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Water conservation through plumbing and nudging

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In this paper, we investigate two solutions to urban water security challenges: plumbing and nudging. Using anonymized monthly billing data from 1.5 million accounts in Singapore over ten years, our staggered difference-in-differences estimates show that a nationwide Home Improvement Programme that improves the efficiency of plumbing reduces residential water consumption by 3.5%. This effect persists over a decade and is robust across population subgroups. Efficiency improvements could enhance the efficacy of other conservation polices and mitigate the effects of excessive heat, rainfall and air pollution. The savings from efficiency improvements on utility bills are small, but the increase in housing value exceeds the private cost of the Home Improvement Programme. However, an evaluation of a nationwide peer-comparison nudging programme finds no evidence of reduced water consumption. Overall, we show that plumbing improvements generate long-lasting effects on water conservation.

Mega-cities worldwide are facing water security challenges due to rapid population growth with declining supply and quality of water resources. As such, governments have responded with infrastructure developments and demand management through pricing, efficiency improvements and behavioural nudges. In this paper, we study the effect of efficiency improvements through plumbing and the effect of behavioural nudging through peer comparison, using 98.2 million observations of monthly water consumption from 1.5 million households over ten years in Singapore.

There has been a dearth of credible evidence on the effectiveness and cost-effectiveness of efficiency subsidies and standards[1,2]. Studies[3–6] on energy efficiency retrofitting have found electricity savings through residential weatherization or appliance replacement to be small and with substantial rebound effects[7]. Other studies have found that energy standards and building codes effectively reduce energy consumption[8–11], with the long-term effects varying by energy source[12]. Evaluations on water efficiency retrofitting have identified large but non-causal effects of efficient plumbing fixtures on residential water use through before-and-after comparisons[13–16]. Causal evaluations are rare and rely on rebate programmes for efficient plumbing with very low take-up rates, which may incur substantial selection bias[17]. Behaviour adjustments upon water efficiency improvements are less well documented than those in the energy sector.

Many studies, mostly randomized controlled trials, have shown that nudging consumers via peer comparison to conserve water and energy is effective in the short run[18–21]. However, the effect tends to decay or even disappear in the medium term, with limited long-term effects detected under strict conditions[22–25]. The effectiveness of a large-scale norm-based behavioural intervention remains unclear, as it is affected by many factors including delivery mode[21], type of information[26], frequency of information provision[27–29], target group[30] and welfare implications[31,32]. Some research has shown that the efficacy of norm-based randomized controlled trials is substantially overstated due to site selection bias[33], while others believe that publication bias also contributes to the overstatement[34].

In this study, we causally evaluate the effect of water efficiency improvements, leveraging on the nationwide Home Improvement Programme (HIP) in Singapore, which provides (among other things) heavily subsidized optional replacement of plumbing fixtures. Using anonymized monthly billing data for all public housing households (1.5 million accounts) from 2011 to 2019, our estimates from a staggered difference-in-differences approach show that efficiency improvements reduce residential water use by 3.5% ($P<0.001$; 95% confidence interval (CI), (−0.038, −0.031)), much lower than the estimates documented[35], due to behavioural adjustments. The effect persists over a decade, without obvious behaviour changes over time or technology disadoption, and is consistent across different population subgroups. We show that efficiency improvements enhance the effectiveness of water conservation policies such as nudging. They also mitigate the uncertainty in water use under extreme weather and pollution conditions. We further conduct a cost–benefit analysis for HIP and find that, from the household's perspective, although the savings on utility bills are small, the increase in housing value resulting from the entire upgrade is more than sufficient to cover the private cost. From the government's perspective, although the pecuniary benefits fall short of the costs, the main intended social benefit of improved public health and safety is substantial. We also investigate nationwide nudging through peer comparison, relying on a quasi-experimental research design, but find no credible evidence that it reduces water consumption. This may be due to boomerang effects on consumers with low water usage and conflicting nudges from national and neighbourhood peer comparisons.

We contribute to the literature by showing that (1) efficiency improvements have causal impacts on residential water use, (2) efficient plumbing provides long-lasting effects on water conservation without behavioural rebound over time, (3) efficiency improvements could mitigate the effects of extreme weather and pollution

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on water use, and (4) we find no evidence that nudging through peer comparison achieves similar outcomes if the messages are not carefully calibrated.

Effect of efficiency improvements through plumbing

HIP. In Singapore, over 80% of the population lives in public housing developed and managed by the Housing and Development Board (HDB), of which about 90% of the residents own their homes. Currently, there are more than one million HDB flats, with the oldest flats built in the 1960s.

HIP is an upgrading programme introduced in 2007 to resolve common maintenance problems of ageing HDB flats. It first targeted flats built before 1986 and expanded to flats built before 1997 in 2018, covering 55% of all HDB blocks. The government offered the upgrade to eligible blocks in a sequence. The residents then collectively decided whether to proceed with the upgrade. Among the blocks offered, 99.6% voted to proceed. By December 2019, 56% of the eligible blocks in the initial programme had been upgraded, while the remaining blocks were scheduled to be upgraded.

According to the official guide on HIP, upgrading work for the entire neighbourhood typically takes 18 months after the announcement of a successful poll, with ten working days of upgrading work per flat. Using this cut-off, 2,262 blocks or close to 360,000 flats had completed the upgrade by December 2019. The distributions of locations and completion times for the upgrades are illustrated in Extended Data Figs. 1 and 2.

HIP provides essential improvements necessary for public health and safety, the costs of which are fully covered by the government. It also provides optional improvements, such as replacing plumbing fixtures in all bathrooms, which affects water usage as the new fixtures are required to meet minimal water efficiency standards. The optional improvements are heavily subsidized, with households paying 5% to 12.5% of the total cost on the basis of their flat type (Supplementary Table 6). On average, the take-up rate for the bathroom upgrade is 70%.

Average intent-to-treat effect. To evaluate the average effect of efficiency improvements on water consumption, we use a staggered difference-in-differences regression comparing the monthly water consumption of HIP flats before and after project completion, relative to flats that do not qualify or have not yet been upgraded. The validity of the empirical method relies on the parallel-trends assumption that, without HIP, the water consumption of HIP and non-HIP flats should follow similar trends. As shown in Fig. 1, the average monthly water consumption of pre-HIP and non-HIP flats is similar throughout the sample period.

In our estimation (equation (1)), we control for time-invariant household characteristics, seasonality, spatial variations in weather and pollution, economy-wide common shocks including nationwide water price increase, and group-specific pre-trends in water consumption. We find that upon completing HIP, treated households reduce their water consumption by 3.5% ($P<0.001$; 95% CI, (−0.038, −0.031)). Evaluated at the pre-treatment mean monthly water consumption of 17.24 m^3 for HIP flats, 0.6 m^3 of water is saved per household per month. With approximately 360,000 flats completing the upgrade, the annual total water consumption is estimated to decline by 2,592,000 m^3 by December 2019.

Note that the effect we estimate should be considered as an average intent-to-treat effect. About 70% of the treatment group opted for the bathroom upgrade, but we do not have information on individual decisions. This estimate is also much smaller than the engineering estimates documented in the literature. The difference is probably due to behaviour adjustments upon the changes in water fixtures. For example, to compensate for the low flow rate of the new fixtures, individuals may prolong the use of water taps or repeat the flushing of toilets, both of which would reduce the actual water savings.

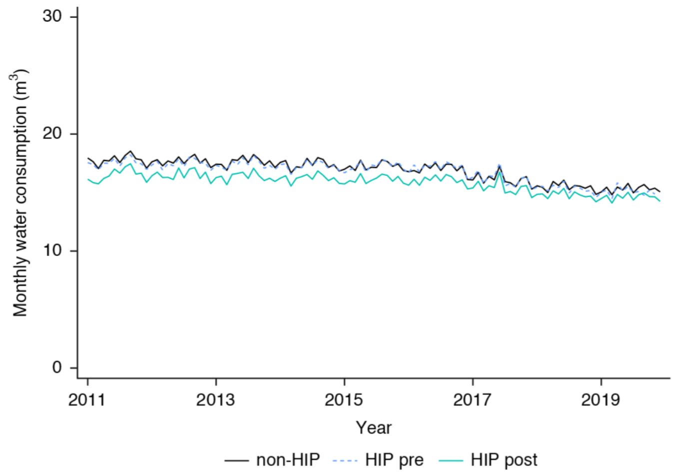

Fig. 1 | Trend of monthly water consumption. The trend in monthly mean water consumption (in cubic metres) for non-HIP flats, HIP flats before HIP completion (HIP pre) and HIP flats after HIP completion (HIP post) over time using the baseline sample of 98,291,320 observations.

The rebound effect is expected to be small, as the cost of water is low and accounts for a small proportion of household income (Supplementary Table 13). Limited by data availability, we are only able to jointly estimate the engineering and behavioural effects of water efficiency improvements.

Selection bias. If HIP flats differ systematically from non-HIP flats or if the flats that implemented HIP earlier differ from those implementing it later, our estimate of the effect of efficiency improvements on water consumption may be biased. To address this selection bias, we first compare HIP and non-HIP flats. In terms of the outcome variable, Fig. 1 shows very similar trends in mean monthly water consumption for pre-HIP and non-HIP flats. However, the flat and demographic characteristics of HIP and non-HIP flats are expected to differ, as HIP flats were built earlier, catering to the housing demand of older generations (Extended Data Fig. 3). To understand whether this difference leads to biased estimates, we conduct robustness checks by (1) restricting the sample by the age of the flat to eliminate potential differences in building technology between new and old flats; (2) restricting the sample according to HIP eligibility during different phases to eliminate unknown factors used in determining eligibility criteria; (3) restricting the sample to HIP flats only, thus eliminating all non-HIP flats and any potential differences between the two groups; and (4) comparing water consumption for flats built just before and after the eligibility cut-off, as they are likely to have similar characteristics, using both difference-in-differences and regression discontinuity approaches. The HIP effects remain robust across the abovementioned checks. (Supplementary Table 3).

Second, we compare HIP flats by cohort. We observe no clear evidence of prioritization by location over time (Extended Data Fig. 2) and no major variations in flat or demographic characteristics across HIP cohorts (Extended Data Fig. 4), except the tendency to prioritize older flats in earlier years. To formally evaluate whether selection timing poses any potential concern, we estimate the effect of HIP on water consumption by cohort. As shown in Fig. 2a, we do not observe statistically significant differences across cohorts except for the flats that completed HIP in 2018 ($\beta_{\mathrm{diff}}=-0.018$; $P=0.002$; 95% CI, (−0.029, −0.007), when comparing with the smallest effect size for the 2016 cohort), which experienced larger efficiency improvements due to older flat ages (Extended Data Fig. 4b).

Last, as 99.6% of the blocks voted to proceed when offered HIP, we do not expect our estimates to be biased by self-selection.

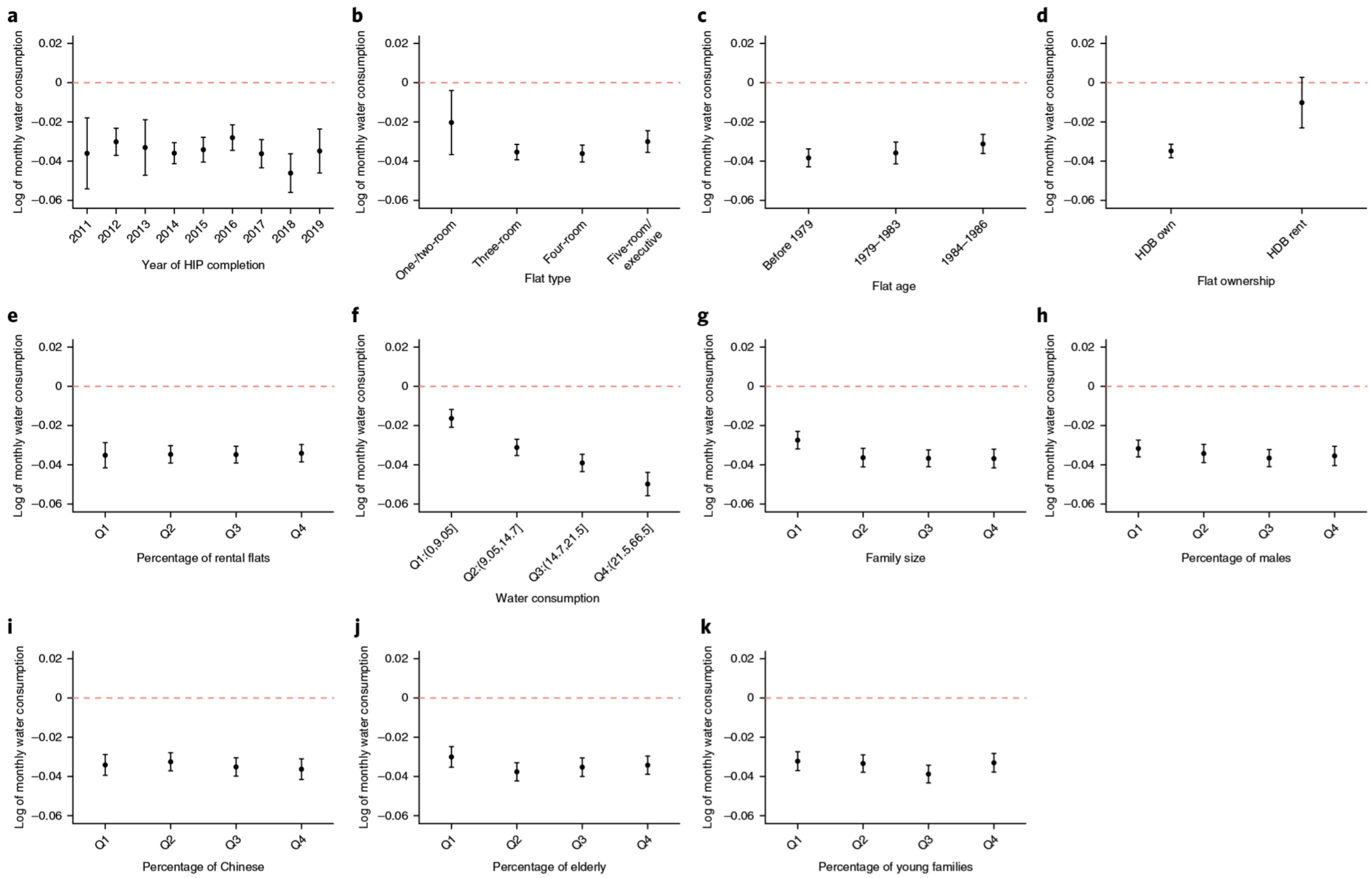

Fig. 2 | Heterogeneous effects by housing characteristics, water demand and block-level demographics. a–k, Estimated coefficients and corresponding 95% CIs (error bars) for the heterogeneous effect of HIP on monthly water consumption for each subgroup. The values were obtained by estimating equation (2) using the baseline sample of 98,291,320 observations. Detailed estimates are provided as source data. Panels **a–d** show the heterogeneous effects by HIP cohort, flat type, flat age and flat ownership. Panels **e–k** show the heterogeneous effects by quartiles of percentage of rental flats, water consumption, family size, percentage of males, percentage of Chinese, percentage of elderly and percentage of young adults.

Omitted variable bias. There might be concerns that other contemporaneous changes that happened around the same time as HIP could bias our results. As selection into the programme is exogenously determined by the government, with the implementation carried out over more than ten years, it is unlikely that any changes in family characteristics would coincide with efficiency improvements. Nonetheless, if there are such systematic changes such as family expansion, we should observe changes in the pattern of housing transactions around the same time. However, we find no credible evidence of a sharp discontinuity in the number of sales 24 months before and after HIP completion using all 18,160 relevant resale transactions (Extended Data Fig. 5).

Household decisions on installing other water-saving technology around the same time as HIP may lead to the overestimation of HIP effects. However, the rate of technology adoption is likely to differ across income groups due to the costs involved. If such technology adoption is common, the HIP effect should increase with income. In contrast, we find no evidence of such a pattern in the heterogeneous HIP effects by flat type, which approximates income levels (Fig. 2b).

Other robustness checks. To further verify the robustness of our results, we consider (1) alternative cut-offs for project completion, using 24 and 30 months post-announcement as well as the date when households are billed for HIP and removing observations between project announcement and hypothetical completion date; (2) inverse hyperbolic sine-transformed dependent variables; (3) alternative samples excluding extremely old flats, new flats regulated by mandatory efficiency standards and flats with extreme water consumption; and (4) alternative specifications and clustering for standard errors. The changes in effect size across models are small, if any (see the Supplementary Discussion for more details).

Heterogeneous effects. We further explore how the effects of efficiency improvements varied with housing characteristics, baseline water demand and block-level demographics (by estimating equation (2)). First, we investigate the effect of efficiency improvements by housing characteristics such as flat type, age and ownership. As flat type is a proxy for income level (Supplementary Table 6), we may observe heterogeneous HIP effects on water consumption if the take-up rate for the optional upgrades differs across income groups. Figure 2b shows that HIP has a significant effect in reducing water consumption across all flat types with effect sizes of 2.0% ($P=0.015$; 95% CI, (−0.037, −0.004)), 3.5% ($P<0.001$; 95% CI, (−0.039, −0.031)), 3.6% ($P<0.001$; 95% CI, (−0.040,−0.032)) and 3.0% ($P<0.001$; 95% CI, (−0.036,−0.024)) for HDB one-/two-room, three-room, four-room and five-room/executive flats, respectively. Pairwise comparisons show that these effect sizes are similar, except that the effect on four-room flats is larger than that on five-room/executive flats ($P=0.024$).

Similarly, if water efficiency for plumbing fixtures in newer flats is higher, we would observe smaller HIP effects for such flats. We divide the flats into four groups by year built: before 1980, 1980–1983, 1984–1986 and after 1987. Flats in the first three groups qualified for the first phase of the upgrade, with each group having a

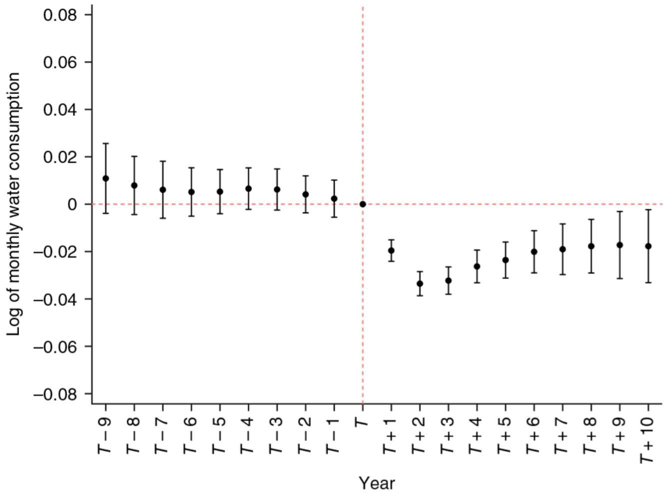

Fig. 3 | Evolutionary effect of HIP on water consumption. Estimated coefficients and corresponding 95% CIs (error bars) for the difference in water consumption between flats that completed and did not complete HIP each year before and after HIP completion. The values were obtained by estimating equation (3) using the baseline sample of 98,291,320 observations. Detailed estimates are provided as source data. The vertical line indicates the time of HIP completion defined as 18 months after the announcement of a successful poll.

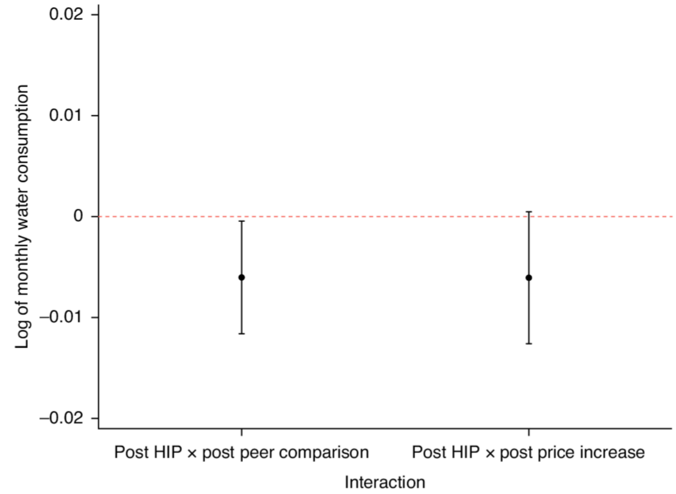

Fig. 4 | Interaction effect between HIP and other conservation policies. Estimated coefficients and corresponding 95% CIs (error bars) for the differences in the effects of peer comparison and price increase for post-HIP and non-HIP flats. The values were obtained by estimating equation (4) using the baseline sample of 98,291,320 observations. Detailed estimates are provided as source data.

similar number of HIP flats. Although flats built between 1987 and 1997 qualified for the second phase of HIP (announced in August 2018), none had completed the upgrade by the end of 2019. Figure 2c shows that, as expected, the HIP effects on residential water consumption are 3.8% ($P<0.001$; 95% CI, (−0.043, −0.034)), 3.6% ($P<0.001$; 95% CI, (−0.041, −0.030)) and 3.1% ($P<0.001$; 95% CI, (−0.036, −0.026)) for flats built before 1980, in 1980–1983 and in 1984–1986, respectively. The effect size is larger for flats built before 1980 than for those built in 1984–1986 ($P=0.023$).

Flat ownership may motivate households to undergo efficiency improvements. Figure 2d shows that the HIP effect is smaller ($P=0.025$) among public rental flats ($\beta_{\text{post-HIP}}=1.02\%$; $P=0.12$; 95% CI, (−0.023, 0.003)) than among flats with private ownership ($\beta_{\text{post-HIP}}=3.5\%$; $P<0.001$; 95% CI, (−0.038, −0.031)). As the costs of all upgrades for public rental flats are fully borne by the government, the small effect is probably a result of a low take-up rate due to the inconvenience during upgrade. Although we do not have information on the rental status of each privately owned HDB flat, we can divide the blocks into quartiles on the basis of the percentage of flats on rent from May 2019 to May 2021. We observe similar HIP effects on water consumption across groups in Fig. 2e. This is intuitive, as flat owners are still incentivized to undergo home improvements to secure higher rental or housing valuation.

Next, we divide the sample into quartiles on the basis of the pre-treatment mean water usage, as baseline water demand determines the cost of conservation. Figure 2f shows that, consistent with our hypothesis, HIP significantly reduces water consumption across all subgroups, and the magnitude of reduction increases from 1.6% ($P<0.001$; 95% CI, (−0.020, −0.012)) for the lowest quartile to 3.1% ($P<0.001$; 95% CI, (−0.035, −0.027)), 3.9% ($P<0.001$; 95% CI, (−0.043, −0.035)) and 4.9% ($P<0.001$; 95% CI, (−0.056, −0.044)) for subsequent quartiles ($P<0.001$ for all pairwise comparisons). The trend of increasing effect size as water consumption increases also holds across subgroups with varied housing characteristics (Supplementary Fig. 8).

Lastly, we evaluate the heterogeneous HIP effects by block-level demographic characteristics such as family size, gender, ethnicity and age. We divide HDB blocks into quartiles on the basis of their 2011 mean family size and percentage of males, Chinese, elderly and young adults. Figure 2g–k shows that HIP effects are similar across subgroups, with a few exceptions. For example, the effect on the lowest quartile of family size is smaller than that on subsequent quartiles ($P<0.001$ for all pairwise comparisons). This is consistent with our previous results, as smaller households are likely to have lower water consumption and reduction capacity.

Dynamic effect. In addition to the immediate change in water use behaviour, individuals may adjust their water use over time as they adapt to the efficient fixtures or remove the fixtures if they are unable to adapt[36]. To address potential concerns about behavioural adjustments and technology disadoption over time, we study the long-term and evolutionary effects of efficiency improvements by conducting event studies (equation (3)).

Figure 3 shows that before HIP, there is no statistically significant difference ($P=0.204$ for the difference between the largest and smallest effect sizes) in the mean water consumption between the treatment and control groups, which validates the difference-in-differences research design. Upon the completion of HIP, there is an immediate reduction ($\beta_{T+1}=-1.95\%$, where T is the year of HIP completion; $P<0.001$; 95% CI, (−0.024, −0.015)) in water consumption for the treatment group. The effect persists throughout the ten years after HIP completion. We observe that the HIP effect is smaller during period $T+1$ than during period $T+2$ ($\beta_{\text{diff}}=0.0139$; $P<0.001$; 95% CI, (0.010, 0.018)), which could be a result of delays in project completion and meter readings. As meter readings are conducted every other month with water usage for the in-between month estimated using the previous two readings, the HIP effect may take up to five months to be fully reflected in water bills for some households. We also observe the effect size reducing from period $T+2$ to $T+4$ ($\beta_{\text{diff}}=0.007$; $P<0.001$; 95% CI, (0.003, 0.011)), which is probably due to cohort differences rather than a deterioration of the HIP effects. When conducting event studies by cohort (Extended Data Fig. 6), we do not observe a similar reduction in effect size over time.

The evidence for the long-term HIP effect shows that although the realized conservation through water efficiency improvements is smaller than the engineering estimates documented in the literature, it is persistent, with limited long-term behaviour adjustments and technology disadoption.

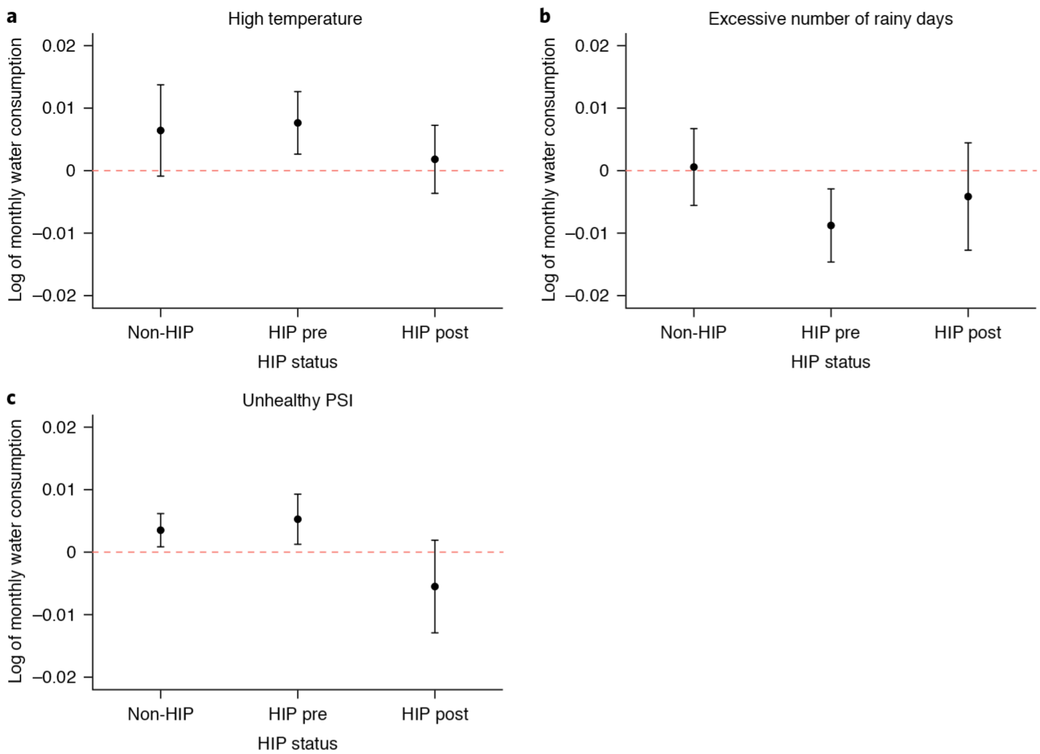

Fig. 5 | Interaction effects between HIP and extreme environmental conditions. a–c, Estimated coefficients and corresponding 95% CIs (error bars) for the associations between high temperature (top 10% observations, which is equivalent to mean monthly temperature > 28.9 °C) (**a**), excessive rainfall (top 10% observations, which is equivalent to monthly number of rainy days > 22) (**b**) and unhealthy PSI (PSI > 100) (**c**), and water consumption for non-HIP flats (β_1) and for HIP flats before ($\beta_1+\beta_2$) and after ($\beta_1+\beta_2+\beta_3$) project completion. The values were obtained by estimating equation (5) using the baseline sample of 98,291,320 observations. The estimates for the full models are shown in Supplementary Table 14, columns 4–6, and the full results for hypothesis testing are provided as source data.

Interaction of HIP and other water conservation policies. Efficiency improvements not only affect water consumption directly but also influence households' responses to other water conservation polices. In Singapore, there has been continuous effort to reduce residential water demand. During our sample period, nationwide initiatives on peer comparison and water price increase were implemented in August 2016 and July 2017, respectively. Although the effects of these initiatives are accounted for by year–month fixed effects, we could compare their effects on HIP and non-HIP flats (equation (4)). Figure 4 shows that the effect of peer comparison on water consumption is 0.69% larger ($P = 0.03$; 95% CI, (−0.012, −0.004)) for post-HIP flats, as households with efficient plumbing can respond to conservation polices more effectively. The differential effect of price increase is 0.75% ($P = 0.07$; 95% CI, (−0.013, 0.004)), but this is not statistically significant at the conventional level. The effect of price increase on water consumption is documented in detail in a separate study by Sumit Agarwal, Eduardo Araral, Mingxuan Fan, Yu Qin, and Huanhuan Zheng (unpublished).

Interaction of HIP and extreme environmental conditions. Research has shown that temperature, precipitation and air pollution could all affect residential electricity and water consumption in Singapore and around the world[37–39]. Households may choose to stay indoors to avoid excessive heat, rain or pollution. If outdoor activities are necessary, they may increase efforts to mitigate the impacts of heat or rain and health risks related to air pollution. Both avoidance and mitigation behaviours are likely to affect water use.

The distribution, trend and spatial variations in temperature, rainfall and air quality are presented in Extended Data Fig. 7. We focus on how efficiency improvements modify the relationship between water consumption and extreme environmental changes in the Singapore context by interacting the indicators for high temperature (top 10% or mean temperature > 28.9 °C), excessive rainfall (top 10% or number of rainy days > 22) and unhealthy air pollution level (Pollutant Standards Index (PSI) > 100) with the HIP variables (equation (5)).

Upon HIP completion, the increase in water consumption associated with high temperature declines by 0.6% ($P = 0.024$; 95% CI, (−0.011, −0.001)), while that associated with unhealthy air pollution level drops by 1.1% ($P = 0.001$; 95% CI, (−0.017, −0.005)). Excessive rainfall is associated with a reduction of 0.98% ($P = 0.003$; 95% CI, (−0.016, −0.004)) in water consumption for pre-HIP flats; the reduction is 0.5% ($P = 0.175$; 95% CI, (−0.002, 0.011)) smaller upon completion of HIP and is no longer statistically significant ($P = 0.219$; 95% CI, (−0.012, 0.003)). The associations between excessive heat, rain and pollution and water consumption for non-HIP flats and HIP flats before and after the upgrade are presented in Fig. 5.

Overall, the findings in this section suggest that in addition to directly reducing water consumption, efficiency improvements mitigate the effects of extreme weather and air pollution. We note that the change in water use due to avoidance behaviour could be a shift from other locations to home. Whether this will generate a net reduction in the water system depends on the differences in the efficiency of fixtures and water use behaviour between home and public places.

Cost-effectiveness of HIP. The estimated 3.5% ($P < 0.001$; 95% CI, (−0.038, −0.031)) reduction in water consumption after HIP is equivalent to conserving an average of 0.6 m^3 of water per household per month. This accumulates to savings of 182 Singapore dollars (S$) in water bills over ten years without discounting. The private benefit of savings in utility bills is smaller than the average cost of S$657 to households for the optional upgrades (Supplementary Table 6), which could be paid upfront or by instalments. We consider a ten-year frame to be consistent with the evaluation conducted in this paper. As the lifespan for some plumbing fixtures such as the toilet is 25 years[16], the actual savings from water bills are likely to be much higher. Additionally, the cost of the optional upgrade includes items such as gates, doors and refuse chutes that do not affect water usage but cannot be excluded due to unknown itemized costs.

As water conservation is not the main purpose of HIP, it is not surprising that savings in water bills due to HIP constitute a small proportion of the total benefit. The largest private benefit of the programme is the increment in housing value. Using all 178,185 transactions involving HDB resale flats from 2011 to 2019, we show that HIP increases the resale value by S$12,320 per flat. This is more than sufficient to cover the private cost of upgrade (S$657), but it still falls short when including government subsidies for HIP (S$22,820).

Details on the costs and private benefits of HIP are described in the Supplementary Discussion. Fully evaluating the social benefits of HIP is out of the scope of this paper. Nonetheless, the benefits from improved public health and safety and welfare redistribution should be accounted for.

Nationwide nudging through peer comparison

To encourage utility conservation through peer comparison, the utility bill for all residential consumers was redesigned in August 2016. The new bill allows consumers to view and compare their past six months of water consumption with the national and neighbourhood averages for the same flat type. Consumers receive one of four norm-based messages: their household's water consumption is (1) below the neighbourhood and national averages, (2) below the neighbourhood but above the national average, (3) above the neighbourhood but below the national average, or (4) above the neighbourhood and national averages.

To evaluate the effect of nationwide peer comparison, we rely on a quasi-experimental research design. Upon including time-invariant household characteristics, seasonality, spatially varying weather and pollution conditions, other shocks (drought and water price increase), and water consumption trend (equation (6)), our results support the model with the null hypothesis of no nudging effect over the alternative model that controls for nudging through peer comparison ($\beta_{\mathrm{nudge}} = -0.3\%$; $P = 0.544$; 95% CI, (-0.012, 0.006)) with a Bayes factor (BF) of 0.00013. With more than 1.5 million accounts, this null effect is probably not due to the lack of statistical power, as we can identify a minimal effect size of 0.014% at the 95% confidence level with 80% power. Delayed responses and meter readings are probably not the drivers for the null effect, as we do not observe any increasing effect over the few months post-intervention and before other external shocks (Extended Data Fig. 8 and equation (7)).

This overall null effect of peer comparison could be attributed to the boomerang effects on households with low pre-treatment water usage[18,40,41]. We divide households into deciles by their pre-treatment mean water consumption and compare the effect of peer comparison for each decile (equation (8)). Figure 6a shows that households with below-median baseline water consumption increase their water usage post-treatment, and the effects are large enough to reverse the conservation achieved by consumers with above-median baseline water consumption. As our study evaluates the effect of nationwide nudging that targets all consumers, the boomerang effects are larger than the effects identified through experiments, for which utilities tend to target higher-usage consumers[24,33]. Although some studies show that including injunctive norms may reduce the boomerang

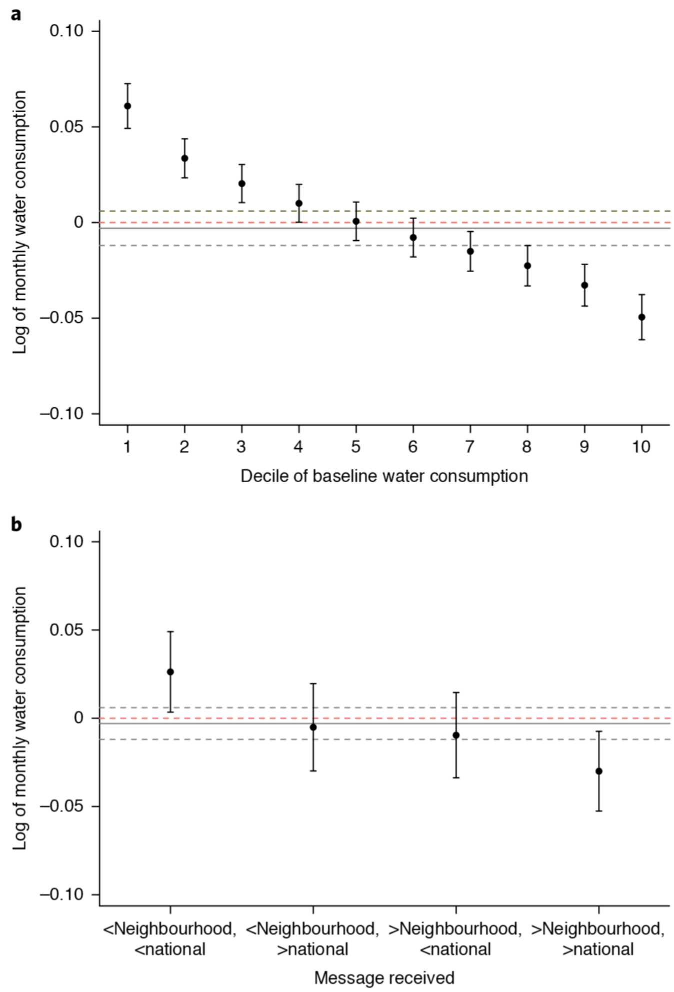

Fig. 6 | Effect of social comparison by baseline water consumption and message received. a,b, Estimated coefficients and corresponding 95% CIs (error bars) for the change in monthly water consumption by deciles of baseline water consumption (**a**) and by messages received (**b**). The values were obtained by estimating equations (8) and (9), respectively. Panel **a** uses the baseline sample of 98,291,320 observations, while **b** uses 96,786,609 observations, which is less than the number of observations in the baseline sample because norm-based messages are determined by the previous month's water consumption. The first observation for each account is therefore dropped from the sample. The detailed estimates are provided as source data. The grey horizontal lines indicate the estimated average effect (solid) and the corresponding 95% CI (dashed).

effect[40], others show that it does not work when implemented at a large scale[18]. However, we are unable to directly test this due to the lack of injunctive norms in the policy design.

The effect of nudging through peer comparison also depends on the information received. When evaluating the effect of each norm-based message (Fig. 6b and equation (9)), we find that the post-treatment water consumption drops by 2.5% ($P = 0.002$; 95% CI, (-0.037, -0.013)) for households that receive message 4 (36% of the sample) and increases by 2.7% ($P < 0.001$; 95% CI, (0.018, 0.037)) for households that receive message 1 (53% of the sample). However, there is no credible evidence that water consumption changes for households that receive message 2 ($\beta_{\mathrm{message2}} = -0.5\%$; $P = 0.70$; 95% CI, (-0.030, 0.020); $BF_{10} = 0.00016$) or message 3 ($\beta_{\mathrm{message3}} = -0.9\%$; $P = 0.47$; 95% CI, (-0.034, 0.015); $BF_{10} = 0.0001$), which represents 5% and 6% of the sample, respectively. Neither is there a sharp discontinuity when comparing the post-treatment

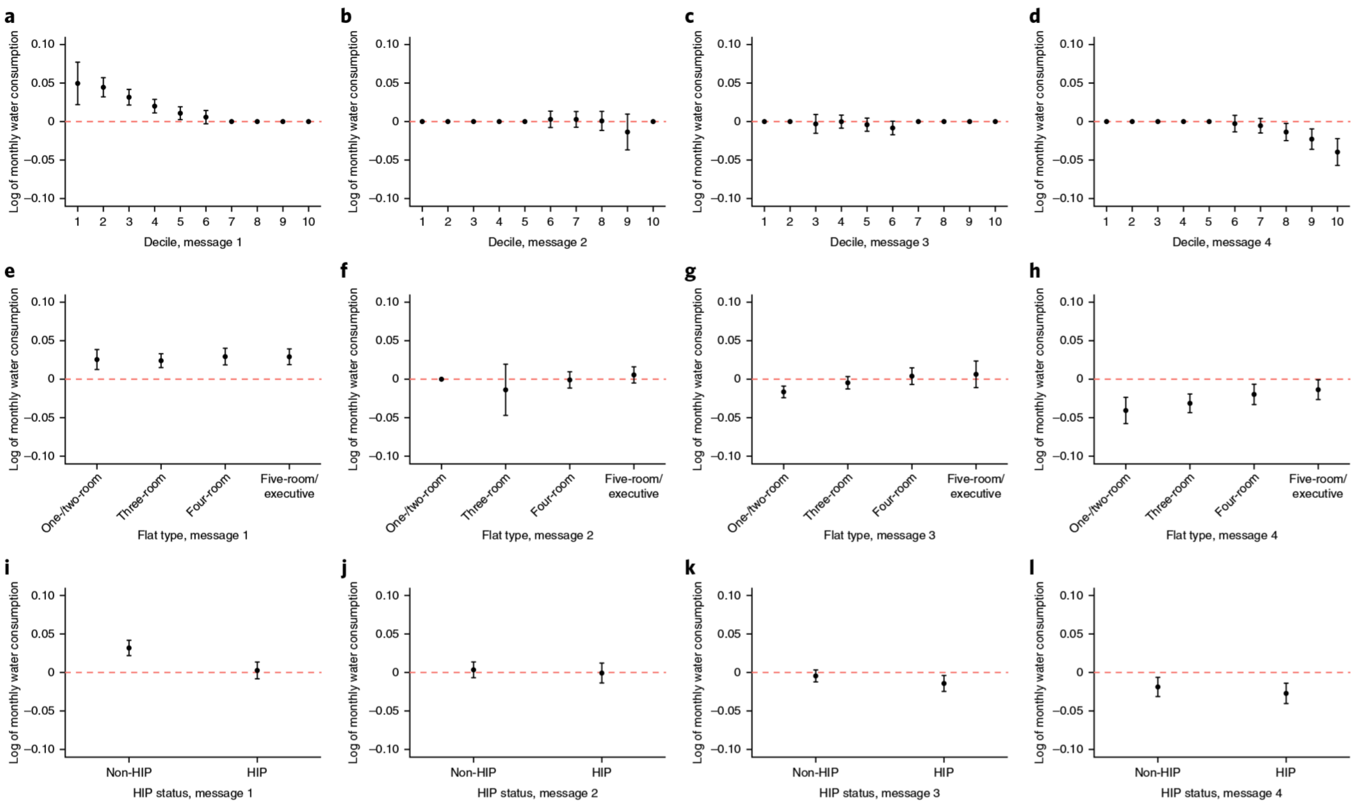

Fig. 7 | Heterogeneous effects of social comparison by message received. a–l, Estimated coefficients and corresponding 95% CIs (error bars) for the heterogeneous effects of peer comparison by baseline water consumption decile (**a–d**), flat type (**e–h**) and HIP status (**i–l**) for groups of households that receive each message. The values were obtained by estimating equation (11) using 96,786,609 observations. Detailed estimates are provided as source data.

observations just above and just below each norm (Extended Data Fig. 9 and equation (10)).

The effects of peer comparison (that is, messages 2 and 3) may be suppressed by the potentially conflicting nudges provided through the national and neighbourhood averages. We evaluate the effect of each message by baseline water consumption decile (equation (11)). Unlike in Fig. 6a, where the effect of nudging increases for households whose baseline consumption deviates further from the median, there is no credible evidence of any effect of message 2 (Fig. 7b) across households with various baseline water consumption rates ($\beta_{\text{decile6}} = 0.29\%$; $P = 0.591$; 95% CI, (−0.008, 0.014); $\beta_{\text{decile7}} = 0.29\%$; $P = 0.590$; 95% CI, (−0.008, 0.013); $\beta_{\text{decile8}} = 0.08\%$; $P = 0.892$; 95% CI, (−0.015, 0.013); $\beta_{\text{decile9}} = -1.35\%$; $P = 0.249$; 95% CI, (−0.036, 0.097)). Similarly, we do not observe credible evidence for the boomerang effects of message 3 (Fig. 7c) across households with various baseline water consumption rates ($\beta_{\text{decile3}} = -0.30\%$; $P = 0.623$; 95% CI, (−0.015, 0.009); $\beta_{\text{decile4}} = -0.009\%$; $P = 0.983$; 95% CI, (−0.009, 0.008); $\beta_{\text{decile5}} = -0.41\%$; $P = 0.349$; 95% CI, (−0.013, 0.045); $\beta_{\text{decile6}} = -0.83\%$; $P = 0.06$; 95% CI, (−0.017, 0.0004)). The responses to messages 1 and 4 (Fig. 7a,d), however, increase as households' baseline water consumption deviates more from the median ($\beta_{\text{decile1}} - \beta_{\text{decile6}} = 4.38\%$; $P < 0.001$; 95% CI, (0.039, 0.050); $\beta_{\text{decile6}} - \beta_{\text{decile10}} = 3.69\%$; $P < 0.001$; 95% CI, (0.033, 0.041)).

Additional analyses on the heterogeneous effects of peer comparison by message received are conducted by flat type and HIP status (Fig. 7e–l). We find the effect of each message to be consistent across flat types. However, upon completing HIP, the boomerang effect of message 1 is significantly reduced ($P < 0.001$) from 3.2% ($P < 0.001$; 95% CI, (0.022, 0.042)) to 0.3% ($P = 0.626$; 95% CI, (−0.008, 0.014)), while messages 3 and 4 reduce water consumption for post-HIP flats ($\beta_{\text{message3}} = 1.4\%$; $P = 0.007$; 95% CI, (−0.025, −0.004); $\beta_{\text{message4}} = 2.7\%$; $P < 0.001$; 95% CI, (−0.040, −0.014)) more ($P = 0.003$ and $P = 0.003$) than for non-HIP flats ($\beta_{\text{message3}} = 0.5\%$; $P = 0.250$; 95% CI, (−0.012, 0.003); $\beta_{\text{message4}} = 1.9\%$; $P = 0.03$; 95% CI, (−0.031, −0.006)).

On average, we are unable to attribute any clear reduction in water consumption to nationwide nudging through peer comparison. We acknowledge the limitations of this evaluation, as it relies on a quasi-experimental design that does not allow us to fully account for all possible confounding factors. However, it implies that more needs to be done to avoid potential boomerang effects and ensure the effectiveness of the policy at the national level, even though the literature has shown a promising local treatment effect both globally and in Singapore[42].

Discussion

We present causal evidence that improving plumbing could generate long-lasting effects in water conservation. Using anonymized monthly billing data for all public housing households in Singapore over ten years, we show that the nationwide HIP reduces residential water consumption by 3.5% ($P < 0.001$; 95% CI, (−0.038, −0.031)) on average, or 0.6 m^3 per household per month. Although the savings on water tariffs alone are small, the benefit of housing value appreciation is enough to recover a household's upfront cost of upgrades. From the government perspective, though the cost of upgrade is higher, this is probably offset by the intended main benefits of social improvements in public health and safety and welfare redistribution. As Singapore aims to reduce residential water consumption from 141 litres per person per day in 2018 to 130 litres in 2030, our back-of-the-envelope estimation shows that this 3.5% savings in water consumption could contribute to half of this conservation target for the HIP households.

We find that the effect of efficiency improvements on water consumption lasts at least a decade, in contrast to the short-term effect of nudging through peer comparison shown in the literature. We show that efficiency improvements could achieve water conservation across population subgroups, while low-usage consumers may increase water consumption upon receiving norm-based messages. In terms of policy design, efficiency improvements are more straightforward, unlike behavioural interventions that require careful calibrations to ensure effectiveness. Additionally, efficiency improvements may help in improving the efficacy of other conservation polices and mitigating the effects of extreme environmental conditions on water use.

There are a few caveats in our findings. First, we are unable to control for time-varying household characteristics due to a lack of data. However, it is unlikely that the average changes in household characteristics for the treatment group would differ from those of the control group given the exogenous selection into the programme and the fact that our data cover all HDB flats over ten years. Second, we do not have information on the specifications of plumbing fixtures before or after HIP. The estimated effect is a combination of the engineering effect, based on the average technological advancement, and the behavioural responses. Third, apart from the overall take-up rate of 70%, we do not have information on individual households' decisions on the optional upgrades and are only able to estimate the intent-to-treat effect of efficiency improvements. Lastly, the effect of national nudging through peer comparison is evaluated under a quasi-experimental setting, which may not be causal. Besides, the effect of injunctive norms in a scaled-up setting cannot be directly tested due to policy design.

This paper contributes to the literature by showing causal evidence that efficient plumbing provides long-lasting effects in water conservation and mitigates the effects of extreme environmental conditions on water use. Our non-causal evaluation shows that peer-comparison nudging may not work when scaling up to the national level.

Methods

Data. *Water consumption.* We used water consumption data obtained from PUB, Singapore's national water agency. The dataset contains monthly water consumption based on water bills for all HDB flats, with 1,506,296 unique anonymized accounts from January 2011 to December 2019. The data include anonymized account numbers that change every time a household moves, block identifiers or postal codes, and flat types classified by the number of rooms.

Block-level housing characteristics and demographics. Block-level housing characteristics such as year of completion, public rental status and resale transactions were collected through a publicly available database provided by the government of Singapore. The rental statuses of privately owned HDB flats from 2019 to 2021 were collected from SRX.com.sg and were used to determine the percentage of flats on rent for each block.

We also have access to administrative data on the demographics and residential addresses for 2.8 million adult Singaporeans in 2011. Although we were unable to match these individuals to account-level water consumption due to the anonymization of the account identifiers in the water consumption data, we could derive block-level demographics, such as mean family size, percentage of males (versus females), percentage of Chinese (versus other ethnicities), percentage of elderly (born before 1950) and percentage of young adults (born after 1990).

Weather and air quality. We acquired daily weather observations by station from the Meteorological Service Singapore and historical 24-hour PSI readings by monitors from the National Environmental Agency. We generated block-specific monthly weather and air quality indicators such as mean temperature, number of rainy days and mean PSI using observations across all stations within a 10-km radius of the block using the inverse distance weighting method.

Sample. No statistical methods were used to pre-determine the sample sizes, but our sample sizes are larger than those of previous studies[13,14,17,19,22,25]. In our baseline analysis, we included data from January 2011 to December 2019. We excluded extreme values of the top and bottom 1% of observations in water consumption for each flat type to account for potential measurement errors caused by water leakage, bill adjustment and problematic meter readings. We excluded accounts with missing information on HIP status. The resulting baseline sample consists of 98,291,320 observations from 1,503,350 accounts in 10,188 HDB blocks.

Sample statistics are shown in Supplementary Table 15. The mean monthly water consumption is 17.24 m^3 for HIP flats before project completion, higher than the mean of 16.8 m^3 for non-HIP flats, while the post-project mean for HIP flats is reduced to 15.42 m^3.

The treatment and control groups comprise a different mix of flats in terms of year of construction and flat type. This is expected as only older flats built before 1997 were eligible for HIP, and the composition of flat types evolved over time to accommodate the changing demographics. Similarly, we observe differences in demographic composition between HIP and non-HIP flats. During the sample period, the differences in weather and air quality between the treatment and control groups were small.

Empirical method. Empirical analysis in this paper was conducted using Stata v.16. All test statistics are two-sided. The data distribution was assumed to be normal, but this was not formally tested.

Effect of efficiency improvements. We analysed the effect of efficiency improvements on residential water consumption using a staggered difference-in-differences regression approach. The treatment group is the HDB flats that completed HIP before December 2019, and the control group is the HDB flats that did not implement or complete the project. We used data from January 2011 to December 2019; therefore, the pre-treatment periods range from 1 to 107 months, while the post-treatment periods range from 1 to 124 months due to the staggered implementations of HIP.

To evaluate the average effect of efficiency improvements on water consumption, we first estimated the following specification:

$$\ln W_{ijt} = \delta \text{Post}_t \times \text{Treat}_i + \mathbf{X}_{jt}\beta + \theta_k \tau + \alpha_i + \gamma_t + \varepsilon_{ijt} \quad (1)$$

The dependent variable is the natural logarithm of monthly water consumption W for household i living in block j in time period t. Post_t is an indicator variable that takes the value of 1 for time periods after the completion of HIP. Treat_i is an indicator variable for the treatment group—that is, households that completed HIP. $\mathbf{X}_{jt}$ is a vector of weather and air quality controls such as the log of mean temperature, number of rainy days and mean PSI, which vary by block and time. We allowed the control and treatment groups to have different water consumption trends by including the group-specific linear time trend τ. We included household fixed effects α_i to account for time-invariant household characteristics and time fixed effects γ_t to account for seasonality and other economy-wide common shocks including water price increase. ε is the idiosyncratic error term. The coefficient of interest δ measures the average post-completion monthly water consumption for the treatment group relative to the control group. The coefficient β measures the effect of the respective control on monthly water consumption while θ measures the effect of group-specific time trend. Standard errors in the baseline estimation are two-way clustered by block and year–month.

We studied the heterogeneous effects of efficiency improvements on subgroups of the population by HIP cohort, housing characteristics (flat type, age, ownership and percentage of rental flats), water demand (water consumption quartile) and block-level demographic characteristics (quartile of family size, percentage of males, percentage of Chinese, percentage of elderly and percentage of young adults), using the following specification:

$$\ln W_{ijt} = \sum_{n=1}^{N} \delta_n G_i \times \text{Post}_t \times \text{Treat}_i + \mathbf{X}_{jt}\beta + \theta_k \tau + \alpha_i + \gamma_t + \varepsilon_{ijt} \quad (2)$$

where N is the number of subgroups and G_i is the subgroup indicator. The coefficients δ_1 to δ_N measure the heterogeneous effects of efficiency improvements.

We further explored the dynamics of water consumption change due to efficiency improvements through an event study analysis and estimated the following model:

$$\ln W_{ijt} = \sum_{l=-9}^{10} \delta_l D_{it}^{\text{Year}} \times \text{Treat}_i + \mathbf{X}_{jt}\beta + \theta_k \tau + \alpha_i + \gamma_t + \varepsilon_{ijt} \quad (3)$$

where we interact the treatment indicator with a set of relative time dummies D_{it}^{Year} that correspond to each 12-month lead and lag of the treatment timing. In our sample, the data cover observations up to nine years before and ten years after the HIP implementation. The coefficients of interest δ_l measure the average difference in water consumption between the control and treatment groups in each 12-month period. In addition, this setting allows us to explicitly test the parallel trend assumption of the difference-in-differences design.

To evaluate how HIP modifies the effects of other water conservation policies, we estimated the following model:

$$\begin{aligned} \ln W_{ijt} = {} & \delta \text{Post}_t \times \text{Treat}_i + \beta \text{Post}_t \times \text{Treat}_i \times \text{Policy}_t \\ & + \mathbf{X}_{jt}\beta + \theta_k \tau + \alpha_i + \gamma_t + \varepsilon_{ijt} \end{aligned} \quad (4)$$

where Policy_t is an indicator variable that takes the value of 1 for the time periods after the implementation of other water conservation polices such as peer comparison and price increase. The coefficient of interest β measures the differences in policy effects between post-HIP flats and pre-HIP or non-HIP flats.

We are particularly interested in whether efficiency improvements modify the effects of environmental conditions. To this end, we estimated the interaction effects between weather/air quality variables and HIP through the following model:

$$\ln W_{ijt} = \delta \text{Post}_t \times \text{Treat}_i + \beta_1 X_{jt} + \beta_2 X_{jt} \times \text{Treat}_i + \beta_3 X_{jt} \times \text{Treat}_i \times \text{Post}_t + \theta_k \tau + \alpha_i + \gamma_t + \varepsilon_{ijt} \quad (5)$$

where X_{jt} is a weather or pollution control variable for all households in block j during time t. The coefficients β_1, $\beta_1+\beta_2$ and $\beta_1+\beta_2+\beta_3$ represent the associations between weather/pollution and water consumption for non-HIP flats and for HIP flats before and after project completion, respectively.

Effect of nudging through peer comparison. To evaluate the effect of nudging through peer comparison on water consumption, we first relied on a fixed-effects model comparing monthly water use before and after the implementation of peer comparison through the redesign of utility bills. We estimated the following model:

$$\ln W_{ijt} = \delta \text{Post}_t + \mathbf{Policy}_t \sigma + \mathbf{X}_{jt}\beta + \tau + \alpha_i + \gamma_t^{\text{Month}} + \varepsilon_{ijt} \quad (6)$$

$\mathbf{Policy}_i$ is a vector of indicator variables for other nationwide policy changes such as price increase and common shocks such as severe droughts that affect sources of water import. We include the month fixed effect γ_t^{Month} to account for seasonality. The coefficient of interest δ measures the average change in water consumption after the implementation of peer comparison. Standard errors are two-way clustered by block and year–month.

To explore how the effect of nudging through peer comparison evolves over time, we compared the water consumption in each month after the implementation of peer comparison with the mean water consumption before by estimating the following model:

$$\ln W_{ijt} = \sum_{n=1}^{T} \delta_n D_t + \mathbf{X}_{jt}\beta + \tau + \alpha_i + \gamma_t^{\text{Month}} + \varepsilon_{ijt} \quad (7)$$

where D_t is the indicator variable for each period of interest after the implementation of peer comparison. The coefficient of interest δ_n measures the difference in water consumption between the time period n and the mean water consumption before the implementation of peer comparison.

We next evaluated the effect of peer comparison by deciles of baseline water consumption by estimating the following model:

$$\ln W_{ijt} = \sum_{n=1}^{10} \delta_n D_i \times \text{Post}_t + \mathbf{Policy}_t \sigma + \mathbf{X}_{jt}\beta + \tau + \alpha_i + \gamma_t^{\text{Month}} + \varepsilon_{ijt} \quad (8)$$

where D_i is the indicator variable for the pre-treatment water consumption decile that a household belongs to. The coefficient of interest δ_n measures the change in water consumption before and after the implementation of peer comparison for the nth decile.

Similarly, we evaluated the effect of peer comparison by the types of messages received by estimating the following model:

$$\ln W_{ijt} = \sum_{m=1}^{4} \delta_m M_{it} \times \text{Post}_t + \mathbf{Policy}_t \sigma + \mathbf{X}_{jt}\beta + \tau + \alpha_i + \gamma_t^{\text{Month}} + \varepsilon_{ijt} \quad (9)$$

where M_{it} is the indicator variable for the message received by household i during time period t. The coefficient of interest δ_m measures the change in water consumption before and after the implementation of peer comparison for the group of households receiving social comparison message m.

We further evaluated the effect of the two norms provided by comparing the water consumption for the post-treatment observations just above and below the national and neighbourhood averages through a regression discontinuity design. We estimate the following model:

$$\ln W_{ijt} = \delta \text{Above}_{it} + f(m) + \mathbf{X}_{jt}\beta + \alpha_i + \gamma_t + \varepsilon_{ijt} \quad (10)$$

where Above_{it} is an indicator variable that takes the value of 1 if the household's water consumption is above the social norm, and $f(m)$ is a function of the running variable, which is the distance between a household's water consumption and the social norm. We included time and spatial varying weather and pollution controls $\mathbf{X}_{jt}$, household fixed effects α_i and year–month fixed effects γ_t.

We conducted an additional analysis on the heterogeneous effects of peer comparison for groups of households that received each of the four messages using the following model:

$$\ln W_{ijt} = \sum_{m=1}^{4} \sum_{n=1}^{N} \delta_{mn} D_i \times M_{it} \times \text{Post}_t + \mathbf{Policy}_t \sigma + \mathbf{X}_{jt}\beta + \tau + \alpha_i + \gamma_t^{\text{Month}} + \varepsilon_{ijt} \quad (11)$$

where D_i is the indicator variable for household characteristics, such as baseline water consumption decile, flat type and HIP status. N is the total number of categories. The coefficient of interest δ_{mn} measures the change in water consumption before and after the implementation of peer comparison for households with the nth category of household characteristics that received social comparison message m.

Reporting Summary. Further information on research design is available in the Nature Research Reporting Summary linked to this article.

Data availability

The water consumption dataset for this study is provided by PUB, Singapore's National Water Agency, under a non-disclosure agreement for the current study. Upon reasonable request to PUB and with the necessary non-disclosure agreements signed with NUS, the dataset is available onsite at NUS to replicate all the results from the deposited Stata code. The data on block-level housing characteristics, block-level demographics, weather, air pollution and HDB resale transactions are provided on GitHub: https://github.com/fmsgp/DataCode-HIP.git. Information on block-level housing characteristics, such as year of construction, HIP status and public rental status, was obtained from https://services2.hdb.gov.sg/web/fi10/emap.html, while block-level private rental information was obtained from https://www.srx.com.sg/hdb/. Block-level demographic data were processed from administrative records. Weather and air pollution records were retrieved from http://www.weather.gov.sg/climate-historical-daily/ and https://www.haze.gov.sg/resources/historical-readings, respectively. HDB resale transactions were collected through https://services2.hdb.gov.sg/web/fi10/emap.html. Source data are provided with this paper.

Code availability

The Stata code used for data analysis in this study is available on GitHub: https://github.com/fmsgp/DataCode-HIP.git.

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Author contributions

All authors contributed to the research design, implementation, data analysis and writing.

Competing interests

The authors declare no competing interests.

Additional information

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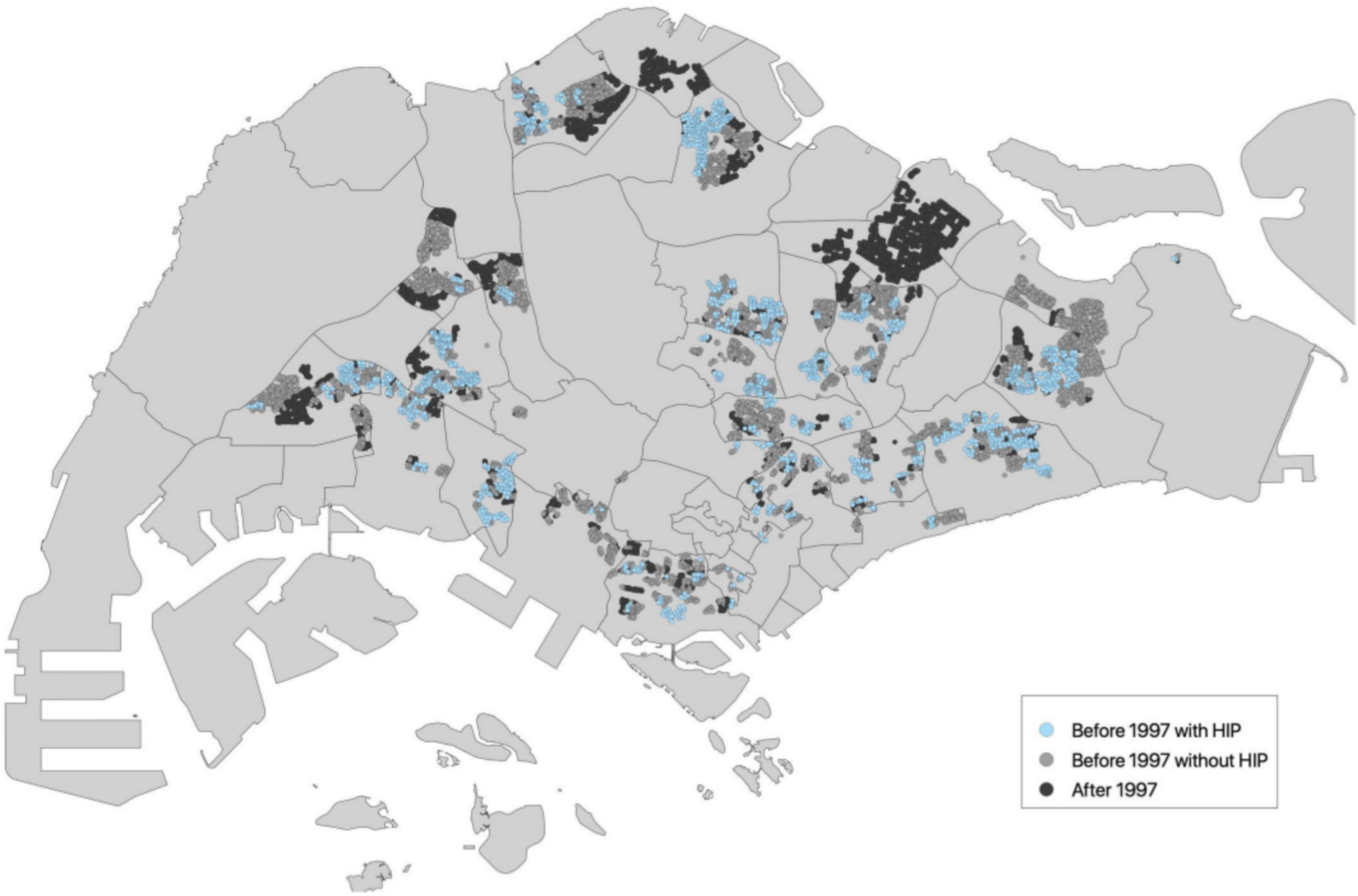
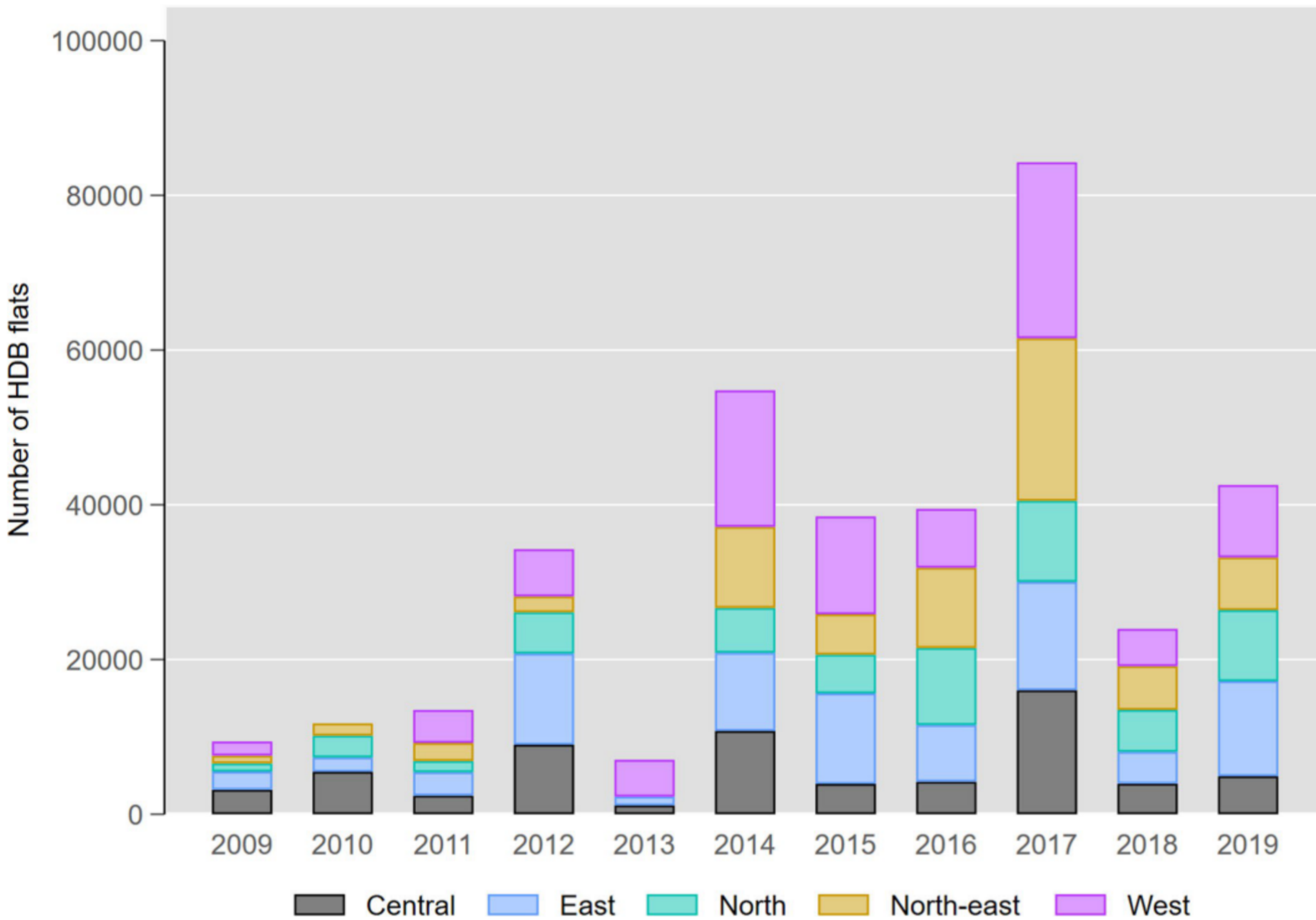
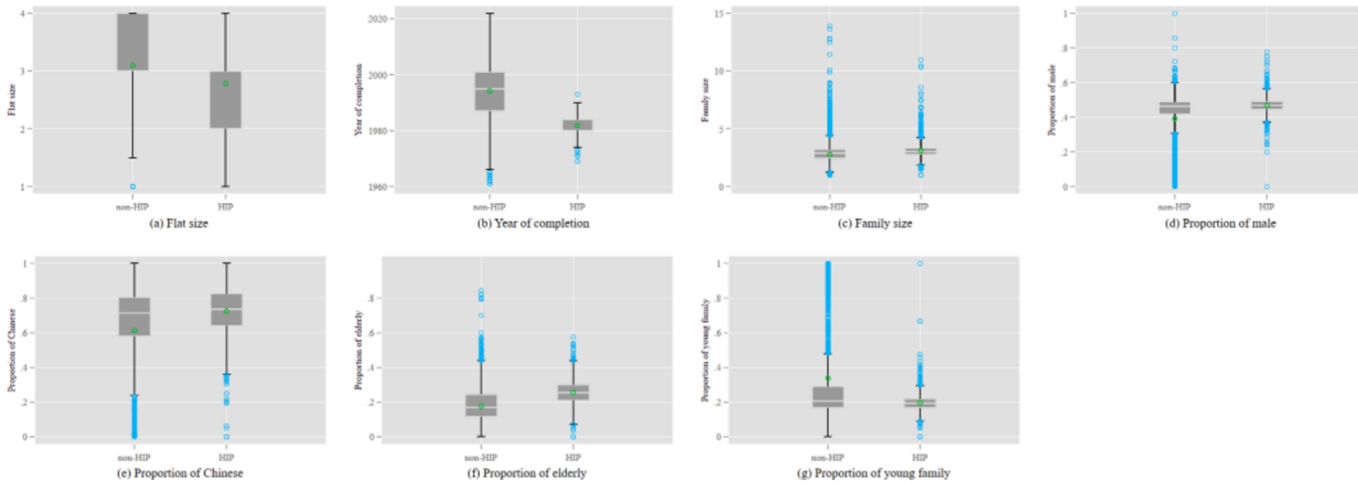


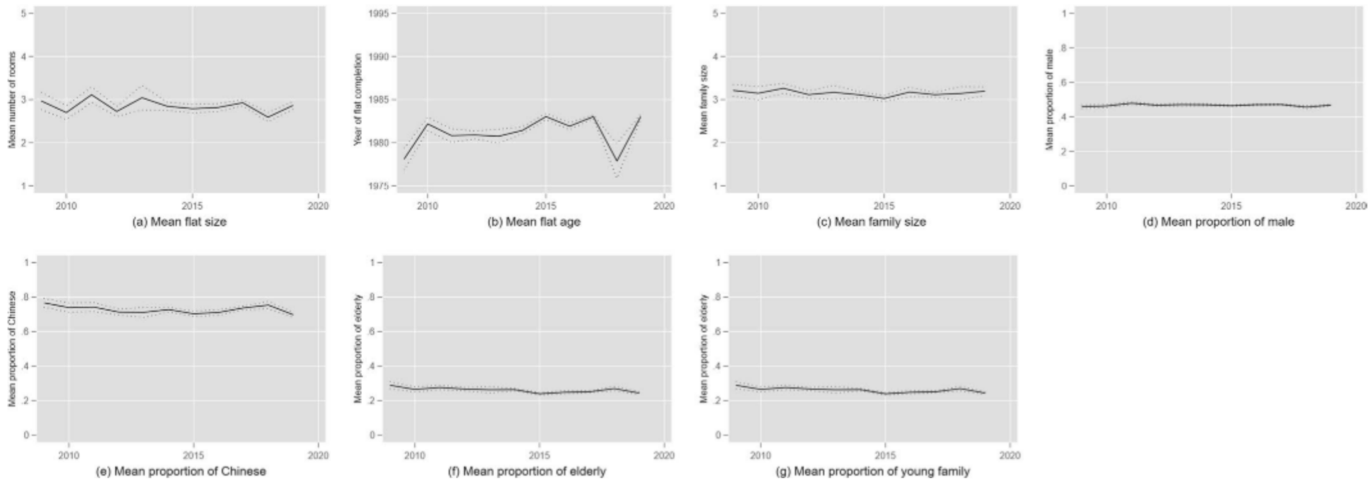
Extended Data Fig. 1 | Map of HDB blocks by HIP status. The map shows the location of all HDB blocks in Singapore. The blue circles represent 2,262 HDB blocks that completed HIP by December 2019; the grey circles represent 3,342 HDB blocks that qualify for HIP but did not go through or complete the upgrade by December 2019. Out of which 1,777 blocks qualify for the initial program (that is, built before 1986) and 1,565 blocks qualify for the expansion (that is, built between 1986 and 1997); the black circles represent 4,586 HDB blocks that do not qualify for HIP (that is, built after 1997). The base map used is available at: https://data.gov.sg/dataset/master-plan-2019-subzone-boundary-no-sea.



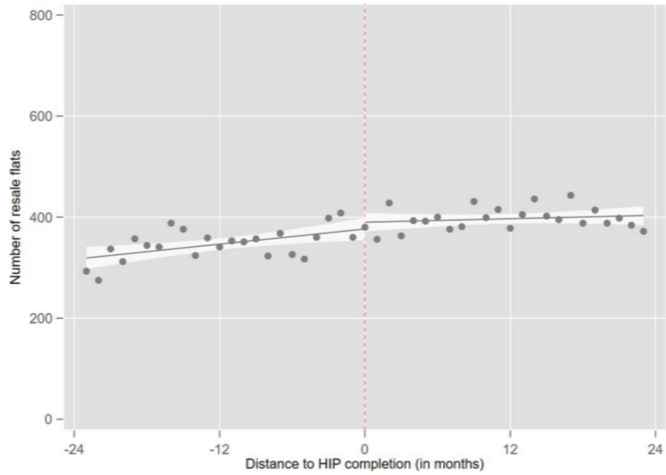
Extended Data Fig. 2 | Distribution of HDB flats by HIP cohort. The figure shows the number of HDB flats in each region (Central, East, North, Northeast, and West) by year of HIP completion. Projects are considered complete 18 months after the announcement of a successful poll. The total number of flats that has completed HIP by December 2019 is 359,496.



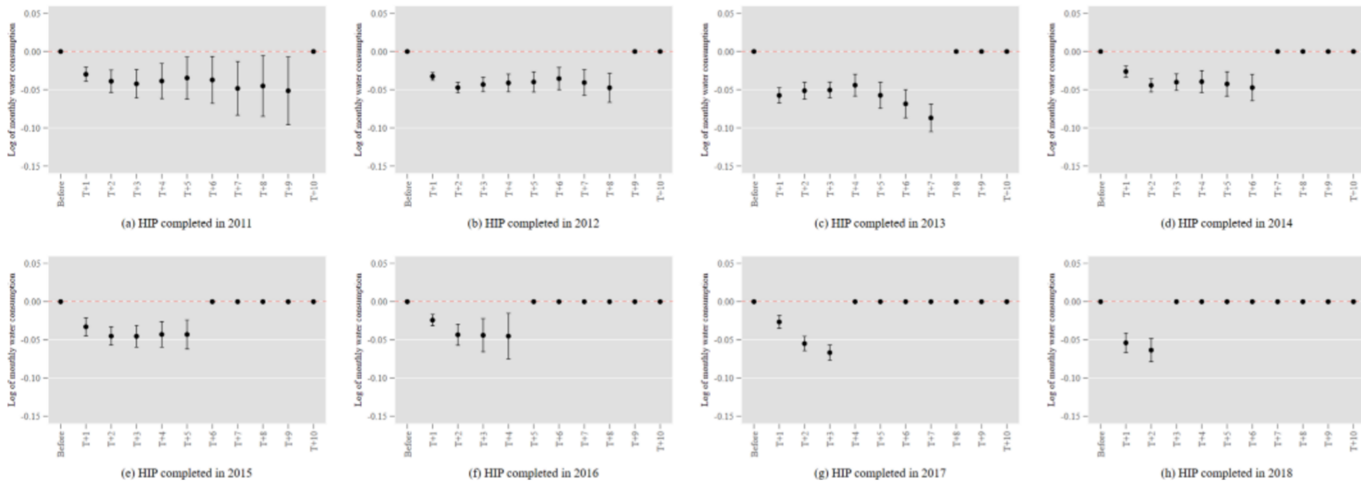
Extended Data Fig. 3 | Flat and household characteristics for HIP vs Non-HIP flats. The figures show the distribution and mean of flat size (sub-figure (**a**)), flat age (sub-figure (**b**)), family size (sub-figure (**c**)), proportion of male (sub-figure (**d**)), proportion of Chinese (sub-figure (**e**)), proportion of elderly (sub-figure (**f**)) and proportion of young adults (sub-figure (**g**)) for HIP and non-HIP flats. The boxes represent the 25th to 75th percentile and the white lines inside represent medians; the error bars show the non-outlier limits, which are 1.5 times the interquartile range. The blue circles show the outliers while the green circles represent the sample mean. In our baseline sample, there are a total of 359,496 HIP flats and 1,143,854 non-HIP flats.



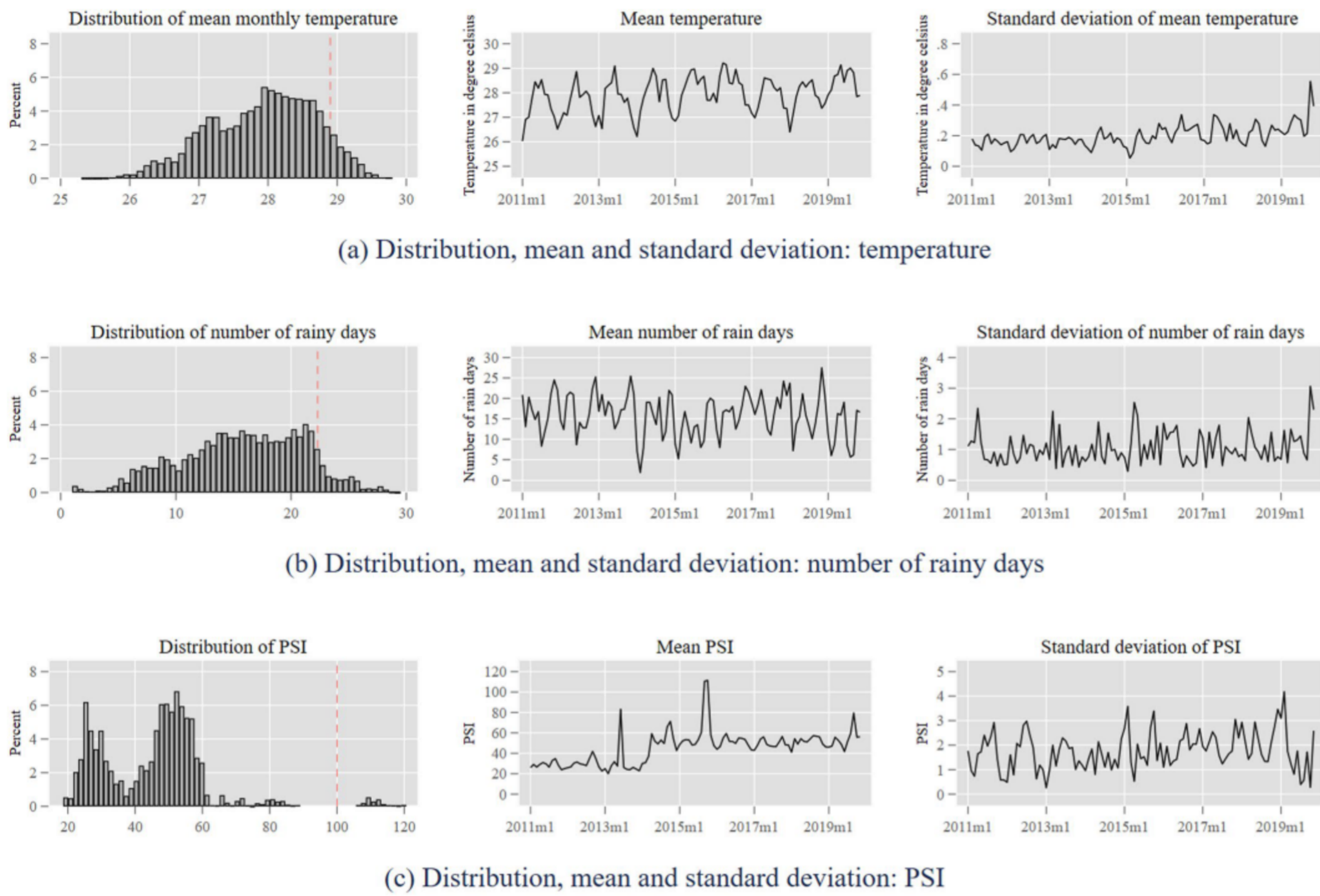
Extended Data Fig. 4 | Flat and household characteristics by HIP cohort. The figures show the mean and 95% confidence intervals for flat size (sub-figure (**a**)), flat age (sub-figure (**b**)), family size (sub-figure (**c**)), percentage of male (sub-figure (**d**)), percentage of Chinese (sub-figure (**e**)), percentage of elderly (sub-figure (**f**)) and percentage of young adults (sub-figure (**g**)) for HIP flats by cohort. The number of HIP flats by cohort are 9,426, 11,755, 13,525, 34,331, 7,061, 54,864, 38,563, 39,542, 84,413, 24,001, and 42,639 for project completion from 2009 to 2019, respectively. Detailed estimates are provided in Source Data Extended Data Figure. 4.



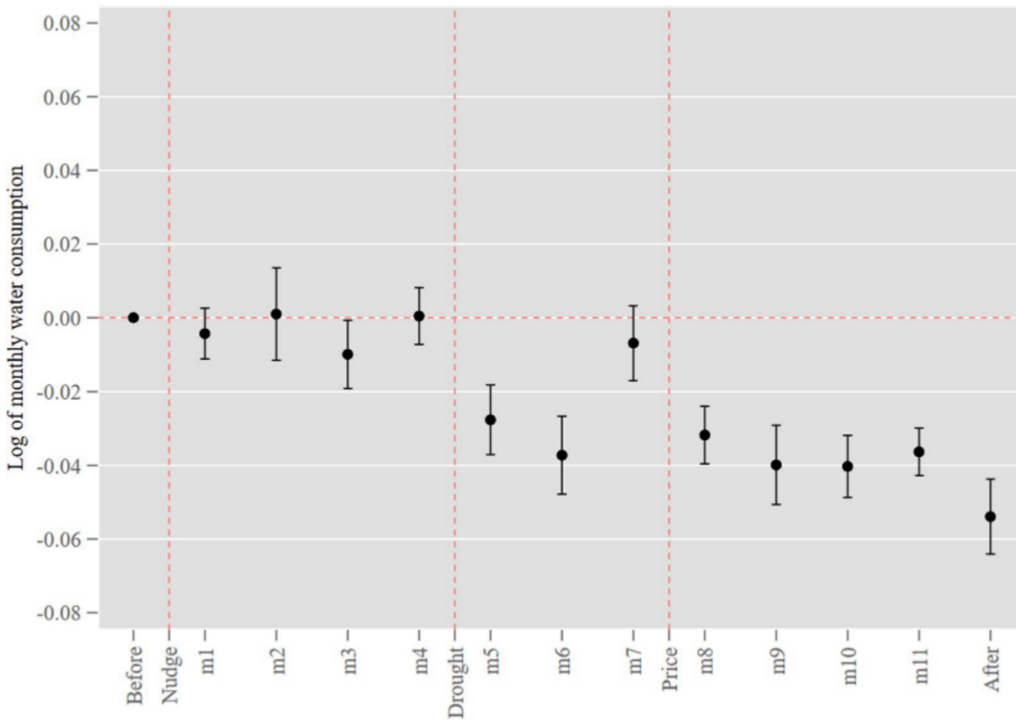
Extended Data Fig. 5 | Number of housing transactions around the time of HIP completion. The figure shows the number of HDB resale transactions each month, the linear trends and 95% confidence intervals before and after HIP completion. There is a total of 18,160 transactions within 24 months before and after HIP completion, out of which 8,719 transactions are pre-HIP and 9,441 post-HIP. The vertical line indicates the time of HIP completion defined as 18-month post the announcement of a successful poll.



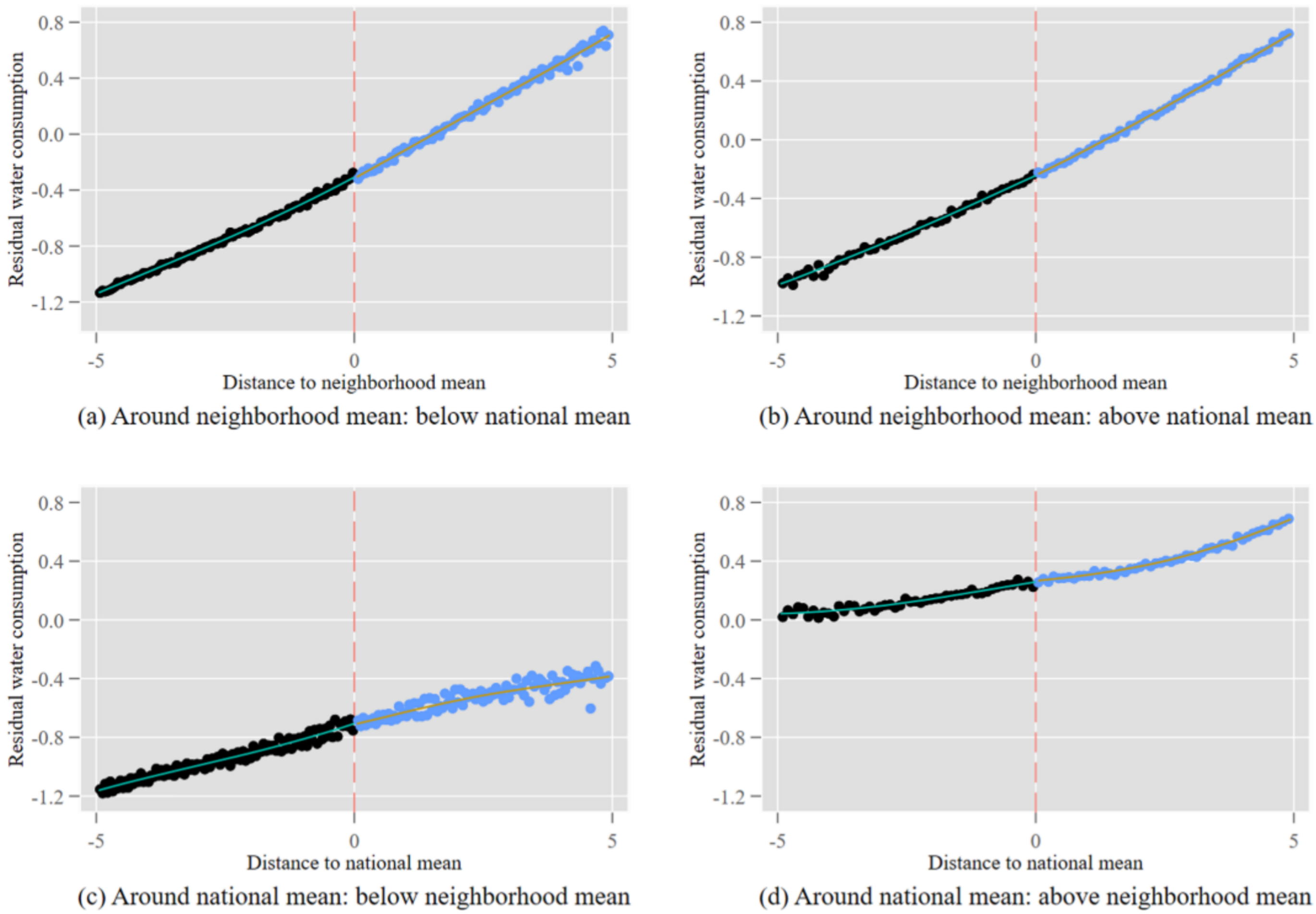
Extended Data Fig. 6 | Event study by year of HIP completion. Extended Data Fig. 1 The figures show the estimated coefficients and corresponding 95% confidence intervals (error bars) for the effect of HIP in each 12-month period after project completion for each HIP cohort by estimating equation 3. The number of observations used for are 936,619 (sub-figure (**a**)), 2,327,234 (sub-figure (**b**)), 490,385(sub-figure (**c**)), 3,705,615 (sub-figure (**d**)), 2,632,263 (sub-figure (**e**)), 2,735,076 (sub-figure (**f**)), 5,841,537 (sub-figure (**g**)), and 1,645,165 (sub-figure (**h**)), respectively. Detailed estimates are provided in Source Data Extended Data Figure. 6. The vertical lines indicate the time of HIP completion defined as 18-month post the announcement of a successful poll.



Extended Data Fig. 7 | Distribution, trend and spatial variation in temperature, rainfall, and air pollution. The figures show the distribution, trend, and spatial variation (in terms of standard deviation) in monthly mean temperature (sub-figure (**a**)), number of rainy days (sub-figure (**b**)), and PSI (sub-figure (**c**)) from January 2011 to December 2019 using the baseline sample of 98,291,320 observations.



Extended Data Fig. 8 | Event study for peer comparison by month. This figure shows the estimated coefficients and corresponding 95% confidence intervals (error bars) for the effect of nudging through peer comparison in each month for the first year after its implementation by estimating equation 10 using the baseline sample of 98,291,320 observations. Detailed estimates are provided in Source Data Extended Data Figure. 9. The vertical lines from left to right indicate the timing of nudging, drought, and the announcement of water price increase.



Extended Data Fig. 9 | Regression discontinuity around national and neighbourhood average. The figures show the monthly water consumption by the distance to neighbourhood mean for households who consume below (sub-figure (**a**)) and above (sub-figure (**b**)) the national mean; and by the distance to national mean for households who consume below (sub-figure (**c**)) and above (sub-figure (**d**)) the neighbourhood mean. Monthly water consumption variable is residual of account fixed effects, year-month fixed effects, and weather and pollution controls. The average residual water consumptions below the cut-offs (distance<0) are shown in black dots and above the cut-offs (distance>0) are shown in blue dots. The fitted lines from robust locally weighted regressions below the cut-offs (distance<0) are shown in green and above the cut-offs (distance>0) are shown in yellow.

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Reporting Summary

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Statistics

For all statistical analyses, confirm that the following items are present in the figure legend, table legend, main text, or Methods section.

n/a	Confirmed	
☐	☒	The exact sample size (*n*) for each experimental group/condition, given as a discrete number and unit of measurement
☐	☒	A statement on whether measurements were taken from distinct samples or whether the same sample was measured repeatedly
☐	☒	The statistical test(s) used AND whether they are one- or two-sided *Only common tests should be described solely by name; describe more complex techniques in the Methods section.*
☐	☒	A description of all covariates tested
☐	☒	A description of any assumptions or corrections, such as tests of normality and adjustment for multiple comparisons
☐	☒	A full description of the statistical parameters including central tendency (e.g. means) or other basic estimates (e.g. regression coefficient) AND variation (e.g. standard deviation) or associated estimates of uncertainty (e.g. confidence intervals)
☐	☒	For null hypothesis testing, the test statistic (e.g. F, t, r) with confidence intervals, effect sizes, degrees of freedom and P value noted *Give P values as exact values whenever suitable.*
☒	☐	For Bayesian analysis, information on the choice of priors and Markov chain Monte Carlo settings
☒	☐	For hierarchical and complex designs, identification of the appropriate level for tests and full reporting of outcomes
☐	☒	Estimates of effect sizes (e.g. Cohen's *d*, Pearson's *r*), indicating how they were calculated

Our web collection on statistics for biologists contains articles on many of the points above.

Software and code

Policy information about availability of computer code

Data collection	No software was used for data collection
Data analysis	Stata/SE 16.1 and the custom code is available at https://github.com/fmsgp/DataCode-HIP.git

For manuscripts utilizing custom algorithms or software that are central to the research but not yet described in published literature, software must be made available to editors and reviewers. We strongly encourage code deposition in a community repository (e.g. GitHub). See the Nature Research guidelines for submitting code & software for further information.

Data

Policy information about availability of data

All manuscripts must include a data availability statement. This statement should provide the following information, where applicable:

- Accession codes, unique identifiers, or web links for publicly available datasets
- A list of figures that have associated raw data
- A description of any restrictions on data availability

The water consumption dataset for this study is provided by PUB, Singapore's National Water Agency under non-disclosure agreement for the current study. Upon reasonable request to PUB and with the necessary non-disclosure agreements signed with NUS, it is available onsite at NUS to replicate all the results from the deposited Stata code. Data on block-level housing characteristics, block-level demographics, weather, air pollution, and HDB resale transactions are provided on GitHub: https://github.com/fmsgp/DataCode-HIP.git. Information on block-level housing characteristics, such as year of construction, HIP status, and public rental status, is obtained from https://services2.hdb.gov.sg/web/fi10/emap.html; while block-level private rental information is obtained from https://www.srx.com.sg/hdb/. Block-level demographics is processed from administrative records. Weather and air pollution records are retrieved from http://www.weather.gov.sg/climate-historical-daily/ and https://www.haze.gov.sg/resources/historical-readings respectively. HDB resale transactions is collected through https://services2.hdb.gov.sg/web/fi10/emap.html.

Field-specific reporting

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For a reference copy of the document with all sections, see nature.com/documents/nr-reporting-summary-flat.pdf

Behavioural & social sciences study design

All studies must disclose on these points even when the disclosure is negative.

Study description	This is a quasi-experimental quantitative study using panel data.
Research sample	The sample for this study is all public housing residents in Singapore from 2011 to 2019.
Sampling strategy	No sampling procedure was used in this study as we obtained administrative data for all public housing residents. No statically methods were used to pre-determine the sample sizes, but our sample sizes are larger than previous studies.
Data collection	No primary data collection was conducted for this study. We used secondary data including monthly water billing information provided by PUB; housing and demographic characteristics from HDB, SRX and administrative records; weather and pollution records from MSS and NEA; and housing transaction data from HDB.
Timing	January 2011 to December 2019.
Data exclusions	We exclude extreme values of the top and bottom 1% observations in water consumption for each flat type to account for potential measurement errors caused by water leakage, bill adjustment, and problematic meter readings. We exclude accounts with missing information on treatment status.
Non-participation	No participants dropped out or declined to participate.
Randomization	The treatment status is externally determined by the Housing and Development Board of Singapore. We find no obvious patterns in the regional distribution of treated flats (Extended Figure 1 and 2). The only selection criteria is the age of flats (i.e. built before 1997). We control the potential effect of flat age by comparing the treatment and control flats of similar age when evaluating the heterogeneous responses (Figure C.6(c) in Supplementary Information) and by conducting various robustness checks (Table A.3 in Supplementary Information).

Reporting for specific materials, systems and methods

We require information from authors about some types of materials, experimental systems and methods used in many studies. Here, indicate whether each material, system or method listed is relevant to your study. If you are not sure if a list item applies to your research, read the appropriate section before selecting a response.

Materials & experimental systems

n/a	Involved in the study	
☒	☐	Antibodies
☒	☐	Eukaryotic cell lines
☒	☐	Palaeontology and archaeology
☒	☐	Animals and other organisms
☒	☐	Human research participants
☒	☐	Clinical data
☒	☐	Dual use research of concern

Methods

n/a	Involved in the study	
☒	☐	ChIP-seq
☒	☐	Flow cytometry
☒	☐	MRI-based neuroimaging