Advancing energy justice

Integrating recognition justice in the HESTIA model to address energy poverty

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by

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https://github.com/Idedroog/Thesis-RecognitionJustice

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Preface

This thesis marks the end of my almost six-year journey at the Faculty of Technology, Policy and Management at TU Delft. I am incredibly grateful for my time at TU Delft, the amazing opportunities it gave me, the knowledge I gained and the people I met. Six years ago, I started with no idea what I would want to do with the rest of my life. Today, I am happy to say that I have found my purpose. I am committed to advancing the energy transition to support a more sustainable and resilient future.

To me, this thesis reflects that. While it may not focus on large-scale projects for renewable energy production, it highlights something equally important: ensuring that everyone has a fair opportunity to participate in the energy transition. A sustainable future isn't truly sustainable if it isn't just.

"All models are wrong, some are useful ..."
– George Box (1979)

Many times during this thesis, I questioned whether what I was doing was truly useful, whether the assumptions I made oversimplified the heterogeneity that underpins recognition justice, and whether there was real logic behind the modelling choices. Thinking about this quote helped me with that uncertainty. Models never fully align with reality. However, every step towards recognition in energy modelling is one more than there was before and an improvement. Ensuring fairness in something as complex as the energy transition is not just an interesting thesis topic; it is necessary. Misrepresentation or exclusion in models can lead to policies that overlook vulnerable groups or reinforce existing inequalities. Even modest adjustments to models such as HESTIA matter if they open the door for more targeted and effective policy design, and more nuanced assessments of justice.

I would like to express my gratitude to my graduation committee: Igor Nikolic, Eugen Popa and Aarthi Sundaram, for offering me this opportunity and for their thoughtful discussions and guidance during this graduation process. Secondly, my family and friends, for their everlasting support not only during the writing of this thesis but also during my whole academic journey. I hope to do you all proud with what you will read here and what I will continue to do in the rest of my career.

Ilse de Droog
Hoofddorp, August 2025

Summary

The energy transition in the Dutch built environment has been slowly progressing for over a decade. It includes retrofitting homes, phasing out the use of natural gas and installing renewable energy systems. This transition has been developing alongside a rise in energy prices, driven by a mix of geopolitical tensions, market dynamics, climate policy, infrastructure limitations, and energy system transformations, all unfolding during a period of increasing demand. Intensifying existing vulnerabilities for at-risk households, this development has made energy poverty an increasingly urgent issue in Dutch policymaking.

Energy poverty is strongly linked to the concept of energy justice. Consisting of three tenets: recognition justice, distribution justice and procedural justice, energy justice promotes a fair distribution of the benefits and costs of energy services, combined with representative and impartial decision making in energy policies. Energy models, increasingly used to determine energy policies, enable policymakers to explore possible transition pathways and calculate the potential impact of policies. These models are mainly techno-economic, not taking into account differences in social or behavioural factors, even though these play a key part in households' adoption of policies. Incorporating principles of energy justice ensures that model outcomes are not only efficient or cost-effective but also just and acceptable for diverse groups, which is a necessary step in the decrease of energy poverty in the Netherlands.

A literature study reveals that when including energy justice in models, the focus has remained mostly on distributive justice, especially in the context of energy poverty. Energy poverty, however, is more than only a distributional issue. Effective policymaking and the models that inform it should account for the diversity and complexity of participation in the energy transition, thus recognising the social, cultural and structural dimensions involved. Recognition justice in energy models is essential to ensure that the experiences and identities of marginalised groups are acknowledged and valued.

This study aims to demonstrate how accounting for recognition justice in energy models influences the assessments of policy outcomes by measuring the percentage of the population at risk for energy poverty every year. This is relevant in the context of energy poverty as policies that fail to recognise the diversity in the needs and vulnerabilities of affected groups risk reinforcing existing inequalities and worsening the problem. For this demonstration, the HESTIA model, developed by PBL and TNO, is used. This model simulates the energy transition in the built environment for the whole Netherlands or on a more local level, making it very suitable for analysing localised impacts of policy interventions for issues such as energy poverty. The main research question for this thesis is therefore:

How can the integration of recognition justice in HESTIA impact the model to better capture the consequences of energy policy interventions, measured through energy poverty?

Using a design study approach, this thesis explores the core components that make up recognition justice and examines how these dimensions are insufficiently addressed in the current Dutch energy policy. Furthermore, it investigates what adjustments are needed to properly incorporate these aspects into HESTIA to account for recognition justice. To this end, model adjustments are designed and tested, using the municipality of The Hague as a case study.

Comparing Axel Honneth's and Nancy Fraser's theories on recognition justice reveals that Fraser's theory more closely aligns with misrecognition in Dutch energy policies. Honneth's theory of recognition is focused on the needs of individuals and states that recognition is grounded in love, law and cultural appreciation. Fraser thinks this is too individualistic a perspective and thinks that recognition justice is rooted in the cultural status order. The cultural status order organises society in ways that privilege some identities while (unintentionally) devaluing others. She defined three forms of misrecognition that prevent participatory parity: cultural domination, non-recognition and disrespect. It occurs when societal norms, values or cultural practices result in the oppression or disrespect of certain groups and deny them the ability to participate in social interactions on equal terms with others fully.

With the Dutch energy poverty policy, participatory parity has not yet been achieved. Challenges in Dutch policy making are stigmatisation, dominant norms shaping policies and certain groups remaining largely invisible in policy making. Energy poverty policies are often short-term, one-size-fits-all policies. This

risks systematically overlooking or misrepresenting the marginalised groups in the population, which can exacerbate and reinforce inequalities and worsen energy poverty. Such misrecognition undermines participatory parity.

Preventing misrecognition in the HESTIA model requires acknowledging the diversity in household decision-making regarding retrofitting and the adoption of sustainable energy technologies. Although HESTIA offers a detailed representation of spatial, technical, and economic processes within the energy transition, it largely overlooks the social dynamics that shape this household behaviour. The model is centred around investment decisions, using relative cost-benefit analysis to determine whether a home will invest in certain technologies or insulation measures. Being a top-down model, not designed to capture endogenous behavioural change emerging from social networks, HESTIA is not suitable to incorporate the diversity in the population's behaviour required for recognition justice. To achieve this, a multi-model design is required where, through a soft-link, an agent-based model can incorporate heterogeneity in households' decision-making in HESTIA.

In alignment with the design science methodology requirements for this ABM are identified as:

1. The model has to generate outputs compatible with HESTIA to allow for exploring diverse policy interventions and improving the assessment of their impact on reducing energy poverty.
2. The model should be able to (dynamically) process input data from HESTIA to initialise household agent attributes and global parameters.
3. The model should assign each household agent a profile including income, household size, dwelling age, home ownership status, dwelling size and energy label.
4. The model should adjust the decision-making rules for the differences in socio-demographic characteristics.
5. The model should assign each agent with an attitude variable that influences their energy-related behaviour, weighted for income and ownership-type.
6. The model should assign agents to an in-group.
7. The model should incorporate subjective norms that evolve over time and with interaction by allowing each agent to form behavioural intentions based on interactions within their social group.
8. The model should convert attitudes, perceived behavioural control and subjective norms into a probabilistic intention to adopt energy behaviours.

To recognise the differences in decision-making between households, the objective socio-demographic characteristics and subjective behavioural characteristics which influence this decision-making have to be included in a household's profile. These objective attributes are household income and size, their homes' age, home ownership type and their energy label. The behavioural patterns are conceptualised through the Theory of Planned Behaviour. Although often criticised for its focus on rational reasoning, which does not fully represent the emotional, non-rational side of energy behaviour, it's structure aligns well with the rational way investment logic is conceptualised in HESTIA and its attributes - attitude, perceived behavioural control and subjective norms - are proven to have a role in shaping energy behaviour in The Netherlands. The resulting *intention to invest* per household is averaged per income group and used to adjust S-curves in HESTIA's investment logic, allowing it to diversify per income class.

The results show that incorporating behavioural characteristics into the investment model leads to a reduction in energy poverty. However, the generalisability of these findings is limited by assumptions in modelling behaviour, and the fact that the study was conducted as a case study in a single city, which meant using localised housing data as well.

This decrease in energy poverty results from adjustments made to the S-curves, which have reduced agents' sensitivity to the cost/benefit ratio of investment options. As a consequence, options with a more favourable cost-benefit ratio have, on average, become less attractive. At a lower cost-benefit, the curves now accurately represent the higher willingness-to-pay among higher-income groups. However, the uniform method used to adjust the S-curves has also caused the tail of the curve to shift upward. This results in a stronger attraction to options with less favourable cost-benefit ratios among lower-income groups. Lower-income households appear to demonstrate a higher willingness to pay than higher-income households, which may not be realistic. A random seed analysis over three seeds shows a very limited variation, thus creating confidence in the results.

A sensitivity analysis comparing the equally weighted base case with runs emphasising perceived behavioural control or subjective norms showed that, over the long term, energy poverty outcomes were most sensitive to subjective norms, while income-class results revealed differing sensitivities between the two runs. This suggests that the relative influence of the behavioural attributes should not be uniformly applied across all agents, as their effects can differ per income group. At the aggregated level, these sensitivities are not reflected in the results. HESTIA seems to be responsive to large shifts in adoption data, but not to smaller behaviour-driven changes.

The adjustments made in this thesis do show an interesting first attempt towards incorporating recognition justice in the HESTIA model. This study provides a contribution to the literature by being one of the few explicitly focusing on recognition justice in energy models and including this concept through *merging*. Further, even though including social and ethical dimensions directly in HESTIA would improve computational efficiency and decrease complexity, this study demonstrates how a soft-link between a top-down and bottom-up model can aid in enhancing the social relevance of techno-economic models.

Future research could focus on extending the inclusion of household heterogeneity in HESTIA by altering the implementation of the behavioural factors used to adjust the functional energy demand. Additionally, future studies could test the consequences of using different behavioural theories to represent energy behaviour or analyse the impact of policy interventions when accounting for different dimensions of energy poverty.

Nomenclature

Abbreviations

Symbol	Description	Page
TNO	Netherlands Organisation for Applied Scientific Research	3
KEV	Climate and Energy Outlook	3
RQ	Research Question	8
ABM	Agent-Based Modelling	8
HEC	Household Energy Consumption	16
PBC	Perceived Behavioural Control	17
SIT	Social Identity Theory	24
TPB	Theory of Planned Behaviour	17
RV	Space heating	20
TW	Water	20
KD	Cooling	20
RO	Downstairs windows	20
DR	Doors	21
RB	Upstairs windows	21
DP	Flat roof	21
PL	Pannels	21
VL	Floors	21
MG	Facade	21
MS	Wall cavities	21
KR	Cracks	21
SIT	Social Identity Theory	24
LIHE	Low income High energy bill	28
LILEK	Low income Low energetic quality	28
HEQ	High energy quotem	28
KNMI	Royal Dutch Meteorology Institute	30

Symbols & Units

Symbol	Description	Page
A	Attribute set used to compute similarity	40
A_j^{inv}	Neighbour j's attitude toward investment	39
$A_{inst,i}$	Attitude based on current building option for agent i	36
$A_{\max}$	Maximum possible value for A_{raw}	36
$A_{\min}$	Minimum possible value for A_{raw}	36
$A_{\text{inst},i}$	Attitude based on current installations for agent i	36
$Ainv_i$	Normalised attitude towards investment for agent i	36
$Ainv_{\text{raw},i}$	Un-normalised attitude towards investment for agent i	36
$Ainv_i$	Total attitude towards investment for agent i	36
$\beta_{\text{nonspecific}}$	Non-technology-specific coefficient	41
β_{option}	Technology-specific coefficient	41
C	Set of income quintiles	35
$C_{j,\text{mostexpensiveoption}}$	Cost of most expensive option for agent j	41
$C_{j,\text{option}}$	Cost of selected option for agent j	41
c_i	Assigned income category for agent i	35

Symbol	Description	Page
$e^{\text{suitability}_{\text{option}}}$	Exponential of suitability score	41
$Iinv_i^{\text{raw}}$	Unnormalised intention to invest for agent i	36
$Iinv_i$	Normalised intention to invest for agent i	36
$Iinv_{\max}$	Maximum possible value of I_i^{raw}	36
$Iinv_{\min}$	Minimum possible value of I_i^{raw}	36
$\text{Odds}_{\text{option,tot}}$	Total odds for technology option	41
$\text{Odds}_{\text{option},i}$	Individualised odds for option	41
$o_{i,tc}$	Technology option selected by agent i in technology category tc	38
$T_{tc,o_{i,tc}}$	The sustainability score of the selected technology option in category tc	38
$P_{t,c}$	Probability of income category c for ownership type t	35
$P50P_{\text{mostexpensiveoption}}$	Median payback of most expensive option	41
$P50P_{\text{option}}$	Median payback of selected option	41
$PBCinv_i$	Perceived Behavioural Control investment score for agent i	39
$pbc_{\text{inv},1,i}$	Score on investment indicator 1 for agent i	36
$pbc_{\text{inv},2,i}$	Score on investment indicator 2 for agent i	36
$\text{Probability}_{\text{option}}$	Probability of choosing a specific option	41
σ_{ij}	Similarity between agent i and contact j	40
$\mathbf{s}_i$	Binary selection vector for survey options of agent i, with $s_{i,k} \in \{0,1\}$	37
SN_i^{inv}	Subjective norms experienced by agent i regarding investments	36
$\text{Suitability}_{\text{option}}$	Suitability score for option	41
T	Set of dwelling ownership types	35
t	A specific ownership type, where $t \in T$	35
TC	Full set of technology categories	38
tc	one specific technology category, where $t \in TC$	38
w_a	Weight assigned to attitude	36
w_c	Vector of weights for income	39
w_{pbc}	Weight assigned to perceived behavioural control	36
w_{SN}	Weight assigned to subjective norms	36
w_t	Vector of weights for ownership type	37
w_{tc}	weight assigned to each technology option	38
wk	Weight vector assigned to each survey option k	37
$\|A\|$	Size of attribute set A	40
$\mathbf{1}[a_i = a_j]$	Indicator: 1 if attribute a is shared, else 0	40

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1 Introduction

Over the last years, the energy transition has been progressing alongside a complex mix of geopolitical events, market dynamics, differing climate policies, infrastructure limits and increasing demands (International Energy Agency [IEA], nd), causing a significant rise in energy prices. A critical point was reached in 2021 and 2022, causing a global energy crisis (International Energy Agency [IEA], nd). This has caused energy poverty to become an increasingly urgent issue on the Dutch policy agenda. In a best-case scenario of rising energy prices, more than 6% of all households (500.000) in the Netherlands will suffer from energy poverty by the end of 2025 (Batenburg et al., 2025). They struggle to pay their energy bills, and some even have to choose between a proper meal and a warm home (Fryslân, 2024). An individual is classified as energy poor when they have a low income, combined with either a house of low energetic value, or a disproportionately high energy bill (Mulder, 2024). In this case, low-income is defined as an income max. 30% above the minimum low-income boundary (Mulder, 2024), which in 2024 was between €12,216.55 and €36,781.05 depending on adult living circumstances (ages 18 and over) (UWV, 2024). Energetic quality is an energy index calculated based on building characteristics, building-related installations and standardised user behaviour.

Energy poverty disproportionately affects vulnerable groups, such as low-income families, the elderly, and social housing residents (Jones and Reyes, 2023). It is also more prevalent among those with lower education, women, disabled or ill people, and migrants (Ooij et al., 2023). As it impacts the physical and mental well-being, social inequality, and housing conditions of households (Jones and Reyes, 2023), energy poverty poses a significant concern for societal well-being. It is an increasing concern, as research indicates that energy poverty numbers could increase by a third by 2030 (van Berkel et al., 2021), affecting a total of 10% of the country.

1.1. Energy poverty as part of energy justice

Energy poverty is strongly connected to the concept of energy justice (van Berkel et al., 2021). Energy justice is a conceptual and analytical decision-making tool focused on a fair distribution of the benefits and costs of energy services globally, combined with representative and impartial decision-making in energy policies (Jenkins et al., 2016; Sovacool and Dworkin, 2015). In this thesis, energy justice is conceptualised as consisting of three foundational tenets, as described in McCauley et al. (2013), and widely used in empirical and conceptual works (Wood and Roelich, 2020). These tenets are procedural justice, distributional justice and recognition justice. Procedural justice guarantees fair participation, distributional justice ensures an equitable share of the transition's up- and downsides, and recognition justice ensures all actors are acknowledged and included in decision-making (Rios-Ocampo et al., 2025).

Energy justice forces acknowledgement of the energy transition as more than a technological issue, but one with social and political dimensions also (Sovacool and Dworkin, 2015). While energy poverty is often framed as an issue of distributive injustice, its foundation is in recognition and procedural injustices. In the context of energy poverty policy, including energy justice indicates *where* resources need to be allocated, *how* democratic legitimacy can be achieved, and *whose* needs should be recognised and prioritised, linking it directly to the three aforementioned tenets of justice (McCauley et al., 2013).

Energy poverty measurement carries significant recognition justice implications, such as policy resistance, social divisions and political tensions (Tarasova, 2024). It can also result in amplification of the already existing injustices between vulnerable and non-energy-poverty suffering groups (Kaufmann et al., 2023). Energy transition policies have to recognise the diverse and complex ways in which vulnerability influences decision-making and participation in the energy transition.

1.2. Current policies and their criticism

Since 2021, different measures have been implemented to aid households with their energy costs. These were mainly focused on lowering the energy price or helping with paying the energy bills. Although these measures helped mitigate immediate issues for a significant number of households, they failed to acknowledge that structural barriers, such as income disparities, hidden energy poverty or poor housing quality, significantly impact a household's ability to manage energy costs and participate in the energy transition (Mesdaghi et al., 2025; Mulder et al., 2023). This caused the aid to primarily help high-energy users, no matter their income level, while neglecting vulnerable groups (Mesdaghi et al., 2025).

Public awareness and engagement efforts aimed to inform households about policy options and measures to improve their situation often fail to reach disadvantaged groups. Information campaigns are mostly in Dutch, excluding non-native speakers, while digital and written formats could be inaccessible for those with low literacy or limited internet access (Kaufmann et al., 2023; Mesdaghi et al., 2025). Failure to consider these factors when designing information services may result in inaccessible or mistrusted advice, further excluding vulnerable groups from participating in energy-saving measures. Even when support options are well-known, barriers are created through complex eligibility criteria or bureaucratic application procedures (Kaufmann et al., 2023). For example, Walker et al. (2014) estimate that due to too specific eligibility criteria like social welfare benefits or age, there is a failure to fully recognise the diverse experiences of fuel poverty, resulting in 40-60% of energy poor groups in Northern Ireland not receiving the policies' benefits, while households not in fuel poverty did qualify. This causes inequalities to increase.

The Netherlands runs this risk as well, as applicants for subsidies or loans get rejected for reasons such as receiving social welfare, not having a permanent employment contract, or having to pay more than €250 in child support (Kaufmann et al., 2023). Further barriers stem from the upfront costs homeowners must bear to qualify for subsidies, resulting in 21% of the population being unable to afford retrofits at present, a much larger population than the 6% considered energy poor (Batenburg et al., 2025). These barriers mean that those most in need of support are often excluded from the benefits of energy transition policies, reinforcing existing socio-economic inequalities (Kaufmann et al., 2023)

The Dutch approach to energy poverty is through decentralised policy. Responsibility for energy poverty largely falls on municipalities (van Binnenlandse Zaken en Koninkrijksrelaties, 2024). But, local governments have varying capacities and resources, resulting in uneven access to support for civilians, which can potentially reinforce existing inequalities (Feenstra et al., 2021). This is evident, as 30% of municipalities have signalled they are unaware of which households need help with energy poverty, and only 35% feel they can effectively reach energy poor households (Vos, 2024).

The inconsistent local action is further complicated by the inadequate national measurement and monitoring of energy poverty, which fails to capture the diversity of the problem. Different demographic groups experience energy deprivation differently. Factors such as housing conditions, gender, migration background or other socio-economic characteristics can significantly impact these experiences. Without detailed, disaggregated data, the complexity and overlapping factors contributing to energy poverty remain largely invisible, leading to one-size-fits-all policies being implemented, which ignore the needs of marginalised groups (Feenstra et al., 2021).

As a result, energy-poor households remain hard to identify and assist, while social and financial vulnerabilities persist (van Eijsden, 2025). The focus in policy making should switch from affordability and efficiency alone to include the lived experiences of affected communities (Woods et al., 2024).

1.2.1. Energy models

In recent years, there has been an increase in the use of energy models to support decision-makers in their policy-making. These models help policymakers explore possible transition pathways and calculate the potential impact of various policies, which can help decision-makers better navigate the increasing complexity of the energy sector (Henrich et al., 2021). Examples are machine-learning technologies to detect, analyse and predict changing trends in local conditions and identify areas at risk for energy poverty (González Garibay et al., 2023), applied for the Netherlands (Longa et al., 2021), and Europe

(Spandagos et al., 2023), or stochastic modelling used to determine the relative influence of various parameters on energy poverty, providing insights at a household and national level, such as for Greece (Papada and Kaliampakos, 2018). Although insightful, such models are predominantly techno-economic and, as of today, not well-equipped to consider the ethical dimensions necessary to achieve just outcomes (Gürsan et al., 2024; Henrich et al., 2021; Shetty, 2023). Energy models are said to often fail in incorporating public perspectives fully, undermining the social relevance of models. This conversion seems to be lacking due to the difficulty of quantifying social and political aspects, such as energy justice considerations (Amin et al., 2024).

There are several strategies for integrating social aspects, such as energy justice, into models. Trutnevyte et al. (2019) identified bridging, iterating, and merging as key approaches. Bridging occurs when modelling and research in social sciences happen at the same time, only meeting when researchers discuss shared concepts. Iterating means that social science narratives are translated into quantitative input assumptions used by the models, and potentially, outputs are used to adjust the narratives. Merging assumes that at least the key societal factors can be modelled, and thus, this strategy means an in-depth integration of the two tracks. This either happens through structurally modifying existing models or creating completely new models (Trutnevyte et al., 2019). Sundaram et al. (2024) highlight that most studies stop at integrating social science narratives into model logic (iterating), through inputs, outputs or model relationships. Embedding justice structurally into the modelling logic is rarely achieved. As a result, energy models claim to address justice, but mainly do so procedurally through stakeholder engagement, rather than embedding justice within the model logic. Ideally, justice is integrated both within the model logic and modelling processes (Sundaram et al., 2024).

When integrating justice concepts in energy models, it seems that the focus remains mostly on distributive justice (Bal et al., 2023; Vågerö and Zeyringer, 2023), especially in the context of energy poverty (Bouzarovski and Simcock, 2017; Menghwani et al., 2020). In their review of energy justice incorporation in energy system models, Vågerö and Zeyringer (2023) noted that focus remains on distributive justice and that although procedural and recognition justice are sometimes acknowledged, they are rarely quantified in the model logic. Identical patterns were identified by Rios-Ocampo et al. (2025) and Sundaram et al. (2024); distributive justice is often overrepresented compared to other tenets due to its quantifiability, which makes it easier to integrate. Recognition justice is acknowledged as important, but most models fail to account for diverse social groups or the structural barriers they face in decision-making (Sundaram et al., 2024). It is rarely included in a meaningful way.

1.3. Problem definition

The literature described above suggests that energy poverty extends beyond a purely distributional issue (McCauley et al., 2013). Effective policymaking, and the models that inform it, should account for the diversity and complexity of participation in the energy transition, recognising the social, cultural, and structural dimensions involved. In particular, incorporating principles of recognition justice in energy models is essential to ensure that the experiences and identities of marginalised groups are acknowledged and valued. Energy models that focus mostly on cost analysis when assessing policies have a lower reliability when ignoring the important role of human behaviour and social equity in policy adherence (Fattahi et al., 2020).

In this thesis, I focus on the HESTIA Model developed by the Netherlands Environmental Assessment Agency (PBL) & the Netherlands Organisation for Applied Scientific Research (TNO). HESTIA's primary goal is to provide the most accurate representation of the housing stock and how it may evolve under various influences. The model calculates the Climate and Energy Outlook (KEV) for households, estimating gas, electricity, and heat consumption, as well as the costs and benefits of investments for relevant stakeholders. Through these insights into HESTIA supports evidence-based policymaking in the built environment (van der Molen, 2023). Currently, HESTIA models households' investment choices for heating options based purely on techno-economic considerations. A household is modelled to only consider the relative cost-benefits of the installation option when choosing between heating installations when considering an investment (van der Molen, 2023), thereby overlooking behavioural differences in population groups.

Demographic characteristics such as income levels, household size, age and gender of the head of the household can be important influences on variations between households' energy demand (Abrahamse and Steg, 2009), as well as their investment behaviour. Accurately modelling the residential energy transition in the Netherlands is essential for effective policymaking. HESTIA primarily focuses on techno-economic aspects while neglecting critical social and cultural dimensions and thus fails to align fully with the principles of energy justice. In particular, there is a need to integrate recognition justice into energy models, including HESTIA, to better reflect the diverse ways different population groups experience and respond to the energy transition. This integration is vital for producing more accurate and just policy analyses.

1.3.1. Research questions

In line with the identified problem and the requirement for integration of recognition justice in energy models, this thesis poses the following research question:

How can the integration of recognition justice in HESTIA impact the model to better capture the consequences of energy policy interventions, measured through energy poverty?

To structure the research process and ensure a systematic analysis of the problem, three sub-questions have been formulated. This way, the study can, in a step-wise manner, provide a well-founded answer. Together with the questions, their objective and research method are briefly mentioned.

1. How are misrecognition in energy policy and energy poverty connected?
    - **objective:** To identify the theoretical framework of recognition justice and examine how its absence shapes current energy poverty policies.
    - **research method:** Systematic literature review
2. What is a suitable conceptualisation for modelling household energy behaviour in HESTIA?
    - **objective:** To identify a suitable conceptualisation for modelling energy behaviour in a way that enables integration of a form of recognition justice in the HESTIA model.
    - **research method:** Systematic literature review
3. How does accounting for misrecognition in HESTIA affect energy poverty estimates?
    - **objective:** To examine how incorporating recognition justice concepts affects the outcomes of the HESTIA model, as measured through energy poverty numbers.
    - **research method:** Agent-based modelling soft-linked to HESTIA modelling.

1.4. Relevance

This thesis aims to improve the integration of recognition justice in the HESTIA model. The focus is specifically on how misrecognition in energy policymaking can lead to seemingly effective policies that inadvertently reinforce energy poverty in the Netherlands. Since energy poverty aggravates social inequalities (Kaufmann et al., 2023), and negatively impacts the physical and mental health of those suffering (Jones and Reyes, 2023), it is important that this is prevented.

Through the inclusion of social diversity in an agent-based extension of the HESTIA model, this study focuses on how the integration of recognition justice shapes modelled household energy behaviours and outcomes. These insights help inform the development of a more effective and equitable policymaking tool.

By addressing these complexities, the research contributes not only to more inclusive policy making but also advances the scientific understanding of behavioural modelling in energy models. More importantly, this study focuses on integrating a form of recognition justice into an energy model - an approach largely overlooked in energy model research.

1.4.1. Engineering and Policy Analysis

This research aligns perfectly with the objectives of the Engineering and Policy Analysis programme. Through addressing misrecognition in energy policymaking and its consequences on energy poverty, the thesis directly targets one of the systemic barriers within the grand challenge that is the energy transition. Moreover, the modelling approach aligns with the program's modelling and analytics focus, and it supports policymaking by decreasing the gap between social science and technical-economic models so that policymakers can be provided with more realistic and just projections of policy effectiveness.

1.5. Thesis outline

This chapter has outlined the problem this thesis addresses. It also includes the research objective and questions. Chapter 2 will detail the chosen research approach and methodology, as well as outline the encompassing research design. Subsequently, chapter 3 will detail the theoretical connection between misrecognition and energy poverty, after which chapters 4 and 5 describe the conceptualisation of incorporating recognition in modelling. Chapter 6 describes the model formalisation, whilst Chapter 7 discusses the results. Chapter 8 includes the discussion and recommendations. Lastly, in the concluding chapter 9, the research questions are answered.

2
Research approach

This chapter describes the methodology used to explore how misrecognition in energy models and policymaking can contribute to the persistence of energy poverty in the Netherlands. Section 2.1 describes the general research approach used, namely design science. Section 2.2 follows this by discussing the details of the methods used for answering the different research questions. section 2.3 explains the choice to use the municipality as the scope for the simulation.

2.1. Design science

In design science, an *artefact* - a model, framework or method - is developed to address a specific problem. This artefact is evaluated based on effectiveness in addressing the problem and its contribution to theory. An artefact can also be an improvement or marginal modification to an existing artefact (Johannesson and Perjons, 2021), which is how this thesis will leverage the approach; improving and modifying the HESTIA model. Design science as a research approach brings the ability to not only understand the problem, but to address it and to adjust the model to get closer to the solution of the complex problem. Another benefit is that this approach is designed to be an iterative process (Johannesson and Perjons, 2021), which allows for opportunities to refine the model and further develop or adjust the underlying theories (Carstensen and Bernhard, 2019), if required.

2.1.1. A brief overview of the design science framework

The structure of this study will be based on the 5-step method framework introduced by Johannesson and Perjons (2021).

Problem explication: In this step, the problem and its underlying cause are identified and analysed. It is split up into problem identification and problem analysis (Johannesson and Perjons, 2021). The problem has been identified in chapter 1 and will be further analysed as part of the first research question in chapter 3.

Requirement definition: In this step, the problem will be translated into requirements for the artefact (Johannesson and Perjons, 2021). These requirements are crucial for the conceptualisation of modelling recognition justice. They build on findings presented in chapter 3, and contribute to answering the second research question. The requirements are outlined in chapter 4.

Design and development of the artefact: The design of the artefact is a key step in the conceptualisation phase and contributes to answering the second research question, see chapter 5. The development of the artefact focuses on the operationalisation of the recognition of justice in household energy behaviour, achieved through an Agent-Based Model (ABM), see chapter 6. This model is based on input from and used as input for the HESTIA model. Before model implementation, the necessary data, identified during the conceptualisation phase, are collected and cleaned.

Demonstration of the artefact: Demonstration is the step in which the developed artefact will be used. In this case, the modified model will be run and experimented with to assess how the incorporation of recognition justice affects the calculations within the model. This phase also includes a sensitivity and random seed analysis to assess the stability of the model results.

Evaluation of the artefact: This step is imperative for answering the third research question. In the design science framework, this activity's purpose is to evaluate the extent to which the artefact fulfils the requirements, and it can address the problem that motivated the research (Johannesson and Perjons, 2021). This evaluation will be done by examining how the inclusion of behavioural differences affects HESTIA's outcomes, specifically energy poverty, by running the model for eight years, 2020-2027, comparing the results to those of the original model.

2.2. Research methods

2.2.1. Systematic literature review

A systematic literature review was applied for the *problem explication and requirement definition* steps of the framework, which align with the first two research questions. The literature review for this thesis is roughly based on the 12-step framework given by Kable et al. (2012). The purpose of the literature review was threefold: To understand the current problem with energy justice in energy poverty, the theory behind recognition justice, and to link this to energy poverty (policy) in the Netherlands. All search terms were applied in both Google Scholar and Scopus, as the initial round of literature search revealed that this could yield differing results. In both search engines, the search was limited to Dutch or English information. Initial filtering of the papers was based on titles. The remaining papers were selected based on their relevance as determined through reading their abstracts. Appendix A shows, per article, the search terms used.

Due to the interdisciplinary nature of this thesis and the several topics the literature review has to cover, using a single search theme proved impossible. It can best be split into three steps, following the design framework. Table 2.1 gives an overview of how the search terms relate to the research questions.

Problem explication

Problem identification

The application of the design science approach began in Chapter 1 with the problem identification. While the formal explanation of the methodology follows in section 2.1, identifying the problem is not only a component of the design science process but also a necessary precursor for determining the appropriate research approach.

To develop a broad understanding of the field, the literature search began with a general search for **”energy justice”** in both Scopus and Google Scholar. This initial search yielded a large volume of results, from which five key papers were selected. The search was then refined by combining **”energy justice”** with **”energy poverty”**, which returned 220 results on Scopus. Despite the volume, only five additional papers were deemed relevant after screening titles and abstracts. To apply the theory to the Dutch policy context, the search was refined by using **(”policy” AND ”energy poverty” AND ”Netherlands”)**, which yielded limited results, with three relevant papers selected for review.

Based on the identified information, a broader conceptual exploration was conducted using **((”justice” OR ”social aspect”) AND ”energy model”)** in Scopus, which returned 24 results, from which one additional paper was included. Insights from these papers informed a more refined search, incorporating key theoretical terms. The final search for the problem identification, using **(”conceptualisation” AND ”energy justice” AND ”model”)**, produced 6 results, two of which were deemed useful based on abstract review.

Problem analysis

As the previous literature resulted mainly in studies applying the concept, and not explaining the theoretical framework, the problem analysis started with the search term applied being **(recognition justice theory)**, resulting in no results through Scopus and many results through Google Scholar. Three papers were selected.

Literature was considered relevant if it discussed energy poverty policy consequences or the connection between energy poverty and recognition justice. Combining this with previously identified literature revealed that the search needed to be broadened to include the term ”policy instruments”. A refined search using **(”policy instruments” AND ”energy poverty” and ”Netherlands”)** did result in one additional paper, which was selected based on the same criteria. To expand the selection, backwards snowballing was applied, which led to the identification of several additional sources. Furthermore, recommendations from my supervisory team helped finalise the literature list as presented in Appendix A.

Requirement definition

For this third objective, the literature review required a more targeted strategy, focusing specifically on literature that explicitly identifies variables and their relationships. Based on previously identified literature, it was identified that the focus specifically had to shift towards behavioural aspects and households, thus extending the search field with terms such as ”households”, ”investment decision making”, ”behavioural theory” and ”energy saving”. This resulted in three additional searches according to the following terms: **(”behaviour” AND ”energy saving” AND ”households)**, **(”behaviour” AND ”energy saving” AND ”netherlands”)**, **(”household investment” AND ”energy policy”)** and **(”investment decision making” AND ”energy policy”)**. This resulted in 713, 32, 15 and 50 results, respectively, highlighting once again that specificity in search terms is very important.

Nevertheless, these searches - filtered first on their title, second on their abstract and lastly on their contents - ultimately yielded only three additional relevant papers. Further insights for this objective were identified through both forward and backwards snowballing from the newly selected papers as well as the previously reviewed literature.

Table 2.1: Overview of connection search terms, research questions, and design science framework steps

Search Terms	Chapter	Framework step
”energy justice”	Ch1	Problem explication - identification
(”energy justice” and ”energy poverty”)	Ch1	Problem explication - identification
(”policy” and ”energy poverty” and ”Netherlands”)	Ch1	Problem explication - identification
(”policy instruments” AND ”energy poverty” and ”Netherlands”)	Ch1 & Ch3	Problem explication - identification and analysis
(”conceptualisation” AND ”energy justice” AND ”model”)	Ch1	Problem explication - identification
((”justice” OR ”social aspect”) AND ”energy model”)	Ch1 & Ch3	Problem explication - identification and analysis
Recognition justice theory	RQ1	Problem explication - analysis
(”behaviour” AND ”energy saving” AND ”households”)	Ch4	Requirement definition
(”behaviour” AND ”energy saving” AND ”Netherlands”)	Ch4	Requirement definition
(”household investment” AND ”energy policy”)	Ch4	Requirement definition
(”investment decision making” AND ”energy policy”)	Ch4	Requirement definition

2.2.2. Multi-modelling

The energy transition in the built environment describes a transition in a complex system. Modelling such a complex system often means not being able to sufficiently incorporate the different paradigms that make up such a system (Fishwick et al., 1994). As found in the literature review, it is difficult to quantify social parameters, causing them to often be left out of energy models, as occurs in HESTIA as well. Such socio-demographic parameters can be included in techno-centric energy models through the inclusion of, for example, an Agent-Based Model (ABM) (Fattahi et al., 2020). For the artefact design, a multi-modelling approach is used through which the HESTIA model is linked to an Agent-Based Model. The ABM enables the incorporation of socio-demographic characteristics of households in the HESTIA modelling logic.

In multi-modelling, there are three ways to connect the two models: hard-linking, soft-linking and integrating. With hard-linking, a reduced version of one model transfers its data to a larger model, and both run in parallel. Soft-linking means that two stand-alone models are linked together manually, and the processing and transferring of information between the models is iteratively controlled by the user. Lastly, by integrating two models that internally interact through a shared model architecture (Fattahi et al., 2020).

The link between HESTIA and the ABM is through a soft-link. The models will communicate by exchanging .csv files used for model input. This is a suitable choice as the models do not run at the same time and do not share one memory; in fact, they need to run consecutively. Both could run separately, but in order to establish the desired integration of more agent heterogeneity in HESTIA to decrease the misrecognition in the model, the two need each other's output from $t = n$ for the calculations in $t = n+1$.

Agent-based modelling

An agent-based modelling (ABM) is a model in which *agents* - a person, organisation or animal - are represented in a computer program. The actions and interactions of the autonomous agents are simulated within a defined environment (Dijkema et al., 2013).

A socio-technical system like the one studied in this thesis is defined by intertwined social and technical elements where human behaviour, human relationships and societal norms interact with infrastructure, technologies and organisational frameworks (Chappin et al., 2020). ABM is very suitable for simulating socio-technical systems, such as those examined in this thesis, due to its ability to represent heterogeneous agents, incorporate adaptation and learning and capture micro-level interactions (Chappin et al., 2020; Dijkema et al., 2013; Fattahi et al., 2020).

As a form of incorporating recognition justice, this study focuses on integrating social heterogeneity into the behavioural dynamics of the HESTIA model through the ABM. The methods' relevance and suitability for this study are further highlighted in chapter 4.

2.3. Case study: The municipality of The Hague

The environment in which the ABM operates is the residential housing sector of the municipality of The Hague. Concentrating on a smaller area and not the entire country significantly reduces the required computational power and shortens HESTIA's runtime (van der Molen, 2023). The Hague was selected due to the broad availability of data, its diverse household composition and because, although energy poverty is more severe outside of the Randstad, it still has a higher than average number of households experiencing energy poverty (Klerks, 2024), making it an interesting area to test the effectiveness of the changes. Due to the availability of historical data, the study begins in 2020. From this starting point, the model adjusts the data based on internal interactions and developments. The simulation runs until 2030, both to limit computational demands and to avoid including the phase in which HESTIA begins simulating newly constructed homes.

As there is some room for interpretation with this definition, for this study, the following choice was made. A household is classified as energy poor if it falls within the low-income category and either spends more than 10% of the upper threshold of this income bracket on energy bills, as this is in line with the threshold used by the national association of housing associations (Aedes, nd), or has an energy label of E, F, or G.

3
Linking recognition justice and energy poverty

Including energy justice in energy models is fundamental to achieving just and equal policies. Academic work on energy justice lacks a universally accepted, clear theory of justice (van Uffelen, 2022; Rios-Ocampo et al., 2025). This introduces potential for discrepancies between model assumptions and justice theories, especially in cases where justice modelling includes proxies for measuring, such as energy poverty (Rios-Ocampo et al., 2025). Quantifying recognition justice aspects in energy modelling is challenging. It risks leading to oversimplified interpretations of complex justice issues, which would undermine the accuracy and effectiveness of models, decreasing their potential in policymaking (Rios-Ocampo et al., 2025).

This chapter will thus focus on answering the sub-question *"How are misrecognition and energy poverty connected?"* and establish the theory of recognition justice that will be focused on in the rest of the thesis. The chapter is split into two parts. Firstly, the two main approaches to general recognition justice will be discussed, after which this is linked to the Dutch energy poverty policy context. Appendix A.1 describes the literature review process that led to this content.

3.1. What is recognition?

Recognition is made up of a normative and psychological dimension. Normatively, recognising someone implies acknowledging a specific normative status for a person, such as a free and equal person. Psychologically, recognition is imperative for an individual's development of identity, since it is human nature to depend on social feedback for self-worth (Miller, 2025). Although there are different theories on how to interpret recognition justice, the foundation of this form of justice lies in theories from Axel Honneth and Nancy Fraser (van Uffelen, 2022).

3.1.1. Honneth's self-realisation model

Alex Honneth's theory of recognition justice comes together in the self-realisation model. He argues that all injustices, including procedural or distributional, can be traced back to misrecognition.

A just society, in Honneth's eyes, is one where recognition is available for everyone, and all can fully develop their identity and participate as equals (Honneth, 1996). Recognition injustices can occur at different levels of society and affect one's relation to the self. He identified recognition as founded in love, law and cultural appreciation (Miller, 2025; van Uffelen, 2022). Recognition through love gives one self-confidence, through law it brings one self-respect, and through cultural appreciation it brings one self-esteem. Honneth sees misrecognition in any of these as disrespect, which harms one's relations to oneself. Thus, disrespect is wrong: "each human is worthy of having an unharmed self-identity" (van Uffelen, 2022).

This is a very personal view of recognition as it focuses on the individual gains for people from recognition through love, law and cultural appreciation. Because of this, Honneth's theory of recognition justice is very suitable to apply in the diagnostic phase of injustice. Applying this nuance can aid in finding how and why people feel misrecognised (van Uffelen, 2022).

3.1.2. Fraser's status order model

Nancy Fraser criticises this form of recognition as it focuses too much on ”identity politics” and takes away from the relevance of distribution on the political agenda (Miller, 2025). Recognition, according to Fraser, does not mean recognising group-specific identities but is recognising the status of all individuals in the group as full participants in society (Fraser, 2001).

Recognition and redistribution are seen as interconnected, as cultural stigmatisation often reinforces economic exclusion, and economic disadvantage can worsen cultural misrecognition (van Uffelen, 2022). Thus, she advocates for an effective justice strategy that tackles both symbolic and economic injustices together (Fraser, 1996). To achieve an effective justice strategy, recognition and redistribution should not be addressed separately, but in parallel (Miller, 2025).

In this framework, recognition is grounded in the cultural status order (van Uffelen, 2022). The core of the status order model is participatory parity: all people should be able to participate equally as peers in society. Recognition ensures participatory parity through acknowledging and valuing individuals' diverse identities and experiences, allowing everyone to engage fully and equally in life (van Uffelen, 2022). Fraser describes three forms of misrecognition which can prevent participatory parity: cultural domination, non-recognition and disrespect (Tarasova, 2024).

Misrecognition through cultural domination occurs when cultural norms and institutional practices undervalue certain groups, preventing them from being seen as full members of society. Recognition justice, according to this view, can be seen as targeting cultural injustices rooted in social patterns of representation, interpretation and communication (van Uffelen, 2022), which shape how groups are perceived. There is a hierarchical order in cultural values; one is always more important than another, and these values are deeply embedded in institutions, both formal and informal (van Uffelen, 2022).

Fraser emphasises how misrecognition is not merely an individual issue, as Honneth suggests, but occurs when societal norms, values or cultural practices result in the oppression or disrespect of certain groups and deny them the ability to fully participate in social interactions on equal terms with others (Zurn, 2005). This disrespect occurs when a person ”is persistently denigrated, belittled and stereotyped in dominant discursive representations. It thus connects closely with concepts of stigma and stigmatisation” (Simcock et al., 2021, p. 2).

Non-recognition sounds similar to misrecognition but is a category of misrecognition. It is a mechanism through which misrecognition occurs. More specifically, misrecognition refers to an injustice where individuals or groups are denied the respect, visibility or status required for full participatory parity. Non-recognition is a form of misrecognition where a group is ”not acknowledged, seen or 'counted' in the dominant discourses and value patterns of wider society” (Simcock et al., 2021, p. 2).

Recognition in the context of energy justice targets social stigmas, but also guarantees that diverse voices are included in policy-making. Fraser argues for a focus on taking down barriers to participation while acknowledging people's diversity and the evolving needs of individuals and groups, but not to solely focus on these identities (Tarasova, 2024). Affirming them could only reinforce stereotypes and overlook structural issues. Instead, structurally change the underlying social and institutional conditions that result in disadvantaged groups in the first place; ensure everyone can participate in society equally and fully (Fraser, 2001). Once full participatory parity is achieved, there is recognition justice.

3.2. Misrecognition in the context of energy poverty policies

Energy poverty affects people differently; households in energy poverty should not be seen as a homogenous group (Feenstra and Clancy, 2020; Mesdaghi et al., 2025). Failing to recognise the heterogeneity within groups overlooks the diverse causes of energy poverty and leads to misrepresentation and ineffective policy targeting (Feenstra and Clancy, 2020; Gillard et al., 2017; Walker et al., 2014), excluding many vulnerable households (Walker et al., 2014).

Disrespect, non-recognition and cultural domination in the residential energy transition could result in ignoring diverse needs and decision-making processes related to energy use and investments. In policy frameworks, this translates to certain groups being overlooked or undervalued.

Kaufmann et al. (2023) introduce the possibility that public engagement policies, such as municipal information evenings regarding retrofitting possibilities, are shaped by the priorities and biases of civil servants; certain groups might receive more attention whilst others are overlooked, resulting in certain communities being excluded and less informed. In a way, this reflects Fraser's concept of cultural hierarchies in the status order model, where some social groups are prioritised while others are marginalised. Policies failing to recognise diverse social identities risk marginalising certain groups and reinforcing inequalities, which seems to be exactly what is happening in the Netherlands, as highlighted in section 1.3.

In the context of energy justice, Fraser's dual approach to recognition provides an opportunity to address the distribution inequality and exclusion that occur with energy poverty. The dynamic visualised in Figure 3.1 is evident in the Dutch policy approach, where marginalised communities can be overlooked in the policy design, leading to inadequate support and deepening of energy poverty. Applied to the focus of this study, Figure 3.1 is very relevant in explaining the consequences of misrecognition in HESTIA. As HESTIA is a model used to calculate the consequences of intended policy measures, misrecognition of household energy behaviour can cause misinterpretation of policy consequences. Those who are misrecognised will not be accounted for in policy-making. These people are excluded from procedural spaces, which maintains their misrecognition. This procedural injustice maintains barriers to participation in the energy transition for the misrecognised population. Unequal distribution of resources will increase the inequalities.

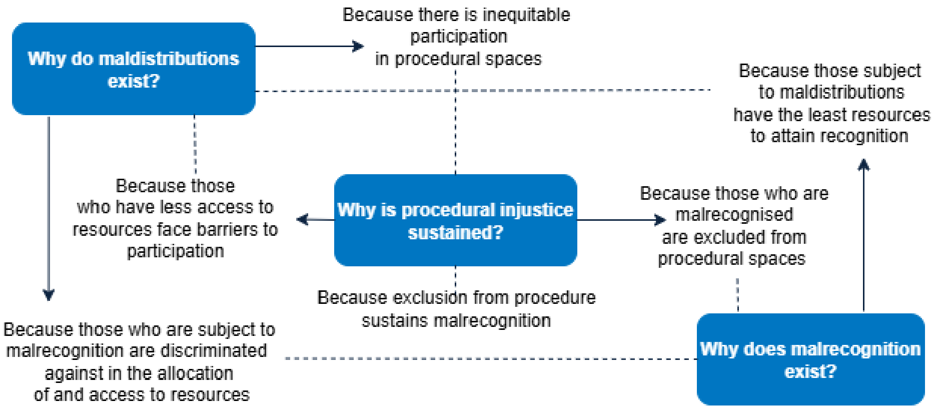

Figure 3.1: A visual representation of the causal and explanatory interconnections between the three tenets of energy justice, by Nathan Wood (Wood, 2023)

Fraser's perspective aligns most with the challenges identified in the Dutch approach against energy poverty visualised in Figure 3.2, where a more short-term, one-size-fits-all method risks *systematically* overlooking or misrepresenting (vulnerable) groups in the population. Figure 3.2 combines the theory on misrecognition with the patterns occurring in Dutch energy poverty policy currently to illustrate how these are combined. In this figure, the opaque boxes illustrate the different levels of the theory, whilst the bottom row connects these categories to policy issues mentioned in section 1.3.

Policies that do not consider the diversity in the population may overlook specific challenges faced by households in the energy transition and consequently reinforce inequalities and hinder true participatory parity in the energy transition. A lack of recognition from policymakers can exacerbate and reinforce distributional inequalities and worsen energy poverty (Figure 3.1). It is imperative to move beyond stereotypical understandings of energy needs if interventions and policy are to have an effect (McCauley et al., 2013; Walker and Day, 2012). Applying a one-size-fits-all understanding would lead to undercounting and hiding the needs of vulnerable households (Snell et al., 2015).

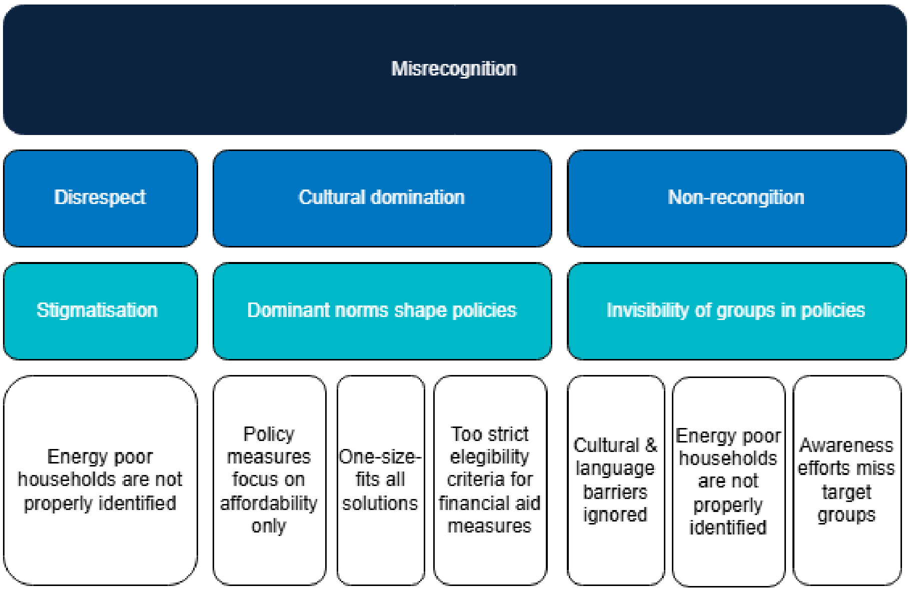

Figure 3.2: Fraser's theory of misrecognition linked to Dutch energy poverty policy

4 Model requirements

Chapter 3 establishes the theoretical framework that links misrecognition to Dutch energy poverty policymaking. Aiming to take a step forward in preventing misrecognition in energy modelling, this chapter outlines the key factors required to conceptualise a heterogeneity of households in HESTIA, thereby improving the model. In line with the design science method, these key factors will be summarised as the requirements for the to-be-designed artefact in this chapter.

Improvement of a model according to design science can relate to efficiency, usability, maintainability, or other aspects of the artefact (Johannesson and Perjons, 2021). For this study, it will be used to increase HESTIA's usability and correctness. Usability is the effectiveness, efficiency and ease with which a user can use an artefact to achieve a goal (Johannesson and Perjons, 2021). By allowing for more detail in household behaviour, to improve the simulation of household investment decisions in HESTIA, the model will be more effective in calculating the KEV, thus improving its usability. Secondly, correctness, a quality only applicable to models, is the degree to which a model corresponds to the domain it represents. Correctness in this application can also be seen as accuracy (Johannesson and Perjons, 2021). As the goal is a more accurate representation of reality by accounting for differences in decision-making on energy consumption and savings in the population, to ultimately create a more effective and equitable policymaking tool, the correctness of the model can also be improved.

The first section of the chapter introduces the high-level requirements, which help outline the structure of the artefact to be designed. Once these are established, the low-level requirements will specify the functional elements that must be incorporated to ensure the artefact is fit-for-purpose.

4.1. Why does HESTIA need a separate artefact?

The Netherlands Environmental Assessment Agency (PBL) aims to include more behavioural dynamics in HESTIA. This would allow the model to be more widely used for socio-economic questions. While it is already positioned as a tool for socio-economic analysis (Tigchelaar, 2023), its current techno-economic focus mainly frames the energy transition in the built environment as a technical challenge solvable through retrofits. HESTIA offers a detailed representation of spatial, technical, and economic processes within the energy transition, but it largely overlooks the social and behavioural dynamics that make up households' energy behaviour. Investment decisions are simulated by first determining whether a household considers an upgrade to their dwelling, based on the lifespan of existing components, renovation opportunities and policy incentives. The model will assess various investment options for a home, considering technical possibilities and policy.

A serious effort is made to include behavioural diversity among households in their decision-making through the incorporation of varying activation probabilities, for example, based on the range of nominal lifespan of appliances and several building components. Nevertheless, the model simulates investment decisions by assessing the attractiveness of different options for each household based only on the cost-benefit ratio of each option (van der Molen, 2023).

A corrective factor ís included to compensate for the lack of consideration of non-financial and non-rational factors (van der Molen, 2023), but this is a large simplification and neglects factors that make up a household's identity, which impacts how they make investment decisions. For these calculations, there is once again that one-size-fits-all assumption, which can lead to blind spots in policy assessment.

Furthermore, HESTIA allows users to scale the demand for functional energy products in real-time (van der Molen, 2023). This behavioural adjustment factor modifies energy consumption based on user assumptions and is supposed to reflect actions such as reducing shower time to save energy based on a sustainability concern. The model applies this factor across multiple domains, including space heating, cooling, domestic hot water, electrical equipment, and cooking. In its current version, HESTIA does not support the specification of behavioural factors for distinct building or population groups; instead, a uniform factor is applied to all resident objects (van der Molen, 2023). Again, applying a one-size-fits-all strategy.

The model currently fails to account for misrecognition as theorised by Fraser, which emphasises how cultural norms and institutional practices systematically undervalue or marginalise certain social groups through the denial of their needs, identities, and modes of interaction. As HESTIA reduces individuals' diversity to singular behavioural profiles based on dominant norms (van der Molen, 2023), certain groups are undervalued, and thereby their experiences, constraints, and motivations are ignored. Assuming uniform, rational decision-making across all households, failing to recognise behavioural heterogeneity, thus constitutes a form of misrecognition. This necessitates a shift toward the household perspective, whereas HESTIA has a technological, stock-based perspective, recognising households not merely as a passive unit within the built environment, thereby introducing a bottom-up view of the system.

While HESTIA is a powerful tool for assessing policy impacts and the influence of investments, it is a top-down model, not designed to capture social interactions between households. Investment decisions in HESTIA are primarily driven by cost-benefit calculations, activation moments, and policy impulses, all specified exogenously through scenario-based input and static behavioural profiles (van der Molen, 2023). As such, the model does not include a structural representation of dynamic, endogenous behavioural change resulting from social networks, shifting attitudes, or peer influence.

To bridge this gap, a complementary approach is needed; one that simulates heterogeneous households interacting with each other and their environment, and allows for behavioural change from the bottom up. These requirements align with the core principles of Agent-Based modelling. ABMs seek to replicate real-world concepts, actions, relations or mechanisms by simulating the behaviour of heterogeneous agents within a defined environment (Nikolic et al., 2013b; Anderson et al., 2013). Instead of assuming uniformity, ABM enables the exploration of complex, dynamic systems through a bottom-up perspective, simulating individual decisions and interactions and capturing how this affects macro-level behaviour (Derkenbaeva et al., 2024). This leads to the following conclusion for the required artefact:

Artefact definition

The artefact should be a separate agent-based model, in which households are the agents.

As the artefact is a separate model, it must produce results that can effectively interact with HESTIA and its inputs. This ensures that household heterogeneity, which is identified as imperative for avoiding misrecognition in the model, is incorporated in the model. Consequently, the high-level requirement for the artefact becomes:

Requirement 1

The model has to generate outputs compatible with HESTIA to allow for exploring diverse policy interventions and improving the assessment of their impact on reducing energy poverty.

4.2. Household requirements

It is increasingly acknowledged that people do not always make their energy-related decisions based on economic logic alone. Their choices are shaped by the social contexts and interpersonal relationships (Derkenbaeva et al., 2024), rather than the economically optimal choice like in HESTIA. To effectively include diversity in energy decisions, it is important to understand: (1) which household characteristics contribute to this diversity, and (2) how these characteristics drive energy decisions.

Trotta (2018, p. 530) distinguishes between energy-saving behaviours and energy efficiency investment behaviours. Vasseur and Marique (2019) makes a similar distinction, distinguishing between technical and behavioural energy saving measures. The resulting total set of categories, henceforth referred to as *energy behaviour*, represents the full range of actions and patterns related to energy use in the context of the HESTIA model.

- Household energy consumption (HEC) - standard levels of energy use;
- Energy saving behaviour - which are actions that can be executed daily at home. These actions are often related to energy consumption through electricity, water or heating (Nie et al., 2020; Niehoff and Kuttschreuter, 2021; van der Molen, 2023);
- Energy efficiency investment tendencies.

On a household level, multiple studies have analysed the factors influencing energy behaviour. Although they identified some significant factors of influence, determining the specific contribution of one factor to a home's energy use has proven difficult (Vasseur and Marique, 2019). Results differ per study due to, for example, different datasets being used and different areas being analysed. Nevertheless, there is a consensus on the key role of individual characteristics and how these should be split into objective and subjective factors. Combined, objective and subjective factors account for a household's energy behaviour (Guo et al., 2018).

Linking the ABM to the HESTIA model first includes extracting data from this model. This puts forward a crucial requirement. HESTIA is calibrated based on real-world data, shaping the characteristics of the dwellings in the model (van der Molen, 2023). This data provides details for the ABM, such as household demographics and socio-economic variables, and energy demand. This data is crucial for the initialisation and decision-making of the agents in the ABM. As such, the ABM has to reflect up-to-date conditions and should be able to dynamically integrate HESTIA's data, to stay up-to-date during whilst running. Moreover, HESTIA contains policy and scenario data which provide insights into existing and future regulations which create the external conditions in which agents operate and influence their investment decisions. Accordingly, the model's environment must be structured to include these inputs.

Requirement 2

The model should be able to (dynamically) process input data from HESTIA to initialise household agent attributes and global parameters.

4.2.1. Socio-demographic characteristics

Various studies have analysed the socio-demographic determinants of energy behaviour (Abrahamse and Steg, 2009; Abrahamse et al., 2011; Brown et al., 2023; Guo et al., 2018; Mashhoodi and van Timmeren, 2018; Mashhoodi et al., 2019; Niamir et al., 2020; Zhang et al., 2018). These studies examine household characteristics such as average income, household size or number of family members, average age in the household, and the type of dwelling. Other frequently considered factors include building age, dwelling size, level of education, gender, and the overall energy quality of the home. Factors identified to be significant are context-dependent across the various areas investigated. For studies focusing on the Netherlands, factors identified to be significant are:

- **Household income**: This can be seen as economic comfort. A higher income is generally associated with a higher tendency to invest in energy-saving technologies (Niamir et al., 2020), such as house insulation or solar panels. Households with a lower income are more inclined to increase their energy-saving behaviour in an attempt to decrease their monthly bills - this is less of an issue for people with higher economic comfort (Niamir et al., 2020). Higher incomes are associated with *increased* energy consumption (Abrahamse and Steg, 2009; Abrahamse et al., 2011; Mashhoodi et al., 2019; Niamir et al., 2020; Vasseur and Marique, 2019).
- **Household size**: Logically, household size generally has a negative relationship with the household's total energy consumption (Niehoff and Kuttschreuter, 2021). Mashhoodi et al. (2019) also identified that within the Netherlands, indicators can function as either local or national determinants. Household size, for example, has been identified as a local determinant. Specifically for The Hague, it identified household size to have a negative coefficient related to HEC. A larger household size indicates a lower HEC per capita. According to Mashhoodi et al. (2019, p. 402), this finding is in line with other studies and caused by economies of scale in large households.
- **Building age**: Several dwelling characteristics play a role in HEC as well as energy-saving investments. Older buildings are generally less energy-efficient and thus associated with higher HEC

(Mashhoodi et al., 2019). This association is weaker in the Randstad than outside (Mashhoodi and van Timmeren, 2018), but as this thesis is limited to one area within the Randstad, distinguishing between strengths for this factor is unnecessary.

- **Home ownership**: Ownership status of a dwelling is a strong predictor of energy-saving investment tendencies (Mashhoodi et al., 2019; Niamir et al., 2020; Vasseur and Marique, 2019). As a renter, there is usually less access to options to avoid energy poverty (Feenstra and Clancy, 2020).
- **Energy label**: Energy label is also identified as having a significant influence on energy saving behaviour, specifically heating and cooling (Niamir et al., 2020). A lower energy label is assigned to a home due to its higher energy loss. This loss generally gives a higher motivation to decrease HEC to save on energy costs.

Requirements resulting from this list of variables are:

Requirement 3 & 4

- The model should assign each household agent a profile including income, household size, dwelling age, home ownership status, dwelling size and energy label.
- The model should adjust the decision-making rules for the differences in socio-demographic characteristics.

Interestingly, there seems to be a conflict on whether education levels have a significant impact on energy behaviour. Wang et al. (2023) found that in China, education levels had a positive and signification effect on HEC. In Ireland, however, Leahy and Lyons (2010) found it to have an insignificant effect. For the Netherlands, Vasseur and Marique (2019, p. 19) found no significance for the influence of education on taking technical energy saving measures and barely any significance for behavioural energy saving measures. It was only found to be significant for ”turn off the lights when you are not there”. Niamir et al. (2020) states the opposite, highlighting that the probability of households investing and their education levels are highly correlated and that education levels play an important role in the energy transition.

Niamir et al. (2020) focus on Overijssel, whilst Vasseur and Marique (2019) use a dataset representative for the entire Netherlands. As Mashhoodi et al. (2019) found that the influence of socio-demographic factors varies across different locations within the Netherlands, and given the distinct characteristics of the Randstad compared to other regions, it is not logical to adopt the conclusions from Niamir et al. (2020). A broader, nationally representative conclusion is therefore more appropriate. For this study, education is thus seen as not significant.

4.2.2. Behavioural characteristics

In the literature, there is a consensus that energy behaviour decisions are partly determined through subjective characteristics grounded in behavioural theory. Subjective factors reflect individual behavioural attitudes, preferences, and perceived behavioural control (Zhang et al., 2018). Different studies apply different behavioural theories and test the influence of different subjective characteristics. Several studies prove that attitudes, subjective norms, and perceived behavioural control shape energy behaviour (Abrahamse and Steg, 2009; Conradie et al., 2023; Abrahamse et al., 2011). These are aspects part of the Theory of Planned Behaviour (TPB) by Icek Ajzen (Ajzen, 1985).

According to the TPB, behavioural intentions shape actual behaviour (Ajzen, 1985). These intentions are influenced by three core components: attitude towards the behaviour, subjective norms and perceived behavioural control. Attitude refers to an individual’s overall support for or against the behaviour. Subjective norms capture the perceived social pressure from others to perform this behaviour (Guo et al., 2018). The Theory of Reasoned Action states that attitude and subjective norms are the key determinants of an individual’s intention towards a behaviour. The TPB expands the Theory of Reasoned Action by including Perceived Behavioural Control (PBC) (Guo et al., 2018). This refers to a person’s perception of their ability to perform a certain behaviour (Ajzen, 1985).

A person can have a positive attitude towards taking an action and can experience support from their social circle, but if they perceive that they are missing some crucial resources, they may still not undertake that action. The interaction between the three variables differs per type of behaviour and per individual. The relative importance of each factor can vary depending on the behaviour and the individual’s characteristics (Ajzen, 1985).

TPB applied to energy behaviour

Applying the TPB to household energy behaviour, Abrahamse et al. (2011) found that intentions to reduce HEC were positively related to attitudes and perceived behavioural control. Notably, there seem to be at least two types of relevant attitudes: attitudes towards adopting energy-saving measures and attitudes towards taking technical measures, such as investing in energy-efficient technologies (Nie et al., 2020).

Nie et al. (2020) reports estimates which indicate that technological measures are closely linked to income and home-ownership. For example, renters were initially found to be 28.6% less likely to invest in improving house insulation, but this estimate dropped to 26.3% when controlling for household characteristics such as income and ownership. Higher-income households have a higher willingness to pay, suggesting a more positive attitude, and are thus more likely to invest in technical improvements.

Requirement 5

The model should assign each agent an attitude variable that influences their energy-related behaviour, weighted for income and ownership type.

Household decision-making tends to be shaped by interactions with peers (Niamir et al., 2020). Agent interaction does not occur in isolation. It is not limited to a single agent's unique characteristics. It occurs through a summation of individual behaviour and the social and spatial structure of their environment.

Agents' behaviours are affected by their interpretation of their neighbours' and acquaintances' behaviour (Ebrahimigharehbaghi et al., 2022). The influence between agents is not just a function of their characteristics but also of their geographical location.

de Vries (2020) highlights that individuals often align their behaviour with people in their "in-group" - those they feel connect to, such as neighbours or friends. In social comparison, people assess and adjust their behaviour based on how they believe others act, especially when it comes to sustainability. These social norms can have an even stronger influence than personal attitudes (de Vries, 2020). Households' behaviour is thus influenced by the dynamics of their social network. Households can experience descriptive or injunctive norms. Descriptive norms are effective as they "describe" the desired behaviour of the in-group. The household sees what their in-group is doing and adjusts itself accordingly, to gain their in-group's approval. Injunctive norms are more intuitive. Households perceive a certain behaviour as in line with their in-group and thus adopt that behaviour (de Vries, 2020).

A household's ability to follow the social norms of its in-group is important to how they are seen and accepted by their in-group. This serves as a big motivator to adhere to these social norms (Davoudi et al., 2014). This motivation is so strong that normative feedback (comparing your energy use to another's) is more effective than informative feedback (receiving information on your energy use) (Davoudi et al., 2014; de Vries, 2020). Accordingly, requirements five and six are formulated as necessary conditions for the model.

Requirement 6 & 7

- The model should allow agents to assess if other agents belong to their in-group.
- The model should incorporate subjective norms that evolve over time and with interaction by allowing each agent to form behavioural intentions based on interactions within their social group.

It has been decided not to conduct an original survey to test which behavioural variables or theories are influential on energy behaviour in The Hague for multiple reasons. Firstly, the goal of this study is not to collect new data and prove hypotheses on behavioural theories that are applicable to energy behaviour. The goal is to show if and how the inclusion of behavioural variables as a form of recognition justice influences the outcomes of the HESTIA model. Secondly, due to time restrictions of this study, including original surveys and their data analysis would make the scope of the study too large. Thirdly, the Theory of Planned Behaviour is a common theory used to analyse energy behaviour (Derkenbaeva et al., 2023) and its assumptions of rational decision making are in line with the investment-decision-making structure in HESTIA.

Requirement 8

The model should convert attitudes, perceived behavioural control and subjective norms into a probabilistic intention to adopt energy behaviours.

5
Model conceptualisation

Following the definition of the requirements for the artefact, the next step in the design science framework is the design and development of the artefact. This chapter will detail the concept formalisation, following the conceptualisation of misrecognition in energy poverty policy and its prevention in models through the requirements. Together with chapter 4, this chapter answers the sub-question *”What is a suitable conceptualisation for modelling household energy behaviour in HESTIA?”*.

5.1. Model design

This section discusses in detail the conceptualisation of the ABM and its link to HESTIA, also visually represented in Figure 5.4.

5.1.1. Investment logic in HESTIA explained

Section 4.1 briefly discusses how, despite its technical detail, HESTIA overlooks the important people-centred perspective when assessing changes in functional energy demand and investment behaviour.

In the model, installations are used to meet the demand for different functional products. Functional products are installations used to meet functional demand. A distinction is made between functional demand and meter demand. Functional demand is the energy requirement of a household, while the meter demand is the actual amount of energy consumed to meet the energy requirement (van der Molen, 2023).

The fuel for these installations can differ from electricity and gas to wood pellets and biomass. In HESTIA, installations are distinguished between being used for space heating (RV), water (TW) and cooling (KD) (van der Molen, 2023). When an agent makes an investment decision for retrofitting their home, there is a choice between improving insulation levels, one or more of the installations or both (van der Molen, 2023).

To allow for a more realistic representation of reality, not every household will consider investing in all attributes of their home every year. Considering an investment in HESTIA means that a part of a dwelling is ”activated” (van der Molen, 2023).

”Activation” means that a selected group of households are activated to look at all investments that are possible for their home. A dwelling is eligible for activation when a building component or installation reaches the end of its service life, during renovation or a move, or if policy mandates it. Renovation occurs when more than 2 building components are activated at the same time, due to their lifespan ending. A moving moment occurs randomly based on a set probability per year. If a moving moment occurs, all building components and installations are activated for retrofitting, to simulate a new occupant renovating their new home before moving in (van der Molen, 2023).

There are three options for activation (van der Molen, 2023):

1. ’ProductActief’ (English: product active), meaning that investment in installations is considered.
2. ’GebouwActief’ (English: building active), investment in insulation improvement is considered;
    - In a dwelling’s building envelope, there are ten building components which can be eligible for insulation improvements: windows (ground floor) (RO), windows (upper floors) (RB), roof

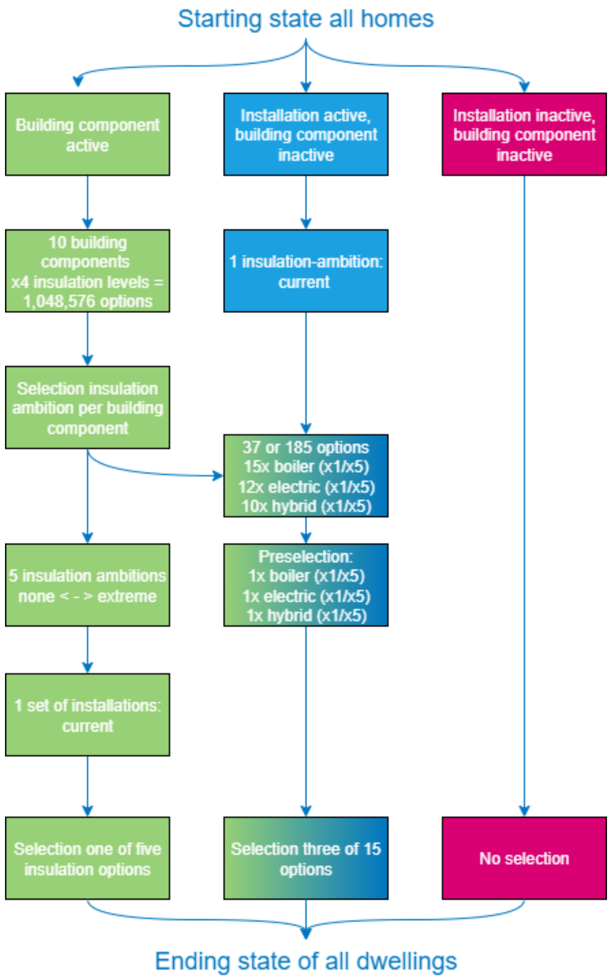

Figure 5.1: Steps in investment logic, left: insulation track, middle: installation track, right: non-activated dwellings (van der Molen, 2023)

(flat) (DP), roof (pitched) (DS), doors (DR), panels (PL), floors (VL), facade (MG), cavity wall (MS), and cracks (KR).

3. A combination of these.

In HESTIA, the investment logic can follow one of three pathways: the insulation track (Dutch: isolatiespoor), installation track (Dutch: installatiespoor) or remain inactive. If a property is activated for both tracks, it starts along the insulation track. Once an insulation ambition has been selected, it moves to the installation track to explore the remaining relevant building options (van der Molen, 2023).

The insulation track focuses on improving a building's thermal performance. Given that the total number of possibilities is over a million, the model narrows the choices to five distinct and technically feasible sets of measures: insulation ambitions (Dutch: isolatie ambitie) (van der Molen, 2023).

The installation track follows a similar structure. Applicable installation types (e.g., boiler, hybrid, or all-electric (section C.3)) are identified based on infrastructure compatibility, policy eligibility, and insulation level (van der Molen, 2023).

An initial selection is then made by choosing one option per system category. From these three options, eventually one will be chosen, with each category having an equal chance of being selected. These tracks are visualised in Figure 5.1.

The initial selection is based on the technological possibilities of a home; is the right infrastructure and insulation level present, and is an investment option available, according to policy? For each possible option, the odds that this option is selected are calculated based on its relative cost-benefit. The top three installation options (one for each category of boiler, hybrid and all-electric) and 1 set of insulation

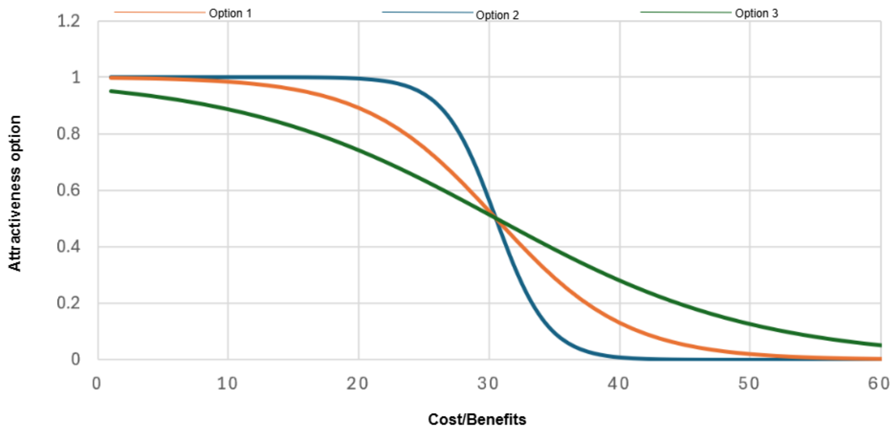

Figure 5.2: Example S-curve concept

options (one option for each of the ten building components) are selected. For these final options, the odds and probability of selection are calculated once more van der Molen (2023).

In the model, the selection of insulation measures and installation options is based on a probabilistic calculation that uses S-curve logic to reflect differences in household behaviour and ambition.

For each insulation ambition level (e.g., Low, Medium, High), each possible insulation measure and each available building option, an S-curve defines the likelihood that a measure will be chosen. These curves are parametrised by a β coefficient, which controls the steepness of the curve and reflects the sensitivity of an option's attractiveness to the cost-benefit ratio, and a P50P point, representing the cost-benefit threshold at which 50% of the population would be expected to adopt the option based on its attractiveness (van der Molen, 2023).

There are three S-curves specified in the model:

- S-curve insulation measures
  - Per insulation measure (combinations of building component and insulation level N1 to N4)
  - Broken down by property type
- S-curve investments
  - Per insulation ambition (none/low/medium/high/extreme)
  - Broken down by property type
  - Broken down by building option category
- S-curve building options
  - Per building option
  - Broken down by property type

The S-curves are based on a cumulative normal-distribution function (van der Molen, 2023), a form of a sigmoid function as in Equation 5.1. It resembles the gradual adoption of a technology, with a low adoption at a very high cost, a growing adoption as the costs decrease, and a plateau of the height of adoption at the lowest cost option. These S-curves, in a way, are the closest to behavioural diversity in the model structure as they reflect differences in perceived attractiveness and adoption probabilities of investment options. The agent heterogeneity in investment decisions is thus integrated in the HESTIA model through this logic.

$$A(\text{cost/benefit}) = \frac{1}{1 + \exp\left(\beta \cdot (\text{cost/benefit} - \text{P50P})\right)} \tag{5.1}$$

5.1.2. Agent-based model

The ABM will be populated with agents based on a synthetic population meant to resemble the population of The Hague. Agent attributes are initialised using secondary survey, census and HESTIA data. The initialised agents interact, causing them to adjust their energy behaviour, following the Theory of Planned Behaviour. Through the requirements, defined in chapter 4, the conceptual model for the ABM can be established. In this conceptualisation, the system, agents, their states and their relationships are officially defined (Nikolic et al., 2013a).

These features can be summarised as follows:

- *Agents:* Households, living in the municipality of The Hague in the Netherlands. Each household has a unique profile comprising socio-demographic, household and behavioural characteristics. The agent decision rules are grounded in the Theory of Planned Behaviour subsection 4.2.2.
- *Agent heterogeneity:* To accurately simulate the demographic diversity of the population, and ensure compatibility with HESTIA, a synthetic population is constructed by combining the existing synthetic population from HESTIA and survey data from the case-study region, based on the requirements identified in chapter 4. This approach can be further justified by the aforementioned time constraints, which limit the opportunities to conduct primary data collection on household profiles and their energy behaviour. The agents are initialised according to the profile given in Figure 5.3.

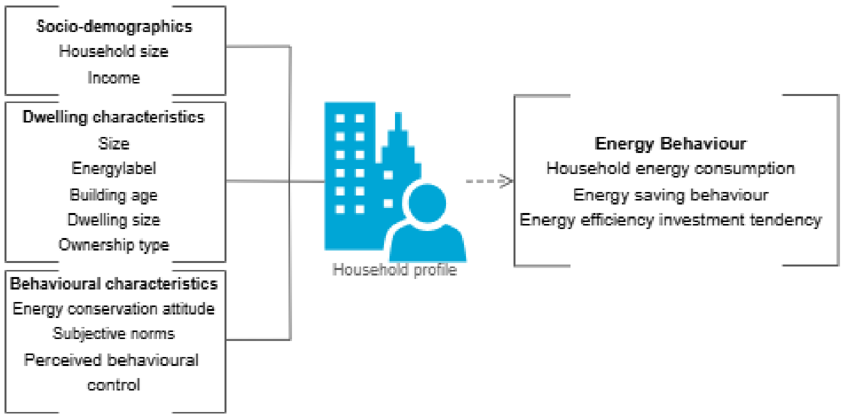

Figure 5.3: Agent profile combining socio-demographic, dwelling and behavioural characteristics

- *Relationships:* The agents interact through their social networks. An agent's opinion about their energy behaviour can be changed through these relationships. As this study has a scope limited to The Hague, social networks are limited to neighbours only. These neighbours are identified using geographic proximity, using each household's assigned coordinates. A household's social network, including friends and family, extends beyond the borders of the municipality. Due to the limited geographical scope of this study, those social connections cannot be included. To avoid wrongly and forcefully restricting every household's social network within the city, friends and family are excluded from the analysis.
- *Environment:* The environment in which the agents exist refers to the built environment of the municipality of The Hague. It provides the context in which the influence of policy measures, energy prices and climate scenarios will be tested.
- *Time step:* In HESTIA, investment occurs once a year. To align with this time step, one step in the ABM also resembles a singular year.

5.1.3. Background of the applied theories

Theory of planned behaviour

Beyond structural and socio-economic attributes, agents are enriched with behavioural variables that influence their decision-making processes, based on the Theory of Planned Behaviour. A recapitulation: the theory states that an agent's intention to act is the result of a decision-making process dependent on three attributes: attitude, subjective norms (SN), and perceived behavioural control (PBC) (Ajzen,

1985) (subsection 4.2.2). In this thesis, a household can demonstrate two types of behaviour: energy saving and investment in energy efficiency measures for the home. For these intentions, the attributes are defined as:

- *Attitude towards investment:* Does the agent see investing in energy efficiency measures as positive and beneficial?
- *Attitude towards saving energy:* Does the agent see decreasing functional energy use as positive and beneficial?
- *Perceived behavioural control of investment:* Does the agent feel they have the resources and opportunities to make an energy investment
- *Perceived behavioural control of energy saving:* Does the agent feel they could decrease their energy use without being uncomfortable, and will this have any actual positive consequences for climate change?
- *Subjective norms for investment:* How much pressure does the agent experience from their social circle to invest or not invest in energy efficiency measures?
- *Subjective norms for energy saving:* How much pressure does the agent experience from their social circle to change their energy consumption behaviour?

This conceptualisation is further elaborated and formalised in the next chapter.

Social identity theory

Social identity theory (SIT) is applied to determine whether an agent will be influenced by the opinion of their neighbour. The theory states that people categorise themselves and others into groups (in-groups vs. out-groups), and want to improve their self-esteem by aligning themselves more with their in-group. Individuals often adopt aspects of the behaviour of others in their in-group, including norms (Worley, 2021).

The SIT applies to the agents in the ABM in a few steps. Firstly, social categorisation. People will classify themselves and others into social groups; households will categorise themselves and their neighbours into groups based on their energy behaviour (McLeod and Guy-Evans, 2023). In this thesis, the characteristics that determine if neighbours are considered to be in a household's in-group are household size, ownership type, installations used for supplying their energy demands, income class, energy use, dwelling type and energy label.

The next step is social identification. If a household considers itself similar to their neighbour, they will start mirroring their norms, values and behaviours (McLeod and Guy-Evans, 2023). The more profile features two neighbours have in common, the more they see each other as part of their in-group and the more influence they have on each other's behaviour. The total pressure of an agent's neighbour interactions in a year nudges the household to adjust its attitudes for the following year. To adhere more to the behaviour of their in-group, decrease social friction and maintain group cohesion. This can mean a positive or negative adjustment.

Thirdly, there is the social comparison. Individuals compare their groups to others and favour their group, leading to in-group favouritism (McLeod and Guy-Evans, 2023; Worley, 2021). Households will adjust their intentions to invest or save energy based on how strongly they feel their neighbour is in their in-group and their investments. If their neighbour belongs to their out-group, they will feel justified in not having similar attitudes as someone ”not like them” and not adjust their behaviour.

5.2. Designing the multi-model link

The agent-based model will, per time step, result in an intention to invest per agent. This value will be averaged per income group. Based on this value, per income group, the S-curve variables will be adjusted to introduce more heterogeneity in the HESTIA model. These intentions will be calculated at the end of year t, and determine investment decisions for the following year $t+1$. This means that the intention for $t = 2020$ impacts investment choices in 2021, the intention for 2021 impacts investment choices in 2022 and so forth. By using a soft-link approach to connect HESTIA with the ABM, a hybrid model is created that offers a solution for the top-down approach of HESTIA. Soft-linking these models allows both to be developed, run and tested independently (Fattahi et al., 2020). Intermediate data can more easily be analysed and validated.

This approach does come with its challenges. As the two models are linked through the S-curve data and income groups, the data must be correctly matched during the exchange. Connecting the two models means accommodating their differing levels of aggregation. While HESTIA performs calculations at a dwelling level, its outputs are aggregated to at least a neighbourhood level. The ABM, on the other hand, operates and reports at the household level. This difference introduces a challenge for the correct matching of the data. The ABM makes it possible to introduce more diverse, household-level variation into the normally homogenous adoption pattern described by HESTIA's S-curves. At the same time, these S-curves present boundaries to the inclusion of the ABM's output.

Using each agent's intention to invest to create their S-curves would result in an unmanageable number of curves, resulting in excessive computational demand. As a compromise, investment intentions are averaged per income group. This reduces the number of S-curves per investment option to six; one per income class. This maintains a realistic balance between more heterogeneity and the computational feasibility of HESTIA.

Figure 5.4 gives a visual representation of the conceptual structure of the integrated model, highlighting the interaction between the ABM and HESTIA.

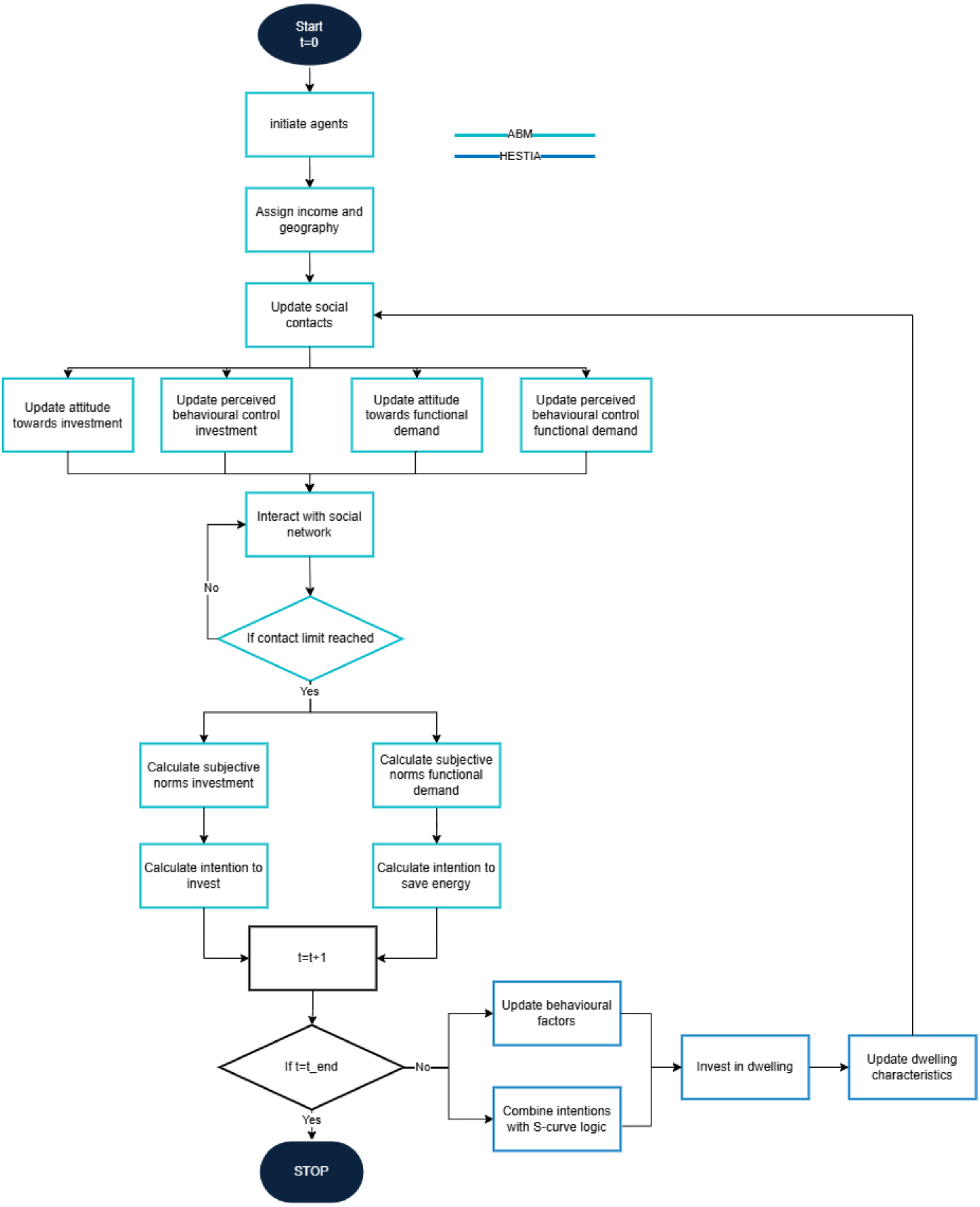

Figure 5.4: Conceptualisation multi-model design

5.2.1. Linking the model design to recognition justice

This thesis represents only a first attempt at including recognition justice in HESTIA, which has to be done based on the availability of secondary data. The inclusion of recognition justice has been limited to what is feasible given the current data constraints. The available data is on energy behaviour and socio-demographic factors across income groups. HESTIA focuses on the cost-effectiveness of energy investments. Thus, an accessible entry point for more diversity in HESTIA, which is seen as the first step towards a more just HESTIA, is through income-based behavioural differences.

Reflecting back on Figure 3.2, in Figure 5.5, the link between the ABM and HESTIA through the investment logic means that this simulation primarily focuses on highlighting misrecognition as cultural domination. This sub-group of misrecognition translates to dominant norms shaping policies. The parameters defining the S-curves are based on calibration, to reproduce past investment behaviour as accurately as possible (van der Molen, 2023), thereby implicitly reflecting dominant norms and average patterns that have historically shaped household decision-making. By adding more socio-demographic detail to households in HESTIA, the uniform application of behaviour is disrupted. It will be tested if this offers a way to reduce misrecognition through improved representation of household circumstances.

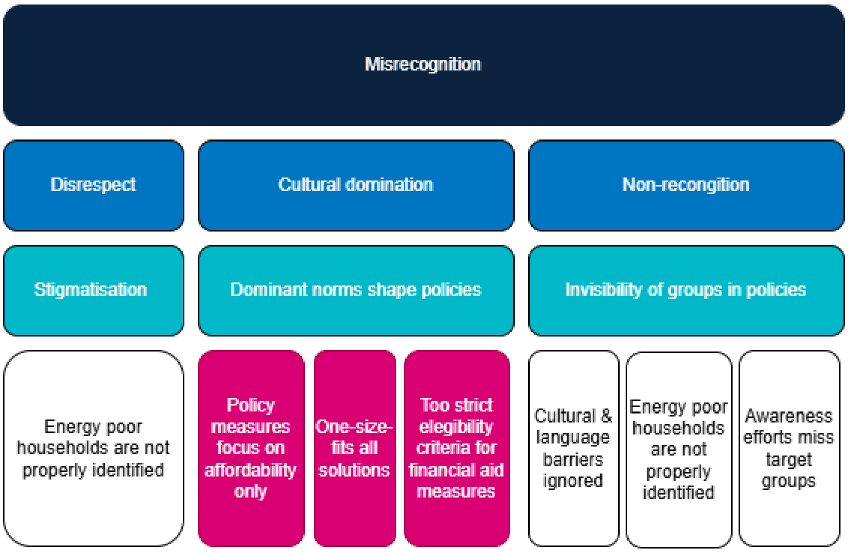

Figure 5.5: Fraser's theory of misrecognition linked to Dutch energy poverty policy targeted in the simulation

A more complete inclusion of recognition justice would require more and differently disaggregated data. To capture non-recognition, data is required on the cultural diversity of households and how different backgrounds shape energy behaviours and influence responsiveness to policy interventions. While MilieuCentraal identified different patterns in energy behaviour for different cultural backgrounds (de la Haije, 2024), there is seemingly a lack of quantitative data on these patterns. Including these dimensions would require strong assumptions about behaviour, risking oversimplification or misrepresentation of the affected groups.

Similarly, to account for energy poverty not being properly defined, which is both disrespect as well as non-recognition, various new definitions and measurements of energy poverty would need to be implemented and systematically compared, which in itself would constitute a separate research problem. By increasing the socio-demographic details of households in the model, the S-curves, based on calibration averages which are shaped by the dominant behaviour, are more diversified, so it is an attempt to show how, when accounting for this diversity, policies may have different effects. The models are conceptually aligned, understanding each other's information, but they are not integrated through shared code or direct software interfaces.

By establishing a soft link between the ABM and the HESTIA model, and modifying HESTIA's investment logic to reflect agent-specific characteristics, recognition justice considerations are directly embedded within the model structure. This aligns with the merging strategy proposed by Trutnevyte et al. (2019), representing a deeper integration of justice aspects into the modelling process. This study accounts for recognition justice by incorporating agent heterogeneity through diversified agent profiles; these profile characteristics (in)directly influence agents' investment choices in HESTIA. Household heterogeneity impacts the investment logic, meaning that recognition justice is embedded in the model dynamics, instead of remaining exogenous.

5.3. Key Performance Indicators

The impact of the adjustments to the HESTIA model will be measured by looking at the energy poverty distribution across the Hague. As mentioned in the section above, although flawed, the definition of energy poverty will not be changed, meaning that TNO's definition of energy poverty will be used to measure its prevalence in The Hague.

Energy poverty is assessed based on several indicators. Low income, High energy cost (LIHE) or Low income, Low energetic quality (LILEK); the household has (1) a low income, which is a maximum of 130% of the low-income threshold (Centraal Bureau voor de Statistiek, 2024a), and (2) either has a high energy bill, or lives in a dwelling with low energetic quality (Loos, 2024). In the case of LIHE, a high energy bill is defined as a bill higher than the average energy bill of homes with an energy label C, as this is used as the reference point for the typical median energy bill (Loos, 2024).

Dwellings are classified as having poor energetic quality if their energy consumption is higher than the average expected use of dwellings with an energy label C (TNO, nd). This can occur with any energy label, although usually it happens with dwellings with energy labels D, E, F or G (Loos, 2024). To apply these indicators, everyone in the lowest income class is included in the calculations. Whilst it could be that their income is higher than 130% of the low-income threshold, this is unknown due to treating income as a categorised variable, and it thus has to be assumed that everyone in this category could qualify for energy poverty if they have low energetic value or high energy cost. This introduces an important limitation. Households can be classified as energy poor even if their income exceeds the income boundary set for energy poverty. This broad classification likely leads to some misrecognition, as not all households in this group will experience energy poverty.

This is why the important distinction is made in this report. Households are not classified as energy poor but as *at risk* for energy poverty. This distinction is crucial, as avoiding premature categorisation helps reduce the risk of incorrect assumptions and misrecognition and ensures a more nuanced interpretation of the results.

Although the High Energy Quotem (HEQ) is normally used as an indicator of energy poverty as well, identifying any household that spends more than 10% of their income on their energy bills as energy poor, despite their income (Centraal Bureau voor de Statistiek, 2024a), it has to be excluded as an indicator in this study. It would introduce too big an assumption. Due to the income classification, applying HEQ in this context would require selecting a specific point within each income class (the lower bound, upper bound, or median) to calculate the 10% threshold. This choice would significantly distort the results, potentially classifying an unrealistically large number of households as energy-poor.

The income classes used in this study are a standardised classification, based on single-person households (van Middelkoop et al., 2023). This standardisation is based on equivalence factors to account for the non-linearity in income increases when household size increases (Arends-Tóth et al., 2022). To ensure consistency in the assessment of energy poverty, CBS standardises the energy bills, using the same equivalence factors (van Middelkoop et al., 2023).

In line with this method, the same equivalence factors are applied to the energy costs of the agents. The energy bill has to be standardised, as the low-income boundary is always given standardised for a single-person household, and if not applied, this would skew the results. Moreover, this resolves any possible skewing of the results due to a multi-family dwelling having a high energy bill due to the many occupants, but only having a ”single-person income”. Standardisation thus helps avoid distortions and ensures that households with disproportionately high energy costs relative to their adjusted income are accurately identified.

The equivalence factors of CBS cover households up to eight inhabitants (Arends-Tóth et al., 2022). HESTIA includes a very small number of households with a household size larger than this. These households are assigned the same equivalence factor as eight-person households. This might introduce some minor distortion of the results. The impact is seen as negligible due to the small number of households this size and the likelihood that economies of scale reduce per-person energy needs in larger households (Mashhoodi et al., 2019). These agents are kept in the model to maintain a complete representation of households in The Hague.

The low-income boundary represents the minimum purchasing power assumed to be sufficient for a single-person household not to avoid living in poverty (Centraal Bureau voor de Statistiek, 2023b). This value is based on the social benefits levels of 1979, when these were relatively high. Yearly, this amount is indexed based on inflation to reassess the low-income boundary (Centraal Bureau voor de Statistiek, 2024a) (see Table C.2 in Appendix C).

Energy poverty risk is analysed over time to capture the impact of the model changes. To demonstrate the broader influence of incorporating behavioural aspects into HESTIA, changes in energy label distributions over time are analysed. This output is viewed as a high-level indicator of how investment trends change when more agent heterogeneity is included, across all households, not just those at risk of energy poverty.

In addition to these more aggregated results, a few individual households are selected to illustrate on an agent level how their energy use, energy bills and investment choices differ to create a complete understanding of the effects of changes to the model.

It is a conscious decision not to use policy compliance as a performance metric. Although it is intuitive to expect changes in policy compliance in the model as more behavioural heterogeneity is included, in HESTIA's policy logic, it is a fixed variable (van der Molen, 2023). Modifying this logic as part of the household's behaviour would thus introduce inconsistencies in the comparison with the base case, reducing the meaningfulness of the results.

5.4. Experimental design

5.4.1. Policies

HESTIA can simulate four different policy options: subsidies, norms, bans, and activation policies, which refer to instruments that increase the probability of a specific demographic investing in specific parts of their dwelling. Due to data availability and computational limitations, the analysis in this thesis is restricted to 8 years from 2020-2027, thus mainly focusing on historical policies. As the focus of this study is not to test specific policies, the simulation will be run with the policies provided in the standard configuration of HESTIA.

In this list of policies, only one is an "activation" policy, focusing on increasing the insulation of social housing for labels E, F and G. No policies focus on informing agents on how to adjust their behaviour or on supporting them through measures beyond financial incentives. The existing policies are limited to subsidies or regulatory norms for retrofitting. This once again highlights the issues of misrecognition in energy (poverty) policy identified in section 3.2; the policies have focused mainly on the affordability of investments and are generalised in nature, failing to account for the diverse needs and constraints of different households. As a result, these policies risk overlooking structural and informational barriers that prevent certain groups, like energy-poor households, from participating in the energy transition. This underlines the need for more inclusive, targeted approaches that address not only financial, but also social and behavioural dimensions of energy-related decision-making.

5.4.2. Scenarios

HESTIA includes several scenario possibilities. As the goal of this study is not to provide policy advice for a robust policy in an uncertain future, but to show the impact of including behavioural considerations in policies, the scenario settings are kept as simplistic as possible, while still being realistic. This means that spatial development, meaning the development of new-build houses, is not taken into account.

When considering building investments, a cost comparison is made in the model. These costs can either be calculated in a national cost method or an end-user cost method (van der Molen, 2023). This choice is an important model-setting. The national cost method was selected because, with the end-user method, only costs for building owners are taken into account when calculating the business cases for the different investment options (van der Molen, 2023). The national cost method also includes any costs for renters in the business case assessment, allowing more room for their considerations in investment decisions. In the context of accounting for recognition justice, it is important to apply the national cost method as this allows for a broader societal perspective. It ensures that the cost-benefit consideration for tenants is also included. This acknowledgement of these experiences and potential constraints makes the model more inclusive and just.

HESTIA has energy prices included exogenously. It is based on historical data for the years 2000-2022. Prices for 2022-2030 are determined using the national energy outlook calculation system and the MONIT-database (van der Molen, 2023). Although the predicted prices for 2023 and 2024 might not fully align with reality, this data is still used so as not to change too much of the model outside of the study's scope. These prices can also be found in Appendix C.

The climate scenario signifies how much the average outside temperature changes over time, which influences the spatial heating and cooling demand. HESTIA presents four possible climate scenarios, provided by the Royal Netherlands Meteorological Institute (KNMI) (KNMI, 2014):

- GL (global temperature increase in 2050: +1° C with low change in air flow pattern).
- GH (global temperature increase in 2050: +1° C with high change in air flow pattern).
- WL (global temperature increase in 2050: +2° C with low change in air flow pattern).
- WH (global temperature increase in 2050: +2° C with high change in air flow pattern).

These scenarios provide a predicted temperature for 2030 and 2050, as well as the temperature in 1995 for a baseline value. Temperatures for years in between these are estimated through linear interpolation van der Molen (2023).

WH is selected as the scenario for this thesis as global warming is very likely to reach 1.5° C between 2030 and 2052 and potentially up to 2° C in this century (Masson-Delmotte et al., 2018), making 1° C an underestimate of the consequences. The choice of WH over WL is not relevant for the relatively short run time of this project (2020-2028). WH was selected due to the large changes this brings in comparison with the current situation. Even though the scenario's impact on the short-term scope of this study is limited, should the run time be increased, it would provide a substantially different situation, which would create an interesting insight into how the energy transition in the built environment would adjust.

6 Model formalisation

This chapter describes the model implementation following the conceptualisation described in the previous chapter. It details the mathematical functions for the creation of the synthetic population, along with the underlying data and assumptions informing agent behaviour. This is part of the development phase of the artefact, according to design science.

The Agent-Based Model is formalised using the programming language Python, specifically with the MESA framework. This modular framework is specifically designed for building agent-based models (ter Hoeven et al., 2025). By applying object-oriented programming, this framework allows agents and model components to be modularly structured as classes, which is very helpful for clarity, model management and thus improves transparent model development.

6.1. Agent profiles

This section explains how the agents are initialised to create a realistic but synthetic representation of the population of The Hague. Table 6.1 gives all the data sources used for this initialisation. Input data from the HESTIA model is the main source of information, extended by CBS data. HESTIA's primary goal is to provide a realistic and detailed representation of the housing stock and how it evolves under varying conditions. For this purpose, it offers a comprehensive delineation of the built environment in the Netherlands starting from 2000, constructed using input data from, e.g. CBS, BAG, Arcadis, CEDelft and the Kadaster (van der Molen, 2023).

The simulation will run from 2020 up to and including 2027. The year 2020 was selected as the start year, as most external datasets used in the model are available for this point in time. Although the data for perceived behavioural control is for 2018, it is assumed that data captured at such a disaggregated level as the neighbourhood level is relatively stable over short periods. It is considered to be representative of 2020.

An important consideration in the creation of the synthetic population is the limitation of presenting HESTIA data at such a disaggregated level. HESTIA computes at a dwelling level so it can process data at any scale it is available, and that data on any cross-section of the population can be provided (van der Molen, 2023). However, since HESTIA employs pseudo-random allocations for data, the data associated with any individual dwelling might be slightly inaccurate. This is to ensure the information cannot be traced back to individual addresses or people (van der Molen, 2023). As such, HESTIA's results should always be reported at a higher aggregation level. Although the dwelling-level data is extremely useful for constructing a detailed synthetic population, the outcomes of simulations based on this data should be reported at a minimum of the neighbourhood level, to ensure reliability and avoid misrepresentation van der Molen (2023).

From table 6.1 it becomes clear that not all input data is available at a dwelling level or municipal level. To enable their use in the ABM, national distributions are assumed to be representative of The Hague. These distributions are used to probabilistically assign values to dwellings within each neighbourhood, matching the distributions from the aggregated data. This way, the overall pattern preserves the original patterns of the data, ensuring that the synthetic population remains representative of the broader population structure. Moreover, this pseudo-random assignment aligns with HESTIA methods and maintains a certain level of anonymity, as individual households aren't directly linked to specific data points, while still preserving the statistical characteristics of the population.

Table 6.1: Datasets used for population generation

Dataset	Used for	Aggregation level	Source
Startcomponenten	Dwelling components, household size, location, functional energy demand	Dwelling level	van der Molen (2023)
Energieverbruik huishoudens naar inkomen, 2020	Household income	National / quartile level	van Middelkoop et al. (2023)
Buurten Den Haag	Geographical information on dwelling location	Neighbourhood level	Gemeente Den Haag (2018)
H4 Maatwerktabel - Duurzaam wonen 2020	Installation attitude	National level	Kloosterman et al. (2021)
Bereidheid energietransitiemaa-tregelen 2018	Perceived behavioural control	Neighbourhood level	Centraal Bureau voor de Statistiek (CBS) (2023)

6.1.1. Dwelling characteristics

Based on the input from HESTIA, a total of 264,056 households or dwellings are initialised, with the relevant profile characteristics from requirement 3. This figure does not fully align with the approx. 271,000 households were reported in The Hague's official census data. Similar discrepancies are also present when comparing HESTIA data to census data on specific dwelling characteristics, such as ownership type (fig. 6.1) and housing typology (fig. 6.2). This misalignment in data can be chalked up to agents being considered as households, while being based on dwelling data. Some of these dwellings are occupied by more than one household, which explains the difference in household count. This introduces a key distinction between the two datasets. This discrepancy is addressed in post-processing of the results, through the standardisation of the energy bill as described in section 5.3.

Surprisingly, the census data contains an 'other' bin for both characteristics. As HESTIA does not have such a category, and it is impossible to determine what would make a household classify for this 'other', this small subset (0.9% for ownership and 1.8% for dwelling type) of households is excluded from comparison and assumed to be included in the other categories. The misalignment between value counts per category can in part be attributed to the above-described difference in data aggregation between HESTIA and The Hague census data. Nevertheless, the categories' value counts all remain within a comparable range. It is therefore decided that the alignment is sufficiently close to justify using HESTIA as the source for the generation of the synthetic population.

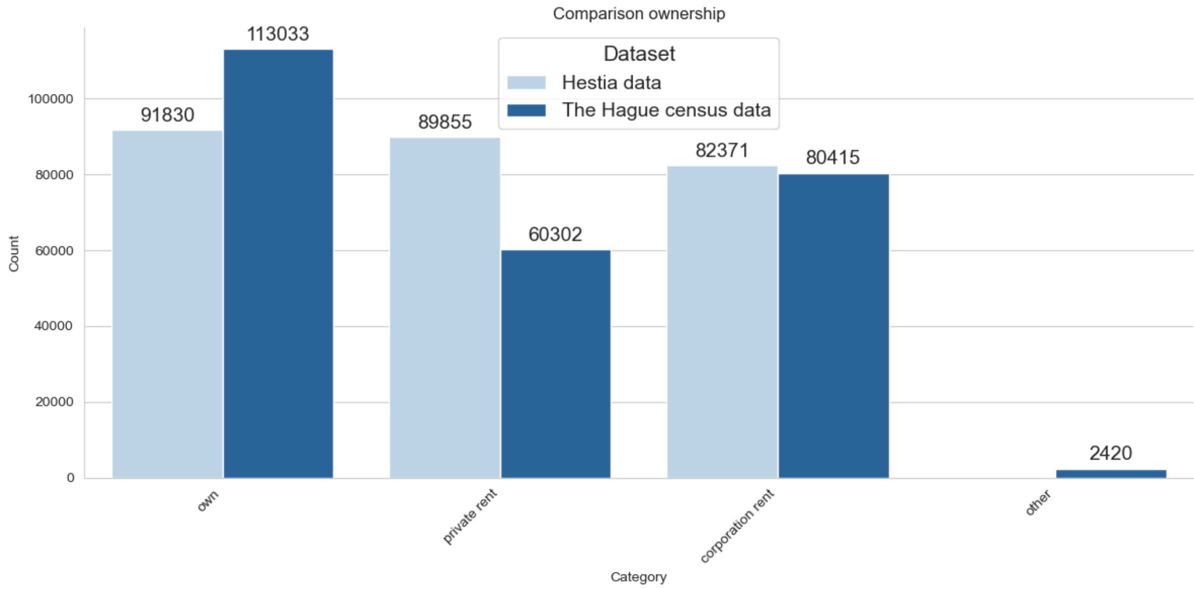

Figure 6.1: Comparison ownership type count HESTIA vs. The Hague census data (van der Molen et al., 2024; Gemeente Den haag [Gemeentelijke Belastingdienst], 2025)

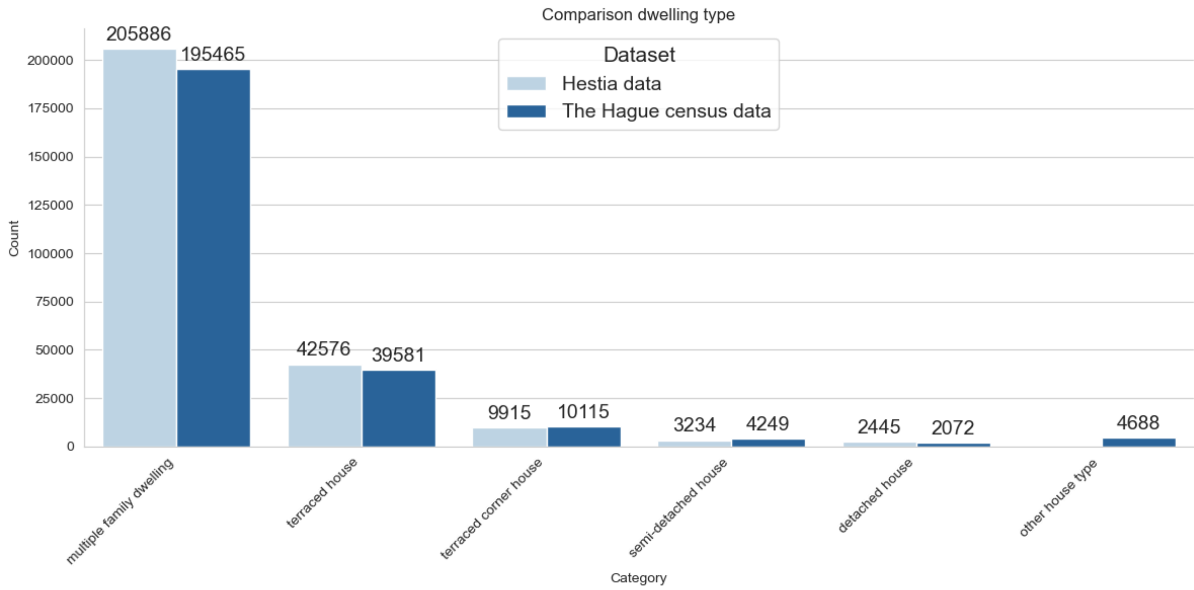

Figure 6.2: Comparison housing typology count HESTIA vs. The Hague census data (van der Molen et al., 2024; Gemeente Den Haag [Gemeentelijke belastingdienst], 2025)

6.1.2. Address allocation

The Hague is a densely populated municipality. Its inhabitants are divided over 44 areas (Dutch: wijken) or 113 neighbourhoods (Dutch: buurten) (Figure 6.3). Location of the households is an important factor in this model as it provides the spatial data required to assign agents their neighbours in the ABM, which in turn influences their social networks.

HESTIA links each dwelling to a *planregio* (van der Molen, 2023), which, when combined with geospatial data (Gemeente Den Haag, 2023), allows for spatial positioning of agents and their neighbours. *Planregios* represent an older system for neighbourhood identification but can be directly mapped to present-day neighbourhood coding (van der Molen et al., 2024). These codes are all unique combinations of letters and numbers. For example, the code BU05184214 consists of: BU (a neighbourhood or *buurt*), 0518 (municipality code for The Hague), followed by the district or area (42) and the neighbourhood (14), these combined identify Waterbuurt (GeoGap B.v., nd).

Figure 6.3: Aggregation levels The Hague Areas vs. Neighbourhoods (Gemeente Den Haag, 2023)

Within each neighbourhood, agents are assigned geographic coordinates randomly. Through this method, buildings cannot be linked to actual addresses, thus maintaining the population's anonymity. Although this does reduce spatial accuracy, it provides sufficient information for assigning neighbours to the agents.

Matching the households (agents) to geographic coordinates results in a population density as visualised in Figure 6.4. Neighbourhoods with zero inhabitants - Oostduinen (neighbourhood 10), Vliegeniersbuurt (neighbourhood 107) and Tedingerbroek (neighbourhood 109) (Allecijfers.nl, 2025) - are excluded from further analysis, as they do not contribute to the population-based outcomes being studied. In Appendix B, the map is enlarged and an overview of all neighbourhood IDs and their names is given.

Overall, the maps appear largely similar, though a few notable discrepancies stand out. In particular, the neighbourhoods of Vissershaven (02), De Bras, Waterbuurt (114), Vlietzoom-Oost (116), and De Vissen (118) exhibit significant differences. Appendix B contains a larger map with a detailed legend of each neighbourhood and neighbourhood ID. These variations could be caused by the interpolation method used in HESTIA to calculate inhabitants per building. As the specific number of household members is unknown, it is estimated in the model by using a formula that distinguishes by housing type and area, determined in 'VIVET-project Referentieverbruiken Woningen' (Beijnum and Wijngaart, 2023; van der Molen, 2023). It is the same formula for all areas in the Netherlands, based on average national information. Since some areas are more densely populated than others, it is not surprising that this introduces some errors in the calculations. This indicates that the synthetic data does not perfectly mirror the census data, but the general patterns are sufficiently aligned to support the use of the HESTIA dataset, as the primary goal is not to model The Hague with perfect demographic accuracy,

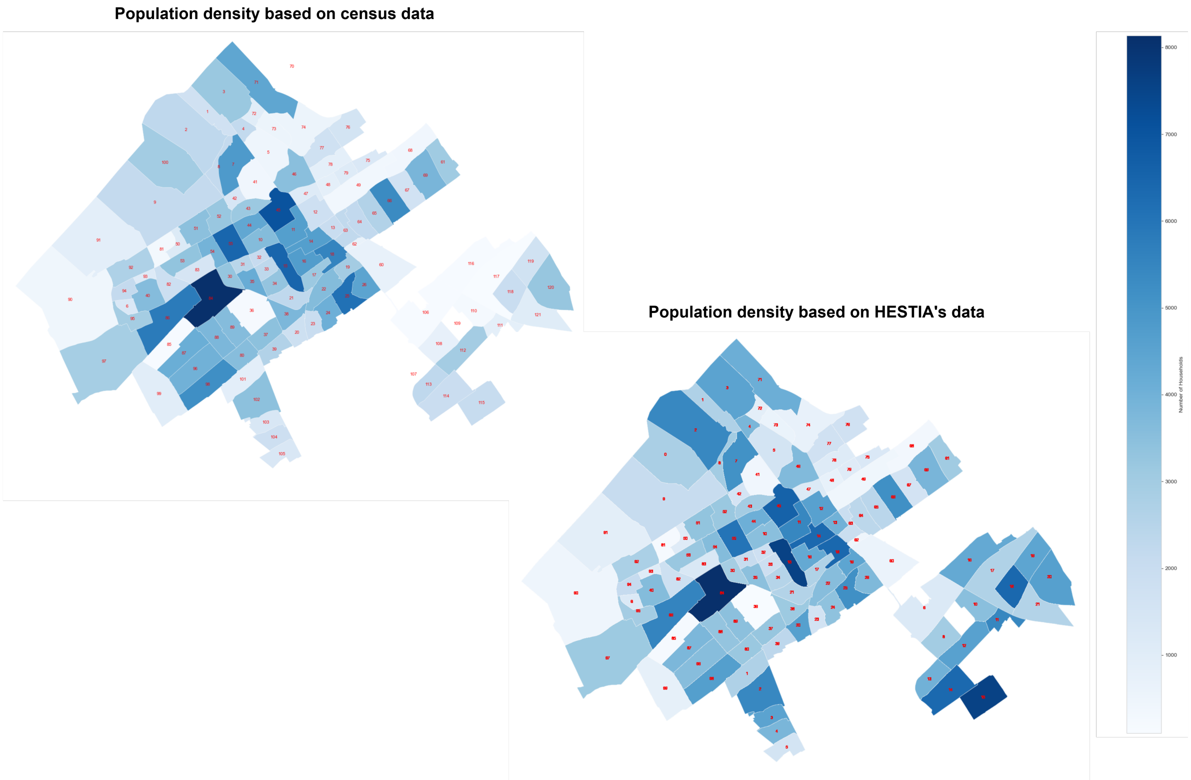

Figure 6.4: Population density census data vs HESTIA (Gemeente Den Haag [Dienst Publieke Zaken], 2021)

but to determine the impact of incorporating recognition justice into HESTIA's logic.

6.1.3. Income allocation

Income is an important indicator for a household's energy behaviour as it is a determinant for the behavioural factors in the ABM. Including income as a factor for a household/dwelling in HESTIA would, moreover, make the investment logic more elegant, given that the costs/benefit consideration for an investment would also depend indirectly on income.

The dataset 'Energieverbruik naar huishouden en inkomen, 2020' (English: 'Energy consumption by household and income, 2020') provides, on a national level, the distribution of income quartiles per ownership type (van Middelkoop et al., 2023). By aligning the synthetic data with these distributions, income classes can be assigned to the synthetic population based on ownership type, ensuring realistic patterns. To ensure alignment with The Hague census data and facilitate easy validation, this distribution is transformed into a quintile-based distribution before assigning it to the population. This approach enhances accuracy and ensures consistency with established demographic norms.

Income, in this case, is standardised disposable income: gross income excl. income transfers paid, income insurance premiums, health insurance premiums, and taxes on income and capital (van Middelkoop et al., 2023). Income is assigned pseudo-randomly. Since income is a key determinant in calculations of energy poverty and determining behavioural intention, re-assigning income pseudo-randomly in each simulation year would undermine the ability to make consistent year-to-year comparisons. Reassigning this variable every year would introduce unnecessary randomness that could compromise the result analysis. So, agents are assumed to remain within their assigned income class throughout the analysis. The changes in economic circumstances for the agents are considered to be outside the scope of this study.

Agents are assigned an income class according to equation 6.1. For every ownership type t in T, the sum of the distribution is 1, meaning that all households within an ownership type are distributed over the six income classes (when including 'other'), and an income is assigned based on the odds of Pt:

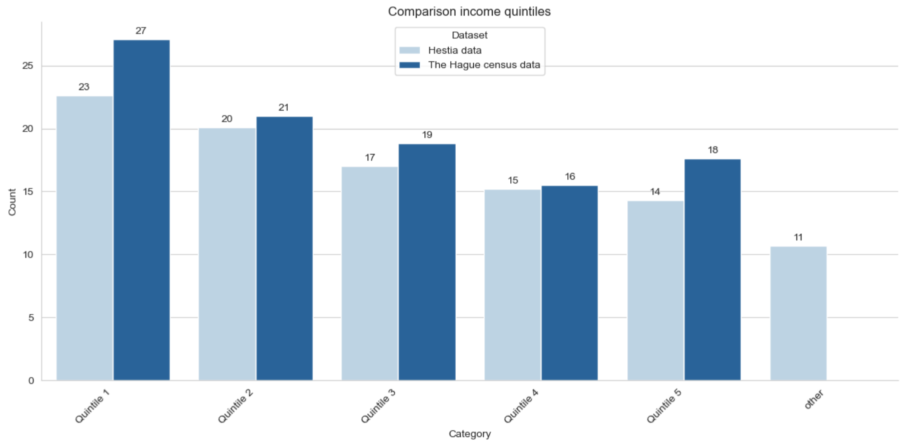

Figure 6.5: Comparison income distribution HESTIA vs. The Hague census data (Gemeente Den Haag [DHIC/Centraal Bureau voor de Statistiek (IIV)], 2024)

$$\forall t \in T : \sum_{c \in C} P_{t,c} = 1 \quad \text{with} \quad P_{t,c} \geq 0 \tag{6.1}$$

$$c_i \sim \text{Categorical}(P_t) \tag{6.2}$$

where:

- $t \in T$ denotes one specific ownership type.
- $c_i \in C$ denotes one specific income category.
- $C = \{1, 2, 3, 4, 5, \text{other}\}$ is the set of income categories.
- $P_{t,c}$ is the categorical distribution over income categories for ownership type t.

Applying this logic to the HESTIA data yields the results shown in Figure 6.5, where it is compared with the census data (Gemeente Den Haag [DHIC/Centraal Bureau voor de Statistiek (IIV)], 2024). As previously discussed in the context of dwelling characteristics such as ownership and population density, absolute numbers do not align directly with the census data. For validation purposes, the focus is instead placed on the percentual distribution.

The income distribution in the HESTIA data had to be derived from national-level distributions (van Middelkoop et al., 2023), as The Hague census data does not provide income distributions per ownership type. It is thus expected that the distributions do not perfectly align with the The Hague census data. In Figure 6.5, it becomes clear that the distributions align closely enough so the national census percentages can be considered a reasonable proxy. The differences that do occur are small and can (in part) be attributed to the The Hague census data not including the 'other' category in its analysis.

For the remainder of the analysis, it is assumed that individuals in the 'other' category have an unclear income status, likely due to non-response in the original survey. In any calculations involving income, these individuals are treated as having an equal probability of belonging to any income category.

6.2. Intention to invest

Intention to invest is implemented through a series of formulas, used to calculate the separate variables of the Theory of Planned Behaviour. To facilitate the connection with HESTIA and its S-curves, as described in 5.1.1, the total intention to invest is normalised. Moreover, this enables comparability across agents, which eases interpretation.

As of right now, there is no specific information known about the difference in weights for subjective norms, attitude and perceived control. de Vries (2020) does state that subjective norms can weigh more strongly in energy decisions than one's perceptions or attitudes. At the same time, Ajzen (1985) has made it clear that the weights for the attributes can differ per person. The weights may differ per household, or could be similar within specific household groups. Assigning equal weights to all three attributes provides a neutral and balanced baseline for determining agents' investment intentions in the absence of detailed empirical data. This approach avoids arbitrary prioritisation of a single attribute and ensures that no single factor disproportionately drives the outcome. The ratio of the weights in Equation 6.3 w_a:w_{sn}:w_{pbc} is 1:1:1. The intention to invest is normalised before further use in the HESTIA model in Equation 6.4. By normalising these intentions to be compatible with HESTIA, requirements 1 and 8 are met.

$$Iinv_i^{\text{raw}} = w_a \cdot A_i^{\text{inv}} + w_{\text{sn}} \cdot SNinv_i + w_{\text{pbc}} \cdot PBC_i^{\text{inv}} \tag{6.3}$$

$$I_i^{\text{inv}} = \frac{Iinv_i^{\text{raw}} - I_{\text{min}}^{\text{inv}}}{I_{\text{max}}^{\text{inv}} - I_{\text{min}}^{\text{inv}}} \tag{6.4}$$

Where:

- $Iinv_i^{\text{raw}}$ is the un-normalised intention to invest for agent i
- I_i^{inv} is the normalised intention to invest for agent i
- A_i^{inv} is the total attitude towards investment for agent i
- SN_i^{inv} is the total subjective norms agent i experienced regarding investments
- w_a = is the weight assigned to attitude
- w_{sn} = is the weight assigned to the subjective norms
- w_{pbc} = is the weight assigned to the perceived behavioural control
- $I_{\text{max}}^{\text{inv}}$ is the maximum possible value for $Iinv_i^{\text{raw}}$
- $I_{\text{min}}^{\text{inv}}$ is the minimum possible value for $Iinv_i^{\text{raw}}$

6.2.1. Attitude

Simply stating that households with higher incomes are more likely to hold positive attitudes toward investment would not align with the principles of recognition justice. To introduce more diversity, the concept of attitude towards investment has been divided into two distinct variables. The first focuses specifically on the attitude towards investing in renewable technologies, using responses from a national survey on attitude towards solar panel installation as a proxy (Kloosterman et al., 2021). The second attitude variable is derived from the installations in a dwelling (see 5.1.1).

As these installations have different fuels, energy demands and efficiencies, they serve as a proxy for the household's attitude towards sustainability. The total attitude towards investment is defined in equations 6.5 and 6.6. Each attitude variable gets normalised as well, to ensure that the intention to act will not be disproportionately influenced by either.

$$Ainv_i^{\text{raw}} = A_{\text{i}}^{\text{sp}} + A_{\text{i}}^{\text{inst}} \tag{6.5}$$

$$A_i^{\text{inv}} = \frac{Ainv_i^{\text{raw}} - A_{\text{min}}^{\text{inv}}}{A_{\text{max}}^{\text{inv}} - A_{\text{min}}^{\text{inv}}} \tag{6.6}$$

Where:

- A_i^{raw} is the un-normalised attitude towards investment for agent i
- A_i is the normalised attitude towards investment for agent i
- A_{i}^{sp} is the total attitude based on current installations for agent i
- $A_{\text{i}}^{\text{inst}}$ is the attitude based on current building option for agent i
- $A_{\text{max}}^{\text{inv}}$ is the maximum possible value for A_i^{raw}
- $A_{\text{min}}^{\text{inv}}$ is the minimum possible value for A_i^{raw}

Attitude based on installation plans

This attitude is based on a 2020 study by CBS examining the views and behaviour of the Dutch population regarding climate change and the energy transition (Kloosterman et al., 2021). Specifically, it uses data concerning attitudes toward sustainable living, with a focus on the willingness to install solar panels. Solar panel adoption serves as a proxy for a positive attitude toward all green energy investments, based on the assumption that the decision to install solar panels reflects both an awareness of and willingness to engage with sustainable technologies. The survey provides a distribution per income class across the following statements:

1. Solar panels are currently present on the home;
2. The respondent does not know whether solar panels are present;
3. The respondent has concrete plans to install solar panels within the next two years;
4. The respondent is unsure whether they will install solar panels within the next two years;
5. The respondent is certain they will not install solar panels within the next two years.

The data is reported per income quartile, but for application in the model, it is resorted per income quintile. By following a distribution per income class, this conceptualisation follows (partially) requirement 5. Due to the absence of more detailed data, four key assumptions are made to generalise the data for use in this model:

1. The nationwide distribution applies to The Hague;
2. Solar panels are used as a proxy for planning to do any retrofitting to the home;
3. Although the survey was for homeowners, it is generalised to renters as well;
4. Based on the percentages per income category, that percentage of agents with that income class is assigned values randomly;
5. Categories 1 and 2 are mutually exclusive: an individual who is aware of the presence of solar panels on their home cannot simultaneously be unaware of their presence, and vice versa. Similarly, categories 3, 4, and 5 are also mutually exclusive, as an individual who has concrete plans to install solar panels cannot at the same time be unsure about those plans or certain that they will not proceed with installation.

Using this data as a basis for the assumption helps to reduce some of the uncertainty typically associated with quantifying subjective variables like attitude, thereby strengthening the validity of the analysis. Moreover, breaking the data down by income class reflects the influence of income on investment behaviour (Niamir et al., 2020), and introduces a layer of diversity that aligns more closely with the principles of recognition justice. By accounting for differences across income groups, the varied capacities and opportunities individuals have to engage with sustainable technologies are acknowledged, rather than treating attitudes as homogenous across the population.

The investment attitude score based on the investment survey is defined as follows:

$$A_i^{\text{sp}} = w_{\text{t,i}} \cdot \sum_{k=1}^{5} w_k \cdot s_{i,k} \tag{6.7}$$

Where:

- $\mathbf{s}_i = [s_{i,1}, s_{i,2}, s_{i,3}, s_{i,4}, s_{i,5}]^\top$ is a binary selection vector for survey options of agent i,
- $w_k = [w_1, w_2, w_3, w_4, w_5]^\top$ is the vector of weights assigned to each installation choice
- $w_t = [w_1, w_2, w_3, w_4]$ is the vector of weights assigned to each ownership category

These weights are further elaborated in section C.3. The weights per ownership type are the same throughout the entire model. A higher ownership-weight represents more agency in investment decisions. By including this weight, the model design now fully fulfils requirement 5.

Important to note in this calculation is the mutual exclusivity of the response categories of the survey and how these translate to attitudes:

- $\mathbf{s}_i = [s_{i,1}, s_{i,2}, s_{i,3}, s_{i,4}, s_{i,5}]^\top$ is a binary selection vector for survey options of agent i,
- The binary variables follow the constraints:
  - Exactly one option selected from the first group: $s_{i,1} + s_{i,2} = 1$,
  - Exactly one option selected from the second group: $s_{i,3} + s_{i,4} + s_{i,5} = 1$,
  - Each $s_{i,k} \in \{0, 1\}$,

Attitude based on installations

Each agent's home has one building option per time step. Such a building option is a set of installations used to supply their functional demand for space heating, water supply and cooling. Each of these categories can have a different installation for base and peak demand, meaning that a combination of six installations together makes a building option.

Given the wide range of available technologies to improve energy efficiency in one's home, the assumption is made that the choices made by households reflect their attitude toward sustainability. Appendix C.3 includes all possible installations, the building options they sum up to and the sustainability ratings given to each with an elaboration.

Not only do income level and ownership status significantly affect the feasibility of adopting specific technologies, but a building's age also plays a part in the technological possibilities. Thus, basing attitude partially on the presence of these technologies, this approach presents an opportunity to, indirectly, incorporate the influence of contextual factors, following requirements 4 and 5. These factors are income and ownership status, in subsection 4.2.1 identified to correlate with attitudes toward investment.

$$A_i^{\text{inst}} = \sum_{tc \in TC} w_{tc} \cdot T_{tc,\, o_{i,tc}} \tag{6.8}$$

Where:

- $tc \in TC$: One specific technology category.
- TC: The full set of technology categories, $TC = \{$RVb, RVp, TWb, TWp, KDb, KDp$\}$
- w_{tc}: The weight assigned to each technology category
- $o_{i,tc}$: The technology option selected by agent i in category tc
- $T_{tc,o_{i,tc}}$: The sustainability score of the selected technology option in category tc

Each agent has one technology choice per category. The overall attitude is calculated by multiplying the sustainability score of the selected technology by the weight of its category and summing these products. The weights of these categories are determined based on the importance of each category, determined by the height of their energy use. For the weights, no distinction is made between base and peak demand. The reasoning behind these weights and the sustainability scores of each technology option are also further elaborated in section C.3.

6.2.2. Perceived behavioural control

Perceived behavioural control in this context refers to a household's perception of the difficulty of investment, based on both internal factors, such as knowledge, as well as external factors like financial resources or ownership. In the model, this PBC will be weighted against both income and ownership type to reflect this external influence.

The assignment of PBC indicators to the agents is based on survey information from the Hague, which reflects, per neighbourhood, people's feelings on two indicators (Centraal Bureau voor de Statistiek (CBS), 2023):

1. *Person wants to invest in a more economical home, provided it pays off*;
   - This indicator reflects a conditional willingness to invest in a more efficient home, but only if they are able to get a financial return. This is seen as a positive indicator of perceived behavioural control because the agent would feel capable of taking action if there is a financial reward in return.

2. *Person does not want to invest in a more economical home, does not know how, finds it too expensive, and/or has not yet got around to it.*
    - This indicator reflects a low perceived control as it is characterised by an individual not wanting to invest for a variety of reasons, ranging from monetary to time-related barriers.

Weighing these controls against income and ownership type to make it more personalised results in the perceived control for investment being calculated with Equation 6.9.

$$PBC_i^{\text{inv}} = w_{\text{c,i}} \cdot w_{\text{t,i}} \cdot (pbc_{\text{inv,1,i}} + pbc_{\text{inv,2,i}}) \tag{6.9}$$

Where:

- $w_{c,i}$ is the weight corresponding to agent i's income category
- $pbc_{\text{inv},1,i}$ is the score on Indicator 1 for agent i
- $pbc_{\text{inv},2,i}$ is the score on Indicator 2 for agent i

The choice for these weights is further elaborated in section C.3. By accounting for the influence of income and ownership type in a household's perceived control to invest, once again, this formalisation fulfils requirement 5.

6.3. Social networks

6.3.1. Identification of neighbours

The create the social networks of each agent, they are assigned ten neighbours, based on geographical proximity. The number of neighbours is an assumption. This assumption is based on two things. Firstly, neighbours usually only make up a relatively small part of a person's social network (Völker, 2000). Secondly, since streets differ in length and layout, ten neighbours roughly represent the five closest households plus the next five nearby, covering an immediate local circle where interaction and visible peer effects are plausible. Looking out a window, a person would, for example, see their direct neighbours' solar panels and potentially their neighbours' solar panels as well, but they do not see changes made 5 doors down; this is why the simulation runs for 10 neighbours.

This assignment occurs through the KD-tree algorithm, as Vermeulen et al. (2017) proved that of different k-nearest neighbour queries, a KD-tree offers the best performance on finding agent neighbours when they are assigned 2D coordinates. The KD-tree algorithm is a spatial partitioning method that, by repeatedly splitting the space in which data points exist to ease the search for agents' neighbours (Vermeulen et al., 2017).

This algorithm uses Euclidean distance as the distance metric between agents (Scikit-learn developers, nd). The agents' location must be based on a projected coordinate system, as Euclidean distance does not account for the curvature of the Earth. If the agent's location was given in a geographic coordinate system, it would have had to have been recalculated. However, as the geographical data used in this study uses a planar coordinate system: EPSG:28992 Amersfoort/RD new (Gemeente Den Haag, 2023), no such adjustments are required.

The KD-tree is constructed by recursively splitting the set of agents into smaller sets, based on their coordinates (Vermeulen et al., 2017). One step, the data set is split in half by the median of the y-axis, and the next step by the median of the x-axis, in the case of the Dutch RD coordinate system, northing and easting (NSGI, nd) (visualised in figure 6.6). Such a split of the geographic region creates a ”leaf” on the tree, providing a smaller geographic region in which to search for neighbours. This splitting continues until the data cannot be split any further.

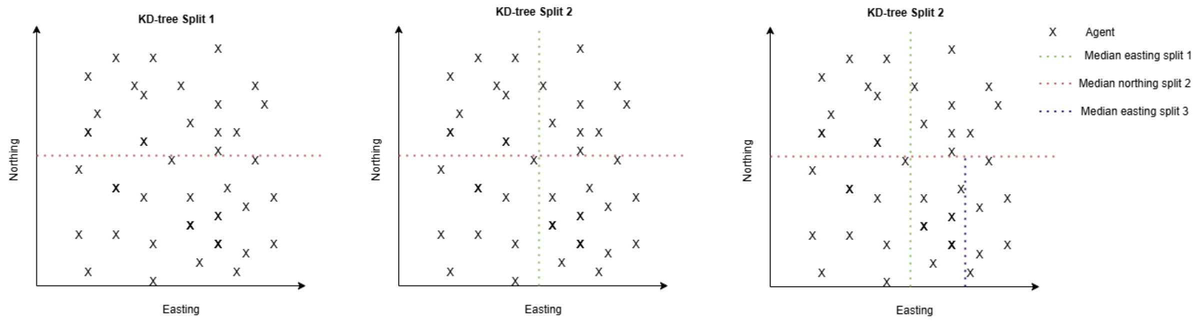

Figure 6.6: Example splitting of geographical space

When searching for the closest neighbours to an agent, the algorithm starts at the "root" of the "tree" to find the leaf in which the agent belongs. Each closest neighbour it finds in the closest leaves is saved as the best, until one is identified as being closer to the agent (Friedman et al., 1977). The algorithm does not stop when it has selected the first ten neighbours it finds, but finds the actual closest agents (see Figure 6.7).

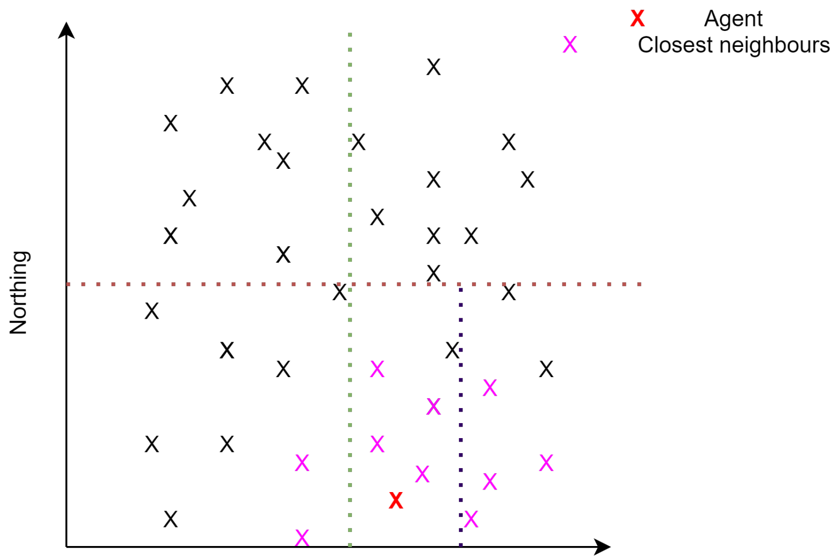

Figure 6.7: Example of nearest neighbour selection

6.3.2. Subjective norms

An agent has a social network consisting of their neighbours. The difference these agents have in attitude influences the subjective norms an agent experiences from their neighbours. The strength of this influence is determined by how strongly the agent perceives the social connection as part of their in-group.

As explained in subsection 5.1.3, agents determine if a neighbour is part of their in-group by assessing the similarity of several agent profile characteristics: income, ownership type, functional energy demands the installed energy systems to supply this demand. Based on these characteristics, agents experience descriptive norms: their neighbours have a certain attitude, so the agent adjusts their attitude as they want to adjust to the behaviour of the people they identify (de Vries, 2020).

Injunctive norms, where agents believe their neighbours expect them a certain way (de Vries, 2020), so they adjust their behaviour accordingly, are excluded from this study. Including perceived social approval would require big assumptions about agents' beliefs and social expectations, which would be very complex to operationalise or validate.

Shared characteristics increase perceived in-group membership between agents. This increases the strength of the behavioural influence of a neighbour. Even when they have only one or two characteristics in common, the agents will begin to identify with each other. The strength of influence is not binary, but increases with the degree of similarity between agents:

$$SN_i^{\text{inv}} = \begin{cases} \frac{\sum\limits_{j \in N_i} \sigma_{ij} \cdot \left(A_j^{\text{inv}} - A_i^{\text{inv}}\right)}{\sum\limits_{j \in N_i} \sigma_{ij}} & \text{if } \sum\limits_{j \in N_i} \sigma_{ij} > 0 \\ 0 & \text{otherwise} \end{cases} \tag{6.10}$$

Where:

- A_i^a: Attitude of agent i with respect to neighbour's investment attitude
- A_j^a: Investment attitude of neighbour j with respect to agent's investment attitude
- N_i: Set of agent i's neighbours
- σ_{ij}: Similarity between agent i and neighbour j, defined as:

$$\sigma_{ij} = \frac{1}{|A|} \sum_{a \in A} \nVdash_{[a_i = a_j]}$$

  Where:

  - A: Set of attributes used to assess similarity
  - $|A|$: Total number of attributes in set A
  - a_i, a_j: Value of attribute a for agent i and neighbour j
  - $\nVdash_{[a_i = a_j]}$: Indicator function that equals 1 if $a_i = a_j$, and 0 otherwise

The subjective norm can take a negative value. This occurs when an agent's attitude is higher than that of its neighbours. In such a case, an agent would adjust its behaviour downward, align more with its in-group. This reflects more realistic social dynamics where an agent not only listens to their social network if they have a positive influence, but also when they are less optimistic. By including these social dynamics, requirements 6 and 7 are fulfilled.

6.4. Establishing the multi-model link

The intention to invest is included in the HESTIA model logic by diversifying the β and P50P values for each option, for each S-curve.

Specifically, in the ABM, an investment intention is determined for each income group. This intention is then multiplied by the corresponding β and P50P values, resulting in a broader set of S-curves, one for each technology category within each income group. It was decided to link the models based on income, as household income is one of the main determinants of whether a household will experience energy poverty (Feenstra and Clancy, 2020). The beta and P50P are determined using calibration of historic data, but are generalised for the entire population - everyone with a certain investment option uses the same values in their probability calculation (van der Molen, 2023). By adjusting these factors for behavioural intentions per income group, the model incorporates a little more agent heterogeneity in the investment logic. The differentiation in β and P50P not only leads to varying sensitivities to cost-based attractiveness across income groups but also results in different midpoints for each group, reflecting different investment thresholds per income group.

The β and P50P variables are used in several formulas during the investment process. The first steps of the insulation track and installation tracks differ slightly, but the probability calculation for the actual investment determination is the same for both tracks and described in Equation 6.14 and Equation 6.15. Firstly, it is determined if the insulation ambition changes or will remain constant:

$$Insulationscore = \frac{Area_{\text{building component}}}{Area_{\text{total}}} \cdot efficiencygains \cdot \beta_{\text{ambition}} - Costs \cdot L_c \cdot VAT \cdot Subsidy \cdot P50P \tag{6.11}$$

Using this score per insulation measure the probability of adoption is calculated per insulation measure, per insulation ambition, in Equation 6.12.

$$Odds_{\text{xx}} = e^{\textbf{insulationscore}} \cdot \beta_{\textbf{ambition}} \cdot \beta_{\textbf{measure}} \tag{6.12}$$

Which leads to the probability calculation per insulation measure, per insulation ambition in Equation 6.13.

$$Probability = \frac{Odds\mathbf{x}}{TotalOdds_{\mathbf{xx}}} \tag{6.13}$$

In the first step of the installation track process, available options are selected for the dwelling based on the insulation ambition of the dwelling, as well as the technical match of an option and the dwelling and a business case calculation. Next, the suitability of the available options is calculated, in Equation 6.14. In this function, P50P values for the building options in this function bring the indication of what cost-benefit ratio is acceptable to the households (van der Molen, 2023).

$$Suitability_{\text{option}} = C_{\text{j,mostexpensiveoption}} * P50P_{\text{mostexpensiveoption}} - C_{\text{j,option}} * P50P_{\text{option}} \tag{6.14}$$

The option-specific odds for each building option are based on the suitability as well as the βs.

$$Odds_{\text{option}} = e^{\text{Suitability}_{\text{option}} * \beta_{\text{option}} * \beta_{\text{nonspecific}}} \tag{6.15}$$

The probability calculation, the final step in the investment logic, performs a randomised weighted draw to select an agent's final choice. The investment choices of households result in changes in agents' profile characteristics. In time step $t = t + 1$, these changes get incorporated in the ABM, changing the behavioural attributes, which are subsequently used in HESTIA to determine the next round of investments. This fulfils requirement 2. Figure 6.8 illustrates this exchange of .csv files. This soft-link is repeated for all time steps.

Ideally, this exchange is established by using Python's subprocess module. This module would allow a user to run programs from Python code. It brings the opportunity to send such a program's data, retrieve its outputs a programs outputs, and integrate these programs with a Python model (All, 2024). However, due to time limitations of this project, this module could not be implemented, and the soft link was manually established.

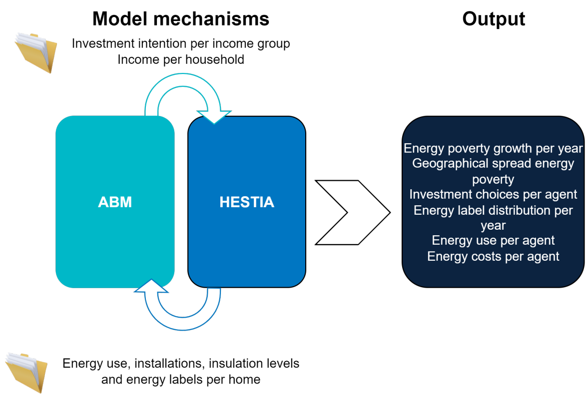

Figure 6.8: Soft-link ABM and HESTIA, inspired by (Fattahi et al., 2020, p. A-15)

7 Results

This chapter presents the results of the simulation, split into four parts. Section 7.1 discusses the individual model's results: HESTIA without any adaptations. This control run has a dual purpose. Firstly, for verification, to ensure that the model performs as intended and to establish a baseline for comparison with the adjusted version later on. The second purpose is validation. This base case is used to check if the key outputs, such as energy poverty prevalence, are realistic and in line with reality. The second section, 7.2.1, analyses the baseline results of the multi-model simulation. It shows the behavioural changes of the agents, specifically focusing on the changes in the intention to invest and how this factor influences the S-curves. This analysis of the behaviour's impact serves as the first step in understanding the results. The behavioural dynamics are not validated against empirical data, but serve as internal verification of the ABM logic and demonstrate the influence of behavioural diversity. This section also discusses the consequences of including more behavioural diversity in the HESTIA logic for the household's investment patterns and the energy poverty estimates. In section 7.3, the results of the multi-model link are compared for 3 seeds to test the robustness of the results. Lastly, a sensitivity analysis in section 7.4. The sensitivity analysis is used as further verification of both models. It is used to indicate how the model's results are affected by the weights of the three attributes of the Theory of Planned Behaviour.

7.1. HESTIA's individual results

A control run is essential as it establishes a reference based on which the impact of including greater agent heterogeneity within the HESTIA model can be assessed. This control run consists of the standard HESTIA configuration, without any extra behavioural mechanisms incorporated. The policy interventions are included as a standard HESTIA run, which is one with policy logic.

7.1.1. Municipal level results

Figure 7.1 shows a growth of energy poverty risk from 9% to 11.4% between 2020 and 2022. This trend from the model closely mirrors the real-life developments (Duurzaam Den Haag, 2023). It increases from 2020 to 2022, when it spikes, aligning with the peak of the energy crisis (Secretariaat-generaal van de Raad, 2025). The risk remains at a higher percentage in 2023 and 2024, but does decrease slightly, also in line with reality (Duurzaam Den Haag, 2023).

As the energy poverty indicator HEQ is left out of consideration in this study, this difference with historic data is expected to be higher. The irregularity in these results can also be explained by the implementation of the LIHE and LILEK indicators. As the model tests every household with income class 1 for their risk of energy poverty, those with an income above the low-income energy-poverty boundary are also included, which likely compensates for the households being wrongfully excluded by leaving HEQ out of consideration.

From 2025, no validation with real-life data is possible. The risk for energy poverty keeps decreasing, but remains very limited. This is in line with HESTIA's input data, as the predicted energy prices differ with significantly smaller margins in 2025-2030, compared to the historic prices from 2020-2024. Although this trend aligns with HESTIA's input data, the model's predictions do not match reports from TNO and CBS, which state that the decrease in support measures and the rise in energy prices have led to a 54% increase in energy poverty between 2024 and 2025. They also anticipate that, due to rising energy prices and the discontinuation of support measures, the number of energy-poor households in 2025 the

Netherlands will beyond the levels seen during the 2023 energy crisis (de Volkskrant, 2025; TNO, 2025).

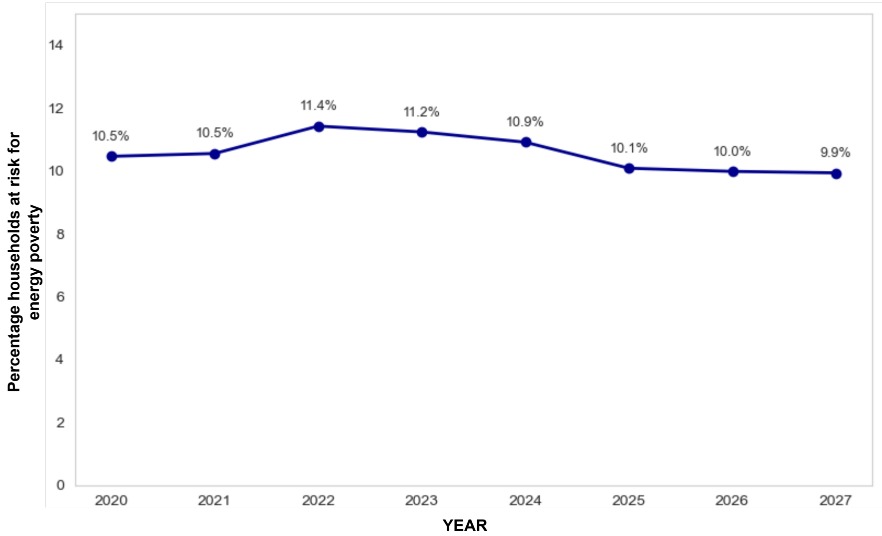

Figure 7.1: Evolution of energy poverty risk over time, control run

Figure 7.2 shows the distribution of energy labels over the years. It reflects how a significant number of households have invested in their homes to increase their insulation levels to reduce their energy bills. This figure further supports the energy poverty percentages shown in Figure 7.1 as the amount of lower energy labels decreases, but never reaches zero, reflecting the persistence of dwellings with poor energetic quality. Although energy poverty is not solely determined by a dwelling's energetic quality, it does play a big role in the household's energy use, specifically the difference between functional demand and meter demand.

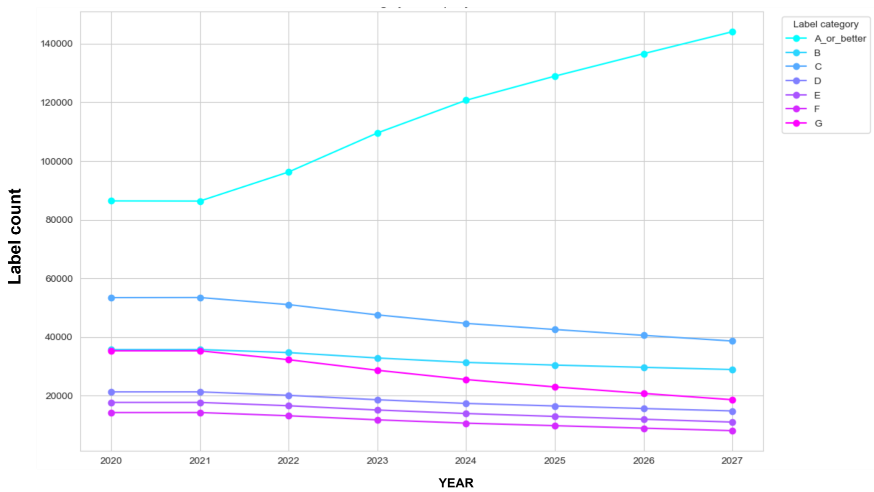

Figure 7.2: Energy label count across the years, control run

7.1.2. Agent level results

To better understand this aggregated trend, the behaviour of five agents was analysed [1]. These agents, although all with different profiles, at one time or another were at risk for energy poverty. Together, they provide good examples of the differences in how the risk for energy poverty can be created and prevented. Table 7.1 presents an overview of their profile characteristics. Appendix D contains more

[1]HESTIA results are normally not suited to be reported on a dwelling level. However, the changes in the dwelling investment decisions have to be analysed to test the impact of the agent heterogeneity. These are only intermediary results; the actual results of energy poverty growth and prevalence are reported on a municipal level

information on the investment choices made per agent. Across all agents, total energy bills increased steeply between 2021 and 2022, which aligns with patterns resulting from the energy crisis in 2022. It becomes clear that different household situations can still lead to a risk of energy poverty. The evolution of their risk at energy poverty is visualised in Figure 7.3.

Agent 15 is continuously at risk for energy poverty. This 3-person household in a privately rented home never adjusts its energy demand, causing its energy bill to follow the patterns of the energy prices. As this household rents their home, they are dependent on the retrofitting choices of their landlord, and as no investments are made, they are stuck with low efficiency installations and poor energetic quality.

Agents 2262662 and 227399, two agents with similar profiles, illustrate the relativity of the current energy poverty indicators. Both are renters, one in social housing and the other in the private sector, and are largely dependent on their landlords' investment decisions. Different upgrades to their installations occur in 2026 and 2027, respectively. Yet, at different times before these upgrades, and for agent 2262662 even afterwards, both households experience periods when they are classified as not at risk of energy poverty. This highlights that, for vulnerable households, small fluctuations in the thresholds used to define energy poverty can easily shift their risk assessment, even when their underlying situation has not really changed. Measurement of energy poverty relies too heavily on broad averages instead of more household-specific realities. As these households bounce back and forth across the energy poverty line on paper, it does not mean they are suddenly struggling more or less in practice. This shows a clear example of misrecognition as disrespect or non-recognition: energy-poor households are not properly identified (section 3.2). This emphasises the need for more nuanced measurement and recognition of the diverse ways households experience energy poverty.

Agents 105 and 40517 are both homeowners who have autonomy over their investment decisions, yet their experiences with energy poverty risk differ. Agent 40517 represents a household that, around the height of the energy crisis in 2022, entered energy poverty. Although this is not treated as an investment motivator in the modelling logic, this household demonstrates how combining technical upgrades, structural insulation improvements, and solar panels is great to address the root causes of high energy costs. Amid the energy crisis, this household invests in solar panels and new heating installations, These measures immediately lifted them out of energy poverty by improving both the energetic quality of the home and installation efficiency. On top of this, the solar panels even allowed the net energy demand to fall below zero, and this agent has a negative energy bill, most likely due to feed-in tariffs.

Agent 105 shows a contrasting situation. This homeowner remains at risk for energy poverty, as it has not made significant investments. Their situation illustrates how targeted retrofitting could substantially improve energy efficiency, lower consumption. After all, if this household were, for example, to improve its insulation levels, its home would increase its energetic quality and lower its energy use and bills, potentially significantly improving its situation.

Table 7.1: Household profile agents of interest

Agent	*15*	*105*	*40517*	*262662*	*227399*
Neighbourhc	Uilennest	Scheveningen badplaats	Zeeheldenkwartie	Laakkwartier-Oost	Transvaalkwartier-Noord
Dwelling type & building period	Terraced house, 1930-1945	Multiple-family dwelling, low 1965-1974	Multiple-family dwelling high, pre 1930	Multiple-family dwelling, low 1930-1945	Multiple-family dwelling, low 1975-1991
Household size	3	2	2	2	2
Ownership type	Private rent	Own	Own	Private rent	Corporation rent
Energy label	E	E	F	D	A(+)

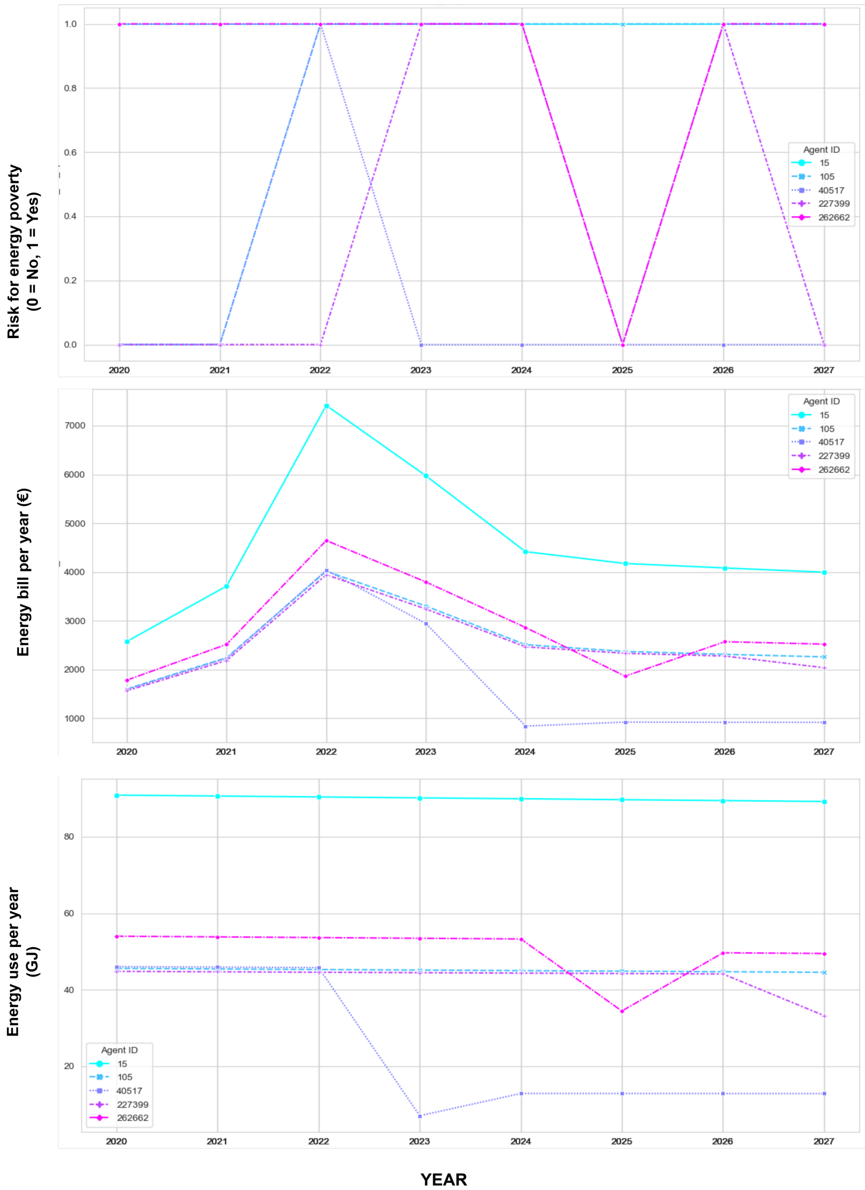

Figure 7.3: Evolution of agent's energy risk, bills and use per year, control run

Together, these agents can enter or exit energy poverty through many different pathways, and it is not solely a matter of dwelling energy efficiency or technologies. Autonomy, affordability, policy design, and measurement methods all shape who is at risk for energy poverty, and why. Renter's ability to escape energy poverty depends heavily on the willingness and capacity of property owners to invest in energy efficiency and renewable measures (Feenstra and Clancy, 2020). While some policies acknowledge this structural imbalance by targeting rental properties and incentivising landlords to invest (section C.2), this is not always sufficient. Inaction by landlords should not trap households in energy poverty. To mitigate this risk, households should get opportunities to improve their situation if their landlords choose not to act, for example, by supporting individual behavioural changes or small-scale measures that tenants can implement themselves. Strengthening policies that empower residents to take control, even within structural limitations, is crucial. Good examples are initiatives such as the *Energiehulpnetwerk* from Milieu Centraal, which assists tenants with practical guidance and small-scale energy-saving measures (Milieu Centraal, nda).

Summarised, these agent-level insights confirm that while the average data for the municipality may improve over time, households can still become at risk for energy poverty. Broad improvements in energy efficiency do not have to mean an improved situation for individual households. By focusing the policy on financial measures to improve technical upgrades, or mandates for technical upgrades, the policy overlooks the everyday struggles of households for whom the issue is deeper than that. Recognising this mismatch and accounting for the behavioural differences of the population that can lead to this energy poverty risk is crucial. Without addressing the social aspects of energy usage and energy poverty, efficiency-focused interventions alone can perpetuate and exacerbate inequalities. Improving the buildings is not always enough to help people out of energy poverty.

7.2. Multi-model baseline results

This section analyses the effects of the above-discussed changes in the S-curves. These effects are measured by looking at the energy poverty prevalence, energy label counts, and by analysing the investment choices of the same agents as in section 7.1.

7.2.1. Behavioural analysis

S-curves

Figures 7.4 and 7.5 are used to describe the impact of incorporating the behavioural heterogeneity in HESTIA's investment module. Firstly, Figure 7.4 demonstrates the consequence of diversifying the investment logic per income class. This S-curve shows the consideration for the option geen_koop in 2021, which is one of the options that can be considered in the installation track for homeowners with income class 1. The attractiveness of an option depends on the ratio between costs and benefits and on homeowners' assessment of that cost-benefit ratio (van der Molen, 2023). The figure shows that the multiplication of the β and P50P value with the differing intentions to invest per income class has significantly dampened the steepness of the curve. By lowering the curve, the percentage of a group that finds an option attractive at a higher cost-benefit ratio decreases (van der Molen, 2023).

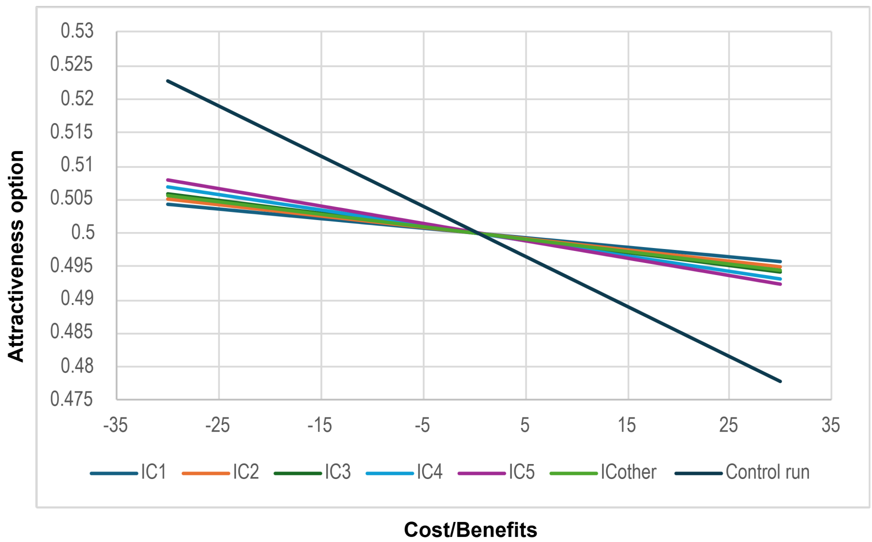

Figure 7.4: Example changes in S-curves per income class

The split of the singular curve into multiple, allows for diversity in investment considerations per income class, but the flattening of the curve indicates that within such a group, there is less diversity in the assessment of attractiveness of an option. The β parameter indicates the sensitivity to the value of the cost-benefit factor (van der Molen, 2023). For lower-income classes, this β is lower, indicating that it has less sensitivity to the value of the cost-benefit factor. This is visible in Figure 7.4 as well, although the highest attractiveness for income class 1 is lower than for higher income classes, the lowest point remains higher than for the other classes, as the lower the income class, the less sensitivity to the cost-benefit ratio. Following Equation 6.15, this shift has caused the odds of the different options being selected to be closer together. This effect is visible in Figure 7.5, where two building options for income class 1 are compared in both the base case and the multi-model scenario run.

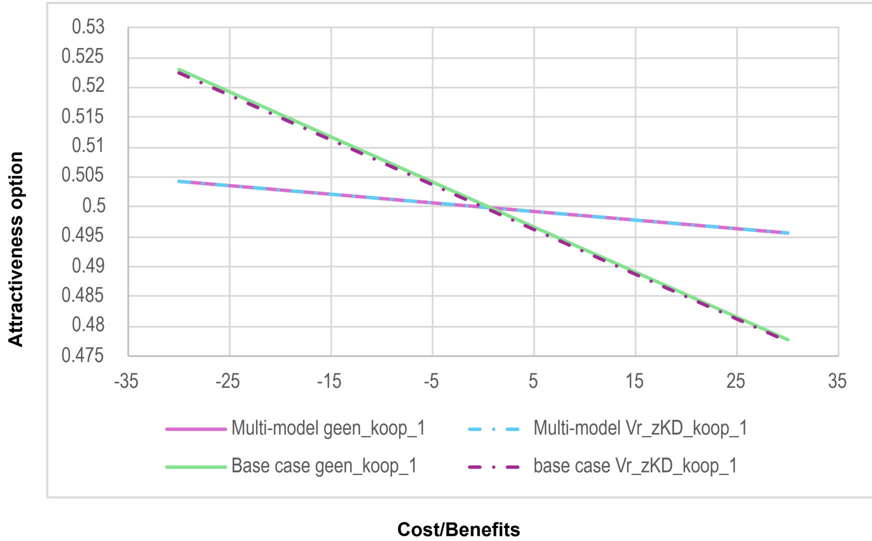

Figure 7.5: Comparison S-curve of different options, base-case vs. multi-model

For the insulation choices, a similar pattern occurs for S-curves themselves, but in the mathematics of the choices, the β_{ambition} has a slightly different meaning. The lower this coefficient, the less likely far-reaching insulation measures. There will be less ambition to ensure a high insulation level. In this way, with a "Low" insulation ambition, a set of measures will be chosen from a perspective that seeks to avoid high costs and does not place a high value on energy savings (van der Molen, 2023). By decreasing β_{ambition} and the P50P used to calculate the insulation ambition of a dwelling, followed by calculating the odds of an insulation measure being selected with a reduced β_{measure}, the insulation track will reflect similar patterns as the installation track. The insulation decreases as well. Overall, this will result in reduced odds per option. As with the building options, the overall attractiveness of all options is lowered, and the differences in attractiveness per option decrease.

Intentions to invest

Figure 7.6 shows the changes in investment intentions over time. With all income classes included, the changes per income class are hardly visible. The visualisation clearly shows a positive relationship between household income and the intention to invest. Higher income groups consistently show greater average intention levels, reflecting their increased sense of control and more favourable attitudes toward investment. This trend is likely influenced by the fact that individuals in higher income brackets are more likely to own their homes, which provides them with greater autonomy and decision-making power. They also more often have already invested or plan to invest in sustainable technologies. subsection D.2.1 includes a visualisation per income class in which the changes over time are more clearly visible. This change is the result of investments made by the agents and their neighbours, which influences their attitude based on changing scores of building options and the subjective norms they experience.

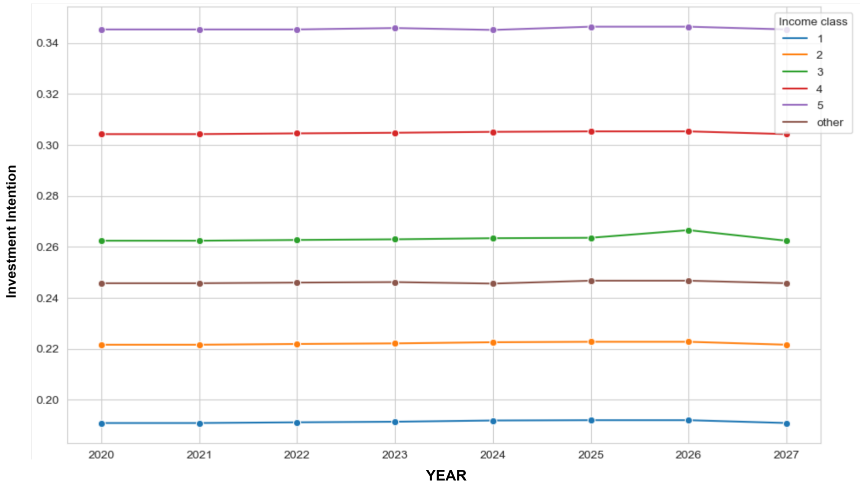

Figure 7.6: Comparison of investment intentions per income group

The limited changes in the average intentions per income class can at least partly be attributed to the fact that these are averages across a large and diverse group of respondents. Taking an average across so many agents dampens the extremes and nuances of individual differences. This argument is supported by Figure 7.7, which compares the intention to invest of income class 1 to invest of the same 5 agents. The ABM was able to recognise a real difference in the agents' behavioural intention, despite their similar income class; they had enough profile characteristics and neighbourly influences that they were not all as willing to invest in retrofitting their homes. Another reason for this limited change is that the intention to act is only partly influenced by dynamic variables; the remainder is determined by static parameters. Since these parameters remain constant over time, they inherently constrain the extent to which intentions can change.

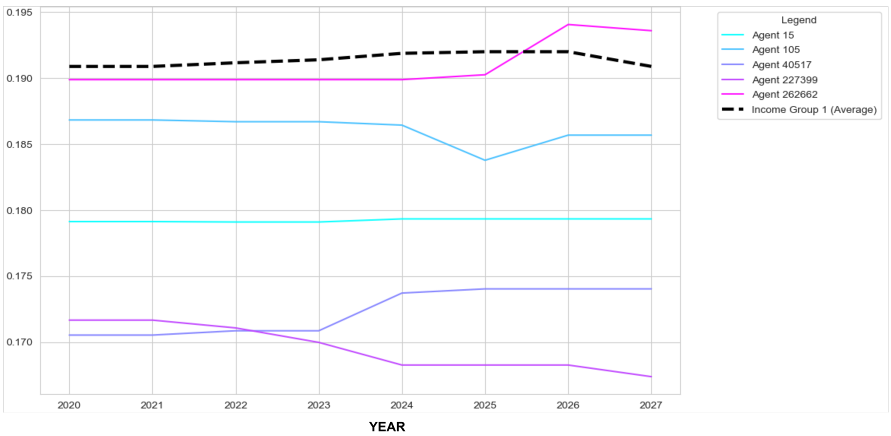

Figure 7.7: Comparison of agent investment intentions to income group average

7.2.2. Municipal level results

The soft-link of the Agent-Based Model to HESTIA has resulted in a slightly changed energy poverty risk assessment for The Hague. Interestingly, although Figure 7.4 and Figure 7.5 show that the S-curves have significantly changed, the percentage of households at risk for energy poverty per year does not differ by a lot. By changing the investment option selection to be diversified per income group based on investment intention, the energy poverty risk per year seems to be slightly lower. Where in the base case, at its peak in 2022, energy poverty was at 11.4% (Figure 7.1), in the multi-model simulation, energy poverty does not go above 10.8%.

Although the trend of energy poverty risk still follows the same pattern in the first years, a small increase between 2020 and 2021, a larger increase in 2022, the pattern in the second half of the simulation is different. There is a steeper decrease in energy poverty risk after 2023, and this larger decrease continues to 2027, whereas in the base case, the decrease over time almost stagnates Figure 7.8. This only modest change in numbers shows that although the investment patterns have changed due to the relative attractiveness of options being less distinct, resulting in more and more drastic investments, the general attraction of investments has lowered enough to limit this effect.

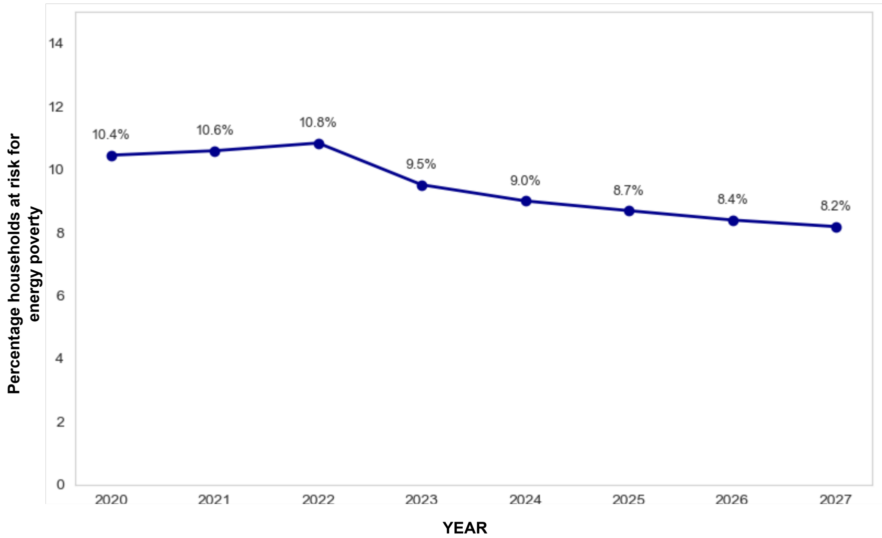

Figure 7.8: Evolution of energy poverty risk multi-model

The energy label distribution does show a large difference compared to the control run, highlighting a difference in the impact of the changes for the lowest income class only and the entire agent population. The base case run of the multi-model shows a faster and stronger switch from the lower energy labels to better labels. Both runs display the same trend: all energy labels below A(+) decline over time, while label A(+) increases. This decrease in "bad" labels reflects the stimulation for retrofitting investments driven by policy incentives and embedded in HESTIA's investment logic. Figure 7.9.

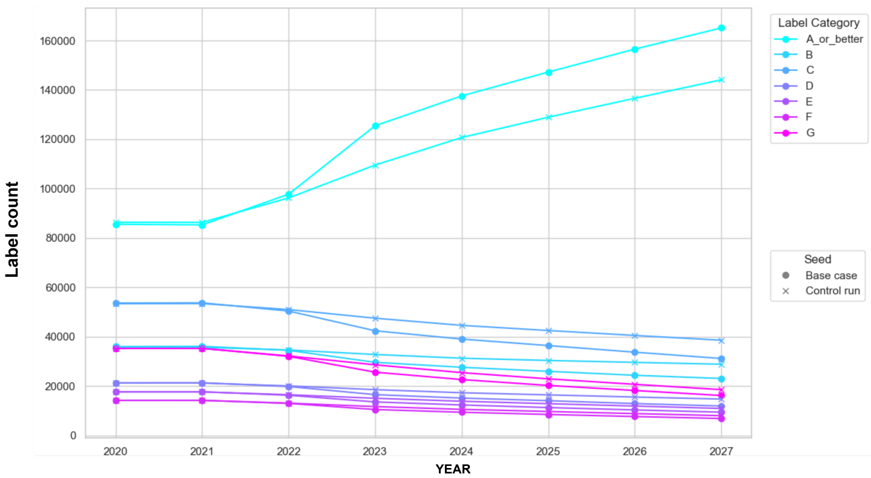

Figure 7.9: Energy label count across years compared for control run and multi-model

As visualising the investments of all households to analyse where the change in energy poverty comes from is not possible, the investments per category, per income group, and per year are counted. These comparisons are summarised in section D.2. The results show that although investments in installations significantly increase, investments in the insulation of the building envelope decrease in the multi-model simulation.

The results show that in the first investment moment, from 2020 to 2021, there are no differences in investment choices. However, as the model continues, and the intentions to invest grow, albeit a little, there seem to be more and more consequences. All income classes show the largest difference in the investments in heating installations, for both spatial heating and water heating. The results show that for every income class, investments per category grow significantly over the years, in comparison to the base case. The intentions to invest grow over time, leading to an upward shift of the S-curve and a higher attraction to investments compared to the start of the run. Lower-income classes know relatively more growth as their distinction between different options is less, thus increasing the probability of investment options being selected over not investing. This explains the decrease in energy poverty; investments in installations, generally, mean investments in more sustainable technologies, decreasing the energy use, bills or both.

The results in section D.2 show that during the initial years of the simulation, the investments in insulation are less than in the base case. This explains the lack of improvement in the energy label distribution, as seen in Figure 7.9. This decrease balances the effects of the increase in investments in the building options.

Based on the changes made to HESTIA's model logic, the results can be very easily explained. The insulation ambitions are significantly decreased due to β_{ambition} and its matching P50P value having been adjusted by the intentions to invest. This, in combination with less attractive insulation measures due to the change of β_{measure} in Scurve_isolatie.csv, has allowed the odds of every insulation option to be so significantly decreased that more often than not, the choice for no investment will be made. In the later years, policy comes into play that stimulates investments in insulation measures, and as the intentions to invest start to increase, so do the βs. For social housing specifically, norms are introduced that ensure that anytime a dwelling makes the choice to invest in insulation, the energy label has to be improved up to at least D. As the years progress, the compliance of this policy measure increases, ensuring that more and more dwellings update their energy labels. This explains why the difference in investment with the base case decreases over time, even growing to a surplus for some building components for some years.

For the investment in building options, the reasoning is slightly different. Yes, the curves are lowered, reflecting a generally lower attractiveness of the different investment options. However, there is less freedom in the investments for building options, since if an installation's lifespan has ended, there is no other choice but to invest in a new technology. Choices are limited as the initial selection of building options is not determined with S-curve data, but based on the technical specifications of the dwelling and the business case of the installations.

This large increase in investment in building options explains the general lower energy poverty risk; more investments in installations means more improvements to dwellings, lower energy use and consequently lower energy bills for the people who choose to invest. Especially the relatively high increase in investments for income class 1 explains this decrease in energy poverty, as that is only calculated based on the lowest income class.

7.2.3. Agent level results

To analyse the impact of the changes on an agent level, the same agents are selected as in the base case. The evolution of their energy risk, energy bills and energy use is visualised in Figure 7.10.

Agent 15 illustrates that, even with the diversification of investment choices by income group, the original model's investment patterns remain true for certain households. This agent's investment behaviour remains unchanged; they consistently stay in energy poverty. Similarly, agent 105 shows no change in investment patterns or energy poverty status, reinforcing the finding that model adjustments do not affect all households equally.

40517 also maintains its pattern for energy poverty risk, but does show a different investment pattern. In the control run, this agent only improves some insulation levels, while leaving their wall insulation at the lowest level. In the multi-model, however, they upgrade their building envelope so that none of its components remain at this lowest insulation level. This matches with the adjustments to the insulation-related S-curves: although the general attractiveness of investing in insulation has lowered, the tail of the S-curve has shifted upwards. As a result, relatively higher cost, lower-benefit measures -such as investing in higher insulation levels even though this does not significantly increase the energetic value- are relatively more attractive and thus this investment decision is made.

The biggest changes are for agents 227399 and 262662. Where both agents bounced back and forth between being at risk and not at risk in the control run, this pattern has now shifted. Agent 262662 now invests in insulation alongside their building option upgrades, improving the home's energetic quality enough to achieve an A(+) energy label.

That they are no longer at risk for energy poverty after these investments, when they were in this state in the control run, is a testament to the averages used to calculate energy poverty. While their energy use increases again after these investments, it remains relatively lower than that of agents such as 205 and 227399, whereas in the control run, it rose above their demand. This further illustrates that even marginal efficiency improvements can shift a household's position relative to the average benchmark.

Agent 227399 continues to fluctuate between being at risk and not at risk, but now follows a different pattern due to substantial improvements in insulation levels. This once again highlights how energy poverty is treated as relative. Although this home has a high energy label, its energy bills do not decrease significantly. Through the LIHE indicator, which is based on the average energy bill of households with an energy label C, this dwelling will still be classified as energy poor between 2025 and 2027 until further improvements to the building are made.

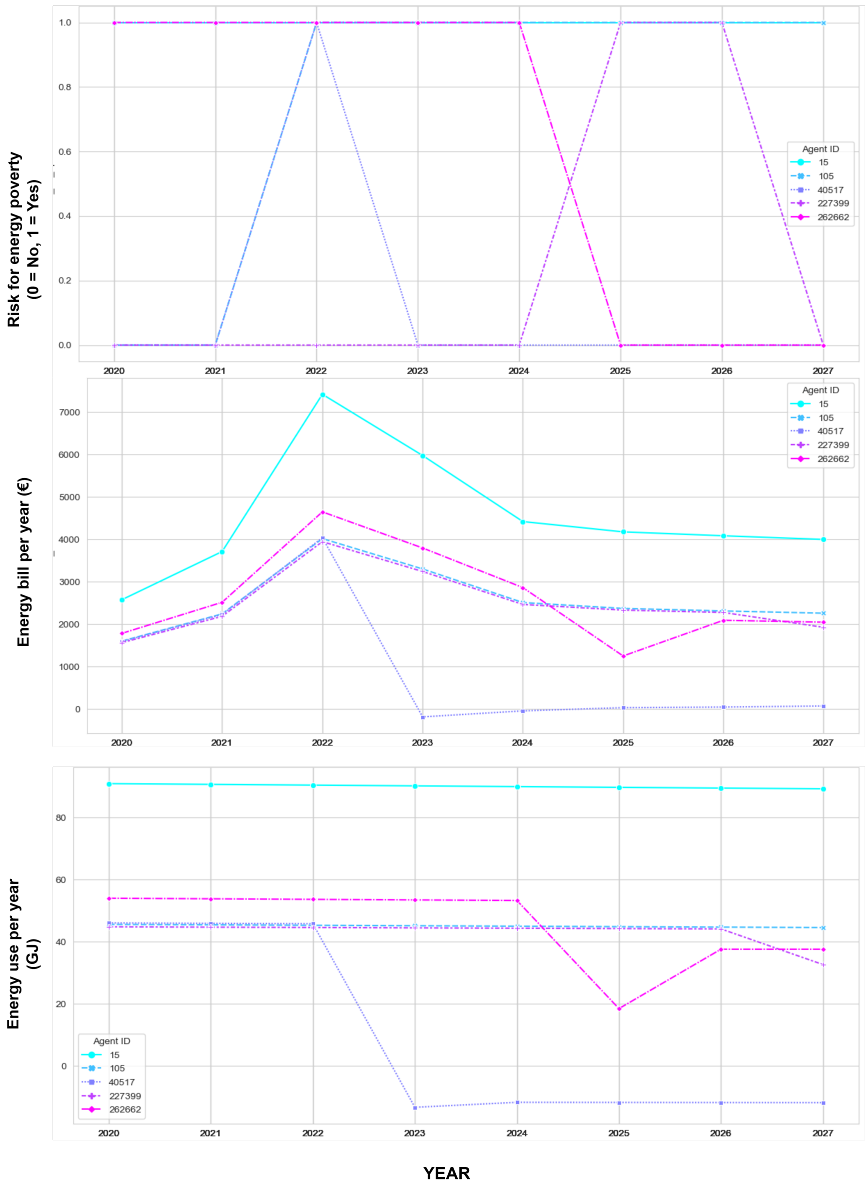

Figure 7.10: Evolution of agent's energy risk, bills and use per year, multi-model

Broadly, the structural patterns of energy poverty and investment behaviour remain consistent with the control run; however, individual agent outcomes shift. The diversity in agent responses illustrates the complex dynamics between affordability, energy efficiency, and model assumptions. These results underscore the importance of considering both technical and socio-economic factors in policy design, as well as the limitations of aggregate measures in capturing the lived experience of energy poverty.

7.3. Random seed analysis

Both the ABM and HESTIA use pseudo-random assignment of parameter values. To assess if the results are robust rather than noise introduced by this random initialisation, the model was run using multiple random seeds.

Changing the seed of the model leads to different dwelling configurations. The outcomes of this robustness test can thus not be analysed on an individual agent level. There is no guarantee that under a different seed, the same agent-ID has the same profile characteristics, making it impossible to compare the investment decisions across different seeds. It would be like comparing apples with oranges. Instead, only the risk of energy poverty per year and the energy label count per year are analysed.

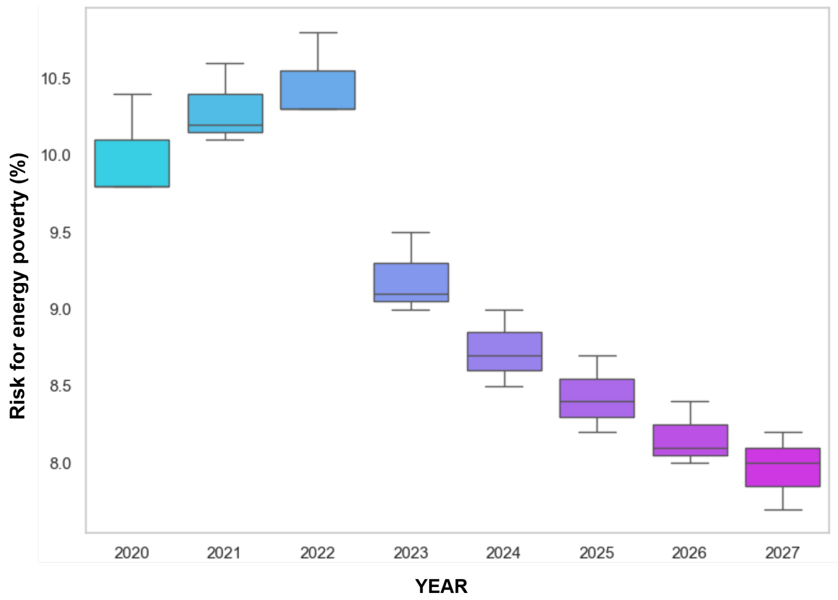

Figure 7.11: Risk of energy poverty across years for multiple seeds

The box-plots in Figure 7.11 show the distribution of the risk for energy poverty per year for the different seeds. Appendix E contains a table with more detailed information. This table shows that the interquartile distances, which describe the size of a box, are within an acceptable range (varying between 0.3 and 0.20). This indicates that the variation between model runs with different seeds is limited and confirms the stability of the results.

The analysis of the energy labels over these three seeds also shows a variation within an acceptable range (Figure 7.12). The variation between the three values differs between a few dozen and a few thousand, but compared to the range of totals for these counts (80000 - 160000), this is not very large, as clear from the whiskers of the box-plots. The three seeds tell the same story; over time, the lower energy labels get improved to higher labels as investments are made to improve the energy efficiency of the dwellings.

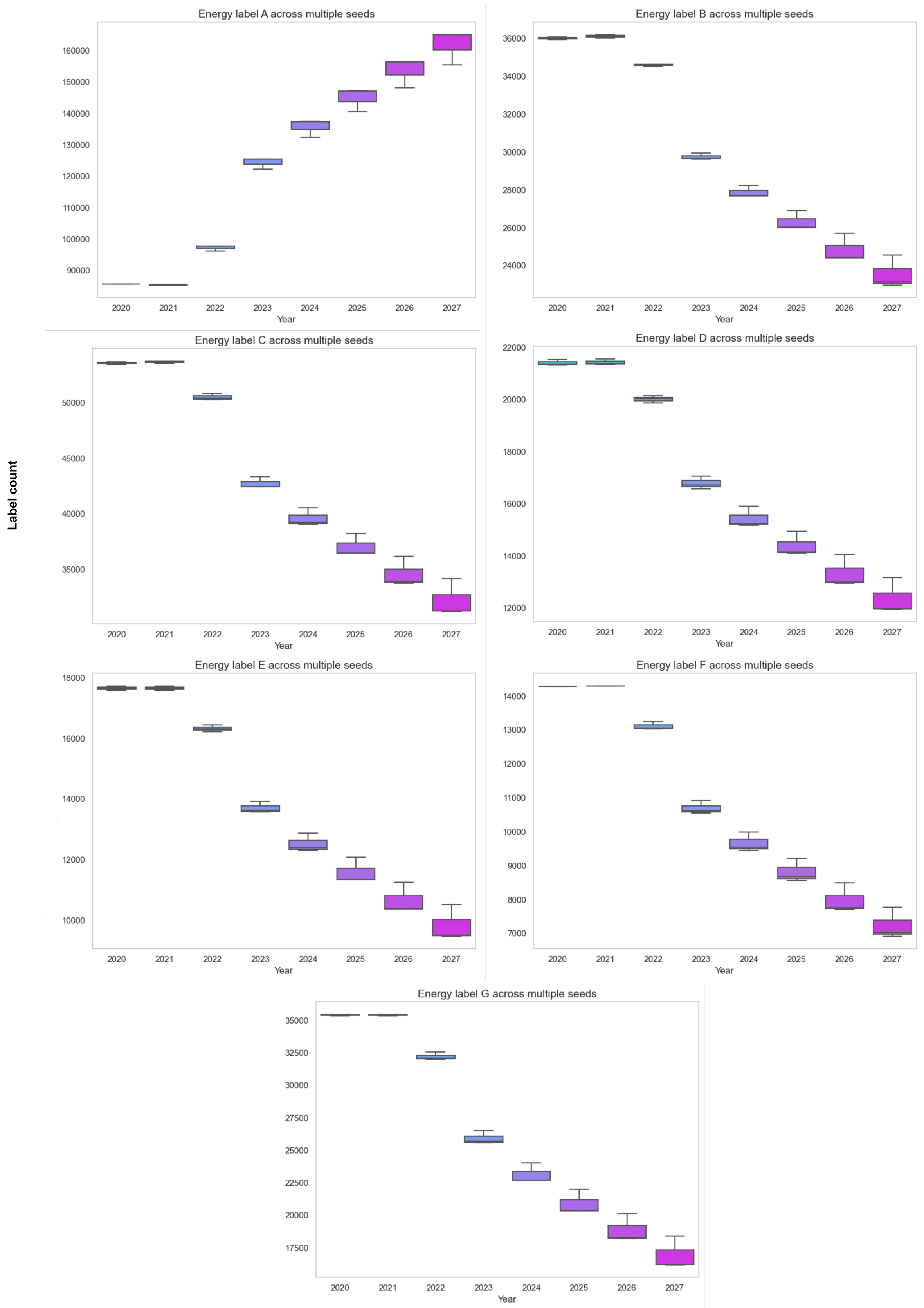

Figure 7.12: Energy label count across years for multiple seeds

A pattern that becomes clear in the energy label count but not in the energy poverty assessment is that over the years, the variation seems to increase compared to its minimal start. Many agent attributes are randomly assigned at initialisation, as is the neighbour assignment, which does not change over time. It can be assumed that small seed-induced differences are gradually increased as the neighbourly influence and subjective norms influence the attitude calculations and thus intentions to invest of the agents. Although the variation in the later years is still within an acceptable range, it does show that the model is somewhat sensitive to stochastic variation.

Using only three seeds means a very limited view of the stability of the results. A test with a minimum of 5 and ideally 10 or more seeds would have been ideal, but due to time restrictions, this was not possible. Nevertheless, the differences in the outcomes do not seem to be systematically higher or lower for one seed. Plus, even though the energy label count does show there is some sensitivity to stochastic variation, the acceptable range does create confidence in the results.

7.4. Sensitivity analysis

This section presents the sensitivity analysis, which is applied to understand the uncertainty in the model's outputs and how these relate to the uncertainty in the model's inputs. As part of the validation process, it tests the robustness of model outcomes to variations in key parameters. Sensitivity analysis strengthens confidence in the reliability and applicability of the results (Salciccioli et al., 2016). If a model has similar results under this variation of parameters, these are seen as robust results (Hernán and Hernández-Díaz, 2013). A deviation in the results is also possible, and this is important to note, as it provides valuable information for assessing the validity of recommendations based on a model's results (Hernán and Hernández-Díaz, 2013). In such a case, it is important to investigate the relative influence of each uncertain parameter on this variation in the model outputs (Wagener and Pianosi, 2019).

As part of the multi-model, the ABM introduces limitations to the available techniques for the sensitivity analysis. The emergent properties and non-linear interactions within an ABM often result in an unclear relationship between the model's inputs and outputs. This makes it difficult to use traditional statistical methods to conclude the effect of parameter changes. In literature, three sensitivity methods are discussed for an ABM: On-Factor-At-A-Time analysis (OFAT), regression-based analysis and the Sobol method (ten Broeke et al., 2016). Regression and Sobol analyses are both approaches that try to provide a complete picture of parameter sensitivity, but they do come with drawbacks for an ABM. Regression models struggle with the high variance and outliers common in ABM results, while Sobol is sensitive to skewed or extreme outputs. In addition, these methods are computationally expensive and offer little insight into the underlying mechanisms of the model behaviour (ten Broeke et al., 2016). Although technically possible, this makes these methods less suitable for ABMs.

ten Broeke et al. (2016) recommends OFAT-analysis. This simple, local approach addresses sensitivity related to chosen parameter estimates and not for the entire parameter distribution (Hamby, 1994). One uncertain variable is varied at a time, while keeping all others fixed. Several of the parameters in the ABM are based on assumptions, In the sensitivity analysis, only the parameters with high uncertainty and high impact are included. A variable is deemed to have high uncertainty if it is completely based on an assumption and a parameter with a large influence on the intention to invest indicator. For the ABM, the main parameters based on assumptions are the weights used to calculate the TPB attributes. As these weights are sets, one set is seen as one variable. More specifically, the OFAT-analysis is applied to the weights of the Theory of Planned Behaviour attributes, applied in Equation 6.3. The choice to test the sensitivity of the results to this set of weights is based on its uncertainty and impact. It is fully elaborated in subsection D.2.5.

In the base case, the weights for attitude, subjective norms and perceived behavioural control are set equally, to avoid prioritisation of a specific single parameter. Nevertheless, de Vries (2020) and Davoudi et al. (2014) imply that subjective norms carry more weight than your attitudes. Another argument can be made that PBC should weigh the heaviest, as if someone does not feel they have the ability to invest, they will not, despite their attitude or peer pressure. Thus, the sensitivity analysis is run twice with adjusted weights for the PBC attributes; once where PBC weighs heavier than SN and once vice versa, but both are still higher than attitude, to follow the findings from the literature. The experimental design is summarised in Table 7.2. The resulting outputs are compared to the base case run of the multi-model, making it easy to interpret (Wagener and Pianosi, 2019).

Table 7.2: Experimental design analysis ABM

Run	Variable
Multi-model run	$\{w_{\text{a}}, w_{\text{sn}}, w_{\text{pbc}}\} = \{0.33, 0.33, 0.33\}$
Sensitivity SN	$\{w_{\text{a}}, w_{\text{sn}}, w_{\text{pbc}}\} = \{0.1667, 0.5, 0.33\}$
Sensitivity PBC	$\{w_{\text{a}}, w_{\text{sn}}, w_{\text{pbc}}\} = \{0.1667, 0.33, 0.5\}$

Figure 7.14 illustrates that the differing weights of the behavioural attributes have a differing effect on the energy poverty risk estimates. The base run results in higher intentions to invest, followed by the PBC-heavy run, and the SN-heavy run results in the lowest scores. The energy poverty risk assessment for both sensitivity runs starts off being almost equal, even though the intentions to invest for income group 1 at risk for energy poverty do, in fact, differ. Over time, the results start to diverge. This lowest intention to invest for SN results in the lowest energy poverty risk, as the lower the intention, the flatter the S-curves, and the less distinction between attractiveness of investment options, leading to more investments.

Given that energy poverty risk is assessed solely for the lowest income class, the sensitivity analysis of the energy poverty risk does not reflect the complete model's sensitivity to the parameters. The overview of intentions to invest over time per income class, visualised in Figure 7.13, gives the impression of larger sensitivity to the changes in parameters than are reflected in the model's risk calculations. Notably, the intention to invest has a very different sensitivity per income class. While the PBC- and SN-heavy runs yield comparable outcomes for income class 1; both differing from baseline but relatively close to each other, the difference between the scores per run within an income class changes alongside the income groups. At the aggregated level, these sensitivities are not reflected at all, as the energy label distribution over time is almost identical per configuration.

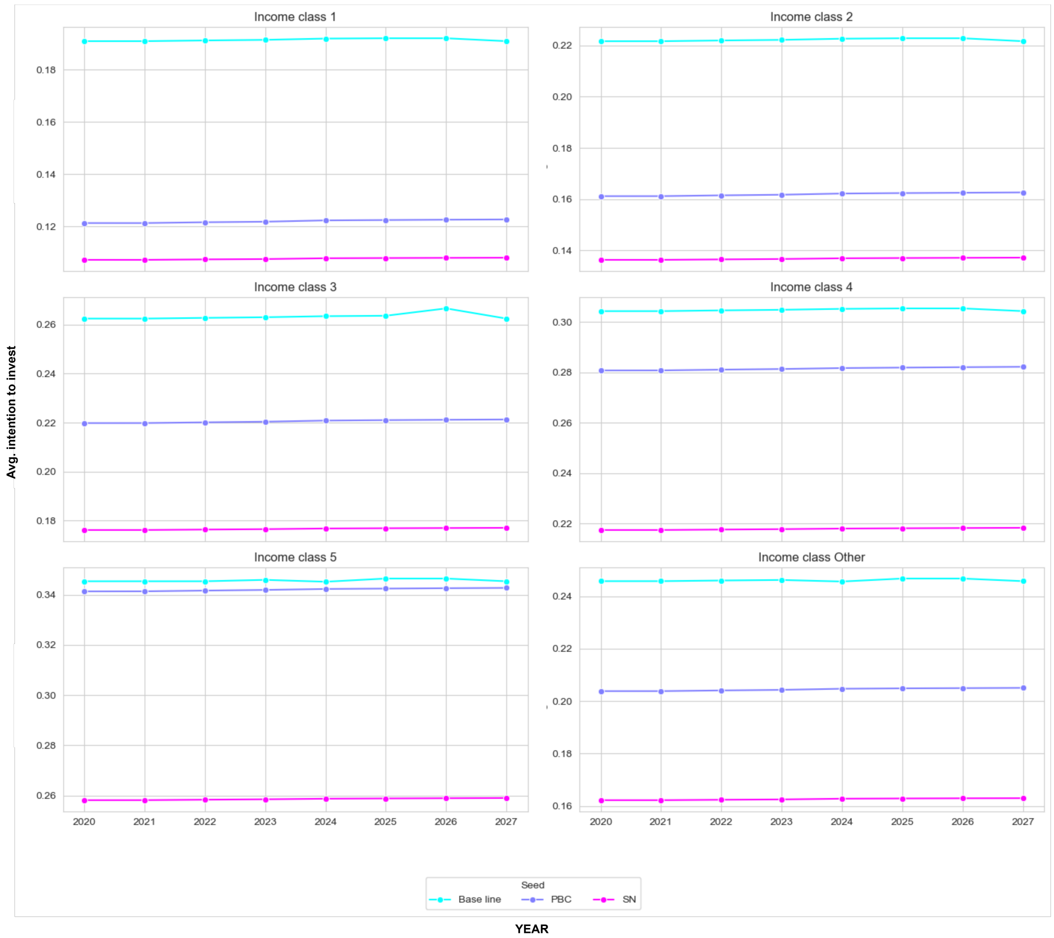

Figure 7.13: Evolution of intentions to invest per income class under sensitivity analysis

The sensitivity analysis results highlight three significant points: Firstly, small differences in intentions to invest do not seem to have a large impact on the overall results in HESTIA. It seems that HESTIA is responsive to large shifts in adoption data, like those caused by the multi-model integration, but not sensitive to smaller behaviour-driven changes. Secondly, the subjective norm-heavy configuration only starts resulting in differing outcomes, reflecting that it takes time before social influence can shape the outcomes of the model. Lastly, the ABM's sensitivity results differing across income classes underscore the importance of carefully calibrating behavioural weights in the model design. These findings suggest that the relative influence of the behavioural attributes should not be uniformly applied across the agent population, as their effects may vary significantly by socioeconomic status.

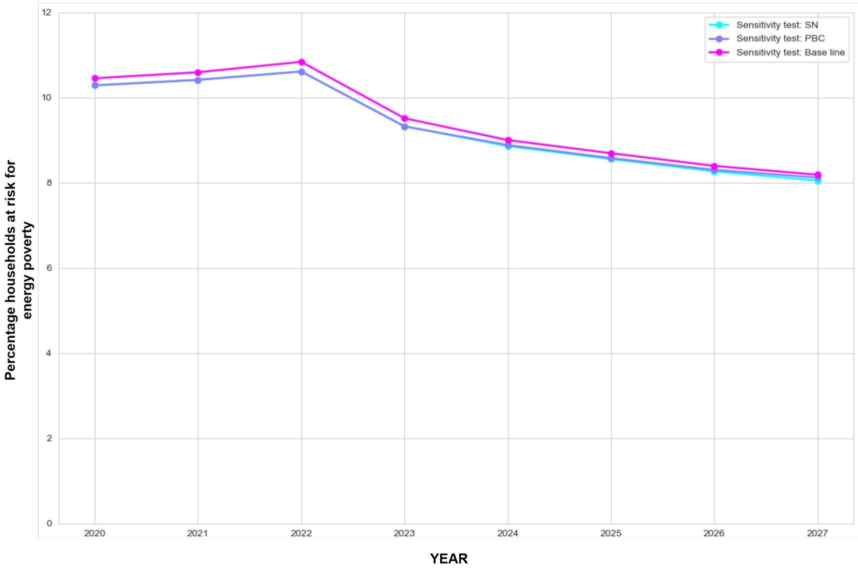

Figure 7.14: Evolution of energy poverty risk under sensitivity analysis

8 Discussion

This chapter includes a discussion of the findings from this thesis. It starts by reflecting on the study and the modelling choices. This is followed by a more detailed discussion of the assumptions, data and theories used in the model and their role in shaping the outcomes. It briefly discusses the academic implications of this study before moving on to the implications for policymakers. The chapter ends with recommendations for future research.

8.1. Reflecting on this study

8.1.1. Inaccuracy vs. injustice

This thesis set out to include the incorporation of recognition justice in the HESTIA model by increasing the detail of households' investment behaviour, under the premise that an inaccurate aggregated representation of this behaviour means misrecognition and would potentially result in wrong policy recommendations, with the chance of reinforcing energy poverty. An important question to ask about this premise is:

Does inaccuracy mean injustice?

Nancy Fraser argued that recognition justice is a three-pronged issue, which can only be completely eradicated if it is tackled in parallel with economic inequality, one of the factors that plays a role in energy poverty. Misrecognition occurs if certain groups are undervalued by cultural norms or institutional practices.

The sensitivity analysis has shown that intentions to invest differ per income group and that these income groups have a different sensitivity to attributes of the Theory of Planned Behaviour. This suggests that the influence of behavioural attributes on investment decisions should not be uniformly applied across the population. As HESTIA assumes uniformity in investment behaviour, the current representation of household behaviour in HESTIA is therefore *inaccurate*. Not all households intend to behave in the same way under the same circumstances. Overlooking this diversity in a model intended to be used by governmental agencies to calculate policy targets risks undervaluing certain population groups, in institutional practices such as policy design and resource allocation aimed at decreasing energy poverty. In this situation, inaccuracy does mean *injustice*.

A second question that should then be asked is:

Is the applied method for the incorporation of recognition justice the most suitable one?

The current adjustments to the model have led to a flattening of the investment dynamics. This has the side effect of making unfavourable investment options appear relatively more attractive to lower incomes, whereas in practice this is rarely the case. The inclusion of the agent heterogeneity through the S-curve parameters (β and P50P) meant that the intention to invest had to be normalised. Multiplying the S-curve parameters with un-normalised values would in some cases result in βs higher than 1. If the β is allowed to be 1 or higher, the curve would more closely resemble a step function, as illustrated in Figure 8.1, which is the curve for one of the building options, as Figure 5.2, but with an β of 3.2. This would result in erratic behaviour, where adoption would be extremely low until a certain price is reached, after which adoption would suddenly be at its highest.

The original S-curve data is calibrated based on aggregated adoption data of the different options

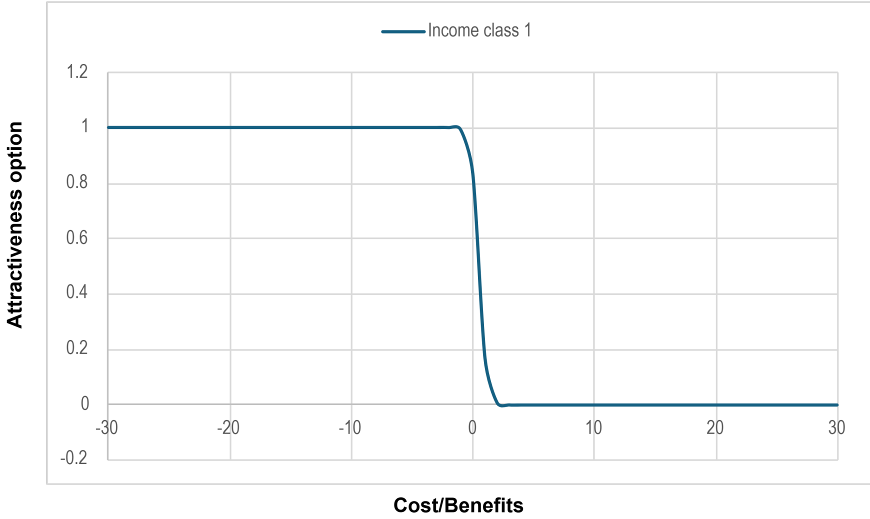

Figure 8.1: Example S-curve with β >1

(van der Molen, 2023). The goal of the adjustments to the S-curves was not to redefine the adoption dynamics of specific technologies, but to add more variation across population groups. This is why the S-curves were "split" as it were between income groups. It introduces more heterogeneity whilst the investment structure itself is mostly unchanged.

The adjustment of the S-curve parameters resulted in flatter curves, reflecting less sensitivity in the attractiveness of an option, based on cost changes. The maximum attraction score of every option is lower than in the control run, correctly reflecting a lower intention to invest. Unintentionally, the shift of the curve led to the right side of the curve, the attraction of an option at a less beneficial cost-benefit ratio, moving up compared to the control run.

As a lower income group has a lower intention to invest, according to Equation 8.1, the multiplication with their lower intention to invest results in a more flattened curve than for a higher income class. The higher intention to invest for higher income groups results in a higher attraction for options at a more beneficial cost-benefit ratio. At a less beneficial cost-benefit ratio, the attractiveness is higher for lower-income classes. This causes a relatively higher increase in investments for the lowest income groups in comparison to the higher income groups.

$$A(\text{cost/benefit}) = \frac{1}{1 + \exp\left(\beta \cdot (\text{cost/benefit} - \text{P50P})\right)} \tag{8.1}$$

Although mathematically this makes sense, the accuracy of this representation of investment behaviour can be questioned. After all, households with a lower income generally have less tendency to invest in energy-saving technologies (Niamir et al., 2020), as is also clear from the results, and would thus not find a higher cost-benefit ratio more attractive than groups with more income.

This limitation does not discredit this approach or this research. This thesis presents only a first attempt at adjusting HESTIA for recognition justice, and applying the investment intention in this way was necessary with the limitations of the current model structure. It does reflect the difficulty of including agent heterogeneity through behavioural elements to improve recognition justice in an existing model structure. The investment structure, as it is, is not suitable for capturing the diversity of behavioural responses required for meaningful representation of agent heterogeneity, and thus is not yet able to properly account for recognition justice. This raises the question of whether the HESTIA model is suitable for socio-economic analyses at all. The model logic would need to be fundamentally restructured to explicitly account for household-level decision processes, behavioural feedback and the interaction of these aspects with technical measures. Only then could policy outcomes determined through this model be said to have accounted for recognition justice.

8.1.2. The multi-modelling method

It was already established, in section 4.1, that due to HESTIA being a top-down model, the most suitable way to incorporate such adjustments would be to incorporate these household-level adjustments through an additional, separate model layer.

This additional model layer significantly increased the complexity of the overall simulation. It also once more highlighted how the current modelling architecture has no proper mechanism to represent household behaviour. The incorporation of the ABM results was only possible by grouping them per income group, as adjusting the S-curve data for each agent would require too immense storage capacity for all CSV files, as well as substantial computational power in terms of processing time and system resources.

The applied multi-modelling method brought advantages such as the ability to model the entire Theory of Planned Behaviour structure in a bottom-up perspective whilst maintaining the top-down structure of HESTIA. Although discrete-step data exchange in a soft-linked model preserves the modularity of both models, enabling separate development, updates, and easier debugging, this does reduce the user-friendliness of the model design. Data must be extracted and exchanged in a specific order to prevent errors, and the manual extraction of data from HESTIA before loading it into the ABM adds to the total runtime. Additionally, since the models are manually linked, each must complete a full run before exchanging data.

There is no automatic back-and-forth data exchange. As a result, both models lack memory across runs. To keep agent data and investment history, both must rerun all previous years cumulatively at each step. This means one run consists of running 2020 for both models, then running 2020+2021, then 2020+2021+2022, etc.. This significantly increases the runtime and further reduces the ease of use.

8.2. Limitations

The behavioural logic in the Agent-Based Model is based on several assumptions and simplifications. While these were essential to create a functional model, it is equally important to take the limitations that these assumptions bring into account when discussing the takeaways from the results, as they can influence the generalisability and validity of the conclusions. This section will discuss the three most important assumptions, as well as the limitations they impose.

8.2.1. Dwellings vs. households

A conscious decision was made to treat the agents as households, rather than dwellings, as they are in HESTIA. This choice was made to more easily attach behavioural variables to the agents. The agents are based on HESTIA data, which does mean that they are based on dwelling characteristics. Multiple-family homes (77% of all dwellings in The Hague) are treated as a single household in the ABM. This simplification is addressed during the post-processing of results by applying standardisation, ensuring that the energy cost and use do not distort the energy poverty estimates.

This choice does have an impact on the assignment of neighbours and subjective norms that are a result of social interactions. It is a reasonable deduction that inhabitants of a multi-family building, such as an apartment complex, see each other as direct neighbours and might even collectively decide on retrofitting decisions for the building. These in-building social dynamics are excluded, as these buildings are considered as one agent. This simplification aligns with the model's abstraction levels.

Furthermore, as the focus of the study is on showing the effects of inclusion of recognition justice and not on correctly predicting dwelling's investment choices, such detailed dynamics are not as relevant, and this limitation is accepted. In future research, these dwellings could be split up into separate agents, and by including different levels of neighbourly influence, group dynamics could be distinguished between intra-building and inter-building influences. It is recommended that an extensive literature review/ exploratory survey is conducted to determine how size of the effect of splitting households on investment decisions and energy poverty prevalence. If found to be insignificant, it is not needed to introduce unnecessary detail in the model.

8.2.2. Agent profiles

For the agents' initialisation, several assumptions were made the agent profile characteristics that play a role in its energy behaviour are limited to income, household size and dwelling characteristics such as building age, home ownership, dwelling size and energy labels. As discussed in subsection 4.2.1, there is a conflict in the literature on the impact that education levels within a household have on their energy behaviours (Niamir et al., 2020; Vasseur and Marique, 2019). Future research could explore the role of education in energy behaviour, especially in the context of The Hague. If found to be significant, it would be a valuable addition to the behavioural logic in this model.

Another profile characteristic that could have an interesting impact on a household's energy behaviour is political orientation, as there is an ideological divide on climate change views in Western European countries (McCright et al., 2016). Several studies have found that a household's political convictions are a good predictor of their energy investment decisions (Dokshin and Gherghina, 2024; Gromet et al., 2013). These studies are all applied to the United States. Although such behaviour seems plausible to also occur in the Netherlands, there is no literary evidence and as such it has been left out of consideration. Again, if such a relationship is found to be significant in future research, it would add extra depth to the agent profiles and potentially be a valuable addition to the model.

The third limitation of the agents' profile is in their geographical location. Based on the initialisation data from HESTIA, the agents are assigned a neighbourhood. To prevent that, all agents are initialised on the same point within their respective neighbourhoods, and they are given an "address", consisting of their coordinates within their neighbourhood. Addresses are randomised within the neighbourhood to ensure that the home cannot be traced back to a specific person. This might result in a house being positioned in the middle of a road, or even a body of water. However, as this low spatial resolution is out of the scope of this simulation, this is irrelevant. This randomised address assignment can result in neighbours, assigned purely based on geographical proximity, having completely different building characteristics, even though buildings on the same street usually share comparable attributes. The realism of the social network structure might be weakened as a consequence. This limitation is accepted, however, as the general patterns caused by neighbourly influences are considered more important than the individual relationships between households.

In the current simulation, energy poverty risk can only be assessed by excluding HEQ as an indicator and assessing all agents in the lowest income class for Low income/ High energy cost (LIHE) or Low income/Low energetic quality (LILEK), causing an overestimation of energy poverty. This approach brings the large assumption that only the lowest income group can be at risk for energy poverty, ignoring that households in higher income classes can suffer the same fate due to rising energy costs or overall insufficient structural interventions. The distribution of energy poverty is somewhat skewed as income is randomly assigned based on the income distribution per ownership type, which is sourced from national distribution data. While this ensures a representative population overall, it can lead to unrealistic combinations at the household level. For example, very low-income households occupying expensive, energy-efficient dwellings that would likely be unaffordable in reality. This can slightly distort the calculated energy poverty risk and may overestimate how much technical efficiency alone can mitigate poverty. This does highlight the interesting point of how both models and policies risk misrecognising the structural roots of energy poverty when they assume that energy performance improvements alone will be sufficient, overlooking how affordability, ownership type, or the housing market shape real households' options.

Lastly, although the weights in the behavioural attribute calculations can differ per agent based on their characteristics, they remain constant throughout the entire simulation. The weights for the attitude, subjective norm and perceived behavioural control are the same for every agent, and remain static as well. This is a generalisation since the relative importance of each TPB attribute can differ per individual (Ajzen, 1985). Despite this generalisation and staticity of the weights, they still represent an improvement in terms of recognition justice, as they allow for the inclusion of behavioural aspects, which are not incorporated into HESTIA at all currently.

8.2.3. Behavioural logic

In this thesis, the three constructs of the TPB, attitude, subjective norms and perceived behavioural control were used to determine an agent's intention to invest in energy efficiency measures around their home. The Theory of Planned Behaviour offers the opportunity to incorporate behavioural heterogeneity into the model, which is crucial for recognition justice. The TPB is widely used as a behavioural theory in ABMs due to its providing an uncomplicated way of explaining the individual choices an agent makes during the decision-making process (Muelder and Filatova, 2018). The theory has several well-known points of criticism. As the Theory of Planned Behaviour forms the foundation on which the ABM model is built, it is important to reflect on how these critiques are dealt with in this study.

Firstly, it has an exclusive focus on rational reasoning, overlooking the role of unconscious processes and emotions in decision-making (Sniehotta et al., 2014). Especially in the context of energy behaviour, this is a relevant critique as although investment decisions might seem rational, people tend to be driven by status quo bias, loss or risk aversion, availability bias or temporal discounting (Frederiks et al., 2015). Three perspectives are often used to analyse energy behaviour: an economic, psychological and sociological perspective. The economic perspective suggests that people are utility maximisers who base their decisions completely on rational cost-benefit analyses (Davoudi et al., 2014). This is a common criticism of the Theory of Planned Behaviour; it ignores unconscious influences and the role of emotions beyond anticipated affective outcomes on behaviour (Sniehotta et al., 2014). As the decision logic in HESTIA follows this pattern, the Theory of Planned Behaviour is actually a fitting theory to apply. However, Christie et al. (2011) highlights how energy efficiency decisions are not only influenced through a benefit assessment but also by perceived social risks. Homeowners are influenced by their desire to fit in. They do not want to be the first to install a technology and stand out. To address this, the subjective norms are loosely based on social identity theory, reflecting how much a person will adjust their behaviour to improve their sense of belonging. While the decision to follow their group's behaviour remains an active rational choice (Davoudi et al., 2014), it allows the model to capture some of the behavioural diversity linked to social belonging.

Another important critique of the TPB is its predictive validity; how it deals with the intention-behaviour gap (Sniehotta et al., 2014). Generally, when the TPB is used, the intention to act is seen as a threshold. If crossed, an agent will act. The intention-behaviour gap illustrates the occurrences when the threshold is crossed by an agent, but no action is undertaken (Sheeran, 2002; Sniehotta et al., 2014). Sheeran (2002, p. 3) state that intentions to act explain about 28% of the variation in behaviour. This means that people's intention to act only explains about 28% of people's behaviour. 72% of behaviour cannot be explained by intentions alone.

Intention to act is treated differently in this study. Not as a static threshold, but as a normalised continuous value which increases the likelihood that an agent will make an energy investment. This is more in line with Klabunde et al. (2015), where intention is used to calculate the probability that the agent will migrate. This increases if the intention increases. Although applied in very different cases, both concepts share the underlying principle that a high intention increases the likelihood of behaviour, rather than crossing a certain threshold of intention, which is equivalent to behaviour. Moreover, behaviour is not completely determined by the result of the TPB attributes. The intention is only one extra component in a multi-step behavioural logic in HESTIA. Although a heightened intention to act increases the odds that a technology will be adopted by a household, there is still a chance that nothing will happen, reflecting a more realistic gap between intentions and actual behaviour.

The subjective and interpretive nature of TPB attributes brings challenges to the quantitative operationalisation of behaviour in an ABM (Muelder and Filatova, 2018). Different interpretations by different modellers result in different ABM formalisations, even if the study contains the same factors; the architecture, meaning how these factors form behavioural rules, can be completely different (Muelder and Filatova, 2018). There is also the risk of different factors being identified as relevant, or differences in data distribution impacting a model's sensitivity. This hinders the comparability of this study's results. To prevent these challenges as much as possible, as much transparency as possible in documenting the data sources, assumptions and tests performed is imperative (Muelder and Filatova, 2018). To achieve this, this study has included a detailed description of the calibration and validation steps, as described in chapter 6.

The TPB is also criticised for its static explanatory nature, meaning that the TPB does not help in explaining how the effects of behaviour influence future behaviour (Sniehotta et al., 2014). This study partially addresses this limitation. Specifically, the intention derived from installations present in the building, a proxy of the "sustainability" attitude, changes once installation investments have been made. Not only does this impact the future attitude towards investments, but it also indirectly impacts the subjective norms of the agent themselves as well as their neighbours. Nevertheless, perceived behavioural control and the other attitude component based on installation plans remain static. So, although a limited feedback structure is present, the model does not fully reflect the dynamic nature of energy-related decision making, and this limitation of the TPB is not fully addressed.

8.2.4. Generalisability of results

The generalisability of these results is very limited due to a pair of reasons. Firstly, this study was done using the municipality of The Hague as a case study. To this end, local census data was used in the initialisation of the agents as well as in their behavioural rules. As Mashhoodi and van Timmeren (2018) and Mashhoodi et al. (2019) have shown, there is a difference in the strength and relevance of energy behaviour indicators. When studying a different geographical scope, it is important to use data from that region to more accurately reflect the local energy behaviour.

Secondly, this research only indicates possible results. A big limitation arises due to a combination of time limits and computational power. This restricted the opportunity to run the analysis for a longer time frame. The investment cycle for retrofitting decisions is presumably longer than the seven years included in this scope, as the lifespan of an installation is 10+ years (van der Molen, 2023).

8.2.5. Bug identified in the HESTIA model

Throughout this thesis, working with the HESTIA model, a bug was identified. Even though it does not stop the model's execution, they do reduce its usability.

The first identified bug concerns the housing stock. New construction in HESTIA starts from 2021 onwards. Scenarios indicate in which period how many homes will be built and where. At the start of each 9-year time frame (for example, 2021-2030), the new houses are added to the model (van der Molen, 2023). In theory, it is possible to disable this scenario setting (Listing 8.1), which would exclude new constructions from the simulation.

```
container Basis : Using = "Units"
{
  unit<uint32>    PlanRegio         := Invoer/RuimtelijkeData/StudieGebied/buurt, Descr = "CBS-buurten worden als definitie van plangebied gehanteerd", IsHidden = "True";
  attribute<bool> BS_isActive (Classifications/BebouwingsSectorBase) : [ true, false ], Descr = "Welke gebouwen worden meegenomen?  [ Woningen, Utiliteit ]", IsHidden = "True";

  parameter<bool> RuimtelijkeOntwikkelingAan := false, Descr = "Wordt nieuwbouw meegenomen JA/NEE";

  parameter<string> RuimtelijkeOntwikkelingScenario := 'BAU'; //Keuze uit:
    //GR, NOS, OO, VW, BAU
...
}
```

Listing 8.1: New build scenario settings, in Basis.dms

When disabling this scenario setting, it does not exclude the new builds. All new builds between the start year of the run and 2050 are added to the model's intermediary results, even if these results are for a year in which the building is not supposed to be built yet. All the information for these dwellings is set to zero, but they are still added to the data hindering compatibility of results. The choice of this model setting is thus not between including or excluding new builds; it is between including them all at once or gradually. In most situations that HESTIA will be used for, new builds will have to be taken into account to create a realistic simulation of the energy transition in the built environment and this bug will not introduce any problems. However, in studies such as this one, where the changes in energy efficiency of the existing buildings have to be assessed under *ceteris paribus*, this does create some issues. Whereas normally key performance indicators such as annual energy label counts or metrics per building type can typically be exported directly from HESTIA, in this study, the results had to be exported on a dwelling level. This was necessary as the unintended new builds had to be manually excluded before aggregating and calculating the final indicators.

8.3. Implications for literature

This thesis brings three contributions to the literature. Firstly, as discussed in subsection 1.2.1, energy models have a predominantly techno-economic focus. The HESTIA model is no exception. By establishing a soft-link between an Agent-Based Model and HESTIA, the problem of a model focusing too much on technical detail is attempted to be resolved by developing an ABM that includes stakeholder behaviour and neighbourhood effects, as loosely suggested by Fattahi et al. (2020). This demonstrates how techno-economic energy models can incorporate social and ethical dimensions, thereby enhancing their social relevance.

The second and third contributions lie in the integration of energy justice in models. Generally, when models incorporate justice aspects, they focus on distributional justice, sometimes procedural justice, but rarely recognition justice. Vågerö and Zeyringer (2023) demonstrated this occurrence when, out of 33 studies they analysed for their inclusion of justice tenets in models, 79% (26) focused on distributional justice, and only one considered recognition justice. Not only is this thesis, to this author's knowledge, one of the few considering the implications for recognition justice in energy models, but it also demonstrates an application of merging, the highest level of justice integration in models.

By establishing a soft link between the ABM and the HESTIA model, and modifying HESTIA's investment logic to reflect agent-specific characteristics, recognition justice considerations are directly embedded within the model structure. This aligns with the merging strategy proposed by Trutnevyte et al. (2019), representing a deeper integration of justice aspects into the modelling process. This study accounts for recognition justice by incorporating agent heterogeneity through diversified agent profiles; these profile characteristics (in)directly influence agents' investment choices in HESTIA. Household heterogeneity impacts the investment logic, meaning that recognition justice is embedded in the model dynamics, instead of remaining exogenous. This approach contributes to the literature, as most studies, according to Sundaram et al. (2024), remain at the stage of iterating.

8.4. Recommendations for policy developers

It is important to remember that those who are and are not recognised in the energy transition can be determined by political contexts (Tarasova, 2024). On paper, policies tested in HESTIA appear to be working. Energy labels are improving, resulting in a more energy-efficient housing stock and reducing energy poverty. The agent-level analysis has shown that while some households can make changes to reduce their energy usage enough to escape the risk of energy poverty, others cannot, even if they do invest in insulation or more efficient installations.

The results have illustrated how the relativity of energy poverty risk allows households to not be classified as at risk, or the other way around, when their conditions would not be expected to result in this classification. The current indicators LILEK and LIHE rely too heavily on the broad averages of households with energy label C (Loos, 2024), instead of focusing on household-specific realities. The identification metrics for energy poverty are classified under misrecognition as disrespect and non-recognition. An important policy advice, to improve the integration of recognition justice in HESTIA as well as energy poverty policies in general, would be to apply more nuanced measurement and recognition of the diverse ways households experience energy poverty.

A second advice that arises from this thesis is to enable further investigation into ways to improve the accuracy of HESTIA concerning recognition justice. Improvements are required in the representation of household behaviour, particularly for those most at risk of energy poverty. These improvements would enhance HESTIA's capacity to identify the impact of a policy in a more targeted manner and decrease the risk of policies that miss structurally disadvantaged people and those who depend heavily on the choices of others, preventing them from benefiting fully.

When linking the results back to recognition theory from Nancy Fraser, it is relevant to acknowledge that although recognition of individual (group) challenges is important in establishing energy poverty policy, it is more important not to focus completely on this (group) identity. Recognition should be focused on the social status of people and whether or not they are prevented from participating as peers in society (Fraser, 2001). Designing policies based on a specific identity or disadvantage would risk increasing the very inequalities the policies aim to solve. Recognition in the status order model means transformative remedies: *de-institutionalising patterns that impede parity of participation and to replace them with patterns that foster it* (Fraser, 2001, p. 25). Energy poverty policies, including a levelling effect, could aid in achieving this. It would entail measures that are available to everyone but structured in a way that disproportionately benefits those who need it most.

When using HESTIA to calculate the consequences of policy measures and determine how these are implemented, the insights on patterns within specific groups should be kept in mind, but, in line with Fraser's theory, should not be used to design targeted policies, as this would be identity politics. Instead, allow this information to inform inclusive designs that work for everyone while improving the position of the worst-off. This would bring society closer to participatory parity, ensuring that everyone participates in and benefits equally from the energy transition.

8.5. Future research recommendations

In the above-discussed limitations, several suggestions for future research are already mentioned. Based on the insights from this study, future research can consider several modifications and adjustments to further investigate how recognition justice aspects can be merged into the model logic.

Firstly, as mentioned in subsection 8.1.1, there is doubt whether the current HESTIA model structure is even suitable for more agent heterogeneity in its investment module. Future studies should explore whether the investment logic can be formalised differently, without the S-curve structures, to allow for more diversity in investment choices, to more accurately represent agent heterogeneity. If this is not possible, another avenue to explore is how, while applying the S-curve logic, more household heterogeneity can be introduced in the model to (1) allow for diversity reaching further than income classes only and (2) for barriers to investment to be more accurately represented.

Secondly, as section 4.1 mentions, HESTIA does include a corrective behavioural factor. This factor is included in functional energy demand calculations to represent energy demand adjustments caused by shortening shower time or lowering the average temperature of spatial heating (van der Molen, 2023). These factors, although differing per functional demand category, are one-size-fits-all. It is the same factor for all households, as it does not change during a model run (van der Molen, 2023). This current research has focused solely on incorporating recognition justice aspects into the investment module of HESTIA. Future work could extend this incorporation of recognition justice by developing behavioural adjustment factors which can vary over time and per household (group), to more accurately reflect the diverse realities of household energy consumption. It could be extended by researching how these behavioural adjustment factors can be calculated per year and diversified per household (group) to more accurately represent energy-saving behaviour. Such a primary investigation into the aspects that influence energy behaviour in the region that is studied will provide more insights into the significance of local determinants, such as education levels.

As discussed, applying the Theory of Planned Behaviour was suitable as it's rational perspective on behaviour aligns with the rational way decision-making is represented in HESTIA and because the attributes for this theory have been proven to have a significant impact on energy behaviour in the Netherlands. While the variables and theoretical approach behind the agents' profiles and behaviour are supported in literature, due to time restrictions, there was no opportunity to perform a local survey to validate the relevance or relative importance of these variables for residents of the municipality of The Hague. This means that in several calculations, heterogeneity is limited to diversity per income group, neighbourhood or ownership type. Although this brings more heterogeneity to HESTIA than the original, it still means focusing on group identities, as more individualistic data is unknown. For future studies, it would be interesting to perform such surveys and analyse whether different behavioural theories are better suited to represent energy-saving and energy investment behaviour of Dutch households.

Energy poverty affects households for different reasons. Vulnerable groups are more often than not low-income families, the elderly, lower educated people, women-led households or migrant s (Jones and Reyes, 2023; Ooij et al., 2023). In this thesis, the focus was more on income-based recognition and energy poverty. The aggregation in HESTIA's dwelling-level data made it not possible to fairly include other identity-based dimensions, such as cultural backgrounds or gender. For future research, it would be very valuable to focus on different dimensions of energy poor, as this could influence how recognition is conceptualised in models and how outcomes are interpreted through a justice lens.

Lastly, while this thesis calls for a move away from one-size-fits-all policies to allow for policies to recognise the needs of groups vulnerable to energy poverty and be more levelling between vulnerable and non-vulnerable population groups, this raises important questions. Such questions are: What would happen to the pace of the energy transition in the built environment? Can fully achieving participatory parity hinder the achievement of the climate goals? Investigating the trade-off between inclusivity and the energy transition could provide very valuable insights into how to balance energy justice with the urgency of the energy transition.

9 Conclusion

9.1. The research questions

To find the answer to the main question of this study, three sub-questions were asked. In this section, these questions are answered.

9.1.1. Sub research question 1

How are misrecognition and energy poverty connected?

Most theories on recognition justice are founded on the theories of Axel Honneth and Nancy Fraser. Axel Honneth's theory of recognition justice is centred around the idea that social justice is achieved when individuals receive recognition in three key spheres: love, law, and cultural appreciation. Misrecognition in one of these spheres leads to disrespect and harm to one's self-identity. This theory would be very suitable for application in the diagnostic phase of justice and help in determining why people feel misrecognised, as it focuses on how individuals and groups experience misrecognition in their daily lives.

In contrast, Nancy Fraser's framework is more suited for analysing structural misrecognition in policies, as it combines both cultural recognition and economic redistribution. Fraser argues that justice requires addressing both of these dimensions simultaneously, as neither misrecognition nor economic inequality alone could fully explain social injustice. Recognition is grounded in the cultural status order, and misrecognition occurs when cultural norms and institutional practices undervalue certain groups, preventing them from participating as full members of society. Injustices are then reproduced through systemic and institutional arrangements, rather than only through interpersonal relations, like in Honneth's theory. Misrecognition occurs in three forms: cultural domination, non-recognition and disrespect.

Misrecognition in Dutch energy poverty policies occurs through one-size-fits-all policies based on dominant norms mainly based on affordability, institutional blind spots causing energy-poor households to not be properly identified, and awareness efforts not being targeted at the right groups and ignoring cultural & language barriers. In line with Fraser's theory of misrecognition, these shortcomings represent, respectively, cultural domination, disrespect and non-recognition.

Policies that do not consider the diversity in the population may overlook specific challenges faced by households in the energy transition, and consequently, reinforce inequalities and hinder true participatory parity in the energy transition. A lack of recognition of the diversity in households' energy behaviour from policymakers can exacerbate and reinforce distributional inequalities and worsen energy poverty.

9.1.2. Sub research question 2

What is a suitable conceptualisation for modelling household energy behaviour in HESTIA?

HESTIA offers a detailed representation of spatial, technical, and economic processes within the energy transition, but largely overlooks the social dynamics that influence the energy transition of the built environment. By reducing individuals' diversity in energy behaviour to singular behavioural profiles based on dominant norms, HESTIA preserves misrecognition. To prevent this, a shift towards a household perspective, with a bottom-up view of the system, is required. While HESTIA is a powerful tool for assessing policy impacts and the influence of investments, it is a top-down model, not designed to capture social interactions between households.

To bridge this gap, a complementary approach is needed; one that simulates heterogeneous households interacting with each other and their environment, and allows for behavioural change from the bottom up. An agent-based model is a suitable complementary addition to HESTIA as it allows for the analysis of complex, dynamic systems through a bottom-up perspective. It enables a simulation of micro-level individual decisions and interactions, and how this affects macro-level behaviour.

People's energy-related decisions are not based on economic rationality alone, but are shaped by social context and interpersonal relationships. This household's behavioural diversity is made up of objective household characteristics and subjective behavioural factors. Objective profile characteristics affect household energy consumption, while behavioural factors influence their decisions regarding energy saving and investment. Objective factors that have been identified to have of impact on energy behaviour are household income, household size, building age, home ownership, dwelling size and the dwelling's energy label.

The Theory of Planned Behaviour has been criticised for its focus on rational decision making, excluding unconscious and irrational influences on behaviour. Nevertheless, it offers a structured and operational framework that aligns well with HESTIA's decision-making logic. Moreover, its attributes have been proven to have a significant impact on energy behaviour in the Netherlands. Thus, this theory is used to capture intention-based behavioural dynamics in the simulation. The inclusion of the social identity theory ensures that social norms and influences are reflected. Households assess their similarity to their neighbours and adjust their behavioural intention according to the difference in attitudes with their neighbours, weighted for how close the neighbours are. Attitudes towards investment are influenced by a household's income, whilst Perceived Behavioural Control is weighted for income and housing ownership.

By linking the weighted sum of these behavioural dynamics as intention to invest to the investment logic in HESTIA, more household heterogeneity is introduced in HESTIA. This method (indirectly) captures a range of behavioural differences across household profiles, thereby increasing household behavioural heterogeneity and decreasing misrecognition in household energy decision-making. Moreover, by giving each agent their profile, weighing the behavioural variables based on their objective profile factors and varying the weights of the subjective norms based on how much they identify with their neighbours, allowing their attitudes to vary over time based on HESTIA's intermediate outputs, the conceptualisation adheres to the requirements defined for the artefact.

This conceptualisation is realistic and feasible as a way to increase recognition of justice in HESTIA. It enables the model to more realistically reveal how different households, especially marginalised groups, choose their investments. This, in turn, aids policy developers in developing more effective policies, stepping away from one-size-fits-all solutions.

9.1.3. Sub research question 3

How does accounting for misrecognition in HESTIA affect energy poverty estimates?

Accounting for recognition justice by incorporating agent heterogeneity in HESTIA seemingly decreases energy poverty risk over time. The adjustment of the investment logic, specifically by varying the S-curve parameters β and P50P for the insulation ambition, chosen insulation measures and investment in installations for the dwelling, by investment intention per income group, aimed to improve the different willingness to invest per income class. Through this inclusion, HESTIA was able to acknowledge that different income groups might have a different appreciation of investment options, based on their relative cost-benefits.

These changes resulted in separate S-curves per income group, but also lowered and slightly moved the curves to the left, resulting in a generally dampened response to the cost-benefit ratios. Through these changes, the investment patterns in the HESTIA model changed. By moving the curve, the attractiveness of the different options came closer together, increasing the odds that more expensive options were selected. This increase was seen particularly for income class one, as their general attractiveness was suddenly, and probably unrealistically, higher at a higher cost-benefit ratio than in the base case. As energy poverty is only monitored for this income group, their increase in investments and improvements of their homes resulting in lower bills and energy use explains the decrease in energy poverty risk, especially as in the base case, the attractiveness decreases way more steeply, leaving.

This would appear to mean that incorporating more recognition by acknowledging diversity in investment intentions would result in potentially more effective policies than initially thought, as energy poverty seems to be lower. Although the S-curve adjustments correctly differentiated adoption attractiveness per income group at lower cost/benefit ratios, the uniform adjustment of the curves also caused an upward shift of the attraction to options with a less beneficial cost/benefit ratio, resulting in unrealistic attractiveness rankings for the most expensive options. This suggests that one term adjusting the entire curve is insufficient to represent structural investment barriers and the nuance in investment behaviour.

9.2. Final conclusion

Summarising these answers leads to the answer of the main research question, which is also the conclusion of this thesis:

How can the integration of recognition justice in HESTIA improve the model to better capture the consequences of energy policy interventions, measured through energy poverty?

Misrecognition in energy poverty policies occurs through one-size-fits-all policies, institutional blind spots, and the awareness efforts not being properly targeted at the people who need them. A step towards preventing misrecognition in HESTIA, which could give a better idea of how different groups respond to policy, and enable policies to be improved to further participatory parity, would be to allow more agent heterogeneity in the investment logic of the model.

Measured in the percentage of the population that is at risk for energy poverty, adjusting the investment logic for each income group's intention to invest seems to have worked to capture a diversity in investment choices that leads to a decreased estimate of energy poverty risk. Based on the results of this study, no definitive conclusions can be made regarding the assessment of policy effectiveness, as the adjustments do allow for diversity in decision-making to be introduced, but also dampen the response to different options within such a group. On the one hand, the adjustments made to the model have introduced recognition of a level of diversity. On the other hand, the dampening of the response to different options takes away some detail in the decision-making that might be crucial for an accurate representation of the investment decision-making process of households. The conclusion of this study:

Recognition justice in energy models used to determine energy policy is imperative to improve energy poverty in the Netherlands. The method tested in this thesis is an initial test of how more social dynamics can be included in HESTIA to provide this recognition. It showed that more and more nuanced changes are required to fully capture the investment dynamics of households and incorporate the recognition that is required to simulate the consequences of energy policy interventions on energy poverty.

Bibliography

Abrahamse, W. and Steg, L. (2009). How do socio-demographic and psychological factors relate to households' direct and indirect energy use and savings? *Journal of Economic Psychology*, 30(5):711–720. https://doi.org/10.1016/j.joep.2009.05.006.

Abrahamse, W., Steg, L., and Abrahamse1, W. (2011). Factors Related to Household Energy Use and Intention to Reduce It: The Role of Psychological and Socio-Demographic Variables. *Human Ecology Review*, 18(1):30–40.

Aedes (n.d.). Hoe zit het met ... energiearmoede? [what about ... energy poverty?]. https://aedes.nl/over-aedes/hoe-zit-het-met-energiearmoede.

Ajzen, I. (1985). *From Intentions to Actions: A Theory of Planned Behavior*, pages 11–39. Springer Berlin Heidelberg, Berlin, Heidelberg. https://doi.org/10.1007/978-3-642-69746-3_2.

All, M. (2024). An Introduction to Python Subprocess: Basics and Examples. https://www.datacamp.com/tutorial/python-subprocess.

Allecijfers.nl (2025). Alle wijken en buurten in de gemeente Den Haag [All areas and neighbourhoods in municipality The Hague]. https://allecijfers.nl/gemeente-overzicht/den-haag/.

Amin, R., Mathur, D., Ompong, D., and Zander, K. K. (2024). Integrating social aspects into energy system modelling through the lens of public perspectives: A review. *Energies 2024, Vol. 17, Page 5880*, 17:5880. https://doi.org/10.3390/EN17235880.

Anderson, K., Lee, S., and Menassa, C. (2013). Impact of Social Network Type and Structure on Modeling Normative Energy Use Behavior Interventions. *Journal of Computing in Civil Engineering*, 28(1):30–39. https://doi.org/10.1061/(ASCE)CP.1943-5487.0000314.

Arends-Tóth, J., Arts, K., van den Brakel, M., Dost, M., Gidding, K., Huynen, B., Link, K., Lok, R., Menger, J., Nieuweboer, J., Otten, F., Pouwels-Urlings, N., and Wesselius, N. (2022). Materiële Welvaart in Nederland 2022 [Material Wellbeing in the Netherlands 2022]. Technical report, CBS. https://longreads.cbs.nl/materiele-welvaart-in-nederland-2022/bijlagen/.

Bal, M., Stok, M., Bombaerts, G., Huijts, N., Schneider, P., Spahn, A., and Buskens, V. (2023). A fairway to fairness: Toward a richer conceptualization of fairness perceptions for just energy transitions. *Energy Research & Social Science*, 103:103213. https://doi.org/10.1016/j.erss.2023.103213.

Batenburg, A., Hopman, B., Kleinherenbrink, E., and Mulder, P. (2025). Energiearmoedescenario's bij stijgende energieprijzen in 2025 [energy poverty scenarios with rising energy prices in 2025]. Technical report, TNO. https://publications.tno.nl/publication/34643855/XvPG98yo/TNO-2025-R10431.pdf.

Beijnum, B. v. and Wijngaart, R. v. d. (2023). Referentie warmtebehoefte woningen: Praktijkwaarden van warmtebehoefte en energieverbruik [reference heat demand for homes: Practical values for heat demand and energy consumption].

Bouzarovski, S. and Simcock, N. (2017). Spatializing energy justice. *Energy Policy*, 107:640–648. https://doi.org/10.1016/J.ENPOL.2017.03.064.

Brown, A., Hampton, H., Foley, A., Furszyfer Del Rio, D., Lowans, C., and Caulfield, B. (2023). Understanding domestic consumer attitude and behaviour towards energy: A study on the Island of Ireland. *Energy Policy*, 181:113693. https://doi.org/10.1016/J.ENPOL.2023.113693.

Brui, A. (2025). Gas Boiler vs Electric Boiler: Which is Better? https://www.greenmatch.co.uk/boilers/compare/types/electric-vs-gas.

Carstensen, A. K. and Bernhard, J. (2019). Design science research – a powerful tool for improving methods in engineering education research. *European Journal of Engineering Education*, 44(1-2):85–102. https://doi.org/10.1080/03043797.2018.1498459.

Centraal Bureau voor de Statistiek (2023a). Laagste armoederisico in 45 jaar door energietoeslag [Lowest poverty risk in 45 years thanks to energy allowance]. https://www.cbs.nl/nl-nl/nieuws/2023/45/laagste-armoederisico-in-45-jaar-door-energietoeslag#:~:text=De%20lage%2Dinkomensgrens%20staat%20voor,netto%20per%20maand%20in%202022.

Centraal Bureau voor de Statistiek (2023b). Lage-Inkomensgrens [Low income boundary]. https://www.cbs.nl/nl-nl/nieuws/2023/49/inkomen-agrarische-huishoudens-in-2021-hoger-dan-gemiddeld/lage-inkomensgrens#:~:text=Een%20laag%20inkomen%20is%20een,(in%20prijzen%20van%202021).

Centraal Bureau voor de Statistiek (2024a). Lage-Inkomensgrens [Low income boundary]. https://www.cbs.nl/nl-nl/nieuws/2024/27/compensatie-en-energiebesparing-remden-energiearmoede/lage-inkomensgrens.

Centraal Bureau voor de Statistiek (2024b). Nieuwe armoedemeting: 540 duizend mensen arm in 2023 [New poverty measurement: 540,000 people will be living in poverty in 2023]. https://www.cbs.nl/nl-nl/nieuws/2024/42/nieuwe-armoedemeting-540-duizend-mensen-arm-in-2023.

Centraal Bureau voor de Statistiek (CBS) (2023). Bereidheid energietransitiemaatregelen 2021 [Readiness for energy transition measures 2021]. https://www.cbs.nl/nl-nl/maatwerk/2023/14/bereidheid-energietransitiemaatregelen-2021.

Chappin, □. J., Nikolic, I., and Yorke-Smith, N. (2020). Agent-based modelling of the social dynamics of energy end use. *Energy and Behaviour*. https://doi.org/10.1016/B978-0-12-818567-4.00029-6.

Christie, L., Donn, M., and Walton, D. (2011). The 'apparent disconnect' towards the adoption of energy-efficient technologies. *Building Research and Information*, 39:450–458. https://doi.org/10.1080/09613218.2011.592485.

Conradie, P., Van Hove, S., Pelka, S., Karaliopoulos, M., Anagnostopoulos, F., Brugger, H., and Ponnet, K. (2023). Why do people turn down the heat? Applying behavioural theories to assess reductions in space heating and energy consumption in Europe. *Energy Research & Social Science*, 100:103059. https://doi.org/10.1016/J.ERSS.2023.103059.

Davoudi, S., Dilley, L., and and, J. C. (2014). Energy consumption behaviour: rational or habitual? *disP - The Planning Review*, 50(3):11–19. https://doi.org/10.1080/02513625.2014.979039.

DCN Duurzaamheidscentrum Noord (n.d.). De voor- en nadelen van een doorstroomboiler [the pros and cons of flow through water heater]. https://dcnduurzaam.nl/kenniscentrum/de-voor-en-nadelen-van-een-doorstroomboiler/.

de la Haije, M. (2024). Milieu Centraal lanceert Energiehulpnetwerk om 400.000 huishoudens in energiearmoede te helpen [Milieu Centraal launches Energy Assistance Network to help 400,000 households in energy poverty]. https://www.milieucentraal.nl/persberichten/milieu-centraal-lanceert-energiehulpnetwerk-om-400-000-nederlandse-huishoudens-in-energiearmoede-

de Volkskrant (2025). Stijging energiearmoede: meer dan half miljoen huishoudens in de problemen [increase in energy poverty: more than half a million households in difficulty]. https://www.volkskrant.nl/binnenland/stijging-energiearmoede-meer-dan-half-miljoen-huishoudens-in-de-problemen~ba0c134d/.

de Vries, G. (2020). Public Communication as a Tool to Implement Environmental Policies. *Social Issues and Policy Review*, 14(1):244–272. https://doi.org/10.1111/SIPR.12061.

Derkenbaeva, E., Hofstede, G. J., van Leeuwen, E., Halleck Vega, S., and Wolfers, J. (2024). ENERGY Pro: Spatially explicit agent-based model on achieving positive energy districts. *MethodsX*, 12:102779. https://doi.org/10.1016/J.MEX.2024.102779.

Derkenbaeva, E., Hofstede, G. J., van Leeuwen, E., and Vega, S. H. (2023). Simulating households' energy transition in amsterdam: An agent-based modeling approach. *Energy Conversion and Management*, 294:117566. https://10.1016/J.ENCONMAN.2023.117566.

Dijkema, G., Lukszo, Z., and Weijnen, M. (2013). Introduction. In *Agent-Based modelling of Socio-Technical Systems*, chapter 1, pages 1–35. Springer Dordrecht, Dordrecht. https://doi.org/10.1007/978-94-007-4933-7.

Dokshin, F. A. and Gherghina, M. (2024). Party affiliation predicts homeowners' decisions to install solar PV, but partisan gap wanes with improved economics of solar. *Proceedings of the National Academy of Sciences of the United States of America*, 121(29):e2303519121. https://doi.org/10.1073/PNAS.2303519121.

Duurzaam Den Haag (2023). Energiebank Den Haag en Duurzaam Den Haag bundelen krachten [Energy Bank The Hague and Sustainable The Hague join forces]. https://duurzaamdenhaag.nl/nieuws-tips/energiebank-den-haag-en-duurzaam-den-haag-bundelen-krachten.

Ebrahimigharehbaghi, S., Qian, Q. K., de Vries, G., and Visscher, H. J. (2022). Identification of the behavioural factors in the decision-making processes of the energy efficiency renovations: Dutch homeowners. *Building Research and Information*, 50(4):369–393. https://doi.org/10.1080/09613218.2021.1929808.

Energiewacht (n.d.). Lucht-lucht warmtepomp [Air-to-air heat pump]. https://www.energiewacht.nl/kennisbank/warmtepompen/lucht-lucht-warmtepomp.

Energy Saving Trust (2024). Hybrid heat pumps - Energy Saving Trust. https://energysavingtrust.org.uk/advice/hybrid-heat-pumps/.

Fattahi, A., Sijm, J., and Faaij, A. (2020). A systemic approach to analyze integrated energy system modeling tools: A review of national models. *Renewable and Sustainable Energy Reviews*, 133:110195. https://doi.org/10.1016/j.rser.2020.110195.

Feenstra, M. and Clancy, J. (2020). *A View from the North: Gender and Energy Poverty in the European Union*, pages 163–187. Springer International Publishing. https://doi.org/10.1007/978-3-030-43513-4_8.

Feenstra, M., Middlemiss, L., Hesselman, M., Straver, K., and Herrero, S. T. (2021). Humanising the energy transition: Towards a national policy on energy poverty in the netherlands. *Frontiers in Sustainable Cities*, 3. https://doi.org/10.3389/frsc.2021.645624.

Fishwick, P., Narayanan, N., Sticklen, J., and Bonarini, A. (1994). A multi-model approach to reasoning and simulation. *Systems, Man and Cybernetics, IEEE Transactions on*, 24:1433 – 1449. https://doi.org/10.1109/21.310527.

Fraser, N. (1996). Social justice in the age of identity politics: Redistribution, recognition, and participation. In *THE TANNER LECTURES ON HUMAN VALUES*.

Fraser, N. (2001). Recognition without ethics? *Theory, Culture and Society*, 18(2-3):21–42. https://doi.org/10.1177/02632760122051760.

Frederiks, E. R., Stenner, K., and Hobman, E. V. (2015). Household energy use: Applying behavioural economics to understand consumer decision-making and behaviour. *Renewable and Sustainable Energy Reviews*, 41:1385–1394. https://doi.org/10.1016/J.RSER.2014.09.026.

Friedman, J. H., Bentley, J. L., and Finkel, R. A. (1977). An Algorithm for Finding Best Matches in Logarithmic Expected Time. *ACM Transactions on Mathematical Software (TOMS)*, 3(3):209–226. https://doi.org/10.1145/355744.355745.

Fryslân, O. (2024). Kiezen tussen eten of een warm huis: in deze gemeente is veel energie-armoede. https://www.omropfryslan.nl/nl/nieuws/16640681/kiezen-tussen-eten-of-een-warm-huis-in-deze-gemeente-is-veel-energie-armoede.

Gemeente Amsterdam (n.d). Wat is een laag inkomen en weinig vermogen [What is low income and low wealth?]. https://www.amsterdam.nl/werk-en-inkomen/regelingen-bij-laag-inkomen-pak-je-kans/wat-is-een-laag-inkomen-en-weinig/#mc1qfj22sk9uxrfjili.

Gemeente Den Haag (2018). Buurten Den Haag - CKAN [Neighbourhoods The Hague -CKAN]. https://ckan.dataplatform.nl/dataset/buurten.

Gemeente Den Haag (2023). Wijken Den Haag [Neighbourhoods The Hague]. https://ckan.dataplatform.nl/dataset/wijken.

Gemeente Den Haag [DHIC/Centraal Bureau voor de Statistiek (IIV)] (2024). 20 https://denhaag.incijfers.nl/viewer?workspace_guid=fc52eafc-9d69-489c-8346-43e3c8e427e0.

Gemeente Den Haag [Dienst Publieke Zaken] (2021). Aantal inwoners per 1-1 - 2020 - Buurten[Number of inhabitants as of 1 January 2020 - Neighbourhoods]. https://denhaag.incijfers.nl/viewer?workspace_guid=afb16c8e-3119-4f23-946c-058a25d45a46.

Gemeente Den haag [Gemeentelijke Belastingdienst] (2025). Eigendom - 2020 - Gemeenten [Ownership - 2020 - Municipalities]. https://denhaag.incijfers.nl/viewer?workspace_guid=21f945fd-6bd8-4e6e-8cd5-c44deba9d514.

Gemeente Den Haag [Gemeentelijke belastingdienst] (2025). Woningtype in 11 klassen - 2020 - Gemeenten [Housing types in 11 classes - 2020 - Municipalities]. https://denhaag.incijfers.nl/viewer?workspace_guid=d70f6482-7adb-4990-a918-6efbf93a8680.

GeoGap B.v. (n.d.). Buurt: Waterbuurt [Neighbourhood: Waterbuurt]. https://kadastralekaart.com/buurten/waterbuurt-BU05184214?srsltid=AfmBOoohpAfghUQFDDmiGrTiSqYp17uMBFiPrvowqswwRjqSzTc9O8ik.

Gillard, R., Snell, C., and Bevan, M. (2017). Advancing an energy justice perspective of fuel poverty: Household vulnerability and domestic retrofit policy in the united kingdom. *Energy Research & Social Science*, 29:53–61. https://doi.org/10.1016/J.ERSS.2017.05.012.

González Garibay, M., Primc, K., and Slabe-Erker, R. (2023). Insights into advanced models for energy poverty forecasting. *Nature Energy 2023 8:9*, 8(9):903–905. https://doi.org/10.1038/s41560-023-01311-x.

Griffioen, E. and Schulenberg, R. (2021). Raming aantal personen/ huishoudens onder de lage-inkomensgrens in 2021 en 2022 [estimated number of persons/households below the low-income threshold in 2021 and 2022]. Technical report, CPB. https://www.cpb.nl/sites/default/files/omnidownload/CPB-Notitie-Raming-personen-huishoudens-onder-lage-inkomensgrens-2021-2022.pdf.

Gromet, D. M., Kunreuther, H., and Larrick, R. P. (2013). Political ideology affects energy-efficiency attitudes and choices. *Proceedings of the National Academy of Sciences of the United States of America*, 110(23):9314–9319. https://doi.org/10.1073/PNAS.1218453110/.

Guo, Z., Zhou, K., Zhang, C., Lu, X., Chen, W., and Yang, S. (2018). Residential electricity consumption behavior: Influencing factors, related theories and intervention strategies. *Renewable and Sustainable Energy Reviews*, 81:399–412. https://doi.org/10.1016/J.RSER.2017.07.046.

Gürsan, C., de Gooyert, V., de Bruijne, M., and Raaijmakers, J. (2024). District heating with complexity: Anticipating unintended consequences in the transition towards a climate-neutral city in the netherlands. *Energy Research & Social Science*, 110:103450. https://doi.org/10.1016/J.ERSS.2024.103450.

Hamby, D. (1994). A review of techniques for parameter sensitivity analysis of environmental models. *Environmental Monitoring and Assessment*, 32:135–154. https://doi.org/10.1007/BF00547132.

Henrich, B. A., Hoppe, T., Diran, D., and Lukszo, Z. (2021). The use of energy models in local heating transition decision making: Insights from ten municipalities in the netherlands. *Energies*, 14. https://doi.org/10.3390/en14020423.

Hernán, M. A. and Hernández-Díaz, S. (2013). Sensitivity Analysis. *Clinical Trials*, 9(1):48–55. https://doi.org/10.1177/1740774511420743.

Honneth, A. (1996). *The struggle for recognition : the moral grammar of social conflicts*. The MIT Press, 6 edition.

International Energy Agency [IEA] (n.d.). Global Energy crisis. https://www.iea.org/topics/global-energy-crisis.

Jenkins, K., McCauley, D., Heffron, R., Stephan, H., and Rehner, R. (2016). Energy justice: A conceptual review. *Energy Research & Social Science*, 11:174–182. https://doi.org/10.1016/j.erss.2015.10.004.

Johannesson, P. and Perjons, E. (2021). An introduction to design science. *An Introduction to Design Science*, pages 1–211. https://doi.org/10.1007/978-3-030-78132-3.

Jones, E. C. and Reyes, A. (2023). Identifying themes in energy poverty research: Energy justice implications for policy, programs, and the clean energy transition. *Energies*, 16. https://doi.org/10.3390/en16186698.

Kable, A. K., Pich, J., and Maslin-Prothero, S. E. (2012). A structured approach to documenting a search strategy for publication: A 12 step guideline for authors. *Nurse Education Today*, 32:878–886. https://doi.org/10.1016/J.NEDT.2012.02.022.

Kaufmann, M., Veenman, S., Haarbosch, S., and Jansen, E. (2023). How policy instruments reproduce energy vulnerability - a qualitative study of dutch household energy efficiency measures. *Energy Research & Social Science*, 103:103206. https://doi.org/10.1016/J.ERSS.2023.103206.

Klabunde, A., Willekens, F. J., Zinn, S., and Leuchter, M. (2015). An agent-based decision model of migration, embedded in the life course - Model description in ODD+D format. Mpidr working papers, Max Planck Institute for Demographic Research, Rostock, Germany. https://doi.org/10.4054/MPIDR-WP-2015-002.

Klerks, M. (2024). Energiearmoede in Den Haag: bijna 30.000 huishoudens geraakt, maar minder hard dan gemiddeld [Energy poverty in The Hague: nearly 30,000 households hit, but lower than average]. https://www.ad.nl/den-haag/energiearmoede-in-den-haag-bijna-30-000-huishoudens-geraakt-maar-minder-hard-dan-gemiddeld~a3a7fb

Kloosterman, R., Akkermans, M., Reep, C., Wingen, M., Molnár-In 't Veld, H., and van Beuningen, J. (2021). 4. Duurzaam wonen [4. Sustainable living]. https://www.cbs.nl/nl-nl/longread/rapportages/2021/klimaatverandering-en-energietransitie-opvattingen-en-gedrag-van-nederlanders-in-2020/4-duurzaam-wonen.

KNMI (2014). KNMI'14 Climate Scenarios for the Netherlands (Leaflet). https://www.knmi.nl/kennis-en-datacentrum/publicatie/knmi14-klimaatscenario-samenvatting.

Leahy, E. and Lyons, S. (2010). Energy use and appliance ownership in ireland. *Energy Policy*, 38(8):4265–4279. https://doi.org/10.1016/j.enpol.2010.03.056.

Longa, F. D., Sweerts, B., and van der Zwaan, B. (2021). Exploring the complex origins of energy poverty in the netherlands with machine learning. *Energy Policy*, 156:112373. https://doi.org/10.1016/J.ENPOL.2021.112373.

Loos, M. (2024). Energiearmoede in nederland 2019-2023 [energy poverty in the netherlands 2019-2023]. Technical report, TNO. https://publications.tno.nl/publication/34642677/ESNuvbuC/TNO-2024-R10801-samenvatting.pdf.

Mashhoodi, B., Stead, D., and van Timmeren, A. (2019). Spatial homogeneity and heterogeneity of energy poverty: a neglected dimension. *Annals of GIS*, 25:19–31. https://doi.org/10.1080/19475683.2018.1557253.

Mashhoodi, B. and van Timmeren, A. (2018). Local determinants of household gas and electricity consumption in randstad region, netherlands: application of geographically weighted regression. *Spatial Information Research*, 26:607–618. https://link.springer.com/article/10.1007/s41324-018-0203-1.

Masson-Delmotte, V., Zhai, P., Pörtner, H.-O., Roberts, D., Skea, J., Shukla, P. R., Pirani, A., Moufouma-Okia, W., Péan, C., Pidcock, R., Connors, S., Matthews, J. B. R., Chen, Y., Zhou, X., Gomis, M. I., Lonnoy, E., Maycock, T., Tignor, M., and Waterfield, T. (2018). Summary for policymakers. In *Global Warming of 1.5°C. An IPCC Special Report on the impacts of global warming of 1.5°C above pre-industrial levels and related global greenhouse gas emission pathways, in the context of strengthening the global response to the threat of climate change, sustainable development, and efforts to eradicate poverty*, pages 3–24. Cambridge University Press, Cambridge, UK and New York, NY, USA.

McCauley, D., Heffron, R., Stephan, H., and Jenkins, K. (2013). Advancing energy justice: The triumvirate of tenets. *International Energy Law Review*, 32(3):107–110. https://www.storre.stir.ac.uk/handle/1893/18349.

McCright, A. M., Dunlap, R. E., and Marquart-Pyatt, S. T. (2016). Political ideology and views about climate change in the European Union. *Environmental Politics*, 25(2):338–358. https://doi.org/10.1080/09644.

McLeod, S. and Guy-Evans, O. (2023). Social identity theory in psychology (tajfel & turner, 1979). https://www.simplypsychology.org/social-identity-theory.html.

Menghwani, V., Zerriffi, H., Korkovelos, A., Khavari, B., Sahlberg, A., Howells, M., and Mentis, D. (2020). Planning with justice: Using spatial modelling to incorporate justice in electricity pricing – the case of tanzania. *Applied Energy*, 264. https://doi.org/10.1016/j.apenergy.2020.114749.

Mesdaghi, B., Hess, T. S., and Straver, K. (2025). Beleidsverkenning energiearmoede en de energietransitie [policy exploration of energy poverty and the energy transition]. Technical report, TNO. https://open.overheid.nl/documenten/29028d7f-51df-416b-bbac-a78679c3023e/file.

Milieu Centraal (n.d.a). Over het energiehulpnetwerk [About the energy help network]. https://www.energiehulpnetwerk.nl/over-het-energiehulpnetwerk/.

Milieu Centraal (n.d.b). Pelletkachel of biomassaketel: milieu tips [Pellet stove or biomass boiler: environmental tips]. https://www.milieucentraal.nl/energie-besparen/houtstook-verwarmen-met-hout/pelletkachel-en-biomassaketel/#soorten-kachels.

Milieu Centraal (n.d.c). Verwarmen met infraroodpanelen [Heating with infrared panels]. https://www.milieucentraal.nl/energie-besparen/duurzaam-verwarmen-en-koelen/infraroodpanelen-voor-verwarming/.

Miller, D. (2025). Justice. In Zalta, E. N. and Nodelman, U., editors, *The Stanford Encyclopedia of Philosophy*. Metaphysics Research Lab, Stanford University, spring 2025 edition. https://plato.stanford.edu/archives/spr2025/entries/justice/.

Muelder, H. and Filatova, T. (2018). One Theory - Many Formalizations: Testing Different Code Implementations of the Theory of Planned Behaviour in Energy Agent-Based Models. *Journal of Artificial Societies and Social Simulation*, 21(4). https://doi.org/10.18564/JASSS.3855.

Mulder, P. (2024). Tno brengt niveau energiearmoede in kaart. https://www.tno.nl/nl/newsroom/2024/09/niveau-energiearmoede-in-kaart/.

Mulder, P., Longa, F. D., and Straver, K. (2023). Energy poverty in the netherlands at the national and local level: A multi-dimensional spatial analysis. *Energy Research & Social Science*, 96. https://doi.org/10.1016/j.erss.2022.102892.

Niamir, L., Ivanova, O., Filatova, T., Voinov, A., and Bressers, H. (2020). Demand-side solutions for climate mitigation: Bottom-up drivers of household energy behavior change in the Netherlands and Spain. *Energy Research & Social Science*, 62:101356. https://doi.org/10.1016/J.ERSS.2019.101356.

Nie, H., Kemp, R., Xu, J. H., Vasseur, V., and Fan, Y. (2020). Split incentive effects on the adoption of technical and behavioral energy-saving measures in the household sector in Western Europe. *Energy Policy*, 140:111424. https://doi.org/10.1016/J.ENPOL.2020.111424.

Niehoff, E. and Kuttschreuter, M. W. M. (2021). Energy Saving within Households: How the Antecedents of our Behaviour Influence Energy Consumption. Master's thesis, University of Twente, Enschede. https://essay.utwente.nl/86775/1/Niehoff_BA_BMS.pdf.

Nikolic, I., Dam, K. H., and Lukszo, Z. (2013a). Practice. In *Agent-Based modelling of Socio-Technical Systems*, chapter 3, pages 73–135. Springer Dordrecht, Dordrecht. https://doi.org/https://doi.org/10.1007/978-94-007-4933-7.

Nikolic, I., Dam, K. H., and Lukszo, Z. (2013b). Theory. In *Agent-Based modelling of Socio-Technical Systems*, chapter 2, pages 36–71. Springer Dordrecht, Dordrecht. https://doi.org/https://doi.org/10.1007/978-94-007-4933-7.

NSGI (n.d). Amersfoort / RD New - Netherlands - Holland - Dutch - EPSG:28992. https://epsg.io/28992.

Ooij, C. V., Batenburg, A., Nguyen, N. C., and Straver, K. (2023). Energy poverty: A science and policy state of play. Technical report, TNO. https://publications.tno.nl/publication/34640524/86Phvt/TNO-2023-P10119.pdf.

Papada, L. and Kaliampakos, D. (2018). A stochastic model for energy poverty analysis. *Energy Policy*, 116:153–164. https://doi.org/10.1016/J.ENPOL.2018.02.004.

Rios-Ocampo, M. A., Romero, J. C., Centeno, E., and Mora, S. (2025). A just energy transition is not just a transition: Framing energy justice for a quantitative assessment. *Energy Research & Social Science*, 119:103900. https://doi.org/10.1016/j.erss.2024.103900.

Salciccioli, J., Crutain, Y., Komorowski, M., et al. (2016). Sensitivity analysis and model validation. In Nguyen, A. T., Rubin, B. D. A., and Cooke, D. L., editors, *Secondary Analysis of Electronic Health Records*, chapter 17. Springer, Cham (CH). https://www.ncbi.nlm.nih.gov/books/NBK543636/.

Scikit-learn developers (n.d). 1.6. Nearest neighbors. https://scikit-learn.org/stable/modules/neighbors.html#kdtree-and-balltree-classes.

Secretariaat-generaal van de Raad (2025). Energieprijzen en voorzieningszekerheid. https://www.consilium.europa.eu/nl/policies/energy-prices-and-security-of-supply/#:~:text=de%20energiecrisis%20veroorzaakt?-,Hoe%20reageerde%20de%20EU%20op%20de%20energiecrisis?,naar%20schonere%20energie%20te%20versnellen.

Sheeran, P. (2002). Intention—Behavior Relations: A Conceptual and Empirical Review. *European Review of Social Psychology*, 12(1):1–36. https://doi.org/10.1080/14792772143000003.

Shetty, V. (2023). Exploring justice considerations in energy model use cases in the netherlands. Master's thesis, Delft University of Technology.

Simcock, N., Frankowski, J., and Bouzarovski, S. (2021). Rendered invisible: Institutional misrecognition and the reproduction of energy poverty. *Geoforum*, 124:1–9. https://doi.org/10.1016/J.GEOFORUM.2021.05.005.

Snell, C., Bevan, M., and Thomson, H. (2015). Justice, fuel poverty and disabled people in england. *Energy Research & Social Science*, 10:123–132. https://doi.org/10.1016/J.ERSS.2015.07.012.

Sniehotta, F. F., Presseau, J., and and, V. A.-S. (2014). Time to retire the theory of planned behaviour. *Health Psychology Review*, 8(1):1–7. https://doi.org/10.1080/17437199.2013.869710.

Sovacool, B. K. and Dworkin, M. H. (2015). Energy justice: Conceptual insights and practical applications. *Applied Energy*, 142:435–444. https://doi.org/10.1016/j.apenergy.2015.01.002.

Spandagos, C., Tovar Reaños, M. A., and Lynch, M. A. (2023). Energy poverty prediction and effective targeting for just transitions with machine learning. *Energy Economics*, 128:107131. https://doi.org/10.1016/j.eneco.2023.107131.

Sundaram, A., Huang, Y., Cuppen, E., and Nikolic, I. (2024). Operationalizing justice in models used as decision-support tools in local and regional energy transition planning. *Proceedings of the 12th International Workshop on Simulation for Energy, Sustainable Development & Environment (SESDE 2024)*. https://doi.org/10.46354/I3M.2024.SESDE.002.

Tarasova, E. (2024). Rethinking justice as recognition in energy transitions and planned coal phase-out in poland. *Energy Research & Social Science*, 112. https://doi.org/10.1016/j.erss.2024.103507.

ten Broeke, G., van Voorn, G., and Ligtenberg, A. (2016). Which sensitivity analysis method should i use for my agent-based model? *Journal of Artificial Societies and Social Simulation*, 19(1):5. https://jasss.soc.surrey.ac.uk/19/1/5.html.

ter Hoeven, E., Kwakkel, J., Hess, V., Pike, T., Wang, B., rht, and Kazil, J. (2025). Mesa 3: Agent-based modeling with Python in 2025. *Journal of Open Source Software*, 10(107):7668. https://doi.org/10.21105/joss.07668.

Tigchelaar, C. (2023). Economische inzichten door Hestia [Economic insights through HESTIA]. https://www.youtube.com/watch?v=0vjti7IuS5E.

TNO (2025). Scenario's energiearmoede voor 2025 bij stijgende energieprijzen [energy poverty scenarios for 2025 with rising energy prices]. https://www.tno.nl/nl/newsroom/2025/03/scenario-energiearmoede-2025-energie/.

TNO (n.d.). TNO Energiearmoede kaart Nederland [TNO Energy Poverty Map of the Netherlands]. https://energiearmoede.tno.nl/.

Trotta, G. (2018). Factors affecting energy-saving behaviours and energy efficiency investments in British households. *Energy Policy*, 114:529–539. https://doi.org/10.1016/J.ENPOL.2017.12.042.

Trutnevyte, E., Hirt, L. F., Bauer, N., Cherp, A., Hawkes, A., Edelenbosch, O. Y., Pedde, S., and van Vuuren, D. P. (2019). Societal transformations in models for energy and climate policy: The ambitious next step. *One Earth*, 1:423–433. https://doi.org/10.1016/J.ONEEAR.2019.12.002.

U.S. Department of Energy (n.d.). Electric resistance heating. https://www.energy.gov/energysaver/electric-resistance-heating.

US department of energy (n.d.a). Geothermal heat pumps. https://www.energy.gov/energysaver/geothermal-heat-pumps.

US department of energy (n.d.b). Heat pump systems. https://www.energy.gov/energysaver/heat-pump-systems.

UWV (2024). Sociaal minimum [Social minimum]. https://www.uwv.nl/nl/toeslag/sociaal-minimum.

van Berkel, P., Kruit, K., and Dehens, J. (2021). Energiearmoede in de warmtetransitie. Technical report, CE Delft. https://ce.nl/publicaties/energiearmoede-in-de-warmtetransitie-onderzoek-naar-beleidsinstrumenten/.

van Binnenlandse Zaken en Koninkrijksrelaties, M. (2024). Aanpak energiearmoede. https://www.volkshuisvestingnederland.nl/onderwerpen/aanpak-energiearmoede.

van der Molen, F. (2023). Functioneel ontwerp hestia 1.0 [functional design hestia 1.0]. Technical report, PBL, Den Haag. https://www.pbl.nl/uploads/default/downloads/pbl-2023-functioneel-ontwerp-hestia-1.0-5196.pdf.

van der Molen, F., Hilferink, M., Poorthuis, W., Zwamborn, A., and van Bemmel, B. (2024). GitHub - Pbl-nl/model-Hestia-public: Hestia Model Openbare repository. https://github.com/pbl-nl/model-hestia-public.

van Eijsden, A. (2025). GroenLinks-PVDA wil isolatie offensief tegen energiearmoede en dat mag best wat kosten. https://www.trouw.nl/politiek/groenlinks-pvda-wil-isolatie-offensief-tegen-energiearmoede-en-dat-mag-best-wat-kosten~b8c2f50e/.

van Middelkoop, M., van der Meer, L., and Geijtenbeek, L. (2023). Energieverbruik huishoudens naar inkomen, 2020 [Household energy consumption by income, 2020]. https://www.cbs.nl/nl-nl/maatwerk/2023/07/energieverbruik-huishoudens-naar-inkomen-2020.

van Uffelen, N. (2022). Revisiting recognition in energy justice. *Energy Research & Social Science*, 92:102764. https://doi.org/10.1016/J.ERSS.2022.102764.

Vasseur, V. and Marique, A. F. (2019). Households' willingness to adopt technological and behavioral energy savings measures: An empirical study in the netherlands. *Energies 2019, Vol. 12, Page 4294*, 12:4294. https://doi.org/10.3390/EN12224294.

Vermeulen, J. L., Hillebrand, A., and Geraerts, R. (2017). A comparative study of k-nearest neighbour techniques in crowd simulation. *Computer Animation and Virtual Worlds*, 28(3-4):e1775. https://doi.org/10.1002/CAV.1775.

Völker, B. (2000). 16 MILJOEN BUREN-DE ROL VAN BUREN IN PERSOONLIJKE NETWERKEN IN NEDERLAND [16 MILLION NEIGHBOURS – THE ROLE OF NEIGHBOURS IN PERSONAL NETWORKS IN THE NETHERLANDS]. *Sociologos*, 21(4). https://doi.org/10.21825/sociologos.86510.

Vos, S. (2024). Derde gemeenten weet niet waar energiearmoede speelt [Third of municipalities do not know where energy poverty occurs]. https://www.binnenlandsbestuur.nl/sociaal/energiearmoede-nog-steeds-vaak-verborgen.

Vågerö, O. and Zeyringer, M. (2023). Can we optimise for justice? reviewing the inclusion of energy justice in energy system optimisation models. *Energy Research & Social Science*, 95:102913. https://doi.org/10.1016/j.erss.2022.102913.

Wagener, T. and Pianosi, F. (2019). What has Global Sensitivity Analysis ever done for us? A systematic review to support scientific advancement and to inform policy-making in earth system modelling. *Earth-Science Reviews*, 194:1–18. https://www.sciencedirect.com/science/article/pii/S0012825218300990?via

Walker, G. and Day, R. (2012). Fuel poverty as injustice: Integrating distribution, recognition and procedure in the struggle for affordable warmth. *Energy Policy*, 49:69–75. https://doi.org/10.1016/J.ENPOL.2012.01.044.

Walker, R., Liddell, C., McKenzie, P., Morris, C., and Lagdon, S. (2014). Fuel poverty in northern ireland: Humanizing the plight of vulnerable households. *Energy Research & Social Science*, 4:89–99. https://doi.org/10.1016/J.ERSS.2014.10.001.

Wang, Y., Hou, L., Hu, L., Cai, W., Wang, L., Dai, C., and Chen, J. (2023). How family structure type affects household energy consumption: A heterogeneous study based on chinese household evidence. *Energy*, 284:129313. https://doi.org/https://doi.org/10.1016/j.energy.2023.129313.

Wikipedia-bijdragers (2025). Wijken en buurten in Den Haag [Areas and neighbourhoods in The Hague]. https://nl.wikipedia.org/wiki/Wijken_en_buurten_in_Den_Haag.

Wood, N. (2023). Problematising energy justice: Towards conceptual and normative alignment. *Energy Research & Social Science*, 97:102993. https://doi.org/10.1016/J.ERSS.2023.102993.

Wood, N. and Roelich, K. (2020). Substantiating Energy Justice: Creating a Space to Understand Energy Dilemmas. *Sustainability 2020, Vol. 12, Page 1917*, 12(5):1917. https://doi.org/10.3390/SU12051917.

Woods, R., Heidenreich, S., Korsnes, M., and Solbu, G. (2024). Energy-efficiency policies reinforce energy injustices: The caring energy practices of low-income households in norway. *Energy Research & Social Science*, 116:103663. https://doi.org/10.1016/j.erss.2024.103663.

Worley, D. (2021). Tajfel and turner intergroup conflict theories 1997. https://doi.org/10.13140/RG.2.2.30820.60809.

Zhang, C. Y., Yu, B., Wang, J. W., and Wei, Y. M. (2018). Impact factors of household energy-saving behavior: An empirical study of Shandong Province in China. *Journal of Cleaner Production*, 185:285–298. https://doi.org/10.1016/J.JCLEPRO.2018.02.303.

Zurn, C. F. (2005). Recognition, redistribution, and democracy: Dilemmas of honneth's critical social theory. *European Journal of Philosophy*, 13:89–126. https://doi.org/10.1111/J.0966-8373.2005.00223.X.

A

Literature review process

A.1. Research question 1

This appendix provides a table (table A.1) summarising all literature used in different stages of the literature review process. These are sorted alphabetically by the first author's name for consistency with the bibliography.

Through this process, I realised that my initial search terms were too broad, yielding many irrelevant results and creating a chaotic process for myself. Consequently, I had to adopt several different search strategies. For future research, I have learned the importance of developing a more focused search strategy and refining it iteratively as the literature review progresses. A.1.

Table A.1: Papers used

Author	Year	Title	Search method	Search engine
Abrahamse & Steg	2009	How do socio-demographic and psychological factors relate to households' direct and indirect energy use and savings	”demographic heterogeneity in energy modelling” and ”recognition justice”	Google Scholar
Abrahamse & Steg	2011	Factors related to household energy use and intention to reduce it: The role of psychological and socio-demographic variables	Forward snowballing from Abrahamse & Steg (2009)	Google Scholar
Amin	2024	How do socio-demographic and psychological factors relate to households' direct and indirect energy use and savings?	(justice OR ”social aspect”) AND ”energy model”	Google Scholar
Bal et al.	2023	A fairway to fairness: Toward a richer conceptualization of fairness perceptions for just energy transitions	”conceptualisation” AND ”energy justice” AND ”model”	Scopus
Bouzarovski	2017	Spatializing energy justice	”energy justice” AND ”energy poverty”	Google Scholar
Ebrahimigharehbaghi et al.	2022	Identification of the behavioural factors in decision-making processes of the energy efficiency renovations: Dutch homeowners	”behaviour” AND ”energy saving” AND ”Netherlands”	Google Scholar
Feenstra et al.	2021	Humanising the energy transition: Towards a national policy on energy poverty in the Netherlands	”energy justice” AND ”energy poverty”	Scopus
Fraser	1996	Social justice in the age of identity politics: Redistribution, recognition, and participation	recognition justice theory	Google Scholar
Gillard et al.	2017	Advancing an energy justice perspective of fuel poverty: Household vulnerability and domestic retrofit policy in the United Kingdom	”conceptualisation” AND ”energy justice” AND ”model”	Google Scholar
Guo et al.	2018	Residential electricity consumption behaviour: Influencing factors, related theories and intervention strategies	Forward snowballing from Abrahamse & Steg (2009)	Google Scholar
Honneth	1996	The struggle for recognition: The moral grammar of social conflicts	recognition justice theory	Google Scholar
Jenkins et al.	2016	Energy justice: A conceptual review	”Energy justice”	Google Scholar
Jones & Reyes	2023	Identifying themes in energy poverty research: Energy justice implications for policy, programs, and the clean energy transition	”Energy justice” AND ”energy poverty”	Scopus

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Author	Year	Title	Search method	Search engine
Kaufmann et al.	2023	How policy instruments reproduce energy vulnerability - a qualitative study of Dutch household energy efficiency measures	”policy instruments” AND ”energy poverty” AND ”Netherlands”	Google Scholar
Mashhoodi & van Timmeren	2018	Local determinants of household gas and electricity consumption in Randstad region, Netherlands: Application of geographically weighted regression	Backward snowballing Mashhoodi (2019)	Google Scholar
Mashhoodi et al.	2019	Spatial homogeneity and heterogeneity of energy poverty: a neglected dimension	”policy” AND ”energy poverty” AND ”Netherlands”	Scopus
Menghwani et al.	2020	Planning with justice: Using spatial modelling to incorporate justice in electricity pricing - the case of Tanzania	”conceptualisation” AND ”energy justice” AND ”model”	Scopus
Mesgadhi et al.	2025	Beleidsverkenning energiearmoede en de energietransitie [Policy discovery energy poverty and the energy transition]	”policy instruments” AND ”energy poverty” AND ”Netherlands”	Google Scholar
Miller	2025	Justice	Recommendation supervisory team	-
Mulder et al.	2023	Energy poverty in the Netherlands at the national and local level: A multi-dimensional spatial analysis	”policy” AND ”energy poverty” AND ”Netherlands”	Scopus
Niamir et al.	2020	Demand-side solutions for climate mitigation: Bottom-up drivers of household energy behaviour change in the Netherlands and Spain	Forward snowballing Abrahamse & Steg (2019)	Google Scholar
Nie et al.	2020	Split incentive effects on the adoption of technical and behavioural energy-saving measures in the household sector in Western Europe	”behaviour” AND ”energy saving” AND ”Netherlands”	Scopus
Niehoff & Kuttscheurter	2021	Energy Saving within Households: How the Antecedents of our Behaviour Influence Energy Consumption	”behaviour” AND ”energy saving” AND ”Netherlands”	Google Scholar
Rios-Ocampo et al.	2025	A just energy transition is not just a transition: Framing energy justice for a quantitative assessment	”energy justice” and ”energy poverty”	Scopus
Snell et al.	2015	Justice, fuel poverty and disabled people in England	-	-
Sundaram et al.	2024	Operationalizing justice in models used as decision-support tools in local and regional energy transition planning	Recommendation from supervisory team	-
Tarasova	2024	Rethinking justice as recognition in energy transitions and planned coal phase-out in Poland	”recognition justice in energy models”	Google Scholar
Trotta	2018	Factors affecting energy-saving behaviours and energy efficiency investments in British households	”behaviour” AND ”energy saving” AND ”households”	Google Scholar
van Ooij et al.	2023	Energy poverty: A science and policy state of play	”policy” AND ”energy poverty” AND ”Netherlands”	Google Scholar
van Uffelen	2022	Revisiting recognition in energy justice	recognition justice theory	Google Scholar
Vassuer & Marique	2019	Household’s willingness to adopt technological and behavioural energy saving measures: An empirical study in the Netherlands	”behaviour” AND ”energy saving” AND ”households”	Scopus
Vågerö & Zeyringer	2023	Can we optimise for justice? Reviewing the inclusion of energy justice in energy system optimisation models	”recognition justice in energy models”	Scopus
Walker et al.	2014	Fuel poverty in Northern Ireland: Humanizing the plight of vulnerable households	Backward snowballing Gillard ()	Google Scholar
Wang et al.	2023	How family structure type affects household energy consumption: A heterogeneous study based on Chinese household evidence	”behaviour” AND ”energy saving” AND ”households”	Scopus
Wood	2023	Problematising energy justice: Towards conceptual and normative alignment	Recommendation supervisory team	-
Wood & Roelich	2020	Substantiating Energy Justice; creating a space to understand energy dilemmas	Recommendation supervisory team	-
Woods et al.	2024	Energy-efficiency policies reinforce energy injustices: The caring energy practices of low-income households in Norway	”Energy justice” AND ”Energy poverty”	Scopus

B

Case study scope

This thesis uses the municipality of The Hague as a field of study. The Hague was selected due to the broad availability of data, its diverse household composition and because, although energy poverty is more severe outside of the Randstad, it still has a higher than average number of households experiencing energy poverty (Klerks, 2024), making it an interesting area to test the effectiveness of the changes. This appendix once again shows the map of the municipality, on a neighbourhood level (Figure B.1). It also includes a clear list of every neighbourhood ID, its neighbourhood name and the area it belongs to.

Table B.1: The Hague neighbourhood identification (Wikipedia-bijdragers, 2025)

Neighbourhood ID	Neighbourhood name	Area
01	Oud Scheveningen	Scheveningen
02	Vissershaven	Scheveningen
03	Scheveningen Badplaats	Scheveningen
04	Visserijbuurt	Scheveningen
05	Van Stolkpark en Scheveningse Bosjes	Van Stolkpark en Scheveningse Bosjes
06	Waldeck-Zuid	Waldeck
07	Statenkwartier	Geuzen- en Statenkwartier
08	Geuzenkwartier	Geuzen- en Statenkwartier
09	Vogelwijk	13
10	Rond de Energiecentrale	Regentessekwartier
11	Kortenbos	Centrum
12	Voorhout	Centrum
13	Uilebomen	Centrum
14	Zuidwal	Centrum
15	Schildersbuurt-West	Schildersbuurt
16	Schildersbuurt-Noord	Schildersbuurt
17	Schildersbuurt-Oost	Schildersbuurt
18	Huygenspark	Stationsbuurt
19	Laakhaven-Oost	Laakkwrtier en Spoorwijk
20	Moerwijk-Oost	Moerwijk
21	Groente- en Fruitmarkt	Transvaal
22	Laakhaven-West	Laakkwartier en Spoorwijk
23	Spoorwijk	Laakkwartier en Spoorwijk
24	Laakkwartier-West	Laakkwartier en Spoorwijk
25	Laakkwartier-Oost	Laakkwartier en Spoorwijk
26	Noordpolderbuurt	Laakkwartier en Spoorwijk
30	Rustenburg	Rustenburg en Oostbroek
31	Oostbroek-Noord	Rustenburg en Oostbroek
32	Transvaalkwartier-Noord	Transvaalkwartier
33	Transvaalkwartier-Midden	Transvaalkwartier
34	Transvaalkwartier-Zuid	Transvaalkwartier

35	Oostbroek-Zuid	Rustenburg en Oostbroek
36	Zuiderpark	Zuiderpark
37	Moerwijk-West	Moerwijk
38	Moerwijk-Noord	Moerwijk
39	Moerwijk-Zuid	Moerwijk
40	Nieuw Waldeck	Waldeck
41	Zorgvliet	Zorgvliet
42	Stadhoudersplantsoen	Duinoord
43	Sweelinckplein e.o.	Duinoord
44	Koningsplein e.o.	Duinoord
45	Zeeheldenkwartier	Zeeheldenkwartier
46	Archipelbuurt	Archipelbuurt
47	Willemspark	Willemspark
48	Nassaubuurt	Benoordenhout
49	Haagse Bos	Haagse bos
50	Bloemenbuurt-West	Bomen- en Bloemenbuurt
51	Bloemenbuurt-Oost	Bomen- en Bloemenbuurt
52	Bomenbuurt	Bomen- en Bloemenbuurt
53	Vruchtenbuurt	Vruchtenbuurt
54	Heesterbuurt	Valekboskwartier
55	Valkenboskwartier	Valekboskwartier
60	Binckhorst	Binckhorst
61	Landen	Mariahoeve en Marlot
62	Rivierenbuurt-Zuid	Stationsbuurt
63	Rivierenbuurt-Noord	Stationsbuurt
64	Bezuidenhout-West	Bezuidenhout
65	Bezuidenhout-Midden	Bezuidenhout
66	Bezuidenhout-Oost	Bezuidenhout
67	Kampen	Mariahoeve en Marlot
68	Marlot	Mariahoeve en Marlot
69	Burgen en Horsten	Mariahoeve en Marlot
70	Oostduinen	Oostduinen
71	Belgisch Park	Belgisch Park
72	Rijslag	Scheveningen
73	Westbroekpark	Westbroekpark
74	Duttendel	Westbroekpark
75	Uilennest	Benoordenhout
76	Duinzigt	Benoordenhout
77	Waalsdorp	Benoordenhout
78	Arendsdorp	Benoordenhout
79	Van Hoytemastraat e.o.	Benoordenhout
80	Morgenstond-Zuid	Morgenstond
81	Bosjes van Pex	Bohemen en Meer en Bos
82	Rosenburg	Waldeck
83	Eykenduinen	Vruchtenbuurt
84	Leyenburg	Leyenburg
85	Kerketuinen en Zichtenburg	Loosduinen
86	Houtwijk	Loosduinen
87	Venen, Oorden en Raden	Bouwlust en Vrederust
88	Morgenstond-West	Morgenstond
89	Morgenstond-Oost	Morgenstond
90	Ockenburgh	Kijkduin en Ockenburg
91	Kijkduin	Kijkduin en Ockenburg
92	Bohemen en Meer en Bos	Bohemen en Meer en Bos
93	Componistenbuurt	Waldeck
94	Waldeck-Noord	Waldeck
95	Kom Loosduinen	Loosduinen
96	Zijden, Steden en Zichten	Bouwlust en Vrederust

97	Kraayenstein en Vroondaal	Kraayenstein en Vroondaal
98	Dreven en Gaarden	Bouwlust en Vrederust
99	De Uithof	Bouwlust en Vrederust
100	Duindorp	Duindorp
101	Erasmus Veld	Wateringse Veld
102	Hoge Veld	Wateringse Veld
103	Parkbuurt Oosteinde	Wateringse Veld
104	Lage Veld	Wateringse Veld
105	Zonne Veld	Wateringse Veld
106	Vlietzoom-West	Hoornwijk
107	Vliegeniersbuurt	Hoornwijk
108	Bosweide	Ypenburg
109	Tedingerbroek	Ypenburg
110	De Reef	Hoornwijk
111	De Venen	Ypenburg
112	Morgenweide	Ypenburg
113	Singels	Ypenburg
114	Waterbuurt	Ypenburg
115	De Bras	Ypenburg
116	Vlietzoom-Oost	Ypenburg
117	De Rivieren	Forepark
118	De Lanen	Leischenveen
119	De Velden	Leischenveen
120	De Vissen	Leischenveen
121	Rietbuurt	Leischenveen

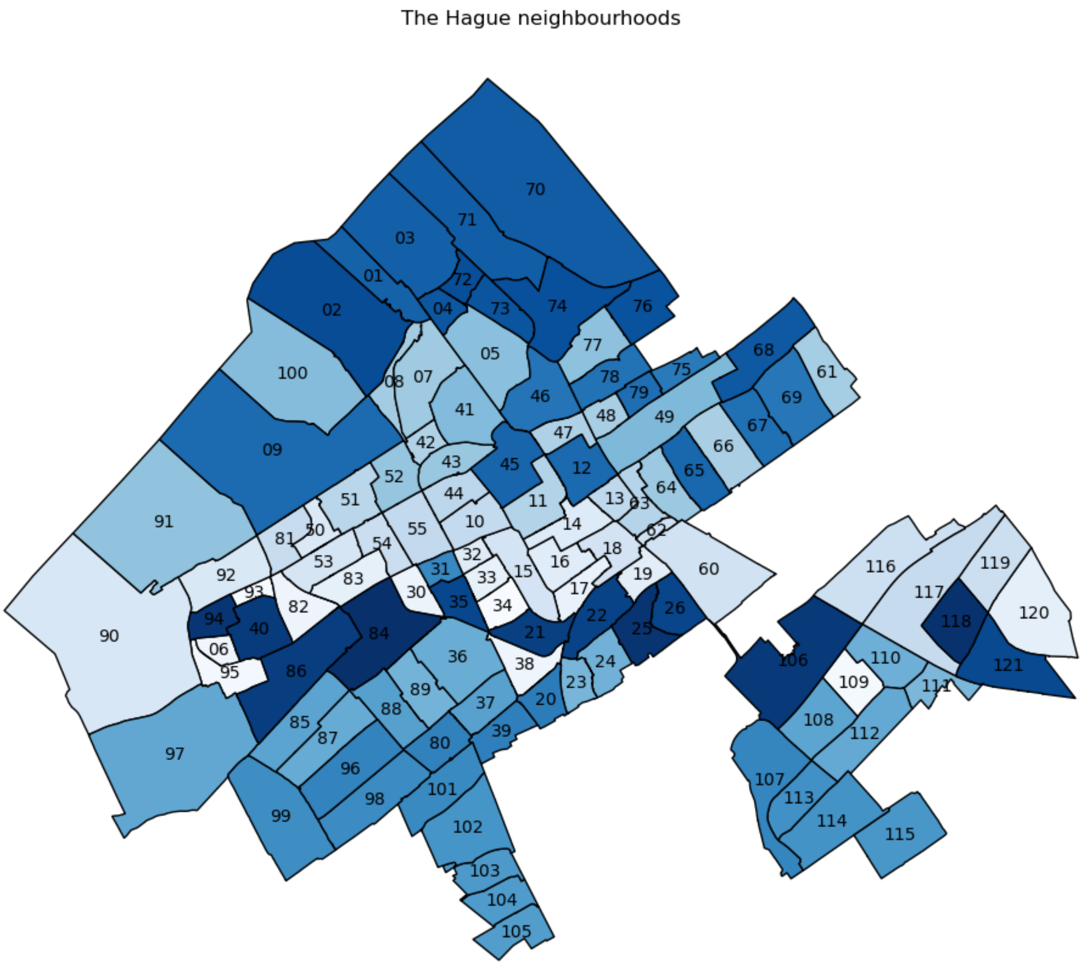


Figure B.1: Neighbourhoods overview

C

Model development

This appendix gives more detail on the choices and assumptions made in the model development, as well as some relevant input variables.

C.1. Energy prices

Figures C.2 and C.1 are screenshots from the CSV files HESTIA uses as input for energyprices: *20220709_Euro2020_ga* and *20220709_Euro2020_gas.csv*. As the simulation only runs from 2020 to 2025, only these prices were included. The entire file can be found in the GitHub repository for HESTIA: Github/model=hestia-public.

Year	2020	2021	2022	2023	2024	2025	2026	2027	2028	2029	2030
Commodity cost (€/kWh)	0.13	0.3013	1.0508	0.7596	0.4621	0.4178	0.4058	0.3937	0.3817	0.3696	0.3577
Supplier margin (€/kWh)	0.1105	0.2561	0.8932	0.6457	0.3928	0.3551	0.3449	0.3347	0.3245	0.3142	0.3041
Network costs (€/kWh)	0	0	0	0	0	0	0	0	0	0	0
Energy tax (€/kWh)	0.3331	0.3388	0.3333	0.3609	0.3743	0.3874	0.4001	0.4042	0.4083	0.4141	0.4141
Surcharge for sustainable energy (€/kWh)	0.0775	0.0827	0.0794	0.0829	0.0883	0.0907	0.0833	0.082	0.0816	0.0874	0.0914
Connection fee (€/connection)	31.92	31.9617	30.315	30.315	30.315	30.315	30.315	30.315	30.315	30.315	30.315
fixed fee (€/connection)	18.01	17.4885	16.5142	16.5142	16.5142	16.5142	16.5142	16.5142	16.5142	16.5142	16.5142
Capacity tariff (€/connection)	93.66	93.4375	84.2122	84.2122	84.2122	84.2122	84.2122	84.2122	84.2122	84.2122	84.2122
Metering tariff (€/connection)	22	21.5325	20.8018	20.8018	20.8018	20.8018	20.8018	20.8018	20.8018	20.8018	20.8018
NO_x emission factor (kg/GJ)	20	20	20	20	20	20	20	20	20	20	20
SO_2 emission factor (kg/GJ)	0	0	0	0	0	0	0	0	0	0	0
VOC emission factor (kg/GJ)	0	0	0	0	0	0	0	0	0	0	0
Particulate matter emission factor (kg/GJ)	0	0	0	0	0	0	0	0	0	0	0
CO_2 emission factor (kg/kWh)	1.78	1.78	1.78	1.78	1.78	1.78	1.78	1.78	1.78	1.78	1.78
Taks reduction (€/connection)	0	0	0	0	0	0	0	0	0	0	0

Figure C.1: Gas prices used in HESTIA

Year	2020	2021	2022	2023	2024	2025	2026	2027	2028	2029	2030
Commodity cost (€/kWh)	0.13	0.3013	1.0508	0.7596	0.4621	0.4178	0.4058	0.3937	0.3817	0.3696	0.3577
Supplier margin (€/kWh)	0.1105	0.2561	0.8932	0.6457	0.3928	0.3551	0.3449	0.3347	0.3245	0.3142	0.3041
Network costs (€/kWh)	0	0	0	0	0	0	0	0	0	0	0
Energy tax (€/kWh)	0.3331	0.3388	0.3333	0.3609	0.3743	0.3874	0.4001	0.4042	0.4083	0.4141	0.4141
Surcharge for sustainable energy (€/kWh)	0.0775	0.0827	0.0794	0.0829	0.0883	0.0907	0.0833	0.082	0.0816	0.0874	0.0914
Connection fee (€/connection)	31.92	31.9617	30.315	30.315	30.315	30.315	30.315	30.315	30.315	30.315	30.315
fixed fee (€/connection)	18.01	17.4885	16.5142	16.5142	16.5142	16.5142	16.5142	16.5142	16.5142	16.5142	16.5142
Capacity tariff (€/connection)	93.66	93.4375	84.2122	84.2122	84.2122	84.2122	84.2122	84.2122	84.2122	84.2122	84.2122
Metering tariff (€/connection)	22	21.5325	20.8018	20.8018	20.8018	20.8018	20.8018	20.8018	20.8018	20.8018	20.8018
NO_x emission factor (kg/GJ)	20	20	20	20	20	20	20	20	20	20	20
SO_2 emission factor (kg/GJ)	0	0	0	0	0	0	0	0	0	0	0
VOC emission factor (kg/GJ)	0	0	0	0	0	0	0	0	0	0	0
Particulate matter emission factor (kg/GJ)	0	0	0	0	0	0	0	0	0	0	0
CO_2 emission factor (kg/kWh)	1.78	1.78	1.78	1.78	1.78	1.78	1.78	1.78	1.78	1.78	1.78
Taks reduction (€/connection)	0	0	0	0	0	0	0	0	0	0	0

Figure C.2: Electricity prices used in HESTIA

C.2. Policies

Table C.1 gives an overview of the policies implemented in HESTIA. Historic policies, meaning any that were given with HESTIA, but were implemented before 2020, are also included as these determine the starting situation of the dwellings in the start year.

Table C.1: Policy Subsidies Overview

Code	Time	Target group	Basis	Height subsidy	Conditions	Compliance
sub_ZonPV	2012/ 2013	Own	solarpanels	15%	Max. € 650	0.8
sub_HR	2009/ 2010	Own	RO_N3, RB_N3*	35/m^2, max. €1100		0.8
sub_SchZun1	2010/ 2011	All homes	insulation	€300	Label steps: 1	0.8
sub_SchZun2	2010/ 2011	All homes	insulation	€ 750	Label steps: 2 to 6	0.8
sub_Eprem1	2013	All homes	MS_N2, MS_N3, MS_N4	6/m^2	0.01	
sub_Eprem2	2013	All homes	MG_N2, MG_N3, MG_N4	15/m^2		0.01
sub_Eprem3	2013	All homes	DP_N2, DP_N3, DP_N4, DS_N2,DS_N3, DS_N4	10/m^2		0.01
sub_Eprem4	2013	All homes	VL_N2, VL_N3, VL_N4	7.5/m^2		0.01
sub_Eprem5	2013	All homes	RO_N3, RB_N3	20/m^2		0.01
sub_Eprem6	2013	All homes	solar boilers	€455		0.01
sub_Eprem7	2013	All homes	heat pumps	€2700		0.01
sub_Eprem8	2013	All homes	LTAS	€230		0.01
sub_Eprem9	2013	All homes	hybrid heat pumps	€2000		0.01
sub_ISDE1	2016-2020	Own	installations	20%		0.9
sub_ISDE2	2021/ 2022	Own	insulation,(hybrid) heat pumps, solar boilers	20%		0.9
sub_ISDE3	2021-2026	Own	district heating connection	€ 3325		0.9
sub_ISDE4	2023-2026	Own	(installations	15%	1 measure	0.9
sub_ISDE5	2023-2026	Own	installations	30%	Min. measures 2	0.9
sub_ISDE7	2027-2030	Own	district heating connection	€ 3325		0.9
sub_ISDE8	2027-2030	Own	district heating connection	€ 3325	Min. and max. measure 1	0.9
sub_ISDE9	2027-2030	Own	district heating connection	30%	Min. measures 2	0.9
sub_SEEH	2016-2020	Own, Social rental	insulation	20%	Min. measures 2	1
sub_STEP1	2014-2015	Social rental	insulation, installations	€4500	Label steps: 6	0.8
sub_STEP2	2014 -2015	Social rental	insulation, installations	€3500	Label steps: 5	0.8
sub_STEP3	2014-2015	Social rental	insulation, installations	€2600	Label steps: 4	0.8
sub_STEP4	2014-2015	Social rental	insulation, installations	€2000	Label steps: 3	0.8
sub_STEP5	2016-2018	Social rental	insulation, installations	€9500	Label steps: 9	0.8
sub_STEP6	2016-2018	Social rental	insulation, installations	€8300	Label steps: 8	0.8
sub_STEP7	2016-2018	Social rental	insulation, installations	€7200	Label steps: 7	0.8
sub_STEP8	2016 -2018	Social rental	insulation, installations	€6200	Label steps: 6	0.8
sub_STEP9	2016 -2018	Social rental	insulation, installations	€4800	Label steps: 5	0.8

Code	Time	Target group	Basis	Height subsidy	Conditions	Compliance
sub_STEP10	2016-2018	Social rental	insulation, installations	€3600	Max. € 3800 & Label steps: 4	0.8
sub_STEP11	2016-2018	Social rental	insulation, installations	€2800	Label steps: 3	0.8
sub_STEP12	2016-2018	Social rental	insulation, installations	€1500	Label steps: 2	0.8
sub_SAH1	2020-2023	All rentals	closing gas	40%	Max. € 1200	0.094
sub_SAH2	2020-2023	All rentals	district heating connection	30%	Max. € 3800	0.094
PresWoCoInvest	2022-2025	Social rental	solar panels, (hybrid) heat pumps	100%	Current label: A,B,C,D	0.075
SVOH	2022-2025	Private rental	insulation, installation, ventilation	75%	Max. € 6000	0.2
SEEH1	2021-2030	Own, multi-family	insulation	15%	1 Measure	0.06
SEEH2	2021-2030	Own, multi-family	installations	30%	Min. measures 2	
nrm_EPC1	2000-2005	New builts	DR_N0, MG_N3, DP_N2, DS_N2, RO_N2, RB_N2, MS_N2, VL_N2	-	-	1
nrm_EPC2	2006-2010	New builts	DR_N0, MG_N3, DP_N2, DS_N2, RO_N2, RB_N2, MS_N2, VL_N2	-	-	1
nrm_EPC3	2011-2014	New builts	DR_N0, MG_N3, DP_N2, DS_N2, RO_N2, RB_N2, MS_N3, VL_N2	-	-	1
nrm_EPC4	2015-2019	New builts	DR_N0, MG_N3, DP_N2, DS_N2, RO_N3, RB_N3, MS_N3, VL_N4	-	-	1
nrm_EPC6	2000-2005	Existing builts	DR_N0, MG_N3, DP_N2, DS_N2, RO_N2, RB_N2, MS_N2, VL_N2	-	Renovation of 25% of dwelling	0.1
nrm_EPC7	2006-2010	Existing builts	DR_N0, MG_N3, DP_N2, DS_N2, RO_N2, RB_N2, MS_N2, VL_N2	-	Renovation of 25% of dwelling	0.1
nrm_EPC8	2011-2014	Existing builts	DR_N0, RO_N2, RB_N2, MS_N2, VL_N2	-	Renovation of 25% of dwelling	0.1
nrm_EPC9	2015-2019	Existing builts	DR_N0, RO_N3, RB_N2, MS_N2, VL_N2	-	Renovation of 25% of dwelling	0.1
nrm_EPC11	2000-2005	new built	VT_Mec_Glk_new	-	-	1
nrm_EPC12	200-2023	new built	VT_Mec_Vst_Glk_new	-	-	1
nrm_EPC13	2000-2005	Existing builts	VT_Mec_Glk_new	-	Renovation of 25% of dwelling	0.1
nrm_EPC14	2006-2023	Existing builts	VT_Mec_Vst_Glk_new	-	Renovation of 25% of dwelling	0.1
nrm_EPC15	2011-2014	Existing builts	MG_N3, DP_N3, DS_N3	-	Renovation of 25% of dwelling	0.1
nrm_EPC16	2015-2019	Existing builts	MG_N3, DP_N3, DS_N3	-	Renovation of 25% of dwelling	0.1
nrm_EPC17	2020-2050	Existing builts	MG_N3, DP_N3, DS_N3	-	Renovation of 25% of dwelling	0.1
PresWoCo (norm)	2022-2028	Existing built, social housing	Minimum label: D	-	Minimum label: D	0.4-1 (increase by 0.1 per year)

Code	Time	Target group	Basis	Height subsidy	Conditions	Compliance
PresWoCoAct	2027-2028	Existing builts, social housing	Building components	-	Current label: E, F or G	0.5-1
PresWoCoCV (ban)	2025-2030	social housing	VR, HR	-	Current label A, B, C or D	

Per policy this table contains:

- *Code:*the code used in the HESTIA model to track the subsidies.
- *Time:* This is the time window in which the subsidy is available. Any subsidies starting before 2020 but ending after are also included as they are available policies within the scope of the study.
- *Target group:* This shows which demographic groups are eligible to receive the subsidy. It is categorised based on the ownership type of the dwelling.
- *Basis:* Shows what type of measures (installations or insulation levels) the subsidy applies to.
- *Height subsidy:* Indicates the amount of the subsidy either as a percentage of the investment, the set amount available or the amount per square meter of improved building envelope.
- *Conditions:* Each subsidy can have a maximum of two conditions that must be met before it is granted.
- *Compliance:* For each subsidy, a random draw is made per home with the weighting of the percentage entered. If this percentage is 75%, for 1 in 4 homes, they ignore the possibility of a subsidy and make their investment decisions as if the subsidy does not exist at all.

Energy poverty

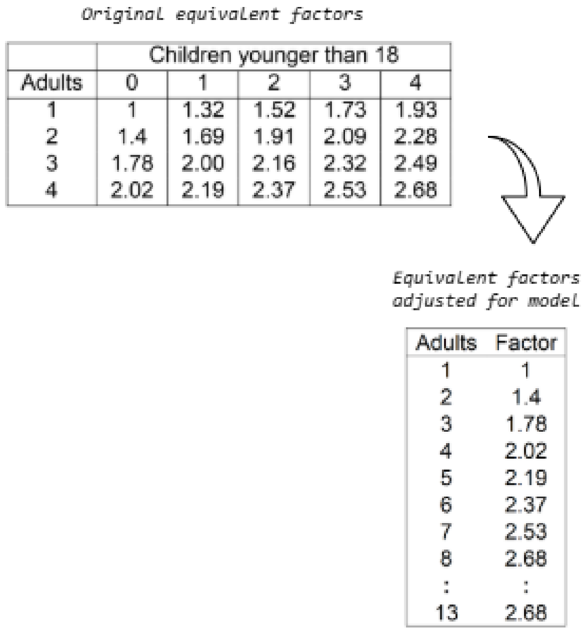
The energy bills for a household are determined by summing the following costs:

- Electricity costs
- Gas costs
- Biomass costs
- Oil costs, including tax*
- Pellet costs
- Maintenance costs LO
- Administrative costs LO
- Standing costs for the connections of the heat, gas, electricity and cold network.

An agent can have costs for a few or all of these options, depending on the installations they have for their homes. These costs together make up all the energy costs spread over the different bills a household receives. In HESTIA, oil has two cost items: the regular fuel costs and its taxes. Oil taxes are considered separately as they vary over time, regardless of the basic price (van der Molen, 2023).

This total sum is standardised to a single-person household bill using equivalent factors from CBS's biannual publication on material well-being (Arends-Tóth et al., 2022). These factors express the extent of economies of scale from joint households over single-person households. This means that, for example, in the case of energy bill standardisation, for a single-person household, the factor is 1. Each additional adult and/or child increases the factor, but as households increase in size, the increments of the factor become smaller because the economies of scale in household energy consumption also increase (Arends-Tóth et al., 2022). This is why using the same factor for any households with over eight inhabitants is seen as a valid assumption; there would only be marginal differences from this size on. The equivalence factors used differentiate between adults and children—for example, a household with four adults receives a slightly different factor than one with four children (Arends-Tóth et al., 2022).

In this study, the assumption is made that age-related differences in energy demand have a limited impact on a total household's energy demand, meaning that a home with two adults and one child is assumed to have the same energy needs as one with three adults. For any household size higher than four, the equivalence factors are determined by using the values corresponding to four adults, with the increasing count of children. This ensures that the highest available factors are used, preventing the potential underestimation of the energy needs of larger homes (see Figure C.3). These factors have been the same since 2018 (Arends-Tóth et al., 2022), allowing for standardisation over the entire runtime with the same factors.



Original equivalent factors

	Children younger than 18				
Adults	0	1	2	3	4
1	1	1.32	1.52	1.73	1.93
2	1.4	1.69	1.91	2.09	2.28
3	1.78	2.00	2.16	2.32	2.49
4	2.02	2.19	2.37	2.53	2.68

Equivalent factors adjusted for model

Adults	Factor
1	1
2	1.4
3	1.78
4	2.02
5	2.19
6	2.37
7	2.53
8	2.68
:	:
13	2.68

Figure C.3: Recalculation equivalent factors

Table C.2 shows the yearly low-income boundary over the years in the scope of this project, as well as how much the energy poverty boundary was in those years.

Table C.2: Low-income and energy poverty boundary

Year	Low-income boundary (€ per year)	Energy poverty boundary (€ per year)	Source
2020	€13,247	€17,221.10	Griffioen and Schulenberg (2021)
2021	€13,560	€17,628.00	Centraal Bureau voor de Statistiek (2023b)
2022	€14,400	€18,720.00	Centraal Bureau voor de Statistiek (2023a)
2023	€18,120	€23,556.00	Centraal Bureau voor de Statistiek (2024b)
2024	€26,664	€34,663.20	Gemeente Amsterdam (nd)

C.3. Agent Based model

This section focuses on the rationale behind the weights and indicators in the formulas.

C.3.1. Income

This section elaborates on the variables used in the income assignment per agent. It reiterates the entire equation and its symbols' explanation, to put the explanation of, for example, the chosen weights into context. The assignment of income according to Equation 6.1 & Equation 6.2:

$$\forall t \in T : \sum_{c \in C} P_{t,c} = 1 \quad \text{with} \quad P_{t,c} \geq 0$$

$$c_i \sim \text{Categorical}(P_t)$$

Where:

- $t \in T$ denotes one specific ownership type.
- $c_i \in C$ denotes one specific income category.
- $C = \{1, 2, 3, 4, 5, \text{other}\}$ is the set of income categories.
  - In addition to the five income quintiles, the 'other' category accounts for households that could not be monitored for their energy behaviour because their income is unknown, they share a dwelling due to being institutionalised or students, have unknown energy consumption, or live in non-residential units (Centraal Bureau voor de Statistiek (CBS), 2023).
  - This 'other' category is not included in the census data, but is added to ensure a complete distribution for the synthetic population.
- $P_{t,c}$ is the categorical distribution over income categories for ownership type t.

C.3.2. Intention to invest

This section brings more detail on the equations used to calculate an agent's intention to invest. According to Equation 6.3, the intention to invest is calculated by summing the weighted attributes of the theory of planned behaviour, after which this intention is normalised to use in HESTIA.

$$Iinv_i^{\text{raw}} = w_a \cdot Ainv_i + w_{\text{sn}} \cdot SNinv_i + w_{\text{pbc}} \cdot PBCinv_i$$

$$Iinv_i = \frac{Iinv_i^{\text{raw}} - Iinv_{\text{min}}}{Iinv_{\text{max}} - Iinv_{\text{min}}}$$

Where:

- $Iinv_i^{\text{raw}}$ is the un-normalised intention to invest for agent i
- $Iinv_i$ is the normalised intention to invest for agent i
- $Ainv_i$ is the total attitude towards investment for agent i
- $SNinv_i$ is the total subjective norms agent i experienced regarding investments
- w_a = is the weight assigned to attitude, set at 0.1667
- w_{sn} = is the weight assigned to the subjective norms, set at 0.5
- w_{pbc} = is the weight assigned to the perceived behavioural control, set at 0.33
- $Iinv_{\text{max}}$ is the maximum possible value for $Iinv_i^{\text{raw}}$
- $Iinv_{\text{min}}$ is the minimum possible value for $Iinv_i^{\text{raw}}$

As all three attributes are weighed equally, the weight for attitude is 0.33, for subjective norms 0.33, and for PBC it is 0.33 as well.

C.3.3. Attitude

The total attitude towards investment is calculated by summing and then normalising an intention based on installation plans and an attitude based on the installations present in the home used to supply the functional energy demand.

$$Ainv_i^{\text{raw}} = A_{\text{sp,i}} + A_{\text{inst,i}}$$

$$Ainv_i = \frac{Ainv_i^{\text{raw}} - Ainv_{\text{min}}}{Ainv_{\text{max}} - Ainv_{\text{min}}}$$

Where:

- A_i^{raw} is the un-normalised attitude towards investment for agent i
- A_i is the normalised attitude towards investment for agent i
- $A_{\text{inst,i}}$ is the total attitude based on current installations for agent i
- $A_{\text{inst,i}}$ is the attitude based on current building option for agent i
- A_{max} is the maximum possible value for A_i^{raw}
- A_{min} is the minimum possible value for A_i^{raw}

Attitude installation plans

In the calculation of attitude based on installation plans, five response options to the question of whether solar panels will be installed on the dwelling are considered. The attitude towards solar panels is used as a proxy for all household energy installations in this thesis. Since responses 1 and 2, and responses 3, 4, and 5 are mutually exclusive, agents are assigned a binary score for one of the two groups according to the distribution observed in the survey results (Kloosterman et al., 2021). These scores are then weighted to reflect the extent to which each response indicates a positive attitude toward installations. Mathematically, this is expressed as:

$$A_i^{\text{sp}} = w_{\text{t,i}} \cdot \sum_{k=1}^{5} w_k \cdot s_{i,k} \tag{C.1}$$

where:

- $\mathbf{s}_i = [s_{i,1}, s_{i,2}, s_{i,3}, s_{i,4}, s_{i,5}]^\top$ is a binary selection vector for survey options of agent i,
- $w_k = [w_1, w_2, w_3, w_4, w_5]^\top$ is the vector of weights assigned to each installation choice
- $w_t = [w_1, w_2, w_3, w_4]$ is the vector of weights assigned to each ownership category where:
  - $A_{\text{sp},i}$ is the total attitude based on current installations for agent i
  - $\mathbf{s}_i = [s_{i,1}, s_{i,2}, s_{i,3}, s_{i,4}, s_{i,5}]^\top$ is a binary selection vector for survey options of agent i,
  - The binary variables follow the constraints:
    * Exactly one option selected from the first group: $s_{i,1} + s_{i,2} = 1$,
    * Exactly one option selected from the second group: $s_{i,3} + s_{i,4} + s_{i,5} = 1$,
    * Each $s_{i,k} \in \{0, 1\}$,
  - $w_k = [w_1, w_2, w_3, w_4, w_5]^\top$ is the vector of weights assigned to each category, with:
    * $w_1 = 0.8$
    * $w_2 = -0.3$
    * $w_3 = 0.5$
    * $w_4 = 0.3$
    * $w_5 = 0.0$

The explanation behind the weights is:

- w_1 = 0.8 - *installations present*: this reflects a strong positive intention towards sustainability, but there might be room for improvement.
- w_2 = -0.3 *Unsure of installations*: Not knowing whether sustainability installations are present indicates a lack of engagement or awareness, suggesting a weak sustainability attitude.

- w_3 = 0.5 - *Plans to install*: This is a good indicator of intention, though intention is not actual behaviour, which is why this weight reflects cautious optimism
- w_4= 0.3 - *Uncertain about installation*: Uncertainty does not reflect a strong commitment, but it can also be due to external factors, which is why a moderate positive weight is still assigned.
- w_5= 0.0 - *No plans*: This can imply simple disinterest, but it could also be due to lack of feasibility or because the building is already upgraded to its limit. This response is seen as neutral, not negative.
- $w_t = [w_1, w_2, w_3, w_4]$ is the vector of weights assigned to each ownership category, with:
  - w_1 is the weight for owning the home, set at 1
  - w_2 is the weight for private renters, set at 0.75
  - w_3 is the weight for social housing, set at 0.5
  - w_4 is the weight for ownership category 'other' set at 0.25

Attitude based on building option

A building option is a set of installations for space heating, hot water supply and cooling, used in a building to supply the energy demand for these categories. Table C.3 presents an overview of all possible installation combinations of technology and their corresponding building options and energy labels.

$$A_{\text{inst},i} = \sum_{tc \in TC} w_{tc} \cdot T_{tc,\, o_{i,tc}} \tag{C.2}$$

Where:

- $A_{\text{inst},i}$: The installation-based attitude for agent i
- $tc \in TC$: One specific technology category.
- TC: The full set of technology categories, $TC = \{\text{RVb, RVp, TWb, TWp, KDb, KDp}\}$
- w_{tc}: The weight assigned to each technology category, with:
  - $w_{\text{RVb}} = 0.15, \quad w_{\text{RVp}} = 0.15$
  - $w_{\text{TWb}} = 0.05, \quad w_{\text{TWp}} = 0.05$
  - $w_{\text{KDb}} = 0.05, \quad w_{\text{KDp}} = 0.05$
- $o_{i,tc}$: The technology option selected by agent i in category tc
- $T_{tc,o_{i,tc}}$: The sustainability score of the selected technology option in category tc

Table C.3: Overview of building options and associated technologies (van der Molen, 2023)

Optie	Cat.	RVb1	RVp1	TWb1	TWp1	KDb1	KDp1	Label
VR_zKD	ketel	Vr-ketel	Vr-ketel	Vr-ketel	Vr-ketel	-	-	G+
VR_vKD	ketel	Vr-ketel	Vr-ketel	Vr-ketel	Vr-ketel	AC (vast)	AC (vast)	G+
VR_mKD	ketel	Vr-ketel	Vr-ketel	Vr-ketel	Vr-ketel	AC (mobiel)	AC (mobiel)	G+
HR_zKD_hTWds	hybride	Hr-ketel	Hr-ketel	Doorstroom	Hr-ketel	-	-	G+
HR_vKD_hTWds	hybride	Hr-ketel	Hr-ketel	Doorstroom	Hr-ketel	AC (vast)	AC (vast)	G+
HR_mKD_hTWds	hybride	Hr-ketel	Hr-ketel	Doorstroom	Hr-ketel	AC (mobiel)	AC (mobiel)	G+
HR_zKD_TWds	hybride	Hr-ketel	Hr-ketel	Doorstroom	Doorstroom	-	-	G+
HR_vKD_TWds	hybride	Hr-ketel	Hr-ketel	Doorstroom	Doorstroom	AC (vast)	AC (vast)	G+
HR_mKD_TWds	hybride	Hr-ketel	Hr-ketel	Doorstroom	Doorstroom	AC (mobiel)	AC (mobiel)	G+
HR_zKD	ketel	Hr-ketel	Hr-ketel	Hr-ketel	Hr-ketel	-v	-	G+
HR_vKD	ketel	Hr-ketel	Hr-ketel	Hr-ketel	Hr-ketel	AC (vast)	AC (vast)	G+
HR_mKD	ketel	Hr-ketel	Hr-ketel	Hr-ketel	Hr-ketel	AC (mobiel)	AC (mobiel)	G+
Pellet_zKD	ketel	Pelletkachel	Hr-ketel	Hr-ketel	Hr-ketel	-	-	G+
Pellet_vKD	ketel	Pelletkachel	Hr-ketel	Hr-ketel	Hr-ketel	AC (vast)	AC (vast)	G+
Pellet_mKD	ketel	Pelletkachel	Hr-ketel	Hr-ketel	Hr-ketel	AC (mobiel)	AC (mobiel)	G+
Olie_zKD	ketel	Oliekachel	Oliekachel	Oliekachel	Oliekachel	-	-	G+
Olie_vKD	ketel	Oliekachel	Oliekachel	Oliekachel	Oliekachel	AC (vast)	AC (vast)	G+

Continued on next page

Table C.3 – continued from previous page

Optie	Cat.	RVb1	RVp1	TWb1	TWp1	KDb1	KDp1	Label
Olie_mKD	ketel	Oliekachel	Oliekachel	Oliekachel	Oliekachel	AC (mobiel)	AC (mobiel)	G+
Bioketel_zKD	ketel	Bioketel	Bioketel	Bioketel	Bioketel	-	-	G+
Bioketel_vKD	ketel	Bioketel	Bioketel	Bioketel	Bioketel	AC (vast)	AC (vast)	G+
Bioketel_mKD	ketel	Bioketel	Bioketel	Bioketel	Bioketel	AC (mobiel)	AC (mobiel)	G+
LweWP_zKD	electric	eWP (lucht)	eWP (lucht)	eWP (lucht)	eWP (lucht)	-	-	B+
LweWP_wKD	electric	eWP (lucht)	eWP (lucht)	eWP (lucht)	eWP (lucht)	eWP (lucht)	eWP (lucht)	B+
BweWP_zKD	electric	eWP (bodem)	eWP (bodem)	eWP (bodem)	eWP (bodem)	-	-	B+
BweWP_wKD	electric	eWP (bodem)	eWP (bodem)	eWP (bodem)	eWP (bodem)	eWP (bodem)	eWP (bodem)	B+
LleWP_zKD	electric	eWP (vent.)	eWP (vent.)	eWP (vent.)	eWP (vent.)	-	-	B+
LleWP_wKD	electric	eWP (vent.)	eWP (vent.)	eWP (vent.)	eWP (vent.)	eWP (vent.)	eWP (vent.)	B+
hEWV_TWg_zKD	hybride	EWV	Hr-ketel	Hr-ketel	Hr-ketel	-	-	D+
hEWV_TWg_vKD	hybride	EWV	Hr-ketel	Hr-ketel	Hr-ketel	AC (vast)	AC (vast)	D+
hEWV_TWg_mKD	hybride	EWV	Hr-ketel	Hr-ketel	Hr-ketel	AC (mobiel)	AC (mobiel)	D+
hEWV_TWeb_zKD	hybride	EWV	Hr-ketel	eBoiler	eBoiler	-	-	D+
hEWV_TWeb_vKD	hybride	EWV	Hr-ketel	eBoiler	eBoiler	AC (vast)	AC (vast)	D+
hEWV_TWeb_mKD	hybride	EWV	Hr-ketel	eBoiler	eBoiler	AC (mobiel)	AC (mobiel)	D+
EWV_TWeb_zKD	electric	EWV	EWV	eBoiler	eBoiler	-	-	A+
EWV_TWeb_vKD	electric	EWV	EWV	eBoiler	eBoiler	AC (vast)	AC (vast)	A+
EWV_TWeb_mKD	electric	EWV	EWV	eBoiler	eBoiler	AC (mobiel)	AC (mobiel)	A+
IR_TWeb_zKD	electric	Infrarood	Infrarood	eBoiler	eBoiler	-	-	A+
IR_TWeb_vKD	electric	Infrarood	Infrarood	eBoiler	eBoiler	AC (vast)	AC (vast)	A+
IR_TWeb_mKD	electric	Infrarood	Infrarood	eBoiler	eBoiler	AC (mobiel)	AC (mobiel)	A+
hEWV_hTWds_zKD	hybride	EWV	Hr-ketel	Doorstroom	Hr-ketel	-	-	D+
hEWV_hTWds_vKD	hybride	EWV	Hr-ketel	Doorstroom	Hr-ketel	AC (vast)	AC (vast)	D+
hEWV_hTWds_mKD	hybride	EWV	Hr-ketel	Doorstroom	Hr-ketel	AC (mobiel)	AC (mobiel)	D+
hEWV_TWds_zKD	hybride	EWV	Hr-ketel	Doorstroom	Doorstroom	-	-	D+
hEWV_TWds_vKD	hybride	EWV	Hr-ketel	Doorstroom	Doorstroom	AC (vast)	AC (vast)	D+
hEWV_TWds_mKD	hybride	EWV	Hr-ketel	Doorstroom	Doorstroom	AC (mobiel)	AC (mobiel)	D+
EWV_TWds_zKD	electric	EWV	EWV	Doorstroom	Doorstroom	-	-	A+
EWV_TWds_vKD	electric	EWV	EWV	Doorstroom	Doorstroom	AC (vast)	AC (vast)	A+
EWV_TWds_mKD	electric	EWV	EWV	Doorstroom	Doorstroom	AC (mobiel)	AC (mobiel)	A+
IR_TWds_zKD	electric	Infrarood	Infrarood	Doorstroom	Doorstroom	-	-	A+
IR_TWds_vKD	electric	Infrarood	Infrarood	Doorstroom	Doorstroom	AC (vast)	AC (vast)	A+
IR_TWds_mKD	electric	Infrarood	Infrarood	Doorstroom	Doorstroom	AC (mobiel)	AC (mobiel)	A+
HWP_zKD_TWg	hybride	eWP (lucht)	Hr-ketel	Hr-ketel	Hr-ketel	-	-	D+
HWP_wKD_TWg	hybride	eWP (lucht)	Hr-ketel	Hr-ketel	Hr-ketel	eWP (lucht)	eWP (lucht)	D+
HWP_zKD_TWeb	hybride	eWP (lucht)	Hr-ketel	eBoiler	eBoiler	-	-	D+
HWP_wKD_TWeb	hybride	eWP (lucht)	Hr-ketel	eBoiler	eBoiler	eWP (lucht)	eWP (lucht)	D+
HWP_zKD_hTWds	hybride	eWP (lucht)	Hr-ketel	Doorstroom	Hr-ketel	-	-	D+
HWP_wKD_hTWds	hybride	eWP (lucht)	Hr-ketel	Doorstroom	Hr-ketel	eWP (lucht)	eWP (lucht)	D+
HWP_zKD_TWds	hybride	eWP (lucht)	Hr-ketel	Doorstroom	Doorstroom	-	-	D+
HWP_wKD_TWds	hybride	eWP (lucht)	Hr-ketel	Doorstroom	Doorstroom	eWP (lucht)	eWP (lucht)	D+
hIR_zKD_TWg	hybride	Infrarood	Hr-ketel	Hr-ketel	Hr-ketel	-	-	C+
hIR_vKD_TWg	hybride	Infrarood	Hr-ketel	Hr-ketel	Hr-ketel	AC (vast)	AC (vast)	C+
hIR_mKD_TWg	hybride	Infrarood	Hr-ketel	Hr-ketel	Hr-ketel	AC (mobiel)	AC (mobiel)	C+
hIR_zKD_TWeb	hybride	Infrarood	Hr-ketel	eBoiler	eBoiler	-	-	C+
hIR_vKD_TWeb	hybride	Infrarood	Hr-ketel	eBoiler	eBoiler	AC (vast)	AC (vast)	C+
hIR_mKD_TWeb	hybride	Infrarood	Hr-ketel	eBoiler	eBoiler	AC (mobiel)	AC (mobiel)	C+
hIR_zKD_hTWds	hybride	Infrarood	Hr-ketel	Doorstroom	Hr-ketel	-	-	C+
hIR_vKD_hTWds	hybride	Infrarood	Hr-ketel	Doorstroom	Hr-ketel	AC (vast)	AC (vast)	C+
hIR_mKD_hTWds	hybride	Infrarood	Hr-ketel	Doorstroom	Hr-ketel	AC (mobiel)	AC (mobiel)	C+
hIR_zKD_TWds	hybride	Infrarood	Hr-ketel	Doorstroom	Doorstroom	-	-	C+
hIR_vKD_TWds	hybride	Infrarood	Hr-ketel	Doorstroom	Doorstroom	AC (vast)	AC (vast)	C+
hIR_mKD_TWds	hybride	Infrarood	Hr-ketel	Doorstroom	Doorstroom	AC (mobiel)	AC (mobiel)	C+

All these installations have a different level of energy efficiency and sustainability. They are all graded separately on their sustainability. The categories in which they are used are also given a weight, because using a sustainable installation in a category that consumes significantly more energy is more important than improving something that gets barely used. The total tech scores of all installations in a building, multiplied by the weights of their respective categories, make up the raw building option attitude score.

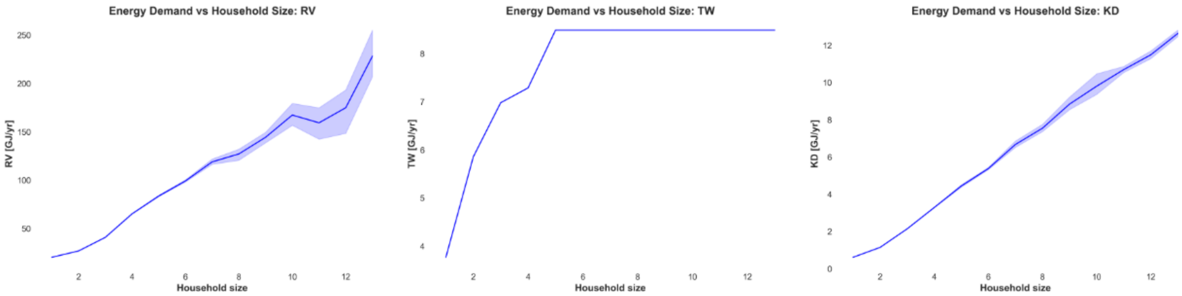


Figure C.4: Functional demand per number of people in a household

Figure C.4 shows a significant scale difference in energy use for RV (space heating) in comparison to TW (tap water) and KD (cold). This illustrates that it is significantly more important to improve the sustainability of the production of energy for RVs than for the other two categories. Thus, the weights are **RV: 0.3, TW: 0.1 and KD: 0.1**. As all three categories occur twice, this gives a total weight of 1 to ensure proportional contributions to the weighted average.

Although the installation categories are split into base and peak demand, these are assigned equal weights. This is because they are based on the functional demand for these categories, which is not divided into base and peak, and therefore no assessment can be made on a difference in the importance of the categories. Any difference in sustainability between peak and base is compensated for by the grade given to the technology. These grades, unless otherwise specified, are based on the information provided in the HESTIA documentation van der Molen (2023).

Oil heater: 2

- This is an outdated technology where the boiler burns fuel to generate heat. They are quite inefficient, bad for the environment and they are being phased out in countries such as Belgium and Denmark.

Pellet stove: 5

- A great option for heating the house without needing natural gas. It has a relatively good efficiency of around 80%. However, it can only be used to heat one room, meaning more or other technologies are required to heat the rest of the dwelling.
- There is also growing concern about the CO_2 emissions and climate impact of deforestation for fuel production (Milieu Centraal, ndb).
- It is thus graded with a 6: it is better than gas options but has its downsides.

Biomass heater: 5.5

- Can be used to heat the whole house, and can be used to heat water. It has an efficiency of 87%. This makes it better than a regular pellet stove, although it does have the same environmental considerations (Milieu Centraal, ndb).

Low efficiency boiler: 4

- Compared to other options, relatively inefficient (RV: 83% and TW 72%). It is fossil fuel-based without any renewable components and is not future-proof.

High efficiency boiler: 4.5

- Better efficiency than the VR (RV: 104% and TW: 76%), but still fossil fuel-based. Scores a little higher than the VR due to its improved efficiency, which makes it slightly more sustainable.

Air source heat pump: 9

- Very high efficiency (up to 466%). It is fuelled by electricity, meaning it is suitable for use after the built environment is electrified, making it very future-proof. Part of its sustainability depends on the source of that electricity.

Ground-source heat pump: 10

- Extremely high efficiency (over 500%) for all three categories. Long lifespan of 30 years, making it future-proof. Extract heat from the ground, which has a very stable temperature, thus saving energy (US department of energy, nda). No production of CO_2 occurs in heat production due to the use of the ground heat.

Ventilation heat pump: 8.5

- Whereas air source and ground source heat pumps can replace the entire heating system, including radiators and floor heating, ventilation can only heat the air. It transfers heat between the house and the outside air (US department of energy, ndb).
- Its efficiency varies with the seasons, in colder times, it needs to work harder to provide the same amount of heat, decreasing its efficiency (Energiewacht, nd).

Electric boiler: 6

- Electrically fuelled, so theoretically very sustainable. At the point of use they convert 100% of the electricity in heat. The efficiency decreases significantly when accounting for the entire electricity supply chain and energy losses during generation, transmission and distribution of the electricity (Brui, 2025).

Fixed air conditioning: 5.5

- Only used to cool, fixed in one location means it has to work extra hard if it is used to cool more spaces. Good efficiency.

Mobile air conditioning: 5

- Significantly less efficient than fixed air conditioning (200% vs 350%).

Heat pump: 8.5

- Significantly contributes to the use of less natural gas when that is still used in a home. It does require a fossil-fuelled boiler, for example in cold periods (Energy Saving Trust, 2024). Other heat pump options are more sustainable, but it is a better option than, e.g. infrared heating, hence the score of 8.5.

Infrared heating: 7.5

- Delivers direct heat to objects and people, resulting in minimal transmission losses (Milieu Centraal, ndc).
- When applied in well-insulated spaces, it can be energy-efficient. It consumes significantly more electricity than a heatpump (Milieu Centraal, ndc), and its sustainability depends on the source of that electricity.
- Without renewable power, its environmental impact remains relatively high.

Electric resistance heater: 7

- While electric resistance heating converts all electrical energy into heat, and thus has 100% efficiency, it is often fueled with fossil fuels. Fossil fuels have an energy efficiency of only about 30%, still making this a less sustainable option (U.S. Department of Energy, nd).

On-demand water heating system: 6.5

- Instantaneous water heating energy efficient for low demand, less so for peak moments. Requires high power, which, if fossil fuelled, makes this less of a sustainable option (DCN Duurzaamheidscentrum Noord, nd).

Area option: 10

- This includes heat networks, cooling networks or hydrogen networks. Collective systems for meeting the demand for heat, cooling and/or warm water in buildings where a certain amount of this supply is produced outside the building. Due to economies of scale, it provides significant opportunities to reduce emissions.

None:10

- If no technology is specified, it gets a score of 10 since this occurs only in KD. In the Netherlands, air conditioning is often unnecessary, except for a few summer days and nights, making not using one at all the most sustainable and energy-efficient option.

C.3.4. Perceived behavioural control

Perceived behavioural control of investments represents whether people believe they have the resources and opportunities to invest in the energy efficiency of their home. Perceived behavioural control in this study is based on survey data from Centraal Bureau voor de Statistiek (CBS) (2023) and weighted for income and ownership type as these external factors:

$$PBCinv_i = w_{\text{c,i}} \cdot w_{\text{t,i}} \cdot (pbc_{\text{inv,1,i}} + pbc_{\text{inv,2,i}})$$

Where:

- $w_{c,i}$ is the weight corresponding to agent i's income category, with
  - *incomeclass 1* = 0.2;
  - *incomeclass 2* = 0.4;
  - *incomeclass 3* = 0.6;
  - *incomeclass 4* = 0.8;
  - *incomeclass 5* = 1.0;
  - *Note:* For income category ”other”, one of these weights is randomly assigned per agent.
- $w_{t,i}$ is the weight corresponding to agent i's ownership type.
  - *other*= 0.25;
  - *corporation rent* = 0.5;
  - *private rent* = 0.75;
  - *own* = 1.0;
- $pbc_{\text{inv,1},i}$ is the score on Indicator 1 for agent i, with:
  - *low* = 0.0
  - *medium* = 0.5
  - *high* = 1.0
- $pbc_{\text{inv,2},i}$ is the score on Indicator 2 for agent i, with:
  - *high* = 0.0
  - *medium* = 0.5
  - *low* = 1.0

The indicator outcomes are categorised as Low, Medium, or High based on how regional averages compare to the national average. Since the two indicators measure different aspects, individuals can score high on one, both, or neither. High on indicator one would indicate high perceived control, whilst it would indicate the opposite for the other indicator. The first indicator is predominantly positive, whilst the second reflects more of a negative sense of control. Due to these opposing polarities, identical labels imply opposite levels of perceived control. This is useful because it allows both indicators to be combined directly without requiring an additional transformation step.

C.4. HESTIA

The HESTIA section provides a description and justification for the code modifications. All code is sourced from van der Molen et al. (2024); the caption mentions the authors of the adjustments of the original code.

C.4.1. Income assignment

In order to allow HESTIA to filter based on income, each dwelling needs to be linked to its income class. The first step in this income assignment is to define income as an attribute in the model, see Listing C.1. HESTIA is formalised in GEOdms. GeoDMS source code is organised in .dms files (van der Molen et al., 2024).

Classifications.dms configures almost all classifications used in the model. The following code excerpt was added to this document:

```
unit<uint32> Inkomensklasse : nrofrows = 6
{
    attribute<string> label: DialogType = "LabelText",
        ['1', '2', '3', '4', '5', 'other'];
    attribute<string> name := label;
}
```

Listing C.1: Definition of the income class unit in Classifications.dms, by Ilse de Droog (author)

To properly assign income to the dwellings, so they can be referenced in multiple steps in the model, the attribute needs to be added to the dwelling definition in bag.dms, Bebouwing.dms and Vastgoedprojectie.dms (Listing C.2, Listing C.3, Listing C.4). Income is assigned to each household and its dwelling during agent initialisation in the ABM. The dwelling IDs with their individually assigned income are exported in income_distribution_vbo.csv. This file is read in bag.dms to match the income to the correct dwelling.

```
unit<uint32> vbo_woonfunctie_studiegebied := select_with_org_rel(
      import/vbo/gebruiksdoelen/woon&& studiegebied/GeselecteerdeGemeente[import/
         vbo/gemeente_rel]
    && IsDefined(import/vbo/pand_rel)&& IsDefined(import/pand/woonpand_type[import/
        vbo/pand_rel])
    && MakeDefined(import/vbo/oppervlak_filters/wonen, 0000[Units/m2]) >=  10[Units
        /m2]
    && MakeDefined(import/vbo/oppervlak_filters/wonen, 9999[Units/m2]) < 1000[Units
        /m2]
    )
  , DialogType = "Map"
  , DialogData = "geometry"
  , FreeData   = "False"
  , KeepData   = "True"
  {
    unit<uint32> incomeclass: StorageName="%projDir%/Adjust_Ilse/
        income_distribution_vbo.csv", StorageType = "gdal2.vect", StorageReadOnly =
        "True"
    {
        attribute<string> agent_identificatie:= vbo_id;
    attribute<string> income_class := income;
    }
    attribute<string> identificatie := select_data(., import/vbo/identificatie);
    attribute<string>label:= rjoin(select_data(.,import/vbo/nummeraanduiding_id),
        import/nummeraanduiding/identificatie, import/nummeraanduiding/adres_key);
    attribute<string> inkomen := rjoin(identificatie,incomeclass/
        agent_identificatie,incomeclass/income_class);
    attribute<Classifications/Inkomensklasse>     inkomensklasse_rel := rlookup(
        inkomen,Classifications/Inkomensklasse/label);
    attribute<rdc_meter> geometry                   := select_data(., import/vbo/
        geometry);

....
}
```

Listing C.2: Add incomeclass to bag information in bag.dms, by Ilse de Droog (author)

```
unit<uint32> Woning := union_unit(BagWoning, VastgoedProjectie/results)
  {
```

```
    attribute<string> code  := =replace(unionExpr, '@ATTR', 'code');
    attribute<string> label := =replace(unionExpr, '@ATTR', 'label');
    attribute<rdc_meter> Geometry := =replace(unionExpr, '@ATTR', 'Geometry');
    attribute<Invoer/RuimtelijkeData/StudieGebied/buurt> buurt_rel := =replace(
        unionExpr, '@ATTR', 'buurt_rel');

        attribute<Classifications/Inkomensklasse>     inkomensklasse_rel    := =
            replace(unionExpr, '@ATTR', 'inkomensklasse_rel');
        ...
}
```

Listing C.3: Add income class to Woning unit in Bebouwing.dms, by Wessel Poorthuis (PBL)

```
unit<uint32> results := ='union_unit('+AsItemList('NieuwbouwObjecten/'+Periode/name
    +'/BebouwingsObject')+')'
  {
    attribute<Classifications/combines/WBE> ModelObjectKey := =replace(unionExpr, '
        @ATTR', 'ModelObjectKey');
    attribute<string> code := =replace(unionExpr, '@ATTR', 'code');
    attribute<string> label := =replace(unionExpr, '@ATTR', 'label');
    attribute<rdc_meter> Geometry := =replace(unionExpr, '@ATTR', 'Geometry');
        attribute<Classifications/Inkomensklasse> inkomensklasse_rel := const((0/0)
            [Classifications/Inkomensklasse], results);
        ...
}
```

Listing C.4: Add income class to Woning unit in Vastgoedprojectie.dms, by Wessel Poorthuis (PBL)

C.4.2. S-curve logic

Once the income is part of the dwelling attributes, it can be used as a selection criterion in the investment logic. For this, the S-curve code has to be adjusted in several documents. The adjustments once again start in Classifications.dms, where the S-curve csv files are read (C.5. As these csv files change with the ABM output per year, as visualised in Figure C.5, the code needs to be adjusted to read different values per year, whilst HESTIA is running.

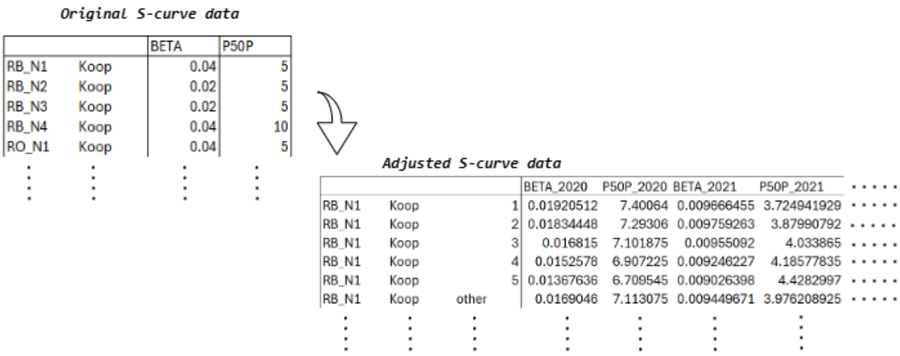


Figure C.5: Example of changes to S-curve .csv files

```
  unit<uint32> Scurve_gebouwoptie_base := combine(Eigendom,GebouwOptie,
      Inkomensklasse), StorageName = "%projDir%/Adjust_Ilse/Scurves_gebouwoptie_base
      .csv", StorageType = "gdal2.vect", StorageReadOnly = "True"
  {
    attribute<GebouwOptie> GebouwOptie_rel := second_rel;
    attribute<Eigendom>    Eigendom_rel    := first_rel;
    attribute<Inkomensklasse>  Inkomensklasse_rel    := third_rel;
    attribute<string>      GebouwOptieName := GebouwOptie/name[second_rel];
    attribute<string>      EigendomName    := Eigendom/name[first_rel];
    attribute<string>      InkomensklasseName := Inkomensklasse/label[third_rel];
```

```
    attribute<string>      name            := GebouwOptieName + '_' +EigendomName+'
        _'+ InkomensklasseName;
    attribute<string>      label           := GebouwOptie/label[second_rel] + '.' +
         Eigendom/label[first_rel] +'.' + Inkomensklasse/label[third_rel],
        DialogType = "LabelText";
        container jaren := for_each_ind('ne', Classifications/Rekenjaar/name, '
            ScurveT('+Classifications/Rekenjaar/label+')');
    template ScurveT

    {
      parameter<uint32> rekenjaar;
      parameter<string> rekenjaar_str := string(rekenjaar);
      attribute<string> BETA_C (..) := ="replace(BETA_"+rekenjaar_str+", ',', '.')
          ";
      attribute<string> P50P_C (..) := ="replace(P50P_"+rekenjaar_str+", ',', '.')
          "; // Use a string replacement to look for a variable based on the
          rekenjaar
      attribute<bool> Validity (..) := IsDefined(float64(BETA_C)) && IsDefined(
          float64(BETA_C));
      attribute<float64> BETA_f (..) := float64(BETA_C), IntegrityCheck = "Validity
          "; // Cast variable to float if valid
      attribute<float64> P50P_f (..) := float64(P50P_C), IntegrityCheck = "Validity
          "; // Cast variable to float if valid

    }
  }

  unit<uint32> Scurve_investering_data_base : StorageName = "%projDir%/Adjust_Ilse/
      Scurves_investering_base.csv", StorageType = "gdal2.vect", StorageReadOnly = "
      True" // Load the file

                {
                              attribute<string> key := field_2 + '_'+ field_3 + '_
                                  ' + field_4 + '_'+ field_5;
                }
    unit<uint32> Scurve_investering_base := combine(Eigendom,IsolatieAmbitie,
        GebouwOptieCategorie,Inkomensklasse)

    {
        attribute<Eigendom>              Eigendom_rel              := nr_1;
        attribute<IsolatieAmbitie>       IsolatieAmbitie_rel       := nr_2;
        attribute<GebouwOptieCategorie> GebouwOptieCategorie_rel := nr_3;
        attribute<Inkomensklasse>                         Inkomensklasse_rel
                    := nr_4;
        attribute<string>                EigendomName              := Eigendom/name[
            nr_1]; // Make naming of relationships explicit
        attribute<string>                IsolatieAmbitieName       := IsolatieAmbitie
            /name[nr_2];
        attribute<string>                GebouwOptieCategorieName :=
            GebouwOptieCategorie/name[nr_3];
        attribute<string>      InkomensklasseName := Inkomensklasse/label[nr_4]; //
             Make naming of relationships explicit
        attribute<string>                name                      :=
            IsolatieAmbitieName+'_'+ GebouwOptieCategorieName+'_'+EigendomName+'_'+
            InkomensklasseName;
        attribute<string>                label                     := IsolatieAmbitie
            /label[nr_2]+'.'+GebouwOptieCategorie/label[nr_3]+'.'+Eigendom/label[
            nr_1]+'.'+Inkomensklasse/label[nr_4], DialogType = "LabelText";
        attribute<Scurve_investering_data_base> data_rel  := rlookup(uppercase(name
            ), uppercase(Scurve_investering_data_base/key));
        container jaren := for_each_ind('ne', Classifications/Rekenjaar/name, '
            ScurveT('+Classifications/Rekenjaar/label+')');

```

```
template ScurveT
  {
    parameter<uint32> rekenjaar;
    parameter<string> rekenjaar_str := string(rekenjaar);
    attribute<string> BETA_C (..) := ="replace(data_rel->BETA_"+rekenjaar_str+", ',', '.')";
    attribute<string> P50P_C (..) := ="replace(data_rel->P50P_"+rekenjaar_str+", ',', '.')";
    attribute<bool> Validity (..) := IsDefined(float64(BETA_C)) && IsDefined(float64(BETA_C));
    attribute<float64> BETA_f (..) := float64(BETA_C), IntegrityCheck = "Validity";
    attribute<float64> P50P_f (..) := float64(P50P_C), IntegrityCheck = "Validity";
  }
}
unit<uint32> Scurve_isolatie_data_base: StorageName = "%projDir%/Adjust_Ilse/Scurves_isolatie_base.csv", StorageType = "gdal2.vect", StorageReadOnly = "True"
{
  attribute<string> key := field_2+'_'+field_3+'_'+field_4;
}

unit<uint32> Scurve_isolatie_base := combine(Eigendom,IsolatieMaatregel, Inkomensklasse)
{
  attribute<Eigendom>          Eigendom_rel          := nr_1;
  attribute<IsolatieMaatregel> IsolatieMaatregel_rel := nr_2;
  attribute<Inkomensklasse>  Inkomensklasse_rel    := nr_3;
  attribute<string>            EigendomName          := Eigendom/name[nr_1];
  attribute<string>            IsolatieMaatregelName := IsolatieMaatregel/name[nr_2];
  attribute<string>            InkomensklasseName    := Inkomensklasse/label[nr_3];
  attribute<string>            name                  := IsolatieMaatregelName + '_' +EigendomName+'_'+ InkomensklasseName;
  attribute<string>            label                 := IsolatieMaatregel/label[nr_2] + '.' + Eigendom/label[nr_1] + '.' + Inkomensklasse/label[nr_3], DialogType = "LabelText";
  attribute<Scurve_isolatie_data_base> data_rel  := rlookup(uppercase(name), uppercase(Scurve_isolatie_data_base/key)); // Create link between this domain and the domain of the input-file. The ordering of the Scurve_investering_base/name and Scurve_investering_data_base/key is very important.

  container jaren := for_each_ind('ne', Classifications/Rekenjaar/name, 'ScurveT('+Classifications/Rekenjaar/label+')');

template ScurveT
  {
    parameter<uint32> rekenjaar;
    parameter<string> rekenjaar_str := string(rekenjaar);
    attribute<string> BETA_C (..) := ="replace(data_rel->BETA_"+rekenjaar_str+", ',', '.')";
    attribute<string> P50P_C (..) := ="replace(data_rel->P50P_"+rekenjaar_str+", ',', '.')";
    attribute<bool> Validity (..) := IsDefined(float64(BETA_C)) && IsDefined(float64(BETA_C)); // Check if every category in the domain has a value associated with it
    attribute<float64> BETA_f (..) := float64(BETA_C), IntegrityCheck = "Validity"; // Cast variable to float if valid
    attribute<float64> P50P_f (..) := float64(P50P_C), IntegrityCheck = "Validity"; // Cast variable to float if valid
```

```
    }
  }
```

Listing C.5: Adjust S-curve definition based on adjusted format .csv files in Classifications.dms, by Wessel Poorthuis (PBL) and Ilse de Droog (author)

The parameters for the S-curves are used in different files. ActieveWoning.dms and GebouwoptieT.dms together determine the investments in upgrading installations. BouwdeelActieveWoning.dms together with ActieveWoning.dms determine investments in insulation. ActieveWoning.dms is a key component in the investment logic, as it is the code in this file that determines if a dwelling is activated for investment.

```
...
parameter<yr_uint16>                Zichtjaar_jaar := Classifications/Zichtjaar/
    jaar[Zichtjaar_rel], ishidden = "true";
  parameter<string>                   ZichtjaarName  := Classifications/Zichtjaar/
      name[Zichtjaar_rel], ishidden = "true";
  //
  parameter<string>                   RekenjaarName  := Classifications/Rekenjaar/
      name[Rekenjaar_rel], ishidden = "true";
  parameter<string> jaar      := string(Zichtjaar_jaar);
  parameter<string> j     := 'J'+jaar;
        ...
    attribute<Float64> SpecificBeta  (GeschikteOptie)     := = "Classifications/
        Scurve_gebouwoptie_base/jaren/J"+jaar+"/beta_f[combine_data(Classifications/
        Scurve_gebouwoptie_base, BO/Eigendom_rel[GeschikteOptie/BO_rel],
        combine_data(combine(Classifications/GebouwOptie,/Classifications/
        Inkomensklasse), GeschikteOptie/GebouwOptie_rel, BO/Inkomensklasse_rel[
        GeschikteOptie/BO_rel]))]";
    ...
        attribute<Float64> P50P (xInvesteringsOptie) := =
    "Classifications/Scurve_investering_base/jaren/J"+jaar+"/P50P_f[
      combine_data(
        Classifications/Scurve_investering_base,
        Eigendom[Choice_per_xInvesteringsOptie/GeschikteOptie_rel],
        combine_data( combine(combine(Classifications/IsolatieAmbitie,
            Classifications/GebouwOptieCategorie),Classifications/Inkomensklasse),
          MinIsolatieAmbitie[Choice_per_xInvesteringsOptie/GeschikteOptie_rel],
          combine_data(
            combine(Classifications/GebouwOptieCategorie, Classifications/
                Inkomensklasse),
            GebouwOptieCategorie[Choice_per_xInvesteringsOptie/GeschikteOptie_rel],
            Inkomensklasse[Choice_per_xInvesteringsOptie/GeschikteOptie_rel]
          )
        )
      )
    ]";

        ...
        attribute<Float64> SpecificBeta (xInvesteringsOptie) := =
      "Classifications/Scurve_investering_base/jaren/J"+jaar+"/beta_f[
        combine_data(
          Classifications/Scurve_investering_base,
          Eigendom,
          combine_data( combine(combine(Classifications/IsolatieAmbitie,
              Classifications/GebouwOptieCategorie), Classifications/Inkomensklasse)
              ,
            MinIsolatieAmbitie,
            combine_data(
              combine(Classifications/GebouwOptieCategorie, Classifications/
                  Inkomensklasse),
              GebouwOptieCategorie,
              Inkomensklasse
            )
          )
```

```
        )
      ]";

}
```

Listing C.6: Add income class to Woning unit in ActieveWoning.dms, by Wessel Poorthuis (PBL) and Ilse de Droog (author)

```
...
parameter<yr_uint16>                Zichtjaar_jaar := Classifications/Zichtjaar/
    jaar[Zichtjaar_rel], ishidden = "true";
  parameter<string>                   ZichtjaarName  := Classifications/Zichtjaar/
      name[Zichtjaar_rel], ishidden = "true";
     ...

     parameter<string> jaar     := string(Zichtjaar_jaar); //WORKS
    parameter<string> j     := 'J'+jaar; //WORKS
    container SpecificBeta := ="for_each_nedv(classifications/IsolatieMaatregel/
       name
    , replace('Classifications/Scurve_isolatie_base/jaren/J"+jaar+"/beta_f[
       @EDxIMxIK]'
      , '@EDxIMxIK', 'combine_data(Classifications/Scurve_isolatie_base, BO/
         Eigendom_rel[BO_rel], combine_data(combine(classifications/
         IsolatieMaatregel, /Classifications/Inkomensklasse),@IM, BO/
         Inkomensklasse_rel[BO_rel]))'
      , '@IM',    'classifications/IsolatieMaatregel/V/'+classifications/
         IsolatieMaatregel/name
      )
    , AmbitieBerekening, float64
    )";

        ...

}
```

Listing C.7: Add income class to Woning unit in BouwdeelActieveWoning.dms, by Wessel Poorthuis (PBL) and Ilse de Droog (author)

```
...

  parameter<yr_uint16>                Zichtjaar_jaar := Classifications/Zichtjaar/
      jaar[Zichtjaar_rel], ishidden = "true";
  parameter<string>                   ZichtjaarName  := Classifications/Zichtjaar/
      name[Zichtjaar_rel], ishidden = "true";
  parameter<string> jaar      := string(Zichtjaar_jaar); //WORKS
  parameter<string> j     := 'J'+jaar; //WORKS
  unit<uint32> results := GeschiktObject
  {
    attribute<Float64> P50P               (GeschiktObject) := = "Classifications/
       Scurve_gebouwoptie_base/jaren/J"+jaar+"/p50p_f[combine_data(Classifications/
       Scurve_gebouwoptie_base, BO/Eigendom_rel[GeschikteOptie/BO_rel],
       GeschikteOptie/GebouwOptie_rel)]";

        ...

}
```

Listing C.8: Add income class to Woning unit in GebouwOptieT.dms, by Wessel Poorthuis (PBL) and Ilse de Droog (author)

D

Results

D.1. Control case

In this section, more detail of the results of the control run is given.

D.1.1. Agent level results

Per agent, this section provides a table describing (1) when investments were made, (2) which installations were modified, and (3) which parts of the building envelope were insulated and to what level.

Some agents have an extra row, describing what ”extra” installations they had installed, if these installations changed over time. Following the example of HESTIA, a distinction is made between installations that meet the demand for space heating. (RV), tap water (TW) and cooling (KD), which determine the building options, and other installations, including those for cooking, solar power and ventilation. A generalised calculation method is used for the energy demand calculations of RV, TW and KD, and their associated installations are treated in the same way in the investment process (van der Molen, 2023). The other installations are so different that the investment process is different for each one. The categories for these installations are cooking, ventilation, rooftop installations, and delivery systems. The default installations for these categories are a gas stove for cooking, none for ventilation and rooftop systems, and a medium-temperature distribution system (MTAS) for delivery (van der Molen, 2023). A delivery system is a system used to transfer heat into a home, as many systems do not heat the air in the home directly, but rather heat water in a pipe system.

Some households installed solar panels on their roofs. These installations have different utility rates. As HESTIA is unable to know the orientation of every roof, it uses averages for determining the utilisation rates of solar panels (van der Molen, 2023). This means that for some homes, their generation will be overestimated, whilst for others it is underestimated. There are four configurations as shown in Table D.1.

Table D.1: Solar power generation types on flat and sloping roofs (van der Molen, 2023)

Data type	Generation (flat roof)	Generation (pitched roof)
Maximum 100%	812 kWh/year/kWp	813 kWh/year/kWp
Optimum 50%	875 kWh/year/kWp	846 kWh/year/kWp
Minimum 10%	875 kWh/year/kWp	846 kWh/year/kWp
Optimum+ Solar boiler 40%	875 kWh/year/kWp	846 kWh/year/kWp

Table D.2: Retrofitting Details: Installations and Insulation Upgrades – Agent 15

Agent 15	
Year	2020
Installation RVb	Low efficiency boiler
Installation RVp	Low efficiency boiler
Installation KDb	None
Installation KDp	None
Installation TWb	Low efficiency boiler
Installation TWp	Low efficiency boiler
Insulation level DP	0
Insulation level DR	1
Insulation level DS	0
Insulation level KR	0
Insulation level MG	0
Insulation level MS	0
Insulation level PL	0
Insulation level RB	1
Insulation level RO	1
Insulation level VL	1
Energy label	E
Extra installations	-

Table D.3: Retrofitting details: installations and insulation upgrades – Agent 105

Agent 105	
Year	2020
Installation RVb	High efficiency boiler
Installation RVp	High efficiency boiler
Installation KDb	None
Installation KDp	None
Installation TWb	High efficiency boiler
Installation TWp	High efficiency boiler
Insulation level DP	0
Insulation level DR	1
Insulation level DS	0
Insulation level KR	0
Insulation level MG	4
Insulation level MS	1
Insulation level PL	0
Insulation level RB	1
Insulation level RO	1
Insulation level VL	2
Energy label	E
Extra installations	-

Table D.4: Retrofitting details: installations and insulation upgrades - Agent 40517

Agent 40517			
Year	2020	2023	2024
Installation RVb	High efficiency boiler	High efficiency boiler	High efficiency boile
Installation RVp	High efficiency boiler	High efficiency boiler	High efficiency boile
Installation KDb	None	Mobile airconditioning	Mobile airconditionin
Installation KDp	None	Mobile airconditioning	Mobile airconditionin
Installation TWb	High efficiency boiler	High efficiency boiler	High efficiency boile
Installation TWp	High efficiency boiler	High efficiency boiler	High efficiency boile
Insulation level DP	0	3	3
Insulation level DR	1	4	4
Insulation level DS	0	3	3
Insulation level KR	0	0	0
Insulation level MG	0	3	
Insulation level MS	0	4	3
Insulation level PL	0	0	4
Insulation level RB	3	4	0
Insulation level RO	3	4	
Insulation level VL	0	4	4
Energy label	F	A(+)	4
Extra installations	-	Solar PV 100%, renewed their ventilation system	4

Table D.5: Retrofitting details: installations and insulation upgrades - Agent 227399

Agent 227399		
Year	2020	2027
Installation RVb	Low efficiency boiler	small electric resistance heater
Installation RVp	Low efficiency boiler	hHRz
Installation KDb	None	None
Installation KDp	None	None
Installation TWb	Low efficiency boiler	hHRz
Installation TWp	Low efficiency boiler	hHRz
Insulation level DP	0	0
Insulation level DR	1	1
Insulation level DS	0	0
Insulation level KR	0	0
Insulation level MG	0	0
Insulation level MS	2	2
Insulation level PL	0	0
Insulation level RB	3	3
Insulation level RO	3	3
Insulation level VL	2	2
Energy label	A(+)	A(+)
Extra installations	-	-

Table D.6: Retrofitting details: installations and insulation upgrades - Agent 262662

Agent 262662			
Year	2020	2025	2026
Installation RVb	High efficiency boiler	High efficiency boiler	High efficiency boiler
Installation RVp	High efficiency boiler	High efficiency boiler	High efficiency boiler
Installation KDb	None	None	Mobile airconditioning
Installation KDp	None	None	Mobile airconditioning
Installation TWb	High efficiency boiler	High efficiency boiler	High efficiency boiler
Installation TWp	High efficiency boiler	High efficiency boiler	High efficiency boiler
Insulation level DP	0	0	0
Insulation level DR	0	0	0
Insulation level DS	0	0	0
Insulation level KR	0	0	0
Insulation level MG	0	0	0
Insulation level MS	0	0	0
Insulation level PL	0	0	0
Insulation level RB	0	0	0
Insulation level RO	0	0	0
Insulation level VL	0	0	0
Extra installations	-	Solar PV 50%	Solar PV 10%
Energy label	D	A	D

D.2. Multi-model

This section of the results appendix contains the results of the multi-model run. This information is relevant to explain the general results, but provides too much detailed information to make it relevant for the main text.

D.2.1. Behavioural analysis

This section includes Figure D.1. This visualisation shows the growth in intention to invest per income group. Although the plots seemingly show that there is a significant growth over time with a steep decrease in 2027, this growth remains within very small bounds. This can partly be attributed to the fact that these are averages across a large and diverse group of respondents: taking an average across so many agents dampens the extremes and nuances of individual differences, keeping the final values moderate even if there are subgroups with high intentions.

D.2.2. Municipal level results

Tables D.7 to D.18 provide, per income class, per category, the difference in investments in the base case and the multi-model run. subsection D.2.3 provides a tabular overview of the investments of the same 5 agents as in the base case. It only gives the information for the start year (2020) and the years in which investments were made, and thus, something in the dwelling changed.

Table D.7: Absolute increase investments per category base case vs. multi-model run (Income class 1)

Functional demand tech category	2020	2021	2022	2023	2024	2025	2026	2027
KDb	0	0	104	414	269	374	599	534
KDp	0	0	104	414	269	374	599	534
RVb	0	0	1612	1509	5103	1598	938	1096
RVp	0	0	1612	1501	5272	1567	964	1185
TWb	0	0	1637	1420	5032	1660	1125	1143
TWp	0	0	1461	1278	4939	1487	888	981
DK	0	0	575	382	613	757	651	582
VT	0	0	-247	-322	-71	448	471	449
KK	0	0	1286	1262	4854	1204	1120	1137

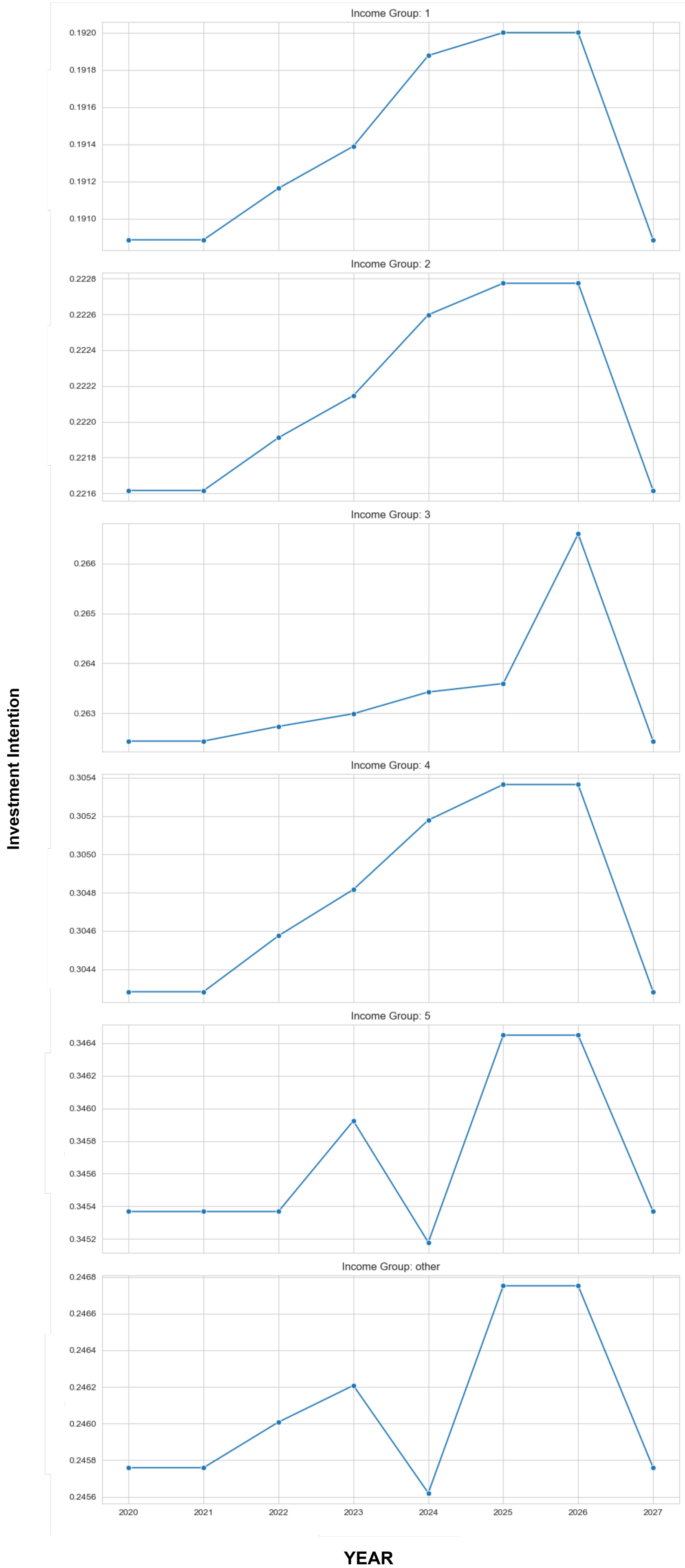


Figure D.1: Comparison of agent investment intentions per income class

Table D.8: Absolute increase investments per insulation category base case vs. multi-model run (Income class 1)

Insulation categories	2020	2021	2022	2023	2024	2025	2026	2027
DP	0	-1950	-9	996	1351	2604	815	731
DP	0	-897	-610	-516	-352	423	-432	422
DS	0	-2210	-96	512	814	2348	356	319
KR	0	-2238	-83	477	785	2349	370	348
MG	0	-2105	-51	132	350	1898	85	19
MS	0	-2093	-108	272	498	2106	223	206
PL	0	-406	-38	1569	1575	1331	773	693
RB	0	0	-2693	124	632	984	2880	499
RO	0	-1161	-767	-495	-379	571	-528	-507
VL	0	-1833	64	663	826	2126	395	273

Table D.9: Absolute increase investments per category base case vs. multi-model run (Income class 2)

Functional demand tech category	2020	2021	2022	2023	2024	2025	2026	2027
KDb	0	0	226	253	254	164	488	502
KDp	0	0	226	253	254	164	488	502
RVb	0	1486	1300	4667	1435	815	1067	
RVp	0	0	1488	1289	4800	1416	825	1150
TWb	0	0	1491	1200	4557	1515	858	1139
TWp	0	0	1354	1069	4467	1343	641	988
DK	0	0	608	342	508	520	598	567
VT	0	0	-216	-311	-48	398	468	452
KK	0	0	1189	1045	4330	997	967	982

Table D.10: Absolute increase investments per insulation category base case vs. multi-model run (Income class 2)

Insulation categories	2020	2021	2022	2023	2024	2025	2026	2027
DP	0	-1761	85	781	1278	2406	747	515
DP	0	-868	-553	-473	-303	353	-379	429
DS	0	-1982	-1	387	822	2075	380	200
KR	0	-2034	22	353	764	2125	361	235
MG	0	-1915	-152	99	418	1664	96	11
MS	0	-1881	-43	234	486	1887	237	64
PL	0	-388	-52	1427	1394	1154	665	573
RB	0	0	-2437	146	583	994	2580	452
RO	0	-1057	-654	-500	-356	494	-438	-519
VL	0	-1671	133	460	757	1886	391	212

Table D.11: Absolute increase investments per category base case vs. multi-model run (Income class 3)

Functional demand tech category	2020	2021	2022	2023	2024	2025	2026	2027
KDb	0	0	229	218	278	235	397	422
KDp	0	0	229	218	278	235	397	422
RVb	0	0	1234	1120	3845	1176	723	824
RVp	0	0	1234	1109	3962	1148	758	886
TWb	0	0	1218	1032	3841	1193	826	855
TWp	0	0	1114	929	3762	1069	659	724
DK	0	0	483	351	400	476	448	501
VT	0	0	-158	-218	-50	345	391	358
KK	0	0	974	970	3577	812	784	748

Table D.12: Absolute increase investments per insulation category base case vs. multi-model run (Income class 3)

Insulation categories	2020	2021	2022	2023	2024	2025	2026	2027
DP	0	-1470	-54	860	936	1999	655	448
DR	0	-699	-476	-346	-353	-352	-365	-420
DS	0	-1669	-35	450	476	1835	360	166
KR	0	-1661	-33	438	536	1836	289	115
MG	0	-1583	-273	179	227	1464	62	-119
MS	0	-1611	-64	328	315	1626	156	4
PL	0	-306	-25	1166	1119	1023	609	487
RB	0	0	-2061	57	645	654	2232	374
RO	0	-875	-563	-344	-396	455	-406	-454
VL	0	-1404	-21	600	458	1624	335	147

Table D.13: Absolute increase investments per category base case vs. multi-model run (Income class 4)

Functional demand tech category	2020	2021	2022	2023	2024	2025	2026	2027
KDb	0	0	156	244	255	126	393	363
KDp	0	0	156	244	255	126	393	363
RVb	0	0	1101	992	3480	1105	680	721
RVp	0	0	1101	985	3591	1089	689	765
TWb	0	0	1125	934	3446	1146	759	796
TWp	0	0994	816	3363	1011	597	647	
DK	0	0	503	313	500	371	453	359
VT	0	0	-190	-181	-45	347	378	295
KK	0	0	878	836	3305	728	656	717

Table D.14: Absolute increase investments per insulation category base case vs. multi-model run (Income class 4)

Insulation categories	2020	2021	2022	2023	2024	2025	2026	2027
DP	0	-1320	-17	735	873	1751	552	444
DP	0	-672	-442	-343	-294	262	-314	-298
DS	0	-1463	-50	461	582	1595	314	178
KR	0	-1493	2	440	559	1584	277	143
MG	0	-1402	-161	160	244	1258	72	9
MS	0	-1394	-63	249	359	140	146	5
PL	0	-315	-69	1096	965	860	497	386
RB	0	0	-1794	84	544	628	1962	341
RO	0	-816	-486	-364	-293	360	-344	-354
VL	0	-1209	141	502	536	1381	274	201

Table D.15: Absolute increase investments per category base case vs. multi-model run (Income class 5)

Functional demand tech category	2020	2021	2022	2023	2024	2025	2026	2027
KDb	0	0	162	216	188	143	350	380
KDp	0	0	162	216	188	143	350	380
RVb	0	0	982	983	3187	982	590	678
RVp	0	0	982	976	3287	967	603	744
TWb	0	0	1013	936	3169	976	663	736
TWp	0	0	914	845	3098	844	512	612
DK	0	0	391	280	296	453	456	453
VT	0	0	-145	-126	-1	321	346	314
KK	0	0	820	766	2965	665	729	674

Table D.16: Absolute increase investments per insulation category base case vs. multi-model run (Income class 5)

Insulation categories	2020	2021	2022	2023	2024	2025	2026	2027
DP	0	-1238	99	620	876	1593	558	401
Dr	0	-627	-424	-325	-207	259	-271	-243
DS	0	-1381	34	337	577	1450	296	181
KR	0	-1398	41	362	501	1435	308	176
MG	0	-1292	-122	109	232	1173	45	3
MS	0	-1353	-11	172	347	1224	109	31
PL	0	-268	-21	946	976	804	555	442
RB	0	0	-1727	163	513	656	1750	344
RO	0	-749	-436	-348	-258	374	-309	-309
VL	0	-1190	116	447	506	1278	287	171

Table D.17: Absolute increase investments per category base case vs. multi-model run (Income class other)

Functional demand tech category	2020	2021	2022	2023	2024	2025	2026	2027
KDb	0	0	22	112	95	50	228	243
KDp	0	0	22	112	95	50	228	243
RVb	0	0	767	706	2448	749	469	493
RVp	0	0	766	695	2533	729	480	533
TWb	0	0	755	639	2415	797	488	560
TWp	0	0	681	562	2358	699	384	467
DK	0	0	269	240	275	343	270	361
VT	0	0	-150	-202	-13	178	241	221
KK	0	0	586	612	2371	564	503	518

Table D.18: Absolute increase investments per insulation category base case vs. multi-model run (Income class other)

Insulation categories	2020	2021	2022	2023	2024	2025	2026	2027
DP	0	-935	-18	426	676	1208	459	290
DP	0	-475	-283	-247	-195	202	-196	-238
DS	0	-1033	27	214	409	1125	271	139
KR	0	-1060	-16	167	406	1155	244	135
MG	0	-981	-52	9	166	895	75	13
MS	0	-1005	-52	93	235	974	162	45
PL	0	-195	-24	706	723	631	385	307
RB	0	0	-1291	70	247	500	1363	293
RO	0	-576	-336	-289	-199	301	-218	-264
VL	0	-881	1	251	405	957	234	104

D.2.3. Agent level results

Table D.19: Retrofitting Details: Installations and Insulation Upgrades – Agent 15, multi-model

Agent 15	
Year	2020
Installation RVb	Low efficiency boiler
Installation RVp	Low efficiency boiler
Installation KDb	None
Installation KDp	None
Installation TWb	Low efficiency boiler
Installation TWp	Low efficiency boiler
Insulation level DP	0
Insulation level DR	1
Insulation level DS	0
Insulation level KR	0
Insulation level MG	0
Insulation level MS	0
Insulation level PL	0
Insulation level RB	1
Insulation level RO	1
Insulation level VL	1
Energy label	E
Extra installations	-

Table D.20: Retrofitting details: installations and insulation upgrades – Agent 105, multi-model

Agent 105	
Year	2020
Installation RVb	High efficiency boiler
Installation RVp	High efficiency boiler
Installation KDb	None
Installation KDp	None
Installation TWb	High efficiency boiler
Installation TWp	High efficiency boiler
Insulation level DP	0
Insulation level DR	1
Insulation level DS	0
Insulation level KR	0
Insulation level MG	4
Insulation level MS	1
Insulation level PL	0
Insulation level RB	1
Insulation level RO	1
Insulation level VL	2
Energy label	E
Extra installations	-

Table D.21: Retrofitting details: installations and insulation upgrades - Agent 40517, multi-model

	Agent 40517		
Year	2020	2023	2024
Installation RVb	High efficiency boiler	small electric resistance heater	small electric resistance heater
Installation RVp	High efficiency boiler	hHRz	hHRz
Installation KDb	None	Mobile airconditioning	Mobile airconditioning
Installation KDp	None	Mobile airconditioning	Mobile airconditioning
Installation TWb	High efficiency boiler	electric boiler	hHRz
Installation TWp	High efficiency boiler	electric boiler	hHRz
Insulation level DP	0	4	4
Insulation level DR	1	4	4
Insulation level DS	0	4	4
Insulation level KR	0	4	4
Insulation level MG	0	4	4
Insulation level MS	0	1	1
Insulation level PL	0	4	4
Insulation level RB	3	3	3
Insulation level RO	3	3	3
Insulation level VL	0	2	2
Energy label	F	A(+)	A(+)
Extra installations	-	Solar PV 100%	4

Table D.22: Retrofitting details: installations and insulation upgrades - Agent 227399, multi-model

Agent 227399		
Year	2020	2027
Installation RVb	Low efficiency boiler	High efficiency boiler
Installation RVp	Low efficiency boiler	High efficiency boiler
Installation KDb	None	Airconditioning
Installation KDp	None	Airconditioning
Installation TWb	Low efficiency boiler	High efficiency boiler
Installation TWp	Low efficiency boiler	High efficiency boiler
Insulation level DP	0	2
Insulation level DR	1	4
Insulation level DS	0	4
Insulation level KR	0	4
Insulation level MG	0	3
Insulation level MS	2	4
Insulation level PL	0	2
Insulation level RB	3	3
Insulation level RO	3	3
Insulation level VL	2	2
Energy label	A(+)	A(+)
Extra installations	-	-

Table D.23: Retrofitting details: installations and insulation upgrades - Agent 262662, multi-model

Agent 262662			
Year	2020	2025	2026
Installation RVb	High efficiency boiler	High efficiency boiler	High efficiency boiler
Installation RVp	High efficiency boiler	High efficiency boiler	High efficiency boiler
Installation KDb	None	None	Airconditioning
Installation KDp	None	None	Airconditioning
Installation TWb	High efficiency boiler	High efficiency boiler	High efficiency boiler
Installation TWp	High efficiency boiler	High efficiency boiler	High efficiency boiler
Insulation level DP	0	0	0
Insulation level DR	0	0	4
Insulation level DS	0	0	2
Insulation level KR	0	0	4
Insulation level MG	0	0	0
Insulation level MS	0	0	2
Insulation level PL	0	0	3
Insulation level RB	0	0	3
Insulation level RO	0	0	2
Insulation level VL	0	0	0
Extra installations	-	Solar PV 100%	-
Energy label	D	A(+)	A(+)

D.2.4. Seed analysis

Table D.24 provides more detail on the outcomes of the random seed analysis on the energy poverty estimates. Tables D.25 until D.30 provide extra information on the outcomes for the energy label counts, per energy label. For this analysis, the multi-model simulation was run with 5 different seeds to test the sensitivity to the random initialisation.

Table D.24: Yearly variation in energy poverty risk across random seeds

Year	Mean	Std.dev	Min	Max	IQR
2020	10.00	0.346410	9.80	10.40	0.3
2021	10.30	0.264575	10.1	10.60	0.25
2022	10.467	0.288675	10.30	10.60	0.25
2023	9.2	0.264575	9.00	9.50	0.25
2024	8.73	0.251661	8.50	9.00	0.25
2025	8.43	0.251661	8.20	8.70	0.25
2026	8.167	0.208167	8.00	8.40	0.20
2027	7.967	0.251661	7.70	8.20	0.25

Table D.25: Yearly variation in energy label A count across random seeds

Year	Mean	Std.dev	Min	Max	IQR
2020	85668.66667	70.28	85595	85676	70
2021	85415.00	71.02	85343	85485	71
2022	97253.00	944.12	96163	67815	826
2023	124431.00	1852.43	122292	125504	1606
2024	135783.33	2894.31	132444	137570	2563
2025	144967.33	3774.73	140610	147240	3315
2026	153726.33	4753.30	148238	156521	4141.5
2027	161907.00	5564.22	155842	165125	4821.5

Table D.26: Yearly variation in energy label B count across random seeds

Year	Mean	Std.dev	Min	Max	IQR
2020	36018.67	81.99	35927	36085	79
2021	36134.33	88.21	36037	34643	86
2022	34594	63.69	34522	29956	60.5
2023	29748	180.68	29630	28247	163
2024	27870.33	326.55	27667	26912	290
2025	26306.33	524.70	26017	25707	461
2026	24846	745.74	24404	24543	651.5
2027	23536.33	866.75	23127	165125	787

Table D.27: Yearly variation in energy label C count across random seeds

Year	Mean	Std.dev	Min	Max	IQR
2020	53607.67	117.49	53472	53676	102
2021	53692.33	119.80	53554	53762	104
2022	50521.67	288.74	50284	50843	279.5
2023	42749.67	534.63	42438	43367	464.5
2024	39621.33	806.38	39088	40549	730.5
2025	37064.00	1034.10	36455	38258	901.5
2026	34618	1337.98	33779	36161	1191.5
2027	32213.33	1678.28	31218	34151	1466.5

Table D.28: Yearly variation in energy label D count across random seeds

Year	Mean	Std.dev	Min	Max	IQR
2020	21410.33	110.93	21356	21536	105
2021	21437.33	111.94	21356	21565	104.5
2022	20017.33	141 14	19876	20147	140
2023	16789.33	246.01	16584	17062	239
2024	15447.67	394.80	15188	15902	357
2025	14406.0	462.73	14123	14940	408.5
2026	13341	622.04	12965	14059	547
2027	12365	692.87	11957	13165	604

Table D.29: Yearly variation in energy label E count across random seeds

Year	Mean	Std.dev	Min	Max	IQR
2020	17655	78.54	17578	17735	78.5
2021	17656.33	77.14	17582	17736	77
2022	16326	106.13	16223	16435	106
2023	13704.33	185.07	13573	13916	171.5
2024	12526.00	312.02	12300	12882	291
2025	11594.00	429.55	11344	12090	372.5
2026	10673.67	508.67	10375	11261	443
2027	9839.33	596.74	9475	10528	526.5

Table D.30: Yearly variation in energy label F count across random seeds

Year	Mean	Std.dev	Min	Max	IQR
2020	85668.66667	6.4	14278	14290	6.0
2021	85415.00	3.6	14295	14302	3.5
2022	97253.00	120.2	13030	13250	110
2023	124431.00	198.8	10554	10924	185
2024	135783.33	286.62	9454	9990	268
2025	144967.33	359.00	8553	9225	336
2026	153726.33	437.34	7710	8489	389.5
2027	161907.00	459.65	6918	7765	423.5

Table D.31: Yearly variation in energy label G count across random seeds

Year	Mean	Std.dev	Min	Max	IQR
2020	35398	46.49	35409	35438	45.5
2021	35410.33	46.26	35360	35451	45.5
2022	32222	299.28	32014	32656	275.5
2023	25928	523.93	25575	26530	477.5
2024	23136.33	777.41	22690	24034	674.5
2025	20894.67	968.72	18182	20134	849
2026	18859.00	1104.89	16180	18415	976
2027	16940.33	1277.31	155842	165125	1117.5

D.2.5. Sensitivity analysis

Figure D.2 visualises the main weights used in the ABM for their uncertainty and impact on the intention to invest calculation.

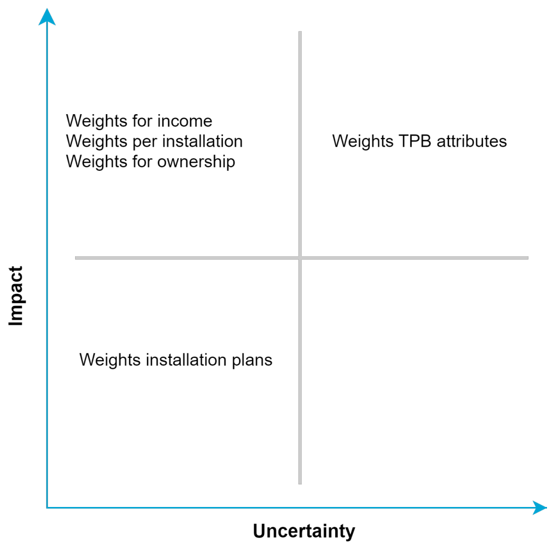


Figure D.2: Uncertainty matrix of weights in the ABM

Some weights used in the model, although very important in the calculations, are based on data or references and thus have a lower uncertainty. These are:

- Weights for income: these weights, used in Equation 6.9, are not seen as having high uncertainty. The income classes assigned to the population are based on the national distribution of income per ownership type. Although income is not equally distributed across each class, this weight is still grounded in realistic investment logic. Households with a higher income are more likely to invest in energy-saving technologies (Niamir et al., 2020). These weights reflect this tendency accurately and are thus excluded from the sensitivity analysis.

- Weights for installation categories: These weights, used in Equation 6.8 and meant to reflect the importance of using sustainable technologies for the energy supply in each category, are based on HESTIA's output (see section C.3). Although the weights are assumed, they are based on a very clear difference in energy use per category, which makes a clear distinction of importance per category. Thus, the weights are not seen as very uncertain.
- Weights for ownership: Although more subjective than the weights for income, ownership weights still reflect realistic agency of households in their investment decisions. Renters do have less power than owners (Feenstra and Clancy, 2020), and are, for big retrofitting measures, dependent on their landlords to make the decisions. These weights are also not seen as an extreme uncertainty

By excluding these less uncertain parameters from the sensitivity analysis, the focus can be on testing model robustness for complete assumptions.

The installation weights used in Equation 6.7 are intended to reflect a household's attitude towards sustainability based on their installation plans for solar panels. In the determination of these weights, it was decided that already having solar panels, and having set plans to install them in the next two years, is exceptionally better than not having plans at all or being unsure. The weights of the attitudes for installation plans, although completely based on assumptions, are seen as having a lighter influence on the final intentions to invest. These weights do play a role in the calculation of attitude based on installations already present around the home. But this is only a smaller part of the total intention calculations, which is why it is seen as having a lower impact.

The weights for the attributes of the Theory of Planned Behaviour in Equation 6.3 are uncertain and are the main determinants in the calculation of intention to invest. In the base case, the weights for attitude, subjective norms and perceived behavioural control are set equally. This choice was made to avoid prioritisation of a specific single parameter. The weights for these factors can differ from person to person, and it is unknown how the population of the Hague values these three parameters in their decision-making. Nevertheless, de Vries (2020) and Davoudi et al. (2014) do imply that subjective norms carry more weight than your attitudes. Another argument can be made that PBC should weigh the heaviest, as if someone does not feel they have the ability to invest, they will not, despite their attitude or peer pressure.