Green Technology Adoption over the Life Cycle

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Abstract

Government policy and households' green choices are critical for achieving climate targets. Using a quantitative, life-cycle model calibrated to U.K. data we examine homeowners' decisions regarding green technology adoption (heat pumps). Given the empirical residential and wealth distributions, the model is consistent with historically low adoption rates. Counterfactuals show that fiscal policy can increase uptake. Subsidies to installation costs provide immediate incentives to adopt for less wealthy households due to liquidity constraints. Lower electricity taxes incentivize adoption among wealthier households and shift the fiscal liability to the future. Commodity price uncertainty affects adoption rates more when changing electricity taxation but does not change the (unintended) distributional differences across policies.

Keywords: green technology adoption, liquidity constraints, life cycle models, climate policy, decarbonisation.

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1 Introduction

Climate change is among the most challenging problems facing humanity. The consequences of global heating, if unabated, can be devastating across countries and continents and pose existential risks for many societies. Economic losses are expected to rise significantly with the increase in global temperatures: the world economy is set to lose up to 18% GDP by 2050 from climate change if no action is taken (SwissRE, 2021). In addition, 20% of countries are at risk from ecosystem collapse as biodiversity declines (SwissRE, 2020). These projections combined with increasing breadth, frequency and intensity of floods, hurricanes, typhoons and other natural catastrophes have generated repeated calls for climate action (IPCC, 2022, 2021, 2018).

Although there are green technology success stories (solar photovoltaics, electric vehicles), other such technologies are not being deployed sufficiently fast around the world (IEA, 2023). A particularly important example is heating in buildings, which is required by about 40% of world population at least part of the year, and generates 10% of annual carbon dioxide emissions globally (IEA, 2022). In the UK, these emissions are 17% of total emissions due to widespread use of natural gas in heating and cooking (DESNZ, 2023). Therefore, eliminating these emissions has become an important policy priority and many countries have committed by law to reduce greenhouse gas (GHG) emissions to net zero by 2050.[1] Nevertheless, despite the importance of decarbonisation of the housing sector, the adoption of green heating technologies at the household level is very low.

In this paper, we develop a structural quantitative framework to investigate household decisions on the adoption of low carbon technologies. This framework can be used to understand adoption rates for a range of green technologies and in different economic policy environments. A structural quantitative framework is necessary to evaluate these policies for several reasons. First, identifying behavioral responses is crucial to designing economic policies that incentivize households to make choices aligned with climate targets. Second, merely identifying mechanisms is insufficient; the policy questions require a quantitative evaluation to understand the potential impact comprehensively (Hassler, Krusell, and Olovsson, 2018).

We develop and employ an incomplete markets framework where households live in

[1] A website (netzerotracker.net) collects data on the large number of countries that have adopted net zero targets.

houses differing by size and energy needs, face uninsurable labor income risk, a hump-shaped life-cycle earnings profile, and liquidity constraints that affect their ability to smooth consumption and invest in green technologies. These features endogenously generate a relationship between wealth and green technology adoption. Therefore, our heterogeneous agent framework also allows us to quantify the consequences of different policies on wealth inequality.

In our life-cycle model, the decision to adopt low-carbon technology hinges on two main factors: the upfront payment and the operating cost. Many low-carbon alternatives require significant upfront investments. This high initial cost creates a significant barrier to adoption, especially for those households with limited liquidity. However, once installed, green technologies are more energy efficient, meaning that their operating costs could be significantly lower. Commodity price uncertainty adds another layer of complexity. Not only is the level of electricity prices compared to fossil fuel prices important, but the volatility of these prices also plays a significant role in shaping adoption decisions. High volatility in electricity or fossil fuel prices can make the future operating costs of green technologies unpredictable, thereby increasing the perceived financial risk to households. This uncertainty can deter adoption even if average electricity prices are low.

Taking these features into account, our model captures these critical trade-offs. By considering the heterogeneous upfront costs faced by households with varying housing levels, as well as both the level and volatility of commodity prices, our framework offers a comprehensive analysis of the factors influencing household decisions to invest in low-carbon technologies.

As an application of this framework, we focus on heat pumps, as they have been consistently recognized as a key and cost-effective solution to address heating emissions (Rosenow, Gibb, and Nowak, 2022). Heat pumps use electricity to convert heat from ambient air, water, or ground to generate heat and hot water inside a home. If they run on renewable electricity, they produce zero emissions. Even if they run on a fossil-fuel grid, they still use 3 to 5 times less energy because of their higher efficiency. To quantitatively assess the potential impacts of various fiscal policies on the adoption of heat pumps, our model is calibrated to the UK economy because the UK has one of the lowest adoption rates. According to the Climate Change Committee (CCC), domestic heat pumps will likely be necessary in almost 80% of homes by 2050 to meet the Net Zero target. To support this goal, the UK government has set

interim installation targets of 600,000 heat pumps per year by 2028.[2]

The calibration strategy involves a two-phase approach. Initially, we estimate heating demand and characterize the housing distribution using detailed information at the residential level on physical attributes such as floor area, type of dwelling, age, number of bedrooms and location, allowing us to calculate heating expenditures and potential heat pump installation and running costs. Subsequently, we integrate these housing characteristics with individual labor income data over the life cycle. By aligning heating demand with household income profiles, we calibrate model parameters to reflect the heterogeneous income trajectories and financial constraints of households across the housing distribution. This comprehensive calibration ensures that our model accurately represents the key features of the real-world economic environment, providing a solid foundation to evaluate the effectiveness of fiscal policies in promoting the adoption of green technologies.

Our baseline calibration reveals that without policy intervention, zero technology adoption is expected. Previous subsidies did not provide a sufficiently strong incentive to achieve pre-announced targets. Many households with liquidity constraints do not have sufficient resources to incur the upfront installation cost. On the other hand, wealthier households are less likely to be liquidity constrained but own larger houses and therefore are faced with a larger upfront expenditure. Moreover, because the electricity to gas price ratio is high, the marginal benefit from adopting is not as strong. At the same time, uncertainty about the relative electricity to gas price further reduces the incentive to adopt. We view this baseline calibration as an accurate description of the state of household heat pump adoption in the UK in 2023. We therefore use this quantitative model as a laboratory to explore the effects of different counterfactual policies. In this paper, we conduct an analysis of two primary policy interventions that have received policy attention: subsidies targeting upfront investment costs and adjustments in tax rates on electricity prices to modify the relative running costs of heating.

Our findings suggest that a lump sum subsidy of £6,500 or a proportional subsidy covering 60% of the initial cost is necessary to achieve the target adoption rate of 2% per year. Over 5 years, these measures would result in a cumulative cost of 2.1% or 1.4% of GDP, respectively. Over 20 years, the costs would be 2.9% and 2.7% of GDP, respectively. Furthermore, our analysis indicates that reducing the electricity tax by 17% can also achieve the

[2]See https://researchbriefings.files.parliament.uk/documents/POST-PN-0699/POST-PN-0699.pdf.

target adoption rate. This policy would have a 5-year cumulative cost of 0.6% of GDP but would incur higher long-term costs, amounting to 3.3% of GDP over 20 years. Interestingly, a government report published in February 2024 shows higher heat pump adoption after the subsidy increase.[3]

When we shift our focus to electricity tax reductions, the adoption dynamics are notably different. Reducing the electricity tax primarily benefits wealthier, older households with larger homes. This is because the financial savings from adopting energy-efficient technologies increase with heating demand, which is proportional to housing size. Larger homes, which have higher energy consumption, experience greater cost savings from reduced electricity taxes, making adoption more attractive. However, this policy does little to address liquidity constraints, which explains why households in smaller homes, typically associated with less wealth and facing tighter liquidity constraints, do not adopt as readily under a tax reduction policy.

The rich heterogeneity embedded in our model allows us to investigate the (re)distributional effects of policy interventions across various population segments. Subsidies help mitigate liquidity constraints enabling adoption earlier in life. As a result, households that are younger, less wealthy, and more liquidity-constrained benefit more due to the reduction in upfront costs. This is particularly true under lump-sum subsidies; in the model nearly all households in smaller houses adopt the technology by retirement age. Lower electricity taxes on the other hand benefit wealthier households more and can have substantial unintended consequences on wealth inequality.

In our framework, the effectiveness of policy is influenced by uncertainty in commodity prices. Specifically, commodity price uncertainty has minimal impact on subsidy policies but significantly affects adoption dynamics under tax policies. This divergence can be explained by the inherent nature of subsidies. Since the subsidy directly reduces the upfront cost of green technologies, its attractiveness remains largely unaffected by changes in commodity prices, ensuring stable adoption rates even in volatile markets. In contrast, the dynamics under tax policies are markedly different. Taxes primarily target ongoing operational costs, which are directly influenced by the volatility of commodity prices. When commodity prices are uncertain, households face greater variability in potential savings from adopting energy-efficient technologies. This uncertainty discourages adoption, as future operating

[3]See https://www.gov.uk/government/news/demand-for-heat-pumps-surges-as-grant-application-increase-by-39.

costs become less predictable and households are risk averse. In fact, our results show that removing this uncertainty leads to a significant increase in adoption compared to baseline scenarios with higher commodity price volatility.

Despite the differences in aggregate adoption from different policies in the presence of commodity price uncertainty, the distributional effects of taxation and subsidy policies remain unchanged. Specifically, regardless of the level of commodity price volatility, taxes tend to favor more wealthy households that can more easily afford the upfront investment, while subsidies disproportionately favor lower-income households, that are more liquidity constrained. Thus, the distributional disparities between tax and subsidy policies persist, regardless of the level of uncertainty in commodity prices.

Related Literature Studies on the consequences of environmental policies have been growing significantly. Burr (2016), De Groote and Verboven (2019) and Feger, Pavanini, and Radulescu (2022) estimate structural models of green technology adoption and evaluate different policies. In the context of carbon pricing policies, Clara, Cocco, Naaraayanan, and Sharma (2022) investigate the role of regulation in green technology adoption, while Känzig (2023) shows that poor households are more affected by increases in carbon taxes than richer ones. Similarly, Glaeser, Gorback, and Poterba (2023) demonstrate that gasoline taxes are regressive and are expected to become increasingly so as wealthier households transition to electric vehicles, while Berkouwer and Dean (2022) show how credit constraints can prevent green technology adoption using data from Kenya.

We contribute to this discussion by presenting an analysis based on a quantitative structural model that explicitly takes into account the life cycle and the endogenous wealth distribution of households. Fried (2024) underscores the importance of incorporating household heterogeneity in evaluating environmental policies. Aggregate welfare losses can be substantially larger in a model with endogenous wealth heterogeneity compared to one with a representative household.

Our work is closely related to Kuhn and Schlattmann (2024) and Lanteri and Rampini (2023) in terms of economic mechanisms. The former examines household adoption of commitment goods in Germany, while the latter focuses on heterogeneous firms adopting clean technologies. Both studies highlight how the larger upfront costs of clean technologies cause financially constrained households or firms to delay investments more than their wealthier

counterparts.

Our contribution to this strand of the literature is twofold. First, we base our analysis on a uniquely detailed dataset on technology-specific parameters of efficiency and energy consumption, focusing on heating systems. Second, we emphasize the significant and distinct layers of uncertainty in these investments: the acquisition cost and the future energy price, particularly the comparison between electricity and fossil fuel alternatives.

The rest of the paper is structured as follows. Section 2 outlines the background on residential heating decarbonization. Section 3 introduces the theoretical model. Section 4 provides details on the calibration process. Section 5 present the baseline economy, without policy interventions. Section 6 conducts quantitative exploration through counterfactual policy experiments. Section 7 examine the role of commodity price uncertainty in shaping adoption decision. Section 8 explores robustness to different household preference parameters. Finally, Section 9 concludes. Technical details about the model, additional results, and information about the data sample are provided in the Appendix.

2 Background on Residential Heating Decarbonisation

There are multiple heating technologies that can help decarbonise the buildings sector and achieve net zero emissions. Among them heat pumps are recognised as the key technology (IEA, 2022). Invented in the 1850s, a heat pump extracts heat from a low temperature source, such as the ambient air, ground or water, and converts it or "pumps" it to a higher temperature that is suitable to provide hot water and heat buildings. Heat pumps use the same operating principle as refrigerators, cooling down the environment and heating buildings. They use electricity and are much more efficient than direct electric heaters or boilers (measured in units of useful output heat per units of input energy). If the electricity supplied to the system is derived from renewable or other zero carbon sources, heat pumps will produce zero carbon heat. But even if the electric grid is based on fossil fuels, there can be significant savings in fossil fuel consumption due to the high efficiency of heat pumps. Moreover, heat pumps can be used to heat buildings in the winter and cool them in the summer, thus also addressing the increasingly frequent heat waves.

The heat source plays an important role regarding efficiency and costs. Air-source heat pumps are the most popular choice for retrofits. They have a seasonal coefficient of perfor-

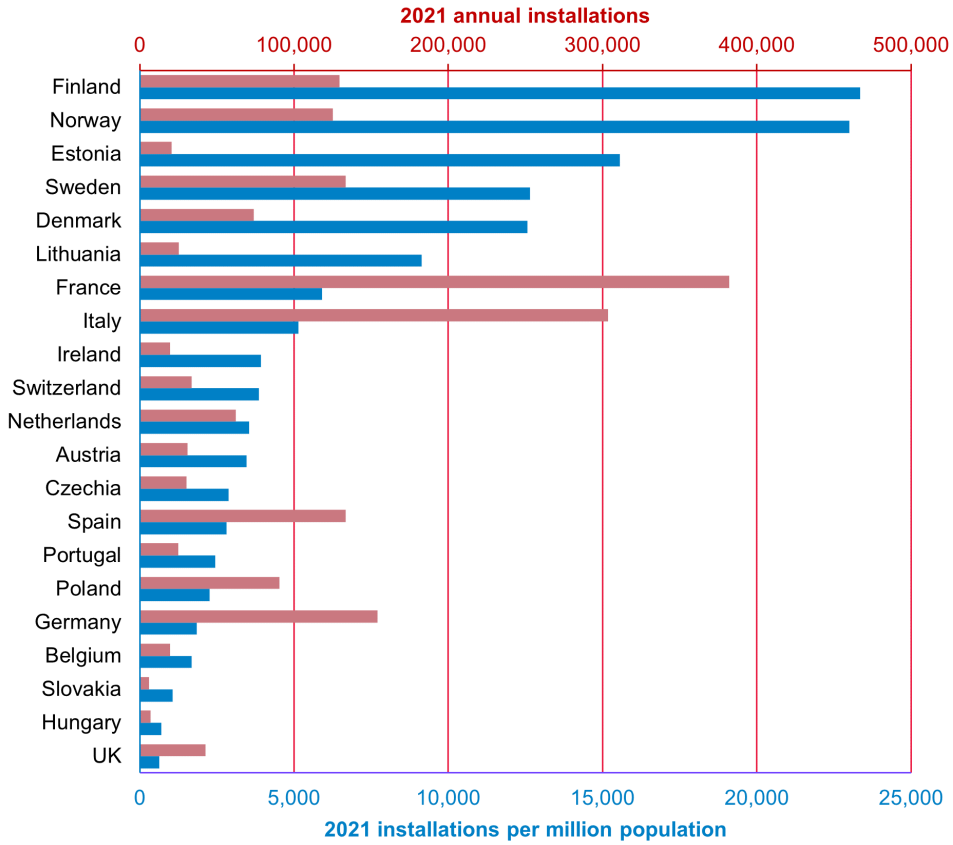
mance (SCOP) (demand-weighted annual average performance) of around 3, making them more than 3 times more energy efficient than gas boilers. Air-source heat pumps have lower capital costs than other heat pumps. Water- and ground-source heat pumps on the other hand are more expensive, but also more efficient (SCOP of around 4). Ground-source heat pumps require either a large area of land for a shallow heat collection loop, expensive deep borehole heat exchangers, or have the collector be embedded within the building foundation. Therefore, they are challenging for retrofitting the existing housing stock, but potentially advantageous in new buildings.

There were around 220 million heat pumps installed globally by the end of 2022, but the UK is lagging with just over 250,000 installations, representing less than 1% of all household heating systems. Norway is at the opposite end of heat pump penetration with nearly 60% of households having installed one. Figure 1 presents the heat pump markets in Europe as of 2021. The figure reports heat pump installations both in absolute numbers and per million of population. It highlights the UK's position at the bottom of the scale in terms of heat pump installations, underscoring the country's comparatively low adoption rate.

Among the policies designed to support and accelerate heat pump adoption are capital subsidies to cover the cost of purchasing and installing the unit, a subsidy to the electricity price (changing operating expense of running a heat pump), a fossil fuel tax (to make the alternative heating system more expensive), as well as energy efficiency standards and a direct ban on a fossil fuel system. For example, the UK government offers a capital subsidy of £7,500 per installation (increased from £5,000 in late 2023). Another potential fiscal intervention involves using the tax system to change the relative price of electricity to gas. Between 2011 and 2021, the UK electricity to gas price ratio was the third highest in Europe: 3.8 compared to 3.1 on average. Between 2018 and 2022 the gap has widened with UK electricity being on average 4.4 times more expensive than gas. Moreover, in the UK 25% of the household electricity bill constitutes environmental and social obligation costs, while gas bills do not have any such charge.

Figure 2 reports the average percentage of heat pump sales from 2018 to 2021, alongside the ratio of electricity to gas prices for various European countries. The figure illustrates that countries where the cost of electricity is high relative to gas tend to have lower heat pump sales percentages. This underscores the significant influence of energy prices on technology adoption decisions across different countries.

FIGURE 1: Heat pump markets in Europe (2021)



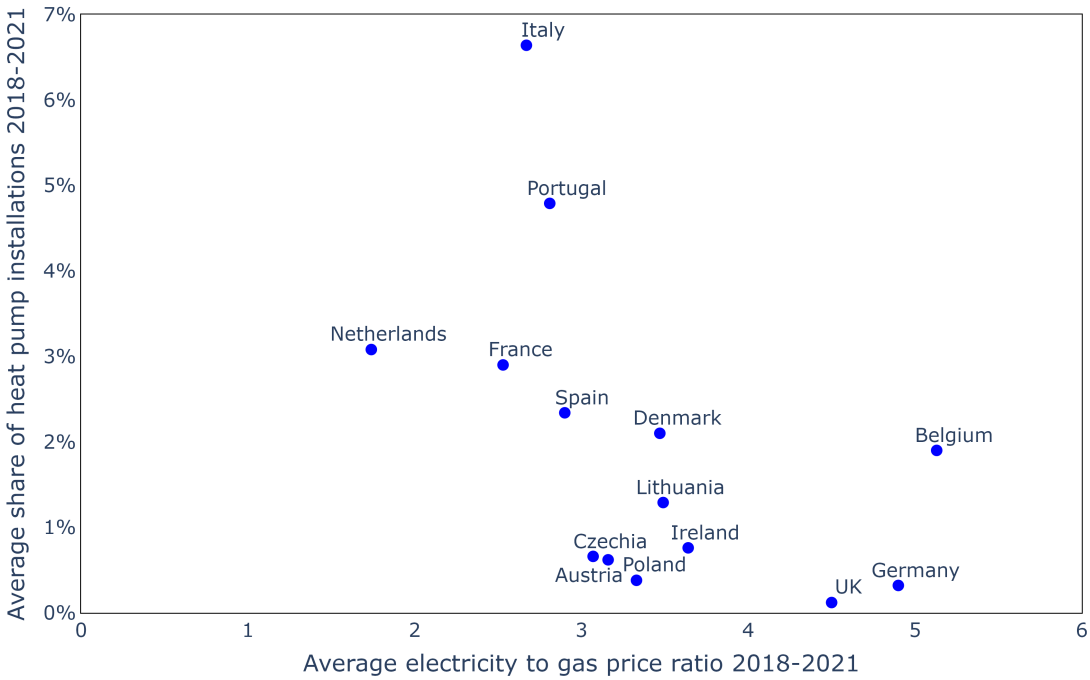
Note: Source: EHPA (2023) European Heat Pump Market and Statistics: Report 2022; UN (2023) 2022 Revision of World Population Prospects. Installation numbers are for 2021, population estimates are from 2022.

To achieve its net-zero ambition by 2050, the UK government has set targets for the installation of heat pumps. The Committee on Climate Change (CCC), an advisory body on climate change, recommends that by 2028, 10% of UK households should have heat pumps installed. Furthermore, the CCC suggests that by 2030, the total number of heat pumps installed across the UK should exceed 4.7 million, covering approximately 17% of all households. Figure 3 reports the CCC's proposed targets for heat pump installations in the UK over the next decade. The dashed red line emphasizes the 10% adoption rate targeted for the next 5 years (2028). One of our main contributions is to investigate, through a quantitative model, the policies that need to be implemented to achieve this goal.[4]

In summary, there is much lower green technology adoption in the UK than in other

[4]We note that not all existing buildings would be able to adopt the technology. So called listed buildings, which constitute between 1 and 2% of all buildings across the UK, are of historic value, and often are subject to stringent planning application rules, and may not be able to upgrade the dwellings to the required energy efficiency standard to enable the satisfactory functioning of the heat pump technology.

FIGURE 2: Average heat pumps sales (%) and ratio of electricity to gas (2018-2021)



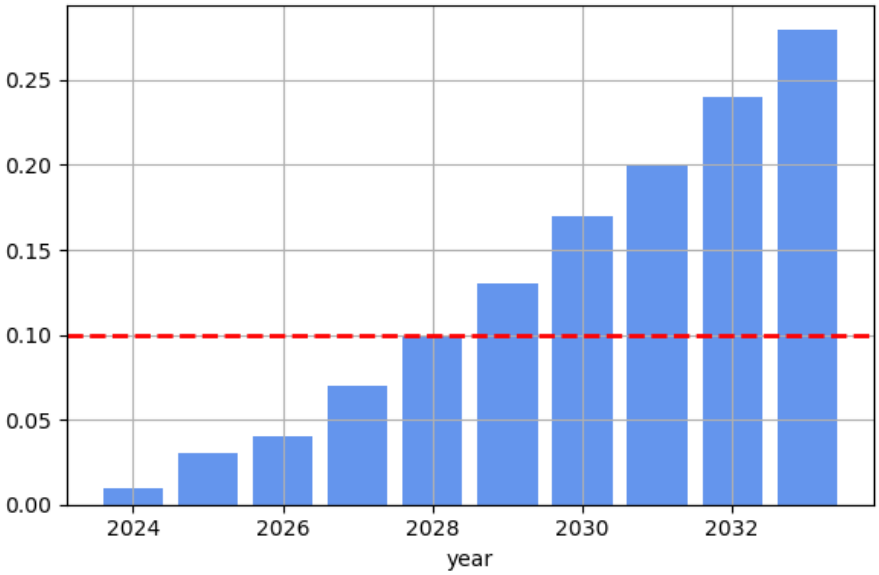
Note: Source: Eurostat, DUKES for UK data post 2019. Link to data source.

countries. Factors preventing uptake include both the high fixed cost of installation and the high variable cost (a high relative price of electricity to gas) associated with running the technology. Announced policies focus on addressing these two factors. Our quantitative life-cycle model allows us to evaluate these policies and provide estimates of likely fiscal costs.

3 Model

Individuals start their economic life at the age of $tb = 25$ and retire at $tr = 65$, with the possibility of living up to the age of $td = 100$. In the model, the variable t indicates the individual's age, where each period $\tilde{t}$ is equivalent to $t - tb$. From 25 to 65 years (working life), households supply labor inelastically. The total population of individuals lives in N different house sizes, indicated as i. These dwellings differ from each other according to the varying heating requirements $q(i)$. In every period, individuals make decisions about consumption, c, saving, a, and choose whether to replace their heating technology by switching to an electric heating system $h = \{g, f\}$ where g stands for an electric-heating system (green

FIGURE 3: CCC Heat Pumps Installation Target



Note: The figure illustrates the target adoption rate of heat pumps in the UK as recommended by the Committee on Climate Change (CCC). The dashed red line highlights the 10% adoption rate targeted for the next 5 years, which will serve as the benchmark in the model. Source: CCC

technology), and f for a fossil fuel heating system.[5]

All individuals are initially endowed with fossil fuel heating technology. In each period, they have the opportunity to invest in a more efficient green and electricity-powered technology. Once this choice is made, it becomes permanent and cannot be altered in subsequent periods. These assumptions align with the focus of our study. Firstly, we focus on *premature adoption* rather than *end-of-life* adoption. This means that we assume that it is a proactive decision of individuals to transition to a new heating technology before the end of the lifespan of their current system, as opposed to waiting until it reaches the end of its usable life (*end-of-life* adoption). This reflects the reality that transitioning heating systems require advance planning. Unlike sudden replacements due to equipment failure, the decision to switch from a fossil-fueled heating system to an electricity-powered technology entails significant preparatory work within the house. Second, we assume that this choice is permanent and irreversible. This assumption is justified given our target time horizon of 5-10 years, which is notably shorter than the typical lifespan of a heat pump (20-25 years).

[5]The theoretical model addresses the investment decisions of owner-occupiers, where the same persons bear the cost of installation and the cost of operating the heating systems. A large share of the housing stock is, however, in the rental market, and presents a different challenge: the house owner would incur the capital cost, while the lessees would have to cover the operating costs. Owner-occupiers represent around 65% of all homes. Private landlords account for approximately 18%, with the rest divided between council homes (owned by the local authorities) and cooperatives. We ignore this complication at this stage of our research and make the assumption that the costs and benefits and correctly internalized if the costs and benefits accrue to different economic agents.

Individuals are exposed to nondiversifiable labor income risk and face borrowing limits. Their decisions about consumption, savings, and investment are constrained by the borrowing limit and a budget constraint.

Preferences and Budget Constraint Individuals maximize their utility over their lifetime, subject to budget constraints. The period utility takes the form:

$$u(c) = \left(\frac{c}{1-\gamma}\right)^{(1-\gamma)} \tag{1}$$

where γ is the coefficient of constant relative risk aversion. We model only homeowners and assume that housing services enter separably in the utility function and can be taken as exogenous.

For each class of housing size i, the budget constraint depends on assets, labor income, heating technology, and whether they choose to invest in the most sustainable and efficient technology. Formally, it is:

$$e^h + c + a' + \mathbb{I}(\chi_1 P(q_i) - \chi_2) = y + (1+r)a \tag{2}$$

Here, e^h represents the annual individual expenditure for heating, y is the individual's income, a represents a risk-free asset, and r the rate of return on this asset. Expenses that individuals incur if they decide to invest in the electric heating system are denoted by $(\chi_1 P(q_i) - \chi_2)$, and $\mathbb{I}$ is an indicator variable that takes the value 1 if they choose to adopt the new technology and 0 otherwise. In the equation, χ_1 and χ_2 are two policy instruments; χ_1 is a proportional subsidy to the acquisition price and χ_2 is a lump-sum subsidy, while $P(q_i)$ represents the acquisition price.

The acquisition price is a function of the individual's heating demand that depends on the size of the heating technology, which, in turn, depends on the household's heating demand (house size):

$$P(q_i) = \nu_1 + \nu_2 [Peak(q_i)]^{1+\zeta} + \epsilon^P \tag{3}$$

where ν_1 is the fixed component of the total cost. This specification includes both the base cost of installing the technology and any adjustments required to integrate it into the household's existing infrastructure. The coefficient ν_2 defines the variable cost component of the

acquisition price, which is dependent on the size of the required heating technology, which, in turn, is a function of the size of the house. In fact, $Peak(q_i)$ represents the peak heating demand of the household, which drives the size of the heating technology, and ζ is a parameter governing the relationship between the heating demand and the size of the heating technology. Finally, ϵ^P is a random variable capturing the uncertainty in the installation cost. This uncertainty arises from households not having exact information about the total cost before installation. It mainly captures factors such as unforeseen adjustments needed during installation. The distribution of ϵ^P reflects the range of potential deviations from the fixed cost ν_1 that households may encounter. In the calibration section, additional details are provided regarding the assumptions underlying this functional form and the specific values assigned to the parameters.

Heating expenditure An individual's heating expenditure consists of a fixed component and a variable component, the latter contingent on energy consumption and influenced by the technology in use. Formally:

$$e^h = 365\omega^h + (1+\tau^h)\frac{q_i}{\phi^h}p^h \tag{4}$$

In equation (4), ω^h represents the energy standing charge, which is multiplied by 365, as it is a fixed daily fee individuals pay to access the energy grid, and this can be different for the fossil fuel and electricity grids. The parameter τ^h represents the tax on energy consumption, applied as a percentage of the energy consumed. It directly influences the variable component of heating expenditure, and therefore scales with the quantity of energy used. This tax varies depending on the type of fuel used. In simulated policy scenarios τ^h can transition from 0 to negative values, implying a shift from no tax to a situation where consumers receive a tax-credit for using energy-efficient heating technologies.

The total demand for heating is denoted by q_i, while the parameter ϕ specifies how many units of fuel (fossil fuel or electricity) are required to produce 1 kWh of heat. Consequently, a higher value of ϕ indicates a less efficient technology. The fuel price is denoted by p^h. Both the price of electricity p^g and the price of fossil fuel p^f are assumed to follow an AR(1) model to capture the dynamics of these prices over time. In particular:

$$\log(p_t^h) = \rho_{p^h}\log(p_{t-1}^h) + \varepsilon_{p^h,t} \tag{5}$$

where $\varepsilon_{p^h,t} \sim \mathcal{N}(\mu_{p^h}, \sigma^2_{p^h})$, for $h = g, f$.

It is important to note that adoption may not be economically justifiable if the user cost is not significantly lower. The trade-off between the two technologies becomes apparent only when the positive acquisition price is balanced by reduced heating expenditure from utilising the clean technology.

Asset holdings Individuals save in a one period risk-free asset that delivers the rate of return r. Current bond holdings are denoted a. Asset accumulation is subject to the credit constraint:

$$a \geq -\underline{a}$$

where $\underline{a} \geq 0$ is an exogenous credit limit.

Individual income process Prior to retirement, an individual's income is a function of age t and individual labor productivity l:

$$y = g_i(t) \cdot l \tag{6}$$

The function $g_i(t)$ is a deterministic function of age, capturing the typical hump-shaped profile in life cycle labor income. It is important to note that $g(t)$ varies across different i, indicating that individuals residing in different housing types also experience distinct life cycle income growth profiles.

The stochastic process for labor productivity is the product of a persistent component and a transitory shock:

$$l = z \cdot \epsilon \tag{7}$$

where ϵ is log-normal with $log(\epsilon) \sim \mathcal{N}(0, \sigma^2_\epsilon)$, and $z_t \in Z$, follows a Markov chain with n_z states. The realization of this chain can take values from the set $Z = \{z_1, z_2, \ldots, z_{n_z}\}$. The transitions between these states are determined by the matrix $\Pi(z|z')$, which is obtained discretizing the following AR(1) process for log-z:

$$\log(z_t) = \rho \log(z_{t-1}) + \varepsilon_{z,t} \tag{8}$$

where $\varepsilon_{z,t} \sim \mathcal{N}(\mu_z, \sigma_z^2)$.

During retirement, an individual's income is defined as:

$$y = \kappa \cdot l_{tr}$$

Here, $\kappa \in (0, 1)$ represents the replacement ratio and l_{tr} is the individual labor income upon retirement.

Recursive formulation The Bellman equation of the individuals owning a green technology, $h = g$ is:

$$V_i^g(a, z, p^g, t) = \max_{c,a'} u(c) + \beta\varphi(t)\, \mathbb{E}_{l',p^{g'}}[V_i^g(a', z', p^{g'}, t')]. \tag{9}$$

In equation (9), β represents the discount factor, and $\varphi(t)$ denotes the probability of surviving from age t to age t', conditional on having survived until age t. Note that, given the assumption that adoption is an irreversible choice, individuals who have adopted the technology in any previous period no longer face any discrete choices. Their choice set is simply how to allocate resources between saving and consumption.

The Bellman equation of the households that in period t own a fossil fuel technology, and are not adopting is:

$$V_i^f(a, z, p^f, t) = \max_{c,a'} u(c) + \beta\varphi(t)\, \mathbb{E}_{l',p^{f'}}[V_i^f(a'z', p^{f'}, t')]. \tag{10}$$

Adoption decision Every period, households owning a fossil fuel technology face the choice whether to switch to the green option or keep the current one. The decision is based on comparing the value of continuing without adopting $V_i^f(a, l, t)$ to the value of switching, taking into account the initial investment cost implied by adopting $P(q_i)$ and other variable costs. Formally, for each level of housing size i:

$$V_i(a, z, p^f, p^g, t) = max[V_i^f(a, z, p^f, t), V_i^g(a - P, z, p^g, t)] \tag{11}$$

Note that in a complete markets economy with frictionless financing, the adoption decision is simple. Since households can spread the required down payment to transition

to clean technology, the decision focusses primarily on the relative heating expenditures between conventional and green technologies. Consequently, the promise of future energy cost savings universally motivates adoption across all households, regardless of their wealth status. Conversely, within the model, borrowing constraints give rise to a positive correlation between wealth and adoption. Households with greater financial resources are more likely to overcome borrowing constraints and thus adopt the green technology at a higher rate compared to less wealthy households.

4 Calibration

In this section, we describe the calibration strategy used for the quantitative exercise. The values of the baseline parameters are reported in Table 1. We calibrate the model to the United Kingdom because in this country these policies have been discussed and partly implemented and the abundance of data allows a quantitative calibration. We set the base year at 2020.

In Panel A of Table 1, the discount factor β is set to 0.98 to match the average wealth in the baseline economy, while the risk aversion parameter γ is set to 5, and the annual risk-free rate at 2%. In the following sections, we will explore how changes in these parameters influence model outcomes. We will analyze the sensitivity of wealth accumulation and its subsequent impact on adoption patterns to variations in discount factor, risk aversion, and idiosyncratic productivity processes. These comparative statics are intended to both understand the model better but also provide insight into the robustness of our model in capturing the dynamics of individual decision-making.

Panel B in Table 1 outlines the parameters governing idiosyncratic productivity processes. Here, σ_ϵ and μ_ϵ represent the variance and the mean of the i.i.d. component of labour income, while σ_z and μ_z denote the variance and mean, of the persistent component of labour income. Furthermore, ρ_z represents the persistence of the idiosyncratic productivity process. The parameters in Panel C of Table 1 govern the life span and career trajectory of households within the model. The parameter κ represents the proportion of earnings replaced by retirement income and is set at 0.68. The maximum number of years an individual can live, denoted by td, is set to 100. Furthermore, tb, representing the first year of work, is set at 25. The retirement age, denoted as tr, is set at 65.

TABLE 1: Baseline calibration: Preferences and Life Cycle

Parameter	Value	Description
Panel A: Preferences and interest rate		
γ	5	risk aversion
β	0.98	discount factor
r	0.02	return risk free asset
Panel B: Idiosyncratic productivity process		
σ_ϵ	0.1	s.d. i.i.d component
σ_z	0.1	s.d. persist. component
μ_ϵ	0	mean i.i.d component
μ_z	0	mean persist. component
ρ_z	0.9	persistence
Panel C: Life Cycle		
κ	0.68	replacement ratio
td	100	max end of life year
tb	25	first year of work
tr	65	retirement age

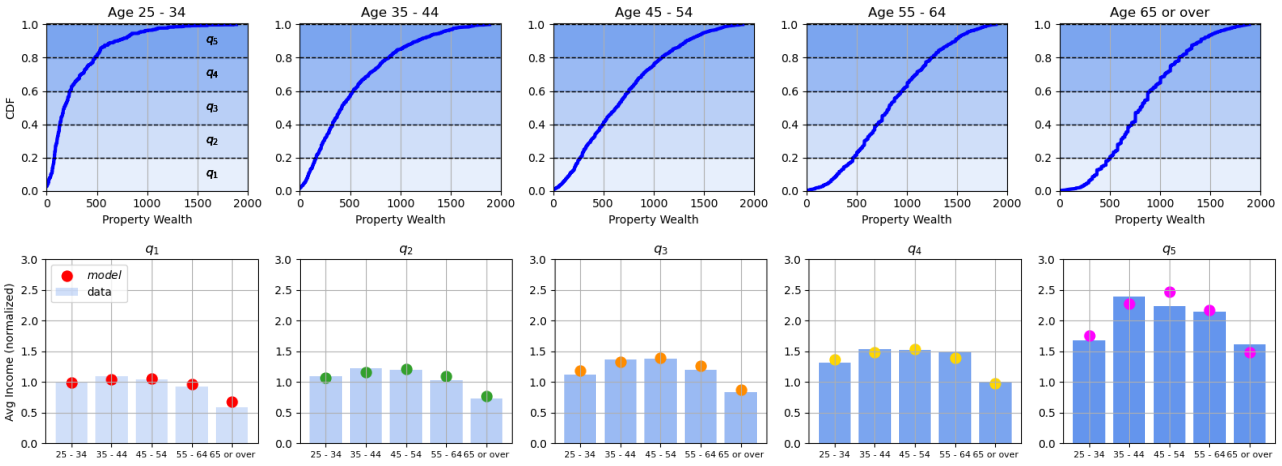
Note: The table summarizes the baseline calibration parameters for preferences and the life cycle.

To capture essential features in our model, such as heterogeneous income profiles among households within different housing sizes and heating demands, we leverage micro data at the household level from two distinct sources. We use the Wealth and Asset Survey (WAS) dataset that provides detailed individual-level information on income, housing, financial assets, and demographic characteristics such as age. We use the WAS data to calibrate the life cycle component of the individual income process. We also use the English Housing Survey (EHS) dataset which includes household financial and demographic information, but also offers unit-level details about the dwelling. The use of the EHS data allows us to allocate heating demand to each housing sizes in our model. Finally, to ensure a focused analysis aligned with the context of heat pump adoption, we have restricted our dataset to individuals who are homeowners. This decision is based on the assumption that the decision to install a heat pump is made predominantly by homeowners.[6]

As defined in Eq. (6), household's income during the working-age period consists of two components: a deterministic part that is a function of age and a stochastic part. We select the parameters of $g(t)$ to align the model with the income pattern over the life cycle observed in the WAS data. In (WAS) dataset, age is categorized into six groups: 16-24, 25-34,

[6]Details on the data provided in the Appendix.

FIGURE 4: Housing distribution and Labor Income over the life cycle

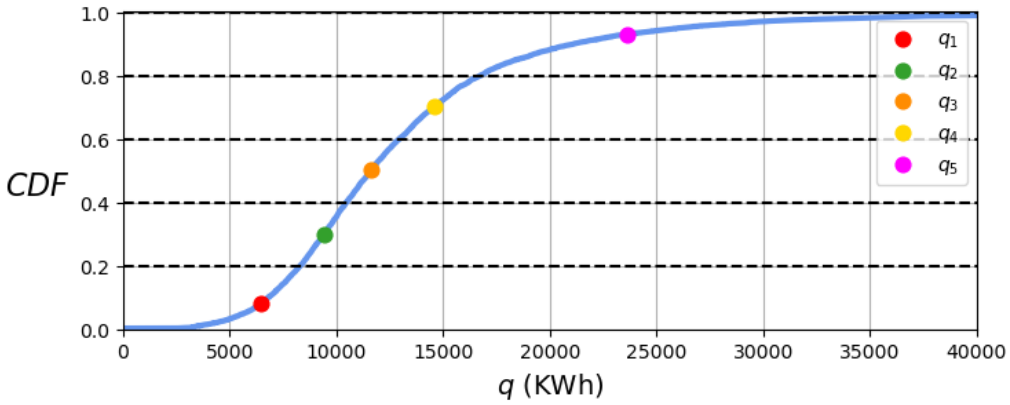


Note: Cumulative distribution of housing for different age groups (top panel). Household labor income over the life cycle (bottom panel): Data vs. calibration. Data Source: Wealth and Asset Survey

35-44, 45-54, 55-64, and 65 and over. Notably, we exclude the first category (16-24) from our analysis due to the limited number of observations once conditioning on home-ownership. Within each age group, we compute the distribution of housing. Subsequently, for each age group, we calculate the average income for each quintile. This process enables us to capture the variation in labor income across different levels of housing within specific age cohorts and calibrate the income process accordingly. Hence, we select the parameter values of the function g such that our model closely matches the data. Figure 4 plots the exogenous model assumptions and their empirical counterparts. The top panels present the cumulative distribution of housing across the five age groups, which is an input in the model. These panels emphasize the quintile division within each age group, older households tend to have larger houses for each quintile. The bottom panel offers a visual comparison between the calibrated labor income process and the data. It shows the average income in the data for each quintile and age group using bar graphs and the calibrated income process (represented by dots).

Heating Demand In this section, we explain the methodology used to establish the configuration of five nodes for the heating demand, denoted (q_i), with (i) ranging from 1 to 5. Each node (q_i) is representative of the average heating demand within its respective quintile, determined by the distribution of the heating demand between homeowners. Figure 5 illustrates the cumulative distribution function (CDF) of the heating demand for homeowners.

FIGURE 5: Owners' heating demand distribution



Note: Heating demand distribution. The five circles are the average heating demand for five quintiles based on the English Housing Survey.

To obtain this distribution, we leverage the Cambridge Housing Model,[7] which is based on the English Housing Survey (EHS). This data set contains information on 14,951 representative English dwellings, and these are weighted so that their cumulative total is equal to the overall number of dwellings in England, which stands at 22.8 million. The data set contains detailed information on various characteristics of the dwelling, based on which the heating demand is estimated using a Standard Assessment Procedure (SAP) method. The SAP method is the standardised heat-loss calculation method for buildings in the UK. Finally, filtering the data set for homeowners only, we construct the distribution of heating demand. Figure 5 shows the distribution function, with each point indicating the values corresponding to each quintile, q_i.

Acquisition price Recall the acquisition price for heat pumps defined in Eq. (3):

$$P(q_i) = \nu_1 + \nu_2[Peak(q_i)]^{1+\zeta} + \epsilon^P$$

where ν_1 is the fixed installation cost of heat pumps, which we set to 5,000 GBP based on data from the UK Department of Business, Energy & Industrial strategy (BEIS)[8] on the installation costs of domestic heating technologies. The two parameters that describe the correlation between heat pump cost and size are determined based on market data of heat pumps in the UK.[9] Based on a regression of technology costs versus nameplate capacity, ν_2 is set equal to 1300.4 GBP/kW, and ζ is equal to -0.419. The random variable ϵ^P captures

[7] `https://www.gov.uk/government/publications/cambridge-housing-model-and-user-guide`.
[8] `https://www.gov.uk/government/publications/cambridge-housing-model-and-user-guide`.
[9] Olympios, Mersch, Sapin, Pantaleo, and Markides (2021).

TABLE 2: Baseline calibration: Heating Expenditure and Policy Measures

Parameter	Value	Description
Panel A: Acquisition Price		
ν_1	£ 5,000	installation fix component
ν_2	0.076	installation variable component
ζ	-0.419	exponential variable component
Panel B: Heating Expenditure		
ω^g	0	electricity standing charge
ω^f	0.3	gas standing charge
ϕ^g	2.93	HP efficiency
ϕ^f	0.85	gas boiler efficiency
Panel C: Energy Prices		
ρ_{p^g}	0.9	persistence of electricity price
ρ_{p^f}	0.9	persistence of fossil fuel price
σ_{p^g}	0.1	standard deviation of electricity price
σ_{p^f}	0.1	standard deviation of fossil fuel price
μ_{p^g}	0.2424	mean of electricity price (exp)
μ_{p^f}	0.07	mean of fossil fuel price (exp)
Panel D: Policy Instruments (baseline)		
$\tau^{g,f}$	0	tax on fuel (gas,electricity)
$\chi_{1,2}$	0	adoption subsidy (proportional, lump-sum)

Note: The table summarizes the calibration for parameters related to the acquisition price of heat pumps and the heating demand associated with heat pumps and gas boilers, respectively.

the uncertainty component of the installation price. It follows a discretized uniform distribution with five equally spaced nodes based on the range for installation cost provided by BEIS.

The size of the heat pump depends on the peak of the heating demand in a year and therefore *Peak(q)* is an estimate of the highest heating demand required by a dwelling over one year. It is calculated based on the annual heat demand of the buildings shown in Figure 5, and the hourly heat demand profile calculated using the method of Watson, Lomas, and Buswell (2019).

Heating Expenditure The heating expenditure is as defined in Eq. (4)

$$e^h = 365\omega^h + \frac{q}{\phi^h} p^h$$

with ω^h being the energy standing charge (GBP per day), p^h the unit price (GBP per kWh), q the heat demand and ϕ^h the energy efficiency of the technology. Electricity standing charges and gas standing charges are fixed daily fees that consumers pay to their energy suppliers regardless of how much electricity or gas they actually use. These charges are separate from the unit price of electricity or gas and are designed to cover the costs associated with providing and maintaining the energy supply infrastructure, customer service, and administrative overhead.

For this study we assume that customers always have to pay the electricity standing charge. Therefore, the costs are not specifically attributed to the heat pump and the parameter is set to zero. However, for natural gas, it is assumed that buildings would be able to disconnect from the gas grid if switching to heat pumps, saving standing charge. The implicit assumption is that no gas is being used for cooking or other purposes. Therefore, the natural gas standing charge is specifically attributed to the gas boiler. The value here is taken from the price cap [10] set by the UK energy regulator OFGEM.

$$\omega^h = \begin{cases} 0 & \text{if } h = g \\ 0.30 & \text{if } h = f \end{cases}$$

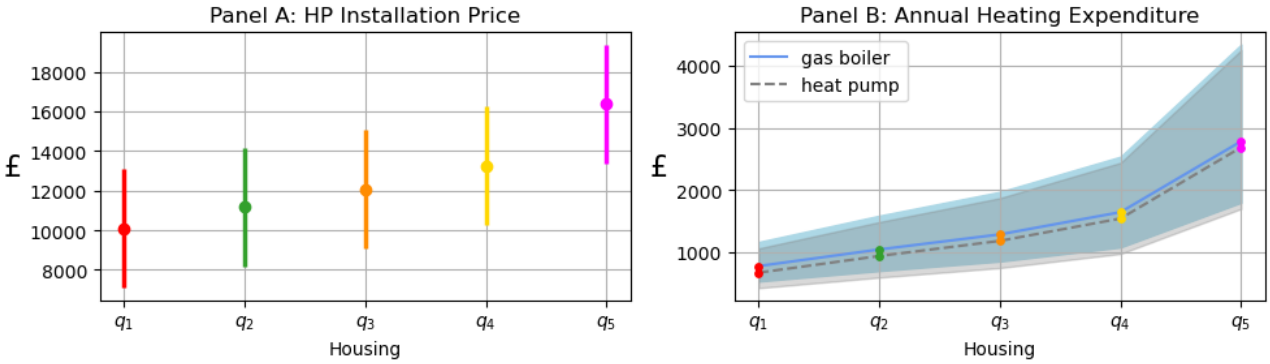
The efficiency parameter of the heat pump is assumed to be equal to the seasonal coefficient of performance (SCOP) of an average UK home. To account for interannual variation, it is determined from UK weather data for a typical meteorological year. The efficiency-temperature correlation developed by Olympios et al. (2021) is used to calculate the performance during each hour of the year based on the ambient temperature. These hourly performance values are then weighted with the corresponding heat demand to calculate the SCOP. For boilers, an efficiency of 85% is assumed:

$$\phi^h = \begin{cases} 2.93 & \text{if } h = g \\ 0.85 & \text{if } h = f \end{cases}$$

The average of the electricity price is determined based on the "Cosy Octopus" rate[11] designed for heat pumps, using a central London location. It is assumed here that half of

[10] https://www.ofgem.gov.uk/information-consumers/energy-advice-households/energy-price-cap
[11] https://octopus.energy/smart/cosy-octopus/

FIGURE 6: Installation price and heating expenditure across the 5 housing sizes



Note: **Panel A** illustrates the installation prices of heat pumps for each housing size. The error bars denote the range of possible prices. **Panel B** shows the annual heating expenditure by housing size. The shaded bands represent the range of variation in expenditure, with the lighter blue band denoting the variability for gas boilers and the lighter gray band representing the same for heat pumps. The solid line traces the heating expenditure associated with gas boilers, while the dashed line delineates the expenditure linked to heat pumps, at their respective average values.

the electricity is consumed during off-peak hours and the other half during regular hours, while the peak hours are avoided. Gas prices are based on the OFGEM price cap:[12]

$$\mu_{ph} = \begin{cases} \frac{1}{2}0.1818\frac{\text{GBP}}{\text{kWh}} + \frac{1}{2}0.303\frac{\text{GBP}}{\text{kWh}} & \text{if } h = g, \\ 0.07\frac{\text{GBP}}{\text{kWh}} & \text{if } h = f \end{cases}$$

In the model, we make the simplifying assumption that the gas price and electricity price have a correlation coefficient of 1. This assumption is based on empirical data, where we find a very high correlation between wholesale (day-ahead) electricity and gas prices over the last 5 years. Specifically, the correlation coefficient between these prices is reported to be 98.4% when analyzed on a monthly basis. Moreover, when considering retail prices for average household energy consumption, which includes elements like the standing charge and variable costs, the correlation remains remarkably high at 96.6%. This interdependence between the two commodities prices stems from the reliance on natural gas as a primary fuel source for electricity generation. Consequently, fluctuations in gas prices directly influence the cost of producing electricity, leading to a close alignment between gas and electricity prices in the market. Therefore, the assumption of a correlation coefficient of 1 in the model reflects this fundamental relationship, capturing the intrinsic linkages that exist within the energy market.

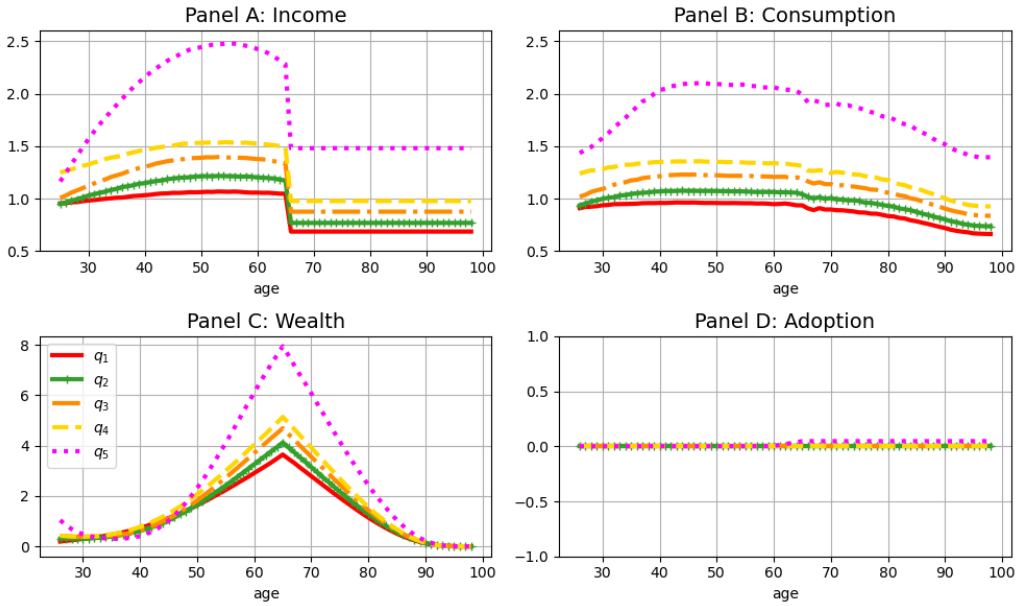
[12] `https://www.ofgem.gov.uk/information-consumers/energy-advice-households/energy-price-cap`.

Figure 6 shows the installation price of the heat pump (Panel A) and the annual heating expenditure for heat pumps and gas boilers (Panel B). The dots in Panel A represent the installation price and associated expenditure for each quintile. We add the uniform distribution illustrating the uncertainty associated with installation costs for each quintile. Panel B shows the associated heating expenditure of each technology and each quintile, and also shows the associated uncertainty emanating from the commodity prices.

5 Quantitative Results

5.1 Baseline Economy

FIGURE 7: Baseline Economy, no policy intervention



Note: Relevant values are scaled relative to the annual average initial labor income of households in the housing size q_1 in the cohort of individuals aged between 25 and 35.

The life-cycle profiles from the baseline economy are shown in Figure 7 for the five different housing sizes. As shown in the first panel of figure 7 (Panel A), the (exogenous) average labor income across the five housing sizes differs not only in scale, but also in growth rates. Households in the lowest quintile (q_1) start at age 25 with a lower income than those in any other quintile and have a lower growth rate as they age. Panel B displays the (endogenous) average consumption over the life cycle, mirroring the income process but exhibiting a smoother trajectory. This smoothness is achieved through wealth accumulation, as depicted in Panel C. During working age, households accumulate wealth for precautionary saving and consumption smoothing, anticipating a decline in income post-retirement. As

expected, after retirement, households gradually decumulate their wealth. Finally, Panel D in the figure illustrates the adoption rate, revealing that, without any policy support, adoption is almost zero.

5.2 Households Preferences

In this section, the focus is on conducting a series of experiments designed to enhance the understanding of the underlying mechanisms that drive adoption decisions among the 5 heterogeneous housing sizes and over the life cycle within the model. Central to this investigation is the consideration that in this framework wealth serves as a primary channel (or barrier) influencing adoption. At the same time, wealth also serves as a device by which households auto-insure themselves against labour income fluctuations, given their inability to borrow. As this mechanism operates, adoption becomes a contender to use wealth to fund the initial investment in installation. Hence, it is crucial to explore how assumptions about preferences in intertemporal consumption, consumption smoothness, and parameters related to the income process influence households decisions about saving and adoption. This, in turn, has potentially significant implications for the overall effectiveness of policies aimed at promoting adoption. To scrutinize the model's outcomes in this respect, we explore variations in the assumed values of preference parameters and the interest rate.

Specifically, we explore two alternative calibrations, one with higher discount factor (β increasing to 0.99 from 0.98 in the baseline calibration)., the second with lower risk aversion ($\gamma = 2$ instead of $\gamma = 5$ as in the baseline. Regarding the first case, in the model higher discount factor leads to higher average wealth, while lower risk aversion results in lower wealth. When examining the effect of these different specifications on adoption behavior, we observe minimal variation, with aggregate adoption remaining nearly zero. This trend holds true for all housing types except for q_5, where a small increase in adoption is observed.

6 Assessing Policy Intervention on Adoption

We use the model economy as a laboratory to examine how various fiscal measures influence household adoption decisions. We assess the efficiency of these measures by evaluating their costs relative to their effectiveness in achieving the desired level of adoption. After examining the impact of the different policies, our framework allows us to evaluate the heterogeneous effects of these fiscal measures on different segments of the population, including

various demographics and housing size. This comprehensive approach allows us to also understand the (unintended) redistributional implications of each policy. In this section, we present these results.

The initial set of policies under examination focusses on incentivising adoption by mitigating the upfront cost barrier. This is achieved by reducing the initial financial burden associated with adoption, which is defined as the installation price in the model. Within this framework, two subsidy types are devised: a lump sum subsidy, which remains constant across all households, and a subsidy proportional to the technology's installation cost. The latter implies that households with higher installation costs, particularly those with greater heating demands (and larger houses), receive larger subsidies.

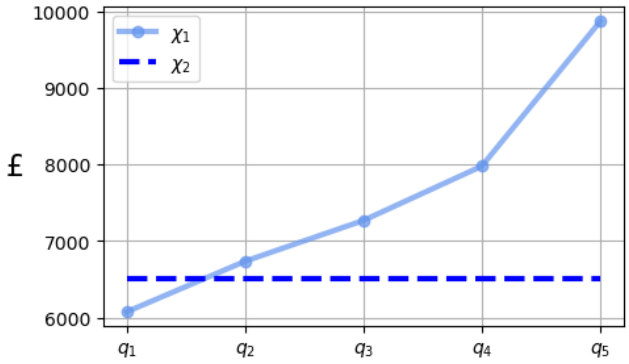
The second set of policies diverges from the first by focussing on heating expenditure rather than upfront investment costs. Instead of focussing on the upfront cost barrier, this policy changes the relative running costs of the two technologies. Within this new framework, we explore changes in tax rates on electricity and gas consumption to make heating with electricity relatively cheaper.

6.1 Evaluating Subsidies

The first fiscal incentives under examination are subsidies to adopt, represented by parameters χ_1 and χ_2 in Eq (2). These two policy tools are designed to encourage adoption by reducing initial capital investment. χ_1 is a proportional subsidy that covers a fixed percentage of installation costs, meaning that the transfer will be higher for households with higher heating demands. In contrast, χ_2 is a lump sum subsidy that provides a fixed amount regardless of installation costs.

In this exercise, the values of χ_1 and χ_2 are chosen to achieve the same adoption rate in the economy. In particular, the goal is to align with the proposition of U.K. Climate Change Committee (CCC) of heat pump adoption of 10% in 5 years. To achieve this objective, the selected value for χ_1 is 0.6, indicating that the subsidy covers 60% of the installation cost, with actual values ranging from £6,048 for households in the first housing group to £9,827 for households in the fifth group. Alternatively, the target can be achieved by granting a lump-sum subsidy of χ_2=£6,498. Figure 8 reports the transfer received upon installation for each housing size, and under the two different type of subsidies (the solid increasing line for the proportional subsidy and the constant dotted line for the lump-sum subsidy).

FIGURE 8: Comparison of transfers under different installation subsidy schemes



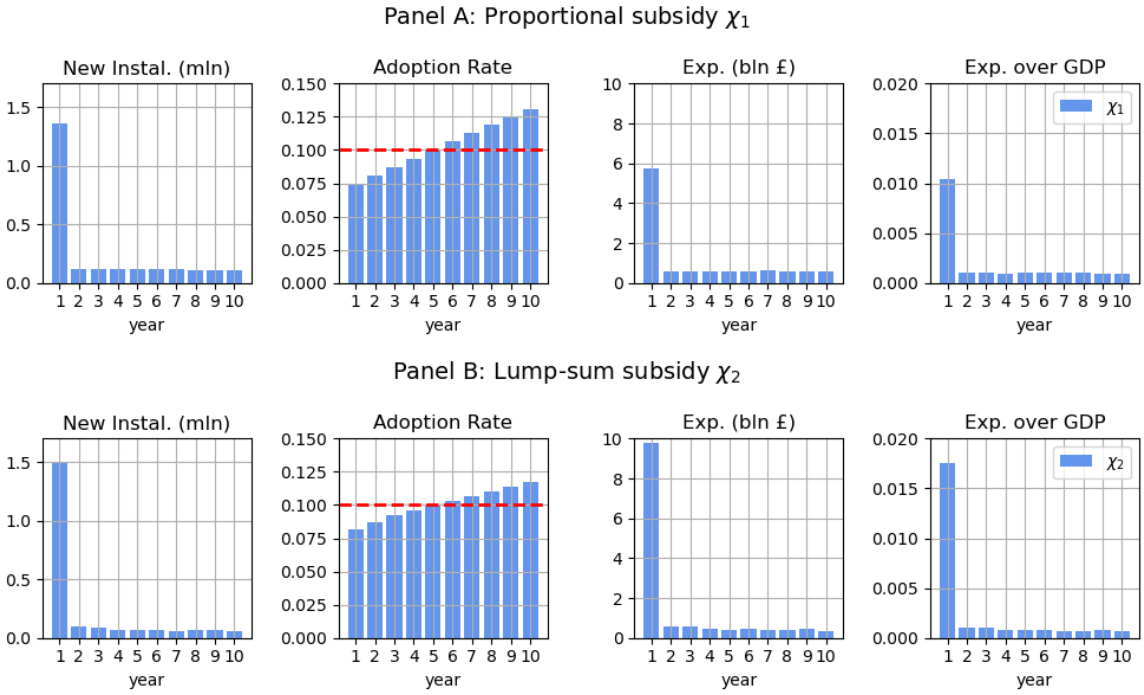
Note: Transfers to households implied by two different types of subsidies across five housing types. The solid line represents transfers under a proportional subsidy (χ_1), while the dashed line is the constant transfer amount of a lump-sum subsidy (χ_2).

Figure 9 presents the results of two policy scenarios in terms of the aggregate adoption rate and expenditure. Note that this analysis involves aggregation across various cohorts of individuals. Given that in the data we only have information on the range of ages in a specific group (eg 25-34), we first categorise households into five cohorts: those who are 25, 35, 45, 55, and 65 years old at the time t_0. To reflect the demographic composition of the population, we weight each cohort according to the age distribution in our data set (Figure B.18 in the appendix).

Panel A (B) shows the effects of the proportional (lump-sum) subsidy. The first two plots on the left show the adoption dynamics and indicate that the installation dynamics under the two policy scenarios are very similar. There is an initial significant uptake in the first year for either policy, followed by a more gradual uptake for the following years. Note that in the model, the initial uptake is too large due to the assumption of perfectly elastic supply, an assumption that might not be satisfied in practice. Without considering supply constraints, the model may overestimate the immediate adoption of the policy since it assumes that everyone who desires to adopt can do so without limitations. However, factors such as resource availability, infrastructure limitations, and production capacities can significantly impact the initial uptake. Therefore, while the model may show a substantial initial uptake, the actual adoption rate could be slower and more constrained by supply side limitations.

The second column presents the cumulative adoption rate for each year (the share of households adopting). Even if the policy instrument achieves a 10% adoption rate in 5 years, as aligned with the target for reaching net-zero, the policy's impact on adoption falls short

FIGURE 9: Effects of proportional and lump-sum subsidies



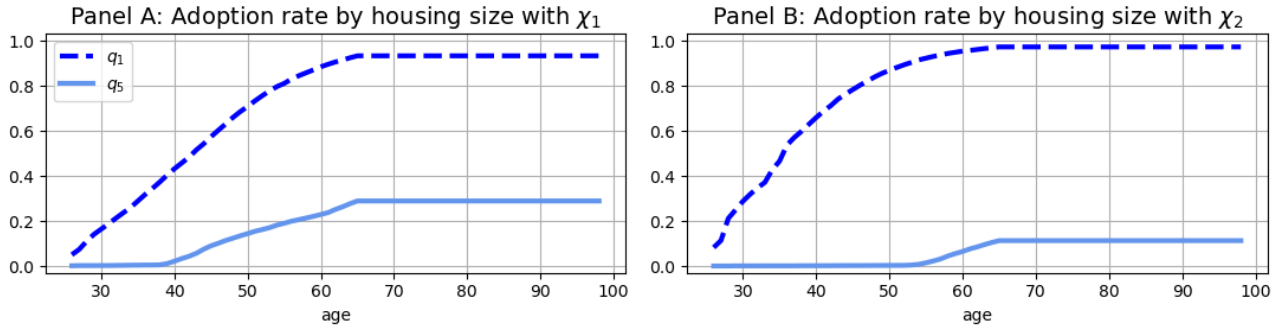
Note: Panel A reports outcomes on installation, adoption rates and fiscal costs related to the proportional subsidy (χ_1). **Panel B** refers to the policy scenario with the lump-sum subsidy (χ_2). To calculate the absolute number of installations and total expenditure in £, we use the household population figure corresponding to the UK population in 2022. The dotted line is the target for net-zero according to The Climate Change Committee (CCC).

of the target over a longer time period. According to the Climate Change Committee, adoption rates need to reach 30% within 10 years to attain net-zero emissions. However, in our model economy, adoption only reaches less than 13% within this time frame for either policy. This upper bound on cumulative adoption rates persists across all the policy experiments considered in our analysis, as we will show later.

The figures on the fiscal cost related to both policies are shown on the third and fourth columns and they reflect the installation uptake. The third column is in levels reflects the new installations graph, and the costs in terms of GDP follow a similar pattern. The differences in fiscal costs across the different policies arise because adoption rates vary across different size houses.

The difference in fiscal expenditure at time $t = 1$ between the two types of subsidies comes from two factors. First, the number of households adopting the technology under the χ_2 program is greater. Second, under χ_2, adoption is predominantly concentrated within housing group q_1, where the transfer amount for this group in the lump-sum subsidy scenario is higher than that provided in the proportional subsidy program. Consequently, the

FIGURE 10: Heterogeneous Adoption under two subsidy schemes



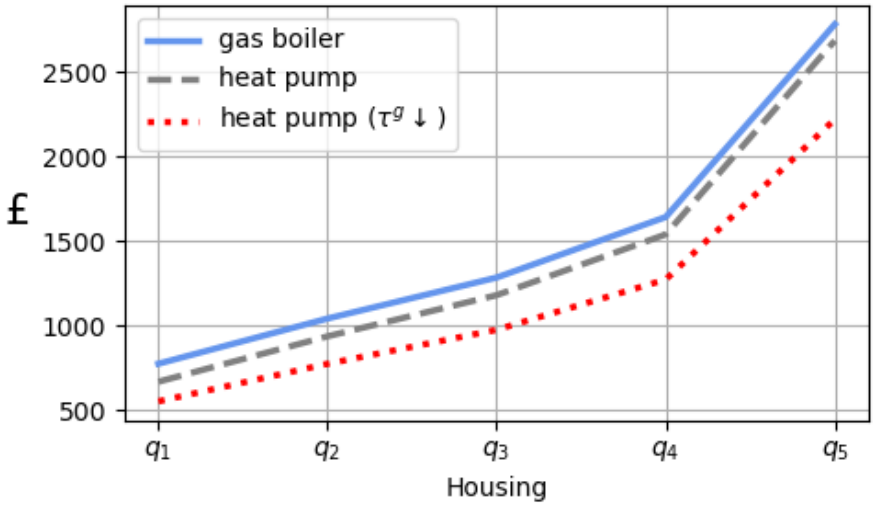
Note: Panel A illustrates adoption rates over the life-cycle with proportional subsidies χ_1 for two housing groups: q_1 (dashed dark blue line) and q_5 (solid light blue line). Similarly, **Panel B** displays adoption rates over the life-cycle for the same two housing groups, but under the scenario of lump-sum subsidies χ_2.

combination of a larger number of adopters, mainly from q_1, and higher transfer amounts per household in this housing group results in a significantly greater fiscal burden for the lump-sum subsidy program at this initial stage. Table A.4 in the appendix provides a detailed breakdown of the number of new installations and the associated fiscal expenditure by housing group at time $t = 1$.

Figure 10 shows adoption across different housing size under the two subsidy schemes. Panel A shows adoption rates over the life-cycle with proportional subsidies χ_1 for the smallest housing size, q_1 (dashed dark blue line), and the largest size, q_5 (solid light blue line). Panel B presents adoption rates over the life-cycle for the same two housing groups under the scenario of lump-sum subsidies χ_2. As presented in the figure, adoption patterns exhibit similarities across the two types of subsidies, with households in smaller houses (q_1) adopting more readily compared to those in larger houses (q_5). This trend is particularly pronounced in the case of lump-sum subsidies. By retirement, nearly all households in q_1 have adopted the technology, whereas less than 20% of households in q_5 have done so. Whereas, under proportional subsidies, approximately 90% of households in q_1 have adopted, and over 20% of households in q_5 have followed suit. Furthermore, the analysis reveals that technology uptake occurs at an earlier stage of life for q_1 households under lump-sum subsidies, whereas the opposite trend is observed for proportional subsidies, where technology adoption tends to occur earlier for q_5 households under proportional subsidies.

These results underscore the critical role of liquidity constraints in adoption dynamics. Subsidies effectively alleviate liquidity constraints, enabling households to overcome financial barriers and adopt the technology. Notably, lump-sum subsidies have an even more

FIGURE 11: Households' annual heating expenditure



Note: This plot compares the annual heating expenditure for different housing types using a gas boiler and a heat pump. The x-axis represents different the housing types, while the y-axis represents the annual expenditure in pounds (£). The annual expenditure for heating using a gas boiler is represented by the blue line. The dashed gray line represents the annual expenditure for heating using a heat pump. The dotted red line shows the annual expenditure for heating using a heat pump with a decreased τ^g (tax on electricity price). We assumed an electricity price of £0.2424 and a gas price of £0.07, which are consistent with the assumptions made during the simulations.

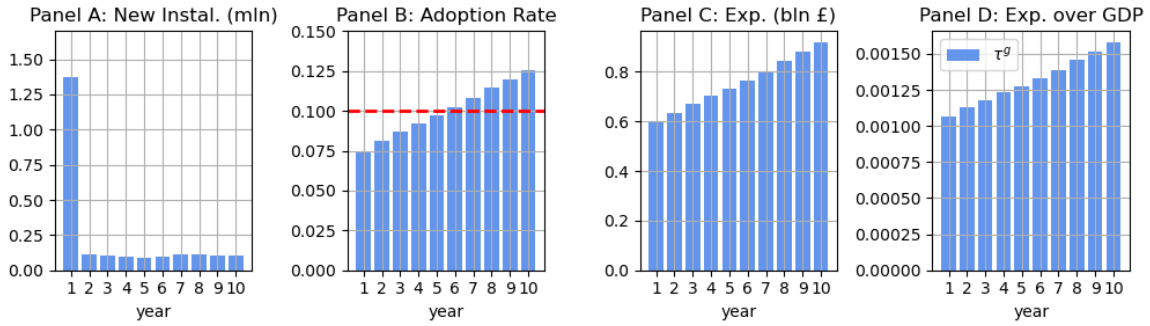
pronounced impact on the less wealthy segment of the population, particularly younger individuals residing in smaller households. It is worth recalling that in the model, housing size, wealth, and income are all positively correlated.

6.2 Evaluating taxation policies

Another approach to incentivize technology adoption is by manipulating the relative running cost of heating associated with each technology. In the model, this can be achieved by adjusting the tax rates for electricity and gas consumption, denoted as τ^g and τ^f, respectively. Specifically, decreasing τ^g or increasing τ^f both lead to a reduction in the cost of heating with electricity compared to heating with gas. It is worth noting that although these measures have opposite fiscal implications - reducing τ^g entails a fiscal expenditure while increasing τ^f generates revenue - what matters for adoption is the relative expenditure ratio which can be equivalently influenced by either policy change.

In this experiment, we focus solely on the effects of reducing τ^g, aligning with the approach taken in previous exercises of promoting adoption by providing incentives for adoption, contrary to disincentivizing non-adoption. In addition, reducing the tax rate on electricity is seen as more politically feasible than increasing taxation on gas consumption. It is

FIGURE 12: Fiscal expenditure and adoption under τ^g change



Note: The figure reports outcomes on installation, adoption rates and fiscal costs related to the change in electricity consumption tax rate ($\tau^g < 0$). To calculate the absolute number of installations and total expenditure in £, we use the household population figure corresponding to the UK population in 2022. The dotted line is the target for net-zero according to The Climate Change Committee (CCC).

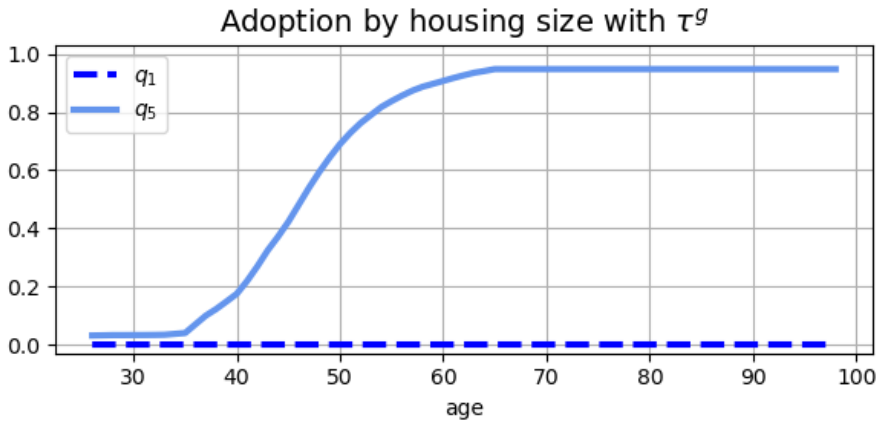
important to note that both policies, whether reducing τ^g or increasing τ^f, produce similar results in terms of adoption outcomes both at the aggregate level and across heterogeneous groups in the population. Therefore, the insights derived from this analysis also apply to the increasing scenario τ^f. Figure A.16 in the appendix provides a detailed view of the adoption dynamics associated with an increase in τ^f,

Figure 11 illustrates the impact of a change in τ^g on households' annual heating expenditure for each housing group. The selected τ^g is chosen to achieve a 10% adoption rate within 5 years, in line with the previous experiments. In the model, to reach this adoption rate, the price of electricity needs to be reduced by almost 20%, $\tau^g = -0.17$. Due to different heating needs across housing, this policy leads to different amounts of saving gained from switching to the green technology. In particular, the change in τ^g leads to savings increasing across housing groups within a range of £222 for households in housing group q_1, up to £562 annually in the electricity bill for households in housing group q_5.

Figure 12 shows the dynamics of adoption and the associated expenditure resulting from the change in τ^g. Adoption remains consistent with patterns seen in previous experiments, showing a significant uptake in the first period the policy is in place, followed by gradual growth over time. However, the magnitude and dynamics of fiscal expenditure in this scenario are notably different.

In the initial year, the fiscal cost is significantly lower compared to the subsidy scenario. Despite both scenarios witnessing similar adoption rates, the financial incentive provided to households through reduced electricity expenditure is notably lower compared to the subsidies received. However, unlike the subsidy scenario, in this case, the fiscal cost exhibits

FIGURE 13: Adoption dynamics under electricity tax variation



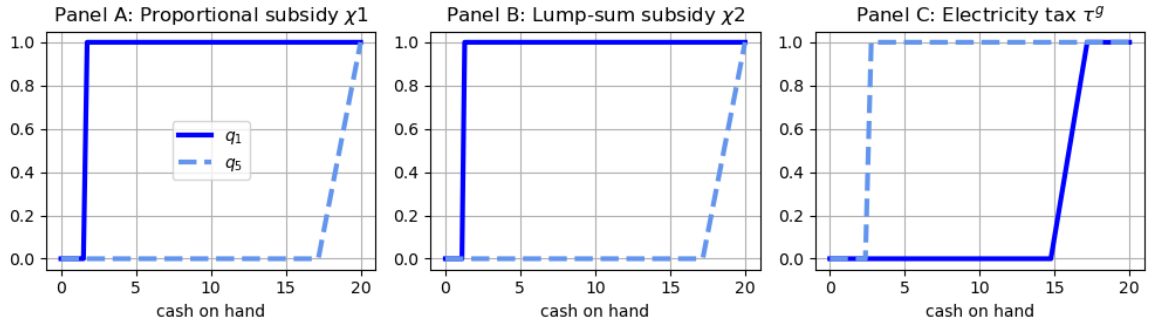
Note: The figure reports adoption rates for two housing size, q_1 (dashed blue line), and q_5 (solid light blue line), over the life-cycle, corresponding to a variation in electricity tax rate τ^g.

an upward-sloping dynamic. This occurs because the fiscal expenditure increases over time in response to the growing number of installations. Unlike subsidies, which target new adopters, the transfer associated with τ^g is distributed to all households with heat pumps, contributing to the rising expenditure as the penetration of the new technology in the economy increases. Consequently, over a decade, the cumulative fiscal burden of the tax cut approach aligns with that of subsidies.

Moreover, note that the fiscal costs associated with this policy might be underestimated in our model. This is because, unlike in the model, the reduction in electricity taxation would apply to the entire electricity consumption of households, not solely to electricity associated with heating. Therefore, the value derived from this experiment should be interpreted as the lower bound of the actual expenditure the government would face if implementing this policy.

The adoption dynamics depicted in Figure 13 shed light on the impact of the change in the electricity tax rate (τ^g) on households of different housing sizes. Notably, the figure shows adoption rates for two housing sizes, q_1 (dashed blue line) and q_5 (solid light blue line), over the life-cycle. Unlike subsidies, this policy promotes adoption among the largest houses (q_5). This can be attributed to several factors. Firstly, the savings gained from adopting a new technology increase with heating demand, and consequently with housing size, as showed in the previous figure. Additionally, this policy does not address the liquidity constraint problem. Given the correlation in the model between housing size and wealth, smaller houses (q_1), which are also less wealthy and more liquidity-constrained, do

FIGURE 14: Policy functions under different policy scenarios



Note: The figure illustrates households adoption policy function. Each subplot represents a different policy scenario: proportional subsidy (χ_1), lump-sum subsidy (χ_2), and electricity tax (τ^g). Solid lines depict adoption rates for housing size q_1, while dashed lines represent housing size q_5. The x axes reports cash on hand, while on the y axes adoption is represented by the value of one, while non-adoption is represented by the value of zero.

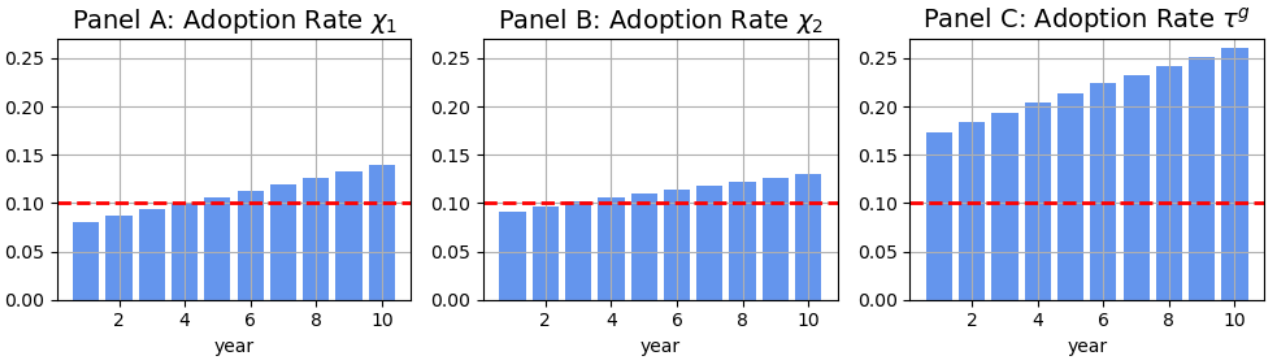
not adopt under this policy. Moreover, even among the largest houses, adoption tends to occur later in life. This delay in adoption among younger households, even within the group of wealthiest households residing in larger houses, is again attributed to liquidity constraints. As younger households are more liquidity-constrained, adoption under this policy occurs later in life as they accumulate wealth.

Figure 14 offers additional insights into how the different policy scenarios impact household adoption decisions. Each panel in the figure displays the adoption policy function for three distinct policy scenarios: proportional subsidy (χ_1), lump-sum subsidy (χ_2), and electricity tax (τ_e).

The solid lines depict adoption rates for households in housing size q_1, while the dashed lines represent households in housing size q_5. It is evident from the figure that households in q_1 tend to adopt more. Conversely, households in q_5 exhibit higher adoption under the electricity tax policy. Notably, in all cases, the poorest households never adopt, highlighting the persistent challenge of affordability and liquidity constraints faced by these households in adopting energy-efficient technologies.

Figure A.17 in the appendix shows both the share of adopters under each policy by housing group and the associated financial transfers, offering further insight into the distributional and cumulative financial impacts of each policy scenario across housing groups.

FIGURE 15: Adoption with no commodity price uncertainty



Note: The three panels report aggregate adoption rates in the model economy with no uncertainty on the commodity prices, corresponding to the level of subsidy (**Panel A** and **Panel B**) and taxes (**Panel C**) that achieve a 10% adoption rate in the baseline model economy.

7 Understanding the role of commodity price uncertainty

To delve deeper into the dynamics of adoption across different policy regimes, we conducted additional experiments focusing on the role of commodity price uncertainty. Specifically, we reassessed the subsidy and tax cut scenarios while eliminating uncertainty in commodity prices. Figure 15 depicts the total adoption associated with each policy instrument in an economy without commodity price uncertainty.

As illustrated in the figure, commodity price uncertainty has minimal impact on subsidy policies, but it significantly influences adoption dynamics under tax policies. This divergence can be attributed to the nature of subsidy policies, which provide a fixed financial incentive to households regardless of fluctuations in commodity prices. Thus, the certainty or uncertainty of commodity prices does not alter the attractiveness of subsidies to potential adopters.

In contrast, commodity price uncertainty emerges as a critical factor in shaping adoption dynamics under the tax policy. By removing uncertainty in commodity prices, we observed a significant increase in adoption compared to the baseline scenario. When commodity prices are uncertain, households face greater variability in the potential savings associated with adopting energy-efficient technologies. Therefore, reducing uncertainty in commodity prices enhances the predictability of the financial benefits derived from adopting such technologies under tax policies.

8 Robustness to Different Preferences

TABLE 3: Comparison of adoption under different risk aversion and discount factor

	Baseline γ=5 β=0.98	**Higher discount factor** γ=5 β=0.99	**Lower risk aversion** γ=2 β=0.98
χ_1	0.10	0.16	0.02
χ_2	0.10	0.14	0.05
τ^e	0.10	0.15	0.04

Note: The values reported in the table refers to adoption rate at time t_5

In this section, we explore the implications of varying the value of household risk aversion and discount factors on the examined policy scenarios. We specifically investigate how these changes influence adoption within the model economy. The assumption on households' risk aversion and discount factor impact household behavior in terms of wealth accumulation and investment decisions. These are particularly relevant given the uncertainties embedded within the model. Testing for lower risk aversion is crucial for understanding how households make decisions under uncertainty. Moreover, lower risk aversion leads households to accumulate less wealth, leaving them more likely to face liquidity constraints. On the other hand, a higher discount factor prompts households to accumulate more wealth, potentially mitigating the financial barrier to adoption associated with upfront installation costs. Furthermore, a higher discount factor directly influences adoption as households become more inclined to invest in the technology, attributing greater value to future cost savings.

Table 3, presents the outcome of this investigation, comparing adoption rates under different levels of household risk aversion and discount factors. The adoption rates reported in the table refer to year 5, which is the target year in the model. The policy instruments $\chi 1$, $\chi 2$, and τ_g are the ones that lead to 10% adoption in year 5. The values reported in the table indicate how adoption rates change when keeping the policy instrument constant while varying one preference parameter at a time.

The baseline scenario represents the adoption rates when the risk aversion parameter γ is set to 5 and the discount factor β is 0.98. When we increase the discount factor to 0.99 while keeping risk aversion constant, adoption rates notably rise across all policy instruments. Conversely, when we lower risk aversion to 2 while maintaining the discount factor at 0.98, adoption rates decrease significantly. These results underscore the sensitivity of adoption

outcomes to individual risk preferences and the time preference for future utility.

Despite these adjustments, the fundamental mechanism of the model remains unchanged. Consequently, the adoption patterns over the life-cycle, and across the housing groups persist, maintaining consistency with the earlier analysis. In fact, while preference specifications influence the magnitude of fiscal instruments and their associated costs, they wield less influence over understanding adoption decisions and the redistributional impact of policies. Despite variations in preference parameters, the primary mechanisms remain unchanged. Consequently, while precise parameter values are essential for quantitative accuracy, they play a less important role in elucidating the underlying drivers and mechanisms of adoption and redistribution.

9 Conclusion

We employ a quantitative life-cycle model calibrated to UK data to investigate the determinants of green technology adoption, focusing particularly on heat pumps, a key solution for reducing residential carbon emissions. The analysis explores adoption rates under various economic policies, considering both subsidies targeting upfront investment costs and adjustments in tax rates to modify running costs. Our findings reveal that achieving a target adoption rate of 10% within 5 years requires subsidies or a significant reduction in electricity prices compared to the current economic environment.

All the policies have distributional consequences revealing a strong correlation between adoption rates, wealth levels, and housing sizes. We find that adjustments in electricity tax rates result in higher adoption rates among households owning larger houses, while lump sum subsidies tend to benefit households owning smaller houses. However, regardless of the policy scenario, wealthier households consistently exhibit higher adoption rates, primarily due to their greater financial capacity to absorb upfront costs, emphasizing the significant role of financial constraints as a barrier to adoption.

These insights provide valuable guidance for policymakers aiming to design effective and equitable interventions to accelerate the transition to green technologies. Recognizing the heterogeneity within the population is pivotal for fostering widespread adoption and propelling the transition to sustainable solutions across all groups in the economy. In countries where households may face even tighter liquidity constraints, we expect these policy

trade-offs will then be even stronger.

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Appendices

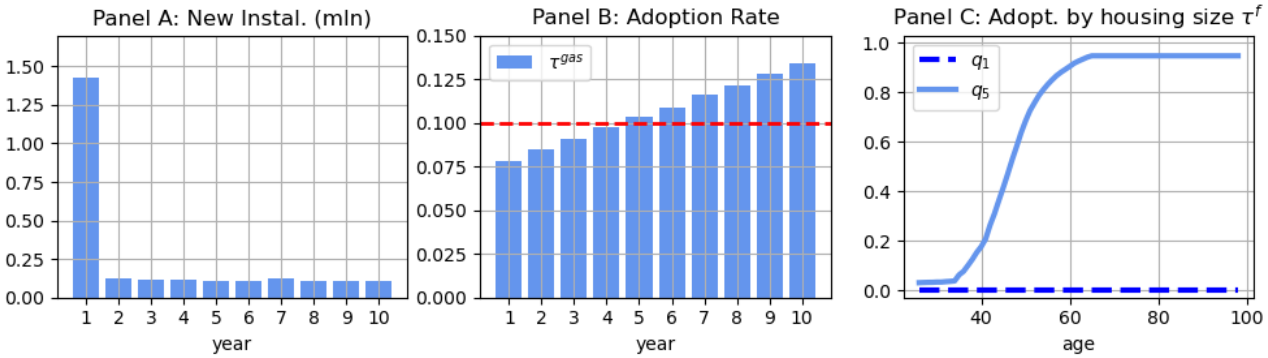
A Additional results

TABLE A.4: Installations and Fiscal Expenditure by Housing Group ($t = 1$)

Housing	**New Installations (in mln)**		**Expenditure (in mln)**	
	χ_1	χ_2	χ_1	χ_2
q1	1.16	1.46	4.65	9.47
q2	0.07	0.0004	0.33	0.0025
q3	0.0001	0	0.0004	0
q4	0.008	0	0.043	0
q5	0.10	0.04	0.69	0.27
Total	**1.34**	**1.50**	**5.72**	**9.74**

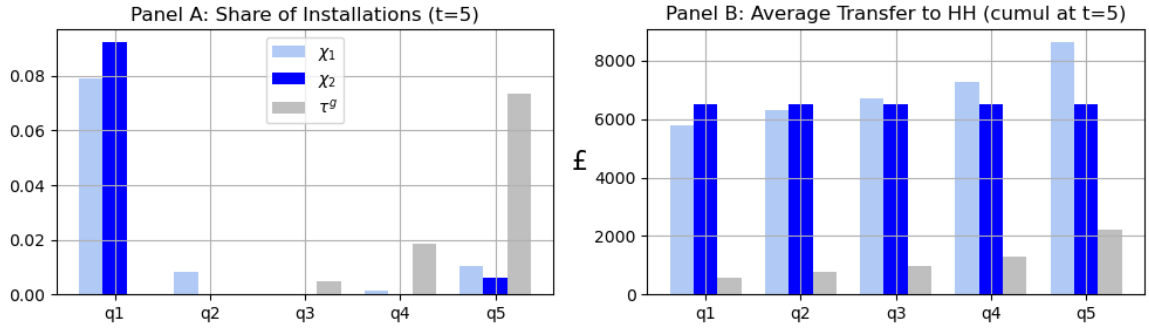
Note: The table compares the number of new installations and the associated fiscal expenditure for two types of subsidies across five housing groups. The columns labeled χ_1 correspond to proportional subsidies, while those labeled χ_2 correspond to lump-sum subsidies. All figures are presented in millions.

FIGURE A.16: Fiscal expenditure and adoption under τ^g change



Note: The figure reports outcomes on installation (Panel A), adoption rates (Panel B) associated to the change in gas consumption tax rate ($\tau^f > 0$). To calculate the absolute number of installations and total expenditure in £, we use the household population figure corresponding to the UK population in 2022. The dotted line is the target for net-zero according to The Climate Change Committee (CCC). Panel C in the figure reports adoption rates for two housing size, $q1$ (dashed blue line), and $q5$ (solid light blue line), over the life-cycle, corresponding to a variation in gas tax rate τ^f.

FIGURE A.17: Adoption rates and fiscal transfers by housing group under different policies



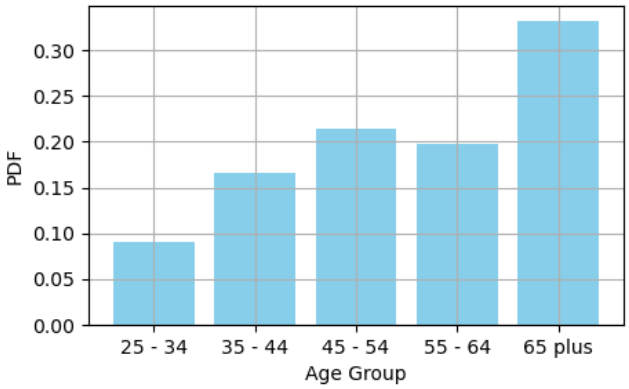
Note: In the figure, Panel A shows the proportion of households in each housing group ($q1$ to $q5$) that adopted green technology by time 5, under three policy scenarios. The light blue bars represent the proportional subsidy policy (χ_1); dark blue bars show adoption under a lump-sum subsidy (χ_2); and gray bars represent adoption due to an electricity tax cut (τ_g). Panel B displays the average fiscal transfer to households that adopted green technology, accumulated over five years ($t = 1$ to $t = 5$) across policies and housing groups. For the subsidy policies (χ_1 and χ_2), the cumulative transfer represents a one-time subsidy at adoption, whereas for the tax cut policy (τ_g), it represents the discounted total of savings on electricity bills over five years.

B Wealth and Asset Survey Data

The Wealth and Assets Survey (WAS) is a longitudinal survey that collects information concerning all forms of assets held by individuals within private households, including their financial wealth, housing, physical wealth, and private pension wealth. In this paper, we utilize data from wave 5 of the survey, which corresponds to the year 2020.

Figure B.18 displays the age distribution of homeowners based on the WAS data from wave 5. This distribution provides information about the demographic composition of homeowners in the dataset, and is used to compute aggregate variables in the main analysis.

FIGURE B.18: Age distribution of homeowners



Note: The plot presents the distribution of ages among homeowners in the surveyed population. The x-axis represents age groups, while the y-axis indicates the proportion of homeowners within each age group.

C EHS Data

The second source of input data is the English Housing Survey (EHS) dataset. The EHS releases data in two combinations; both will be used here: The EHS household data set and the EHS housing stock data.

EHS Household Dataset 2020 - 2021 Household interviews achieved 7,474 (significantly fewer than in previous years due to data collection during COVID). Grossing factors have to be used to weigh the data to produce national estimates. Weighted cases represent 23.958 million households.

EHS Housing Stock Data 2010 - 2011 In 2011, the English Housing Survey (EHS) provided data on 14,951 representative English dwellings. Each of these 14,951 cases represents a specific quantity of dwellings in England. These representations are weighted to ensure that their cumulative total is equal to the overall number of dwellings in England, which stands at 22.8 million.

C.1 Household Dataset

TABLE C.5: Share of households by tenure

	Owners	**Private Renter**	**Social Renter**
Share	0.65	0.18	0.17
Avg Total income (GBP)	47,428	38,607	22,241

C.2 Housing Stock Dataset: Owner Occupied Sample

TABLE C.6: Owner Occupied Dwellings by Type

	Flat (purpose built)	**Flat (converted)**
Share	0.06	0.02
Heating Demand (KWh)	6006	10519
Floor Area (m2)	63	82
	Semi-Detached	**Detached**
Share	0.33	0.31
Heating Demand (KWh)	12835	16481
Floor Area (m2)	101	147
	Mid-terrace	**End-terrace**
Share	0.17	0.10
Heating Demand (KWh)	11030	12696
Floor Area (m2)	90	95

Table C.6 provides an overview of statistics related to different types of residence within our data set, conditional on the ownership. The first row present the proportional representation of each building type within the sample. The second row illustrates the average heating demand associated with each category of buildings, while the third row outlines the average floor area for these same types of buildings.

It is particularly noteworthy that semi-detached and detached houses are prevalent within the data set.

When considering the heating demands, detached and semi-detached houses emerge as the main consumers of energy for heating, suggesting a correlation between the type of home and the heating requirements. This correlation may also be attributed to dwelling size. In fact, when considering average floor areas, detached houses claim the most substantial spaces, with an average of 147 square units, while purpose-built flats have the most modest floor area and also the lowest heating demand, averaging at 63 square units.

Table C.7 provides a view of the geographical coverage of the data-set, having owner occupied dwellings categorised by region. South East emerges as a region with the highest representation, accounting for 17% of the data set. In contrast, the North East exhibits the lowest representation at 5%.

Upon examination of heating demands, Yorkshire and the Humber and the North West

TABLE C.7: Owner occupied Dwelling by Region

	East Midlands	**East of England**	**London**	**North East**	**North West**
Share	0.09	0.12	0.11	0.05	0.14
Heating Demand (KWh)	13418	12442	12729	13204	14366
Floor Area (m2)	111	111	102	104	109
	South East	**South West**	**West Midlands**	**Yorkshire and The Humber**	
Share	0.17	0.11	0.11	0.10	
Heating Demand (KWh)	12194	12558	13042	14810	
Floor Area (m2)	109	117	108	105	

regions show the highest average demand, while London exhibits the lowest demand at 10,197.5 KWh. Finally, considering floor area, the South West region has the most extensive living spaces, with average floor areas of 117 square metres. Conversely, London has the smallest average floor area at 102 square meters.