Rain, Rain, Go away: 176 potential exclusion-restriction violations for studies using weather as an instrumental variable

Jonathan Mellon (University of Manchester)

2021-04-21

Abstract

Instrumental variable (IV) analysis assumes that the instrument only affects the dependent variable via its relationship with the independent variable. Other possible causal routes from the IV to the dependent variable are exclusion-restriction violations and make the instrument invalid. Weather has been widely used as an instrumental variable in social science to predict many different variables. The use of weather to instrument different independent variables represents strong prima facie evidence of exclusion violations for all studies using weather as an IV. A review of 217 social science studies reveals 176 variables which have been linked to weather, all of which represent potential exclusion violations. I conclude with practical steps to systematically review existing literature to identify possible exclusion violations when using IV designs. I demonstrate how sensitivity analysis can quantify the vulnerability of a particular IV estimate to exclusion restriction violations in the literature.

Note: This is a working paper. Comments and corrections are very welcome at

jonathan.mellon@manchester.ac.uk

Endogeneity is one of the most pervasive challenges faced by social scientists. Naively, we might assume that the causal relationship between two social science variables X and Y can be estimated simply by their observed relationship (showed in the left directed acyclic graph (DAG) in figure 1). However, social scientists are usually skeptical of this simple picture and believe that most sets of variables inevitably share some unmeasured confounders U (middle DAG). One strategy for conducting causal research even in the presence of endogeneity is instrumental variable (IV) regression where a third variable W—thought to be uncorrelated with the error term—is used to predict X and this prediction $\hat{X}$ is then used to predict Y, on the assumption that W is uncorrelated with the error term, and is associated with Y only through its relationship with X (referred to as the exclusion restriction). W's ability to causally manipulate X independently of U allows the consistent causal estimation of the relationship between X and Y using two stage least squares (2SLS). The DAG for the IV model is shown in the right panel of figure 1).

One widely used instrument is the weather. The weather is intuitively appealing as a source of exogenous

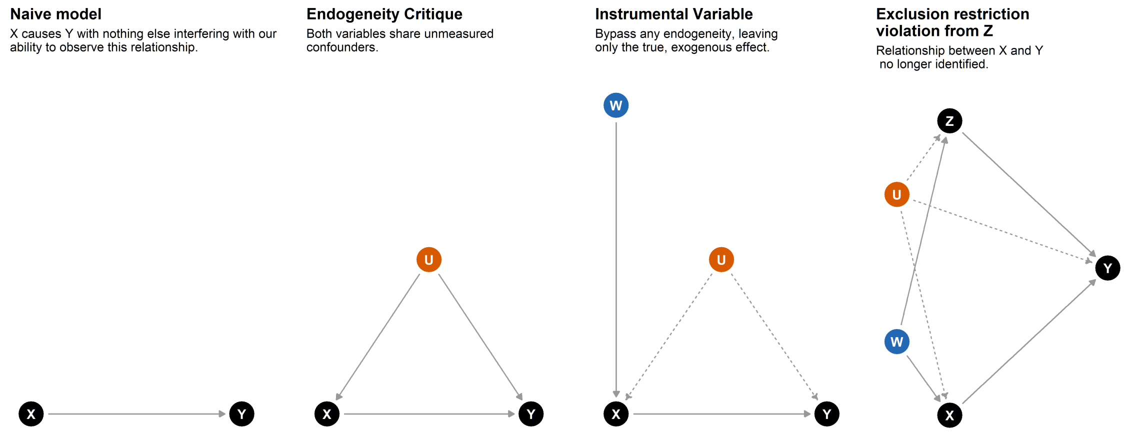

Figure 1: Instrumental variables as a fix for endogeneity

variation because it seems instantly plausible that the weather is essentially random, uninfluenced by human behavior, and presumably only related to human outcomes through specific narrow causal paths. In this paper, I examine whether the IV DAG really represents a plausible account of IV weather studies. In particular, I ask whether the vital exclusion restriction assumption of IV models is plausible in the case of weather as an IV.[1]

Rather than independently validating possible confounding routes from weather to outcomes, I use the IV literature itself to identify alternative causal pathways (similar arguments have been made against the use of population size as an instrument by Bazzi and Clemens (2013)). I review 128 papers using weather as an instrumental variable and an additional 89 papers looking at the direct effect of weather on other outcomes. In total, I conservatively identify 176 variables which social science has linked to weather, through many different causal pathways. As Bartels (1991) shows, even small violations of the IV assumptions can lead IV regression to be highly biased (even to the point of underperforming simple OLS). Consequently, this review calls into question many findings based on weather IVs.

Any exclusion restriction violation has the potential to bias an IV regression. However, in practice, researchers might be willing to live with small violations of this assumption. To assess how serious these violations are, I use the first-stage IV estimates of weather on possible Z variables, to conduct sensitivity analysis (Cinelli and Hazlett 2020a, 2020b) on the reduced-form equations of weather IV regressions. This

[1]Thanks to Jack Bailey, Chris Prosser, and the University of Manchester Democracy and Elections Group for feedback on drafts of this paper.

allows me to show how large a relationship would have to exist between Z variable and a dependent variable in order to make an IV estimate insignificant or reduce it to zero. For some combinations of exclusion restriction violations and IV studies, Z would have to explain as little as 0.01% of the variance in Y to reduce the IV estimate of X on Y to zero. However, in other cases, plausible Z variables would have to explain more than 20% of variance in Y in order to make the IV estimate of X on Y insignificant. While both cases have exclusion restriction violations, the sensitivity of the IV estimate in the former case, should concern us much more in practice.

Using weather as an IV has not been without its critics. Kubitza and Krishna (2020) mentions the overuse of rainfall as an instrument in impact evaluations even where the theoretical plausibility is questionable. Sarsons (2015) points out a likely exclusion restriction violation in IV models of rainfall on economic growth, as she finds that rain predicts conflict in India even where incomes were not affected.[2] Additionally, Gallen and Raymond (2019) include rainfall as one of several instrumental variables which are overused within economics. However, this paper expands on that analysis by analyzing studies in other fields such as political science and quantifying the strength of the exclusion restriction violations using sensitivity analysis. Betz, Cook, and Hollenbach (2019) and Cooperman (2017) point out that rainfall and many other instruments suffer from spatial interdependence which is rarely adequately accounted for in practice. Auffhammer et al. (2013) note several practical problems with weather variables including coverage bias, spatial autocorrelation, the use of interpolated data, and country heterogeneity. These issues are also taken up by Dell, Jones, and Olken (2014) who carefully dissect many other measurement and analysis issues when studying weather effects in social science. Finally, K. A. Schultz and Mankin (2019) point out that conflict (usually considered an outcome in the weather→income→conflict causal chain) actually predicts poorer weather measurement.[3]

While the plausibility of the exclusion restriction is not directly testable, future work can at least try to avoid using instruments which have well-documented alternate paths to the outcome of interest in the existing literature. In other words, our *minimum* standard for accepting the exclusion restriction assumption should

[2] This finding could potentially have been enough to stop people using weather as an instrument. However, my review contains 50 IV-weather papers from 2016-2020, so more evidence appears to be needed.

[3] I do not assess violations of the other IV assumptions in this paper but there are reasons to think these may sometimes be violated in practice. For instance, monotonicity is likely violated when areas with different industries or crops have opposite responses to increased rainfall. Similarly, W. C. Kang (2019) found the opposite pattern of turnout and rainfall in South Korea because (they argue) rainfall led young people to cancel their other plans and vote instead.

be that it is not disproven within the existing literature. To help with this I set out a systematic process for searching the existing literature for relationships which could represent possible exclusion restrictions for a particular IV and for conducting a sensitivity analysis to estimate how substantial the exclusion restriction violation would have to be in order to undermine the result. If the instrument you are considering has been linked to a vast series of important variables, it is probably not exogenous and IV is not an appropriate identification strategy.

This paper proceeds as follows. First, I describe the exclusion criterion in more detail. Second, I outline my review strategy. Third, I show the results of the review, and the scale of the exclusion violations for weather as an IV. Next, I explain specific threats to particular IV inferences and describe a strategy for finding possible exclusion restriction violations in the existing literature. Finally, I conclude by discussing what these results might indicate about the use of IVs in social science more generally.

1 Throwing caution to the wind? Weather and the Exclusion restriction

We assume the true data generating model (DGM) for Y is: $Y = \alpha + \delta X + \psi U + \epsilon$. However, because we do not observe U (the unobserved variables which make X and Y endogenous), the OLS estimator $\hat{\delta}_{OLS}$ for the effect of X in our model is: $Y = \hat{\alpha} + \hat{\delta}_{OLS} X + \eta$, where η is the combined error term that includes the true random error ϵ and the non-random error resulting from not including U in the model (Cunningham 2018). This means our estimate of $\hat{\delta}_{OLS}$ of δ is biased as follows:

$$\hat{\delta}_{OLS} = \delta + \psi \frac{Cov(U, X)}{Var(X)} \tag{1}$$

However, if weather is correlated with X, we can estimate the local average treatment effect (LATE) of X on Y, δ, consistently as follows:

$$\hat{\delta}_{IV} = \frac{Cov(Y, weather)}{Cov(X, weather)} \tag{2}$$

provided that $Cov(U, weather) = 0$ and $Cov(\epsilon, weather) = 0$. These two requirements are collectively referred to as the exclusion restriction and mean that the instrument cannot be correlated with either part of the combined error term η.

In summary, weather is exogenous and causally affects X, while not affecting Y in any way, except through weather's relationship to X. Importantly, this DAG assumes no other routes from weather to Y exist. If other routes existed, this would be an exclusion violation and IV regression would no longer provide a valid identification strategy.

2 Getting wind of exclusion restriction violations statistically

While most sources agree that the exclusion restriction is fundamentally theory-based and cannot be tested with statistical methods alone (Cunningham 2018; Kippersluis and Rietveld 2018; Cinelli and Hazlett 2020a), there are statistical techniques which are relevant to the exclusion restriction. I briefly review these to explain why they do not address the concerns raised in the rest of this paper.

The first of these tests is the Sargan-Hansen test for over-identifying restrictions. The Sargan-Hansen test is applicable to the specific situation where more instruments are included than instrumented variables. In this case, it is possible to test whether the residuals for the second stage model (not including instrument I) are correlated with the instruments, which could indicate an exclusion violation. Weather-IV studies rarely use multiple instruments, so this test is not that relevant in most of the studies reviewed in this paper. Additionally, the Sargan Hansen test does not test the validity of the instruments but merely that they do the same thing as each other. The test itself assumes that at least enough instruments to "just-identify" the model are valid (Kiviet 2020).

The zero-first-stage test looks at the effect of the treatment in a sub-sample where the effect of the instrument on X should be zero and verifies that there is no relationship between the instrument and outcome in that subset. While this will pick up on *some* exclusion violations, it cannot affirmatively prove there are no violations. This may be the case for weather effects. It is plausible that the same factors reduce the influence of weather on multiple potential instrumented variables. A dammed river probably reduces the effect of rainfall on income, migration, and conflict, but does nothing to distinguish the causal ordering of income, migration, and conflict. Most of the plausible zero-first-stage subsets for weather are simply going to be situations where weather is generally less important. In other words, if the subset of cases where $Cov(X, weather) = 0$ are also cases where $Cov(U, weather) = 0$, then the test does not exclude the possibility that $Cov(U, weather) \neq 0$ across the whole sample.

Both of these tools are valuable, but they do not remove the need for researchers to think through the theoretical plausibility of their instruments.

3 Approach for reviewing the flood of weather IV papers

The goal of this paper is not to give an exhaustive or representative review of studies using weather as an IV. Exclusion violations are threats to the validity of studies using weather as an IV, whether the set of exclusion violations is exhaustive or representative of all known violations. For the same reason, I included studies regardless of whether they are published studies, working papers or theses.

I reviewed the first 500 results for the search term 'weather "instrumental variable"' in Google Scholar (the search returned 12,700 results in total). Additionally, I added in the first 100 results from 'rain "instrumental variable",' a handful of studies I had previously identified, and any other relevant studies cited within the initial searches. This produced 128 studies which used weather as an IV, and an additional 89 studies which used weather directly. These studies were most commonly in economics, political science, and international development, but almost all social science disciplines have used weather as an IV to some extent.

All studies were entered into a table tracking the instrumental variable, instrumented variable and outcome variable. If more than one combination of these was present, I included a row for each combination. I also included a measure of the time-period over which the weather was measured and spatial resolution of the weather measurement.

For the purposes of this analysis, I also include studies which do not explicitly use IV designs but follow the same logic as IV studies. This includes some studies on rainfall and turnout, which explicitly see weather as affecting other outcomes via turnout, but do not always use 2SLS models for their analysis (e.g. Gomez, Hansford, and Krause 2007; W. C. Kang 2019), although others do explicitly use IV models (e.g. Artés 2014; Arnold and Freier 2016; Lind 2019; Lo Prete and Revelli 2020)). However, these studies still generally refer to the importance of weather's exogeneity and random assignment as reasons to believe the conclusions reached about the mechanisms linking rainfall to the outcome of interest.

For analysis, I recoded the variables into coarser theoretical categories. For instance, the following variables were recoded as "income": GDP, household income, average income, economic growth, permanent income, income, agricultural income, growth, per-capita income, crop revenue per hectare, poverty, transitory income, agricultural growth, and farm financial performance. Less coarse categories would better distinguish concepts but would inflate the count of potential exclusion violations. The number of exclusion concerns in this paper is therefore a relatively conservative count. Similarly, I recoded all weather-related variables into a single category of weather.

The existence of other causal pathways into the social world for weather does not necessarily prove that a particular use of an instrument is invalid. However, it is worth recalling why we use IV regression in the first place. Most variables of interest in social science are embedded in complex endogenous causal networks that we cannot hope to fully disentangle. Simple OLS estimators are therefore presumptively biased in social science. The appeal of IV regression is that we have an exogenous variable that enters this network only in one specific place analogous to an experimenter manipulating a variable directly. However, if weather enters the causal network in many places, it becomes unclear whether arguing for the validity of weather as an instrument is different to arguing that a particular independent variable of interest is not confounded by some unspecified set of other variables. The full table of studies is shown in appendix A.

4 Any way the wind blows doesn't really matter

Not all weather IVs are interchangeable. There are two main ways in which weather IVs might be differentiated: temporally and by weather phenomena.

If a weather phenomenon has an effect at the daily level, it is at least plausible that this effect will aggregate to confound relationships over longer periods. Long-period weather IV studies (long term climate differences or differences on the order of years) are therefore vulnerable to exclusion violations identified in all other weather IV studies. However, the inverse is not necessarily true. Many studies which use weather IVs over short time periods (e.g. the rain on election day) control for the long-term trend in weather in that area. While controlling for other time periods will inevitably be imperfect, it is at least conceivable that variation in weather in other time periods could be accounted for (although this is done haphazardly in practice).

However, even short-term studies will be vulnerable to other mechanisms acting at time periods not controlled for. For instance, many turnout IV studies, control for the average weather on that day of the year over the previous decade. However, this does not account for the fact that the weather on election day will be correlated with the weather over the past week or month in that area. This means that medium-term weather effects will still potentially confound short-term studies.

To show the different mechanisms that might confound different studies, I show both the overall causal network related to weather and the causal network from studies using weather variation at the monthly level or more frequently.

In terms of variation by weather phenomena, there are certainly cases where specific weather phenomena (e.g. strength of monsoon seasons) are not relevant to another setting (e.g. turnout in British elections). However, this is the exception, as it is generally the case that all weather variables are part of a complex causal network and are therefore non-independent. This complexity means that the nature of confounding relationships across weather phenomena may be hard to predict in advance but still represent confounding relationships (remember that the lines in DAGs do not represent simple linear relationships but causal connections). At the simplest level, precipitation, temperature, and wind speed are all correlated (Auffhammer et al. 2013). A relationship between one weather variable and an outcome of interest therefore implies the existence of some relationship to all other weather variables.

Looking across countries, there is a reasonably high correlation between average precipitation and temperature (r=0.41). Over-time weather correlations within a location are often considerably stronger. For instance, Nicholls, Drosdowsky, and Lavery (1997) finds correlations between -0.52 and -0.77 for yearly precipitation and temperature in Australia, and M. Xu et al. (2006) finds a correlation of 0.7 between yearly wind speed and temperature in China. In general, studies find correlations in the -0.3 to -0.8 range between precipitation and temperature in individual locations, with North America showing particularly strong correlations (Trenberth and Shea 2005).

It is also worth bearing in mind that these correlations reflect the measured values of each variable and do not account for measurement error. Correlations between different country-level datasets measuring the *same* weather phenomena range from as r=0.269 to r=0.917 (Auffhammer et al. 2013), so the correlations between different weather phenomena are not necessarily much lower than the correlations between different measurements of the same phenomena.

5 Results of the rain check

Figure 2 shows the causal web derived from the 217 social science studies that use weather as a variable. It is useful to contrast this figure with the assumed DAG in figure 1. In that figure, weather entered the causal network only through the single X variable of interest. In reality, weather enters the causal network of interest to social science in 99 places, and indirectly reaches a total of 176 variables of interest to social scientists. These all represent potential exclusion violations for the DAG in figure 1.

As mentioned above, shorter-term weather-variation IVs may not be confounded by long term variables. I therefore also plot the causal network for studies with a weather frequency of a month or less. It should be noted that the outcome variables in these studies often take place over longer periods of time (e.g. government spending via the outcome of an election), so not all variables represent plausible exclusion violations for all other variables. Even this reduced set of studies have 35 instrumented variables and 73 variables in total on the causal graph.

These variables include several important variables that represent plausible routes to many social science outcomes including: pollution, crime, economic activity, mood, leisure activities, consumer sentiment, stock market performance, health, and skin tone.

For both causal graphs, some of these relationships are more directly relevant to some studies than others. Most researchers are probably justified in assuming that "helicopter flying conditions" and "pirate attacks" are not exclusion violations for their research. However, some causal routes have wide relevance to almost all research outcomes.

The first of these causal routes is mood. Several studies establish a link between weather conditions and mood. These studies then claim a large number of links between mood and other variables including: decision making speed, investment decisions, inflation expectations, risk aversion, financial decisions, and perceived life expectancy. It is hard to think of a social science variable which could not be plausibly causally influenced by at least one of these variables or directly by mood itself. Mood is a threat to both long-term and short-term weather IV studies.

The next major causal route is pollution. Pollution levels have been instrumented by many aspects of

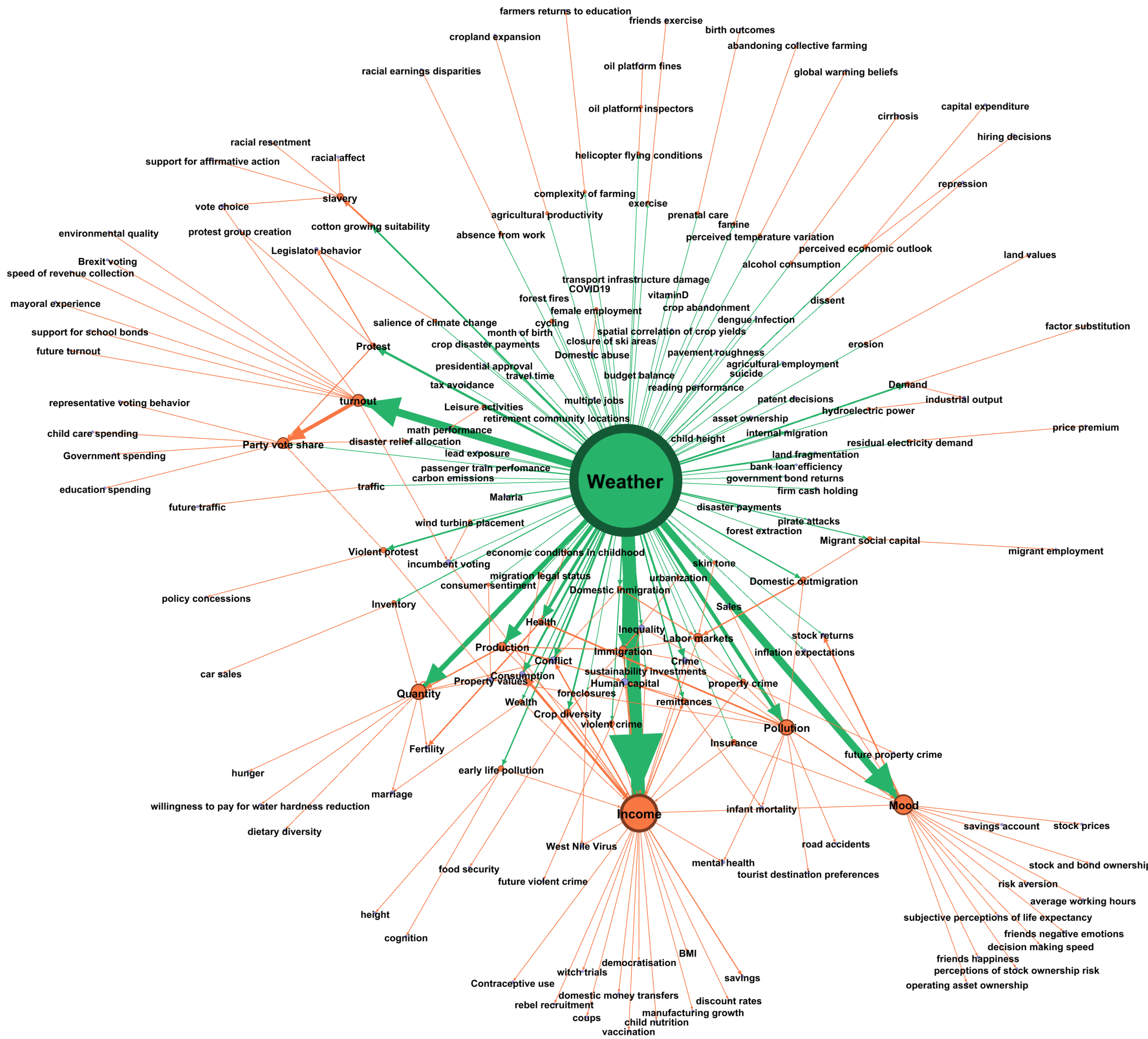

Figure 2: The causal web of weather as derived from 217 social science papers. Size of nodes and ties are proportional to the number of instances appearing in the literature. Color key: weather (green), instrumented variable (orange), and outcome (purple)

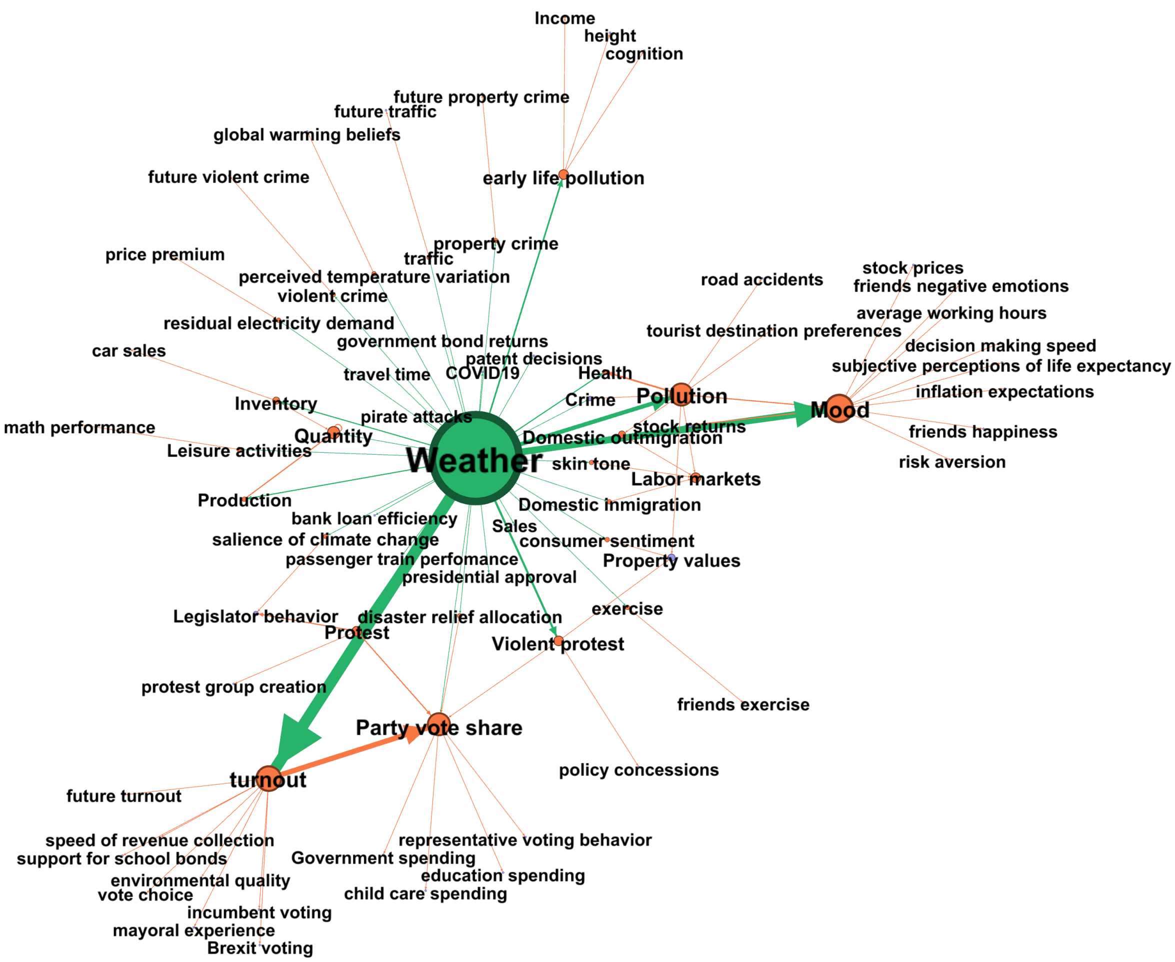

Figure 3: The causal web of weather as derived from 69 social science papers using weather varying monthly or more frequently. Size of nodes and ties are proportional to the number of instances appearing in the literature. Color key: weather (green), instrumented variable (orange), and outcome (purple).

weather including wind speed (Peet 2020; Zheng et al. 2019; Xinye and Wei 2019; Bondy, Roth, and Sager 2020), wind direction (Luechinger 2014; Fan and Wang 2020), atmospheric inversions (Bondy, Roth, and Sager 2020; C. Cui et al. 2019; Sager 2019), rainfall (Peet 2020; Fontenla, Ben Goodwin, and Gonzalez 2019) and many others. Perhaps most surprisingly, warmer weather is strongly correlated with lead exposure (Levin et al. 2020) (blood lead levels rise 10%-60% in warm weather). Pollution in turn has been linked to crime (Bondy, Roth, and Sager 2020), mental health (Gu et al. 2020), mortality (Fan and Wang 2020), road accidents (Sager 2019), retail sales (H. Kang, Suh, and Yu 2019), house prices (Fontenla, Ben Goodwin, and Gonzalez 2019), mobility (C. Cui et al. 2019), cognition (Peet 2020), and mood (Zheng et al. 2019; Xinye and Wei 2019). Once again, it is difficult to argue that any variable in social science is not affected by some of these factors. Importantly, pollution can be a threat to both long-term and short-term weather IV studies.

The next major causal route is a recently discovered link: skin tone. Katz et al. (2020) observe that some workers become darker skinned when exposed to sunlight while others do not tan. They use an IV approach to claim that the gap in labor market outcomes, between those who tan and those who do not, widens during sunny periods. Given the pervasiveness of colorism in societies around the world, the confounding effect of skin tone with weather is another major point of entry into the messy causal web of the social world. The upshot of this is that weather instruments are now plausibly proxying for racial prejudice. Skin tone could potentially be a confounding variable for long-term or short-term IV studies.

The last major causal entry I consider is crime. Studies have claimed that crime is affected directly by weather (Chia et al. 2016; Ranson 2014; Reichhoff 2017; Horrocks and Menclova 2011; Jacob, Lefgren, and Moretti 2007; Bruederle, Peters, and Roberts 2017), or indirectly through income (Mehlum, Miguel, and Torvik 2006; Blakeslee and Fishman 2018; Pereira and Menezes 2020) or pollution (Bondy, Roth, and Sager 2020). Indirect or direct exposure to crime is also associated with psychological distress (Heinze et al. 2017; Burdette and Hill 2008) and substantial behavioral changes (Burdick-Will, Stein, and Grigg 2019; Berens and Dallendörfer 2019).

There are also major causal routes that are particularly relevant to studies using longer term weather and climate as instruments (although these can certainly affect inferences using short-term weather as an instrument if long-term climate is not accounted for).

The most widely instrumented variable in economics and political economy studies is income, both in terms of individual or household incomes and aggregate incomes. The mechanism for this link is most often described in terms of the success or failure of crops, but many papers acknowledge that the mechanisms could be more varied. Income is a hugely important variable, so it represents a large exclusion violation for other studies using weather as an IV.

Conflict has usually been modeled as resulting from changes in income instrumented by weather. However, recent studies cast doubt on this interpretation, with Sarsons (2015) finding that conflict increases in response to weather shocks regardless of income changes. As (Sarsons 2015) indicates, this is concerning for claims that weather's relationship to income fulfills the exclusion restriction. Similar concerns are raised by (Landis et al. 2017) who find that distance from rivers only slightly mediates the effect of rainfall on conflict. Overall, these results suggest that there can be some form of relationship between weather and conflict that does not flow through income. This means that conflict represents a potential exclusion violation for weather-IV studies in general.

Migration follows a similar pattern. These studies generally justify the use of weather as an IV by weather's effect on income (lower incomes provide a push factor for emigrants and higher incomes are a pull factor for immigrants) (Strobl and Valfort 2015; Nawrotzki, Riosmena, and Hunter 2013; Pajaron and Vasquez 2020). However, these studies also offer (usually qualitatively) other possible links between weather and migration including direct displacement by disaster (Nandi, Mazumdar, and Behrman 2018), violence, political unrest, and health (Pajaron and Vasquez 2020). However, these studies usually do not explicitly model the income to migration step of the process and often do not consider the other possible causal routes from income to their dependent variable of interest. In fact, one study which did examine the income-migration link (Marchiori, Maystadt, and Schumacher 2017), dismissed the role of income variability as "negligible." Even outside of low income countries, there is evidence for non-economic links between migration patterns and weather, with Moretti (1998) finding that good weather predicts the location of retirement communities within the US, and Rappaport (2007) finding the same pattern for internal US migration more generally.

Taken together, the existing literature suggests that migration is a potential exclusion violation for weather-IV studies including those instrumenting income using the weather.

The next major causal route is via the legacy of slavery. Acharya, Blackwell, and Sen (2016) use cotton growing suitability as an instrument for slavery in the southern United States. That measure, in turn, contains climate as an input. For studies in the US, the use of weather as an IV potentially introduces a confound with legacies of slavery. The legacy of slavery is primarily a threat to inferences in studies using long-term weather IVs or not otherwise accounting for long-term weather.

6 If a butterfly flaps its wings does it causes a hurricane for IV studies?

So far, the review of the literature has clearly exposed a plethora of exclusion restriction violations for weather IV studies. However, this does not necessarily mean that IV estimates will be greatly biased. If we could measure Z, would including it change the conclusions of the IV study? As discussed in Cinelli and Hazlett (2020a), if we are interested in the null hypothesis of zero effect, which I focus on here, we only need to worry about the sensitivity of the reduced form.[4]

The extent to which an exclusion restriction violation will change the conclusions of a weather IV study depend on two quantities: the partial R^2 of the relationship between the instrument W and an exclusion restriction variable Z ($R^2_{Z\sim W|K}$) and the partial R^2 of the relationship between the Z and the dependent variable of interest Y ($R^2_{Y\sim Z|W,K}$), where K is the set of exogenous predictors in the original study.

Based on a given pair of partial R^2 values for a particular Z, I can estimate the bias of the coefficient (Cinelli and Hazlett 2020a) using the *sensemakr* package (Cinelli, Ferwerda, and Hazlett 2020) (where n is the sample size and p is the number of predictors):

$$bias = SE\sqrt{\frac{R^2_{Y\sim Z|W,K}R^2_{Z\sim W|K}}{1-R^2_{Z\sim W|K}}(n-p-1)} \tag{3}$$

[4]Cinelli and Hazlett (2020a) shows that the sensitivity of the Anderson-Rubin IV confidence intervals are exactly equal to the sensitivity of the reduced-form estimates.

and the corrected standard error:

$$SE_{corrected} = SE\sqrt{\frac{1 - R^2_{Y\sim Z|W,K}}{1 - R^2_{Z\sim W|K}} \cdot \frac{n-p-1}{n-p-2}} \tag{4}$$

These can be used to calculate a new central estimate for the reduced-form equation and an adjusted confidence interval accounting for both the bias and corrected standard error.

This allows the use of sensitivity analysis (Cinelli and Hazlett 2020a, 2020b) to estimate two hypotheticals: 1) how strong a set of confounders would be required to make an IV estimate insignificant and 2) how strong a pair of confounders would be required to reduce an IV estimate to zero.

6.1 Are the exclusion restriction violations a storm in a teacup?

But how large are the relevant partial R^2 values likely to be? The answer comes specifically from the IV literature's first stage estimates of the relationship between weather and various X variables. For a given study, all the other studies' estimates of X, W relationships represent estimates of possible confounding Z, W relationships. The F-statistics ($F_{X,W|K}$) measure the strength of the relationship between weather and an X variable conditional on various other predictors. These can be converted to a partial R^2.[5]

It should be noted that these partial R^2 values will not transfer perfectly across studies. Different studies use different measurements of weather (both in terms of weather type and temporal scales). To the extent that an existing IV relationship in the literature refers to a different weather type the level of confounding an exclusion restriction violation represents will be reduced the weaker the correlation between the two weather variables. Importantly, however, it is the underlying correlation between the true causal variables not the measured correlation of the weather indicators that is important here, so the true correlations are likely to be higher than the raw correlations reported in the literature.

Another reason why the first stage statistics from the literature might not perfectly transfer across studies is that different studies use different sets of exogenous controls K. This does not necessarily imply that a

[5] It is possible to derive $R^2_{Y\sim X|K}$ for a model predicting Y using X and a set, K, of p exogenous predictors from the F-statistic $F_{Y,X|K}$ using the following formula: $R^2_{Y\sim X|K} = \frac{F_{Y,X|K} \cdot p}{n-p-1+F_{Y,X|K} \cdot p}$, where n is the number of observations.

partial R^2 in one study will be lower when transferred to another (the difference could be in either direction) but reduces how precisely we should expect the partial R^2 values to transfer.

Finally, the first stage statistics will only transfer across studies imperfectly because different studies examine different contexts where first stage effects will be of genuinely different sizes. Studies focused on Britain, for instance, likely do not need to worry about the very strong correlation between rainfall and dengue fever prevalence found in studies of tropical countries. The variability of first stage effect sizes is visible for the same variable across studies. For instance, in the 19 studies with a weather $\rightarrow$ income first stage, the implied partial R^2 values range from 0.00015 to 0.26.

Nevertheless, the first stage statistics from these studies represent plausible (but highly uncertain) values for the magnitude of potential exclusion restriction violation confounders $R^2_{Z\sim W|K}$ unless we have a good reason to think that a number should not generalize to another study. In other words, there is no reason to think that these estimates will systematically overstate the size of exclusion restriction violations for a given study.

Given particular values of $R^2_{Z\sim W|K}$, it is then possible to ask how large the conditional association between Z and Y, $R^2_{Y\sim Z|W,K}$, would have to be in order to either 1) make an existing result insignificant or 2) reduce its magnitude to zero. If the relationship between a particular Z and Y would have to be very large to overturn a result, then we can be reasonably confident that that exclusion restriction violation is unlikely to greatly change the substantive conclusion of a particular study. However, if the relationship between Z and Y can be very small and still overturn the result, we should be wary of trusting that study's results if we think that it is plausible that that Z could exist as a confounder.

While I look at confounders in the direction of reducing an effect's magnitude, exclusion restriction violations could also mean that the true magnitude of the effect is arbitrarily larger than the observed value, depending on the sign of the $W \rightarrow Z$ and $Z \rightarrow Y$ relationships. This is also highly undesirable in terms of bias.[6]

[6] The literature review in this paper also raises other shortcomings in the IV literature. Despite the standard advice to report the first-stage, reduced form and F-statistics from IV models (Angrist and Pischke 2008, p212–213), this is far from universal in practice which greatly reduces the ability of readers to assess the plausibility of a given model.

6.2 Do any results weather the storm?

The literature produced 74 first stage estimates that could be converted into $R^2_{Z\sim W|K}$ values. The literature review also contained 45 IV studies which included reduced form estimates or included enough information to reverse-engineer the reduced form relationship subject to the assumptions in appendix C.

I test the robustness of the 45 weather IV studies with reduced form estimates to exclusion restriction violations from the 74 first stage estimates in the literature. The number of test cases is considerably smaller the total number of IV studies because many studies use multiple weather instruments (i.e. rainfall in two seasons, or drought and flooding shocks) or provide insufficient information to derive the reduced-form equation. The sensitivity analysis I conduct here is designed specifically to work with the reduced-form stage of the IV regression in the case of a single instrument. However, there is no reason to think that multiple instrument studies are systematically less susceptible to confounding bias.

Figure 4 shows the distribution of robustness to different confounding variables of the IV estimates from the 45 studies with a single instrument that included sufficient information to derive the reduced-form. Four exclusion restriction variables are shown with relationships to weather ranging from very weak (mood with $R^2_{Z\sim W|K} = 0.0025$) to strong (domestic inmigration with $R^2_{Z\sim W|K} = 0.11$).

The results show that most studies (64%) would require that mood (a weak confounder) explain at least 1% of the variance in that study's dependent variable in order to make the result insignificant and most (84%) would require that it explain at least 10% to reduce the result to zero. However, there is still a sizeable minority of studies where even a very weak relationship between mood and the dependent variable would overturn the result of the study.

At the other end of the scale, domestic inmigration (people moving into an area of the country) has such a strong relationship with weather in the existing literature, that it could make 58% of the studies insignificant even if it only explained 0.1% of the variance in the dependent variable. Additionally, if domestic inmigration explained 1% of the variance in the dependent variable it would be sufficient to reduce the IV relationship between X and Y to zero in 40% of cases.

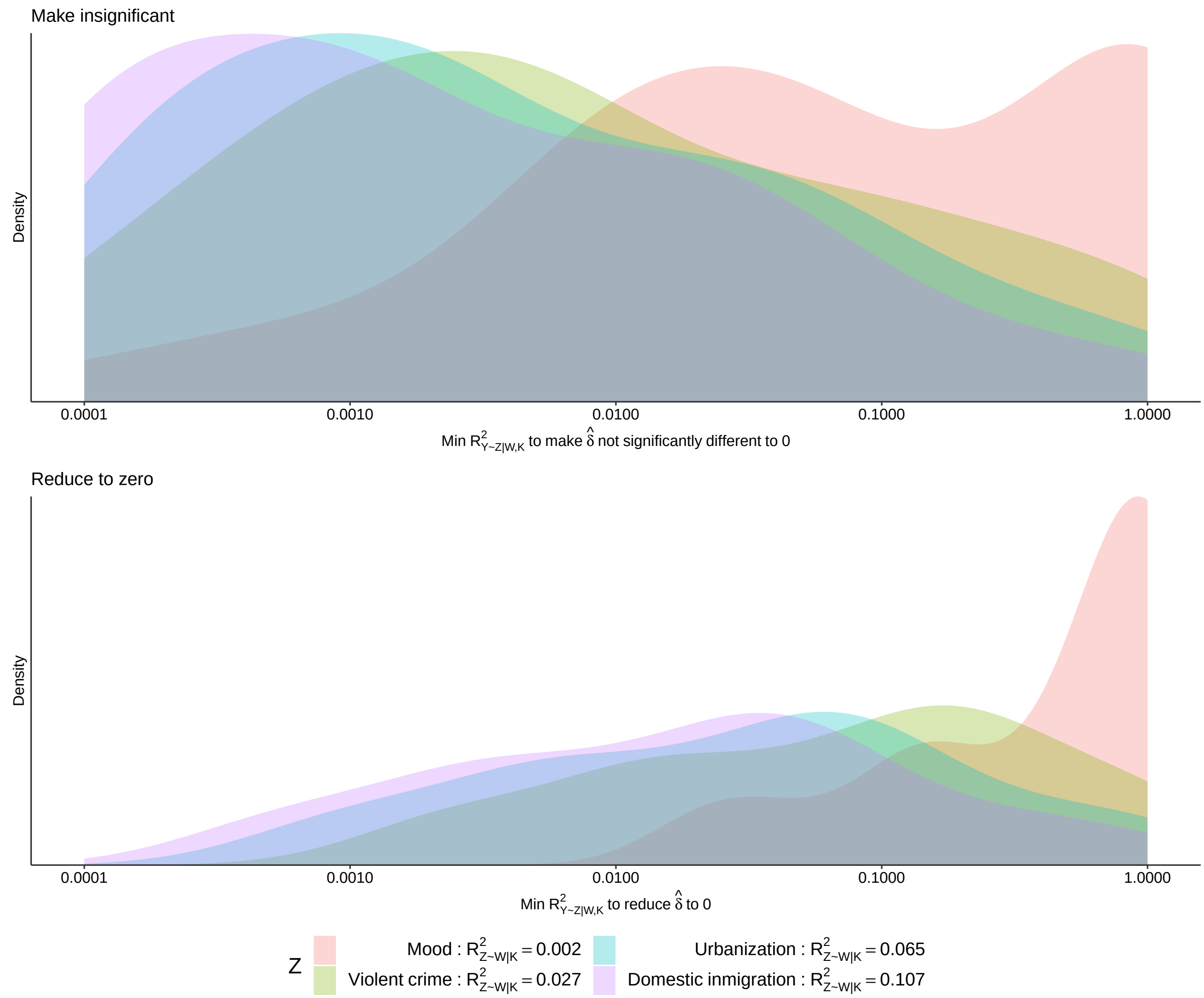

Figure 4: Density plot of minimum relationship between exclusion restriction violation variable, Z, and dependent variable Y ($R^2_{Y\sim Z|W,K}$) required to overturn (make insignificant or reduce to zero) the IV relationship between X and Y ($\hat{\delta}$) estimated in 44 weather IV studies. Results shown for four example Z variables with $R^2_{Z\sim W|K}$ values taken from other weather IV studies' first stages. X-axis shown on a log 10 scale.

Table 1: Sensitivity of three weather IV studies to potential exclusion restriction violations implied by first stages in the literature. $R^2_{Z\sim W|K}$ column shows the implied weather-Z relationship from the first stages in the literature (median $R^2_{Z\sim W|K}$ if there are multiple studies). Count shows the number of studies the $R^2_{Z\sim W|K}$ value is based on. The column for each paper shows the minimum $R^2_{Y\sim Z|W,K}$ between the dependent variable, Y, for that paper and the Z variable to make the paper's result insignificant.

Z	$R^2_{Z\sim W\|K}$	Count	Chhaochharia (2019)	Stokes (2016)	Chin (2011)
Perceived temperature variation	0.2400	1	0.00035	0.00841	0.0001
Wind turbine placement	0.1619	1	0.00061	N/A	0.0001
Domestic inmigration	0.1074	2	0.00101	0.0326	0.00011
Slavery	0.1025	2	0.00107	0.03482	0.00012
Production	0.0966	3	0.00115	0.03787	0.00013
Urbanization	0.0652	1	0.00179	0.06456	0.00023
Migrant social capital	0.0600	1	0.00197	0.07212	0.00025
Disaster relief allocation	0.0540	1	0.00221	0.08297	0.00029
Erosion	0.0456	1	0.00265	0.1043	0.00036
Violent protest	0.0454	2	0.00267	0.10492	0.00036
Property crime	0.0445	2	0.00272	0.10763	0.00037
Price	0.0352	2	0.0035	0.14966	0.00048
Violent crime	0.0270	2	0.00462	0.22461	0.00065
Leisure activities	0.0162	1	0.00786	None	0.00114
Pollution	0.0131	5	0.00974	None	0.00143
Party vote share	0.0122	3	0.01052	None	0.00155
Turnout	0.0115	6	0.01116	None	0.00164

Income	0.0075	19	0.01727	None	0.00256
Crop diversity	0.0072	2	0.01789	None	0.00266
Agricultural productivity	0.0066	1	0.01955	None	0.00291
Remittances	0.0064	1	0.02015	None	0.003
Inventory	0.0058	1	0.02238	None	0.00333
Prenatal care	0.0054	1	0.02424	None	0.00361
Traffic	0.0038	1	0.035	None	0.00523
Insurance	0.0027	1	0.04944	None	0.0074
Migration legal status	0.0025	1	0.05297	None	0.00793
Mood	0.0025	4	0.05385	None	0.00806
Domestic outmigration	0.0018	3	0.0744	None	0.01114
Perceived economic outlook	0.0002	1	N/A	None	0.19394
Exercise	0.0001	1	None	None	None
Dissent	0.0001	1	None	None	None

To illustrate the range of confounders and their ability to overturn existing results, I show three existing studies with different levels of sensitivity in table 1 and how they are affected by all of the exclusion restriction violations implied by other IV studies' first stages.

The first column of table 1 shows a particular variable that has been instrumented using weather in the literature.[7] The R^2 column shows the size of the $R^2_{Z\sim W|K}$ value implied by the first-stage F-statistic reported in that study. The following three columns then show the minimum size of the relationship ($R^2_{Y\sim Z|W,K}$) between that Z variable and the dependent variable Y of three different weather IV studies from Chhaochharia et al. (2019), Stokes (2016), and Chin (2011) would have to have in order to make the result in that study insignificant.

[7]This table does not include studies that instrument the level of Mexican immigration to US cities based on the weather in origin states in Mexico. While there are plausible exclusion restriction violations that this could imply, the F-statistics cannot be straightforwardly transferred across since the independent variable applies to outflows from Mexico.

These papers are published in well-regarded political science and economics journals and cover a range of robustness levels. In terms of how large a confounder would be required to make the results insignificant, these papers ranks at the 29th (Chin 2011), 56th (Chhaochharia et al. 2019), and 89th (Stokes 2016) percentiles. The percentiles shift if we look at robustness in terms of the size of the confounder required to bring the IV estimate to zero with the studies at the 11th (Chin 2011), 20th (Chhaochharia et al. 2019), and 91st (Stokes 2016) robustness percentiles. The ranking of robustness can differ on the two definitions because a large effect size can still be barely significant if the sample size is small.

The first study I focus on is by Chhaochharia et al. (2019) published in the *Journal of Financial Economics*. This paper uses monthly weather as an instrument for managers' perceived economic outlook (with the logic that gloomy weather makes managers economically pessimistic). The paper finds that mood-driven economic expectations have a substantial effect on firm-level managerial decisions. I focus on the robustness of the effect on hiring decisions. Importantly, the paper views weather as a direct proxy for mood, so is interested in the weather relationship's causal effect on hiring through the single causal pathway (i.e. even if other weather effects work via economic expectations that still conflicts with the paper's use of the variable).

For the strongest confounders, the relationship between Z and hiring decisions would only need to be very small. For instance, internal migration would only need to explain 0.1% of variance in hiring decisions to make the IV estimate insignificant (although the weather-internal migration relationship is likely lower in the US context).

Other plausible confounders, require relatively small relationships to make the result insignificant or zero. The median weather-income relationship implies that income would have to explain as little as 1.7% of the variance in hiring decisions to make the result insignificant or 4.1% to reduce the IV estimate to zero. Income is plausibly related to hiring decisions as a higher income in an area means that more economic activity is taking place and demand for a company's goods and services will tend to be higher. Similarly, if weather has the median relationship with property crime as found in the literature, then property crime would only have to explain 0.27% of the variance in hiring decisions to make the result in Chhaochharia et al. (2019) insignificant.

The second study—which was published in the *American Journal of Political Science*—looks at the effects of building wind turbines on voting for local incumbents (Stokes 2016). The IV analysis uses the average wind power in precincts as an instrument for a wind project being proposed within 3KM of the precinct by 2011. In total, the IV analysis finds that a proposed wind power project reduces incumbent vote share by 7.7 percentage points (SE=2.6 percentage points) in that precinct—a large effect by the standards of accountability studies.

Overall, the relationship between various potential confounding variables and changes in incumbent vote share would have to be extremely strong to make the relationship Stokes (2016) finds non-significant and larger still to make the IV estimate zero. Most of the potential exclusion restrictions in table 1 would not be able to overturn the result even if they were perfectly correlated with incumbent voting. The variables that would require more reasonable correlations with incumbent voting to overturn the result do not seem plausible to have even that level of relationship to the dependent variable. For instance, there is no reason to believe perceived variation in temperature explains 0.84% of variation in incumbent voting. It is perhaps plausible that levels of domestic inmigration might explain 3.3% of variation in incumbent voting, but that $R^2_{Z\sim W|K}$ estimate size is mostly derived from studies in agricultural economies that are unlikely to generalize to migration variation within Ontario. Similarly, levels of urbanization could be related to changes in incumbent voting but seem unlikely to explain 6.5% of the variation, especially given that precincts in major cities are excluded from the sample. Perhaps the most plausible variable for explaining away incumbent voting would be property crime, but this would have to explain 11% of the variation in the change in incumbent voting, far larger than the crime-accountability effect seen in previous studies (Hopkins and Pettingill 2018; Hagerty 2006; Cummins 2009).[8]

The third study is by Chin (2011) published in the *Journal of Population Economics*. Chin (2011) looks at the effect of female labor force participation on spousal violence. Rainfall is argued to be an instrument for female labor force participation in rice-growing regions of India because rainfall affects the demand for labor more strongly in rice-growing areas. The OLS estimate suggests that female labor force participation

[8]This analysis purely consider the robustness of the IV estimate to confounding and does not consider the additional positive evidence of the placebo analysis with Liberal vote share in 2003 as the dependent variable, finding no effect or the matching design showing a similar effect size or the additional problems that affect many IV analyses such as weak first stages, spatial auto-correlation and researcher degrees of freedom.

increases spousal violence but the IV estimate suggests that female labor force participation actually reduces spousal violence.

The paper attempts to avoid the most obvious alternate causal route between weather and spousal violence—agricultural income—by restricting the sample to rural households that do not own land. However, this does not entirely eliminate this alternate route because higher agricultural income in a region will have substantial knock-on effects on the local economy more generally. Most directly, agricultural income will also be reflected in agricultural wages for men and women. Using the median weather-income relationship found in the literature, income would only need to explain 0.26% of variance in violence against women to make the IV estimate insignificant or 1% of variance to reduce the IV estimate to zero.

Another plausible alternate explanation is weather-driven immigration. Numerous studies find that areas receiving positive weather shocks receive more migrants (Badaoui, Strobl, and Walsh 2013; Strobl and Valfort 2015; Bhavnani and Lacina 2015). The median weather-immigration relationship in the literature would require migration to explain only 0.41% of variation in spousal violence to make the IV relationship insignificant and 1.6% of variance to reduce the IV estimate to zero. Immigration could explain variance by changing the composition of the sample that Chin (2011) uses (i.e. if migrants had different levels of spousal violence than longstanding residents) or through the effects that migrants have on households who were already present.

Of these three examples, only Stokes' (2016) results are out of the range that could be easily overturned by exclusion restriction violations implied by other weather IV studies. This analysis suggests that many weather IV studies will be sufficiently sensitive to exclusion restriction violations, that the exclusion restriction assumption is not warranted. However, it also suggests that strong enough findings at both stages may be sufficient for a result to hold up.

6.3 Studies that are not blown away

One line of research which is not affected by these problems, are papers using reduced-form equations to look at the total causal effect of weather on particular outcomes (Dell, Jones, and Olken 2014). This paper merely suggests that interpreting the mechanisms behind these total effects will be challenging. However, for studies hoping to predict the effects of climate change and extreme weather on the social and economic world, this may be less important. Indeed the plethora of variables studied, suggests that weather effects are very numerous.

7 The tip of the iceberg?

While this paper focuses on weather as an IV, the message is more general: a good instrument is hard to find. This paper could just as easily have been written about other widely used instruments (population density, historical splits in countries, lead exposure, colonialism, distance from the equator and distance from anything else are possible examples). Indeed, many of these instruments have been criticized for similar reasons (Morck and Yeung 2011; Gallen and Raymond 2019).

Weather is also a confounder for many instruments. Distance from the equator is associated with weather for obvious reasons, which has a knock-on effect of confounding colonialism and population density as instruments. Countries tend to split in contiguous parts which rarely have the same weather. Weather is correlated with month of birth. Lead poisoning is highly seasonal and seems to be increased by warm weather in a variety of ways (Levin et al. 2020).

These concerns also apply to the inevitable papers that will be written using the COVID-19 pandemic as an instrument. COVID-19 has affected everything, so it is not plausibly a natural experiment or a random assignment for anything but itself. COVID-19 may also be affected by the weather (Shen, Cai, and Li 2020), causally attaching it to the messy web of relationships described in the rest of this paper.

8 A ray of hope? Practical advice for IVs

The problem with the exclusion-restriction is that its plausibility is fundamentally theory-based. Whether or not you can reasonably use an instrument depends on whether you offer convincing arguments for the specific case of interest.

Is it possible to offer any practical guidance on finding or excluding instruments? The following approach does not guarantee the theoretical plausibility of an instrument but would at least exclude most cases where the exclusion restriction is already disproven in the literature. Compared to current practice, this would be a marked improvement. This approach can also be used by reviewers when assessing IV studies.

Once you have a plausible instrument, I, instrumented variable, X, and dependent variable, Y, you should aim to build a possible network of causal connections from the literature.

First, you should search for articles which already link I and Y. If you find any such articles, do they posit or prove plausible pathways that for the I-to-Y link that do not run through X. If so, you should probably discard the instrument. However, if you choose to continue (if, for instance, you can show that the confounding variable comes after Y in the causal ordering), you should clearly document your reasons for believing that the mechanism that the paper posits does not represent an exclusion violation in your study (this applies to all of the following steps as well).

Second, review the literature on Y for all other variables that have been found to be associated with it. For each associated variable, Q, search the literature for "I + Q" to find any existing research which links the associated variable to your instrument. If these searches find plausible links, then you have discovered a plausible exclusion violation in the literature. This probably means that you should discard the instrument.

Third, review the literature on I and closely related concepts to I. For each associated variable R, search the literature for "Y + R" to find existing research which links your associated variable R to the dependent variable. Once again, any plausible links mean that you have discovered an exclusion violation and should probably discard the instrument.

Finally, review the two lists of associated variables Q and R for any possible links between them. Follow up on any links you find even slightly plausible. If you discover causal pathways, you should probably abandon the instrument.

It should be noted that the literature review should include studies with observational or causal links between variables and accept studies from any discipline. Even if two variables are associated non-causally, it still indicates that there is some pathway between them in a DAG, even if indirectly. This is sufficient to undermine the exclusion restriction, except in very specific circumstances.

It is also possible to use this literature review to conduct sensitivity analysis similar to that in section 6.2. Partial R^2 between the instrument and variables on the Q and R lists can be derived from correlations, first-stage F-statistics, directly re-analysing a paper's data, or novel analyses of other datasets. The sensitivity of any given IV estimate will be a function of the size of the relationship between the instrument and a potential confounder, the magnitude of the reduced-form estimate (which relies on both the strength of the first-stage and second-stage relationships), and the power of the study (where sensitivity is defined in terms of significance). As the analysis in this paper shows, this represents a high hurdle for many but not all existing weather IV studies. This therefore represents a practical set of additional robustness tests that can be integrated into applied working using an IV design.

This approach is not a substitute for other theoretical consideration of the instrument and its relationships and should always be used in addition to existing validation procedures. However, if this approach had been followed for weather IV studies, the many exclusion restriction violations would have been immediately apparent along with their likely impact on the inferences from these studies.

Perhaps the most valuable part of this approach would be requiring scholars to make their standards for accepting the exclusion restriction assumption explicit. This approach provides a systematic way of generating potential exclusion violations rather than leaving the reader to guess what possible violations were considered too minor to worry about.

9 Are IVs on thin ice?

This paper shows that a very commonly used instrumental variable (IV) is flawed because it systematically fails the exclusion restriction for most plausible uses.

More importantly these results suggest our standards for accepting instruments are too generous and atheoretical. The causal revolution in social science has exposed the wishful thinking that underlies much of naïve regression modeling. However, the same rigor that is used to critique the implicit assumptions of exogeneity for selection on observables also needs to be applied to all the assumptions of IV regression.

Nothing in this paper disproves the empirical claims of any particular paper. Many of the papers using weather IVs provide other independent sources of evidence, and additional robustness checks such as placebo tests. However, these results do suggest that the underlying assumptions (as embodied in the IV DAG) are not strictly true.

A reader might wonder whether these results are such a problem. In any particular case, surely the confounding routes to the dependent variable are not so great as to overturn a result. This could be true in some cases, but the identification strategy is starting to sound less like the clean logic of the IV model and more like selection on observables with extra steps.

Nonetheless, this paper does demonstrate how sensitivity analysis (Cinelli and Hazlett 2020a, 2020b) can be used to quantify how strong an exclusion restriction violation would have to be in order to overturn results. In addition to systematically reviewing the literature for exclusion restriction violations, the sensitivity analysis allows scholars to quantify how large a relationship between Z and Y would have to exist for a result to be overturned.

The evidence for poor exclusion-restriction practices adds to a body of evidence that IV regression studies are often not well conducted. Brodeur, Cook, and Heyes (2018) found that IV studies showed more evidence of p-hacking than DID, RCT or RDD studies, with nearly a quarter of marginally significant claims in IV papers being misleading. Similarly, D. L. Lee et al. (2020) finds that the standard first stage F-test used in IV regression is underpowered, and that more than half of IV papers in the American Economic Review were no longer significant after accounting for this.

This paper does offers a way forwards for improving IV inference by proposing a method for systematically reviewing the literature for exclusion restriction violations. We cannot hope to systematically prove the exclusion restriction, but we can aspire to at least recognize exclusion violations which are already well documented in the scientific literature.

Cunningham (2018) argues that a good instrument should have a “certain ridiculousness.” Until the secret endogenous route to causation is explained, the linkage between the instrument and the outcome seem absurd. In a world where Australians and Californians cannot leave their houses for months at a time due to forest fires, and 1-3 billion people are projected to be left outside of temperature ranges that humans have historically inhabited (C. Xu et al. 2020), linkages between weather and the social world are just not ridiculous enough.

10 References

Abiona, Olukorede. 2017. "The Impact of Unanticipated Economic Shocks on the Demand for Contraceptives: Evidence from Uganda." *Health Economics* 26 (12): 1696–1709. https://doi.org/10.1002/hec.3487.

Acharya, Avidit, Matthew Blackwell, and Maya Sen. 2016. "The political legacy of American Slavery." *Journal of Politics* 78 (3): 621–41. https://doi.org/10.1086/686631.

Achen, Christopher H, and Larry M. Bartels. 2016. *Democracy for realists: Why Elections Do Not Produce Responsive Government*. Princeton University Press.

Aguiar-Moya, José P., Jorge A. Prozzi, and Andre de Fortier Smit. 2011. "Mechanistic-empirical IRI model accounting for potential bias." *Journal of Transportation Engineering* 137 (5): 297–304. https://doi.org/10.1061/(ASCE)TE.1943-5436.0000200.

Aklilu, Solomon. 2007. "Weather variability, income shocks and savings of rural households in Peru." *The Latin Americanist* 51 (1): 23–46. https://doi.org/10.1111/j.1557-203x.2007.tb00084.x.

Akobeng, Eric. 2017. "The invisible hand of rain in spending: Effect of rainfall-driven agricultural income on per capita expenditure in Ghana." *South African Journal of Economics* 85 (1): 98–122. https://doi.org/10.1111/saje.12131.

Allcott, Hunt, Allan Collard-Wexler, and Stephen D. O'Connell. 2016. "How do electricity shortages affect industry? Evidence from India." *American Economic Review* 106 (3): 587–624. https://doi.org/10.1257/aer.20140389.

Angrist, Joshua D., Kathryn Graddy, and Guido W. Imbens. 2000. "The interpretation of instrumental variables estimators in simultaneous equations models with an application to the demand for fish." *Review of Economic Studies* 67 (3): 499–527. https://doi.org/10.1111/1467-937X.00141.

Angrist, Joshua D., and Jörn Steffen Pischke. 2008. *Mostly Harmless Econometrics: An Empiricist's Companion; Mastering 'Metrics: The Path from Cause to Effect*. Princeton University Press. https://doi.org/10.1080/14697688.2015.1080490.

Apergis, Nicholas, Panagiotis Artikis, and Emmanuel Mamatzakis. 2012. "Is weather important for US banking? A study of bank loan inefficiency." *Journal of Applied Finance and Banking* 2 (3): 1–38. http://search.proquest.com/docview/1321672647?accountid=10297%7B/%%7D5Cnhttp://sfx.cranfield.ac.uk/cranfield?url%7B/_%7Dver=Z39.88-2004%7B/&%7Drft%7B/_%7Dval%7B/_%7Dfmt=info:ofi/fmt:kev:mtx:journal%7B/&%7Dgenre=article%7B/&%7Dsid=ProQ:ProQ:abiglobal%7B/&%7Datitle=Is+weather+important+for+US+banking?+A+study+of.

Aral, Sinan, and Christos Nicolaides. 2017. "Exercise contagion in a global social network." *Nature Communications* 8: 1–8. https://doi.org/10.1038/ncomms14753.

Arnold, Felix, and Ronny Freier. 2016. "Only conservatives are voting in the rain: Evidence from German local and state elections." *Electoral Studies* 41: 216–21. https://doi.org/10.1016/j.electstud.2015.11.005.

Artés, Joaquín. 2014. "The rain in Spain: Turnout and partisan voting in Spanish elections." *European Journal of Political Economy* 34: 126–41. https://doi.org/10.1016/j.ejpoleco.2014.01.005.

Asfaw, Solomon, Alessandro Palma, and Leslie Lipper. 2016. "Diversification strategies and adaptation deficit: Evidence from rural communities," 45.

Atalla, Tarek, Simona Bigerna, and Carlo Andrea Bollino. 2018. "Energy demand elasticities and weather worldwide." *Economia Politica* 35 (1): 207–37. https://doi.org/10.1007/s40888-017-0074-2.

Auffhammer, Maximilian, Solomon M. Hsiang, Wolfram Schlenker, and Adam Sobel. 2013. "USING WEATHER DATA AND CLIMATE MODEL OUTPUT IN ECONOMIC ANALYSES OF CLIMATE CHANGE." *NBER Working Paper Series* 53 (9): 1689–99. https://doi.org/10.1017/CBO9781107415324.004.

Badaoui, Eliane El, Eric Strobl, and Frank Walsh. 2013. "The Impact of Internal Migration on Local Labour Markets in Thailand." *Working Paper*. https://doi.org/10.4135/9789353287788.n12.

Bae, Sanghyuk, Youn Hee Lim, and Yun Chul Hong. 2020. "Causal association between ambient ozone concentration and mortality in Seoul, Korea." *Environmental Research* 182 (October 2019): 109098. https://doi.org/10.1016/j.envres.2019.109098.

Bai, Ying, and James Kai sing Kung. 2014. “The shaping of an institutional choice: Weather shocks, the Great Leap Famine, and agricultural decollectivization in China.” *Explorations in Economic History* 54 (642010): 1–26. https://doi.org/10.1016/j.eeh.2014.06.001.

Barrios, Salvador, Luisito Bertinelli, and Eric Strobl. 2010. “Trends in rainfall and economic growth in Africa: A neglected cause of the african growth tragedy.” *Review of Economics and Statistics* 92 (2): 350–66. https://doi.org/10.1162/rest.2010.11212.

Bartels, Larry M. 1991. “Instrumental and " Quasi-Instrumental" Variables.” *American Journal of Political Science* 35 (3): 777–800.

Bauer, Michael, Tasha Glenn, Martin Alda, Ole A. Andreassen, Raffaella Ardau, Frank Bellivier, Michael Berk, et al. 2012. “Impact of sunlight on the age of onset of bipolar disorder.” *Bipolar Disorders* 14 (6): 654–63. https://doi.org/10.1111/j.1399-5618.2012.01025.x.

Bayani-Arias, Jaimie Kim, and Rosalina Palanca-Tan. 2017. “Analyzing the Relationship Between Exposure to Extreme Weather and Economic Inequality in the Philippines.” *Journal of Economics, Management & Agricultural Development* 3: 27–39. https://cem.uplb.edu.ph/jemad-volume-3-number-1/finish/5-journals/289-jemad-volume-3-number-1.

Baylis, Patrick, Nick Obradovich, Yury Kryvasheyeu, Haohui Chen, Lorenzo Coviello, Esteban Moro, Manuel Cebrian, and James H. Fowler. 2018. “Weather impacts expressed sentiment.” *PLoS ONE* 13 (4): 1–11. https://doi.org/10.1371/journal.pone.0195750.

Bazzi, Samuel, and Michael A. Clemens. 2013. “Blunt instruments: Avoiding common pitfalls in identifying the causes of economic growth.” *American Economic Journal: Macroeconomics* 5 (2): 152–86. https://doi.org/10.1257/mac.5.2.152.

Beaudin, Laura, and Ju Chin Huang. 2014. “Weather conditions and outdoor recreation: A study of New England ski areas.” *Ecological Economics* 106: 56–68. https://doi.org/10.1016/j.ecolecon.2014.07.011.

Ben Lakhdar, Christian, and Eric Dubois. 2006. “Climate and Electoral Turnout in France.” *French Politics* 4 (2): 137–57. https://doi.org/10.1057/palgrave.fp.8200100.

Berens, Sarah, and Mirko Dallendörfer. 2019. "Apathy or Anger? How Crime Experience Affects Individual Vote Intention in Latin America and the Caribbean." *Political Studies* 67 (4): 1010–33. https://doi.org/10.1177/0032321718819106.

Berry, Steven, and Wolfram Schlenker. 2011. "Technical Report for the ICCT : Empirical Evidence on Crop Yield Elasticities." *The International Council on Clean Transportation*, 1–18.

Bertelli, Olivia. 2015. "The more the merrier? Adjusting fertility to weather shocks" 33 (0).

Betz, Timm, Scott J. Cook, and Florian M. Hollenbach. 2019. "Spatial interdependence and instrumental variable models." *Political Science Research and Methods*. https://doi.org/10.1017/psrm.2018.61.

Bhavnani, Rikhil R., and Bethany Lacina. 2015. "The Effects of Weather-Induced Migration on Sons of the Soil Riots in India." *World Politics* 67 (4): 760–94. https://doi.org/10.1017/S0043887115000222.

Blakeslee, David S., and Ram Fishman. 2018. "Weather shocks, agriculture, and crime: Evidence from India." *Journal of Human Resources* 53 (3): 750–82. https://doi.org/10.3368/jhr.53.3.0715-7234R1.

Bondy, Malvina, Sefi Roth, and Lutz Sager. 2020. "Crime Is in the Air: The Contemporaneous Relationship between Air Pollution and Crime." *Journal of the Association of Environmental and Resource Economists* 7 (3): 555–85. https://doi.org/10.1086/707127.

Boustan, Leah Platt, Price V. Fishback, and Shawn Kantor. 2010. "The effect of internal migration on local labor markets: American cities during the great depression." *Journal of Labor Economics* 28 (4): 719–46. https://doi.org/10.1086/653488.

Branco, Danyelle, and Jose Feres. 2020. "Weather Shocks and Labor Allocation Evidence from Rural Brazil." *American Journal of Agricultural Economics* 0 (0): 1–19. https://doi.org/10.1111/ajae.12171.

Brodeur, Abel, Nikolai Cook, and Anthony Heyes. 2018. "Methods Matter: P-Hacking and Causal Inference in Economics." *IZA Discussion Papers*, no. 11796. www.iza.org.

Bruckner, Markus, and Antonio Ciccone. 2011. "Rain and the Democratic Window of Opportunity." *Econometrica* 79 (3): 923–47. https://doi.org/10.3982/ecta8183.

Bruederle, Anna, Jörg Peters, and Gareth Roberts. 2017. *Weather and crime in South Africa.*

Bui, Anh Tuan, Mardi Dungey, Cuong Viet Nguyen, and Thu Phuong Pham. 2014. “The impact of natural disasters on household income, expenditure, poverty and inequality: Evidence from Vietnam.” *Applied Economics* 46 (15): 1751–66. https://doi.org/10.1080/00036846.2014.884706.

Bui, Quang Nhat, Trung Xuan Hoang, Minh Khac Nguyen, and Trung Tien Nguyen. 2020. “Land fragmentation, women empowerment and school dropout of children in Vietnam.” *Land Use Policy* 97 (September 2019): 104749. https://doi.org/10.1016/j.landusepol.2020.104749.

Burdette, Amy M., and Terrence D. Hill. 2008. “An examination of processes linking perceived neighborhood disorder and obesity.” *Social Science and Medicine* 67 (1): 38–46. https://doi.org/10.1016/j.socscimed.2008.03.029.

Burdick-Will, Julia, Marc L. Stein, and Jeffrey Grigg. 2019. “Danger on the way to school: Exposure to violent crime, public transportation, and absenteeism.” *Sociological Science* 6: 118–42. https://doi.org/10.15195/V6.A5.

Burgess, Robin, Olivier Deschenes, Dave Donaldson, and Michael Greenstone. 2014. “The Unequal Effects of Weather and Climate Change: Evidence from Mortality in India.” *Journal of Economic Growth,* 15 (4): 291–321.

Cachon, Gérard P., Santiago Gallino, and Marcelo Olivares. 2019. “Does adding inventory increase sales? Evidence of a scarcity effect in U.S. Automobile dealerships.” *Management Science* 65 (4): 1469–85. https://doi.org/10.1287/mnsc.2017.3014.

Caruso, Raul, Ilaria Petrarca, and Roberto Ricciuti. 2016. “Climate change, rice crops, and violence: Evidence from Indonesia.” *Journal of Peace Research* 53 (1): 66–83. https://doi.org/10.1177/0022343315616061.

Cashin, Paul, Kamiar Mohaddes, and Mehdi Raissi. 2017. “Fair weather or foul? The macroeconomic effects of El Niño.” *Journal of International Economics* 106: 37–54. https://doi.org/10.1016/j.jinteco.2017.01.010.

Chalfin, Aaron. 2014. “What is the contribution of Mexican immigration to U.S. crime rates? Evidence from rainfall shocks in Mexico.” *American Law and Economics Review* 16 (1): 220–68. https://doi.org/10.1093/aler/aht019.

Chang, Hung Hao, and David Zilberman. 2014. “On the political economy of allocation of agricultural disaster relief payments: Application to Taiwan.” *European Review of Agricultural Economics* 41 (4): 657–80. https://doi.org/10.1093/erae/jbt037.

Chen, Roger B., and Hani S. Mahmassani. 2015. “Let it rain: Weather effects on activity stress and scheduling behavior.” *Travel Behaviour and Society* 2 (1): 55–64. https://doi.org/10.1016/j.tbs.2014.08.001.

Chhaochharia, Vidhi, Dasol Kim, George M. Korniotis, and Alok Kumar. 2019. “Mood, firm behavior, and aggregate economic outcomes.” *Journal of Financial Economics* 132 (2): 427–50. https://doi.org/10.1016/j.jfineco.2018.10.010.

Chia, Wei Han, Calvin Tay, Jan Ertl, Jasmine Zhang, and Bill Cai. 2016. “Intergenerational Mobility and Crime Rates: Using Climate as an Instrumental Variable.” *Working Paper.*

Chin, Yoo Mi. 2011. “Male backlash, bargaining, or exposure reduction?: Women’s working status and physical spousal violence in India.” *Journal of Population Economics* 25 (1): 175–200. https://doi.org/10.1007/s00148-011-0382-8.

Cinelli, Carlos, Jeremy Ferwerda, and Chad Hazlett. 2020. “Sensemakr: Sensitivity Analysis Tools for OLS in R and Stata.” *SSRN Electronic Journal* VV (Ii): 1–28. https://doi.org/10.2139/ssrn.3588978.

Cinelli, Carlos, and Chad Hazlett. 2020a. “An Omitted Variable Bias Framework for Sensitivity Analysis of Instrumental Variables.”

———. 2020b. “Making sense of sensitivity: extending omitted variable bias.” *Journal of the Royal Statistical Society. Series B: Statistical Methodology* 82 (1): 39–67. https://doi.org/10.1111/rssb.12348.

Cohen, Alexander. 2011. “The photosynthetic President: Converting sunshine into popularity.” *Social Science Journal* 48 (2): 295–304. https://doi.org/10.1016/j.soscij.2010.11.007.

Collins, William J., and Robert A. Margo. 2007. "The economic aftermath of the 1960s Riots in American Cities: Evidence from property values." *Journal of Economic History* 67 (4): 849–83. https://doi.org/10.1017/S0022050707000423.

Considine, Timothy J. 2000. "The impacts of weather variations on energy demand and carbon emissions." *Resource and Energy Economics* 22 (4): 295–314. https://doi.org/10.1016/S0928-7655(00)00027-0.

Cook, Duncan, and Sally Garrett. 2013. "Somali piracy and the monsoon." *Weather, Climate, and Society* 5 (4): 309–16. https://doi.org/10.1175/WCAS-D-13-00001.1.

Cools, Sara, Martin Flatø, and Andreas Kotsadam. 2020. "Rainfall shocks and intimate partner violence in sub-Saharan Africa." *Journal of Peace Research* 57 (3): 377–90. https://doi.org/10.1177/0022343319880252.

Cooperman, Alicia Dailey. 2017. "Randomization inference with rainfall data: Using historical weather patterns for variance estimation." *Political Analysis* 25 (3): 277–88. https://doi.org/10.1017/pan.2017.17.

Corbi, Raphael, and Tiago Ferraz. 2018. "Rainfall, Internal Migration and Local Labor Markets in Brazil." *Working Paper.*

Coviello, Lorenzo, Yunkyu Sohn, Adam D. I. Kramer, Cameron Marlow, Massimo Franceschetti, Nicholas A. Christakis, and James H. Fowler. 2014. "Detecting emotional contagion in massive social networks." *PLoS ONE* 9 (3): 1–6. https://doi.org/10.1371/journal.pone.0090315.

Cui, Can, Zhen Wang, Pan He, Shanfeng Yuan, Beibei Niu, Ping Kang, and Chaogui Kang. 2019. "Escaping from pollution: The effect of air quality on inter-city population mobility in China." *Environmental Research Letters* 14 (12). https://doi.org/10.1088/1748-9326/ab5039.

Cui, Xiaomeng. 2020. "Beyond Yield Response: Weather Shocks and Crop Abandonment." *Journal of the Association of Environmental and Resource Economists* 7 (5): 901–32. https://doi.org/10.1086/709859.

Cummins, Jeff. 2009. "Issue voting and crime in gubernatorial elections." *Social Science Quarterly* 90 (3): 632–51. https://doi.org/10.1111/j.1540-6237.2009.00635.x.

Cunningham, Scott. 2018. *Causal Inference: The Mixtape.* tufte-latex.googlecode.com.

Dacuycuy, Connie B. 2016. "Weather events and welfare in the Philippine households." *PIDS Discussion Paper Series.*

Davies, Simon. 2010. "Do shocks have a persistent impact on consumption?: The case of rural Malawi." *Progress in Development Studies* 10 (1): 75–79. https://doi.org/10.1177/146499340901000105.

Deisenhammer, E. A. 2003. "Weather and suicide: The present state of knowledge on the association of meteorological factors with suicidal behaviour." *Acta Psychiatrica Scandinavica* 108 (6): 402–9. https://doi.org/10.1046/j.0001-690X.2003.00209.x.

Dell, Melissa, Benjamin F. Jones, and Benjamin A. Olken. 2009. "Temperature and income: Reconciling new cross-sectional and panel estimates." *American Economic Review* 99 (2): 198–204. https://doi.org/10.1257/aer.99.2.198.

———. 2014. "What do we learn from the weather? The new climate-economy literature." *Journal of Economic Literature* 52 (3): 740–98. https://doi.org/10.1257/jel.52.3.740.

Di Falco, Salvatore, Peter Berck, Mintewab Bezabih, and Gunnar Köhlin. 2019. "Rain and impatience: Evidence from rural Ethiopia." *Journal of Economic Behavior and Organization* 160: 40–51. https://doi.org/10.1016/j.jebo.2019.02.016.

Di Falco, Salvatore, and Jean Paul Chavas. 2008. "Rainfall shocks, resilience, and the effects of crop biodiversity on agroecosystem productivity." *Land Economics* 84 (1): 83–96. https://doi.org/10.3368/le.84.1.83.

Dustmann, Christian, Francesco Fasani, and Biagio Speciale. 2017. "Illegal migration and consumption behavior of immigrant households." *Journal of the European Economic Association* 15 (3): 654–91. https://doi.org/10.1093/jeea/jvw017.

Elum, Zelda Anne, Godwell Nhamo, and Michael Akwasi Antwi. 2018. "Effects of climate variability and insurance adoption on crop production in select provinces of South Africa." *Journal of Water and Climate Change* 9 (3): 500–511. https://doi.org/10.2166/wcc.2018.020.

Falco, Salvatore Di, Felice Adinolfi, Martina Bozzola, and Fabian Capitanio. 2014. "Crop Insurance as a

Strategy for Adapting to Climate Change." *Journal of Agricultural Economics* 65 (2): 485–504. https://doi.org/10.1111/1477-9552.12053.

Falco, Salvatore Di, and Angela Doku. 2019. "Weather Shocks and Self Esteem." *Working Paper*.

Fan, Maoyong, and Yi Wang. 2020. "The impact of PM2.5 on mortality in older adults: Evidence from retirement of coal-fired power plants in the United States." *Environmental Health: A Global Access Science Source* 19 (1): 1–13. https://doi.org/10.1186/s12940-020-00573-2.

Farah, Naima, and Gregory L Torell. 2018. "Defensive Investment in Water Hardness Reduction Naima Farah Defensive Investment in Municipal Water Hardness." *Texas A & M AgriLife Research at El Paso Working Paper Series*.

Feng, Shuaizhang, Alan B. Krueger, and Michael Oppenheimer. 2010. "Linkages among climate change, crop yields and Mexico-US cross-border migration." *Proceedings of the National Academy of Sciences of the United States of America* 107 (32): 14257–62. https://doi.org/10.1073/pnas.1002632107.

Feng, Shuaizhang, Michael Oppenheimer, and Wolfram Schlenker. 2012. "Climate Change, Crop Yields, and Internal Migration in the United States." *National Bureau of Economic Research Working Paper Series* No. 17734: 1–43. http://www.nber.org/papers/w17734.pdf.

Fichera, Eleonora, and David Savage. 2015. "Income and Health in Tanzania. An Instrumental Variable Approach." *World Development* 66: 500–515. https://doi.org/10.1016/j.worlddev.2014.09.016.

Fisher-Vanden, Karen, Erin T. Mansur, and Qiong Juliana Wang. 2015. "Electricity shortages and firm productivity: Evidence from China's industrial firms." *Journal of Development Economics* 114: 172–88. https://doi.org/10.1016/j.jdeveco.2015.01.002.

Flyr, Matthew, Jesse Burkhardt, Christopher Goemans, Liesel Hans, Abbye Neel, and Alexander Maas. 2019. "Modeling commercial demand for water: Exploring alternative prices, instrumental variables, and heterogeneity." *Land Economics* 95 (2): 211–24. https://doi.org/10.3368/LE.95.2.211.

Fontenla, Matías, M. Ben Goodwin, and Fidel Gonzalez. 2019. "Pollution and the choice of where to work and live within Mexico City." *Latin American Economic Review* 28 (1).

https://doi.org/10.1186/s40503-019-0072-6.

Fraga, Bernard, and Eitan Hersh. 2011. “Voting costs and voter turnout in competitive elections.” *Quarterly Journal of Political Science* 5 (4): 339–56. https://doi.org/10.1561/100.00010093.

Frijters, Paul, Chitwan Lalji, and Debayan Pakrashi. 2020. “Daily weather only has small effects on wellbeing in the US.” *Journal of Economic Behavior and Organization* 176: 747–62. https://doi.org/10.1016/j.jebo.2020.03.009.

Fujiwara, Thomas, Kyle Meng, and Tom Vogl. 2016. “Habit formation in voting: Evidence from rainy elections.” *American Economic Journal: Applied Economics* 8 (4): 160–88. https://doi.org/10.1257/app.20140533.

Fukumoto, Kentaro, Kyosuke Kikuta, and Masato Yanagi. 2019. “After a Storm Come Votes?: Addressing Simultaneity between Electoral Outcomes and Disaster Relief,” 1–33.

Gajate-Garrido, Gissele. 2013. “The impact of adequate prenatal care on urban birth outcomes: An analysis in a developing country context.” *Economic Development and Cultural Change* 62 (1): 95–130. https://doi.org/10.1086/671716.

Gallen, Trevor, and Ben Raymond. 2019. “Broken instruments.” *Bureau of Labor Statistics*.

Gillett, N. P., A. J. Weaver, F. W. Zwiers, and M. D. Flannigan. 2004. “Detecting the effect of climate change on Canadian forest fires.” *Geophysical Research Letters* 31 (18). https://doi.org/10.1029/2004GL020876.

Giulietti, Corrado, Jackline Wahba, and Yves Zenou. 2018. “Strong versus weak ties in migration.” *European Economic Review* 104: 111–37. https://doi.org/10.1016/j.euroecorev.2018.02.006.

Goetzke, Frank, and Tilmann Rave. 2011. “Bicycle use in Germany: Explaining differences between municipalities with social network effects.” *Urban Studies* 48 (2): 427–37. https://doi.org/10.1177/0042098009360681.

Gomez, Brad T., Thomas G. Hansford, and George A. Krause. 2007. “The Republicans should pray for rain: Weather, turnout, and voting in U.S. presidential elections.” *Journal of Politics* 69 (3): 649–63.

https://doi.org/10.1111/j.1468-2508.2007.00565.x.

Gong, Huan, and Cynthia L. Rogers. 2014. "Does Voter Turnout Influence School Bond Elections?" *Southern Economic Journal* 81 (1): 247–62. https://doi.org/10.4284/0038-4038-2013.061.

Graddy, Kathryn. 2006. "The fulton fish market." *Journal of Economic Perspectives* 20 (2): 207–20. https://doi.org/10.1257/jep.20.2.207.

Graddy, Kathryn, and Peter E. Kennedy. 2010. "When Are Supply And Demand Determined Recursively Rather Than Simultaneously?" *Eastern Economic Journal* 36: 188–97.

Groppo, Valeria, and Kati Kraehnert. 2017. *The impact of extreme weather events on education*. Vol. 30. 2. Journal of Population Economics. https://doi.org/10.1007/s00148-016-0628-6.

Gu, Hejun, Weiran Yan, Ehsan Elahi, and Yuxia Cao. 2020. "Air pollution risks human mental health: an implication of two-stages least squares estimation of interaction effects." *Environmental Science and Pollution Research* 27 (2): 2036–43. https://doi.org/10.1007/s11356-019-06612-x.

Gurgand, Marc. 2003. "Farmer education and the weather: Evidence from Taiwan (1976-1992)." *Journal of Development Economics* 71 (1): 51–70. https://doi.org/10.1016/S0304-3878(02)00133-5.

Guven, Cahit, and Indrit Hoxha. 2015. "Rain or shine: Happiness and risk-taking." *Quarterly Review of Economics and Finance* 57: 1–10. https://doi.org/10.1016/j.qref.2014.10.004.

Hagerty, Michael R. 2006. "Quality of life from the voting booth: The effect of crime rates and income on recent U.S. presidential elections." *Social Indicators Research* 77 (2): 197–210. https://doi.org/10.1007/s11205-005-4506-y.

Hales, Simon, Clare Salmond, G. Ian Town, Tord Kjellstrom, and Alistair Woodward. 2000. "Daily mortality in relation to weather and air pollution in Christchurch, New Zealand." *Australian and New Zealand Journal of Public Health* 24 (1): 89–91. https://doi.org/10.1111/j.1467-842X.2000.tb00731.x.

Han, Peter, and Jeremy Foltz. 2015. "Polygyny: Cooperation vs . Competition Among Wives on Child Health."

Hanandita, Wulung, and Gindo Tampubolon. 2014. "Does poverty reduce mental health? An instrumental variable analysis." *Social Science and Medicine* 113: 59–67. https://doi.org/10.1016/j.socscimed.2014.05.005.

Hansford, Thomas G., and Brad T. Gomez. 2010. "Estimating the electoral effects of voter turnout." *American Political Science Review* 104 (2): 268–88. https://doi.org/10.1017/S0003055410000109.

Healy, Andrew, and Neil Malhotra. 2010. "Random events, economic losses, and retrospective voting: Implications for democratic competence." *Quarterly Journal of Political Science* 5 (2): 193–208. https://doi.org/10.1561/100.00009057.

Heinze, Justin E., Sarah A. Stoddard, Sophie M. Aiyer, Andria B. Eisman, and Marc A. Zimmerman. 2017. "Exposure to violence during adolescence as a predictor of perceived stress trajectories in emerging adulthood." *Journal of Applied Developmental Psychology* 49: 31–38. https://doi.org/10.1016/j.appdev.2017.01.005.

Henderson, John, and John Brooks. 2016. "Mediating the electoral connection: The information effects of voter signals on legislative behavior." *Journal of Politics* 78 (3): 653–69. https://doi.org/10.1086/685380.

Henderson, Susan A., and Tatyana Ryabova. 2020. "How do sustainability investments affect financial performance? An Instrumental Variable Approach." *Journal of Accounting and Finance* 20 (3): 104–26.

Hendricks, Nathan P., Joseph P. Janzen, and Aaron Smith. 2015. "Futures prices in supply analysis: Are instrumental variables necessary?" *American Journal of Agricultural Economics* 97 (1): 22–39. https://doi.org/10.1093/ajae/aau062.

Herrnstadt, Evan, and Erich Muehlegger. 2014. "Weather, salience of climate change and congressional voting." *Journal of Environmental Economics and Management* 68 (3): 435–48. https://doi.org/10.1016/j.jeem.2014.08.002.

Hoang, Trung Xuan. 2018. "Unexpected effects of land fragmentation," no. October.

Hodler, Roland, and Paul A. Raschky. 2014. "Economic shocks and civil conflict at the regional level." *Economics Letters* 124 (3): 530–33. https://doi.org/10.1016/j.econlet.2014.07.027.

Hoogeveen, Johannes, Bas Van Der Klaauw, and Gijsbert Van Lomwel. 2011. "On the timing of marriage, cattle, and shocks." *Economic Development and Cultural Change* 60 (1): 121–54. https://doi.org/10.1086/661215.

Hopkins, Daniel J., and Lindsay M. Pettingill. 2018. "Retrospective Voting in Big-City US Mayoral Elections." *Political Science Research and Methods* 6 (4): 697–714. https://doi.org/10.1017/psrm.2016.54.

Horiuchi, Yusaku, and Woo Chang Kang. 2018. "Why Should the Republicans Pray for Rain? Electoral Consequences of Rainfall Revisited." *American Politics Research* 46 (5): 869–89. https://doi.org/10.1177/1532673X17745631.

Hornbeck, Richard, Abhijit Banerjee, Nick Bloom, Geoff Cunfer, Joe Doyle, Price Fishback, Tim Guinnane, et al. 2012. "THE ENDURING IMPACT OF THE AMERICAN DUST BOWL: Short-and Long-run adjustments to environmental catastrophe." *American Economic Review.*

Horrocks, James, and Andrea Kutinova Menclova. 2011. "The effects of weather on crime." *New Zealand Economic Papers* 45 (3): 231–54. https://doi.org/10.1080/00779954.2011.572544.

Hsiang, Solomon M., Marshall Burke, and Edward Miguel. 2013. "Quantifying the influence of climate on human conflict." *Science* 341 (6151). https://doi.org/10.1126/science.1235367.

Hsiang, Solomon M., Kyle C. Meng, and Mark A. Cane. 2011. "Civil conflicts are associated with the global climate." *Nature* 476 (7361): 438–41. https://doi.org/10.1038/nature10311.

Hu, Maggie Rong, and Adrian D. Lee. 2020. *Outshine to outbid: Weather-induced sentiment and the housing market.* Vol. 66. 3. https://doi.org/10.1287/mnsc.2019.3517.

Huang, Fang, Shuisen Zhou, Shaosen Zhang, Hongju Wang, and Linhua Tang. 2011. "Temporal correlation analysis between malaria and meteorological factors in Motuo County, Tibet." *Malaria Journal* 10: 1–8. https://doi.org/10.1186/1475-2875-10-54.

Huang, Henry He, Joseph Kerstein, and Chong Wang. 2018. "The impact of climate risk on firm performance and financing choices: An international comparison." *Journal of International Business Studies* 49 (5): 633–56. https://doi.org/10.1057/s41267-017-0125-5.

Huet-Vaughn, Emiliano. 2013. "Quiet Riot: The Causal Effect of Protest Violence." *SSRN Electronic Journal*, no. September: 1–37. https://doi.org/10.2139/ssrn.2331520.

Ito, By Koichiro, and Mar Reguant. 2016. "Sequential Markets, Market Power, and Arbitrage." *The American Economic Review* 106 (7): 1921–57.

Jacob, Brian, Lars Lefgren, and Enrico Moretti. 2007. "The dynamics of criminal behavior: Evidence from weather shocks." *Journal of Human Resources* 42 (3): 489–527. https://doi.org/10.3368/jhr.xlii.3.489.

Jacobsen, Ben, and Wessel Marquering. 2008. "Is it the weather?" *Journal of Banking and Finance* 32 (4): 526–40. https://doi.org/10.1016/j.jbankfin.2007.08.004.

Jacoby, Hanan G., and Emmanuel Skoufias. 1997. "Risk, Financial Markets, and Human Capital in a Developing Country." *Review of Economic Studies* 64 (3): 311–35. https://doi.org/10.2307/2971716.

Kang, Hyunju, Hyunduk Suh, and Jongmin Yu. 2019. "Does Air Pollution Affect Consumption Behavior? Evidence from Korean Retail Sales." *Asian Economic Journal* 33 (3): 235–51. https://doi.org/10.1111/asej.12185.

Kang, Woo Chang. 2019. "Liberals should pray for rain: weather, opportunity costs of voting and electoral outcomes in South Korea." *Political Science* 71 (1): 61–78. https://doi.org/10.1080/00323187.2019.1643744.

Katz, Tamar Kricheli, Tali Regev, Shay Lavie, Haggai Porat, and Ronen Avraham. 2020. "Those who tan and those who don't: A natural experiment on colorism." *PLoS ONE* 15 (7 July): 1–14. https://doi.org/10.1371/journal.pone.0235438.

Keele, Luke, and Jason Morgan. 2013. "Stronger Instruments by Design." *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.2280347.

Khanthavit, Anya. 2017a. "Instrumental-variable estimation of Bangkok-weather effects in the stock exchange of Thailand." *Asian Academy of Management Journal of Accounting and Finance* 13 (1): 83–111. https://doi.org/10.21315/aamjaf2017.13.1.4.

———. 2017b. "Weather-Induced Mood Effects on Stock Returns." *Thammasat Review* 20 (1): 1–18.

https://doi.org/10.13140/RG.2.2.20384.99849.

———. 2019a. "Time-varying weather effects on thai government bond returns." *DLSU Business and Economics Review* 28 (2): 122–32.

———. 2019b. "Weather, investor sentiment, and stock returns in the Stock Exchange of Thailand." *ABAC Journal* 39 (1): 1–14.

———. 2019c. "WEATHER-DRIVEN STOCK-RETURN CORRELATIONS." *ABAC Journal* 39 (3): 42–55.

Kim, Nam Kyu. 2016. "Revisiting Economic Shocks and Coups." *Journal of Conflict Resolution* 60 (1): 3–31. https://doi.org/10.1177/0022002713520531.

Kim, Yong J, Juan P Sesmero, and Brigitte S Waldorf. 2018. "Temporary Migration as a Strategy against Weather Shocks: Evidence from Rural India."

Kippersluis, Hans van, and Cornelius A. Rietveld. 2018. "Beyond plausibly exogenous." *Econometrics Journal* 21 (3): 316–31. https://doi.org/10.1111/ectj.12113.

Kiviet, Jan F. 2020. "Testing the impossible: Identifying exclusion restrictions." *Journal of Econometrics* 218 (2): 294–316. https://doi.org/10.1016/j.jeconom.2020.04.018.

Kleemans, Marieke, and Jeremy Magruder. 2018. "Labour Market Responses To Immigration: Evidence From Internal Migration Driven By Weather Shocks." *Economic Journal* 128 (613): 2032–65. https://doi.org/10.1111/ecoj.12510.

Knack, Steve. 1994. "Does rain help the Republicans? Theory and evidence on turnout and the vote." *Public Choice* 79 (1-2): 187–209. https://doi.org/10.1007/BF01047926.

Kochar, Anjini. 1999. "Smoothing consumption by smoothing income: Hours-of-work responses to idiosyncratic agricultural shocks in Rural India." *Review of Economics and Statistics* 81 (1): 50–61. https://doi.org/10.1162/003465399767923818.

Koks, E. E., J. Rozenberg, C. Zorn, M. Tariverdi, M. Vousdoukas, S. A. Fraser, J. W. Hall, and S. Hallegatte. 2019. "A global multi-hazard risk analysis of road and railway infrastructure assets." *Nature*

Communications 10 (1): 1–11. https://doi.org/10.1038/s41467-019-10442-3.

Kovács, Balázs. 2017. "Too hot to reject: The effect of weather variations on the patent examination process at the United States Patent and Trademark Office." *Research Policy* 46 (10): 1824–35. https://doi.org/10.1016/j.respol.2017.08.010.

Kubik, Z, and J May. 2018. "Weather shocks, food prices and food security: Evidence from South Africa." *The 56th Annual Conference of the Agricultural Economics Association of South Africa*, 42.

Kubitza, Christoph, and Vijesh V. Krishna. 2020. "Instrumental variables and the claim of causality: Evidence from impact studies in maize systems." *Global Food Security* 26 (May): 100383. https://doi.org/10.1016/j.gfs.2020.100383.

Lagerlöf, NP, and SA Basher. 2006. "Geography, population density, and per-capita income gaps across US states and Canadian provinces," no. 369. http://mpra.ub.uni-muenchen.de/369/.

Lahiri, Bidisha. 2018. "Racial Earnings Disparities with Endogenous Labor Market Participation." *Journal of Economics, Race, and Policy* 1 (1): 16–25. https://doi.org/10.1007/s41996-018-0007-7.

Laidley, Thomas, and Dalton Conley. 2018. "The effects of active and passive leisure on cognition in children: Evidence from exogenous variation in weather." *Social Forces* 97 (1): 129–56. https://doi.org/10.1093/SF/SOY020.

Landis, Steven T., Babak Rezaeedaryakenari, Yifan Zhang, Cameron G. Thies, and Ross Maciejewski. 2017. "Fording differences? Conditions mitigating water insecurity in the Niger River Basin." *Political Geography* 56: 77–90. https://doi.org/10.1016/j.polgeo.2016.10.002.

Lee, Chien Chiang, and Yi Bin Chiu. 2011. "Electricity demand elasticities and temperature: Evidence from panel smooth transition regression with instrumental variable approach." *Energy Economics* 33 (5): 896–902. https://doi.org/10.1016/j.eneco.2011.05.009.

Lee, David L., Justin McCrary, Marcelo J. Moreira, and Jack Porter. 2020. "Valid t-ratio Inference for IV." http://arxiv.org/abs/2010.05058.

Lee, Wang-Sheng, and Ben Li. 2020. "Extreme Weather and Long-term Health: Evidence from Two

Millennia of Chinese Elites." *Journal of Health Economics.*

Leimdörfer, August Wadell, and Vincent Karlberg Hauge. 2020. "Can death predict life ?" *Bachelor Thesis.*

Levin, Ronnie, Carolina L. Zilli Vieira, Daniel C. Mordarski, and Marieke H. Rosenbaum. 2020. "Lead seasonality in humans, animals, and the natural environment." *Environmental Research* 180 (June 2019): 108797. https://doi.org/10.1016/j.envres.2019.108797.

Li, Ye, Eric J. Johnson, and Lisa Zaval. 2011. "Local warming: Daily temperature change influences belief in global warming." *Psychological Science* 22 (4): 454–59. https://doi.org/10.1177/0956797611400913.

Lind, Jo Thori. 2019. "Rainy day politics. An instrumental variables approach to the effect of parties on political outcomes." *European Journal of Political Economy* 61 (179552): 101821. https://doi.org/10.1016/j.ejpoleco.2019.101821.

Lis, Eliza M., and Christiane Nickel. 2010. "The impact of extreme weather events on budget balances." *International Tax and Public Finance* 17 (4): 378–99. https://doi.org/10.1007/s10797-010-9144-x.

Lo Prete, Anna, and Federico Revelli. 2020. "Voter Turnout and City Performance." *The Journal of Law, Economics, and Organization* 0 (0). https://doi.org/10.20955/r.85.67.

López-córdova, Ernesto. 2006. *Globalization, Migration and Development: The Role of Mexican Migrant Remittances.* Vol. 20. https://doi.org/10.1016/j.worlddev.2005.05.004.

Luechinger, Simon. 2014. "Air pollution and infant mortality: A natural experiment from power plant desulfurization." *C* 37: 219–31.

Maccini, Sharon, and Dean Yang. 2009. "Under the weather: Health, schooling, and economic consequences of early-life rainfall." *American Economic Review* 99 (3): 1006–26. https://doi.org/10.1257/aer.99.3.1006.

Madestam, Andreas, Daniel Shoag, Stan Veuger, and David Yanagizawa-Drott. 2013. "DO POLITICAL PROTESTS MATTER? EVIDENCE FROM THE TEA PARTY MOVEMENT." *Quarterly Journal of Economics*, 1633–85. https://doi.org/10.1093/qje/qjt021.Advance.

Magnusson, Andres. 2000. "An overview of epidemiological studies on seasonal affective disorder." *Acta*

Psychiatrica Scandinavica 101 (3): 176–84. https://doi.org/10.1046/j.0902-4441.2000..x.

Marchiori, Luca, Jean François Maystadt, and Ingmar Schumacher. 2012. “The impact of weather anomalies on migration in sub-Saharan Africa.” *Journal of Environmental Economics and Management* 63 (3): 355–74. https://doi.org/10.1016/j.jeem.2012.02.001.

Marchiori, Luca, Jean-François Maystadt, and Ingmar Schumacher. 2017. “Is environmentally induced income variability a driver of human migration?” *Migration and Development* 6 (1): 33–59. https://doi.org/10.1080/21632324.2015.1020106.

Maunder, W. J. 1973. “Weekly Weather and Economic Activities on a National Scale: an Example Using United States Retail Trade Data.” *Weather* 28 (1): 2–19. https://doi.org/10.1002/j.1477-8696.1973.tb02217.x.

Maystadt, Jean François, and Olivier Ecker. 2014. “Extreme weather and civil war: Does drought fuel conflict in Somalia through livestock price shocks?” *American Journal of Agricultural Economics* 96 (4): 1157–82. https://doi.org/10.1093/ajae/aau010.

Mehlum, Halvor, Edward Miguel, and Ragnar Torvik. 2006. “Poverty and crime in 19th Century Germany.” *Journal of Urban Economics* 59 (3): 370–88.

Miguel, Edward, and Shanker Satyanath. 2011. “Re-examining economic shocks and civil conflict.” *American Economic Journal: Applied Economics* 3 (4): 228–32. https://doi.org/10.1257/app.3.4.228.

Miguel, Edward, Shanker Satyanath, and Ernest Sergenti. 2004. “Economic shocks and civil conflict: An instrumental variables approach.” *Journal of Political Economy* 112 (4): 725–53. https://doi.org/10.1086/421174.

Morck, Randall, and Bernard Yeung. 2011. “ECONOMICS, HISTORY, AND CAUSATION.” *Business History Review* 85 (1): 39–63.

Moretti, Enrico. 1998. “Social returns to education and human capital externalities: evidence from cities.” *Centre for Labour Economics, Working Paper.* http://darp.lse.ac.uk/PapersDB/Moretti%7B/_%7D(98).pdf.

Moretti, Enrico, and Matthew Neidell. 2011. "Pollution, health, and avoidance behavior: Evidence from the ports of Los Angeles." *Journal of Human Resources* 46 (1): 154–75. https://doi.org/10.3368/jhr.46.1.154.

Muehlenbachs, Lucija, and Mark A Cohen. 2014. "The Effect of Inspector Group Size and Familiarity on Enforcement and Deterrence: Evidence from Oil Platforms." *IZA Discussion Paper* 7876.

Mulder, Machiel, and Bert Scholtens. 2013. "The impact of renewable energy on electricity prices in the Netherlands." *Renewable Energy* 57: 94–100. https://doi.org/10.1016/j.renene.2013.01.025.

Munshi, Kaivan. 2003. "Networks in the modern economy: Mexican migrants in the U.S. Labor market." *Quarterly Journal of Economics* 118 (2): 549–99. https://doi.org/10.1162/003355303321675455.

Nadolnyak, Denis, and Valentina Hartarska. 2012. "Agricultural disaster payments in the southeastern US: Do weather and climate variability matter?" *Applied Economics* 44 (33): 4331–42. https://doi.org/10.1080/00036846.2011.589813.

Nandi, Arindam, Sumit Mazumdar, and Jere R. Behrman. 2018. "The effect of natural disaster on fertility, birth spacing, and child sex ratio: evidence from a major earthquake in India." *Journal of Population Economics* 31 (1): 267–93. https://doi.org/10.1007/s00148-017-0659-7.

Nawrotzki, Raphael J., Fernando Riosmena, and Lori M. Hunter. 2013. "Do Rainfall Deficits Predict U.S.-Bound Migration from Rural Mexico? Evidence from the Mexican Census." *Population Research and Policy Review* 32 (1): 129–58. https://doi.org/10.1007/s11113-012-9251-8.

Nicholls, Neville, Wasyl Drosdowsky, and Beth Lavery. 1997. "Australian rainfall variability and change." *Weather* 52 (3): 66–72. https://doi.org/10.1002/j.1477-8696.1997.tb06274.x.

Nillesen, Eleonora E., and Philip Verwimp. 2011. "Grievance, Commodity Prices and Rainfall: A Village-level Analysis of Rebel Recruitment in Burundi." *SSRN Electronic Journal* 2009 (May 2009). https://doi.org/10.2139/ssrn.1425023.

Nübler, Laura, Karen Austrian, John A. Maluccio, and Jessie Pinchoff. 2020. "Rainfall shocks, cognitive development and educational attainment among adolescents in a drought-prone region in Kenya." *Environment and Development Economics*, 1–22. https://doi.org/10.1017/S1355770X20000406.

Oster, Emily. 2004. "Witchcraft, Weather and Economic Growth in Renaissance Europe." *Journal of Economic Perspectives* 18 (1): 215–28.

Pajaron, Marjorie C. 2017. "The role of remittances as a risk-coping mechanism: Evidence from agricultural households in rural Philippines." *Asian and Pacific Migration Journal* 26 (1): 3–30. https://doi.org/10.1177/0117196816680625.

Pajaron, Marjorie C., and Glacer Niño A. Working Vasquez. 2020. "Weathering the storm: Weather shocks and international migrants from the Philippines." *GLO Discussion Paper*.

Parham, Paul Edward, and Edwin Michael. 2010. "Modeling the effects of weather and climate change on malaria transmission." *Environmental Health Perspectives* 118 (5): 620–26. https://doi.org/10.1289/ehp.0901256.

Paxson, Christina H. 1992. "American Economic Association Using Weather Variability to Estimate the Response of Savings to Transitory Income in Thailand." *The American Economic Review* 82 (1): 15–33.

Peet, Evan D. 2020. "Environment and Human Capital: The Effects of Early-Life Exposure to Pollutants in the Philippines." *Environment and Development Economics*, 1–25.

Pereira, Rogério, and Tatiane Almeida de Menezes. 2020. "Does per capita income cause homicide rates? An application of an IV spatial model." *Regional Science Policy and Practice*, no. September 2019: 1–13. https://doi.org/10.1111/rsp3.12301.

Persson, Mikael, Anders Sundell, and Richard Öhrvall. 2014. "Does Election Day weather affect voter turnout? Evidence from Swedish elections." *Electoral Studies* 33: 335–42. https://doi.org/10.1016/j.electstud.2013.07.021.

Pinckney, Jonathan. 2019. "Did the Women's March Work? Re-Evaluating the Political Efficacy of Protest," 1–22.

Pipitpukdee, Siwabhorn, Witsanu Attavanich, and Somskaow Bejranonda. 2020. "Climate change impacts on sugarcane production in Thailand." *Atmosphere* 11 (4): 1–15. https://doi.org/10.3390/ATMOS11040408.

Pitt, Mark M, and Wendy Sigle. 1997. "SEASONALITY, WEATHER SHOCKS AND THE TIMING OF

BIRTHS AND CHILD MORTALITY."

Pugatch, Todd, and Dean Yang. 2011. "The Impact of Mexican Immigration on U.S. Labor Markets: Evidence from Migrant Flows Driven by Rainfall Shocks." *SSRN*.

Ranson, Matthew. 2014. "Crime, weather, and climate change." *Journal of Environmental Economics and Management* 67 (3): 274–302. https://doi.org/10.1016/j.jeem.2013.11.008.

Rappaport, Jordan. 2007. "Moving to nice weather." *Regional Science and Urban Economics* 37 (3): 375–98. https://doi.org/10.1016/j.regsciurbeco.2006.11.004.

Reichhoff, Martin. 2017. "The Effect of Weather on Crime: An Investigation of Weather and Annual Crime Rates." *MSc Thesis*.

Ritter, E, and C Conrad. 2016. "Preventing and Responding to Dissent: The Observational Challenges of Explaining Strategic Repression." *American Political Science Review* 110 (1): 85–99. http://papers.ssrn.com/sol3/papers.cfm?abstract%7B/_%7Did=2108885.

Roenneberg, T, and J Aschoff. 1990. "Annual Rhythm of Human Reproduction." *Journal of Biological Rhythms* 5 (3): 195–239.

Rudolph, Lukas. 2020. "Turning out to turn down the EU: the mobilisation of occasional voters and Brexit." *Journal of European Public Policy* 0 (0): 1–21. https://doi.org/10.1080/13501763.2019.1706623.

Sager, Lutz. 2019. "Estimating the effect of air pollution on road safety using atmospheric temperature inversions Lutz Sager October 2016 Grantham Research Institute on Climate Change and the Environment." *Journal of Environmental Economics and Management* 98 (251).

Santeramo, Fabio Gaetano, and Stephanie Searle. 2019. "Linking soy oil demand from the US Renewable Fuel Standard to palm oil expansion through an analysis on vegetable oil price elasticities." *Energy Policy* 127 (December 2018): 19–23. https://doi.org/10.1016/j.enpol.2018.11.054.

Sarsons, Heather. 2015. "Rainfall and conflict: A cautionary tale." *Journal of Development Economics* 115: 62–72. https://doi.org/10.1016/j.jdeveco.2014.12.007.

Sayers, Adrian, Kate Tilling, Barbara J. Boucher, Kate Noonan, and Jon H. Tobias. 2009. "Predicting ambient ultraviolet from routine meteorological data; its potential use as an instrumental variable for vitamin D status in pregnancy in a longitudinal birth cohort in the UK." *International Journal of Epidemiology* 38 (6): 1681–88. https://doi.org/10.1093/ije/dyp237.

Schachner, Ramona. 2014. "Weather shocks' impact on education outcomes in Mongolia Comparison of Difference-in-Differences Approach and Propensity Score Matching." *Bachelor Thesis.* https://doi.org/2014.

Schultz, Kenneth A., and Justin S. Mankin. 2019. "Is Temperature Exogenous? The Impact of Civil Conflict on the Instrumental Climate Record in Sub-Saharan Africa." *American Journal of Political Science* 63 (4): 723–39. https://doi.org/10.1111/ajps.12425.

Schultz, T. Paul. 2011. "Fertility in Developing Countries." *SSRN Electronic Journal.* https://doi.org/10.2139/ssrn.985363.

Seo, S. N. 2019. "Will farmers fully adapt to monsoonal climate change through technological developments? An analysis of rice and livestock production in Thailand." *Journal of Agricultural Science* 157 (2): 97–108. https://doi.org/10.1017/S0021859619000418.

Shen, Xinyi, Chenkai Cai, and Hui Li. 2020. "Quantifying socioeconomic activities and weather effects on the global spread of COVID-19 epidemic." http://arxiv.org/abs/2005.10223.

Shifa, Abdulaziz B. 2015. "Does Agricultural Growth Cause Manufacturing Growth?" *Economica* 82: 1107–25. https://doi.org/10.1111/ecca.12142.

Siyi, Liu, Weng Ruoyu, and Yang Daoguang. 2017. "Natural disaster, fiscal pressure and tax avoidance: a typhoon-based study." *China Journal of Accounting Studies* 5 (4): 468–509. https://doi.org/10.1080/21697213.2017.1429531.

Skoufias, Emmanuel, and Katja Vinha. 2012. "Climate variability and child height in rural Mexico." *Economics and Human Biology* 10 (1): 54–73. https://doi.org/10.1016/j.ehb.2011.06.001.

Stokes, Leah C. 2016. "Electoral Backlash against Climate Policy: A Natural Experiment on Retrospective

Voting and Local Resistance to Public Policy." *American Journal of Political Science* 60 (4): 958–74. https://doi.org/10.1111/ajps.12220.

Strobl, Eric, and Marie Anne Valfort. 2015. "The effect of weather-induced internal migration on local labor markets. Evidence from Uganda." *World Bank Economic Review* 29 (2): 385–412. https://doi.org/10.1093/wber/lht029.

Swamy, Anand V., and Brian Fikkert. 2002. "Estimating the contributions of capital and labor to GDP: An instrumental variable approach." *Economic Development and Cultural Change* 50 (3): 693–708. https://doi.org/10.1086/342250.

Tack, Jesse B., and Matthew T. Holt. 2016. "The influence of weather extremes on the spatial correlation of corn yields." *Climatic Change* 134 (1-2): 299–309. https://doi.org/10.1007/s10584-015-1538-4.

Tamada, Keiko. 2009. "The Effect of Election Outcomes on the Allocation of Government Spending in Japan." *Japanese Economy* 36 (1): 3–26. https://doi.org/10.2753/jes1097-203x360101.

Tevie, J., A. Bohara, and R. B. Valdez. 2014. "Examination of the geographical variation in human West Nile virus: A spatial filtering approach." *Epidemiology and Infection* 142 (12): 2522–29. https://doi.org/10.1017/S0950268814000090.

Theisen, Ole Magnus. 2012. "Climate clashes? weather variability, land pressure, and organized violence in Kenya, 1989-2004." *Journal of Peace Research* 49 (1): 81–96. https://doi.org/10.1177/0022343311425842.

Tiwari, Sailesh, Hanan G. Jacoby, and Emmanuel Skoufias. 2017. "Monsoon Babies: Rainfall shocks and child nutrition in Nepal." *Economic Development and Cultural Change* 65 (2): 167–88. https://doi.org/10.1086/689308.

Trenberth, Kevin E., and Dennis J. Shea. 2005. "Relationships between precipitation and surface temperature." *Geophysical Research Letters* 32 (14): 1–4. https://doi.org/10.1029/2005GL022760.

Vahedi, Sajad. 2015. "Children's Skill Formation : The Role of Childhood Exposure to Pollution." *Working Paper*, 1–39.

Veljanoska, Stefanija. 2018. "Can Land Fragmentation Reduce the Exposure of Rural Households to Weather

Variability?" *Ecological Economics* 154 (May): 42–51. https://doi.org/10.1016/j.ecolecon.2018.06.023.

Ventura-Cots, Meritxell, Ariel E. Watts, Monica Cruz-Lemini, Neil D. Shah, Nambi Ndugga, Peter McCann, A. S. Barritt, et al. 2019. "Colder Weather and Fewer Sunlight Hours Increase Alcohol Consumption and Alcoholic Cirrhosis Worldwide." *Hepatology* 69 (5): 1916–30. https://doi.org/10.1002/hep.30315.

Viswanathan, Brinda, and K. S.Kavi Kumar. 2015. "Weather, agriculture and rural migration: Evidence from state and district level migration in India." *Environment and Development Economics* 20 (4): 469–92. https://doi.org/10.1017/S1355770X1500008X.

Vo, Thang T. 2020. "Short-run and Long-run Gasoline Demand Elasticities : A Case Study of Short-run and Long-run Gasoline Demand Elasticities : A Case Study of Australia." *International Energy Journal* 20 (September): 299–310.

Völker, Marc, and Hermann Waibel. 2010. "Do rural households extract more forest products in times of crisis? Evidence from the mountainous uplands of Vietnam." *Forest Policy and Economics* 12 (6): 407–14. https://doi.org/10.1016/j.forpol.2010.03.001.

Wang, Li, Xianghong Zhou, Minghui Lu, and Zhaocai Cui. 2020. "Impacts of haze weather on tourist arrivals and destination preference: Analysis based on Baidu Index of 73 scenic spots in Beijing, China." *Journal of Cleaner Production* 273: 122887. https://doi.org/10.1016/j.jclepro.2020.122887.

Wasow, Omar. 2020. "Agenda Seeding: How 1960s Black Protests Moved Elites, Public Opinion and Voting." *American Political Science Review*, 638–59. https://doi.org/10.1017/S000305542000009X.

Wiwanitkit, Viroj. 2006. "An observation on correlation between rainfall and the prevalence of clinical cases of dengue in Thailand." *Journal of Vector Borne Diseases* 43 (2): 73–76.

Wolpin, Kenneth I. 1982. "A New Test of the Permanent Income Hypothesis: The Impact of Weather on the Income and Consumption of Farm Households in India." *International Economic Review* 23 (3): 583. https://doi.org/10.2307/2526376.

Wright, Phillip G. 1929. "The Tariff on Animal and Vegetable Oils." *Institute of Economics Investigations in International Commercial Policies* 38 (5): 619–20. https://doi.org/10.1086/254144.

Xia, Yuanni, Jos N. Van Ommeren, Piet Rietveld, and Willem Verhagen. 2013. "Railway infrastructure disturbances and train operator performance: The role of weather." *Transportation Research Part D: Transport and Environment* 18 (1): 97–102. https://doi.org/10.1016/j.trd.2012.09.008.

Xinye, Zheng, and Chu Wei. 2019. *Household energy consumption in china: 2016 report.* https://doi.org/10.1007/978-981-13-7523-1.

Xu, Chi, Timothy A. Kohler, Timothy M. Lenton, Jens Christian Svenning, and Marten Scheffer. 2020. "Future of the human climate niche." *Proceedings of the National Academy of Sciences of the United States of America* 117 (21). https://doi.org/10.1073/pnas.1910114117.

Xu, Ming, Chih Pei Chang, Congbin Fu, Ye Qi, Alan Robock, David Robinson, and Huai Min Zhang. 2006. "Steady decline of east Asian monsoon winds, 1969-2000: Evidence from direct ground measurements of wind speed." *Journal of Geophysical Research Atmospheres* 111 (24): 1–8. https://doi.org/10.1029/2006JD007337.

Yang, Dean, and Hwa Jung Choi. 2007. "Are remittances insurance? Evidence from rainfall shocks in the Philippines." *World Bank Economic Review* 21 (2): 219–48. https://doi.org/10.1093/wber/lhm003.

Zaveri, Esha, Jason Russ, and Richard Damania. 2020. "Rainfall anomalies are a significant driver of cropland expansion." *Proceedings of the National Academy of Sciences of the United States of America* 117 (19): 10225–33. https://doi.org/10.1073/pnas.1910719117.

Zhang, Tony Huiquan. 2016. "Weather effects on social movements: Evidence from Washington, D.C., and New York City, 1960-95." *Weather, Climate, and Society* 8 (3): 299–311. https://doi.org/10.1175/WCAS-D-15-0072.1.

Zheng, Siqi, Jianghao Wang, Cong Sun, Xiaonan Zhang, and Matthew E. Kahn. 2019. "Air pollution lowers Chinese urbanites' expressed happiness on social media." *Nature Human Behaviour* 3 (3): 237–43. https://doi.org/10.1038/s41562-018-0521-2.

Appendix A: Literature review table

Table 2: Relationships identified in the literature. IV studies have an X and Y variable listed, while studies looking at the relationship between weather and another variable have weather listed as the X variable.

Source of IV estimate/observed correlation	X	Y	Context
Cashin, Mohaddes, and Raissi (2017)	Weather	Quantity	21 Countries
Cashin, Mohaddes, and Raissi (2017)	Weather	Income	21 Countries
Cashin, Mohaddes, and Raissi (2017)	Weather	inflation expectations	21 Countries
Cashin, Mohaddes, and Raissi (2017)	Weather	Quantity	21 Countries
Bauer et al. (2012)	Weather	Mood	24 countries
Bruckner and Ciccone (2011)	Income	democratisation	Africa
Hodler and Raschky (2014)	Income	Conflict	Africa
Miguel, Satyanath, and Sergenti (2004)	Income	Conflict	Africa
Marchiori, Maystadt, and Schumacher (2017)	Income	Immigration	Africa
Marchiori, Maystadt, and Schumacher (2017)	urbanization	Immigration	Africa
Barrios, Bertinelli, and Strobl (2010)	Weather	Income	Africa
Marchiori, Maystadt, and Schumacher (2012)	Weather	internal migration	Africa
Marchiori, Maystadt, and Schumacher (2012)	Weather	Immigration	Africa
Cools, Flatø, and Kotsadam (2020)	Weather	Domestic abuse	Africa
Vo (2020)	Weather	Consumption	Australia
Khanthavit (2017a)	Weather	stock returns	Bangkok, Thailand

Source of IV estimate/observed correlation	X	Y	Context
Wang et al. (2020)	Pollution	tourist destination preferences	Beijin
Pereira and Menezes (2020)	Income	Crime	Brazil
Corbi and Ferraz (2018)	Domestic outmigration	Labor markets	Brazil
Branco and Feres (2020)	Weather	multiple jobs	Brazil
Branco and Feres (2020)	Weather	agricultural employment	Brazil
Nillesen and Verwimp (2011)	Income	rebel recruitment	Burundi
Reichhoff (2017)	Weather	Crime	California
S. A. Henderson and Ryabova (2020)	sustainability investments	Income	California
Tevie, Bohara, and Valdez (2014)	foreclosures	West Nile Virus	California and Colorado
Tevie, Bohara, and Valdez (2014)	Income	West Nile Virus	California and Colorado
Gillett et al. (2004)	Weather	forest fires	Canada
C. Cui et al. (2019)	Pollution	Domestic outmigration	China
Zheng et al. (2019)	Pollution	Mood	China
Gu et al. (2020)	Pollution	mental health	China
W.-S. Lee and Li (2020)	economic conditions in childhood	Health	China

Source of IV estimate/observed correlation	X	Y	Context
Giulietti, Wahba, and Zenou (2018)	Migrant social capital	Domestic outmigration	China
Xinye and Wei (2019)	Pollution	Mood	China
Bai and Kung (2014)	famine	abandoning collective farming	China
Siyi, Ruoyu, and Daoguang (2017)	Weather	tax avoidance	China
Fisher-Vanden, Mansur, and Wang (2015)	Demand	industrial output	China
Fisher-Vanden, Mansur, and Wang (2015)	Demand	factor substitution	China
Hales et al. (2000)	Weather	Health	Christchurch, New Zealand
Hales et al. (2000)	Pollution	Health	Christchurch, New Zealand
Zhang (2016)	Weather	Protest	DC and NY
Zhang (2016)	Weather	Violent protest	DC and NY
T. P. Schultz (2011)	Quantity	Fertility	England
T. P. Schultz (2011)	Quantity	marriage	England
Di Falco et al. (2019)	Income	discount rates	Ethiopia
Flyr et al. (2019)	Weather	Demand	Fort Collins municipal utility
Ben Lakhdar and Dubois (2006)	Weather	turnout	France
Huet-Vaughn (2013)	Violent protest	policy concessions	France
Graddy (2006)	Quantity	Quantity	Fulton Fish Market (New York)

Source of IV estimate/observed correlation	X	Y	Context
Graddy and Kennedy (2010)	Inventory	Quantity	Fulton Fish Market (New York)
Angrist, Graddy, and Imbens (2000)	Production	Quantity	Fulton Fish Market (New York)
Luechinger (2014)	Pollution	infant mortality	Germany
Mehlum, Miguel, and Torvik (2006)	Income	property crime	Germany
Mehlum, Miguel, and Torvik (2006)	Income	violent crime	Germany
Guven and Hoxha (2015)	Mood	savings account	Germany
Guven and Hoxha (2015)	Mood	stock and bond ownership	Germany
Guven and Hoxha (2015)	Mood	operating asset ownership	Germany
Guven and Hoxha (2015)	Mood	Insurance	Germany
Arnold and Freier (2016)	turnout	Party vote share	Germany
Goetzke and Rave (2011)	cycling	cycling	Germany
Akobeng (2017)	Income	Consumption	Ghana
Wolpin (1982)	Income	Consumption	India
Blakeslee and Fishman (2018)	Weather	Crime	India
Viswanathan and Kumar (2015)	Production	Immigration	India
Burgess et al. (2014)	Weather	Health	India
Sarsons (2015)	Weather	Conflict	India
Chin (2011)	female employment	Domestic abuse	India

Source of IV estimate/observed correlation	X	Y	Context
Bhavnani and Lacina (2015)	Domestic inmigration	Conflict	India
Y. J. Kim, Sesmero, and Waldorf (2018)	Weather	Immigration	India
Allcott, Collard-Wexler, and O'Connell (2016)	Weather	hydroelectric power	India
Allcott, Collard-Wexler, and O'Connell (2016)	hydroelectric power	industrial output	India
Jacoby and Skoufias (1997)	Income	Human capital	India
Kochar (1999)	Income	Consumption	India
Kleemans and Magruder (2018)	Domestic outmigration	Labor markets	Indonesia
Hanandita and Tampubolon (2014)	Income	mental health	Indonesia
Maccini and Yang (2009)	Weather	Health	Indonesia
Maccini and Yang (2009)	Weather	Human capital	Indonesia
Maccini and Yang (2009)	Weather	asset ownership	Indonesia
Caruso, Petrarca, and Ricciuti (2016)	Production	Conflict	Indonesia
Tack and Holt (2016)	Weather	spatial correlation of crop yields	Iowa and Illinois
Dustmann, Fasani, and Speciale (2017)	migration legal status	Consumption	Italy
Falco et al. (2014)	Insurance	Income	Italy
Falco et al. (2014)	Crop diversity	Income	Italy
Lo Prete and Revelli (2020)	turnout	environmental quality	Italy

Source of IV estimate/observed correlation	X	Y	Context
Lo Prete and Revelli (2020)	turnout	speed of revenue collection	Italy
Lo Prete and Revelli (2020)	turnout	mayoral experience	Italy
Di Falco and Chavas (2008)	Weather	Production	Italy
Di Falco and Chavas (2008)	Crop diversity	Production	Italy
Fukumoto, Kikuta, and Yanagi (2019)	disaster relief allocation	Party vote share	Japan
Theisen (2012)	Weather	Conflict	Kenya
Nübler et al. (2020)	Weather	Human capital	Kenya
Nübler et al. (2020)	Weather	math performance	Kenya
Nübler et al. (2020)	Weather	reading performance	Kenya
Bondy, Roth, and Sager (2020)	Pollution	Crime	London
Moretti and Neidell (2011)	Pollution	Health	Los Angeles
Davies (2010)	Weather	Consumption	Malawi
Han and Foltz (2015)	Weather	Health	Mali
López-córdova (2006)	remittances	infant mortality	Mexico
López-córdova (2006)	remittances	Human capital	Mexico
López-córdova (2006)	remittances	Human capital	Mexico
Feng, Krueger, and Oppenheimer (2010)	Production	Immigration	Mexico
Nawrotzki, Riosmena, and Hunter (2013)	Weather	Immigration	Mexico
Skoufias and Vinha (2012)	Weather	child height	Mexico
Fontenla, Ben Goodwin, and Gonzalez (2019)	Pollution	Labor markets	Mexico City

Source of IV estimate/observed correlation	X	Y	Context
Fontenla, Ben Goodwin, and Gonzalez (2019)	Pollution	Property values	Mexico City
Munshi (2003)	Migrant social capital	migrant employment	Mexico/US
Groppo and Kraehnert (2017)	Production	Human capital	Mongolia
Schachner (2014)	Production	Human capital	Mongolia
Tiwari, Jacoby, and Skoufias (2017)	Income	child nutrition	Nepal
Guven and Hoxha (2015)	Mood	risk aversion	Netherlands
Guven and Hoxha (2015)	Mood	subjective perceptions of life expectancy	Netherlands
Guven and Hoxha (2015)	Mood	average working hours	Netherlands
Guven and Hoxha (2015)	Mood	inflation expectations	Netherlands
Guven and Hoxha (2015)	Mood	decision making speed	Netherlands
Guven and Hoxha (2015)	Mood	perceptions of stock ownership risk	Netherlands
Xia et al. (2013)	Weather	passenger train perfomance	Netherlands
Mulder and Scholtens (2013)	Production	Quantity	Netherlands and Germany
Beaudin and Huang (2014)	Weather	closure of ski areas	New England

Source of IV estimate/observed correlation	X	Y	Context
Horrocks and Menclova (2011)	Weather	Crime	New Zealand
Asfaw, Palma, and Lipper (2016)	Crop diversity	Income	Niger
Asfaw, Palma, and Lipper (2016)	Crop diversity	food security	Niger
Asfaw, Palma, and Lipper (2016)	Crop diversity	Inequality	Niger
Leimdörfer and Hauge (2020)	Health	Fertility	Niger
Landis et al. (2017)	Weather	Conflict	Niger River Basin
Bertelli (2015)	Health	Fertility	Nigeria
Falco and Doku (2019)	Income	Mood	Nile Basin Region of Ethiopia
Hansford and Gomez (2010)	turnout	Party vote share	non-Southern US
Hansford and Gomez (2010)	turnout	incumbent voting	non-Southern US
Lagerlöf and Basher (2006)	Weather	Income	North America
C. C. Lee and Chiu (2011)	Quantity	Consumption	OECD countries
Stokes (2016)	wind turbine placement	incumbent voting	Ontario
Aklilu (2007)	Income	savings	Peru
Peet (2020)	early life pollution	cognition	Philippines
Peet (2020)	early life pollution	Income	Philippines
Peet (2020)	early life pollution	height	Philippines
Pajaron (2017)	Income	Consumption	Philippines
Pajaron (2017)	Income	remittances	Philippines

Source of IV estimate/observed correlation	X	Y	Context
Pajaron (2017)	Income	domestic money transfers	Philippines
Dacuycuy (2016)	Income	Consumption	Philippines
Pajaron and Vasquez (2020)	Weather	Immigration	Philippines
Bayani-Arias and Palanca-Tan (2017)	Weather	Inequality	Philippines
Bayani-Arias and Palanca-Tan (2017)	Weather	Inequality	Philippines
Yang and Choi (2007)	Income	remittances	Philippines
Yang and Choi (2007)	Income	Consumption	Philippines
Gajate-Garrido (2013)	prenatal care	birth outcomes	Philippines
Oster (2004)	Income	witch trials	Renaissance Europe
Chen and Mahmassani (2015)	Weather	travel time	San Francisco
Chen and Mahmassani (2015)	Weather	Mood	San Francisco
Pitt and Sigle (1997)	Health	Fertility	Senegal
Bae, Lim, and Hong (2020)	Pollution	Health	Seoul
Maystadt and Ecker (2014)	Quantity	Conflict	Somalia
Cook and Garrett (2013)	Weather	pirate attacks	Somalia
Elum, Nhamo, and Antwi (2018)	Income	Insurance	South Africa
Kubik and May (2018)	Quantity	dietary diversity	South Africa
Kubik and May (2018)	Quantity	hunger	South Africa
Bruederle, Peters, and Roberts (2017)	Weather	Crime	South Africa
W. C. Kang (2019)	turnout	Party vote share	South Korea
H. Kang, Suh, and Yu (2019)	Pollution	Sales	South Korea
Artés (2014)	turnout	vote choice	Spain

Source of IV estimate/observed correlation	X	Y	Context
Ito and Reguant (2016)	residual electricity demand	price premium	Spain/Portugal
Persson, Sundell, and Öhrvall (2014)	Weather	turnout	Sweden
Hu and Lee (2020)	consumer sentiment	Property values	Sydney
Gurgand (2003)	complexity of farming	farmers returns to education	Taiwan
Chang and Zilberman (2014)	Weather	disaster payments	Taiwan
Parham and Michael (2010)	Weather	Malaria	Tanzania
Fichera and Savage (2015)	Income	BMI	Tanzania
Fichera and Savage (2015)	Income	vaccination	Tanzania
Khanthavit (2019a)	Weather	government bond returns	Thailand
Pipitpukdee, Attavanich, and Bejranonda (2020)	Weather	Production	Thailand
Paxson (1992)	Income	savings	Thailand
Badaoui, Strobl, and Walsh (2013)	Domestic outmigration	Labor markets	Thailand
Badaoui, Strobl, and Walsh (2013)	Domestic inmigration	Labor markets	Thailand
Khanthavit (2019b)	Mood	stock prices	Thailand
Seo (2019)	Weather	Production	Thailand
Khanthavit (2019c)	Mood	stock returns	Thailand
Khanthavit (2017b)	Mood	stock returns	Thailand

Source of IV estimate/observed correlation	X	Y	Context
Wiwanitkit (2006)	Weather	dengue infection	Thailand
F. Huang et al. (2011)	Weather	Malaria	Tibet
Veljanoska (2018)	Weather	Quantity	Uganda
Strobl and Valfort (2015)	Domestic inmigration	Labor markets	Uganda
Abiona (2017)	Income	Contraceptive use	Uganda
Sayers et al. (2009)	Weather	vitaminD	UK
Sager (2019)	Pollution	road accidents	UK
Rudolph (2020)	turnout	Brexit voting	UK
Chhaochharia et al. (2019)	perceived economic outlook	hiring decisions	United States
Chhaochharia et al. (2019)	perceived economic outlook	capital expenditure	United States
Boustan, Fishback, and Kantor (2010)	Weather	Immigration	United States
Ritter and Conrad (2016)	dissent	repression	United States
J. Henderson and Brooks (2016)	Party vote share	representative voting behavior	United States
Hornbeck et al. (2012)	erosion	land values	United States
Chalfin (2014)	Immigration	Crime	United States/Mexico
Apergis, Artikis, and Mamatzakis (2012)	Weather	bank loan efficiency	US
Coviello et al. (2014)	Mood	friends happiness	US

Source of IV estimate/observed correlation	X	Y	Context
Coviello et al. (2014)	Mood	friends negative emotions	US
Moretti (1998)	Weather	retirement community locations	US
Chia et al. (2016)	violent crime	Inequality	US
Chia et al. (2016)	property crime	Inequality	US
Herrnstadt and Muehlegger (2014)	salience of climate change	Legislator behavior	US
Fujiwara, Meng, and Vogl (2016)	turnout	future turnout	US
Wasow (2020)	Violent protest	Party vote share	US
Horiuchi and Kang (2018)	turnout	Party vote share	US
Gomez, Hansford, and Krause (2007)	turnout	Party vote share	US
Knack (1994)	turnout	Party vote share	US
Madestam et al. (2013)	Protest	Party vote share	US
Madestam et al. (2013)	Protest	Legislator behavior	US
Healy and Malhotra (2010)	Income	incumbent voting	US
Pinckney (2019)	Protest	Party vote share	US
Pinckney (2019)	Protest	Legislator behavior	US
Pinckney (2019)	Protest	protest group creation	US
Keele and Morgan (2013)	turnout	Party vote share	US

Source of IV estimate/observed correlation	X	Y	Context
Farah and Torell (2018)	Quantity	willingness to pay for water hardness reduction	US
Ranson (2014)	Weather	Crime	US
Fan and Wang (2020)	Pollution	Health	US
Fan and Wang (2020)	Weather	Pollution	US
Nadolnyak and Hartarska (2012)	Weather	crop disaster payments	US
Frijters, Lalji, and Pakrashi (2020)	Weather	Health	US
Frijters, Lalji, and Pakrashi (2020)	Weather	Mood	US
Cooperman (2017)	Weather	turnout	US
Rappaport (2007)	Weather	internal migration	US
X. Cui (2020)	Weather	crop abandonment	US
Cachon, Gallino, and Olivares (2019)	Inventory	car sales	US
Laidley and Conley (2018)	Leisure activities	math performance	US
Vahedi (2015)	Pollution	Human capital	US
Jacob, Lefgren, and Moretti (2007)	violent crime	future violent crime	US
Jacob, Lefgren, and Moretti (2007)	property crime	future property crime	US
Jacob, Lefgren, and Moretti (2007)	traffic	future traffic	US
Katz et al. (2020)	skin tone	Labor markets	US

Source of IV estimate/observed correlation	X	Y	Context
Gong and Rogers (2014)	turnout	support for school bonds	US
Aguiar-Moya, Prozzi, and de Fortier Smit (2011)	Weather	pavement roughness	US
Considine (2000)	Weather	carbon emissions	US
Considine (2000)	Weather	Consumption	US
Considine (2000)	Weather	Consumption	US
Lahiri (2018)	absence from work	racial earnings disparities	US
Berry and Schlenker (2011)	Quantity	Quantity	US
Achen and Bartels (2016)	Weather	incumbent voting	US
Cohen (2011)	Weather	presidential approval	US
Kovács (2017)	Weather	patent decisions	US
Maunder (1973)	Weather	Sales	US
Wright (1929)	Weather	Quantity	US
Li, Johnson, and Zaval (2011)	perceived temperature variation	global warming beliefs	US and Australia
Collins and Margo (2007)	Violent protest	Property values	US cities
Feng, Oppenheimer, and Schlenker (2012)	Income	Immigration	US Corn Belt
Pugatch and Yang (2011)	Immigration	Labor markets	US/Mexico
Deisenhammer (2003)	Weather	suicide	various
Levin et al. (2020)	Weather	lead exposure	various

Source of IV estimate/observed correlation	X	Y	Context
Hoang (2018)	Weather	land fragmentation	Vietnam
Q. N. Bui et al. (2020)	Weather	land fragmentation	Vietnam
A. T. Bui et al. (2014)	Weather	Income	Vietnam
A. T. Bui et al. (2014)	Weather	Consumption	Vietnam
Völker and Waibel (2010)	Weather	forest extraction	Vietnam
Santeramo and Searle (2019)	Quantity	Production	whole world
Baylis et al. (2018)	Weather	Mood	worldwide
Miguel and Satyanath (2011)	Income	Conflict	worldwide
Hendricks, Janzen, and Smith (2015)	Production	Quantity	worldwide
Swamy and Fikkert (2002)	Labor markets	Income	worldwide
Swamy and Fikkert (2002)	Wealth	Income	worldwide
Shifa (2015)	Income	manufacturing growth	worldwide
Ventura-Cots et al. (2019)	alcohol consumption	cirrhosis	worldwide
N. K. Kim (2016)	Income	coups	worldwide
Atalla, Bigerna, and Bollino (2018)	Weather	Demand	worldwide
Lis and Nickel (2010)	Weather	budget balance	worldwide
Hsiang, Burke, and Miguel (2013)	Weather	Conflict	worldwide
Hsiang, Meng, and Cane (2011)	Weather	Conflict	worldwide
Koks et al. (2019)	Weather	transport infrastructure damage	worldwide

Source of IV estimate/observed correlation	X	Y	Context
H. H. Huang, Kerstein, and Wang (2018)	Weather	firm cash holding	worldwide
Zaveri, Russ, and Damania (2020)	agricultural productivity	cropland expansion	worldwide
Shen, Cai, and Li (2020)	Weather	COVID19	worldwide
Magnusson (2000)	Weather	Mood	worldwide
Roenneberg and Aschoff (1990)	Weather	month of birth	worldwide
Dell, Jones, and Olken (2009)	Weather	Income	worldwide
Hoogeveen, Van Der Klaauw, and Van Lomwel (2011)	Wealth	marriage	Zimbabwe
Jacobsen and Marquering (2008)	Mood	stock returns	worldwide
Aral and Nicolaides (2017)	exercise	friends exercise	worldwide
Fraga and Hersh (2011)	Weather	turnout	United States

Table 3: IV Relationships identified in the literature for IV studies where there are multiple intermediate variables. All studies have weather as an initial IV.

Source of IV estimate/observed correlation	X	Y	Context	NA
Muehlenbachs and Cohen (2014)	helicopter flying conditions	oil platform inspectors	oil platform fines	Gulf of Mexico
Tamada (2009)	turnout	Party vote share	Government spending	Japan
Lind (2019)	turnout	Party vote share	child care spending	Norway

Source of IV estimate/observed correlation	X	Y	Context	NA
Lind (2019)	turnout	Party vote share	education spending	Norway
Acharya, Blackwell, and Sen (2016)	cotton growing suitability	slavery	vote choice	US
Acharya, Blackwell, and Sen (2016)	cotton growing suitability	slavery	support for affirmative action	US
Acharya, Blackwell, and Sen (2016)	cotton growing suitability	slavery	racial resentment	US
Acharya, Blackwell, and Sen (2016)	cotton growing suitability	slavery	racial affect	US

Appendix B: Full sensitivity results

Table 4: Full sensitivity estimates for all 45 IV estimates reduced-forms with regards to Mood: R2(W~Z|K)=0.002 Violent crime: R2(W~Z|K)=0.027 , Urbanization: R2(W~Z|K)=0.065 and Domestic inmigration: R2(W~Z|K)=0.107 exclusion restriction violations. $R^2_{Y\ Z|W,K} = 0.0001$ is the lowest confounding level tested.

Source of IV estimate with available reduced-form	X	Y	Z	Sensitivity	Reduction
Fukumoto, Kikuta, and Yanagi (2019)	disaster relief allocation	LDP vote share	Mood	0.00001	Insignificant
Guven and Hoxha (2015)	happiness	average working hours	Mood	0.00001	Insignificant
Pajaron (2017)	income	remittances	Mood	0.00001	Insignificant
Pajaron (2017)	income	domestic money transfers	Mood	0.00001	Insignificant
Artés (2014)	turnout	vote choice	Mood	0.00001	Insignificant
Berry and Schlenker (2011)	crop prices	crop yields	Mood	0.00001	Insignificant
Abiona (2017)	agricultural income	Contraceptive use	Mood	0.0001	Insignificant
Kleemans and Magruder (2018)	internal outmigration	labor market	Mood	0.00038	Insignificant

Source of IV estimate with available reduced-form	X	Y	Z	Sensitivity	Reduction
Guven and Hoxha (2015)	happiness	savings account	Mood	0.00072	Insignificant
Bruckner and Ciccone (2011)	income	democratisation	Mood	0.00147	Insignificant
Guven and Hoxha (2015)	happiness	risk aversion	Mood	0.00399	Insignificant
Paxson (1992)	transitory income	savings	Mood	0.00646	Insignificant
Lind (2019)	Right wing party vote share	education spending	Mood	0.00696	Insignificant
Hodler and Raschky (2014)	income	civil conflict	Mood	0.00728	Insignificant
Madestam et al. (2013)	tea party protest attendance	congressional voting behavior	Mood	0.00748	Insignificant
Chin (2011)	female employment	intimate partner violence	Mood	0.00806	Insignificant
Madestam et al. (2013)	tea party protest attendance	Republican vote share	Mood	0.01284	Insignificant
Guven and Hoxha (2015)	happiness	operating asset ownership	Mood	0.01439	Insignificant

Source of IV estimate with available reduced-form	X	Y	Z	Sensitivity	Reduction
Fontenla, Ben Goodwin, and Gonzalez (2019)	air quality	house prices	Mood	0.01818	Insignificant
C. Cui et al. (2019)	air quality	inter-city population mobility	Mood	0.02117	Insignificant
Falco and Doku (2019)	income	self esteem	Mood	0.02399	Insignificant
Farah and Torell (2018)	water price	willingness to pay for water hardness reduction	Mood	0.03099	Insignificant
Acharya, Blackwell, and Sen (2016)	slavery	racial resentment	Mood	0.0402	Insignificant
Chhaochharia et al. (2019)	perceived economic outlook	capital expenditure	Mood	0.04472	Insignificant
Chhaochharia et al. (2019)	perceived economic outlook	hiring decisions	Mood	0.05385	Insignificant
Guven and Hoxha (2015)	happiness	stock and bond ownership	Mood	0.066	Insignificant
Guven and Hoxha (2015)	happiness	life insurance ownership	Mood	0.06614	Insignificant

Source of IV estimate with available reduced-form	X	Y	Z	Sensitivity	Reduction
N. K. Kim (2016)	economic growth	coups	Mood	0.0788	Insignificant
Acharya, Blackwell, and Sen (2016)	slavery	vote choice	Mood	0.1005	Insignificant
Fichera and Savage (2015)	income	BMI	Mood	0.1232	Insignificant
Miguel and Satyanath (2011)	income	conflict	Mood	0.2329	Insignificant
Pereira and Menezes (2020)	per capita income	crime	Mood	NA	Insignificant
Xinye and Wei (2019)	air quality	happiness	Mood	NA	Insignificant
Di Falco et al. (2019)	income	discount rates	Mood	NA	Insignificant
Arnold and Freier (2016)	turnout	Conservative vote share	Mood	NA	Insignificant
Bhavnani and Lacina (2015)	internal inmigra-tion	riots	Mood	NA	Insignificant
Dustmann, Fasani, and Speciale (2017)	migration legal status	consumption	Mood	NA	Insignificant
Fontenla, Ben Goodwin, and Gonzalez (2019)	air quality	wages	Mood	NA	Insignificant
Stokes (2016)	wind turbine placement	incumbent voting	Mood	NA	Insignificant
Pajaron (2017)	income	consumption	Mood	NA	Insignificant

Source of IV estimate with available reduced-form	X	Y	Z	Sensitivity	Reduction
Gajate-Garrido (2013)	prenatal care	birth outcomes	Mood	NA	Insignificant
Rudolph (2020)	turnout	Brexit voting	Mood	NA	Insignificant
Chia et al. (2016)	property crime	intergenerational income mobility	Mood	NA	Insignificant
Acharya, Blackwell, and Sen (2016)	slavery	support for affirmative action	Mood	NA	Insignificant
Acharya, Blackwell, and Sen (2016)	slavery	racial affect	Mood	NA	Insignificant
Fukumoto, Kikuta, and Yanagi (2019)	disaster relief allocation	LDP vote share	Violent crime	0.00001	Insignificant
Guven and Hoxha (2015)	happiness	average working hours	Violent crime	0.00001	Insignificant
Pajaron (2017)	income	remittances	Violent crime	0.00001	Insignificant
Pajaron (2017)	income	domestic money transfers	Violent crime	0.00001	Insignificant
Artés (2014)	turnout	vote choice	Violent crime	0.00001	Insignificant
Abiona (2017)	agricultural income	Contraceptive use	Violent crime	0.00001	Insignificant

Source of IV estimate with available reduced-form	X	Y	Z	Sensitivity	Reduction
Berry and Schlenker (2011)	crop prices	crop yields	Violent crime	0.00001	Insignificant
Bruckner and Ciccone (2011)	income	democratisation	Violent crime	0.0001	Insignificant
Guven and Hoxha (2015)	happiness	savings account	Violent crime	0.0001	Insignificant
Kleemans and Magruder (2018)	internal outmigration	labor market	Violent crime	0.0001	Insignificant
Madestam et al. (2013)	tea party protest attendance	congressional voting behavior	Violent crime	0.00028	Insignificant
Guven and Hoxha (2015)	happiness	risk aversion	Violent crime	0.00031	Insignificant
Paxson (1992)	transitory income	savings	Violent crime	0.00046	Insignificant
Lind (2019)	Right wing party vote share	education spending	Violent crime	0.00056	Insignificant
Hodler and Raschky (2014)	income	civil conflict	Violent crime	0.00062	Insignificant

Source of IV estimate with available reduced-form	X	Y	Z	Sensitivity	Reduction
Chin (2011)	female employment	intimate partner violence	Violent crime	0.00065	Insignificant
Madestam et al. (2013)	tea party protest attendance	Republican vote share	Violent crime	0.00089	Insignificant
Fontenla, Ben Goodwin, and Gonzalez (2019)	air quality	house prices	Violent crime	0.00114	Insignificant
Guven and Hoxha (2015)	happiness	operating asset ownership	Violent crime	0.00124	Insignificant
Falco and Doku (2019)	income	self esteem	Violent crime	0.00156	Insignificant
C. Cui et al. (2019)	air quality	inter-city population mobility	Violent crime	0.00174	Insignificant
Acharya, Blackwell, and Sen (2016)	slavery	racial resentment	Violent crime	0.00233	Insignificant
Farah and Torell (2018)	water price	willingness to pay for water hardness reduction	Violent crime	0.00274	Insignificant

Source of IV estimate with available reduced-form	X	Y	Z	Sensitivity	Reduction
Chhaochharia et al. (2019)	perceived economic outlook	capital expenditure	Violent crime	0.00384	Insignificant
Chhaochharia et al. (2019)	perceived economic outlook	hiring decisions	Violent crime	0.00462	Insignificant
Acharya, Blackwell, and Sen (2016)	slavery	vote choice	Violent crime	0.00541	Insignificant
N. K. Kim (2016)	economic growth	coups	Violent crime	0.00563	Insignificant
Guven and Hoxha (2015)	happiness	stock and bond ownership	Violent crime	0.00568	Insignificant
Guven and Hoxha (2015)	happiness	life insurance ownership	Violent crime	0.00569	Insignificant
Miguel and Satyanath (2011)	income	conflict	Violent crime	0.00718	Insignificant
Fichera and Savage (2015)	income	BMI	Violent crime	0.00941	Insignificant
Gajate-Garrido (2013)	prenatal care	birth outcomes	Violent crime	0.01815	Insignificant
Acharya, Blackwell, and Sen (2016)	slavery	support for affirmative action	Violent crime	0.02293	Insignificant

Source of IV estimate with available reduced-form	X	Y	Z	Sensitivity	Reduction
Arnold and Freier (2016)	turnout	Conservative vote share	Violent crime	0.03033	Insignificant
Pajaron (2017)	income	consumption	Violent crime	0.05105	Insignificant
Xinye and Wei (2019)	air quality	happiness	Violent crime	0.06799	Insignificant
Fontenla, Ben Goodwin, and Gonzalez (2019)	air quality	wages	Violent crime	0.06847	Insignificant
Dustmann, Fasani, and Speciale (2017)	migration legal status	consumption	Violent crime	0.08728	Insignificant
Pereira and Menezes (2020)	per capita income	crime	Violent crime	0.1206	Insignificant
Stokes (2016)	wind turbine placement	incumbent voting	Violent crime	0.2246	Insignificant
Chia et al. (2016)	property crime	intergenerational income mobility	Violent crime	0.2508	Insignificant
Rudolph (2020)	turnout	Brexit voting	Violent crime	0.5342	Insignificant
Di Falco et al. (2019)	income	discount rates	Violent crime	NA	Insignificant

Source of IV estimate with available reduced-form	X	Y	Z	Sensitivity	Reduction
Bhavnani and Lacina (2015)	internal inmigration	riots	Violent crime	NA	Insignificant
Acharya, Blackwell, and Sen (2016)	slavery	racial affect	Violent crime	NA	Insignificant
Bruckner and Ciccone (2011)	income	democratisation	Urbanization	0.00001	Insignificant
Kleemans and Magruder (2018)	internal outmigration	labor market	Urbanization	0.00001	Insignificant
Fukumoto, Kikuta, and Yanagi (2019)	disaster relief allocation	LDP vote share	Urbanization	0.00001	Insignificant
Guven and Hoxha (2015)	happiness	average working hours	Urbanization	0.00001	Insignificant
Pajaron (2017)	income	remittances	Urbanization	0.00001	Insignificant
Pajaron (2017)	income	domestic money transfers	Urbanization	0.00001	Insignificant
Artés (2014)	turnout	vote choice	Urbanization	0.00001	Insignificant
Abiona (2017)	agricultural income	Contraceptive use	Urbanization	0.00001	Insignificant
Madestam et al. (2013)	tea party protest attendance	congressional voting behavior	Urbanization	0.00001	Insignificant

Source of IV estimate with available reduced-form	X	Y	Z	Sensitivity	Reduction
Berry and Schlenker (2011)	crop prices	crop yields	Urbanization	0.00001	Insignificant
Guven and Hoxha (2015)	happiness	savings account	Urbanization	0.0001	Insignificant
Guven and Hoxha (2015)	happiness	risk aversion	Urbanization	0.0001	Insignificant
Paxson (1992)	transitory income	savings	Urbanization	0.00013	Insignificant
Lind (2019)	Right wing party vote share	education spending	Urbanization	0.00019	Insignificant
Chin (2011)	female employment	intimate partner violence	Urbanization	0.00023	Insignificant
Hodler and Raschky (2014)	income	civil conflict	Urbanization	0.00024	Insignificant
Madestam et al. (2013)	tea party protest attendance	Republican vote share	Urbanization	0.00025	Insignificant
Fontenla, Ben Goodwin, and Gonzalez (2019)	air quality	house prices	Urbanization	0.00029	Insignificant
Falco and Doku (2019)	income	self esteem	Urbanization	0.00045	Insignificant
Guven and Hoxha (2015)	happiness	operating asset ownership	Urbanization	0.00048	Insignificant

Source of IV estimate with available reduced-form	X	Y	Z	Sensitivity	Reduction
C. Cui et al. (2019)	air quality	inter-city population mobility	Urbanization	0.00064	Insignificant
Acharya, Blackwell, and Sen (2016)	slavery	racial resentment	Urbanization	0.00065	Insignificant
Farah and Torell (2018)	water price	willingness to pay for water hardness reduction	Urbanization	0.00108	Insignificant
Chhaochharia et al. (2019)	perceived economic outlook	capital expenditure	Urbanization	0.00149	Insignificant
Acharya, Blackwell, and Sen (2016)	slavery	vote choice	Urbanization	0.00173	Insignificant
Chhaochharia et al. (2019)	perceived economic outlook	hiring decisions	Urbanization	0.00179	Insignificant
N. K. Kim (2016)	economic growth	coups	Urbanization	0.00201	Insignificant
Miguel and Satyanath (2011)	income	conflict	Urbanization	0.0022	Insignificant
Guven and Hoxha (2015)	happiness	stock and bond ownership	Urbanization	0.00221	Insignificant
Guven and Hoxha (2015)	happiness	life insurance ownership	Urbanization	0.00222	Insignificant

Source of IV estimate with available reduced-form	X	Y	Z	Sensitivity	Reduction
Fichera and Savage (2015)	income	BMI	Urbanization	0.00354	Insignificant
Gajate-Garrido (2013)	prenatal care	birth outcomes	Urbanization	0.00644	Insignificant
Acharya, Blackwell, and Sen (2016)	slavery	support for affirmative action	Urbanization	0.00799	Insignificant
Arnold and Freier (2016)	turnout	Conservative vote share	Urbanization	0.01113	Insignificant
Pajaron (2017)	income	consumption	Urbanization	0.01736	Insignificant
Fontenla, Ben Goodwin, and Gonzalez (2019)	air quality	wages	Urbanization	0.02446	Insignificant
Xinye and Wei (2019)	air quality	happiness	Urbanization	0.02509	Insignificant
Dustmann, Fasani, and Speciale (2017)	migration legal status	consumption	Urbanization	0.03356	Insignificant
Pereira and Menezes (2020)	per capita income	crime	Urbanization	0.04496	Insignificant
Stokes (2016)	wind turbine placement	incumbent voting	Urbanization	0.06456	Insignificant
Chia et al. (2016)	property crime	intergenerational income mobility	Urbanization	0.07437	Insignificant
Rudolph (2020)	turnout	Brexit voting	Urbanization	0.1086	Insignificant

Source of IV estimate with available reduced-form	X	Y	Z	Sensitivity	Reduction
Bhavnani and Lacina (2015)	internal inmigration	riots	Urbanization	0.2631	Insignificant
Di Falco et al. (2019)	income	discount rates	Urbanization	0.6072	Insignificant
Acharya, Blackwell, and Sen (2016)	slavery	racial affect	Urbanization	NA	Insignificant
Bruckner and Ciccone (2011)	income	democratisation	Domestic inmigration	0.00001	Insignificant
Guven and Hoxha (2015)	happiness	savings account	Domestic inmigration	0.00001	Insignificant
Kleemans and Magruder (2018)	internal outmigration	labor market	Domestic inmigration	0.00001	Insignificant
Fukumoto, Kikuta, and Yanagi (2019)	disaster relief allocation	LDP vote share	Domestic inmigration	0.00001	Insignificant
Guven and Hoxha (2015)	happiness	average working hours	Domestic inmigration	0.00001	Insignificant
Pajaron (2017)	income	remittances	Domestic inmigration	0.00001	Insignificant

Source of IV estimate with available reduced-form	X	Y	Z	Sensitivity	Reduction
Pajaron (2017)	income	domestic money transfers	Domestic inmigration	0.00001	Insignificant
Artés (2014)	turnout	vote choice	Domestic inmigration	0.00001	Insignificant
Abiona (2017)	agricultural income	Contraceptive use	Domestic inmigration	0.00001	Insignificant
Madestam et al. (2013)	tea party protest attendance	congressional voting behavior	Domestic inmigration	0.00001	Insignificant
Berry and Schlenker (2011)	crop prices	crop yields	Domestic inmigration	0.00001	Insignificant
Fontenla, Ben Goodwin, and Gonzalez (2019)	air quality	house prices	Domestic inmigration	0.0001	Insignificant
Guven and Hoxha (2015)	happiness	risk aversion	Domestic inmigration	0.0001	Insignificant

Source of IV estimate with available reduced-form	X	Y	Z	Sensitivity	Reduction
Lind (2019)	Right wing party vote share	education spending	Domestic inmigration	0.0001	Insignificant
Paxson (1992)	transitory income	savings	Domestic inmigration	0.0001	Insignificant
Madestam et al. (2013)	tea party protest attendance	Republican vote share	Domestic inmigration	0.0001	Insignificant
Chin (2011)	female employment	intimate partner violence	Domestic inmigration	0.00011	Insignificant
Hodler and Raschky (2014)	income	civil conflict	Domestic inmigration	0.00013	Insignificant
Falco and Doku (2019)	income	self esteem	Domestic inmigration	0.00016	Insignificant
Acharya, Blackwell, and Sen (2016)	slavery	racial resentment	Domestic inmigration	0.00023	Insignificant

Source of IV estimate with available reduced-form	X	Y	Z	Sensitivity	Reduction
Guven and Hoxha (2015)	happiness	operating asset ownership	Domestic inmigration	0.00027	Insignificant
C. Cui et al. (2019)	air quality	inter-city population mobility	Domestic inmigration	0.00034	Insignificant
Farah and Torell (2018)	water price	willingness to pay for water hardness reduction	Domestic inmigration	0.00062	Insignificant
Acharya, Blackwell, and Sen (2016)	slavery	vote choice	Domestic inmigration	0.00076	Insignificant
Chhaochharia et al. (2019)	perceived economic outlook	capital expenditure	Domestic inmigration	0.00084	Insignificant
Miguel and Satyanath (2011)	income	conflict	Domestic inmigration	0.00093	Insignificant
Chhaochharia et al. (2019)	perceived economic outlook	hiring decisions	Domestic inmigration	0.00101	Insignificant

Source of IV estimate with available reduced-form	X	Y	Z	Sensitivity	Reduction
N. K. Kim (2016)	economic growth	coups	Domestic inmigra-tion	0.00103	Insignificant
Guven and Hoxha (2015)	happiness	stock and bond ownership	Domestic inmigra-tion	0.00125	Insignificant
Guven and Hoxha (2015)	happiness	life insurance ownership	Domestic inmigra-tion	0.00126	Insignificant
Fichera and Savage (2015)	income	BMI	Domestic inmigra-tion	0.00194	Insignificant
Gajate-Garrido (2013)	prenatal care	birth outcomes	Domestic inmigra-tion	0.00331	Insignificant
Acharya, Blackwell, and Sen (2016)	slavery	support for affirmative action	Domestic inmigra-tion	0.00406	Insignificant
Arnold and Freier (2016)	turnout	Conservative vote share	Domestic inmigra-tion	0.00599	Insignificant
Pajaron (2017)	income	consumption	Domestic inmigra-tion	0.00886	Insignificant

Source of IV estimate with available reduced-form	X	Y	Z	Sensitivity	Reduction
Fontenla, Ben Goodwin, and Gonzalez (2019)	air quality	wages	Domestic inmigration	0.01311	Insignificant
Xinye and Wei (2019)	air quality	happiness	Domestic inmigration	0.01377	Insignificant
Dustmann, Fasani, and Speciale (2017)	migration legal status	consumption	Domestic inmigration	0.01903	Insignificant
Pereira and Menezes (2020)	per capita income	crime	Domestic inmigration	0.0251	Insignificant
Stokes (2016)	wind turbine placement	incumbent voting	Domestic inmigration	0.0326	Insignificant
Chia et al. (2016)	property crime	intergenerational income mobility	Domestic inmigration	0.03828	Insignificant
Rudolph (2020)	turnout	Brexit voting	Domestic inmigration	0.05394	Insignificant
Bhavnani and Lacina (2015)	internal inmigration	riots	Domestic inmigration	0.1076	Insignificant

Source of IV estimate with available reduced-form	X	Y	Z	Sensitivity	Reduction
Di Falco et al. (2019)	income	discount rates	Domestic inmigration	0.3058	Insignificant
Acharya, Blackwell, and Sen (2016)	slavery	racial affect	Domestic inmigration	NA	Insignificant
Farah and Torell (2018)	water price	willingness to pay for water hardness reduction	Mood	0.00001	Zero
Kleemans and Magruder (2018)	internal outmigration	labor market	Mood	0.02065	Zero
Guven and Hoxha (2015)	happiness	savings account	Mood	0.02097	Zero
Guven and Hoxha (2015)	happiness	average working hours	Mood	0.02586	Zero
Chin (2011)	female employment	intimate partner violence	Mood	0.0308	Zero
Hodler and Raschky (2014)	income	civil conflict	Mood	0.04563	Zero
Guven and Hoxha (2015)	happiness	operating asset ownership	Mood	0.05645	Zero

Source of IV estimate with available reduced-form	X	Y	Z	Sensitivity	Reduction
Chhaochharia et al. (2019)	perceived economic outlook	capital expenditure	Mood	0.1109	Zero
Chhaochharia et al. (2019)	perceived economic outlook	hiring decisions	Mood	0.125	Zero
Guven and Hoxha (2015)	happiness	life insurance ownership	Mood	0.1378	Zero
Guven and Hoxha (2015)	happiness	stock and bond ownership	Mood	0.138	Zero
Guven and Hoxha (2015)	happiness	risk aversion	Mood	0.1436	Zero
Lind (2019)	Right wing party vote share	education spending	Mood	0.151	Zero
C. Cui et al. (2019)	air quality	inter-city population mobility	Mood	0.1734	Zero
Artés (2014)	turnout	vote choice	Mood	0.184	Zero
Fukumoto, Kikuta, and Yanagi (2019)	disaster relief allocation	LDP vote share	Mood	0.3416	Zero

Source of IV estimate with available reduced-form	X	Y	Z	Sensitivity	Reduction
Berry and Schlenker (2011)	crop prices	crop yields	Mood	0.3463	Zero
Paxson (1992)	transitory income	savings	Mood	0.4172	Zero
Fichera and Savage (2015)	income	BMI	Mood	0.4933	Zero
Pajaron (2017)	income	domestic money transfers	Mood	0.6721	Zero
N. K. Kim (2016)	economic growth	coups	Mood	0.7295	Zero
Madestam et al. (2013)	tea party protest attendance	Republican vote share	Mood	0.7416	Zero
Abiona (2017)	agricultural income	Contraceptive use	Mood	0.806	Zero
Bruckner and Ciccone (2011)	income	democratisation	Mood	NA	Zero
Pereira and Menezes (2020)	per capita income	crime	Mood	NA	Zero
Xinye and Wei (2019)	air quality	happiness	Mood	NA	Zero
Di Falco et al. (2019)	income	discount rates	Mood	NA	Zero
Arnold and Freier (2016)	turnout	Conservative vote share	Mood	NA	Zero

Source of IV estimate with available reduced-form	X	Y	Z	Sensitivity	Reduction
Bhavnani and Lacina (2015)	internal inmigration	riots	Mood	NA	Zero
Dustmann, Fasani, and Speciale (2017)	migration legal status	consumption	Mood	NA	Zero
Fontenla, Ben Goodwin, and Gonzalez (2019)	air quality	wages	Mood	NA	Zero
Fontenla, Ben Goodwin, and Gonzalez (2019)	air quality	house prices	Mood	NA	Zero
Falco and Doku (2019)	income	self esteem	Mood	NA	Zero
Stokes (2016)	wind turbine placement	incumbent voting	Mood	NA	Zero
Pajaron (2017)	income	consumption	Mood	NA	Zero
Pajaron (2017)	income	remittances	Mood	NA	Zero
Gajate-Garrido (2013)	prenatal care	birth outcomes	Mood	NA	Zero
Rudolph (2020)	turnout	Brexit voting	Mood	NA	Zero
Chia et al. (2016)	property crime	intergenerational income mobility	Mood	NA	Zero
Acharya, Blackwell, and Sen (2016)	slavery	vote choice	Mood	NA	Zero

Source of IV estimate with available reduced-form	X	Y	Z	Sensitivity	Reduction
Acharya, Blackwell, and Sen (2016)	slavery	support for affirmative action	Mood	NA	Zero
Acharya, Blackwell, and Sen (2016)	slavery	racial resentment	Mood	NA	Zero
Acharya, Blackwell, and Sen (2016)	slavery	racial affect	Mood	NA	Zero
Madestam et al. (2013)	tea party protest attendance	congressional voting behavior	Mood	NA	Zero
Miguel and Satyanath (2011)	income	conflict	Mood	NA	Zero
Farah and Torell (2018)	water price	willingness to pay for water hardness reduction	Violent crime	0.00001	Zero
Kleemans and Magruder (2018)	internal outmigration	labor market	Violent crime	0.00185	Zero
Guven and Hoxha (2015)	happiness	savings account	Violent crime	0.00188	Zero
Guven and Hoxha (2015)	happiness	average working hours	Violent crime	0.00232	Zero
Chin (2011)	female employment	intimate partner violence	Violent crime	0.00276	Zero

Source of IV estimate with available reduced-form	X	Y	Z	Sensitivity	Reduction
Hodler and Raschky (2014)	income	civil conflict	Violent crime	0.00409	Zero
Guven and Hoxha (2015)	happiness	operating asset ownership	Violent crime	0.00505	Zero
Chhaochharia et al. (2019)	perceived economic outlook	capital expenditure	Violent crime	0.00992	Zero
Chhaochharia et al. (2019)	perceived economic outlook	hiring decisions	Violent crime	0.01118	Zero
Guven and Hoxha (2015)	happiness	life insurance ownership	Violent crime	0.01233	Zero
Guven and Hoxha (2015)	happiness	stock and bond ownership	Violent crime	0.01235	Zero
Guven and Hoxha (2015)	happiness	risk aversion	Violent crime	0.01285	Zero
Lind (2019)	Right wing party vote share	education spending	Violent crime	0.01352	Zero

Source of IV estimate with available reduced-form	X	Y	Z	Sensitivity	Reduction
C. Cui et al. (2019)	air quality	inter-city population mobility	Violent crime	0.01552	Zero
Artés (2014)	turnout	vote choice	Violent crime	0.01646	Zero
Fukumoto, Kikuta, and Yanagi (2019)	disaster relief allocation	LDP vote share	Violent crime	0.03056	Zero
Berry and Schlenker (2011)	crop prices	crop yields	Violent crime	0.03099	Zero
Paxson (1992)	transitory income	savings	Violent crime	0.03733	Zero
Fichera and Savage (2015)	income	BMI	Violent crime	0.04413	Zero
Pajaron (2017)	income	domestic money transfers	Violent crime	0.06013	Zero
N. K. Kim (2016)	economic growth	coups	Violent crime	0.06527	Zero
Madestam et al. (2013)	tea party protest attendance	Republican vote share	Violent crime	0.06634	Zero
Abiona (2017)	agricultural income	Contraceptive use	Violent crime	0.0721	Zero

Source of IV estimate with available reduced-form	X	Y	Z	Sensitivity	Reduction
Falco and Doku (2019)	income	self esteem	Violent crime	0.1101	Zero
Fontenla, Ben Goodwin, and Gonzalez (2019)	air quality	house prices	Violent crime	0.1261	Zero
Pajaron (2017)	income	remittances	Violent crime	0.1404	Zero
Dustmann, Fasani, and Speciale (2017)	migration legal status	consumption	Violent crime	0.1539	Zero
Arnold and Freier (2016)	turnout	Conservative vote share	Violent crime	0.1575	Zero
Bruckner and Ciccone (2011)	income	democratisation	Violent crime	0.1712	Zero
Gajate-Garrido (2013)	prenatal care	birth outcomes	Violent crime	0.1777	Zero
Acharya, Blackwell, and Sen (2016)	slavery	racial resentment	Violent crime	0.1787	Zero
Acharya, Blackwell, and Sen (2016)	slavery	vote choice	Violent crime	0.1792	Zero
Xinye and Wei (2019)	air quality	happiness	Violent crime	0.2316	Zero
Acharya, Blackwell, and Sen (2016)	slavery	support for affirmative action	Violent crime	0.248	Zero

Source of IV estimate with available reduced-form	X	Y	Z	Sensitivity	Reduction
Pereira and Menezes (2020)	per capita income	crime	Violent crime	0.2715	Zero
Miguel and Satyanath (2011)	income	conflict	Violent crime	0.288	Zero
Fontenla, Ben Goodwin, and Gonzalez (2019)	air quality	wages	Violent crime	0.3265	Zero
Madestam et al. (2013)	tea party protest attendance	congressional voting behavior	Violent crime	0.3613	Zero
Pajaron (2017)	income	consumption	Violent crime	0.4501	Zero
Di Falco et al. (2019)	income	discount rates	Violent crime	NA	Zero
Bhavnani and Lacina (2015)	internal inmigration	riots	Violent crime	NA	Zero
Stokes (2016)	wind turbine placement	incumbent voting	Violent crime	NA	Zero
Rudolph (2020)	turnout	Brexit voting	Violent crime	NA	Zero
Chia et al. (2016)	property crime	intergenerational income mobility	Violent crime	NA	Zero

Source of IV estimate with available reduced-form	X	Y	Z	Sensitivity	Reduction
Acharya, Blackwell, and Sen (2016)	slavery	racial affect	Violent crime	NA	Zero
Farah and Torell (2018)	water price	willingness to pay for water hardness reduction	Urbanization	0.00001	Zero
Kleemans and Magruder (2018)	internal outmigration	labor market	Urbanization	0.00074	Zero
Guven and Hoxha (2015)	happiness	savings account	Urbanization	0.00075	Zero
Guven and Hoxha (2015)	happiness	average working hours	Urbanization	0.00092	Zero
Chin (2011)	female employment	intimate partner violence	Urbanization	0.0011	Zero
Hodler and Raschky (2014)	income	civil conflict	Urbanization	0.00163	Zero
Guven and Hoxha (2015)	happiness	operating asset ownership	Urbanization	0.00201	Zero
Chhaochharia et al. (2019)	perceived economic outlook	capital expenditure	Urbanization	0.00395	Zero

Source of IV estimate with available reduced-form	X	Y	Z	Sensitivity	Reduction
Chhaochharia et al. (2019)	perceived economic outlook	hiring decisions	Urbanization	0.00445	Zero
Guven and Hoxha (2015)	happiness	stock and bond ownership	Urbanization	0.00491	Zero
Guven and Hoxha (2015)	happiness	life insurance ownership	Urbanization	0.00491	Zero
Guven and Hoxha (2015)	happiness	risk aversion	Urbanization	0.00511	Zero
Lind (2019)	Right wing party vote share	education spending	Urbanization	0.00538	Zero
C. Cui et al. (2019)	air quality	inter-city population mobility	Urbanization	0.00617	Zero
Artés (2014)	turnout	vote choice	Urbanization	0.00655	Zero
Fukumoto, Kikuta, and Yanagi (2019)	disaster relief allocation	LDP vote share	Urbanization	0.01215	Zero
Berry and Schlenker (2011)	crop prices	crop yields	Urbanization	0.01232	Zero
Paxson (1992)	transitory income	savings	Urbanization	0.01484	Zero

Source of IV estimate with available reduced-form	X	Y	Z	Sensitivity	Reduction
Fichera and Savage (2015)	income	BMI	Urbanization	0.01755	Zero
Pajaron (2017)	income	domestic money transfers	Urbanization	0.02391	Zero
N. K. Kim (2016)	economic growth	coups	Urbanization	0.02595	Zero
Madestam et al. (2013)	tea party protest attendance	Republican vote share	Urbanization	0.02638	Zero
Abiona (2017)	agricultural income	Contraceptive use	Urbanization	0.02867	Zero
Falco and Doku (2019)	income	self esteem	Urbanization	0.04378	Zero
Fontenla, Ben Goodwin, and Gonzalez (2019)	air quality	house prices	Urbanization	0.05012	Zero
Pajaron (2017)	income	remittances	Urbanization	0.05582	Zero
Dustmann, Fasani, and Speciale (2017)	migration legal status	consumption	Urbanization	0.06119	Zero
Arnold and Freier (2016)	turnout	Conservative vote share	Urbanization	0.06263	Zero
Bruckner and Ciccone (2011)	income	democratisation	Urbanization	0.06808	Zero
Gajate-Garrido (2013)	prenatal care	birth outcomes	Urbanization	0.07064	Zero

Source of IV estimate with available reduced-form	X	Y	Z	Sensitivity	Reduction
Acharya, Blackwell, and Sen (2016)	slavery	racial resentment	Urbanization	0.07107	Zero
Acharya, Blackwell, and Sen (2016)	slavery	vote choice	Urbanization	0.07125	Zero
Xinye and Wei (2019)	air quality	happiness	Urbanization	0.0921	Zero
Acharya, Blackwell, and Sen (2016)	slavery	support for affirmative action	Urbanization	0.09861	Zero
Pereira and Menezes (2020)	per capita income	crime	Urbanization	0.108	Zero
Miguel and Satyanath (2011)	income	conflict	Urbanization	0.1145	Zero
Fontenla, Ben Goodwin, and Gonzalez (2019)	air quality	wages	Urbanization	0.1298	Zero
Madestam et al. (2013)	tea party protest attendance	congressional voting behavior	Urbanization	0.1436	Zero
Pajaron (2017)	income	consumption	Urbanization	0.1789	Zero
Chia et al. (2016)	property crime	intergenerational income mobility	Urbanization	0.4056	Zero
Stokes (2016)	wind turbine placement	incumbent voting	Urbanization	0.4474	Zero
Rudolph (2020)	turnout	Brexit voting	Urbanization	0.6075	Zero
Di Falco et al. (2019)	income	discount rates	Urbanization	0.8553	Zero

Source of IV estimate with available reduced-form	X	Y	Z	Sensitivity	Reduction
Bhavnani and Lacina (2015)	internal inmigration	riots	Urbanization	NA	Zero
Acharya, Blackwell, and Sen (2016)	slavery	racial affect	Urbanization	NA	Zero
Farah and Torell (2018)	water price	willingness to pay for water hardness reduction	Domestic inmigration	0.00001	Zero
Kleemans and Magruder (2018)	internal outmigration	labor market	Domestic inmigration	0.00043	Zero
Guven and Hoxha (2015)	happiness	savings account	Domestic inmigration	0.00044	Zero
Guven and Hoxha (2015)	happiness	average working hours	Domestic inmigration	0.00054	Zero
Chin (2011)	female employment	intimate partner violence	Domestic inmigration	0.00064	Zero
Hodler and Raschky (2014)	income	civil conflict	Domestic inmigration	0.00095	Zero

Source of IV estimate with available reduced-form	X	Y	Z	Sensitivity	Reduction
Guven and Hoxha (2015)	happiness	operating asset ownership	Domestic inmigration	0.00117	Zero
Chhaochharia et al. (2019)	perceived economic outlook	capital expenditure	Domestic inmigration	0.00229	Zero
Chhaochharia et al. (2019)	perceived economic outlook	hiring decisions	Domestic inmigration	0.00258	Zero
Guven and Hoxha (2015)	happiness	stock and bond ownership	Domestic inmigration	0.00285	Zero
Guven and Hoxha (2015)	happiness	life insurance ownership	Domestic inmigration	0.00285	Zero
Guven and Hoxha (2015)	happiness	risk aversion	Domestic inmigration	0.00296	Zero
Lind (2019)	Right wing party vote share	education spending	Domestic inmigration	0.00312	Zero

Source of IV estimate with available reduced-form	X	Y	Z	Sensitivity	Reduction
C. Cui et al. (2019)	air quality	inter-city population mobility	Domestic inmigration	0.00358	Zero
Artés (2014)	turnout	vote choice	Domestic inmigration	0.0038	Zero
Fukumoto, Kikuta, and Yanagi (2019)	disaster relief allocation	LDP vote share	Domestic inmigration	0.00705	Zero
Berry and Schlenker (2011)	crop prices	crop yields	Domestic inmigration	0.00715	Zero
Paxson (1992)	transitory income	savings	Domestic inmigration	0.00861	Zero
Fichera and Savage (2015)	income	BMI	Domestic inmigration	0.01017	Zero
Pajaron (2017)	income	domestic money transfers	Domestic inmigration	0.01386	Zero
N. K. Kim (2016)	economic growth	coups	Domestic inmigration	0.01505	Zero

Source of IV estimate with available reduced-form	X	Y	Z	Sensitivity	Reduction
Madestam et al. (2013)	tea party protest attendance	Republican vote share	Domestic inmigration	0.01529	Zero
Abiona (2017)	agricultural income	Contraceptive use	Domestic inmigration	0.01662	Zero
Falco and Doku (2019)	income	self esteem	Domestic inmigration	0.02538	Zero
Fontenla, Ben Goodwin, and Gonzalez (2019)	air quality	house prices	Domestic inmigration	0.02906	Zero
Pajaron (2017)	income	remittances	Domestic inmigration	0.03236	Zero
Dustmann, Fasani, and Speciale (2017)	migration legal status	consumption	Domestic inmigration	0.03547	Zero
Arnold and Freier (2016)	turnout	Conservative vote share	Domestic inmigration	0.03631	Zero
Bruckner and Ciccone (2011)	income	democratisation	Domestic inmigration	0.03947	Zero

Source of IV estimate with available reduced-form	X	Y	Z	Sensitivity	Reduction
Gajate-Garrido (2013)	prenatal care	birth outcomes	Domestic inmigration	0.04095	Zero
Acharya, Blackwell, and Sen (2016)	slavery	racial resentment	Domestic inmigration	0.0412	Zero
Acharya, Blackwell, and Sen (2016)	slavery	vote choice	Domestic inmigration	0.0413	Zero
Xinye and Wei (2019)	air quality	happiness	Domestic inmigration	0.05339	Zero
Acharya, Blackwell, and Sen (2016)	slavery	support for affirmative action	Domestic inmigration	0.05716	Zero
Pereira and Menezes (2020)	per capita income	crime	Domestic inmigration	0.06258	Zero
Miguel and Satyanath (2011)	income	conflict	Domestic inmigration	0.06638	Zero
Fontenla, Ben Goodwin, and Gonzalez (2019)	air quality	wages	Domestic inmigration	0.07525	Zero

Source of IV estimate with available reduced-form	X	Y	Z	Sensitivity	Reduction
Madestam et al. (2013)	tea party protest attendance	congressional voting behavior	Domestic inmigration	0.08326	Zero
Pajaron (2017)	income	consumption	Domestic inmigration	0.1037	Zero
Chia et al. (2016)	property crime	intergenerational income mobility	Domestic inmigration	0.2351	Zero
Stokes (2016)	wind turbine placement	incumbent voting	Domestic inmigration	0.2593	Zero
Rudolph (2020)	turnout	Brexit voting	Domestic inmigration	0.3521	Zero
Di Falco et al. (2019)	income	discount rates	Domestic inmigration	0.4958	Zero
Bhavnani and Lacina (2015)	internal inmigration	riots	Domestic inmigration	0.7846	Zero
Acharya, Blackwell, and Sen (2016)	slavery	racial affect	Domestic inmigration	NA	Zero

Appendix C: Recovering the reduced-form from the first stage and IV estimates

Equation 13 of Cinelli and Hazlett (2020a) gives the derivation of the ILS IV estimate variance:

$$Var(\hat{\tau}_{ILS}) = \frac{1}{\hat{\theta}^2}(Var(\hat{\lambda}) + \hat{\tau}_{ILS}^2 Var(\hat{\theta}) - 2\hat{\tau}_{ILS} Cov(\hat{\lambda}, \hat{\theta})) \tag{5}$$

where $\hat{\tau}_{ILS}$ is the IV ILS estimate, $\hat{\theta}$ is the first-stage estimate and $\hat{\lambda}$ is OLS the reduced-form estimate. This can be rearranged to give the reduced form estimate:

$$Var(\hat{\lambda}) = -\hat{\tau}_{ILS}^2 Var(\hat{\theta}) + 2\hat{\tau}_{ILS} Cov(\hat{\lambda}, \hat{\theta}) + Var(\hat{\tau}_{ILS})\hat{\theta}^2 \tag{6}$$

However, this unfortunately includes a term that is not typically reported, $Cov(\hat{\lambda}, \hat{\theta})$. I therefore can only estimate the range of possible standard errors based on different correlations of $\hat{\lambda}$ and $\hat{\theta}$: $\rho(\hat{\lambda}, \hat{\theta})$. Decomposing the covariance into variance and correlations gives:

$$Var(\hat{\lambda}) = Var(\hat{\tau}_{ILS})\hat{\theta}^2 - \hat{\tau}_{ILS}^2 Var(\hat{\theta}) + 2\hat{\tau}_{ILS}\rho(\hat{\lambda}, \hat{\theta})\sqrt{Var(\hat{\lambda})}\sqrt{Var(\hat{\theta})} \tag{7}$$

Re-expressed in terms of the standard errors:

$$SE(\hat{\lambda})^2 = SE(\hat{\tau}_{ILS})^2\hat{\theta}^2 - \hat{\tau}_{ILS}^2 SE(\hat{\theta})^2 + 2\hat{\tau}\rho(\hat{\lambda}, \hat{\theta})SE(\hat{\lambda})SE(\hat{\theta}) \tag{8}$$

Rearranging this equation to solve for $SE(\hat{\lambda})$ (using Wolfram Alpha) gives:

$$SE(\hat{\lambda}) = \sqrt{SE(\hat{\tau}_{ILS})^2\hat{\theta}^2 + \hat{\tau}_{ILS}^2 SE(\hat{\theta})^2(\rho(\hat{\lambda}, \hat{\theta})^2 - 1)} + \hat{\tau}_{ILS} SE(\hat{\theta})\rho(\hat{\lambda}, \hat{\theta}) \tag{9}$$

$$
\begin{aligned}
Var(\hat{\lambda}) = 2\hat{\tau}_{ILS}^2\rho(\hat{\lambda},\hat{\theta})^2 Var(\hat{\theta}) \\
- 2\sqrt{\hat{\tau}_{ILS}^4\rho(\hat{\lambda},\hat{\theta})^4 Var(\hat{\theta})^2 - \hat{\tau}_{ILS}^3\rho(\hat{\lambda},\hat{\theta})^2 Var(\hat{\theta})^2 + Var(\hat{\tau}_{ILS})\hat{\tau}_{ILS}^2\rho(\hat{\lambda},\hat{\theta})^2 Var(\hat{\theta})\hat{\theta}^2)} \\
- \hat{\tau}_{ILS} Var(\hat{\theta}) + Var(\hat{\tau}_{ILS})\hat{\theta}^2 \quad (10)
\end{aligned}
$$

I can then estimate the maximum and minimum standard errors of the reduced form equation given the coefficients and standard errors of the first stage and IV estimates by assuming either $\rho(\hat{\lambda},\hat{\theta}) = -1$ or $\rho(\hat{\lambda},\hat{\theta}) = 1$. In practice I use $\rho(\hat{\lambda},\hat{\theta}) = 0$ which gives results close to reported estimates in most cases where I have reduced form, first stage and IV estimates given in a single paper.