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The Cost of Adapting to Climate Change: Evidence from the US Residential Sector

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Abstract

Using household-level data from the American Housing Survey, this paper assesses the cost of adapting housing to temperature increases. We account for both energy use adjustments and capital adjustments through investments in weatherization and heating and cooling equipment. Our best estimate of the present discounted value of the cost for adapting to the A2 "business-as-usual" climate scenario by the end of the century is $5,600 per housing unit, including both energy and investment costs. A more intense use of air conditioners will be compensated for by a reduction in heating need, leading to a shift from gas to electricity consumption.

JEL Codes: D12, Q47, Q54, R22.

Keywords: Climate change, adaptation, home improvements, residential energy consumption.

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1. Introduction

The latest report by the International Panel on Climate Change makes clear that, even if greenhouse gas emissions are drastically cut, the world's climate will inevitably shift and the global temperature will continue to increase (IPCC, 2013). The costs of climate change remain largely uncertain, in particular because of limited knowledge about the capacity of human societies to adapt.[1] Using historical data, a growing empirical literature arguably provides ex post estimates of the impact of climate change on various economic outcomes and in diverse sectors (see the literature survey by Dell, Jones, & Olken, 2014). However, these studies commonly exploit short-term (typically annual) variations in climate and economic outcomes, which make it difficult to identify longer-term adaptation strategies (for a methodological discussion, see Hsiang, 2016, or Dell et al., 2014).

Consider the residential sector, which we study in this paper. When outdoor temperatures increase, the only adaptation option available to home occupiers in the short term is to adjust energy consumption. That is, they consume more electricity during heat waves if their home is equipped with air-conditioning; symmetrically, they reduce space heating during winter, and thus consume less gas or electricity depending on the heating technology available in their homes. 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 (e.g. insulation, roofing and sidings). Most of the existing empirical works only examine short-term energy adjustments.[2] For example, Auffhammer and Aroonruengsawat (2011) and Deschênes and Greenstone (2011) forecast the impact of temperature increases on residential energy consumption, but they assume no change in the stock of energy-related durables.

In contrast with current standard empirical practice, we analyze the decisions made by households to adapt their dwellings 1) by adjusting energy consumption in the intensive margin and 2) by adjusting their investment in cooling and heating equipment and in weatherization in the extensive margin. In doing so, we are able to estimate the overall cost of adapting existing housing units, accounting for energy costs and investment expenditures. This tractable cost estimate constitutes the major contribution of this paper to the literature.

We use microdata from 14 biannual and national waves of the American Housing Survey (AHS, 1985-2011), which includes information on energy expenditure and investments in

[1] For an overview of economic impact studies, see Tol (2009).

[2] See Auffhammer and Mansur (2014) for a review of the empirical literature on how climate impacts energy consumption. More information on this literature is given below.

weatherization, heating and cooling equipment made in a large panel of US homes in 128 localities in the USA. This data is matched with climatic data from the Global Historical Climatic Network (GHCN) Daily. We then use annual variations in location-specific temperature variables (cooling degree days, heating degree days) to identify the impact of temperature increases on the size of adaptation investments. The same data is used to estimate energy expenditure.

We then combine our econometric estimates with predicted temperature changes from a climate model to predict the impact of the A2 (high emissions) scenario of the Intergovernmental Panel on Climate Change on adaptation expenditure made by home occupiers in response to temperature increases (investment costs and energy costs). This "business-as-usual" scenario assumes a relatively high amount of GHG emissions released into the atmosphere, leading to a global average surface warming of 6.1°F in 2090-2099 relative to 1980-1999 (IPCC, 2007). The calculation of state- and month-specific temperature averages relies on the output of the Regional Climate Change Viewer (RCCV), which provides state-specific climate forecasts obtained by downscaling global climate simulations made with the ECHAM climate model.

Our best estimate of the present discounted value of the cost for adapting to temperature increases under the A2 scenario is $5,600 per housing unit, accounting for both energy and investment costs. Even though the null hypothesis of a zero cost is rejected at 10%, this is still moderately low when we consider that the average price of a housing unit in our data is around 205,000 in real 2011 dollars: the cost of adaptation represents around 2.7% of the price of a US home. The reason is that the installation and more intensive use of additional air-conditioners are partially offset by reduced space heating needs. Consequently, we predict a major shift from gas, which is the main heating fuel, to electricity, which fuels air conditioners. Gas expenditure is expected to decrease by 25%, mostly in colder states, whereas electricity expenditure would increase by 29%, mostly in warmer states. Total residential energy expenditure would increase by 13% since electricity is sold at a higher price.

The empirical literature on adaptation in the residential sector is limited. The studies by Deschênes and Greenstone (2011) and Auffhammer and Aroonruengsawat (2011, 2012) are the most closely related to this paper. However, both papers only deal with intensive margin adjustments[3]. Deschênes and Greenstone (2011) estimate that, by the end of this century, residential energy consumption could rise by 10-11% in the US as a result of climate change.

[3] See Auffhammer and Mansur (2014) for a recent review of the empirical literature on how climate impacts energy consumption.

Using a very large sample of monthly and geolocalized data, Auffhammer and Aroonruengsawat examine household-level electricity consumption data in California from 2003-2006. They find a modest 3-6% increase under the A2 scenario. Like us, all of these studies adopt a panel data approach with location-specific and time-fixed effects. Our simulations however produce higher energy cost estimates than those obtained by Auffhammer, Aroonruengsawat, Deschênes, and Greenstone because we account for energy-use changes that are induced by changes in the capital stock, and we predict a surge in air conditioning investments that mostly consume electricity. However, we do not evaluate household welfare. We only look at the monetary cost of adaptation, and ignore non-monetary benefits resulting from milder indoor temperatures (e.g. lower mortality, more comfort).[4] If households make rational investment decisions, one might expect extensive margin adjustments to improve welfare.[5]

A few papers deal with the extensive margin, but with a more limited scope than ours. In a unified framework, Mansur et al. (2008) examine short-term energy consumption decisions and long-term fuel choices. Their (cross-sectional) analysis does not deal with the size of the investments associated with these decisions. Other studies focus on the diffusion of air conditioning. Davis and Gertler (2015) use microdata from Mexico to describe how electricity consumption increases with temperature given current levels of air conditioning, and how climate and income drive air conditioning adoption decisions. Like us, they predict a much larger increase in electricity consumption after incorporating the extensive margin; they do not provide any investment cost estimate. Rapson (2014) develops a structural model of demand for air conditioners, but does not focus on climate variables.

In the medium term, the margins of adaptation are constrained by the existing housing stock.[6] More adaptation options are available if the time horizon is extended further: households can move into new dwellings that are more adapted to the new climatic regime (in particular, because they are located in less exposed areas); firms develop new cooling and heating technologies; public authorities redesign urban spaces, etc. Neither this paper nor any of the studies mentioned above consider these longer-term adjustments. In this paper, we however

[4] Note that, in addition to energy consumption, Deschênes and Greenstone (2011) measure the welfare impacts associated with higher mortality.

[5] The potential benefits of home adaptation can be huge, as illustrated by Barreca et al. (2016) who find that the progressive adoption of air conditioning throughout the 20th century explains 90% of the entire drop in the impact of excess heat on mortality in the US.

[6] Constructing new buildings that integrate the new climatic conditions into their design can mitigate the problem (Kahn, 2010), but most adaptation in the next decades will involve existing dwellings.

discuss their implications for the cost estimate we provide. In general, the availability of additional strategies to adapt to climate change should reduce further the cost of climate change adaptation.

The remainder of this paper is structured as follows. The next section presents a conceptual framework and the equations that describe investment behavior and energy use. Section 3 describes the data and section 4 presents the estimation results. Section 5 assesses the magnitude of the estimates of the effect of climate change by simulating the A2 scenario.

2. Analytical framework

Figure 1 presents the framework that will be used throughout the paper. Temperature potentially affects energy use through two channels. First, it directly influences the quantity of energy used by installed energy-consuming durables (A in Fig. 1). The second is indirect: temperature modifies home occupiers' investment behavior and thus the housing capital stock (B), leading to further energy use adjustments (C). The paper primarily seeks to identify these causal links in order to evaluate the impact on investment and energy expenditures. To do so, we estimate two sets of equations, i.e. investment equations that relate the size of investments made in each period to temperature variations, and energy equations that relate the level of energy expenditures to temperature and to the stock of energy-related durables.

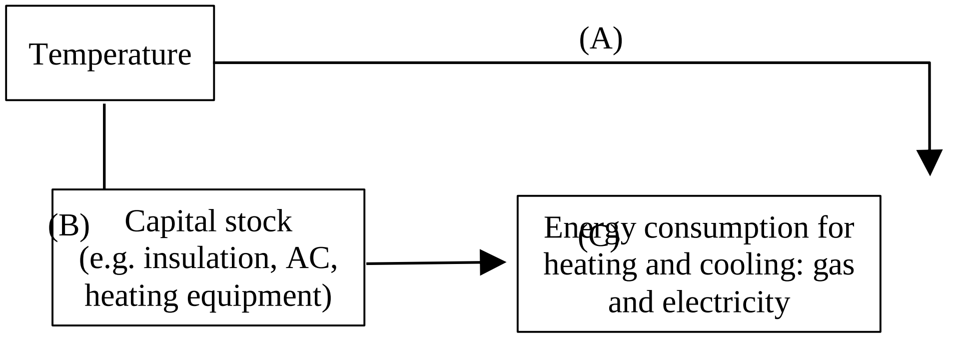

Figure 1: Causal relationships between temperature, energy consumption, and home capital stock

2.1. Investment equations

The dependent variable is the investment made in its dwelling by household i in period t (the data only describe homeowners). In order to limit potential aggregation biases, we consider specific categories of investment that are related to adaptation. The full panel of the AHS data (1985-2011) only makes it possible to identify two categories of adaptation-related home improvements: 1) the installation of major energy-consuming equipment, including major space-heating appliances and air conditioners (either room or central air conditioners); and 2) weatherization, (i.e. addition/replacement of foam, weather stripping and caulking) and, by extension, improvements to doors and windows, roofing and sidings that improve the energy integrity of dwellings[7]. The regressions will thus not produce specific results for investments in space heating and air conditioning. However, when performing the simulations in section 5, we introduce the assumption that investments in space heating and air conditioning are separable and strictly influenced by heating and cooling needs respectively to mitigate the problem.[8]

To identify the relationship between this variable and temperature variations, we fit the following linear equation:

$$I_{iht} = \alpha_h CDD_{it} + \beta_h HDD_{it} + \gamma_h X_{it} + \mu_{ih} + \tau_{ht} + \varepsilon_{iht} \quad (1)$$

where I_{iht} denote the level of investment made by household i in category h (with h = equipment, weatherization) and in period t. α_h, β_h, and γ_h are (vector of) parameters to be estimated. The last term ε_{iht} is the random error term.

CDD_{it} and HDD_{it} capture the impact of temperature on investment. They are expected annual cooling degree days and annual heating degree days in year t and in the location of household i's housing unit, respectively. These are standard measurements designed to reflect the demand for heating and for cooling. The precise definition of cooling degree days is the number of degrees a day's average temperature rises above 65° F, which is the temperature at which it is assumed that people start using air conditioning to cool their buildings. Symmetrically, heating degree days are the number of degrees that a day's average is below 65° F.

A crucial point is that CDD_{it} and HDD_{it} are *expected* degree days, not the contemporaneous values of these variables. The lifetime of investments in housing is relatively long so that the

[7] Another less interesting category corresponds to all other indoor investments not directly related to climate change, i.e. changes to the bathroom; changes to the kitchen; home extensions; and other major indoor improvements. These are studied in Appendix K. As expected, we find no significant impact of temperature.
[8] We also look at a shorter panel (1997-2011) in Appendix A, for which the distinction between investments in air conditioning and heating is possible. Results are less precise but qualitatively similar to those presented in the core of this paper.

benefits from installing air conditioning or insulating in a house depend on future needs. Thus, if rational, households base their investment behavior on their expectations of future temperatures.

These expectations are however not observed in historical climate data. To solve this problem, we adopt an adaptive expectation framework. It assumes that households adjust their expectations based on some averaging of past climate values that are observed in the data.[9] Consider the case of cooling degree days and let cdd_{it} denote the contemporaneous number of cooling degree days that is actually observed in year t by household i. The adaptive model assumes the following relationship between expected degree days and observed (real) degree days:

$$CDD_{it} = CDD_{it-1} + \lambda(cdd_{it-1} - cdd_{it}) \qquad (2)$$

Eq. (2) means that the current expectation is composed of past expectations and an "error adjustment" term, which raises or lowers the expectations depending on the realized number of degree days.[10] The parameter $\lambda \in [0; 1]$ captures the adjustment speed between past and current expectations. When applying Eq. (2) recurrently over all past periods, expectations at time t of the CDD at t + 1 are equivalent to an exponentially weighted moving average:

$$CDD_{it} = \lambda \sum_{k=0} (1-\lambda)^k \; (cdd_{it-k-1})^{k+1} \qquad (3)$$

We use the same formula to calculate expected heating degree days. We estimate the value of λ by assuming that all households use a value that would make their predictions as accurate as possible. More specifically, we fit a non-linear regression based on Eq. (3).[11] The estimated results are used to predict current values based on a weighted average of past values for all households in our data. We then choose the λ that minimizes the prediction errors. The estimate is $\lambda \approx 0.30$. This is equivalent to assuming that expectations mostly rely on the past 7-8 years.[12]

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[9] Gelain and Lansing (2014) provide recent evidence that backward-looking expectations may operate on the housing market. They argue that such expectations are a better predictor of high volatility in price-rent ratios compared to rational expectations.

[10] Note that this formula precisely gives the value of the cooling degree days in year t + 1 as expected in year t. We use the formula to calculate expectations in years t+1, t+2, t+3… Hence we implicitly assume that the household considers that the climate is stable during the investment lifetime.

[11] This equation is slightly modified to account for the fact that we have a limited amount of lags in the model. We assume that since tends to one only when the number of lags tends to infinity for low values of .

[12] We obtain similar results with a distributed lag model that includes three-year lags as control variables. Using current values provides results that are less precise. This assumes that households only consider contemporaneous heating degree days and cooling degree days when making long-term decisions (Appendix E).

Using degree days may fail to account for potential nonlinearities in the marginal impact of temperature changes on investments. That is, it is assumed that a one-degree increase has the same effect on investment, whether it occurs on a mild day with temperatures of 70°F or during a 90°F heatwave. As a robustness check, we also estimate a more flexible specification including temperature bins, which gives estimates of the specific impact on investments at different temperature ranges (like in Deschênes and Greenstone, 2011). Results are not substantially different.

Let us now turn to the control variables included in vector X_{it}. The choice of adequate controls is complicated by the fact that climate potentially influences many variables. Take the example of household income. This is an obvious control candidate as it influences the propensity to invest. However, it is also reasonable to assume that temperature has an impact on its level. Recent empirical studies have actually confirmed this hypothesis (e.g., Dell et al. 2009). If this variable is included in X_{it}, the coefficients $\alpha_{\hbar}$ and $\beta_{\hbar}$ will then not identify the full effect of climate, but only the direct effect of temperature, ignoring the indirect effect that passes through changes in income. This will then skew the results of our simulations.

To reduce this risk of "over-controlling", Dell et al. (2014) and Hsiang (2016) suggest excluding from the equation factors that are assumedly not influenced by temperature. Accordingly, in addition to income, we do not incorporate information on the investment prices because temperature probably influences local prices of energy-related investments: e.g. a higher demand for air conditioning induced by very hot summers will increase the local price of air-conditioners. In the same vein, we do not control for electricity and gas prices, even though they are clear determinants of the demand for heating and air conditioning equipment: temperature has direct impacts on energy production, transmission and distribution, and thus on energy prices. Finally, we also exclude the impact of past investments on current investments, because past investments depend on past expectations about climate. Hence, they are correlated with current weather shocks in a causal manner, provided that home occupiers form expectations with some rationality. Ultimately, we limit ourselves to control the number of individuals living in the house, annual precipitation levels, and whether the neighborhood has a pipe gas supply.

The equation also includes time dummies (τ_{ht}) and household-category fixed effects (μ_{ih}). This means that we exploit location-specific time-varying variations of the temperature variables to predict the impact on investments. However, the coefficients α_h and β_h do not only identify the direct causal effect of a change in temperature on the demand for investments, but also the correlation between temperatures and investment levels, including income effects, and demand-side and supply-side effects. This assessment of temperature changes then yields a more complete measurement of their overall impact on investments. The negative side is that excluding these variables will limit the external validity of our results.

Note that household-category fixed effects control for residential sorting, a standard concern in this spatial setting. In our context, sorting is a form of adaptation: households that suffer less from intense heat are more likely to move into dwellings that are more exposed to heat, thereby reducing cooling energy and investment expenditures. The inclusion of household fixed effects leads us to ignore this role of relocation in adaptation.

Other issues

A common concern in the empirical literature is that investments are lumpy, with long periods of no investment ($I_{iht} = 0$) interrupted by more active investment periods (e.g. Doms and Dunne, 1998). In our case, households may prefer to make all the necessary improvements at one point in time because of the hidden fixed costs. For example, home renovation limits the ability to live in a dwelling while it is being renovated.

Interpreting home improvements as a left-censored variable –investments are only observed when their value is positive– is a popular approach to deal with this problem. In Appendix F, we estimate two different latent variable models. The first is a panel tobit model with fixed effects based on Honore (1992). A weakness of this approach is to assume symmetric errors. To relax that assumption, we estimate the Wooldridge's (2005) dynamic random effect panel tobit model, which specifies a functional form for the fixed effect. Another advantage is that the model accommodates persistent behavior. Results in Appendix F are very similar when it comes to the relative effect of heating and cooling degree days on investments. We however prefer the fixed-effect linear model, principally because it produces estimates of the fixed effects, whereas Wooldridge's approach requires additional controls to mimic a fixed-effect specification.[13]

Energy efficiency policies (e.g. tax credits or subsidized loans) that are implemented to influence investments in space heating, air cooling and weatherization in some states may create biases, as their existence is likely to be correlated with climate shocks. We simply exclude from the sample all observations in which households have benefited from energy efficiency

[13] In addition, the model does not always converge due to the many dummy variables introduced to proxy a fixed-effect specification. It is common that dummy variables create convergence problems in random effect tobit models.

subsidies (2% of the observations). As a robustness check, we use this piece of information to construct a dummy variable that is included in the equation. As this variable is likely to be endogenous – it reflects the existence of policies promoting energy efficiency at a local level[14] – we use a control function approach. We observe only very slight differences in the results obtained by the two approaches (see Online Appendix H).

2.2. Energy expenditures

We separately estimate the demand for electricity and gas, which are the two main energy sources used in the US residential sector. Like Greenstone and Deschênes (2011) and Aufhammer and Aroonruengsawat (2011, 2012) we use a log-linear specification. The dependent variable is E_{ift}, the logarithm of the annual energy expenditure in fuel *f* (with f = gas, electricity) of household *i* at time *t*:

$$\ln\left(E_{ift}\right) = \theta_f cdd_{it} + \lambda_f hdd_{it} + \sum_{h=1}^{3} \phi_{hf} K_{iht} + \omega_f Y_{it} + \mu_{if} + \tau_{ft} + \epsilon_{ift} \quad (4)$$

cdd_{it} and hdd_{it} are cooling degree days and heating degree days. Importantly, we use on-the-year values and not expectations, since energy consumption immediately reacts to temperature changes.

K_{iht} measures the amount of capital in the housing unit in each investment category h. As explained above, this is what distinguishes this paper from previous works on climate's impact on residential energy use. K_{iht} roughly equals the sum of current and past investments I_{iht}, I_{iht-1}, I_{iht-2}… that are discounted to account for obsolescence[15]. Its precise calculation is described in Appendix B. Note that, in addition to equipment and weatherization, we consider a third category including all other investments. The last category includes home improvements, like kitchen renovation, that could influence energy expenditure.

Y_{it} is the vector of controls, which includes the log of family size, annual precipitation, and connection to pipe gas in the neighborhood. For the reasons discussed previously, we do not control for income and energy prices, as they are likely to be influenced by temperature. The equation includes a full set of household-by-fuel fixed effects, μ_{if}, which absorb all household-specific time invariant household specificities. It also includes a set of time-by-fuel dummies,

[14] In particular, this variable only captures information about households that actually performed alterations. For the other households, we do not know whether they had access to government aid or not. In addition, this is a binary variable, whereas household choices are driven by the size of subsidies.

[15] One difficulty is that investments are not observed before the year of purchase or construction. We estimate the stocks in that year relying on the sales price. All details are provided in Appendix B.

τ_{tf}, which, for instance, control for the general evolution of energy prices in the US that might affect energy expenditure. ϵ_{ift} is an error term. Finally, λ_f, ϕ_f, θ_f, and ω_f are (vectors of) parameters to be estimated.

Sample selection

The fact that Eq. (4) is estimated separately for gas and electricity potentially generates a sample selection bias, as households choose the type of fuel used in their homes. This risk is however limited by the inclusion of household-by-fuel effects, which control for fuel selection prior to moving into the house. We also control for the availability of pipe gas, a major determinant of choosing gas over other fuel types. More generally, fuel switching occurs when installing new equipment and is thus infrequent: households report a change in main heating fuel concomitant to home equipment improvements in only 0.6% of observations in the data. Appendix T also presents a specification in which the dependent variable is the sum of electricity and gas expenditure levels. This is to consider that households jointly choose both expenditure levels. Results are similar to those obtained using separate equations.

Endogeneity of capital stocks

In Eq. (4), the different capital stocks variables are likely to be endogenous: they include the investments I_{iht} made in year *t*, which are simultaneously determined with E_{ift}. As a result, any unobserved shock that affects investment is likely to be correlated with the error term.

One solution is to instrument for the stocks of capital in every category *h* with the lagged values of these stocks. The availability of these lags is very convenient to produce instruments since the past capital stocks are not correlated with current shocks on energy expenditure. One difficulty, however, is that they are correlated with past shocks, implying that they are pre-determined. This precludes using a standard fixed effect IV model based on demeaning.

GMM estimators can circumvent this problem (Arellano and Bond 1991; Blundell and Bond, 1998). These are controversial tools when used to estimate dynamic panel data models where the dynamic component of the model is instrumented with its own lags.[16] However, our concern is different – the choice of I_{iht} and the choice of E_{ift} are simultaneous – and we do not need a dynamic model. In our case, the exclusion restriction implies no correlation between the error

[16] In this case, the exclusion restriction requires that the deeper lags of the dependent variable are not correlated with the contemporaneous error values. This is a strong assumption in many real situations.

term and the deeper lags of the capital stocks, which is weaker than assuming no correlation between the error term and the lagged dependent variable as requested in a dynamic model.

We use the system-GMM estimator, which offers high efficiency levels. This efficiency gain comes at the cost of an additional assumption compared to the alternative difference GMM model: the variables used in the model should be mean stationary. This seems a reasonable assumption in the case of residential gas and electricity demand in the US, since the real-time series of residential energy bills were not subject to trends or breaks during the sample period (see figure 2 below).[17]

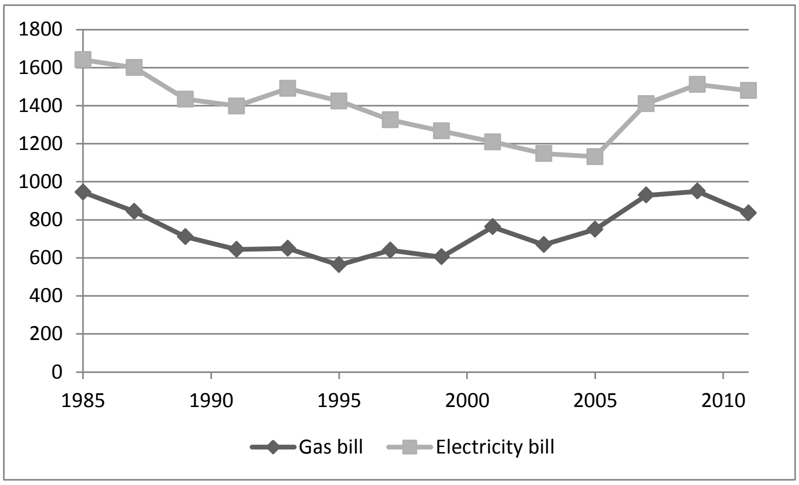


Figure 2: Average energy bills in the sample used (in real 2011 dollars)

[17] We cannot formally test for mean stationarity using unit root tests since our panel is not balanced.

System GMM can be calibrated in a series of ways. Our baseline specification uses the first-differenced third lags of the capital stock as instruments. We use first differences, and not orthogonal deviations, because the data does not include many gaps. We make multiple robustness checks to ensure that the results do not depend on these two choices.[18]

3. Data

We rely on three main data sources: the American Housing Survey for data on housing units, home improvements, energy consumptions and household characteristics; the Global Historical Climatology Network (GHCN) Daily for meteorological data; and the ECHAM model for climate change predictions. This section briefly describes the data sources and reports summary statistics.

3.1. Data sources

AHS data

The data on housing units, home improvements, energy expenditures and households are taken from the national sample of the American Housing Survey, which covers Metropolitan Statistical Areas (MSAs). We use longitudinal data from 14 waves of the national AHS from 1985 to 2011.[19] The housing units are located in the 128 MSAs with more than 100,000 inhabitants. These MSAs are spread all over the United States, and experience very different climatic conditions. Note also that the sample only includes owner-occupied units for which information on renovation investments is available.

The AHS includes information on nine different types of home improvement. The weatherization variable is constructed by adding together investments made in the following four categories: roofing; insulation; sidings; and storm doors and windows. The equipment variable is identified as a single category in the survey, precluding, as mentioned above, the distinction between investments in air conditioning and space heating.[20] Nevertheless, households report their main heating fuel and their main fuel for air conditioning. This

[18] We provide results of models using orthogonal deviations (Appendix N), the 4th lags of the capital stock as instruments (Appendix O), and the difference GMM estimator (Appendix P). We also estimate a model where we have excluded all of the endogenous capital variables (Appendix Q) and a dynamic panel data model (Appendix S).
[19] Waves prior to 1985 cannot be used in a panel data analysis because the AHS was redesigned in 1985 and the units surveyed before and after 1985 are different.
[20] In 1997, the typology was refined, but we had to stick to the previous typology to be able to use the entire study sample from 1985. We perform robustness checks on the reduced panel of 1997-2011 in Appendix A. Results are imprecise due to the halving of the sample, but consistent with those obtained with the full panel.

information is used in some specifications to construct interaction variables used to proxy the specific impact of investments in heating and cooling equipment (more detail in subsection 5.1).

For each type of home improvement, we observe the level of biannual investments between 1985 and 2011. However, the value of the stock of capital already embodied in a home before 1985 is unobserved, which is vital for constructing the capital stock variables included in energy equations. We derive this initial stock – and from this the value of K_{iht} – from the purchase price or the construction cost of the housing units as registered in the American Housing Survey after a transaction, or after construction for new buildings. Appendix B precisely presents the method.

The AHS also provides information on home occupiers. In particular, it identifies when a household left a given housing unit and when new occupiers moved in. This information is used to construct household-specific fixed effects. Information on the level of energy expenditure, on whether the neighborhood has access to pipe gas, and commuting times (this variable is used as an instrument in Appendix S) is also extracted from the AHS.

Information on the precise location of each housing unit – a decisive variable to relate each unit to local climatic conditions – is not available for all areas. We thus take the centroid of the MSA as a proxy. This choice is likely to generate limited biases since temperature anomalies do not vary much within a given MSA.

Weather data

The weather data are taken from the Global Historical Climatology Network (GHCN) Daily. We extracted land-based (*in situ*) historical observations recorded from 1970 to 2011 by 22,000 meteorological stations that match the MSAs included in our sample and that operate at least a certain number of days during a year. More specifically, we only selected stations located within a 50km radius of the centroid of an MSA and that record daily information for at least 20 days each month of the year, and calculated averages for each MSA.

The key variables are the annual heating degree days, cooling degree days, and annual precipitations in millimeters. We estimate alternative specifications using the number of days that fall within 10°F temperature bins (the first bin is “below 10°F” and the last one “above 90°F”). We also look at nonlinearities in the impact of days with precipitations. We use as variables the number of days without precipitation, and the number of days with precipitations between 1-50mm, 50-100mm, 100-200mm and above 200mm.

Climate change prediction data

State-level monthly average temperature predictions are drawn from the 5th version of ECHAM, an atmospheric general circulation model developed at the Max Planck Institute for Meteorology. To ease comparability with other studies, we focus on the "business-as-usual" A2 scenario and its predictions for the end of the century (2080-2099). A2 is a scenario in which a relatively high amount of GHG emissions is released into the atmosphere, leading to a global average surface warming of 6.1°F in 2090-2099 relative to 1980-1999 (IPCC, 2007).

US state-specific averages are accessible using the US Geological Survey's Regional Climate Change Viewer (RCCV). The RCCV uses a downscaling method of the output of ECHAM, averages temperatures within states, and then compares the historical period of 1980-1999 with the ECHAM model's output for 2080-2099. This gives a predicted daily mean temperature increase for each month and state. This increase is added to all the days of the historic weather data to compute daily average temperature forecasts for 2080-2099. We then use these daily temperature forecasts to predict state-level changes in heating degree days and cooling degree days.

3.2. Summary statistics

Investment, energy expenditure, and household data

Table 1 provides descriptive statistics for the AHS data used as a basis for model estimations. The sample is composed of a panel of 58,887 observations[21]. This includes 10,522 housing units and 24,680 households. The investment frequency is low (7.1% for the installation of equipment and 19.0% for weatherization), but the average investment size is significant (around $3,700). This lumpiness could justify the use of a latent variable model; Appendix F presents tobit results that are however similar to those of the base linear model. Note that adaptation-related investments do not constitute the biggest share of renovation expenditures. In particular, the capitalized investment in equipment is minor compared to the other categories.

Weather and Climate Change Statistics

Detailed weather statistics for the entire sample and by US climatic region are provided in Table 2. We report information on daily temperature, number of heating and cooling degree days, and number of days below 10°F and above 90°F. Using the same format, Panel B presents the impacts of climate change based on the ECHAM model and for the A2 scenario. These figures

[21] This is far fewer than the 262,872 observations of geographically located and owner-occupied units between 1985 and 2011. However, many values are missing, in particular the values of the purchase price or construction cost. Outliers have also been excluded (see more details in Appendix C).

show high heterogeneity between regions in terms of daily temperature, but also of the number of days with extreme temperature (cold or hot). The US is obviously not representative of the climatic conditions observed all over the world, but it nevertheless provides a significantly diversified sample.

Table 1: Descriptive statistics of AHS data

Variable	Unit	Mean	Std. deviation
Investments in equipment			
Capitalized investments	$	9,902	6,628
Respondents declaring an investment	%	7.1	-
Expenditure if an investment is made	$	3,699	2,701
Investments in weatherization			
Capitalized investments	$	52,660	35,614
Respondents declaring an investment	%	19.0	-
Expenditure if an investment is made	$	3,792	4,369
Investments in other indoor amenities			
Capitalized investments	$	100,188	67,374
Respondents declaring an investment	%	32.6	
Expenditure if an investment is made	$	5,043	9,046
Energy expenditure and consumption			
Annual electricity expenditure	$	1,304	745
Annual gas expenditure	$	684	656
Annual electricity consumption	MM.btu/year	36.9	22.8
Annual gas consumption	MM.btu/year	59.7	57.6
Other relevant variables			
Number of people in household	#	2.76	1.51
Housing units connected to pipe gas	%	76.1	-
Commuting time	min.	21.0	17.5
Square footage of unit	sq. ft.	2,130	1,266
House price at time of purchase	$	206,042	157,562

Notes: Source: AHS. Survey years: 1985-2011. Max. number of observations: 58,874. Comments: all the variables in dollars are expressed in 2011 real dollars. The correction of nominal values was made using the US Consumer Price Index of the Bureau of Statistics of the US Department of Labor.

Figure 3 shows the average number of days falling within a given temperature bin. The grey bars report the averages as observed with the GHCN data of NOAA over the 1985-2011 period and the black bars report the averages as predicted by ECHAM under the A2 scenario. The A2 scenario predicts a dramatic increase in hot days (80-90°F) and very hot days (>90°F) in 2090-2099, mostly in hot regions. In contrast, the number of days below 70°F decreases uniformly across the different temperature bins.

Table 2: Summary statistics of climate data

Annual averages	Daily temperature	Heating degree days	Cooling degree days	Days <10°F	Days > 90°F
Panel A. Historical temperature data (1985-2011)					
All housing units	55.7	4,534	1,128	2.6	2.4
Cold regions	50.8	5,871	681	4.1	0.0
Central	51.9	5,732	959	4.7	0.0
Northwest	49.6	5,730	116	0.1	0.0
West North Central	50.3	6,357	1,005	11.7	0.0
East North Central	47.5	7,061	666	13.1	0.0
Northeast	52.7	5,397	907	1.3	0.1
Hot regions	63.2	2,474	1,799	0.2	6.2
South	65.6	2,319	2,552	0.3	2.3
Southeast	60.6	3,238	1,635	0.1	0.0
Southwest	62.6	3,289	2,430	1.1	31.3
West	62.9	1,972	1,223	0.0	3.1
Panel B. Predicted change from ECHAM model under the A2 scenario (2080-2099)					
All housing units	+7.4	-1,529	+1,168	-1.8	+12.9
Cold regions	+7.4	-1,834	+869	-2.8	+2.4
Central	+7.6	-1,736	+1,029	-3.5	+4.1
Northwest	+6.3	-1,787	+527	-0.1	0.0
West North Central	+7.4	-1,684	+1,026	-6.4	+6.9
East North Central	+7.7	-1,951	+850	-8.2	+1.5
Northeast	+8.0	-1,891	+1,021	-1.1	+3.2
Hot regions	+7.4	-1,064	+1,620	-0.2	+28.9
South	+7.8	-889	+1,959	-0.2	+68.2
Southeast	+7.1	-1,264	+1,327	0.0	+8.7
Southwest	+8.2	-1,290	+1,721	-0.7	+38.8
West	+6.9	-1,008	+1,514	0.0	+11.3

Notes: The climate variables are averaged over all of the observations of the AHS datasets used in the regressions and the simulation. Hence, regional averages are not representative of the regions, but of the sample of housing units within each region. When a unit is located in a metropolitan area that overlaps two or three states, it enters the calculation of the averages in all of the states it overlaps, but with a weight of 1/2 or 1/3.

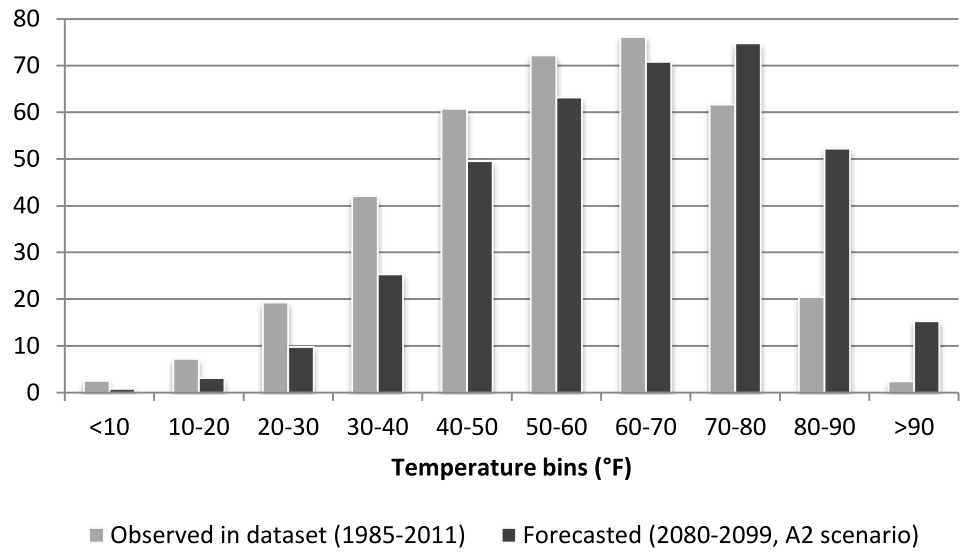


Figure 3: Observed and forecasted number of days falling within each temperature bin

Notes: Figure 3 shows the historical average and the predicted average in the distribution of daily mean temperatures across ten temperature-day bins. The "Observed in dataset" bars represent the average number of days per year in each temperature category for the all of the observations in the sample, covering the period 1985-2011. The "Forecasted" bars represent the average number of days per year in each temperature category based on the output of the ECHAM model under the A2 scenario and for the period 2080-2099, and for all of the observations of the sample used in the simulation.

4. Results

This section is divided into two subsections. The first provides estimates of the relationship between temperature and capital investments, and the second examines the impact of temperature and investment on energy expenditure.

4.1. Adaptation investments

The base results for investments in equipment and weatherization are displayed in Table 3. In Appendices E-J, most of the hypotheses used to calibrate the models are tested in a series of robustness checks that confirm our findings (using contemporaneous or lagged degree days, estimating left-censored models, excluding investments made before leaving the house, including observations for which an energy efficiency subsidy was granted, including regional trends or interactions between time and degree days).

We find a statistically significant impact of expected heating and cooling degree days on investments in equipment. The two coefficients are positive, consistent with the hypothesis that households purchase more (or larger) heaters when winter temperatures fall and more air conditioners when summer temperatures increase. The impact of heating and cooling degree days on weatherization is also positive and significant. Note that precipitation has no significant impact. As a robustness check, we show in Appendix K that investments in other indoor amenities (changes to the bathroom; changes to the kitchen; home extensions; and other major indoor improvements) are not sensitive to changes in expected heating and cooling degree days, confirming the specificity of investments in equipment and weatherization.

Table 3: Main results for investments in energy-related home improvements

Type of investment	Equipment	Weatherization
Expected heating degree days	0.106	0.328
	(0.0501)	(0.153)
Expected cooling degree days	0.264	0.441
	(0.114)	(0.223)
Expected precipitations	-0.00159	0.0291
	(0.00738)	(0.0206)
No. people in unit	6.039	23.31
	(9.809)	(19.46)
Connection to pipe gas	225.0	245.5
	(61.07)	(88.33)
Observations	42,221	42,010

Notes: standard errors (clustered at household level) in parentheses. Models include household fixed effects and time-dummies. Constant terms are not reported. Standard errors are clustered at household level.

Table 4 displays the results of alternative models using temperature bins. The existence of nonlinearities in the relationships between degree days and investments is confirmed. The impact at the extremes is stronger than that observed in the comfort zone of 60-70°F[22]. We also find a local investment maximum at 30-40°F, when it starts freezing and snowing.

[22] Note that the coefficients for the coldest bin are not statistically significant, probably due to too few observations.

Table 4: Linear investment models using temperature bins

Type of investment	Equipment	Weatherization
Expected # days with temperature:		
Below 10°F	1.349	8.333
	(5.788)	(13.10)
Between 10-20°F	10.78	21.75
	(5.130)	(10.77)
Between 20-30°F	-5.469	7.710
	(3.722)	(8.040)
Between 30-40°F	3.687	10.90
	(1.915)	(6.149)
Between 40-50°F	2.437	7.812
	(2.349)	(5.302)
Between 50-60°F	2.810	7.938
	(2.032)	(4.343)
Between 60-70°F	-	-
Between 70-80°F	2.343	4.618
	(1.791)	(3.813)
Between 80-90°F	4.414	9.424
	(2.531)	(4.888)
Above 90°F	14.03	23.62
	(6.661)	(9.806)
Expected days with precipitations:		
No precipitation	-	-
Between 0-50mm	1.017	2.033
	(0.893)	(1.823)
Between 50-100mm	-5.467	-3.430
	(3.017)	(5.723)
Between 100-200mm	2.043	6.030
	(3.103)	(6.022)
Above 200mm	-0.328	9.834
	(3.537)	(9.460)
No. people in unit	6.094	23.42
	(9.806)	(19.45)
Connection to pipe gas	225.3	246.4
	(60.97)	(88.38)
Observations	42,221	42,010

Notes: standard errors (clustered at household level) in parentheses. Models include household fixed effects and time-dummies. Standard errors are clustered at household level.

4.2. Energy expenditure

Table 5 displays results for gas and electricity expenditure. For each fuel type, we estimate the base model described by Eq. (4) and a variant where we use interactions of the equipment capital with the fuel used to heat and cool the house. Columns (1) and (3) thus provide estimates of the average impact of a change in equipment on energy demand across all households and years, while this impact can differ according to the main heating and the main cooling fuel declared by households in columns (2) and (4). The nature of the fuel gives an indication of the type of equipment installed in the housing unit. We will use the results obtained with these models when running simulations in the next section in order to deal with the problem that we cannot distinguish between investments in heating or cooling in the data.

In the base specifications (1) and (3), households use more gas and electricity when the number of heating degree days increases as expected. It is also intuitive that cooling degree days increase electricity expenditure as most homes are equipped with electric air conditioners. In contrast, the significant and positive impact of cooling degree days on gas expenditure is more surprising, as gas is rarely used for cooling (around 3% of the households in the sample). Its interpretation highlights the fact that changes in energy prices are also a channel through which climate change affects adaptation expenditures: In the US, natural gas usage has two seasonal peaks. The first peak occurs during the winter, when cold weather increases the demand for natural gas space heating in the residential and commercial sectors. A second peak occurs in the summer when air conditioning use pushes up demand for electric power, an increasing portion of which is provided by natural gas-fired generators. Surprisingly enough, and for reasons related to gas storage technologies, gas prices only peak in summer months. The seasonal variation is high: during the study period (1985-2011), the annual maximum price of natural gas delivered to residential consumers, generally observed either in July or August, was on average 45% higher than the minimum price observed in December or January.[23] Figure 4 illustrates this pattern by plotting the evolution of residential gas prices between January 2005 and December 2011. Coming back to the results of model (4), gas expenditure increases with cooling degree days because households continue to use gas in summer months to fuel water heaters, stoves, dryers, and other equipment so that the summer price peak significantly inflates their gas bill. The global warming expected in the future would reinforce this effect: by increasing the electricity consumption of air conditioners, higher summer temperatures would boost gas consumption by electric power generators, and push up gas prices in summer months.

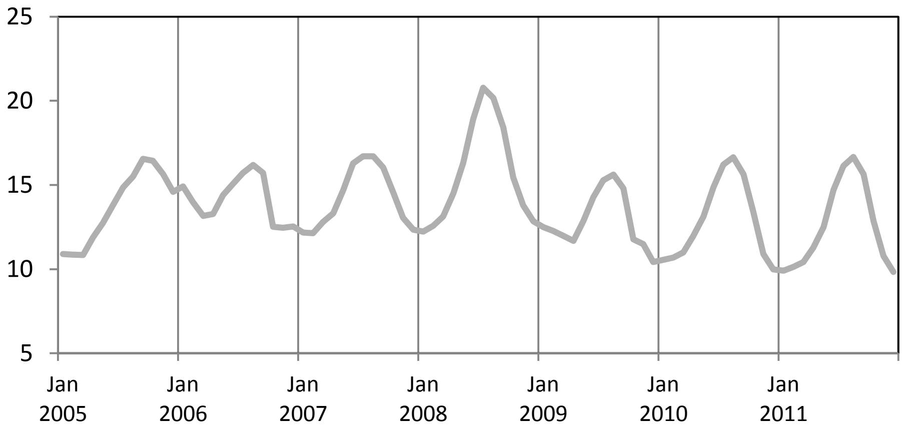
[23] See: https://www.eia.gov/dnav/ng/hist/n3010us3m.htm

Table 5: System GMM estimation of energy expenditure models

Dependent variable	Ln. Electricity Expenditure		Ln. Gas Expenditure	
	(1)	(2)	(3)	(4)
Heating degree days	0.0137	0.00808	0.142	0.139
	(0.00462)	(0.00565)	(0.00570)	(0.00586)
Cooling degree days	0.176	0.129	0.0868	0.0856
	(0.0110)	(0.0209)	(0.0144)	(0.0144)
Capital in equipment	0.0131		0.00385	
	(0.00507)		(0.00619)	
x heating fuel is electricity		0.0176		
		(0.0119)		
x AC fuel is electricity		0.0203		
		(0.00778)		
x heating fuel is gas				0.0184
				(0.00925)
x AC fuel is gas				0.00104
				(0.0191)
Capital in weatherization	-0.00360	-0.00287	-0.00219	-0.00291
	(0.00173)	(0.00171)	(0.00210)	(0.00211)
Capital in other amenities	0.00141	0.00128	0.00218	0.00122
	(0.000887)	(0.000889)	(0.00107)	(0.00109)
Precipitations	0.0139	0.0146	0.0154	0.0161
	(0.000771)	(0.000784)	(0.000997)	(0.00105)
No. people in unit	0.0852	0.0852	0.0433	0.0444
	(0.00220)	(0.00218)	(0.00242)	(0.00244)
Connection to pipe gas	-0.173	-0.0925	0.193	0.160
	(0.00856)	(0.0556)	(0.0376)	(0.0406)
Observations	50,000	50,000	37,244	37,244
Hansen test	0.12	0.36	0.09	0.16
Number of instruments	85	107	85	107

Notes: standard errors (clustered at household level) in parentheses. Models include household fixed effects and time-dummies. Constant terms are not reported. Capital variables are instrumented using third lags. Interactions are instrumented using third lag of capital in equipment times a dummy variable that takes the value of one if main heating/cooling fuel is different from gas or electricity. This is to avoid instruments to be correlated with changes in fuel choice. For heating degree days, cooling degree days, precipitations and all the capital variables, the reported coefficients have been rescaled since the model is log-linear. They correspond to a marginal change in the log of the dependent variable when the independent variables increase by 1000.

Figure 4: US price of natural gas delivered to residential consumers from Jan 2005 to Dec 2011 (in dollars per cubic feet)



Source: US Energy Information Administration (http://www.eia.gov)

Turning next to the capital variables, all of the results are in line with expectations. The stock of equipment appears to have a positive impact on electricity expenditures in model (1). When the variable is interacted in model (2), results show that the positive effect is in fact only recorded when electricity is used for air conditioning. In columns (3) and (4), we find that investment in equipment increases gas expenditure when gas is used as the main heating fuel.

Weatherization also tends to reduce energy expenditures, but this negative impact is only statistically significant for electricity. Note also that capital in other amenities is positively correlated with gas and electricity use, which indicates that some of these investments increase heating and cooling needs, e.g. in the case of home extensions. The coefficients of the control variables show the expected signs, i.e. family size drives expenditure upwards and connection to pipe gas encourages households to choose gas heating.

Similar results are obtained when the specification is slightly changed. Appendix M gives results with alternative climate variables. In Appendix U, we estimate a model of energy consumption instead of energy expenditure and control for electricity and gas prices, where prices are instrumented using pre-sample information. The magnitude and statistical significance of the coefficients are very similar.

5. Impacts of climate change

This section aims to exploit the empirical results of investment and energy expenditure to estimate the impact of higher temperatures on energy expenditure and the resulting adaptation cost. The predictions are calibrated for the A2 scenario of IPCC and they rely on the ECHAM model of the Max Plank Institute, as described in section 3.

5.1. Simulation methodology

We proceed in three steps. First, we use the estimated coefficients of the fixed-effect investment models to compute the impact of a change in expected heating or cooling degree days on the average amount of equipment and the weatherization level in the housing unit. Second, we use the output of the panel models of energy expenditure to derive energy expenditure estimates that account for potential adjustments in capital calculated in the first step. Third, we calculate the cost of adaptation by adding up the variations of capital and energy expenditures induced by the shift from the situation observed during the study period to the A2 scenario.[24] We describe these steps in turn.

Step 1: Predicting investments

The first step involves no particular challenge. The estimated impact of predicted temperature changes in equipment investments in a given housing unit and year is calculated as follows:

$$\Delta I_{iet} = \hat{\alpha}_e \Delta HDD_{it} + \hat{\beta}_e \Delta CDD_{it}$$

That is, the predicted change in heating and cooling degree days ΔHDD_{it} and ΔCDD_{it} is multiplied by the corresponding impact on investment ($\hat{\alpha}_e$ and $\hat{\beta}_e$).

Step 2: Predicting energy expenditure

The second step is more challenging and requires a number of assumptions. The first problem is that Eq. (4) does not distinguish between investments in cooling and heating equipment and thus relies on the simplifying assumption that purchasing cooling or heating equipment has the same impact on energy expenditure. Denoting $K_{it}^{cooling}$ and $K_{it}^{heating}$ as the respective stock of cooling and heating equipment, this formally translates into:

$$\frac{\partial \ln\left(E_{ift}\right)}{\partial K_{it}^{cooling}} = \frac{\partial \ln\left(E_{ift}\right)}{\partial K_{it}^{heating}} = \phi_{ef}$$

This restriction is problematic as temperature increases typically modify the composition of the equipment stock: home occupiers purchase more cooling equipment while reducing their stock of heating equipment.

To circumvent the problem, we proceed as follows. We first use the investment equation to predict investments in the two categories of equipment by assuming that, if a change in heating degree days increases the amount of capital invested, this corresponds to an increase in the level of investments in heating equipment. Formally, the estimated impact of predicted temperature changes on heating equipment investments in a given housing unit and year is:

$$\Delta I_{it}^{heating} = \hat{\alpha}_e \Delta HDD_{it}$$

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[24] The simulation of the impacts of climate change was obtained employing econometric models that use heating and cooling degree days as the main variables of interest. Alternatively, we could have used models with temperature bins. Point estimates are similar when doing so for the entire sample, although confidence intervals widen because the effects of some temperature bins are imprecisely estimated. The use of heating and cooling degree days constrains the model to make linear extrapolations of the effect that these extreme days have on energy demand. This actually leads to more reliable results.

Symmetrically, if a change in cooling degree days increases the amount of capital invested, this corresponds to the purchase of cooling equipment so that $\Delta I_{it}^{cooling} = \hat{\beta}_e \Delta CDD_{it}$.

The investment models predict the annual flows of investments while we need the capital stocks to use the energy expenditure model. We derive the value of $\Delta K_{it}^{cooling}$ and $\Delta K_{it}^{heating}$ by assuming that these variations equal the predicted variations of annual investments divided by the depreciation rate of capital. This is equivalent to assuming that the same investment has been made in all previous periods. This assumption is not heroic as we make long-term predictions in which home occupiers have plenty of time to adjust their capital stocks. We set the depreciation rate of capital to 2%, which corresponds to the depreciation rate of real estate as estimated by Harding *et al.* (2007) based on AHS data

Then we infer the marginal impacts of $\Delta K_{it}^{cooling}$ and $\Delta K_{it}^{heating}$ from the results of models (2) and (4) where the equipment capital is interacted with binary variables indicating the fuel used. In these models, the estimated marginal impact of the equipment capital is:

$$\frac{\partial \ln\left(E_{ift}\right)}{\partial K_{iet}} = \left(\phi_{f1} \cdot a_{ft}\right) + \left(\phi_{f2} \cdot b_{ft}\right) \tag{5}$$

where a_{ft} and b_{ft} indicate whether the fuel used for heating and cooling is f, respectively. This equation assumes that any equipment that uses a fuel other than f has no impact on the expenditure for f: $\partial ln\left(E_{ift}\right)/\partial K_{iet} = 0$ if $a_{ft} = b_{ft} = 0$.

Consider now the case where the fuel f is only used for heating ($a_{ft} = 1$ and $b_{ft} = 0$). It sounds reasonable to assume that any impact of K_{iet} on the consumption of fuel f is exclusively due to an adjustment of the heating equipment stock. Formally, this writes:

$$\frac{\partial \ln\left(E_{ift}\right)}{\partial K_{iet}} = \frac{\partial \ln\left(E_{ift}\right)}{\partial K_{it}^{heating}} = \phi_{f1} \quad \text{if } \ a_{ft} = 1 \text{ and } \ b_{ft} = 0$$

Symmetrically, we have

$$\frac{\partial \ln\left(E_{ift}\right)}{\partial K_{iet}} = \frac{\partial \ln\left(E_{ift}\right)}{\partial K_{it}^{heating}} = \phi_{f2} \quad \text{if } \ a_{ft} = 0 \text{ and } \ b_{ft} = 1$$

Last, if we further assume no complementarities between heating and cooling investments, the marginal impacts of $K_{it}^{cooling}$ and $K_{it}^{heating}$ continue to be equal to ϕ_{f1} and ϕ_{f2} in the case where $a_{ft} = 1$ and $b_{ft} = 1$.[25] The coefficients ϕ_{f1} and ϕ_{f2} thus measure the marginal effects that apply to any fuel combination.

From this we can derive the formula that gives the impact of predicted changes in equipment investments on the log of the expenditure for fuel f in a given housing unit and year:

$$\hat{\phi}_{f1}\Delta K_{it}^{heating} + \hat{\phi}_{f2}\Delta K_{it}^{cooling}$$

A second problem is that the panel data model does not estimate fixed effects, although these are important to make counterfactual predictions with a log-linear specification. This is because a one-unit increase in log expenditure has a different impact on the expenditure level finally predicted depending on the initial value of the log expenditure. To circumvent this problem, a micro-simulation is calibrated using the observed data. Hence, if the observed electricity (or gas) expenditure is \$100 and the model prediction without climate change is \$70, then we take into account that there is an error term of \$30 that needs to be considered before calculating a new expenditure level under climate change.

Third, we cannot directly use the standard errors estimated in Table 5 because they fail to integrate uncertainties pertaining to the influence of the investment stock variables that were estimated in the first-stage equation. This leads us to conduct a Monte-Carlo analysis. For each observation, we use the output of the investment models to produce 1,000 draws of investments (separately for equipment and weatherization). Then, we make predictions based on the variance-covariance matrix associated with the vector of parameters estimated from the investment equations. We denote each equiprobable set of investments I_{it}^{π} for individual *i* at time *t* and draw π. We plug each simulated draw of investments into the electricity and gas expenditure equations. Mathematically, we have $E_{ift}^{\pi} = F_{if}^{\pi}(I_{it}^{\pi})$ where E_{ift}^{π} is the predicted energy expenditure for individual i, fuel *f* and draw π at time *t*. Importantly, E_{ift}^{π} depends on I_{it}^{π} but also on the functional form of $F_{if}^{\pi}(.)$ linking investments to the expenditure for fuel *f*. This functional form is assumed to be random and specific to household i, fuel *f*, and draw π. Instead of using the set of parameters as estimated with the electricity and gas expenditure specifications, we also take random draws of $F_f(.)$ based on the variance-covariance matrix of the parameters previously estimated with the energy expenditure model.

[25] These assumptions have actually been tested empirically by estimating a more flexible specification in which none of the coefficients proved to be statistically significant at 5%, either for gas or electricity.

In the end, we obtain 1,000 estimates per observation of electricity and gas expenditure differentials between a scenario with no change in temperature and the A2 scenario. Averaging these numbers provides us with point estimates. We identify the bounds of the confidence interval by looking at the 2.5% lowest and highest draws for each observation. From these observation-specific confidence intervals, we derive a conservative estimate of the sample intervals by making the simplifying assumption that the bounds of the confidence intervals are reached for the same set of parameters across observations.[26]

Step 3: Calculating the cost of adaptation

The last step is straightforward as we sum the predicted variations of energy expenditures and investments calculated in steps 1 and 3 over a 25-year period using a discount rate of 4%.

5.2. Results

National averages

Table 6 first compares the differences in average annual investment in equipment and weatherization, and annual electricity and gas expenditure between temperatures, as observed for our sample and the A2 scenario at national level. It also provides an estimate of the present discounted value of the adaptation cost.

We predict that annual investments in equipment will increase by 56% (+$73 per housing unit). The reason for this substantial increase is a considerable need for air conditioning on very hot days (+$154), which is only partially offset by a reduction in equipment for heating (-$81). Investments in weatherization remain stable: we predict a non-significant $7 increase.

The model predicts a 29% increase in electricity bills and a 25% decrease in gas expenditure. Although statistically significant at 1%, these estimates are characterized by significant confidence intervals. In total, energy expenditure would increase by 13%.

The present discounted value of the adaptation cost is estimated to be slightly less than $5,600, which is significant at the 10% level. This appears to be a moderate loss. This represents about 2.7% of the average purchase price of a housing unit included in the sample. The corresponding annual expenditure is $335, which is approximately 0.4% of the sample average annual household income. Taking a conservative estimate at the upper bound of the confidence interval, the cost would be around $13,000. This is equivalent to an annual cost of about $780,

[26] This assumption overestimates the average confidence interval for the sample but is necessary to ensure computable confidence intervals.

which corresponds to an increase in expenditure of around 0.9% of the average US family budget, or around 40% of the average energy expenditure in the sample.

Region-specific averages

Table 6 shows national averages, which may hide significant heterogeneous impacts across regions for obvious reasons, such as, the current and future climates of Oregon and Texas are radically different. We now examine spatial heterogeneity in temperature increase impacts across nine climatic regions as defined by NOAA. We could simply rely on the estimates obtained with the national models to calculate regional averages. This approach however rests on the simplifying assumption that elasticities to temperature shocks are uniform over the country. This hypothesis overlooks the fact that the residential sector in Texas is already more adapted to hot temperatures than Oregon. Further adaptation is still possible in Texas as we will see, but it consists in different types of investment and energy adjustment.

To address this concern, we first use specifications for the electricity and gas models that take into account different elasticities of demand to temperature shocks by interacting degree days with region-fixed effects (see the results in Appendix R). However, this approach appears infeasible for the investment equations because too few investments are performed in each region. We thus use national estimates in the simulations. The concern with this strategy is that investment propensity may be lower in hot regions. In particular, most houses already have central air conditioning in these regions. In 2011, the AHS data actually highlights that 91% of households are equipped with central air conditioning in the southeast region, while the rate is 77% at national level. This could imply the existence of a cap on cooling investments made in these dwellings when temperature increases.

Appendix L however shows there is no such saturation effect. We proceed as follows. When central AC is already installed in a house, the only possible investment in adapting equipment consists in acquiring a more powerful AC system, which more efficiently reduces the indoor temperature during heat waves. In the appendix, we take advantage of the fact that AHS data provide information on the investments specifically performed in central AC from 1997 onwards. Using data from 1997 to 2011, we estimate a simple fixed-effect linear regression where we correlate the amount invested in central AC and the total number of cooling degree days. We are then able to show that each additional expected cooling degree day leads to an extra investment of 23 cents per housing unit and per year. This is roughly equal to the average elasticity of investments to expected cooling degree days in our national model, at 26 cents.

This suggests that there is no saturation: even when a house is equipped with central AC, occupiers continue to invest to increase cooling performance.[27]

The results obtained under these assumptions show sharp differences between cold and hot regions where adaptation is much more costly (see Table 7). A maximum of around $29,000 is predicted in the South region. This represents around 21% of the housing price observed in the data for this region. The main reason is a drastic increase in electricity expenditure in hot regions associated with important investments in energy-using cooling equipment. In contrast, temperature increases are predicted to yield only small costs, if any, in cold regions.

No capital adjustments

As claimed above, the present study contributes to the literature by integrating household investment behavior to evaluate the impact of temperature increases. It is thus useful to look at simulation results that would be obtained assuming a fixed capital stock ($\Delta K_{it}^{heating} = \Delta K_{it}^{cooling} = 0$). As shown in Table 8, this leads to a much lower adaptation cost: around $2,000 per housing unit instead of $5,600. The first reason for this result is obvious: by assumption, the investment cost is set at zero while the base model predicts a surge of investments. The second reason is an underestimation of energy cost increases (+6% instead of +13%) because the simulation ignores the impact of capital changes on energy use, in particular, that of newly installed cooling equipment on electricity consumption.

As mentioned above, Auffhammer and Aroonruengsawat (2011, 2012) and Deschenes and Greenstone (2011) have all examined the impact of global warming on residential energy use. The results of Deschenes and Greenstone (2011) are easily comparable with ours because they also study the US. They find that total energy consumption should increase by around 10% under the A2 scenario, due to both demand- and supply-side effects of temperature on energy generation, transmission, distribution and consumption. Our own estimate at +13% is in fact higher in magnitude. Climate-induced investment is a major reason for the difference in magnitude, as our estimate drops to +6% when capital stock is held fixed (see Table 8).

Auffhammer and Aroonruengsawat (2011, 2012) only examine electricity consumption in California. They find a much lower increase in electricity use; their analysis suggests an increase of around 3-6% under the A2 scenario (assuming no change in population and energy

[27] Our baseline estimate of 26 cents is furthermore robust to the inclusion of region-specific linear and quadratic trends (see Appendix I), confirming the fact that this estimate is robust to the generally observed trend that more and more households are equipped with air conditioning.

prices, and no adaptation), whereas we predict a 14% increase for the West climate region (which includes California, see Table 7). A gap thus persists, which probably relates to the fact that our model takes capital adjustments into account (this appears to double the effects). To sum up, our results seem in line with those of previous studies provided the capital stock is held fixed.

5.3. Discussion of the limitations

To conclude this section, a series of considerations is needed to qualify the validity of these results. First, we have only assessed the cost borne by households to adapt existing dwellings. As mentioned in the introduction, additional adaptation strategies come into play in the longer run. One of these is building new houses that are more resilient to hotter temperatures. For these new houses, adaptation needs would be considered in the design and, therefore, we could expect lower adaptation costs than in existing buildings, where constraints may prevent the choice of least-cost options. In 2013, around 990,000 building permits were issued for a total stock of housing units of around 132 million[28]. These numbers suggest limited bias in the predictions.

[28] USA Quick facts from the Census Bureau, consulted in March 2014: http://quickfacts.census.gov/qfd/states/00000.html

Table 6: Estimated impact of the A2 scenario (2080-2099) on annual investments and energy expenditure for a representative US housing unit

	Sample average 1985-2011	Variation under the A2 scenario		
		In level		In percent
		Mean	95% confidence interval	
Annual investment in equipment	$131	+$73	[-$59, +$205]	+56%
• *For heating*		-$81**	[-$156, -$6]	-
• *For cooling*		+$154**	[+$23, +$285]	-
Annual investment in weatherization	$362	+$7	[- $380, + $320]	+2%
Annual electricity bill	$1,304	+$374***	[+$134, +$717]	+29%
Annual gas bill	$684	-$168***	[-$282, -$73]	-25%
Total annual energy expenditure	$1,988	+$252*	[-$33, +$626]	+13%
Present discounted cost of adaptation†	-	+$5,578*	[-$358, +$12,976]	-

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. † Discounted cost of adaptation is calculated for 25 years with a 4% discount rate. All monetary numbers are in 2011$.

Table 7: Estimated impact of the A2 scenario (2080-2099) on a representative US housing unit in different US regions

US Climate Region (as defined by NOAA)	Investments			Energy bills			Present discounted cost of adaptation
	Heating	Cooling	Weatherization	Electricity	Gas	Total energy	
Central	-$92**	+$136**	-$58	+$382***	-$183***	+$199	+$3,062
Northwest and	-$95**	+$70**	-$177	+$43	-$48	-$5	-$3,417
West North Central	-$89**	+$135**	-$50	+$306	+$45	+$351	+$5,762
East North Central	-$104**	+$112**	-$132	+$161**	-$87	+$74	-$842
Northeast	-$101**	+$135**	-$85	+$509***	-$193***	+$316**	+$4,402
South	-$47**	+$259**	+$286	+$1309***	-$88***	+$1,221***	+$28,570***
Southeast	-$67**	+$175**	+$85	+$444***	-$127***	+$318*	+$8,493***
Southwest	-$69**	+$227**	+$168	+$830***	-$60**	+$770***	+$18,216***
West	-$54**	+$200**	+$168	+$162	-$32	+$130	+$7,394***

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Observations overlapping two or three regions are given a weight of 1/2 or 1/3 in each. Discounted cost of adaptation is calculated for 25 years with a 4% discount rate. All values are in 2011$.

Table 8: Estimated impact of the A2 scenario (2080-2099) assuming capital in equipment and weatherization is fixed

Type of expenditure	Sample average 1985-2011	Variation under the A2 scenario		
		In level		In percent
		Mean	95% confidence interval	
Annual electricity bill	$1,304	+$206***	[+$143; +$272]	+16%
Annual gas bill	$684	-$82***	[-$69; -$95]	-12%
Total annual energy expenditure	$1,988	+$124***	[+$48; +$203]	+6%
Present discounted cost of adaptation†	-	+ $2,058***	[+ $802; + $3,378]	-

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. † Discounted cost of adaptation is calculated for 25 years with a 4% discount rate. All monetary numbers are in 2011 $.

Households can also migrate to cooler areas; note that this would go against the current trend by which net migration is slightly positive in the South (Molloy, Smith, and Wozniak, 2011). Alternatively, even without moving long distances, households can self-select by choosing dwellings that correspond better to their heating/cooling preferences: e.g. households that put more value on warm indoor temperatures would move to homes that are better insulated and/or equipped with powerful air conditioning. In both cases, this would reduce the adaptation cost. We control for residential sorting by including household fixed effects and we are thus not able to account for this type of adaptation. In Appendix I, we are more stringent and consider the fact that residential sorting could affect investments in a differentiated manner across the US climate regions. We add region-specific time trends to our investment model and find no effect of these trends on the climate variables of interest to us.

Adaptation costs could also be reduced by technological improvements in heating and cooling systems. Under this assumption, the impact of heating and cooling degree days on investments would reduce over time. In Appendix J, we test this hypothesis by introducing in the investment models interactions between time and expected heating degree days / cooling degree days. We find no evidence to support this theory: on the contrary, we observe an increase in household response to heating and cooling degree days by investing in weatherization, which may be caused by changes in preferences.

Another potential weakness is the existence of possible nonlinearities of the impact of temperature on the residential sector. We make “out of sample” predictions, while the A2 scenario features temperatures that are much higher than the historical values used to estimate our models (+6.1°F in 2090-2099 relative to 1980-1999). We have however estimated more flexible models with temperature bins, which give similar predictions (see Table M.1 and Appendix M). Results are available upon request.

Last, it is important to underline that these results do not integrate the (significant) uncertainties surrounding climate predictions. The size of the confidence intervals is thus underestimated.

6. Conclusion

This research has developed a new approach to analyze the adaptation of US homes to climate change. In the first stage, we analyzed the responsiveness of residential renovation efforts to climatic change. The results of our first stage were then used in the second stage to predict how residential electricity and gas demand could evolve under climate change.

The main finding concerns the cost of adaptation. Our best estimate of the present discounted value of the cost for adapting homes to the A2 "business-as-usual" scenario is $5,600 per household. This value is only statistically different from zero at 10%. This corresponds to around 2.7% of the average purchase price of the housing units included in the sample, or 0.4% of the sample average annual household income if translated into annual expenditure. These numbers hide important disparities between hot regions, where households would invest massively in air conditioning, and cold regions, which would benefit most from milder winters. The adaptation cost even reaches $29,000 in the South climate region.

Overall, the US housing sector appears quite resilient to temperature changes. However, adapting housing may have important implications for residential energy demand. We predict that climate change might increase electricity demand by 29% and reduce gas demand by 25% nationwide. This shift from gas to electricity would entail a significant reallocation of energy use across the country, with gas expenditure decreasing sharply in colder regions, and electricity expenditure surging in hotter areas. In total, energy expenditure would increase by 13%.

It is important to stress the influence of changes in housing capital, which have been ruled out in previous studies. Not accounting for adaptation investments in cooling and heating equipment and weatherization, as is the case in most previous studies, leads to large downward biases in the estimates. In particular, using our data, the present discounted value of the cost is 60% lower when ignoring investments.

However, our results should be interpreted with caution. We assume no economic growth or demographic evolution, and no change in the technologies available to households for space heating and air-conditioning, in terms of energy efficiency as well as fuel choice for space heating and air-conditioning. In addition, we only study the impact of climate change on existing homes, whereas it will also influence the design of new homes. It could also accelerate the pace of renewal of the housing stock. Furthermore, we only consider the impact of temperature and not the increased risk of flooding associated with sea level rise or any potential increase in liabilities due to a change in the frequency of disasters, about which large uncertainties remain.

One should also be cautious when extrapolating to other countries. The US housing sector is relatively specific, with a high share of gas consumption and air-conditioning already present in many US homes – 78% of households in our sample declared having at least one air conditioner at home. Last, unlike Deschênes and Greenstone (2011), we do not assess welfare losses associated with higher indoor temperatures.

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Main appendices

The main appendices are appendices A to D. Online supplementary appendices E to L relate to the investment model. Those relating to the energy expenditure models are online appendices M to U.

A: Looking separately at central air conditioning and central heating

In 1997, the American Housing Survey adopted a more detailed nomenclature for investments in the home. From that year on, it is possible to separately identify investments in central air conditioning and central heating.

Below, we run the investment and expenditure models with specific investment and capital variables that separately capture investments in central air conditioning and central heating. Capital variables are constructed using the methodology described in Appendix B. We consider that equipment capital is split equally between heating and air conditioning, since we do not have separate cost information for these two categories in NAHB (2010). Overall, regression results are imprecise, very plausibly because the length of our panel has been reduced by half, but they point in the same direction as our base models: heating degree days increase investments in heating, cooling degree days increase investments in cooling, and investments in air conditioning have an effect on electricity consumption.

Table A.1: Investment models with separate effects for central heating and air conditioning

	Central heating	Central air conditioning
Expected heating degree days	0.0940	0.130
	(0.159)	(0.146)
Expected cooling degree days	0.0682	0.279
	(0.169)	(0.258)
Expected precipitations	-0.0117	0.0104
	(0.0146)	(0.0138)
No. people in unit	3.584	4.364
	(17.24)	(21.06)
Connection to pipe gas	535.5	-49.90
	(223.7)	(125.5)
Observations	9,987	9,972

Notes: standard errors (clustered at household level) in parentheses. Models include household fixed effects and time-dummies.

Table A2: System GMM estimation of energy expenditure models with separate effects for central heating and air conditioning

	Electricity	Gas
Heating degree days	0.000622	0.0189
	(0.00167)	(0.00201)
Cooling degree days	0.0197	0.0105
	(0.00364)	(0.00482)
Capital in air conditioning	0.00322	0.00237
	(0.00149)	(0.00177)
Capital in central heating	-0.00450	-0.00744
	(0.00279)	(0.00671)
x heating fuel is electricity	0.00501	
	(0.00409)	
x heating fuel is gas		0.00187
		(0.00666)
Capital in weatherization	-0.000230	0.000153
	(0.000385)	(0.000451)
Capital in other amenities	0.000108	0.000118
	(0.000184)	(0.000219)
Precipitation	0.00191	0.00240
	(0.000194)	(0.000265)
No. people in unit	0.0124	0.00548
	(0.000542)	(0.000648)
Connection to pipe gas	-0.0130	0.0404
	(0.0101)	(0.0109)
Observations	14478	11457
Hansen test	0.77	0.08
Number of instruments	63	63

Notes: standard errors (clustered at household level) in parentheses. Models include household fixed effects and time-dummies. Capital variables are instrumented using second lags. For heating degree days, cooling degree days, precipitations and all the capital variables, the reported coefficients have been rescaled since the model is log-linear. They correspond to a marginal change in the log of the dependent variable when the independent variables increase by 1000.

B: Method used to recover the capital stocks

As mentioned previously, a difficulty is that investments are not observed before the year of purchase or construction. We estimate the stocks in that year relying on the sales price. Let τ_i denote the date of construction or sale of the dwelling and $k_{i,t}$, the amount of capital embodied in the home of household *i* at time *t*, *excluding* all of the home improvements I_{hit} that are observed in the data. For the years in which the housing units are either sold or built, k_{it} is equal to the sales price. For the years following the sale/construction of the house, we input the value of k_{it} by applying a depreciation rate on housing capital:

$$k_{it} = (1-\delta)^{\tau_i} k_{it-\tau_i}$$

τ_i represents the observed date of construction or sale. We take 2% as the value of the depreciation rate of past investments (i.e. $\delta = 2\%$). This value corresponds to the depreciation rate of real estate as estimated by Harding *et al.* (2007) based on AHS data.

Similarly, we do not observe the initial capitalized investments net of home improvements for the years that precede a sale. We infer this value from the sales price of the home at a later date:

$$k_{i\tau_i - s} \approx \frac{k_{i\tau_i}}{(1-\delta)^s},$$

where s represents the lag between the observed purchase and the time of interest for the calculation of k. This technique gives us a proxy of the amount of capital in a home before home investments are made, provided that we observe at least one sale or the construction cost of the unit.

We expect k_{it} to be representative of the value of all the services delivered by the housing unit net of any observed investment $I_{\hbar it}$. This is not sufficient as we need to know the initial stock of capital by investment category (equipment, weatherization, others). To do so, we use the information provided by the National Association of Home Builders (NAHB, 2010) on construction costs. According to the NAHB, 20.3% of the construction cost of a single-family unit depends on the lot price. Furthermore, the NAHB also provides a breakdown of the construction cost of a house. According to this study, heating, ventilation and air-conditioning systems represent 4.0% of the construction cost, and appliances 1.6% on average. We use this information to calculate the initial stock of capital in equipment and in weatherization. More specifically, in order to calculate k_{iet}, i.e. ? the capitalized investments in equipment, net of any improvement performed to the home after τ_i, we apply the following formula:

$$k_{iet} = k_{it} * (1 - 20.3\%) * (4\% + 1.6\%)$$

We proceed in the same way for the other two investment categories.[29]

In the last step, we add the value of all home improvements performed in the home since the last purchase (τ_i), or subtract the sum of all home improvements done between time t and the observed future purchase (in τ_i) to proxy the value of capitalized investments in a specific type h of housing services at time t:

[29] According to NAHB (2010), Insulation represents 1.5% of construction costs, windows represent 2.8%, exterior doors 0.9%, framing and trusses 15.6%, roof shingles 3.8% and sidings 5.8%. To assess the initial capital for all other home improvements, we consider that it corresponds to the remaining share, excluding outdoor features and fees, i.e. landscaping and sodding (3.2%), wood decks and patios (0.9%), asphalt driveways (1.4%), building fees (1.9%) and impact fees (1.4%).

$$K_{\hbar it} = \begin{cases} k_{\hbar it} + \sum_{s=\tau_i}^{t} I_{\hbar is}(1-\delta)^{t-s} & \text{if } t \geq \tau_i \\ k_{\hbar it} - \sum_{s=t}^{\tau_i} I_{\hbar is}(1-\delta)^{\tau_i - s} & \text{if } t < \tau_i \end{cases}$$

To obtain comparable values of $K_{\hbar it}$ through time, $k_{\hbar it}$ and $I_{\hbar is}$ are deflated using the US consumers' price index (CPI) of the Bureau of Labor Statistics.

C: Exclusion of outliers

Using energy price statistics from the State Energy Data System, the 2.5% of units in regions with very high or very low values for electricity and gas prices have been excluded. This is because there could be differences in the response of households living in regions where energy is either very cheap or very expensive (these households may already be very well equipped or on the contrary underequipped in terms of energy conservation). Furthermore, among the observations that perform an investment in one investment category, we dropped the 2.5% of observations that invested the highest amounts, considering that the investments performed by these households are likely to be structural and would have occurred anyway. Likewise, our data registers frequent small investments in all of the three categories, corresponding to minor maintenance efforts. To distinguish these minor maintenance works from home improvements, we considered that the cheapest alterations recorded in our data should be disregarded (below 2.5% percentile).[30] They enter into the calculation of the total embodied capital in the home but are not used in the panel tobit and the linear investment models. We also excluded the 2.5% observations with the smallest and the 2.5% observations with largest amounts of capital in either equipment, weatherization or other indoor amenities as well as the 2.5% observations with very high or very low but non-null levels of either gas or electricity expenditure.

All of these filters were applied at the same time to identify outliers. However, we did not apply them to homes located in the Northwest and West North Central regions of the US. This is because our sample includes a limited number of houses in these colder regions and we aimed to keep a sample as representative as possible of the US.

[30] When separating investments in air conditioning and heating in Appendix A, these filters are applied separately to these two categories.

D: Errors clustered by metropolitan statistical area

Below, we use Metropolitan Statistical Areas as clusters to cluster standard errors instead of households. Results are almost unchanged for home improvements. Standard errors are wider in the case of the energy expenditure models, but remain statistically significant at very high levels. The only change relates to heating degree days, whose significance is lost for the electricity equation. However, their economic importance was already low in the model with standard errors clustered at household level.

Table D1: Main results for investments in energy-related home improvements

Type of investment	Equipment	Weatherization
Expected heating degree days	0.106	0.328
	(0.0420)	(0.0918)
Expected cooling degree days	0.264	0.441
	(0.104)	(0.215)
Expected precipitations	-0.00159	0.0291
	(0.00661)	(0.0152)
No. people in unit	6.039	23.31
	(10.47)	(19.55)
Connection to pipe gas	225.0	245.5
	(94.96)	(144.4)
Observations	42,221	42,010

Notes: standard errors (clustered at MSA level) in parentheses. Models include household fixed effects and time-dummies. Constant terms are not reported.

Table D2: System GMM estimation of energy expenditure models

Dependent variable	Ln. Electricity Expenditure		Ln. Gas Expenditure	
Level of cluster	Households	MSAs	Households	MSAs
Heating degree days	0.0137	0.0137	0.142	0.142
	(0.00462)	(0.0106)	(0.00570)	(0.0141)
Cooling degree days	0.176	0.176	0.0868	0.0868
	(0.0110)	(0.0227)	(0.0144)	(0.0245)
Capital in equipment	0.0131	0.0131	0.00385	0.00385
	(0.00507)	(0.00493)	(0.00619)	(0.00655)
Capital in weatherization	-0.00360	-0.00360	-0.00219	-0.00219
	(0.00173)	(0.00155)	(0.00210)	(0.00179)
Capital in other amenities	0.00141	0.00141	0.00218	0.00218
	(0.000887)	(0.000760)	(0.00107)	(0.000899)
Precipitations	0.0139	0.0139	0.0154	0.0154
	(0.000771)	(0.00274)	(0.000997)	(0.00403)
No. people in unit	0.0852	0.0852	0.0433	0.0433
	(0.00220)	(0.00507)	(0.00242)	(0.00334)
Connection to pipe gas	-0.173	-0.173	0.193	0.193
	(0.00856)	(0.0214)	(0.0376)	(0.0396)
Observations	50,000	50,000	37,244	37,244
Hansen test	0.12	0.61	0.09	0.35
Number of instruments	85	85	85	85

Notes: standard errors in parentheses. Models include household fixed effects and time-dummies. Constant terms are not reported. Capital variables are instrumented using third lags. Interactions are instrumented using a third lag of equipment capital times a dummy variable that takes the value of one if the main heating/cooling fuel is not gas or electricity. This is to avoid instruments being correlated with changes in fuel choice. For heating degree days, cooling degree days, precipitations and all capital variables, the reported coefficients have been rescaled since the model is log-linear. They correspond to a marginal change in the log of the dependent variable when the independent variables increase by 1,000.

Online supplementary appendices

Investment model

E: Contemporaneous and lagged values of climate variables

Instead of using the expected values for heating and cooling degree days and precipitation, we use contemporaneous values. Results are relatively similar even though the impact of cooling degree days on equipment is imprecisely estimated and attenuated.

Table E1: Linear investment models using contemporaneous values

Type of investment	Equipment	Weatherization
Heating degree days	0.0544	0.154
	(0.0255)	(0.0728)
Cooling degree days	0.0651	0.249
	(0.0488)	(0.0990)
Precipitations	0.0000234	0.00540
	(0.00329)	(0.00773)
No. people in unit	6.932	16.94
	(9.623)	(19.01)
Connection to pipe gas	231.4	265.9
	(59.51)	(87.18)
Observations	44,539	44,327

Notes: standard errors (clustered at household level) in parentheses. Models include household fixed effects and time-dummies.

If consumers are backward-looking, it would make sense to use a distributed lag model, which includes lagged values for heating and cooling degree days.[31] This type of model confirms that lagged values need to be taken into account, with results closer to the base model with expected values.

[31] Backward-looking consumers is one of the eventualities studied by Anderson et al. (2013), who aim to understand how consumers shape their expectations about future gasoline prices.

Table E2: Distributed lag model for investments

Type of investment	Equipment	Weatherization
Heating degree days:	0.0207	0.0583
	(0.0314)	(0.0741)
First year lag	0.0438	0.129
	(0.0302)	(0.0638)
Second year lag	-0.0593	-0.0470
	(0.0343)	(0.0742)
Third year lag	0.0703	0.0784
	(0.0353)	(0.0802)
Cooling degree days:	0.103	0.272
	(0.0544)	(0.107)
First year lag	0.00393	-0.0793
	(0.0495)	(0.105)
Second year lag	0.131	0.123
	(0.0550)	(0.108)
Third year lag	-0.0211	-0.0249
	(0.0482)	(0.0935)
Precipitation:	0.000227	0.00646
	(0.00342)	(0.00787)
First year lag	-0.00195	0.0135
	(0.00404)	(0.00862)
Second year lag	0.00102	0.0152
	(0.00369)	(0.00811)
Third year lag	-0.0000101	0.0117
	(0.00424)	(0.00849)
No. people in unit	2.889	19.17
	(9.676)	(19.20)
Connection to pipe gas	233.8	262.5
	(60.14)	(86.61)
4-year cumulative impact:		
Heating degree days	0.0755	0.2186
	(0.0438)	(0.1238)
Cooling degree days	0.2171	0.2912
	(0.1137)	(0.2168)
Precipitation	-0.0007	0.0468
	(0.0069)	(0.0193)
Observations	43,584	43,367

Notes: standard errors (clustered at household level) in parentheses. Models include household fixed effects and time-dummies.

F: Left-censored investment models

Panel tobit model based on Honore (1992)

In this appendix, we use a panel data tobit model instead of a fixed-effect linear model to estimate investments. This approach is relevant because investments are only observed with a positive value. This latent variable approach is similar to that of Helms (2003), except that we take advantage of the data's panel structure.[32] Using formal notation we assume that investment I_{iht} depends on a latent variable I^*_{iht} which is defined by:

$$I_{iht} = \begin{cases} I^*_{iht} \; if \; I^*_{iht} > 0 \\ 0, \text{otherwise} \end{cases}$$

Next we assume that I^*_{iht} is equal to the right hand-side of Eq. (1). We estimate this model using the estimator developed by Honoré (1992) for panel data tobit models. This estimator includes household-specific fixed effects.

Table F.1 provides the results of the investment equations when panel tobit models are applied. The absolute value of the coefficients between a linear model and a panel tobit model are different due to the change in model used. However, significance levels are similar between the two models (i.e. Table F.1 versus Table 3), along with the relative impact of heating and cooling degree days on investments.

Table F.1: Results of investment equations using a Honore's (1992) panel tobit model

	Equipment	Weatherization
Expected heating degree days	1.154	2.071
	(0.657)	(0.956)
Expected cooling degree days	2.401	2.396
	(1.301)	(1.392)
Expected precipitation	-0.0451	0.163
	(0.0986)	(0.129)
No. people in unit	98.18	129.9
	(116.7)	(108.2)
Connection to pipe gas	2965.6	1899.1
	(951.0)	(786.2)
Observations	54,476	54,272

Notes: standard errors (clustered at household level) in parentheses. Models include household fixed effects and time-dummies.

This model is not used as our base specification because it does not produce estimates of fixed effects, which are necessary to make accurate predictions at the simulation stage. Moreover, it imposes the additional assumption that errors are symmetric. This is a strong assumption in the current situation.

[32] An alternative approach would consist in using two stages instead of a latent variable model. The first stage would be a logit or a probit model to predict the probability of investment, and the second stage a linear equation for the amount invested, provided that an investment is made. We tried to adopt this approach but could not obtain satisfying results, principally because we do not have many observations with a positive investment. It follows that we rarely observe two home improvements of the same type for a given household. In the second stage, this approach involves using a fairly restricted sample of observations, implying significant losses in terms of efficiency.

Dynamic panel tobit model based on Wooldridge (2005)

In addition, we run a dynamic panel tobit model using the method by Wooldridge (2005), which circumvents the initial conditions problem by specifying the shape of the fixed effects. In the present case, the fixed effect is estimated with dummies for Statistical Metropolitan Areas, the type of house (attached, detached, semi-detached), area, and the panel-specific mean values of all of the time-varying independent variables included in the model, i.e. expected heating and cooling degree days, expected precipitation, number of people in the household, connection to pipe gas, marital status, sex and age of the householder, and the year of observation. The specification for the fixed effect also comprises the initial value of the dependent variable, and a dummy variable equal to 1 if this value is censored (i.e. equal to 0), as recommended in Wooldridge (2005). Likewise, the lagged dependent variable is assumed to have a different impact on the latent variable when it is uncensored (>0) and censored (=0).

We report the results of a pooled tobit model, and not a random effects tobit model as suggested by Wooldridge (2005), because the random effects model does not converge. This is likely due to the large number of dummy variables included in the model.

When it comes to the impact of expected heating and cooling degree days, results are very similar to those of the linear model in the case of main equipment. We do not use this model since we cannot be sure that the shape of the fixed effects is properly specified.

Table F.2: Results of investment equations using Wooldridge's (2005) dynamic panel tobit model

	Equipment	Weatherization
Lagged dependent variable (>0)	-0.0792	0.0622
	(0.0911)	(0.0357)
Lagged dependent variable (=0)	-2049.5	-1800.1
	(397.8)	(191.1)
Expected heating degree days	1.693	1.459
	(0.695)	(0.558)
Expected cooling degree days	4.001	1.476
	(1.527)	(1.150)
Expected precipitation	0.0372	-0.00670
	(0.100)	(0.0835)
No. people in unit	28.98	-191.3
	(149.0)	(105.9)
Connection to pipe gas	2519.7	1522.0
	(729.9)	(517.3)
Age of householder	17.53	-35.25
	(35.38)	(27.57)
Sex of householder	5.615	40.80
	(514.8)	(426.0)
Square footage of unit	0.387	-0.101
	(0.160)	(0.130)
Fixed effect specification		
Initial dependent variable (>0)	-0.103	0.0429
	(0.0897)	(0.0349)
Initial dependent variable (=0)	-895.9	-765.5
	(426.8)	(190.2)
Panel-specific mean of time-varying variables plus income	Yes	Yes
Observations	28,376	28,141

Notes: standard errors (clustered at household level) in parentheses. Models include time dummies and dummies for the Metropolitan Statistical Areas, the type of house (detached, attached, semi-detached) and marital status (incl. single, married, separated, divorced and widowed).

G: Excluding improvements made just before households leave the unit

In this section we exclude the last observation before the housing unit changes owners to reduce the risk that investments are not affected by households' selling plans. Results lose precision but coefficients remain stable (except for the impact of cooling degree days on weatherization).

Table G1: Results of investment models with last observation prior to selling is excluded.

	Equipment	Weatherization
Expected heating degree days	0.0776	0.193
	(0.0611)	(0.176)
Expected cooling degree days	0.200	-0.0837
	(0.152)	(0.304)
Expected precipitation	0.000205	0.0460
	(0.00939)	(0.0266)
No. people in unit	6.873	26.90
	(12.47)	(26.17)
Connection to pipe gas	299.4	378.6
	(90.19)	(128.9)
Observations	31,427	31,297

Notes: standard errors (clustered at household level) in parentheses. Models include household fixed effects and time-dummies. Constant terms are not reported.

H: Using observations that benefitted from a public grant or a loan

Investments in space heating, air-cooling and weatherization are also influenced by energy efficiency policies. If these policies are correlated with climate shocks or expectations, our estimates of the impact of climate adaptations on home improvements could be biased. In the base specification, we exclude any observations that benefitted from public support, considering that only around 2% of home improvements in our sample actually benefitted from government grants or loans.

Alternatively, this piece of information can be used as a dummy variable in the home improvement models. However, this additional variable is likely to be endogenous. The reason is that it incorrectly measures the availability of policies promoting energy efficiency at local level.[33] We report alternative specifications where we use a control function approach to treat this endogeneity. As an instrument we use the share of households within the same metropolitan statistical area and year who benefitted from government support to invest in other amenities. This captures the likelihood of access to government support at local level at time t for investment h. This factor is however exogenous to specific households since it does not depend

[33] In particular, this variable only provides information about households that actually performed alterations. For the other households, we do not know if they had access to government support or not. In addition, this is a binary variable whereas household choices are driven by the size of subsidies.

on household *i's* characteristics. In addition, we also use the squared value of this share to build a second instrument to be able to run an over-identification test. Standard identification tests using a linear 2SLS model were performed and corroborate the validity of our instruments. Only slight differences in results are found with this specification and our base specification.

Table H1: 2SLS investment models using observations that benefitted from a public grant or a loan

	Equipment	Weatherization
Benefitted from a public grant or a loan	-653.9	-754.0
	(634.2)	(1061.7)
Expected heating degree days	0.0985	0.342
	(0.0482)	(0.145)
Expected cooling degree days	0.240	0.372
	(0.114)	(0.218)
Expected precipitation	-0.00412	0.0230
	(0.00721)	(0.0198)
No. people in unit	3.369	13.57
	(9.507)	(18.77)
Connection to pipe gas	222.7	263.6
	(61.99)	(86.38)
Weak identification test:		
Kleibergen-Paap rk Wald F statistic	468	410
Overidentification test†:		
Hansen J statistic (p-value)	0.34	0.48
Observations	44,443	44,215

Notes: standard errors (clustered at household level) in parentheses. Models include household fixed effects and time-dummies. Two instruments are used to treat the endogeneity of the policy variable: the share of households that benefitted from a public grant or loan in the same MSA, and the squared value of this share.

I: Investment models with regional trends

The specification below includes regional linear and quadratic trends to control for region-specific unobservable factors that could be correlated with heating and cooling degree days across the nine climatic regions of the US. We observe no difference at all with these trends for main equipment. However, results for weatherization are identical with a region-specific linear trend, but become less precise with a quadratic trend.

Table I.1: Main results for investments in main equipment

Type of investment	Base model	(1)	(2)
Expected heating degree days	0.106	0.0559	0.0607
	(0.0501)	(0.0559)	(0.0559)
Expected cooling degree days	0.264	0.234	0.225
	(0.114)	(0.115)	(0.116)
Expected precipitations	-0.00159	0.00125	-0.00443
	(0.00738)	(0.00742)	(0.00825)
No. people in unit	6.039	6.512	6.453
	(9.809)	(9.827)	(9.824)
Connection to pipe gas	225.0	223.8	223.9
	(61.07)	(60.31)	(60.28)
Linear regional trend	No	Yes	No
Quadratic regional trend	No	No	Yes
Observations	42,221	42,221	42,221

Notes: standard errors (clustered at household level) in parentheses. All specifications include household fixed effects and time-dummies. Constant terms are not reported.

Table I.2: Main results for investments in weatherisation

Type of investment	Base model	(1)	(2)
Expected heating degree days	0.328	0.266	0.210
	(0.153)	(0.130)	(0.131)
Expected cooling degree days	0.441	0.430	0.267
	(0.223)	(0.224)	(0.229)
Expected precipitations	0.0291	0.0336	0.0441
	(0.0206)	(0.0210)	(0.0213)
No. people in unit	23.31	24.42	26.05
	(19.46)	(19.45)	(19.40)
Connection to pipe gas	245.5	237.8	234.2
	(88.33)	(88.47)	(88.46)
Linear regional trend	No	Yes	No
Quadratic regional trend	No	No	Yes
Observations	42,010	42,010	42,010

Notes: standard errors (clustered at household level) in parentheses. Models include household fixed effects and time-dummies. Constant terms are not reported.

J: Interaction between time and climate variables

Due to technical progress and improvements in the quality of houses, the impact of heating and cooling degree days on investments could reduce over time. We test this hypothesis by introducing interactions between time and expected heating degree days / cooling degree days. We find no evidence to support such a theory: on the contrary, we observe an increase in household response to invest in weatherization to heating and cooling degree days, which may be caused by changes in preferences.

Table J.1: Fixed-effect investment models with an interaction between climate variables and time

	Equipment	Weatherization
Expected heating degree days	0.113	0.323
	(0.0503)	(0.149)
x time	0.000675	0.00906
	(0.00260)	(0.00483)
Expected cooling degree days	0.263	0.349
	(0.125)	(0.266)
x time	0.00125	0.0180
	(0.00547)	(0.0114)
Expected precipitation	0.00894	0.0538
	(0.0104)	(0.0257)
x time	-0.00130	-0.00289
	(0.000976)	(0.00206)
No. people in unit	5.847	23.81
	(9.799)	(19.40)
Connection to pipe gas	227.6	251.3
	(60.81)	(88.62)
Observations	42221	42010

Notes: standard errors (clustered at household level) in parentheses. Models include household fixed effects and time-dummies.

K: Investment model of other indoor amenities

This section reports the results of a fixed-effect model using investments in other indoor amenities (changes to the bathroom; changes to the kitchen; home extensions; and other major indoor improvements) as a dependent variable.

Table K.1: Fixed-effect investment model of other indoor amenities

	Other indoor amenities
Expected heating degree days	0.0808
	(0.272)
Expected cooling degree days	0.206
	(0.456)
Expected precipitation	0.0519
	(0.0371)
No. people in unit	41.32
	(38.72)
Connection to pipe gas	-7.500
	(183.1)
Observations	54,157

Notes: standard errors (clustered at household level) in parentheses. Models include household fixed effects and time-dummies.

L: Investment costs in housing units equipped with central air conditioning

We exploit the information we have on the amount invested in central air conditioners between 1997 and 2011 in the AHS data to compare the marginal cost of cooling investments in a housing unit equipped with central AC compared to the marginal cost in the average unit. We run a simple fixed effect linear regression where we correlate the amount invested in central air conditioning, conditional on an investment being performed, and the total amount of cooling degree days. Results are provided below and show that each additional expected cooling degree day is correlated with an extra investment of 4.1 dollars. This figure translates into an annual average additional investment of 23 cents per year for each additional cooling degree day, assuming a lifetime of 17.9 years for central AC systems. This lifetime is estimated using AHS data with a method that is available upon request. This amount of 23 cents per year is in fact higher than the average elasticity of investments to expected cooling degree days in our base model, at 26 cents every two years.

Table L.1: Main results for investments in energy-related home improvements

	Central air conditioning
Expected cooling degree days	4.13
	(1.99)
Observations / Households	1,488 / 1,409

Notes: standard error in parentheses. Models include household fixed effects and time-dummies. Constant term is not reported.

M: Expenditure models with bins

Here we report the results when temperature and precipitation bins are used in the energy expenditure model (without interactions with main heating and cooling fuel used). For concision, only the coefficients for the bins are reported since all the other coefficients are practically unchanged.

Table M.1: Estimation results of energy expenditure models with temperature bins

Type of fuel	Electricity	Gas
Expected days with temperature:		
Below 10°F	-0.00100	0.000626
	(0.000656)	(0.000655)
Between 10-20°F	0.000912	0.00635
	(0.000506)	(0.000613)
Between 20-30°F	-0.000485	0.00545
	(0.000339)	(0.000415)
Between 30-40°F	0.000818	0.00425
	(0.000227)	(0.000286)
Between 40-50°F	0.00195	0.00198
	(0.000238)	(0.000267)
Between 50-60°F	-0.000159	-0.000286
	(0.000229)	(0.000283)
Between 60-70°F	-	-
Between 70-80°F	0.00198	0.00150
	(0.000195)	(0.000236)
Between 80-90°F	0.00368	0.000459
	(0.000256)	(0.000316)
Above 90°F	0.00503	0.00270
	(0.000333)	(0.000448)
Expected days with precipitation:		
No precipitation	-	-
Between 0-50mm	0.000475	0.000454
	(0.000103)	(0.000121)
Between 50-100mm	-0.000535	0.00207
	(0.000314)	(0.000400)
Between 100-200mm	0.00138	0.00421
	(0.000354)	(0.000457)
Above 200mm	0.00411	-0.000944
	(0.000451)	(0.000579)

Notes: standard errors (clustered at household level) in parentheses. Models include household fixed effects and time-dummies. Capital variables are instrumented using third lags.

N: Energy expenditure models using orthogonal deviations

Instead of estimating the energy model with past values as instruments, we use orthogonal deviations. Results are similar (see Table N.1). The estimator used below is System GMM.

Table N.1: Estimation of energy expenditure model using System GMM and orthogonal deviations

	Electricity	Gas
Heating degree days	0.0167	0.143
	(0.00506)	(0.00624)
Cooling degree days	0.185	0.0890
	(0.0122)	(0.0159)
Capital in equipment	0.0128	0.00700
	(0.00528)	(0.00617)
Capital in weatherization	-0.00451	-0.00114
	(0.00182)	(0.00211)
Capital in other amenities	0.00215	0.00140
	(0.000941)	(0.00106)
Precipitations	0.0147	0.0167
	(0.000794)	(0.00102)
No. people in unit	0.0865	0.0439
	(0.00217)	(0.00238)
Connection to pipe gas	-0.177	0.197
	(0.00850)	(0.0341)
Observations	50,000	37,244
Hansen test (p-value)	0.20	0.25
Number of instruments	82	82

Notes: standard errors (clustered at household level) in parentheses. Models include household fixed effects and time-dummies. Capital variables are instrumented using third lags. For heating degree days, cooling degree days, precipitations and all the capital variables, the reported coefficients have been rescaled since the model is log-linear. They correspond to a marginal change in the log of the dependent variable when the independent variables increase by 1000.

O: Energy expenditure models with 4th lags as instrument

Instead of using the 3rd lags of the capital stocks, the model in this section uses the 4th lags. Results are similar to those presented in Appendix N.

Table O.1: Estimation of energy expenditure model using System GMM and 4th lags of capital stocks as instruments

	Electricity	Gas
Heating degree days	0.0179	0.147
	(0.00555)	(0.00718)
Cooling degree days	0.185	0.0985
	(0.0133)	(0.0183)
Capital in equipment	0.0296	0.00948
	(0.00657)	(0.00739)
Capital in weatherization	-0.00578	0.00116
	(0.00231)	(0.00256)
Capital in other amenities	0.00127	0.000173
	(0.00115)	(0.00124)
Precipitations (mm)	0.0141	0.0159
	(0.000805)	(0.00106)
No. people in unit	0.0849	0.0434
	(0.00225)	(0.00248)
Connection to pipe gas	-0.173	0.189
Heating degree days	0.0179	0.147
Observations	50,000	37,244
Hansen test (p-value)	0.63	0.51
Number of instruments	79	79

Notes standard errors (clustered at household level) in parentheses. Models include household fixed effects and time-dummies. Capital variables are instrumented using fourth lags. For heating degree days, cooling degree days, precipitations and all capital variables, the reported coefficients have been rescaled since the model is log-linear. Coefficients correspond to a marginal change in the log of the dependent variable when the independent variables increase by 1,000.

P: Energy expenditure model using difference GMM

The table below displays the results of the panel data model of energy expenditure using an Arellano-Bond estimator. The model fails to significantly capture the impact of the lagged dependent variable and produces imprecise results.

Table P.1: Estimation of energy expenditure models using difference GMM

	Electricity	Gas
Heating degree days	0.0354	0.0162
	(0.0113)	(0.0140)
Cooling degree days	0.0651	0.0165
	(0.0175)	(0.0236)
Capital in equipment	-0.0138	0.00214
	(0.0139)	(0.0164)
Capital in weatherization	-0.00359	0.00414
	(0.00474)	(0.00604)
Capital in other amenities	0.00727	0.00385
	(0.00286)	(0.00390)
Precipitations (mm)	0.00206	0.00270
	(0.00133)	(0.00178)
No. people in unit	0.0468	0.0204
	(0.00444)	(0.00564)
Connection to pipe gas	-0.0438	0.156
	(0.0220)	(0.0647)
Observations	27,659	19,970
Hansen test (p-value)	0.20	0.08
Number of instruments	51	51

Notes: standard errors (clustered at household level) in parentheses. Models include household fixed effects and time-dummies. Capital variables are instrumented using third lags. For heating degree days, cooling degree days, precipitations and all capital variables, the reported coefficients have been rescaled to account for the log-linear form. Coefficients correspond to a marginal change in the log of the dependent variable when the independent variables increase by 1,000.

Q: Energy expenditure models without capital variables

In this section we present the results of energy expenditure models without capital variables using system GMM. Results are similar. The estimated coefficients of the crucial temperature variables (i.e. CDD for electricity consumption, HDD for gas consumption) show little differences with the base model.

Table Q.1: Blundell-Bond estimation of energy expenditure model without capital stocks

Type of fuel	Electricity	Gas
Heating degree days	0.00712	0.127
	(0.00247)	(0.00253)
Cooling degree days	0.178	0.0688
	(0.00483)	(0.00562)
Precipitations	0.00925	0.0101
	(0.000695)	(0.000855)
No. people in unit	0.0951	0.0489
	(0.00213)	(0.00234)
Connection to pipe gas	-0.147	0.210
	(0.00771)	(0.0356)
Observations	56812	40466

Notes: standard errors (clustered at household level) in parentheses. Models include household fixed effects and time-dummies. Constant terms are not reported. For heating degree days, cooling degree days and precipitations, the reported coefficients have been rescaled since the model is log-linear. They correspond to a marginal change in the log of the dependent variable when the independent variables increase by 1,000.

R: Energy expenditure models with region-specific elasticities to temperature shocks

This section reports results of the baseline energy expenditure model while interacting heating degree days and cooling degree days with variables indicating the climate region in which the housing unit is situated. This allows us to estimate region-specific elasticities to climate shocks. Table R.1 displays the coefficients obtained for heating and cooling degree days for each region. For the sake of concision, we do not report the other coefficients, which have not changed substantially.

In general, more heating or cooling degree days increase electricity and gas consumption, but the intensity of the response is different from one region to the other. This is reflected in the simulation, where we find that climate change may impact energy demand less strongly in cold regions than in hot regions.

Table R.1: System GMM estimation of energy expenditure models with region-specific elasticities to temperature shocks

	Electricity	Gas
Annual heating degree days:		
x Central	0.0237	0.133
	(0.00745)	(0.00614)
x Northwest	0.0333	0.0742
	(0.00768)	(0.00870)
x West North Central	0.0325	0.0852
	(0.0335)	(0.0510)
x East North Central	0.0182	0.0973
	(0.00707)	(0.00604)
x Northeast	0.0273	0.143
	(0.00624)	(0.00667)
x South	0.0365	0.134
	(0.0110)	(0.00982)
x Southeast	0.0729	0.178
	(0.0153)	(0.0121)
x Southwest	0.0230	0.0822
	(0.00692)	(0.00704)
x West	0.0875	0.0420
	(0.0133)	(0.0127)
Annual cooling degree days:		
x Central	0.187	0.101
	(0.0286)	(0.0206)
x Northwest	0.152	0.0642
	(0.222)	(0.310)
x West North Central	0.226	0.289
	(0.207)	(0.316)
x East North Central	0.0872	0.186
	(0.0373)	(0.0337)
x Northeast	0.286	0.0655
	(0.0381)	(0.0242)
x South	0.199	0.0200
	(0.0194)	(0.0132)
x Southeast	0.129	0.0564
	(0.0202)	(0.0182)
x Southwest	0.145	0.0507
	(0.0221)	(0.0125)
x West	0.0718	0.0330
	(0.0260)	(0.0152)
Observations	50,000	37,244
Hansen test	0.34	0.07
Number of instruments	123	123

Notes: standard errors (clustered at household level) in parentheses. Models include household fixed effects and time-dummies, and interactions between equipment capital and main fuels used for heating and cooling. Capital variables are instrumented using third lags. Interactions are instrumented using third lags of equipment capital times a dummy variable that takes the value of one if main heating/cooling fuel is not gas or electricity. This is to avoid instruments being correlated with changes in fuel choice. The reported coefficients have been rescaled since the model is log-linear. Coefficients correspond to a marginal change in the log of the dependent variable when the independent variables increase by 1,000.

S: Dynamic energy expenditure model

To model energy expenditure, the use of a dynamic model would be justified by the fact that energy expenditure slowly adjusts over time due to persistent expenditure patterns and habits within a household. There are several econometric difficulties in using a dynamic model; in particular the instrumentation of the lagged dependent variable has often been criticized (this is also discussed in the main part of this paper).

In this section we report the results of a dynamic panel data model. Finding an exogenous instrument for the lagged dependent variable is particularly difficult as the endogenous variable and the dependent variable are closely related. A standard strategy in dynamic panel data models is to use deeper lags. This approach imposes the assumption that there is no complex serial correlation structure in the dependent variable. To avoid this assumption, we opt for a different type of instrument that captures exogenous variations in the time spent in the home. A first instrumental variable is average commuting time from home to work in year $t-1$ of all household members over 14. Commuting time is necessarily correlated with the time spent in the house – it indicates less leisure time – and thus with the expenditure of energy-using housing services. We assume that commuting time at $t-1$ is not correlated with the error term at t. The validity argument is that commuting time has no persistent direct effect on energy expenditure. A potential problem is that commuting time at $t-1$ is correlated with commuting time at t because both are driven by long-term choices of where to live, work or study. In addition, commuting time is obviously contemporaneously correlated with variables like income and energy prices that are included in the error term. To avoid this problem, commuting time at t is included in the specification as an additional control variable. Interestingly, commuting time also depends on multiple factors that are clearly uncorrelated with energy expenditure, such as changes in school, departure time, road traffic conditions, and transit availability. All of these factors vary over time.

The impact of commuting time on energy expenditure is stronger if the house or apartment is large (simply because energy expenditure depends on dwelling size). In order to strengthen the instrumentation, we thus add a second instrumental variable that makes commuting time at $t-1$ interact with dwelling size (in square feet) at the time of purchase[34]. As a result, commuting times can have a different effect on energy expenditure depending on the size of the dwelling.

[34] We use the size of the house at the time of purchase and not at time t to avoid our instrument capturing the effect of home extensions (i.e. between time t-1 and time t) on energy expenditure.

We also add the same variable but at time t as a control. Results of this dynamic specification show that there is substantial uncertainty about the capital variables, in particular in the case of gas. The coefficient signs are identical to the main results for electricity.

Table S.1: Blundell-Bond estimation of dynamic energy expenditure models

	Electricity	Gas
Lagged dependent variable (ln)	0.263	0.349
	(0.0909)	(0.101)
Capital in equipment	-0.00204	0.00356
	(0.00589)	(0.00705)
Capital in weatherization	-0.00306	-0.00262
	(0.00216)	(0.00260)
Capital in other amenities	0.00207	0.00164
	(0.00108)	(0.00124)
Heating degree days	0.00636	0.0852
	(0.00521)	(0.0146)
Cooling degree days	0.124	0.0344
	(0.0211)	(0.0166)
Precipitations	0.0110	0.00947
	(0.00163)	(0.00166)
Connection to pipe gas	-0.131	0.161
	(0.0190)	(0.0574)
No. people in unit	0.0585	0.0269
	(0.00583)	(0.00454)
Average commuting time	-0.00195	-0.000683
	(0.000508)	(0.000648)
x sq. footage at time of	0.000953	0.000511
Purchase (‘000)	(0.000217)	(0.000287)
Observations	18761	13488
Hansen test	0.12	0.24
Number of instruments	118	118

Notes: standard errors (clustered at household level) in parentheses. Models include household fixed effects and time-dummies. Capital variables are instrumented using third lags. The lagged dependent variable is instrumented using first lag of average commuting time and interaction between commuting time and square footage of unit at time of purchase. For heating degree days, cooling degree days, precipitation and all capital variables, the reported coefficients have been rescaled since the model is log-linear. They correspond to a marginal change in the log of the dependent variable when the independent variables increase by 1,000.

T: Joint estimation of electricity and gas expenditure levels

Instead of estimating energy expenditure models separately for electricity and gas, we could estimate the demand for both fuels together, since we could consider that both decisions are made simultaneously. Results are provided below and suggest an increase in energy expenditure under climate change, as for the main specifications.

Table T.1: System GMM estimation of energy expenditure models

Dependent variable	Ln(Gas and electricity expenditure)
Capital in equipment	0.0125
	(0.00447)
Capital in weatherization	-0.00336
	(0.00155)
Capital in other amenities	0.00208
	(0.000802)
Heating degree days	0.0744
	(0.00447)
Cooling degree days	0.205
	(0.0108)
Precipitations (mm)	0.0146
	(0.000726)
No. people in unit	0.0779
	(0.00191)
Connection to pipe gas	0.312
	(0.00841)
Observations	50,000
Hansen test	0.16
Number of instruments	82

Notes: standard errors (clustered at household level) in parentheses. Models include household fixed effects and time-dummies. Constant terms are not reported. Capital variables are instrumented using third lags. Interactions are instrumented using third lags of equipment capital times a dummy variable that takes the value of one if main heating/cooling fuel is not gas or electricity. This is to avoid instruments being correlated with changes in fuel choice. For heating degree days, cooling degree days, precipitations and all capital variables, the reported coefficients have been rescaled since the model is log-linear. They correspond to a marginal change in the log of the dependent variable when the independent variables increase by 1,000.

U: Using energy consumption instead of energy expenditure in the energy models

Instead of using expenditure levels, we estimate a model of electricity and gas consumption levels. We obtain consumption levels by dividing energy expenditures by the average price of fuel in each US State. The energy price data is taken from the State Energy Data System (SEDS) administered by the US Energy Information Administration. The data includes information on residential and industrial energy prices for each US State from 1985 to 2011. We combine the energy price data with the AHS data by matching the metropolitan statistical areas of the AHS with the state-level information of the SEDS. Each time an MSA is situated in more than one state, average price values are obtained by calculating the average energy price corresponding to the different states that a metropolitan statistical area overlaps.

In these alternative models we include energy prices as control variables. A complication with this approach is that prices are endogenous due to the simultaneous determination of energy prices and residential energy demand. To deal with this endogeneity we construct instruments based on pre-sample information on energy prices between 1970 and 1983. The use of pre-sample information to construct instruments has been implemented recently in several studies, in particular by Blundell, Griffith and Windmeijer (2002). We predict state-level gas and electricity prices for 1985-2011 with the pre-sample information we have. For each metropolitan statistical area, we run two Autoregressive Integrated Moving Average (ARIMA) models on the energy data, using only the years before 1983: one for residential electricity prices and one for residential gas prices. We use a model with two autoregressive orders for residential electricity and gas prices. In addition, we include four time dummies for 1973, 1974, 1979 and 1980. These dates correspond to the first and second oil shocks. We therefore obtain:

$$p_{rft} = a_{0,r} + a_{1,r}p_{rft-1} + a_{2,r}p_{rft-2} + \sum_x a_{x,r} + e_{rft},$$

$$wit\hbar\, x \in \{1973, 1974, 1979, 1980\}$$

where p_{rft} is the price of fuel f in area r at time t. x corresponds to the dates of the oil shocks (1973, 1974, 1979 and 1980). $a_{0,r}$, $a_{1,r}$, $a_{2,r}$ and $a_{x,r}$ are parameters specific to each MSA *r* and estimated by the ARIMA models. e_{rft} is an error term.

We take the predictions of these models for 1985-2011 and use them as instruments. By construction, instruments capture trends in energy prices based on pre-sample information. We extrapolate these price trends for 1985-2011 based on the information available in 1983. The predicted prices will only take information prior to 1985 into account and are therefore unrelated to any shock in energy demand during 1985-2011. Predicted prices using past data should integrate factors such as previous knowledge about fossil fuel exhaustion and therefore be correlated with real prices.

Results using energy consumption are globally similar to those obtained using energy expenditure. In Table U.1 we report the results where we separate the effect of capital stock according to main heating and cooling fuel.

Table U.1: System GMM estimation of energy consumption models, controlling for energy prices

	Electricity consumption	Gas consumption
electricity $/Mbtu	-0.0252	0.00593
	(0.000816)	(0.000959)
natural gas & LG $/Mbtu	0.0108	-0.0899
	(0.00399)	(0.00551)
Capital in equipment	0.0130	0.00492
	(0.00506)	(0.00623)
Capital in weatherization	-0.00381	-0.00222
	(0.00171)	(0.00208)
Capital in other amenities	0.00153	0.00201
	(0.000885)	(0.00107)
Heating degree days	0.0160	0.152
	(0.00404)	(0.00498)
Cooling degree days	0.164	0.116
	(0.0109)	(0.0136)
Precipitation	0.0135	0.0176
	(0.00101)	(0.00124)
No. people in unit	0.0852	0.0422
	(0.00219)	(0.00242)
Connection to pipe gas	-0.166	0.195
	(0.00976)	(0.0381)
Observations	50,000	37,244
Hansen test (p-value)	0.21	0.11
Number of instruments	87	87

Notes: standard errors (clustered at household level) in parentheses. Models include household fixed effects and time-dummies. Capital variables are instrumented using third lags. Interactions are instrumented using third lags of equipment capital times a dummy variable that takes the value of one if main heating/cooling fuel is not gas or electricity. This is to avoid instruments being correlated with changes in fuel choice. We also instrument energy prices using predictions of these prices based on pre-sample data. For heating degree days, cooling degree days, precipitations and all capital variables, the reported coefficients have been rescaled since the model is log-linear. They correspond to a marginal change in the log of the dependent variable when the independent variables increase by 1,000.