Utrecht University

Master's Thesis - master Energy Science

Irrationality in Energy Retrofits

The influence of cognitive biases on the outcomes of the energy retrofit related decision-making process of Dutch homeowners

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Abstract

The heat transition in the Dutch built environment is lagging behind the goals set by the Dutch government. One of the operations in the heat transition is the retrofitting of dwellings with sustainable heating installations and insulation. These measures need to be undertaken by the homeowners. However, there are financially beneficial investments that they do not make. Thus, non-financial factors are also at play. This thesis examines the influence of cognitive biases on the outcomes of the decision-making process of Dutch homeowners concerning investments in home energy retrofits.

The research is done by incorporating cognitive biases included in Prospect Theory into the built environment model Hestia. Comparing the distribution of heating installations and energy labels between a baseline scenario with only financial considerations and multiple simulation runs with differing bias strengths allows for separating the influence of the biases without any other factors being present. Parameter sweeps are done on a municipal geographic scope to examine the behaviour over a large range of bias strengths. In addition, runs with realistic values are done on a national scale. These simulation results are also compared to empirical validation data.

The inclusion of the reference dependence bias increases the share of gas-fired heating installations and decreases the shares of energy labels A and B. For loss aversion, no effect is found on a national scale. In the parameter sweeps, this bias increases the shares of gas-fired heating installations and energy label B, while decreasing that of energy label A. Diminishing sensitivity in only gains leads to an increase in gas and a decrease in energy label A. Diminishing sensitivity in only losses leads to the inverse. When diminishing sensitivity is active in both domains, the share of gas-fired heating options increases while that of label A decreases. In the case where all biases are combined, we see the same effects.

From these results, we conclude that the cognitive biases included in Prospect Theory decrease the number and/or ambition of investments into sustainable heating technologies and insulation. However, the effects did not change trends i.e. turning a decrease into an increase or vice versa. The biases brought the distribution of heating installations more in line with the validation data, while for the distribution of energy labels it is not clear.

Preface

Before you lies the thesis Irrationality in Energy Retrofits: The influence of cognitive biases on the outcomes of the energy retrofit related decision-making process of Dutch homeowners. The thesis was done at the Planbureau voor de Leefomgeving (PBL), while I was also doing an internship there.

Only after more than four months did the research take its final shape. The months beforehand were spent getting knowledgeable about the topic, learning to work with the Hestia model and trying different research angles. Through good discussions with my supervisors Dr. Wen Liu, Dr. Ir. Graciela Luteijn and Folckert van der Molen I finally settled on my research questions.

These have been answered in this work. My hope is that through a better understanding of the decision-making process the energy transition, and particularly the heat transition, can be advanced.

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List of used abbreviations

CBS Centraal Bureau voor de Statistiek

CPT Cumulative Prospect Theory

DS Diminishing sensitivity

EET Energy Efficiency Technologies

EoL End of Life

ER Energy Retrofit

EUT Expected Utility Theory

GHG Greenhouse gas

KEV Klimaat en Energie Verkenning

LA Loss aversion

LED Light Emitting Diode

PBL Planbureau voor de Leefomgeving

RD Reference dependence

SV Subjective valuation

TNO Nederlandse Organisatie voor Toegepast-Natuurwetenschappelijk Onderzoek

WoON WoonOnderzoek Nederland

1 Introduction

1.1 Background and societal relevance

Major changes in society are needed to keep global warming beneath 1.5 degrees Celsius and to mitigate the worst effects of climate change (IPCC, 2021) (IPCC, 2022). At COP21, 196 countries signed the Paris Agreement, signifying the aim to keep global warming beneath 2 °C, and preferably below 1.5 °C (UNFCCC, 2015). In line with these targets, the European union has set its own goals pertaining to the reduction in greenhouse gas (GHG) emissions: compared to emission levels in 1990: a reduction of 55% of GHG emission in 2030, climate neutrality in 2050 and negative emissions afterwards (European Commission, 2021). Being a EU member state, the Dutch government has to comply with these standards. In the Dutch Climate Agreement (Klimaatakkoord), the ways of achieving these goals have been laid down (Ministerie van Economische Zaken en Klimaat, 2019).

One of the areas targeted in the Climate Agreement is the built environment. The built environment in the Netherlands is responsible for 13% of the Dutch GHG emissions (CBS, 2021b). Of these emissions from the built environment, 71% are caused by dwellings, the places where people live (CBS, 2021b). One of the goals the Climate Agreement specifies, is that in 2050, 7 million of these homes and 1 million other buildings should be natural gas free. In 2019, 92% of Dutch dwellings still used natural gas for space and water heating purposes (CBS, 2021a). Of newly built dwellings, only 34% is delivered gas free (CBS, 2021a). This shows that integration of alternative heating sources into the existing housing stock is necessary. To be able to integrate some of these alternative heating sources, like heat pumps and district heating, many dwellings need to upgrade their insulation (Lingard, 2021). For homes that are not yet close to being gas free, better insulation still helps reduce energy use, and thus GHG emissions (Bardsley et al., 2019).

These energy retrofits (ER) need to be taken by homeowners, be they owner-occupants, social housing corporations or landlords. Investing in energy efficiency measures can be advantageous for the homeowners. Although ER are extensive and often expensive, they can save money in the long term. This happens because of a decrease in energy use due to increased insulation and the higher efficiency of heat pumps compared to gas-fired boilers (Lei et al., 2017). This prospect has become more prominent since the increase of gas prices in Europe in 2021 and 2022 (Eurostat, 2022). However, retrofit rates are well below expectations.

The Dutch government has put in place multiple measures to increase the number of ER in the Dutch housing stock, such as providing information on insulation measures (Rijksoverheid, 2022a). There also exist financial instruments like subsidies for insulation and heat pumps (Rijksoverheid, 2022b). These measures make it more attractive for homeowners to retrofit by increasing awareness and lowering financial barriers. However, not all considerations in the decision-making are financial. Hassle (Vries de et al., 2019), transaction costs (Ebrahimigharehbaghi et al., 2020), and household characteristics (Wilson et al., 2018) have been shown to influence how and when homeowners choose to invest in ER.

As the research into the factors playing into ER decision-making is recent, these considerations are not taken into account in policies meant to increase retrofit rates. With more and better information about the process, polices could be adapted. Thus, it is important to understand these other motivations and barriers to facilitate policymakers in making targeted and effective tools to promote changes towards a more sustainable future.

1.2 Scientific relevance

Research into these motivations and barriers has been done. (Liu et al., 2022) identified 689 factors influencing ER investment behaviour within seven categories, including social influence, dwelling characteristics and decision maker characteristics. Environmental factors have also been found to influence decision-making on ER (Organ et al., 2013). These factors can however be group and location specific. The landlord-tenant interaction is a factor of influence for landlords considering ER (Lang et al., 2021), while this is non-existent for owner-occupants. In the same vein, environmental values have been found not to influence retrofit behaviour for landlords (Lang et al., 2022), while this is a factor of importance for other groups (Liu et al., 2022). In rural areas, farming households are less likely to insulate exterior walls than non-farm households (Kaya et al., 2021). This differentiation of barriers between groups shows that research into the barriers and motivations of Dutch homeowners specifically is necessary.

Some research within this specific scope has been done. (Broers et al., 2021) categorised Dutch homeowners into different segmentation groups, in order to lay the groundwork for understanding the heterogeneity in the adoption of solar photovoltaics. They showed that these different groups have different concerns involving this technology. Based on the Dutch housing survey energy modules, WoonOnderzoek Nederland, (WoON), (Azizi et al., 2020) identified behavioural factors influencing the decision-making process homeowners go through when considering energy efficiency improvements. The study found that the sort of factors considered when evaluating a home improvement measure (building characteristics, personal factors, and motivational factors) differ per measure.

The insights gained by these studies can be used to design more effective policies. However, policy design is often influenced by the idea that actors will act rationally. This way of thinking has led to policies that are not as effective as previously thought (Li, 2017). Thus, it is important to gain insight into behaviour that deviates from this homo economicus.

Interesting research in this direction has been done using the Prospect Theory (PT) framework. This framework gives a description of how certain cognitive biases influence the decision-making process of actors, making them act irrationally to a certain degree. The biases included are *reference dependence*, *loss aversion* and *diminishing sensitivity*. An in depth treatment of these biases will be given in the Theoretical Background, Chapter 2.

One research into this area has been done by (Knobloch et al., 2019). In this paper, *loss aversion* was introduced into a global energy model, simulating future heating technology diffusion both globally and for 59 world regions. It shows that the inclusion of *loss aversion* drives the penetration of sustainable technologies downwards. The mix of technologies becomes subject to what they call a 'conservative shift', where more established technologies come to have a larger market share than in the scenario without *loss aversion*.

(Ebrahimigharehbaghi et al., 2022) used an extended version of PT, Cumulative Prospect Theory (CPT), to compare this decision-making theory with Expected Utility Theory (EUT), a neoclassical, rational, one. CPT includes an additional bias called *probability weighting*, which describes how decision makers base their decisions on a subjective interpretation of probabilities, given choices with uncertain outcomes. In this research, the sources of uncertainty were multiple modelled future energy price paths. The conclusion was made that CPT predicts investment behaviour into the two ER studied, insulation and double glazing, better than EUT.

Even though these papers give insight into the investment behaviour into ER using the PT framework, there is still room for other avenues of exploration. It is known that the PT framework can explain the discrepancy between expected and actual investment behaviour (Häckel et al., 2017). However, it is unknown what the influence of these biases is in isolation, that is, considering only financial costs, financial benefits and the biases, for the Dutch housing stock.

1.3 Problem definition and research questions

Thus, it is still unclear what the isolated effect of the cognitive biases on ER investment behaviour for Dutch homeowners is. This leads us to formulate the research question:

What is the effect of the cognitive biases included in Prospect Theory on the implementation of energy efficiency measures in the Dutch residential built environment?

This research question will be answered through the following sub research questions:

1. What is the effect of reference dependence on the implementation of energy efficiency measures?
2. What is the effect of loss aversion on the implementation of energy efficiency measures?
3. What is the effect of diminishing sensitivity on the implementation of energy efficiency measures?
4. What is the effect of subjective valuation on the implementation of energy efficiency measures?

Subjective valuation is not a single bias, but the combination of all biases included in PT. The sub-research questions will be answered by integrating PT into a model called Hestia. More information on Hestia can be found in Chapter 2.3.

1.4 Scope

The spatial scope of this research will be dwellings, that is residential properties, in the Netherlands. These can be owned by inhabitant-owners, social housing corporations or private landlords. Because aggregated national statistics will be used for validation, no differentiation will be made between these different groups of owners. Industry, commercial buildings and other utility built environment is not considered in this research. The temporal scope of the research is 2000 to 2018. This is due to the fact that validation data is available in the years 2000, 2006, 2012 and 2018. More information about this data can be found in Chapter 3.3.

1.5 Thesis structure

In the following chapter, Chapter 2, the theoretical background of the research will be given. The chapter contains information about PT and Hestia, the model used. In the PT section, the nature and mathematical descriptions of the biases are given, alongside some background information concerning the use and history of the PT framework. For Hestia, a brief overview is given of the background information needed to sketch the context the model is designed for. The design of the decision-making process is treated more in depth, as this is where modifications are made for this research.

Chapter 3 is the Methodology chapter. Here, information on the validation data and the integration of PT into Hestia is given. Also, the concrete analysis steps done to answer the sub-question are presented.

The results of the research are shown in Chapter 4. These will be presented per sub-question. In the subsequent chapter, Chapter 5, these results will be interpreted. Also limitations in the research, opportunities for future research and policy implications are given.

In the final chapter, Chapter 6, conclusion from these interpretations are drawn.

This thesis ends with some acknowledgements, the bibliography and the appendices.

2 Theoretical background

2.1 Prospect Theory

2.1.1 Overview

Prospect theory is a behavioural economic theory devised by Daniel Kahneman and Amos Tversky (Tversky & Kahneman, 1979). It is a descriptive model that aims to show how decisions are really made, in contrast to neo-classical economic models which are normative. The theory has its origin in describing decisions made under uncertain outcomes, but since then it has been modified and used in a multitude of contexts (Tversky & Kahneman, 1991). It is a departure from Expected Utility Theory (EUT), which presupposes a rational decision maker (Mongin, 1998). The way in which PT departs from EUT is in the introduction of several cognitive biases. These skew the decision-making process so that seemingly irrational choices are made.

In Table 2.1 an overview of the biases included in the theory can be seen. All biases but one, *reference dependence*, are mathematically regulated by one or two parameters. These modify the strength of the bias. The mathematical description of the individual biases will follow after a short discussion on the total framework.

Table 2.1: Overview of cognitive biases included in PT.

Cognitive bias	Parameters	Description
Reference dependence	None	The valuation of gains and losses is not based on the absolute wealth of the individual after the decision, but on the relative change in wealth.
Loss aversion	λ	Actors weigh a loss in wealth heavier than an equivalent gain.
Diminishing sensitivity	α, β	The impact of a change in wealth decreases with the distance to the reference points.

The version of PT that is used in this thesis is one that evaluates each choice between options on multiple dimensions or attributes. The general mathematical form of this version of PT can be seen in Equation 2.1.1. The PT-score is a function of the changes in wealth with respect to the reference situation Δx_i which are modified by the value function $v()$. This means that for every considered attribute i of an option, the subjective valuation of the decision result in that dimension is computed. An example of this multi-attribute evaluation is shown in Figure 2.1.

$$PT = \sum_{i=1}^{n} v(\Delta x_i) \tag{2.1.1}$$

The sum over all these dimensions yields a PT-score. This PT-score is a measure of expected utility modified by the cognitive biases. A PT-score can be calculated for every option. Using these scores, the options can be ordered from least attractive, the option with the lowest score, to most attractive, the option with the highest score. As long as the PT-score is higher than zero, the subjective expected utility of the option is positive and thus the option is more attractive than the reference situation. It should be noted however, that these scores cannot be interpreted monetarily, as they are indications of subjective value.

In the remainder of this section, information on the different cognitive biases and their mathematical representation is given.

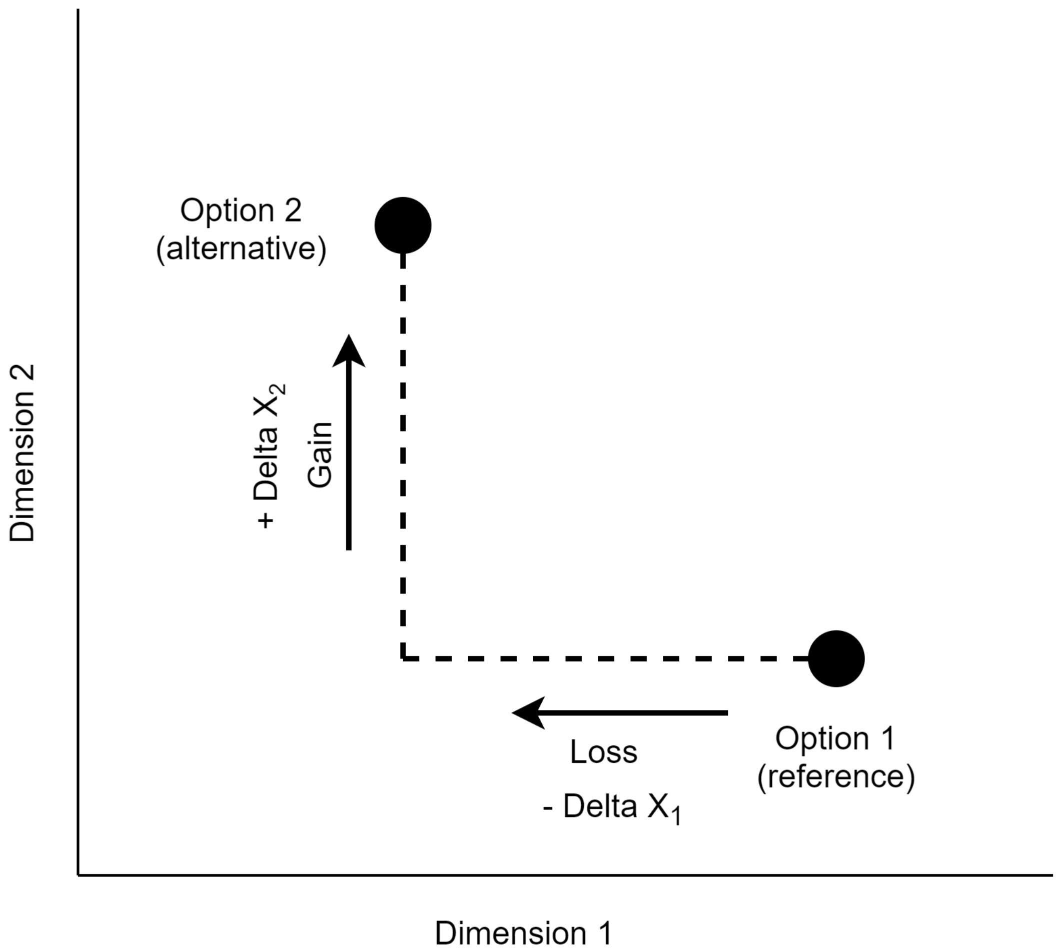

Figure 2.1: In a move from the reference option to the alternative option, losses and gains are evaluated as differences in attributes relative to the reference point. In the example pictured, there is a loss in dimension 1, and a gain in dimension 2 when choosing option 2 over option 1.

2.1.2 Cognitive biases

The first variable that is to be discussed is Δx_i. This variable is the change in wealth from the reference situation in dimension i. It is the mathematical representation of the *reference dependence* bias. In neoclassical economic theory, like EUT, the utility function is a function of the absolute wealth that results from the choice. In PT, the relative change from the starting situation is the input for the utility function. Δx_i is calculated by subtracting the starting wealth from the wealth resulting from the choice, as seen in Equation 2.1.2.

$$\Delta x_i = x_{i,choice} - x_{i,reference} \tag{2.1.2}$$

This Δx_i is then modified by the value function $v()$, which is defined as in Equation 2.1.3. It is a piecewise function, with the form depending on the sign of Δx_i, or whether the outcome of the choice will yield an increase or a decrease in wealth.

$$v(\Delta x_i) = \begin{cases} (\Delta x_i)^\alpha & if \quad \Delta x_i \geq 0 \\ \lambda \cdot (\Delta x_i)^\beta & if \quad \Delta x_i < 0 \end{cases} \tag{2.1.3}$$

With $\alpha, \beta, \lambda > 0$.

There are two representations of cognitive biases in this function. The first is *loss aversion*, of which the strength is regulated by the parameter λ. This bias only manifests when the outcome of the decision is negative, i.e. when there is a loss in wealth. When $\lambda > 1$, the decision maker is loss averse, which means that a loss is valued more heavily than a gain. For example, if $\lambda = 2$, a loss is values twice as negatively as an equivalent gain would be valued positively. In Figure 2.2, a value curve under the influence of *loss aversion* can be seen.

Loss aversion can lead to what is called the endowment effect (Kahneman et al., 1991). The endowment effect means that a product has a higher worth when a person is in possession of it, than when they still need to obtain it. This is due to the fact that giving up property feels like a loss, which is felt more strongly, while buying something feels like a gain.

The second bias included in the value function is *diminishing sensitivity*. This bias describes how a marginal change in wealth further from the reference point is valued as less important than one closer to it. An example value curve can be seen in Figure 2.3. The strength of the bias is regulated by two parameters: α, for gains, and β for losses. This means that the strength of the bias can differ between gains and losses.

The curve of the combination of these two biases, of the total value function, can be seen in Figure 2.4. This is the curve associated with the total *subjective valuation* mentioned in sub research question 4, as all biases are included.

It should be noted that these biases can act on changes in wealth in different dimensions individually. If we look at Figure 2.1, there is a loss in dimension 1, so *loss aversion* will come into play there. However, in dimension 2 there is a gain, so no *loss aversion* will occur. This means that, given the fact that in this case $\Delta x_1 = \Delta x_2$, the choice to switch to option 2 will have a negative PT-score, if the loss is multiplied by a factor $\lambda > 1$. In this case, a decision maker under the influence of *loss aversion* would not make this switch, while a decision maker not under the influence of this bias would find both options equally preferable.

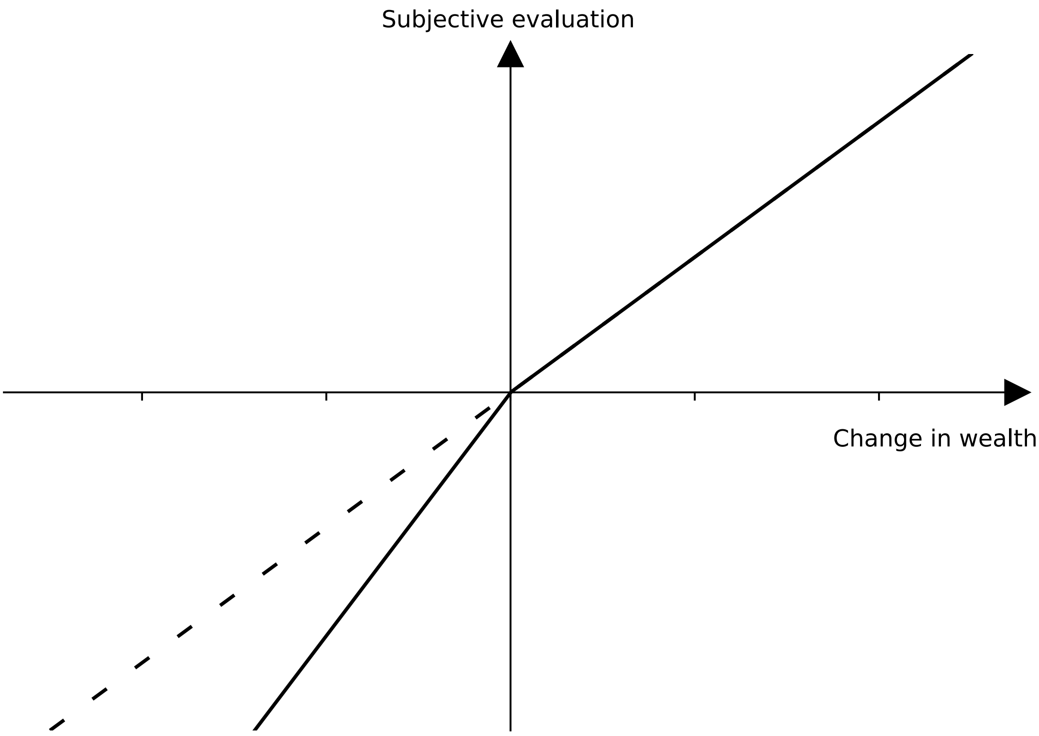

Figure 2.2: The loss aversion value curve, indicated by the black line, shows that for negative changes in wealth, the loss is experienced greater than proportionately, which is indicated by the dashed line. For gains, the bias has no effect.

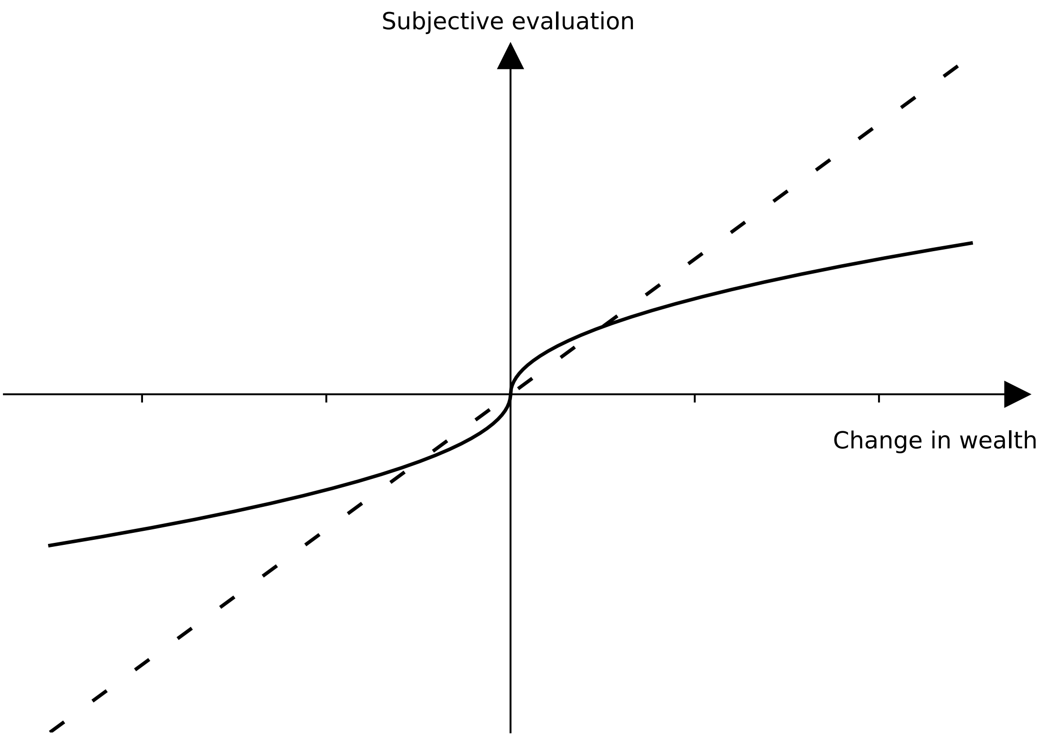

Figure 2.3: The diminishing sensitivity value curve, indicated by the black line, shows that at larger changes in wealth the subjective valuation is less than proportionate, which is indicated by the dotted line. In this example, $\alpha = \beta$, although these strength can and do differ.

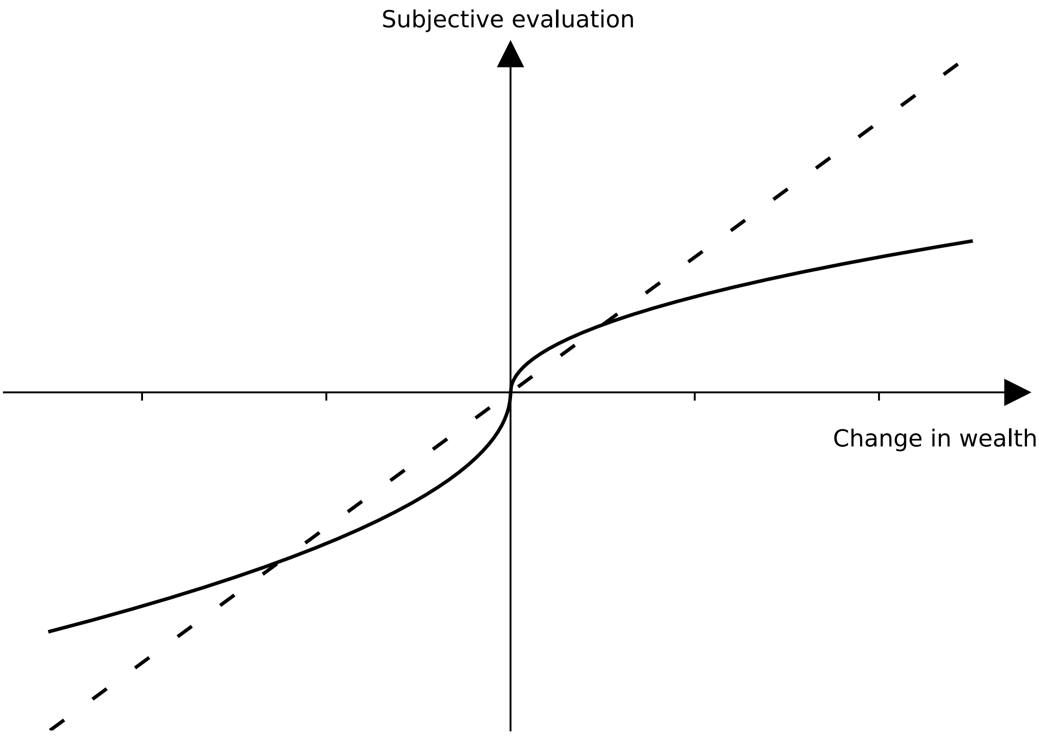

Figure 2.4: The total subjective valuation curve shwon included both loss aversion and diminishing sensitivity. The diminishing sensitivity manifests itself in the convexity of the curve in the gains domain and the concavity in the losses domain. The fact that the curve trends downwards in the losses domain more quickly than it increases in the gains domain is a manifestation of loss aversion.

2.2 Earlier ER related research using PT

There are multiple version of PT, with slight modifications depending on their use. Cumulative Prospect Theory (CPT) is a version of PT that is used in analysing decisions under risk, also devised by (Tversky & Kahneman, 1992). Here, an additional bias, *probability weighting*, is introduced to describe how decision makers deal with multiple probable outcomes. The theory is a mainstay in finance and economics (Rieger et al., 2017), but it has seen little use in gaining insight into the decision-making process of homeowners considering ER. However, two interesting studies have been conducted.

(Häckel et al., 2017) compared CPT with a more common economic theory, Expected Utility Theory (EUT). This second theory assumes a rational decision maker, although a risk aversion parameter is included. In the research, investment decisions were evaluated for a dwelling with characteristics common for a German home. No particular ER was chosen, but multiple combinations of investment costs and energy savings were evaluated. Three scenarios were considered with different combinations of biases. The first using only *reference dependence* and *diminishing sensitivity*; the second using those and a *loss aversion* of 2.25; and the third using those and *probability weighting*. Based on simulated energy price paths, they evaluated the business case using both theories. The results show that CPT can explain the difference between the expected en the actual investment behaviour in ER. This is because the business case needs to be better as the various cognitive biases decrease the subjective valuation of the business case. The *loss aversion* bias was shown to have the biggest influence in the evaluation.

(Ebrahimigharehbaghi et al., 2022) also compared CPT with EUT, but their analysis is more grounded in reality. Instead of using a hypothetical model home, they clustered different types of homes based on their characteristics. And instead of working with combinations of investment costs and energy savings, real ER were considered: insulation and double glazing. When cognitive bias parameter values from literature were used, CPT predicted investment behaviour better than EUT. In addition, a further step was taken, as based on the data, new values were also found for the parameters. These values complied with the expected trends, although for some biases the values were far greater than those from the literature, indicating that for some homeowners the biases were much stronger.

Apart from CPT, there have also been studies into ER that use part of the PT framework, most notably *loss aversion*. There are two studies that I would like to highlight.

(Schleich et al., 2019) did research into the effect of *loss aversion*, risk aversion and standard time discounting in the adoption of Energy Efficiency Technologies (EET). These EETs included, LEDs, energy efficient appliances and ER. The ER in question were all insulation based. Subjects from multiple European countries were tested in context-free price list experiments on their *loss aversion*, and were also asked about their adoption of the EETs. In their findings, subjects with higher *loss aversion* were less likely to have adopted LEDs and energy efficient appliances, but it seemed to have no influence on the adoption of ER.

Already mentioned in the introduction, but worth taking a closer look at is the paper by (Knobloch et al., 2019). They introduced *loss aversion* into a global energy model (FTT:Heat) to evaluate how this addition would change the uptake of sustainable heating systems. Five different scenarios were evaluated: one business as usual scenario, two different carbon tax scenarios, a technology subsidy scenario, and a scenario with a combination of taxes and subsidies. For all scenarios, *loss aversion* decreased the uptake of sustainable heating systems. For more stringent policy scenarios differences in technology diffusion between scenarios with and without *loss aversion* were smaller, with subsidies being especially effective. The conclusion being that subsidies decrease investment costs and thus the feeling of loss when buying a new heating installation.

2.3 The model Hestia

2.3.1 Overview

Hestia is a model that is being built by the Netherlands Environmental Assessment Agency, Planbureau voor de Leefomgeving (PBL), and the Netherlands Organisation for Applied Scientific Research, Nederlandse Organisatie voor Toegepast-Natuurwetenschappelijk Onderzoek (TNO). It is the intended successor of the Vesta MAIS and SAWEC models. These are models that are used to estimate the future energy use of the Dutch housing stock. The most important use of the model is to create prognoses for the "Klimaat en Energie Verkenning" (KEV), which is a yearly report that evaluates the Dutch climate and energy policies and their effects (PBL et al., 2021). In this research, the model will be used to see how the cognitive biases in PT can influence the ER investment behaviour of Dutch homeowners.

The model simulates the energy use, investments in insulation measures and functional installations, and the associated costs for every dwelling in the Netherlands. Different levels of insulation per building part, multiple gas based, all-electric based and hybrid based heating options, as well as other technologies such as solar photovoltaics and ventilation installations are included. The model can also exogenously account for new developments and demolition of buildings, as well as the development of district heating networks. In this way, a prognosis of the state of the Dutch housing stock can be made for years ranging from 2020 to 2040. The model is also open source. The code can be found on GitHub (Wijngaart van den, 2022a). However, Hestia is still in development. At the time of writing, the model is still in an early test version. It is possible that major changes will be enacted before the final release.

In the rest of this section, some explanation in my own words concerning the investment process of homeowners is given. I will not go into fullest of detail, but only highlight what is important background information to this thesis. For extensive information on the model, I refer to the Hestia design document (Molen van der et al., 2022).

2.3.2 Activation

Activation triggers

Activation is the process in Hestia that make a part of a building be considered for modification. Building parts can be classified into two categories:

1. Installations: these are the building components which satisfy an energy function in the dwelling. Energy functions are: space heating, water heating, cooling, ventilation, cooking.
2. Dwelling components: these are the parts of a building that have an influence on the amount of heat that is trapped in a dwelling. They are eligible for insulation measures. Building components include but are not limited to: roofs, windows, facade, windows, floors.

The ways in which these parts can be activated are summarised in Table 2.2. Multiple assumptions about the possibility and need for replacements are made. For example, it is assumed that for 5% of the housing stock all building parts will be under consideration for replacement. This mechanism represents people moving into a new home and considering if they want to have anything changed at an opportune moment, as well as miscellaneous other reasons for activation. In a similar way, probabilities are assigned to other ways of activation, such as for cooking and cooling. There is also a mechanism that represents a home renovation. When three or more building parts are activated, all other parts become activated too. This again, could be an opportune moment to consider taking measures in many places of the home at once. Finally, there is End of Life activation. This way of activation represents installation and dwelling component failure, requiring a new investment.

Table 2.2: Overview of ways of activation

Effect	Description
Moving and miscellaneous	Base 5% chance that the all building parts will be activated.
End of Life (EoL)	The chance of activation of building parts increases over their lifetime.
Base cooling	Each dwelling has a 10% that base demand for cooling must be satisfied.
Peak cooling	Whenever there is base cooling, there is a 50% chance that peak cooling demand must be satisfied.
Electric cooking, natural	At the EoL of cooking equipment there is a 95% chance that the cooking will become electric (induction).
Electric cooking, independent	Activated cooking equipment not at EoL has a 20% chance of becoming electric (induction).
Renovation	When 3 or more building parts are activated, all other parts of the building also become activated.

End of life activation

The End of Life (EoL) activation is a mode of activation that requires a more in depth treatment. The EoL activation chance is modelled as per Equation 2.3.1. This equation gives a probability of activation for the building part for every year. The building part is then either activated or not activated based on the drawing of a randomly generated number. In the equation, the $SimulationYear$ variable is the year that is currently considered in the model; $LastReplacementYear$ is the year in which the building part in question was last changed; and $Lifespan$ is the nominal lifespan of the installation of insulation. The parameters $Spread$ and $Tail$ regulate the slope and position of the activation chance curve.

$$Odds_{Activation} = \left(\frac{1}{1 - Spread} \cdot Tail\right) \cdot \left(\frac{SimulationYear - LastReplacementYear}{Lifespan} - Spread\right) \tag{2.3.1}$$

In Figure 2.5, three different combinations of these two parameters can be seen. In this figure, the lifespan of the installation is 15 years, and the last replacement was in simulation year 0. The continuous line is drawn according to the default parameters of the model that were taken from Vesta MAIS and which have also been used in this research: $Tail = 0.5$, $Spread = 0.8$. We can see that the first

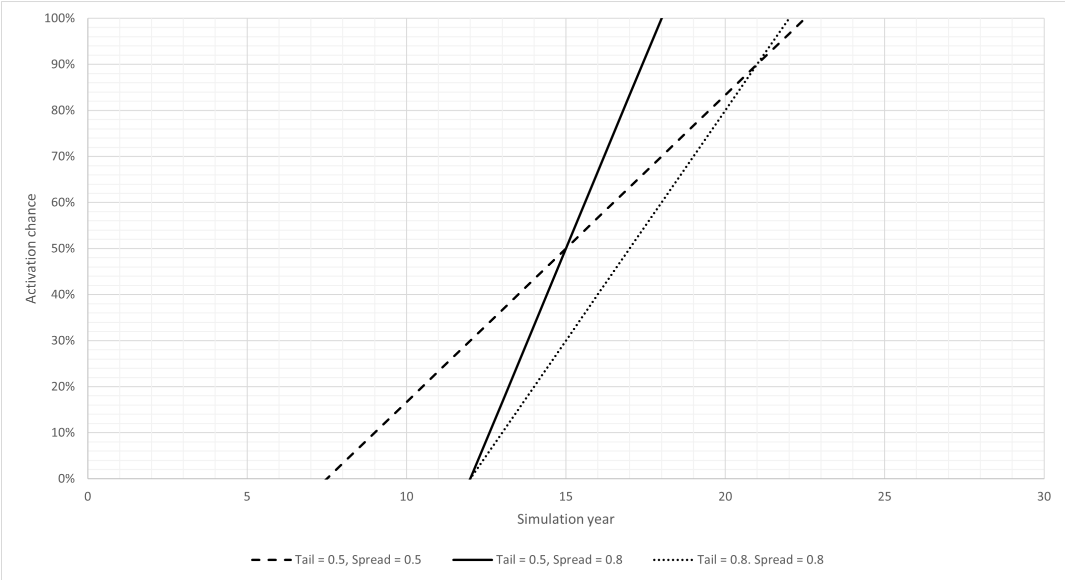

Figure 2.5: Activation odds curves for three different combinations of Tail and Spread parameters.

year where $Odds = 0$ is year 12, which is $Spread \cdot Lifespan$. At $SimulationYear = Lifespan = 15$, $Odds = 0.5 = Tail$. These formulas hold when we look at the other combinations of the parameters. The dashed line has a $Spread = 0.5$, which has made the slope less steep, and the year where $Odds = 0$ is different. At $Simulationyear = Lifespan$, the odds are the same as for the solid curve. The dotted line has the same $Spread$ as the solid curve, but a $Tail = 0.3$, which in this case has also flattened the slope and changed the activation odds in the year that the $Lifespan$ is reached. However, the year where $Odds = 0$ is the same as in the default case.

The slope of the activation curve can be found by differentiation of Equation 2.3.1 and leads to Equation 2.3.2.

$$Slope = \frac{Tail}{Lifespan \cdot (1 - Spread)} \tag{2.3.2}$$

2.3.3 Selection of options

Once a building part is activated, a selection of possible options is made. These selection procedures differ between installations and dwelling components. As there are many options for both categories, the selection process is done is steps, by first choosing one out of a group of similar options, and then choosing between the resultant different options.

Installations

For installations, first all possible options are categorised. The categories that the options are placed in are: gas-fired installations, electric installations and hybrid installations. Within each category, one option is chosen on the basis of an indicative cost-benefit analysis and a modification through S-curves. Information of the S-curves will be given in later in this section. Once this first selection has been made, the final three options are compared using a more detailed cost-benefit calculation and another set of S-curves.

Insulation

Dwelling components are grouped into five different sets of options. The five sets are based on five insulation ambitions, which range from None to Extreme. This pre-selection is based on an indicative costs-benefit calculation and an S-curve. Once the pre-selection has been made, a more thorough business case is made for all options. This business case depends on the heating installation used. This means that if the installation is also activated, there are 5 $Insulation\ Ambitions \cdot 3\ Installation\ Categories = 15\ Options$ to compare. This final comparison is also regulated by an S-curve.

Costs and benefits

In this section a brief overview of the business case calculations is given. This description is a simplification of the more detailed process that happens in Hestia, but it is meant to show in broad strokes which elements factor into the costs and benefits.

When a cost-benefit analysis is done, really only costs are computed. The benefits are only relative to other options under consideration, of which the current configuration may be one. The total costs are calculated on an annual basis. These costs consist of the total (annualised) capital costs, maintenance costs, administration costs and energy costs. When an indicative costs-benefit analysis is computed, reference values for some of the variables are used. This is done because in some pre-selections, the information needed for the detailed costs calculation is not yet available, as it can depend on choices made later in the decision-making process.

The capital costs consist of all investment costs for the building parts, minus the relevant subsidies. Maintenance and administration costs are calculated as an installation specific percentage of the investment costs of that installation. The energy costs consist of the yearly flat costs of having a connection the necessary grid (electricity, gas, heat, hydrogen), and the fuel costs. The fuel costs in turn, are a product of the necessary energy needed to fulfil the energy needs of the dwelling multiplied by the costs per unit of energy.

S-curves

In Hestia, the S-curves conceptually model the fact that preferences in cost-benefit ratios differ over the population. What one homeowner might find an attractive business case, another might not. The way this differentiation is done, is by transforming the costs calculated in the business case into an attractiveness score, which determines the probability the option will get chosen. The spread in preferences can be shown as a normal distribution. When this normal distribution is shown cumulatively, the shape of the curve resembles the letter S, which is where the S-curves get their name from.

There are three different S-curves included in Hestia.

1. Insulation S-curves: which are used in the pre-selection of insulation measures to determine which measure are included in the insulation ambitions.
2. Building option S-curves: which are used to do the pre-selection of installations into the three energy carrier categories.
3. Investment S-curves: which are used in the final investment decision.

Although the S-curves are used in different steps in the decision-making process, they act in the same way. Every option in Hestia that can be considered, be it some kind of insulation or a type of heating system, has its own S-curve. Each curve is defined by two parameters. The first is $P50P$. This parameter changes the 50% point, the business case where 50% of the decision makers would accept the option, i.e. it moves the S-curve horizontally. The second parameter is β. This parameter changes the costs sensitivity of the option, i.e. it changes the slope of the S-curve. These parameters are used to modify the business case of an option in the following way.

First the *Suitability* of an option is calculated according to Equation 2.3.3. Here, the costs of the option that is under consideration are compared with the costs of the most expensive option under consideration.

$$Suitability_{Option} = Costs_{MostExpensiveOption} - Costs_{Option} \cdot P50P_{Option} \tag{2.3.3}$$

After the suitability of an option has been computed, the *Odds* of an option are calculated, as can be seen in Equation 2.3.4. Here, β_{Option} is the β parameter associated with the option, while $\beta_{General}$ is a global parameter that influences the costs sensitivity for all options.

$$Odds_{Option} = e^{Suitability_{Option} \cdot \beta_{General} \cdot \beta_{Option}} \tag{2.3.4}$$

Then, the *Odds* of all options are normalised according to Equation 2.3.5. Finally using the drawing of a randomly generated number, a decision is made.

$$Probability_{Option} = \frac{Odds_{Option}}{\sum_{i=1}^{N} Odds_{Optioni}} \tag{2.3.5}$$

In this research, the β and P50P of every option is set equal to 1, so there are no modifications to the probabilities. They are purely based on costs.

3 | Methodology

In this chapter, the methodology of the research is given. This information helps understand how the research questions are answered. Firstly, the research steps are discussed. These are the actions taken that will produce the data that will answer the research questions. To be able to see the influences of the biases on the decision-making outcomes, the PT biases need to be implemented in Hestia. The mathematical forms have already been discussed in Section 2, but the practical matters involved will be discussed here. The validation data discussed in Section 3.3 is needed to see how the real world Dutch housing stock has evolved over time. We can use this to compare the modelling results against, to see how close the outcomes come to describing the implementation of ER over time.

3.1 Research steps

3.1.1 Overview

There are two kinds of variables that will be looked at in this research. These are the distribution of types of space heating installations, and the energy label distribution over the Dutch housing stock. In space heating, a distinction is made between gas-fired central heating; collective heating options like district heating; and other heating systems, which will include heat pumps, but also oil stoves, wood stoves and other installations. However, we assume that this "Other" category consists of mostly sustainable heating options. This assumption can be made because non sustainable options like oil or biomass stoves are uncompetitive due to their low efficiency, high fuel prices and similar installation costs compared to sustainable options like heat pumps. The variables of different kinds of heating installations and energy labels are chosen because they serve as proxies to investments in sustainable heating installations and investments in insulation respectively.

In this research, Hestia simulates the state of the Dutch housing stock from the year 2000 to the year 2018, because between these years there is validation data available. In the Results section (4), the starting year, 2000, will be displayed as year 0. The year 2018 is represented as simulation year 18.

Because we are interested in the influence of different values of the bias parameters, multiple runs with differing values for these parameters need to be done. Each of the configurations of parameter values is one scenario. The scenarios are bundled into scenario families. Within a scenario family, the same (set of) parameters(s) is varied, meaning that the scenarios in a families act on the same bias(es). The scenario families are named by an abbreviation of the name of the cognitive bias that is studied through the family, with an optional number suffix to distinguish between families that study the same bias but vary different parameters. An overview of the scenario families can be found in Table 3.1.

The baseline scenario is the scenario where no biases are active. Thus, these results are created by a model run where only financial considerations are taken into account. This happens because the S-curves, described in Section 2.3.3, are all set to 1, i.e. the model in uncalibrated. This baseline scenario is then used to compare the other results too, to see the influence the biases have on the outcomes of the decision-making.

While in DS1 and DS2, only one of the *diminishing sensitivity* coefficients is varied, in DS3 and SV both are. For the DS3 and SV scenario families, $\alpha = \beta$. For DS3, this is done to minimise computation time. For SV, it is necessary that $\alpha = \beta$ when *loss aversion* is present in riskless decision-making (al-Nowaihi et al., 2008).

For each scenario family, multiple kinds of scenarios are run. For all, a broad parameter sweep, a narrow parameter sweep, and national scope runs are done. More information on these can be found in Section 3.1.2. The broad parameter sweep tests the influence of the bias over a large range of values, while the narrow parameter sweep gathers information about the effects of more realistic values. Together with literature, they inform the scenario design of the national runs. Because the broad and narrow sweeps consist of many scenarios, a smaller spatial scope is chosen in order to reduce computation time.

Here, the municipality of Zeewolde (municipality code 0050), is chosen. Zeewolde is a small municipality with around 23.000 inhabitants, located in the province of Flevoland. It is a relatively young municipality,

Table 3.1: Scenario family overview. One scenario family consists of multiple scenarios, one for each (combination of) parameter values(s).

Scenario family	Active biases	Varied parameter
Baseline	None	None
RD	Reference Dependence	None
LA	Reference Dependence	None
	Loss Aversion	λ
DS1	Reference Dependence	None
	Diminishing Sensitivity	α
DS2	Reference Dependence	None
	Diminishing Sensitivity	β
DS3	Reference Dependence	None
	Diminishing Sensitivity	α & β
SV	Reference Dependence	None
	Loss Aversion	λ
	Diminishing Sensitivity	α & β

in the sense that it was created in 1984. This means that the housing stock is comprised of more new dwellings compared to the national average. The low number of inhabitant means that there are also few dwellings, which speeds up computation times. The results of these runs are not representative for a run on national scale because the housing stock has different characteristics, and there are no heat networks present at the start of the simulation. However, these runs can still provide information about the investment behaviour under the influence of the biases. One can see at which parameter values there is no change in outcome anymore and how quickly the outcomes change. This information then informs the scenario design for the national runs.

3.1.2 Scenario design

Broad parameter sweeps

In the broad parameter sweeps, the values of the parameter(s) in question are varied over a large range. This is done to see what all the possible influences are the bias can effect. The aim is to see if there are cognitive bias parameter values that give a maximum deviation form the reference scenario, after which a higher or lower value does not change the modelling outcomes. Tipping points in the model behaviour might also be found using this method. In Table 3.2 the range of parameter values can be seen. For all parameters in all scenario families, the values are the same. When multiple parameters are changeable in a family, the Cartesian product of the possible parameter values informs the scenario design. That is, if there are two parameters, all possible values for the one are tried for each of the possible values of the other.

The narrow parameter sweeps are meant to look at the influence the biases for parameter values that are more realistic. This means that no $\lambda < 1$ and no $\alpha, \beta > 1$ are present. In those cases, the biases would work in the opposite direction compared to what is empirically observed. The ranges of the parameters are also smaller than in the broad parameter sweep. This allows for more detail in the comparison of the results. The chosen values are shown in Table 3.3.

Table 3.2: Overview of the parameter values for the broad sweeps.

Run No.	Parameter values
1	1 000 000
2	100 000
3	10 000
4	1000
5	100
6	10
7	1
8	0.1
9	0.01
10	0.001
11	0.0001
12	0.000 01
13	0.000 001

Table 3.3: Overview of the parameter values for the narrow sweeps.

Scenario family	Varied parameter(s)	Values									
Baseline	None										
RD	None										
LA	λ	1	2	3	4	5	6	7	8	9	10
DS1	α	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	
DS2	β	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	
DS3	$\alpha = \beta$	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	
SV	λ	1	2	3	4	5	6	7	8	9	10
	$\alpha = \beta$	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	

Table 3.4: Overview of the parameter values for the national scope runs.

Scenario family	Varied parameter(s)	Values			
Baseline	None				
RD	None				
LA	λ	1.2	2.25	5	10
DS1	α	0.8	0.85	0.9	0.95
DS2	β	0.8	0.85	0.9	0.95
DS3	$\alpha = \beta$	0.2	0.5	0.7	0.9
SV	λ	1.2	2.25	5	10
	$\alpha = \beta$	0.2	0.5	0.7	0.9

National scope runs

In Table 3.4, the scenario design for the national runs can be seen. The parameter values chosen for the scenario families are based on both literature and the results of the broad and narrow parameter sweep. The aim is to use the widest possible range wherein the values are still somewhat realistic.

For *loss aversion* the highest value of $\lambda = 10$ is chosen because (Ebrahimigharehbaghi et al., 2022) found that to be the highest *loss aversion* factor for Dutch homeowners concerning ER. $\lambda = 2.25$ is taken from (Tversky & Kahneman, 1979). $\lambda = 1.2$ and $\lambda = 5$ are chosen as a lower bound where there is only a slight *loss aversion* and as a middle ground between the two literature values.

For DS1 and DS2 the values of the varying parameter are more informed by the results of the narrow parameter sweep. These results show that for $\alpha, \beta < 0.8$ there is almost no variation in outcomes. Thus, a narrow band of values is chosen to obtain a better resolution. In the scenarios where both parameters are varied, DS3, the results show that there is a noticeable difference over the range $0.1 \leq \alpha = \beta \leq 0.9$. Thus, for the national runs a broader range is chosen for DS3 than for DS1 and DS2.

The SV scenario family is a combination of the LA family and the SV3 family. Here, the ranges for the parameter values are taken from the other families and the Cartesian product of them is made to create the new scenarios.

3.1.3 Analysis

After the simulations have been ran, the output data is analysed. The results of a run are compared with the other results from the same scenario family and a reference scenario. In order to easily compare the large number of scenarios, the most important tool used is a graphic comparison, made by plotting the curves for all scenarios of the same family in the same graph. In this way, it can be seen how changing cognitive bias parameter values influences the outcomes of the decision-making process. When more detailed comparisons need to be made, a numerical comparison is done.

3.2 Integration of PT

For the integration of CPT into Hestia, a non-calibrated version of the model is used. The reasoning behind this is as follows. In a calibrated model, the modelling results are congruent with the validation data. This means that the real world interactions are captured in the model, be it explicitly or implicitly. As PT is not explicitly modelled in Hestia, it's influence would be included implicitly through another mechanism, for example the S-curves. To then add a module that explicitly models the influence of PT would make that influence felt twice.

In addition, keeping all S-curve parameters at a value of 1 makes them not have any influence. This means that all considerations in the decision-making process are financial. In this way it is possible to see the isolated influence of the biases included in PT on ER decision-making without taking into account any other factors.

Within Hestia, only costs are considered, which means that a higher number is less attractive, while PT calculates a utility score, which means a higher number is more attractive. Thus, at the end of the PT calculations, when the PT-score is finally computed, the negative of this score is passes to Hestia as if they were costs. The complete code of the PT module can be found in Appendix A or on GitHub (Wijngaart van den, 2022b). For each bias, a option to turn it either on or off in provided, to be able to see their effects separately.

3.2.1 Reference dependence

The implementation of the *reference dependence* bias consists of two parts. First, the reference option needs to be determined, and afterwards the Δx_i need to be computed.

One of the possible options in the decision-making process in Hestia is to reinvest in the current configuration. To be able to determine the Δx_i, it is necessary to know which configuration this is and what the associated costs are. However, this re-investment is presented as just one of the options, without any way of identifying it as such. Thus a way to determine which investment option is the re-investment or the reference option is devised.

Every investment option is based on a configuration of multiple building parts. As noted in Chapter 2.3, these consist of installations and dwelling components. For an investment option, it is possible to check how many of these building parts are the same as in the current configuration of the dwelling. For every building part that is identical, a similarity-score is increased by one. The investment option with the highest score is taken to be the re-investment into the reference situation option, as it is the option which is most alike the current configuration.

When this reference investment option is determined, it is possible to determine the Δx_i of each option. The two dimensions of which the Δx_i is evaluated are the investment costs and the longer term yearly costs.

The calculations for the investment and yearly costs follow Equations 3.2.1 and 3.2.2 respectively. The investment costs $C_{investment}$ are calculated by addition of all possible one-time costs C_i, the subtraction of all relevant subsidies S_i and the multiplication with the appropriate sales taxes ST_i. Even though these costs and subsidies are one-off, the values that are used in the calculations are the annualised values. The conversion from one-time to annual is regulated by only a factor, and at the end of the entire calculation the investment costs are added to the yearly costs. For this to work they need to have the same unit, which makes euro/year the unit of choice. The yearly costs consists of only costs C_j, as there are no subsidies available, although sales taxes ST_j still apply.

$$C_{investment} = \sum_{i=1}^{N} (C_i - S_i) \cdot ST_i \tag{3.2.1}$$

$$C_{yearly} = \sum_{j=1}^{M} C_j \cdot ST_j \tag{3.2.2}$$

The Δx_i of an option are then calculated as per Equation 2.1.2, which in this case evaluates to Equations 3.2.3 and 3.2.4. Because we are working with costs instead of utility, the order of the reference and the option under consideration are reversed compared to Equation 2.1.2, as to keep the Δx_i a measure of utility.

$$\Delta x_{investment} = C_{investment-reference} - C_{investment-option} \tag{3.2.3}$$

$$\Delta x_{yearly} = C_{yearly-reference} - C_{yearly-option} \tag{3.2.4}$$

Once the Δx_i have been calculated for both dimensions, the final PT score is computed by addition of those two Δx_i after the relevant biases have been applied, as per Equation 3.2.5. The negative of this PT-score is then passed on to Hestia as a yearly costs.

$$PTscore = v(\Delta x_{investment}) + v(\Delta x_{yearly}) = -costs_{Hestia} \tag{3.2.5}$$

3.2.2 Other biases

The other biases in PT are anchored on the *reference dependence* bias, as they act on the Δx_i. Thus, when *loss aversion* or *diminishing sensitivity* are active, *reference dependence* is also active. At the start of the run, Hestia checks which biases are active and evaluates certain blocks of code so that the active ones are taken into account in the calculations. The implementation of the other biases follows Equation 2.1.3.

For *loss aversion*, the introduction of the bias is quite simple. After the Δx_i have been evaluated for both the investment and yearly costs, there is a check to see whether their values are positive or negative. If a Δx_i is positive, it is passed on without modification. if it is negative, it is multiplied with a factor λ, the *loss aversion* bias coefficient. This modified Δx_i, is then passed on to be summed with the other, possibly also modified, Δx_i. In this way, *loss aversion* can work in the two dimensions separately.

The *diminishing sensitivity* bias is implemented in a similar way. Once the Δx_i has been calculated, there is a check to see if it is positive or negative. If it is positive, it is raised to the power of α, if negative to the power of β. These modified Δx_i are then passed on.

It is also possible to have both *loss aversion* and *reference dependence* active. In this case, when Δx_i is negative, it is first raised to the power β, after which it is multiplied by λ. In the positive case, there is only the raising to the power of α.

3.3 Validation data

In addition to seeing how the biases change the results in comparison with a reference scenario, it is also interesting to see how the results relate to the real world. For this, validation data about the composition of the Dutch housing stock is needed. This validation data is gathered from the WoonOnderzoek Nederland (WoON) energy module. The WoON is a housing survey conducted by the Centraal Bureau voor de Statistiek (CBS), the central bureau of statistics of the Netherlands, every three years. It covers roughly 40.000 homes. The energy module is a sub-survey that is conducted every six years. In this survey, the focus lies on the energy use of the inhabitants, on which information is gathered through a survey, and the energetic qualities of the dwelling, on which information is gathered through a technical assessment done by an expert. The energy module covers around 4.500 dwellings. Although these 4.500 dwellings are only a small part of the total housing stock, which consists of around 7 million dwellings, it is still representative due to a weighting factor associated with each dwelling.

As the energy module contains information on, among other things, the heating installations and energy labels, it is a complete source of validation data. The energy module survey has been conducted in the years 2000, 2006, 2012 and 2018. This means that there are four data points per variable on which a comparison can be made. There is no information on the state of the housing stock in the years between those data points, but we assume that the changes in energy characteristics over the housing stock are gradual, as ER are often costly and labour intensive measures.

The information on the distribution of energy labels and heating installations is found through the public publications based on the data. The publications used are: (Stuart-Fox et al., 2019) for 2018, (Tichelaar & Leidelmeijer, 2013) for 2012, (Ministerie van VROM, 2010) for 2006 and both (Ministerie van VROM, 2002) and (Ministerie van VROM, 2003) for 2000. The data gathered is shown in Tables 3.5 and 3.6. To make these numbers clearer, the evolution over time of these variables is shown in Figures 3.1 and 3.2.

From these figures we gather that over time, the Dutch housing stock has become better insulated. The shares of energy labels A, B and C have increased over the time period, while the shares of the F and G labels have decreased. The shares of labels D and E fluctuate, but stay relatively stable. This might be caused by the fact that dwellings with a worse energy label insulate to D or C, while at the same time dwellings with energy label C or D insulate to a better one.

When looking at the shares of heating installations we see that the shares are stable in comparison with the energy labels. The share of gas-based heating systems increases slightly over time, mostly because of the decrease in other heating options. These are mostly direct heating installation i.e. stoves. The share of collective heating options diminishes in 2018. There are three possible explanations for this. Either some district heating networks have been disbanded, which seems unlikely; the total number of dwellings has increased with those new dwellings not having a collective heating option; or fewer homes with collective heating were in the survey sample.

Table 3.5: Projected relative distribution of energy labels of Dutch dwellings.

Year	A(+)	B	C	D	E	F	G	Total
2000	0%	3%	10%	17%	18%	25%	27%	100%
2006	3%	13%	21%	16%	14%	17%	16%	100%
2012	5%	14%	24%	21%	16%	12%	8%	100%
2018	17%	16%	29%	16%	10%	6%	5%	100%

Table 3.6: Projected relative distribution of heating installations of Dutch dwellings.

Year	Gas-based central heating	Collective heating	Other	Total
2000	79%	11%	10%	100%
2006	84%	10%	6%	100%
2012	84%	11%	5%	100%
2018	87%	6%	7%	100%

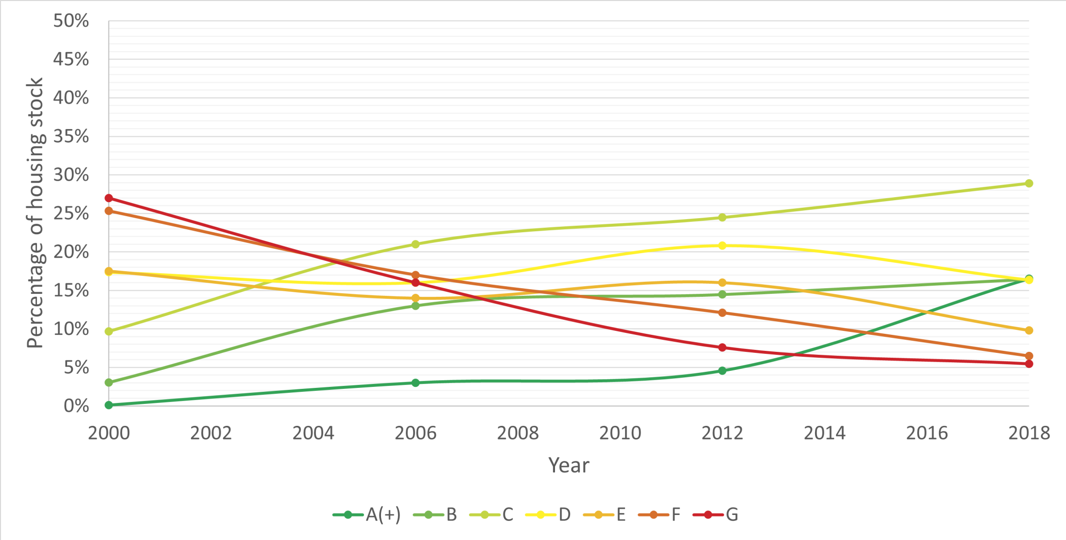

Figure 3.1: Overview of the projected energy label distribution over time.

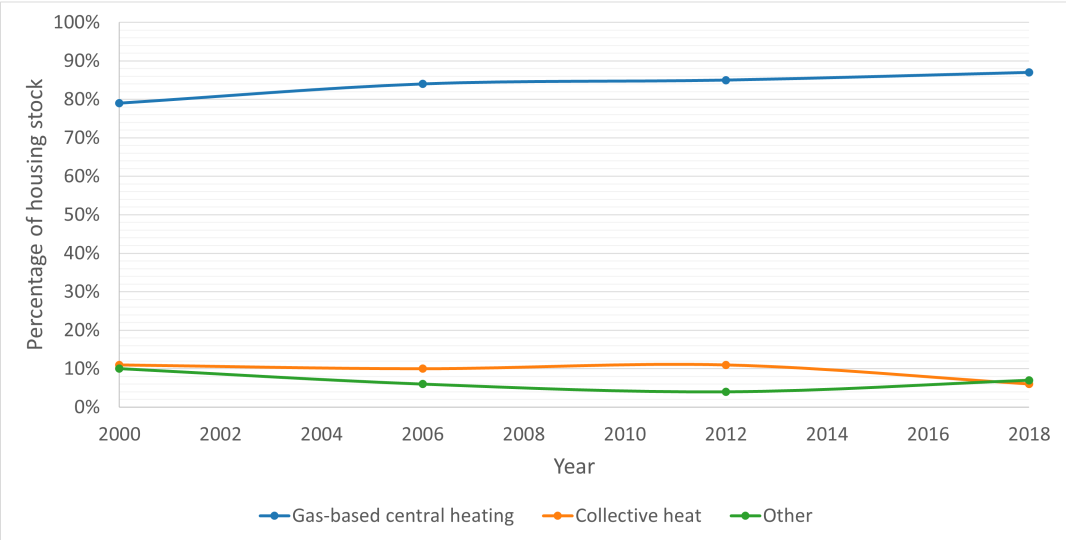

Figure 3.2: Overview of the projected heating system distribution over time.

4 Results

In this chapter, the results of the different simulation runs will be shown. They are organised per cognitive bias. For each bias, first the results of the parameter sweeps, if present, will be given. Afterwards, the results from the national runs are presented.

4.1 Baseline

The first scenario that is to be discussed is the baseline scenario. Here, no cognitive biases are present, so all considerations are financial. In Figures 4.1 and 4.2, the evolution of the heating system and energy label distributions can be seen. For completeness and to get a sense of the numbers, in Appendix B the model output is given for every relevant variable, for every year. Here, one can also see that the total number of dwellings grows, as new ones are built.

In Figure 4.1, it can be seen that the share of gas fired boilers decreases quickly, from about 95% of the total number of dwellings in the starting year, 2000, to around 53% in year 18, which would be 2018. The share of collective heating options does not change much. There is about a 1.5% increase. The other heating options do however increase sharply. Starting at a share of 0%, in the final year 41% of dwelling has an alternative heating installation installed.

When we turn to the energy labels in Figure 4.2, we can see that there is also a large increase, this time in the dwellings with energy label A. Starting from a 7% share and growing to a 47% share. All other energy labels have a decreasing share over the runtime. The label G decreases the most, from 22% to 9%. The share of label B increases in the first year, but then decreases as the rest does.

In addition to looking at how the distributions of heating installation and energy label shares evolve over time, we can also see how the modelling results compare to the validation data. Concerning heating, it is clear that the share of gas diminishes far quicker than it should according to the data. In contrast and because of this, the share of alternative heating sources grows far quicker. The share of collective heating is a bit lower than in the validation data. There is a discrepancy between the starting values of the model and the data. This is caused by an assumption in the model. In the starting year, every dwelling that is not connected to a heat network is assumed to use a gas boiler. This is why the share of alternative heating options starts at 0% and the share of gas-based installations at 100% minus the share of collective heating.

In the case of the energy label distribution, there are similar patterns. The first is that here too the values in the starting year are very different between the validation data and the model. For labels A, B and C, the shares from the model are much higher than those from the WoON, while for label F the opposite is true. The shares of labels D, E and G do not align precisely between the two sources, but they are closer to each other. The other trend that is visible both for the labels and the heating installations, is that there is a very rapid move towards sustainability. In the model there is a large and quick increase in the share of energy label A, which is not visible in the data, just like the increase in alternative heating options.

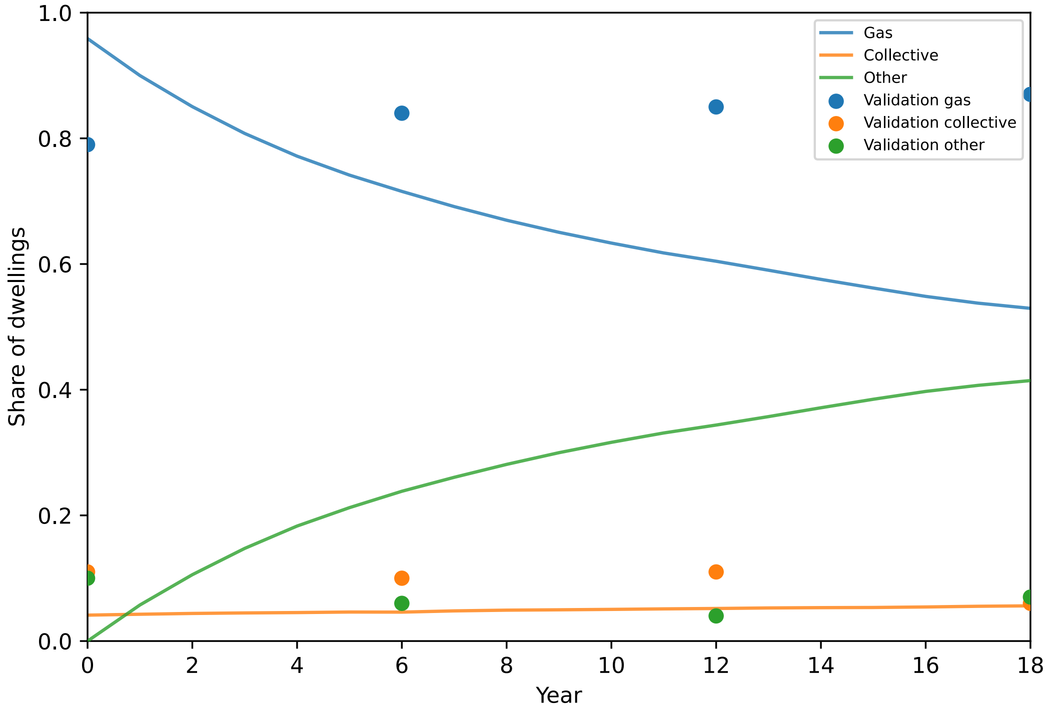

Figure 4.1: Distribution of heating installations over time in the baseline scenario.

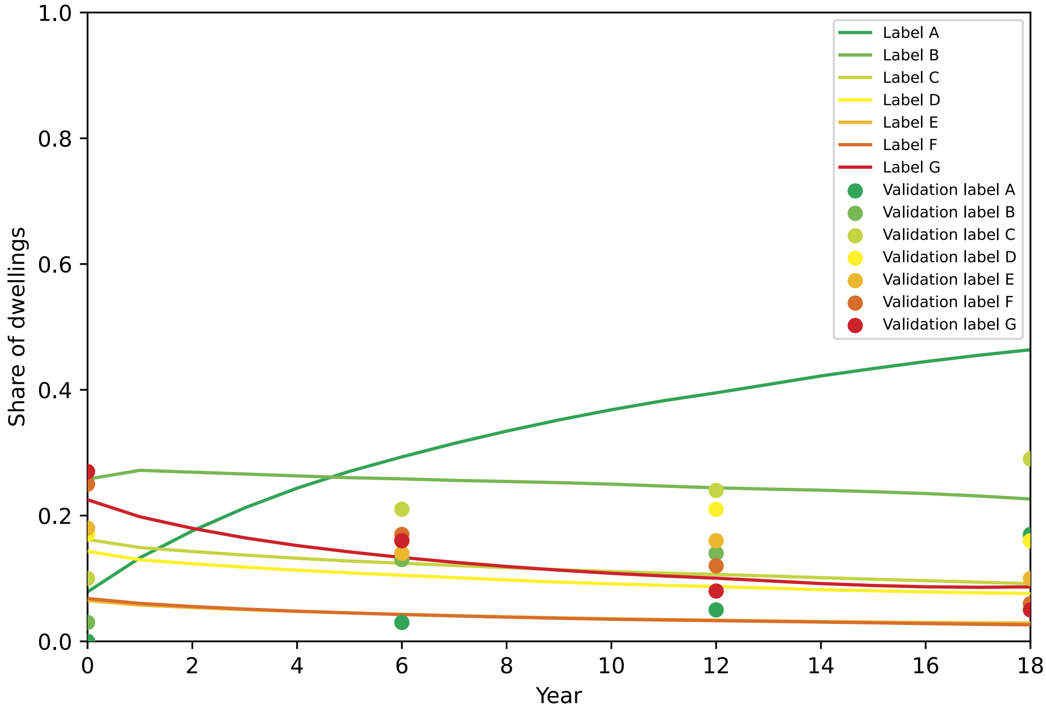

Figure 4.2: Distribution of energy labels over time in the baseline scenario.

4.2 Reference dependence

In Figures 4.3 and 4.4, the influence of the *reference dependence* cognitive bias can be seen. The figures show simulation results for a run with *reference dependence* and the baseline scenario, to contrast.

When we look at the heating installation, we see the same trends as in the baseline scenario. Gas-based installations decrease in share over time, while alternatives grow. However, the changes are smaller in the RD scenario. Instead of falling to a share of 53% in 2018, the share of gas-based heating options is 57%. As there is almost no difference in the share of collective heating options, this also means that the share of alternative heating options is lower in the RD scenario. In 2018, it is 37% instead off 41%. The outcomes of the *reference dependence* scenario are thus closer to the validation data than those of the baseline.

In the case of the energy labels, differences are also visible. Here the trends are also the same. The largest difference is found in the share of energy label A. In the RD scenario, it is lower than in the baseline scenario. At the end of the simulation, the share of label A is 39% compared to of 46% in the baseline scenario, bringing it more in line with the validation data. The share of energy label B is also lower in the RD scenario. However, the difference is much smaller, measuring only 1.5% at most. For all the other energy labels, the share is larger in the RD scenario. In all cases, the difference is 2.5% or smaller over the entire runtime. Of course, because an energy label is computed for each dwelling, all the differences between the shares sum to zero.

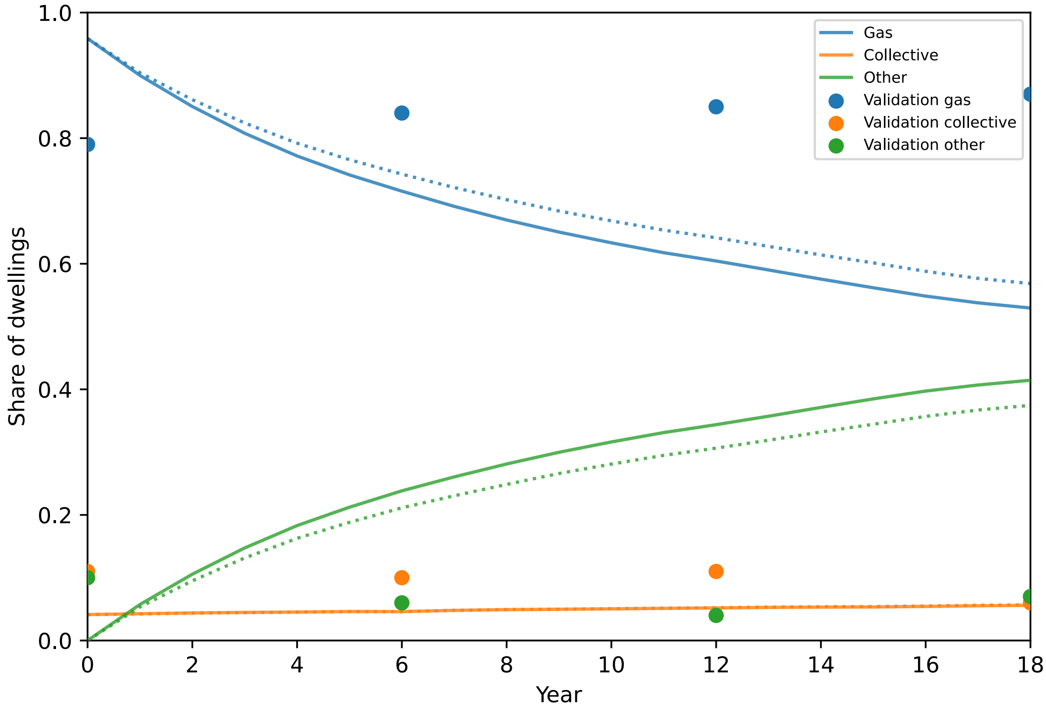

Figure 4.3: National reference dependence results for heating installations. The solid line represents the reference scenario, while the dotted lines represent the scenarios with reference dependence.

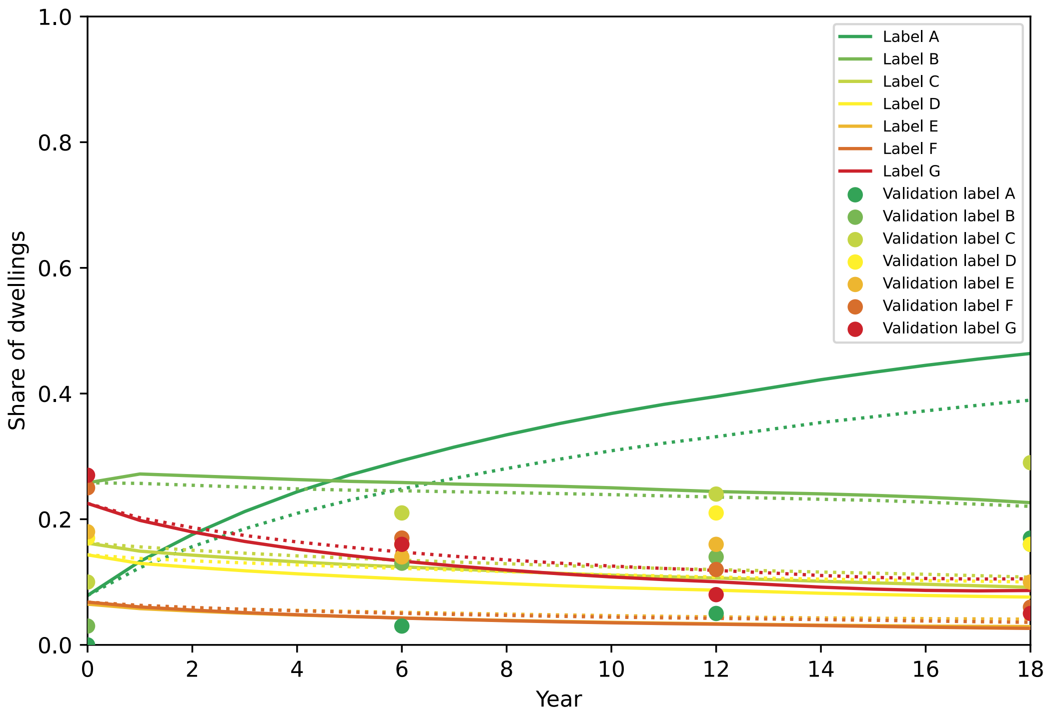

Figure 4.4: National reference dependence results for energy labels. The solid line represents the reference scenario, while the dotted lines represent the scenarios with reference dependence.

4.3 Loss aversion

4.3.1 Broad parameter sweep

Figures 4.5 and 4.6 show the simulation results for the broad parameter sweep performed for the municipality of Zeewolde. In the figures, the solid lines represent the RD scenario and the dotted lines represent the results for differing *loss aversion* parameter strengths. The parameter values used in the runs are shown in Tables 3.2, 3.3 and 3.4. In order to only consider the effects of *loss aversion*, the results must be compared to a simulation that includes *reference dependence* and not the baseline. Otherwise the effect of the *reference dependence* is also included in the comparison.

The influence of *loss aversion* on the share of heating installations can be seen in Figure 4.5. The trend is the same for all values of λ and the reference scenario. When looking at the share of gas, the bundle of dotted lines above the solid line represent the group of scenarios with $\lambda \geq 10$. Between these scenarios there is little difference. The dotted lines lower than the reference scenario are all runs where $\lambda < 1$. However, the decrease in the share of gas-based heating installations does not follow the decrease in λ. The lowest shares are found for $\lambda = 0.1, 0.01, 0.001$, while for smaller values of λ the share of gas is slightly higher. Thus, there appears to be a tipping point in the behaviour. As the share of collective heat differs very little between the scenarios, the differences in the shares of gas are mirrored in the share of other heating options.

The same pattern that holds for the heating systems also holds for the energy labels, as can be seen in Figure 4.6. The differences between the scenarios are most pronounced for the share of energy label A. Here, the dotted lines underneath the solid line represent the scenarios where $\lambda \geq 10$. Thus, the share of dwellings with energy label A is lower at these values. The two bundles of dotted lines above the solid line are grouped in the same way as with the heating systems. The topmost bundle consists of the results of the scenarios where $\lambda = 0.1, 0.01, 0.001$, while for the slightly lower bundle $\lambda \leq 0.0001$. As the total share of dwellings is 1, the increases and decreases in the share of energy label A lead to decreases and increases respectively in the sum of the shares of the other labels.

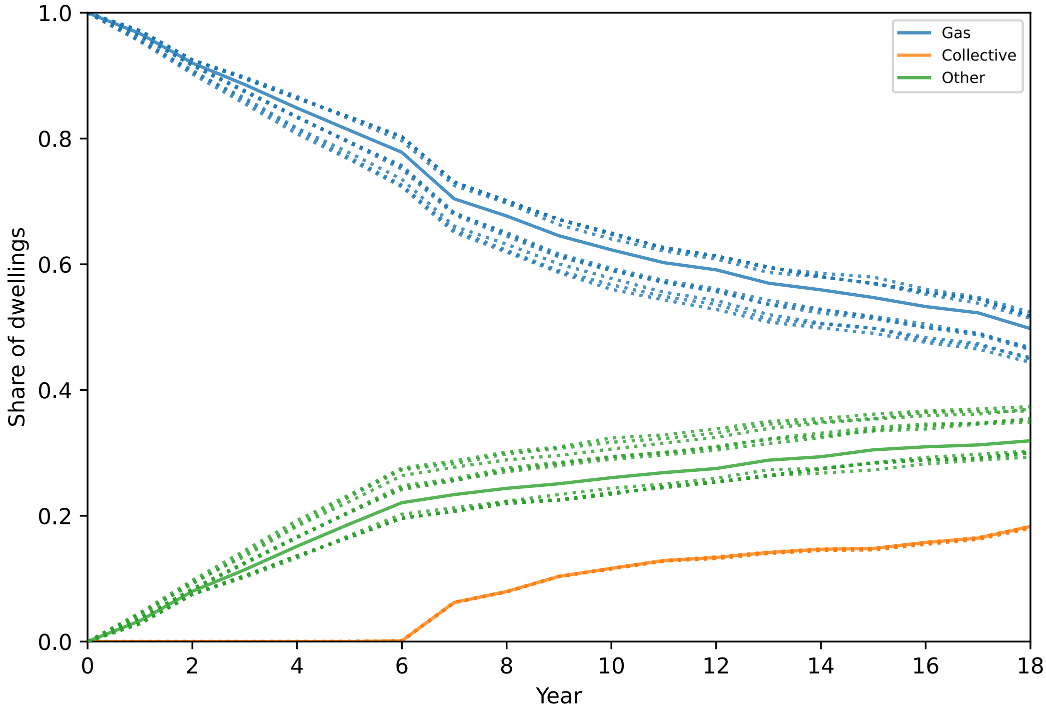

Figure 4.5: Loss aversion broad parameter sweep results for heating installations. The solid line represents the reference scenario, while the dotted lines represent the scenarios with loss aversion.

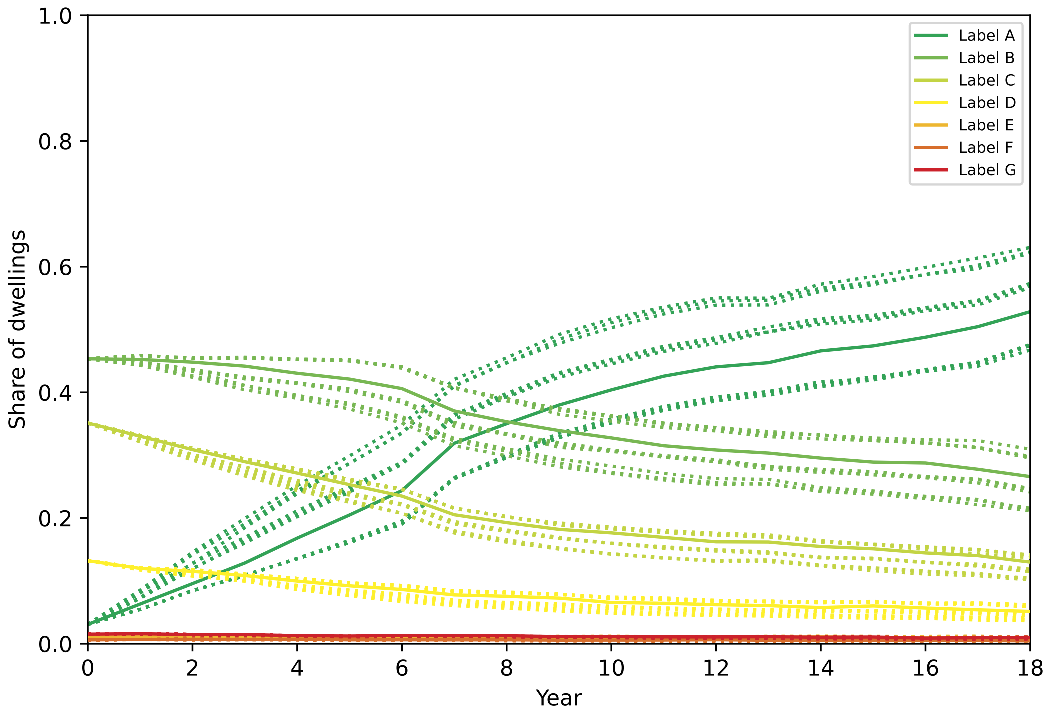

Figure 4.6: Loss aversion broad parameter sweep results for energy labels. The solid line represents the reference scenario, while the dotted lines represent the scenarios with loss aversion.

4.3.2 Narrow parameter sweep

The effects of the narrow parameter sweep can be seen in Figures 4.7 and 4.8. The differences between the reference scenario and the *loss aversion* scenarios are smaller than with the broad sweep. In all cases, the share of gas increases in comparison with the reference. However, this increase is not monotonic with respect to λ. The share of gas-based heating options fluctuates with respect to λ, although generally with higher λ there is a higher share of gas. As the shares of collective heating are very similar, the share of other heating options exhibit the inverse behaviour compared too the gas-based heating option shares.

When we look at the energy labels in Figure 4.8, we can see that the differences between scenarios are smaller than in the broad sweep. In all cases, the LA scenarios lower the share of energy label A compared to the reference. Although here too the relation is not monotonic, the behaviour is not so erratic as with the gas-based heating options. Although the absolute differences in shares stay roughly the same between years, in 2006 there is a large percentage-wise difference between the reference scenario and the *loss aversion* ones. This is due to the lower overall share of dwellings with energy label A. As the shares of dwellings with energy label A are lower in the *loss aversion* scenarios, the others must be higher. The label with the largest increase in share is energy label B, while labels C and D also exhibit a small increase. For a more detailed look at the relationships between λ and the shares see Figures C.1 for gas and C.2 for energy label A.

4.3.3 NL runs

The results of the national runs are shown in Figures 4.9 and 4.10. In both cases, the influence of *loss aversion* is very small. The difference between the reference and the *loss aversion* scenarios is never larger than a few thousand dwellings in any direction in any variable. This is about 0.1% of the total number of dwellings.

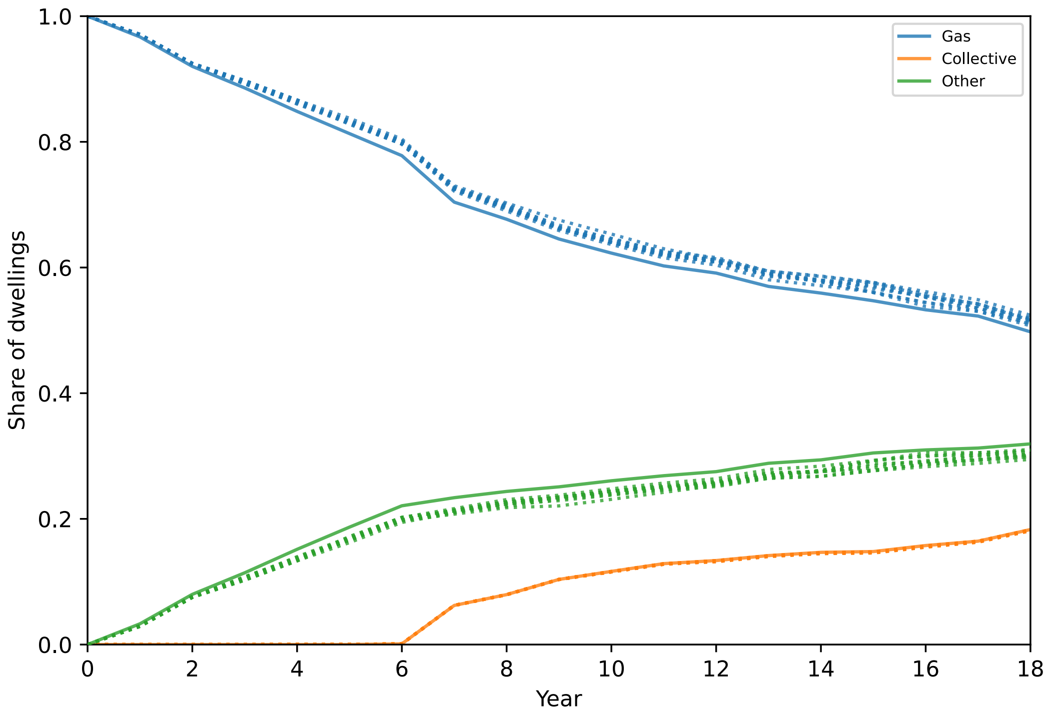

Figure 4.7: Loss aversion narrow parameter sweep results for heating installations. The solid line represents the reference scenario, while the dotted lines represent the scenarios with loss aversion.

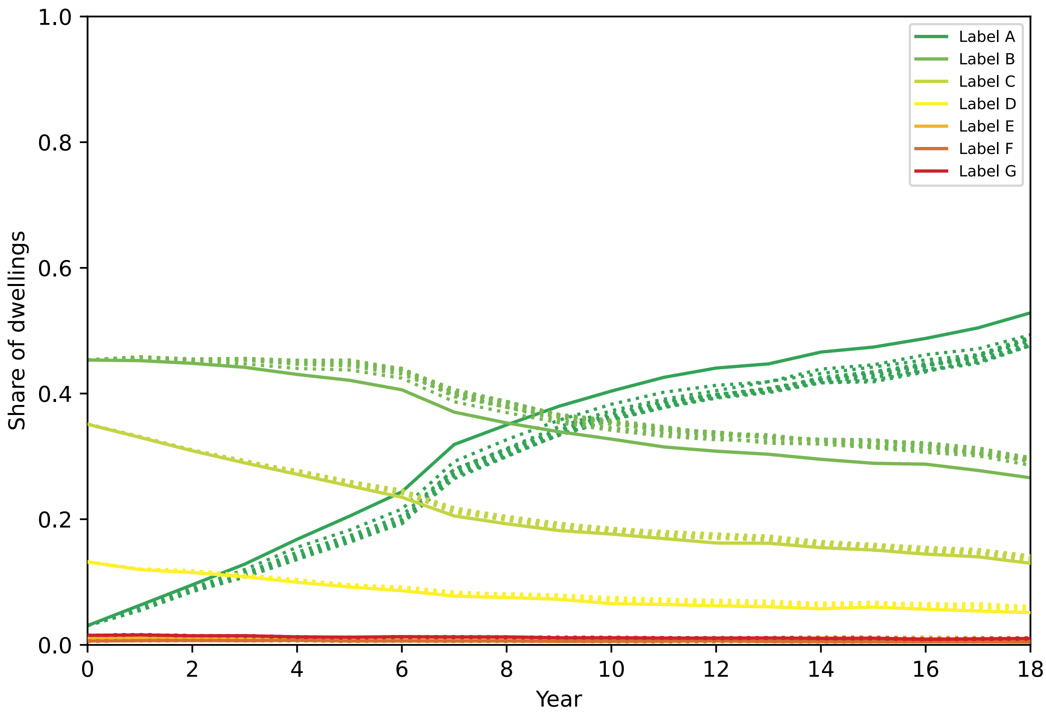

Figure 4.8: Loss aversion narrow parameter sweep results for energy labels. The solid line represents the reference scenario, while the dotted lines represent the scenarios with loss aversion.

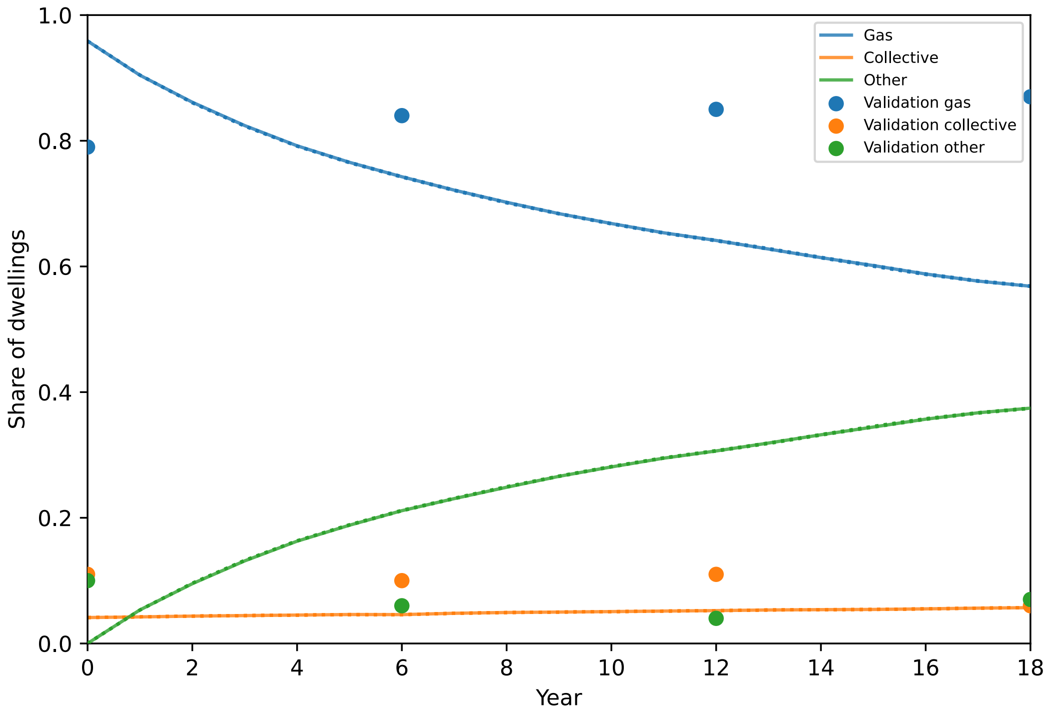

Figure 4.9: National loss aversion results for heating installations. The solid line represents the reference scenario, while the dotted lines represent the scenarios with loss aversion.

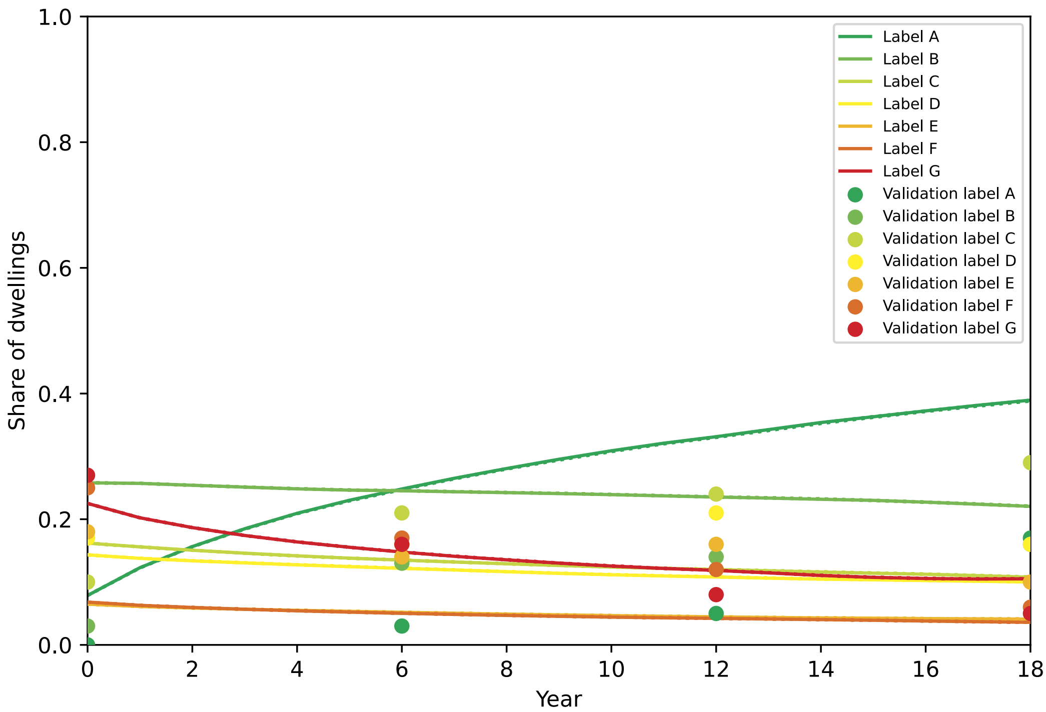

Figure 4.10: National loss aversion results for energy labels. The solid line represents the reference scenario, while the dotted lines represent the scenarios with loss aversion.

4.4 Diminishing sensitivity

Because the *diminishing sensitivity* cognitive bias is regulated by two parameters, α and β, the analysis of the influence of the bias is done is separate steps. First, the influence of each parameter individually is assessed. Then, the influence of both parameters together is discussed. Just as with *loss aversion*, the reference scenario that the *diminishing sensitivity* scenarios are compared with is the *reference dependence* one, in order to isolate the effect of the cognitive bias. The values of the parameters used can be seen in Tables 3.2, 3.3 and 3.4.

4.4.1 Broad parameter sweep

In Figures 4.11 and 4.12, the results for scenario family DS1 are shown, giving the influence of the α parameter. When looking at the share of gas-based heating installations, we can see that there are scenarios that do not differ much from the reference scenario. These are the scenarios with $\alpha < 1$. In the scenarios with $\alpha > 1$, the share of gas is lower than in the reference scenario. The higher the value of α, the lower the share of gas-based heating installations. For these scenarios there is also a slightly lower share of collective heating options. Thus, the share of other heating installations is greater than in the reference scenario.

The energy labels show a different behaviour. When the share of energy label A is considered, it can be seen that there are three bundles of curves around the reference curve. The one above represents the scenarios where $\alpha = 10$ and $\alpha = 100$. For higher values of α, the share of energy label A is lowest. For $\alpha < 1$, there is a slight decrease in comparison with the reference scenario. These trends hold in reverse for the other energy labels.

Figure 4.13 shows the influence of the broad parameter sweep on heating installations for DS2. For $\beta \geq 1000$ there is a large increase in the share of gas-based heating installations, inversely proportional to the parameter value. For all other values of β, there is a decrease in comparison with the reference scenario. For these scenarios there is no clear relation between the share of gas and the value of β. In the scenarios with $\beta \geq 1000$ the share of collective heating options is slightly lower than in the reference. For $\beta = 1000$ the share of alternative heating options is even lower than the share of collective heating options.

With the energy labels, shown in Figure 4.14, there is a clear demarcation between scenarios where $\beta > 1$ and those where $\beta < 1$. In the first case there is a decrease in the share of energy label A, which is quite substantial for $\beta \geq 1000$. This decrease in the share of energy label A comes with an increase in the shares of all other energy labels. The second group of scenarios show an increase in the share of energy label A, with the highest share being achieved for $\beta = 0.1$. For all other energy labels, the share is decreased.

The results for DS3, where both α and β are varied, are shown in Figures 4.15 and 4.16. In the case of the heating installations, we see that the scenarios with $1000 \leq \alpha, \beta \leq 1000000$ have an extremely high share of gas. For these scenarios, only some collective heating options are more attractive. These are also the scenarios where the share of collective options is lower than the reference scenario. For $\alpha, \beta = 10, 100$ the share of gas is lower than the reference, while for $\alpha, \beta < 1$ the share is higher again, although it is still lower than the extreme cases detailed above.

For the energy labels the same extremes are visible for $1000 \leq \alpha, \beta \leq 1000000$. The share of energy label A does not increase until year 6. From then on the share increases in line with the share of collective heating options. It can be seen that for the other labels for these scenarios the shares are higher, especially for label C and B. Apart from these extremes, all other configurations also bring about a lower share of energy label A. For energy label B, the scenarios where $\alpha, \beta < 1$ follow the same trend as for the scenarios where $1000 \leq \alpha, \beta \leq 1000000$, but after year 5 the share starts to drop to become more in line with the other scenarios. For the other energy labels the shares are a bit higher than in the reference scenario.

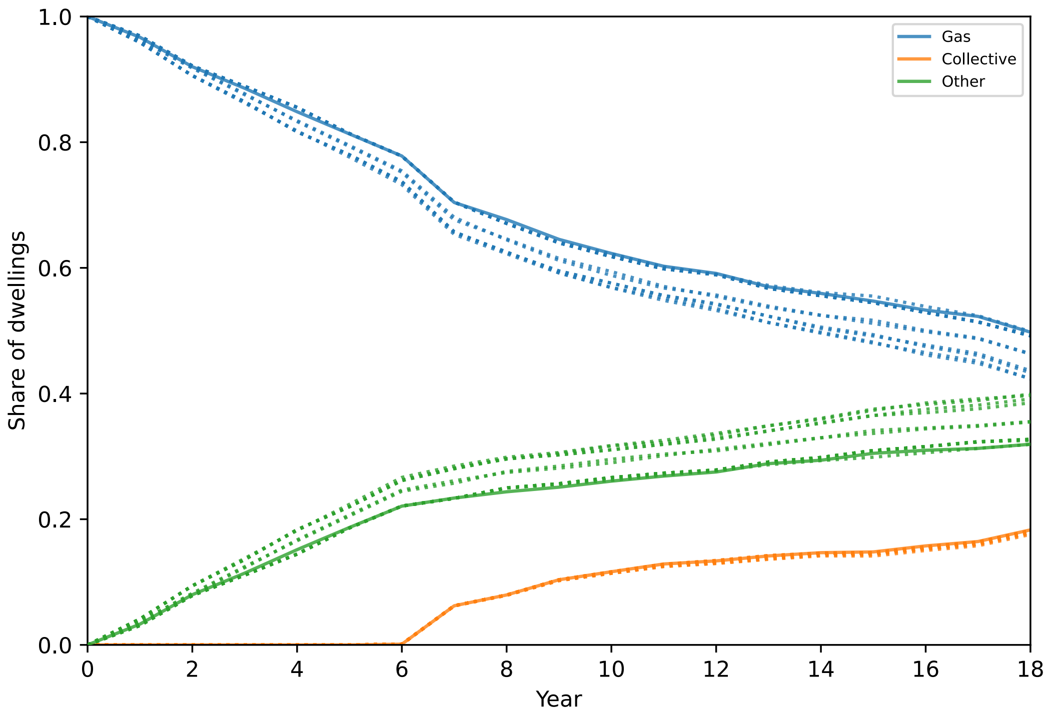

Figure 4.11: Diminishing sensitivity α broad parameter sweep results for heating installations. The solid line represents the reference scenario, while the dotted lines represent the scenarios with a different value for α.

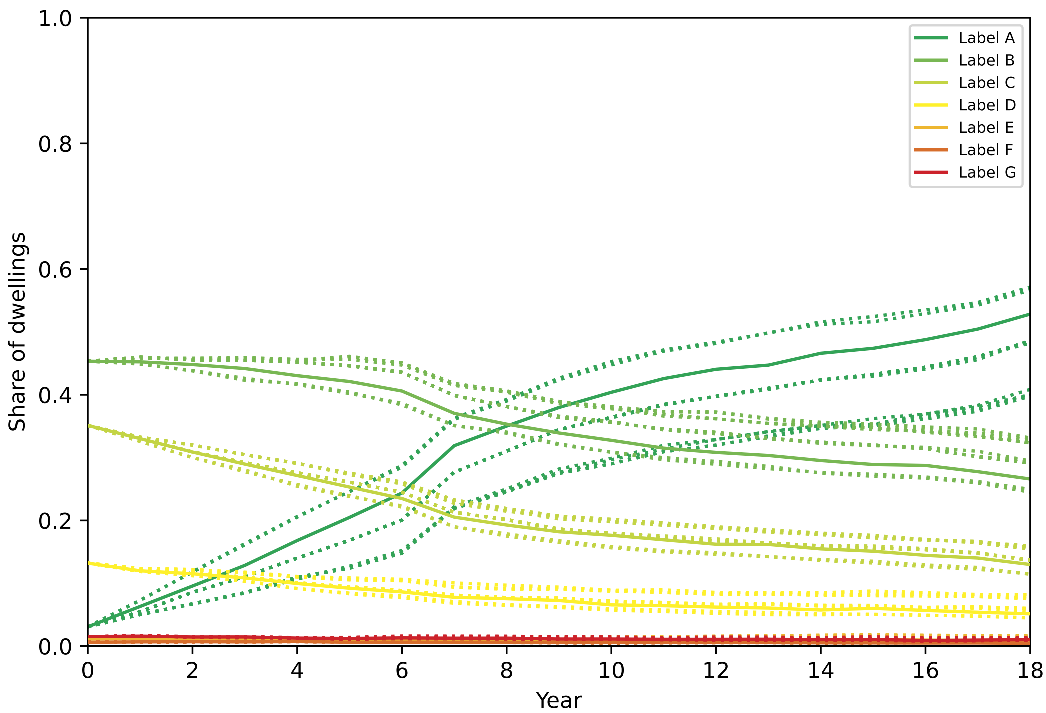

Figure 4.12: Diminishing sensitivity α broad parameter sweep results for energy labels. The solid line represents the reference scenario, while the dotted lines represent the scenarios with a different value for α.

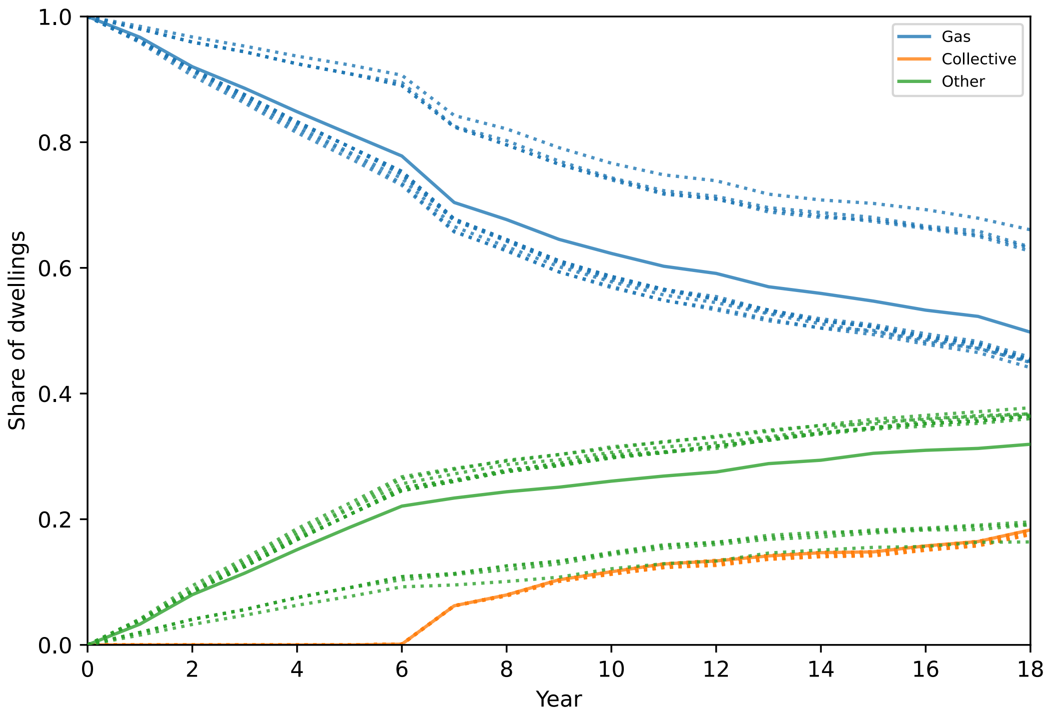

Figure 4.13: Diminishing sensitivity β broad parameter sweep results for heating installations. The solid line represents the reference scenario, while the dotted lines represent the scenarios with a different value for β.

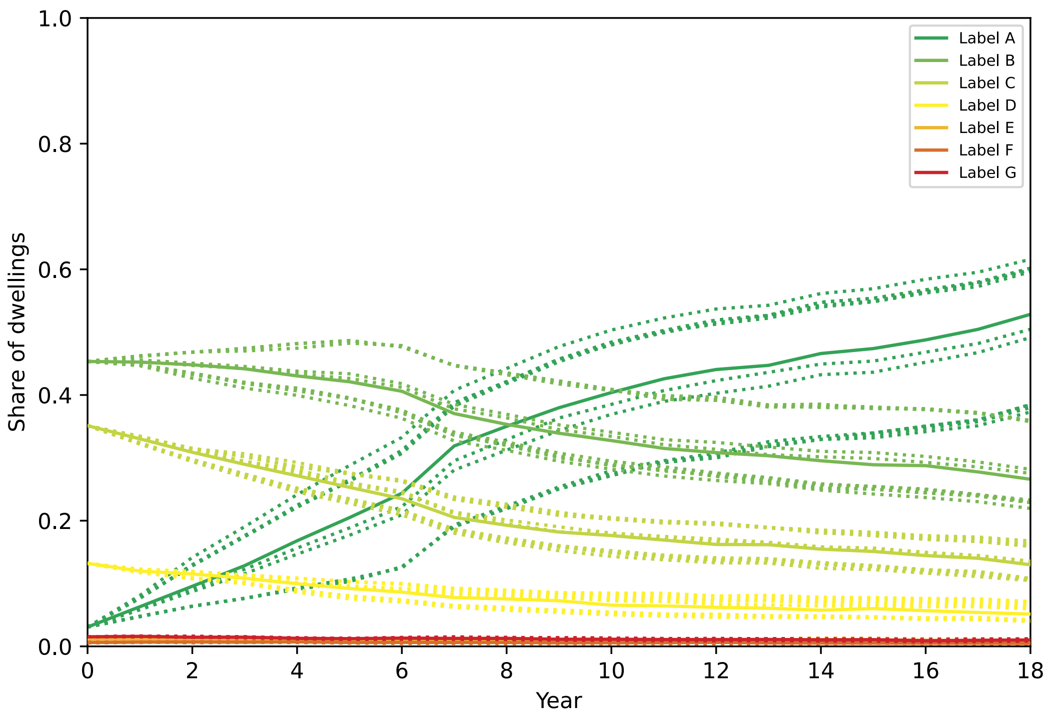

Figure 4.14: Diminishing sensitivity β broad parameter sweep results for energy labels. The solid line represents the reference scenario, while the dotted lines represent the scenarios with a different value for β.

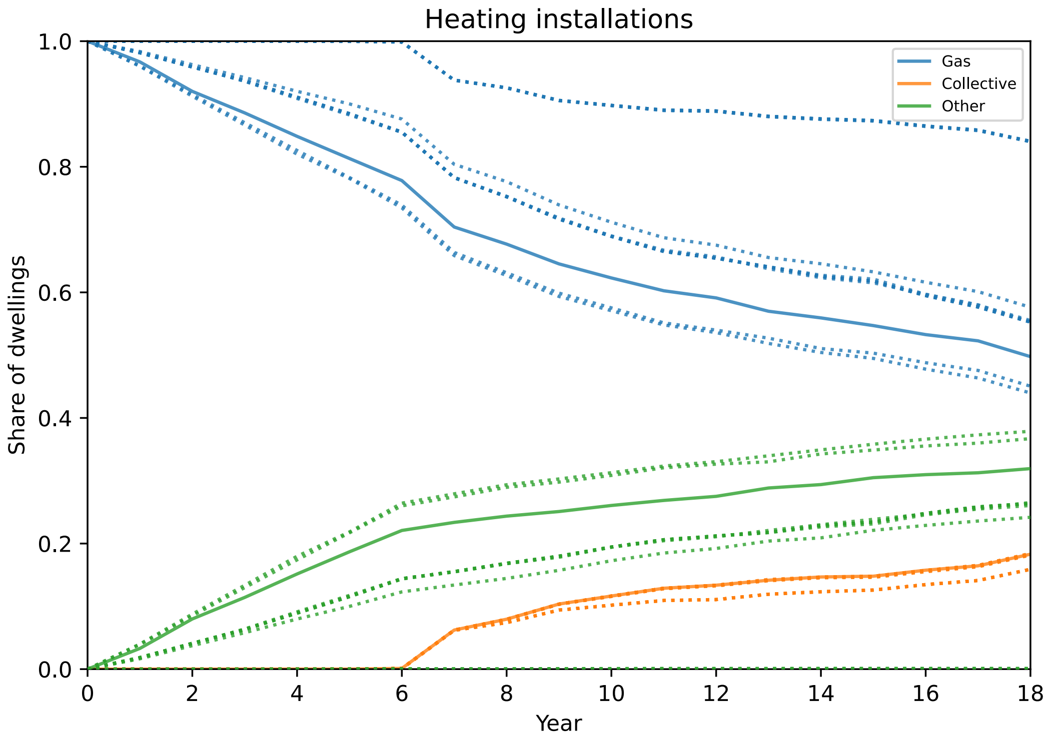

Figure 4.15: Diminishing sensitivity broad parameter sweep results for heating installations. The solid line represents the reference scenario, while the dotted lines represent the scenarios with different values for α and β.

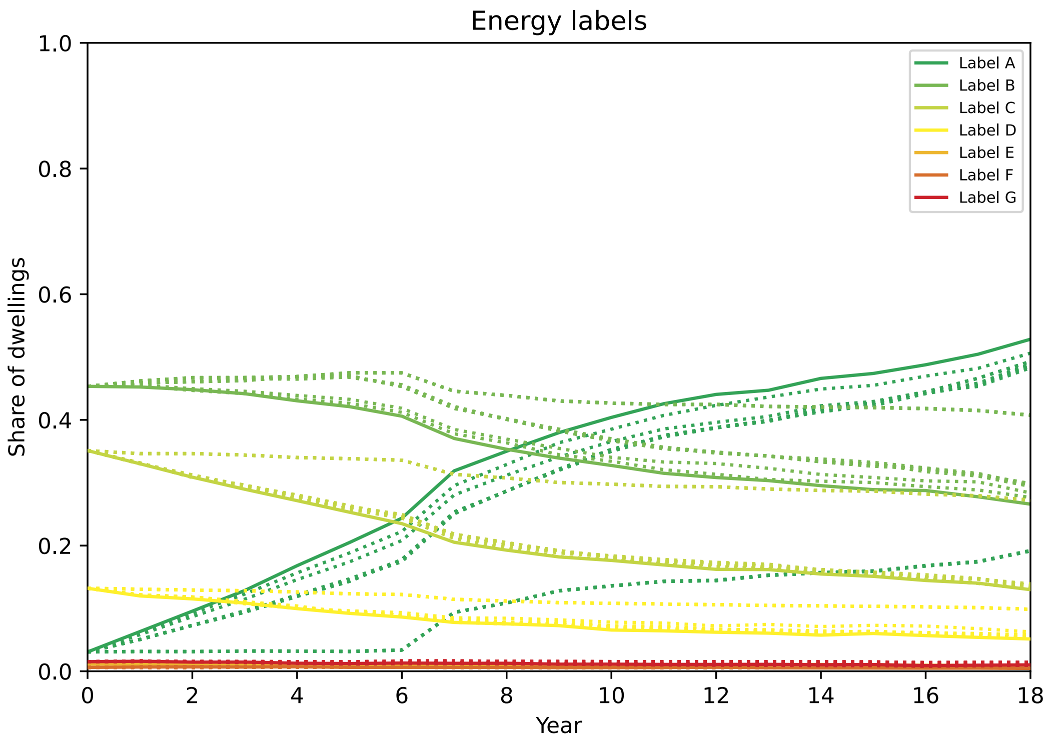

Figure 4.16: Diminishing sensitivity broad parameter sweep results for energy labels. The solid line represents the reference scenario, while the dotted lines represent the scenarios with different values for α and β.

4.4.2 Narrow parameter sweep

In addition to the broad parameter sweeps, narrow parameter sweeps for DS1 and DS2 were also done. The results of the narrow sweep for α (dotted) and β (dashed) on the uptake of heating installations are shown in Figure 4.17. For these scenarios there are only small differences with the reference scenario. In the cases where α is varied, for most of the simulated years the share of gas is higher and the share of alternative installations is lower.

Concerning the share of gas-based heating options in the scenarios where β is varied, there is a visible difference between the reference scenario and the curve for $\beta = 0.9$, which is a bit lower. A bit lower still is that of $\beta = 0.8$. The rest of the scenario curves are situated in a bundle with few differences. The scenario where $\beta = 0.8$ converges with the bundle at the end of the simulation, while the scenario with $\beta = 0.9$ converges to the reference scenario.

Figure 4.18 shows how the narrow sweeps of α and β influence the shares of energy labels. In all cases where α is varied, the share of label A is lower than in the reference scenario. The one curve between the reference curve and the bundle of curves below represents $\alpha = 0.9$. For energy labels other than label A, the inverse picture is true. Every scenario brings about a slightly higher share, with $\alpha = 0.9$ a bit lower than the rest.

The effect on the distribution of energy labels for scenarios with changing β can also be seen, in dashed curves. Again, there is a noticeable difference between the reference scenario, the scenario with $\beta = 0.9$, the one with $\beta = 0.8$ and the bundle of the others. With lower β the share of energy label A increases. The inverse is true for the other labels. With energy label B there is still a noticeable difference between the reference and $\beta = 0.9$, while the difference between $\beta = 0.8$ and the bundle is lost. For the other labels there is not such a clear difference between the scenarios.

For the scenarios where $\alpha = \beta$, DS3, the changes in the shares of heating installations are shown in Figure 4.19. The curves of the different scenarios are almost all clearly individually visible. All scenarios provide a higher share of gas, inversely proportional to the values of α and β. These differences are mirrored in the other heating installations, as the share of collective options does not change between scenarios.

When looking at the energy labels in Figure 4.20, the same demarcation between the curves can be seen for label A and label B. For all scenarios, there is a lower share of label A and a higher share of label B compared to the reference scenario. For the other labels, the differences between the different DS3 scenarios and between the scenarios and the reference is minimal.

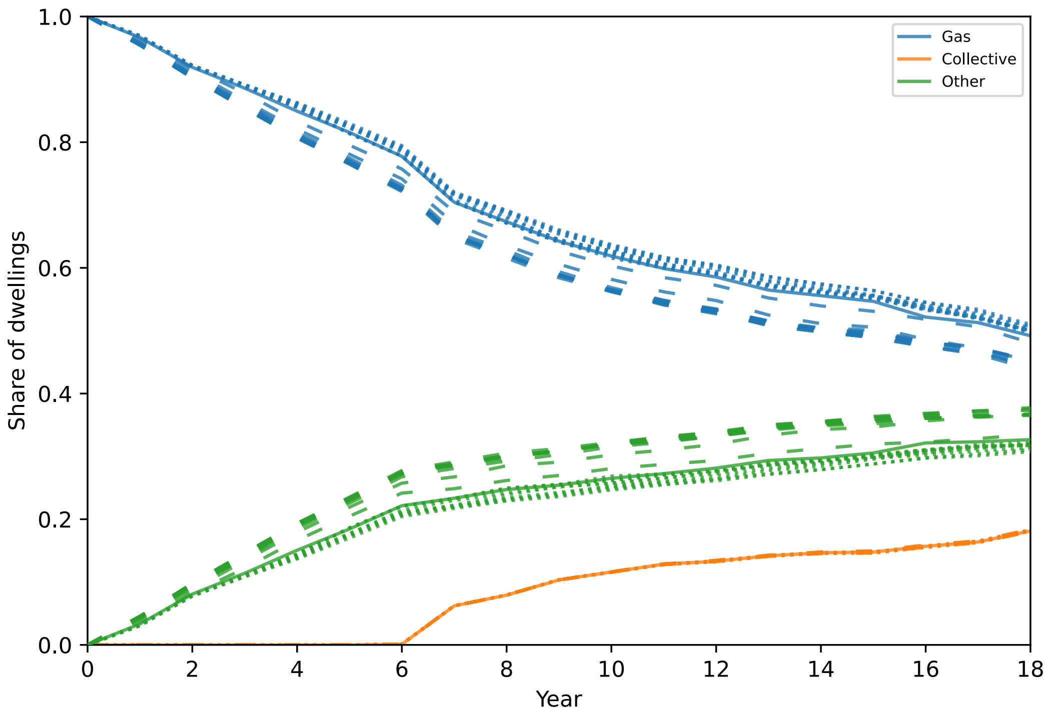

Figure 4.17: Diminishing sensitivity α and β narrow parameter sweep results for heating installations. The solid line represents the reference scenario, the dotted lines represent the scenarios with different values for α and the dashed lines those with different values for β.

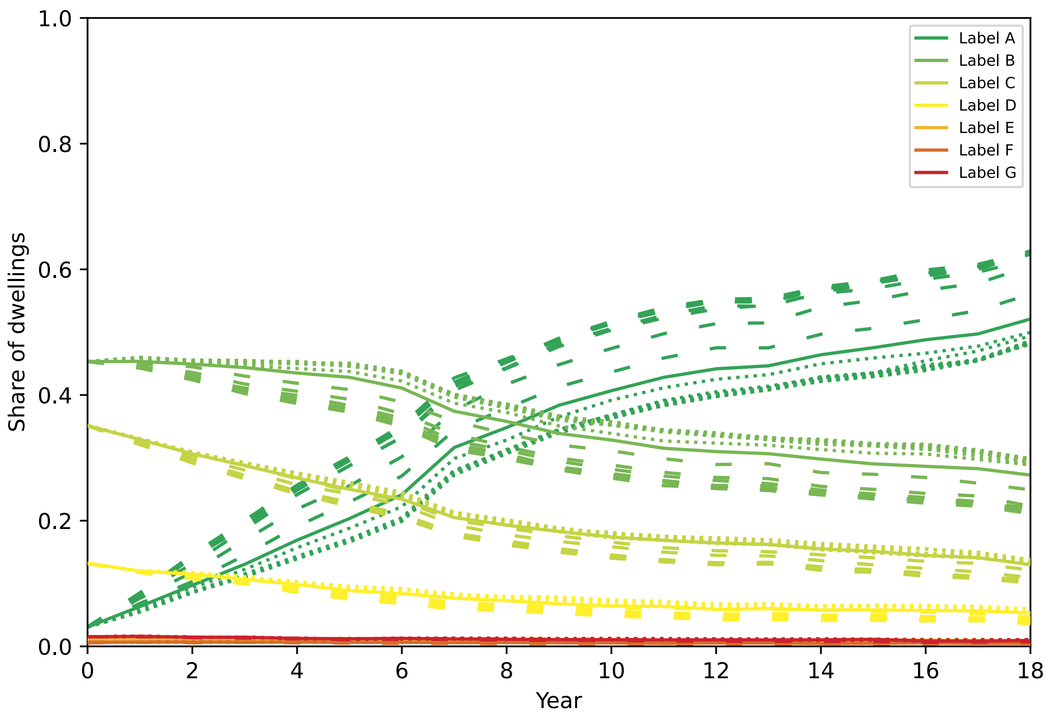

Figure 4.18: Diminishing sensitivity α and β narrow parameter sweep results for energy labels. The solid line represents the reference scenario, while the dotted lines represent the scenarios with different values for α and the dashed lines those with different values for β.

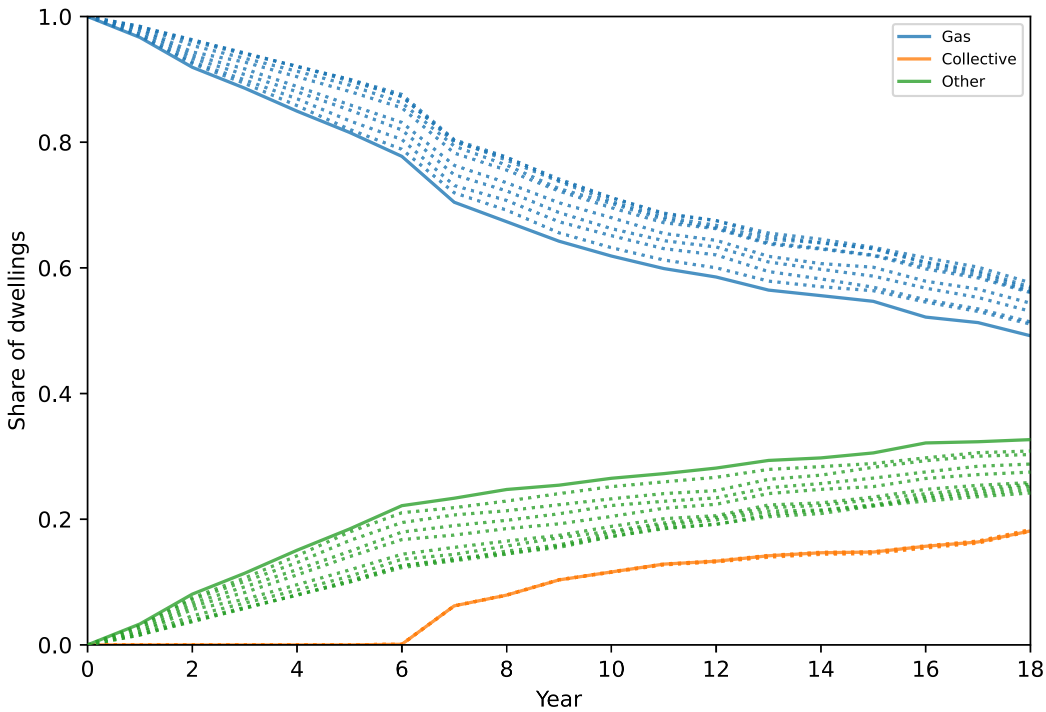

Figure 4.19: Diminishing sensitivity narrow parameter sweep results for heating installations. The solid line represents the reference scenario, while the dotted lines represent the scenarios with different values for α and β.

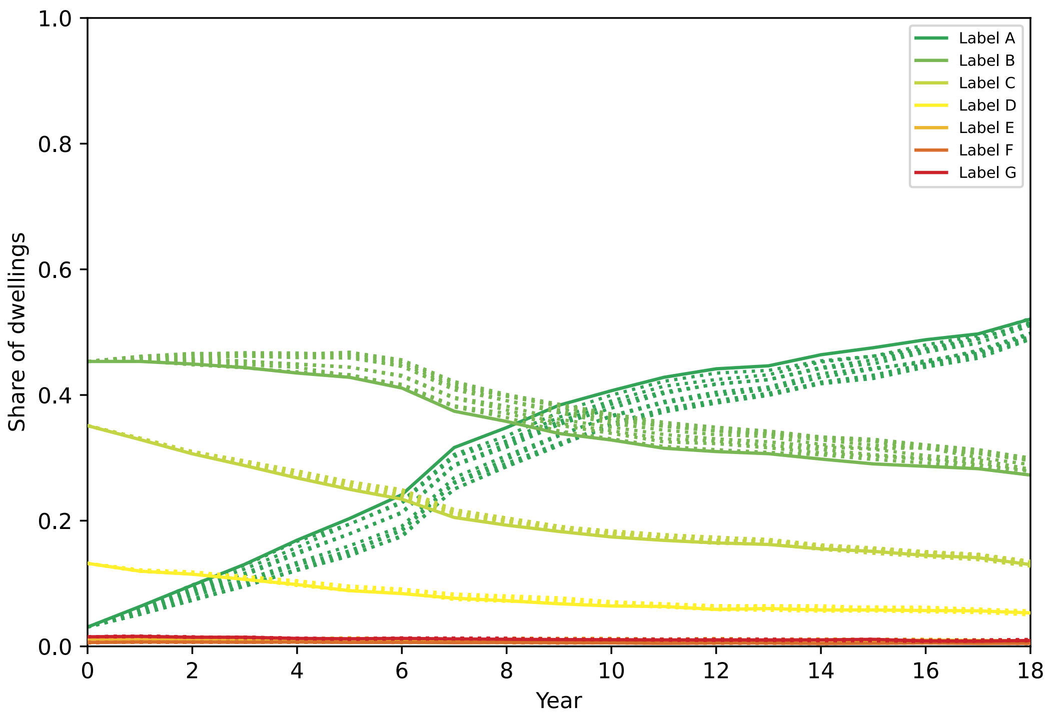

Figure 4.20: Diminishing sensitivity narrow parameter sweep results for energy labels. The solid line represents the reference scenario, while the dotted lines represent the scenarios with different values for α and β.

4.4.3 NL runs

Figure 4.21 shows the influence of *diminishing sensitivity* on the shares of heating installations for the entirety of the Netherlands. For most parameter values, there is little change in the outcomes of the simulation. Only for $\alpha = \beta = 0.2$ and $\alpha = \beta = 0.5$ the curves can be distinguished. $\alpha = \beta = 0.2$ brings about the curves where the share of gas is the highest and the share of alternatives is the lowest. For $\alpha = \beta = 0.5$ the share of gas is slightly higher than the reference, while the share of other heating options is slightly lower. None of the scenarios bring about significant changes in the uptake of collective heating options. According to these results, a lower α and β bring the model output closer to the validation data.

In Figure 4.22 the distribution of energy labels can be seen. Again, most scenarios show little difference from the reference. The curve that shows a higher share of energy label A is the scenario where $\alpha = 1, \beta = 0.7$. In this scenario the share of label B is slightly lower than the reference. The other curve that deviates from the bundle around the reference curve for label A, being lower, is the scenario where $\alpha = \beta = 0.2$. The shares of the other energy labels are slightly higher in this case, with the largest increase in the share of energy label B.

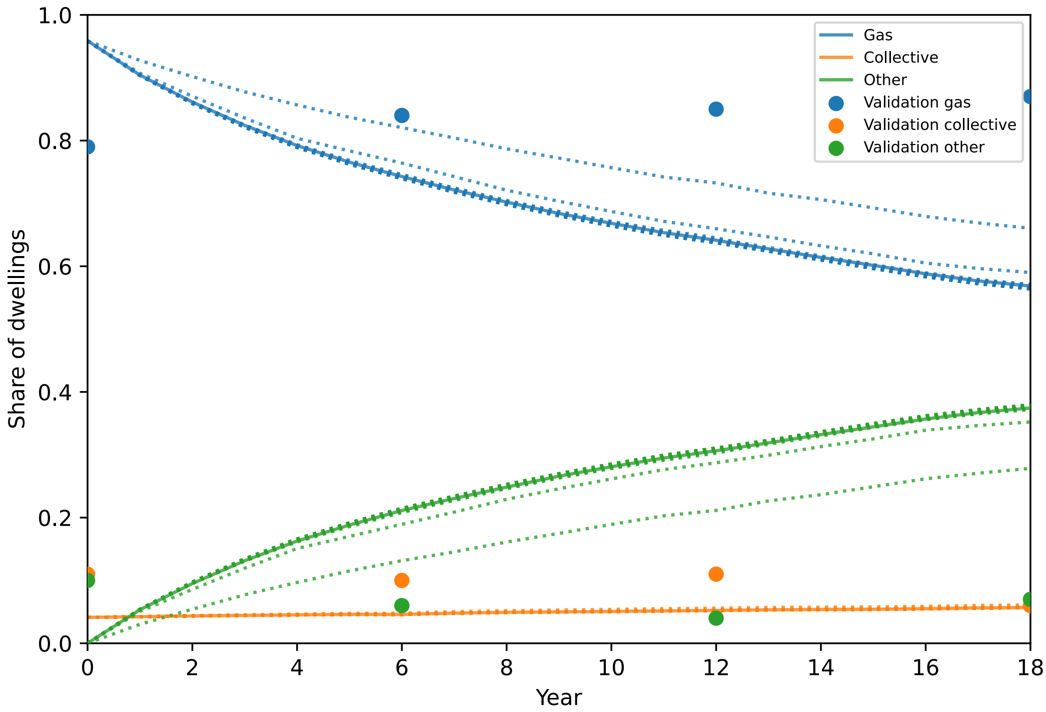

Figure 4.21: National diminishing sensitivity results for heating installations. The solid line represents the reference scenario, while the dotted lines represent the scenarios with diminishing sensitivity.

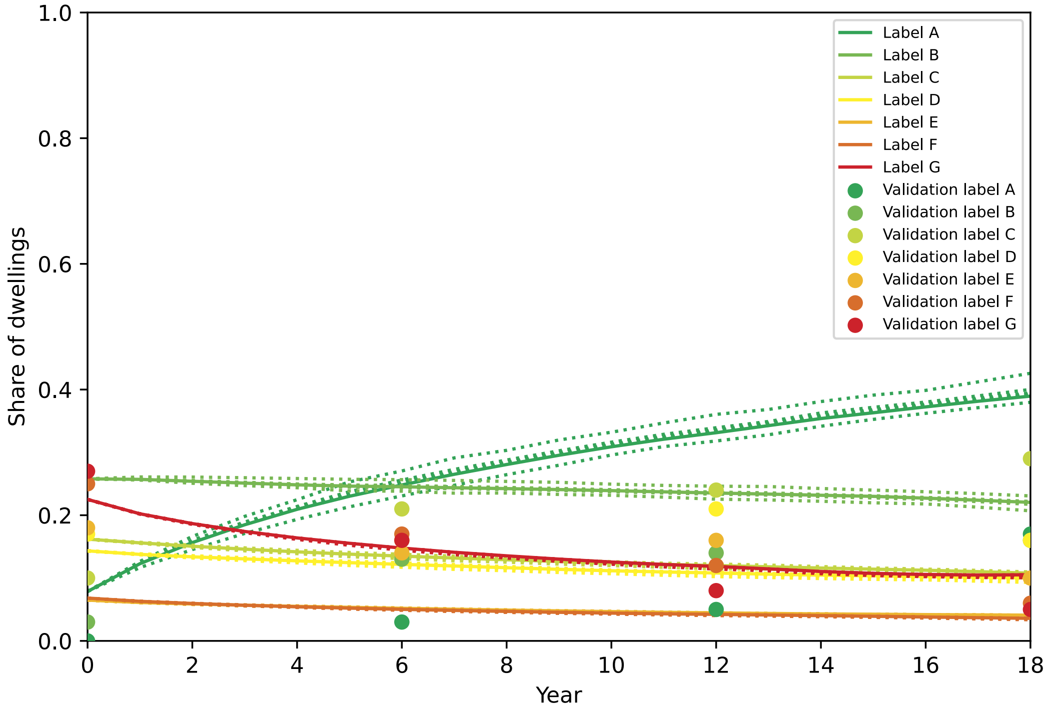

Figure 4.22: National diminishing sensitivity results for energy labels. The solid line represents the reference scenario, while the dotted lines represent the scenarios with diminishing sensitivity.

4.5 Subjective valuation

In this research, *subjective valuation* is defined as the inclusion of all biases in PT. Thus, λ, and α and β can have different values. In all scenarios concerning *subjective valuation*, $\alpha = \beta$. As with the other biases, first broad and narrow parameter sweeps are discussed, after which the results for the national runs are shown. The parameter values used can be seen in Tables 3.2, 3.3 and 3.4.

4.5.1 Broad parameter sweep

For the SV broad parameter sweep the results are shown in Figures 4.23 and 4.24. When we look at the heating installations, three bundles of curves can be distinguished. There is one bundle of almost identical scenarios where the share of gas is very high, being only decreased because of collective options. In these cases, $\alpha, \beta > 1000$, the share of collective options is lower than in the reference situation. The second bundle also lies above the reference situation. Within this bundle there is more internal variation. These are the scenarios where $\alpha, \beta < 1$ and $0.01 < \lambda < 1000000$. For $\lambda \leq 0.01$ and $\alpha, \beta < 1$ the bundle around and under the reference is created. Here, the share of gas increases with diminishing α and β. Even though some scenarios have a higher share of gas than the reference scenario at some point, in all cases the share of gas is lower at the end of the simulation.

In Figure 4.24 the distribution of energy labels is shown. Again, for $\alpha, \beta > 1000$ there is a bundle of identical results. For these scenarios, the shares of the labels do not change until collective heating options are introduced. When this happens, the share of label A increases in conjunction with the share of collective options, with all other shares decreasing. The bundle of curves clearly distinguishable above the rest of the curves for label A represents the scenarios where $\alpha, \beta = 1$ and $0.001 \leq \lambda \leq 0.1$. This means that only *loss aversion* is active. For energy label B these can also be distinguished, but for the other labels they are not distinguishable. The scenarios that yield a curve higher than the reference curve for label A are those where $\lambda < 0.01$ and $\alpha, \beta < 1$. For the other labels the curves are situated lower than in the reference situation. All other combinations of parameter values yield a curve that shows a lower share of energy label A, with the curves for the other energy labels being higher.

4.5.2 Narrow parameter sweep

In Figure 4.25 the results for the narrow parameter sweep pertaining to the heating systems are shown. For all combinations of parameter values, the share of gas is higher than in the reference, and the share of other installations is lower. In order to understand how the individual parameters influence these shares, a few combinations are shown in isolation. We will look at the results for two different values of α and β. As the influence of λ on the results is small for the same α and β, a comparison for those scenarios is not made here. For completeness, the figures can be found in Appendix C, Figures C.3 and C.4. In Figure 4.26 the results for $\alpha, \beta = 0.1$ (dotted) and $\alpha, \beta = 0.9$ (dashed) are shown. In these cases, the differences between the scenarios with the same values for α and β are small. For $\alpha, \beta = 0.9$, the shares of the heating installations are close to the reference situation, while for $\alpha, \beta = 0.1$ they are further from it. However, in all cases the trend is the same as the reference.

The simulation results with regard to the energy labels are shown in Figure 4.27. For all cases, the share of label A is lower than the reference, while the shares for the other energy labels are higher. The curves are not uniformly distributed. Closer to the reference their density is lower. Again, to see the influence of the individual parameters, we will consider the case where $\alpha, \beta = 0.1, 0.9$. However, because for the energy labels there are differences for varying λ, we will also consider the scenario's where $\lambda = 2, 10$.

In Figure 4.28 the results for $\alpha, \beta = 0.1$ (dotted) and $\alpha, \beta = 0.9$ (dashed) are shown. The dotted curves are tight bundles with a sizeable gap between the reference curves and the bundles. The results for $\alpha, \beta = 0.9$, show curves closer to the reference curves. Here, the bundles are more spread out. Figure 4.29 shows the results for the cases where $\lambda = 2$ (dotted) and $\lambda = 10$ (dashed). In comparison with the former, the curves in the latter are closer to each other. There is a gap between the bundle and the reference. In the case where $\lambda = 2$, the gap is smaller. However, the furthest curves are approximately the same distance away from the reference curve.

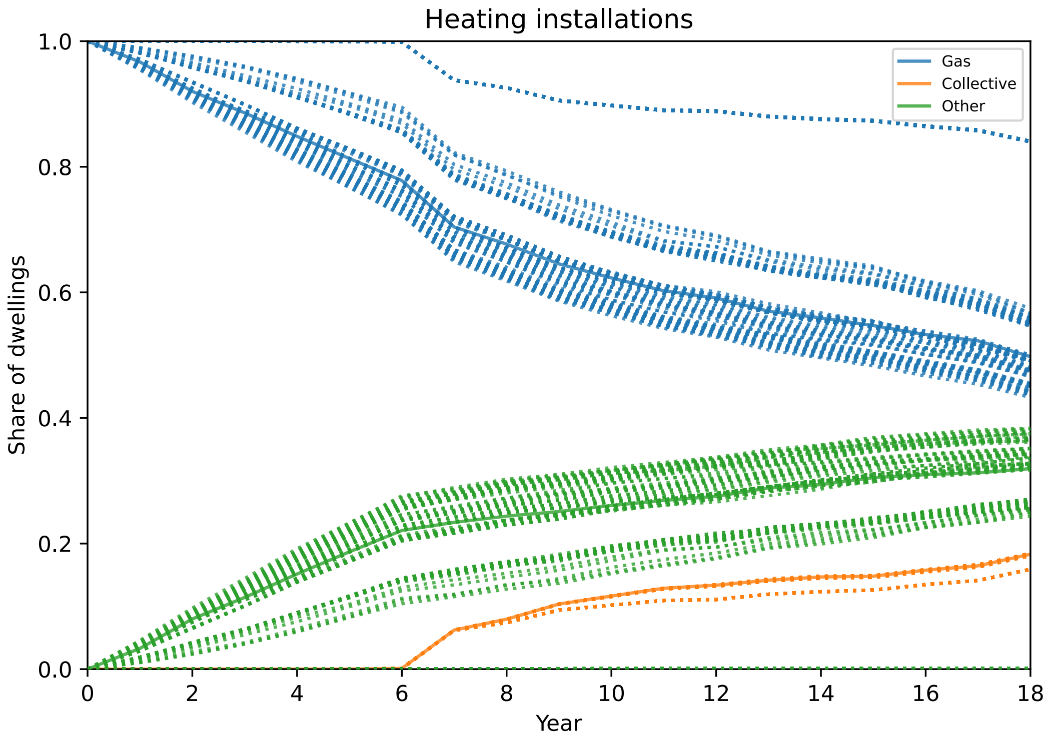

Figure 4.23: Subjective valuation broad parameter sweep results for heating installations. The solid line represents the reference scenario, while the dotted lines represent the scenarios with different values for α, β and λ.

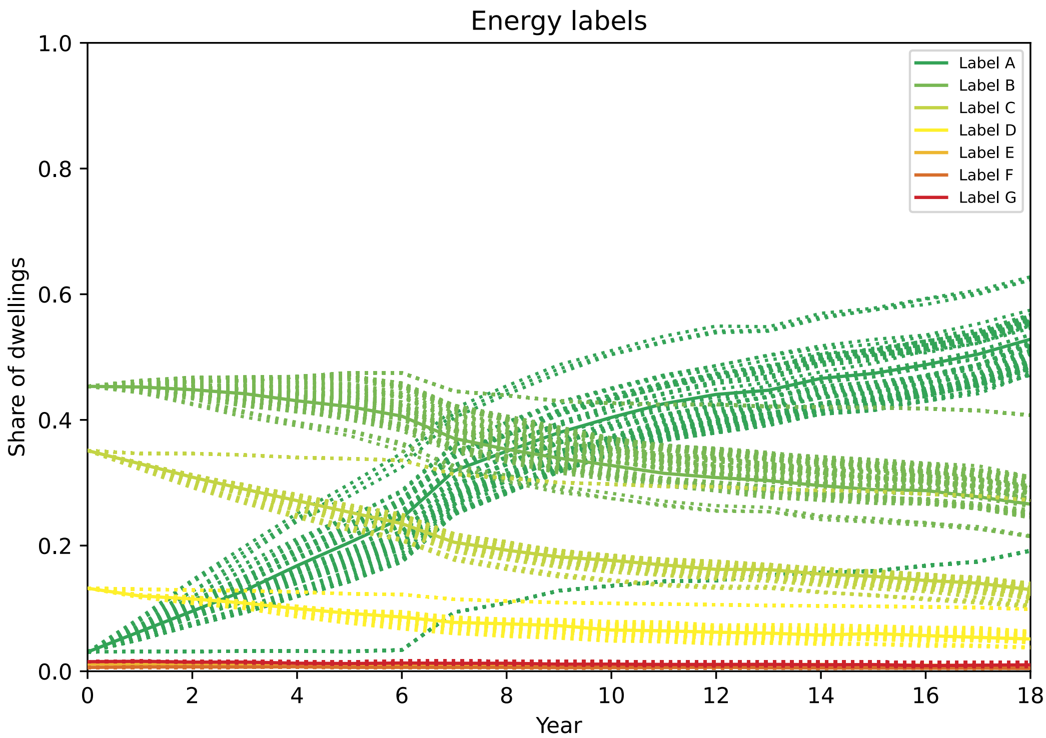

Figure 4.24: Subjective valuation broad parameter sweep results for energy labels. The solid line represents the reference scenario, while the dotted lines represent the scenarios with different values for α, β and λ.

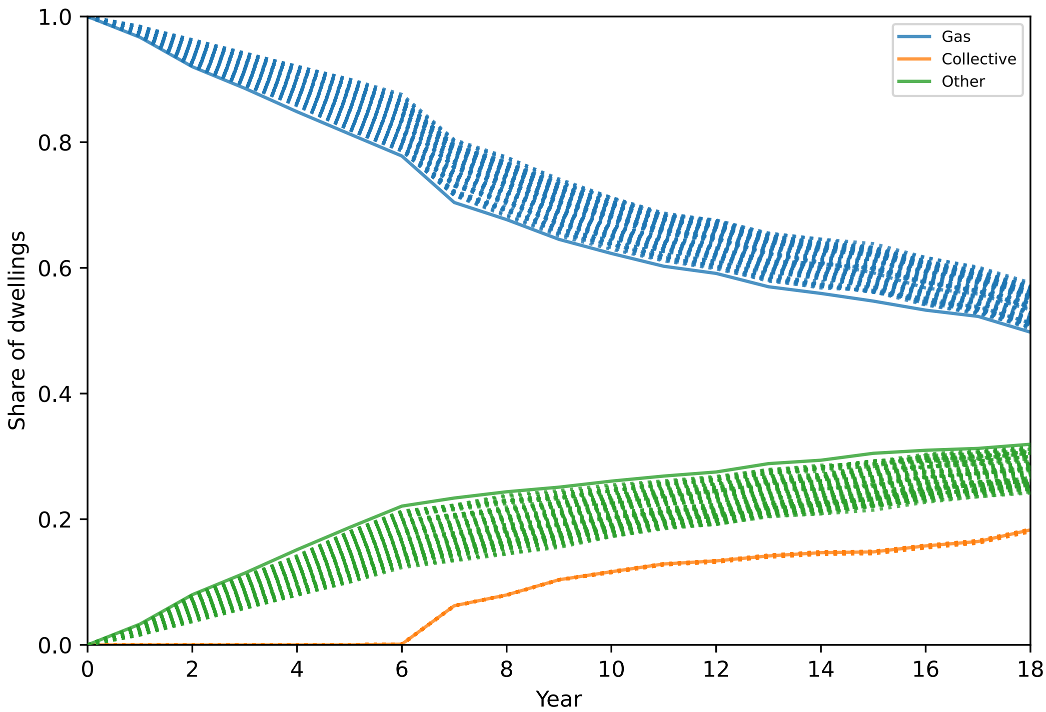

Figure 4.25: Subjective valuation narrow parameter sweep results for heating installations. The solid line represents the reference scenario, while the dotted lines represent the scenarios with different values for α, β and λ.

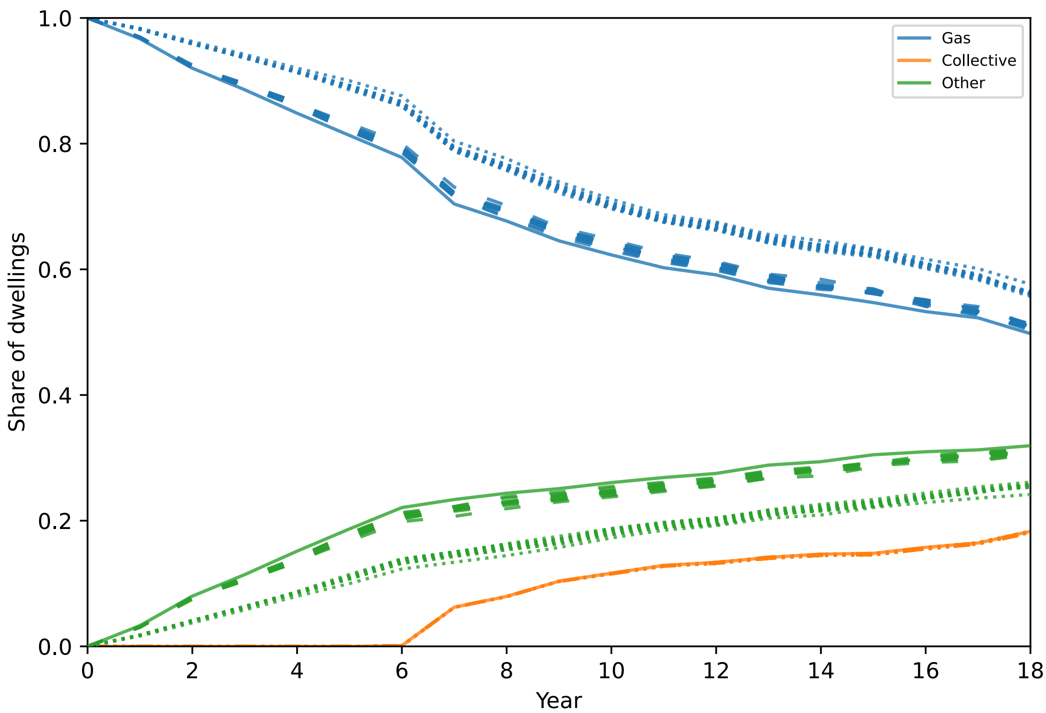

Figure 4.26: Subjective valuation narrow parameter sweep results for heating installations $\alpha, \beta = 0.1, 0.9$. The solid line represents the reference scenario, the dotted lines represent the scenarios where $\alpha = \beta = 0.1$ and the dashed lines represent those where $\alpha = \beta = 0.1$, both with different values for λ.

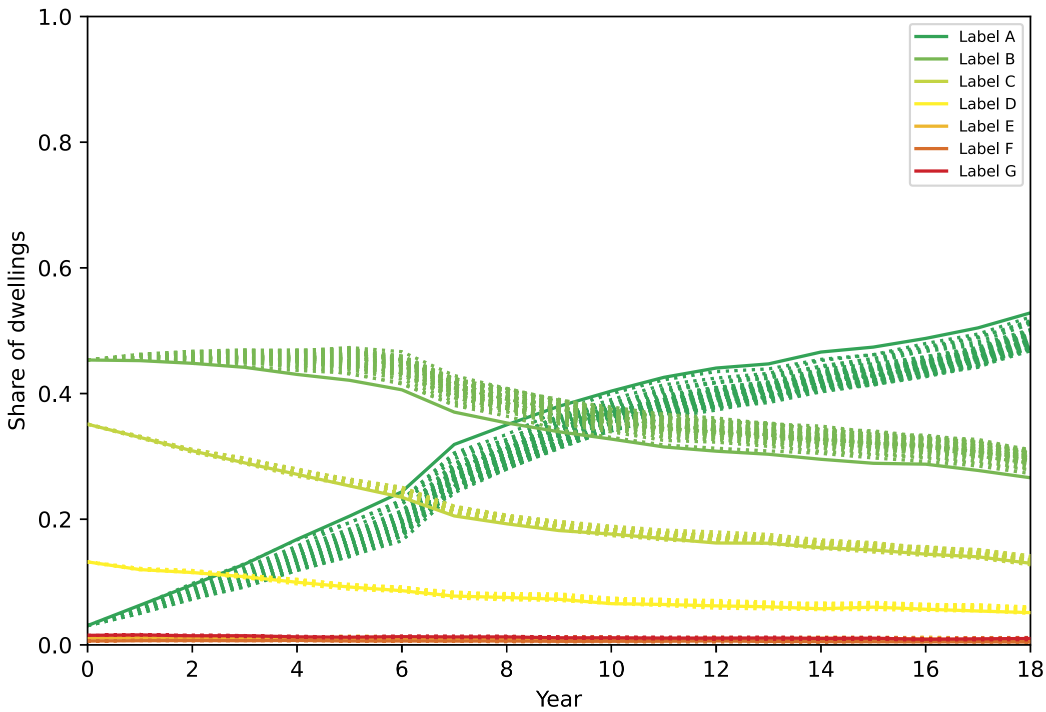

Figure 4.27: Subjective valuation narrow parameter sweep results for energy labels. The solid line represents the reference scenario, while the dotted lines represent the scenarios with different values for α, β and λ.

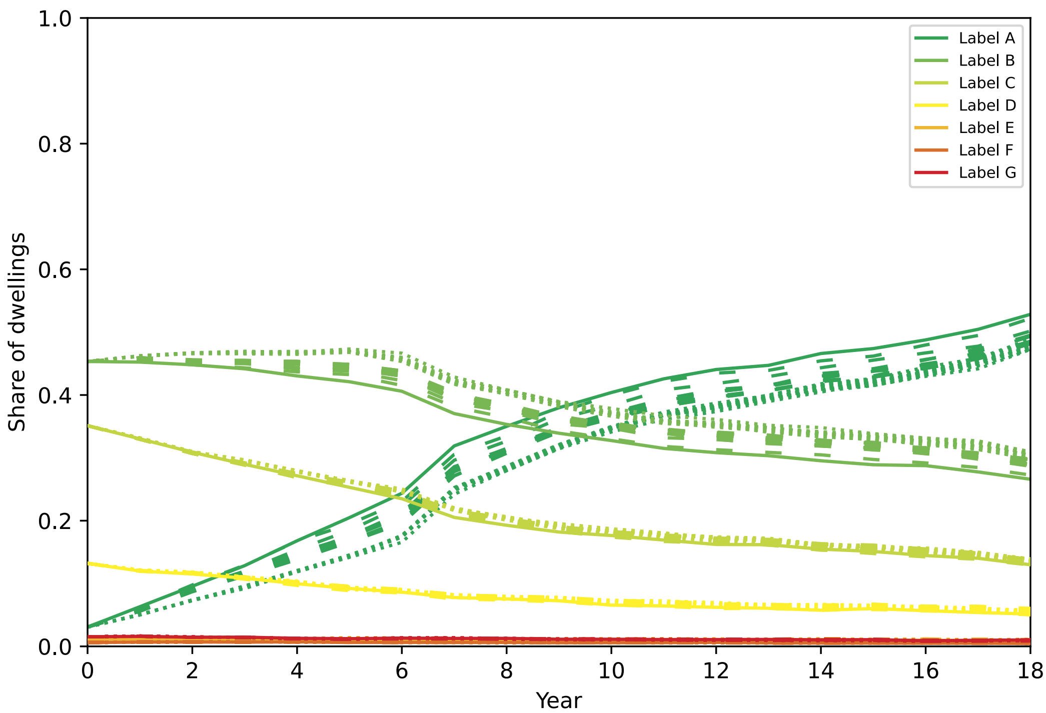

Figure 4.28: Subjective valuation narrow parameter sweep results for energy labels $\alpha, \beta = 0.1, 0.9$. The solid line represents the reference scenario, the dotted lines represent the scenarios where $\alpha = \beta = 0.1$ and the dashed lines represent those where $\alpha = \beta = 0.1$, both with different values for λ.

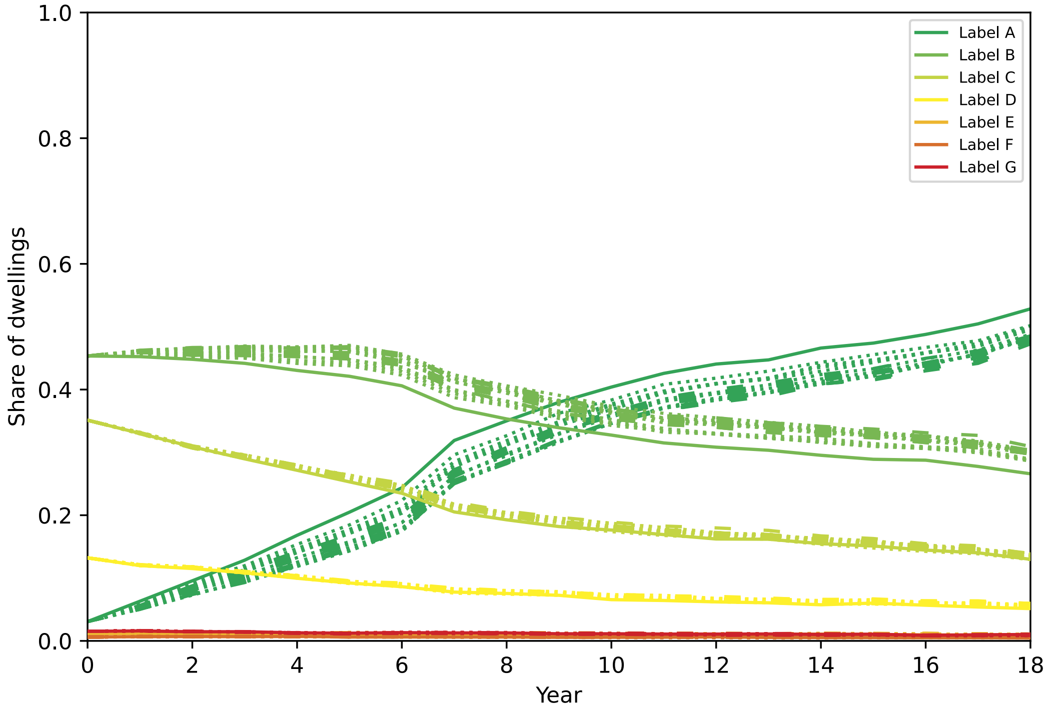

Figure 4.29: Subjective valuation narrow parameter sweep results for heating installations where $\lambda = 2, 10$. The solid line represents the reference scenario, the dotted lines represent the scenarios where $\lambda = 2$ and the dashed lines represent those where $\lambda = 10$, both with different values for α and β.

4.5.3 NL run

The modelling results for the *subjective valuation* runs on national scale can be seen in Figures 4.30 and 4.31. Regarding the heating installations, one bundle of scenario curves can clearly be distinguished from the rest. These are the scenarios where $\alpha = \beta = 0.2$. When looking within the bundle, the curves are ordered on the basis of λ. A higher λ brings about a lower share of gas, and thus a higher share of alternative heating options. Furthermore, the share of gas decreases with increasing α and β. For $\alpha = \beta = 0.9$, the share of gas is lower than in the reference scenario, regardless of λ. The difference in the shares of collective heating options are small, but here also the share increases with lower α and β. This shows that higher λ and lower α, β bring the results closer to the validation data.

In the case of the energy labels, there are little differences with the reference scenario. When $\alpha = \beta = 0.2$, the share of energy label A is lower, which is compensated mostly by an increase in label B. However, in all other cases the differences are insignificant.

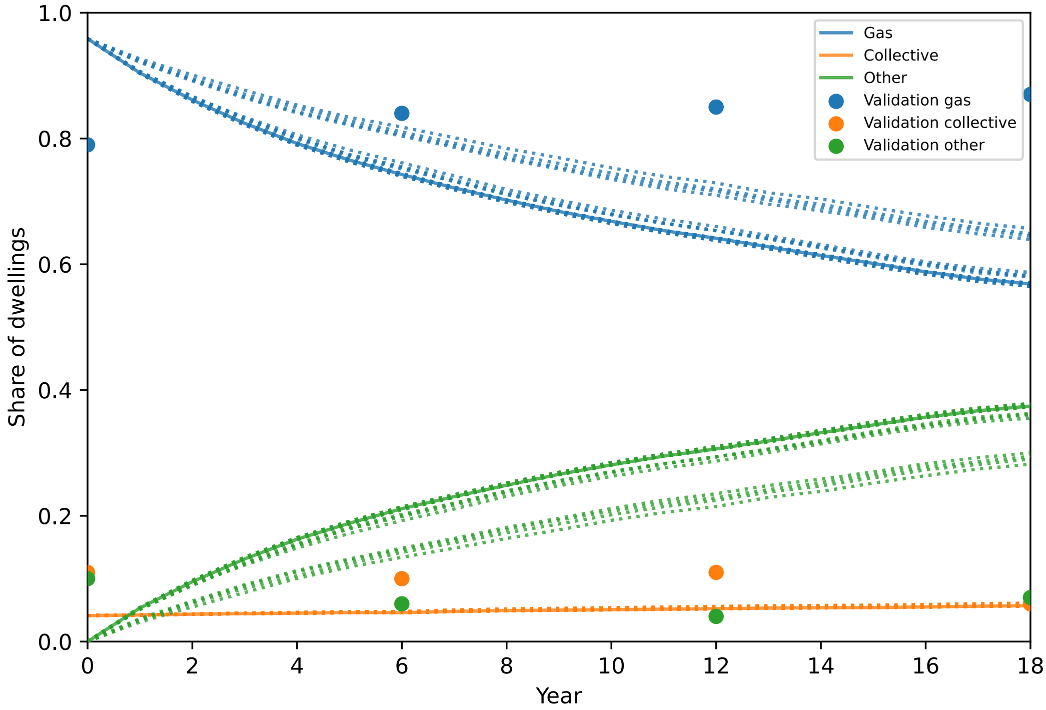

Figure 4.30: National subjective valuation results for heating installations. The solid line represents the reference scenario, while the dotted lines represent the scenarios with different values for α, β and λ.

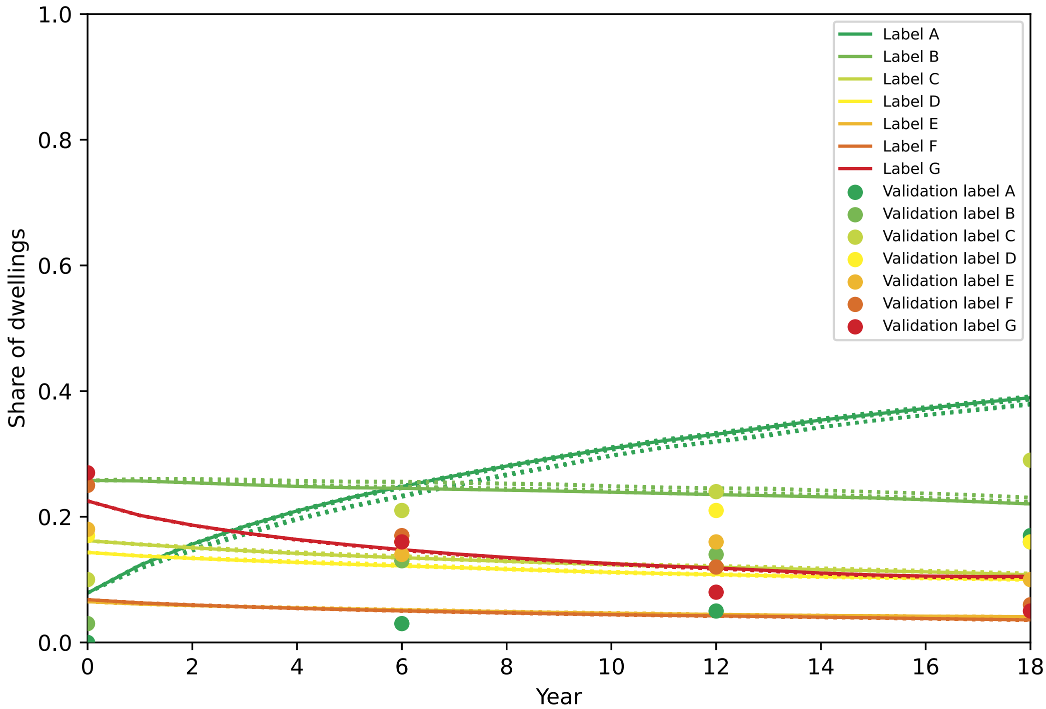

Figure 4.31: National subjective valuation results for energy labels. The solid line represents the reference scenario, while the dotted lines represent the scenarios with different values for α, β and λ.

5 | Discussion

In this chapter the results shown in the previous chapter will be interpreted. General conclusions will be drawn and reasons for the outcomes given. In this way, the research questions are answered. Furthermore, a reflection on this research, its strengths and weaknesses, its place in the academic literature and avenues for possible future research are given.

5.1 Findings

Reference dependence

When *reference dependence* is present, fewer investments in alternative heating options and good insulation are done. The latter can be glanced from the fact that both energy label A and energy label B have a lower share in the label distribution with *reference dependence* present. For heating installations, the bias clearly changes the results to be closer to the validation data. For the energy labels, it is less clear. In the case of energy label A, the decrease puts the curve closer to the validation data. However, for some other labels, the change makes the curve come closer to the validation data is some years, while bringing it further from it in others.

It should be noted that there is already a kind of reference dependence in Hestia, as all options are compared to the one with the highest costs. Also, in Hestia, the current configuration is not always an available option. This can be due to multiple reasons: the option has not been chosen out of all the possible options due to random chance, which is more prevalent when active on lots of dwelling parts; insulation norms are present which force certain non-present types of insulation into all options; or building parts are so old that they are no longer included into any option, which can happen for single pane glass. It can also be the case that multiple options have the same similarity-score. Then, one of them is chosen as the reference at random. However, the costs can differ between the options.

Loss aversion

Considering *loss aversion*, the results for the municipality of Zeewolde and the national results differ greatly. In Zeewolde, the share of gas is higher than in the reference situation, and the share of energy label A is lower. There is an increase in the shares of the other labels, especially in label B. For $\lambda > 10$, the differences between the scenarios are very small. This may be due to the model architecture. There is a hard cap on the suitability score of an option in order to avoid overflow. This means that when the differences between the PT scores get too large, multiple options will reach the cap, have the same suitability score and thus the same probability of getting chosen. Further increases in λ will lead to more extreme PT scores, but not to different suitability scores, probabilities and ultimately distributions.

However, on the national scale there are no clear differences between the reference scenario and the *loss aversion* ones. The differences that are present are so small that they may be caused by the inherent randomness present in the workings of Hestia, making them insignificant. Thus, the bias did also not make the results more or less in line with the validation data.

Diminishing sensitivity

In the case of *diminishing sensitivity* we can look at the effects of the parameters separately and combined. For realistic values of α, there is an increase in the share of gas, a decrease in the share of energy label A and increases in the shares of all other energy labels. For β, the inverse holds, while for the scenarios where both parameters are unequal to one, the trend from the α scenarios is seen again.

α works on positive Δx, which means that gains are decreased in value, while losses are not changed. With gas-based heating systems being the reference situation for most decision makers, alternative options often require significant investment compared to maintaining the reference situation, which pays off later due to lower yearly costs. However, because of the diminished gains, investing into such a heating installation becomes less attractive, resulting in a higher share of gas. The same logic holds for insulation measures, which leads to fewer homes with energy label A.

In contrast, β diminishes losses. This means that the subjective evaluation of a large upfront investment is regarded less negatively than without the bias, making them more attractive. This results in more investment into alternative heating systems and extensive insulation measures.

In the case where both α and β are active, both gains and losses are diminished, bringing the suitability scores and thus the probabilities of all investment options closer together. In addition, one would expect that alternative heating options and insulation investments become more attractive. These investment decisions generally have high upfront costs, which results in high losses, with their yearly gains being lower. While losses and gains are diminished by the same factor, the larger losses are absolutely reduced more, bringing about a higher suitability score.

However, the results show an increase in the share of gas and a decrease in the share of energy label A. As of now, it is unclear why this happens. The broad and narrow parameter sweep show that for the same values, the scenarios where β is varied differ more from the reference than in those where α is varied. This would suggest that β has a stronger influence on the decision-making process, while the fact that the scenarios where both are varied show the same trend as the α scenarios indicates otherwise.

The results concerning the heating installations were brought closer to the validation data because the share of gas remained higher than in the reference situation, which in turn also diminished the share of alternative heating options. With the energy labels it is not clear if the bias has brought the modelling results closer to the validation data.

Subjective valuation

The results for *subjective valuation* are are combination of those of *loss aversion* and *diminishing sensitivity*, as expected. It seems that *diminishing sensitivity* dominates *loss aversion*, although this may be due to the extreme values of α and β in comparison with λ. For less extreme values of α and β, the effect of *loss aversion* can be more clearly seen, especially in the distribution of energy labels. Overall, the effect of *subjective valuation* is more pronounced in heating installations than in energy labels. Because *subjective valuation* is a combination of the other biases, and they all brought the heating results closer too the validation data, so does *subjective valuation.* However, for energy labels, the same ambiguity as with the other biases is present.

In general

For realistic values, those based on literature, all biases decrease the uptake of both non-gas-based heating systems and insulation investments. In all cases where the entirety of the bias is active, i.e. all relevant parameters are varied, the share of gas-based heating options is higher, while the share of energy label A is lower. The biases have a compounding effect, as the effects of each one stack on top of each other. However, in all cases the trends of the shares remained the same. The biases did not turn decreases into increases or vice versa. For all biases where an effect was found on the national scale, the distribution of types of heating installations was brought more in line with the validation data. For the shares of energy labels, it is difficult say if this is the case or not.

In all cases, the differences between the reference and the bias scenario are less pronounced in national runs than in runs that have Zeewolde as the geographic scope. In the case of *loss aversion* even so much that the differences between the scenarios are insignificant. Possible causes for this effect may lie in the characteristics of the housing stock. Different dwellings can have differing options and costs depending on the insulation and heating installation present, as well as on different characteristics like living area, envelope, location and type of dwelling. As Zeewolde is a relatively young municipality, its housing stock consists of many newer dwellings. In addition to this, compared to the entirety of the Netherlands there are fewer multi-family homes and there is a relatively high share of district heating.

We also see that for many biases, the effects of the cognitive biases on heating installations are larger than those on the energy labels. A possible cause for this might be that there are investment made in insulation that do not change the energy label of the dwelling. These cases are not registered in the model output. Thus, when a such an investment decision is changed due to a cognitive bias, this change is also not registered.

There were only minor differences in the share of collective heating options for most cases. Only in a few extreme broad sweep cases does that share differ significantly. The reason for this is that the district heating networks are modelled exogenously. The heat networks do not come to be as a results of the decisions of the homeowners, but they appear in the model when they do in real life. This can clearly be seen in the collective heating share in Zeewolde. Before 2006 there was no heat network present in the municipality. After that, the network expanded gradually and more and more dwellings were connected. It seems that connecting to a heat network is such a good financial decision for a homeowner, that only under extreme circumstances it is not done. There is a discrepancy between the validation data for collective heating options and the modelling results. This is caused by the fact that Hestia only district heating is reported, while for the validation data also block heating is included.

For all but one of the biases, the share of energy label A behaved differently from the others. It could be expected that when insulation investments are less attractive, the shares of other good energy labels, like energy label B or C, would also decrease. However, this is only seen in the case of *reference dependence*, where the share of energy label B also decreased. There are two possible explanation, which are not mutually exclusive.

The first is that decision makers decide on less ambitious insulation investment due to the biases. Instead of a package that would yield label A, an option that yields label B is chosen. This could balance out or even overcome the number of would be label B investments that are scaled down as well, to investments resulting in worse energy labels.

The second possible explanation is that the marginal costs to insulate to energy label A are far higher than the marginal costs to insulate to energy label B or C. This would mean that those investment decision are influenced more by the cognitive biases, as the biases add a multiplication or a power to the Δx_i of an investment decision. This would also explain why for *reference dependence* the share of energy label B also decreases. In this case, there is no numerical parameter which influences the Δx_i. Only a comparison with the reference is made, which does not scale with the costs.

5.2 Significance of study and policy implications

As with (Häckel et al., 2017) and (Ebrahimigharehbaghi et al., 2022), *reference dependence* has a large influence on ER decisions, making sustainable options less attractive. In the case of Zeewolde, there is a status quo bias due to *loss aversion*, as seen by (Kahneman et al., 1991). However, for the national scope this was absent. (Häckel et al., 2017) found loss aversion to be a major driver in the inhibition of ER investments. This effect was not found in this study. *Diminishing sensitivity* was found to be a significant factor by (Ebrahimigharehbaghi et al., 2022) and this research also shows that *diminishing sensitivity* has an influence on ER investment decision-making.

Strengths and limitations

The findings of this research are strengthened by the fact that the model used, Hestia, is a very detailed model. This makes the simulation very realistic over the time period chosen, with all building norms, subsidies and other policies accurately implemented. In addition, all dwellings in the Netherlands are individually simulated. The fact that the model is uncalibrated means that only financial considerations are taken into account. In this way, the effect of the cognitive biases can be studied in isolation, without interference of other non-financial decision-making factors.

There are also limitations to the research. The first of which is that the version of Hestia used is also an early test version. As it is not ready for public use, there is a possibility of (coding) errors being present. If these are present, they could distort the results in this thesis. Even without those errors, major changes to the model architecture might still be done to create a more realistic simulation. This would mean that the results computed here are flawed.

A second limitation concerns the validation data. The first concern is the harmonisation with the model starting conditions. The shares of the heating installations and energy labels in the starting year did not match between the modelling results and the validation data. This made it difficult to say whether a cognitive bias effected a change towards or from the validation data. In addition to this, for the energy labels an increase in one label could bring it more in line with the data, while at the same time a decrease in another would bring that one further from it. As no mathematical measure of closeness was developed, these situations remain ambiguous. Also, only four data points are available. This means that for the years in between the assumption that the changes are smooth needed to be made.

There is also a mismatch between the contents of the "Other" category in Hestia and the validation data. Within the results produced by Hestia, the other category consists mostly of sustainable heating options like heat pumps. This is because currently these are usually a better option than other non-gas-based heating options like oil and biomass stoves. However, historically this has not been the case. In the validation data the "Other" category mostly consist of pre-existing stoves. Heat pumps are only present in very small number, although throughout the years these numbers grow. Thus it is difficult to compare the changes is the "Other" category due to the biases. This is part of why the focus of this thesis is on the gas-based heating installations.

A final limitation is that no differentiation between existing buildings and new construction is made. The aim of the research is to look into investment decision-making for retrofits, but the results are shown for all dwellings. Newly built ones have a better energy label and often sustainable heating systems that affect the distribution of shares, which might distort the apparent the influence of the biases.

Policy implications

As the results indicate that these cognitive biases might inhibit investments into alternative heating systems and good insulation measures, policy to combat, circumvent or exploit these biases could be useful to support the energy transition in the Netherlands.

Although *loss aversion* did not have a significant influence on the national scale, in Zeewolde there were differences between the scenarios. Thus a policy recommendation is still made here. As losses are evaluated more heavily than gains, they can be exploited to nudge decision makers into investing in more sustainable technologies. One way of doing this is by focusing on fines instead of subsidies. As fines are losses, their subjective weight is greater than an equivalent gain, which usually takes the form of a subsidy. However, fines can only be instantiated when a decision maker does not comply with a standard. This would mean that stricter standards would be needed for this structure of fines to speed up the energy transitioning the built environment. The mandatory aspect of this structure stands in contrast with the voluntary nature of applying for subsides and could be experienced negatively.

Policy concerning *diminishing sensitivity* could also be made. As a small amount of costs is experienced relatively heavier than higher costs, there is an opportunity for policy that could make it more attractive to spend a large amount on an ER investment. This could be done by, for example, implementing a subsidy that a homeowner would only be eligible for after a certain threshold of spending is reached. Alternatively, the smaller gains are valued marginally more than larger gains. This could be exploited by creating a structure where multiple smaller payments or subsidies are paid, instead of one large sum being deposited to the homeowner.

Future research

Future research into the role cognitive biases play in the ER decision-making process of homeowners could take multiple directions. One is to dive deeper into the Prospect Theory framework and include the *probability weighting* bias. This bias concerns uncertainty about the future, in particular future prices. (Häckel et al., 2017) and (Ebrahimigharehbaghi et al., 2022) have made the first forays into this territory, by simulating possible price paths for energy carriers.

As in none of the scenarios studied in this research the distribution of energy labels or heating installations came close to those of the real world, there must be other factors playing a role in the decision-making process of Dutch homeowners. As the cognitive biases from PT and financial factors are included here, these other considerations must be non-financial in nature. One of these considerations is the transaction cost of the investment. The time and effort investment and the inconvenience that comes with taking ER measures can be large as ER are usually extensive operations. Network effects like social influences could also play a role. The effect of exposure to technologies on the decision maker could be explored in a modelling context.

All in all, we have found that the bias studied here do influence ER decision-making in the Hestia model. Although in this thesis Prospect Theory was only researched in a modelling context, in combination with existing literature it is clear that the biases play a role in the real world decision-making of homeowners. Thus, it is important to be aware of the cognitive biases in order to tackle them through policy instruments in order accelerate the energy transition in the Dutch built environment.

6 Conclusion

Given that the energy transition in the Dutch built environment is lacking in pace to adhere to the goals set by the Dutch government, and given that this transition must be done by homeowners, it is important to understand the barriers to investing in energy retrofits. In this research the question of what the effect of Prospect Theory cognitive biases on the outcomes of the decision-making process of those homeowners are, was asked. The research was done through simulating the Dutch and Zeewolde housing stocks between 2000 and 2018. Many simulations were done, for different strengths of the cognitive biases, as well as scenarios without the biases for comparison. The model used, Hestia, is uncalibrated, so all non-bias considerations are financial. In this way the effect of the cognitive biases is studied in isolation.

We found that most biases do influence energy retrofit uptake, although between Zeewolde and the Netherlands there were large differences in effect. For Zeewolde, all biases diminished the number of sustainable investments. For the Netherlands, the individual biases of *reference dependence* and *diminishing sensitivity* both reduced the amount of sustainable investment compared to taking only financial considerations into account. *Loss aversion* was found to not have an impact on investment behaviour. The combination of all biases, as they manifest in reality, did negatively impact energy retrofit investments. In the case of heating installations, the inclusion of the cognitive biases brought the distribution of shares of types of installations more in line with the validation data. For the distribution of energy labels this remains unclear. Taking all this into account, policy makers should be aware of these biases and their effects when creating instruments concerning the energy transition in the Dutch residential built environment.

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Appendices

A | PT module code

In this appendix, the code used to implement the PT biases in Hestia is shown. Note that in some places instead of PT, CPT is used. This is because in an earlier stage of the research, the aim was to also include the *probability weighting* bias. This idea was dropped, but some of the code was already written and kept that way.

```
////////////////////////////////////////////////////////////////////////////////////////
//                                                                                    //
//                   (C) Hestia 2021 - PBL & TNO                                      //
//                                                                                    //
////////////////////////////////////////////////////////////////////////////////////////

container CPT
{
 // Invoer gebruik biases en parameterwaardes
 unit<uint32> KalibratieInputs : StorageName = "%projDir%/runs/KalibratieInput.csv", StorageType = "gdal2.vect",
     StorageReadOnly = "True"
 {
  parameter<bool>          Input_use_CPT            := first(CPT)[bool];
  parameter<bool>          Input_use_LossAversion   := first(LossAversion)[bool];
  parameter<bool>          Input_use_DimSens        := first(DiminishingSensitivity)[bool];
  parameter<units/ratio>   Input_LA_lambda          := first(lambda)[units/ratio];
  parameter<units/ratio>   Input_DS_alpha           := first(alpha)[units/ratio];
  parameter<units/ratio>   Input_DS_beta            := first(beta)[units/ratio];
 }

 // Settings voor het meenemen van verschillende cognitive biases
 // OPM: Wanneer CPT gebruikt wordt, wordt automatisch reference dependence toegepast
 parameter<bool> use                            := KalibratieInputs/Input_use_CPT;
 parameter<bool> loss_aversion_use              := KalibratieInputs/Input_use_LossAversion;
 parameter<bool> diminishing_sensitivity_use    := KalibratieInputs/Input_use_DimSens;

 // Parameterwaarden van de cognitive biases
 parameter<ratio> loss_aversion_lambda          := KalibratieInputs/Input_LA_lambda;
 parameter<ratio> dimishing_sensitivity_alpha   := KalibratieInputs/Input_DS_alpha;
 parameter<ratio> dimishing_sensitivity_beta    := KalibratieInputs/Input_DS_beta;

 // Vinden referentie gebouwoptie
```

```
container vergelijking
{
 // Kijk naar bouwdelen en installaties on referentiegebouwoptie te vinden
 container bouwdelen_oorsponkelijk    := BO/Bouwdelen/Isolatie;
 container installatie_oorsponkelijk := BO/InstallatiePerProduct;
 container bouwdelen_nieuw           := GeschiktObject/Bouwdelen/Isolatie;
 container installatie_nieuw         := GeschiktObject/InstallatiePerProduct;

 container bouwdeel := For_Each_nedv(classifications/bouwdeel/name, 'bouwdelen_oorsponkelijk/' + classifications/bouwdeel/
    name + '[geschiktobject/BO_rel] == bouwdelen_nieuw/' + classifications/bouwdeel/name, geschiktobject, bool)
 {
  attribute<uint32> bouwdeel_score (GeschiktObject) := ='add(' + AsItemList('uint32(' + classifications/bouwdeel/name + ')')
     +')';
 }

 container installatie := For_Each_nedv(classifications/product/name, 'installatie_oorsponkelijk/' + classifications/product/
    name + '[geschiktobject/BO_rel] == installatie_nieuw/' + classifications/product/name, geschiktobject, bool)
 {
  attribute<bool>    KK_score          (GeschiktObject) := installatie_oorsponkelijk/KK[GeschiktObject/BO_rel] ==
     installatie_nieuw/KK;
  attribute<bool>    DK_score          (GeschiktObject) := installatie_oorsponkelijk/DK[GeschiktObject/BO_rel] ==
     installatie_nieuw/DK;
  attribute<bool>    VT_score          (GeschiktObject) := installatie_oorsponkelijk/VT[GeschiktObject/BO_rel] ==
     installatie_nieuw/VT;
  attribute<bool>    AS_score          (GeschiktObject) := installatie_oorsponkelijk/AS[GeschiktObject/BO_rel] ==
     installatie_nieuw/AS;
  attribute<uint32> product_score     (GeschiktObject) := ='add(' + AsItemList('uint32(' + classifications/product/name + ')
     ') +')';
  attribute<uint32> installatie_score (GeschiktObject) := add(uint32(KK_score), uint32(DK_score), uint32(VT_score), uint32(
     AS_score), product_score);
 }
}

container referentie
{
 attribute<uint32>          totaal_score              (GeschiktObject) := vergelijking/installatie/installatie_score +
    vergelijking/bouwdeel/bouwdeel_score;
```

```
 attribute<GeschiktObject> referentie_geschiktobject (GeschiktObject) := max_index(totaal_score, GeschiktObject/BO_rel)[
     GeschiktObject/BO_rel];
}

// Berekening delta x
container deltax_berekening
{
 container jaarlijks
 {
  container kosten
  {
   attribute<Eur_yr> Kj_elek        (GeschiktObject) := Geschikteoptieberekening/Results/jaarlijks/Kj_elek;
   attribute<Eur_yr> Kji_gv         (GeschiktObject) := Geschikteoptieberekening/Results/jaarlijks/Kji_gv;
   attribute<Eur_yr> Kj_OH_LO       (GeschiktObject) := Geschikteoptieberekening/Results/jaarlijks/Kj_OH_LO;
   attribute<Eur_yr> Kj_Adm_LO      (GeschiktObject) := Geschikteoptieberekening/Results/jaarlijks/Kj_Adm_LO;
   attribute<Eur_yr> Kj_gas         (GeschiktObject) := Geschikteoptieberekening/Results/jaarlijks/Kj_gas;
   attribute<Eur_yr> Kj_biomassa    (GeschiktObject) := Geschikteoptieberekening/Results/jaarlijks/Kj_biomassa;
   attribute<Eur_yr> Kj_olie        (GeschiktObject) := Geschikteoptieberekening/Results/jaarlijks/Kj_olie;
   attribute<Eur_yr> Kj_olie_eh     (GeschiktObject) := Geschikteoptieberekening/Results/jaarlijks/Kj_olie_eh;
   attribute<Eur_yr> Kj_pellets     (GeschiktObject) := Geschikteoptieberekening/Results/jaarlijks/Kj_pellets;
   attribute<Eur_yr> Kj_H2          (GeschiktObject) := Geschikteoptieberekening/Results/jaarlijks/Kj_H2;
   attribute<Eur_yr> Kj_vastrecht_g (GeschiktObject) := Geschikteoptieberekening/Results/jaarlijks/Kj_vastrecht_g;
   attribute<Eur_yr> Kj_jaarlijks   (GeschiktObject) := BTW_Factor * add(Kj_elek, Kj_OH_LO, Kj_Adm_LO, Kj_gas, Kj_biomassa,
       Kj_olie, Kj_olie_eh, Kj_pellets, Kj_H2, Kj_vastrecht_g )
                 + BTW_Factor_gv * Kji_gv;
  }
  attribute<Eur_yr> Kj_referentie (GeschiktObject) := kosten/Kj_jaarlijks[referentie/referentie_geschiktobject];
  attribute<Eur_yr> Kj_optie      (GeschiktObject) := kosten/Kj_jaarlijks;
  attribute<eur_yr> delta_x       (GeschiktObject) := Kj_referentie - Kj_optie;

 }

 container eenmalig
 {
  container kosten
  {
   attribute<Eur_yr> Kji_Enet     (GeschiktObject) := Geschikteoptieberekening/Results/kapitaallasten/Kji_enet;
   attribute<Eur_yr> Kji_Gnet     (GeschiktObject) := Geschikteoptieberekening/Results/kapitaallasten/Kji_Gnet;
```

```
   attribute<Eur_yr> Kji_Asl_Wnet  (GeschiktObject) := Geschikteoptieberekening/Results/kapitaallasten/Kji_Asl_Wnet;
   attribute<Eur_yr> Kji30_LO      (GeschiktObject) := Geschikteoptieberekening/Results/kapitaallasten/Kji30_LO;
   attribute<Eur_yr> Kji20_LO      (GeschiktObject) := Geschikteoptieberekening/Results/kapitaallasten/Kji20_LO;
   attribute<Eur_yr> Kji15_LO      (GeschiktObject) := Geschikteoptieberekening/Results/kapitaallasten/Kji15_LO;
   attribute<Eur_yr> Kji_gv        (GeschiktObject) := Geschikteoptieberekening/Results/kapitaallasten/Kji_gv;
   attribute<Eur_yr> Kji_LTAS      (GeschiktObject) := Geschikteoptieberekening/Results/kapitaallasten/Kji_LTAS;
   attribute<Eur_yr> Kji_DK        (GeschiktObject) := Geschikteoptieberekening/Results/kapitaallasten/Kji_DK;
   attribute<Eur_yr> Kji_KK        (GeschiktObject) := Geschikteoptieberekening/Results/kapitaallasten/Kji_KK;
   attribute<Eur_yr> Kji_VT        (GeschiktObject) := Geschikteoptieberekening/Results/kapitaallasten/Kji_VT;
   attribute<Eur_yr> Kji_eenmalig  (GeschiktObject) := BTW_Factor * add(Kji_Enet, Kji_Gnet, Kji_Asl_Wnet, Kji30_LO, Kji20_LO,
      Kji15_LO, Kji_LTAS, Kji_DK, Kji_KK, Kji_VT)
               + BTW_Factor_gv * Kji_gv;
  }
  container subsidies
  {
   attribute<Eur_yr> Oji_Gnet      (GeschiktObject) := Geschikteoptieberekening/Results/kapitaallasten/Oji_Gnet;
   attribute<Eur_yr> Oji_Asl_Wnet  (GeschiktObject) := Geschikteoptieberekening/Results/kapitaallasten/Oji_Asl_Wnet;
   attribute<Eur_yr> Oji30_LO      (GeschiktObject) := Geschikteoptieberekening/Results/kapitaallasten/Oji30_LO;
   attribute<Eur_yr> Oji20_LO      (GeschiktObject) := Geschikteoptieberekening/Results/kapitaallasten/Oji20_LO;
   attribute<Eur_yr> Oji15_LO      (GeschiktObject) := Geschikteoptieberekening/Results/kapitaallasten/Oji15_LO;
   attribute<Eur_yr> Oji_gv        (GeschiktObject) := Geschikteoptieberekening/Results/kapitaallasten/Oji_gv;
   attribute<Eur_yr> Oji_LTAS      (GeschiktObject) := Geschikteoptieberekening/Results/kapitaallasten/Oji_LTAS;
   attribute<Eur_yr> Oji_DK        (GeschiktObject) := Geschikteoptieberekening/Results/kapitaallasten/Oji_DK;
   attribute<Eur_yr> Oji_KK        (GeschiktObject) := Geschikteoptieberekening/Results/kapitaallasten/Oji_KK;
   attribute<Eur_yr> Oji_VT        (GeschiktObject) := Geschikteoptieberekening/Results/kapitaallasten/Oji_VT;
   attribute<Eur_yr> Oji_totaal    (GeschiktObject) := BTW_Factor * add(Oji_Gnet, Oji_Asl_Wnet, Oji30_LO, Oji20_LO, Oji15_LO,
      Oji_LTAS, Oji_DK, Oji_KK, Oji_VT)
               + BTW_Factor_gv * Oji_gv;
  }
  attribute<Eur_yr> Kj_eenmalig_totaal (GeschiktObject) := kosten/Kji_eenmalig - subsidies/Oji_totaal;
  attribute<Eur_yr> Kj_referentie      (GeschiktObject) := Kj_eenmalig_totaal[referentie/referentie_geschiktobject];
  attribute<Eur_yr> Kj_optie           (GeschiktObject) := Kj_eenmalig_totaal;
  attribute<eur_yr> delta_x            (GeschiktObject) := Kj_referentie - Kj_optie;
 }
}


attribute<eur_yr> subjective_value_jaarlijks (GeschiktObject) :=
```

```
= loss_aversion_use && diminishing_sensitivity_use ? "deltax_berekening/jaarlijks/delta_x < float64(0) ? neg(
    loss_aversion_lambda * neg(deltax_berekening/jaarlijks/delta_x)^ dimishing_sensitivity_beta) : deltax_berekening/
    jaarlijks/delta_x ^ dimishing_sensitivity_alpha"
  : loss_aversion_use                          ? "deltax_berekening/jaarlijks/delta_x < float64(0) ? loss_aversion_lambda *
     deltax_berekening/jaarlijks/delta_x                                          : deltax_berekening/jaarlijks/delta_x"
  : diminishing_sensitivity_use                ? "deltax_berekening/jaarlijks/delta_x < float64(0) ? neg(neg(
     deltax_berekening/jaarlijks/delta_x)^ dimishing_sensitivity_beta)                        : deltax_berekening/jaarlijks/
     delta_x ^ dimishing_sensitivity_alpha"
  : "deltax_berekening/jaarlijks/delta_x"
  ;

attribute<eur_yr> subjective_value_eenmalig (GeschiktObject) :=
= loss_aversion_use && diminishing_sensitivity_use ? "deltax_berekening/eenmalig/delta_x < float64(0) ? neg(
    loss_aversion_lambda * neg(deltax_berekening/eenmalig/delta_x)^ dimishing_sensitivity_beta) : deltax_berekening/eenmalig/
    delta_x ^ dimishing_sensitivity_alpha"
  : loss_aversion_use              ? "deltax_berekening/eenmalig/delta_x < float64(0) ? loss_aversion_lambda * deltax_berekening
     /eenmalig/delta_x                 : deltax_berekening/eenmalig/delta_x"
  : diminishing_sensitivity_use            ? "deltax_berekening/eenmalig/delta_x < float64(0) ? neg(neg(deltax_berekening/
     eenmalig/delta_x)^ dimishing_sensitivity_beta)                             : deltax_berekening/eenmalig/delta_x ^
     dimishing_sensitivity_alpha"
  : "deltax_berekening/eenmalig/delta_x"
  ;

// Berekening CPT-score
//OPM: De CPT-score is een maat van utiliteit. De rest van Hestia rekent met kosten, dus de negatieve van de score wordt
    gebruikt als kosten
attribute<eur_yr> CPT_score (GeschiktObject) := subjective_value_jaarlijks + subjective_value_eenmalig;
}
```

B | Baseline scenario results

Table B.1: This table shows the numeric output for the baseline scenario. The growth of the total housing stock, the uptake of non-gas-based heating installations and shifts in the energy label distribution can be seen.

Year	Total	Label A	Label B	Label C	Label D	Label E	Label F	Label G	Gas	Collective	Other
0	6,617,545	520,543	1,706,870	1,071,612	948,150	429,299	450,906	1,489,856	6,344,549	272,996	0
1	6,696,086	889,939	1,821,123	999,021	868,560	386,423	404,137	1,326,534	6,025,960	285,668	384,458
2	6,766,861	1,188,572	1,820,545	966,673	835,489	363,910	375,141	1,216,186	5,754,910	297,367	714,584
3	6,832,364	1,450,030	1,818,256	937,261	805,987	344,461	351,128	1,124,902	5,519,196	305,752	1,007,416
4	6,899,199	1,680,929	1,815,286	911,634	780,705	328,192	331,249	1,050,869	5,323,829	312,688	1,262,682
5	6,973,158	1,885,067	1,814,899	890,845	759,836	315,176	315,109	991,902	5,170,632	322,107	1,480,419
6	7,057,035	2,069,944	1,823,697	876,320	741,373	303,053	301,086	941,238	5,049,880	324,955	1,682,200
7	7,140,166	2,247,825	1,827,618	861,712	723,617	2921,25	288,993	897,957	4,936,686	342,827	1,860,653
8	7,221,187	2,414,233	1,836,051	845,913	704,826	281,952	277,895	860,003	4,835,983	355,090	2,030,114
9	7,293,992	2,568,398	1,840,848	830,813	687,236	272,695	267,744	825,940	4,744,544	362,750	2,186,698
10	7,353,191	2,708,045	1,838,261	815,977	672,064	264,224	258,838	795,470	4,657,153	370,581	2,325,457
11	7,412,435	2,837,146	1,830,336	804,378	660,433	257,506	251,767	770,533	4,578,041	379,621	2,454,773
12	7,465,029	2,950,486	1,822,145	794,595	650,290	251,152	245,814	750,125	4,512,138	386,846	2,566,045
13	7,509,160	3,068,161	1,818,302	780,993	635,478	244,383	239,024	722,349	4,431,362	395,641	2,682,157
14	7,548,631	3,185,893	1,814,638	764,717	620,275	237,334	231,611	693,697	4,344,757	401,305	2,802,569
15	7,591,505	3,293,559	1,806,764	749,946	609,712	232,929	224,018	674,111	4,264,721	405,550	2,921,234
16	7,642,114	3,399,960	1,796,471	737,224	600,831	228,468	215,789	662,908	4,191,691	414,448	3,035,975
17	7,702,115	3,503,080	1,781,011	724,728	594,618	226,918	209,162	662,123	4,141,677	426,306	3,134,132
18	7,763,009	3,600,073	1,757,536	711,560	590,625	226,655	203,959	672,088	4,110,372	434,983	3,217,654

C | Complimentary figures

In Figures C.1 and C.2, the normalised shares of gas and energy label A are shown for the narrow sweep of the *loss aversion* bias, for different values of λ. It can be seen that the shares do not monotonically increase or decrease with increasing λ.

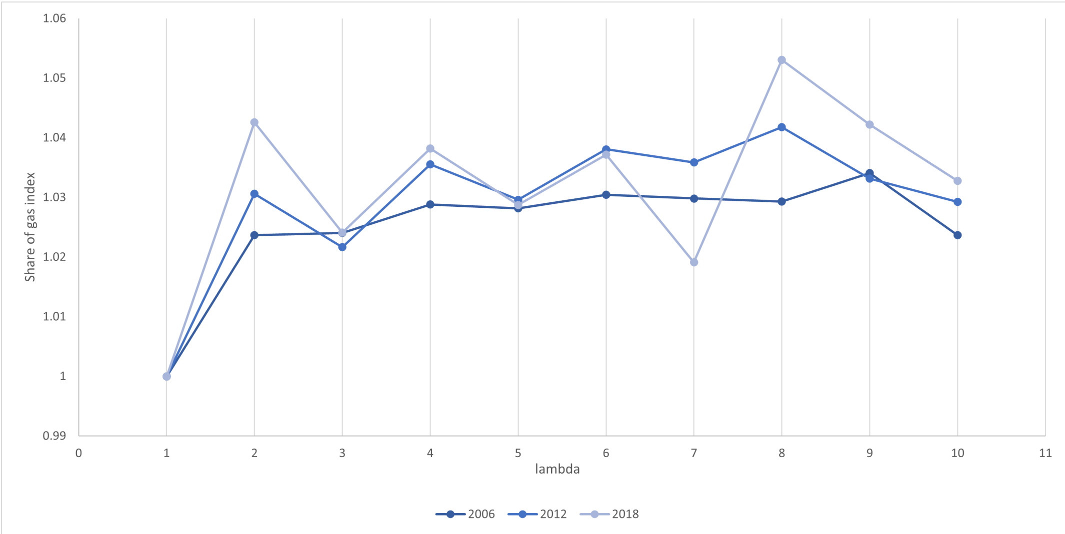

Figure C.1: Gas shares in years 6, 12 and 18 of the narrow LA sweep. In order to be able to compare the relative differences, the shares of gas are normalised with respect to the reference scenario where $\lambda = 1$.

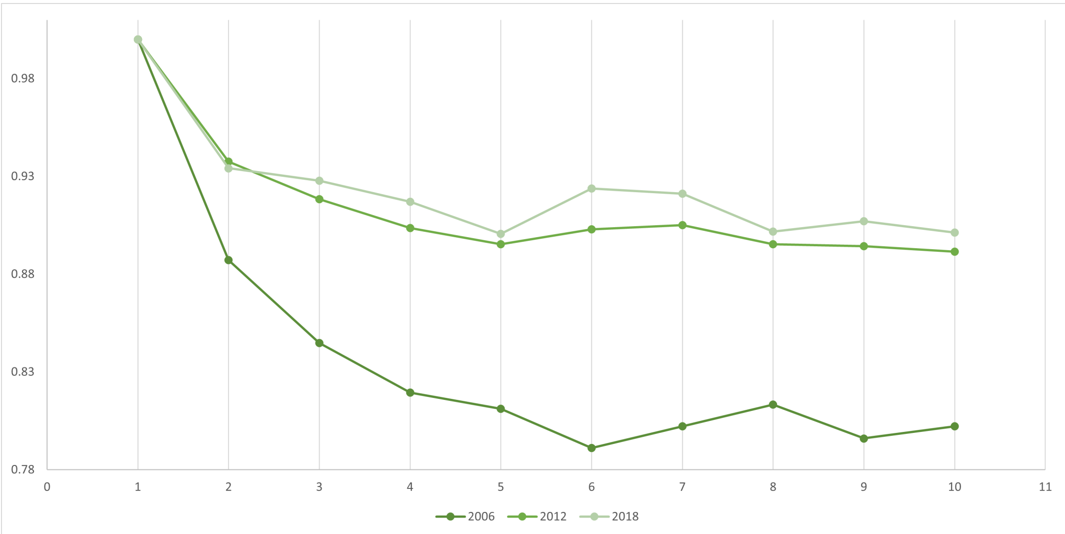

Figure C.2: Energy label A shares in years 6, 12 and 18 of the narrow LA sweep. In order to be able to compare the relative differences, the shares of the energy label are normalised with respect to the reference scenario where $\lambda = 1$.

Figure C.3 and C.4 show the heating installation distribution for $\lambda = 2$ and $\lambda = 10$ in the *subjective valuation* narrow parameter sweep. Between the cases there is little difference in the distribution of the shares.

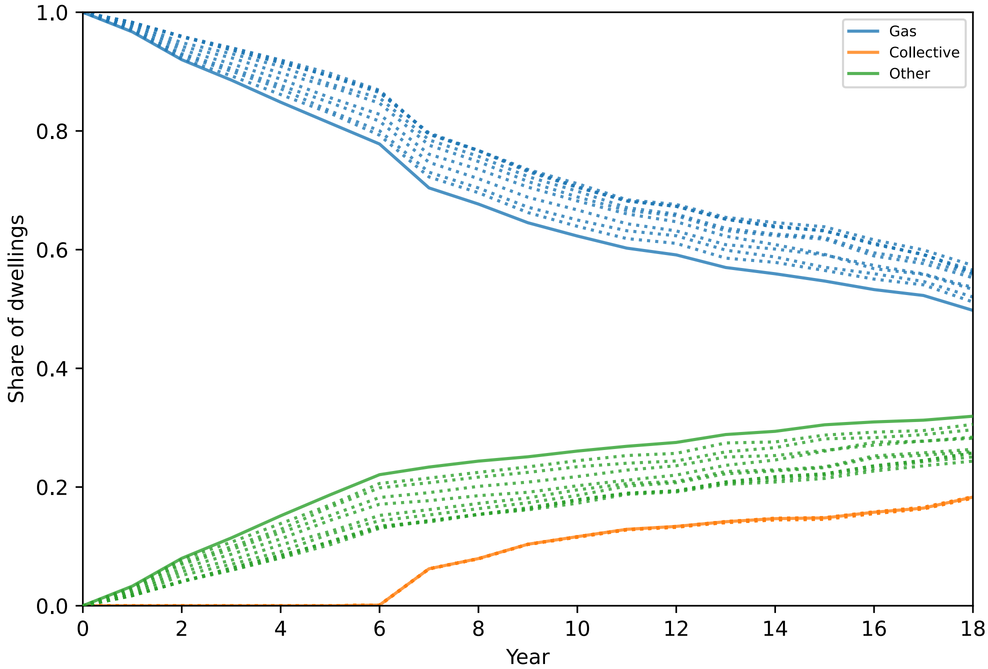

Figure C.3: Subjective valuation narrow parameter sweep results for heating installations where $\lambda = 2$. The solid line represents the reference scenario, while the dotted lines represent the scenarios with different values for α and β.

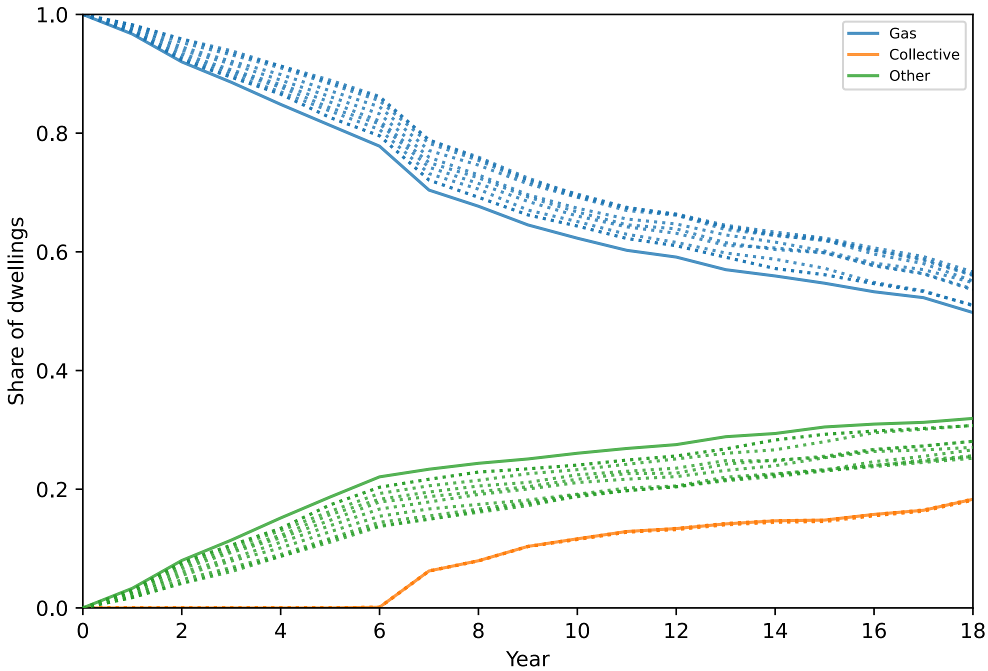

Figure C.4: Subjective valuation narrow parameter sweep results for heating installations where $\lambda = 10$. The solid line represents the reference scenario, while the dotted lines represent the scenarios with different values for α and β.