Extreme Temperatures and Adaptive Health Investment: Evidence from Sanitation Behaviors 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 encourage adaptive investment in health technologies in rural India. Using district-level daily temperature and annual latrine construction data, I find that an additional day of extreme heat or cold within a three-year period cumulatively increases latrine investment by 1-10%. The heterogeneity analysis by baseline temperatures underscores the discomfort channel, whereby households construct latrines to avoid walking outside for open defecation under extreme temperatures. My estimates suggest that an additional day of extreme temperatures could decrease diarrheal mortality rates by 0.12-0.90% through increased 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.

However, little is known about the persistent positive effects of weather shocks on human welfare over time. I document that temperature shocks can induce adaptive investment in indoor health technologies by discouraging outdoor health behaviors that entail greater discomfort. If the outdoor behaviors are harmful to health, weather-induced investment in health technologies can ultimately improve health over time. My focus on the persistent positive effect through a new channel of adaptive health investment adds a new perspective that differs from past studies mostly focusing on the persistent negative effects of temperatures.[1]

This paper examines the effect of extreme temperatures on health investment by investigating the case of sanitation behaviors, that is, the construction of latrines that continue 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, specifically extremely high 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

[1]A limited number of studies examine the persistent effects of weather shocks, focusing on negative impacts on economic growth (Dell et al., 2012; Foreman, 2020) and educational outcomes (Park, 2020).

this policy, the Indian government subsidizes latrine construction in rural areas up to about 150 US dollars, which covers most of the initial cost of basic latrines. Thus, my empirical results are more likely to capture the discomfort channel than the income channel, which is attenuated by the subsidy. For the empirical analysis, I use administrative data on the district-level number of latrines under the SBM and raster data on daily temperature and rainfall from 2012 to 2019.

To examine the causal effect of temperature on latrine investment in rural 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 investigate the nonlinear relationship between temperature and latrine investment. I also employ a distributed-lag model that includes lagged temperature for up to 10 years to test the persistence of the effect. In this model, I test whether cumulative effects, defined as the sum of contemporaneous effects and lagged effects, are statistically different from zero.

I find that extremely low and high temperatures increase latrine investment, and this effect persists over multiple years. An additional cold day with an average temperature below 5°C (of 5-10°C) leads to an increase in latrine investment by 26.8 (20.3) per 1,000 households, relative to a day in the 15-20°C range, over three years. This cumulative effect amounts to a 10% (7.6%) increase in latrine investment from the pre-SBM period. As for high temperatures, the effects are more nuanced because the income channel offsets the discomfort channel especially in the case of extremely high temperatures. However, I find that an additional hot day with average temperatures of 25-30°C and 20-25°C leads to an increase in the number of latrines by 3.4 and 5.4 per 1,000 households (1.3% and 2.0% increase from the pre-SBM period), respectively, over three years. The overall positive cumulative effects suggest that the discomfort channel dominates the income channel, and the effects persist over the years.

A variety of robustness checks corroborate my findings on the positive effects of extreme temperatures on latrine investment. Specifically, the results are robust to changes in the number of lagged years in the distributed lag model, to the placebo test examining the contemporaneous effect, and to the consideration of measurement errors in the outcome and baseline latrine coverage that affect subsequent latrine construction.

Heterogeneity analysis by the baseline temperature level underscores the role 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 high temperatures and therefore feel more discomfort. While overall positive effects suggest a limited role of the income channel, heterogeneity analysis by crop areas suggests the existence of the income channel in the case of hot days. The positive net effects of high temperatures become smaller in districts with larger crop areas that are more affected by the negative effects of the income channel, suggesting that the income channel offsets the positive effects of the discomfort channel. However, I find a similar magnitude of positive effects of low temperatures in districts with both smaller and larger crop areas, which is consistent with the fact that only high temperatures negatively affect agricultural output.

Conversely, I find that extreme temperatures generally do not affect the extent of latrine use at the intensive margin after construction, except in the case of very hot temperatures. To examine the effect of temperature on latrine use conditional on ownership, I use the household-level panel dataset in 120 villages of four Indian states, where open defecation is widely prevalent, over two survey rounds in 2013-2014 and 2018 (Coffey et al., 2014; Gupta et al., 2019). I do not find the effect of temperature on the proportion of household members using latrines at the intensive margin across most temperature bins over periods ranging from a week to one year. This is likely due to the high baseline latrine use rate (an average rate of 79%), coupled with the limited occurrence of cold days and adaptation to high temperatures in the sample states with hot climates. However, I find that extremely hot days (above 35°C) increase latrine use in the short run, ranging from one week to one month. This result suggests the role of discomfort channel in increasing the latrine use rate at the intensive margin after construction.

Taken together, my analysis highlights that extreme temperatures can promote adaptive investment in health technologies by increasing the discomfort of walking outside, which ultimately improves human health. Temperature-induced latrine investment can have long-lasting health benefits, including reduced rates of diarrheal diseases and mortality among children. A back-of-the-envelope calculation shows that in rural India, an additional cold or hot day could decrease the diarrheal post-neonatal mortality rate by 0.12-0.90%.

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. However, 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. My results show that extreme temperatures can induce 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 technology adoption by showing that temperature is another major determinant in the adoption of indoor health technologies. In developing countries, outdoor health activities are prevalent, including open defecation (e.g., Cameron et al., 2022), the collection of unsafe spring water (e.g., Kremer et al., 2011), and the collection and usage of biomass for cooking (e.g., Hanna et al., 2016). These outdoor activities are closely linked to water pollution and air pollution, causing significant health damage to households 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) can promote the adoption of health-improving technologies and thus reduce reliance on these harmful outdoor activities. I complement these studies by showing that weather shocks are another important determinant of health technology adoption, which can discourage outdoor behaviors detrimental to human health.

Lastly, I contribute to the behavioral economics literature on the intertemporal bias of consumers in the purchase of 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 in their choices of goods, including cold weather items and cars (Conlin et al., 2007; Busse et al., 2015). In the same vein, I demonstrate that the year-to-year temperature shocks affect the construction of latrines, which are durable goods used for multiple years. Although rational households should decide whether to construct latrines by considering the future climate trajectory and calculating the discomfort level of open defecation over multiple years, my findings suggest that this decision is excessively influenced by short-term weather shocks. This result of intertemporal bias in developing countries is important, as the bias may be larger than in developed countries due to lower education levels and more limited access to climate and weather forecasts.

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 called 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 sanitation behaviors: (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 and use latrines or maintain open defecation practices in two ways.

First, extreme temperatures can have a positive effect on latrine investment and use 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 use as an adaptation behavior. This discomfort channel is implied in past epidemiological studies that found that seasonality matters in latrine use (Routray et al., 2015; Sinha et al., 2017). Their results show that the likelihood of latrine use is higher during the dry cold season and the rainy 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, specifically extremely high temperatures, can have a negative effect on latrine investment and use by reducing income (income channel).[2] 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, 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 use latrines. Suppose that the discomfort of

[2] Another potential channel underlying the negative effect could be more delay and higher costs in latrine construction under more extreme temperatures (construction feasibility channel) discussed 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.

walking outside for open defecation, s, depends on the latrine use rate $l \in [0, 1]$, as well as on ambient temperature $a \in [0, 1]$. l can also be thought of as the probability of constructing a latrine in the case of latrine investment. Conversely, $1 - l$ is the rate of practicing open defecation. Denote the cost of constructing a latrine for use as p.[3] 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, people experience more discomfort with a higher rate of practicing open defecation (lower rate of latrine use): $\frac{\partial s}{\partial l} < 0$.

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 $s(a, 1-l)$: $U(x, s(a, 1-l))$ 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: $\frac{dI}{da} < 0$.

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 latrine use rate to balance the trade-off between the marginal cost of latrine use and the marginal benefit of latrine use that comes from the reduced discomfort of walking outside for open defecation.

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

[3] As for latrine use, p represents the cost of emptying latrines. After construction, using latrines incurs costs associated with hiring tankers or people to regularly empty pits or septic tanks every few years.

$$
\begin{aligned}
\frac{dl}{da} &= \frac{\partial l}{\partial s}\frac{ds}{da} + \frac{\partial l}{\partial I}\frac{dI}{da} \\
&= \frac{1}{p}\left\{ \underbrace{-\frac{U_s}{U_x}\frac{ds}{da}}_{Discomfort\ channel\ >0} + \underbrace{\frac{dI}{da}}_{Income\ channel\ <0} \right\}
\end{aligned}
\tag{4}
$$

which shows two opposing channels: (i) a positive effect of extreme temperatures on latrine investment and use 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 use 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.[4]

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 via the income channel is expected to be limited. In this setting, the positive effect of extreme temperatures via the

[4] This conceptual framework adopts a static model to illustrate the two underlying channels. For simplicity, the persistence of the effect of extreme temperatures on latrine investment is not examined using a dynamic model. However, the persistence comes from the fact that latrines are durable goods that continue to be used over multiple years after construction.

discomfort channel is expected to be larger than the negative effect in the income channel. Therefore, I expect extreme temperatures to generally have a net positive effect on latrine investment.

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 northern India to examine the effect of temperature on latrine use at the 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 (2023). 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 Use

Another outcome variable is the status of latrine use. I use the household-level panel data of latrine use 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).

The SQUAT surveys tract households across two periods in 157 villages across 11 districts in four states in northern India, including Rajasthan, Madhya Pradesh, Uttar Pradesh, and Bihar, where open defecation was widely prevalent in rural areas.

In the SQUAT dataset, I use the status of latrine ownership of each household and latrine use of each household member in each survey round.[5] For the empirical analysis, I construct the household-level latrine use rate by calculating the proportion of household members using latrines out of the total number of members.[6]

I also use the village-level GPS coordinates rounded to the nearest 0.25 degree to match this SQUAT dataset with the weather data.[7] My analysis focuses on 120 villages out of 157 villages where GPS information is available.

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 use, 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

[5] The SQUAT survey asked about a usual practice of defecation (open defecation or latrine use).

[6] The latrine use rate is calculated based on household members who have lived in the house for more than two months in the past year and are above two years old, who were asked about their latrine use in the survey.

[7] I 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.

on the 2011 district boundaries.[8]

To examine the effect of temperature on latrine use, I construct a balanced panel dataset on latrine use and weather variables of 1,188 households in 120 villages over two survey rounds. I spatially match the household-level survey data with village-level daily weather variables based on the village GPS coordinates. Out of 1,188 households in total, 437 households in 107 villages owned latrines in both survey rounds, which is the sample for analyzing the effect of temperature on latrine use 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 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.[9] 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:

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

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

[8] I deal with the changes in the district boundary by ensuring that all data are organized according to the 2011 boundary, which follows Motohashi (2023). Latrine data based on the 2019 boundary are aggregated to follow the 2011 boundary by considering the district splits from 2011 to 2019.

[9] This approach that uses temporal variations in temperature aligns with the methodology adopted in Deschênes and Greenstone (2011).

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. However, 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 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 average temperatures of 25-30°C and 20-25°C leads to an increase in the number of latrines by 3.4 and 5.4 per 1,000 households, respectively, 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 1.3 and 2.0% increase from the pre-SBM period.[10] Moreover, cold temperature bins have larger positive effects on latrine investment. An additional day with average temperatures below 5°C and of 5-10°C within a three-year period cumulatively increases the number of latrines by 26.8 and 20.3 (10.0% and 7.6% from the pre-SBM period) 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. Households 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 (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.[11] 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.

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

[11] 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.

4.3 Robustness Checks

The results are robust to various checks, including changes in the number of lagged years in the distributed lag model, to the placebo test examining the contemporaneous effect, and to the consideration of measurement errors in the outcome and baseline latrine coverage that affect subsequent latrine construction.

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 C1, 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 are less likely to affect the latrine investment in the same year than in subsequent years. Thus, I conduct a placebo test that examines the contemporaneous effect 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 B1). 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 in 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 B2, 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.

Baseline Latrine Coverage Affecting Subsequent Latrine Construction.—During the study period of this paper under the SBM, latrine coverage in India increased significantly, approaching closer to universal coverage across rural India, regardless of the pre-SBM baseline coverage. Consequently, areas with lower baseline coverage were more likely to experience a larger increase in latrine construction. If the occurrence of extreme temperatures is negatively correlated with baseline latrine coverage, my baseline results might merely be capturing the effect of this baseline coverage. To check this potential concern, I conducted a heterogeneous analysis by comparing the effects of temperature in districts with higher baseline coverage than the sample median to those in districts with lower baseline coverage.

As shown in Appendix Figure B3, I find positive cumulative effects of extreme temperatures in both districts with higher and lower baseline coverage. Finding similar results in both cases suggests that my analysis is not merely capturing the effect of baseline latrine coverage correlated with the occurrence of extreme temperatures.

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 Mechanisms

Alternative mechanisms 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.[12] I evaluate these alternative channels but find their limited role.

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.[13] 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 areas experience smaller (or more negative) effects of 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

[12] 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.

[13] 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.

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 Use

Extreme temperatures can affect not only latrine investment but also the extent of latrine use conditional on latrine ownership. To examine this effect at the intensive margin, I leverage village-level inter-temporal temperature variations and a household-level panel dataset on latrine use. I find that extreme temperatures generally do not affect the proportion of household members using latrines at the intensive margin, except in the case of very high temperatures.

5.1 Empirical Strategy

I exploit presumably random variation in village-level temperature across two survey rounds in the SQUAT dataset to examine the effect of temperature on latrine use. Specifically, I adopt a two-way fixed effects specification, following the same approach as the regression 5.

$$LatrineUse_{hvtm} = \sum_j \beta_j^{USE} BinTemp_{jvtm} + \sum_k \delta_k^{USE} DecileRain_{kvtm} + \eta_v + \nu_t + \theta_m + \varepsilon_{hvtm} \tag{6}$$

where h indexes households, j indexes temperature bins, v indexes villages, k indexes rainfall bins, t indexes the two SQUAT survey rounds in 2013-2014 and 2018, and m indexes the survey months. $LatrineUse_{hvtm}$ is a latrine use rate of household h in survey round t in survey month m, which is the proportion of household members using latrines out of the total number of members. $BinTemp_{jvtm}$ 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 use exploits the village-level variation in temperature. I include village fixed effects (η_v) to exploit the presumably random variation in village-level temperature across two periods and to control for time-invariant village-level unobservables that can affect latrine use. I also include survey-round fixed effects (ν_t) to control for the trend in latrine use (e.g., increase in latrine use because of extensive promotion under the SBM). Survey month fixed effects (θ_m) are included to control for seasonality in latrine use behavior, potentially driven by weather variations within the year. Standard errors are clustered at the village level because the variation in temperature is observed at the village level. The coefficients of interest are β_j^{USE}'s, which measures the effect of an additional day in the temperature bin j on the latrine use rate relative to a day in the 15-20°C bin.

As a baseline specification, I examine the effect on latrine use conditional on latrine ownership to capture the effect at the intensive margin without including the effect on latrine investment. Therefore, I limit the sample to households that own latrines in both survey periods. Specifically, the baseline specification focuses on 437 households out of 1,188 households.[14]

I construct the treatment variable, $BinTemp_{jvtm}$, by counting the number of days in temperature bin j within a given reference period until the survey date of household h. Each SQUAT survey round took multiple months to be completed, which resulted in the variation in survey dates among households.[15] I specifically use daily temperatures from X period before to 1 day before each survey date, where the choices of reference periods (X) are 1 week, 2 weeks, 1 month, 6 months, and 12 months.

The analysis of latrine use focuses on the short-run effects rather than persistent effects, as latrine use behaviors may differ from day to day. The outcome used in the analysis is a self-reported usual practice of latrine use at the survey timing. Due to recall bias, respondents may report more recent behaviors that are affected by recent temperature shocks. Therefore, I adopt shorter reference periods (1 week, 2 weeks, and 1 month), where I expect the effects to be larger. As a robustness check, I also adopt longer reference periods (6 and 12 months),

[14] As a robustness check, I also show the results of the effect of latrine use unconditional on latrine ownership by using all sample households in the following section.

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

where I anticipate less significant effects.

5.2 Results

I find that extreme temperatures generally do not affect the proportion of household members using latrines at the intensive margin. However, I find that very high temperatures increase the latrine use rate in the short run, which suggests the discomfort channel.

In Figure 6 and Table 5, I do not find the effect of temperatures on latrine use rate conditional on latrine ownership in most temperature bins regardless of the choices of reference periods.[16] This result, coupled with findings on latrine investment, suggests that while extreme temperatures cumulatively increase latrine investment, they do not impact the extent of latrine use at the intensive margin after construction.

Several reasons may explain the limited effect on latrine use. First, the baseline rate of latrine use, conditional on ownership, is already high: on average, 79% of household members use latrines if the household owns one in the first survey round. Therefore, if latrine use among household members is already common conditional on ownership, the potential for increased use due to extreme temperatures is limited. Second, this result pertains specifically to the four northern states in India included in the SQUAT dataset, known for their hot climates. As discussed in Section 4.4, people in these states are better adapted to high temperatures, resulting in a limited impact of hot days on latrine use. Additionally, the predominantly hot climate challenges the estimation of effects during very cold days, with temperatures below 5°C and between 5-10°C, across most reference periods. The sample lacks data for these cold temperature bins, with the exception of the 5-10°C bin for the 12-month reference period (Panel B of Figure 1).

However, I find that very high temperatures increase the latrine use rate in the short run. Figure 6 and columns 1-3 of Table 5 show the positive effects of extremely high temperatures (above 35°C bin) when adopting reference periods of 1 week, 2 weeks, or 1 month. An additional hot day with average temperatures above 35°C leads to an increase in the latrine use rate by 0.15-0.49 (18-62% from the baseline use rate) per 1,000 households, relative to a day in the 15-20°C range. This result suggests the role of discomfort channel in increasing the latrine use rate at the intensive margin after construction.[17]

[16] I find similar results when using all sample households without conditioning on latrine ownership, as shown in Appendix Figure B4 and Appendix Table C2.

[17] The alternative income channel is expected to have limited short-term effects for up to one month, because the costs associated with emptying latrines are incurred only every few years.

6 Conclusion

I document that extreme temperatures have a positive, persistent effect on latrine investment. My analysis suggests that the main underlying mechanism is the discomfort channel, whereby households construct latrines to avoid the greater discomfort of walking outside for open defecation under extreme temperatures. This adaptive latrine investment can reduce the open defecation behavior, which ultimately improves human health in terms of reduced diarrheal diseases and mortality among children.

My results point to the potential benefit of an increased occurrence of extreme weather under climate change, which has not been shown in most past studies focusing on the negative consequences of climate change. Moreover, I find a new mechanism for the persistent effects (rather than short-term effects) of temperature, which is a temperature-induced investment in health technologies that continues to be used over multiple periods.

A back-of-the-envelope calculation shows large welfare gains due to extreme temperatures: a large reduction in diarrheal child mortality through increased latrine investment. The health effect of extreme temperatures through increased latrine investment is calculated by multiplying the effect of temperature on latrine investment estimated in this paper with the effect of latrine construction on diarrheal mortality rate in rural India, as reported in Motohashi (2023).[18] This back-of-the-envelope calculation suggests that an additional day with an average temperature of below 5°C, 5-10°C, 10-15°C, 20-25°C, and 25-30°C could decrease diarrheal post-neonatal mortality rate by 0.90%, 0.68%, 0.15%, 0.18%, and 0.12%, respectively.

My results present several important implications for considering climate change policies and health behaviors in developing countries. First, 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 investment and use) that are conducted indoors. Conversely, climate change mitigation measures can unintentionally decrease the adoption of health-improving technologies used indoors unless these measures are implemented together 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 various outdoor health behaviors in developing countries. For example, under extreme temperatures, people may shift from

[18] Specifically, I use the estimates in column 1 of Table 2 of this paper and the estimated effect from Motohashi (2023), which is a 0.43% reduction in diarrheal post-neonatal mortality rate caused by an additional latrine per square kilometer. More detailed steps are described in Appendix A.

the collection and usage of biomass to the usage of cleaner fuel like 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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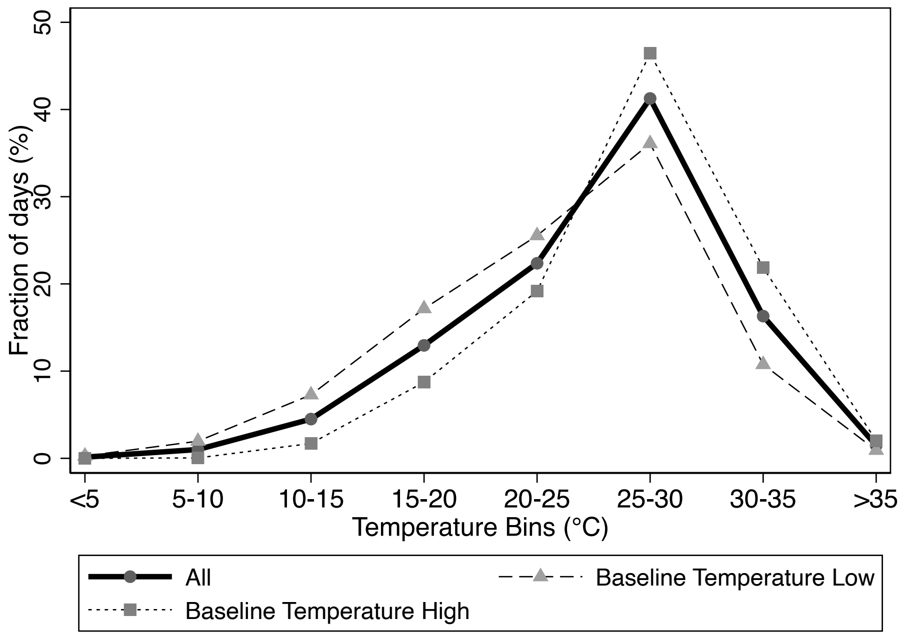
Panel A. Latrine Investment Specification



Panel B. Latrine Use Specification

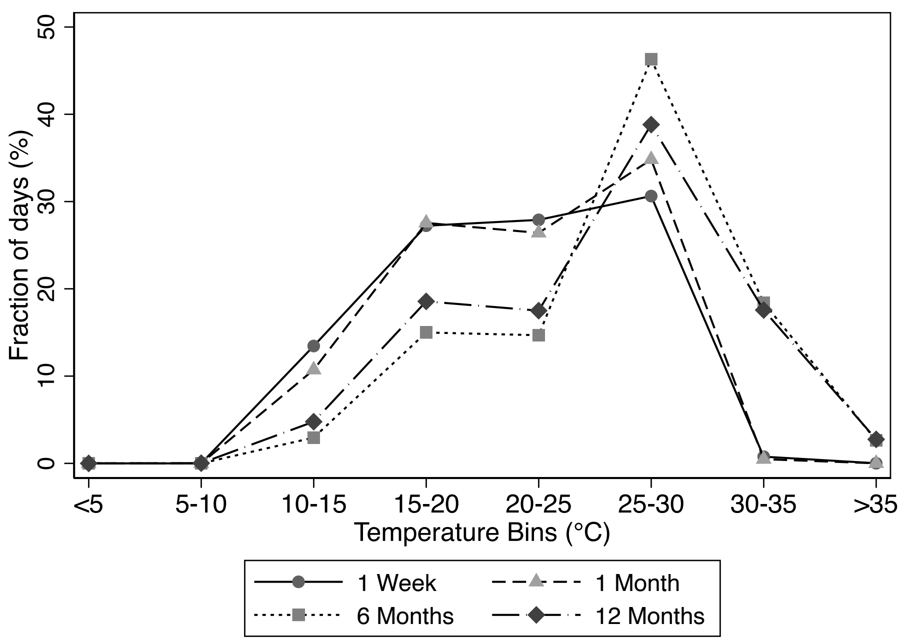
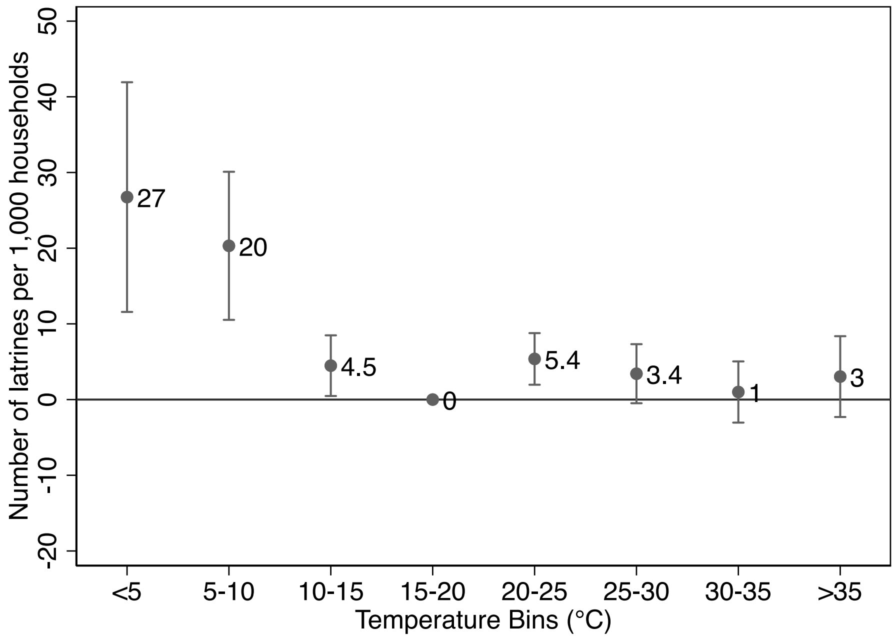


Figure 1: Daily Average Temperature Distributions

Notes: This figure shows the distributions of daily average temperatures that are used for the analysis of latrine investment (Panel A) and the analysis of latrine use (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 temperatures 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

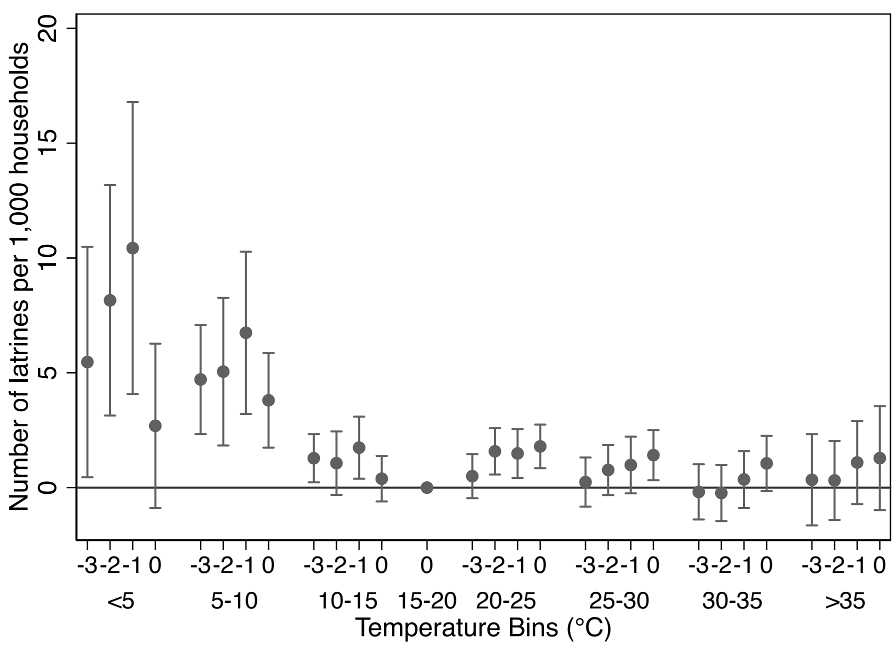
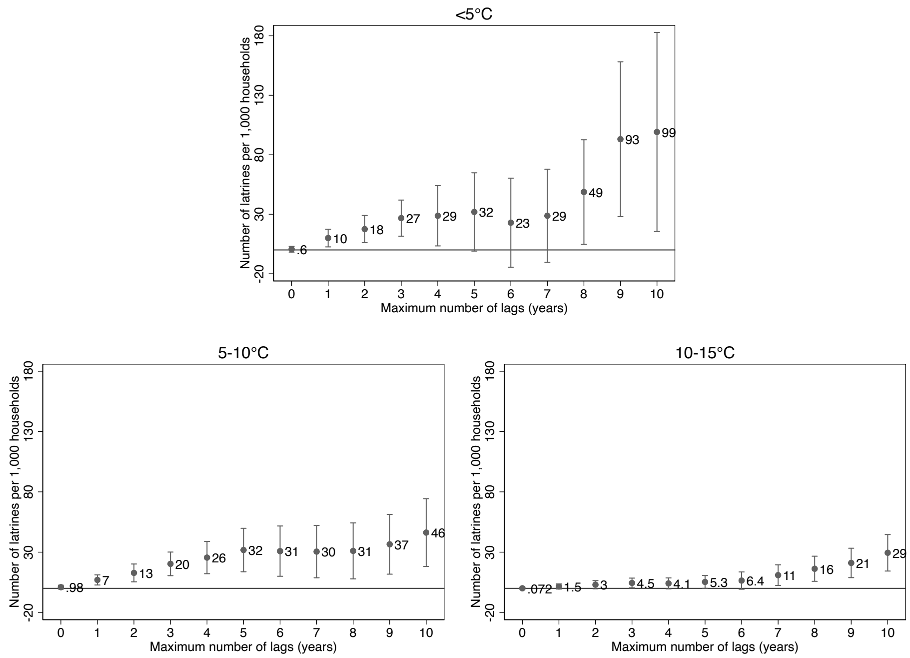


Figure 2: The Effect of Temperature on Latrine Investment

Notes: This figure plots the estimated effects of temperature on latrine investment, when including up to three years of 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. Panel A shows the cumulative effects, representing the total of contemporaneous and lagged effects. Panel B shows all estimates of contemporaneous effects and lagged effects.

Panel A. Low Temperature Bins



Panel B. High Temperature Bins

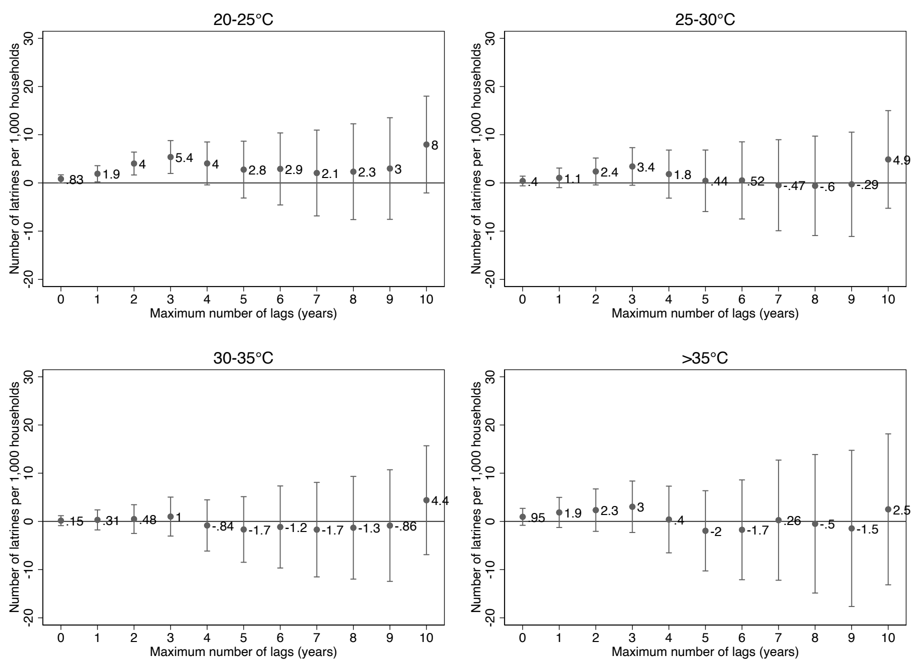


Figure 3: The Cumulative Effects of Temperature on Latrine Investment with Different Maximum Numbers of Lags ($\sum \beta_{jl}^{INV}$)

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

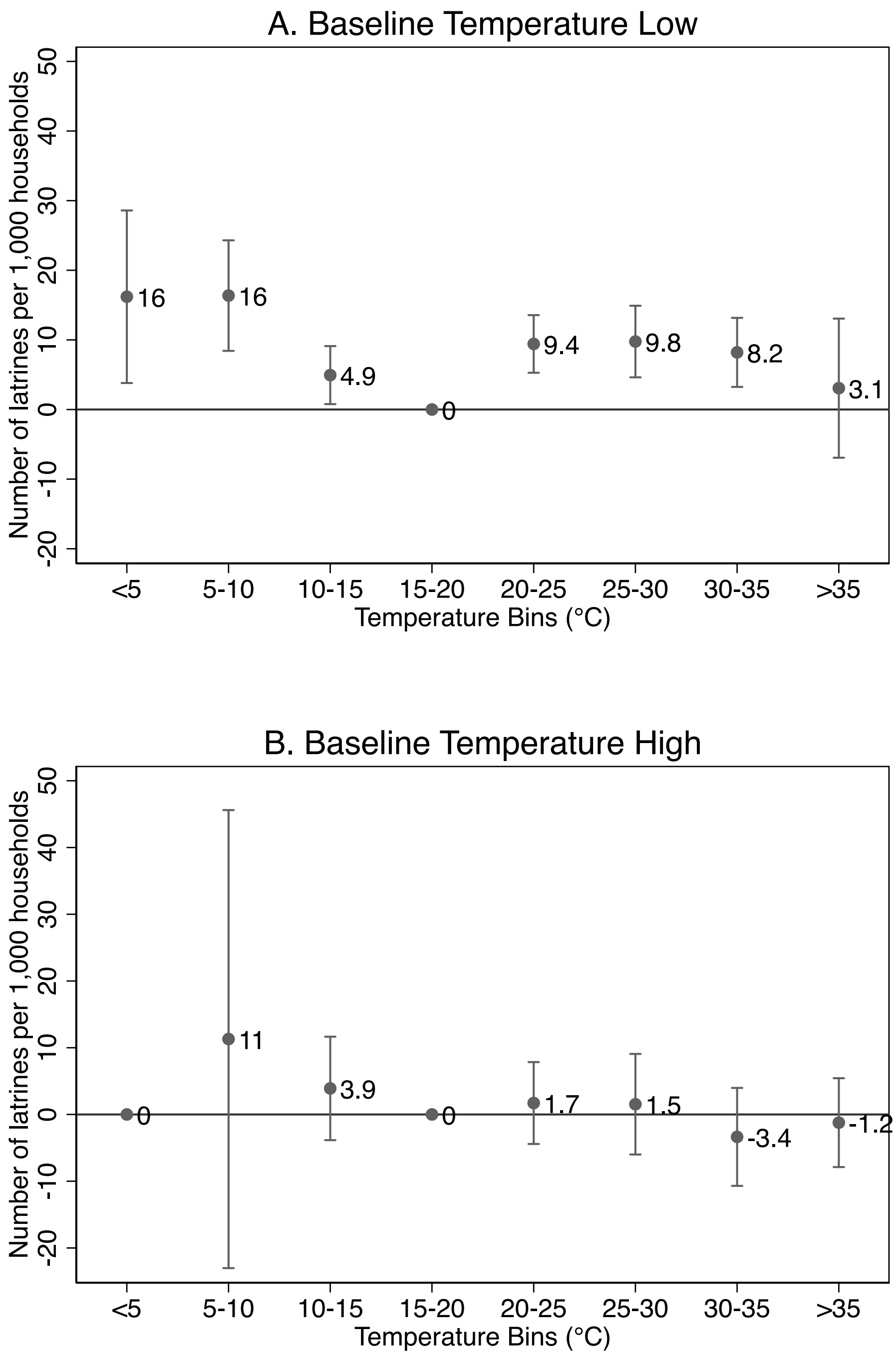


Figure 4: The Heterogeneous Effects of Temperature on Latrine Investment by Baseline Temperature

Notes: This figure plots the estimated effects of temperature on latrine investment. 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, representing the total of contemporaneous and lagged effects, when including up to three years of lagged temperatures. Panel A shows the estimated effects in districts with baseline temperatures lower than the sample median, while Panel B shows the estimated effects in districts with higher baseline temperatures.

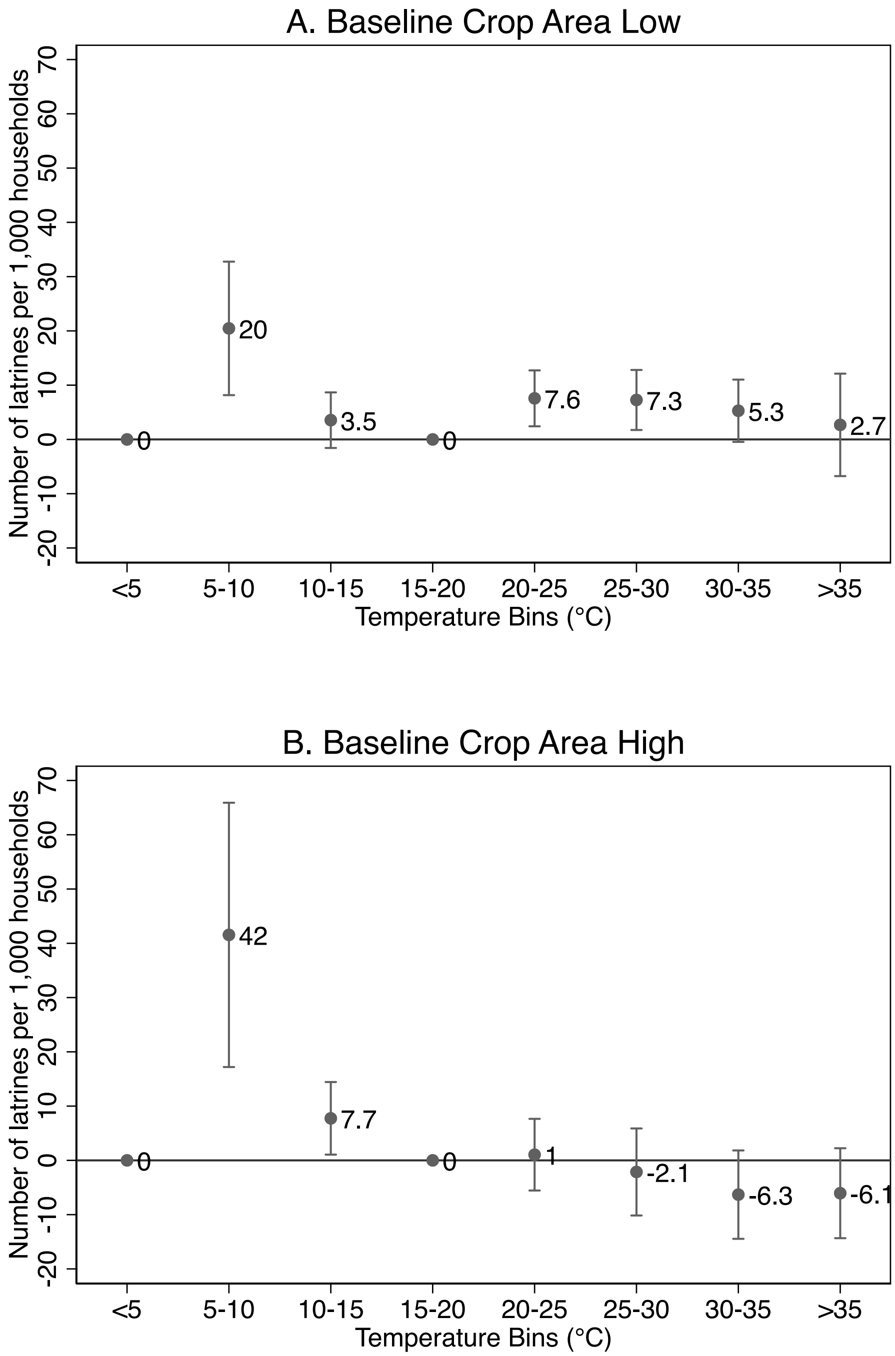


Figure 5: The Heterogeneous Effects of Temperature on Latrine Investment by Baseline Crop Area

Notes: This figure plots the estimated effects of temperature on latrine investment. 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, representing the total of contemporaneous and lagged effects, when including up to three years of lagged temperatures. Panel A shows the estimated effects in districts with baseline crop areas lower than the sample median, while Panel B shows the estimated effects in districts with higher crop areas.

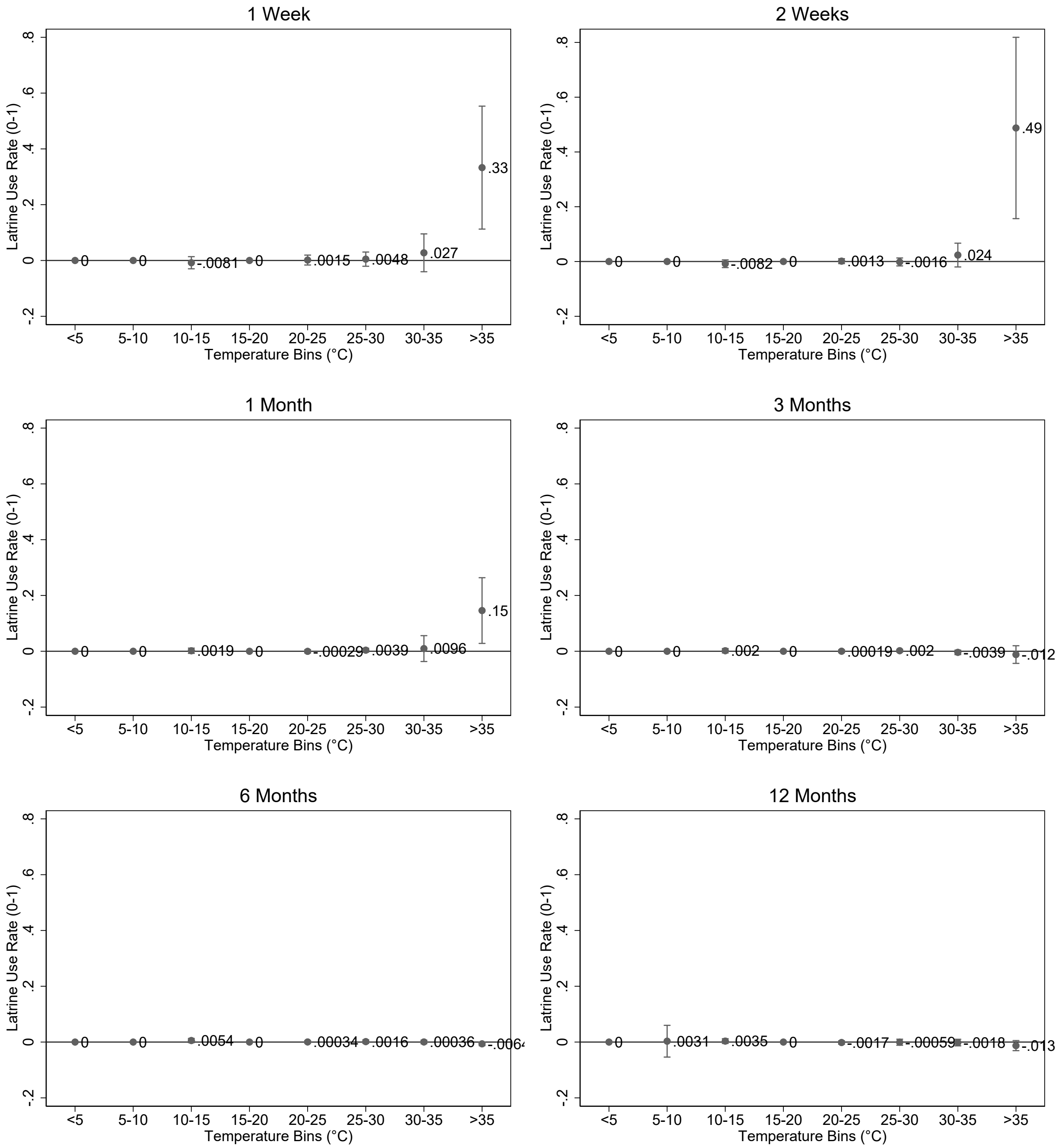


Figure 6: The Effect of Temperature on Latrine Use (Conditional on Ownership)

Notes: This figure plots the estimated effect of temperature on latrine use rates for households owning latrines in both survey rounds for different reference periods. 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. Household-level SQUAT Latrine Data (2013-14, 2018)					
Latrine use rate 2013-2014 (0-1)	0.32	0.43	0	1	1188
Latrine use rate 2018 (0-1)	0.6	0.45	0	1	1188
Latrine use rate conditional on ownership 2013-2014 (0-1)	0.79	0.32	0	1	437
Latrine use rate conditional on ownership 2018 (0-1)	0.91	0.22	0	1	437
Panel C. District-level Average Temperature (2012-2019)					
Number of days below 5°C per year	0.49	3.8	0	57	4888
Number of days between 5-10°C per year	3.68	13.4	0	92	4888
Number of days between 10-15°C per year	16.43	22.52	0	98	4888
Number of days between 15-20°C per year	47.31	29.78	0	109	4888
Number of days between 20-25°C per year	81.69	40.73	0	316	4888
Number of days between 25-30°C per year	150.72	48.99	8	364	4888
Number of days between 30-35°C per year	59.56	41.29	0	192	4888
Number of days above 35°C per year	5.37	8.41	0	97	4888
Panel D. District-level Baseline Characteristics (2011)					
Crop area (thousand Ha)	339.44	258.24	2.5	1412.91	426

Notes: Panel A reports summary statistics of district-level variables on latrine investment. Panel B reports summary statistics of household-level variables on latrine use in each SQUAT survey round. Panel C reports summary statistics on the distribution of daily average temperature at the district level. Panel D reports 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. 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, representing the total of contemporaneous and lagged effects, when including up to three years of lagged temperatures. Column 1 shows the estimated effects in all districts. Column 2 shows the estimated effects in districts with baseline temperatures lower than the sample median, while column 3 shows the estimated effects in districts with higher baseline temperatures. The means of dependent variables are calculated for the pre-SBM period (2012-2013).

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

	All	Baseline Temperature	
	(1)	(2)	(3)
	All	Low	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, when up to three years of lagged temperatures 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 estimated effects in all districts. Column 2 shows the estimated effects in districts with baseline temperatures lower than the sample median, while column 3 shows the estimated effects in districts with higher baseline temperatures. The means of dependent variables are calculated for the pre-SBM period (2012-2013).

Table 4: The Heterogeneous 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. 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, representing the total of contemporaneous and lagged effects, when including up to three years of lagged temperatures. Column 1 shows the estimated effects in all districts with the data of crop area. Column 2 shows the estimated effects in districts with baseline crop areas lower than the sample median, while column 3 shows the estimated effects in districts with higher crop areas. The means of dependent variables are calculated for the pre-SBM period (2012-2013).

Table 5: The Effect of Temperature on Latrine Use (Conditional on Ownership)

	Latrine Use Rate Conditional on Ownership (0-1)					
	(1) 1 Week	(2) 2 Weeks	(3) 1 Month	(4) 3 Months	(5) 6 Months	(6) 12 Months
Number of days below 5°C	-	-	-	-	-	-
	-	-	-	-	-	-
Number of days 5-10°C	-	-	-	-	-	0.003
	-	-	-	-	-	(0.029)
Number of days 10-15°C	-0.008	-0.008	0.002	0.002	0.005	0.003
	(0.011)	(0.007)	(0.005)	(0.004)	(0.004)	(0.004)
Number of days 20-25°C	0.002	0.001	-0.000	0.000	0.000	-0.002
	(0.009)	(0.005)	(0.003)	(0.003)	(0.002)	(0.003)
Number of days 25-30°C	0.005	-0.002	0.004	0.002	0.002	-0.001
	(0.013)	(0.007)	(0.004)	(0.003)	(0.003)	(0.005)
Number of days 30-35°C	0.027	0.024	0.010	-0.004	0.000	-0.002
	(0.034)	(0.022)	(0.023)	(0.004)	(0.003)	(0.006)
Number of days above 35°C	0.333***	0.488***	0.146**	-0.012	-0.006*	-0.013
	(0.111)	(0.167)	(0.059)	(0.016)	(0.003)	(0.009)
Observations	874	874	874	874	874	874
R^2	0.259	0.261	0.264	0.268	0.264	0.265
Number of Households	107	107	107	107	107	107
Number of Villages	107	107	107	107	107	107
Mean of Dep. Variable	0.786	0.786	0.786	0.786	0.786	0.786

Notes: This table reports the estimated effects of temperature on latrine use rates for different reference periods. The sample is limited to households that own latrines in both survey rounds. 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. The means of dependent variables are calculated using the first survey round in 2013-2014.

Appendix

Extreme Temperatures and Adaptive Health Investment:
Evidence from Sanitation Behaviors in India

Kazuki Motohashi

Contents

List of Figures

List of Tables

A Back-of-the-Envelope Calculation on Health Effect

I calculate the health effect of extreme temperatures through increased latrine investment by multiplying the effect of temperature on latrine investment estimated in this paper with the effect of latrine construction on diarrheal child mortality rate in rural India, as reported in Motohashi (2023).

Regarding the effect of temperature on latrine investment, I refer to the statistically significant estimates presented in column 1 of Table 2. Specifically, these estimates include a cumulative increase of 26.8, 20.3, 4.5, 5.3, and 3.4 latrines per 1,000 households, caused by an additional day with temperatures below 5°C, between 5-10°C, 10-15°C, 20-25°C, and 25-30°C, respectively, over a three-year period. By multiplying these estimates by the average number of households per district (389.87 thousand households) and dividing by the average area per district (4,975.91 square kilometers), the estimates translate into a cumulative increase of 2.1, 1.6, 0.35, 0.42, and 0.27 latrines per square kilometer, respectively.

As for the effect of latrine construction on the diarrheal child mortality rate, I refer to the estimated effect in Motohashi (2023), which is a decrease in diarrheal post-neonatal mortality rate by 0.011 (0.43% decrease) caused by an additional upstream number of latrines per square kilometer.

Finally, multiplying both effects yields the health effect of extreme temperatures via increased latrine investment. An additional day with an average temperature below 5°C, between 5-10°C, 10-15°C, 20-25°C, and 25-30°C results in a decrease in diarrheal post-neonatal mortality rate by 0.90% ($2.1 \times 0.43\%$), 0.68% ($1.6 \times 0.43\%$), 0.15% ($0.35 \times 0.43\%$), 0.18% ($0.42 \times 0.43\%$), and 0.12% ($0.27 \times 0.43\%$), respectively.

B Additional Figures

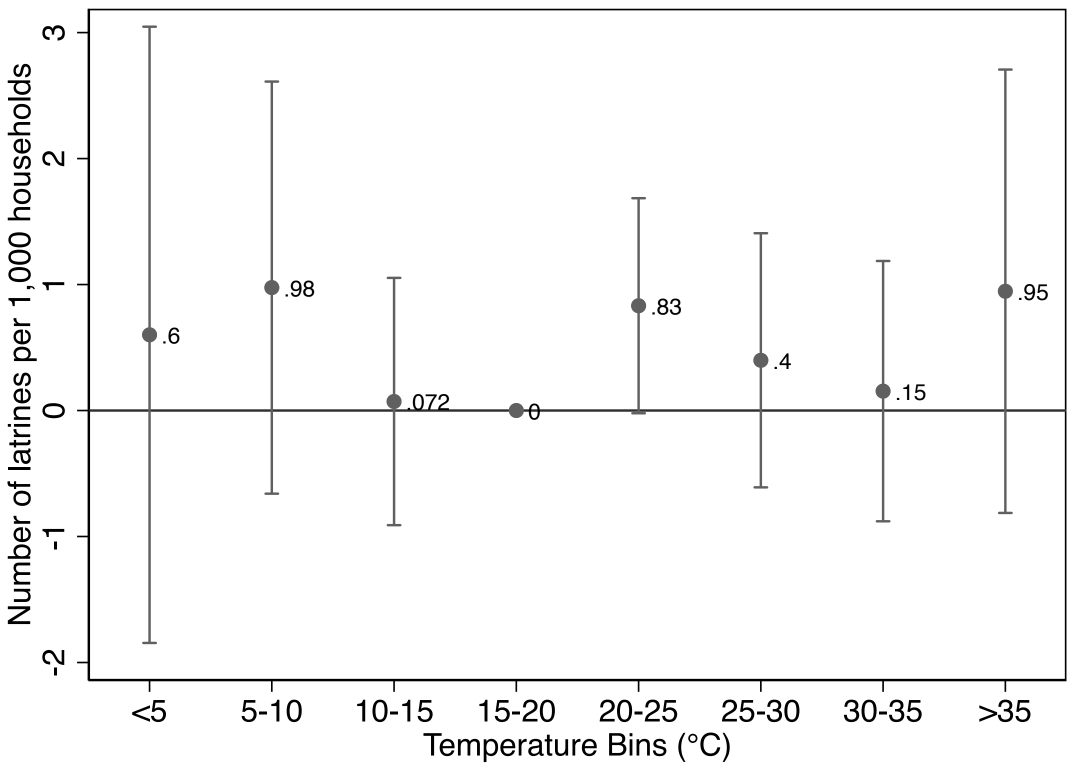


Figure B1: The Contemporaneous Effect of Temperature on Latrine Investment

Notes: This figure plots the estimated contemporaneous effect of temperature on latrine investment, when lagged temperatures are not 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.

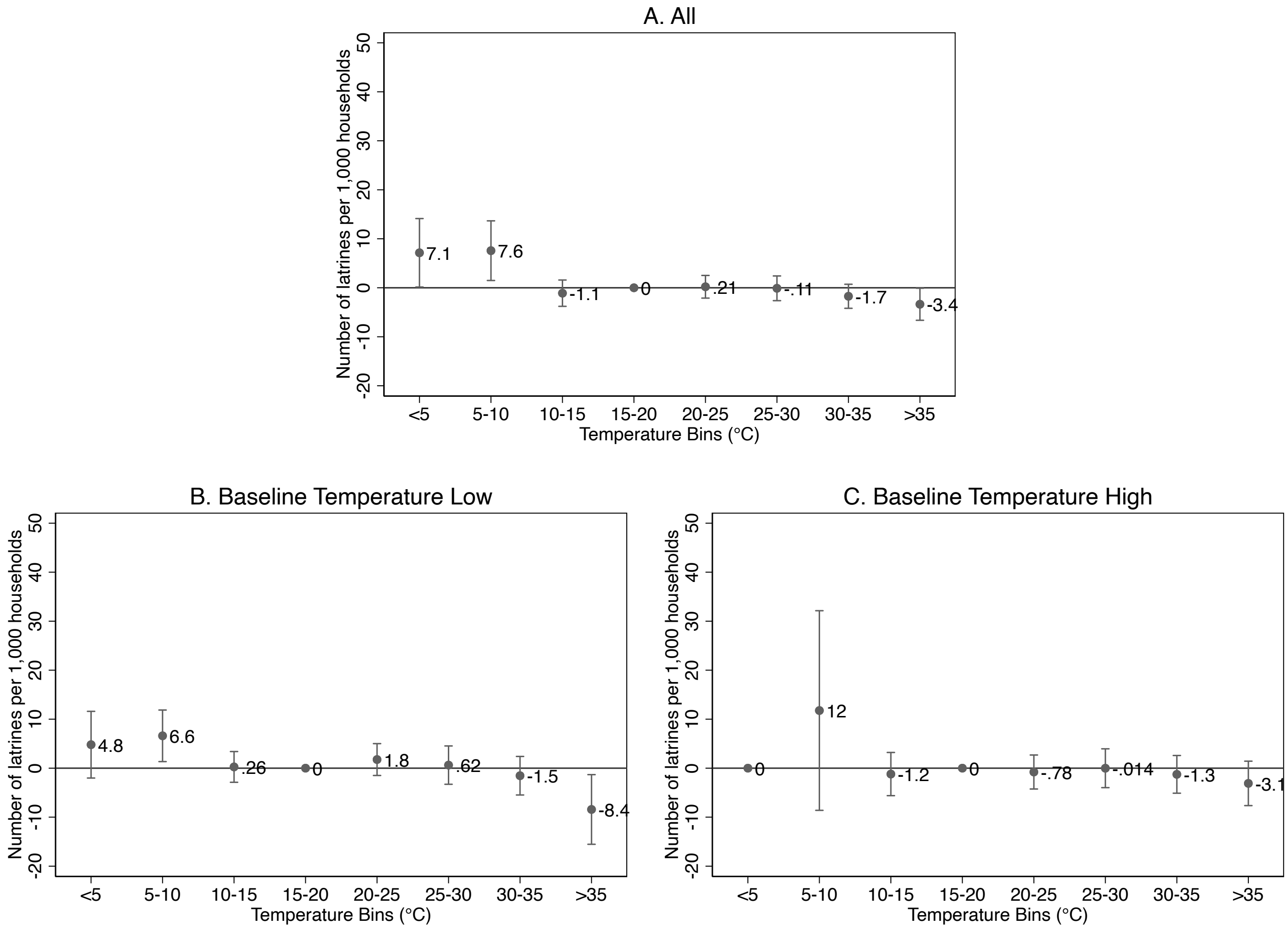


Figure B2: The Cumulative Effects of Temperature on Latrine Investment (Prior to 2016)

Notes: This figure plots the estimated effects of temperature on latrine investment during the period prior to 2016. 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, representing the total of contemporaneous and lagged effects, when including up to three years of lagged temperatures. 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.

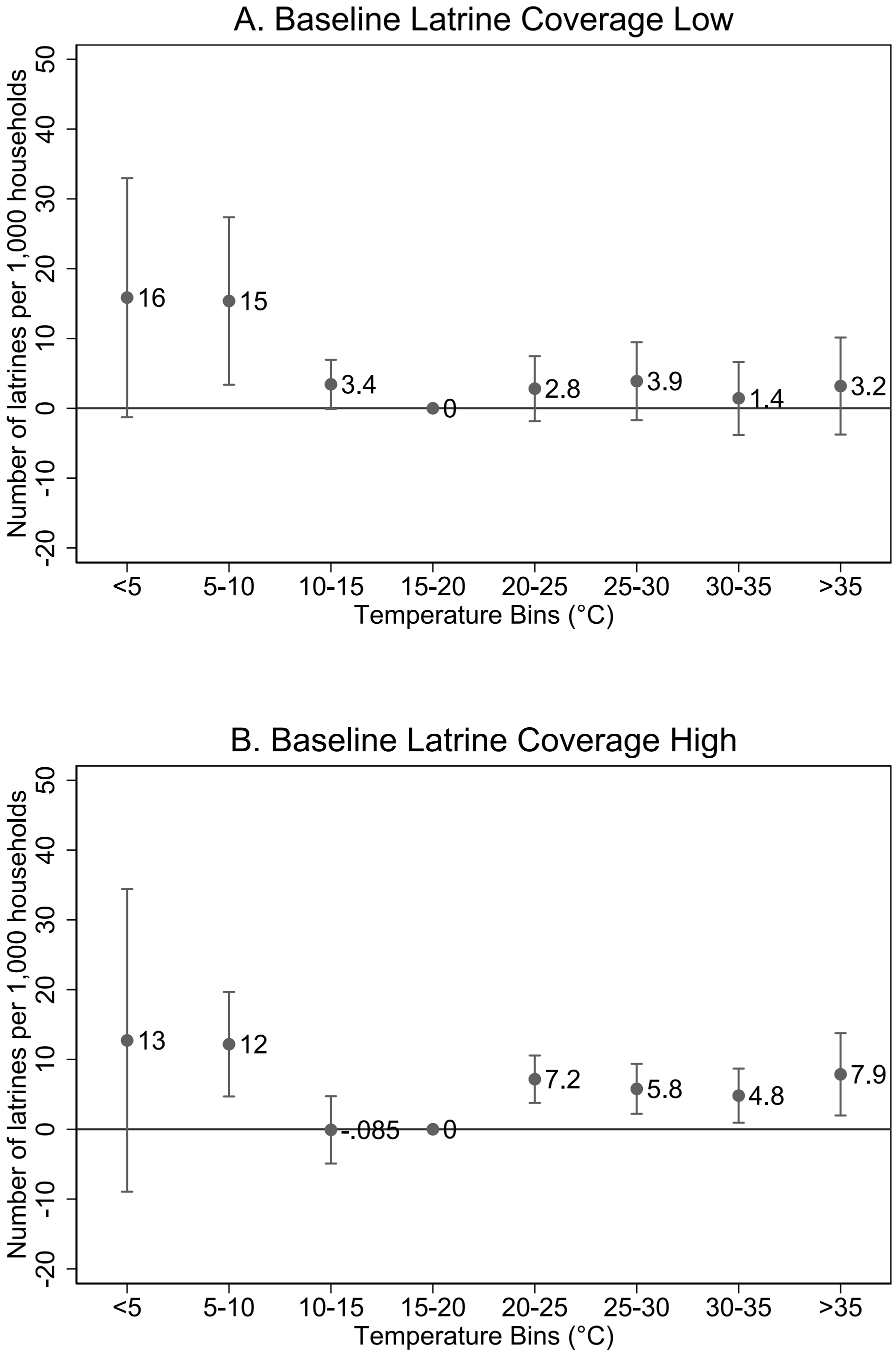


Figure B3: The Heterogeneous Effects of Temperature on Latrine Investment by Baseline Latrine Coverage

Notes: This figure plots the estimated effects of temperature on latrine investment. 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, representing the total of contemporaneous and lagged effects, when including up to three years of lagged temperatures. Panel A shows the estimated effects in districts with baseline latrine coverage lower than the sample median, while Panel B shows the estimated effects in districts with higher baseline latrine coverage.

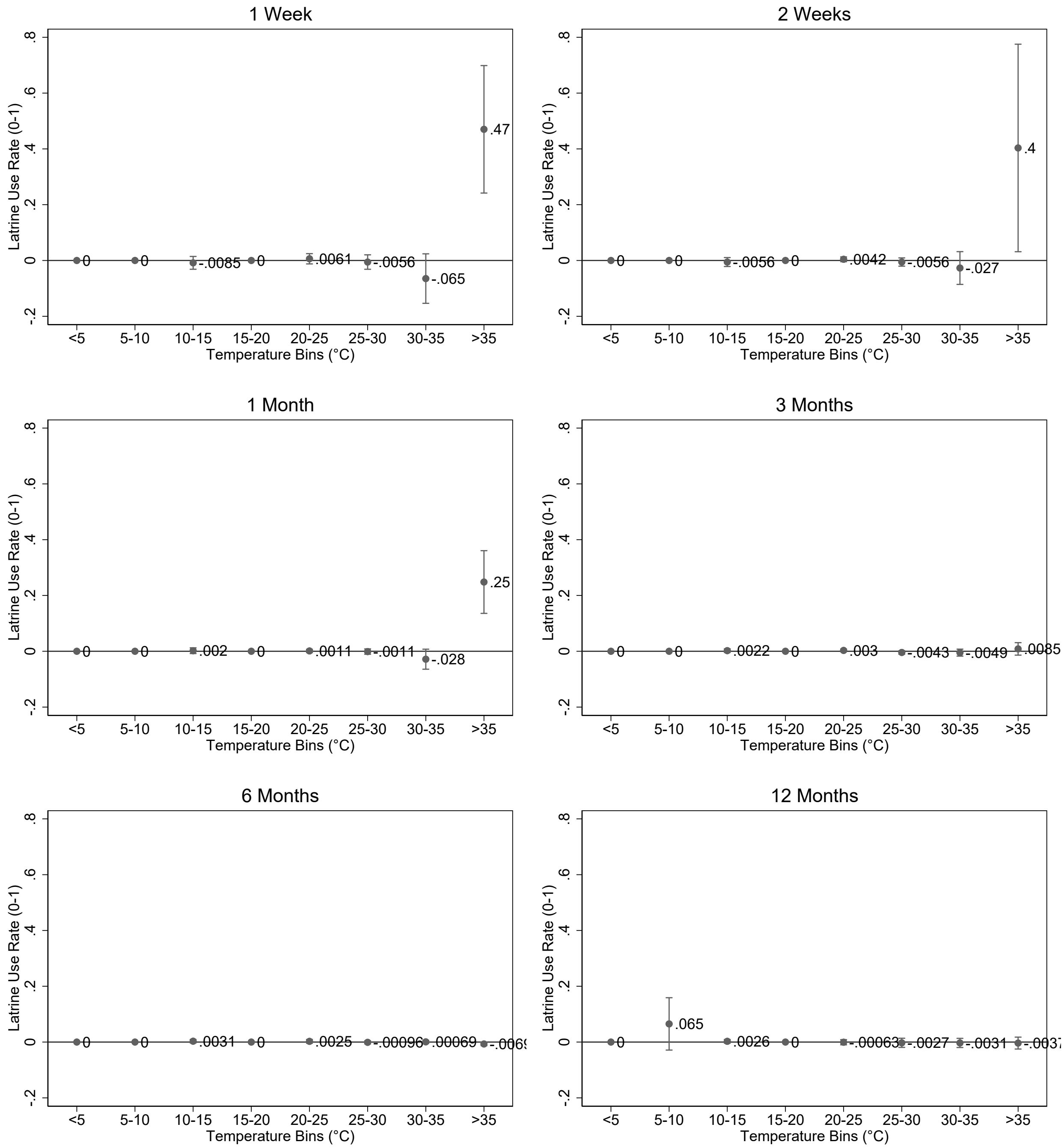


Figure B4: The Effects of Temperature on Latrine Use (Unconditional on Ownership)

Notes: This figure plots the estimated effect of temperature on latrine use rates for all households, irrespective of toilet ownership status, for different reference periods. 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.

C Additional Tables

Table C1: The Cumulative Effects of Temperature on Latrine Investment (Number of Latrines per 1,000 Households) with Different Number of Lags

	Maximum 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 maximum number of lags (years). The 15-20°C bin serves as a reference bin and is dropped from the regression. All columns show the cumulative effects, representing the total of contemporaneous and lagged effects. Standard errors, clustered at the district level, are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. The means of dependent variables are calculated for the pre-SBM period (2012-2013).

Table C2: The Effect of Temperature on Latrine Use (Unconditional on Ownership)

	Latrine Use Rate Unconditional on Ownership (0-1)					
	(1) 1 Week	(2) 2 Weeks	(3) 1 Month	(4) 3 Months	(5) 6 Months	(6) 12 Months
Number of days below 5°C	-	-	-	-	-	-
	-	-	-	-	-	-
Number of days 5-10°C	-	-	-	-	-	0.065
	-	-	-	-	-	(0.047)
Number of days 10-15°C	-0.008	-0.006	0.002	0.002	0.003	0.003
	(0.012)	(0.008)	(0.005)	(0.003)	(0.003)	(0.003)
Number of days 20-25°C	0.006	0.004	0.001	0.003	0.003	-0.001
	(0.009)	(0.004)	(0.003)	(0.003)	(0.003)	(0.005)
Number of days 25-30°C	-0.006	-0.006	-0.001	-0.004	-0.001	-0.003
	(0.013)	(0.007)	(0.005)	(0.003)	(0.003)	(0.008)
Number of days 30-35°C	-0.065	-0.027	-0.028	-0.005	0.001	-0.003
	(0.045)	(0.030)	(0.018)	(0.006)	(0.003)	(0.008)
Number of days above 35°C	0.470***	0.403**	0.248***	0.009	-0.007**	-0.004
	(0.115)	(0.188)	(0.057)	(0.011)	(0.003)	(0.011)
Observations	2,376	2,376	2,376	2,376	2,376	2,376
R^2	0.297	0.296	0.298	0.298	0.296	0.296
Number of Households	120	120	120	120	120	120
Number of Villages	120	120	120	120	120	120
Mean of Dep. Variable	0.322	0.322	0.322	0.322	0.322	0.322

Notes: This table reports the estimated effects of temperature on latrine use rates for different reference periods. 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. The means of dependent variables are calculated using the first survey round in 2013-2014.