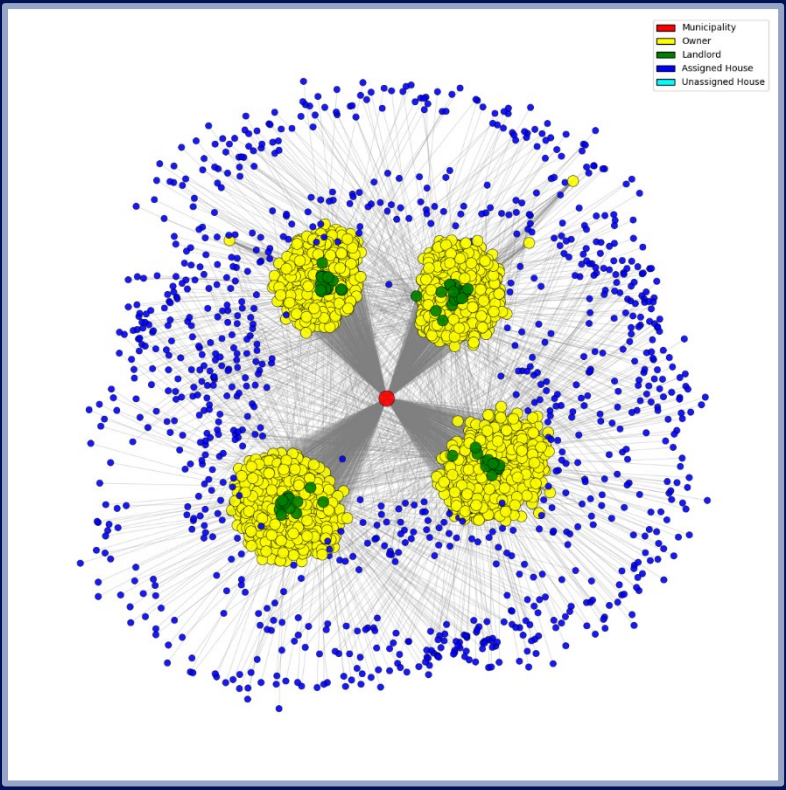
Residential Energy Label Transitions

An ABM on Policy Design for Delft Municipality



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Abstract

Municipalities play an important role in reducing residential energy consumption by stimulating energy label transitions in the housing stock. Energy labels are practical indicators to track energy efficiency in houses and guide policy intervention. However, designing policy mixes that achieve ambitious targets while remaining cost-effective is difficult due to heterogeneous owner incomes and differing awareness levels. This study addresses the question:

"What is the energy saved per euro of municipal expenditure for house label transitions in Delft with the goal of increasing energy savings by 90% over a 30-year period compared to a no policy case?"

We developed an agent-based model representing homeowners, landlords, houses, and municipal policies, including subsidies and information campaigns. Results show that subsidies predominantly drive transition rates, while campaigns enhance their effectiveness. Achieving the 90%-target requires 3.3 kWh/€ municipal expenditure. Our model shows the trade-off between cost-effectiveness and ambitious targets in policy design.

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1. Introduction

This project aims to model the socio-technical characteristics of residential energy label transitions and their policy-driven properties. Europe aims to transition towards higher energy labels, but the transition is complex and depends on multiple agents: homeowners, landlords, and policymakers, with their own characteristics and decision-making processes. Previous studies have shown that behavioural and social factors were critical in predicting demographic and spatial patterns of solar PV diffusion (Hansen et al., 2019). The cost for the electricity mix transition was also evaluated in an ABM (Bersoux et al., 2024). However, policy effects (subsidies, informational campaign), considering social influence, remain unexplored in the energy label transition. Considering a carbon-intensive energy mix, increased energy savings are required to limit climate change impacts related to energy use. Considering the goal of increasing energy savings by 90% over 30 years, compared to a projection without any policies implemented (business as usual), we need to understand which policies, at what cost would be necessary to achieve our goal. We are interested in cost-effectiveness, by achieving our target at the lowest cost. This leads to the following research question:

"What is the energy saved per euro of municipal expenditure for house label transitions in Delft with the goal of increasing energy savings by 90% over a 30-year period compared to a no policy case?"

This project followed this workflow: Conceptualization of the model to decide which agents, environment, agent states, interactions, and decision rules are applicable. Formalization of the model to determine how to make the conceptual model implementable. Implementation will translate the formalized model into code; we will verify the model and apply sensitivity analysis. The model will then be validated and tested through an experimental design for which output metrics & KPIs will be defined and results reported and interpreted.

2. Methods

Agent-Based Modelling (ABM) is a computational approach in which a system is represented as a collection of autonomous, interacting agents that follow simple behavioural rules, whose interactions lead to emergent, system-level patterns (Wilensky & Rand, 2015). This makes ABM particularly useful for research in the field of sustainability science, where the energy transition is a complex socio-technical system characterized by adaptive and dynamic behaviour of actors, leading to emergent patterns (Wilensky & Rand, 2015).

2.1. Conceptualization of model

The aim of this model is to investigate how municipal subsidies, informational campaigns and social influence interact in driving energy label upgrading behaviour. Figure 1 provides a visual overview of the model, highlighting the key agents, their interactions, and the role of the active environment.

The following subsections elaborate on the model description (agents), the model environment, and the KPIs and output metrics.

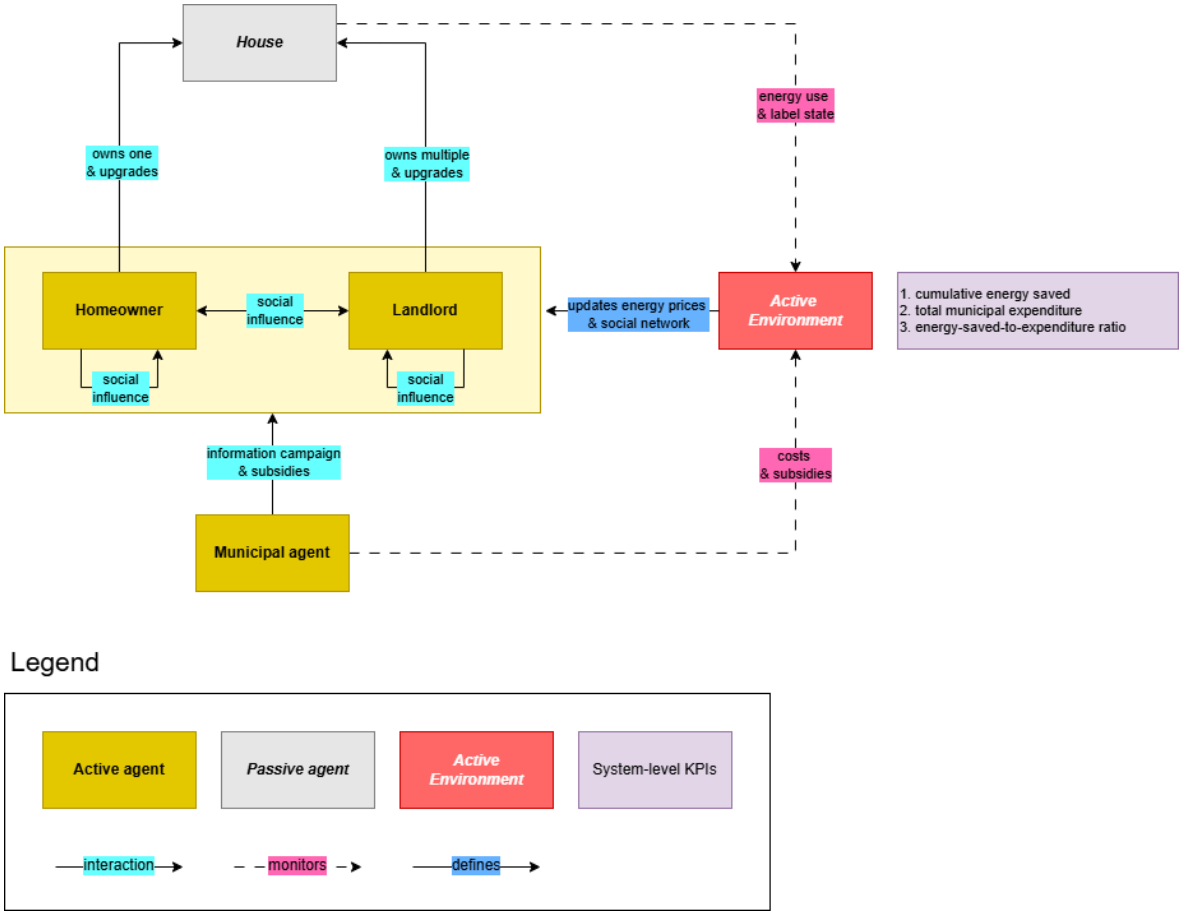


Figure 1. Conceptual visualization of model

2.1.1. Model description

The model contains 3 active agents – landlords, homeowners, and municipality – and 1 passive agents – houses. Table 1 provides an overview of the main agent states and behaviour. Figure 1 highlights the interactions between the agents and environment.

Table 1. Description of agents

Agents	Main Agent States	Role & Behaviour
Municipality	Price_campaign (float); Subsidies_cost (float); Total_cost (float); Timing_campaign (int); Owner_transition_subsidies(list); Landlord_transition_subsidies (list);	Active agent. Stimulates energy label transitions through informational campaigns and subsidies.
Landlord	Financial_status (float); Information_scale (float); Income_subsidy (float); Houses_owned (float) ;	Active agent. Owns multiple houses, may upgrade its label. Annually decides to transition based on social influence and financial attractiveness.
Homeowner	Financial_status (float); Information_scale (float); Income_subsidy (float);	Active agent. Same actions as landlord, but owns only one house and subsidies consider the financial status of the homeowner.
House	Current_label Owner_id Landlord_id	Passive agent. Stores current energy label and determines energy use.

2.1.2. Environment

The model environment represents the municipality of Delft as a network structure. The environment uses a clustered neighbourhoods in a small-world Watts-Strogatz network, as this operationalizes social influence in an urban setting like Delft. In this network, agents are represented as nodes and social relationships as edges (Figure 2).

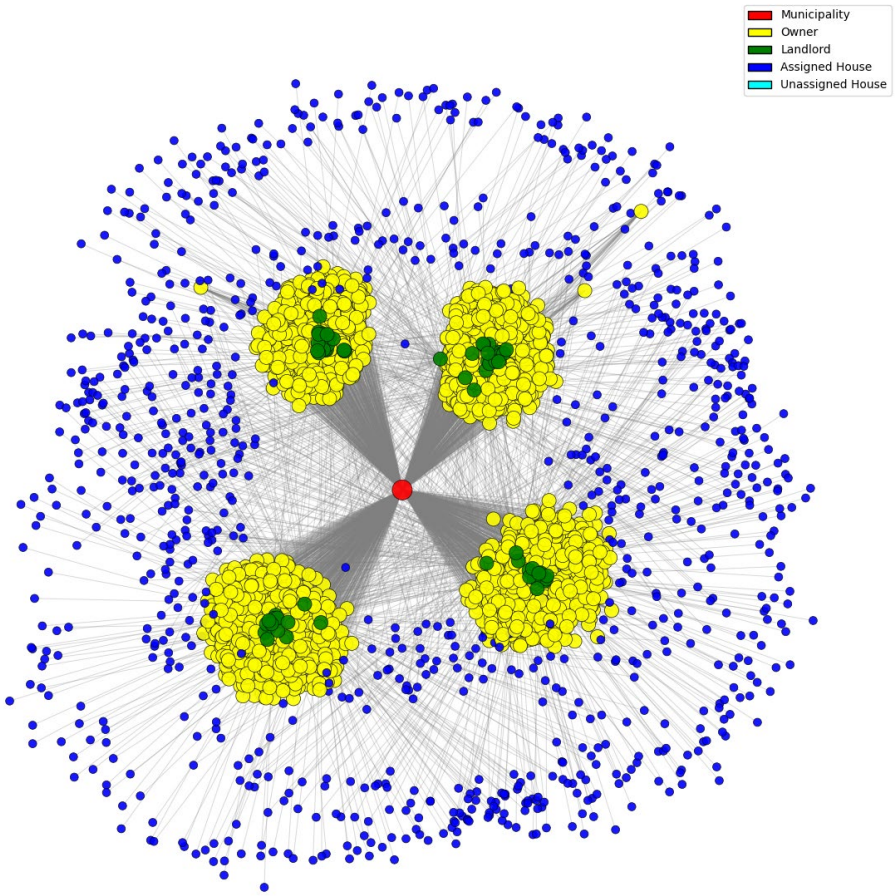


Figure 2. Model environment of a single run at year 30

The environment shapes interactions and system dynamics. It is designed to enable social influence, allowing information about energy transitions to spread between homeowners, landlords, and municipality.

Every year in the model, the environment updates energy prices, slightly changes the social network, calculates yearly energy saved from current house labels, and executes decision steps of the agents.

2.1.3. Output Metrics & KPIs

The research question investigates the energy saved for each euro municipal expenditure for energy label transitions. This is evaluated through 3 KPIs:

1. Cumulative energy saved;
2. Cumulative municipal expenditure;
3. Energy saved to expenditure ratio.

See Appendix A for a detailed explanation.

2.2. Formalization of model

2.2.1. Transition rules

Figure 3 and Figure 4 show an overview of the transition logic for homeowners and landlords which will be further detailed in the following sections.

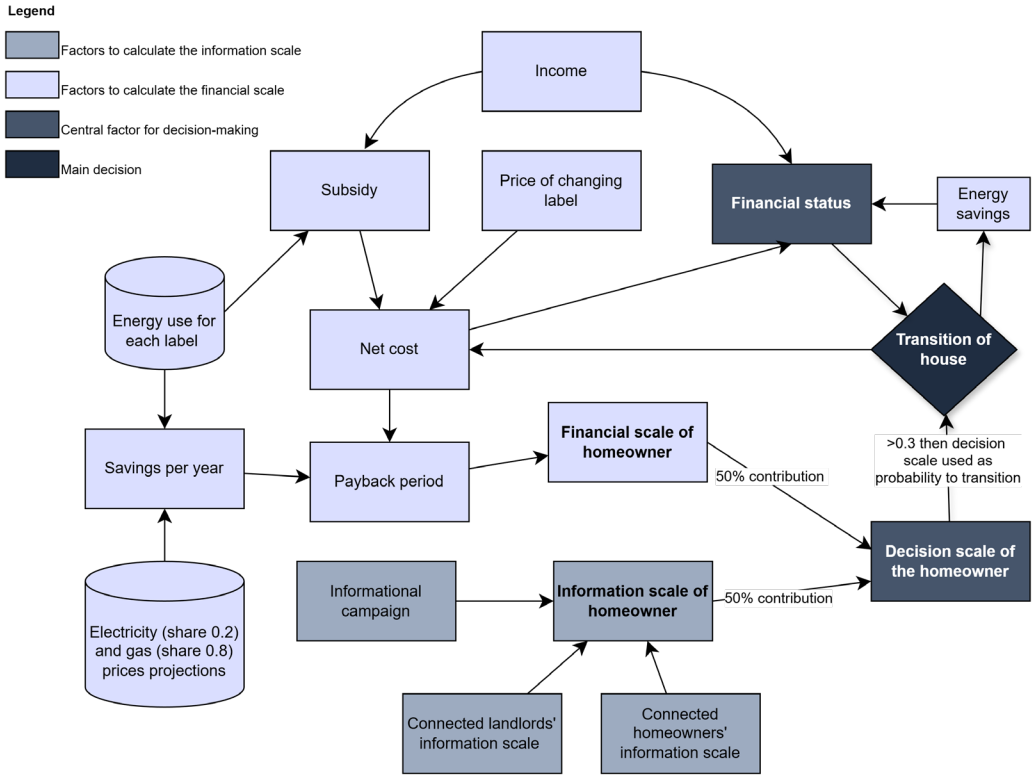


Figure 3. Transition logic of homeowners

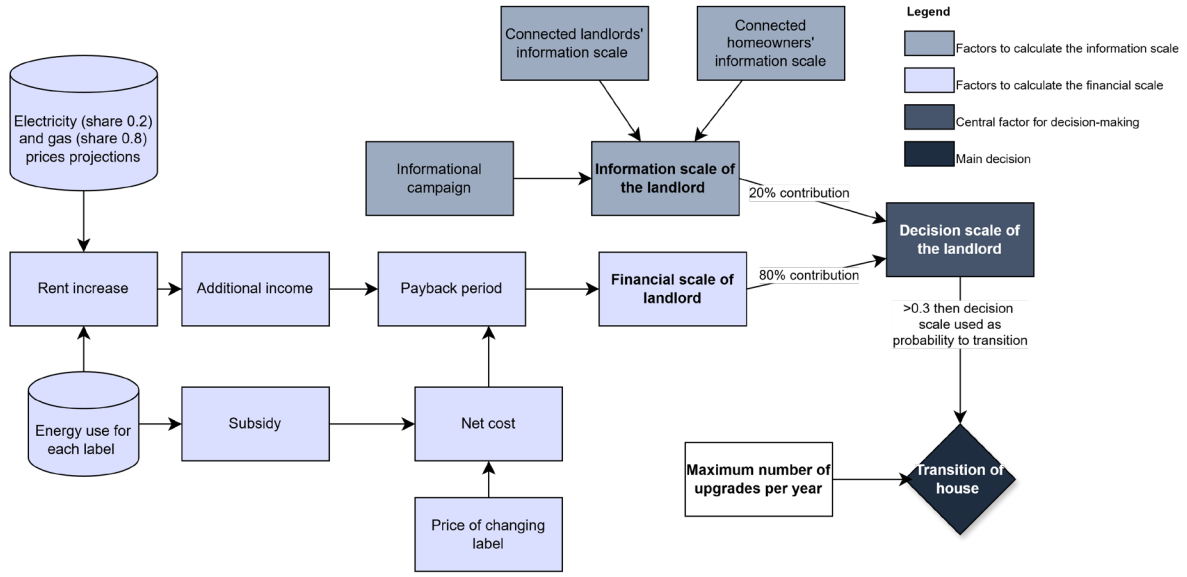


Figure 4. Transition logic of landlords for each of their houses

2.2.2. Rules and transition logic calculations

Table 2 describes the main transition rules and calculations of the model.

Table 2. Description of rules and transition logic

Rules	Description	Calculation	Justification
Decision scale – Homeowner	The homeowner's decision to transition is determined by a decision scale that combines an informational scale (to represent social influence) and financial attractiveness, constrained by financial affordability. The scale ranges from 0 to 1	$D_i = (w_I \cdot I_i) + (w_F \cdot F_i)$ Eq. 1 Where: D_i = *decision scale for homeowners i* $W_{I\&F}$ = *weight for information and financial scale (0.5; 0.5)* I_i = *information scale* F_i = *financial scale*	A transition *may* occur if the decision scale is higher than 0.3 and if the cost is ≤ to 20% of its financial status. To make the decision more realistic the decision scale is the probability that an owner will transition. If this happens the following updates will happen: • Current financial status minus cost becomes new financial status • Current house label becomes target label • Current annual savings become savings per year
Decision scale - Landlord	The landlord's decision to transition follows the same equation as Eq. 1. The landlord's decision differs slightly, evaluating transitions per house as well as weighing financial performance more than social influence	$D_{i,h} = (w_I \cdot I_i) + (w_F \cdot F_{i,h})$ Eq. 2 Where: D_i = *decision scale for homeowners i* $W_{I\&F}$ = *weight for information and financial scale (0.2; 0.8)* I_i = *information scale* F_i = *financial scale*	A transition *may* occur if the decision scale is higher than 0.3. To make the decision more realistic, the decision scale is the probability that a landlord will transition. If this happens, the same updates happen as with homeowners, plus the following: • House is marked as transitioned for current year • Transition cost, subsidy, and payback period are recorded
Information scale -Homeowners	The homeowner has an information scale ranging from -1 to 1, representing its awareness and attitude towards energy label transitions. Annually, the scale is updated through social interactions, as well as through municipal information campaigns.	$I_i(t+1) = (I_i(t) + \alpha \sum_{j \text{ in } O} I_j + \beta \sum_{k \text{ in } L} I_k + \gamma \cdot C(t))$ Eq. 3 Where: $I_i\,(t)$ = *information scale of homeowners i in said year* O, L = *sum of owner and landlord connections* α, β, γ = *weights (0.02; 0.05; 0.01)* $C(t)$ = *municipal campaign in said year for 70% of agents*	Influence from landlords is weighted more strongly than influence from other homeowners, reflecting their experience with housing and renovations. The information scale is updated by summing weighted influences
Information scale -Landlord	Landlords follow the same logic as homeowners, but have	$I_i(t+1) = (I_i(t) + \alpha \sum_{j \text{ in } L} I_j + \beta \sum_{k \text{ in } O} I_k + \gamma \cdot C(t))$ Eq. 4 Where:	Influence from other landlords is weighted more strongly than influence

	different weights associated to their social influence	L, O = sum of landlord and owner connections α, β, γ = weights (0.02; 0.05; 0.01) $C(t)$ = municipal campaign in said year for 70% of agents	from homeowners to reflect their shared professional experience
Financial attractiveness	For homeowners, the financial attractiveness is determined by the payback period of the transition. For landlords, the same equation logic applies. The main difference is that their payback period per house is based on the additional income per year which they receive for upgrading to a higher label (see Figure 4).	$Payback\ period = \frac{transition\ cost}{savings\ per\ year}$ Eq. 5 $Enery\ gain = (E_{current} - E_{target}) \cdot A \cdot (p_{gas} \cdot s_{gas} + p_{elec} \cdot s_{elec})$ Eq. 6 Where: A = dwelling area (117 m2) $P_{gas\ \&\ elec}$ = gas & electricity price $S_{gas\ \&\ elec}$ = assumed share of gas and electricity consumption (0.8 ;0.2)	Savings per year are calculated as energy reduction associated with one upgrade. The payback period is mapped to a financial attractiveness score between 0 and 1, with 1 as highly attractive and 0 as not attractive at all.
Municipality campaign	The municipality stimulates transitions through periodic information campaigns and tracks the associated expenditure.	$C(t) = C_{max} \cdot (1 - f_{trans}) \cdot (1 - f_{max})$ Eq. 7 Where: $C_{(t)}$ = campaign intensity in year t C_{max} = maximum campaigns per year f_{trans} = fraction of houses that transitioned previous year f_{max} = fraction of houses that already reached A+	A campaign is executed every "t" years, where "t" is defined by a campaign timing parameter. When a campaign occurs, 70% of homeowners and landlords is targeted, and the campaign intensity is determined based on past year's transitions. The campaign intensity is calculated as a function of the fraction of houses that transitioned in the previous year and the fraction of houses that have already reach A+. This ensures that campaigns are stronger when transition rates are low and vice versa. The campaigns are set to 0 if $f_{max} \geq 0.9$ to ensure that campaigning stops once the system is close to the 90% target.

Additional rules of the model:

- **Municipality subsidy**: Subsidies are a policy instrument to reduce the cost of a transition and thereby improving the financial feasibility for homeowners and landlords. For each transition, a subsidy amount is calculated based on the inefficiency of the current energy label and bounded by a maximum subsidy level (€19,000).

- **Network rewiring**: Annually, a small fraction of social connections is rewired within and between neighbourhoods. This allows for information to spread beyond the clusters, simulating more real life spreading.

2.3. Implementation approach

The model is made in Python using the Mesa 3.0.3 library, based on a base model for ABM provided by the course.

2.3.1. Code structure

The code is organized in five main components:

- Helper calculation functions: transitions costs, subsidies, campaigning, and energy savings

- House class: passive agent storing energy labels
- Homeowners and landlords' classes: active agent with their own decision logic
- City model class: simulation loop, global parameters, KPI tracking
- Sensitivity analysis and experimental design

2.3.2. Data structures

Agents use lists to store their states. Dictionaries are used for mapping energy labels to energy use, transition costs, and subsidy fractions. Data of gas and electricity prices are extracted from csv files. For storing results, dataframes are used that we get from Mesa's datacollector.

2.3.3. Key algorithms

To highlight some of the logic used in the code, two core decision-making logic examples will be used.

2.3.3.1. Homeowner transition logic

The homeowner's annual decision to transition controlled by a decision scale based on information and financial attractiveness and constrained by affordability (Figure 5).

```
Homeowner.step():
    social_influence = sum(weighted_information_from_network_neighbors)
    campaign_influence = information_received_from_municipality
    information_scale = information_scale + social_influence +
campaign_influence

    financial_scale = calculate_financial_attractiveness(payback_period)
    decision_scale = 0.5 * financial_scale + 0.5 * information_scale

    IF decision_scale ≥ 0.3 AND cost ≤ 0.2 * financial_status:
        transition_one_label()
        update_financial_status()
```

Figure 5. Pseudocode homeowner transition logic

2.3.3.2. Information campaign influence

Municipal information campaigns increase awareness by updating the information scale of a targeted share of homeowners and landlords (Figure 6).

```
Municipality.run_campaign():
    SELECT 70% of homeowners and landlords
    FOR each selected agent:
        agent.information_scale += campaign_effect
    record_campaign_cost()
```

Figure 6. Pseudocode information campaign

2.4. Assumptions and modelling choices

This section highlights the most important assumptions of the model (Table 3). Additional assumptions are outlined in 29Appendix B.

Table 3. Assumptions and modelling choices.

Category	Assumption	Justification	Implication	Source
System scope	Model represents 1000 houses instead of the full Delft housing stock (~54,000)	This size allows the model to run at a acceptable speed while still capturing heterogeneity of a municipality	This size is not directly representative for Delft, but patterns remain interpretable	(Gemeente Delft, 2025a)
Max transition cost	Maximum renovation cost per house is €90,000	Realistic upper bound for deep renovations (old houses) and aligns with Delft max subsidy scheme. Individual transitions are computed using this number.	Excludes even costlier renovations (outliers), but ensures bounded results	(Gemeente Delft, 2025b)
Max subsidy	Set to €19,000	Covers first upgrade from lowest energy label (G->F) while preventing all houses from transitioning simultaneously	Transitions are highly sensitive to this parameter (see 2.)	-

2.5. Verification

Multiple verification methods were tested for the model, including unit testing, trace validation, edge case testing, boundary testing, and logic checks. To track the behaviour of the model, we visualized additional indicators (see Appendix C).

2.5.1. Edge Case Testing

Edge case testing was used to check if the model works for a minimum of 1 homeowner and 1 landlord. To observe the model's behaviour, we tested 1) higher numbers of landlords and owners with the same repartition as Delft and 2) a different distribution between landlords and owners.

Too high subsidies were identified in the first iteration of the model, which meant that transitions were too fast: it became beneficial for everyone to transition immediately. This was solved by adjusting the values of the subsidies and using the 0.3 decision threshold.

2.5.2. Trace Validation

Different agents from the landlord class and the owner class were tracked. Ten agents of each type were tracked in the model to verify their behaviour regarding the information, financial, and decision scale. The influence of owners and landlords on each other was too high which led to the fast decrease or increase in information scale of the agents.

2.5.3. Unit Testing

Print statements were added to the different functions created to ensure each functions returned the relevant outcomes. This helped identify issues with the gas and electricity prices, as well as the costs, which were later modified and solved.

In conclusion, extensive verification was performed, increasing the robustness of the code. Although additional checks could further enhance the code's robustness, the team believes the model to be reliable enough to fit the purpose of this project.

2.6. Sensitivity analysis

We conduct a global sensitivity analysis to assess how uncertainty in model parameters affects its output. Sobol analysis allows us to quantify the relative importance of parameters and their interaction in explaining output variance (SALib, 2025).

We followed a standard sensitivity analysis approach (see Appendix D for detailed breakdown), and a full table of parameters and ranges can be found in Appendix F.

Table 4 reports the Sobol results. The maximum transition cost is the driving parameter in explaining variance in the cumulative energy saved (0.7 of the variance individually, and 0.8 considering interaction effects). Maximum subsidy is the second most influential parameter. This aligns with our model's design, as economic constraints are the primary drivers of transition decisions. In contrast, social influence parameters contribute negligibly to the output variance, while the maximum campaigning has a small effect (0.01 of the variance).

Table 4. Sobol analysis results

Variables	First-order index	Total order index

Maximum cost	0.658	0.763
Maximum subsidy	0.147	0.386
Landlord-landlord influence	0.000	0.000
Homeowner-landlord influence	0.000	0.000
Landlord-homeowner influence	-0.002	0.001
Homeowner-homeowner influence	-0.001	0.000
Maximum campaign	0.012	0.013

Figure 7 visualizes the interactions between parameters. It highlights strong interaction between maximum transition cost and maximum subsidy, indicating that subsidy effectiveness is highly dependent on the renovation costs. Contrarily, social and especially campaign parameters become somewhat relevant only through their interaction with maximum subsidies, showing that it is a central variable to the model.

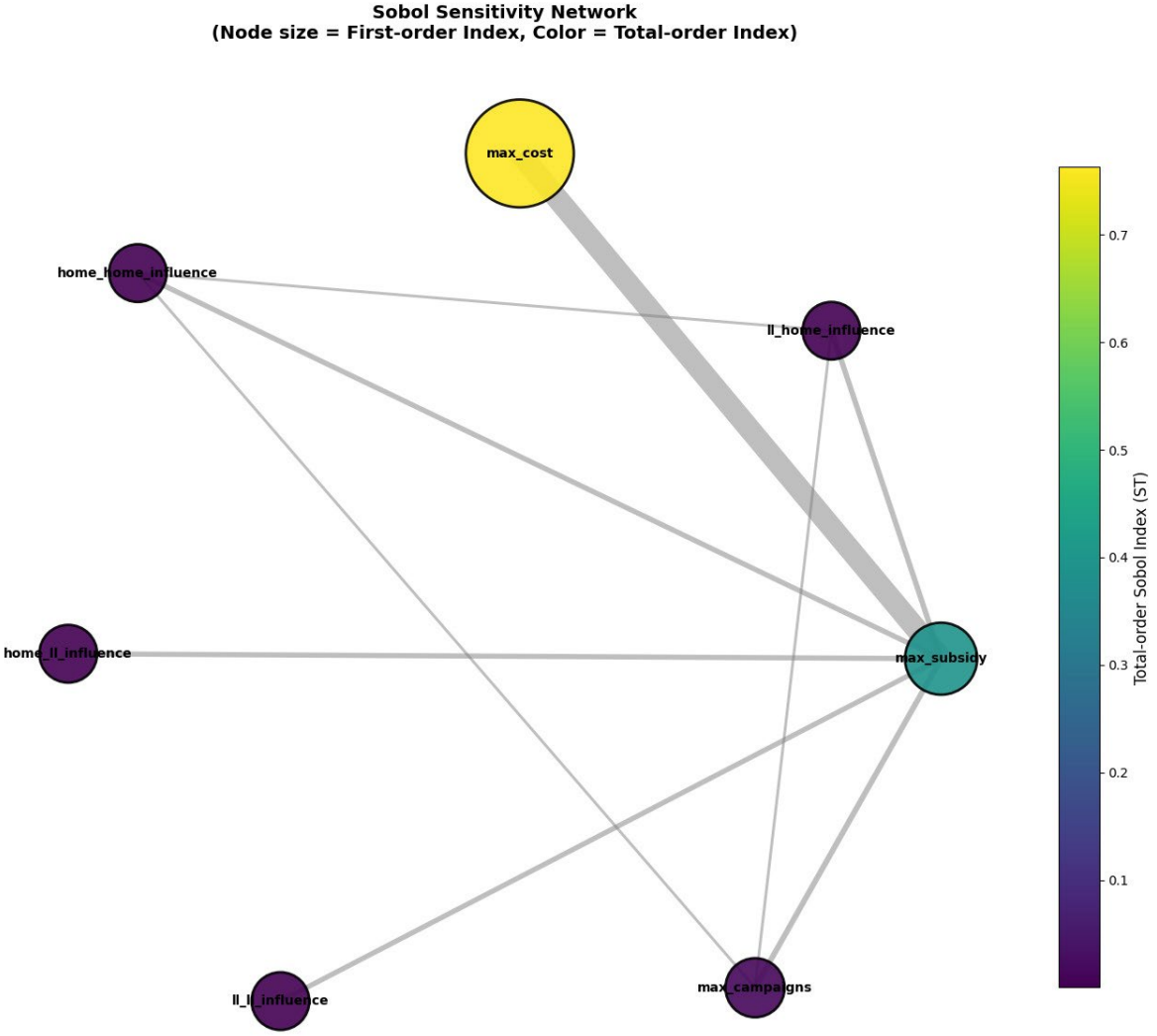


Figure 7. Relationships and effects of parameters visualized

The model's behaviour mostly shows linear responses to economic parameters and interaction effects show dependence between costs and subsidies. However, we show reinforcing effects of social interactions when combined with maximum subsidy.

2.7. Validation

The objective of the validation step is to understand whether the model represents the situation that we envisioned and can answer the research question. For this step, we focused mainly on face validity and literature comparison given the time constraints.

2.7.1. Face validity

Considering the network structure (Figure 8), landlords and owners are represented in different neighbourhoods which are all connected to the municipality, and the assigned houses are connected to the landlords. Agents have most of their links within the neighbourhood and some outside of it. Overall, the network matches our intuition.

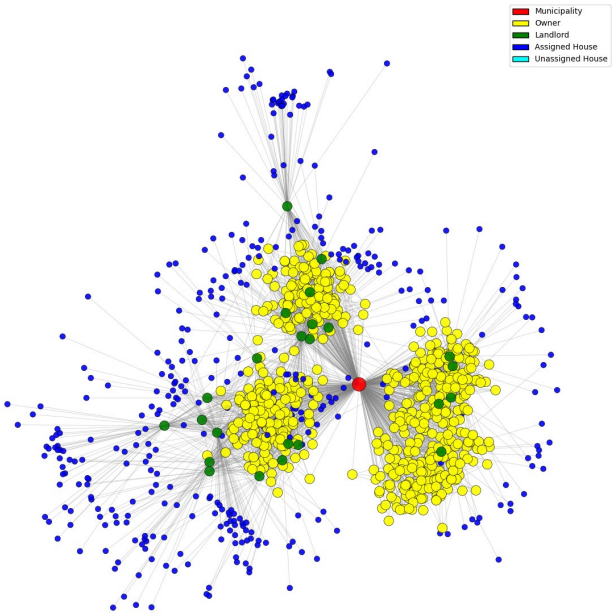


Figure 8. Configuration of the network with the parameters studied

Additionally, transition dynamics for each agent class is observed (Figure 9). At the beginning of the policy, a lot of owners will transition, and this number will gradually decrease as time passes. This matches intuition as the number of possible transitions is higher in the beginning.

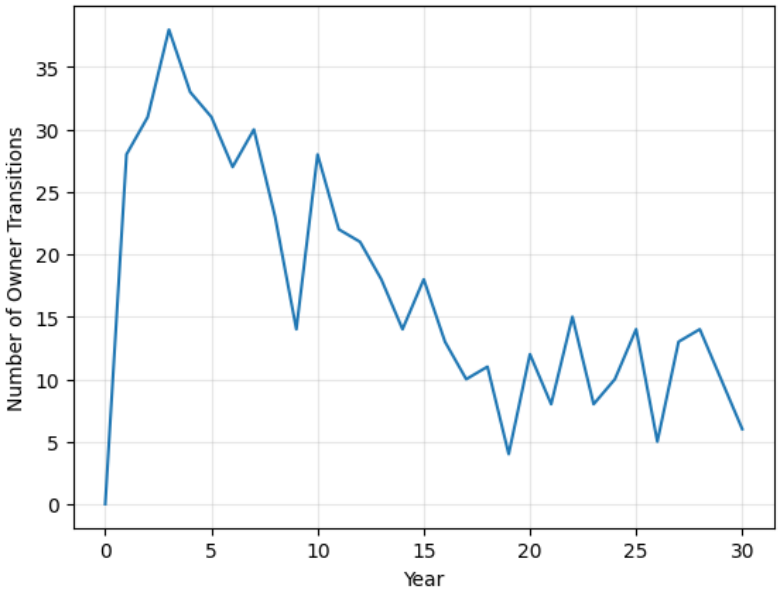


Figure 9. Number of owner transitions per year

Subsequently, KPI's are checked. Figure 11 shows an exponential increase in the cumulative energy saved which corresponds to the intuition: more owners and landlords transition over time leading in an exponential increase in cumulative energy saved as landlord and homeowners get better labels over time which increases the energy saved exponentially.

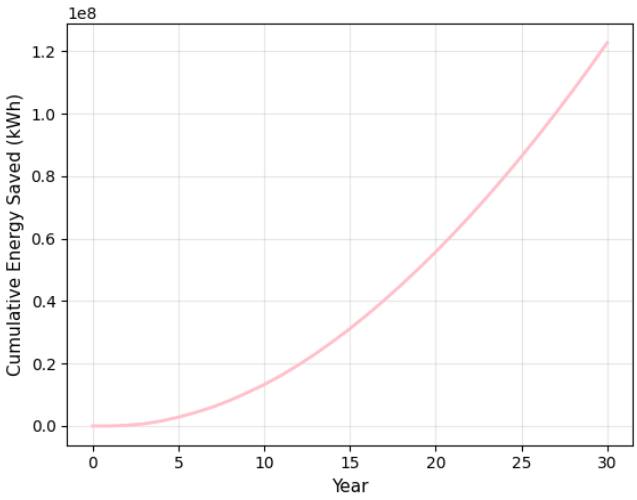


Figure 10. Cumulative energy saved in kWh

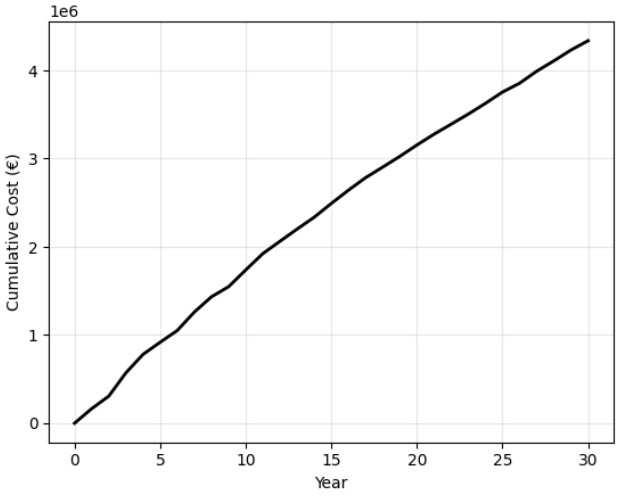


Figure 10. Cumulative municipality cost in €

Figure 10 shows mostly the subsidies given as the campaign costs are negligeable compared with campaign costs. Overall, we see an increasing trend which matches intuition. The slightly concave shape indicates higher subsidies in the beginning that would decrease over time as more landlords and homeowners transition.

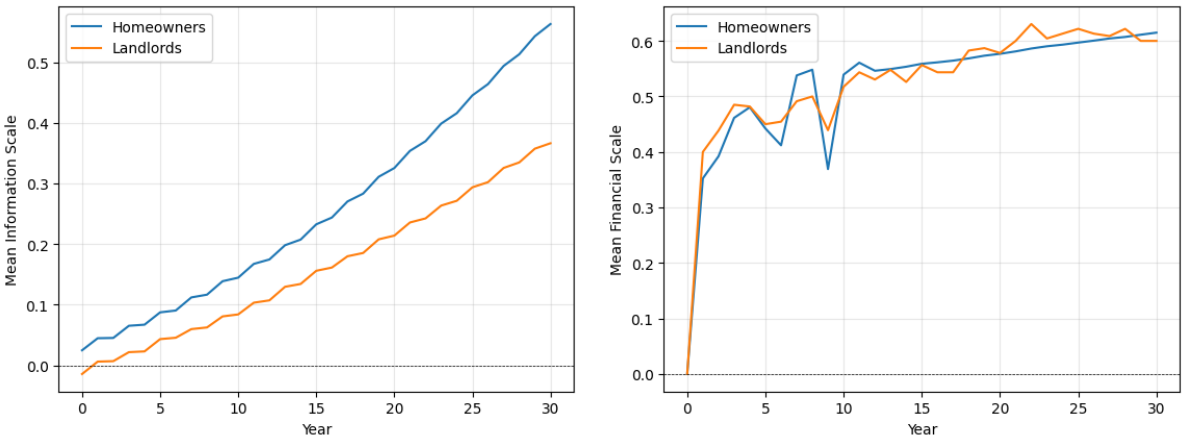


Figure 11. Mean information(left) and financial scale (right) of homeowners and landlords over a simulation

Figure 12 shows the mean information scale increasing over time for both landlords and homeowners, which reflects the interactions between the agents. The mean information scale logically increases because it is evenly distributed at the start and influenced positively by the informational campaigns. The financial scale also shows logical trends in our model: as more agents transition to higher labels, their payback period goes down due to increasing energy savings, and this increases the financial scale.

2.7.2. Literature comparison

Although our model uses sufficient real-world data (e.g. energy prices, campaign cost, etc.), ungrounded numbers have been used for social influences and the "weight" of financial vs social influences. This calls for comparison to existing studies.

Broers (2023) studied the decision-making process for housing renovations for Dutch homeowners and confirms that financial-economic factors are indeed the most important factor to transition. Additional factors, such as social networks or environmental concerns, can play a part. Therefore, our model, while simplifying the behaviours, still represents the most important characteristics.

More generally, a systematic review on homeowners' housing renovation decision-making (Liu et al., 2022) showed 689 factors grouped in seven categories that influenced this decision. Table 5 shows how our model considers the aspects identified.

Table 5. Housing renovation decision-making factors

Liu et al., 2022	Present or absent	Model
Decision-maker characteristics	Present	Information scale, financial scale
Beliefs about energy renovations	Present	Campaigning influence

Dwelling characteristics	Partially	Different energy labels but same area
Authorities and policies	Present	Municipality policies (e.g. subsidies)
Energy renovation work and process	Present	Payback period
Product and services	Absent	Assumption: availability of products and services
Social influence	Present	Influence factors

Our model indeed shows a similar pattern of more constraining factors related to income and a more indirect influence of social connections. Although the main factors are present, important limitations of the model should be considered in further studies.

2.8. Experimental design

To measure the effect of the policy levers on the KPIs, an experimental design was set up which directly answers the research question as established in section 1.

2.8.1. Hypotheses, variables, ranges

Table 6 summarizes the variables, hypotheses, and justification for the experimental design.

Table 6. Summary hypotheses experimental design

Independent variable	Hypothesis	Justification
Max_subsidy	Higher max_subsidy leads to faster energy label transitions	Subsidies increase the possibility to upgrade the energy label, more agents will transition yearly with higher maximum subsidies.
Max_campaign	Higher campaigning leads to faster energy label transitions	Campaigning increases the information scale, which increases the decision scale and thus the probability for a transition.
Both	Campaigning is less effective than subsidies on energy label transitions	Financial scale is more constraining than information scale for transitions (see section 2.), making us believe that subsidies have a higher effect on the transitions.

A baseline scenario is necessary to understand the effect of the policy levers. In this scenario, both maximum subsidy and maximum campaigns per year are set at 0, giving insights in the energy label transition behaviour without these policies in effect.

Table 7 highlights tested parameters, ranges and their justification.

Table 7. Variables, ranges, and justification

Independent variable	Ranges	Justification
Max_subsidy	[2000, 3000, 5000, 5500, 5600, 5650, 5700, 5800 6000,7000, 8000, 9000, 10000, 19000]	Upper bound (19,000) enables the most expensive transition (G->F). Lower numbers are tested to see the impact on transitions.
Max_campaign	[1,2,3,4,5]	Realistic range for campaigning by a municipality.

2.8.2. Scenarios, replications, duration

Table 8 highlights 4 scenarios that we explored. Per scenario, 10 replications were made rather than the advised 5 replications for more robust results. Each simulation lasts 30 steps, corresponding to 30 years. Regarding metrics and analysis plan, time series are plotted as well as the three KPIs: cumulative municipality expenditure, cumulative energy saved, expenditure-to-energy-saved ratio.

Table 8. Scenarios considered

Scenario	**Maximum subsidies**	**Maximum campaigns**	**Explanations**
Scenario 1	Low	Low	The municipality doesn't have the funding to support the transition
Scenario 2	Medium	Medium	Dual strategy: municipality is interested in helping the citizens financially but also informing them
Scenario 3	High	Low	The municipality thinks that the financial constraints are stopping the agents from transitioning
Scenario 4	Low	High	The municipality thinks that the information constraints are stopping the agents from transitioning

3. Results

Results of base case and policy scenarios: The base case corresponds to a maximum subsidy of 0 and maximum campaign of 0. For the purposes of visualisation, we will show the results within the following ranges:

- maximum subsidies = [0,2000, 5700, 6000, 10000]
- maximum campaigns = [0,3,4, 5].

First, the target of the 90% compared to business as usual needs to be defined. From the results of the simulations, on average we found the following:

Base case energy saved: 51,404,037 kWh

Therefore, with a 90% increase our target will be 97,667,672 kWh. The following figures show the energy saved over time through time and at year 30 for the ranges defined for the visualisation.

3.1. Results of Experimental Design

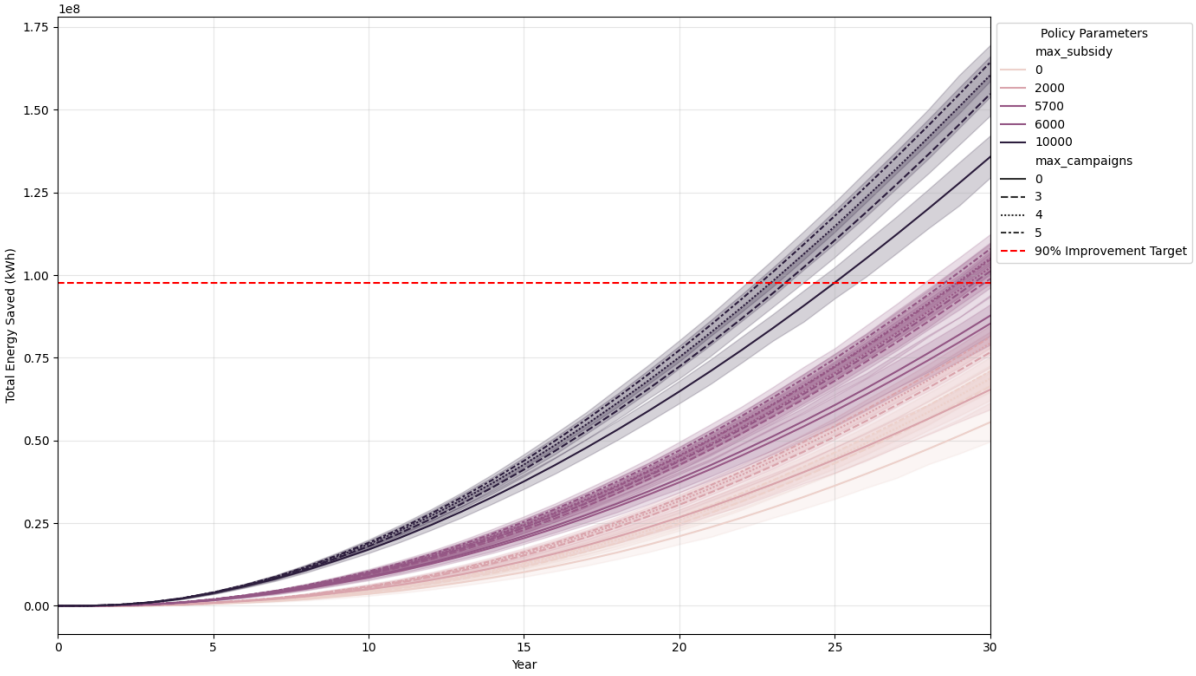


Figure 12. Total energy saved over time (kWh) for 20 configurations.

Figure 12 shows that a maximum subsidy of €10000 will lead to achieving the target earliest (year 23), while a subsidy of €5700 and €6000 the target is reached at year 30. For the €2000 subsidy limit, the target is not reached. Compared to the base case, we see the same evolution pattern, but the magnitude differs. Even when no subsidies or no campaigns are made there is still some energy label transition but at a slower pace. This can be explained based on the initial distribution of information as well as the interactions patterns between the agents.

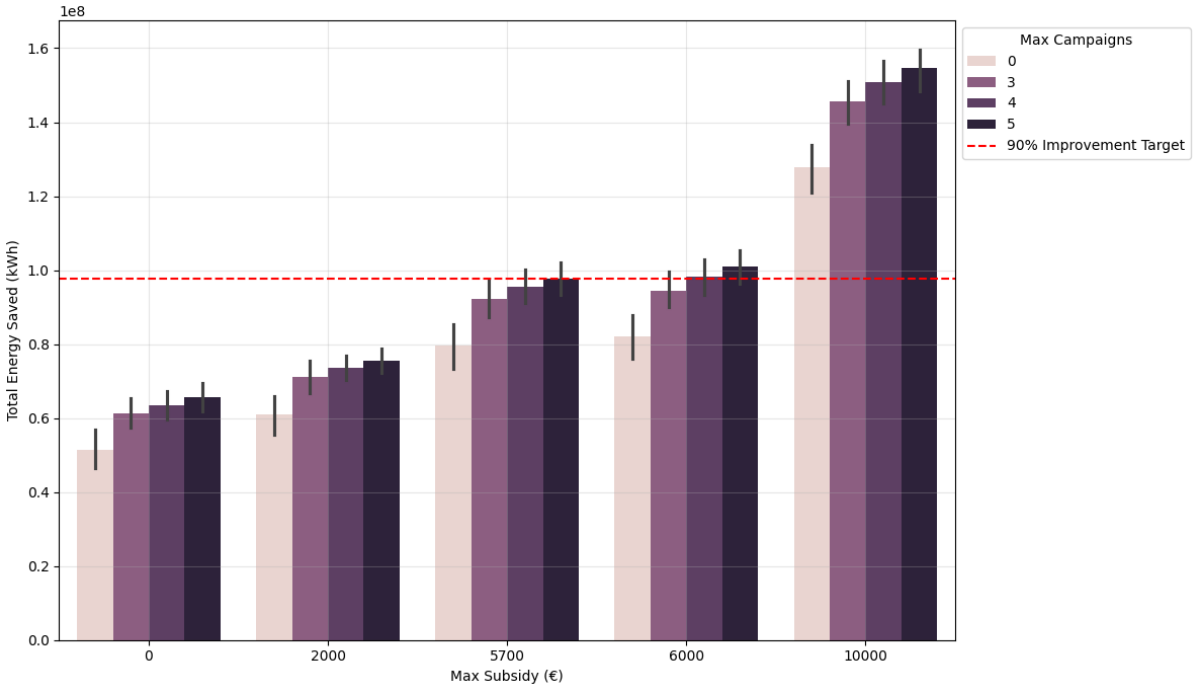


Figure 13. Total energy saved at year 30 per max_subsidy and max_campaign range

Figure 13 shows that at year 30, the maximum subsidy of €5700 combined with 5 maximum campaigns per year reaches the threshold defined. We also observe that to remain at a realistic number of campaigns, the differences between the campaign levels are not very different.

Regarding municipal costs, the higher maximum subsidies combined with higher campaigning intensities show higher expenditures (see Appendix E).

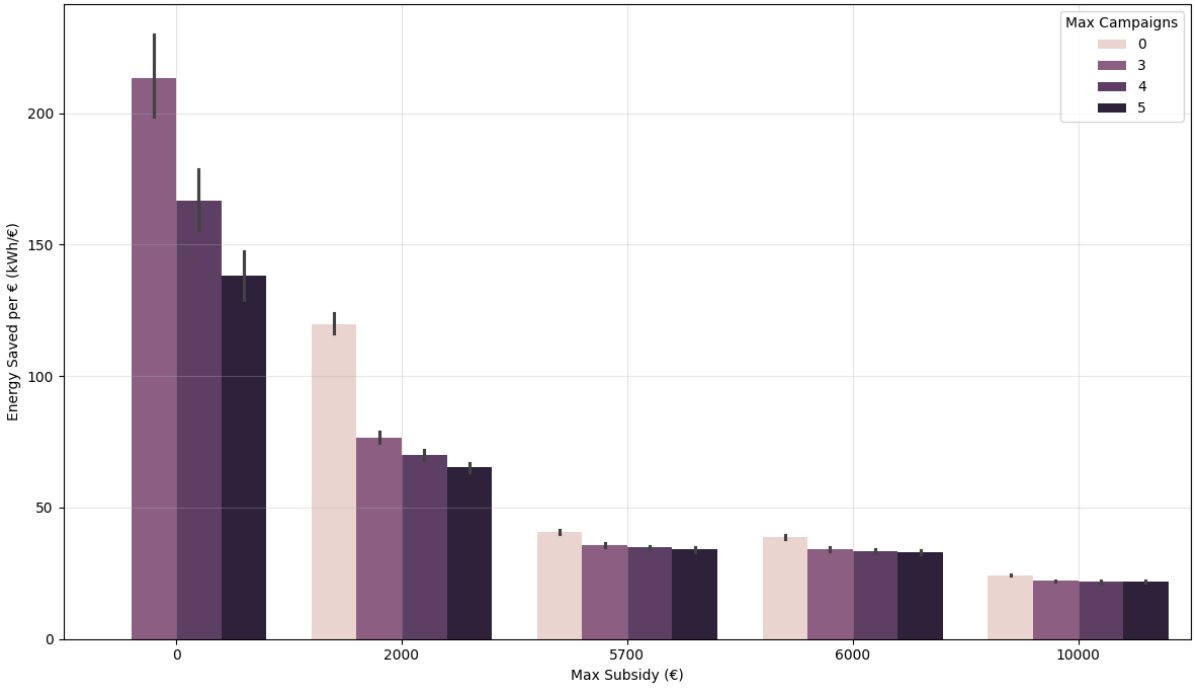


Figure 14. Energy-saved-to-expenditure ratio at year 30 per max_subsidy and max_campaign range

Figure 14 shows that the most cost-effective option amongst the options tested is with campaigns and no subsidies. In the base case, there is no cost-effectiveness as nothing is spent. In the case of only maximum 3 campaigns and no subsidy, the cost is very low but the effect it has is higher than what is spent. However, with the previous figures, we see that with max campaign = 3 and max subsidy = 0, the energy saved at year 30 doesn't reach the target. This highlights a trade-off between the cost-effectiveness and the energy savings target; while smaller interventions can be very cost-effective they might not be sufficient to reach our target.

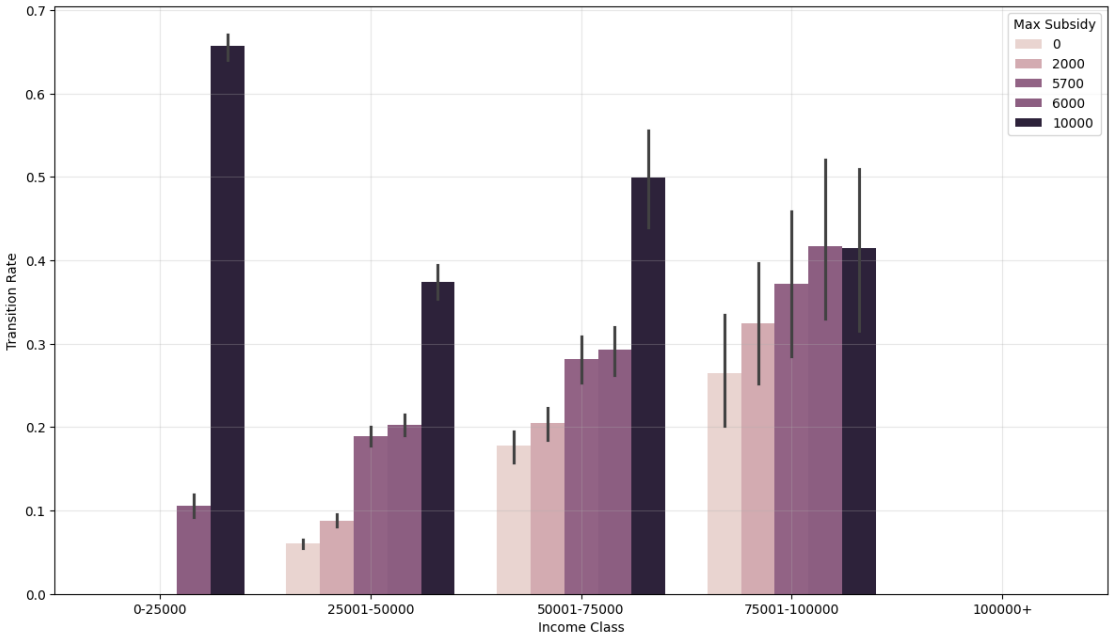


Figure 15. Transitions per income class (owners) at year 30

Figure 15 reflects the transitions per income class for owners depending on the subsidy given. While the information campaigns can have the same effects on all the agents, it is not the case for subsidies. For example, at no subsidy, the higher income range of €75001-€100000 will transition the most. At €10,000 maximum subsidy, the €0-€25000 income class has the highest transition rate of all income classes (0.65) followed by the €50001-€75000 income range. Therefore, higher subsidies allow a wider range of income classes to transition.

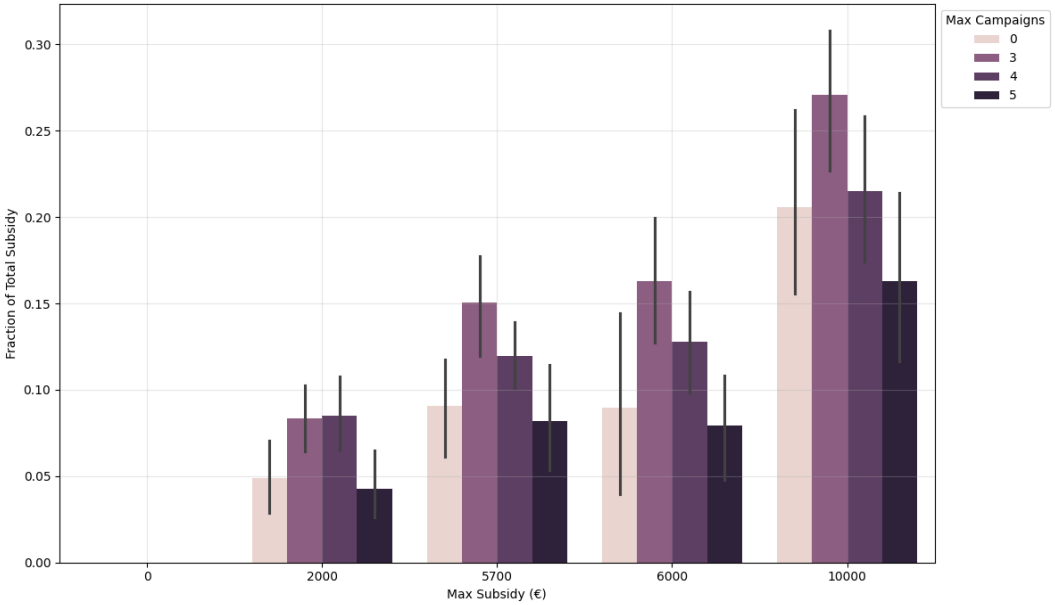


Figure 16. Fraction of total subsidy to owners per max_subsidy and max_campaign ranges

Figure 16 shows the fraction of total subsidy given to homeowners versus landlords. The figure shows that higher subsidies cause homeowners to receive a greater share. Additionally, it seems that more information campaigns lower the share of subsidies that homeowners receive. This means that campaign influence causes landlords to transition more houses than homeowners.

3.2. Emergent Behaviour

Emergent behaviour occurs in our model. Two figures help illustrate two separate trends.

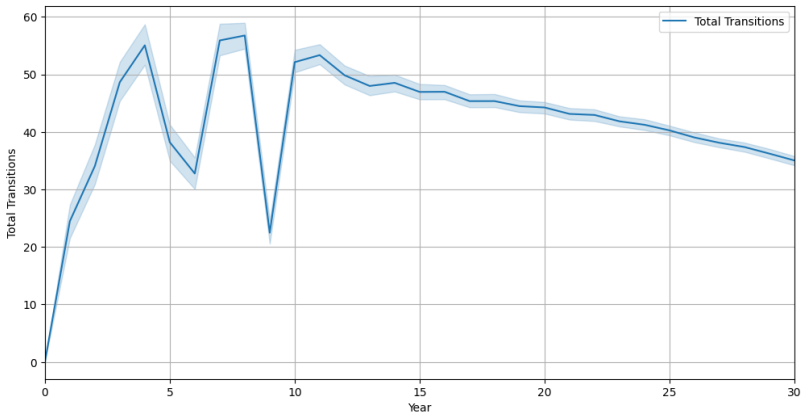


Figure 17. Total transitions per year

Firstly, Figure 17 shows emergent behaviour in the total transitions per year for owners and landlords. It shows peaks in the first ten years, as high subsidies for low labels allow for many early transitions. As the energy labels rise, subsidies decrease which increases costs, resulting in lower total transitions per year.

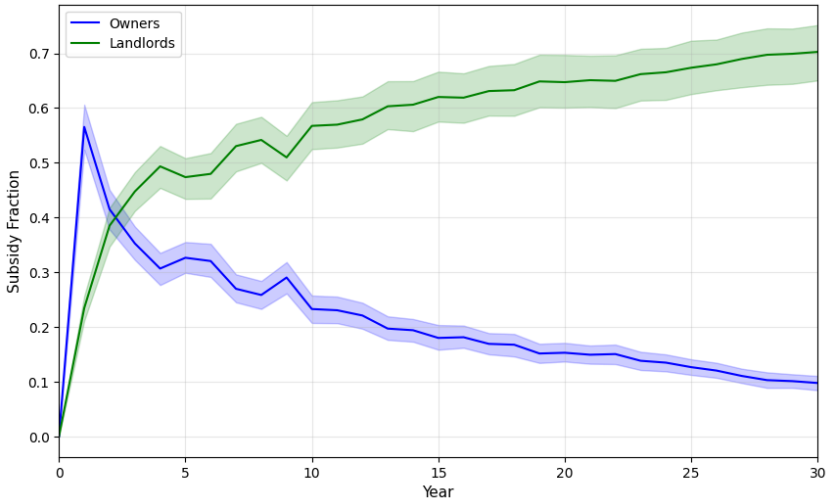


Figure 18. Fraction of given subsidies for homeowners and landlords

Figure 18 shows emergent behaviour in the distribution of given subsidies among homeowners and landlords. In year one, it shows a peak where homeowners receive more subsidies. This is because the low-energy label transition is cheap due to high subsidies; people can only transition one label at a time, and homeowners own approximately two-thirds of the houses. Afterwards, transitions become more expensive due to lower subsidies. Homeowners are limited by their financial status, while landlords are not. Therefore, the distribution becomes higher for landlords.

3.3. Summary of the findings

Table 9 shows that, provided that house characteristics are homogeneous and products and services are available, a policy mix of €5700 in maximum subsidy and 5 in maximum campaign achieves the highest energy-per-expenditure ratio for Delft while reaching the 90% target in our model. Interestingly, higher subsidies also achieve higher energy savings; however, they are less cost-effective than the ideal policy mix.

Table 9. All policies that reach the 90% energy savings target compared to baseline scenario

Max subsidy	Max campaign	Cumulative Municipality Expenditure (€)	Cumulative Energy Saved (kWh)	Energy per Expenditure (kWh/€)
5,700	5	2.87E6	9.78E7	34.02
6,000	4	2.93E6	9.82E7	33.50
6,000	5	3.06E6	1.01E8	32.97
10,000	0	5.27E6	1.28E8	24.28
10,000	3	6.57E6	1.46E8	22.14
10,000	4	6.86E6	1.51E8	21.97
10,000	5	7.04E6	1.55E8	21.97

If the municipality wants to achieve the 90% target with more certainty, they can increase the maximum subsidy from €5700 to €6000. The different runs for this combination show that the target wouldn't be reached with only €5700 maximum subsidies in some cases (see Appendix E).

4. Discussion and Conclusion

This study addresses the question:

"What is the energy saved per euro of municipal expenditure for house label transitions in Delft with the goal of increasing energy savings by 90% over a 30-year period compared to a no policy case?"

Based on our model of Delft, for the sample tested, we find that the energy per euro of 34.02 kWh/€ can meet this target. Our results show that a policy mix combining subsidies (€5700) and information campaigns (5 campaigns) is necessary to reach the 90% reduction within 30 years.

From the experiments, we observe that subsidies are the central driver of energy label transitions in the model. Renovation costs strongly constrain transition behaviour, meaning that higher subsidies directly reduce costs and increase transition rates and cumulative energy savings. Information campaigns amplify transition rates when combined with subsidies by increasing the probability of active agents to act on their improved financial attractiveness. Ultimately, these policies show the trade off in our model, which is that low policy spendings result in high cost-effectiveness for municipality, but higher expenditures are required to reach the 90% target.

Additionally, the model shows that homeowners and landlords receive different shares of total subsidies depending on both the maximum subsidy and the campaigning intensity. Policies are most effective in the early years when many houses have low energy labels and higher subsidies are provided. Once the average label improves over time, transitions decline and energy savings decrease, depicting the cost-effectiveness trade-off.

An important limitation is the absence of more complex social dynamics. Social influences are simplified in this model, and other factors, like budget, are not included in the policy implementation. Additionally, the model assumes homogeneous dwelling characteristics (e.g. area) and does not consider the availability of renovation material/services. The model could break if real-life situations like limited renovation capacity cannot meet transition rates. These limitations impact the external validity of our model, where results may not hold for other countries/cities with differing incomes, housing stocks, or policies.

Future work could improve the model through more detailed social interactions, additional dwelling characteristics, and targeted subsidy schemes by income or housing type. Particularly, considering a fair transition, it is relevant to make targeted subsidies for lower incomes, as our model shows that higher subsidies, while less cost-effective, lead to higher transition rates for lower incomes. From a policy perspective, we advise Delft municipality to balance the number of information campaigns with the number of subsidies for cost-effectiveness, while considering heterogeneity between homeowners and landlords. Overall, this model demonstrates that renovation costs are a limiting factor that should be addressed through subsidies to realize a reduction goal of 90%.

5. Reflection on the Modelling Experience

Regarding the modelling process, it was a very iterative process that allows to take a perspective. This also relates to one of the challenges of the implementation, which is to maintain a clear overview despite the high number of changes that are required. To find errors in the code, it worked really well to visualise and print the results of sections that you add or are analysing. You should then, without looking at these results, think of what they should approximately be and compare the two. This allows you to see what actually happens in the code and if it is correct.

Although some time was spent on the conceptualization and the formalization, a solution could be to also add an order of modifications required in the code to keep track of progress. The verification and validation step also helps to keep this perspective on the model. Regarding teamwork, it worked efficiently as we harnessed the skills of every team member to achieve the work.

6. AI Acknowledgment

In coding, AI was used to understand concepts, suggest code, find errors, and suggest fixes. No AI agents were used, so all code was implemented into the final script by hand. We all agreed that code could only be implemented when fully understood. AI was very useful in helping us understand these new concepts and sped up the learning process.

In reporting, AI was used mostly to help with writing. Some sections were written in bullet points and rewritten using AI in a concise way to maximize content in as little words as possible. Text from AI was not copied but rather kept alongside the bullet points to cherry pick concisely formulated arguments. This ensured understanding of concepts and arguments in as little words as possible. Moreover, the equations in the formalization step were also finetuned based on equations written in the code. Furthermore, the structure of the report is fully adapted from the course manual, while minor structuring was done using AI (e.g. streamlining arguments in Discussion and Conclusion)

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8. Appendices

8.1. Appendix A – Output Metrics & KPI: Elaboration

Table 10 elaborates on the KPIs from section 2.1.3, its hypotheses and expected ranges (normative).

Table 10. System-level KPIs, hypotheses, and expected ranges

KPIs	Explanation	Hypotheses	Expected Ranges
Cumulative energy saved	Represents the total amount of energy saved since the start of the simulation, over all houses and years. This is long-term progress towards the target of 90% increase in residential energy savings.	The longer the program, the higher the cumulative energy saved.	Starts at 0, increasing gradually until it plateaus as additional yearly energy savings decline
Cumulative municipal expenditure	Measures the total municipal cost, including spendings on information campaigns and subsidies. This KPI measures the policy effort required to stimulate the energy transition.	The longer the program, the higher the total municipal expenditure	Starts at 0, increasing as time progresses with fast growth in periods of high transition activity
Energy-saved-per-€	Calculates the ratio between cumulative municipal expenditure and cumulative energy saved. This KPI directly measures the cost-effectiveness of the policy and answers the RQ by indicating how much energy is saved per euro of municipal spending.	The longer the program the lower the cost-effectiveness of the policy (meaning a lower ratio of energy saved per €	High ratio (high cost-effectiveness) in the beginning, decreasing as marginal savings decline and total municipal cost continues

8.2. Appendix B – Assumptions

Table 11 shows key assumptions that had to be redacted from section 2.4 to realize the final word count:

Table 11. Additional key assumptions of the model

Category	Assumption	Justification	Implication	Source
Temporal scope	Transitions occur annually	Transitions and policies usually happen yearly, rather than weekly	Short-term dynamics inside a year are not captured (e.g. influence electricity/gas price on cost)	-
Max transition per year	Homeowners and landlords can	This prevents unrealistic situations where agents	This slows transition pace for interpretability	-

	upgrade once per year	jump multiple labels instantaneously	and to reflect real-world renovations	
Subsidy allocation	For homeowners, subsidies are based 50% on income and 50% on energy label. For landlords, only on energy label.	Reflects a policy balancing income and inefficiency of houses, prioritizing low energy labels and lower incomes.	Other subsidy schemes based on municipality interest change distributional outcomes	-
Social connection	Landlords influence homeowners more strongly than vice versa	Landlords are perceived as more knowledgeable about housing and renovations	Not based on empirical data, so remains a limitation of the study	-
Decision threshold	A minimum decision scale of 0.3 is required for active agents to consider transitioning	This ensures that active agents are in a positive decision state before transitioning	Transition timing is sensitive to this threshold	
Financial attractiveness	Transitions are driven by payback period. Payback period ranges between 0 and 10 years	Payback period is a common decision factor for real-world renovations and links decision to financial capacity.	Improves validity of model	(Schep et al., 2022)
Affordability check	Homeowners do not transition if costs exceed 20% of their financial status	Households usually spend max 20% of disposable income on housing	Adds a sanity check for homeowners but may also underestimate willingness among highly motivated households.	(Yanatma, 2025)
Information campaigns	Reach 70% of homeowners and landlords. Each campaign costs €7500.	Assumed to reflect realistic media reach and TV ad cost of municipal campaigns	Improves validity of model, but may underestimate costs.	(Mediamax, 2025)
Social structure	Social influence is modelled through small-world network	Allows for clustered neighbourhoods and social connection through proximity, suitable for urban areas	Proxies social connection, which is still an underrepresentation of real-world connection and info spreading	-

Less important assumptions and modelling choices:

- **Electricity and gas prices**: Electricity and gas prices are based on real-world residential data from the NL in 2025
- **Calculation electricity:gas share**: assumed to be 0.2;0.8, based on calculations of consumption of dwellings

- **House size**: House size is assumed as the same as the average in the Netherlands for all houses in the model. This is a simplifying assumption as the specific city might have different house types leading to important differences in terms of energy savings (House Size by Country 2025)
- **Income distribution**: the income distribution is assumed the same as the income distribution for the Netherlands. It is also an assumption that simplifies reality as if the city is poorer or richer than the average this distribution might change which can modify the ability to perform a transition
- **Energy label distribution**: The distribution of the energy label is assumed to be the same as the one from the base model. This is because we needed to have a situation where they were transitions to be made. If all houses are already at label A it is less interesting to study the energy label transition.
- **Max rent**: the rent that the landowner charges (and thus receives) is based on a calculation using the maximum rent of social housing in NL in 2024, being 879.66 per month, thus 10555.92 per year. For simplicity's sake, this is rounded off to 10800 per year for houses with label A+. No data was found on other rents, so the lower rents are an expected plausible figure based on the max rent.
- **Number of houses for landlords**: the landlords are divided into three groups; small (private), medium (fund organizations), and big (institutional housing corporations). The amount of houses for small landlords is based on real-world statistics, where most private landlords own a maximum of 8 houses (Kadaster, 2023). No specific data was found for medium and big landlords. Therefore, we extrapolate the first number, and create an expected range for medium landlords owning 11-50 houses, while big landlords own 51-100 houses.
- **Division share of landlords**: It is assumed that of the total share of landlords, 60% are small, 20% medium, and 10% big. This assumption is not grounded on real data, but the shares are chosen to represent the demographic as presented by research on the private rental housing sector (CBS, 2024).
- **Number of total houses**: the number of houses in the model is assumed to be 1000. Although this is not a realistic estimate, as compared to the actual number of houses in Delft being approximately 54,000 (Gemeente Delft, 2025a), this number allows our model to run at a bearable speed. A higher number decreases the speed, while lower numbers reduce the representativeness of the model.
- **Number of landlords and owners**: to mitigate the free choice for number of houses, the share of landlords:owners is adapted from a statistic that 37% of all houses in Delft are rented (landlords), while 63% is purchased (owned).
    - **Landlords**: Of the 37% landlords (370 houses), 222 are houses owned by small landlords, 111 are houses owned by medium landlords, and 37 are houses owned by big landlords. Using the maximum amount of houses owned per landlord class (10, 50, and 100), allows us to compute the amount of landlords, being a maximum of 22 small, 2 medium, and 0 big landlord.
    - **Owners**: as 63% of all houses in delft are purchased, we can assume that 630 houses are owned by owners.

Assumptions based on real world data:

- Electricity price and gas price ((Yanatma & Eurostat, 2025)
- Electricity vs gas share (Centraal Bureau voor Statistiek [CBS], 2025)
- Energy use per energy label (Energy label explained with example | Energy label)
- Payback period simple vs intense renovation (Schep et al., 2022)
- Income distribution of owners is based on Income distribution (standardised income) | CBS
- Max subsidy per year (Gemeente Delft, 2025b)
- Informational campaign price is based on the cost of a TV ad (Mediamax, 2025)
- Income check based on expenditure of 20% income of EU people (Yanatma, 2025)
- Max rent (for A+ labels) is based on highest rent for social housing in NL in 2024 (Koninkrijksrelaties, 2024)
- Number of houses for small landlords is based on max houses that private landlords own being 8 (Kadaster, 2023)

8.3. Appendix C – Verification: Indicators & Visualizations

Main indicators include:

- Energy savings (yearly and cumulative)
- Municipal expenditure (yearly, cumulative, campaign and subsidies)
- Ratio energy saved/total expenditure
- Transitions (yearly, separately homeowners and landlords)
- Mean information and financial scale (homeowners and landlords)

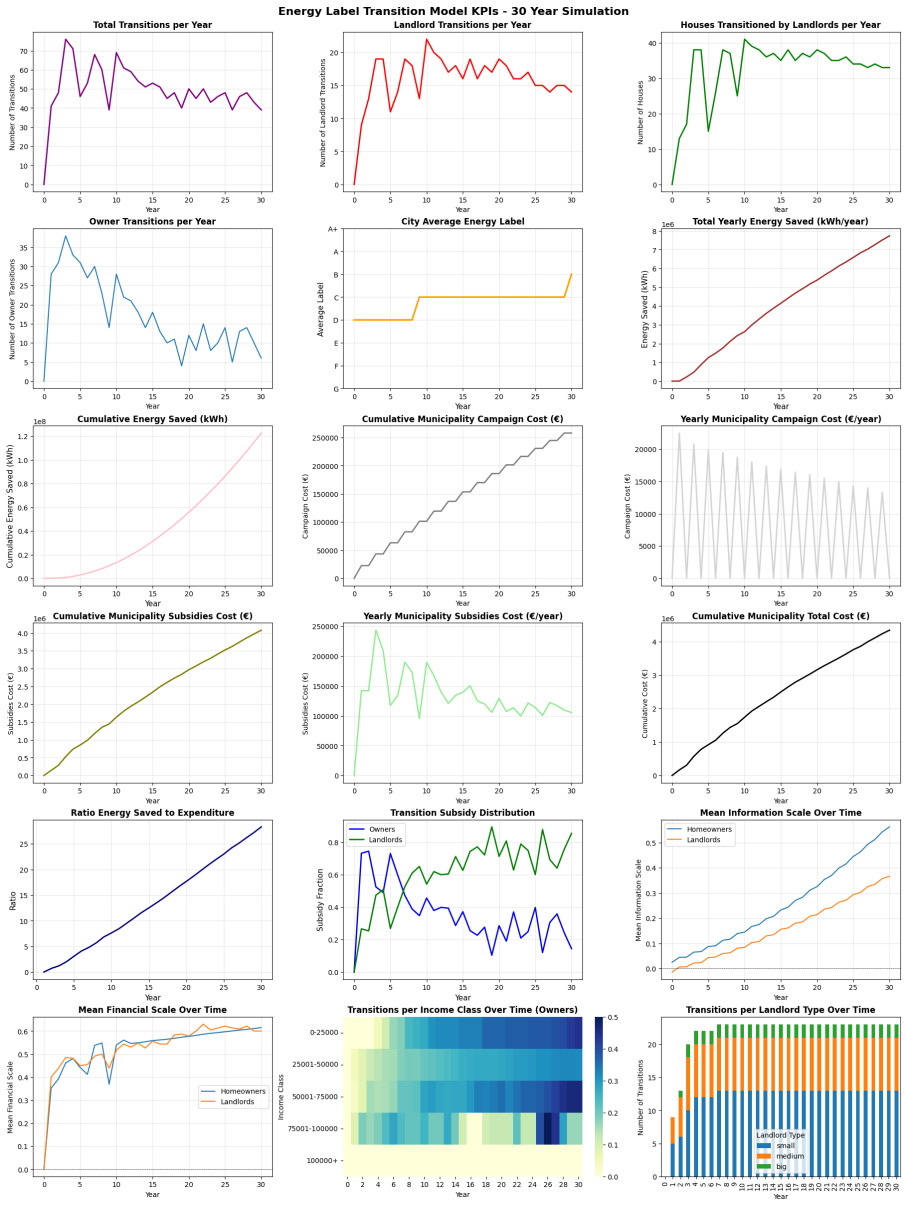


Figure 19. All indicators found in the code to track its behaviour

The full list of visualizations (Figure 19) used to track the behaviour of the model:

- Total transitions per year
- Number of landlord that transitioned per year
- Number of houses owned by landlord that transition per year
- Number of owners' transition per year
- City average energy label
- Yearly energy saved
- Cumulative energy saved
- Cumulative municipality campaign cost
- Yearly municipality campaign cost
- Cumulative municipalities subsidies cost

- Yearly municipality subsidies cost
- Total cumulative municipality cost
- Ratio of energy saved to municipal total expenditure
- The distribution of the subsidies between the landlords and the owners
- The mean information scale of owners and landlords
- The mean financial scale of owners and landlords
- The transition per income class over time for owners
- The transition per landlord type over time

8.4. Appendix D – Sensitivity Analysis: Detailed step-by-step Approach

Step 1) **Selecting parameters & ranges**:

See Table 12

Step 2) **Running the experiments**:

To run the Sobol analysis, for 5 seeds tested, the model is replicated as the agent won't behave exactly the same depending on the seeds. Moreover, the Saltelli sampler is uses and generates N*(2D+2) samples, with N the argument given, here 256 and D the number of parameters tested, here D=7 meaning a total of 4096 parameter combinations. Saltelli is a type of hypercube sampling method, meaning that the samples are taken more uniformly than random samples (Saltelli et al., 2010).

Step 3) **Measuring outputs**:

The output that we are interested in to answer our research question is to understand how the parameters will influence the total energy saved over the simulation as we want to reduce the energy consumption by 90% by 2050.

Step 4) **Analyzing the results**:

See results in section 2.6

8.5. Appendix E – Results: Figures

For all combinations, all the possible outcomes of the model are shown as tested with the experiment (Figure 20).

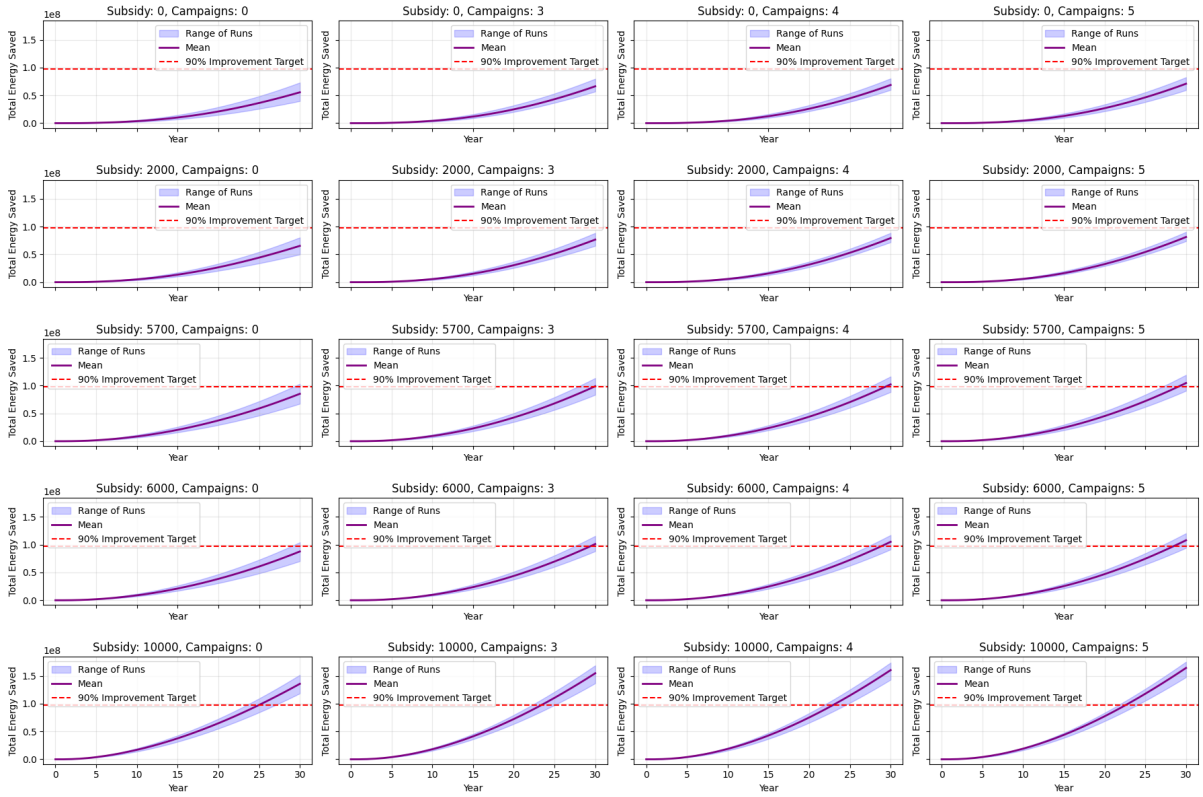


Figure 20. Possible outcomes from the experimental design

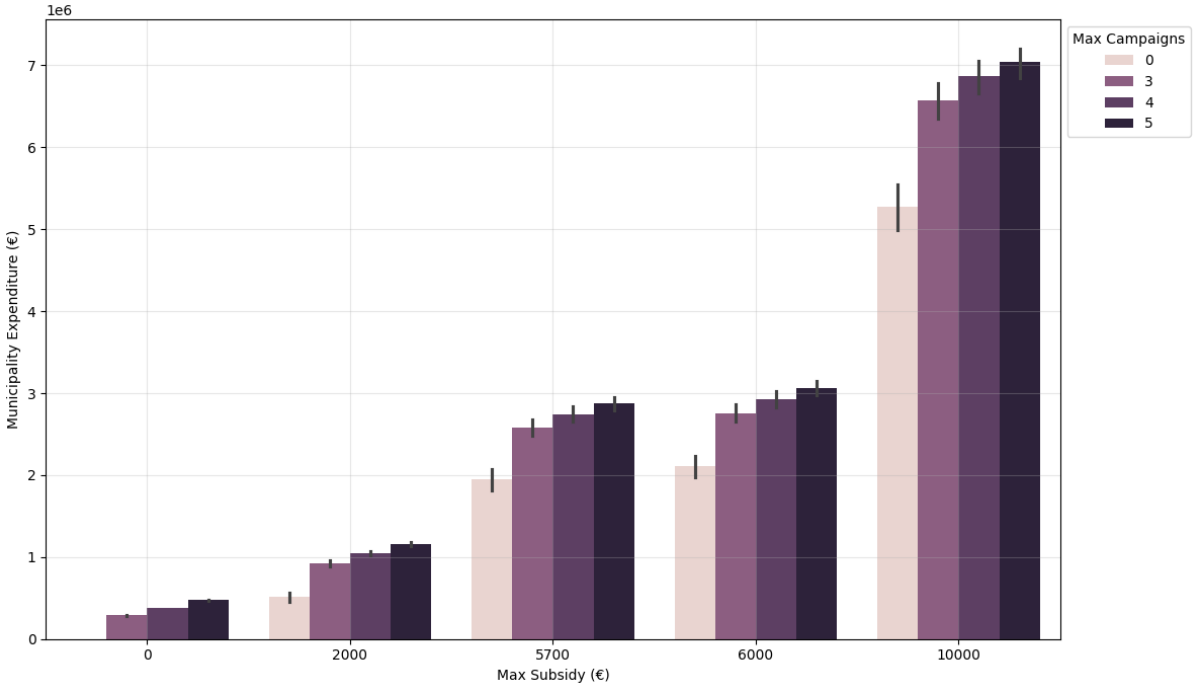


Figure 21. Total municipality expenditure at year 30 per max_subsidy and max_campaign range

8.6. Appendix F – Sensitivity Analysis: Parameter table

Table 12 summarizes the parameters and ranges used for this sensitivity analysis.

Table 12. Parameters, ranges, and justification

Parameter	Category	Range	Unit	Justification choice & range
Max_cost	Cost	[10,000 , 100,000]	€	Directly influences payback period, and thus financial scale. We test 10,000-100,000 as a plausible range for "light" and deep renovations.
Max_subsidy	Subsidy	[5000 , 19,000]	€	Directly reduce transition costs and is likely to be a dominant parameter in the model's behaviour. The range is plausible in our context, as 19,000 (max_subsidy) ensures net zero cost for transition G->F, while 5,000 covers half of the lower range of max_cost tested (10,000)
Ll_ll_influence	Social connection	[0.001, 0.1]	1	We vary social influence of landlords and homeowners, as they directly influence information scale, while the chosen numbers are not grounded in sources. The range 0.001-0.1 meets our goal to test near-zero influence and higher influence.
Home_ll_influence				
Ll_home_influence				
Home_home_influence				
Max_campaigns	Campaigns	[0, 5]	1	Second policy lever which directly influences transition behavior through information scale. The range 0-5 campaigns/year includes a baseline (0) and a realistic upper bound for max yearly campaigning.