcing. An example is fluctuations in insolation arising from solar cycles, for which there is clearly no feedback from earth systems to solar radiative forcing emissions. Such exogenous sources of radiative forcing provide quasi-experiments with as-if random variation in aggregate radiative forcing.

This situation in which an endogenous variable has some measurable sources of exogenous variation has been well-studied in the statistics and econometrics literature. The variable measuring an exogenous source of variation is called an instrumental variable, and the causal effect can be estimated by instrumental variables regression (Stock and Watson (2018, Ch. 12), Wooldridge (2009, Ch. 16)).

We have a total of five instrumental variables, which we consider in two groups. The first group consists of two sources of variation for which there is no plausible feedback from global temperatures: solar cycles and CO_2 emissions from internal combustion engines used for transportation. The historical growth of motor vehicle emissions was based on technology, prices, and demand, none of which depend on mean global temperature. At the same time, growth in these emissions has fluctuated over the decades, for example, flagging during the Great Depression and accelerating after World War II. The resulting variation in radiative forcing from vehicular CO_2 stems from human events that are unrelated to temperature, and therefore provides an additional source of as-if random variation in aggregate radiative forcing.

The second group of three variables includes broader measures of anthropogenic emissions: global anthropogenic CO_2 emissions from burning fossil fuel, flaring natural gas, and cement manufacturing; concentrations of chlorofluorocarbons; and global emissions of sulfur dioxide (SO_2), which reflect solar radiation and thus provide negative radiative forcing. None of these variables are subject to temperature-dependent earth system feedbacks so from that perspective are exogenous. That said, these variables could be subject to an endogenous response to temperature through human channels. For example, some CO_2 and SO_2 emissions come from burning coal to provide electricity for heating and cooling demand. This induces a small feedback from global mean temperature to anthropogenic CO_2 and SO_2 emissions. We use standard statistical techniques, specifically tests of overidentifying conditions, to assess whether these feedbacks are sufficiently large to invalidate their use as instrumental variables.

These five instruments are in different units. We therefore convert all the instruments to their contributions to radiative forcing (expressed in Wm^{-2}). This is done using standard formulas for radiative forcings based on concentrations of different gases. In the case of emissions of CO_2 from anthropogenic sources, we convert the series of emissions into concentrations by applying an empirically estimated second-order autoregressive recursion for concentration, with emissions as the driver, to specific sources of anthropogenic emissions. For a detailed description of these conversions, we refer the reader to Section 3 on the Online Resource.

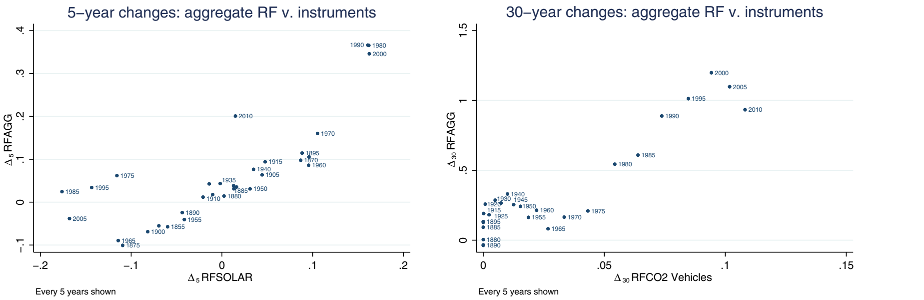
We conduct two sets of analyses, one in which (1) is estimated without any control variables and one in which the radiative forcing from stratospheric SO_2 is included as a control variable. Because stratospheric aerosols arise from volcanic eruptions, their concentrations should be uncorrelated with the instrumental variables so including or excluding them should not substantively change the results but could affect the standard errors. Following other econometric treatments of these data (e.g., Kaufmann et al. (2006a), Pretis (2020), Bruns et al. (2019)), we enter radiative forcing from stratospheric SO_2 separately from radiative forcing from the other sources. One justification for treating radiative forcing from stratospheric SO_2 separately is that, because it is driven by volcanic eruptions and has a residence time only of the order of a couple of years (Robock (2015)), it is largely a series of spikes, so modeling its effect on temperature would require looking at higher-frequency (very short-run) relationships than those of interest involving greenhouse gases. The results reported here include the control variable; results not using this control variable are provided in the Online Resource and are briefly discussed below.

Results using the five instruments separately are provided in the Online Resource. Here, we combine the instruments in each group into a single instrument, computed by summing the instruments (each of which is a radiative forcing). This produces two instrumental variables, the Group A combined instrument and the Group B combined instrument.

The five instruments are useful separately because they capture variation in radiative forcing at different horizons. At the five-year horizon, much of the variation in aggregate radiative forcing is due to the solar cycle (Fig. 2a); in contrast, variation in CO_2 emissions from automobiles is useful in explaining variations in radiative forcing at the 30-year horizon (Fig. 2b).

3 Results

Figure 3 presents the instrumental variables estimates of the (normalized) h-horizon TCR, for horizons 5–30 years, using the combined Group A instruments and combined Group B instruments (two instruments total). These estimates and confidence intervals are presented in Table 1 for h = 10, 20, and 30. The reported statistics address two technical statistical issues. The



(a) Solar radiative forcing $h = 5$ (b) CO emissions from motor vehicles, $h = 30$.

Fig. 2 h-year changes in aggregate radiative forcing and h-year changes in instruments (**a**) Solar radiative forcing, h=5 (**b**) CO_2 emission from motor vehicles, h=30

first is the possibility that the instruments might be weak. To that end, following Andrews et al. (2018), the table reports two confidence intervals in the case of a single instrument: a strong instrument 95% confidence interval computed using the large-sample normal approximation to the sampling distribution of the IV estimator, and an alternative that is robust to weak instruments. The penultimate column of Table 1 reports the first-stage effective F statistic, which is sufficiently large for the Group A + Group B case to justify reporting only the strong instrument confidence interval in Table 1 and Fig. 3. In all cases, heteroskedasticity- and autocorrelation-robust standard errors are computed using the Newey-West (1987) estimator, with a truncation parameter of $2h$ and critical values evaluated using Kiefer and Vogelsang (2005) "fixed-b" asymptotics (Lazarus et al. (2018)). See the Online Resource for details.

Two features of these results are noteworthy. First, the test of overidentifying restrictions (Table 1, final column) fails to reject, indicating that the endogeneity in the Group B instruments

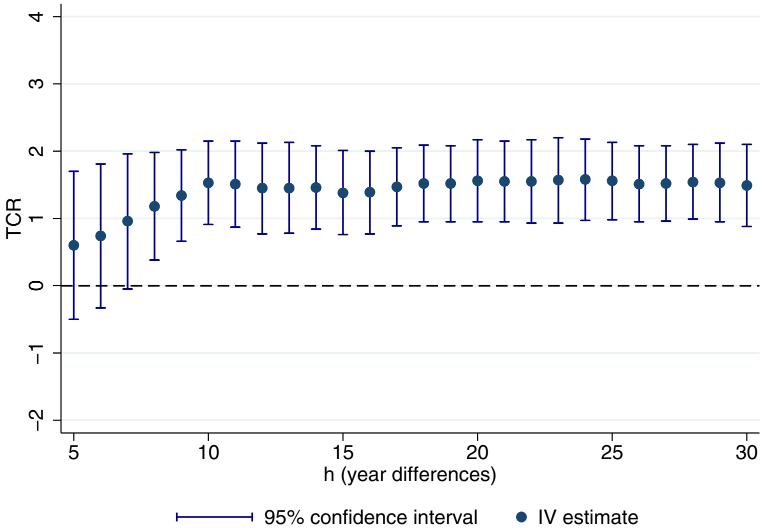


Fig. 3 Instrumental variables estimate of TCR_h using two instruments: Group A combined (solar and motor vehicle emissions) and Group B combined (non-vehicle anthropogenic CO_2, anthropogenic SO_2 and CFCs). Confidence bars indicate 95% confidence intervals computed for strong instruments with HAR standard errors and fixed-b asymptotics

Table 1 Instrumental Variables Estimates of TCR_h

Instruments (Z_t)	*h*	*No. obs*	*Estimated* TCR_h	*95% CI for TCR* (strong, fixed b asymptotics)	*95% CI for TCR* (weak, fixed b asymptotics)	*First stage F*	*Over identification test (p-value)*
Group A combined:	10	155	0.95	(-0.38, 2.28)	(-1.45, 2.11)	18.0	n.a.
Solar +	20	145	1.15	(0.29, 2.01)	(-0.33, 2.41)	15.2	n.a.
CO_2-Vehicles	30	135	1.54	(0.52, 2.57)	(0.93, 9.42)	13.2	n.a.
Group B combined:	10	155	1.63	(0.90, 2.35)	(0.96, 2.37)	355.5	n.a.
CO_2-Anth + SOX	20	145	1.60	(0.89, 2.30)	(0.96, 2.30)	475.7	n.a.
+ CFCs	30	135	1.47	(0.75, 2.20)	(0.82, 2.19)	647.1	n.a.
Group A + Group B	10	155	1.53	(0.91, 2.15)		1197.5	0.363
(2 instruments)*	20	145	1.56	(0.95, 2.17)		1184.1	0.622
	30	135	1.49	(0.88, 2.10)		1688.2	0.482
OLS	10	155	1.56	(0.97, 2.15)			
	20	145	1.49	(0.91, 2.08)			
	30	135	1.45	(0.88, 2.01)			

Notes: The TCR is computed as 5.35ln(2) β_h, where β_h is the coefficient on $\Delta_h RF_t$ in the IV regression of $\Delta_h Temp_t$ on $\Delta_h RF_t$ and $\Delta_h RF_t^{Vol}$ (RF from volcanic aerosols) including an intercept. All confidence intervals and the first-stage F are HAR; weak confidence intervals are Anderson-Rubin. HAR inference uses a Bartlett (Newey-West) kernel, window width = $2h$. The first-stage F is the effective F-statistic from Montiel Olea and Pflueger (2013). Fixed-b confidence intervals are based on Kiefer and Vogelsang (2005) and Vogelsang (2012). Overidentification test uses a window width = h; a statistically significant test statistic (p-value<0.05) indicates that the instruments may not be valid. The last three rows show OLS estimates for reference (confidence intervals are also HAR and based on fixed-b asymptotics).

*CO_2-Anth excludes CO_2 from vehicles to avoid double-counting.

arising from human-induced temperature response is sufficiently small that the Group B instruments can be used. Second, when both the Group A and Group B instruments are used, the estimated TCR_h is stable across horizons, particularly for $h > 10$, with an estimate of approximately 1.5.

Results for all instruments individually, at all horizons $5 \leq h \leq 30$, are given in the Online Resource, along with first-stage scatterplots like those in Fig. 2.

The Online Resource also reports the results of three sensitivity checks. First, we replace the HadCRUT4 temperature series with the Berkeley Earth Surface Temperature series (Rohde et al. (2013a, b)). Doing so results in estimates that are comparable to those in Table 1, for example, the Group A + Group B 95% confidence interval for TCR_{20} is (0.95, 2.17) using HadCRUT4 and (0.85, 2.05) using the Berkeley series.

The second sensitivity check addresses the possibility that even if the instruments are exogenous in the sense that there is no feedback from temperature to their values, slow earth dynamics might induce correlation between the error term in (1) and the instrument, thereby invalidating the instrument. Specifically, because of dynamic adjustment, radiative forcing from years prior to $t–h$ will have lagged impact on $\Delta_h Temp_t$, and this lagged effect appears in the error term u_t. If the instrumental variables are serially correlated, then they could be correlated with the error term through this channel. To address this concern, we include an h-lag of the instrument as a control variable in the instrumental variables estimation of (1). For example, if the instrument is $Z_t = \Delta_h RF_t^{Group\ A}$, then we include $Z_{t-h} = \Delta_h RF_{t-h}^{Group\ A}$ as a control. For a serially correlated instrument, controlling for its h-lag reduces the remaining variation in the instrument, thereby decreasing the first-stage effective F statistic and the precision of the estimator; this is especially so for the Group A instruments and at the shorter horizons. The estimates of TCR_h are also reduced at shorter horizons; however, they are similar to those in Table 1 at $h = 20$, with the Group A + Group B 95% confidence interval being (0.85, 2.03) when Z_{t-h} is included as a control variable (HadCRUT4 temperature series).

Third, we consider specifications in which radiative forcing from stratospheric SO_2 concentrations is excluded as an additional control variable. Because this is an exogenous control that ought not matter for the relevance nor exogeneity of the instrument(s), excluding it should not substantively change the results and in fact that is what we find. For example, we find that the estimated TCR_h when using Group A and Group B instruments is on average approximately 1.6. Excluding this control variable does not substantially change the precision of the estimates, at least in the cases in which the instruments are strong.

4 Discussion

Two issues arise when estimating the TCR from observational data. First, trends in the data have the potential to introduce spurious correlation. Second, earth systems feedback from temperature to concentrations creates an endogeneity, or simultaneity, problem. To address these concerns, we exploit quasi-experimental variation in the observational record that mimics an experiment in which the earth is subject to randomly chosen radiative forcings. In particular, we consider five sources of as-if random variation in radiative forcing that are not subject to earth system temperature feedback.

These instrumental variables allow us to identify a TCR by horizon. The 20-year TCR (normalized to 70 years) that we estimate using all five instrumental variables is 1.56 °C (95% confidence interval = (0.95, 2.17)), and the 30-year TCR is 1.49 °C (95% confidence interval = (0.88, 2.10)).

It is useful to compare these estimates to existing econometric ones based on modeling trends. Our estimates are in close agreement to those obtained by Pretis (2020), who uses data from 1955–2011, and Bruns et al. (2020), whose data cover 1850–2014. Both these authors look at cointegration relations in an energy balance model that explicitly models the role of the ocean. From this long-run equilibrium relation, Pretis (2020) estimates an equilibrium climate sensitivity (ECS) of 2.16°C (95% confidence interval = (1.1, 3.25)) for one preferred specification. Because the ECS gives the equilibrium or long-run response over a very long horizon, it is expected to be larger than the TCR (Otto et al. 2013); how much larger depends on the rate of adjustment of the climate variables. Pretis (2020) uses the model's short-run dynamic structure to estimate a TCR between 1.24 °C and 1.38 °C, depending on the specification. Based on a multicointegrating I(2) model, Bruns et al. (2020) estimate an ECS of 2.8 °C and a TCR of 1.64 °C for their main specification. They suggest that leaving out the slow-dynamic role of the ocean from the cointegrating relationships may lead to overestimating the rate of adjustment.

It is more difficult to compare our estimates to ones that only report long-run relations. Kaufmann et al. (2006a) and Phillips et al. (2020) use cointegration methods to estimate long-run relations among the trends in the series. The timescale for these relationships is ambiguous: the data sets (129 years for Kaufmann et al. (2006a) and 41 years for Phillips et al. (2020)) are far shorter than the multiple centuries of adjustment associated with the equilibrium climate response. With that being said, the long-run relationships represent an equilibrium convergence over the time frame associated with the data span.[1] In any event, these estimates would be expected to be larger than ours because of this additional adjustment, and indeed they are. Kaufmann et al. (2006a) find temperature sensitivity to a doubling in CO_2 equal to 2.1 °C, with a 95% confidence interval of (1.8 °C, 2.5 °C). Phillips et al. (2020) obtain an estimated temperature sensitivity of 2.8 °C with a 95% confidence interval of (2.36 °C, 3.24 °C).

Finally, our results are in line with the IPCC-AR5 range of 1–2.5 °C for the (70-year) TCR (Bindoff et al. (2013)), especially considering that more temperature adjustment would occur over 70 than 20 or 30 years. Our estimates of the short-run TCRs thus provide an independent check on model-derived estimates that do not rely on statistical models of trends and align with the methods used for causal inference in statistics and econometrics.

An additional relevant question is the extent to which the endogeneity of concentrations results in bias in standard OLS estimates. For 20 and 30-year differences, the OLS estimates are 1.49 °C and 1.45 °C, slightly smaller than the corresponding IV estimates at 1.56 °C and 1.49 °C. The OLS confidence intervals are also somewhat tighter than the IV intervals, which is to be expected given that IV tends to deliver larger standard errors. Overall, evidence suggests that the bias introduced by simultaneous causality is not too large, as least within the shorter time scales that we analyze. This is an important finding because it suggests that OLS estimates, which dominate this literature, appear not to be badly biased – a conclusion that, of course, could not be reached without actually computing the quasi-experimental instrumental variables estimates in this paper.

We believe that our estimates of short-horizon effects of emissions are of independent interest for two reasons. First, by essentially just compiling the outcomes of natural experiments, they stay close to the data – and in particular, appeal neither to complex earth system models nor to advanced time-series econometric methods for modeling trends. Second, they are on a timescale relevant to non-experts and policymakers. From 2008 to 2018, atmospheric CO_2 concentrations increased at the rate of 0.58% per year. If this rate continues for 10 more years, then the 10-year TCR estimate of 1.53 implies another 0.13 °C (95% confidence interval (0.08, 0.18)) increase in mean surface temperatures over the next decade from these additional emissions alone. This estimate neglects warming over the coming decade that will occur because of lagged dynamic effects of CO_2 that has already been emitted; yet, this warming alone is fully one-eighth of the total warming from the pre-industrial period to the present.

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[1] Through a simulation exercise, Kaufmann et al. (2006a) find that "about 95% of the temperature increase implied by the coefficient from the long-run relationship occurs at the time that the atmospheric concentration of CO_2 doubles," from which they conclude that their cointegration estimate should be interpreted as the TCR (see also Kaufmann et al. (2006b)).

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