Extreme Temperatures and Health Investment: Persistent Improved Sanitation Behaviors as Adaptation in India

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Abstract

Extreme temperatures negatively affect economic activity and health in the short run, but little is known about the persistent effects of temperature shocks over time. This paper shows that extreme temperatures can persistently improve human health by inducing adaptive investment in health technologies in rural India. Using district-level daily weather and annual latrine construction data, I find that an additional day with extremely hot or cold temperatures within a three-year period cumulatively increases latrine investment by about 1-10%. This result is consistent with the discomfort channel where households build latrines to avoid walking outside for open defecation under extreme weather. I find the limited role of an income channel with an opposing negative effect. My estimates suggest that an additional day with extreme temperatures decreases diarrheal mortality by 0.3-2.7% through increasing latrine investment.

JEL: I15, O13, Q54, Q56

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1 Introduction

Policymakers and researchers increasingly recognize the significant negative impact the changing climate can have on human welfare. Climate change increases the frequency of extreme weather events, which in turn reduce human welfare either directly, by increasing morality (e.g., Deschênes and Greenstone, 2011), or indirectly by causing damages to agriculture (e.g., Schlenker and Roberts, 2009) and labor productivity (e.g., Somanathan et al., 2021). These short-run negative welfare consequences have been well known.

But little is known about the persistent positive effects of weather shocks on human welfare over time. I document that temperature shocks can have a persistent positive effect on human health by inducing adaptive investment in health-improving durable goods to avoid behaviors that involve walking outside. If these outside behaviors are harmful to health, weather-induced investment in these goods can persistently improve health over time. My focus on the persistent positive effect on health differs from several past studies that show the persistent negative effects of temperature on economic growth (Dell et al., 2012) and educational outcomes (Park, 2020).

This paper examines the effect of extreme temperatures on health investment by investigating the case of sanitation behaviors, i.e., the construction of latrines, which continued to be used over multiple years as durable goods. Extreme temperatures can affect a household's decision of whether to construct latrines or maintain open defecation practices in two ways. First, extreme temperatures can have a positive effect on latrine investment by increasing the discomfort of open defecation (discomfort channel). Because open defecation involves walking outside from home to the place of open defecation, extreme temperatures can increase the discomfort of open defecation. This increased discomfort can discourage people from practicing open defecation and increase the likelihood of latrine construction as an adaptation behavior.

Second, as an opposite effect, extreme temperatures can have a negative effect on latrine investment by reducing income (income channel). Extreme hot temperatures have been shown to negatively affect people's income by reducing agricultural output and labor productivity (Burgess et al., 2017; Colmer, 2021). The reduced income can exacerbate financial constraints on latrine investment, which reduces the likelihood of latrine construction. This paper empirically examines which of these two channels dominates.

I examine the effect of temperature on latrine investment in the context of India's nationwide sanitation policy, the Swachh Bharat Mission (SBM), which started in 2014. Under this policy, the Indian government subsidizes latrine construction up to about 150 US dollars, which covers most of the initial cost of basic latrines in rural India. Thus, my empirical results are more likely to capture the discomfort channel than the income channel, which is attenuated by the subsidy. In the empirical analysis, I use administrative panel datasets on the number of latrines under the SBM in each district and daily temperature and rainfall from 2012 to 2019.

To examine the causal effect of temperature on latrine investment in India, I exploit presumably random year-to-year variation in temperature at the district level after controlling for district fixed effects, year fixed effects, and rainfall. I group the daily temperature measures into eight bins to capture the nonlinear relationship between temperature and latrine investment. I employ a distributed-lag model that includes lagged temperature for up to 10 years to test the persistence of the effect.

I find that extremely cold and hot temperatures increase latrine investment, and this effect persists over multiple years. An additional hot day with an average temperature exceeding 35°C leads to an increase in latrine investment by 3 per 1,000 households relative to a day in the 15-20°C range, which amounts to a 1.1% increase from the pre-SBM periods. An additional cold day with an average temperature below 5°C leads to an increase in latrine investment by 27 (10%) per 1,000 households. These estimates are cumulative effects, which are the sum of contemporaneous effects and lagged effects (up to three years). The overall positive cumulative effects suggest that the discomfort channel dominates the income channel, and the effects persist over three years.

The net positive effect of extreme temperatures on latrine investment suggests that the discomfort channel dominates the income channel. Heterogeneous effects by the baseline temperature level further illustrate the dominance of the discomfort channel. I find that the positive effects of hot temperatures on latrine investment are concentrated in districts with lower baseline temperatures because people in these districts are less adapted to hot temperatures and therefore feel more discomfort. To better isolate the income channel, I examine heterogeneous effects by crop area. The positive net effects of hot temperatures become larger in districts with smaller crop areas that are less affected by the negative effects of the income channel, suggesting the existence of the income channel. However, I find consistent positive effects of cold temperatures in districts with both smaller and larger crop areas, which is consistent with the fact that only hot temperatures negatively affect agricultural output.

I also find that extreme temperatures similarly increase latrine usage at the intensive margin conditional on latrine ownership, which is consistent with the discomfort channel. Extreme temperatures can also affect an individual's decision of whether to use a latrine in addition to a decision of whether to construct a latrine. By using the individual-level panel dataset on latrine usage in 120 villages of 4 states in north India over 2 survey rounds in 2013-2014 and 2018 (Coffey et al., 2014; Gupta et al., 2019), I examine the effect of temperature on latrine usage conditional on latrine ownership. I find an additional hot day with an average temperature of 30-35°C leads to a 14.3% increase in latrine usage from the baseline usage rate relative to a day in the 15-20°C range when using daily temperature from a 1-week reference period before the survey. I also find a positive effect of an additional cold day with a temperature of 5-10°C on latrine usage (12.0% increase from baseline usage rate) when using a 12-month reference period for temperature. But this positive effect is less significant than the effect on latrine investment due to the high baseline latrine usage (77% usage rate on average in the first survey round) and small (or no) observations of very cold days in the four states with hot climates in the sample.

Taken together, my analysis highlights the surprising fact that extreme temperatures can improve health by incentivizing adaptive investment in health technologies as people want to avoid the discomfort of walking outside. Extreme temperatures have a persistent positive effect on latrine investment, which can have long-lasting health benefits in terms of reduced diarrheal diseases and mortality. A back-of-the-envelope calculation shows that in rural India, an additional cold and hot day with an average temperature of below 5°C or above 35°C decreases diarrheal post-neonatal mortality by 2.72% and 0.31%, respectively.

This paper makes three contributions. First, I contribute to the literature on the consequences of climate change by showing the persistent positive effects of weather shocks on human welfare through a new channel: an adaptive investment in health-improving technologies. Most past studies demonstrate the short-run effects (level effects) of weather shocks on labor productivity (Adhvaryu et al., 2020; Somanathan et al., 2021; Heyes and Saberian, 2022), agricultural productivity (Schlenker and Roberts, 2009; Colmer, 2021), and human health (Deschênes and Greenstone, 2011; Barreca et al., 2016; Burgess et al., 2017; Heutel et al., 2021; Carleton et al., 2022), which are reversed after these shocks. But growing literature shows that weather shocks can have persistent effects (growth effects) on economic growth (Dell et al., 2012; Foreman, 2020) and educational outcomes (Park, 2020). Their results suggest that the underlying mechanisms are capital depreciation (Foreman, 2020) and persistent effects of high-stakes exam performance on subsequent graduation (Park, 2020). I complement these limited studies on growth effects by showing that weather shocks can persistently affect health through another mechanism: adaptive investment in health-improving durable goods to avoid outside activities. I show that extreme temperatures can have positive effects on health by inducing behavioral changes away from outside activities that are harmful to human health and towards indoor, health-improving behaviors. These potential benefits of more variable weather caused by climate change can be incorporated into the discussion of the social cost of carbons, which tends to focus on the damages to economic activity and human health.

Second, I contribute to the literature on health behaviors, especially sanitation behaviors, in developing countries by showing that temperature is another major determinant of health behaviors that often involve outdoor activities. In developing countries, outdoor activities are prevalent, including open defecation (e.g., Cameron et al., 2022), collection of unsafe spring water (e.g., Kremer et al., 2011), collection and usage of biomass for cooking (e.g., Hanna et al., 2016). These outside activities are closely linked to water pollution and air pollution, causing health damage for people with limited coping measures. Past studies have shown that interventions such as subsidies and information campaigns (e.g., Yishay et al., 2017; Lipscomb and Schechter, 2018; Cameron et al., 2022) could promote the adoption of health-improving technologies and thus reduce these alternative outdoor activities. However, I show that temperature is another important determinant of health behaviors: extreme temperatures can reduce outdoor activities that are harmful to human health.

Lastly, I contribute to the behavioral economics literature on the intertemporal bias of consumers in the purchase of durable goods by showing this bias in the context of developing countries. Past studies show that consumers are over-influenced by the weather at the time of purchase when they purchase durable goods, including cars (Conlin et al., 2007; Busse et al., 2015). In the same vein, I show that the year-to-year temperature shocks affect the construction of latrines, which are durable goods used for multiple years. Although rational households would decide whether to construct latrines by considering the future climate trajectory to calculate the discomfort level of open defecation over multiple years, my result suggests that this decision on latrine construction is over-influenced by short-run weather shocks. This result on the intertemporal bias in developing countries is important because the bias may be larger than in developed countries due to lower education levels and more limited access to climate and weather information.

2 Background and Conceptual Framework

I present a conceptual framework on the effects of temperature on sanitation behaviors to show two channels that are tested in the empirical analysis. Then, I discuss the implications of this conceptual framework for the setting of this paper: a nationwide sanitation policy, the Swachh Bharat Mission, in rural India.

2.1 Conceptual Framework on Effects of Temperature on Sanitation Behaviors

To motivate the empirical analysis, I present a simple conceptual framework to show that extreme temperatures can have two opposing effects on latrine investment and usage: (i) a positive effect through a discomfort channel and (ii) a negative effect through an income channel. My empirical analysis captures the net effect of both channels; therefore, the sign of the effect can determine which of these two channels dominates.

Extreme temperatures can affect a household's decision of whether to construct/use latrines or keep practicing open defecation in two ways. First, extreme temperatures can have a positive effect on latrine investment and usage by increasing the discomfort of open defecation (discomfort channel). Because open defecation involves walking outside from home to the place of open defecation, extreme temperatures can increase the discomfort of open defecation. This increased discomfort can discourage people from practicing open defecation and increase the likelihood of latrine construction and usage as an adaptation behavior. This discomfort channel is implied in past epidemiological studies that found that seasonality matters in latrine usage (Routray et al., 2015; Sinha et al., 2017). Their results show that latrine usage rates are higher in the dry cold season and in the rainy season than in the dry, hot season, which suggests that people do not prefer walking for open defecation when the weather is not comfortable for them.

Second, as an opposite effect, extreme temperatures can have a negative effect on latrine investment and usage by reducing income (income channel).[1] Extreme temperatures can negatively affect income by reducing agricultural output and labor productivity, especially in the case of hot temperatures (Burgess et al., 2017; Colmer, 2021). The reduced income can exacerbate financial constraints on latrine investment and usage, although government subsidies on latrine construction can mitigate this constraint.

I formally present these two opposing channels in the conceptual framework, where a given household decides whether or not to construct/use latrines. Suppose that the discomfort of walking outside for open defecation, s, depends on the probability of using a latrine $l \in [0, 1]$, as well as on ambient temperature $a \in [0, 1]$. l can also be thought of as the intensity of latrine usage. Conversely, $1 - l$ is the probability/intensity of practicing open defecation. Denote the cost of constructing a latrine for the usage as p.[2] For a, 1 denotes a physically uninhabitable ambient temperature (extremely hot or cold temperature), and 0 denotes the ideal temperature.

Then, the discomfort of walking outside for open defecation can be expressed as $s(a, 1-l)$. People experience more discomfort under more extreme temperatures: $\frac{\partial s}{\partial a} > 0$. Moreover,

[1] Another channel underlying the negative effect could be more delay and higher costs in latrine construction under more extreme temperatures (construction feasibility channel) tested in Section 4.5. I do not consider this channel in the conceptual framework for simplification because this channel has a similar negative effect as the income channel by affecting the budget constraint of the household.

[2] After construction, latrine usage involves costs for hiring tankers or people to regularly empty pits/septic tanks. This emptying cost can be thought of as p for analyzing the income channel in the case of latrine usage.

people experience more discomfort with larger probability/intensity of practicing open defecation (smaller probability/intensity of using a latrine): $\frac{\partial s}{\partial l} < 0$.

The household derives utility from consuming composite good x (price normalized to 1) and experiences disutility from the discomfort of walking outside for open defecation s: $U(x, s(a, 1-l))$ where $U_x > 0, U_s < 0$. The budget constraint is $I(a) = lp + x$. Here, I suppose that income, $I(a)$, is affected by temperature because extreme temperatures can decrease agricultural output and labor productivity. Income decreases under more extreme temperatures: $\frac{\partial I}{\partial a} < 0$.

The maximization problem of the household's utility subject to the budget constraint is:

$$\max_{l} U(x, s(a, 1-l)) \quad s.t. \; I(a) = lp + x \tag{1}$$

The first order condition with respect to l is

$$\frac{dU}{dl} = -U_x p - U_s \frac{\partial s}{\partial l} = 0 \tag{2}$$

$$\underbrace{p}_{MC} = \underbrace{-\frac{U_s}{U_x}\frac{\partial s}{\partial l}}_{MB} \tag{3}$$

which means that the household chooses the probability/intensity of latrine usage to balance the trade-off between the marginal cost of latrine usage and the marginal benefit of latrine usage that comes from the reduced discomfort of walking outside for open defecation.

The effects of extreme temperatures on latrine usage can be decomposed into two channels as follows by using the equation (3).

$$\begin{aligned} \frac{dl}{da} &= \frac{\partial l}{\partial s}\frac{ds}{da} + \frac{\partial l}{\partial I}\frac{dI}{da} \\ &= \frac{1}{p}\left\{ \underbrace{-\frac{U_s}{U_x}\frac{ds}{da}}_{Discomfort\ channel} + \underbrace{\frac{dI}{da}}_{Income\ channel} \right\} \end{aligned} \tag{4}$$

which shows two opposing channels: (i) a positive effect of extreme temperatures on latrine investment and usage because of increased discomfort of walking outside for open defecation ($-\frac{U_s}{U_x}\frac{ds}{da} > 0$) and (ii) a negative effect of extreme temperatures on latrine investment and usage because of reduced income ($\frac{dI}{da} < 0$). The relative magnitudes of discomfort and income channels decide the sign of the overall effect. My empirical analysis examines which channel dominates.[3]

[3] This conceptual framework adopts a static model to illustrate the two underlying channels. The

2.2 The Swachh Bharat Mission in India and Implications of Conceptual Framework

During the study period of this paper, the Indian government aimed to eliminate open defecation by subsidizing latrine construction under the nationwide sanitation policy, Swachh Bharat Mission (SBM), in rural India. So, my empirical results are more likely to capture the positive effect in the discomfort channel than the negative effect in the income channel, which is attenuated by the subsidy under the SBM.

The SBM provided generous subsidies for the latrine construction to eliminate open defecation. In India, a large number of people have historically practiced open defecation, which adversely affects child health by increasing the occurrence of diarrheal diseases and mortality. To eliminate open defecation and improve human health, the Indian government has subsidized the construction of over 100 million latrines at the household level in rural India under the SBM since 2014. Specifically, the SBM subsidized the latrine construction up to about 150 US dollars (12,000 INR) per household, which covers most of the initial cost of basic latrines in rural India. The subsidy is provided to households that have completed the latrine construction.

Given relaxed financial constraints on latrine construction under the subsidy of the SBM, the negative effect of extreme temperatures on latrine investment and usage via the income channel is expected to be limited. The positive effect of extreme temperatures via the discomfort channel is expected to be larger. Therefore, I expect extreme temperatures to generally have a net positive effect on latrine investment and usage.

Another implication from the setting of the SBM is that my analysis is expected to capture a larger increase in the number of latrines in districts with more extreme temperatures. The SBM increased latrine construction across rural India, but the magnitude of the increase in the number of latrines is expected to differ by different exposures to extreme temperatures among different districts.

3 Data

To examine the effect of temperature on latrine investment, I combine administrative datasets on latrine construction and daily weather at the district level across rural India from 2012 to 2019. I also use a household survey dataset on rural sanitation in four states in north India to examine the effects of temperature on latrine use conditional on latrine ownership at the

persistence of the effect of extreme temperatures on latrine investment is not examined by using a dynamic model here for simplicity. But the persistence comes from the fact that latrines are durable goods that are continued to be used over multiple years after construction.

individual/household level.

3.1 Latrine Investment

One outcome variable adopted in this paper is the number of constructed latrines. I use the administrative data on the district-level number of household latrines under the SBM from 2012 to 2019 in rural India, which were compiled in Motohashi (2022). Based on this dataset, I compute the number of latrines per 1,000 households per year by using the baseline number of total households.

One concern about this dataset is that the number of latrines might be systematically over-reported, leading to measurement errors. This dataset is compiled by the Government of India under the SBM policy, which aims to achieve 100% latrine coverage by 2019. So, the over-reporting becomes more plausible when the period is closer to the deadline of the target in 2019. Hossain et al. (2022) validated the same latrine dataset by comparing it with the statistics in National Family and Health Survey-4 and found that it is reliable at least until 2016. Thus, as a robustness check in Section 4.3, I restrict the sample periods until 2016, which yields similar results as the baseline specification.

3.2 Latrine Usage

Another outcome variable is the status of latrine usage conditional on latrine ownership. I use the individual-level panel data of latrine usage over two survey rounds (2013-2014 and 2018) in the Sanitation Quality, Use, Access, and Trends (SQUAT) household surveys (Coffey et al., 2014; Gupta et al., 2019). In the SQUAT dataset, I focus on households that are surveyed in both periods in 157 villages in 11 districts in 4 states in north India, including Rajasthan, Madhya Pradesh, Uttar Pradesh, and Bihar, where open defecation was commonly practiced in rural areas.

In the SQUAT dataset, the status of latrine ownership of each household and latrine usage of each household member is recorded in both survey rounds.[4] I also use the GPS coordinates of each village rounded to the nearest 0.25 degree to match this SQUAT dataset with the weather data.[5] My analysis focuses on 120 villages out of 157 villages where GPS information is available.

[4] The SQUAT survey asked about a usual practice of defecation (open defecation or latrine usage). In the empirical analysis, I use the binary indicator of latrine usage that becomes one if the individual usually uses a latrine.

[5] I am able to obtain only the approximate locations of the surveyed villages at 0.25-degree resolution due to substantial risks for respondents to be known their sanitation behaviors. Thus, when I match the SQUAT dataset to weather data, I consider the weather inside the 0.25-degree buffer of each village's GPS coordinates.

3.3 Weather

As a treatment variable, I use daily gridded temperature at 1-degree resolution provided by the India Meteorological Department (IMD) database (Srivastava et al., 2009). I also use daily gridded rainfall at 0.25-degree resolution as a control variable from the same IMD data source (Rajeevan et al., 2008). These datasets are constructed by interpolating temperature measures from 395 stations and rainfall measures from 1,384 stations across India. For my empirical analysis, I use the average of maximum and minimum temperatures recorded in the IMD temperature dataset.

To match these weather variables with the district-level dataset on latrine investment, I compute the district-level means of daily average temperature and rainfall based on the gridded datasets and 2011 district-level boundary data. Moreover, for the SQUAT dataset on latrine usage, I compute the mean of daily average temperature and rainfall inside the 0.25-degree buffer of each village's GPS coordinates.

3.4 Data Matching and Sample Construction

For the analysis of the effect of temperature on latrine investment, I construct a balanced panel dataset on latrine construction and weather variables of 609 districts from 2012 to 2019. I spatially match the district-level number of latrines and mean daily weather variables based on the 2011 district boundaries.[6]

To examine the effect of temperature on latrine usage, I construct a balanced panel dataset on latrine use and weather variables of 6,478 individuals from 1,186 households in 120 villages over two survey rounds. I spatially match the individual/household-level survey data with village-level daily weather variables based on the village GPS coordinates. Out of 1,214 households in total, 446 households owned latrines in both survey rounds, which is the final sample for analyzing the effect of temperature on latrine usage conditional on latrine ownership.

Table 1 reports the summary statistics of all variables used in the analysis, and Figure 1 shows the distributions of daily average temperature.

4 Effect of Temperature on Latrine Investment

Exploiting presumably random year-to-year variation in temperature, I show that extreme temperatures increase latrine investment, and this effect persists over multiple years. My

[6] I deal with the changes in the district boundary by ensuring that all data are organized according to the 2011 boundary, which follows Motohashi (2022). Latrine data based on the 2019 boundary are aggregated to follow the 2011 boundary by considering the district splits from 2011 to 2019.

results suggest that the main underlying mechanism is the discomfort of walking outside for open defecation (discomfort channel), as discussed in the conceptual framework.

4.1 Empirical Strategy

I exploit presumably random year-to-year variations in temperature at the district level to examine the effect of temperature on latrine investment. I test the persistence of this effect by calculating the cumulative effect in the distributed-lag model, where I include lagged temperatures.

Specifically, I adopt the following two-way fixed effects specification, inspired by Deschênes and Greenstone (2011).

$$Latrine_{dt} = \sum_{l}\sum_{j} \beta_{jl}^{INV} BinTemp_{dtjl} + \sum_{l}\sum_{k} \delta_{kl}^{INV} DecileRain_{dtkl} + \eta_d + \nu_{st} + \varepsilon_{dt} \quad (5)$$

where $Latrine_{dt}$ is a number of latrines per 1,000 households in district d in year t. $BinTemp_{dtjl}$ is the number of days in which average temperature is in the jth bin in district d in l years prior to year t. $DecileRain_{dkdt}$ is the number of days in which rainfall is in the kth decile in district d in l years prior to year t. I include district fixed effects (η_d) to control for time-invariant unobserved district-level determinants of latrine construction, as well as state-by-year fixed effects (ν_{st}) to control for shocks unique to each state each year (e.g., changes in state-level sanitation policies and local economic conditions). Standard errors are clustered at the district level to address the serial correlation.

I define eight temperature bins in $BinTemp_{dtjl}$: <5°C, 5-10°C, 10-15°C, 15-20°C, 20-25°C, 25-30°C, 30-35°C, and >35°C. I adopt these eight temperature bins to estimate a nonlinear latrine-temperature relationship in a flexible way, as well as to obtain precise estimates based on a sufficient observed number of days in each bin. The 15-20°C bin serves as a reference bin and is dropped from the regression. Thus, the coefficient of each temperature bin j (β_{jl}^{INV}) measures the effect of an additional day in the temperature bin j on the number of latrines per 1,000 households relative to a day in the 15-20°C bin.

This regression specification exploits presumably random year-to-year variation in temperature to estimate the causal effect of temperature on latrine investment. By including district fixed effects (η_d) and state-by-year fixed effects (ν_{st}), the temperature effect is identified from the district-specific deviations in temperature around the district averages after controlling for shocks common to all districts in a state. Because of unpredictable and presumably random fluctuation in temperature, the estimates β_{jl}^{INV}'s can have a causal interpretation.

To estimate the persistence of the effect of temperature on latrine investment, I use a distributed-lag model by including lagged temperature. Specifically, I include lagged temperature in l years prior to year t where l is set to be less than or equal to three years ($l \leq 3$) in the baseline specification. Then, I compute the cumulative effect by summing estimates of the contemporaneous temperature and lagged temperatures. If the cumulative effect is statistically different from zero, the effect of temperature is found to be persistent. The baseline specification includes up to three years of lags because it is expected to take several years to decide on latrine construction, apply for the SBM subsidy, and implement the latrine construction. But the results are robust to the change in the maximum number of lags from 1 year to 10 years as discussed in Section 4.3.

The coefficients of interest are β_{jl}^{INV}'s, which determine which channel in the conceptual framework dominates. If the cumulative effect computed from β_{jl}^{INV}'s is statistically significantly positive, the main underlying mechanism is suggested to be the discomfort channel, and the effect of temperature on latrine investment persists over multiple years.

4.2 Baseline Results

I find that extremely cold and hot temperatures increase latrine investment, and this effect persists over multiple years.

In Figure 2 and Table 2, I find the cumulative latrine-temperature relationship is U-shaped, with a steeper slope in the cold temperature bins. As shown in Panel A of Figure 2 and Column 1 of Table 2, an additional day with an average temperature of 25-30°C and above 35°C leads to an increase in the number of latrines by about 3 per 1,000 households relative to a day in the 15-20°C range over three years. This cumulative effect of an additional day in hot temperature bins amounts to a 1.1% increase from the pre-SBM periods.[7] Moreover, cold temperature bins have larger positive effects on latrine investment. An additional day with a temperature of 5-10°C and below 5°C within a three-year period cumulatively increases the number of latrines by 20 and 27 (7.6% and 10.0%) per 1,000 households, respectively.

The positive effect of extreme temperatures is consistent with the discomfort channel in the conceptual framework, although the effects are larger in the cold temperature bins. In light of the discomfort channel, the larger effects of cold temperatures can be explained by the larger discomfort of walking outside for open defecation in colder temperatures. People are less adapted to colder temperatures than hotter temperatures because India has a hot climate on average, e.g., daily average temperature highly concentrates in the 25-30°C range

[7] To calculate the effect in percentage, I divide the estimated coefficient by the mean of the dependent variable in the pre-SBM periods (2012-2013). I adopt the same approach for all the following results.

(Panel A of Figure 1).

Another reason behind the larger effects of cold temperatures can be explained by the income channel in the conceptual framework. The negative effect of temperature on agricultural output has been shown to be concentrated in the case of hot temperatures (Burgess et al., 2017; Colmer, 2021). So, the negative effect of hot temperatures on latrine investment through the income channel is more likely to offset the positive effect through the discomfort channel, which makes the effects of high temperatures smaller. The role of the income channel is further discussed in Section 4.5.

The positive cumulative effect over three years shows that temperature shocks have a persistent effect on latrine investment over at least three years rather than having only short-run effects. Reassuringly, Panel B of Figure 2 and Column 1 of Table 3 show that most estimates of contemporaneous and lagged temperature bins, which compose of the cumulative effect, are consistently positive.[8] The persistence of the effect can be explained by the fact that constructed latrines, induced by extreme temperatures, continue to be used over multiple years as durable goods. Although the baseline specification shows the persistent effect over three years, I find persistent effects extend up to 10 years, especially in cold temperature bins, as discussed in Section 4.3.

4.3 Robustness Checks

The results are robust to various checks, including the change in the number of lagged years in the distributed lag model, the placebo test of examining the contemporaneous effect, and the consideration of measurement errors in the outcome.

Number of Lagged Years.—While the basic specification includes three years of lagged temperatures, I conduct robustness checks that estimate the cumulative effect with different numbers of lagged years ranging from a maximum of 1 year to 10 years.

As shown in Figure 3 and Appendix Table B1, I find that the estimated cumulative effects are consistently positive regardless of the number of lagged years, especially in colder temperature ranges, which causes greater discomfort of walking outside for open defecation for people in India accustomed to a hot climate.

Placebo Test on The Contemporaneous Effect.—Considering the time taken to decide and implement latrine construction and apply for the SBM subsidy, extreme temperatures in a specific year is less likely to affect the latrine investment in the same year than that in subsequent years. Thus, I conduct a placebo test that examines the contemporaneous effect

[8] For compactness, Table 3 only reports the estimates corresponding to the two coldest (below 5°C and 5-10°C) and the two hottest (30-35°C and above 35°C) temperature bins.

of temperature on latrine investment.

As expected, I do not find statistically significant contemporaneous effects in most temperature bins when lagged temperatures are dropped in the regression (Appendix Figure A1). Panel B of Figure 2 and Column 1 of Table 3 also show that the estimates of the contemporaneous temperatures tend to be statistically insignificant in the regression with both contemporaneous and lagged temperatures.

Measurement Errors on The Outcome.—As explained in Section 3.1, the number of latrines reported in the administrative dataset of the SBM is not susceptible to measurement errors at least until 2016. I conduct a robustness check by estimating the main specification using observations prior to 2016.

In Appendix Figure A2, I find that the cumulative effect is still statistically significant and positive prior to 2016, especially in cold temperature bins, although the estimates become smaller than those of the baseline specification. The smaller estimates can be explained by the larger negative effect of the income channel prior to 2016. The usage of subsidies under the SBM had been heavily pushed forward with information campaigns as the deadline for universal latrine coverage by 2019 approached. So, prior to 2016, households in rural India were likely to face more limited access to the subsidy scheme, which resulted in larger financial constraints on latrine construction. A reduced income due to extreme temperatures could have a larger negative impact on latrine construction prior to 2016 than after 2016.

4.4 Mechanism: Discomfort Channel

The net positive effect of extreme temperatures on latrine investment suggests that the discomfort channel dominates the income channel. To further test the discomfort channel, I examine heterogeneous effects by the baseline temperature level.

The discomfort channel suggests that people are likely to feel larger discomfort from walking outside for open defecation when exposed to temperatures they are less adapted to. In other words, people living in districts with a lower baseline temperature could be more sensitive to hot temperature shocks than people living in districts with a higher baseline temperature. Therefore, in the cooler districts, hot temperature shocks are expected to cause a larger increase in latrine investment than cold temperature shocks. Conversely, districts with a higher baseline temperature are expected to experience a larger increase in latrine investment with cold temperature shocks. To test these heterogeneous effects, I compare effects in districts that have a higher baseline average temperature than the sample median (25.7°C) during the pre-SBM periods (2002-2011) with districts that have a lower baseline average temperature.

As expected, I find that the positive effects of hot temperatures on latrine investment concentrate in districts with a lower baseline temperature. As shown in Panel A of Figure 4 and Column 2 of Table 2, an additional day in hot temperature bins increases the number of latrines per 1,000 households by around 8-10 (2.4-3.1%) relative to a day in the 15-20°C range. However, the effect of hot temperature becomes insignificant in districts with a higher baseline temperature (Column 3 of Table 2), possibly because people in these districts are better adapted to hot temperatures.

As for the effects of cold temperature bins, I find positive effects on latrine investment in districts with both higher and lower baseline temperatures (Panel B of Figure 4 and Column 3 of Table 2). I find a positive effect of cold temperature bins even in districts with a lower baseline temperature. This result can be explained by the fact that these districts are still warm given the median temperature is 25.7°C. In districts with a higher baseline temperature, the coefficients are statistically insignificant due to there being very few days in the cold temperature bins, as shown in Panel A of Figure 1.

4.5 Alternative Explanations

Alternative explanations that would link extreme temperatures to latrine investment include a decrease in income, i.e., income channel, and an increase in the difficulty of latrine construction, i.e., construction feasibility channel.[9] I evaluate these alternative channels but find the limited role of these channels.

Income Channel.—As introduced in Section 2.1, the income channel refers to the negative effect of extreme temperatures on latrine investment through a decrease in agricultural output and, consequently, income. The net positive effect in the baseline result suggests that the income channel does not play a major role.

To explicitly test the validity of the income channel, I examine heterogeneous effects by crop area.[10] I compare the effects of temperature in districts with larger crop areas than the sample mean to districts with smaller crop areas. The income channel is expected to be more significant in districts with larger crop areas than those with smaller crop areas, which suggests that districts with larger crop area experience smaller (or more negative) effects of

[9] Another channel could be a government relief channel. The government can construct latrines in response to heat and cold waves. But latrine construction is not included as one of the action plans in response to heat waves in the government relief guideline in India (NDMA, 2019). So, this channel is unlikely in the context of India.

[10] I use the agricultural data obtained from the ICRISAT (International Crops Research Institute for the Semi-Arid Tropics) District Level Database. I calculate the district-level baseline crop area in 2011, which is the total area of all types of crops. Due to the data limitation of the ICRISAT dataset, the heterogeneity analysis by crop area focuses on 426 districts out of 609 districts used in the baseline specification.

temperature on latrine investment. Moreover, the income channel is expected to be more pronounced in the effects of hot temperatures because the negative effects of temperature on agricultural output have been shown to be concentrated in the case of hot temperatures (Deschênes and Greenstone, 2011; Colmer, 2021). In other words, the negative effects of hot temperatures on latrine investment through the income channel are expected to be larger than those of cold temperatures.

In the heterogeneity analysis by crop area, I find suggestive evidence of the income channel in some cases, but the discomfort channel dominates in most cases. Figure 5 and Table 4 show that the cumulative effects of temperature on latrine investment are smaller in districts with larger crop areas, especially in the hot temperature bins. The coefficients of the 30-35°C and above 35°C bins became negative in these districts, while the estimates are imprecise (Panel B of Figure 5 and Column 3 of Table 4). Conversely, in districts with smaller crop areas that are less affected by the income channel, the effects of hot temperature bins are positive and statistically significant, which suggests that the discomfort channel dominates the income channel (Panel A of Figure 5 and Column 2 of Table 4). Moreover, I find consistent positive effects of cold temperatures in all districts, which is consistent with the expectation that the income channel is not pronounced in cold temperatures.

Construction Feasibility Channel.—This channel refers to a short-run negative effect of extreme temperatures on latrine investment through more delay and higher costs in latrine construction. However, I find limited evidence on the short-run contemporaneous effect as discussed in the placebo test in Section 4.3. The net positive effect in the baseline result also suggests that the construction feasibility channel is not a major mechanism.

5 Effect of Temperature on Latrine Usage Conditional on Latrine Ownership

Exploiting village-level inter-temporal variation in temperature and individual-level panel dataset on latrine usage, I examine the effect of extreme temperatures on latrine use conditional on latrine ownership. I find a positive effect of hot and cold days on latrine usage, which is consistent with the discomfort channel discussed in the conceptual framework, while the effect on latrine use is less significant than the effect on latrine investment.

5.1 Empirical Strategy

I exploit presumably random variation in temperature between two survey rounds at the village level to examine the effect of temperature on latrine usage. Specifically, I adopt the following two-way fixed effects specification, which is similar to the specification in Section 4.1.

$$LatrineUse_{ivdt} = \sum_j \beta_j^{USE} BinTemp_{jvdt} + \sum_k \delta_k^{USE} DecileRain_{kvdt} + \eta_i + \nu_t + \varepsilon_{ivdt} \quad (6)$$

where i indexes individuals, j indexes temperature bins, v indexes villages, k indexes rainfall bins, d indexes survey dates, and t indexes the two SQUAT survey rounds in 2013-3014 and 2018. $LatrineUse_{ivdt}$ is a binary indicator of the latrine usage of individual i in survey round t. $BinTemp_{jvdt}$ is the number of days in which the average temperature is in temperature bin j. I define eight temperature bins as in the specification of latrine investment, but the specification of latrine usage exploits the village-level variation in temperature. I include individual fixed effects (η_i) to control for time-invariant unobserved individual-level determinants of latrine usage, as well as survey-round fixed effects (ν_t) to control for the trend in latrine usage (e.g., increase in latrine usage because of extensive promotion under the SBM). Standard errors are clustered at the village level because the variation in temperature is observed at the village level.

To examine latrine usage conditional on latrine ownership, I limit the sample to individuals belonging to households that own latrines in both survey periods. Specifically, my analysis focuses on 446 households (2,542 individuals) out of 1,214 households (6,478 individuals). The coefficients of interest are β_j^{USE}'s, which measures the effect of an additional day in the temperature bin j on latrine usage relative to a day in the 15-20°C bin.

I construct the treatment variable, $BinTemp_{jvdt}$, by counting the number of days in temperature bin j within a given reference period until the survey date d of individual i. Each SQUAT survey round took multiple months to be completed, which results in the variation in survey dates among households/individuals.[11] In the baseline specification, I use daily temperature from X before to 1 day before each survey date d, where the choices of X (reference periods) are 1 week, 1 month, 6 months, 12 months, 15 months, and 20 months.[12]

I include short reference periods because of the potential recall bias in the outcome of this regression. The outcome in the regression is a self-reported usual practice of latrine usage, and latrine usage behavior might not be stable across time. Then, due to recall bias, the respondents might report more recent latrine usage behaviors that are affected by recent

[11] First-round survey was conducted from November 2013 to December 2014, and the second-round survey was conducted from August to December 2018 for individuals in the final sample.

[12] As a robustness check, I also adopt different reference periods, including 2 weeks, 4 months, and 9 months, but the results remain stable as shown in Appendix Figure A3.

temperature shocks. In other words, the latrine usage behavior asked in the questionnaire may be affected by the temperature shortly before the survey date.

5.2 Results

I find a positive effect of hot and cold days on latrine usage conditional on latrine ownership, which again points towards the discomfort channel. However, this effect on latrine usage is less significant than the effect on latrine investment due to the high baseline latrine usage and small (or no) observations of very cold days in the four states with hot climates in the SQUAT sample.

In Figure 6 and Table 5, I find a positive effect of hot days on latrine usage in the 30-35°C temperature bin up to a reference period of one month, which is consistent with the discomfort channel. Specifically, an additional day with an average temperature of 30-35°C leads to an increase in latrine usage rate by 11.1 percentage points (14.3% increase from the baseline usage rate) relative to a day in the 15-20°C range when 1-week reference period is adopted (Column 1 of Table 5). The magnitude of the effects becomes smaller with longer reference periods (from 2 weeks to 1 month), possibly because more historical temperatures may have a weaker effect on the self-reported latrine usage that reflects more recent behavior due to recall bias (Columns 1-2 of Table 5 and Appendix Figure A3).

I also find a positive effect of cold days on latrine usage in the 5-10°C temperature bin. When a 12-month reference period is adopted, an additional day with an average temperature of 5-10°C leads to an increase in latrine usage rate by 9.2 percentage points (12.0% increase from the baseline usage rate) relative to a day in the 15-20°C range (Column 6 of Table 5). The positive effect of the 5-10°C temperature bin is robust to the change in reference periods from 12 months to 15 and 20 months (Columns 4-6 of Table 5 and Appendix Figure A3).

However, these positive statistically significant effects are limited in the above cases for two reasons. First, the baseline latrine usage rate conditional on latrine ownership is high: on average, 77% of individuals use a latrine if they own one in the first survey round, as shown in Table 1. If most individuals generally use latrines conditional on ownership, there is a limited margin of an increase in latrine usage because of extreme temperatures. Second, I cannot estimate the effects of very cold days with temperatures below 5°C and 5-10°C in most reference periods because the SQUAT sample only includes four states in India that all have hot climates. The sample does not cover days with these cold temperature bins, except the days in the 5-10°C bin when the 12/15/20-month reference period is adopted, as shown in Panel B of Figure 1.

Moreover, I find that the effect of temperature on latrine usage becomes negative in the above 35°C bin. When a 1-month reference period is adopted, an additional day with an average temperature in the above 35°C bin leads to a decrease in latrine usage rate by 52.1 percentage points (a 67.1% decrease from the baseline usage rate) relative to a day in the 15-20°C range. These negative results are inconsistent with the original discomfort channel (discomfort of walking outside for open defecation) discussed in the conceptual framework. But this result can be understood by a larger discomfort level of using latrines with hot air inside than that of walking outside for open defecation. Conditional on latrine ownership, the individuals may incorporate this new aspect of the discomfort of hot air inside latrines in their decision of whether to use latrines. Thus, compared with the analysis of latrine investment, the analysis of latrine usage conditional on latrine ownership requires a more augmented view of the discomfort channel. In the case of latrine usage, both people experience discomfort under extreme temperatures from both latrine usage and open defecation, so relative discomfort level matters.

6 Conclusion

I document that extreme temperatures have a positive, persistent effect on latrine investment and usage, which ultimately improve human health by reducing diarrheal diseases and mortality. My analysis suggests that the main underlying mechanism is the discomfort channel, whereby people construct latrines to avoid the greater discomfort of walking outside for open defecation under more extreme temperatures. This adaptive latrine investment can reduce the alternative open defecation behavior, which is harmful to human health. My results point to the potential benefit of an increased occurrence of extreme weather caused by climate change, although most past studies focus on the negative consequences of climate change. Moreover, my results find a new mechanism for the persistent effects (rather than short-term effects) of temperature, which is a temperature-induced investment in durable goods that continues to be used over multiple periods.

A back-of-the-envelope calculation shows large welfare gains because of extreme temperatures: a large reduction of diarrheal mortality through the increased latrine investment. I find that an additional day with an average temperature of below 5°C and above 35°C decreases diarrheal post-neonatal mortality by 2.72% and 0.31%, respectively. These welfare effects are calculated by multiplying the estimated coefficient in my analysis by the estimated effect of latrine construction on diarrheal mortality in rural India in Motohashi (2022).[13]

My results present several important implications for considering measures against cli-

[13] Specifically, I use the estimates in Column 1 of Table 2, the estimated effect in Motohashi (2022), i.e., a 1.3% reduction in diarrheal post-neonatal mortality per 1,000 people caused by an additional latrine per square kilometer, an average number of households per district (389.87 thousand households), and an average area per district (4,975.91 square kilometers).

mate change. First, people's adaptation to larger variability in temperature under climate change might have unintended positive consequences. Under extreme temperatures, people can shift from outside activities that are harmful to human health (e.g., open defecation) into health-improving behaviors (e.g., latrine usage) that are conducted indoors. Conversely, climate change mitigation measures can unintentionally decrease the adoption of health-improving technologies used indoors unless these measures are complemented with incentives for adopting these technologies. Policymakers should be aware of this risk of unintended negative consequences of climate change mitigation.

Second, my findings on the unintended increase in the adoption of health-improving latrines under extreme temperatures have implications for other health behaviors in developing countries. For example, under extreme temperatures, people may shift from the collection and usage of biomass to the usage of cleaner fuel (e.g., liquefied petroleum gas) for cooking, or they may shift from the collection and usage of unsafe spring water to the usage of safe tap water, for avoiding outdoor collection activities. Investigating the potential health benefits of extreme temperatures in different settings may be a fruitful area for future research.

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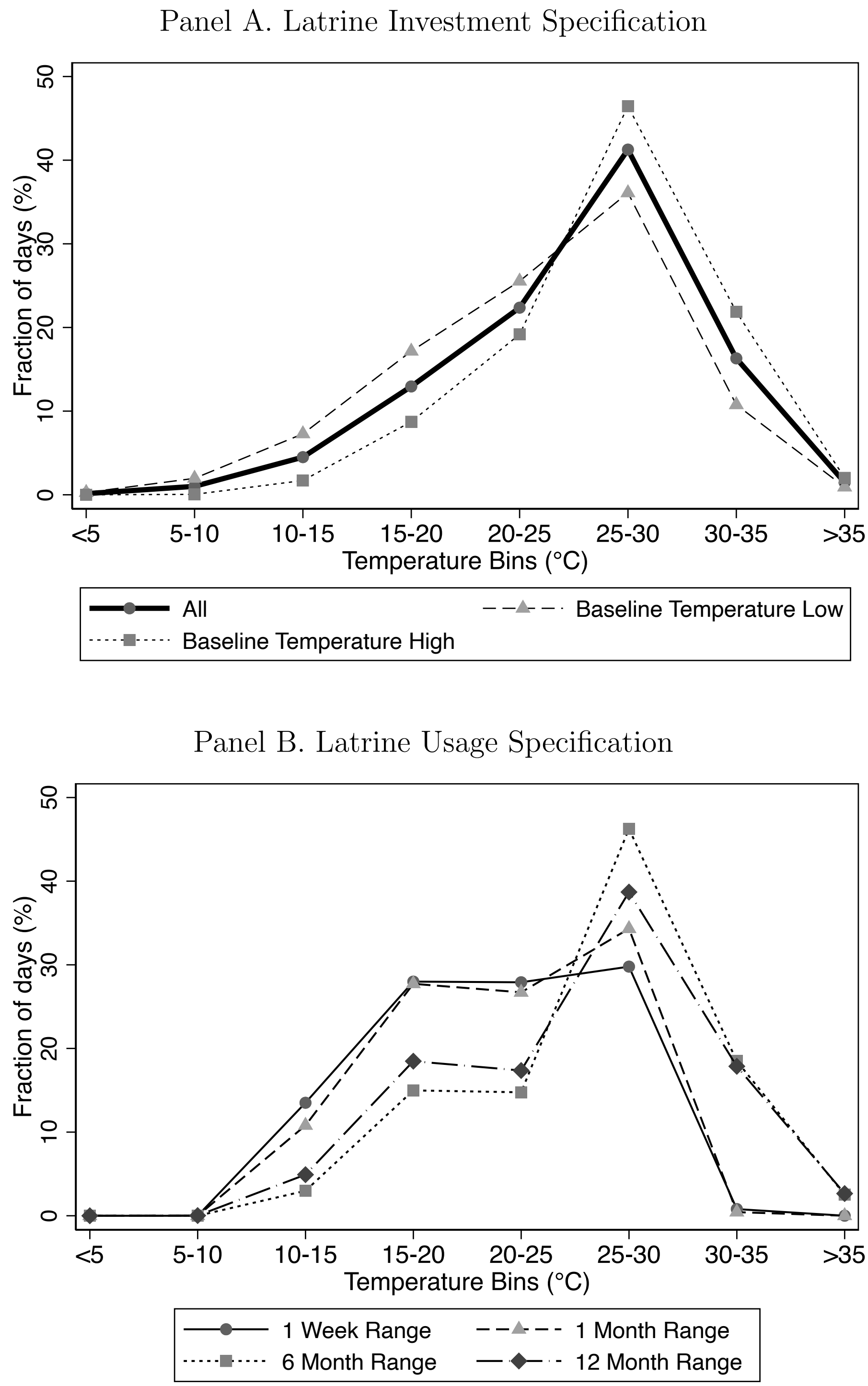


Figure 1: Daily Average Temperature Distributions

Notes: This figure shows the distributions of daily average temperature, which are used for the analysis of latrine investment (Panel A) and the analysis of latrine usage (Panel B). Panel A reports distributions for (i) all districts, (ii) districts with baseline temperatures lower than the sample median, and (iii) districts with higher baseline temperatures, using daily temperature at the district level across India from 2012 to 2019. Panel B reports distributions for different reference periods, using daily temperature at the village level in the SQUAT sample over two survey rounds in 2013-2014 and 2018.

Panel A. Cumulative Effect over Three Years

Panel B. Decomposed Contemporaneous and Lagged Effects

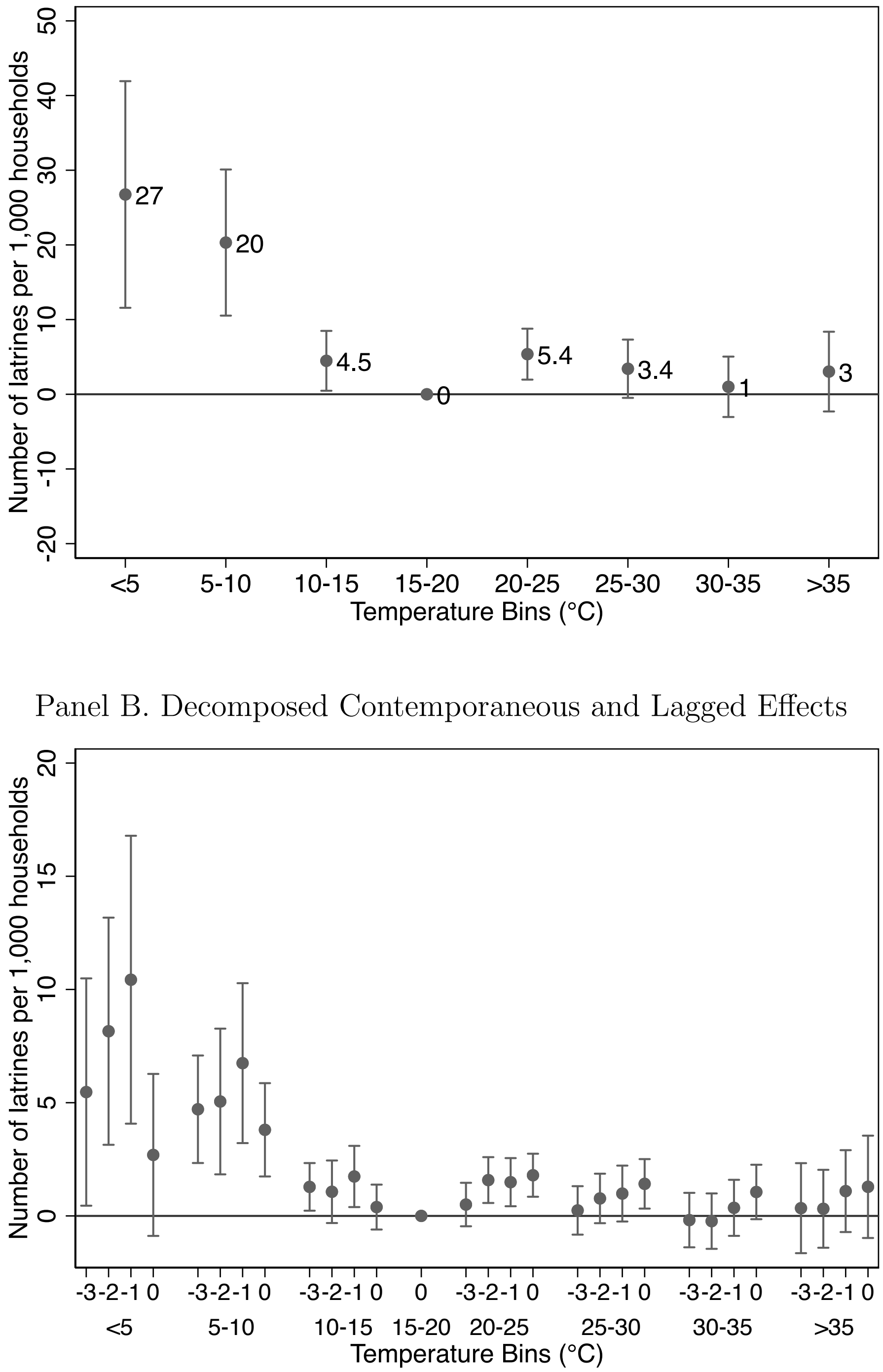
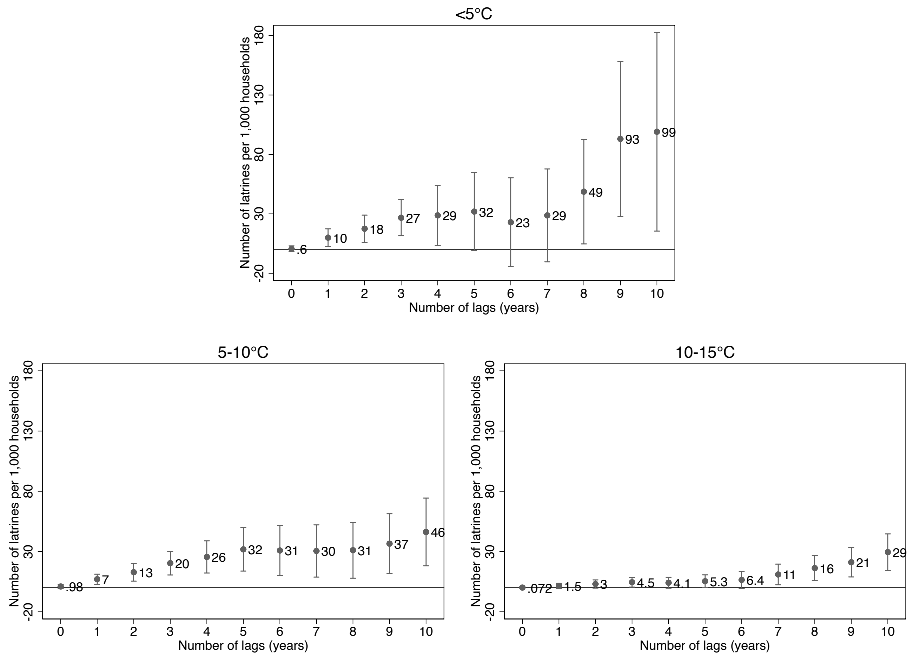


Figure 2: The Effect of Temperature on Latrine Investment

Notes: This figure plots the estimated effects of temperature on latrine investment, which are obtained by fitting equation (5) where three years of lags are included. The 15-20°C bin serves as a reference bin and is dropped from the regression. Markers with whisker lines plot temperature bin estimates and associated 95% confidence intervals. Standard errors are clustered at the district level. Panel A shows the cumulative effects, which are the sum of contemporaneous effects and lagged effects, while Panel B shows all estimates of contemporaneous effects and lagged effects.

Panel A. Colder Temperature Bins



Panel B. Hotter Temperature Bins

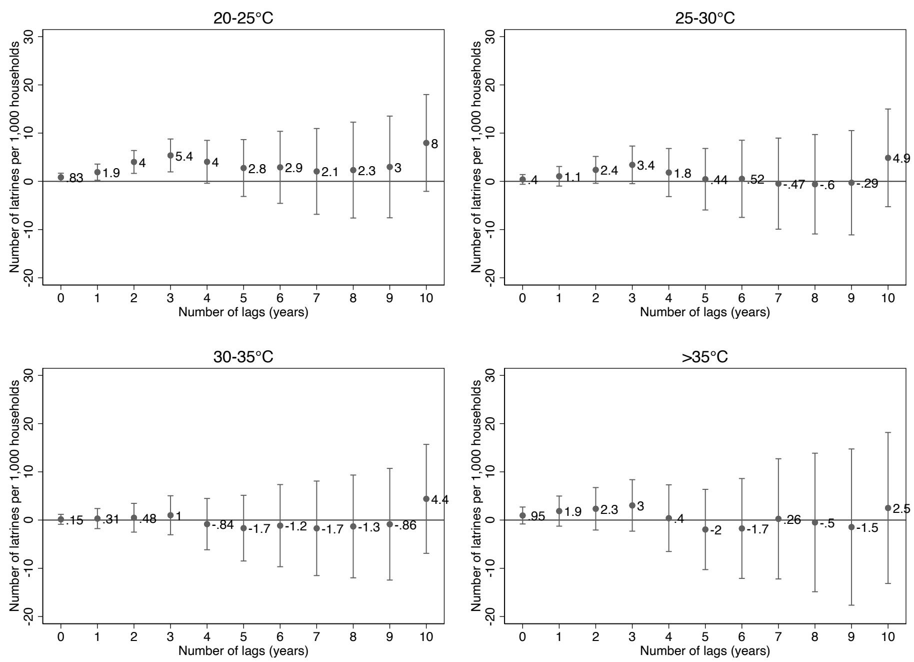


Figure 3: The Cumulative Effects of Temperature on Latrine Investment with Different Numbers of Lags (Years)

Notes: This figure plots the estimated effect of temperature on latrine investment for each temperature bin for each maximum number of lags (years), which is obtained by fitting equation (5). The 15-20°C bin serves as a reference bin and is dropped from the regression. This figure shows the cumulative effects, which are the sum of contemporaneous effects and lagged effects. Markers with whisker lines plot temperature bin estimates and associated 95% confidence intervals. Standard errors are clustered at the district level.

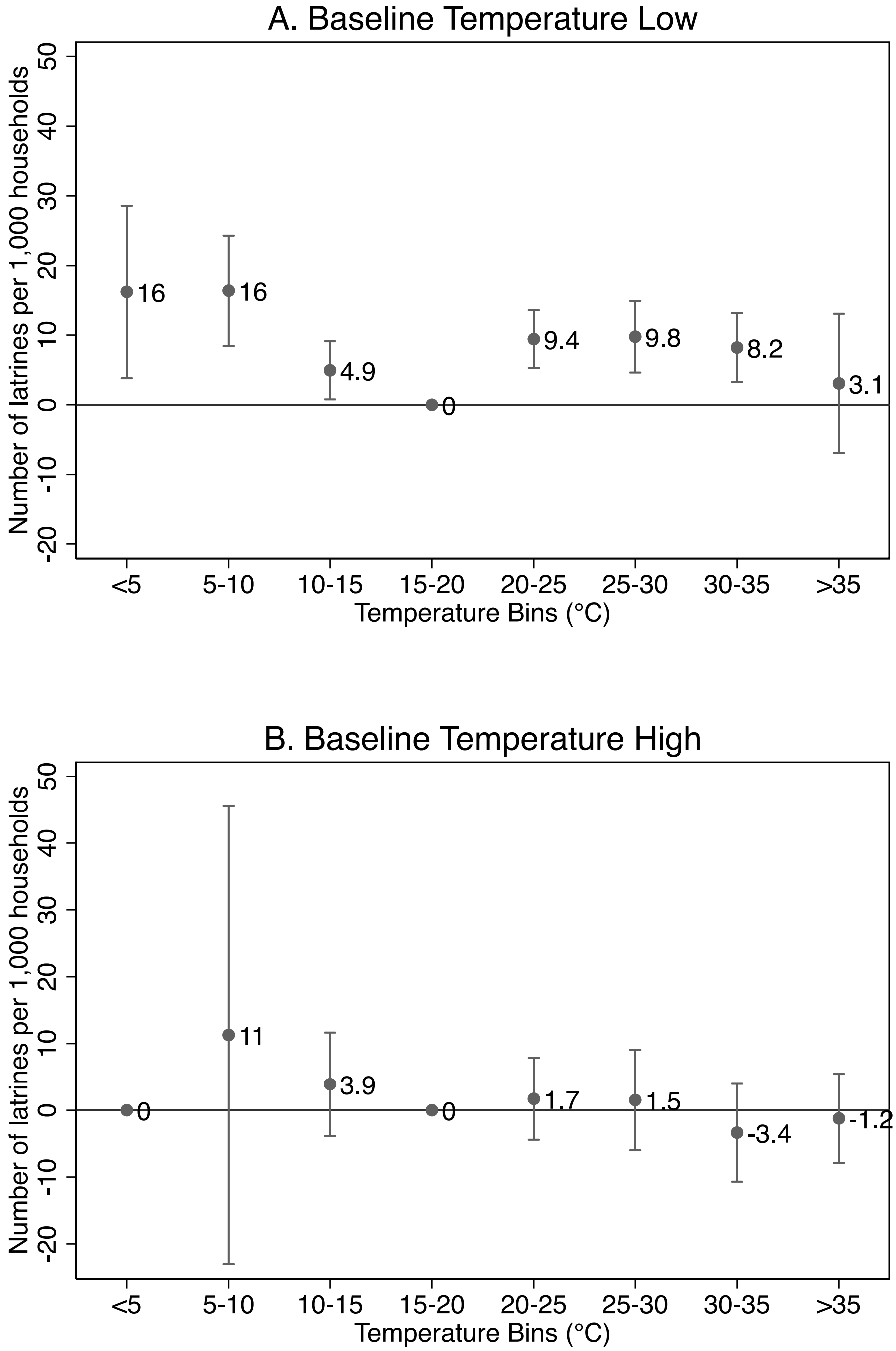


Figure 4: The Cumulative Effects of Temperature on Latrine Investment by Baseline Temperature

Notes: This figure plots the estimated effects of temperature on latrine investment, which are obtained by fitting equation (5) where three years of lags are included. The 15-20°C bin serves as a reference bin and is dropped from the regression. Markers with whisker lines plot temperature bin estimates and associated 95% confidence intervals. Standard errors are clustered at the district level. Both Panels A and B show the cumulative effects, which are the sum of contemporaneous effects and lagged effects. Panel A shows the cumulative effects in districts with baseline temperatures lower than the sample median, while Panel B shows the cumulative effects in districts with higher baseline temperatures.

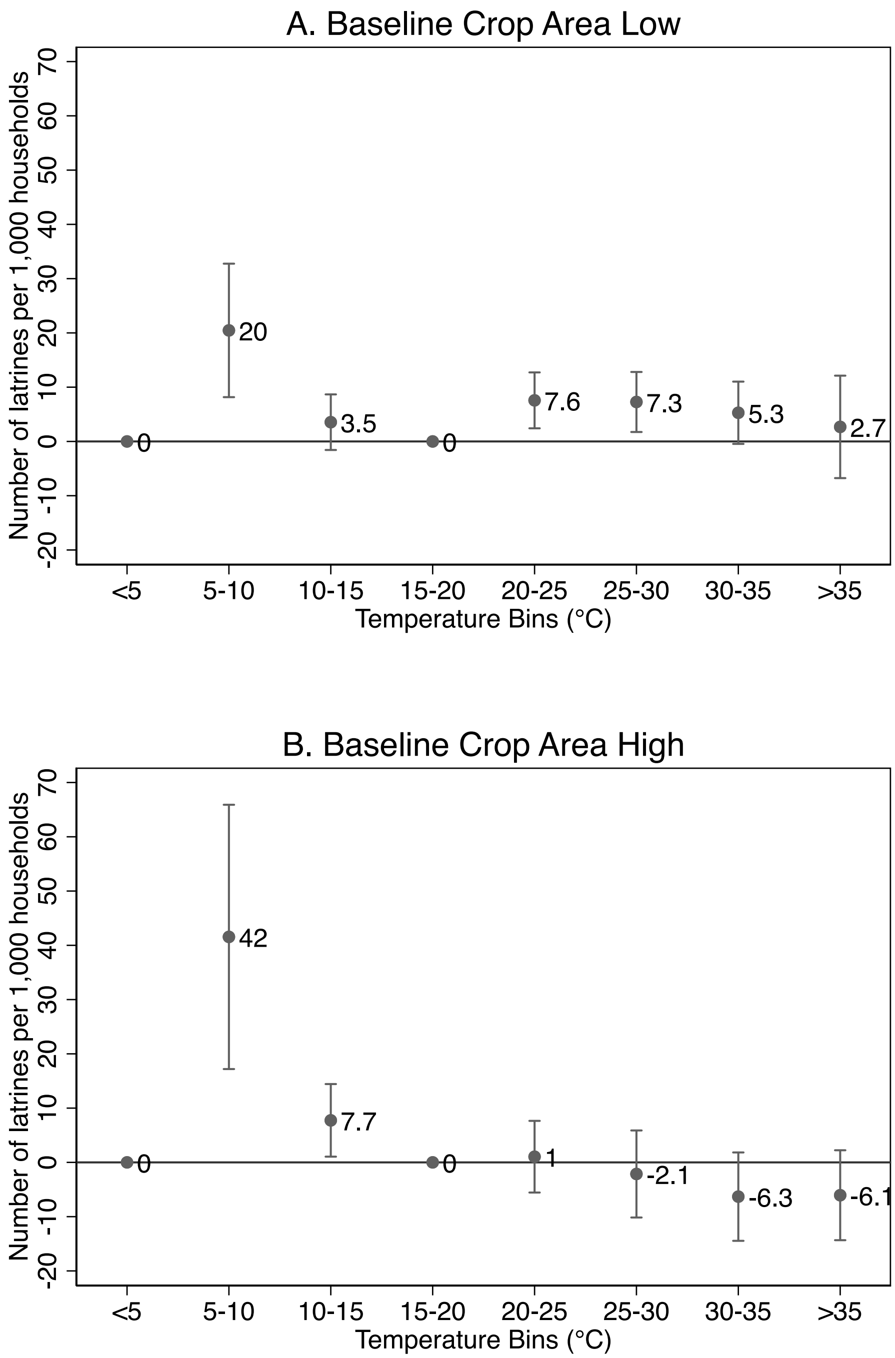


Figure 5: The Cumulative Effects of Temperature on Latrine Investment by Baseline Crop Area

Notes: This figure plots the estimated effects of temperature on latrine investment, which are obtained by fitting equation (5) where three years of lags are included. The 15-20°C bin serves as a reference bin and is dropped from the regression. Markers with whisker lines plot temperature bin estimates and associated 95% confidence intervals. Standard errors are clustered at the district level. Both Panels A and B show the cumulative effects, which are the sum of contemporaneous effects and lagged effects. Panel A shows the cumulative effects in districts with baseline crop areas lower than the sample median, while Panel B shows the cumulative effects in districts with higher crop areas.

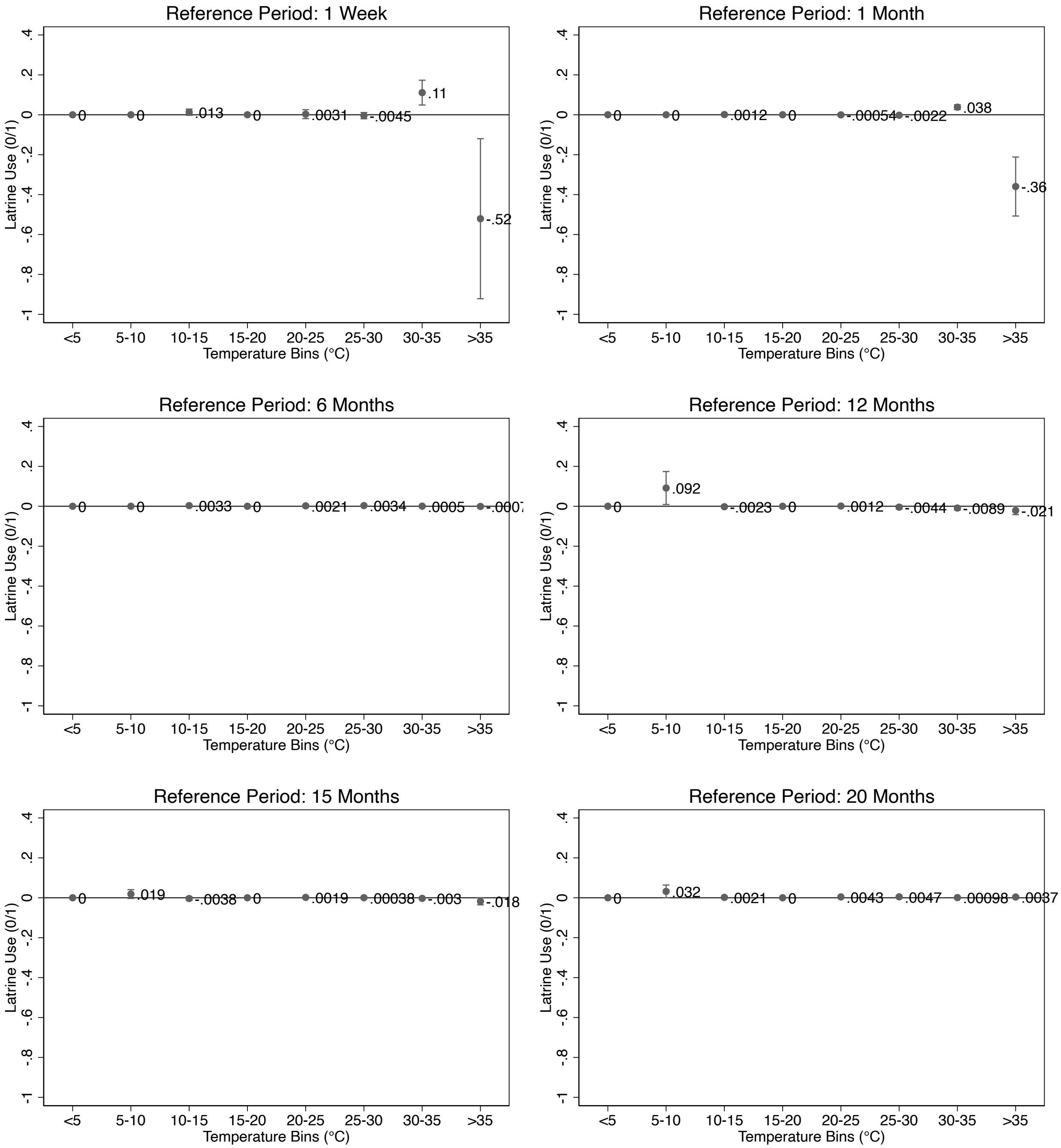


Figure 6: The Effect of Temperature on Latrine Use

Notes: This figure plots the estimated effect of temperature on latrine use for each reference period, which is obtained by fitting equation (6). The 15-20°C bin serves as a reference bin and is dropped from the regression. Markers with whisker lines plot temperature bin estimates and associated 95% confidence intervals. Standard errors are clustered at the village level.

Table 1: Summary Statistics

	Mean	SD	Min	Max	Observations
Panel A. District-level Latrine Investment (2012-2019)					
Number of latrines (thousand)	162.51	161.4	0	1468.74	4888
Number of latrines per 1,000 households	456.81	282.69	0	3456.62	4888
Panel B. SQUAT Latrine Data (2013-14, 2018)					
Latrine usage 2013-2014 (0/1)	0.34	0.47	0	1	6478
Latrine usage 2018 (0/1)	0.6	0.49	0	1	6478
Latrine usage conditional on ownership 2013-2014 (0/1)	0.77	0.42	0	1	2542
Latrine usage conditional on ownership 2018 (0/1)	0.91	0.29	0	1	2542
Latrine ownership 2013-2014 (0/1)	0.39	0.49	0	1	1186
Latrine ownership 2018 (0/1)	0.73	0.44	0	1	1186
Panel C. District-level Average Temperature (2012-2019)					
Number of days above 35°C per year	5.37	8.41	0	97	4888
Number of days between 30-35°C per year	59.56	41.29	0	192	4888
Number of days between 25-30°C per year	150.72	48.99	8	364	4888
Number of days between 20-25°C per year	81.69	40.73	0	316	4888
Number of days between 15-20°C per year	47.31	29.78	0	109	4888
Number of days between 10-15°C per year	16.43	22.52	0	98	4888
Number of days between 5-10°C per year	3.68	13.4	0	92	4888
Number of days below 5°C per year	0.49	3.8	0	57	4888
Panel D. Baseline District-level Characteristics (2011)					
Crop Area (thousand Ha)	339.44	258.24	2.5	1412.91	426

Notes: Panel A shows summary statistics of district-level variables on latrine investment. Panel B reports summary statistics of individual-level variables on latrine usage and household-level variables on latrine ownership in each SQUAT survey round (2013-2014 and 2018). Panel C shows summary statistics on the distribution of daily average temperature at the district level. Panel D shows summary statistics of the district-level crop area in 2011.

Table 2: The Cumulative Effect of Temperature on Latrine Investment (Number of Latrines per 1,000 Households)

	All	Baseline Temperature	
	(1)	(2)	(3)
	All	Low	High
Number of days below 5°C	26.751***	16.198**	-
	(7.742)	(6.323)	-
Number of days 5-10°C	20.313***	16.363***	11.295
	(4.991)	(4.050)	(17.506)
Number of days 10-15°C	4.480**	4.943**	3.905
	(2.044)	(2.125)	(3.954)
Number of days 20-25°C	5.371***	9.417***	1.715
	(1.740)	(2.113)	(3.129)
Number of days 25-30°C	3.417*	9.763***	1.538
	(1.990)	(2.622)	(3.843)
Number of days 30-35°C	0.998	8.205***	-3.357
	(2.063)	(2.530)	(3.743)
Number of days above 35°C	3.036	3.065	-1.224
	(2.724)	(5.098)	(3.396)
Observations	4,872	2,440	2,432
Mean of Dep. Variable	267.977	326.829	208.932
R^2	0.915	0.931	0.902
Number of Districts	609	305	304

Notes: This table reports estimated effects of temperature on latrine investment, which are obtained by fitting equation (5) where three years of lags are included. The 15-20°C bin serves as a reference bin and is dropped from the regression. Standard errors, clustered at the district level, are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. All columns report the cumulative effects, which are the sum of contemporaneous effects and lagged effects. Column 1 shows the cumulative effects in all districts. Column 2 shows the cumulative effects in districts with baseline temperatures lower than the sample median, while Column 3 shows the cumulative effects in districts with higher baseline temperatures.

Table 3: The Contemporaneous and Lagged Effects of Temperature on Latrine Investment (Number of Latrines per 1,000 Households)

	All	Baseline Temperature	
	(1) All	(2) Low	(3) High
Lag 0: Number of days below 5°C	2.694	-0.843	-
	(1.821)	(2.042)	-
Lag 1: Number of days below 5°C	10.431***	7.164**	-
	(3.237)	(2.994)	-
Lag 2: Number of days below 5°C	8.156***	5.265**	-
	(2.554)	(2.138)	-
Lag 3: Number of days below 5°C	5.470**	4.611*	-
	(2.556)	(2.345)	-
Lag 0: Number of days 5-10°C	3.803***	1.974*	-4.980
	(1.049)	(1.141)	(4.637)
Lag 1: Number of days 5-10°C	6.747***	4.880***	6.246
	(1.798)	(1.507)	(6.097)
Lag 2: Number of days 5-10°C	5.053***	4.994***	8.307
	(1.639)	(1.334)	(7.594)
Lag 3: Number of days 5-10°C	4.710***	4.516***	1.722
	(1.209)	(1.167)	(4.385)
Lag 0: Number of days 30-35°C	1.057*	2.973***	-0.470
	(0.612)	(0.790)	(0.920)
Lag 1: Number of days 30-35°C	0.357	1.897**	-0.602
	(0.630)	(0.832)	(1.179)
Lag 2: Number of days 30-35°C	-0.231	1.500*	-0.757
	(0.623)	(0.864)	(1.100)
Lag 3: Number of days 30-35°C	-0.184	1.835**	-1.529
	(0.613)	(0.843)	(1.000)
Lag 0: Number of days above 35°C	1.285	3.437**	-0.840
	(1.151)	(1.524)	(1.271)
Lag 1: Number of days above 35°C	1.095	1.299	-0.045
	(0.921)	(1.656)	(1.432)
Lag 2: Number of days above 35°C	0.315	-0.972	0.119
	(0.876)	(1.607)	(1.168)
Lag 3: Number of days above 35°C	0.342	-0.699	-0.458
	(1.012)	(1.736)	(1.249)
Observations	4,872	2,440	2,432
R^2	0.915	0.931	0.902
Number of Districts	609	305	304
Mean of Dep. Variable	267.977	326.829	208.932

Notes: This table reports estimated contemporaneous and lagged effects of temperature on latrine investment, which are obtained by fitting equation (5) where three years of lags are included. The 15-20°C bin serves as a reference bin and is dropped from the regression. Standard errors, clustered at the district level, are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. Column 1 shows the cumulative effects in all districts. Column 2 shows the cumulative effects in districts with baseline temperatures lower than the sample median, while Column 3 shows the cumulative effects in districts with higher baseline temperatures.

Table 4: The Cumulative Effects of Temperature on Latrine Investment (Number of Latrines per 1,000 Households) by Baseline Crop Area

	All	Baseline Crop Area	
	(1)	(2)	(3)
	All	Low	High
Number of days below 5°C	-	-	-
	-	-	-
Number of days 5-10°C	28.545***	20.460***	41.549***
	(6.396)	(6.276)	(12.424)
Number of days 10-15°C	6.082***	3.548	7.741**
	(2.253)	(2.613)	(3.413)
Number of days 20-25°C	4.998**	7.567***	1.046
	(1.946)	(2.628)	(3.369)
Number of days 25-30°C	2.977	7.270**	-2.137
	(2.273)	(2.822)	(4.092)
Number of days 30-35°C	-0.325	5.282*	-6.314
	(2.315)	(2.928)	(4.155)
Number of days above 35°C	0.203	2.682	-6.052
	(3.111)	(4.816)	(4.229)
Observations	3,408	1,696	1,704
Mean of Dep. Variable	263.067	295.001	231.684
R^2	0.921	0.949	0.892
Number of Districts	426	212	213

Notes: This table reports estimated effects of temperature on latrine investment, which are obtained by fitting equation (5) where three years of lags are included. The 15-20°C bin serves as a reference bin and is dropped from the regression. Standard errors, clustered at the district level, are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. All columns report the cumulative effects, which are the sum of contemporaneous effects and lagged effects. Column 1 shows the cumulative effects in all districts with the data of crop area. Column 2 shows the cumulative effects in districts with baseline crop areas lower than the sample median, while Column 3 shows the cumulative effects in districts with higher crop areas.

Table 5: The Effect of Temperature on Latrine Use

	Reference Periods of Temperature					
	(1) 1 Week	(2) 1 Month	(3) 6 Months	(4) 12 Months	(5) 15 Months	(6) 20 Months
Number of days below 5°C	-	-	-	-	-	-
	-	-	-	-	-	-
Number of days 5-10°C	-	-	-	0.092**	0.019*	0.032*
	-	-	-	(0.042)	(0.011)	(0.016)
Number of days 10-15°C	0.013	0.001	0.003	-0.002	-0.004	0.002
	(0.008)	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)
Number of days 20-25°C	0.003	-0.001	0.002	0.001	0.002	0.004
	(0.011)	(0.003)	(0.003)	(0.003)	(0.002)	(0.003)
Number of days 25-30°C	-0.004	-0.002	0.003*	-0.004	0.000	0.005*
	(0.008)	(0.002)	(0.002)	(0.005)	(0.002)	(0.002)
Number of days 30-35°C	0.111***	0.038***	0.001	-0.009*	-0.003	0.001
	(0.031)	(0.006)	(0.002)	(0.005)	(0.002)	(0.001)
Number of days above 35°C	-0.521**	-0.360***	-0.001	-0.021**	-0.018*	0.004
	(0.202)	(0.075)	(0.003)	(0.010)	(0.009)	(0.003)
Observations	5,084	5,084	5,084	5,084	5,084	5,084
R^2	0.622	0.622	0.618	0.622	0.622	0.619
Number of Individuals	2,542	2,542	2,542	2,542	2,542	2,542
Number of Villages	107	107	107	107	107	107
Mean of Dep. Variable	0.770	0.770	0.770	0.770	0.770	0.770

Notes: This figure plots the estimated effect of temperature on latrine use for each reference period, which is obtained by fitting equation (6). The 15-20°C bin serves as a reference bin and is dropped from the regression. Standard errors, clustered at the village level, are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Appendix

Extreme Temperature May Increase Health Investment:
Persistent Improved Sanitation Behaviors
as Adaptation in India

Kazuki Motohashi

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A Additional Figures

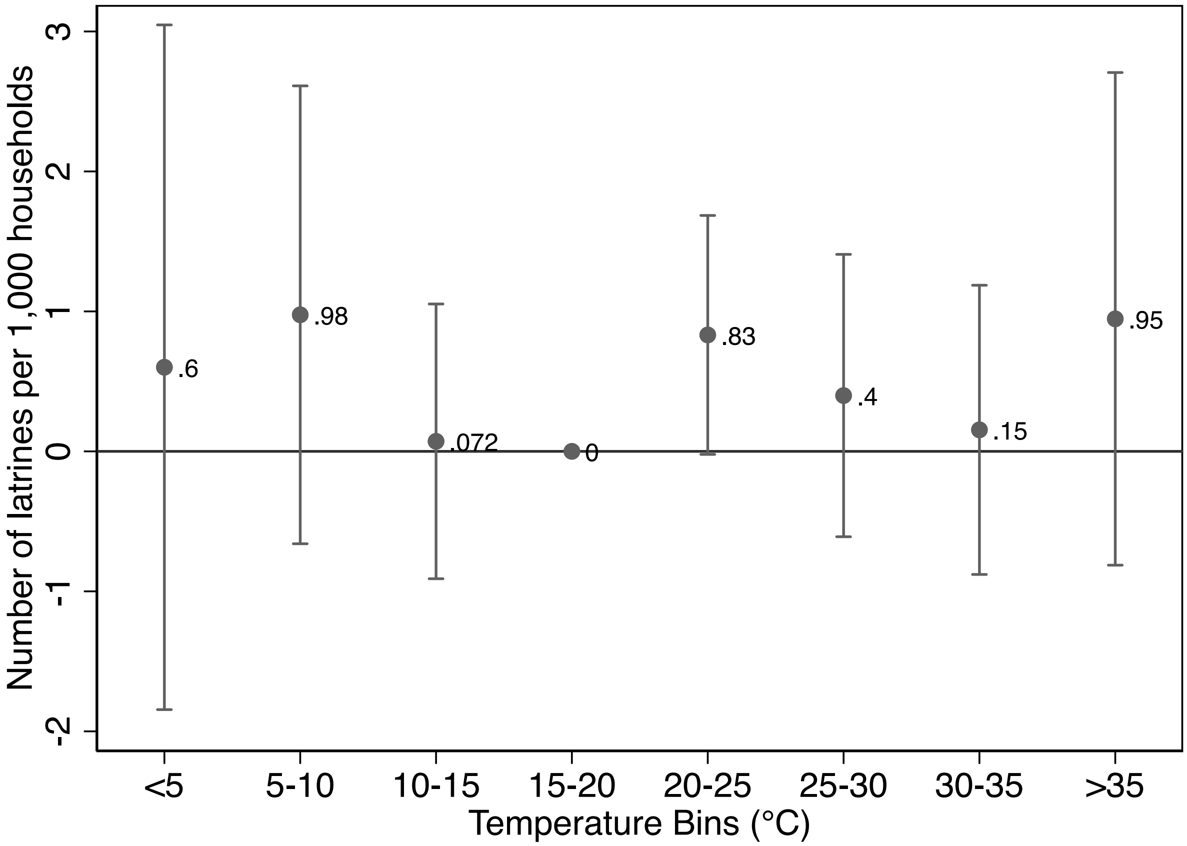

Figure A1: The Contemporaneous Effect of Temperature on Latrine Investment

Notes: This figure plots the estimated contemporaneous effect of temperature on latrine investment, which is obtained by fitting equation (5) without including lagged temperatures. The 15-20°C bin serves as a reference bin and is dropped from the regression. Markers with whisker lines plot temperature bin estimates and associated 95% confidence intervals. Standard errors are clustered at the district level.

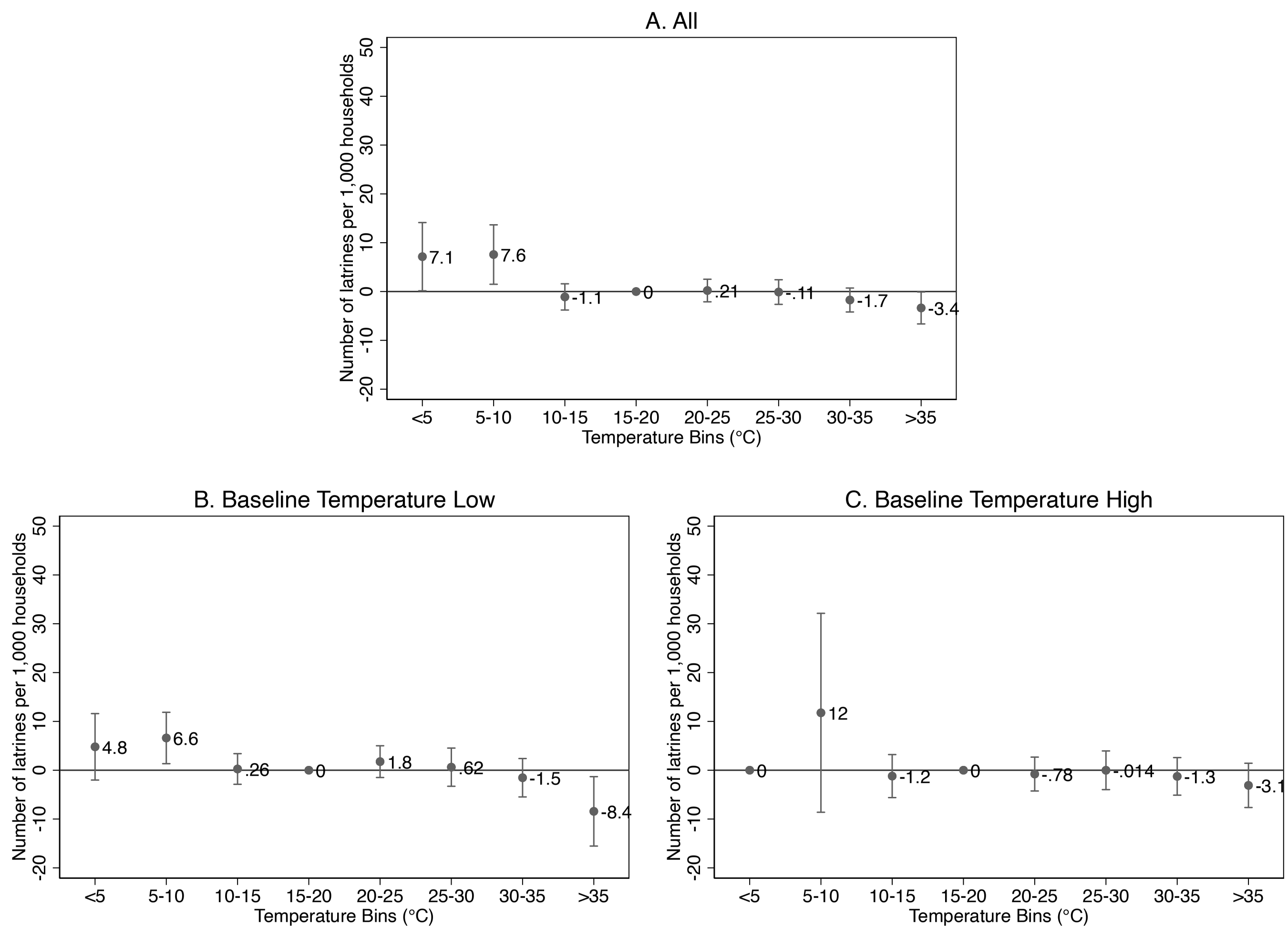

Figure A2: The Cumulative Effects of Temperature on Latrine Investment (Prior to 2016)

Notes: This figure plots the estimated effects of temperature on latrine investment during the period prior to 2016, which are obtained by fitting equation (5) where three years of lags are included. The 15-20°C bin serves as a reference bin and is dropped from the regression. Markers with whisker lines plot temperature bin estimates and associated 95% confidence intervals. Standard errors are clustered at the district level. All panels report the cumulative effects, which are the sum of contemporaneous effects and lagged effects. Panel A shows the cumulative effects in all districts. Panel B shows the cumulative effects in all districts with baseline temperatures lower than the sample median, while Panel C shows the cumulative effects in districts with higher baseline temperatures.

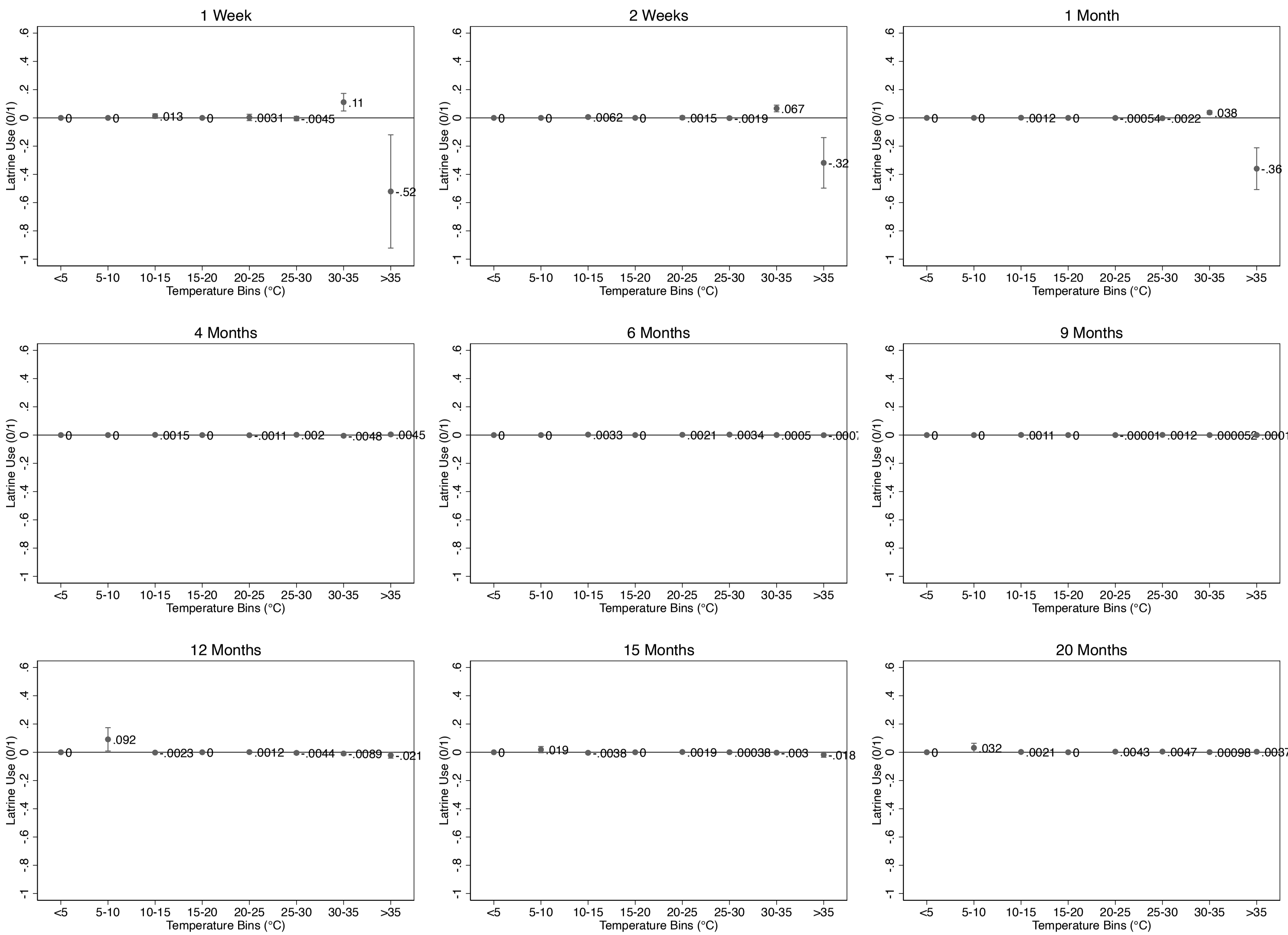

Figure A3: The Effects of Temperature on Latrine Use with Different Reference Periods

Notes: This figure plots the estimated effect of temperature on latrine use for each reference period, which is obtained by fitting equation (6). The 15-20°C bin serves as a reference bin and is dropped from the regression. Markers with whisker lines plot temperature bin estimates and associated 95% confidence intervals. Standard errors are clustered at the village level.

B Additional Tables

Table B1: The Cumulative Effects of Temperature on Latrine Investment (Number of Latrines per 1,000 Households) with Different Number of Lags

	Number of Lags (Years)				
	(1) 1 Year	(2) 3 Years	(3) 6 Years	(4) 8 Years	(5) 10 Years
Number of days below 5°C	9.974***	26.751***	22.915	48.679**	99.116**
	(3.782)	(7.742)	(19.089)	(22.427)	(42.665)
Number of days 5-10°C	6.983***	20.313***	30.853***	31.050***	46.247***
	(2.145)	(4.991)	(10.638)	(11.831)	(14.344)
Number of days 10-15°C	1.543	4.480**	6.433*	16.232***	29.489***
	(1.086)	(2.044)	(3.658)	(5.313)	(7.724)
Number of days 20-25°C	1.902**	5.371***	2.902	2.330	7.960
	(0.855)	(1.740)	(3.811)	(5.069)	(5.120)
Number of days 25-30°C	1.054	3.417*	0.525	-0.604	4.871
	(1.036)	(1.990)	(4.082)	(5.260)	(5.168)
Number of days 30-35°C	0.311	0.998	-1.155	-1.318	4.397
	(1.061)	(2.063)	(4.345)	(5.437)	(5.763)
Number of days above 35°C	1.860	3.036	-1.743	-0.495	2.504
	(1.593)	(2.724)	(5.283)	(7.329)	(7.988)
Observations	4,872	4,872	4,872	4,872	4,872
Mean of Dep. Variable	267.977	267.977	267.977	267.977	267.977

Notes: This table reports the estimated effects of temperature on latrine investment with a different number of lags (years), which is obtained by fitting equation (5). The 15-20°C bin serves as a reference bin and is dropped from the regression. All columns show the cumulative effects, which are the sum of contemporaneous effects and lagged effects. Standard errors, clustered at the district level, are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.