Journal
Indoor Environments, 2(1)

ISSN
29503620

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Publication Date
2025-03-01

DOI
10.1016/j.indenv.2025.100080

Causal effects estimation: Using natural experiments in observational field studies in building science

Abstract

Correlational analysis, such as linear regression, does not imply causation. This paper introduces and applies a causal inference framework and a specific method, regression discontinuity, to thermal comfort field studies. The method utilizes policy thresholds in China, where the winter district heating policy is based on geographical location relative to the Huai River. The approximate latitude of the Huai River can be considered as a natural, geographical threshold, where cities near the threshold are quite similar, except for the availability of district heating in cities north of the threshold, creating a situation similar to a natural experiment. Using the regression discontinuity method, we quantify the causal effects of the experiment treatment (district heating) on the physical indoor environments and subjective responses of building occupants. We found that mean indoor operative temperatures were 4.3 °C higher, and mean thermal sensation votes were 0.6 warmer due to the district heating. In contrast, using conventional correlational analysis, we demonstrate that the correlation between indoor operative temperature and thermal sensation votes does not accurately reflect the causal relationship between the two. We also show that the indoor operative temperature could be either positively or negatively correlated with occupants' thermal satisfaction. However, we cannot conclude that increasing the indoor operative temperature in these circumstances will necessarily lead to higher or lower thermal satisfaction. This highlights the importance of causal inference methods in thermal comfort field studies and other observational studies in building science, where the regression discontinuity method might apply.

Keywords

Causal inference; Regression discontinuity; Thermal comfort; Field study; District heating.

1. Introduction

Scientists and researchers are often interested in the causal relationship, which is distinct from the correlational relationship [1,2]. The correlational relationship describes a "*seeing*" pattern in which a variable changes in unison with another [1]. For example, the number of firefighters at a scene correlates with the amount of damage caused by a fire. However, the firefighters are not the cause of the damage; there are more firefighters because larger fires require a greater response and cause more destruction. Correlational analysis alone can not prove causation and may limit the extent of insights or actionable design or policy recommendations and, in some cases, may even mislead. In contrast, the causal relationship represents a "*doing*" knowledge that if interventions were made on one variable (the 'treatment'), it would lead to changes in another (the 'outcome') [1,3,4]. The causal effect is the quantification of the causal relationship, enabling us to better predict an outcome response if an intervention is made in the treatment.

We strive to understand the kind of "*doing*" causal knowledge and measure the causal effects [2]. This can be achieved by asking and answering causal questions. A causal question asks if a specific intervention could lead to a particular outcome. In building science, we are typically interested in whether interventions in the design, construction, and operation of buildings lead to improvements in building performance and/or the well-being of building occupants. For example, interventions could include obtaining a green building certification, increasing indoor carbon dioxide concentration, or having a window view. The outcomes could include building energy consumption, occupant satisfaction, work performance, and health. Yet, in many cases, there is not a one-to-one relationship between the intervention and the outcome of interest, and there may be many confounding factors and required assumptions. As we will see, this is where data collected from natural experiments is particularly informative.

Though research questions in the building science literature are often not framed using specific cause-and-effect language, many of them indeed ask causal questions, and they may or may not use causal inference methods:

1) Do green certification programs improve *("cause")* building energy efficiency or occupants' satisfaction? [5–12]
2) Does a high indoor carbon dioxide concentration affect *("cause")* human subjects' decreased health and work performance? [13–17]
3) What is the impact *("causal effect")* of a window view on thermal comfort, emotion, and cognitive performance? [18–22]

Some of these causal questions have been answered through the experimental method [13,14,16,21]. Experiments are making interventions that are about "*doing*" and enable the identification of causal knowledge. For example, to study the causal effect of window views on thermal comfort, researchers created two environmental conditions: one with a window view (treatment group) and another without a window view (control group) [21]. If we can maintain all other potential factors influencing thermal comfort (e.g., indoor thermal conditions, occupants' characteristics, etc.) the same between the two groups, then the difference in outcomes between the treatment and the control group (e.g., different thermal sensations) can be attributed to the different experimental conditions. The treatment effect is considered as the causal effect of the window view.

It is not always feasible to conduct experiments to investigate a particular causal relationship. Observational studies might be the only option, especially when an intervention's outcome might harm human subjects' health. For example, epidemiologists might not be entirely satisfied with observing the correlation between smoking and cancer. However, it would be unethical to conduct experiments forcing one group of subjects to smoke while another group refrains from smoking to identify the causal relationship to better inform methods for reducing cancer [23–25,1]. Using another building science example, it would be unethical to intentionally reduce ventilation or remove filtration to identify the impact of these interventions on the COVID-19 infection rate in a space. Another common concern of the experimental method is cost and/or time. For example, building science researchers have observed different thermal responses of occupants in air-conditioned and naturally ventilated buildings [26,27]. They might, therefore, consider conducting experiments in two types of buildings. However, such an experiment could be deemed impractical as it requires a large-scale and long-term control of indoor environments for several months or years to allow for thermal adaptations [28].

The objective of this paper is to introduce a causal inference framework and apply a specific method to observational field studies in building science. The framework mathematically defines the causal effect, which is the foundation of causal inference. The specific method, called regression discontinuity, transforms observational studies into natural experiments, enabling the identification and quantification of causations. The causal inference framework has been successfully applied to many well-known studies in social and medical sciences [24,29–33]. To our knowledge, this study might be the first to introduce and apply it within the building science literature. We use an existing thermal comfort field study dataset that is particularly well-suited for demonstrating applications of the framework and the method. We also apply conventional correlational methods to the same dataset. The results highlight that correlational analysis alone, even with logical reasoning, cannot represent causal effects.

2. Background

Thermal comfort research can be divided into two main categories [34]. The first category is laboratory experiments in climate chambers, where researchers recruit participants, control indoor environmental conditions, and record participants' thermal responses. The second category is field studies in actual buildings, where researchers either continuously monitor the same building occupant's responses and corresponding indoor environmental conditions or sample multiple building occupants across one or multiple spaces in a building in a relatively short period. The intention of the field study method is to capture any contextual effects in real-world buildings that may not be fully represented in laboratory experiments or lost due to relatively short experiment durations.

In this paper, we refer to a typical *field study* as an observational study and a *field experiment* as one that involves interventions in actual buildings, such as manipulating or controlling personal or environmental conditions [35,36]. Historically, this distinction has not been consistent, and the terms have sometimes been used interchangeably within the thermal comfort research community. In thermal comfort literature, most field research has been "field studies" or observational studies that we are more precisely defining here. There are examples of self-described "field studies" that involve randomized and controlled experiments in actual buildings [37,38]. There are also several observational studies that were referred to as "field experiments," though they don't include interventions [39–41]. To emphasize the critical difference between the use of experimental data and observational data in causal inference, we will refer to the typical field study as a "field observational study."

Causal diagrams in Figure 1 visualize the critical difference between laboratory experiments (1a), field observational studies (1b), and field experiments (1c). Variables are categorized as causes and effects, and the diagram is drawn based on domain knowledge. For example, we know that indoor temperature affects thermal sensation, so we can draw an arrow pointing from the former to the latter to indicate the causal relationship. In a laboratory experiment (Figure 1a), indoor environmental conditions (e.g., different indoor temperatures), denoted as the treatment node X, are arbitrarily set by the researchers and are not affected by other factors. Thus, there is no arrow pointing to the indoor temperature. Therefore, the observed relationship τ_1 between the indoor temperature and the outcome, e.g., thermal sensation, denoted as node Y, can be considered as a causal effect, while thermal sensation is also under the influence of other causal factors in the context of a climate chamber, denoted as node E(e.g., limited time of exposure, no window views, , etc.)

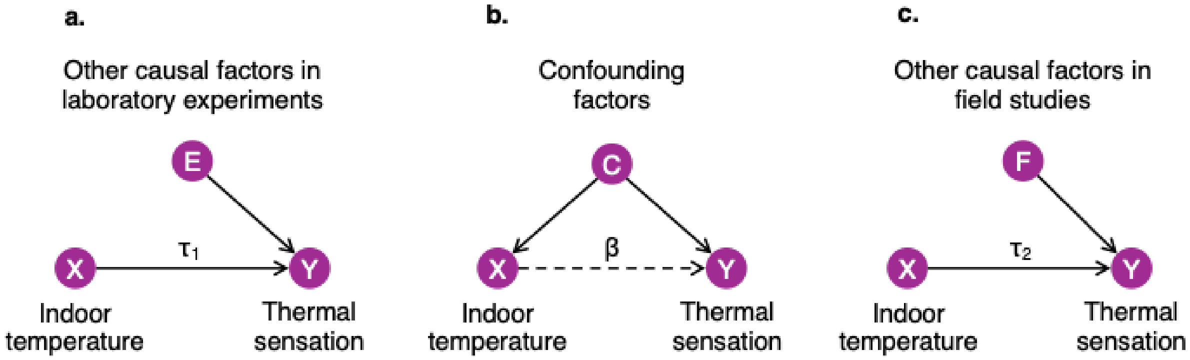

Figure 1 Causal relationships in laboratory experiment (a), typical field study (observational study) (b), and field experiment (c). The arrow represents a directional causal relationship, and the solid line represents the causal effect, denoted as τ. The dashed line represents an observed correlational relationship with the correlational coefficient denoted as β. It has been challenging to measure causal effects in observational studies because of the confounders, denoted as node C. The causal effect τ_1, measured in a laboratory experiment, is different from τ_2 in a field experiment because of the different influences of other causal factors in the climate chamber and in the actual building, denoted as nodes E and F, respectively.

In a field observational study (Figure 1b), researchers do not interfere with the indoor temperature. Instead, the indoor temperature is typically determined by factors like outdoor weather and climate, types of building heating and cooling systems, occupant preferences, and energy costs. Some of these factors can also affect thermal sensations (e.g., solar radiation affects both indoor temperature and thermal sensations). They are referred to as confounding factors in a causal diagram [42], visualized as node C in Figure 1b, which has solid lines and arrows pointing to both the treatment variable (indoor temperature) and the outcome variable (thermal sensation). Confounders can distort the observed correlational relationship between the treatment and the outcome. Therefore, we visualize the observed relationship β between the indoor temperature and the thermal sensation outcome as a dashed line with an arrow pointing from the former to the latter. This acknowledges the existence of the causal relationship, but the observed relationship does not reflect actual causal effects because of the confounders in a field observational study.

In a field experiment (Figure 1c), researchers manipulate and control the indoor temperature in an actual building, similar to a laboratory experiment. The indoor temperature is not intended to be affected by other factors in the field. Therefore, ideally, there would be no confounders in this setup. The observed relationship τ_2 between indoor temperature and thermal sensation can be interpreted as the causal effect under the influence of other causal factors in the context of an actual building. These could be the outdoor climate, window views, or the types of building heating and cooling systems, denoted as node F, which is different than node E.

3. Framework

3.1. Potential outcomes and randomized experiments

In general, the causal effect can be understood as the impact of certain interventions. Mathematically, as shown in the equation (1), causal effect τ is defined as the difference between potential outcomes of the same unit, which could be a single person or a group of people [43,44,3]. The potential outcome is a counterfactual concept, which refers to what would have happened to the unit if the treatment or intervention had been different. For example, if the treatment is bedroom ventilation and the unit is a person, then two potential outcomes could be the sleep quality of that person after sleeping in a bedroom with a high ventilation rate versus the same person's sleep quality after sleeping in the same bedroom but with a low ventilation rate. The potential outcome with the treatment is Y_1, and the potential outcome without the treatment is Y_0.

$$\tau = Y_1 - Y_0 \tag{1}$$

It is impossible to calculate the causal effect at the individual level because we cannot observe both potential outcomes for a single unit. If we expose the person to a well-ventilated bedroom and observe good sleep quality the following day, then we would never know whether the same person would report if they had been exposed to a poorly ventilated bedroom through that same night. By definition, the causal effect has to be the difference between the two potential outcomes simultaneously. If the treatment is applied at two distinct times, time-related factors might not be the same, and the observed differences in the outcome cannot be attributed to the treatment.

However, we could estimate the causal effect at a population level, as we can consider the two groups to be the same unit but with one group under the treatment condition and another one under the control condition at the same time. The central limit theorem states that the sample mean will converge to a standard normal distribution as long as the sample size is large enough. Therefore, the average person of the treatment group and that of the control group could have the same characteristics, such as average age, weight, etc. We can then calculate the difference between two average potential outcomes in the two groups as the estimation of the average causal effects. This is also why the causal effect estimated at the population level may not work on individuals, who could be very different than the average person. The average causal effect estimated at the population level is defined as:

$$\hat{\tau} = \frac{1}{N_1}\sum_{i=1}^{N_1} Y_1 - \frac{1}{N_0}\sum_{i=1}^{N_0} Y_0 \tag{2}$$

The 'gold standard' of causal inference is a randomized and controlled experiment [44–46] where all subject units are randomly assigned to either the treatment or the control group. Therefore, as long as the number of subject units is large enough, the randomization process will eventually cancel out differences between the two groups, including those we cannot measure or don't know yet but may influence the outcome. We can consider two groups as identical, and the differences observed in outcomes between the two groups can be attributed to the treatment only, often referred to as the average treatment effect [47]. Two potential outcomes are considered as two random variables with the same probability (due to the random assignment). Therefore, we can represent the average causal effect as the difference between the expectations of the two random variables.

$$\hat{\tau} = \mathbb{E}[Y_{1i}] - \mathbb{E}[Y_{0i}] \tag{3}$$

3.2. Natural experiments in observational studies

Observational studies don't have random assignment. Though we might be able to find two very similar groups, there are always other unmeasured or even unknown factors that could confound and limit our capability to identify a causal relationship. For example, we might find two groups of people with similar lifestyles, such as the amount of alcohol use, physical exercise, etc. One group of people smokes while the other doesn't, and we want to understand if smoking causes cancer. However, since we couldn't measure the genetics of the two groups, one could argue that the higher rate of cancer in the treatment (smoking) groups could be due to special genetics, which also makes people addicted to smoking [23]. Such arguments would be invalid if random assignment were allowed, as the two groups would have the same genetic characteristics.

In a typical observational thermal comfort field study, as we precisely defined in Section 2, researchers may measure many potential confounding factors, such as the building characteristics (e.g., office versus school, building age, orientation, etc.) or personal variables (e.g., demographics, job titles, or workplace location, etc). They might conduct an analysis on subsets of the dataset to limit some of the variability within any of those confounding factors. The intention is to control the confounding effect to better understand the relationship of interest. For example, in adaptive thermal comfort field studies, the building cooling type (air-conditioned or naturally ventilated) can affect both the indoor temperature and the occupants' behavior, expectations, and thermal responses in a variety of ways. By setting the building cooling type as the unit of analysis, we can stratify and eliminate the confounding effects. However, there are many other confounding factors, including those we cannot measure or are yet unknown, such as genetics and culture, that might have significant impacts on the outcome. This problem cannot be solved through a large sample size and remains the main challenge of causal inference in observational studies.

The opportunity for causal inference in observational studies arises when random assignment happens in a natural way, which is also referred to as the natural experiment [44,48]. In a natural experiment, the difference between the treatment and control group can be solely attributed to different treatment effects. One natural experiment method is regression discontinuity [49–51], which is based on the idea that some rules or policies in the real world are like treatments in the experiment, and the chance that people get the treatment at the threshold of the policy implementation can be considered random [52].

One classic example of applying the regression discontinuity method is estimating the causal effect of alcohol consumption on mortality [30,53]. The legal drinking age in the U.S. is 21, which is an arbitrary policy that provides an opportunity for regression discontinuity research. Whether a young adult's age is just below or just above the 21 threshold is random at the specific date when the data was collected. The drinking policy is like a natural experiment, which randomly assigns those just above age 21 to the treatment group with more alcohol consumption and those just below age 21 to the control group with less alcohol consumption. We can, therefore, consider the difference in mortality near the threshold between the two groups as the causal effect of increased alcohol consumption [30].

4. Causal inference

4.1. Natural experiments at Huai River

We find an opportunity to apply the causal inference framework and the regression discontinuity method to thermal comfort field studies in China because of an arbitrary boundary (Qingling-Huaihe Line, referred to as the Huai River) of the winter district heating policy [54]. Huai River generally flows along the latitude 33 °N. Cities north of the line are provided with district heating; cities south of it are not provided with district heating but may use their own domestic systems, such as electric heaters and heat pumps. The policy provides free or highly subsidized winter heating to offices and homes in cities via central plants burning coal. However, the policy only extended to the north of the Huai River due to budget constraints [55].

Huai River, as the geographical boundary of the district heating policy, can be considered as the threshold in regression discontinuity for causal inference, and the running variable is the relative latitude distance to the threshold [54,56]. Then, the causal effects of district heating can be measured at the threshold (33 °N) because the regression discontinuity method enables us to estimate two potential outcomes of the same group of cities at the threshold, where they should have similar culture, economics, climate, etc. This is equivalent to a randomized experiment that creates two groups that are quite similar to each other, except one group would receive the treatment. Outcomes from the two groups can also considered as two potential outcomes of the same unit.

China's Huai River policy and the latitude threshold have been previously utilized in many well-known causal inference research studies in social sciences. For example, Chen et al., 2013 [54] estimated the causal effects of district heating on outdoor air pollution and life expectancy, respectively, and also indirectly inferred the causal effect of outdoor air pollution on life expectancy. The causal effects of district heating on building energy usage, housing price, and building occupants' innovation activities have been previously estimated at the Huai River [57–59].

We aim to measure the causal effects of the district heating on the indoor thermal environment and building occupants' subjective perceptions of it. We use the Chinese Thermal Comfort Database [60], which contains observational data from thermal comfort field studies across the Huai River. There are 15,992 records collected in both Northern and Southern cities during the winter season. Each individual record has simultaneous measurements of the physical environment (e.g., operative temperature) and thermal perception (e.g., thermal sensation vote). Interested readers can refer to Yang et al., 2023 [60] for a detailed dataset description and summaries of the constituent studies.

We grouped the records by city and added the latitude information, resulting in a total of 33 cities, with 14 in the south and 19 in the north. We also manually corrected several data points. For example, all data points in Baotou (a northern city) are labeled as naturally ventilated, but they should be radiator heating, which is a common terminal form of district heating. This error has been confirmed by the original data contributor [61]. Three cities (Luoyang, Zhengzhou, and Kaifeng) are north of the threshold of 33 °N, but most of their data points are from buildings without district heating, which might be due to the fact that they were collected in rural areas. Since each sample size of the cities is less than 100, their impacts on causal effect estimation are likely to be trivial. Therefore, we assume they have district heating for the convenience of causal estimator development. The documentation of the data cleaning process, the cleaned dataset, and the code to reproduce causal effect estimations are available in a GitHub repository that is attached at the end of this paper.

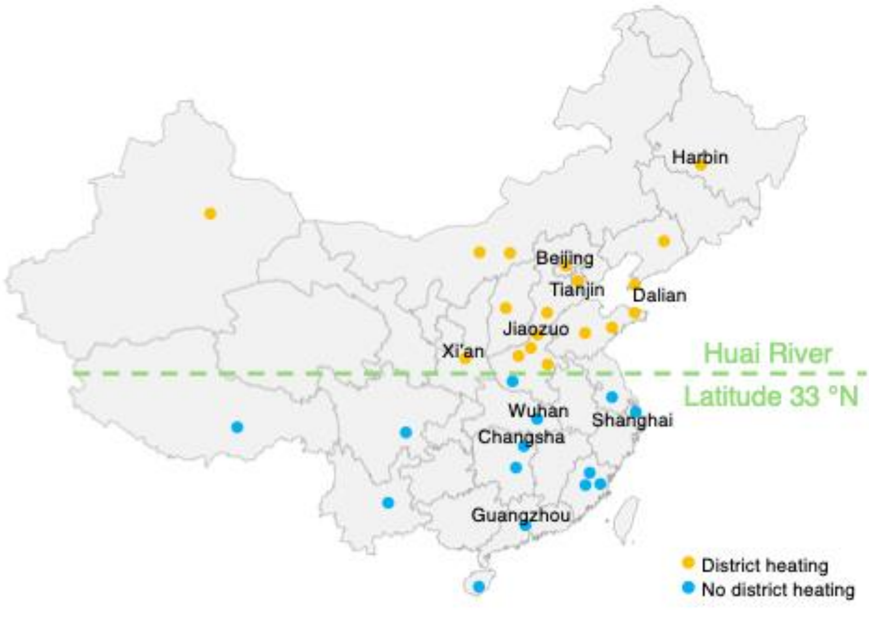

Figure 2 Thirty-three cities in the Chinese Thermal Comfort Database have observational records during the winter heating season. Cities shown with names on the map are major data points, each with over 500 records. Cities north of latitude 33 °N have district heating, whereas cities south of it do not.

4.2. Measuring causal effects at the threshold

The causal effect is calculated as the difference between two potential outcomes at the discontinued threshold, which are estimated using two regression analyses below and above the threshold, respectively. We first define a policy discontinuity variable that has the value of 0 at the threshold, called the running variable. In the case study, we define the running variable as the relative latitude distance between each city and 33°N. The causal effect is defined in (4) at the threshold, represented as $x_i = 0$. Equation (5) shows that the expectation of one potential outcome $\mathbb{E}[Y_{1i}]$ can be estimated based on a regression model using the data where the running variable is larger than 0. $\mathbb{E}[Y_{1i}]$ would equal the intercept α_1 when the $x_i = 0$. Equation (6) shows that the expectation of another potential outcome $\mathbb{E}[Y_{0i}]$ can be estimated by another regression model using the data where the running variable is less than 0, and is equal to the intercept α_2 when the $x_i = 0$. Therefore, the causal effect, which is the difference between two potential outcomes, equals $\alpha_1 - \alpha_0$ at the threshold of the running variable, shown in (7), and is visualized as the intercept jumps at the threshold in Figure 3.

$$\hat{\tau} = \mathbb{E}[Y_{1i}] - \mathbb{E}[Y_{0i}], \qquad x_i = 0 \tag{4}$$

$$y_{1i} = \alpha_1 + \beta_1 x_i + \varepsilon_{1i}, \qquad x_i \geq 0 \tag{5}$$

$$y_{0i} = \alpha_0 + \beta_0 x_i + \varepsilon_{0i}, \qquad x_i < 0 \tag{6}$$

$$\hat{\tau} = \alpha_1 - \alpha_0, \qquad x_i = 0 \tag{7}$$

It is convenient to combine the two regression models, (5) and (6), so that we can utilize existing regression software tools and quickly derive statistical summaries, such as the *p-value*. To achieve this, we need to define a dummy variable D_i that has the value of 1 or 0, depending on whether the running variable is larger than or less than 0, as shown in equation (8). The resulting reduced form of the regression model is (9), and the causal effect $\alpha_1 - \alpha_0$ is represented as the model coefficient of the dummy variable D_i.

$$D_i = \begin{cases} 1, & x_i \geq 0 \\ 0, & x_i < 0 \end{cases} \tag{8}$$

$$y_i = \alpha_0 + (\alpha_1 - \alpha_0)D_i + \beta_0 x_i + (\beta_1 - \beta_0)D_i x_i + \varepsilon_i \tag{9}$$

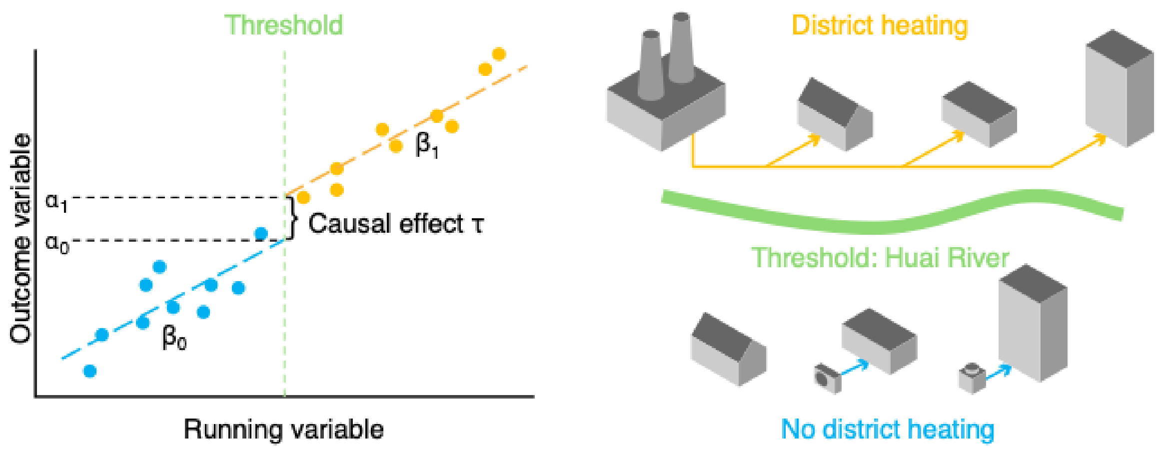

Figure 3 The discontinuity of the winter district heating policy at China's Huai River provides a natural experiment opportunity, enabling causal inference in the observational thermal comfort field study. We define the relative distance north of the Huai River as the running variable. The difference in the outcome variable measured at the threshold is considered the causal effect.

4.3. Estimating causal effects of district heating

We chose two commonly available variables from the Chinese Thermal Comfort Database as the outcomes of interest: indoor operative temperature and thermal sensation vote. Indoor operative temperature is a typical metric used to represent the physical thermal environment, combining the effect of the air temperature and mean radiant temperature (including the effect of air speed on those) [62]. Thermal sensation votes were collected using a seven-point scale ranging from -3 (cold) and 0 (feeling neutral) to +3 (hot). We calculated the mean values of these two variables using all data within each city. Unfortunately, we were unable to calculate mean values at the building level, as records in the dataset lack associated building identification numbers. As a result, the mean value represents an average building within the city, containing various building types, such as offices, homes, and classrooms. Building type is often considered a confounding factor in most thermal comfort field studies. The benefit of a natural experiment such as this one is that all confounding effects, including those measured or unmeasured, can be canceled out in theory. Therefore, the estimated results represent the causal effects on an average indoor thermal environment during the heating season in a city and on the thermal response of an average occupant.

We use the linear model in equation (9) to introduce causal effect estimation for simplicity. However, the linear model might have the problem of misattributing the nonlinearity at the threshold as the discontinuity and interpreting it as the causal effect. This issue can be solved using quadratic models. The representation of the causal effect remains the same as linear models, which is still the difference between the intercepts of two regression models below and above the threshold or the model coefficient of the dummy variable D_i in equation (10). We found that linear and quadratic models have similar estimation results of causal effects. We chose quadratic models to display in the figures because they have smaller p-values and 95% Confidence Intervals (CI), as shown in Table 1.

$$y_i = \alpha_0 + (\alpha_1 - \alpha_0)D_i + \beta_0 x_i + (\beta_1 - \beta_0)D_i x_i + \gamma_0 {x_i}^2 + (\gamma_1 - \gamma_0)D_i {x_i}^2 + \varepsilon_i \qquad (10)$$

Table 1. Estimated causal effects of district heating using linear and quadratic models

Outcome variable	Model	Causal effect	p-value	95% CI
Indoor operative temperature (°C)	Linear	4.4	0.030	0.5 and 8.3
	Quadratic	4.3	0.006	1.3 and 7.2
Thermal sensation vote	Linear	0.6	0.016	0.1 and 1.1
	Quadratic	0.6	0.002	0.3 and 1.0

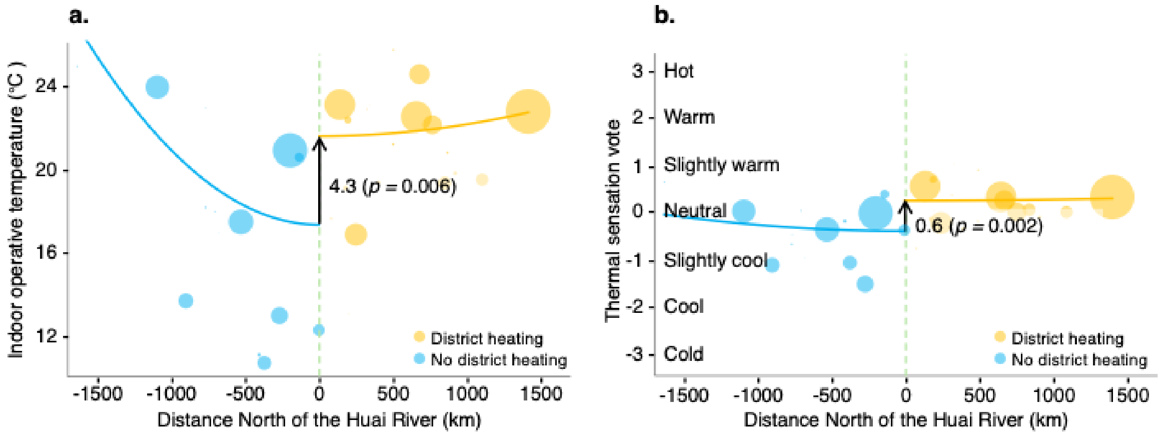

Figure 4 Causal effects of district heating on the mean indoor operative temperature (a) and on mean thermal sensation vote (b). Each data point represents a city, and regressions are weighted based on sample size, represented as the area of each data point. The causal effect is visualized as the intercept jump between regressions. The district heating increases indoor operative temperature by 4.3 °C and thermal sensation vote by 0.6. Both causal effects are statistically significant.

At the threshold of the policy at the Huai River, we can identify the causation and quantify the causal effects. District heating increases the mean indoor operative temperature by 4.3 °C (p = 0.006), from 17.3 °C to 21.6 °C. It also increases the mean thermal sensation vote by 0.6 (p = 0.002), from -0.4 (cooler than neutral) to 0.2 (warmer than neutral). We further infer that the 4.3 °C increase in indoor operative temperature causes the 0.6 increase in the thermal sensation vote if we could assume that the district heating policy mainly affects building occupants' thermal sensation votes through the indoor operative temperature. Other parameters, like relative humidity and clothing insulation, can also affect the thermal sensation vote, but here, we consider them as consequences of indoor operative temperature changes rather than being directly affected by the district heating.

We compared the estimated causal effect of 4.3 °C indoor operative temperature change with prediction results using the Predicted Mean Vote (PMV) model, which is considered a causal model developed from laboratory experiments [4]. We calculated PMV at the threshold for no district heating (control group) and for district heating (treatment group) using the CBE thermal comfort tool based on the ISO standard [63]. We used the same method of estimating the causal effects on indoor operative temperature to calculate other input parameters of the PMV model. For example, the district heating decreases the mean indoor relative humidity level by 20% (p < 0.001), from 53% (control group) to 33% (treatment group). We didn't find causal effects of district heating on mean clothing insulation, air velocity, or metabolic rate.

The mean air speed and metabolic rate are calculated based on the values reported in the Chinese Thermal Comfort Database. The results are very similar between the two groups, 0.1 m/s (still air) and 1 met (seated quietly). The differences in these parameters between the two groups are not statistically significant: 0.01 m/s (p = 0.704) and 0.02 met (p = 0.457). The mean clothing insulation is 1.1 clo in the control group and 0.9 clo in the treatment group, respectively, though the difference is not significant (p = 0.106). As a result, the calculated PMV for the control group is -1.36, the calculated PMV for the treatment group is -0.75, and the delta PMV is 0.61, which matches the causal effect estimation.

It is worth noting that the regression models above and below the threshold in Figure 4 are correlational models, and their slopes only indicate correlations. We can only hypothesize causations that lead to the correlations. For example, indoor temperatures get cooler in southern cities as they get closer to the Huai River. This might be due to the cooler outdoor climate as the north latitude degree increases. Above the threshold, operative temperatures inside buildings provided with district heating are relatively flat regardless of the outdoor climate. This might be due to the design objective of district heating, which is to maintain indoor temperatures at a consistent level, which can be achieved by controlling the amount of heating delivered to buildings in a city based on the outdoor temperature.

5. Correlational analysis

5.1. Correlation strength

The conventional data analysis approach in many observational thermal comfort field studies is correlational analysis. We, therefore, applied a typical correlational analysis, linear regression, to the same Chinese Thermal Comfort Database to show the limitations of this approach. As a common consideration of the building heating mode as a confounder, we divided the data into two groups (one with district heating in northern cities and another without in southern cities) and conducted linear regressions for each group, as shown in Figure 5a. The resulting regression model for the district heating group is $y = 0.09x - 1.8$ ($p < 0.001$, $R^2 = 0.4$), and the resulted regression model for the no-district heating group is $y = 0.1x - 2.4$ ($p < 0.001$, $R^2 = 0.4$).

However, the correlation coefficient *does not represent* causal effects. The correlation coefficients tell us that a 4.3 °C variation in the indoor operative temperature is associated with a 0.4 variation in the thermal sensation vote in both buildings with and without district heating. However, we *cannot infer, based only on this correlation,* that increasing indoor temperature by 4.3 °C would lead to an increase of 0.4 of thermal sensation vote. Similar misinterpretations are particularly common in thermal comfort field study data analysis because we know that indoor temperature causes thermal sensation. However, results of correlational analysis cannot be interpreted as causal effects as the methods and the data do not allow us to do that. Instead, using the causal inference method of regression discontinuity, the estimated causal effects indicate that increasing indoor temperature by 4.3 °C would likely lead to an increase of 0.6 of thermal sensation vote.

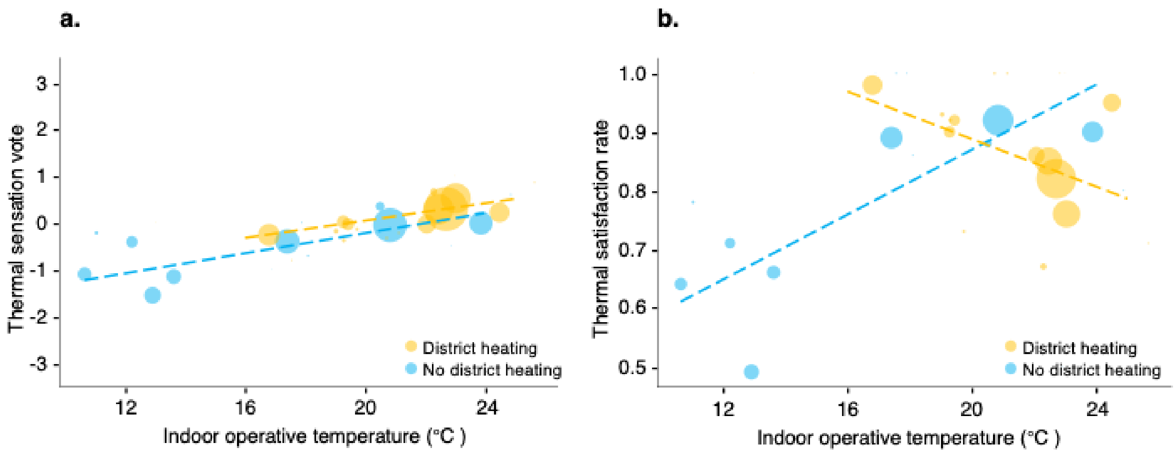

Figure 5 Correlational analysis shows that a 4.3 °C variation in the indoor operative temperature is associated with a 0.4 variation in the thermal sensation vote. However, it does not indicate that increasing indoor temperature by 4.3 °C would lead to an increase of 0.4 of thermal sensation vote. The correlations between indoor operative temperature and thermal satisfaction rate could be either positive or negative but do not indicate causations in each direction.

5.1. Correlation direction

We also calculated the thermal satisfaction rate for each city as the percentage of individual thermal sensation votes between ±2 (excluded), which is considered equivalent to thermal satisfaction if the scale resolution is limited to integers, according to the ASHRAE-55 standard [64]. As shown in Figure 5b, correlational regression analysis between the thermal satisfaction rate and indoor operative temperature in the two groups displays the opposite trend. The regression model of the no-district heating group is $y = 0.03x + 0.3$ ($p < 0.001$, $R^2 = 0.1$), and the regression model of the district heating group is $y = -0.02x + 1.3$ ($p = 0.011$, $R^2 = 0.2$).

The correlations *do not necessarily represent* causations. We *cannot infer, based only on correlations,* that increasing indoor temperature can increase thermal satisfaction in no-district heating buildings or decrease thermal satisfaction in district heating buildings. We might hypothesize causation using domain knowledge, for example, obtained in previous experiments. People are often happier with a warmer indoor temperature in contrast with the cold outdoor weather in winter; this might explain the correlation shown in the no-district heating group, but reversely, the correlation cannot be used to prove or support the causal hypothesis.

Explaining the opposite trend of correlation in the district heating group is beyond the scope of this paper and would require a different approach to causal inference. Interested readers can refer to key literature on causal diagrams for more information [1,42,65]. It might be an example of Simpson’s paradox [66], which means spurious correlations could occur when colliding variables are controlled, and controlling a variable is equivalent to dividing the data into groups [1,42,65]. If we had drawn a causal diagram and identified that the building heating mode is a colliding variable, then controlling it could lead to spurious correlations, which is misleading. Therefore, we should be careful when making logical inferences or drawing conclusions based on correlations, and using causal inference methods would avoid this risk.

6. Limitations

We directly quantified the causal effect of the district heating policy on indoor operative temperature and thermal sensation because this natural experiment allows us to do so. However, it might be inappropriate to infer the indirect causal effect of the indoor operative temperature on the thermal sensation vote. Our assumption is that the district heating policy affects building occupants' thermal sensation votes mainly through the indoor operative temperature, including through consequent changes in relative humidity and clothing insulation. However, it might be possible that the district heating policy affects thermal sensation votes independently of the indoor operative temperature. For example, the perception of subsidized district heating might have a direct and negative psychological impact, such that a higher expectation would lower behavioral adaptations of clothing layers and affect thermal sensations. We suggest further research using another causal inference framework and corresponding algorithms based on causal diagrams [42] to better estimate the indirect causal effect of interest.

It is worth noting that there might not be strict compliance with the policy in regression discontinuity research. Those assigned to the treatment group may not take the treatment, or those assigned to the control group may take the treatment anyway. The fuzzy regression discontinuity method has been developed to deal with the issue [51,52,67]. It requires calculating the different probabilities of the policy assignment in the treatment group and in the control group at the threshold. In the Chinese Thermal Comfort Database, all cities south of the boundary line (the control group) are not provided with district heating, and the probability of district heating is zero. However, there are differences in the extent to which local domestic heating is being used. Three cities north of the boundary line (the treatment group) should be provided with district heating but are not. Due to the small sample size of this non-compliance, their influence on the causal effect measurement is likely trivial. However, further exploration and the application of a fuzzy regression discontinuity design would be valuable.

The opportunity for regression discontinuity because of policy thresholds may seem rare in observational studies. However, it deserves our attention and efforts because the conventional correlational analysis might lead to biases and misinterpretation of causations, as we have demonstrated in Section 5. It is valuable to evaluate the impacts of interventions (causal effects) from observational studies in real buildings because we strive to understand the impacts of interventions so that we can apply the understanding in building design and operation, but many research questions in building science cannot be answered through experiments to prove causation. There are also other natural experiment methods, such as Difference-in-differences [31,68] and Instrumental variables [69–71]. Interested readers can also refer to another causal inference framework that is based on a causal diagram but does not require natural experiment conditions [1,42,65].

7. Discussion

The Huai River (or referred to as Qingling-Huaihe Line) roughly coincides with the 800 millimeter annual precipitation line, the 0 °C average January temperature line of China, and the division between two climate zones for building thermal design. Therefore, we explored using alternative metrics for the regression discontinuity analysis, such as the average January outdoor air temperature and Heating Degree Day (HDD). The HDD is of particular interest because it represents a typical building heating load for a city and could be a better metric to describe the correlations with indoor operative temperature.

We estimate the HDD using a base temperature of 18 °C and the closest weather station data from the BizEE website. We define the threshold as 1800, which seems to divide most northern and southern cities. Estimated differences in indoor operative temperature and thermal sensation vote at the HDD threshold are quite similar to the causal effects estimations based on latitude distance, as shown in Figure 6 in the Appendix. However, we prefer to consider the estimation results based on latitude distance as causal effects because the geographical location explicitly determines the availability of district heating, while the HDD does not. Indeed, HDD depends on the climate, which is also mainly determined by the latitude.

We acknowledge the value of correlational analysis, which describes and summarizes the observed patterns and could also help prediction. However, we emphasize the difference between predicting outcomes based on observations versus based on interventions. When there is an opportunity to analyze data about building occupants' comfort, health and well-being resulting from interventions, this can lead to more substantiated understanding about the true causal relationships. As there are many potential causal factors in the built environment that can affect occupants, we believe the causal inference framework and natural experiment methods would be valuable and can help building scientists better understand the impacts of the built environment on building occupants in observational studies.

8. Conclusion

We demonstrated the applications of a causal inference framework and a particular regression discontinuity method to thermal comfort field studies at China's Huai River, which can be considered a natural experiment of district heating. This approach allowed the estimation of the causal impacts of district heating on both the physical indoor environments and subjective responses of building occupants in winter. We also used conventional correlational analysis and demonstrated that the correlational coefficient does not represent causal effect in observational studies. We found that the indoor operative temperature could be either positively or negatively correlated with the thermal satisfaction rate, showing an example of Simpson's paradox in building science. This highlights the importance of the causal inference framework and method, especially in observational field studies. Causal inference can be applied in other domains of building science where sufficient observational data is collected to add to our understanding of more conventional correlational methods, including indoor air quality field studies, post-occupancy evaluation, and building energy audits. This work also has practical implications for sustainable building design and operation that should rely on actionable causal knowledge.

Appendix

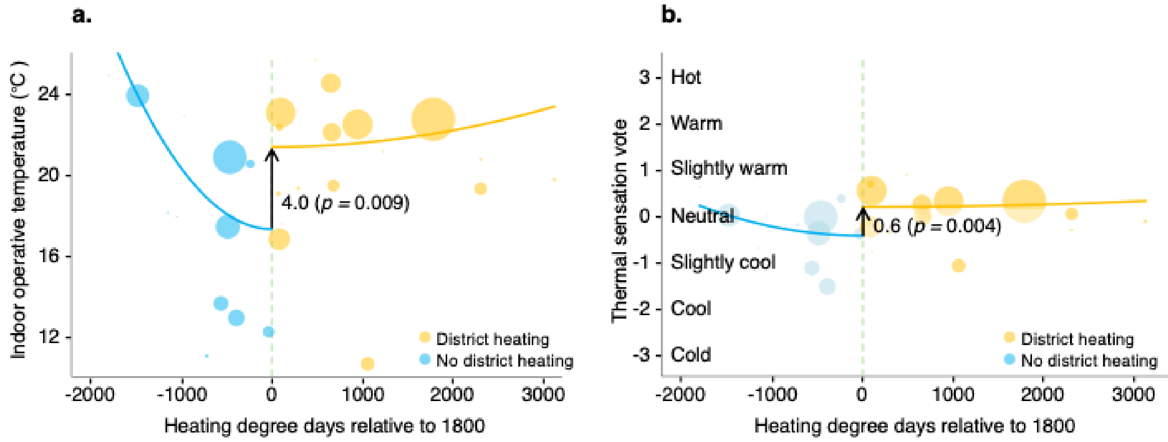

Figure 6 Regression discontinuity analysis based on HDD, assuming that the threshold of the winter district heating policy in China is 1800. The estimations of indoor operative temperature and thermal sensation vote differences at the threshold are not considered causal effects. Though HHD can better represent building heating load, it does not explicitly determine the availability of district heating for a city.

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