

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

Kazuki Motohashi*

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Abstract

Extreme temperatures are known to negatively affect health in the short term, yet their persistent effects remain underexplored. This paper examines how extreme temperatures encourage adaptive investments in health technologies over time. Using data on temperature and latrine construction in rural India, I find that an additional cold or hot day cumulatively increases latrine investment by 1-10%. Heterogeneity analyses highlight the discomfort channel, where households construct latrines to avoid walking outside for open defecation under extreme temperatures. The health benefits from this increased latrine investment are comparable in magnitude to existing estimates of the negative impacts of extreme temperatures.

JEL: I15, O13, Q54, Q56

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* Graduate School of Economics, Hitotsubashi University. Email: kazuki.motohashi@r.hit-u.ac.jp. For helpful comments, I thank Britta Augsburg, Alison Campion, Ujjayant Chakravorty, Yuxian Chen, Kyle Emmerick, Thanh Tam Ho, Marc Jeuland, Yuya Kudo, Motohiro Kumagai, Etienne Makdissi, Yohei Mitani, Adam Storeygard, Shinsuke Tanaka, and Dongqin Wang; the seminar participants at Tufts University, Kyoto University, and Hitotsubashi University; the conference participants at 2023 WASH Economics Conference, 2023 AERE Summer Conference, 2023 SEEPS Annual Conference, 6th JADE Conference, and JADE/J-TREE Joint Workshop. I thank Jingcheng Jiang for great research assistance. This study is supported by Grants-in-Aid for Scientific Research from the Japan Society for the Promotion of Science (grant JP24K16353). I am grateful to the r.i.c.e. for sharing their data on Rural Sanitation Surveys.

1 Introduction

Policymakers and researchers increasingly recognize the significant negative impact of climate change on human welfare. Climate change increases the frequency of extreme weather events, which in turn reduce human welfare both directly, by increasing mortality (e.g., Deschênes and Greenstone, 2011), and indirectly by reducing agricultural productivity (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 investments in indoor health technologies by discouraging outdoor health behaviors that entail greater discomfort under extreme temperatures. When these outdoor behaviors pose risks to health, weather-induced investments in indoor health technologies can ultimately improve health over time through sustained usage. This focus on the persistent positive effect, driven by adaptive health investments, offers a new perspective that differs from growing studies emphasizing persistent negative effects.¹

This paper examines the persistent effect of extreme temperatures on health investment by investigating the case of sanitation behaviors, that is, the construction of latrines, which are used as durable goods over time. Extreme temperatures can affect a household’s decision of whether to construct latrines or maintain open defecation practices in two opposing ways.

First, extreme temperatures can have a positive effect on latrine investment by increasing the discomfort associated with open defecation (discomfort channel). Open defecation requires people to walk outside to a place far from home, and extreme temperatures can intensify the discomfort of this outdoor behavior. The heightened discomfort under extreme temperatures may discourage people from open defecation, thereby motivating them to invest in latrines as a means of adaptation.

Conversely, extreme temperatures, particularly extremely high temperatures, can have a negative effect on latrine investment by reducing income (income channel). Extreme heat has been shown to negatively affect income by reducing agricultural productivity (Burgess et al., 2017; Colmer, 2021). This reduction in income can exacerbate financial constraints, making it more difficult for households to afford latrine construction, thus discouraging this form of health investment.

This paper empirically examines which of these two channels—the discomfort or the income channel—dominates. If the positive effect through the discomfort channel dominates,

¹A limited number of studies have examined the persistent effects of weather shocks, primarily highlighting their negative impacts on economic growth (Dell et al., 2012; Foreman, 2020) and educational attainment (Park, 2020).

constructed latrines continue to be used as durable goods over time, leading to a persistent effect on health investment.

I examine the temperature-induced 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 in rural areas up to about 150 US dollars, which covers most of the initial cost of basic latrines. In this study context, the discomfort channel is expected to be more influential than the income channel, which is attenuated by the subsidy. My empirical analysis uses administrative data on the district-level number of latrines under the SBM, alongside raster data on daily temperature and rainfall from 2012 to 2019.

To examine the causal effect of temperature on latrine investment, 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 regression specification, I test whether cumulative effects, defined as the sum of contemporaneous effects and lagged effects, are statistically different from zero.

I find that both low and high temperatures increase latrine investment, and this positive effect persists over multiple years. Specifically, an additional cold day with an average temperature below 5°C (or 5-10°C) leads to an increase in latrine investment by 26.8 (or 20.3) per 1,000 households, relative to a day in the 15-20°C reference range (moderate temperatures), over a three-year period. This cumulative effect amounts to a 10% (or 7.6%) increase in latrine investment from the pre-SBM period. Conversely, I find smaller positive effects of higher temperatures, as the negative effect of the income channel can offset the positive effect of the discomfort channel. For example, an additional hot day with an average temperature of 25-30°C or 20-25°C results in an increase of 3.4 or 5.4 latrines per 1,000 households (a 1.3% or 2.0% increase), respectively. The effects become imprecise for temperatures exceeding 30°C, as these are more susceptible to the negative effect of the income channel. Overall, the positive cumulative effects, observed across most temperature bins, suggest that the discomfort channel dominates the income channel, with these effects persisting over time.

A variety of robustness checks corroborate my findings on the positive and persistent effects of extreme temperatures on latrine investment. Specifically, the results are robust to multiple checks, including changes in the number of lagged years in the distributed lag model, a placebo test examining the contemporaneous effect, addressing potential measurement

errors in the outcome, and accounting for baseline latrine coverage that may affect subsequent latrine construction.

Further heterogeneity and temperature deviation analyses highlight the discomfort channel as a key underlying mechanism. A heterogeneity analysis by baseline temperatures shows that the positive effects of high temperatures on latrine investment are more pronounced in districts with lower baseline temperatures, but not in those with higher ones. These differential effects align with the discomfort channel, which suggests that individuals in colder climates are less adapted to high temperatures and, therefore, invest in latrines to mitigate the greater discomfort caused by heat. An alternative specification using temperature deviations from historical means—standardized temperature shocks that better capture the variations in discomfort—also demonstrates positive effects on latrine investment, consistent with the baseline findings. Moreover, another heterogeneity analysis by baseline crop areas shows that the positive effects of higher temperatures are less pronounced in districts with larger crop areas, whereas low temperatures show no differential effects. This pattern suggests that the negative effect of the income channel offsets the positive effect of the discomfort channel, particularly in the case of high temperatures.

Conversely, I find that extreme temperatures generally do not impact the extent of latrine use at the intensive margin following construction, with the exception of very high temperatures. To examine the effect of temperature on latrine use conditional on ownership, I use a household-level panel dataset from 120 villages across four Indian states, where open defecation is widely prevalent, over two survey rounds conducted in 2013-2014 and 2018 (Coffey et al., 2014; Gupta et al., 2019). I find that, across most temperature ranges, temperature does not influence the proportion of household members using latrines at the intensive margin, whether measured over periods as short as a week or as long as a year. This is likely due to the high baseline latrine use rate, which averages 79%, as well as the infrequent occurrence of cold days and the population’s adaptation to high temperatures in these predominantly hot states. However, I find that extremely hot days (above 35°C) increase latrine use in the short run, ranging from one week to one month, suggesting the discomfort channel also plays a role in driving latrine use at the intensive margin.

Taken together, my analysis highlights that extreme temperatures can encourage adaptive investment in health technologies by increasing the discomfort of outdoor behaviors, which ultimately improves human health. Temperature-induced latrine investment can have long-lasting health benefits, including a reduction in diarrheal mortality rates 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% through increasing latrine investment. These health benefits are comparable in magnitude to the negative health

impacts of extreme temperatures found in previous studies like Burgess et al. (2017).

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: adaptive investments in health 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 through capital depreciation (Dell et al., 2012; Foreman, 2020) and educational attainment, where lower exam performance affects subsequent graduation outcomes (Park, 2020). I complement these studies on growth effects by showing that weather shocks can persistently improve health through another mechanism: inducing behavioral changes away from outdoor behaviors that are harmful to human health and towards the adoption of health-improving durable goods that are used indoors.

Second, I contribute to the literature on technology adoption in developing countries by showing that weather can be another major determinant in technology adoption. In these countries, outdoor health behaviors, including open defecation (Cameron et al., 2022), the collection of unsafe water (Kremer et al., 2011), and the collection and usage of biomass for cooking (Hanna et al., 2016), are widespread. These outdoor behaviors are closely linked to water and air pollution, leading to significant health risks for households with limited coping measures. Past studies have shown that interventions like subsidies and information campaigns (Yishay et al., 2017; Lipscomb and Schechter, 2018; Cameron et al., 2021; Berkouwer and Dean, 2022) can encourage the adoption of health-improving technologies, thereby reducing the dependence on these harmful outdoor behaviors. I complement these studies by showing that weather shocks are another important determinant of health technology adoption, which can, in turn, 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 have shown that consumers are over-influenced by the weather at the time of purchase in their choices of goods, including cold weather items and cars, in developed countries (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 would 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 yearly 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.

The remainder of this paper is organized as follows. Section 2 discusses the relationship between temperature and sanitation behaviors, as well as the study setting in rural India. Sections 3 and 4 describe my data and empirical strategy, respectively. Section 5 and Section 6 present the results and underlying mechanisms of the effects of temperatures on latrine investment, respectively. Section 7 examines the intensive-margin effect on latrine use. Finally, Section 8 concludes the paper.

2 Temperature and Sanitation Behaviors in India

I present two possible channels through which temperatures can affect sanitation behaviors. I then examine the applicability of these channels within the context of this paper, which focuses on a nationwide sanitation policy called the Swachh Bharat Mission in rural India.

2.1 Temperature and Sanitation Behaviors

Extreme temperatures can have two opposing effects on sanitation behaviors: (i) a positive effect through the discomfort channel and (ii) a negative effect through the income channel.²

First, extreme temperatures can have a positive effect on latrine investment and use by increasing the discomfort associated with open defecation (discomfort channel). Open defecation requires people to walk outside to a place far from home, and extreme temperatures can intensify the discomfort of this outdoor behavior. The heightened discomfort under extreme temperatures may discourage people from open defecation, thereby motivating them to construct and use latrines as a means of adaptation. 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.

Conversely, extreme temperatures, particularly extremely high temperatures, can have a negative effect on latrine investment and use by reducing income (income channel). Extreme heat has been shown to negatively affect income by reducing agricultural productivity (Burgess et al., 2017; Colmer, 2021). This reduction in income can exacerbate financial

² Alternative channels related to construction feasibility and government relief are discussed in Section 6.3. This section focuses on the two primary channels examined in this paper.

constraints, making it more difficult for households to afford latrine construction, thus discouraging this form of health investment. The reduced income can also negatively affect latrine use by making it harder to cover maintenance costs, including hiring tankers and laborers to regularly empty pits and septic tanks. These two channels with opposing effects are formally presented in the conceptual framework in Appendix A.

My empirical analyses in Sections 4 and 5 capture the net effect of the discomfort and income channels. The sign of this effect indicates which of the two channels is dominant: a positive (negative) net effect suggests that the discomfort (income) channel is more significant. Additionally, I conduct heterogeneity analyses in Section 6 to further investigate the presence of both channels.

2.2 Study Setting: The Swachh Bharat Mission in India

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. In this study context, the discomfort channel is expected to be more influential than the income channel, which is attenuated by the subsidy.

The SBM provided substantial subsidies for latrine construction to eliminate open defecation in rural India. Historically, a large number of people in India have practiced open defecation, which has negatively impacted child health by increasing the incidence of diarrheal diseases and mortality. To address this issue and improve human health, the Indian government launched the SBM in 2014, offering subsidies for latrine construction post-verification in rural areas. The subsidy amount is up to approximately 150 US dollars (12,000 INR) per household, covering most of the initial costs of basic latrines in rural India. This generous policy has resulted in the construction of over 100 million household latrines.

This context of the SBM suggests that the negative effect of extreme temperatures via the income channel is limited. The subsidy provided under the SBM relaxes financial constraints for latrine construction, thereby diminishing the influence of the income channel.³ Therefore, I expect that the discomfort channel dominates the income channel, leading to a net positive effect of extreme temperatures on latrine investment.

Another implication of the SBM context is that my analysis examines whether areas experiencing more extreme temperatures see a greater increase in the number of latrines. While the SBM has led to an overall increase in latrine construction across rural India, the magnitude of this increase may vary according to the different levels of exposure to extreme temperatures across districts.

³ The SBM subsidy is provided to households after the verification of constructed latrines, so credit constraints may still be relevant.

3 Data

To examine the effect of temperature on latrine investment, I use administrative data on the district-level number of latrines under the SBM, alongside raster data on daily temperature and rainfall 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.

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 (2024). Based on this dataset, I compute the number of latrines per 1,000 households per year by using the baseline number of households in each district.

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. Thus, 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. Therefore, I conduct a robustness check in Section 5.2, where 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) from 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 is widely prevalent.

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.⁴ 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.⁵

⁴ The SQUAT survey asked about a usual practice of defecation (open defecation or latrine use).

⁵ 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

I also use the village-level GPS coordinates rounded to the nearest 0.25 degree to match this SQUAT dataset with the weather data.⁶ 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 on the 2011 district boundaries.⁷

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.

survey.

⁶ 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.

⁷ I deal with the changes in the district boundary by ensuring that all data are organized according to the 2011 boundary, which follows Motohashi (2024). Latrine data based on the 2019 boundary are aggregated to follow the 2011 boundary by considering the district splits from 2011 to 2019.

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

4 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.⁸ I test the persistence of this effect by estimating the cumulative effect in the distributed-lag model, where I include lagged temperatures.

Specifically, I adopt the following two-way fixed effects specification:

$$Latrine_{dt} = \sum_l \sum_j \beta_{jl}^{INV} BinTemp_{dtjl} + \sum_l \sum_k \delta_{kl}^{INV} DecileRain_{dtkl} + \eta_d + \nu_{st} + \varepsilon_{dt} \quad (1)$$

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 j th bin in district d in l years prior to year t . $DecileRain_{dtkl}$ denotes the number of days in which rainfall is in the k th decile in district d in l years prior to year t . This rainfall variable is included as a control to account for the potential confounding effects of rainfall, enabling a clearer focus on the temperature's impact while accounting for any influence rainfall might have. 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 $BinTemp_{dtjl}$ as follows: $<5^\circ\text{C}$, $5\text{--}10^\circ\text{C}$, $10\text{--}15^\circ\text{C}$, $15\text{--}20^\circ\text{C}$, $20\text{--}25^\circ\text{C}$, $25\text{--}30^\circ\text{C}$, $30\text{--}35^\circ\text{C}$, and $>35^\circ\text{C}$. These bins are used to estimate the nonlinear latrine-temperature relationship in a flexible way, as well as to ensure precise estimates based on a sufficient number of observed days in each bin. The $15\text{--}20^\circ\text{C}$ bin, representing moderate temperatures, serves as a reference bin and is dropped from the regression. Thus, the coefficient for each temperature bin j (β_{jl}^{INV}) captures the effect of an additional cold or hot day in bin j on the number of latrines per 1,000 households, relative to a day in the $15\text{--}20^\circ\text{C}$ 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 iden-

⁸ This approach that uses temporal variations in temperature aligns with the methodology adopted in Deschênes and Greenstone (2011).

tified 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 coefficients β_{jl}^{INV} can have a causal interpretation.

To estimate the persistence of the effect of temperature on latrine investment, I use a distributed-lag model that includes 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 5.2.

The coefficients of interest are β_{jl}^{INV} , which determine which of the two main channels is dominant. If the cumulative effect derived from the β_{jl}^{INV} is statistically significantly positive, this would suggest that the discomfort channel is the primary mechanism at play. Furthermore, it would indicate that the effect of temperature on latrine investment persists over multiple years.

5 Results

5.1 Baseline Results

I find that both low and high temperatures increase latrine investment, and this positive effect persists over multiple years.

In Figure 2 and Table 2, I find the U-shaped cumulative latrine-temperature relationship, with a steeper slope in the low temperature bins. An additional cold day with an average temperature below 5°C or of 5-10°C leads to an increase in the number of latrines by 26.8 or 20.3 per 1,000 households, relative to a day in the 15-20°C range, over a three-year period (Panel A of Figure 2 and column 1 of Table 2). This cumulative effect amounts to a 10% or 7.6% increase in latrine investment from the pre-SBM period.⁹ Conversely, I find smaller positive effects of higher temperatures on latrine investment. For example, an additional hot day with an average temperature of 25-30°C or 20-25°C results in an increase of 3.4 or 5.4 latrines per 1,000 households (a 1.3% or 2.0% increase), respectively.

⁹ 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.

The larger effects of lower temperatures are consistent with the discomfort channel. People living in rural India are generally less adapted to lower temperatures compared to higher ones, as the country typically experiences a hot climate on average, with daily average temperatures highly concentrated in the 25-30°C range (Panel A of Figure 1). Consequently, the discomfort of walking outside for open defecation is more heightened in lower temperatures, which may drive a stronger motivation to invest in latrines.

Another factor contributing to the larger effects of lower temperatures could be the income channel. The negative effect of temperature on agricultural output has been shown to be concentrated in the case of high temperatures (Burgess et al., 2017; Colmer, 2021). This negative effect of the income channel on latrine investment can offset the positive effect of the discomfort channel, thereby making the positive effects of higher temperatures smaller. The positive effects on latrine investment even become insignificant at very high temperatures exceeding 30°C, where the negative income effects are expected to be more pronounced, as shown in Panel A of Figure 2. A more detailed examination of the income channel is presented in Section 6.2.

The positive cumulative effect over a three-year period shows that temperature shocks have a persistent effect on latrine investment over multiple years. Reassuringly, Panel B of Figure 2 shows that most estimates of contemporaneous and lagged temperature bins, which are used to calculate the cumulative effect, are consistently positive.¹⁰ This persistence of the effect can be attributed to the fact that constructed latrines, in response to extreme temperatures, continue to be used over multiple years as durable goods. While the baseline specification shows a persistent effect over a three-year period, I find that this persistence extends up to 10 years, especially in lower temperature bins, as detailed in Section 5.2.

5.2 Robustness Checks

The results are robust to multiple checks, including changes in the number of lagged years in the distributed lag model, a placebo test examining the contemporaneous effect, addressing potential measurement errors in the outcome, and accounting for baseline latrine coverage that may 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 D2, I find that the estimated cumulative

¹⁰ All estimates and standard errors for the results shown in Panel B of Figure 2 can be found in Appendix Table D1.

effects are consistently positive regardless of the number of lagged years, especially in lower temperature ranges.

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, and the magnitudes of the effects are small across most temperature bins when lagged temperatures are excluded from the regression (Appendix Figure C1).

Measurement Errors in the Outcome.—As discussed in Section 3.1, the number of latrines reported in the administrative dataset of the SBM is unlikely to be susceptible to measurement errors, at least until 2016. Therefore, I conduct a robustness check by estimating the baseline specification using observations only prior to 2016.

In Appendix Figure C2, I find that the cumulative effect is still statistically significant and positive prior to 2016, especially in low 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 as the deadline for universal latrine coverage by 2019 approached. Thus, 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 conduct a heterogeneous analysis by comparing the effects of temperature in districts with higher pre-SBM baseline coverage than the sample median (measured in 2013) to those in districts with lower pre-SBM baseline coverage.

As shown in Appendix Figure C3, 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.

6 Mechanisms

Heterogeneity and temperature deviation analyses highlight the discomfort channel as a primary underlying mechanism, rather than the income channel or other alternative explanations.

6.1 Mechanism 1: 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, as well as conduct an alternative analysis using temperature deviations from historical means.

Heterogeneity Analysis by Baseline Temperatures.—I conduct a heterogeneity analysis, comparing effects in districts that have higher baseline temperatures than the sample median (25.7°C) during the pre-sample period (2002-2011) with those that have lower baseline temperatures. The discomfort channel suggests that people feel larger discomfort from walking outside for open defecation when exposed to temperatures they are less adapted to. For example, people living in districts with a lower baseline temperature could be more sensitive to high temperature shocks than people living in districts with a higher baseline temperature. Therefore, in these cooler districts, high temperature shocks are expected to cause a larger increase in latrine investment than low temperature shocks. Conversely, districts with a higher baseline temperature are expected to experience a larger increase in latrine investment with low temperature shocks.

As the discomfort channel suggests, I find that the positive effects of higher temperatures on latrine investment are more pronounced in districts with lower baseline temperatures, but not in those with higher ones. Specifically, as shown in Figure 4 and column 2 of Table 2, an additional day of higher temperatures leads to an increase in the number of latrines per 1,000 households by 8.2-9.8 (2.5-2.9% increase), relative to a day in the 15-20°C range. However, in districts with higher baseline temperatures, the effect of higher temperatures becomes insignificant (column 3 of Table 2), which suggests that people in these districts are better adapted to higher temperatures.

I also find that lower temperatures lead to increased latrine investment, particularly in districts with lower baseline temperatures (Figure 4 and columns 2 and 3 of Table 2). This

positive effect can be explained by the fact that, although these districts are classified as having lower baseline temperatures, they still experience relatively hot climates given the high cutoff temperature of 25.7°C. Consequently, cold days in these areas can also heighten discomfort, prompting a greater investment in latrines. In contrast, in districts with higher baseline temperatures, the effects become less precise, likely due to the limited occurrence of days in the lower temperature bins (as illustrated in Panel A of Figure 1). Despite the imprecise effects, the positive coefficients suggest that the lower temperatures may still have a positive effect on latrine investment in these areas.

Temperature Deviation Analysis.—One limitation of the heterogeneity analysis by baseline temperatures is the use of a fixed reference temperature range of 15-20°C. This approach may not capture the actual variation in discomfort across different districts, as it assumes a uniform reference range that may not reflect local climatic conditions. When a district’s baseline temperature deviates significantly from this fixed range, the actual discomfort experienced may be inaccurately represented.

To overcome this limitation, I conduct an alternative analysis that adjusts the reference bin based on each district’s specific baseline temperatures. This analysis involves using standardized temperature shocks relative to historical means, providing a more consistent measure of discomfort across districts. Specifically, for each day and district, I calculate how many standard deviations (SDs) a given temperature observation deviates from the historical mean, as follows:

$$TempDev_{dt} = \frac{Temp_{dt} - \overline{HistTemp_d}}{\sigma_d} \quad (2)$$

where $Temp_{dt}$ is the average temperature in district d in day t , $\overline{HistTemp_d}$ is the historical mean temperature in district d during the pre-study period (from 2002 to 2011), and σ_d is the historical standard deviation of temperatures in district d .

I construct the treatment variables by counting the number of days in which the $TempDev_{dt}$ falls into seven SD bins: < -1.5 , $[-1.5, -1]$, $[-1, -0.25]$, $[-0.25, 0.25]$, $[0.25, 1]$, $[1, 1.5]$, > 1.5 .¹¹ The reference bin is set to the $[-0.25, 0.25]$ SD range, which represents days with temperatures close to the historical average for each district. I then run the regression from the equation 2, using this number of days in each SD bin as the treatment variable (denoted as $BinTemp_{dtjl}$).¹²

¹¹ The distribution of temperature deviations from the historical mean across the seven SD bins is shown in Appendix Figure C4.

¹² One modification from the baseline specification is the exclusion of observations from 2012 to 2014, as lagged temperature deviation measures up to three years are unavailable for these years.

The temperature deviation analysis similarly shows the positive effects of extreme temperatures on latrine investment, particularly for lower temperatures. As shown in Figure 5, an additional day with a lower temperature more than 1 SD below the historical mean leads to an increase in the number of latrines by 5.9-15, relative to a day in the reference bin.¹³ This effect is comparable in magnitude to the results observed for lower temperatures (5-15°C) in the baseline specification. Although the effects become less precise for higher temperatures, I find their positive coefficients, with a U-shaped relationship between temperature and latrine investment. This result indicates that higher temperatures can also lead to increased latrine investments, though the magnitude of the positive effect may be reduced due to the income channel, as discussed in the following section.

6.2 Mechanism 2: Income Channel

Another mechanism behind the effects of temperature on latrine investment is the income channel. To test this channel, I conduct heterogeneity analyses by crop areas and agricultural seasons. These analyses suggest that, despite the overall positive effects of extreme temperatures, the negative effect of the income channel offsets the positive effect of the discomfort channel, particularly in the case of high temperatures.

As a test of the income channel related to agricultural production, I examine heterogeneous effects by crop areas.¹⁴ Specifically, I compare the effects of temperature in districts with larger crop areas than the sample mean to those with smaller crop areas in 2011, one year prior to the start of the sample period. The income channel, which reflects reduced income due to lower agricultural production under extreme temperatures, is expected to be more pronounced in districts with larger crop areas compared to those with smaller crop areas. Consequently, districts with larger crop areas are likely to experience smaller (or more negative) effects of temperature on latrine investment, as the negative income channel is expected to more strongly offset the positive effects of the discomfort channel. Moreover, the income channel is expected to be more pronounced for high temperatures, as previous studies have demonstrated that the negative effects of temperature on agricultural production are concentrated in higher temperature ranges (Deschênes and Greenstone, 2011; Colmer, 2021). Therefore, the overall impact of temperatures on latrine investment is expected to be smaller for higher temperatures, due to the more substantial negative effects of the income

¹³ All coefficients and standard errors for the results shown in Figure 5 can be found in Appendix Table D3.

¹⁴ Agricultural data for this analysis is sourced from the ICRISAT (International Crops Research Institute for the Semi-Arid Tropics) District Level Database. The district-level baseline crop area for 2011, which includes the total area cultivated with various crops, was calculated. After matching this data with my main dataset, the sample size was reduced from 609 districts to 524 districts for this heterogeneity analysis.

channel.

The heterogeneity analysis by crop areas shows that the positive effects of higher temperatures are less pronounced in districts with larger crop areas, whereas low temperatures show no differential effects. Both Figure 6 and Table 3 show that the cumulative effects on latrine investment are smaller in districts with larger crop areas in the high temperature ranges. Notably, the coefficients of the 30-35°C and above 35°C bins turn negative in these districts, while the effects are imprecise. Conversely, districts with smaller crop areas, which are less susceptible to the income channel, show predominantly positive and statistically significant effects of higher temperatures. This result suggests that the positive effect of the discomfort channel outweighs the small negative effect of the income channel in these areas. Additionally, consistent positive effects of low temperatures are observed across all districts, aligning with the expectation that the income channel plays a minimal role under lower temperature conditions.

Given that the income channel is likely influenced by extreme temperatures specifically during the agricultural growing season, I conduct another heterogeneity analysis by agricultural seasons. Extreme temperatures during the growing season are expected to have a more pronounced negative impact on latrine investments through the income channel, compared to the non-growing season. To explore this differential effect, I modify the treatment variables in equation 2 by counting the number of days in each temperature bin for both the growing and non-growing seasons.¹⁵ I then run a regression that includes treatment variables for both seasons simultaneously. In this analysis, I restrict the sample to districts with larger crop areas, as these areas are more susceptible to the income channel. The results from this analysis provide suggestive evidence that higher temperatures during the growing season lead to more substantial negative effects compared to the non-growing season (Appendix Figure C5). However, likely due to the reduced statistical power after segmenting the data by both crop areas and agricultural seasons, I do not find stark differences in the effects between the two agricultural seasons.

6.3 Alternative Explanations

I explore alternative explanations, such as construction feasibility and government relief interventions, but find that neither plays a significant role within the context of this study.

Construction Feasibility.—Extreme temperatures could negatively affect latrine invest-

¹⁵ In India, the primary agricultural season (*kharif*) runs from June to November, while the secondary agricultural season (*rabi*) runs from October to February. Accordingly, I define the growing season as June through February and the non-growing season as March through May, broadly following the definitions in Garg et al. (2020).

ment in the short term by causing delays and increasing construction costs. However, as discussed in the placebo test in Section 5.2, there is limited evidence to support a significant short-run contemporaneous effect. Moreover, the baseline results, which demonstrate a net positive effect, further indicate that construction feasibility, as a negative factor, is not a key mechanism at play.

Government Relief.—Another possible explanation is government intervention through relief efforts, where latrines could be constructed in response to extreme weather events like heat or cold waves. However, the Indian government’s relief guidelines for heat waves do not include latrine construction as part of their action plan (NDMA, 2019). As a result, this channel is unlikely to be relevant in the context of India.

7 Intensive-Margin Effect on Latrine Use

Extreme temperatures can affect not only latrine investment but also the extent of latrine use after construction at the intensive margin. To examine this effect, I use a household-level panel dataset that captures latrine use over time, exploiting temperature variations at the village level. I find that extreme temperatures generally do not impact the extent of latrine use at the intensive margin following construction, with the exception of very high temperatures.

7.1 Empirical Strategy

I exploit presumably random variation in village-level temperature across two survey rounds from 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 2.

$$LatrineUse_{hvtm} = \sum_j \beta_j^{USE} BinTemp_{jvtm} + \sum_k \delta_k^{USE} DecileRain_{kvtm} + \eta_v + \nu_t + \theta_m + \varepsilon_{hvtm} \quad (3)$$

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. $LatrineUse_{hvtm}$ represents the latrine use rate of household h in survey round t and month m . It is defined as the proportion of household members using latrines out of the total number of members in that household. $BinTemp_{jvtm}$ is the number of days in which the average temperature is in temperature bin j . I categorize temperature into eight bins, which is consistent with the specification of latrine investment, though the latrine use

specification uses 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., an 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, which may be driven by within-year weather fluctuations. Standard errors are clustered at the village level because the temperature variation is observed at that level. The coefficients of interest are β_j^{USE} , which capture 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.

In this analysis, I examine the effect of latrine use, conditional on latrine ownership, to isolate the impact at the intensive margin, without capturing the influence of latrine investment decisions. To do so, I restrict the sample to households that owned latrines during both survey periods. Specifically, the baseline specification focuses on 437 households from the total sample of 1,188 households.¹⁶

The treatment variable, $BinTemp_{jvtm}$, is constructed by counting the number of days that falls into temperature bin j within a specified reference period leading up to the survey date for household h . The SQUAT survey rounds were conducted over multiple months, resulting in variations in survey dates across households.¹⁷ For the treatment variable, I specifically use daily temperature data from X days prior to the survey date up to one day before. The reference periods (X) considered 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 vary from day to day. The outcome of the regression is the self-reported typical practice of latrine use. However, given the potential for recall bias, respondents may base their reports on more recent behaviors, influenced by recent temperature fluctuations. Thus, I use shorter reference periods (1 week, 2 weeks, and 1 month), where I expect the temperature effects to be more pronounced. As a robustness check, I also use longer reference periods (6 and 12 months), where I expect the effects to be less significant.

7.2 Results

I find that, across most temperature ranges, temperature does not influence the proportion of household members using latrines at the intensive margin. However, I find that extremely

¹⁶ As a robustness check, I also provide results on latrine use without conditioning on latrine ownership, using the entire sample.

¹⁷ The first-round survey was conducted between November 2013 and December 2014, and the second-round survey was conducted between August and December 2018 for households included in the final sample.

hot days increase latrine use in the short run, ranging from one week to one month, suggesting the discomfort channel also plays a role in driving latrine use at the intensive margin.

In Figure 7, I do not find a significant effect of temperature on latrine use rates conditional on latrine ownership across most temperature bins, regardless of the reference period used.¹⁸ This result, coupled with findings on latrine investment, shows that while extreme temperatures cumulatively increase latrine investment, they do not affect 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 (as shown in Table 1). With such a high baseline, the potential for further increases in use due to extreme temperatures is limited. Second, this result is specific to the four northern states in India included in the SQUAT dataset, which are known for their relatively hot climates. As discussed in Section 6.1, people in these states are expected to be better adapted to higher temperatures, meaning that hot days may have a limited impact on latrine use except during extreme heat events. Additionally, the hot climate challenges the estimation of the effects of cold days. The dataset lacks sufficient observations for lower temperature bins—below 5°C and between 5-10°C—across most reference periods, except for the 5-10°C bin for the 12-month reference period (as shown in Panel B of Figure 1). Consequently, I could not effectively test the effects of cold days, which are expected to have a more significant impact in hot climates.

However, I find that extremely hot days increase latrine use in the short run. Figure 7 shows the positive effects of temperatures above 35°C when adopting reference periods of 1 week, 2 weeks, or 1 month. Specifically, an additional hot day with average temperatures above 35°C leads to an increase in latrine use rate by 0.15-0.49 (19-62% from the baseline use rate), relative to a day in the 15-20°C range. This result suggests that discomfort from extreme heat also plays a role in driving increased latrine use at the intensive margin after construction.¹⁹

8 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

¹⁸ All coefficients and standard errors for the results shown in Figure 7 can be found in Appendix Table D4. Similar findings are observed when analyzing the full sample of households without conditioning on latrine ownership, as shown in Appendix Figure C6.

¹⁹ Conversely, the income channel is expected to have limited short-term effects for up to one month, as the costs associated with emptying latrines are only incurred every few years.

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 substantial health gains that are comparable to the health damages estimated in previous studies. My results suggest the potential reduction in diarrheal child mortality due to extreme temperatures, which is driven by increased latrine investment. Thus, I calculate this positive health effect by multiplying the effect of temperature on latrine investment, as estimated in this paper, with the effect of latrine construction on the diarrheal mortality rate in rural India, as reported in Motohashi (2024).²⁰ This back-of-the-envelope calculation shows that an additional cold or hot day could decrease diarrheal post-neonatal mortality rate by 0.12-0.90%.²¹ The magnitude of this positive effect is comparable to the negative health impacts of extreme temperatures found in previous studies, such as Burgess et al. (2017), which reported that an additional hot day increased all-age mortality in rural India by 0.21-0.47% during the period 1957-2000, before widespread sanitation investments. This result suggests that the health impact of extreme temperatures is more nuanced than previously thought, as it may not always be negative when accounting for adaptive health investments.

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 outdoor behaviors that are harmful to human health (e.g., open defecation) into health-improving behaviors (e.g., latrine investment) 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

²⁰ Specifically, I use the estimates from column 1 of Table 2 in this paper, along with the estimated effect from Motohashi (2024), which shows that an additional latrine per square kilometer reduces the diarrheal post-neonatal mortality rate by 0.43%. More detailed steps are described in Appendix B.

²¹ More concretely, I find that an additionally with an average temperature of below 5°C, 5-10°C, 10-15°C, 20-25°C, and 25-30°C could decrease the diarrheal post-neonatal mortality rate by 0.90%, 0.68%, 0.15%, 0.18%, and 0.12%, respectively.

be aware of this risk of unintended negative consequences of climate change mitigation.

Second, my findings on adaptive investments in sanitation technologies, driven by extreme temperatures, also have implications for a range of outdoor 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 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 the outdoor collection. Investigating the potential health benefits of extreme temperatures in different settings may be a fruitful area for future research.

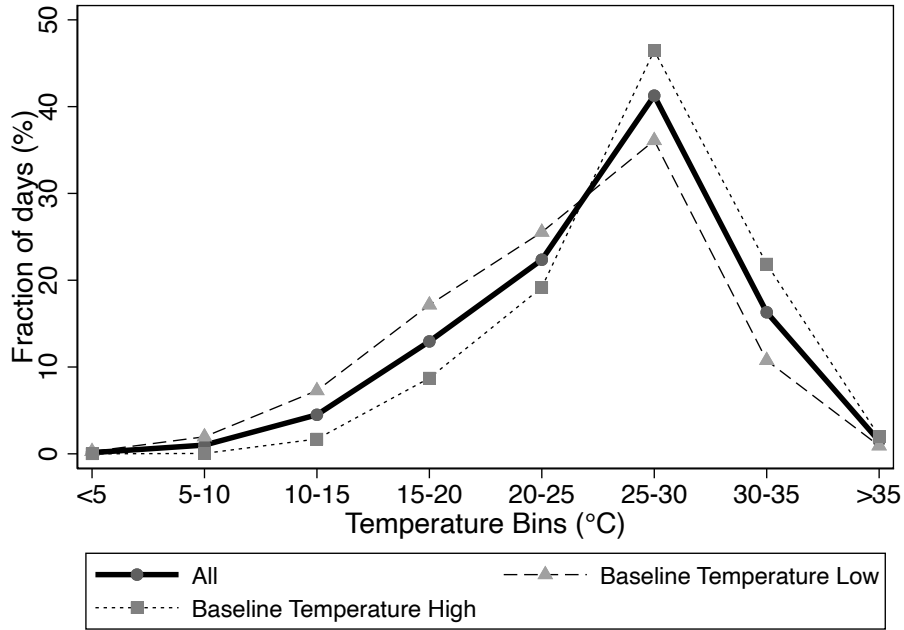
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Panel A. Latrine Investment Analysis



Panel B. Latrine Use Analysis

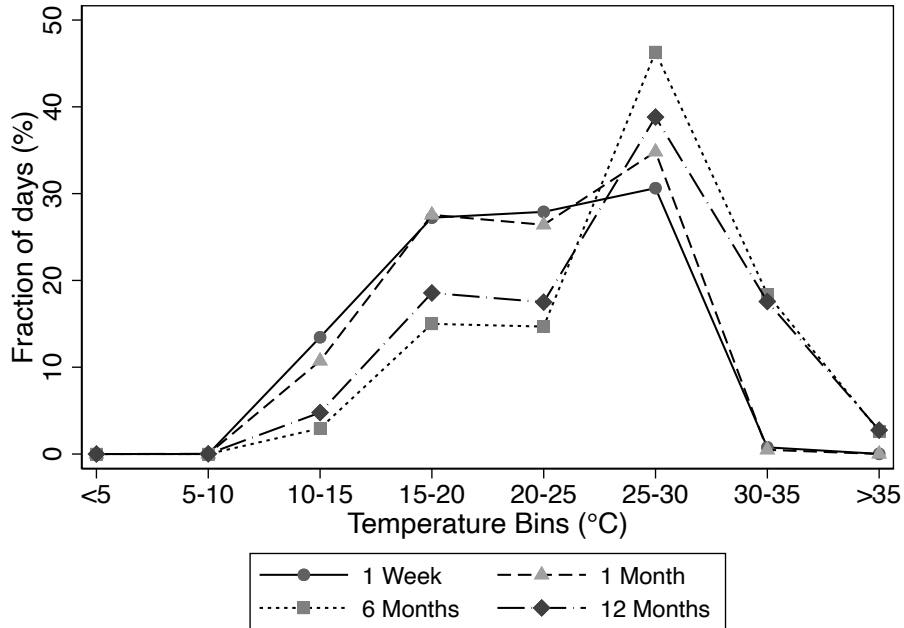


Figure 1: Daily Temperature Distributions

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.

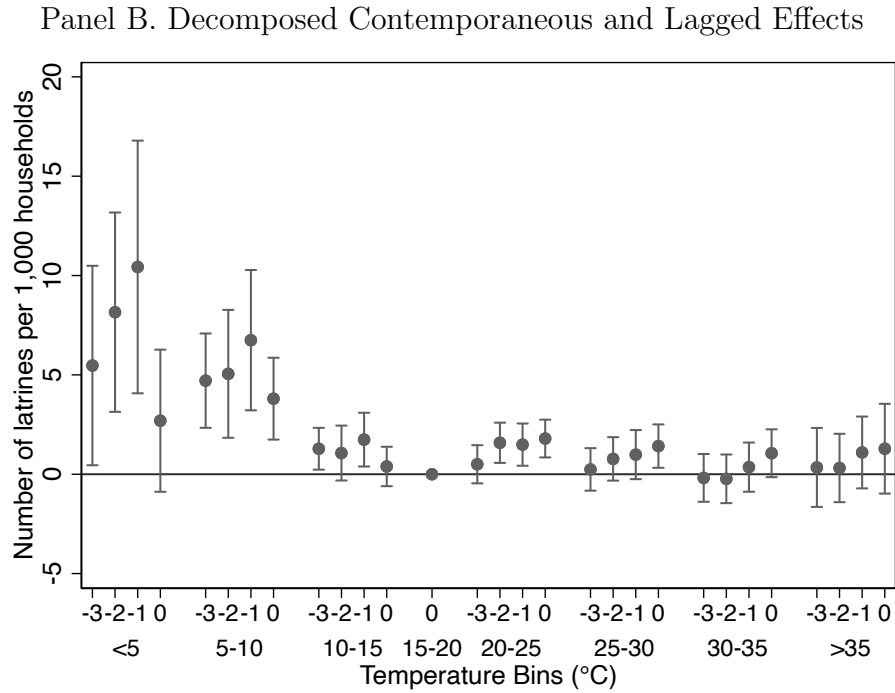
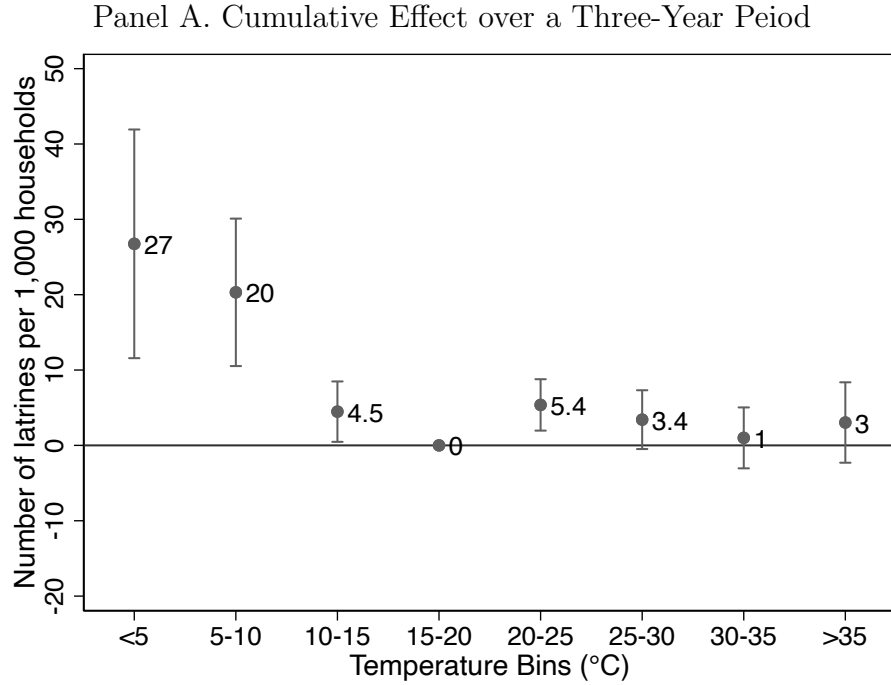
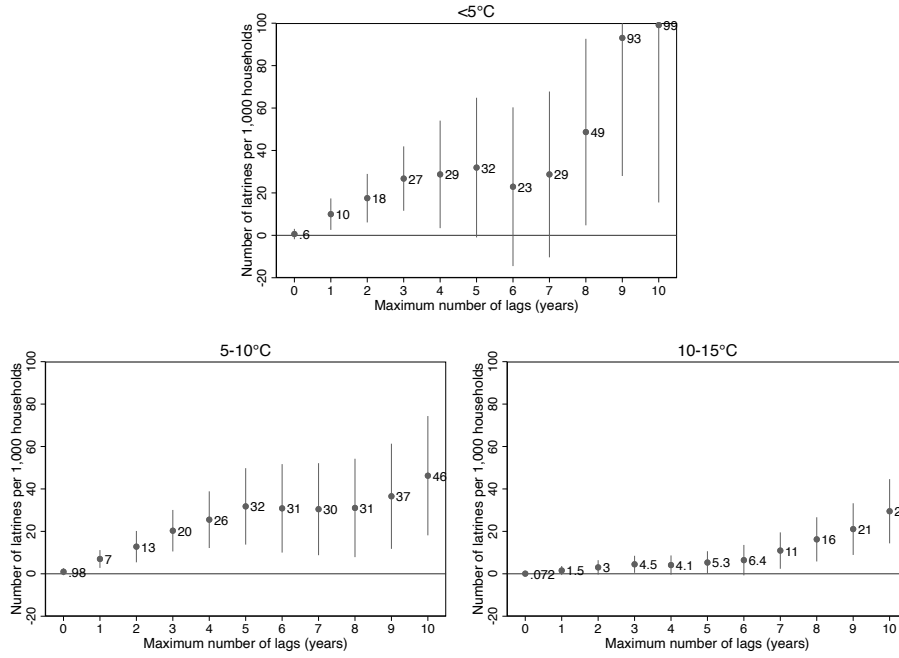


Figure 2: The Effect of Temperature on Latrine Investment

Notes: This figure plots the estimated effects of temperature on latrine investment. Panel A shows the cumulative effects, representing the total of contemporaneous and lagged effects, when including up to three years of lagged temperatures. Panel B shows all estimates of the contemporaneous effect (shown at 0) and the lagged effects (shown at -1 to -3). 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. Low Temperature Bins



Panel B. High Temperature Bins

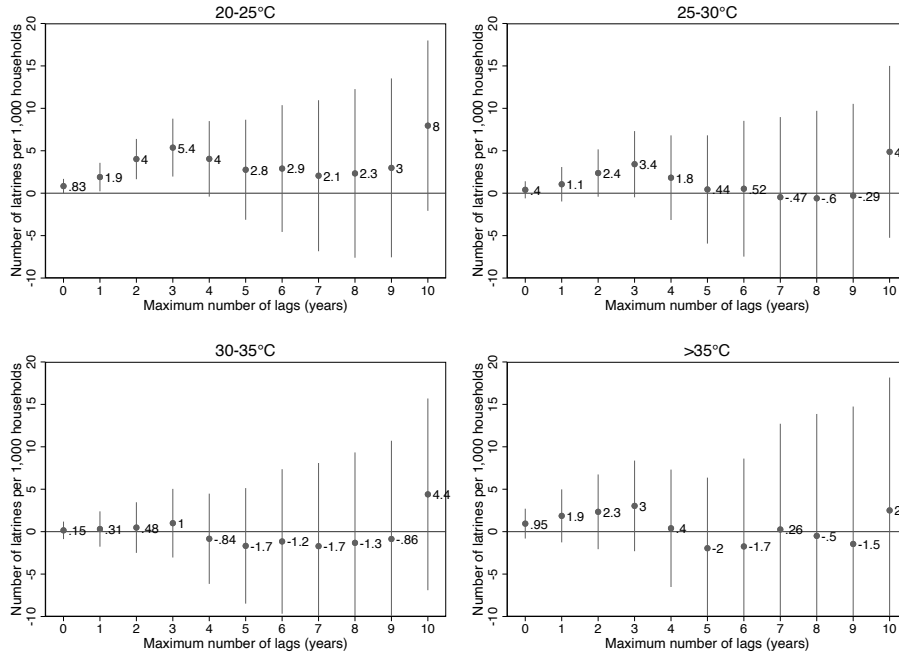


Figure 3: The Cumulative Effects of Temperature on Latrine Investment with Different Maximum Numbers of Lags ($\sum \beta_{jl}^{INV}$)

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

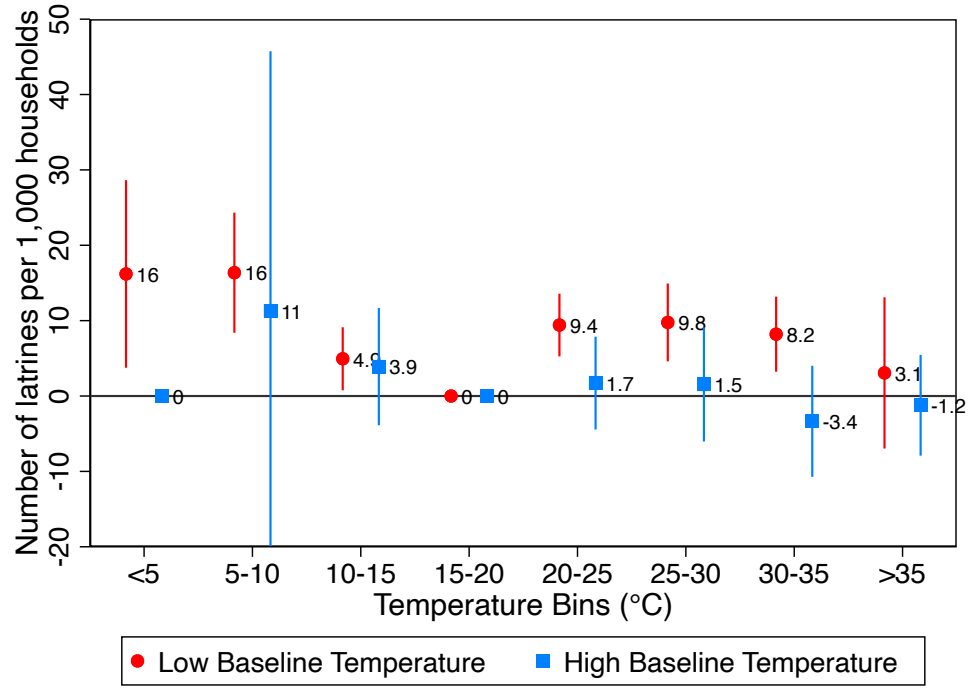


Figure 4: The Heterogeneous Effects of Temperature on Latrine Investment by Baseline Temperature

Notes: This figure plots the estimated effects of temperature on latrine investment in districts with baseline temperatures lower than the sample median and in districts with higher baseline temperatures. This figure shows the cumulative effects, representing the total of contemporaneous and lagged effects, 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. The markers represent temperature bin estimates, while the lines show the associated 95% confidence intervals, which are truncated by the maximum and minimum y-axis values. Standard errors are clustered at the district level.

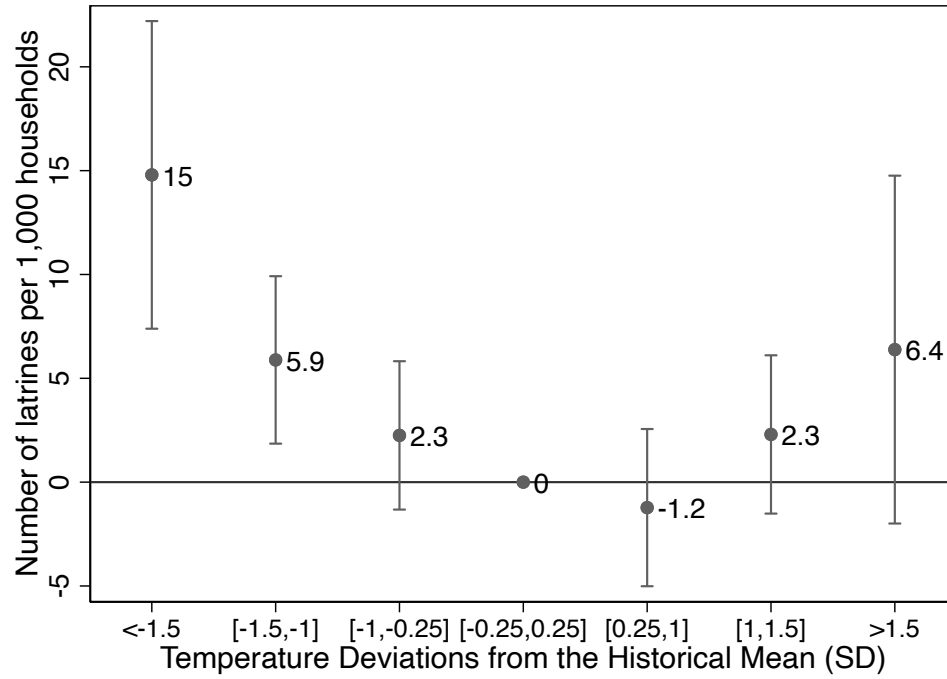


Figure 5: The Effect of Temperature Deviations from the Historical Mean on Latrine Investment

Notes: This figure plots the estimated effects of temperature deviations from the historical mean on latrine investment. This figure shows the cumulative effects, representing the total of contemporaneous and lagged effects, when including up to three years of lagged temperature deviations. The $[-0.25, 0.25]$ standard deviation 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.

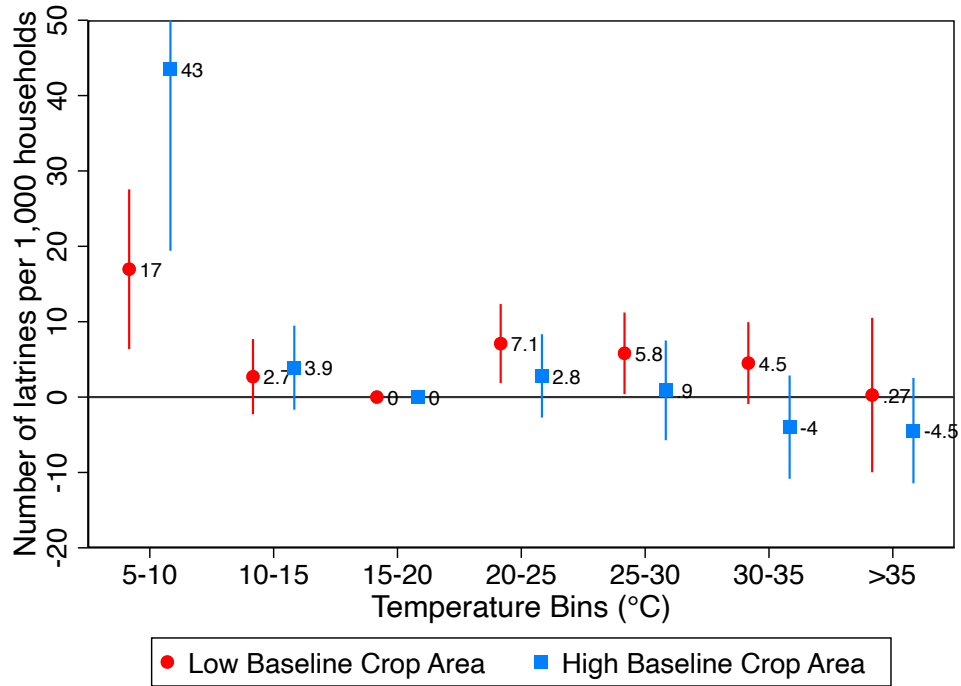


Figure 6: The Heterogeneous Effects of Temperature on Latrine Investment by Baseline Crop Area

Notes: This figure plots the estimated effects of temperature on latrine investment in districts with baseline crop areas lower than the sample median and in districts with higher crop areas. This figure shows the cumulative effects, representing the total of contemporaneous and lagged effects, 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. The coefficients for the below 5°C bin are omitted from this figure due to their large values, although they are presented in Table 3. The markers represent temperature bin estimates, while the lines show the associated 95% confidence intervals, which are truncated by the maximum and minimum y-axis values. Standard errors are clustered at the district level.

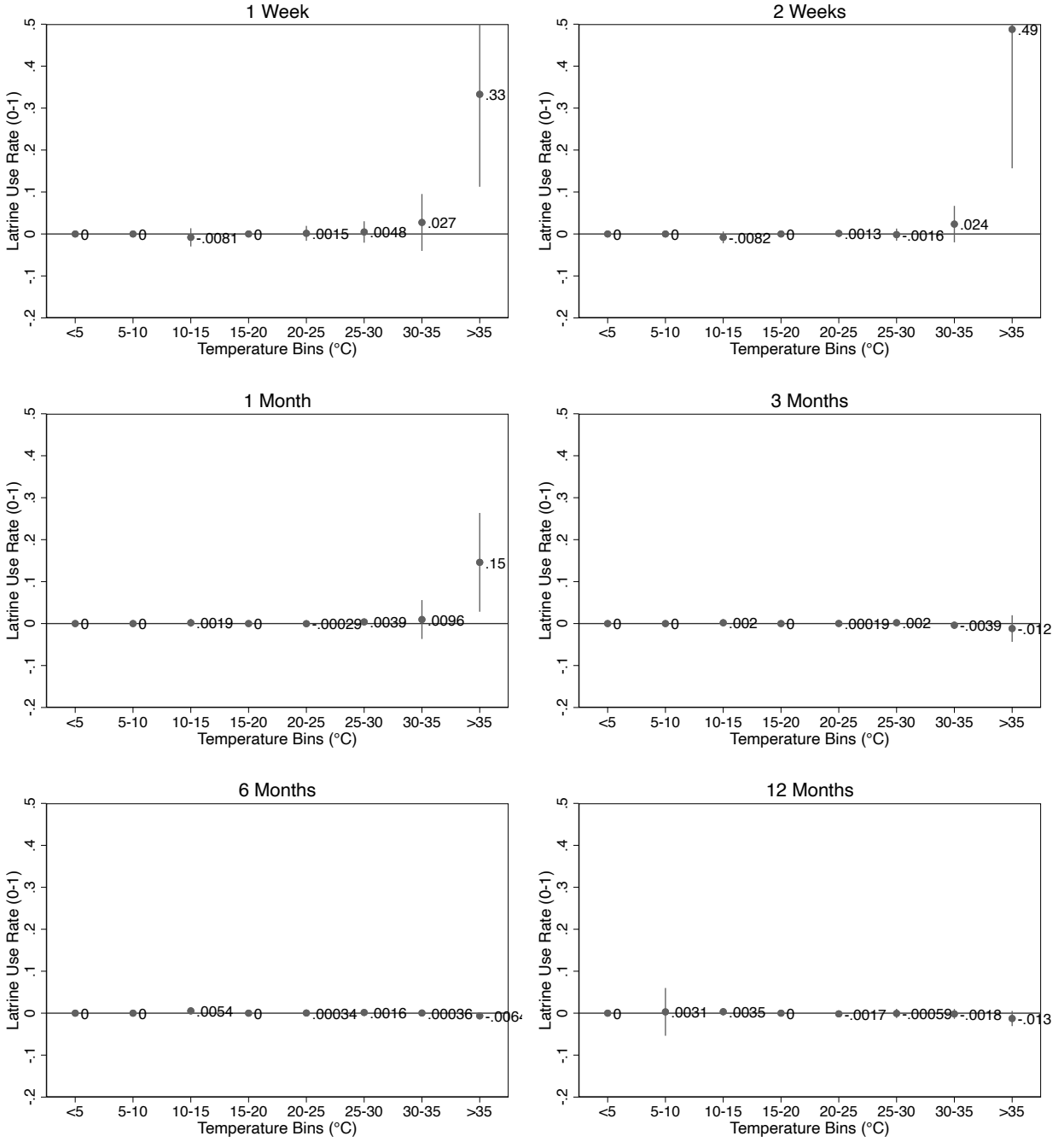


Figure 7: The Effect of Temperature on Latrine Use (Conditional on Ownership)

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. The markers represent temperature bin estimates, while the lines show the associated 95% confidence intervals, which are truncated by the maximum and minimum y-axis values. Standard errors are clustered at the village level.

Table 1: Summary Statistics

	Mean	SD	Min	Max	Observations
<i>Panel A. District-level Latrine Investment (2012-2019)</i>					
Number of latrines (thousand)	162.97	161.47	0	1468.74	4872
Number of latrines per 1,000 households	457.67	282.66	0	3456.62	4872
<i>Panel B. Household-level SQUAT Latrine Data (2013-14, 2018)</i>					
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
<i>Panel C. District-level Average Temperature (2012-2019)</i>					
Number of days below 5°C per year	0.5	3.8	0	57	4872
Number of days between 5-10°C per year	3.68	13.42	0	92	4872
Number of days between 10-15°C per year	16.37	22.46	0	98	4872
Number of days between 15-20°C per year	47.36	29.77	0	109	4872
Number of days between 20-25°C per year	81.73	40.78	0	316	4872
Number of days between 25-30°C per year	150.65	49	8	364	4872
Number of days between 30-35°C per year	59.57	41.35	0	192	4872
Number of days above 35°C per year	5.39	8.42	0	97	4872
Number of days with temperatures >1.5 SD below the mean	34	14.63	0	67	4872
Number of days with temperatures 1-1.5 SD below the mean	40.07	11.63	3	73	4872
Number of days with temperatures 0.25-1 SD below the mean	60.96	17.72	26	149	4872
Number of days with temperatures within 0.25 SD of the mean	56.07	22.85	15	124	4872
Number of days with temperatures 0.25-1 SD above the mean	108.73	32.2	23	170	4872
Number of days with temperatures 1-1.5 SD above the mean	46.1	16.11	9	98	4872
Number of days with temperatures >1.5 SD above the mean	19.31	17.95	0	104	4872
<i>Panel D. District-level Baseline Characteristics</i>					
Pre-SBM latrine coverage 2013	0.4	0.25	0	0.99	609
Baseline (historical) mean temperature 2002-2011	25.11	2.29	16.01	29.14	609
Baseline crop area 2011 (thousand Ha)	355.78	305.21	0.41	1845.11	524

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 baseline district characteristics used in the heterogeneity analyses.

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*** (7.742)	16.198** (6.323)	- -
Number of days 5-10°C	20.313*** (4.991)	16.363*** (4.050)	11.295 (17.506)
Number of days 10-15°C	4.480** (2.044)	4.943** (2.125)	3.905 (3.954)
Number of days 20-25°C	5.371*** (1.740)	9.417*** (2.113)	1.715 (3.129)
Number of days 25-30°C	3.417* (1.990)	9.763*** (2.622)	1.538 (3.843)
Number of days 30-35°C	0.998 (2.063)	8.205*** (2.530)	-3.357 (3.743)
Number of days above 35°C	3.036 (2.724)	3.065 (5.098)	-1.224 (3.396)
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 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 Heterogeneous Effects of Temperature on Latrine Investment (Number of Latrines per 1,000 Households) by Baseline Crop Area

	All	Baseline Crop Area	
	(1) All	(2) Low	(3) High
Number of days below 5°C	101.398*** (22.903)	97.733*** (23.603)	- -
Number of days 5-10°C	25.113*** (5.344)	16.970*** (5.378)	43.497*** (12.230)
Number of days 10-15°C	4.906** (2.015)	2.708 (2.532)	3.899 (2.831)
Number of days 20-25°C	6.030*** (1.801)	7.096*** (2.663)	2.813 (2.808)
Number of days 25-30°C	3.660* (2.035)	5.807** (2.749)	0.895 (3.360)
Number of days 30-35°C	0.878 (2.086)	4.509 (2.760)	-3.984 (3.480)
Number of days above 35°C	1.974 (2.789)	0.270 (5.203)	-4.452 (3.550)
Observations	4,192	2,088	2,096
R ²	0.919	0.944	0.897
Number of Districts	524	261	262
Mean of Dep. Variable	265.125	302.815	228.338

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).

Online Appendix

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

Kazuki Motohashi

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A Conceptual Framework on Effects of Temperature on Sanitation Behaviors

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. A given household decides whether or not to use latrines. Suppose that the discomfort of 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 .²² For a , 1 denotes a physically uninhabitable ambient temperature (extremely high or low 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 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:

$$\max_l U(x, s(a, 1 - l)) \quad s.t. \quad I(a) = lp + x \quad (4)$$

The first order condition with respect to l is

$$\frac{dU}{dl} = -U_x p - U_s \frac{\partial s}{\partial l} = 0 \quad (5)$$

$$\underbrace{p}_{MC} = - \underbrace{\frac{U_s}{U_x} \frac{\partial s}{\partial l}}_{MB} \quad (6)$$

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

²²In the context of latrine use, p represents the maintenance costs associated with emptying pits and septic tanks, as discussed in Section 2.1.

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 (6).

$$\begin{aligned} \frac{dl}{da} &= \frac{\partial l}{\partial s} \frac{ds}{da} + \frac{\partial l}{\partial I} \frac{dI}{da} \\ &= \frac{1}{p} \left\{ \underbrace{-\frac{U_s}{U_x} \frac{ds}{da}}_{\text{Discomfort channel } >0} + \underbrace{\frac{dI}{da}}_{\text{Income channel } <0} \right\} \end{aligned} \quad (7)$$

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.²³

²³ 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.

B 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 (2024).

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 (2024), 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.

C Additional Figures

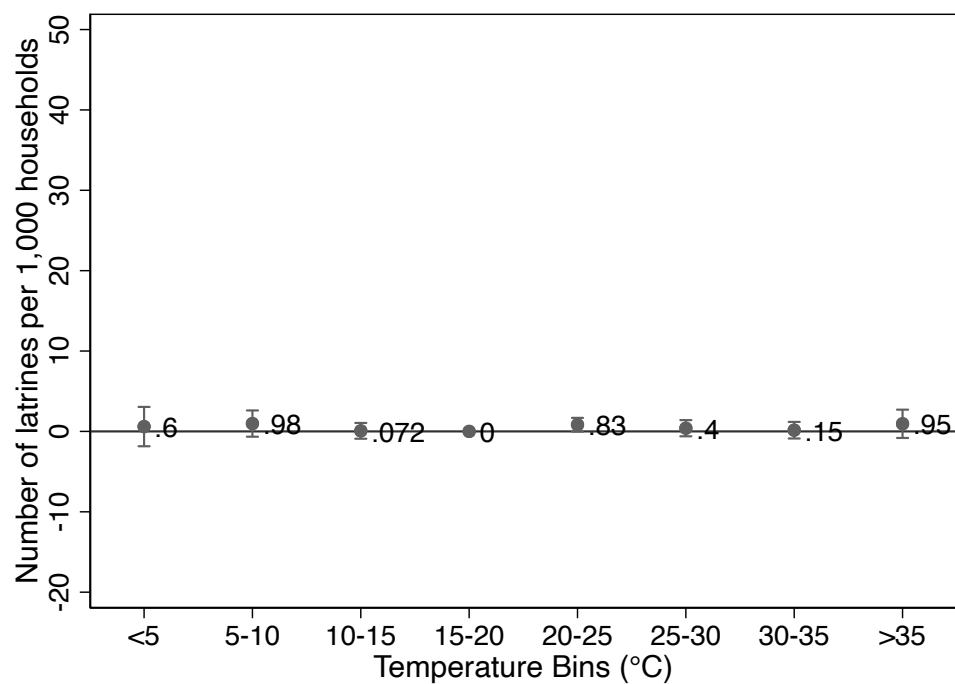


Figure C1: The Contemporaneous Effect of Temperature on Latrine Investment

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.

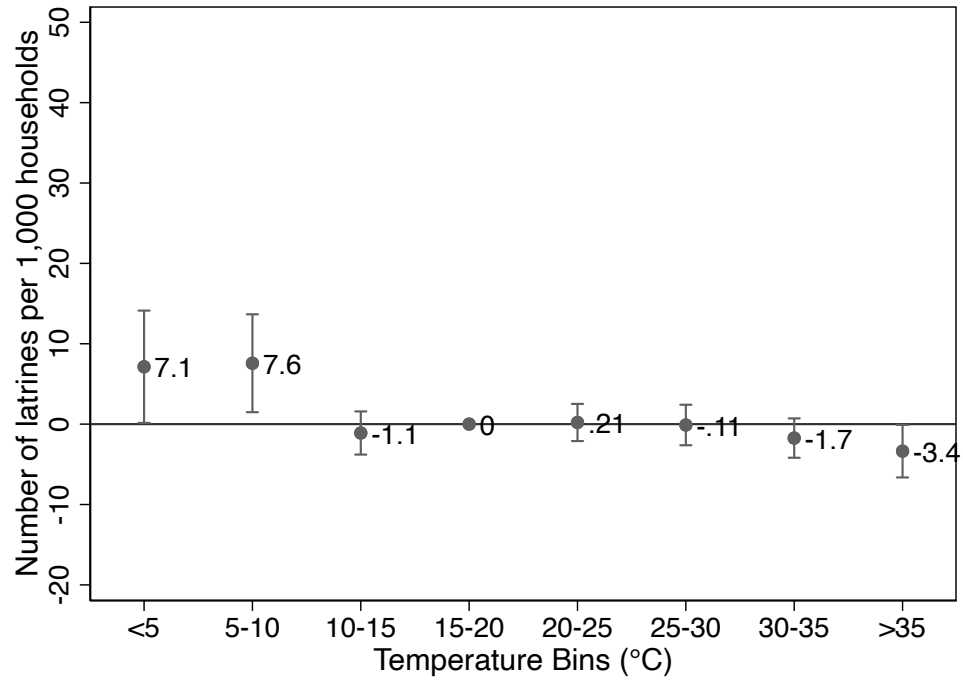


Figure C2: The Cumulative Effects of Temperature on Latrine Investment (Prior to 2016)

Notes: This figure plots the estimated effects of temperature on latrine investment during the period prior to 2016. This figure shows the cumulative effects, representing the total of contemporaneous and lagged effects, 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.

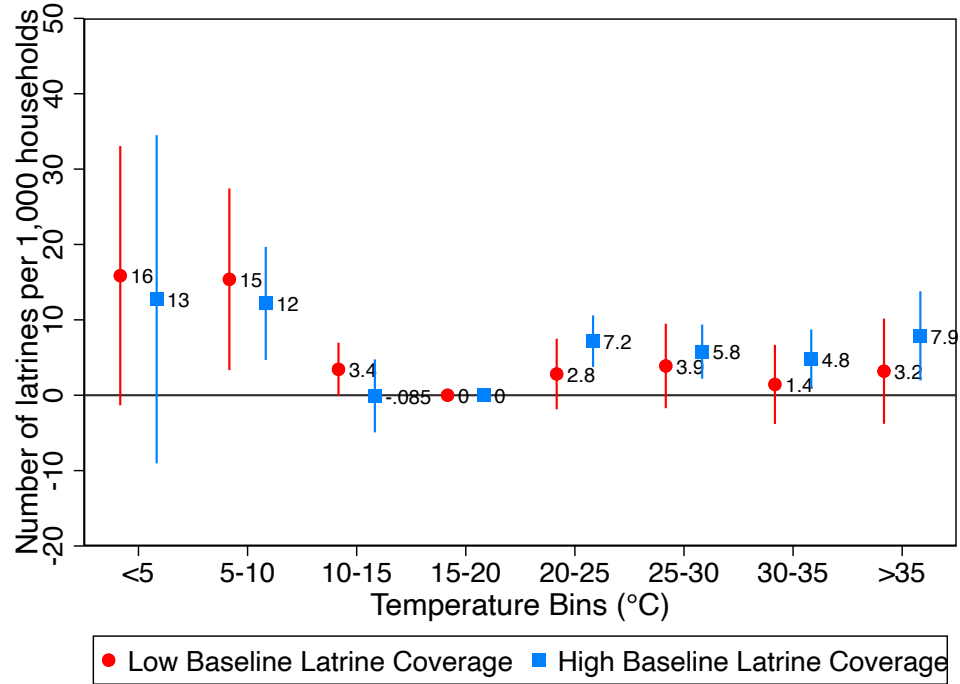


Figure C3: The Heterogeneous Effects of Temperature on Latrine Investment by Baseline Latrine Coverage

Notes: This figure plots the estimated effects of temperature on latrine investment in districts with pre-SBM baseline latrine coverage lower than the sample median and in districts with higher baseline coverage. This figure shows the cumulative effects, representing the total of contemporaneous and lagged effects, 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. The markers represent temperature bin estimates, while the lines show the associated 95% confidence intervals. Standard errors are clustered at the district level.

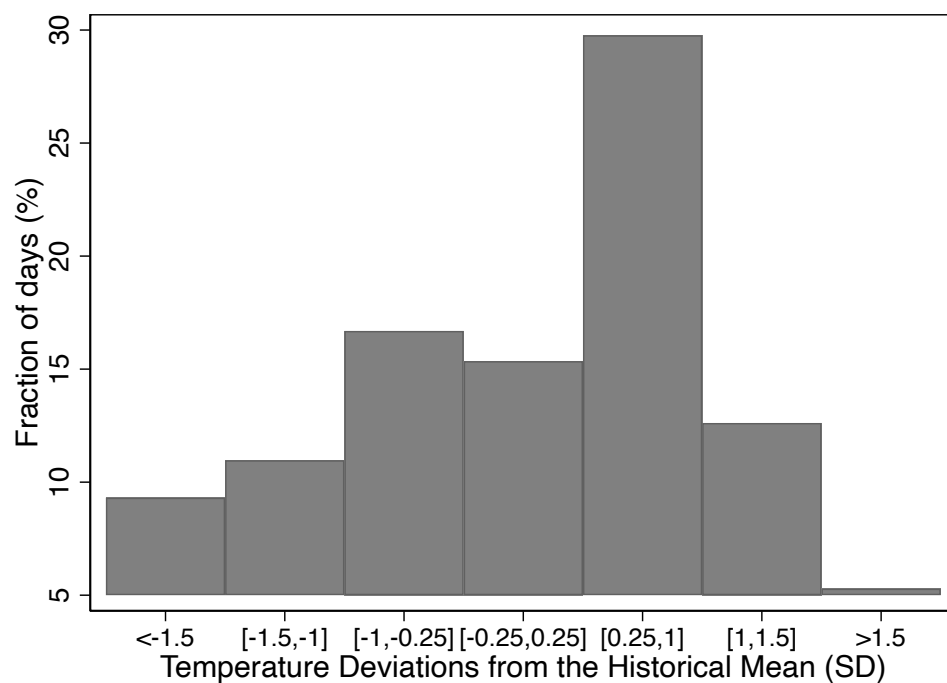


Figure C4: Distribution of Temperature Deviations from the Historical Mean

Notes: This figure shows the distribution of temperature deviations from the historical mean (measured in standard deviations), using daily temperatures at the district level across India from 2012 to 2019.

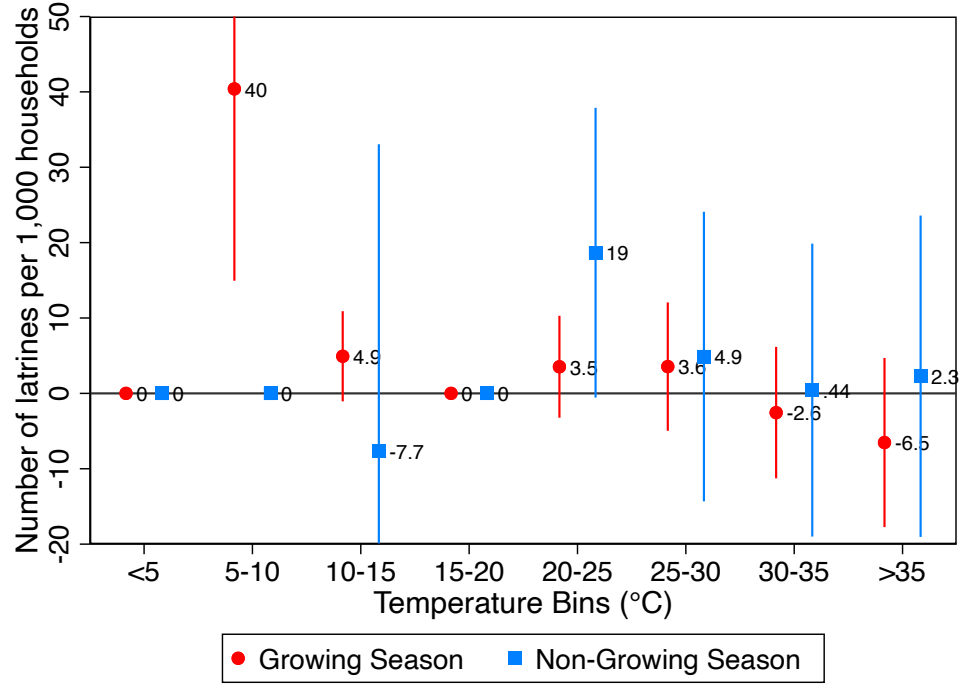


Figure C5: The Heterogeneous Effects of Temperature on Latrine Investment by Agricultural Seasons

Notes: This figure plots the estimated effects of temperature on latrine investment during both the growing and non-growing seasons in districts with higher crop areas. This figure shows the cumulative effects, representing the total of contemporaneous and lagged effects, 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. The markers represent temperature bin estimates, while the lines show the associated 95% confidence intervals, which are truncated by the maximum and minimum y-axis values. Standard errors are clustered at the district level.

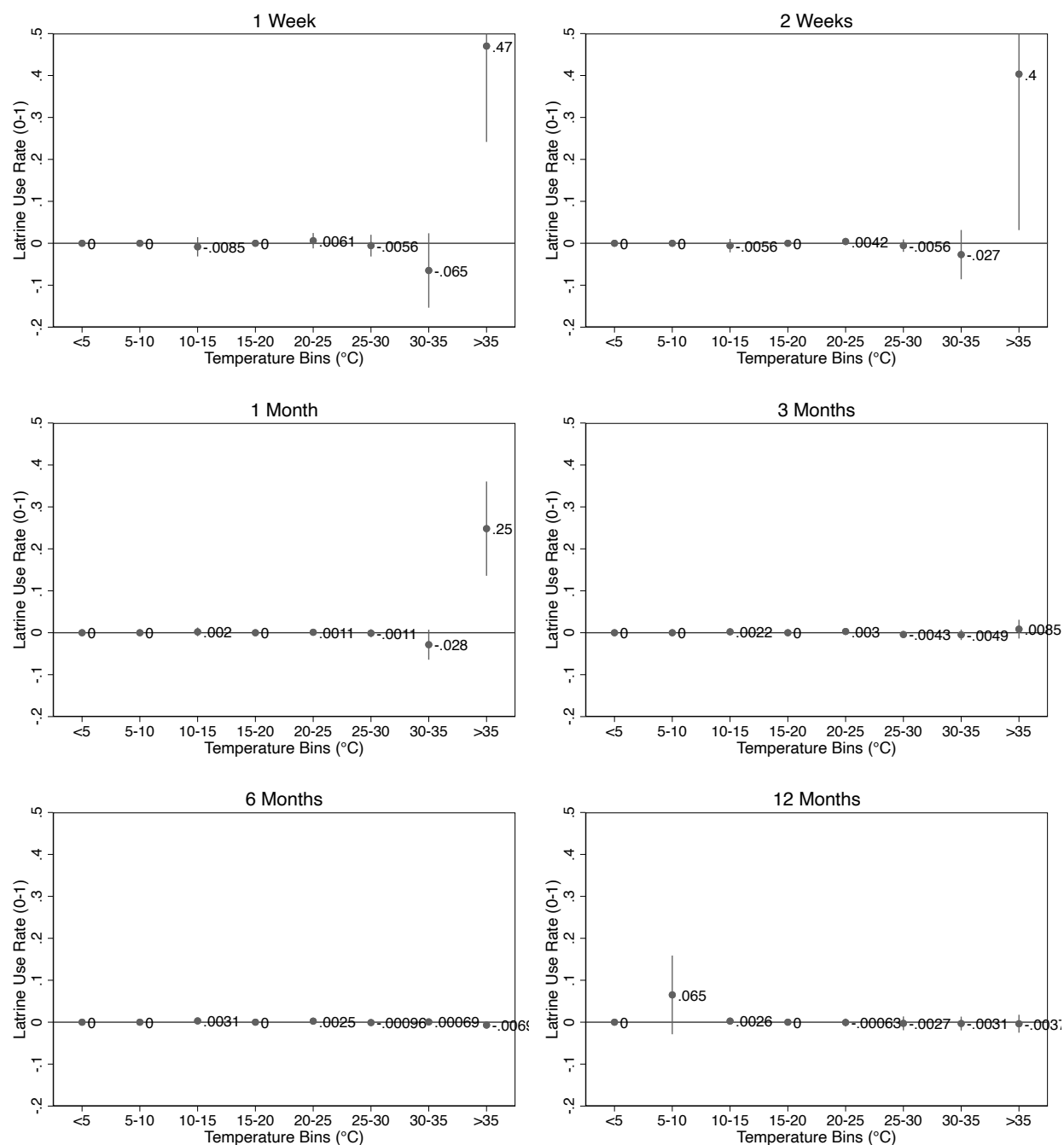


Figure C6: The Effects of Temperature on Latrine Use (Unconditional on Ownership)

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. The markers represent temperature bin estimates, while the lines show the associated 95% confidence intervals, which are truncated by the maximum and minimum y-axis values. Standard errors are clustered at the village level.

D Additional Tables

Table D1: The Contemporaneous and Lagged Effects of Temperature on Latrine Investment (Number of Latrines per 1,000 Households)

		High Temperature Bins	
		(1)	
Low Temperature Bins			
(1)			
Lag 0: Number of days below 5°C	2.694 (1.821)	Lag 0: Number of days 20-25°C	1.796*** (0.484)
Lag 1: Number of days below 5°C	10.431*** (3.237)	Lag 1: Number of days 20-25°C	1.490*** (0.541)
Lag 2: Number of days below 5°C	8.156*** (2.554)	Lag 2: Number of days 20-25°C	1.583*** (0.515)
Lag 3: Number of days below 5°C	5.470** (2.556)	Lag 3: Number of days 20-25°C	0.502 (0.489)
Lag 0: Number of days 5-10°C	3.803*** (1.049)	Lag 0: Number of days 25-30°C	1.416** (0.556)
Lag 1: Number of days 5-10°C	6.747*** (1.798)	Lag 1: Number of days 25-30°C	0.987 (0.629)
Lag 2: Number of days 5-10°C	5.053*** (1.639)	Lag 2: Number of days 25-30°C	0.772 (0.556)
Lag 3: Number of days 5-10°C	4.710*** (1.209)	Lag 3: Number of days 25-30°C	0.242 (0.545)
Lag 0: Number of days 10-15°C	0.390 (0.505)	Lag 0: Number of days 30-35°C	1.057* (0.612)
Lag 1: Number of days 10-15°C	1.742** (0.689)	Lag 1: Number of days 30-35°C	0.357 (0.630)
Lag 2: Number of days 10-15°C	1.066 (0.703)	Lag 2: Number of days 30-35°C	-0.231 (0.623)
Lag 3: Number of days 10-15°C	1.282** (0.536)	Lag 3: Number of days 30-35°C	-0.184 (0.613)
Observations	4,872	Lag 0: Number of days above 35°C	1.285 (1.151)
R ²	0.915	Lag 1: Number of days above 35°C	1.095 (0.921)
Number of Districts	609	Lag 2: Number of days above 35°C	0.315 (0.876)
Mean of Dep. Variable	267.977	Lag 3: Number of days above 35°C	0.342 (1.012)
		Observations	4,872
		R ²	0.915
		Number of Districts	609
		Mean of Dep. Variable	267.977

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. The means of dependent variables are calculated for the pre-SBM period (2012-2013).

Table D2: 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 5C	9.974*** (3.782)	26.751*** (7.742)	22.915 (19.089)	48.679** (22.427)	99.116** (42.665)
Number of days 5-10C	6.983*** (2.145)	20.313*** (4.991)	30.853*** (10.638)	31.050*** (11.831)	46.247*** (14.344)
Number of days 10-15C	1.543 (1.086)	4.480** (2.044)	6.433* (3.658)	16.232*** (5.313)	29.489*** (7.724)
Number of days 20-25C	1.902** (0.855)	5.371*** (1.740)	2.902 (3.811)	2.330 (5.069)	7.960 (5.120)
Number of days 25-30C	1.054 (1.036)	3.417* (1.990)	0.525 (4.082)	-0.604 (5.260)	4.871 (5.168)
Number of days 30-35C	0.311 (1.061)	0.998 (2.063)	-1.155 (4.345)	-1.318 (5.437)	4.397 (5.763)
Number of days above 35C	1.860 (1.593)	3.036 (2.724)	-1.743 (5.283)	-0.495 (7.329)	2.504 (7.988)
Observations	4,872	4,872	4,872	4,872	4,872
R ²	0.912	0.915	0.916	0.917	0.920
Number of Districts	609	609	609	609	609
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. 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. The means of dependent variables are calculated for the pre-SBM period (2012-2013).

Table D3: The Effect of Temperature Deviations from the Historical Mean on Latrine Investment (Number of Latrines per 1,000 Households)

	Number of Latrines per 1,000 Households
	(1)
Number of days with temperatures >1.5 SD below the historical mean	14.795*** (3.772)
Number of days with temperatures 1-1.5 SD below the historical mean	5.885*** (2.053)
Number of days with temperatures 0.25-1 SD below the historical mean	2.251 (1.819)
Number of days with temperatures 0.25-1 SD above the historical mean	-1.226 (1.927)
Number of days with temperatures 1-1.5 SD above the historical mean	2.297 (1.941)
Number of days with temperatures >1.5 SD above the historical mean	6.383 (4.265)
Observations	3,045
R ²	0.925
Number of Districts	609

Notes: This table reports the estimated cumulative effects of temperature deviations from the historical mean on latrine investment, when including up to three years of lagged temperature deviations. The [-0.25,0.25] standard deviation 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.

Table D4: 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 (0.011)	-0.008 (0.007)	0.002 (0.005)	0.002 (0.004)	0.005 (0.004)	0.003 (0.004)
Number of days 20-25°C	0.002 (0.009)	0.001 (0.005)	-0.000 (0.003)	0.000 (0.003)	0.000 (0.002)	-0.002 (0.003)
Number of days 25-30°C	0.005 (0.013)	-0.002 (0.007)	0.004 (0.004)	0.002 (0.003)	0.002 (0.003)	-0.001 (0.005)
Number of days 30-35°C	0.027 (0.034)	0.024 (0.022)	0.010 (0.023)	-0.004 (0.004)	0.000 (0.003)	-0.002 (0.006)
Number of days above 35°C	0.333*** (0.111)	0.488*** (0.167)	0.146** (0.059)	-0.012 (0.016)	-0.006* (0.003)	-0.013 (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	437	437	437	437	437	437
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.