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François Cohen, Matthieu Glachant and Magnus Söderberg

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The Autonomous Adaptation of US Homes to Changing Temperatures

Abstract

Little is known about how households adapt to climate change. Previous research has focused on geographical differences in fuel choice and air conditioning. Using a 28-year panel of homes, we conducted the first longitudinal analysis of eight categories of adaptations and their impact on electricity, gas, and water expenditures. Exposure to cold or warm days correlates with increased spending on doors, windows, equipment, insulation, energy, and water. Our findings suggest cooling costs will rise, offset by lower heating costs. We predict a significant increase in electricity and water use during summer, leading to seasonal utility adjustments.

Keywords: climate change; adaptation; housing; energy; water.

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I. Introduction

Climate change, even if restricted to 2°C, is expected to have wide-ranging socioeconomic and health effects. Many of these impacts can be reduced if appropriate adaptation measures are implemented (Dell, Jones and Olken, 2009; Kahn, 2020). The Global Commission on Adaptation (2019) estimates that global costs amounting to USD 7.1 trillion can be avoided by undertaking investments in adaptation amounting to USD 1.8 trillion. Thus, adaptation can reduce unmitigated costs by 75%.

Large-scale government responses are well documented (e.g., UNFCCC, 2021), but small-scale household investments are difficult to trace (Ford, Ford and Paterson, 2011; Porter, Dessai and Tompkins, 2014; Wamsler, 2016). The main reason for this problem is that detailed household-level datasets that describe small-scale adaptation investments over prolonged periods are rarely available. Thus, only limited knowledge exists about the type of investments people favour when they adapt to climate change or about the overall cost of autonomous adaptation to climate change. This is unfortunate because they may account for a large share of adaptation expenditure.

This problem is particularly present in residential buildings, which have been the primary means for humans to cope with a wide variety of climates. As outdoor temperatures rise, the main short-term adaptation strategy for homeowners is to adjust their energy consumption. During heatwaves, they tend to increase electricity usage if their homes are equipped with air conditioning. Conversely, milder winter temperatures prompt homeowners to reduce space heating, thereby lowering their use of gas or electricity based on their heating technology. In the longer run, they also adjust the stock of durables installed in their dwellings: they can purchase new air conditioners, change their heating equipment, or invest in weatherization.

To date, existing empirical studies have assessed the short-term impact of weather on energy consumption (Auffhammer and Aroonruengsawat, 2011; Deschênes and Greenstone, 2011), as well as the impact of longer-term adaptation on energy use by comparing energy-demand responses to the weather in cold versus hot locations (Auffhammer, 2018 and 2022; Manderson and Considine, 2024; Colelli et al., 2023)[1]. A few studies have been able to directly examine specific investment types (Mansur et al., 2008; Davis and Getler, 2015; Davis et al., 2021). They compared fuel choice and the use of air conditioning (AC) in cold and warm locations to

[1] See Kolstad and Moore (2022) for a discussion of the methods that use historical data on weather to identify long-term climate impacts.

understand the potential implications for energy demand. These studies found that houses in warm locations tend to use electricity rather than gas for heating and are more often equipped with air conditioning. This underpins the strong risk that electricity demand will surge with climate change.

In this study, we investigated the adaptation of residential building stock using 28 years of data from the American Housing Survey (AHS, 1985-2013).[2] Our first contribution to the literature is to provide the first longitudinal analysis of the impact of weather on investments performed in owner-occupied homes. Instead of comparing housing features, such as AC penetration in different regions, the AHS data allows us to observe home improvements over a period long enough to estimate the impact of gradual changes in temperature on the structure of housing units. We do not need to rely on the assumption that cold regions will adapt to climate change in the same way that hot regions have adapted to warm temperatures. Our results are also less subject to omitted variable bias because household-specific fixed effects allow us to control for time-invariant housing and household characteristics that may correlate with the weather.

Another contribution is that we analyse a wider set of investments (eight categories) and their impact on energy and water bills. A comprehensive analysis may lead to different conclusions than a targeted analysis, for instance, focusing on the impact of weather on AC and electricity demand. This is because increases in AC penetration and electricity consumption may be accompanied by other changes; for example, an increase in insulation or a reduction in gas consumption that may mitigate or even offset the surge in electricity demand caused by AC penetration. Taking water consumption into account also allows us to identify other forms of adaptation: more intense watering of gardens or greater use of bathrooms. We seek to be agnostic about the types of investments and utility expenditures that would be affected by rising temperatures.

First, we focused on the impact of temperature changes on investments in housing units. We tracked investments in the following categories: doors and windows, major equipment (including heating and cooling equipment), insulation, roofs, kitchens, bathrooms, siding, and other indoor improvements. Using pseudo-Poisson maximum likelihood models to account for the fact that most households do not invest every year, we correlated investment expenditure in the categories above with information about heating and cooling needs derived from daily

[2] The panel of homes changed after 2013, and the data collected after the COVID-19 pandemic could not be exploited easily, so we exploit the older panel. This allows us to have many years to conduct the analysis.

temperature data in each location.[3] More precisely, we used the daily average temperatures to compute the annual heating and cooling degree days. Cooling degree days on a specific day correspond to the number of degrees above 65 °F. The annual degree days correspond to the sum of all degree days in a year. For example, if the average daily temperature was 66 °F every day of the year, that location would record 365 cooling degree days. Similarly, heating degree days are calculated as the sum of degrees below 65 °F. We find that exposure to cold or warm days correlates with increases in expenditures on doors and windows, major equipment, and insulation. We provide a long list of tests to ensure that these findings are robust to specification and modelling choices.

We then gauge the impact of these investments on demand for energy and water. We distinguish between the short-term impact of temperatures on utility expenditures before adaptation investments are made and the long-term impacts after adaptation investments are made. This is because, for instance, we would expect electricity consumption to be more sensitive to hot temperatures after the AC is installed. We expected changes in water consumption. We estimated the short-term impact of changes in temperature by exploiting biennial variations in utility bills. This is very similar to the results of Auffhammer and Aroonruengsawat (2011), Deschenes and Greenstone (2011), and Davis and Gertler (2015). The long-term model is based on the average differences over three periods of nine years. This type of models in 'long differences' has been used by Dell, Jones and Olken (2012), Burke and Emerick (2016) and Chen and Gong (2021) to estimate long-term impacts of climate change. This study is the first to apply such a model to estimate the long-term impact of climate change on energy and water consumption in the residential sector. We find that cold temperatures increase electricity and gas expenditures, and warm temperatures increase electricity and water expenditures. Furthermore, we observed a stronger response to both cold and hot temperatures in the long term than in the short term. This suggests that home improvements increase weather-induced

[3] This reduced-form approach evaluates whether annual temperature shocks, such as a particularly cold winter, influence home improvements, thereby assessing the marginal effect of temperature variations on investments. This likely captures two responses: (1) reactions to immediate weather conditions, and (2) anticipations of future climate patterns. Uncomfortable temperatures may prompt households to invest in home improvements to enhance comfort, irrespective of their awareness or beliefs about climate change. Additionally, extreme weather events might serve as indicators of climate change, influencing investment decisions. During our study period (1985-2013), climate change awareness rose steadily. A 1986 survey suggested that only 39 percent of households had heard of global warming or the greenhouse effect at that time. The awareness of climate change reached about 80 percent in the 1990s. Between 1992 and 2007, surveys indicate that the proportion of people declaring that they knew fairly or very well what global warming and the greenhouse effect were, rose from 53 to 76 percent (Nisbet and Myers, 2007).

energy and water demands, underpinning the strong effect that climate change adaptation could have on energy and water use.

Our analysis reveals that for every additional 365 heating degree days, investments in doors and windows, major equipment, and insulation increase by 10% to 29%, while 365 cooling degree days lead to increases of 14% to 38% in similar categories. In the long term, an increase of 365 heating degree days correlates with a rise in utility bills by $263 [159; 368], and a similar increase in cooling degree days results in a $281 [136; 426] increase.

We used those estimates for investments and utility expenditures to compute the cost of adaptation to climate change. We rely on forecasts from 20 General Circulation models corresponding to the RCP 4.5 scenario of the Intergovernmental Panel on Climate Change (IPCC) in 2046–2065. Our annual cost estimate for all categories is not statistically different from zero, at minus USD 57 [-397; 282] per year. Even though the order of magnitude is very small compared to the price of a house, our results still suggest that notable adjustments to the building stock will take place. This is because the increase in cooling needs leads to an average additional cost of USD 606 [294; 918] per year, offset by a reduction in heating costs of USD 660 [-934; -385]. These costs stem from changes in utility bills, rather than the total costs of home improvements. Increases in summer costs are mostly related to large increases in electricity and water consumption, possibly beyond sustainable use in water-scarce regions of the U.S.

These results show the importance of analysing all cost entries in conjunction, since increases in certain areas may be offset by reductions in others. Furthermore, we observed a shift in cost from winter to summer months.

This study has some limitations. Our climate change forecasts are out-of-sample predictions because future climate change mid-century under RCP 4.5 is expected to be much larger than the changes in climate observed in the data. We also disregarded the effect of technical progress on costs. Furthermore, this analysis focuses only on existing homes and the impact of changes in temperatures. Finally, the non-monetary costs from temperature exposure and benefits from adaptation were not considered in this analysis. Further research is required to address these limitations. Our results, however, indicate that adaptation costs can be partially paid by reducing cold-related expenditures, but this may come at the cost of an additional use of natural resources such as energy and water in summer.

The remainder of this paper is organized as follows. Section II describes the data sources used in this study. Section III presents our empirical strategy (III.A) and the results (III.B) regarding the impact of temperature on home improvements. Section IV presents our empirical strategy (IV.A) and the results (IV.B) regarding the impact of temperature on energy and water bills. Section V assesses the adaptation cost under climate change based on the outputs of Sections III and IV as well as forecasts from 20 general circulation models. Section VI concludes.

II. Data

American Housing Survey. We relied on data on housing units, home improvements, and households from the national samples of the AHS from 1985 to 2013 (AHS, 1985-2013). Waves prior to 1985 cannot be used in a panel data analysis because the AHS was redesigned in 1985; consequently, the units surveyed before and after 1985 were different. Likewise, the panels are different from 2015 onwards. Moreover, the COVID-19 pandemic strongly limits comparability between 2015-2019 and 2021-2023 and therefore, the possibility of using surveys after 2013.

We extracted observations from housing units in 146 Metropolitan Statistical Areas (MSAs) spread across the US.[4] For homeowners, the AHS records investment expenditures for home improvements performed in housing units. Unfortunately, the same home improvement data are not available for rented properties; therefore, the analysis of home improvements focuses on homeowners. The dollar values reported in the AHS are deflated and converted to constant 2013 USD with the US Consumer Price Index (CPI) for all urban consumers (all items in the US city average, not seasonally adjusted) (U.S. Bureau of Labor Statistics, 1985-2013). The CPI was reported every month and averaged over 12 months (from January to December).

We distinguish between the different investment categories. Before 1997, the waves of AHS broke down home improvements into nine types: major equipment, insulation, doors and windows, roofs, sidings, bathrooms, kitchens, new additions, and other major repairs or improvements. We merge the two rather imprecise categories of ‘new additions’ and ‘other major repairs or improvement’ into an ‘other’ category.

After 1997, home improvements were divided into 43 categories that were more specific. We recategorize these 43 categories so that they match the pre-1997 typology. However, this match

[4] Only those housing units in MSAs with more than 100,000 inhabitants have geographic information in the public use files due to the anonymization process used by the Census Bureau. We only use the panels within the contiguous US states and therefore exclude Anchorage, Alaska, from the analysis. Likewise, we do not use data from Hawaii or Puerto Rico.

can be imperfect. For instance, after 1997, doors and windows included all doors and windows, whereas the pre-1997 typology focused on storm doors and windows. In our statistical analyses, this change in nomenclature was controlled for in levels by including survey year fixed effects. In Appendix B1, we also check whether we observe sharp differences in the amounts invested before and after 1997. We did not observe any discontinuity before or after 1997.

Furthermore, the pre-1997 typology does not specifically identify AC in the 'major equipment' category in the full sample. Likewise, we do not track outdoor investments; the 'other' category only includes indoor home improvements. However, these categories were available after 1997. These are used in the robustness checks in Appendix B9.

All home improvements can usually last a very long time. For example, according to the National Association of Home Builders (2007), doors have a minimum life expectancy of 20 years, with some doors such as exterior fiberglass, steel and wood doors can last as long as the house exists. HVAC systems usually last 15-25 years, and AC units 10-15 years. Depending on the material used, roofs have a life expectancy of 20-50 years, whereas masonry can last more than 100 years.

Finally, the AHS also identifies when a household leaves a given housing unit and when new occupants move. We used this information to create household-specific fixed effects.

Weather data. The weather data corresponded to the 0.5 °× 0.5° gridded daily weather data of the Climate Prediction Center (CPC, 1979-2013). We extracted daily data for 1979–2013:1979 is the earliest year available in the CPC data, and we do not need data beyond 2013 since the last AHS survey we can use for 2013.

We used three variables from the CPC weather dataset: the daily minimum temperature, daily maximum temperature, and daily precipitation. The daily average temperature was calculated as the average of the minimum and maximum temperatures. We used this value to compute the number of annual heating and cooling degree days. Degree-days are standard measurements designed to reflect the demand for heating and cooling. Using the daily average temperature, cooling degree days correspond to the number of degrees above 65 °F. The annual degree days correspond to the sum of all degree days in a year. For example, if the average daily temperature was 66 °F every day of the year, that location would record 365 cooling degree days. Similarly, heating degree days are calculated as the sum of degrees below 65 °F.

We matched the AHS data with the CPC data based on the geographical information included in the AHS. We used the 1990 Census Bureau map of the Metropolitan Statistical Areas (U.S.

Census Bureau, 1990a). We calculated MSA-specific temperature and precipitation variables based on all data points from the CPC gridded weather data that fell within the geographic boundaries of an MSA. Because weather grids have a resolution of approximately 55 km × 55 km, it is possible that no data point falls within the boundaries of an MSA. In this case, we calculated the centroid of an MSA and matched it with the closest weather data point.[5]

We matched the weather data with 316 MSA codes, including those present in the AHS data. The match between MSA codes in the AHS and geographic boundaries is imperfect because geographic boundaries evolve over time and the MSA codes of the AHS do not always have a one-to-one correspondence with the available census bureau maps. However, this is not a concern for this analysis because temperature and precipitation do not vary much over short distances.[6]

Climate change forecasts. We also used climate change data from the data portal of the climatology lab at the University of Idaho. The data correspond to the output of 20 climate change models that have been downscaled using the multivariate adaptive constructed analogs (MACA) method (Abatzoglou and Brown, 2011) with the Livneh (Livneh et al., 2013) observational dataset as training data.

The data is very large. We downloaded only the data corresponding to the centroid of the MSAs in our matched sample with the AHS. Centroids were calculated based on the geographical matches described above.

[5] In rare cases, the centroid fell within water bodies; in such instances, we manually relocated it to nearby land to retrieve weather data. Additionally, MSA codes from the 1990 Census map and those used in the AHS do not fully align: several newer AHS MSA codes are absent from the 1990 map. To recover boundaries for these, we relied on the 2013 Census map of core-based statistical areas (CBSA) (U.S. Census Bureau, 2013a) and a Census file listing the principal cities of metropolitan and micropolitan areas as of February 2013 (U.S. Census Bureau, 2013b). This allowed us to match the remaining AHS MSA codes to suitable geographic boundaries. However, three codes—Lake County (IL); Lawrence-Haverhill (MA/NH); and Middlesex, Somerset, and Hunterdon (NJ)—could not be matched with either the 1990 or 2013 maps. For these, we manually retrieved county FIPS codes and used the 1990 Census county map (U.S. Census Bureau, 1990b) to identify their geographic boundaries.

[6] Due to the resolution of weather maps, our weather variables may contain measurement errors, as local climate variations can differ between individual houses within a Metropolitan Statistical Area (MSA). To address this, we incorporate household fixed effects in our models, controlling for unobserved, time-invariant household characteristics. This approach focuses the analysis on year-to-year weather anomalies rather than geographic differences across households. Weather anomalies display strong geographical correlation, as measured by the Anomaly Correlation Coefficient (generally above 0.6, see European Centre for Medium-Range Weather Forecasts, 2024). This geographical stability significantly reduces the risk of measurement error in our weather variables. Consequently, we are confident that any remaining measurement error is unlikely to substantially influence our results.

The data include daily estimates that reproduce inter-annual weather variability. We used these daily predictions to compute the forecasted average daily temperature and from the annual expected heating and cooling degree days under climate change conditions. In this study, we principally use the predictions from the long-high emissions scenario of IPCC, called RCP 4.5, in the mid-century (2046–2065). In our dataset, the average global warming is 3.5 °F under RCP 4.5 and 2046–2065. We also provide some predictions for other periods until 2086–2099, and for the very high emissions scenario of IPCC called RCP 8.5, in Appendix D. Under this scenario, global warming would reach 4.9 °F in 2046–2065 compared with the historical baseline.

Summary statistics. **Table 1** provides summary statistics for the matched datasets used in this study. Panel A provides summary statistics for the AHS investment variables. On average, households spend approximately USD 100 per 100 square feet and year on home improvements. Naturally, some households do not invest, while households that invest in one category tend to invest in other categories at the same time. In our sample, 49.8 percent of households had invested in at least one category in the 24 months prior to an interview, 22.3 percent in at least two, and 8.9 percent in at least three categories. Panel B provide summary statistics for electricity, gas and water/sewage expenditure in the AHS. We can calculate total expenditure when we have non-missing values for all three categories (electricity, gas, and water and sewage). We then calculate total expenditure and then exclude outliers (this is described in section IV.A). On average, households spend nearly USD 170 dollars per 100 square feet in water and energy expenditure every year. Panel C presents the average heating degree days, cooling degree days, and precipitation registered for observations with non-missing electricity expenditures (after excluding outliers). On average, there are approximately 4,000 heating degree days and 1,500 cooling degree days. The corresponding average daily temperature in the sample was approximately 57.7 °F (14.27°C). During this period, the average US temperature oscillated between 50 °F and 55 °F. This is higher than the average U.S. temperature because warmer areas tend to be more populated than cooler ones. We also provided information on house size (in square feet) and the price of a house in our sample.

In **Appendix A**, we provide summary statistics for the forecasted temperatures in the climate models used to produce the climate change adaptation cost estimates, for different scenarios and periods until 2100. Under RCP4.5 and in 2046-2065, we expect the cooling degree days to increase by approximately 550 and heating degree days to decrease by approximately 700. These figures are large compared to the current numbers of cooling and heating degree days in the sample (see **Table 1**).

Table 1: Summary statistics. Panel A. The mean and standard deviations are expressed in 2013 real dollars per 100 square feet. Values are for average annual investments. Survey weights have been used to weight observations. Observations are for homeowners only since home improvement data is not recorded for rented properties in the AHS. Outliers have been excluded as described in section III.A. **Panel B**. The mean and standard deviations are expressed in 2013 real dollars per 100 square feet. Values are for average annual expenditure per 100 square feet. Survey weights have been used to weight observations. Observations are for homeowners as well as tenants. Outliers have been excluded as described in section IV.A. **Panel C**. These are the summary statistics for the weather variables matched with the AHS observations with non-missing electricity expenditure after excluding outliers. Survey weights have been used to weight observations. Observations are for homeowners as well as tenants. Information on sale price is only available for houses bought or built during the survey period.

Panel A: Home Improvement Variables

Category	Mean	Standard deviation	Share non-zero investments	Number of observations
Doors and windows	8.5	41.9	0.112	212,328
Major equipment	11.0	41.5	0.158	212,170
Insulation	1.1	10.2	0.038	212,487
Roofs	13.3	56.7	0.098	212,342
Kitchens	14.6	93.0	0.063	212,445
Bathrooms	10.1	63.7	0.078	212,437
Siding	4.7	40.5	0.029	212,521
Other	34.8	118.9	0.293	211,968
Total	96.8	220.6	0.499	211,510

Panel B: Utility expenditure

Category	Mean	Standard deviation	Number of observations
Electricity	96.5	67.5	310,329
Gas	45.8	53.3	291,482
Water and sewage	30.2	25.9	198,943
Total	168.7	93.2	190,606

Panel C: Weather variables

Category	Mean	Standard deviation	Number of observations
Annual heating degree days	4,090.1	2,058.9	305,922
Annual cooling degree days	1,426.4	1,029.6	305,585
Annual precipitation (mm)	934.5	398.0	305,034
Size of unit (square feet)	1,764	1,524	310,329
Purchase price (2013 USD)	208,628	190,848	25,983

III. Impact of temperatures on home improvements

III.A. Investment model

Baseline model. We evaluated the impact of a change in temperature on investments in various categories of home improvements. Because households do not perform home improvements every year, there can be many zero values in the dataset, particularly for infrequent types of home improvements. To increase precision despite the presence of many zero values, we used Poisson pseudo-likelihood regression models (Correia, Guimarrães and Zylkin, 2019).

For each investment category separately, we outline:

(1) $$E(I_{i,y,m}) = \exp\left(\alpha CDD_{i,y,m} + \beta HDD_{i,y,m} + \gamma PREC_{i,y,m} + \mu_i + \tau_{y,m}\right)$$

All variables were matched according to the interview month m and year y corresponding to each observation in the AHS. $E(I_{i,y,m})$ is the expected value of $I_{i,y,m}$, which corresponds to the average annual value of the investments made in the dwelling by household i (in the selected investment category), as recorded during the AHS interview that took place in month m and year y. It is expressed in constant 2013 US dollars per 100 square feet to account for the differences in property size across households. As the AHS is a biennial survey, investments in the AHS correspond to the 24 months preceding each interview. We divided the AHS investment variables by two to obtain an annual average value for $I_{i,y,m}$.

The variables of interest are $CDD_{i,y,m}$ and $HDD_{i,y,m}$, which capture the average annual cooling and heating degree days, respectively. Degree days are usual measures of cooling and heating requirements. $CDD_{i,y,m}$ and $HDD_{i,y,m}$ are calculated using the heating and cooling degree days of the interview month and the preceding 23 months, and the total value over 24 months is divided by 2 to represent an annual average. This is to account for the fact that the reference period for the question on home improvements were the 24 months preceding the interview. We also controlled for average annual precipitations, denoted $PREC_{i,y,m}$. α, β and γ are the parameters to be estimated. μ_i are household fixed effects and τ_{my} are the interview month and year fixed effects, respectively.

One advantage of Eq. (1) is that we controlled for time-invariant household characteristics that might correlate with weather due to the inclusion of household fixed effects. This is a notable extension of the existing literature, which has compared differences in AC and fuel choices across locations (Mansur et al., 2008; Davis and Getler, 2015).[7] In addition, we use the survey weights of the AHS to allow the observations from the AHS and our econometric results to be representative of the U.S. urban population. Standard errors are clustered at the MSA level to account for heteroscedasticity and serial correlation. We estimate Eq. (1) using the estimator by Correia, Guimarrães and Zylkin (2019) to allow for high-dimensional fixed effects, cluster-robust standard errors at the level of metropolitan statistical areas, and the use of survey weights. To increase the precision, we exclude outliers.[8]

Finally, owing to how the data on investments are collected in the AHS, the amount invested in each category is likely to be measured with error: households could very well misreport the amounts that they spent on each category. In Eq. (1), the investment variables were used as the dependent variables. Classical measurement errors in the dependent variables do not bias the estimates. Therefore, it is a minor concern, even though such measurement errors may reduce the efficiency of estimates. However, a problem could arise if measurement issues are correlated with our explanatory variables, that is, if misreporting is correlated with heating and cooling degree days. This is very unlikely in our case because reporting occurred during the interview (months m and y), whereas our variables for the weather were computed over a much longer period. There is no reason why the weather one year ago, for instance, would have had an impact on reporting during month m and year y. Therefore, we are confident that our model should provide consistent estimates of the impact of past weather on investments, despite potential measurement errors in the dependent variables.[9]

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[7] We do not include additional control variables in the model, as doing so risks blocking indirect channels through which weather may affect investments. This could lead to "over-controlling" or "bad controls" (Angrist and Pischke, 2009; Dell et al., 2014; Hsiang, 2016), especially since climate can influence many variables. For instance, temperature changes can affect household income (e.g., Dell et al., 2009); controlling for income would thus omit part of the climate effect by capturing only the direct pathway. For similar reasons, we do not control for electricity or gas prices, despite their importance in determining heating and AC demand. Prior studies (e.g., Mulder et al., 2013; Mosquera-López et al., 2024) show strong links between weather conditions and energy prices. Weather affects both energy demand and supply, causing local price fluctuations. On the demand side, extreme temperatures increase consumption (e.g., Considine, 2000, for the US). On the supply side, weather shapes the energy mix: renewables are weather-dependent, while gas-fired plants, with higher marginal costs, typically meet peak demand. Electricity prices rise when renewable output drops, as prices are set by the highest accepted bid. Moreover, nuclear generation depends on cooling water temperatures, and transmission line efficiency also varies with weather. Finally, weather-related supply shocks can cause spillovers across energy markets—for example, gas price shifts affect electricity prices—and the growing role of "prosumers" using solar panels further increases weather sensitivity in supply dynamics.

[8] We disregard the 1st and 99th percentiles of weighted observations with the highest and lowest values for heating degree days, cooling degree days and precipitation. We also disregard the 99th percentile of weighted observations with the highest non-zero values for the expenditure in each utility category. We provide results with outliers in Appendix B6.

[9] The reader may also note that our model is not dynamic since it does not include spending at time t-1 as an explanatory variable. We do not need to explicitly control for past investment shocks in our analysis because our independent variables are weather variables. These variables are considered as good as random after accounting

III.A. Results of investment model

Our baseline results for the effect of cooling and heating degree days on the total expenditure and the eight investment categories are provided in **Figure 1**. We have opted for a visual representation of our regression results instead of a table of coefficients to facilitate interpretation and comparison across the eight investment categories and their total. A full table of the results is provided in Appendix B2.

In **Figure 1**, the y-axis represents the percentage difference in home improvements from an increase in either cooling or heating degree days by 365 points, that is, equivalent to an increase by one degree day or cooling degree days every day of the year. We observed statistically significant effects for three categories of home improvements: major equipment, insulation, and doors and windows. This is an expected result considering that these categories relate to the purchase of heating and cooling equipment or to insulation (either directly or through improvements in doors and windows, which are known to convey significant energy savings).

In terms of magnitude, a 365-increase in heating degree days is equivalent to a 9-percent increase in heating needs (considering that the sample average for heating degree days is approximately 4,000), for which we find a 10-percent increase in spending on major equipment, a 13-percent increase in spending on doors and windows, and a 29-percent increase in spending on insulation work (which is a rather small category consisting of foams and other insulating materials). A net increase in cooling degree days of 365 points represents a net increase in cooling needs of approximately 25 percent. It is associated with a 14-percent increase in major equipment, 16-percent increase in doors and windows and 38-percent increase in insulation. Therefore, these figures are roughly aligned with the relative increases in the heating and cooling needs of households. Refurbishments in insulation appear to be highly sensitive to weather conditions.

We also found an impact of cooling degree days on kitchens. The observed relationship between cooling degree days and kitchen renovations may reflect households upgrading refrigerators and freezers, which are often central to kitchen refurbishments (Riverstone Kitchens and Renovations, 2025). Warmer weather may also encourage kitchen renovations due to practical

for location-specific fixed effects (which are included within the household fixed effects) and time fixed effects. The inclusion of these fixed effects eliminates potential confounding by capturing unobserved heterogeneity across locations and temporal patterns. As a result, there is no systematic correlation between investment shocks at t-1 and our variables of interest. This also implies that our results remain unbiased even if there is a correlation between investments at t and t-1. Such correlation is expected and does not affect the validity of the causal inference.

considerations, since the summer is often recommended for kitchen improvements. In contrast, we did not find clear impacts on roofs, bathrooms, or other indoor improvements.

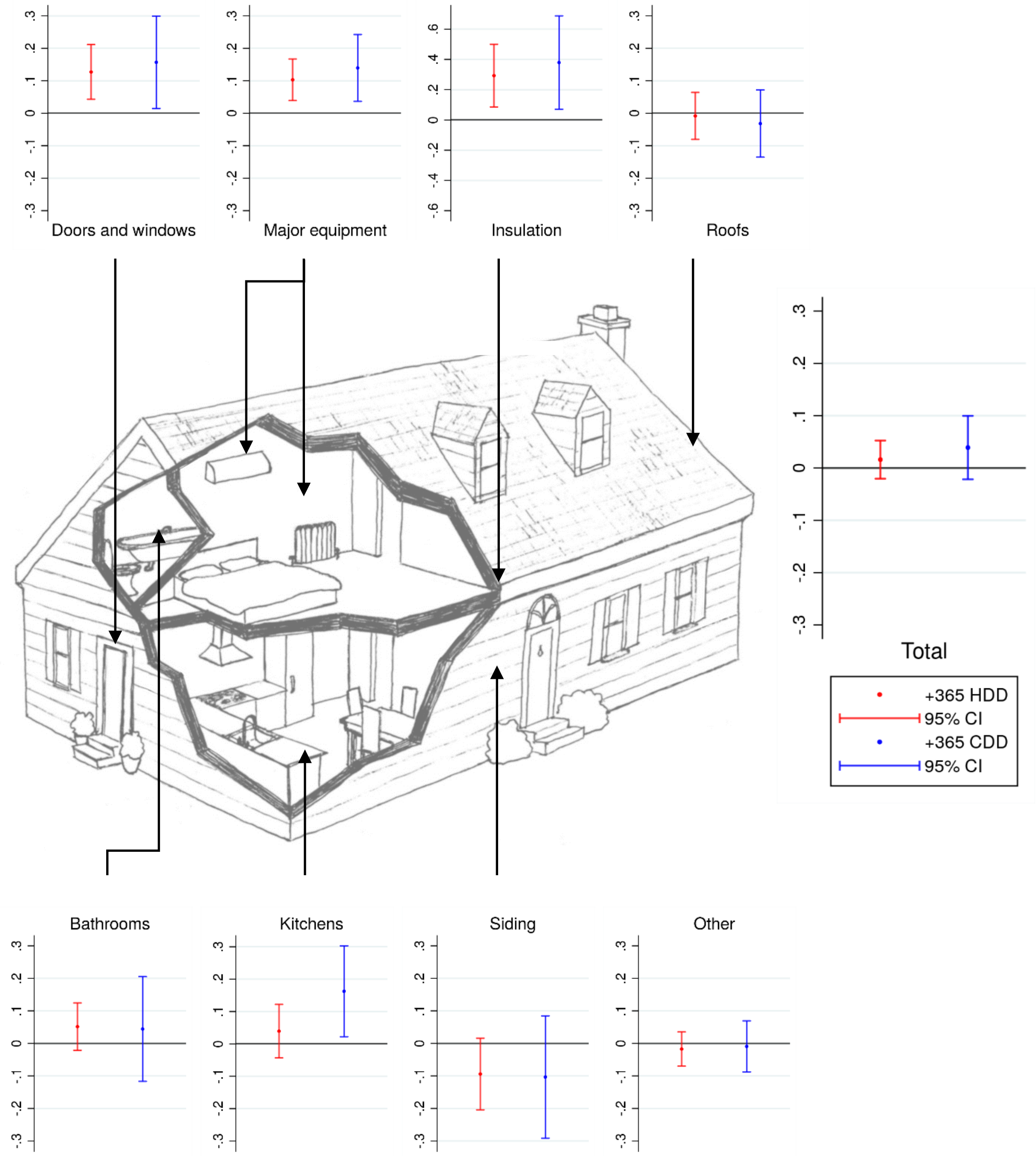

Figure 1. Impact of an increase by 365 heating degree days (HDD in red) or cooling degree days (CDD in blue) on indoor home improvement expenditure. The y-axes are scaled to represent a percentage change in the observed investments. The outcome variables are the annual household expenditures in the categories displayed below or above the x-axis. The two points represent our point estimates and the bars the 95% confidence intervals for a change by 365 HDD or 365 CDD. These results are estimated based on Eq. (1). For the sake of brevity, Figure 1 only provides results for heating and cooling degree days.

When adding all investment categories together, point estimates suggest that investments are increasing in heating and cooling degree days, but the effects are not statistically significant. This could be attributed to two reasons. On one hand, we add categories that are not weather sensitive to this sum, which reduces efficiency. On the other hand, households may offset some of the additional costs of weather-sensitive investments by reducing expenditures in other investment categories, thus reducing the weather-sensitivity of total investments.

Robustness. In Appendix B3, we estimate Eq. (1) with a linear model instead of a Poisson model, using the same fixed effect structure, and then adding MSA-specific quadratic trends. In Appendix B4, we use temperature bins instead of heating and cooling degree days, allowing the reader to see which temperature ranges are associated with higher investment. In Appendix B5, we run a distributed lag model, where we include the first lag of each weather variable. None of the first lags was statistically significant at five percent, hence our preference for a model without such lags. We also provide the results when including the outliers in Appendix B6.

The results of these alternative specifications were similar. Some specifications are less precisely estimated, but the sign and magnitude of the coefficients tend to remain the same for the three types of investments that we found to be weather-sensitive: doors and windows, major equipment, and insulation.

In addition, we argue that our econometric model is superior to cross-sectional analysis. Appendix B7 provides the pooled results (we do not use household fixed effects). We found a negative correlation between heating degree days, cooling degree days, and several investment types, which cannot be interpreted causally.

Finally, we examined the correlation between the weather and air-conditioning and heating equipment separately, as well as outdoor investments, in Appendix B8, using the post-1997 data. The results were estimated using a smaller sample; therefore, the precision was lower. However, they suggested that cooling degree days have an impact on air-conditioning. We also found that heating degree days may positively correlate with heating equipment, and cooling degree days may reduce investments in heating equipment, suggesting that increases in temperature negatively correlate with investments in heating equipment. However, these results are not statistically significant at the 5% level. The results also suggest that outdoor improvements tend to increase in temperature; however, these results are not statistically significant.

IV. Implications for energy and water bills

IV.A. Models for energy and water bills

Many of the aforementioned investments are known to influence energy use and water consumption. Furthermore, a typical US home has a lawn that may require more water on warm days. Water use could also increase when there is a need to fill swimming pools or if people take more showers on warm days.

We can partially assess the implications of the home improvements described in Figure 1 on utility expenditure. It is crucial to differentiate between the short-term impacts of heating and cooling degree days on utility expenditure before adaptation investments are made and the long-term impacts observed after such investments. For instance, consider room air conditioners. In the short term, households with existing AC may turn on their units to mitigate heatwave discomfort, increasing electricity use. In the long term, these households might expand their use by installing additional AC units or adopting central AC systems, leading to higher overall electricity demand. Similarly, households without AC may install it as an adaptation to repeated exposure to hot temperatures, contributing to an upward shift in electricity consumption. On the other hand, households may also invest in home improvements that enhance energy efficiency, such as upgrading insulation or installing efficient windows, thereby reducing the sensitivity of utility bills to weather conditions. Finally, supply-side effects on energy production may also increase or reduce local prices even if consumption remained constant.

Therefore, the observed long-term effects on utility expenditure depend on the net contributions of several mechanisms. In general, differences in the short- and long-term responses of utility bills to temperature changes may arise from the diverse adaptation strategies households and energy-producing firms adopt in response to repeated weather variations. Below, we estimated the short- and long-term responses of the weather on utility bills and compared the short- and long-term results to gauge the specific effect of home improvements on utility expenditure.

Short-term model. We estimated the short-term impact of changes in temperature by exploiting biennial variations in utility bills. Comparable methods have been used in several studies examining the impact of weather on electricity consumption (e.g. Auffhammer and Aroonruengsawat, 2011; Deschenes and Greenstone, 2011; Davis and Gertler, 2015). We use the expenditure variables directly recorded in the AHS for both homeowners and tenants and fit the following equation:

(2) $E_{i,f,y,m} = \theta_f cdd_{i,y,m} + \lambda_f hdd_{i,y,m} + \omega_f prec_{i,y,m} + \mu_{i,f} + \tau_{f,y,m} + \mathrm{y}.\rho_{1,z,f} + \mathrm{y}^2.\rho_{2,z,f} + \epsilon_{i,f,y,m}$

The dependent variable (E_{ifym}) is the expenditure per 100 square feet on utility f (where f = gas; electricity; water and sewage; all utilities) of household i, as recorded during the AHS interview (in month m and year y). Recorded expenditure values correspond to the average monthly cost of electricity and gas and the annual cost of water. We multiplied the monthly values for electricity and gas by 12 to compute the average annual expenditures on these fuels. $E_{i,f,y,m}$ are expressed in constant 2013 USD values. cdd_{iym}, hdd_{iym} and $prec_{iym}$ are the annual cooling degree days, heating degree days, and precipitation corresponding to the month of the interview and the 11 preceding months, respectively. θ_f, λ_f and ω_f are parameters to be estimated; μ_{if} is a household fixed effect specific to fuel f; τ_{fym} corresponds to an interview time (month and year) fixed effect. We also controlled for MSA-specific quadratic trends ($\mathrm{y}.\rho_{1,z,f} + \mathrm{y}^2.\rho_{2,z,f}$). ϵ_{ift} is the error term.

Note that the model directly estimates the impact on utility expenditure and not on physical energy and water consumption. This is because we are interested in the monetary costs of adaptation. This also allowed us to account for the impact of local weather on residential energy and water prices.[10]

Long-term model. The long-term model is based on differences over several years, which we refer to as 'long differences'. This type of model has been used by Dell, Jones, and Olken (2012); Burke and Emerick (2016); and Chen and Gong (2021) to estimate the long-term impacts of climate change. Bento et al. (2020) proposed an alternative approach applicable to daily data based on moving averages to estimate the long-term climate impacts. Both approaches are conceptually similar; however, the approach with long differences is better suited to our survey data. In contrast to the short-term model, the idea is to arrange the data so that households are given sufficient time to invest in their homes in response to weather

[10] As in Eq. (1), we exclude energy prices from the econometric specification in Eq. (2) to avoid "over-controlling." This allows us to capture the effect of temperature variations on energy expenditure through weather-induced changes in energy prices. Estimating Eq. (2) separately for gas and electricity could introduce sample selection bias, since households choose their fuel type. However, this risk is mitigated by household-by-fuel fixed effects, which account for fuel choices made prior to moving in. In general, fuel switching—e.g., from electric to gas—is rare due to high costs and the need for substantial modifications. In the AHS, only 2.4% of observations report a change in the main heating fuel from electricity to gas. This low figure likely includes not only actual switches, but also shifts in usage patterns or reporting differences over time in homes with both gas and electric systems.

variation. However, there is a trade-off because lengthening the interval between each observation increases the risk that confounding factors will bias the estimates.

We proceed as follows. We constructed three 9-year periods with ten years between the first year in each period: 1985–1993, 1995–2003, and 2005–2013. Averaging weather variables over nine years allows us to smooth them from annual perturbations and retain only durable changes in the average temperature. Therefore, these averages are more likely to reflect steady changes in temperature and precipitation than yearly observations. On the other hand, the 10-year differences between the periods (e.g., 1985–1993 vs. 1995–2003) are likely to capture changes in housing structure caused by recurrent changes in the weather. Therefore, this statistical strategy accounts for the effect of climate adaptation investments in US houses on utility bills.

We estimate the following equation:

(3) $$\bar{E}_{x,f,p} = a_f \overline{cdd}_{x,p} + b_f \overline{hdd}_{x,p} + c_f \overline{prec}_{x,p} + d_f \bar{m}_{x,p} + \mu_{x,f} + \mu_{x,p} + \epsilon_{x,f,p}.$$

$\bar{E}_{x,f,p}$ are the average values observed in the AHS for $E_{i,f,y,m}$ during period p (1985–1993, 1995–2003, or 2005–2013) for fuel f and housing unit x. In Eq. (3), each panel is a housing unit, represented by subscript x, and not a household unit, as in Eq. (1) and Eq. (2). Note that very few households remain in the same house or flat for 28 years. In most cases, we would not be able to compute the dependent variable with three sets of 9-year averages for the same household. However, we observed the same housing units from 1985 to 2013, even though households may move in and out. Therefore, we used housing units to construct the panels and not the households.[11] $\overline{cdd}_{x,p}$, $\overline{hdd}_{x,p}$ and $\overline{prec}_{x,p}$ are, likewise, the average values of climatic factors experienced by housing unit x in period p. $\mu_{x,f}$ is a house- and fuel-specific fixed effect, and $\mu_{x,p}$ is likewise a period- and fuel-specific fixed effect. We also controlled for the average month in which the interviews took place during period m ($\bar{m}_{x,p}$). Finally, a_f, b_f, c_f and d_f are the parameters estimated by the model, and $\epsilon_{x,f,p}$ is the error term.[12]

[11] Using the short-term model, we checked whether using household- or housing unit fixed effects affected the results. We found that there was very little impact of using households instead of housing unit fixed effects. Likewise, because we only have three observations for each housing unit, the model in long differences does not control for MSA-specific quadratic trends either. We also checked whether this had an influence on results with the short-term model and found very little effect on estimated coefficients and confidence intervals. This suggests that using housing unit fixed effects without MSA-specific quadratic trends is unlikely to have a strong influence on results for the model in long differences, since it did not have much influence on results with the short-term model.

[12] We also considered a long-differences model for home improvements but found it unsuitable due to the sporadic nature of such investments. Unlike continuous variables like utility expenditures, which are well-suited for long-differences analysis, home improvements occur irregularly. Aggregating data over extended periods in this context can obscure meaningful patterns and lead to unreliable conclusions.

Because the AHS is biennial, the above-mentioned period averages were only computed using data from survey years. If the sample was perfectly balanced, we would have five biennial observations of each variable for each 9-year period. However, the panel is unbalanced. To avoid restricting the analysis to a small sample of houses, we allowed for a maximum of one missing observation while computing period averages. We also provide results in which we only compute the period averages if we have no non-missing values in Appendix C1. The results are very similar, but the sample size is reduced by 45% (from approximately 18,600 to approximately 10,400 observations for expenditures in all categories) and efficiency is also reduced. In Appendix C2, we examined the impact of withdrawing specific survey years on the results obtained with the long-term model to reduce the risk that the results are driven by years when data are available.

When estimating Eq. (2) and (3), standard errors are clustered at the level of MSAs and units are weighted using the survey weights of the AHS. To increase the precision, we exclude outliers.[13] We also provide the results for utility expenditure with no exclusion of outliers in Appendix C3.

IV.B. Results for energy and water bills

Figure 2 summarizes the baseline results obtained using the short- and long-term models.[14] With both models, we find that electricity expenditure increases with heating and cooling degree days. This is an expected result, considering that electricity is used for both space heating and AC. We find that gas expenditure tends to increase with the number of heating degree days, even though the estimates are statistically significant only at 10%. This is in line with the fact that gas is the main heating fuel in many US houses. In contrast, we found no impact of cooling degree days on gas, which aligns with the fact that gas is rarely used for AC. Finally, water and sewage expenditures were positively correlated with the cooling degree days. This is consistent

[13] To ensure robust estimates, we exclude extreme values from our analysis. For Equation (2), we remove weighted observations falling in the 1st and 99th percentiles for heating degree days, cooling degree days, and precipitation. Additionally, we exclude the 99th percentile of weighted observations with the highest non-zero expenditures in each utility category but retain those in the 1st percentile, as zero values for EifymE_{ifym}Eifym often indicate households opting not to consume certain fuels, particularly gas. For Equation (3), after computing 9-year averages, we similarly exclude outliers: the 1st and 99th percentiles of weighted observations for average heating degree days, cooling degree days, and precipitation, as well as the 99th percentile for non-zero average expenditures in each utility category.

[14] We have likewise opted for a graphical representation of results to facilitate comparisons across eight regressions. Results are however very similar to those that would be represented in a standard table of results of regressions.

with the assumption that hotter summer months increase irrigation and recreational water use. The precipitation results are presented in Appendix C4.

In terms of magnitude, in the long-term model and for a hypothetical 1,500-square-foot house, an increase in the 9-year average number of annual heating degree days of 365 (i.e., 1 °F below 65 °F for every day of the year) correlates with an average additional annual expenditure of approximately USD 263 [159; 368] (10.4% of the average bill for a 1,500 square foot house). Estimates by utility category were USD 158 [70; 246] for electricity, USD 80 [-11; 171] for gas, and USD 18 [-25; 61] for water and sewage. Note that the estimates by category do not strictly add up to the total because the estimates for the total come from different estimations.

In parallel, an equivalent increase in the 9-year average number of annual cooling degree days of 365 (i.e., 1 °F degree above 65 °F for every day of the year) corresponds to an average additional annual expenditure of approximately USD 281 [136; 426] (11.1% of the average bill). Therefore, the marginal impacts of the heating and cooling degree days are broadly similar. Estimates by category were USD 162 [51; 271] for electricity, USD 79 [28; 130] for water and sewage, and USD 25 [-94; 144] for gas.

Figure 2 shows weaker short-term impacts, implying that home improvements undertaken to adapt to climate change encourage electricity, gas, and water expenditures. For a hypothetical 1,500-square-foot house, an increase of 365 heating degree days (corresponding to 1°F lower each day of the year) leads to an increase in utility bill expenditure of approximately USD 33 [19; 47] (1.3% of the average bill). A similar short-term increase in temperature of 365 cooling degree days (i.e., 1°F higher for every day of the year) corresponds to an increase in the utility bill of USD 79 [49; 109] (3.1% of the average bill). Both estimates are a degree of magnitude smaller than the estimated long-term impacts. However, relative differences may be imprecisely estimated considering that the confidence intervals are large and the samples differ in construction between Eqs. (2) and (3). Nonetheless, adaptations in the housing stock seem to be responsible for a large share of the impact of weather on utility bills.

These results on short-term vs. longer-term effects echo those of Buchsbaum (2023), who provides a quasi-experimental analysis of residential electricity consumers' price responsiveness, distinguishing between short-run and long-run elasticities. The study finds that consumers exhibit a short-run price elasticity of -0.36, indicating modest responsiveness to immediate price changes. In contrast, the long-run price elasticity is estimated at -2.4, suggesting that consumers are significantly more responsive over extended periods. This substantial difference implies that, given time, households adjust their energy consumption more dramatically in response to persistent price changes, likely through investments in energy-efficient technologies or modifications in consumption behaviour.

They also align with Auffhammer et al. (2022), who found that a 1°F increase in annual average temperature led to a 6% to 9% increase in electricity demand in California. Additionally, they concluded that reductions in gas demand would more than offset the increase in electricity demand from rising temperatures. Our analysis provides complementary insights by incorporating water expenditures and employing an alternative long-difference approach to capture both short- and long-term impacts.

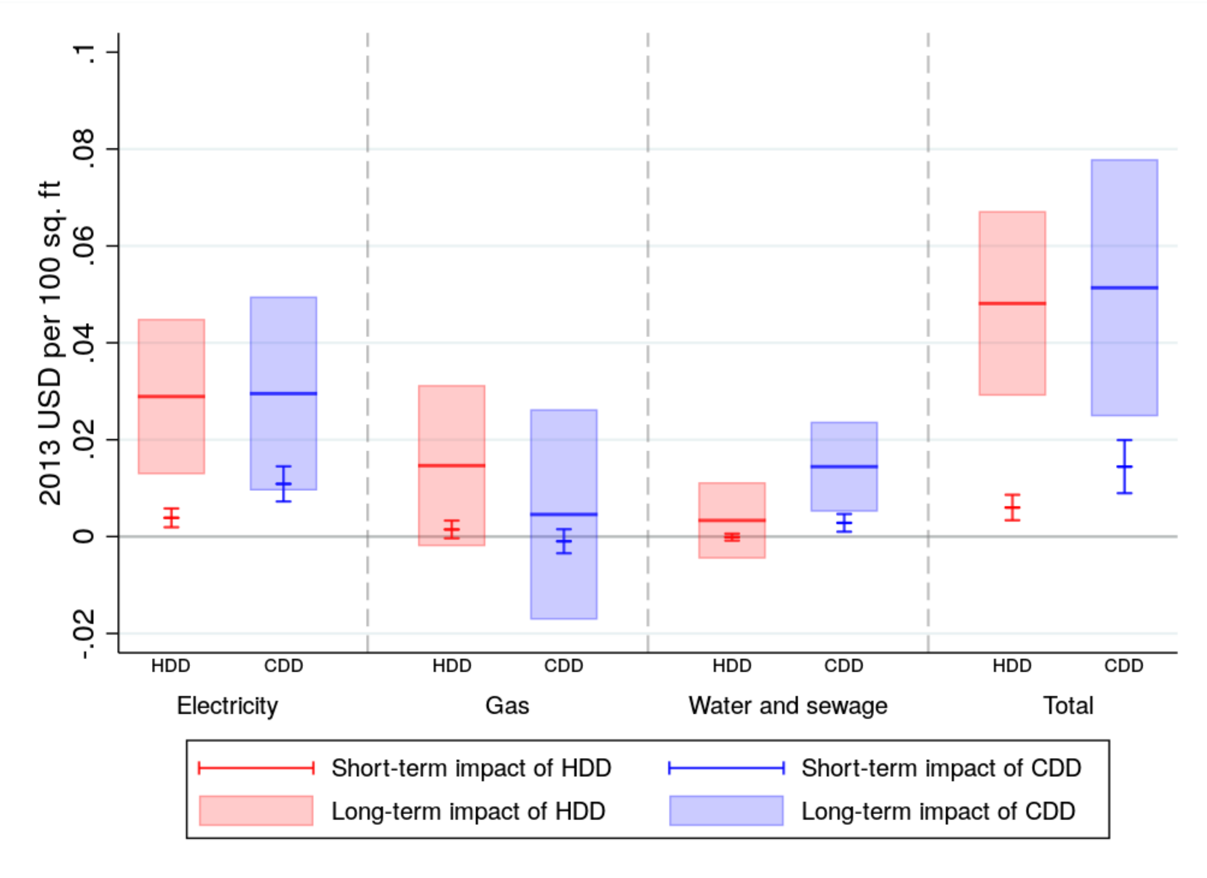

Fig. 2. Short-term (vertical lines) and long-term (bars) impacts of HDD (red) and CDD (blue) on utilities expenditure, for electricity, gas, water and sewage together and for each of these bills separately. The vertical lines and bars represent the point estimates and their 95% confidence intervals. Estimates for different expenditure categories are obtained with separate linear regressions based on Eq. (2) and Eq. (3).

V. Cost of climate change adaptation

Using the above results for investments and utility expenditures, we can compute the total cost of adaptation associated with a given temperature increase. Our method to compute these costs is detailed in Appendix A. In short, we add up the changes in expenditures on home improvements, energy and water that would be induced by a shift in heating and cooling degree days from the situation observed during the study period to the one predicted by the climate change models.[15] To reduce the uncertainty inherent in climate forecasts, we use as baseline the average climate change predictions derived from the output of 20 General Circulation models corresponding to the RCP 4.5 scenario in 2046–2065.

Results are provided in **Table 2**. Caution should be exercised when interpreting these results. Above all, we make out-of-sample predictions for climate change impacts because we can only use the changes in climate and adaptation behavior observed in the data, whereas future climate change mid-century under RCP 4.5 is expected to be much larger. Likewise, our cost estimates do not include the effect that technical progress could have on costs, such as reductions in the cost of producing electricity from renewable sources. Furthermore, this analysis focuses on existing homes only, even though many homes that will be affected by climate change have not yet been built. Finally, non-monetary costs from temperature exposure and benefits from adaptation are not considered in this analysis, even though they may outweigh the directly observable financial costs.

With these limitations in mind, **Table 2** provides estimates of the impact of climate change under RCP 4.5 on annual costs for all categories (home improvements and utilities). We provide the impacts of a reduction in heating degree days (A) and an increase in cooling degree days (B), and then sum the two to derive annual cost estimates (A + B). The figures in brackets correspond to 95% confidence intervals.

The annual cost estimate for all categories is not statistically different from zero, at minus USD 57 per year [-397; +282]. This point estimate is also small because it amounts to approximately 0.03 percent [-0.19%; 0.14%] of the average purchase price of a house (approximately USD 210,000) in our sample. Over 25 years and with a 4 percent discount rate, the cost reductions would remain low, at minus USD 890 [-6,202; +4,405], representing approximately 0.4 percent [-3.0%; +2.1%] of the purchase price of a house in our sample.

[15] For home improvements, please note again that we utilize data exclusively from owner-occupied homes, as information is only available for these units.

The results using the predictions of each climate model separately, instead of their average forecasts, confirm this finding (see Appendix D1). We find that the annual cost estimate is not statistically different from zero at the 5% level in all climate models (20 out of 20). We also provide estimates for different periods (2066–2085 and 2086–2099) and RCP 8.5 in Appendix D2. Likewise, the total cost of adaptation is not statistically different from zero.

Even though these cost estimates are low, the results still suggest that notable adjustments to the building stock will occur. This is because the increase in cooling degree days leads to average additional costs of USD 606 [+294; +918] per year, offset by a reduction in heating costs of USD 660 [-934; -385].

Table 2. Annual cost of adaptation under RCP 4.5 for 2046–2065 broken down by category, climate region and income groups. Table 2 provides the change in annual average expenditure under RCP 4.5 compared with historical values in our sample. The first two columns distinguish the savings from a reduction in heating degree days (A) from the additional costs caused by the increase in cooling degree days (B). The estimates are for the average change in heating and cooling degree days across 20 climate models (-724 and +563 respectively on average in the study sample, even though forecasted changes vary across MSAs). Colder (warmer) regions include all units for which our observations record an average temperature below (above) 55°F. The income variable is expressed in 2013 USD and is equal to total household income divided by the square root of the number of people in the household. The median is around USD 35,600. Non-linearities in the model for home improvements explain that results between column A and B do not strictly add up. Statistically significant point estimates in bold.

	Impact of heating degree days (A)	Impact of cooling degree days (B)	Annual average expenditure (A+B)
Total cost	**-660** [-934; -385]	**+606** [294 - 918]	-57 [-397; +282]
By category:			
Home improvements	-64 [-205; 77]	+117 [-67; 300]	+50 [-117; +216]
Electricity	**-358** [-556; -159]	**+281** [91; 472]	-77 [-307; +153]
Gas	-181 [-387; 24]	+44 [-163; 250]	-138 [-339; +63]
Water and Sewage	-41 [-139; 56]	+137 [49; 226]	+96 [-27; +219]
By climate:			
Colder regions	**-680** [-1239; -120]	+160 [-545; 865]	-539 [-1,061; -18]
Warmer regions	**-596** [-940; -252]	**+836** [405; 1267]	+229 [-107; +566]
By income group:			
Below median income	**-691** [-1179; -202]	+550 [-3; 1103]	-147 [-481; +187]

Above median income	-351 [-746; 44]	**+484** [63; 905]	+133 [-252; +518]

Impacts by category suggest that water and sewage expenditures might increase, while expenditures on energy might decrease. However, the total effects were not statistically different from zero. Above all, the results by category predict a strong reallocation of expenditure from cold days (probably in winter) to warm days (probably in summer). The predicted reduction in annual electricity and gas bills from heating degree days is equal to USD 358 [-556; 159] for electricity and USD 181 [-387; 24] for gas, representing 21% of the average annual electricity bill and 22% of the average gas bill in the sample. Conversely, the increase in annual electricity expenditure from cooling degree days, at USD 281 [91; 472], is equal to 17% of the average annual bill. The annual increase in water expenditure from cooling degree days is also substantial. At USD 137 [49; 226], this is equivalent to 26% of the average water bill.

In **Table 2**, we also break down the costs for two climate regions and two income groups. A housing unit is classified as located in a colder (warmer) area if the average daily temperature registered for this unit in our sample is below (above) 55 °F. We ran our econometric models separately for cold and warm regions and then added the region-specific variations in cooling and heating degree days predicted in the climate models under RCP 4.5. Econometric results by region are provided in Appendix D3. We find that the net cost in colder areas might decrease by USD 539 [-1,061; -18]. In warmer areas, we find a small (and statistically insignificant) increase in the cost of USD 229 [-107; +566]. This suggests that there may be regional heterogeneities, with costs decreasing in colder regions and increasing in warmer regions.

To divide the sample into two income groups, we compute individual disposable income as total household income (in constant 2013 USD) divided by the square root of the number of people in the household. We then separate observations between those with an individual disposable income below and those with an individual disposable income above the median in our sample (about USD 35,600). We ran the econometric models separately for both income groups (see Appendix D3) and then computed the adaptation cost estimates. As displayed in **Table 2**, we do not find discernible differences in behavior between households by income group.

Finally, we disregarded the impact of precipitation on adaptation costs in **Table 2.** This is because climate models only predict a small change in the average precipitation compared with the change in temperature. We examine the impact of precipitation on the adaptation cost in Appendix D4 and find that the increase in precipitation under RCP 4.5 (2046–2065) may lead to an annual decrease in costs of USD 25 [+12; +35].

VI. Conclusion

Our analysis shows that average household costs decrease in winter by roughly as much as they increase in summer, with regional variation. **Figure 1** illustrates the weather sensitivity of certain investment categories: every additional 365 HDD increases spending on doors and windows, major equipment, and insulation by 10%–29%. Likewise, an increase by 365 CDD raises these investments by 14%–38%. **Figure 2** provides further insight into utility expenditures: in the short term, an increase by 365 HDD is associated with an annual increase of USD 33 [19; 47], and +365 CDD with USD 79 [49; 109]. Long-term effects are more substantial, with HDD and CDD raising expenditures by USD 263 [159; 368] and USD 281 [136; 426], respectively. These findings suggest that adaptation over time significantly amplifies utility costs.

While the national cost estimate appears reasonable for the residential sector, adaptation may have significant implications for energy and water supply due to strong seasonal shifts. Higher temperatures could sharply increase summer electricity and water expenditures, by an estimated 17% and 26% of annual bills, respectively. This surge in demand may require additional investments in electricity generation and distribution, especially given that U.S. energy prices already peak in summer. Auffhammer et al. (2017) also highlight that within-day climate effects on energy demand can exceed annual or seasonal averages. Water supply and management systems may likewise need reinforcement, as increased summer water use could exacerbate scarcity and drought in some regions. Under climate change, peak demand for energy and water on very hot days could stress existing infrastructure and warrants further research.

However, this analysis does not capture the full welfare costs of climate change in the residential sector. First, it focuses only on temperature, excluding other major impacts such as increased flooding risks for coastal cities, or the cost of hurricanes intensified by climate change.

Second, we track investment and expenditure levels but lack information on the quality or durability of household improvements. Although our model controls for average spending via household fixed effects, it cannot assess whether extreme weather accelerates depreciation or reduces investment quality. Nor does it capture changes in comfort or health, which may constitute a large share of welfare impacts from temperature changes. In addition, we cannot analyse home improvements in rental properties due to data limitations. As a result, our estimates likely represent an upper bound on total housing adaptation, since split incentives between landlords and tenants, well documented in the literature (e.g., Gillingham, Harding, and Rapson, 2012; Melvin, 2018), typically lead to underinvestment in rentals.

Third, observed shifts in costs may deviate from both private and social optima. Some households may underinvest in protection against heat or cold due to bounded rationality. Market and behavioural failures around energy efficiency and energy-using products are well established (Gillingham et al., 2009), likely leading to suboptimal adaptation, such as inadequate insulation. Moreover, older adults may underinvest in heat protection: they often feel less discomfort (Hansen et al., 2011) despite being more vulnerable to health risks (e.g., Watts et al., 2019). More research is needed to understand how actual household responses diverge from the socially optimal adaptation portfolio.

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ONLINE APPENDICES

A. Climate change and adaptation costs

The average change in heating and cooling degree days by scenario and period is provided below.

Table A1: Corresponding impact of climate change on heating degree days, cooling degree days and precipitation. Summary statistics for the effect of climate change on heating and cooling degree days. We use the same sample as for Table 2. Survey weights have been used to weight observations. Displayed impacts are for the average impact of climate change under RCP4.5 and RCP8.5 across all 20 climate models. Effects are calculated directly from the reference period (1990–2005) used in the climate models. We therefore make the simplifying assumption that the climate in this reference period is equivalent to the one in our survey period (1985–2013).

Scenario and period	*Heating degree days*	*Cooling degree days*	*Precipitation (mm)*
RCP 4.5 scenario			
2026-2045	-510	+384	+21
2046-2065	-724	+563	+28
2066-2085	-848	+689	+31
2086-2099	-906	+728	+36
RCP 8.5 scenario			
2026-2045	-556	+446	+29
2046-2065	-962	+821	+34
2066-2085	-1,359	+1,253	+35
2086-2099	-1,630	+1,659	+36

To compute the cost of adaptation to climate change, we employ a two-step approach that incorporates both home improvement investments and utility expenditures. The following describes the methodology used to derive the results presented in **Table 2**.

To compute category-specific adaptation costs, we calculate the adaptation costs for individual categories (home improvements, electricity, gas, water, and sewage) based on predicted changes in heating degree days (HDD) and cooling degree days (CDD) under the RCP 4.5

scenario for 2046–2065. These changes are derived from the average projections of 20 General Circulation Models.

For each category, we: (1) use the coefficients estimated from the regression models linking HDD and CDD to expenditures in each category (using the long-term model for utility expenditure); (2) multiply the predicted changes in HDD and CDD by these coefficients to compute the expected expenditure shifts; (3) account for the correlation between coefficients within each equation to compute equation-level standard errors, ensuring appropriate confidence intervals for category-specific costs.

To compute the total cost, we sum the predicted changes across two broad categories: all home improvement investments; and all utility costs (electricity, gas, water, and sewage). Separate regression models are run for each of these aggregated categories to compute total cost estimates and their associated standard errors. For these total estimates, we make the simplifying assumption that the estimates for home improvements and utility costs are uncorrelated. This assumption is likely conservative, as a positive correlation between the two categories (e.g., households investing in home improvements also experiencing higher utility bills) would reduce the standard error of the total cost estimate. As such, our standard errors for total adaptation costs are likely overestimated.

To ensure robustness, we perform the analysis using each climate model's predictions individually rather than the average change across 20 models. Results for different time horizons (2066–2085 and 2086–2099) and the RCP 8.5 scenario are provided in Appendix D2.

Results by climate and income group are run by (1) excluding all the observations outside of scope from the dataset; (2) running our models for home improvements and utility bills on the reduced sample; and (3) calculate adaptation costs as described above.

B. Home improvements

B1. Differences in investments before and after 1997

We can check whether we observe sharp differences in the amounts invested before and after 1997. Such difference could bias our results since they could be spuriously correlated with changes in the weather.

To do so, we run the following linear regression:

(4) $$I_{iymg} = \mu_{ig} + \tau_{yg} + \tau_{mg} + \varepsilon_{iymg}$$

We recover the values for the year fixed effects (τ_{yg}) for each of the investment categories. Figure B1 below presents the value of these fixed effects and their 95% confidence interval for the eight investment categories of Fig. 1. We do not observe a discontinuity before and after 1997.

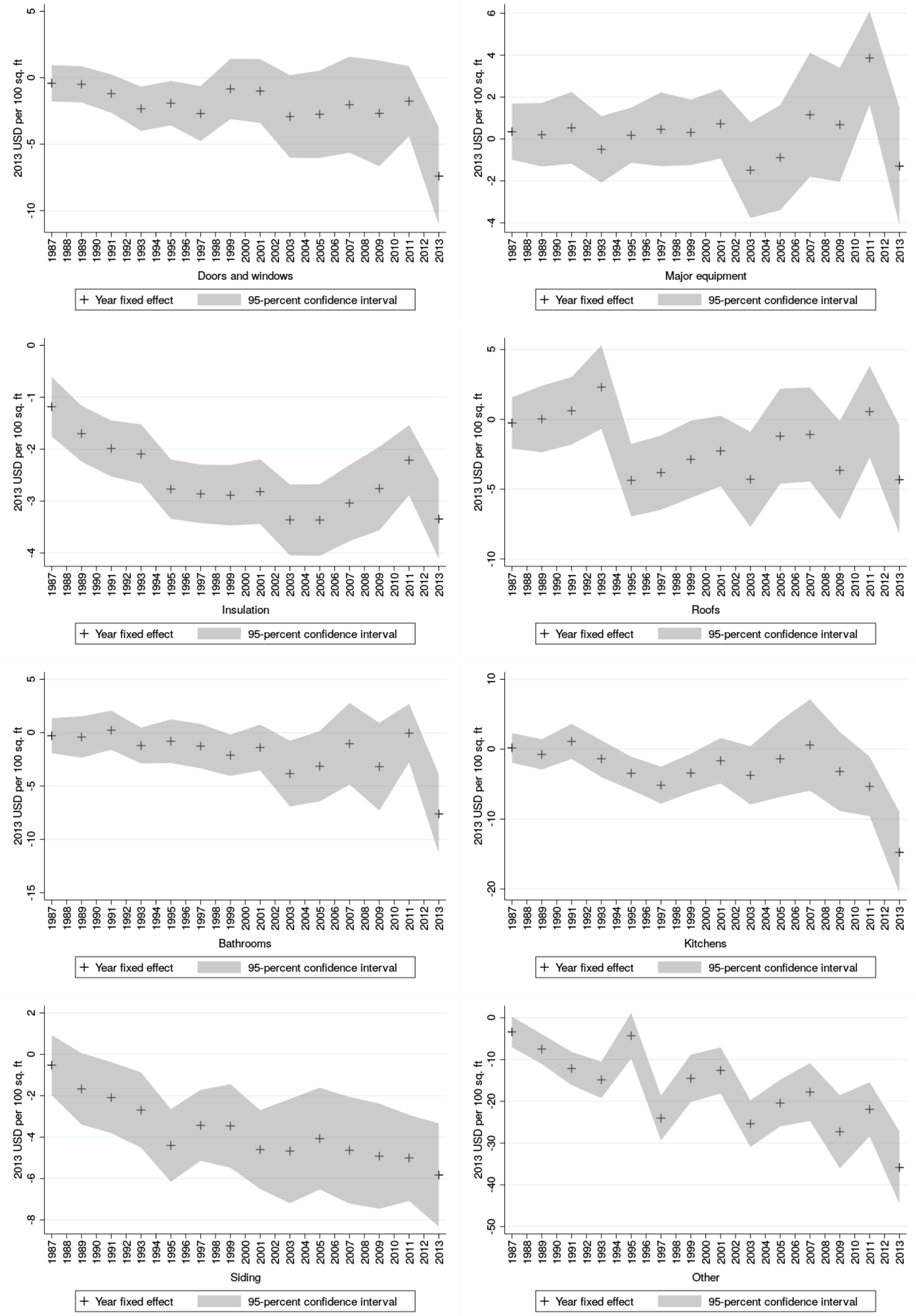


Fig. B1. Estimation of Eq. (4) using ordinary least squares. The outcome variables are the annual household expenditures in the categories displayed below the x-axis. The reference category for the year fixed effects is 1985. Regressions are weighted with survey weights, and the confidence intervals are clustered at the level of MSAs. The 'other' category only includes indoor improvements.

B2. Table of regression results used to produce Fig. 1

We provide our main regression results in the table format below. In addition to the coefficient values for the heating and cooling degree days, we also reported the coefficients for precipitation.

Appendix Table B1. Table of results for the regressions used to produce Fig. 1.

Category	Doors and windows	Major Equipment	Insulation	Roofs	
Heating degree days	0.00032809***	0.00026877***	0.00070405***	-0.00002253	
	(0.00010424)	(0.00008113)	(0.00022403)	(0.00010195)	
Cooling degree days	0.00039951**	0.00035805***	0.00088093***	-0.00008843	
	(0.00017170)	(0.00012633)	(0.00031301)	(0.00014955)	
Precipitations	-0.00000090	0.00010134	-0.00027899	0.00040043***	
	(0.00019945)	(0.00011307)	(0.00026536)	(0.00013214)	
Observations	67,014	84,946	26,789	69,424	
Category	**Bathrooms**	**Kitchens**	**Siding**	**Other indoor**	**Total**
Heating degree days	0.00013748	0.00010550	-0.00027052	-0.00004803	0.00004367
	(0.00009677)	(0.00011097)	(0.00016984)	(0.00007481)	(0.00005014)
Cooling degree days	0.00011858	0.00041252**	-0.00029889	-0.00002533	0.00010497
	(0.00021536)	(0.00016877)	(0.00029309)	(0.00011053)	(0.00008164)
Precipitations	-0.00009361	-0.00006392	0.00006987	0.00012585	0.00010664
	(0.00020913)	(0.00017943)	(0.00025179)	(0.00013105)	(0.00007430)
Observations	50,591	45,365	25,654	107,380	125,497

Notes: The outcome variables are annual household expenditures in each category, in constant 2013 USD per 100 square feet. All results were estimated based on Eq. (1) and therefore include household fixed effects and month-year of interview fixed effects. Observations were weighted using the AHS survey weights. Standard errors clustered at the MSA level. The standard errors are in parentheses. Stars represent statistical significance at the 10 percent (*), 5 percent (**), and 1 percent (***) levels.

B3. Results with linear models

Below, we estimate a linear model instead of a pseudo-Poisson model following Eq. (1). We observed similar effects of heating and cooling degree days on doors, windows, major equipment, and insulation. In Table B3, we have added MSA-specific quadratic trends to control for MSA-specific trends in temperature. The results are very similar, confirming that our findings are not driven by spurious correlations between temperature and investment trends.

Appendix Table B2. Linear estimation of home improvement equation

Category	Doors and windows	Major Equipment	Insulation	Roofs	
Heating	0.0025***	0.0027***	0.0007**	-0.0004	
degree days	(0.0010)	(0.0009)	(0.0003)	(0.0017)	
Cooling	0.0028**	0.0043***	0.0008**	-0.0014	
degree days	(0.0013)	(0.0015)	(0.0004)	(0.0025)	
Precipitations	0.0006	0.0009	-0.0003	0.0052**	
	(0.0017)	(0.0014)	(0.0003)	(0.0022)	
Observations	138,645	138,612	138,786	138,685	
Category	Bathrooms	Kitchens	Siding	Other indoor	Total
Heating	0.0015	0.0015	-0.0008	-0.0009	0.0049
degree days	(0.0011)	(0.0017)	(0.0009)	(0.0027)	(0.0053)
Cooling	0.0013	0.0056**	-0.0011	-0.0016	0.0101
degree days	(0.0022)	(0.0026)	(0.0013)	(0.0044)	(0.0088)
Precipitations	-0.0008	-0.0009	0.0007	0.0047	0.0101
	(0.0022)	(0.0028)	(0.0013)	(0.0052)	(0.0083)
Observations	138,731	138,739	138,805	138,377	138,078

Notes: The outcome variables are annual household expenditures in each category, in constant 2013 USD per 100 square feet. The independent variables included household fixed effects and month-year of interview fixed effects. Observations were weighted using the AHS survey weights. Standard errors clustered at the MSA level. The standard errors are in parentheses. Stars represent statistical significance at the 10 percent (*), 5 percent (**), and 1 percent (***) levels.

Appendix Table B3. Linear estimation of home improvement equation with MSA-specific quadratic trends

Category	Doors and windows	Major Equipment	Insulation	Roofs	
Heating	0.0013	0.0023**	0.0007***	0.0005	
degree days	(0.0009)	(0.0009)	(0.0002)	(0.0016)	
Cooling	0.0034***	0.0039**	0.0009**	-0.0012	
degree days	(0.0012)	(0.0016)	(0.0004)	(0.0025)	
Precipitations	0.0019	0.0014	-0.0001	0.0052**	
	(0.0017)	(0.0015)	(0.0003)	(0.0021)	
Observations	138,645	138,612	138,786	138,685	
Category	Bathrooms	Kitchens	Siding	Other indoor	Total
Heating	0.0016	0.0013	-0.0010	0.0018	0.0061
degree days	(0.0011)	(0.0018)	(0.0009)	(0.0027)	(0.0051)
Cooling	0.0017	0.0058*	-0.0006	-0.0027	0.0097
degree days	(0.0023)	(0.0029)	(0.0013)	(0.0049)	(0.0091)
Precipitations	-0.0004	0.0004	0.0011	0.0057	0.0152*
	(0.0021)	(0.0028)	(0.0015)	(0.0052)	(0.0083)
Observations	138,731	138,739	138,805	138,377	138,078

Notes: The outcome variables are annual household expenditures in each category, in constant 2013 USD per 100 square feet. Independent variables include household fixed effects and month-year of interview fixed effects, and MSA-specific quadratic annual trends. Observations were weighted using the AHS survey weights. Standard errors clustered at the MSA level. The standard errors are in parentheses. Stars represent statistical significance at the 10 percent (*), 5 percent (**), and 1 percent (***) levels.

B4. Results with temperature bins

Appendix Table B4. Estimation of Eq. (1) with temperature bins instead of degree days

Category	Doors and windows	Major Equipment	Insulation	Roofs	
Days >90°F	0.0231*	0.0202***	0.0287**	0.0044	
	(0.0125)	(0.0065)	(0.0112)	(0.0069)	
Days 80-90°F	0.0068*	0.0037	0.0104	-0.0054	
	(0.0035)	(0.0026)	(0.0066)	(0.0033)	
Days 70-80°F	0.0025	0.0019	-0.0002	-0.0036	
	(0.0030)	(0.0023)	(0.0047)	(0.0026)	
Days 60-70°F	-	-	-	-	
Days 50-60°F	0.0073**	0.0010	0.0064	0.0005	
	(0.0029)	(0.0025)	(0.0056)	(0.0027)	
Days 40-50°F	0.0093**	0.0052*	0.0016	-0.0055	
	(0.0039)	(0.0031)	(0.0072)	(0.0035)	
Days 30-40°F	0.0108**	0.0080**	0.0175**	-0.0026	
	(0.0044)	(0.0034)	(0.0077)	(0.0039)	
Days 20-30°F	0.0024	0.0058	0.0140	-0.0062	
	(0.0054)	(0.0046)	(0.0097)	(0.0053)	
Days <20°F	0.0185***	0.0075*	0.0281**	0.0030	
	(0.0049)	(0.0042)	(0.0121)	(0.0054)	
Observations	71,703	91,641	29,092	74,940	
Category	**Bathrooms**	**Kitchens**	**Siding**	**Other indoor**	**Total**
Days >90°F	-0.0098	0.0253***	-0.0102	-0.0009	0.0097*
	(0.0091)	(0.0081)	(0.0186)	(0.0068)	(0.0053)
Days 80-90°F	0.0009	0.0031	-0.0078	-0.0022	-0.0002
	(0.0043)	(0.0040)	(0.0053)	(0.0026)	(0.0019)
Days 70-80°F	0.0039	0.0003	-0.0034	-0.0004	0.0003
	(0.0040)	(0.0033)	(0.0050)	(0.0019)	(0.0014)
Days 60-70°F	-	-	-	-	-
Days 50-60°F	0.0022	-0.0018	-0.0018	0.0009	0.0016
	(0.0031)	(0.0036)	(0.0051)	(0.0019)	(0.0013)
Days 40-50°F	0.0033	0.0053	-0.0069	-0.0016	0.0014
	(0.0038)	(0.0040)	(0.0070)	(0.0021)	(0.0019)
Days 30-40°F	0.0090**	-0.0046	-0.0098	-0.0038	0.0006
	(0.0045)	(0.0050)	(0.0081)	(0.0028)	(0.0020)
Days 20-30°F	0.0062	-0.0058	-0.0078	-0.0004	0.0002
	(0.0069)	(0.0066)	(0.0093)	(0.0043)	(0.0030)
Days <20°F	0.0115**	-0.0040	-0.0122	-0.0052	0.0007
	(0.0058)	(0.0066)	(0.0102)	(0.0039)	(0.0028)
Observations	54,761	49,071	27,210	115,082	133,734

Notes: The outcome variables are annual household expenditures in each category, in constant 2013 USD per 100 square feet. The independent variables include household fixed effects and month-year of interview fixed effects. Observations were weighted using the AHS survey weights. Standard errors clustered at the MSA level. The standard errors are in parentheses. Stars represent statistical significance at the 10 percent (*), 5 percent (**), and 1 percent (***) levels.

B5. Distributed lag model

We provide the results of a model with one lag for the weather variables (we add coefficients for the weather variables during months to 24-47 prior to the interview). In Table AT5, we report the results for the contemporaneous impact of heating degree days, cooling degree days, precipitation (corresponding to months 0-23 prior to the interview), and the first lag (months 24-47). We found that none of the first lags for heating and cooling degree days were statistically significant at the 5% level. This lack of significance suggests that models without such lags are more appropriate for understanding the impact of heating and cooling degree days on investment. For completeness, we also report the cumulative impacts when adding the coefficients for the contemporaneous impacts and the impact of the first lags.

Appendix Table B5. Table of results with 1-period lag (24-47 months before interview)

Category	Doors and windows	Major Equipment	Insulation	Roofs	
Heating	0.000377***	0.000278***	0.000643***	-0.000033	
degree days at t	(0.000121)	(0.000082)	(0.000229)	(0.000104)	
1st lag	0.000156	0.000019	-0.000282*	-0.000031	
(months 24-47)	(0.000121)	(0.000062)	(0.000163)	(0.000086)	
Cooling	0.000373**	0.000382***	0.000919***	-0.000076	
degree days at t	(0.000176)	(0.000127)	(0.000321)	(0.000158)	
1st lag	-0.000046	0.000205	-0.000203	0.000063	
(months 24-47)	(0.000183)	(0.000129)	(0.000260)	(0.000145)	
Precipitations at t	0.000015	0.000121	-0.000267	0.000400***	
	(0.000200)	(0.000116)	(0.000264)	(0.000135)	
1st lag	0.000086	0.000237**	-0.000223	0.000001	
(months 24-47)	(0.000142)	(0.000113)	(0.000211)	(0.000112)	
Observations	67,014	84,946	26,789	69,424	
Cumulative HDD	0.000533**	0.000297***	0.000361	-0.000064	
	(0.000212)	(0.000106)	(0.0003)	(0.000153)	
Cumulative CDD	0.000327	0.000587***	0.000716*	-0.000013	
	(0.000291)	(0.000185)	(0.000414)	(0.000252)	
Cumulative	0.000101	0.000358*	-0.00049	0.000401**	
precipitations	(0.000263)	(0.000186)	(0.000368)	(0.000196)	
Category	**Bathrooms**	**Kitchens**	**Siding**	**Other indoor**	**Total**
Heating	-0.000033	0.000169*	0.000089	-0.000246	0.000034
degree days at t	(0.000104)	(0.000096)	(0.000120)	(0.000191)	(0.000053)
1st lag	-0.000031	0.000075	-0.000080	0.000069	-0.000066*
(months 24-47)	(0.000086)	(0.000111)	(0.000103)	(0.000209)	(0.000039)
Cooling	-0.000076	0.000072	0.000392**	-0.000335	0.000100
degree days at t	(0.000158)	(0.000205)	(0.000176)	(0.000306)	(0.000087)
1st lag	0.000063	-0.000117	-0.000130	-0.000228	-0.000046
(months 24-47)	(0.000145)	(0.000254)	(0.000172)	(0.000315)	(0.000085)
Precipitations at t	0.000400***	-0.000074	-0.000058	0.000074	0.000118
	(0.000135)	(0.000209)	(0.000179)	(0.000247)	(0.000075)
1st lag	0.000001	0.000192	0.000026	0.000051	0.000095
(months 24-47)	(0.000112)	(0.000151)	(0.000192)	(0.000265)	(0.000071)
Observations	50,591	45,365	25,654	107,380	125,497
Cumulative HDD	0.000244	0.00001	-0.000177	-0.00019	-0.000032
	(0.000149)	(0.000188)	(0.000351)	(0.000119)	(0.000076)
Cumulative CDD	-0.000045	0.000262	-0.000562	0.000002	0.000053
	(0.000306)	(0.000275)	(0.000513)	(0.000225)	(0.000143)
Cumulative	0.000119	-0.000032	0.000125	0.000304	0.000212*
precipitations	(0.000279)	(0.000272)	(0.00034)	(0.000189)	(0.000112)

Notes: The outcome variables are annual household expenditures in each category, in constant 2013 USD per 100 square feet. HDD stands for heating degree days, and CDD for cooling degree days. We provide the cumulative effect of weather variables for the reference period (0-23 months) and their 1st lag (i.e. 24-47 months) All results are estimated based on Eq. (1) and therefore include household fixed effects and month-year of the interview fixed effects. Observations were weighted using the AHS survey weights. Standard errors clustered at the MSA level. The standard errors are in parentheses. Stars represent statistical significance at the 10 percent (*), 5 percent (**), and 1 percent (***) levels.

B6. Estimation of Eq. (1) with outliers

The results with outliers lost precision for doors and windows. Point estimates remained positive, suggesting positive associations between heating degree days, cooling degree days, and investments in this category.

Appendix Table B6. Table of results for investment models, with outliers

Category	Doors and windows	Major Equipment	Insulation	Roofs	
Heating	0.000191	0.000186**	0.000590**	-0.000024	
degree days	(0.000119)	(0.000087)	(0.000271)	(0.000106)	
Cooling	0.000177	0.000415***	0.001048**	-0.000247	
degree days	(0.000286)	(0.000134)	(0.000447)	(0.000189)	
Precipitations	-0.000036	0.000070	0.000071	0.000254	
	(0.000201)	(0.000139)	(0.000334)	(0.000157)	
Observations	72,296	92,252	29,365	75,429	
Category	**Bathrooms**	**Kitchens**	**Siding**	**Other indoor**	**Total**
Heating	0.000016	-0.000174	-0.000150	-0.000131	-0.000043
degree days	(0.000126)	(0.000138)	(0.000155)	(0.000091)	(0.000063)
Cooling	0.000029	0.000104	-0.000153	0.000009	0.000062
degree days	(0.000276)	(0.000230)	(0.000289)	(0.000185)	(0.000147)
Precipitations	-0.000266	0.000149	-0.000069	-0.000045	0.000032
	(0.000240)	(0.000177)	(0.000340)	(0.000243)	(0.000147)
Observations	55,229	49,486	27,381	115,849	134,756

Notes: The outcome variables are annual household expenditures in each category, in constant 2013 USD per 100 square feet. All results were estimated based on Eq. (1) and therefore include household fixed effects and month-year of the interview fixed effects. Observations were weighted using the AHS survey weights. Standard errors clustered at the MSA level. The standard errors are in parentheses. Stars represent statistical significance at the 10 percent (*), 5 percent (**), and 1 percent (***) levels.

B7. Pooled estimation

We argue that our econometric model is superior to cross-sectional analyses. Below, we present the pooled results. We use the time-fixed effects but withdraw the household-fixed effects. Therefore, the cross-sectional variation of the sample was used. The results have different signs for several analyses and cannot be easily interpreted. We find many negative coefficients that are difficult to interpret causally.

Appendix Table B7. Table of results for investment models, without household fixed effects

Category	Doors and windows	Major Equipment	Insulation	Roofs	
Heating	0.000059***	0.000050***	-0.000044	-0.000095***	
degree days	(0.000020)	(0.000013)	(0.000031)	(0.000022)	
Cooling	-0.000220***	0.000157***	-0.000249***	-0.000114**	
degree days	(0.000040)	(0.000029)	(0.000065)	(0.000045)	
Precipitations	0.000076	0.000193***	0.000113	0.000058	
	(0.000074)	(0.000048)	(0.000090)	(0.000052)	
Observations	203,722	203,571	203,866	203,731	
Category	Bathrooms	Kitchens	Siding	Other indoor	Total
Heating	-0.000117***	-0.000103***	0.000111***	-0.000081***	-0.000051***
degree days	(0.000025)	(0.000021)	(0.000023)	(0.000017)	(0.000012)
Cooling	-0.000377***	-0.000338***	-0.000040	-0.000133***	-0.000140***
degree days	(0.000047)	(0.000044)	(0.000071)	(0.000029)	(0.000023)
Precipitations	0.000024	0.000010	0.000824***	-0.000069	0.000032
	(0.000105)	(0.000099)	(0.000122)	(0.000062)	(0.000049)
Observations	203,840	203,840	203,893	203,387	202,944

Notes: The outcome variables are annual household expenditures in each category, in constant 2013 USD per 100 square feet. All results were estimated based on Eq. (1), but do not include household fixed effects. Observations were weighted using the AHS survey weights. Standard errors clustered at the MSA level. The standard errors are in parentheses. Stars represent statistical significance at the 10 percent (*), 5 percent (**), and 1 percent (***) levels.

B8. Correlation between hot weather and air conditioning

It is not possible to disaggregate the information on investments in AC and heating before 1997, because the AHS only records investments in major equipment. After 1997, it was possible to examine investments in central AC and built-in heating equipment separately. Therefore, we used the waves of the American Housing Survey from 1997 to 2013 to separate the effects of investments in AC and heating equipment. After 1997, we can also examine investments in outdoor improvements.

The results were estimated using a smaller sample; therefore, the precision was lower. However, they suggested that cooling degree days have an impact on air-conditioning. We also found that heating degree days may positively correlate with heating equipment and cooling degree days otherwise, suggesting that increases in temperature negatively correlate with investments in heating equipment, even though the results are not statistically significant at the 5% level. In contrast, the results suggest that outdoor improvements tend to increase in temperature (the results are not statistically significant).

Appendix Table B8. Table of results for investment models, with outliers

Category	Air conditioning	Built-in heating equipment	Outdoor improvements
Heating	0.000116	0.000172	-0.000107
degree days	(0.000145)	(0.000164)	(0.000119)
Cooling	0.000393**	-0.000216	0.000088
degree days	(0.000189)	(0.000347)	(0.000266)
Precipitations	-0.000069	-0.000173	0.000053
	(0.000238)	(0.000291)	(0.000172)
Observations	13,727	11,282	40,512

Notes: The outcome variables are annual household expenditures in each category, in constant 2013 USD per 100 square feet. All results were estimated based on Eq. (1) and therefore include household fixed effects and month-year of interview fixed effects. Observations were weighted using the AHS survey weights. Standard errors clustered at the MSA level. The standard errors are in parentheses. Stars represent statistical significance at the 10 percent (*), 5 percent (**), and 1 percent (***) levels.

C. energy and water expenditure

C1. Long-term model when periods are always computed with five observations in each period

To estimate Eq. (3), we allowed period averages to be computed from four observations, even though each 9-year period encompasses up to five observations per housing unit. This allows us to include more observations for which there is missing information for a few waves; however, it may also introduce measurement errors. We provide the results when the 9-year averages were computed from five observations. The results were similar, although some precision was lost. We believe that this is because the estimation sample is reduced because our sample is unbalanced, which occurs due to missing values.

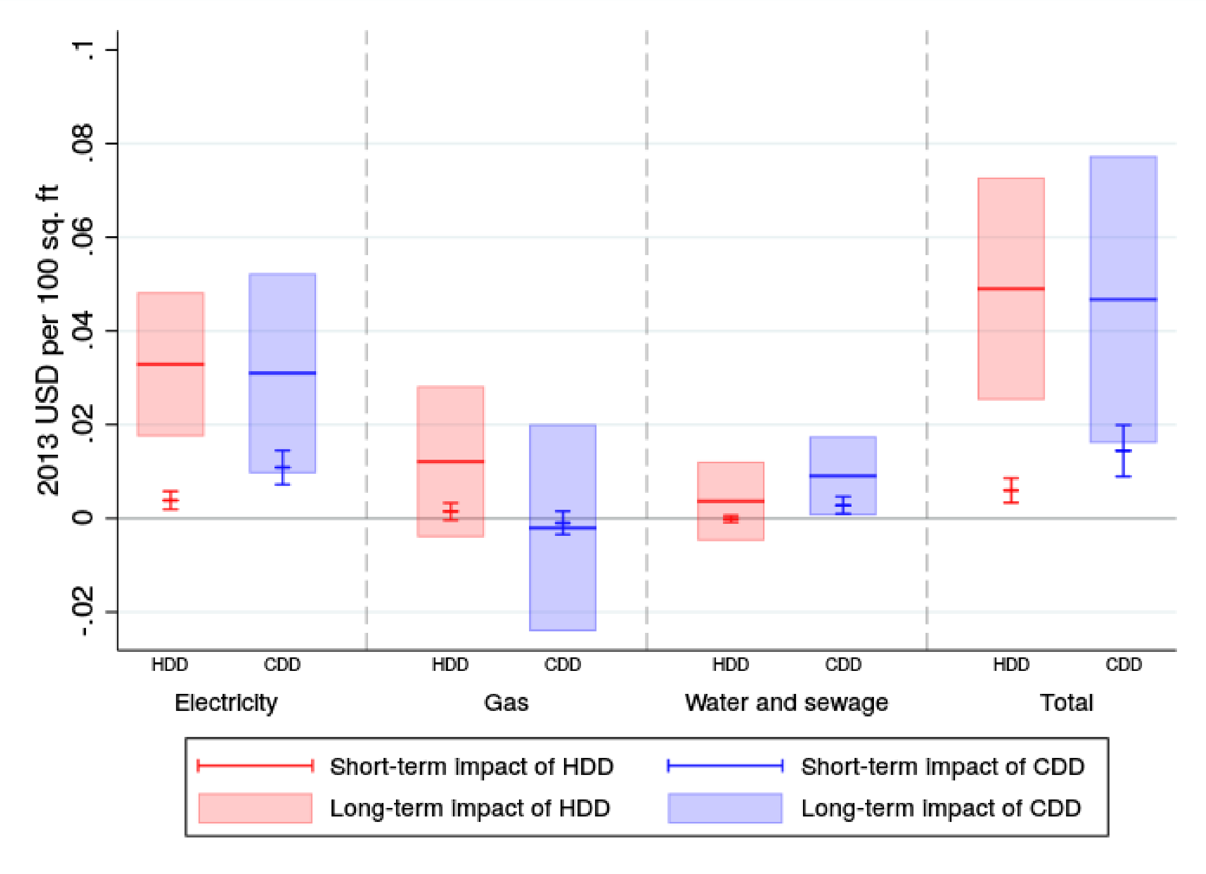


Fig. C1. Short-term (vertical lines) and long-term (bars) impacts of HDD (red) and CDD (blue) on utilities expenditure when always computing period averages from five observations. Vertical lines and bars represent point estimates and 95% confidence intervals. Estimates for different expenditure categories are obtained with separate linear regressions based on Eq. (2) and Eq. (3).

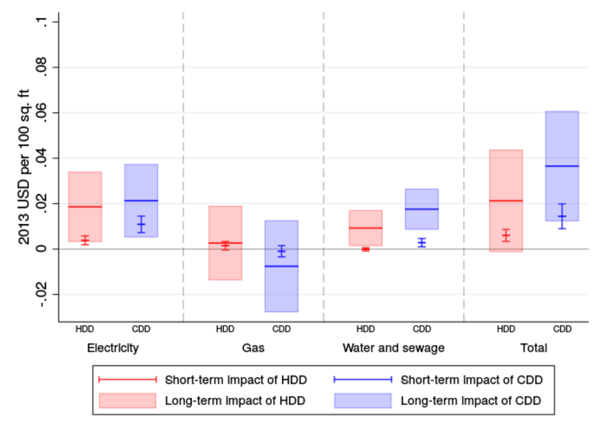
C2. Withdrawing waves while estimating the long-term model

The long-term effects are estimated using three 9-year periods (1985–1993, 1995–2003, and 2005–2013). The choice of these periods is constrained by the fact that there are 15 waves of the AHS and separating the data into three sets of five waves is therefore the best that can be done.

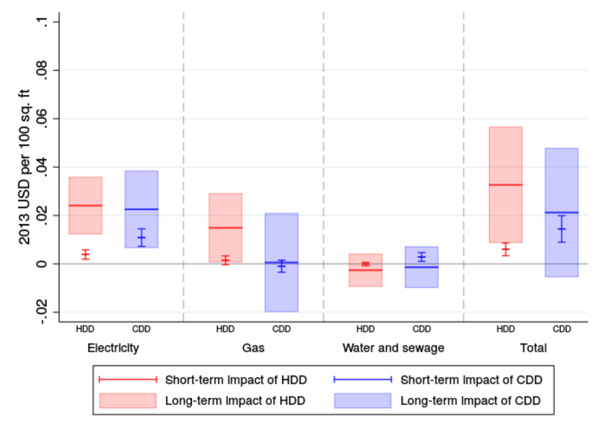
We wanted to minimize the risk that the results would change substantially if data from other years were available. The analysis below performs robustness checks in which three survey waves are withdrawn from the sample (one withdrawal per period) and evaluates whether doing so impacts the results. The 9-year periods were retained (1985–1993, 1995–2003, and 2005–2013), but averages were computed with only four observations per wave, omitting all observations from the withdrawn years.

Figure C2 presents the results obtained after withdrawal: 1985, 1995, and 2005 in panel a; 1987, 1997, and 2007 in panel b; 1989, 1999, and 2009 in panel c; 1991, 2001, and 2011 in panel d; and 1993, 2003, and 2013, respectively. This approach allowed us to test the importance of specific years to obtain the results displayed in Fig. 2. The results in Fig. C2 suggests that our results are robust to changes in the years used to calculate the long-term averages, although precision was lost.

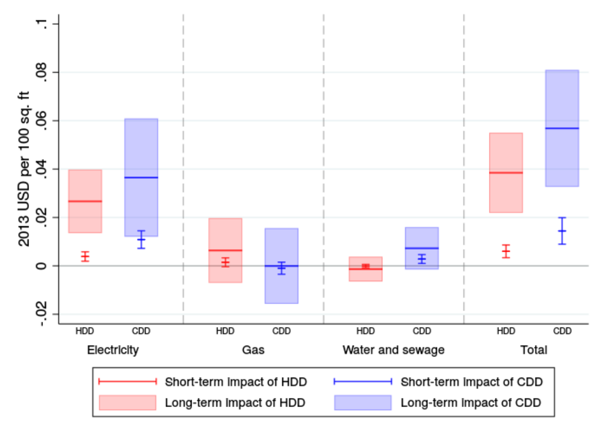
a. 1985, 1995 and 2005 withdrawn



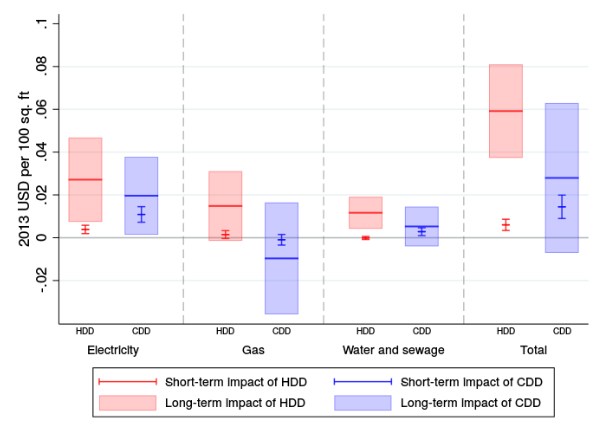
b. 1987, 1997 and 2007 withdrawn



c. 1989, 1999 and 2009 withdrawn



d. 1991, 2001 and 2011 withdrawn



e. 1993, 2003 and 2013 withdrawn

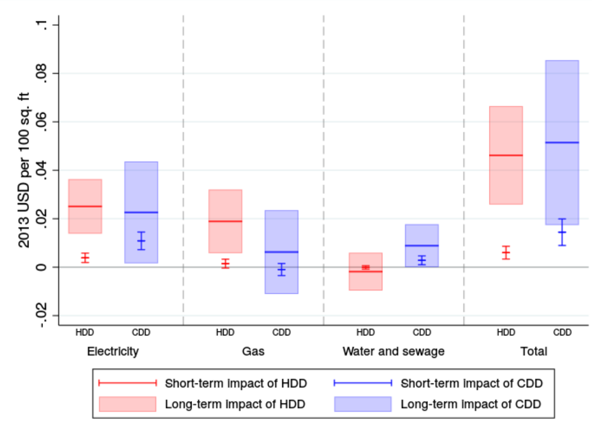


Fig. C2. Short-term (vertical lines) and long-term (bars) impacts of HDD (red) and CDD (blue) on utilities expenditure when excluding observations from specific years. Vertical lines and bars represent point estimates and 95% confidence intervals. Estimates for different expenditure categories are obtained with separate linear regressions based on Eq. (2) and Eq. (3).

C3. Results when outliers are not excluded

In Fig. C3, we provide the results of Fig. 2 when outliers are retained. The results are similar.

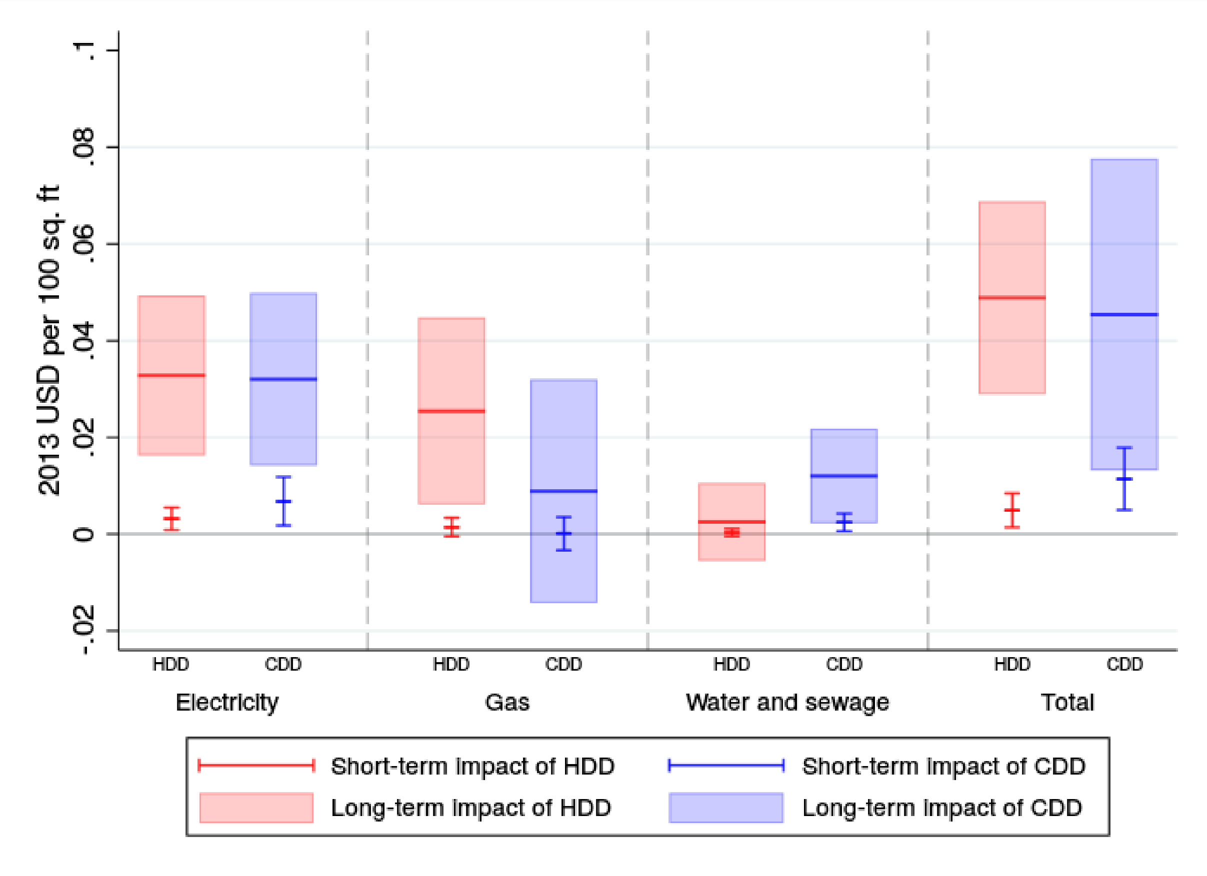


Fig. C3. Short-term (vertical lines) and long-term (bars) impacts of HDD (red) and CDD (blue) on utilities expenditure when keeping outliers. Vertical lines and bars represent point estimates and 95% confidence intervals. Estimates for different expenditure categories are obtained with separate linear regressions based on Eq. (2) and Eq. (3). This figure has been obtained while keeping outliers.

C4. Full results for utility expenditure with the effect on precipitation

While we controlled for precipitation in the production of Fig. 2, detailed results for precipitation are not provided to save space. The full results, including the effects of precipitation, are provided below.

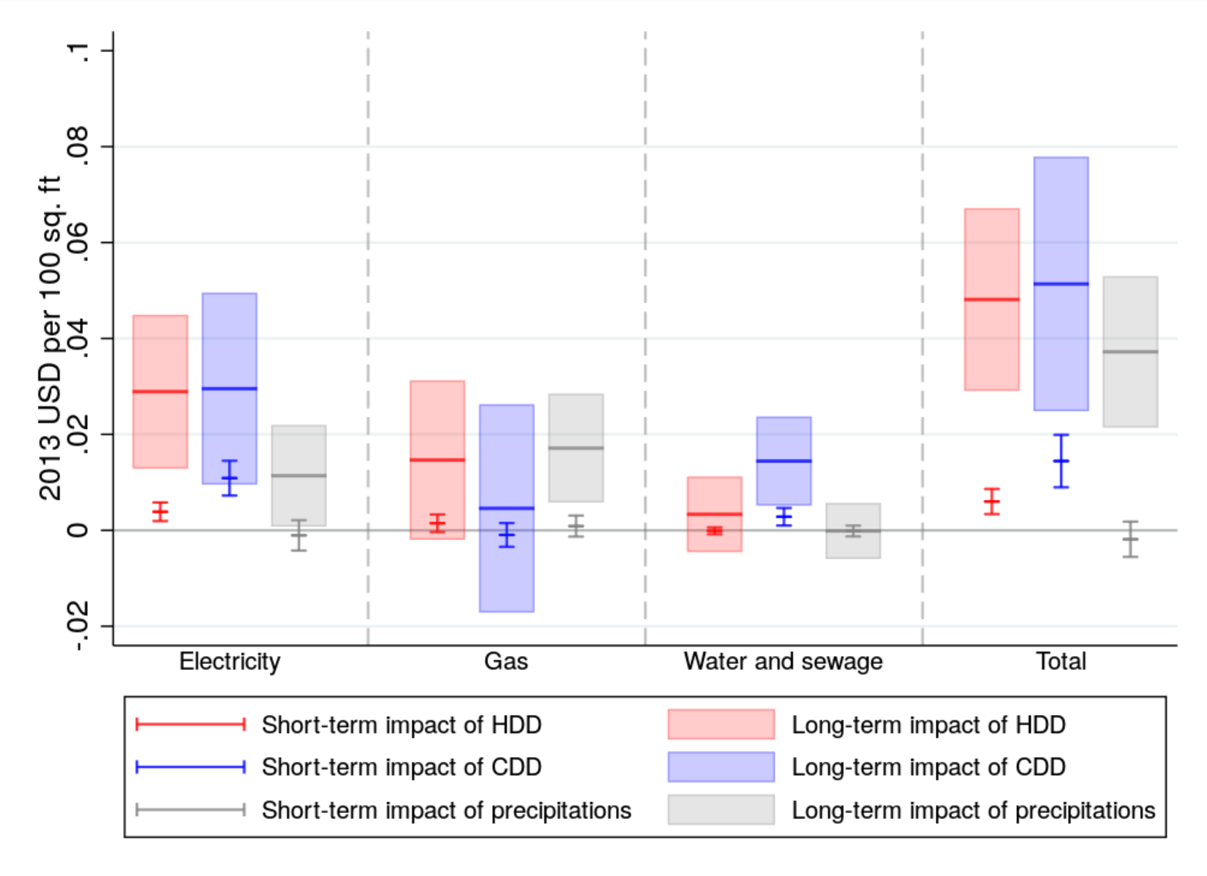


Fig. C4. Short-term (vertical lines) and long-term (bars) impacts of HDD (red), CDD (blue) and precipitation (grey) on utilities expenditure, for electricity, gas, water and sewage together and for each of these bills separately. Vertical lines and bars represent point estimates and 95% confidence intervals. Estimates for different expenditure categories are obtained with separate linear regressions based on Eq. (2) and Eq. (3).

There is an increase in electricity and gas use when precipitations increase. There could be many reasons for this. In general, humid environments are known to make people feel colder when it is cold, and hotter when it is hot, so we could expect additional energy use in wetter regions. Many studies have investigated this (such as Jing et al., 2013; or Kong et al., 2019). Humidity can also have impacts on behaviour. In a small experimental study of 30 people, Jin et al. (2017) find that, under warm and humid conditions, people are more sedentary. In economics, paper such as Connolly (2008) show that rain has an impact on time use. She finds that on rainy days, men shift on average 30 minutes from leisure to work. An intuition possibly explaining in part the results of **Figure C4** could be that, as rainy days become more frequent, people may adapt their activities and spend more time at home.

D. climate change impacts

D1. Separate impacts by climate model

The climate change impacts in Table 2 are for the average change in heating and cooling degree days predicted by the 20 different climate models. Below, we provide the total cost estimates for each of the 20 models.

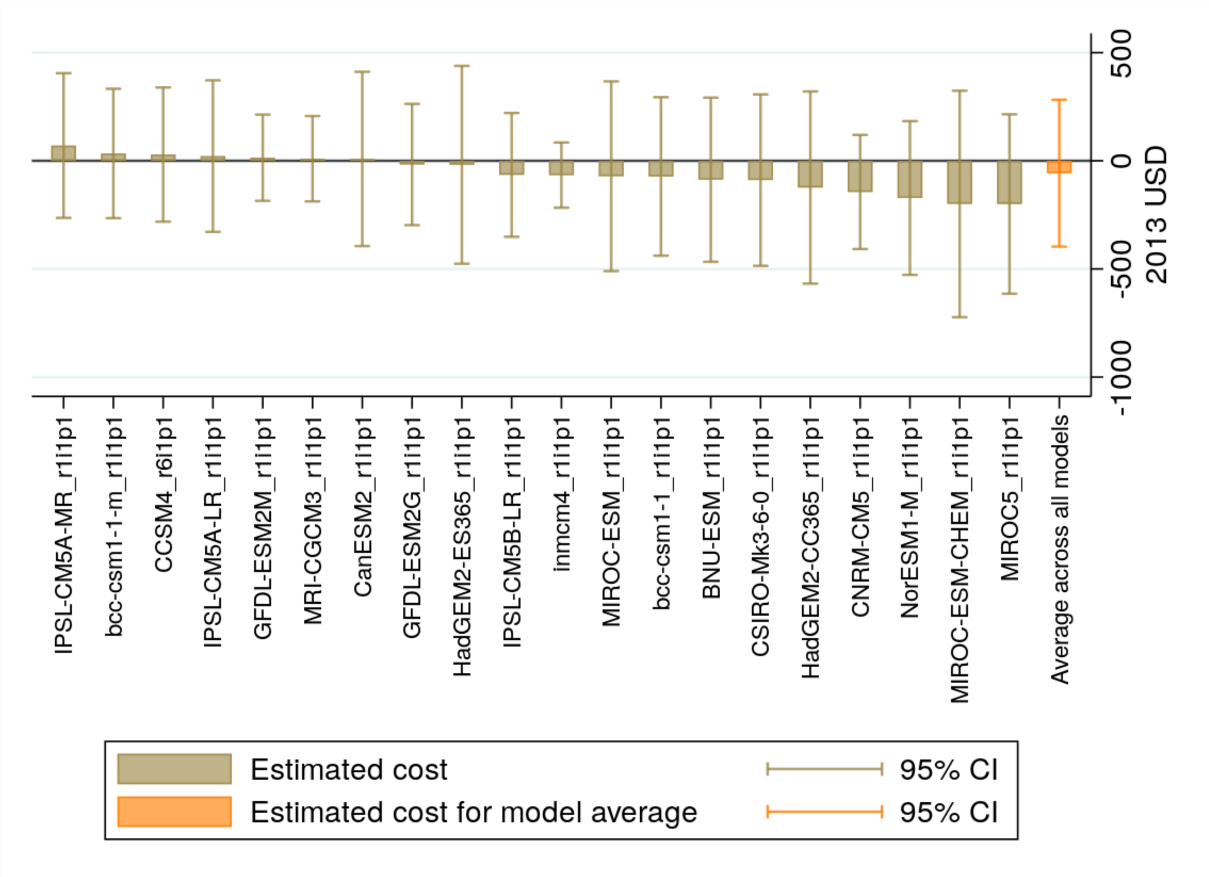


Fig. D1. Annual cost of adaptation under RCP 4.5 for 2046–2065, separately for each of the 20 climate models used in the estimation of Table 2.

D2. Impacts for later periods and for RCP 8.5

Below, we run the same cost estimator as in Table 2 for different periods and for RCP 8.5 as well as for RCP 4.5.

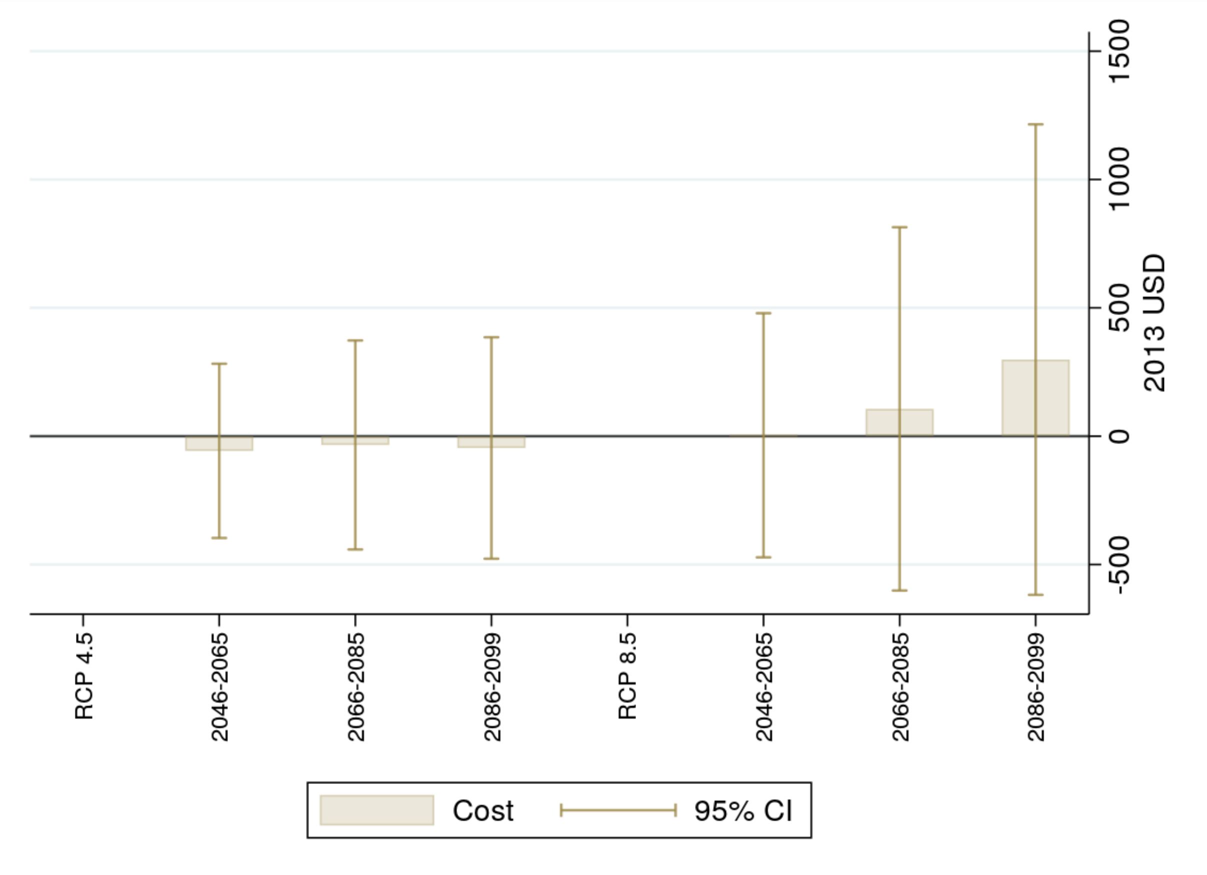


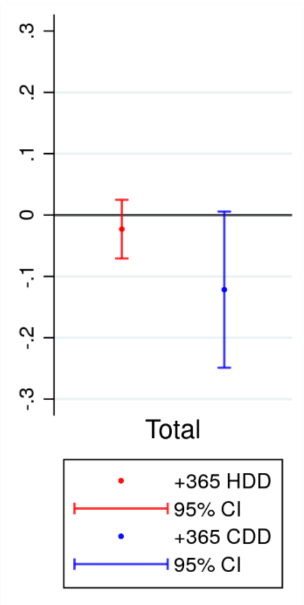
Fig. D2. Annual cost of adaptation under RCP 4.5 and RCP 8.5, for different periods (2046–2065, 2066–2085 and 2086–2099). The cost estimates are for the average change in heating and cooling degree days across 20 climate models.

D3. Econometric results by region and by income group

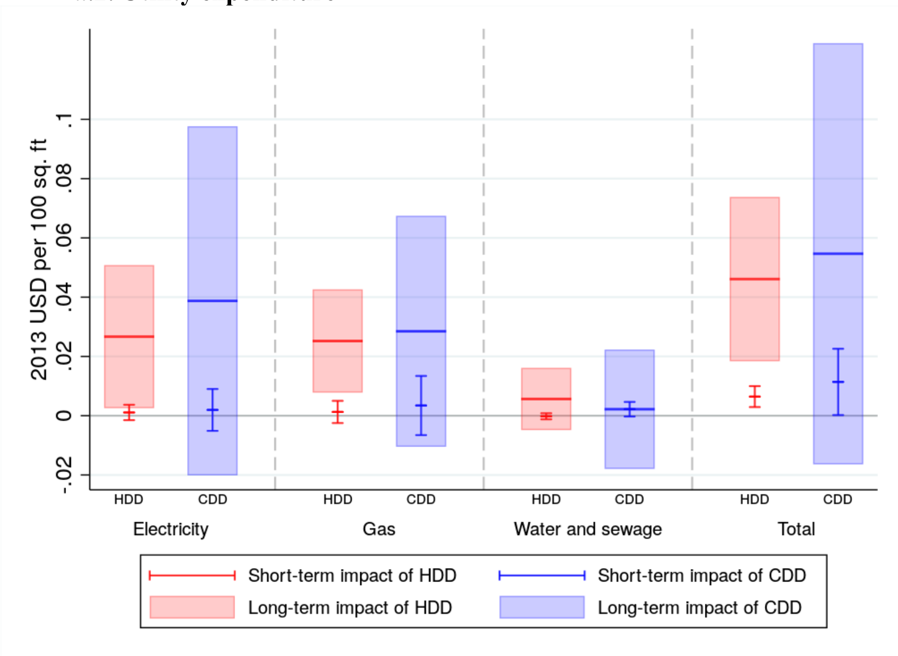
We estimate our econometric models for total expenditure in home improvements, as well as utilities expenditure, separately for two climate regions (colder and warmer regions with average temperatures below or above 55 °F) in Fig. AF8. Similarly, Fig. AF9 provides the results of the econometric models for total expenditure in home improvements as well as public utility expenditures separately for two income groups (as described in the main text). These results were used to compute region-specific and income-specific cost averages under climate change, as shown in Table 2.

a. Colder regions (<55°F)

a.1. Home improvements

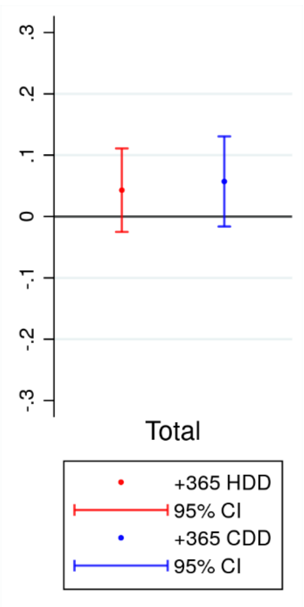


a.2. Utility expenditure



b. Warmer regions (>55°F)

b.1. Home improvements



b.2. Utility expenditure

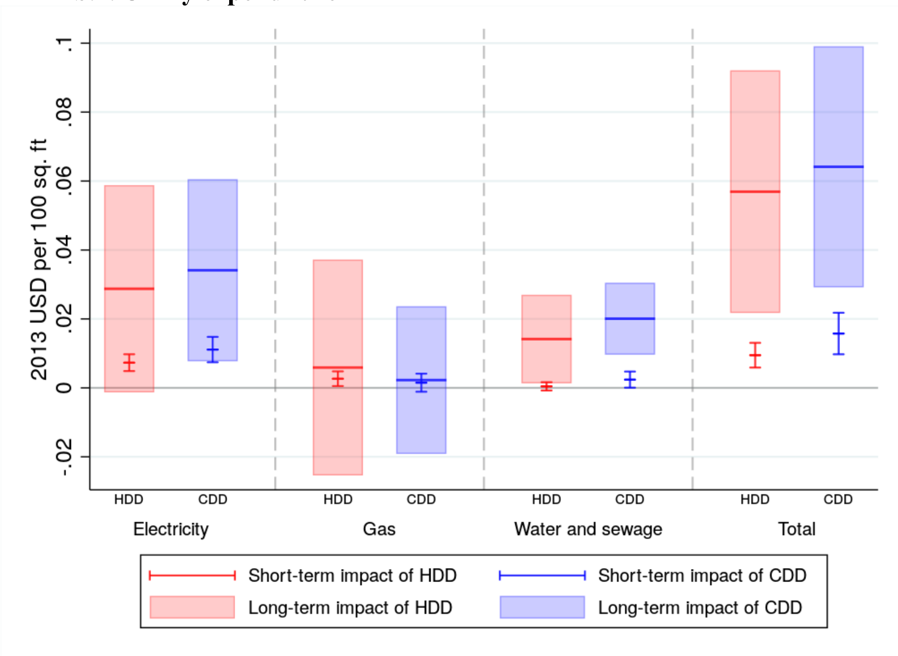


Fig. D3. Econometric results for colder regions (a) and warmer regions (b). Results for home improvements (a.1 and b.1) have been obtained following the same methodology as for Fig. 1, after splitting the sample by region. Results for utility expenditure (a.2 and b.2) have been obtained following the same methodology as for Fig. 2, after splitting the sample by region.

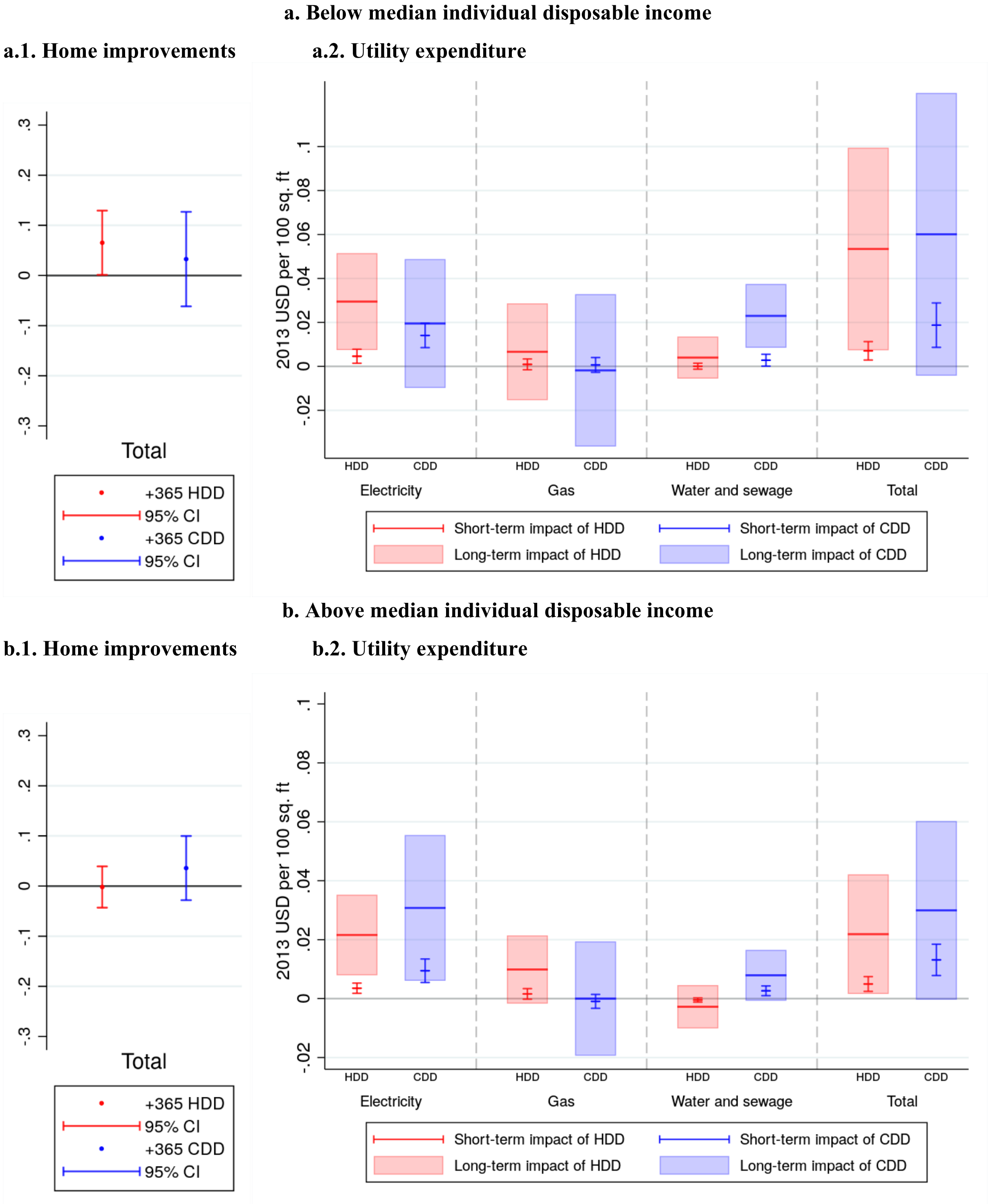


Fig. D4. Econometric results by income group. Results for home improvements (a.1 and b.1) have been obtained following the same methodology as for Fig. 1, after splitting the sample by income group. Results for utility expenditure (a.2 and b.2) have been obtained following the same methodology as for Fig. 2, after splitting the sample by income group.

D4. Impact of precipitation under RCP 4.5 (2046–2065)

We used the results for precipitation and the output of the climate models at our disposal to examine the adaptation cost of an increase in precipitation under RCP 4.5 (2046–2065). The results indicate that precipitation may increase annual costs by approximately USD 25.

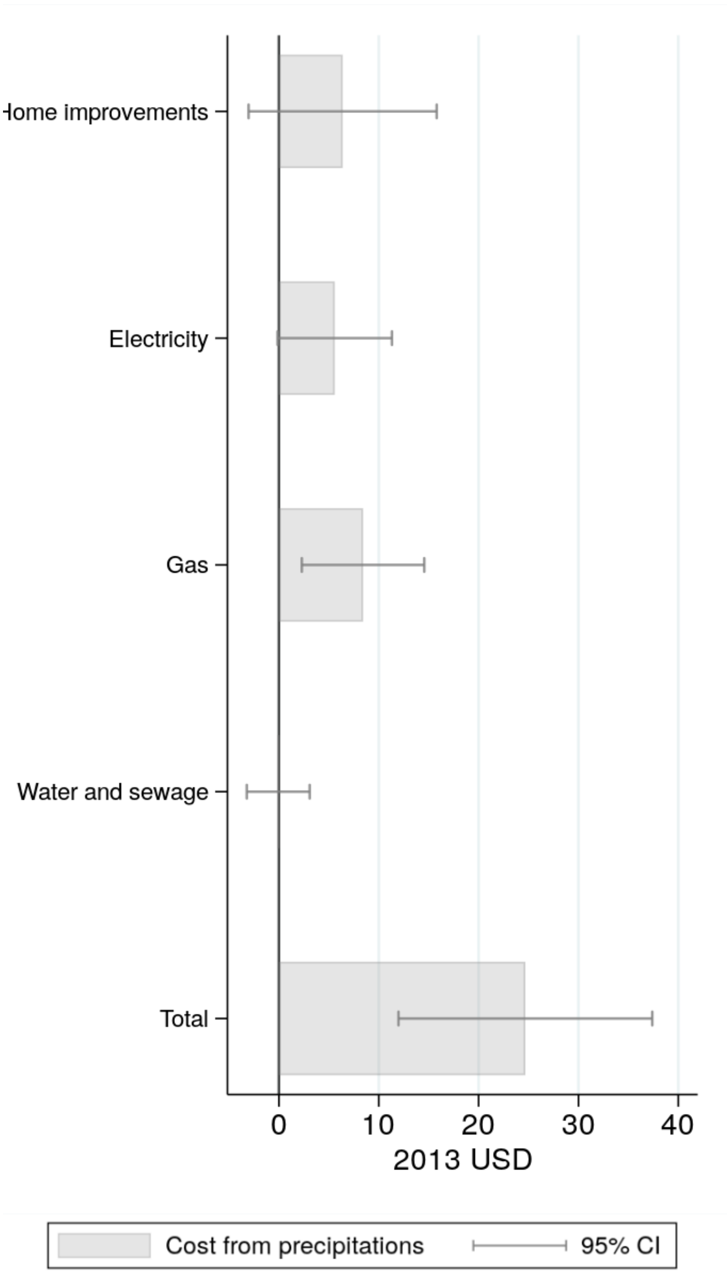


Fig. D5. Annual cost of adaptation caused by a change in precipitation under RCP 4.5 for 2046–2065. The estimates are for the average change in precipitation across the 20 climate models.