D4.3 – Model integration

Integrated socio-economic model on food waste

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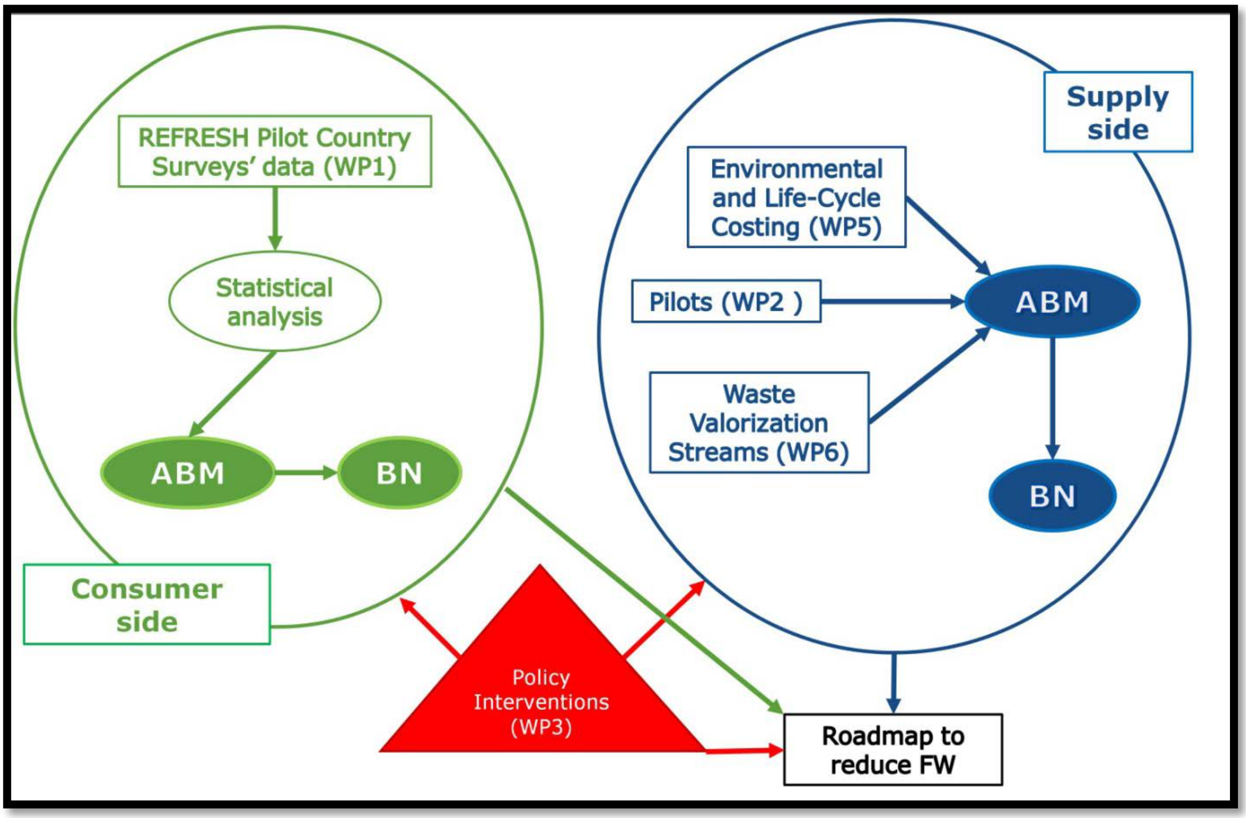
List of abbreviations

ABM	Agent-Based Model
BN	Bayesian Network
CA	Consortium Agreement
CC	Consortium Committee
DoA	Description of Action
GA	Grant Agreement
PCG	Project Coordination Group
PO	Project Office
SPBTT	Science-Policy-Business Think Tank
WP	Work Package

1 Executive summary

REFRESH is a EU research project dedicated to contributing to the achievement of the Target 3 of Sustainable Development Goal 12.3 which aims to halve per capita food waste (hereafter, FW) at the retail and consumer level as well as reducing food losses along the food chain by 2030. Partners across Europe are collecting data, methods and pilot experiences to reduce or repurpose FW. An integrated whole-of-system modelling approach will be developed as a part of the REFRESH project to allow the development of a decision-relevant, and dynamic policy support tool, by which a road map to the reduction of European FW by 50% by 2030 can be developed. The vital first step (highlighted in this report) is to develop the structures to allow model integration between different model types: Agent-Based Models and Bayesian Networks. These structures were developed and tested to ensure that the model types can be integrated. The architecture described in this deliverable provides the framework through which data and simulations from the data on FW at a consumer level and at a retail level can be integrated into simulation models. This report highlights the technical approaches followed to achieve model integration (Figure ES.1).

Figure ES1. Model integration structure



Since a sizable share of the FW is generated either at the consumer level or at the interaction between consumers and retailers, we address the modelling effort with two integrated ABM-BN models. The first model reproduces the dynamic evolution of FW choices of consumers as consequence of social interactions. The second focuses instead on the conditions for the successful diffusion and adoption of innovations to reduce FW at the retailer level.

The systemic modelling approach proposed will allow the development of selected simulation scenarios at the consumer and retail level, facilitating decision making in the face of uncertainty. Therefore, the integrated model will allow:

- An understanding of the differences in terms of consumers' aggregate behaviour of the different socio-economic settings and geographical contexts.
- An understanding of the chances for diffusion of selected innovations (tested within WP2, 5 and 6) in different market composition scenarios and socio-economic contexts.
- An understanding of the consequences of potential decision taken by market agents (i.e. companies).
- An understanding of the implications of different policy interventions, and of their interactions with socio-economic and geographical contexts.
- An understanding of the types and sources of uncertainties faced.

These integrated setups are first iterations of working integrated models, aimed at validating technically the setups as well as the integration process itself. As they are, there are certainly factors that are likely to be important in determining FW, which are not yet included in the models. However, the latter are flexible and can accommodate further details, and variables. Their construction is purposefully flexible in terms of components of decisions. The integration with Bayesian Networks ensure that Agent-Based models will learn from data originated from the other refresh WPs and will evolve, allowing the introduction of new variables and factors that will lead to the improvement of the different simulation scenarios.

2 Introduction and objectives

Food waste and losses occurs along the whole length of the supply chain. From the ‘farm’ to the end ‘consumer’, an estimated 30 to 40% of potentially edible food is wasted (WRAP 2008; Cabinet Office 2008; Stuart 2009; Nellemann 2009). In developed countries, about half of this waste stems from consumers, with the remainder is lost through farm practices, transport and processing, as well as in a retail setting (Godfray et al. 2010; Gustavsson et al. 2011). At each stage of the food supply chain, different ‘actors’ (e.g. primary producers, suppliers, processors and manufacturers, retailers and consumers) interact in different ways that lead to FW. The motivations and interactions within and across the different stages of the FW system are highly complex, and not presently fully understood. Models of FW have generally focused on small subsets of the entire FW system, because of the difficulties in accounting for these complexities.

Empirical data on FW at any part of the system are limited (Xue et al. 2017). Where data are available, they have a high potential for bias (such as self-reported consumer FW), or are limited in scale (single region, single country, single season, etc.). Therefore, there is a requirement to join disparate datasets to offset bias and improve external validity. However, gaps still exist. One approach to address these gaps is to use simulation models based on theory and/or expert opinion. Such models are capable of scaling-up and to generalize from limited experiences and data. By modelling relevant agents and their interactions, simulation models are able to provide information on the dynamics of complex systems such as the socio-economic-technical one contributing to FW. On the other side, dynamic models with interacting agents are better kept simple, as introducing too many variables and variations transforms them into black boxes, in which it is difficult to discern the reason of observed behaviour and to spot potential errors. Furthermore, a simulation model, regardless of its complexity is only as good as the theory that underpins it. These limitations are reduced here building models where as little theory as possible is embedded in the structure of the model and using available data (carefully threated through Bayesian networks) as driver for the model’s parametrization.

Bayesian Networks (BNs) can incorporate uncertainty and complexity in the model structure, but are less effective at incorporating behavioural factors (i.e., idiosyncratic biases of single actors, and interactions among actors) and temporal dynamics (interaction among variables or actors across time). For these types of data, Agent-Based Models (ABMs) are much better suited. To better represent food system complexity whilst incorporating the interactions among and within actors (business, consumers, etc.), there is a need for BNs and ABMs to interact dynamically.

Interactions among consumer behaviour, government policy, business behaviour, and local government services all have a key role to play in the ‘generation’ of FW. To truly capture the complexity of the drivers of FW, a whole-of-system model is needed (*sensu* Wu et al. 2015). Such models can capture emergent phenomena that other models may not adequately express (Wu et al. 2015).

Where BNs and ABMs have been successfully integrated, they have mainly focused on spatially explicit problems (Wu et al. 2015; Kocabas & Dragicevic 2013; Pope &

Gimmlet 2015). For example, Pope & Gimmlet (2015) address water demand in arid agricultural systems where individual farmers (the agents in the ABM) make decisions based on information about the natural environment ‘provided’ by the BN. These decisions, then, go on to influence and change the natural environment through the BN. This approach allows interventions to be tested and examined – with individual differences in farmer decisions explicitly modelled. While our initial effort here is to integrate these two approaches in a non-spatial model, later iterations of the integrated model may have spatial elements included.

Here, the methodological processes involved in the integration of ABMs and BNs are outlined. Combined with data on consumers from the REFRESH pilot countries (from WP1) and on business alliances (from WP2), the integrated model will provide novel insights into the FW system.

The development of an integrated model allows dynamic and transparent prediction of the influence of consumer- and business-focused interventions and behaviours on European FW. The combination of probabilistic modelling (the BNs) and agent-based simulations (the ABMs) allows scaling-up of the drivers identified by REFRESH partners at both the consumer and supply side levels. Pilot data on the effectiveness of interventions can also be scaled-up and effectively tested prior to implementation on a EU scale. The ability to predict beyond the data underlying the models is key in developing and testing scenarios of future waste in the face of policy changes. We are not interested in causation but, rather, in the effect of intervention on FW production. The integrated model will be used to identify the behavioural and socio-demographic drivers of FW across the EU (for both consumers in D4.4 “Behavioural economics consumers” and business in D4.5 “Behavioural Economics business”). The understanding of system dynamics will allow the addition of food-waste-related political, social and economic changes (scenarios) to be tested to allow the prediction of the effects of these changes on FW in the near future (in D4.6 “Pan-European integrated food waste scenario” and D4.7 “Pan-European impact analysis”). The understanding of the effects of these scenarios will allow the identification of the most efficient approaches to the reduction of EU FW, in accordance with SDG Target 12.3 of having per capita FW and reducing food losses by 2030.

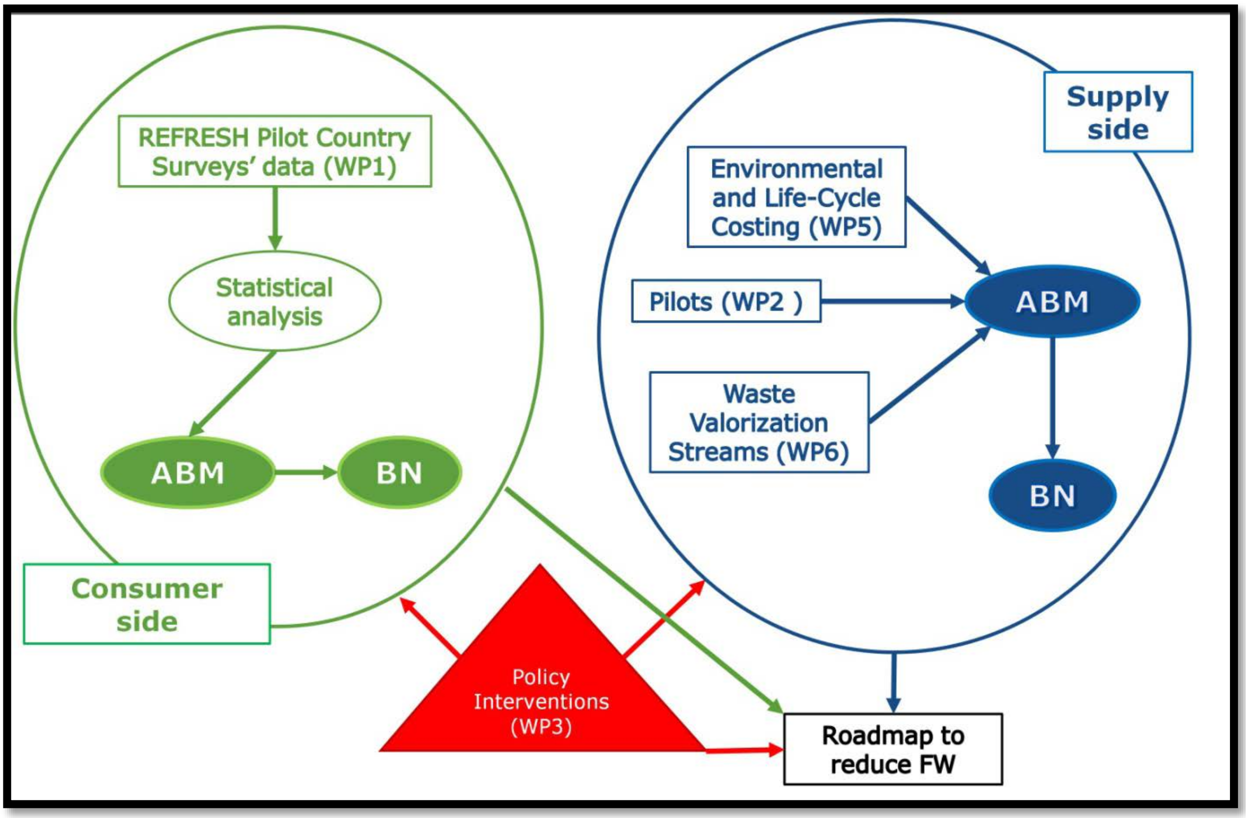
3 The whole-of-system model

The model, conceptually, consists of two main 'modules' representing the supply side (business and retail), and the consumer side of the food system, respectively. Each of these modules consists of integrated ABMs and BNs that interact to simulate an integrated and dynamic food system. In the scheme shown in Figure 1, it is highlighted where (and from which WP of REFRESH) data will be integrated into our models. On the consumer side, data from the WP1 Consumer Questionnaires across four European pilot countries will be converted into a set of 'characteristics' and 'behaviours' (for details see section 7.1.1 in the Appendix) from which populations of agents will be defined. These populations will interact through an ABM, whose results will then feed into a BN that will determine the effect of agent typologies on FW creation.

The supply side module will use data from WP2 and WP5 to approximate the suite of behaviours, and effects of those behaviours, from which a supply side ABM can simulate business behavioural and structural characteristics, and their impact on the patterns of adoption of innovations addressing FW. To address the effects of these simulated business behaviours concerning the adoption of innovation, a BN will be developed from the results of ABM simulations.

In the future, policy interventions can be integrated into the model, where they can affect either (or both) modules through the BN models.

Figure 1. Schematic representation of the FW system.



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3.1 Model integration ‘approach’

For each of the two market sides studied (consumers and retailers), the integration approach selected reflects its characteristics, and the specific data availability.

3.1.1 Consumer models

To integrate the consumer BN and the consumer ABM (Model 1), the first approach identified in D4.2 “Model development and data protocol” will be followed, whereby real-world data (e.g., those of the four REFRESH pilot countries) will be pre-treated to create realistic populations for an ABM (technical details on the process of data pre-treatment for the use within the ABM are provided in Annex 7.1.1 alongside a technical description of the consumer ABM model). ABM simulations will then provide an input into a consumer BN. The integration will allow the study of interactions of behavioural factors and social interactions (see D4.1a “Consumers behavioural economic interrelationships and typologies”, and D4.1b “Business behavioural typologies and interrelationships”) for the evolution of individual opinions and actions regarding FW. From the BN standpoint, consumer behaviour will be an ‘intervention’ enacting upon the probability of producing low, medium or high levels of FW, and extending the cross-sectional data available to a dynamic setting. This allows to simulate the influence of human behaviour and interactions on the consumer FW system.

The consumer ABM can then be run on different populations, based on:

- Different assumptions on socio-demographic characteristics.
- Results from the four REFRESH pilot countries.
- Extrapolations for non-surveyed countries, based on demographic information.

The final values of individual motivations towards food-related topics, FW actions, and saliences of these motivations for individual consumers are extracted from each simulation, both in absolute terms and in relationship with their initial values, with the aim of answering questions such as:

- Has FW increased or decreased through social interactions? For individuals with which characteristics?
- How can FW be expected to evolve because of social interactions?
- Who changed (reduced/increased) her behaviour the most? Which motivations where slowing or accelerating change?

All these questions are answered with a BN fed with the ABM simulations’ results. These results will be added to a BN built on data from WP1, with the aim of extrapolating expected population-level changes in FW.

Beside, the model can be used to study specific interventions implemented by Governments, retailers, municipalities and other entities. Each intervention essentially modifies one or more parameters in the model, thus inducing different results. Comparing the results with and without the intervention allows an assessment of the latter’s impact.

Summing up, the integrated model will deliver: an overview of changes in consumers' FW levels from a baseline, and its dependency on individual characteristics and on societal starting conditions for different countries, and for different socio-demographic assumptions.

3.1.2 Retailers models

For the retailers models, option two from D4.2 "Model development and data protocol" will be followed, whereby outputs of the BN will act as a data reduction engine and data analyst to the outputs from the ABM. The ABM will focus on studying how institutional and behavioural issues interact, fostering and/or hindering the adoption of innovations in the retail sector (technical details on the implementation of the retail ABM model are provided in Annex 7.2.2). The retail sector is chosen as an initial case study due to its key position as a linkage between producers/processors and consumers.

The ABM will be run with a large variety of combination of parameter values, which will be then assessed – with a systemic perspective – through a food system BN. This approach allows an understanding of the interaction among different elements regulating retailer interactions and decision-making concerning the adoption of innovations to reduce or prevent FW. This integrated model is chosen as – at this stage – data to calibrate the model to specific case studies are missing. However, once data become available, the integrated supply model will be studied considering specific scenarios, where the impact is analysed of:

- The characteristics of the innovation (cost, diffusion of information, resulting FW reduction, setting where FW is reduced, etc.).
- The behavioural characteristics of companies (to fit different country scenarios).
- The institutional characteristics of the setup: elasticity of demand to price, proportion of companies of different sizes.

Moreover, with this integrated supply model, the problem of FW valorisation can be treated as a type of innovation generating revenue to the company.

3.1.3 Model integration

BNs will be developed in the open source statistical software R, whilst ABMs will be developed in MatLab. In order to allow integration, the "*RtoMatLab*" package will be used. This allows direct manipulation of MatLab code from the R console, as well as outputs from MatLab to be explored in R.

4 Results

4.1 Consumer module

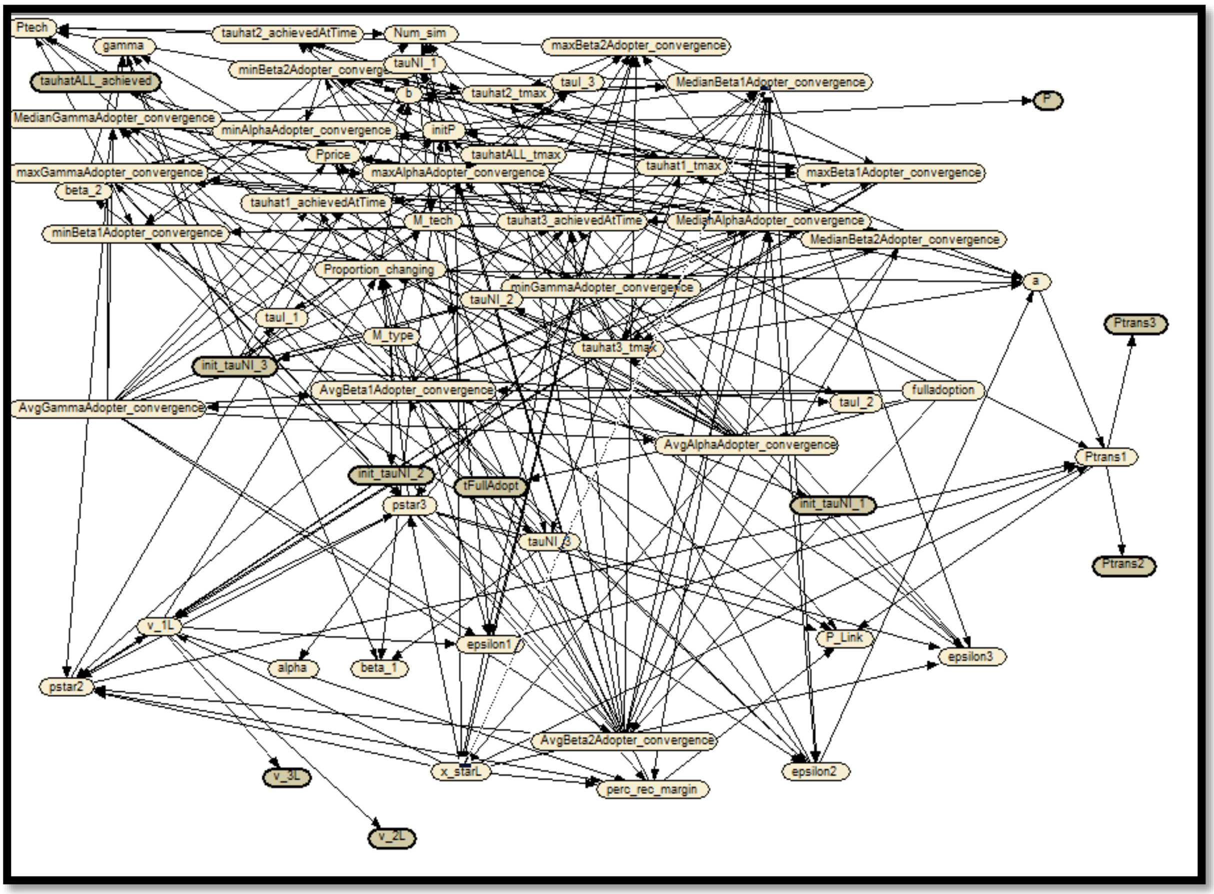
The two types of models (BNs and ABMs) were successfully integrated (see Table 3 for technical details). This means that, with appropriate data, the model is able to simulate the complex dynamics behind consumer FW.

To provide a preliminary assessment of the process of model integration (rather than concrete policy recommendations *per se* at this early stage of model development, in the light of the fact that these models do not integrate data yet) a simplified version of the consumer ABM in the NetLogo software was developed. This simplified model is used to demonstrate the type of information that can be determined through integrated modelling. More details are provided in Box 1.

4.2 Retail module

Again, the two model types were successfully integrated (see Figure 2, and Table 3 for technical details). When data are available, simulations can be run to assess and measure the direction and sign of the relationships among institutional, behavioural and innovation characteristics.

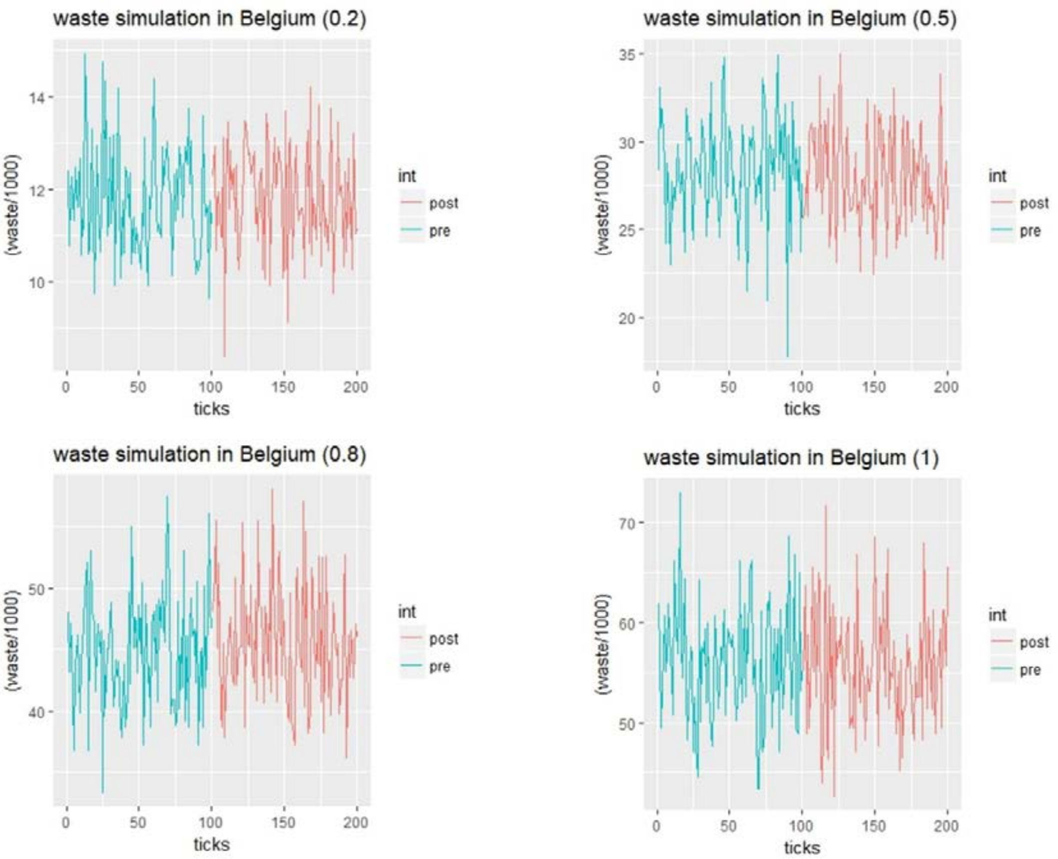
Figure 2. Bayesian network of the ABM for retail model.



Box 1. Integrated Consumer Behaviour Model.

A simplified version of the consumer ABM outlined above was used to simulate the integration between BNs and ABMs. The model relies on a population made of two types of agents generating FW – older people and younger people. The level of FW is randomly assigned to each agent from a Poisson distribution with a mean of 45 grams per week (taken from WRAP's compositional analysis; WRAP 2013). Each agent has an opinion on wasting food. Opinions are interpreted – for the sake of this example - as the willingness to accept an intervention (kept abstract as this is an example) than others, and that they will persist with the intervention for a longer period. The intervention reduces FW by up to 10 % (although this is probably an exaggerated effect size; Abrahmse & Steg 2013). Agents are set-up in a network where they are linked (the probability that two agents are linked can be altered). Agents linked with younger people (we might interpret these as family-like groupings) are more likely to be in favour of adopting interventions to address FW (i.e., they value social cohesion). The distribution of ages comes from the BN (and, in the future, the motivations forming the basis of an agent's opinions will come from the BN too). When the intervention is switched on, agents reduce their waste levels in accordance with their opinions.

Here, 200 time-steps (e.g. weeks) are simulated, and an intervention halfway added. The socio-demographic characteristics of the agent population are set up based on Eurobarometer data from Belgium analysed by means of the BN developed in D4.2. Agents have an initial 50% probability of being in favour of introducing an intervention to reduce FW; this opinion is then mediated by social connections (links) to other agents. Family groups are represented by links between older and younger agents. Families waste more than individuals (as shown by the BN developed in D4.2), and there is little effect of the intervention, because opinions are too strongly fixed to one view. Agents do not easily change their mind about FW after the intervention.



5 Conclusions

The integration of the BN and ABM models will allow the development of a dynamic model structure that can be used to explore the potential for interventions to make a difference to FW on a EU scale. We have shown here that the two models types can be integrated, and we are now prepared for the data from other REFRESH WPs to allow development of a series of linked models examining demand - and retail - side FW. These linked models allow adoption of a systemic approach to identification of contextualised effective interventions for reducing FW directly informing the road map for 50% FW reduction by 2030 (D4.8 “Food waste roadmap”).

Importantly, this systemic modelling approach will allow the development of sected simulation scenarios at the consumer and retail level, facilitating decision making in the face of uncertainty. Therefore, the integrated model will allow:

- An understanding of the differences in terms of consumers’ aggregate behaviour of the different socio-economic settings and geographical contexts.
- An understanding of the chances for diffusion of selected innovations (tested within WP2, 5 and 6) in different market composition scenarios and socio-economic contexts.
- An understanding of the consequences of potential decision taken by market agents (i.e. companies).
- An understanding of the implications of different policy interventions, and their interactions with socio-economic and geographical contexts.
- An understanding of the types and sources of uncertainties faced.

This approach allows the identification of where uncertainties in the system make the largest difference to the desired outcome of 50% FW reduction. This will allow the understanding of the best decision or action to take, given the uncertainties faced, and to allow prioritisation of the uncertainties to be reduced with most urgency for better improving the probability of reaching the 50% target. Research priorities can be highlighted in this way without slowing down decision-making processes (as long as these are adaptable and dynamic).

The models proposed in this deliverable are first iterations of working integrated models, aimed at validating technically the setups and the integration process itself. As they are, there are certainly factors that are likely to be important in determining FW which are not yet included in the models. However, the latter are flexible and can accommodate further details, and variables. Their construction is purpousefully flexible in terms of components of decisions. The integration with Bayesian Networks ensure that Agent-Based models will learn from data originated from the other REFRESH WPs and will evolve allowing the introduction of new variables and factors that will lead to the improvement of the different simulations.

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7 Annex

7.1 Technical details of the individual model components

7.1.1 Consumer Agent Based Models

The agents

Considering a set of N agents $\mathrm{i} \in \{1, \ldots, \mathrm{N}\}$, who can represent either individual consumers, or households. Each agent *i* is characterized by:

- A set of motivations $m \in M$, directly or indirectly related to FW;
- A value $o_i^m \in [0,1]$ for each motivation *m*, which defines the consumer's opinion on that motivation;
- A value $\mathrm{S}_i^m \in [0,1]$ for each motivation *m*, called 'salience', which defines how relevant that motivation is in determining the consumer's action and utility concerning FW (where 0 = not relevant at all; 1 = extremely relevant);
- A set of actions A_i^a affecting FW: each of these actions is performed with a given frequency $f_a \in [\text{never, almost never, occasionally, sometimes, always}]$; each of the frequencies contributes to the definition of the total individual FW;
- An individual level of FW, $\mathrm{FW_i}$ (where 0 = no FW, and 1 = wasting 100% of one's food) resulting from the frequencies of her actions; mapping from frequencies to actions is done through the formula: $\mathrm{FW_i} = \beta_1\,\mathrm{F}_1 + \beta_2\mathrm{F}_2 + \beta_3\mathrm{F}_3 + \beta_4\mathrm{F}_4 + \beta_5\mathrm{F}_5 + \cdots$; frequencies are established on the base of own opinions, while betas are estimated from data with regressions (without considering significance levels);
- A value U_i, which expresses the utility she derives from her level of FW (if action A yields U_A, action B yields U_B, and $U_A > U_B$, then action A is always preferred to action B);
- A consumer typology *T* that constrains the minimum and maximum levels of o_i^m and S_i^m for an individual consumer.

Homogeneous strata with their relative size are identified from real-world populations of consumers, using demographic and socio-economic variables (e.g., age, family size, education level, income level, etc.). Such groups, representing the typologies, with their relative sizes, are replicated in the populations simulated.

Six motivations $\mathrm{m} \in \mathrm{M}$ based on existing literature (Thaler's model of mental accounting) were identified, and are embedded in the survey of REFRESH WP1 (see deliverable D 1.4). These motivations are:

- 'Health' (m_h): concern about the microbiological qualities of the products purchased, for ensuring good health conditions to oneself and one's household members, especially children (0 = consumers are not concerned at all about food quality; 1 = they are extremely concerned about food quality);

- 'Taste preferences' (m_g): relative preference for regional dishes, or for specific tastes, and tendency to manage food provisions with a view to have these products available (0 = consumers are not concerned at all about the taste of food; 1 = they are extremely concerned about the taste of food);
- 'Time' (m_t): concern about the amount of time required to purchase, cook, and adequately store food products (0 = consumers do not care about saving time; 1 = they are very concerned about saving time);
- 'Provision and status' (m_s): desire to maintain a reputation of being an affluent person (both inside and outside the family), and to show generosity, especially if guests are present (0 = consumers do not care about their reputation of good provider/host; 1 = they think that their reputation of good provider/host is very important);
- 'Price' (m_p): attempts to minimize one's expenditure (especially if one's income is low), and to make a good deal in terms of money spent and quality of the food purchased (0 = food costs are not an issue; 1 = food costs are a very important issue);
- 'FW proper' (m_w): concern about one's levels of FW (0 = consumers do not care at all about avoiding FW; 1 = they think that FW should be absolutely avoided).

The level of FW of every household results from the frequency of the actions generated by the interaction of these motivations, and depends on which of them prevails. For example, a pressing need to save money (i.e. high levels of m_p) could either cause households to buy discounted and low-quality food, which gets rotten more easily, or to reuse their leftovers, thus minimizing FW. For each motivation m, the opinion of a consumer i (o_i^m) is a social aspect, being influenced by peers through opinion exchanges. Instead, the salience S_i^m is idiosyncratic, and changes through a replicator dynamic simulating the search for the maximum utility in an evolving world.

The model uses the datasets of the consumer surveys carried out by REFRESH WP1 in the four EU pilot countries to calibrate the ABM. After identifying relevant stratifying variables based on their correlation with the levels of FW, and after measuring the relative size of each stratum, the following variables (i.e., average, median, minimum and maximum values) are obtained for each stratum, and for the entire population:

- The 'salience' S_T^m attributed to each of the six motivations m;
- The opinion o_T^m on each of the six motivations m;
- The self-reported level of FW FW_T.

Then, populations of consumers with idiosyncratic values for all these variables (within the range and according to the distribution observed for their typology) are generated from a BN. In this case, there would be no clusters of agents defined *a priori*, but only populations bootstrapped from the data treated through the BN (where ex-post probabilities of a variable assuming a certain value is obtained from individual features).

Loading this information into a BN, a network of relationships among the motivations is obtained. For example, concern for 'provision and status' could be negatively related to concern for 'price'. It should be noted that each of these relationships could exist either in the whole population, or within a limited number of consumers' typologies. Furthermore, the network of relationships needs not to be a full network: some of them are likely to be insignificant.

The form of the functions linking consumers' opinions o_i^m to their FW action $\mathrm{FW_i}$ are also detected from the datasets of the surveys carried out by REFRESH WP1 in the four EU pilot countries.

Exchange of opinions

When consumers interact with one another, they tend to end up with opinions more similar to their peers. However, it is assumed that they are affected by some degree of 'confirmation bias', implying that they are unwilling to compromise with individuals expressing opinions too far from their priors. The 'interaction threshold' $\mathrm{d_{int}} \in [0;1]$ can be defined as the distance beyond which another consumer's opinion is not taken into consideration. It measures the inverse of the intensity of the confirmation bias expressed by a consumer. At each time step *t*, two randomly chosen individuals i and $i^{'}$ are selected to discuss a motivation *m*. Their opinions evolve according to the rule *à la* Deffuant (Weisbuch et al. 2002):

$$\mathrm{o_i^{t+1}} = \begin{cases} \mathrm{o_i^t} + \mu\left(\mathrm{o_{i'}^t} - \mathrm{o_i^t}\right), \left|\mathrm{o_{i'}^t} - \mathrm{o_i^t}\right| < \mathrm{d_{int}^i} \\ \mathrm{o_i^t}, \quad otherwise \end{cases} \tag{1}$$

where $\mu \in [0;0.5]$ is a parameter indicating the speed of convergence[1]. The same applies to interacting partner i'. In Eq. 1, $\mathrm{d_{int}^i}$ does not need to be equal to $\mathrm{d_{int}^{i'}}$; hence, this setup admits interactions where consumer i changes her opinion while consumer i' does not (and vice versa): social influence can be asymmetric. $\mathrm{d_{int}^i}$ expresses the measure of the confirmation bias (Rabin and Scrang 1999, Yariv 2005, Wilson 2014, Charness and Chetan 2017) affecting individual choices. While it is difficult to estimate this parameter from data, its value can be fixed comparatively for different groups of individuals or for different countries.

Utility functions

Given her individual FW $\mathrm{FW_i}$, and the median FW in the population $\mathrm{Me(FW)}$, every consumer *i* gets a certain level of utility $\mathrm{U_i}$, which is a linear combination of utilities linked to her motivations. Differently from the functions linking consumers' opinions $\mathrm{o_i^m}$ to their FW action $\mathrm{A_i}$, utility functions cannot be detected from the data; their forms are thus set based on FW literature, and on authors' logic:

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[1] $\mu = 0.5$ in all simulations; lower values would simply have the effect of slowing down the evolution of the model.

- Price: $U_p = \left(1 - FW_i * o_p^i\right) * Me(FW)$ (more individual waste implies higher costs to reach the satiation quantity; higher population FW keeps prices lower, increasing one's utility);
- Health: $U_h = 1 - [\alpha FW_i + \beta Me(FW)]$ (FW reduces the utility of the consumers concerned about healthy food);
- Taste preferences: $U_g = 1 - \left({FW_i}^{0.5} * o_g^i\right)^2$ (FW decreases the utility of the consumers concerned about taste);
- Time: $U_t = 1 - FW_i * {o_t^i}^2$ (higher FW implies more shopping time – due to impulsive buying, lack of shopping list, etc. –, more cooking time – e.g. because the family cooks too much, or does not use leftovers –, and more time to dispose waste);
- Provision and status: $U_s = o_s^i * [\alpha FW - \beta Me(FW)]^3$ (consumers get a utility from their own FW – since they show to be affluent persons – and a disutility from others' FW compared to theirs);
- FW proper:

$$U_w = \begin{cases} 1 - \alpha[FW_i - (1 - o_w^i)]^2 - \beta[Me(FW) - (1 - o_w^i)]^2 & \text{if } FW_i > (1 - o_w^i) \cap Me(FW) > (1 - o_w^i) \\ 1 - \alpha[FW_i - (1 - o_w^i)]^2 & \text{if } FW_i > (1 - o_w^i) \cap Me(FW) \le (1 - o_w^i) \\ 1 - \beta[Me(FW) - (1 - o_w^i)]^2 & \text{if } FW_i \le (1 - o_w^i) \cap Me(FW) > (1 - o_w^i) \\ 1 & \text{if } FW_i \le (1 - o_w^i) \cap Me(FW) \le (1 - o_w^i) \end{cases}$$

  (consumers' utility is negatively affected by both individual and population-level FW, if these are above the acceptable FW for them $(1 - o_w^i)$).

Note that $\alpha + \beta = 1$ and $\alpha \gg \beta$, since these parameters weigh the relative importance assigned to one's FW and to the level of FW in the population, respectively.

Timing of the model

At each time step *t*, the ABM evolves according to the following dynamics:

1. A consumer *i* is selected uniformly at random;
2. A motivation *m* is selected for discussion. The probability of discussing each motivation is linearly proportional to the quote of salience $\widehat{S_i^m} = S_i^m / \sum_M S_i^M$ devoted to it by consumer *i*. The extraction is a random process with S_i^m as weights for the random extraction;
3. Another consumer *i'* is selected for discussion, either from the individual network of agent *i*, or based on one of the following criteria: (1) completely at random; (2) considering partial mixing between predefined groups, without a network; (3) using connectivity measures derived from data, if available;

4. The two consumers i and i' discuss the motivation *m* selected, according to the opinion dynamics *à la* Deffuant[2], and their opinions on the selected motivation is, eventually, changed (see paragraph above)[3];

5. If the opinion of consumers i and i' on motivation *m* is too distant, they demote their tie, creating a new tie either with a friend's friend, or randomly (this step is skipped if no network is used);

6. If, because of the exchange of opinions, the opinion concerning the motivation selected changes, all other opinions of consumers *i* and *i'* are reconsidered based on an internal pull mechanism (which makes use of a network of correlations whose signs and intensities are assumed to be fixed at population level):
   - the difference between the current and past opinion on *m* is computed $\Delta o_i^m = o_m^i(t) - o_m^i(t-1)$;
   - for every motivation *m'* significantly correlated with the motivation selected *m*, compute $\Delta o_{m'}^i = \Delta o_m^i \mathrm{Corr}_{m,m'}$;
   - the new opinion of consumer *i* on each motivation *m'* is given by $o_{m'}^i(t) = o_{m'}^i(t-1) + \Delta o_{m'}^i$[4];

7. A mapping of the opinions of consumer *i*, o_m^i's, into a frequency F_{it} of actions affecting FW is performed using the pre-computed functional forms;

8. Frequencies of actions are then mapped into an updated level of FW using the betas estimated from the data;

9. Given her individual FW action FW_i, and the median FW action in the population, $Me(FW)$, consumer *i* gets a certain level of utility U_i, calculated with the function $U_i = S_i^{m_h} U_h + S_i^{m_g} U_g + S_i^{m_t} U_t + S_i^{m_s} U_s + S_i^{m_p} U_p + S_i^{m_w} U_w$, where U_m's are the utility functions described above, and S_i^m are the saliences;

10. Saliences S_i^m (or better said, the importance of each motivation *m*) are updated according to the following rule: with probability P_{evo}, each consumer decides to update her saliences; if this probability is realized, she select another consumer *i'* from her network (or based on one of the criteria described in step 0) who achieved a higher utility in step 0, and copies one of her saliences[5]; hence, combinations of saliences that entail higher U tend to diffuse within the population. Furthermore, to allow innovation of strategies with respect to initial ones,

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[2] Alternative mechanisms to model the opinion dynamics are: relative agreement, Bayesian updating of beliefs, and model learning.

[3] Note that opinion $o_{i \in T}^m$ of agent $i \in T$ cannot overcome the boundaries for agents of typology *T*, i.e. $o_{i \in T}^m \in [\min(o_T^m); \max(o_T^m)]$.

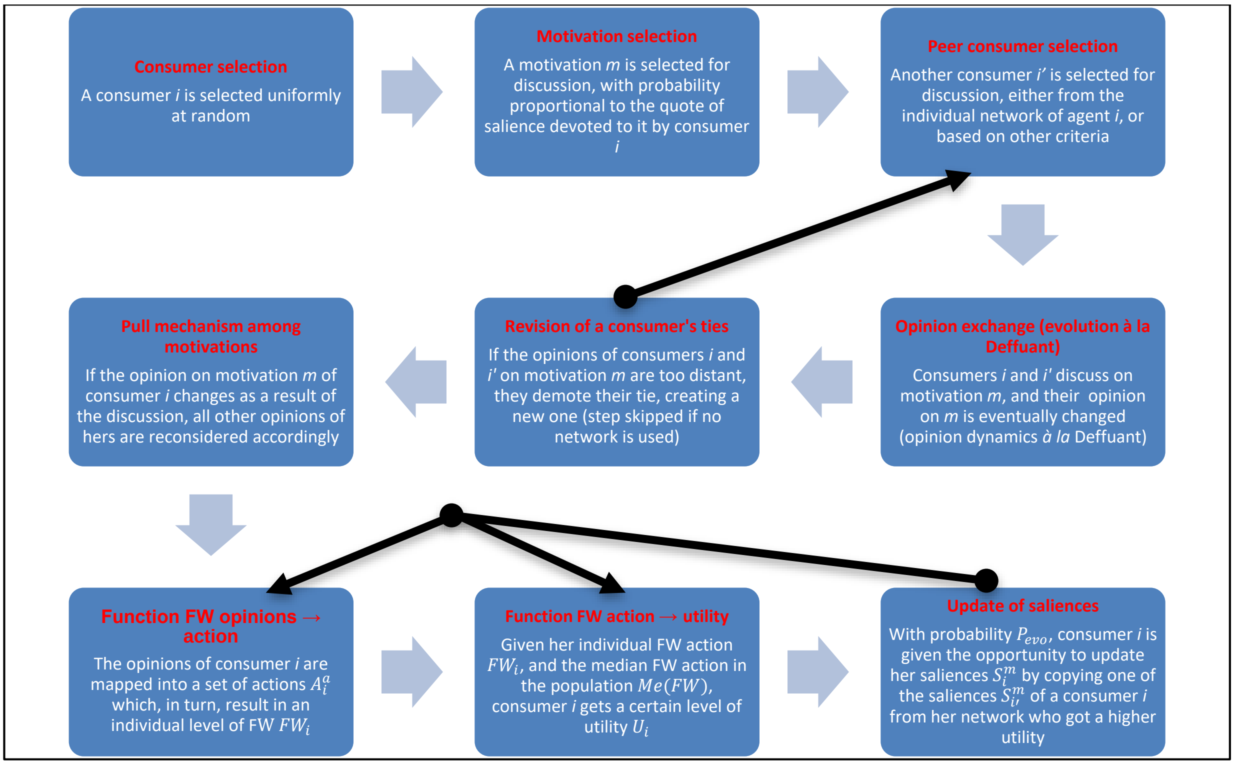
[4] Note that, for a value of correlation equal to 1, the two opinions would move in the same direction with the same distance (strength) while, for correlation –1, the two options would move of the same distance in opposite directions.

[5] Note that salience $S_{i \in T}^m$ of agent $i \in T$ cannot overcome the boundaries for agents of typology *T*, i.e. $S_{i \in T}^m \in [\min(S_T^m); \max(S_T^m)]$.

a small but positive probability φ of random variations of the saliences is assigned.

Figure 3 clarifies the dependencies in the model. Note that the random selection of a motivation *m*, and the boundaries to the salience of each concern should prevent the emergence of trivial corner solutions.

Figure 3. Intra-steps of the model and dependencies.



Observables

Based on the research questions, the observables to be extracted from the simulations are:

- The (average, median, maximum and minimum) individual levels of FW $\mathrm{FW_i}$;
- The changes in the (average, median, maximum and minimum) levels of FW w.r.t. the idiosyncratic characteristics of the consumers, and their distribution;
- The (average, median, maximum and minimum) utility $\mathrm{U_i}$ and, therefore, consumers' welfare.

The input and output variables of the model are reported in Table 1.

Table 1. The input and output variables for the consumer agent-based model.

Name of variable	Input/output	Randomization	Min. value	Max. value
N	Input	Fixed	1000	1000

num_motivations	Input	Fixed	1000	1000
num_types	Input	Fixed	3	3
tmax	Input	Fixed	500k	500k
d	Input	randomized	0.02	0.25
mu	Input	randomized	0.05	0.50
nu	Input	randomized	0.05	0.50
Pevo	Input	randomized	0.001	0.10
num_action_affect-ing_waste	Input	Fixed	10	10
scale_frequencies	Input	Fixed	5	5
UtilityAlpha	Input	randomized	0	1
OpDiff_Health	Output	1 value per agent		
OpDiff_Taste pref-erences	Output	1 value per agent		
OpDiff_Time	Output	1 value per agent		
OpDiff_Provision and status	Output	1 value per agent		
OpDiff_Price	Output	1 value per agent		
OpDiff_FW Proper	Output	1 value per agent		
SaDiff_Health	Output	1 value per agent		
SaDiff_Taste prefer-ences	Output	1 value per agent		
SaDiff_Time	Output	1 value per agent		
SaDiff_Provision and status	Output	1 value per agent		
SaDiff_Price	Output	1 value per agent		
SaDiff_FW Proper	Output	1 value per agent		
UtDiff	Output	NA		
FWDiff	Output	NA		
countsim	Input	Progressive		
type	Input	Progressive per type	1	num_types
Sa_min_out_Health	Input	(same value for all agents of that type)	0	0

Sa_min_out_Taste preferences	Input	(same value for all agents of that type)	0	0
Sa_min_out_Time	Input	(same value for all agents of that type)	0	0
Sa_min_out_Provision and status	Input	(same value for all agents of that type)	0	0
Sa_min_out_Price	Input	(same value for all agents of that type)	0	0
Sa_min_out_FW Proper	Input	(same value for all agents of that type)	0	0
Sa_max_out_Health	Input	(same value for all agents of that type)	1	1
Sa_max_out_Taste preferences	Input	(same value for all agents of that type)	1	1
Sa_max_out_Time	Input	(same value for all agents of that type)	1	1
Sa_max_out_Provision and status	Input	(same value for all agents of that type)	1	1
Sa_max_out_Price	Input	(same value for all agents of that type)	1	1
Sa_max_out_FW Proper	Input	(same value for all agents of that type)	1	1

Preparation of data for the consumer ABM

The ABM structure defined in this section constitutes a multi-opinion model of FW that receives data from WP1 and other sources, and generates data to be analysed with a BN.

Raw data from WP1 consumer surveys need to be elaborated in order to be used within the model. In particular, WP1 data will be used to:

- Identify the correlations existing among various individual motivations;
- Generate populations defined in terms of socio-demographic characteristics (the variables are extracted so that the agents have realistic combinations given the underlying joint distribution);
- 'Salience' (importance) attributed to each of the six motivations;
- Opinion on each of the six motivations;
- Self-reported initial levels of FW (range and variance per consumer group);
- Key demographic characteristics (age, family status), and main fault lines necessary to characterize simulated populations;

- The functional form linking motivations to each action affecting FW.

To build reasonable populations of consumer, a BN of the individual characteristics will be built once data becomes available. From the BN, the joint distribution function of the input variables will be generated. To construct a population with arbitrary characteristics, it is then necessary, for each agent: (1) to extract one value for a random characteristic, according to the known Probability Distribution Function of the population to replicate; (2) to extract values for all other features of that agent, conditionally on the values of previously extracted ones.

To prepare WP1 data for simulations, several steps need to be taken.

For each of the six motivations (opinions) related to FW, questions from the WP1 questionnaire provide an opinion and a salience. Opinions define the absolute importance expressed concerning that action. Saliences represent, instead, the relative importance of each motivation with respect to the others. For each motivation salience is estimated as the number of motivations that the individual judges less important than this one, then normalizing the value to one.

To construct the network of relationships among motivations, with the relative signs and strengths, a correlation matrix is created. Only significant correlations (t-test on the hypothesis that the correlation coefficient is equal to 0) are retained. Then, the FW generated by an individual is assumed to be the result of her actions and, in particular, of their frequency.

From opinions to FW action. To transform opinions into actions, the set of behaviours that can affect different moments of food management (planning, purchasing, storing, cooking, reusing), and that may, influence FW are identified in the WP1 datasets. Each action is then clustered into one or more of the above categories. Then, using WP1 data it is estimated:

- Which opinions, and how, influence significantly the frequency of the actions: for each action, a non-linear function is fitted with actions' frequencies as dependent variables, and the opinions expressed by the individual as independent variables, thus obtaining the functional form linking stated opinions with actions' frequencies; these functions are then encoded into agents' behavioural model, allowing to update the frequency of each action based on interactions.
- The relationship between stated FW levels and each action affecting it: a regression model with FW as dependent variable and actions' frequencies as independent variables is estimated, the resulting betas, which are then used in the model to update FW levels based on the evolving frequency of actions are stored. Within this construction, coefficients' significance levels are disregarded.

During simulations, at each interaction, and after point 6 of the timing of the model, changes in opinions may map into changes of actions- frequencies and, thus into changes in FW levels.

How to model interventions

The model presented in this deliverable reproduces the dynamics evolution of FW choices of consumers as consequence of social interactions. As such it provides a useful benchmark against which to compare the effect of policy interventions or of companies' initiatives affecting consumers. Such interventions can be modelled as exogenous shocks on models' parameters. Comparing the baseline behaviour of the model with the one observed when such shocks are introduced it is possible to estimate the potential impact of initiatives to reduce FW.

To exemplify how specific interventions can be modelled, Table 2 below proposes how they can be implemented in the model presented here.

Table 2. Examples of policy interventions to be modelled.

Intervention	How to implement it
Educational focused campaign (e.g. focused on people's understanding of date labels)	A positive shock in the Opinion on FW of the targeted group
Change in date labels (e.g. best before dates removed from certain products)	A positive exogenous shock in the salience of time.
pubic campaign aimed at getting people to value food more	A positive exogenous shock in the salience of FW proper.
increase in shelf-life of certain products	A positive exogenous shock in the salience of time.
A sustained period of food-price inflation.	A small but persistent positive shock in the concerns for prices of some or all of the agents (those affected by the price changes)

7.1.2 Retail Agent Based Model

Relationship with the DoA and model motivation (from D4.2)

One of the focuses of REFRESH T4.2 is the definition of a framework for the development of an ABM aimed at assessing the behaviour of businesses with respect to FW, and the identification of ways to reduce it. One of the most important opportunities to decrease the levels of FW generated (directly or indirectly) by firms is though the introduction of innovations.

A relevant share of the FW generated along the food supply chain is produced by food processors and retailers. To keep the ABM treatable, it was chosen, however, to separate these two sectors and – at least at a first stage – to study them individually, using two different models. The ABM developed *here* studies the behaviour of retail companies, and their interaction with consumers. It will be extended to the processing sector in a *second* moment. The present document provides an outline of the model design and characteristics.

The choice of separating food retailers from processors is due to the fact that:

- It allows a clearer understanding of the behavioural patterns and incentive structure of the two sectors, and of the consequences of the interaction among individual incentives;

- It allows to disentangle the effects of single changes to the baseline, which would be much more difficult in a more complex setup.

The choice of starting from the retail market, instead, stems from the fact that this is a simpler sector compared to food processing. Indeed, on the one hand, it is polarized between large and small actors; on the other hand, it faces directly the consumption side of the food market, which makes agents (firms) easier to model. Furthermore, retailers present peculiar conditions in terms of economic incentives for addressing FW. Indeed, for them, the FW generated by consumers in their homes represents a financial gain.

To obtain a clear baseline, the ABM will make strong simplifications, that will be then progressively relaxed. This procedure will allow a clearer definition of the drivers of the results.

Research questions

The ABM aims at simulating how innovations to reduce FW spread among retail companies, and how the diffusion process modifies the prices of the food products involved. Following this focus, the objective is to create a model for answering the following questions:

- Which are the main conditions and drivers influencing the adoption and diffusion of innovations to reduce or prevent FW in the shop (or, indirectly, in consumers' homes)? How are these conditions and drivers (as well as the effect of the innovation on FW) influencing its adoption and diffusion?
- How are the prices of foodstuff in a retail market changing because of the introduction of such innovations? How are these prices transferred horizontally within the retail sector? Which conditions (e.g., innovation characteristics, dynamics of price increase, price elasticity of demand) mainly influence price transmission?
- Which characteristics of the innovations for preventing or reducing FW cause them to spread more easily (e.g., investment costs, maintenance costs, resulting FW reduction, place where FW is reduced, etc.)? What are the ideal innovations in terms of diffusion and FW effectiveness?
- How do FW levels in a retail market change due to the introduction and diffusion of such innovations?
- How does the topology of the networks among food retailers influence the outcomes of diffusion (in terms of both time and number of adopter)? At least three network topologies will be considered:
  - Scale-free network with different slopes of power-law;
  - Regular lattice with various densities;
  - Random network with various densities;
  - Other networks from literature.
- How does the pattern of information diffusion among consumers (e.g., speed, types of consumers) influence the outcome in terms of innovation diffusion?

The ABM will include two fundamental types of agents: retail companies, and final consumers. While belonging to one of three homogeneous groups, each retailer will present a set of idiosyncratic features. Instead, consumers will be modelled as homogeneous masses, whose acceptance of the product entailing the innovation (and a different price) determines the paths of innovation diffusion and price transmission.

The market of a single food commodity will be studied and differentiated only for the amount wasted due to its intrinsic characteristics (i.e., its technological level). The market will operate in imperfect conditions, where competition is quantity-based. Retailers will modify the price of the product involved only to recover the costs of introducing the innovation, thus returning to the same margin as before.

Companies

A set of companies (retailers) $j \in J = \{1, 2, \ldots, M\}$, is considered. Companies belong to three groups (typologies) D, based on their structural and managerial characteristics (basically, on the dimension of their market shares τ_j): small retailers (M_s), discount retailers (M_m), and large-scale retailers (M_l)[6]. Hence, $j_D \in J_D = \{1, 2, \ldots, M_D\}$. The market share of retailer *i* is equal to the share of consumers of each group *C* (see next section) who purchase from it: $\tau_j = \sum_C \left(N_C^j / N_c\right)$. The product is homogeneous across all retailers; however, each type D of retailers provides a different service, which justifies the association with a specific typology of consumers.

During the simulation, each retail company can adopt two different types of technology:

- The baseline technology *H*, initially adopted by all companies, that generates a high level of FW;
- The technology *L*, that reduces FW to a low level, and may operate through three different strategies:
  - By preventing or reducing the FW generated by the consumers purchasing the product in their homes (L_C)[7];
  - By preventing or reducing the FW generated within the company (L_R)[8];
  - By preventing or reducing the FW generated both within the company and in consumers' homes (L_{RC}).

[6] The number of stores and/or the market shares of the companies can be obtained from Eurostat data.

[7] Such innovation exerts its beneficial effects at consumer level (where the largest quota of FW is generated), and is introduced against the immediate advantage of the innovator (sales reduction without simultaneous price adaptation).

[8] Retailers have no incentive in introducing innovations reducing the FW they generate, as their market power allows to transfer the related costs to consumers. An example of this are apps designed to push special offers to consumers. Innovation will modify company's costs (raised investment, maintenance, energy costs vs. reduced purchasing and waste costs) and generate a downward supply shift: light sales increase but at a lower price (due to inelasticity of demand).

When an individual company *j* adopts *L*, the products entailing the new technology *L* fully substitute those entailing the old technology *H* within the company. L_C implies a shift in the supply of the company (upward, if costs are reduced), as well as a shift downward in the demand: while the former is assumed to be irreversible, the latter is not[9]; indeed, innovators may increase their prices. Instead, L_R implies only a shift in the supply, as adopters reduce their prices.

Retail companies are characterized by the following variables and parameters:

- p_j is the unit price charged by company *j* for the commodity;
- $\tau_{j_D}^t$ is the market share of companies j_D, of type *D*, at time *t*;
- v_{j_D} is the unit variable cost born by companies j_D of type *D* (which is technology-dependent);
- k_{j_D} are the total fixed costs borne by companies j_D of type *D* (which are technology dependent);
- F_j is the set of connections within the immediate network of company *j*;
- α_j is the importance that company *j* assigns to profit maximization;
- β_{1j} is the importance that company *j* assigns to environmental concerns (due to FW generation) as a tool for image scoring with consumers ('impure altruism');
- β_{2j} is the intrinsic importance that company *j* assigns to environmental concerns (due to FW generation);
- γ_j is the importance that company *j* assigns to the behaviour of the companies in its immediate networkF_{j_D};
- w_{j_D} is the waste generated internally by company j_D (that does not vary with the adoption of L_C).

Furthermore, x_j^i is the satiation quantity of consumer *i*, that is technology-dependent.

Given the variables defined above, the utility function of each individual company is represented by Eq. (1):

$$U_j^t = \alpha_j \left(p_j x_j \tau_j^t - v_{jD}\left(\left(x_j \tau_j^t\right) + w_j\right) - k_{jD}\right) + \beta_j^1 (\theta_1)^{1/2} + \beta_j^2 (\theta_2)^{1/2} + \gamma_j \left(\left[\sum_{y=j} \tau_{yD} \in F_y\right] - \left[\sum_{y \neq j} \tau_{yD} \in F_y\right]\right), \tag{1}$$

$$\text{where } \theta_1 = \begin{Bmatrix} 0 & \text{if technology is H} \\ \Delta(X) * \tau_{jD}^t & \text{if technology is L} \end{Bmatrix},$$

$$\text{and } \theta_2 = \begin{Bmatrix} 0 & \text{if technology is H or } \Delta(\text{X}) < 0 \\ \Delta(X) * \tau_{jD}^t & \text{if technology is L} \end{Bmatrix}.$$

9 Irreversible demand response (Marshall, 1936; Wolffram, 1971).

$\Delta(\mathrm{X}) = \mathrm{x}_j^{H*} - x_j^{L*}$ is the difference considered by retailers to assess their environmental utility in case of adoption of *L*. The terms in β_1 and β_1 are increasing and concave, meaning that the marginal environmental utility a retailer derives from reducing FW is decreasing.

The variables x_j, v_{j_D}, and k_{J_D} are technology-dependent, i.e. they assume the values x_{jH}, v_{j_DH} and k_{J_DH}, respectively, if the high-waste technology *H* is adopted, and the value x_{jL}, v_{j_DL} and k_{J_DL}, respectively, if the low-waste technology *L* is adopted. For what concerns x_j, it can be established that $x_j^H = x_j^{L*} + \Delta(X)$, as each consumer can be satiated either by an amount x_j^H of the good produced with technology *H*, or an amount x_j^H produced with technology *L*[10]. Furthermore, the variable and fixed costs of an innovation, v_{j_D} and k_{j_D}, vary based on the size *D* of a company, although the efficacy of the innovation in terms of reduction of FW is the same for all types of companies.

At each time step *t*, with probability P_{tech}, each retailer is given the opportunity to change technology[11]. P_{tech} measures the unforecastable availability of resources (time, technicians, cash flow, access to capital, information, etc.) inducing potential innovators to keep waiting despite reaching a utility threshold. When a retailer is given the opportunity to change its technology, it faces a discrete choice between keeping the high-waste technology *H*, or adopting the low-waste technology *L*. A company would choose the option entailing the higher utility, calculated using Eq. (1). Note that the price of a commodity is fixed and – in a first stage – it does not change with the changing technology.

Furthermore, at each time step *t*, with probability P_{price}, each company is given the opportunity to change its selling price. The price rule is the following. Each retailer compares the aggregate market share of the companies adopting *L* with a threshold $\bar{\tau}$. The share compared with the threshold $\bar{\tau}$ differs depending on a retailer's dimension *D*: large-scale companies consider the share of adopters among all companies; discount retailers and small ones consider $\overline{\tau_m}$ and $\bar{\tau}_s$ relative to their immediate network F_j. If the share considered is higher than the threshold, the retailer increases its selling price, moving in the direction of recovering the same margins as in *H*[12]. Given this decision rule, large retailers change their price all together, while discounts and small shops make an individual decision.

In theory, price movements can vary in a continuum from very 'prudent' ones, where the new price is set so that the percentage recovered (R_m) amounts to 100% of the original margin, to very 'aggressive' ones, where no change in the price takes place. In the baseline, R_m is a constant whose value is explored in the simulations: it does not change endogenously in the model. A reduction of the price by retailers

[10] Note also that a temporal dynamic of fixed and variable costs can also be introduced. However, a reduction of *k* and *v* is only expected to speed up the diffusion of the innovation.

[11] This probability is assumed to be the same for all companies at system level.

[12] The presence of uncertainty on the share of adopters would not change the result, while introducing also some degree of risk aversion would delay price changes.

adopting the low-waste technology *H* (to avoid losing customers) is excluded, as it is assumed that companies are sufficiently forward-looking to avoid price wars.

An extension (not in the baseline) can be introduced as for the price strategies of the companies. In principle, R_m could evolve endogenously by adopting the following rules. Each company is endowed with a given strategy of price change to recover its previous margins (either 'aggressive' or 'prudent'). When a company is re-selected to change its price, it evaluates its past decisions and, eventually, changes its behavior. The company does it by confronting its own margins against those of all companies (for large-scale retailers), or those of the companies belonging to its individual network (for discounts and small retailers): if the former margins are lower, the company switches to the other pricing strategy. For this extension, each innovating company is initially endowed with a given strategy concerning price changes. These are based on the assumptions that the innovation implies a net increase of costs, and that only large-scale retailers have the possibility to be 'aggressive' (i.e., to support an initial limited margin recovery). Two scenarios can be hypothesised:

- Scenario A: large-scale innovators adopt an 'aggressive' price strategy; large-scale followers, whose market share τ is reduced, replicate the 'aggressive' strategy; discount followers, whose τ is also reduced, innovate but adopt a 'prudent' strategy; finally, small followers, whose τ is also reduced, innovate and adopt a 'prudent' price strategy;
- Scenario B: all innovators adopt a 'prudent' price strategy; large-scale followers, whose market share τ is reduced, innovate and adopt a 'prudent' price strategy; discount retailers, whose τ is not influenced, do not adopt the innovation and, consequently, do not change their price; small followers, whose τ is also reduced, innovate and adopt a 'prudent' strategy.

Box 2. Why a network?

Why a network? Local networks are intended as a limitation for suppliers. The network corresponds to the set of companies each retailer compares with. Due to limitations in their own rationality, small and discount companies can only compare their behaviour with a subset of peers.

Consumers

A unit masses of consumers belonging to three categories of potentially different proportions is considered: junkie consumers (N_m), unsophisticated consumers (N_l), and cool consumers (N_s). Consumers are homogeneous in their satiation quantity x_j, which is technology dependent: their demand of the commodity can be equally satisfied with x_H units of the good produced with technology *H*, or with x_L units of the commodity produced with technologies L_C or L_{RC}, with $x_L < x_H$. Indeed, the low-waste technologies L_C and L_{RC} shift consumers' demand downward, although without modifying its price rigidity.

Different categories of consumers have different price elasticity ε_C (stickiness) of the demand of the commodity, with $\varepsilon_s < \varepsilon_l < \varepsilon_m$ (i.e. junkie consumers are the most sensitive to price variations, cool consumers the least).

Furthermore, while all consumers are informed about the existence of the good produced with technology *H*, each consumer is characterized by a state of information about the existence of the good produced with technology *L*: she can be either Informed (*I*), or Not Informed (*NI*). At the onset of each simulation, there are no consumers informed about its existence. Then, they gradually become informed at a rate that, following Rogers (1962), is defined by Eq. (2):

$$n(t) = \left(a + b\frac{N(I)_t}{N}\right)(N - N(I)_t), \tag{2}$$

where $N(I)_t$ is the number of consumers in the *I* state at time t; $n(t)$ the number of newly-informed consumers at time *t*, which is equally divided among the consumers of the retailers adopting *H* at time *t*; *'a'* is a parameter denoting external influences (advertisement, etc.); and *'b'* is a parameter which depends on the circulation of information among consumers. It is assumed that, when a retailer adopts *L*, the consumers purchasing the good from that company become automatically informed purchaser of *L* from that same company. Once getting informed, consumers can then decide whether to buy the product *H*, or the product *L*.

It is assumed that, at every time step *t*, a proportion P_{change} of consumers considers whether changing the retailer from which they purchase the commodity. P_{change} models the *status quo bias*, which leads consumers to keep purchasing from the same retailer even if it is not rational, i.e. when it is not economically convenient. The process follows these steps:

- One random retail company is selected;
- One type of consumer (*m*, *l* or *s*, either informed or not informed) is selected;
- A random proportion $CTC \sim U(0, max_{CTC})$ of that type of consumers currently purchasing from that company considers whether to change company.

To define how the change of retailer happens, x_i and p_i are defined respectively as the current satiating quantity and price paid by consumer *i*. Furthermore, x_{ij}^* is defined as the satiating quantity for consumer *i*, given the technology adopted by company *j*. Each consumer considers, for all other p_j's available to her (given her state of information about technology *L*, and the prices previously set by all companies), whether

$$\Delta C(x)_D = x_i p_i - x_j p_j - P_{trans}^i > 0, \tag{3}$$

where $x_j = x_j^* - x_j^* * \left(\frac{p_i - p_j}{p_j}\right) * \varepsilon_i$ and P_{trans}^i are transaction costs (higher for junkie consumers N_m). Transaction costs, as well as elasticity to price, are different for each category of consumers, and homogeneous within each category. If, for one or more companies, $\Delta C(x)_D > 0$, then the consumer moves to the company/type of company offering the combination of technology and price that yields $max(\Delta C(x)_D > 0)$. When a movement among companies takes place, each company offering the same technology and price receives the same share of consumers, equal to: $\frac{\#\,movers}{companies\ in\ same\ position}$. However, while informed consumers can move both to companies adopting *L* and companies adopting *H*, uninformed ones can move only to companies adopting *H*.

A number of extensions (not in the baseline) could be introduced on the consumption side of the ABM:

- *Introducing a measure of social acceptability of the product entailing the new technology* L (see REFRESH WP1). Each consumer *i* belonging to group *m*, *l* or *s* can be assigned a utility level $\overline{\Delta C(x)_D}$ above which, when informed, she considers shifting to another retailer. This threshold is to be intended as an objective one, i.e. the potential waste reduction for that group of consumers, and changes from group to group. If $\Delta C(x)_D > \overline{\Delta C(x)_D}$ for some retailers, then the consumer moves to the company/type of company offering the combination of technology and price that yields $max(\Delta C(x)_D > \overline{\Delta C(x)_D})$[13].
- *Differentiating consumers based on demographic and socio-economic characteristics*. Consumers could be further differentiated into demographic or socio-economic groups with different elasticities ε_i or social acceptability levels $\overline{\Delta C(x)_D}$, based on key variables (age, income level, etc.).

Initializing conditions

Each group of retail companies *D* initially (t = 1) supplies the commodity to a specific group of consumers N_C, i.e. $i_C \in I_C = \{1, 2, \dots, N_C\}$. Small companies ($M_s$) supply cool consumers (N_s), discount companies (M_m) junkie consumers (N_m), and large-scale companies (M_l) unsophisticated consumers (N_l).

Each group of consumers N_C related to a specific typology of companies M_D presents homogeneity as for its quality concerns and preferences (e.g., intrinsic food characteristics, services added to food, such as technological innovation, etc.), its willingness/capacity to pay per unit of good, its price elasticity of demand, its transaction costs, and its acceptance of the innovation.

Furthermore, each company belonging to the same group, j_D, is initially (t = 1) endowed with an equal market share:

$$\tau_{jD}^{1} = \frac{N_D}{M_D}.$$

Due to the differences in company dimensions, commodity characteristics, and consumers' preferences, initial market-clearing prices differ per each typology of retailers, with small retailers asking for the highest price, and discounts for the lowest: $p_{js} > p_{jl} > p_{jm}$.

Intra-step timing of the model

At each time step *t*, the ABM evolves according to the following dynamics:

1. Each retailer M_l is offered the possibility to change its technology with probability P_{tech}, according to the utility function of Eq. (1);

[13] Consumers could actually come back to purchasing *H*, if the increased price of product *L* causes $\Delta C(x)_D$ to become negative.

2. Each company is offered the possibility to change its price with probability P_{price} (large-scale retailers simultaneously, small ones based on their individual network);
3. The consumers who were purchasing from a company that changes its technology are reassigned to the same company, but with the new technology;
4. New consumers become informed about the existence of the low-waste technology, according to Eq. (2);
5. Consumers decide whether to move to a different company with probability P_{change}, using decision rule (3);
6. The market shares of the companies are recomputed.

Observables

Based on the research questions, the observables to be extracted from the simulations are:

- The speed of convergence towards a stable share of the companies adopting the low-waste technology *L* ($\hat{\tau}$);
- The market share of the companies adopting *L* (τ_L) at convergence (t_{max}) – both total and per each type *D* of companies;
- The average, median, minimum, and maximum α_L, β_{1L}, β_{1L}, and γ_L of the companies adopting *L*, at convergence;
- The evolution of the average, median, minimum, and maximum values of the last four variables across time.

A summary of the input and output variables of this model is provided in Table 3.

Table 3. Summary of the supply-side model inputs and outputs.

Variable name	Variable description
A	parameter of informed consumers getting info from other sources
Alpha	concern for profit
AvgAlphaAdopter_convergence	average profit concern alpha for adopters of L when 90% is achieved
AvgBeta1Adopter_convergence	average consumer image concern beta_1 for adopters of L when 90% is achieved
AvgBeta2Adopter_convergence	average warmth glow concern beta_2 for adopters of L when 90% is achieved
AvgGammaAdopter_convergence	average imitation concern gamma for adopters of L when 90% is achieved
B	parameter of informed consumers getting info from previously informed
beta_1	concern for image with consumers

beta_2	warmth glow
Countsim	simulation number (in this file)
D	How many different dimensions can a company assume
Dc	how many types of consumers are there
DeltaX	difference between x_stars_H and x_stars_L
Epsilon	elasticities of demand to price. small=1, medium=2, large=3, it should hold that s<l<m
Fulladoption	1 if more than 90% of the market share is from companies adopting L
Gamma	imitation
init_tau	initial market share for each type of consumers ([I, NI] x [s,m,l])
initP	initial market price for each company
k1	fixed costs for small companies (H and L technology respectively)
k2	fixed costs for medium companies (H and L technology respectively)
k3	fixed costs for large companies (H and L technology respectively)
M	Number of companies
M_tech	type of technology (1: H, 2:L) adopted at the end of the simulation
M_type	type of company: 1: small, 2: medium 3: large
M1	how many small companies are there?
M2	how many medium companies are there?
M3	how many large companies are there?
max_moving_in_one_round	maximum proportion of agents of one type in one company changing at each round
maxAlphaAdopter_convergence	max profit concern alpha for adopters of L when 90% is achieved
maxBeta1Adopter_convergence	max consumer image concern beta_1 for adopters of L when 90% is achieved
maxBeta2Adopter_convergence	max warmth glow concern beta_2 for adopters of L when 90% is achieved
maxGammaAdopter_convergence	max imitation concern gamma for adopters of L when 90% is achieved
MedianAlphaAdopter_convergence	median profit concern alpha for adopters of L when 90% above is achieved
MedianBeta1Adopter_convergence	median consumer image concern beta_1 for adopters of L when 90% is achieved
MedianBeta2Adopter_convergence	median warmth glow concern beta_2 for adopters of L when 90% is achieved
MedianGammaAdopter_convergence	median imitation concern gamma for adopters of L when 90% is achieved

minAlphaAdopter_convergence	min profit concern alpha for adopters of L when 90% above is achieved
minBeta1Adopter_convergence	min consumer image concern beta_1 for adopters of L when 90% is achieved
minBeta2Adopter_convergence	min warmth glow concern beta_2 for adopters of L when 90% is achieved
minGammaAdopter_convergence	min imitation concern gamma for adopters of L when 90% is achieved
N	1: unit mass of consumers
N1	proportion of consumers of type 1
N2	proportion of consumers of type 2
N3	proportion of consumers of type 3
P	final market price for each company
P_Link	density in the network of contacts
Pprice	probability that a company consider changing price at each t
Proportion_changing	the proportion of the total number of consumers considering changing company at each step
Pstar	equilibrium prices for each type of consumer
Ptech	probability that a company consider changing technology at each t
Ptrans	transaction costs associated with changing company
S	proportion of the original margins that companies try to recover when tauhat is reached
Tau	final market share for each type of consumers ([I, NI] x [s,m,l])
tauhat1_achievedAtTime	time step at which tau_hat is achieved for small companies
tauhat1_tmax	market share from small companies adopting L at tmax
tauhat2_achievedAtTime	time step at which tau_hat is achieved for medium companies
tauhat2_tmax	market share from medium companies adopting L at tmax
tauhat3_achievedAtTime	time step at which tau_hat is achieved for large companies
tauhat3_tmax	market share from large companies adopting L at tmax
tauhatALL_achieved	time step at which tau_hat is achieved for ALL companies
tauhatALL_tmax	market share from companies adopting L at tmax
Tauhats	market shares to be reached before allowing price changes
tFullAdopt	time step in which the previous condition is achieved
Tmax	number of rounds run in each simulation
v1	variable costs for small companies (H and L technology respectively)

v2	variable costs for medium companies (H and L technology respectively)
v3	variable costs for large companies (H and L technology respectively)
w_par	percentage of waste on production level
x_star	these are the personal satisfaction quantities for each individual, for H and L technology

Data requirement

To calibrate the retailer ABM and obtain reliable results, real-world data are needed. Such data should be provided for each case study to be modelled, either geographically-defined (e.g. one of the REFRESH pilot countries), or referring to a given event (e.g. the adoption of a specific innovation). Furthermore, these data could be either quantitative, like a database allowing to calculate statistically representative shares, ratios, etc., or qualitative, like in-depth semi-structured interviews with the managers of retail companies. Typically, the *entities'* (i.e. the agents') *attributes*, and the *environment and institutions* within which they interact, may be outlined based on statistical data, while their *rules of behaviours*, their *perception of the environment*, as well as their *interaction rules* may be detected by means of qualitative interviews.

Table 4 below provides detailed examples of the types of data needed to calibrate the retail ABM model. For each variable detected from a retail or consumer **survey**, the entire **set of answers** is needed (preferably in the form of a dataset); otherwise, the main descriptive statistics (minimum, maximum, median, mean, standard deviation, 1st and 3rd quartile) should be provided. The terms “innovation” and “product” refer to the innovation for reducing FW considered in the study used to calibrate the model, and to the food product affected by the innovation, respectively.

Table 4. Type of data required to calibrate the ABM retail model.

Variable name	Source
A	In-depth qualitative interviews with retailers, or closed-ended question in a survey (“How often do you get informed from newspapers, conferences...?”).
Alpha	In-depth qualitative interviews with retailers, or closed-ended question in a survey (“How concerned are you about your profit, compared to environmental performance, etc.?”).
AvgAlphaAdopter_convergence	Same as above, calculated only among the adopters of the innovation, after it has become widespread enough.
AvgBeta1Adopter_convergence	In-depth qualitative interviews with retailers, or closed-ended question in a survey (“How concerned are you about your image among consumers, compared to profit, etc.?”) – prevalence calculated only among the adopters of the innovation, after it has become widespread enough.

AvgBeta2Adopter_convergence	In-depth qualitative interviews with retailers, or closed-ended question in a survey ("How much helping others is important for your retailer, regardless of reputation?") – prevalence calculated only among the adopters of the innovation, after it has become widespread enough.
AvgGammaAdopter_convergence	In-depth qualitative interviews with retailers, or closed-ended question in a survey ("How much do you care about being similar/different from other firms in your territory?") – prevalence calculated only among the adopters of the innovation, after it has become widespread enough.
B	In-depth qualitative interviews with retailers, or closed-ended question in a survey ("Did you get information on the innovation from another retailer?").
beta_1	In-depth qualitative interviews with retailers, or closed-ended question in a survey ("How concerned are you about your image among consumers, compared to profit, etc.?").
beta_2	In-depth qualitative interviews with retailers, or closed-ended question in a survey ("How much helping others is important for your retailer, regardless of reputation?").
Countsim	Technical variable not to be provided.
D	This variable is set equal to 3 in this model. If available, cluster or similar analysis on administrative data of the Chamber of Commerce identifying a different number of firm groups.
Dc	This variable is set equal to 3 in this model. If available, cluster or similar analysis on market survey data identifying a different number of consumer groups.
DeltaX	In-depth qualitative interviews with retailers, or open-ended question in a survey ("Which was the absolute and relative reduction of FW achieved by introducing this innovation?").
Epsilon	Any consumer survey, or any study on the elasticity of the demand with respect to price in the country considered, for different typologies of consumers.
Fulladoption	This is a technical variable not to be provided.
Gamma	In-depth qualitative interviews with retailers, or closed-ended question in a survey ("How much do you care about being similar/different from other firms in your territory?").
init_tau	Qualitative interviews with consumers, focus groups, descriptive statistics from market surveys carried out by retailers – 'Dc' percentages summing up to 100%.
initP	In-depth qualitative interviews with retailers, open-ended question in a survey ("Which was the price of the product in your selling points before the introduction of the innovation in the market?"), or any price dataset.
k1	In-depth qualitative interviews with small retailers, or closed-ended question in a survey ("How much are your fixed costs of adopting the innovation?").

k2	In-depth qualitative interviews with middle-size retailers, or closed-ended question in a survey (“How much are your fixed costs of adopting the innovation?”).
k3	In-depth qualitative interviews with large retailers, or closed-ended question in a survey (“How much are your fixed costs of adopting the innovation?”).
M	National statistics office, or administrative data from the Chamber of Commerce – entire number.
M_tech	In-depth qualitative interviews with retailers, or closed-ended question in a survey (“Are you using the innovation”) – share of adopters of a consolidated innovation.
M_type	Technical variable not to be provided.
M1	National statistics office, or administrative data from the Chamber of Commerce – entire number equal to M-M2-M3.
M2	National statistics office, or administrative data from the Chamber of Commerce – entire number equal to M-M1-M3.
M3	National statistics office, or administrative data from the Chamber of Commerce – entire number equal to M-M1-M2.
max_moving_in_one_round	Qualitative interviews with consumers, focus groups, descriptive statistics from market surveys carried out by retailers (“Which type of retailer are you buying from?”; “At which conditions would you consider changing retailer?”).
maxAlphaAdopter_convergence	In-depth qualitative interviews with retailer, or closed-ended question in a survey (“How concerned are you about your profit, compared to environmental performance, etc.?”) – maximum value calculated among adopters of the innovation.
maxBeta1Adopter_convergence	In-depth qualitative interviews with retailer, or closed-ended question in a survey (“How concerned are you about your image among consumers, compared to profit, etc.?”) – maximum value calculated among adopters of the innovation.
maxBeta2Adopter_convergence	In-depth qualitative interviews with retailer, or closed-ended question in a survey (“How much helping others is important for your retailer, regardless of reputation?”) – maximum value calculated among adopters of the innovation.
maxGammaAdopter_convergence	In-depth qualitative interviews with retailer, or closed-ended question in a survey (“How much do you care about being similar/different from other firms in your territory?”) – maximum value calculated among adopters of the innovation.
MedianAlphaAdopter_convergence	In-depth qualitative interviews with retailer, or closed-ended question in a survey (“How concerned are you about your profit, compared to environmental performance, etc.?”) – median value calculated among adopters of the innovation.
MedianBeta1Adopter_convergence	In-depth qualitative interviews with retailer, or closed-ended question in a survey (“How concerned are you about your image among consumers, compared to profit, etc.?”) –median value calculated among adopters of the innovation.

Medi-anBeta2Adopter_convergence	In-depth qualitative interviews with retailer, or closed-ended question in a survey (“How much helping others is important for your retailer, regardless of reputation?”) – median value calculated among adopters of the innovation.
MedianGam-maAdopter_con-vergence	In-depth qualitative interviews with retailer, or closed-ended question in a survey (“How much do you care about being similar/different from other firms in your territory?”) – median value calculated among adopters of the innovation.
minAl-phaAdopter_con-vergence	In-depth qualitative interviews with retailer, or closed-ended question in a survey (“How concerned are you about your profit, compared to environmental performance, etc.?”) – minimum value calculated among adopters of the innovation.
min-Beta1Adopter_convergence	In-depth qualitative interviews with retailer, or closed-ended question in a survey (“How concerned are you about your image among consumers, compared to profit, etc.?”) – minimum value calculated among adopters of the innovation.
min-Beta2Adopter_convergence	In-depth qualitative interviews with retailer, or closed-ended question in a survey (“How much helping others is important for your retailer, regardless of reputation?”) – minimum value calculated among adopters of the innovation.
minGam-maAdopter_con-vergence	In-depth qualitative interviews with retailer, or closed-ended question in a survey (“How much do you care about being similar/different from other firms in your territory?”) – minimum value calculated among adopters of the innovation.
N	National statistics office – population of adult consumers.
N1	Qualitative interviews with consumers, focus groups, descriptive statistics from market surveys carried out by retailers – a percentage from 0% to (100-N2-N3)%.
N2	Same as above – a percentage from 0% to (100-N1-N3)%.
N3	Same as above – a percentage from 0% to (100-N2-N3)%.
P	In-depth qualitative interviews with retailers, open-ended question in a survey (“Which was the price of the product in your selling points after the innovation had already spread in the market?”), or any price dataset.
P_Link	In-depth qualitative interviews with medium-size and small retailers, open-ended question in a survey (“How many retailers in your territory are you in contact with?”), or any network study of retailers in the country studied.
Pprice	In-depth qualitative interviews with retailer, or closed-ended question in a survey (“Which conditions would you require to be in place for deciding to change the price of the product?”).
Proportion_chang-ing	Qualitative interviews with consumers, focus groups, descriptive statistics from market surveys by retailers (“Would you consider changing the price of the product if condition was in place?”) – a series of percentage from 0% to 100%.

Pstar	Qualitative interviews with consumers, focus groups, descriptive statistics from market surveys by retailers ("Which price would you consider fair for the product, so that you would not consider changing retailer?") – a monetary value.
Ptech	In-depth qualitative interviews with retailer, or closed-ended question in a survey ("Which conditions would you require to decide to adopt the innovation for reducing FW?").
Ptrans	Qualitative interviews with consumers, focus groups, descriptive statistics from market surveys by retailers – a monetary estimate of the costs of changing retailer.
S	In-depth qualitative interviews with retailers, closed-ended question in a survey, or any data from the budget of the retailers – a monetary value.
Tau	Any consumer survey carried out by retailers – percentages of consumers belonging to each cluster 'Dc' buying from the retailers belonging to each cluster 'D'.
tauhat1_achievedAtTime	In-depth qualitative interviews with small retailers, closed-ended question in a survey ("When did you introduce the innovation?"), or administrative data – time passed from the introduction of the innovation in the market to its adoption.
tauhat1_tmax	In-depth qualitative interviews with retailers, closed-ended question in a survey ("Have you adopted the innovation yet?"), or administrative data – percentage of small retailers adopting the innovation after it has become widespread.
tauhat2_achievedAtTime	In-depth qualitative interviews with medium-size retailers, closed-ended question in a survey ("When did you introduce the innovation?"), or administrative data – time from the introduction of the innovation in the market to its adoption.
tauhat2_tmax	In-depth qualitative interviews with mid-size retailers, closed-ended question in a survey ("Have you adopted the innovation yet?"), or administrative data – share of mid-size retailers adopting the innovation after it has become widespread.
tauhat3_achievedAtTime	In-depth qualitative interviews with large retailers, closed-ended question in a survey ("When did you introduce the innovation?"), or administrative data – time passed from the introduction of the innovation in the market to its adoption.
tauhat3_tmax	In-depth qualitative interviews with large retailers, closed-ended question in a survey ("Have you adopted the innovation yet?"), or administrative data – share of large retailers adopting the innovation after it has become widespread.
tauhatALL_achieved	Derived for past innovations, extimating the time it took to reach "close to full adoption".
tauhatALL_tmax	Derived for past innovations, extimating the time it took to reach "close to full adoption".
Tauhats	In-depth qualitative interviews with retailers, or closed-ended question in a survey ("Which market conditions do you require for deciding to change the price of the product?").

tFullAdopt	Derived for past innovations, extimating the time it took to reach "close to full adoption".
Tmax	This variable is set exogenously in the model.
v1	In-depth qualitative interviews with small retailers, or closed-ended question in a survey ("How much are your variable costs of adopting the innovation?").
v2	In-depth qualitative interviews with middle-size retailers, or closed-ended question in a survey ("How much are your variable costs of adopting the innovation?").
v3	In-depth qualitative interviews with large retailers, or closed-ended question in a survey ("How much are your variable costs of adopting the innovation?").
w_par	In-depth qualitative interviews with retailers, or closed-ended question in a survey ("Which is the absolute and relative quantity of the product wasted by your retailer before adopting the innovation?").
x_star	Qualitative interviews with consumers, focus groups, descriptive statistics from market surveys carried out by retailers ("How much of the product were you purchasing before the introduction of the innovation to reduce FW in a week/month? And after?)

7.2 BN output of the integrated model

Table 3 illustrates the BN output of the integrated ABM-BN model for both the consumer and the supply side. The relationships among variables can be detected from the table. The local structure of each node is enclosed in square brackets ("[]"). The parents of the node (if any) are listed after a ("|") and separated by colons (":").

Table 5. Bayesian network outputs for the integrated ABM-BN models for the consumer and supply-side.

Supply side	Consumer
Bayesian network learned via Score-based methods	Bayesian network learned via Score-based methods
Model:	Model:
[Ptech][alpha][gamma][M_type][init_tauNI_1|M_type][init_tauNI_2|M_type]	[num_motivations][tmax][d][num_action_affecting_waste][scale_frequencies][type]
[init_tauNI_3|M_type][Num_sim|Ptech][v_1L|Ptech:Num_sim][v_2L|v_1L][v_3L|v_1L]	[Sa_min_out_Taste.preferen-ces][Sa_min_out_Time][Sa_min_out_Provision and status]
[pstar2|Ptech:v_1L:Num_sim][Ptrans1|Ptech:v_1L:pstar2:Num_sim]	[Sa_min_out_Price][Sa_min_out_FW.Proper][Sa_max_out_Health]

[pstar3|Ptech:v_1L:pstar2:Ptrans1:Num_sim][Ptrans2|Ptrans1][Ptrans3|Ptrans1]	[Sa_max_out_Taste.preferences][Sa_max_out_Time][Sa_max_out_Provision.and.status]
[tauhat2_achievedAtTime|Ptech:pstar2:Ptrans1][x_starL|Ptech:v_1L:pstar2:pstar3:Ptrans1]	[Sa_max_out_Price][Sa_max_out_FW.Proper][nu|d][Pevo|d:nu][num_types|Pevo]
[initP|pstar2:pstar3:M_type][P|initP]	[countsim|tmax:d:nu:Pevo][mu|d:nu:Pevo:countsim]
[AvgBeta1Adopter_convergence|x_starL:v_1L:pstar2:pstar3:Num_sim]	[Sa_min_out_Health|num_types:Sa_min_out_Price][UtilityAlpha|d:mu:nu:Pevo:countsim]
[b|Ptech:v_1L:pstar3:Ptrans1:AvgBeta1Adopter_convergence]	[OpDiff_Health|num_motivations:num_types:tmax:d:mu:nu:Pevo:num_action_affecting_waste:scale_frequencies:UtilityAlpha:countsim:type:Sa_min_out_Health:Sa_min_out_Taste.preferences:Sa_min_out_Time:Sa_min_out_Provision.and.status:Sa_min_out_Price:Sa_min_out_FW.Proper:Sa_max_out_Health:Sa_max_out_Taste.preferences:Sa_max_out_Time:Sa_max_out_Provision.and.status:Sa_max_out_Price:Sa_max_out_FW.Proper]
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[MedianBeta1Adopter_convergence|Ptech:v_1L:pstar2:AvgBeta1Adopter_convergence]	[SaDiff_Taste.preferences|num_motivations:num_types:tmax:d:mu:nu:Pevo:num_action_affecting_waste:scale_frequencies:UtilityAlpha:countsim:type:Sa_min_out_Health:Sa_min_out_Taste.preferences:Sa_min_out_Time:Sa_min_out_Pr

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<tr><td>[MedianGammaAdopter_convergence|b:Ptrans1:AvgGammaAdopter_convergence:Num_sim]</td><td>[SaDiff_Provision.and.status|num_motivations:num_types:tmax:d:mu:nu:Pevo:num_action_affecting_waste:scale_frequencies:UtilityAlpha:countsim:type:Sa_min_out_Health:Sa_min_out_Taste.preferences:Sa_min_out_Time:Sa_min_out_Provision.and.status:Sa_min_out_Price:Sa_min_out_FW.Proper:Sa_max_out_Health:Sa_max_out_Taste.preferences:Sa_max_out_Time:Sa_max_out_Provision.and.status:Sa_max_out_Price:Sa_max_out_FW.Proper]</td></tr>
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[Pprice|v_1L:perc_rec_margin:pstar2:b:Proportion_changing]	[SaDiff_FW.Proper|num_motivations:num_types:tmax:d:mu:nu:Pevo:num_action_affecting_waste:scale_frequencies:UtilityAlpha:countsim:type:Sa_min_out_Health:Sa_min_out_Taste.preferences:Sa_min_out_Time:Sa_min_out_Provision.and.status:Sa_min_out_Price:Sa_min_out_FW.Proper:Sa_max_out_Health:Sa_max_out_Taste.preferences:Sa_max_out_Time:Sa_max_out_Provision.and.status:Sa_max_out_Price:Sa_max_out_FW.Proper]
[a|Ptech:Pprice:AvgBeta1Adopter_convergence:AvgGammaAdopter_convergence:Num_sim]	[FWDiff|num_motivations:num_types:tmax:d:mu:nu:Pevo:num_action_affecting_waste:scale_frequencies:UtilityAlpha:countsim:type:Sa_min_out_Health:Sa_min_out_Taste.preferences:Sa_min_out_Time:Sa_min_out_Provision.and.status:Sa_min_out_Price:Sa_min_out_FW.Proper:Sa_max_out_Health:Sa_max_out_Taste.preferences:Sa_max_out_Time:Sa_max_out_Provision.and.status:Sa_max_out_Price:Sa_max_out_FW.Proper]
[maxGammaAdopter_convergence|Pprice:pstar3:AvgGammaAdopter_convergence:MedianBeta1Adopter_convergence]	[OpDiff_Taste.preferences|num_motivations:num_types:tmax:d:mu:nu:Pevo:num_action_affecting_waste:scale_frequencies:UtilityAlpha:OpDiff_Health:countsim:type:Sa_min_out_Health:Sa_min_out_Taste.preferences:Sa_min_out_Time:Sa_min_out_Provision.and.status:Sa_min_out_Price:Sa_min_out_FW.Proper:Sa_max_out_Health:Sa_max_out_Taste.preferences:Sa_max_out_Time:Sa_max_out_Provision.and.status:Sa_max_out_Price:Sa_max_out_FW.Proper]

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<tr><td>[epsilon2|Ptech:Pprice:pstar3:a:MedianGammaAdopter_convergence]</td><td>[OpDiff_FW.Proper|num_motivations:num_types:tmax:d:mu:nu:Pevo:num_action_affecting_waste:scale_frequencies:UtilityAlpha:OpDiff_Health:OpDiff_Provision.and.status:countsim:type:Sa_min_out_Health:Sa_min_out_Taste.preferences:Sa_min_out_Time:Sa_min_out_Provision.and.status:Sa_min_out_Price:Sa_min_out_FW.Proper:Sa_max_out_Health:Sa_max_out_Taste.preferences:Sa_max_out_Time:Sa_max_out_Provision.and.status:Sa_max_out_Price:Sa_max_out_FW.Proper]</td></tr>
<tr><td>[maxAlphaAdopter_convergence|Pprice:a:b:Num_sim]</td><td>[OpDiff_Price|num_motivations:num_types:tmax:d:mu:nu:Pevo:num_action_affecting_waste:scale_frequencies:UtilityAlpha:OpDiff_Taste.preferences:OpDiff_Provision.and.status:OpDiff_FW.Proper:countsim:type:Sa_min_out_Health:Sa_min_out_Taste.preferences:Sa_min_out_Time:Sa_min_out_Provision.and.status:Sa_min_out_Price:Sa_min_out_FW.Proper:Sa_max_out_Health:Sa_max_out_Taste.preferences:Sa_max_out_Time:Sa_max_out_Provision.and.status:Sa_max_out_Price:Sa_max_out_FW.Proper]</td></tr>
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<tr><td>[M_tech|gamma:init_tauNI_3:maxGammaAdopter_convergence]</td><td colspan="2">[UtDiff|num_motivations:num_types:tmax:d:mu:nu:Pevo:num_action_affecting_waste:scale_frequencies:UtilityAlpha:OpDiff_FW.Proper:SaDiff_Health:SaDiff_Taste.preferences:SaDiff_Time:SaDiff_FW.Proper:FWDiff:countsim:type:Sa_min_out_Health:Sa_min_out_Taste.preferences:Sa_min_out_Time:Sa_min_out_Provision.and.status:Sa_min_out_Price:Sa_min_out_FW.Proper:Sa_max_out_Health:Sa_max_out_Taste.preferences:Sa_max_out_Time:Sa_max_out_Provision.and.status:Sa_max_out_Price:Sa_max_out_FW.Proper]</td></tr>
<tr><td>[tauNI_3|gamma:init_tauNI_3:M_tech][taul_1|init_tauNI_3:M_tech]</td><td colspan="2">[OpDiff_Time|num_motivations:num_types:tmax:d:mu:nu:Pevo:num_action_affecting_waste:scale_frequencies:UtilityAlpha:OpDiff_Health:OpDiff_Provision.and.status:OpDiff_Price:OpDiff_FW.Proper:countsim:type:Sa_min_out_Health:Sa_min_out_Taste.preferences:Sa_min_out_Time:Sa_min_out_Provision.and.status:Sa_min_out_Price:Sa_min_out_FW.Proper:Sa_max_out_Health:Sa_max_out_Taste.preferences:Sa_max_out_Time:Sa_max_out_Provision.and.status:Sa_max_out_Price:Sa_max_out_FW.Proper]</td></tr>
<tr><td>[taul_2|init_tauNI_3:M_tech][taul_3|M_tech][fulladoption|Ptech:P_Link:pstar3:Num_sim]</td><td>nodes:</td><td>38</td></tr>
<tr><td>[AvgAlphaAdopter_convergence|Ptech:P_Link:epsilon2:Num_sim]</td><td>arcs:</td><td>373</td></tr>
<tr><td>[AvgBeta2Adopter_convergence|P_Link:pstar2:pstar3:b:Num_sim][beta_1|tauNI_3]</td><td>undirected arcs:</td><td>0</td></tr>
<tr><td>[beta_2|tauNI_3][tFullAdopt|fulladoption]</td><td>directed arcs:</td><td>373</td></tr>
</table>

<table>
<tr><td>[minAlphaAdopter_convergence|P_Link:b:AvgAlphaAdopter_convergence:Num_sim]</td><td>average markov blanket size: 34.05</td></tr>
<tr><td>[minBeta2Adopter_convergence|Pprice:P_Link:Proportion_changing:AvgBeta2Adopter_convergence]</td><td>average neighbourhood size: 19.63</td></tr>
<tr><td>[tauhat1_achievedAtTime|x_starL:b:AvgAlphaAdopter_convergence:AvgGammaAdopter_convergence]</td><td>average branching factor: 9.82</td></tr>
<tr><td>[epsilon3|P_Link:epsilon2:Ptrans1:MedianBeta1Adopter_convergence:minBeta2Adopter_convergence]</td><td></td></tr>
<tr><td>[minBeta1Adopter_convergence|x_starL:AvgBeta1Adopter_convergence:minBeta2Adopter_convergence:Num_sim]</td><td>learning algorithm: Hill-Climbing</td></tr>
<tr><td>[tauhat3_tmax|b:Ptrans1:minBeta2Adopter_convergence:maxGammaAdopter_convergence]</td><td>score: BIC (Gauss.)</td></tr>
<tr><td>[tauNI_1|init_tauNI_3:tauhat3_tmax][tauNI_2|init_tauNI_3:tauhat3_tmax]</td><td>penalization coefficient: 4.258597</td></tr>
<tr><td>[MedianAlphaAdopter_convergence|Pprice:epsilon3:a:b:AvgAlphaAdopter_convergence]</td><td>tests used in the learning procedure: 1971</td></tr>
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<tr><td colspan="2">[tauhat1_tmax|perc_rec_margin:tauhat3_tmax][tauhat2_tmax|x_starL:epsilon3:tauhat3_tmax]</td></tr>
<tr><td colspan="2">[MedianBeta2Adopter_convergence|pstar3:Proportion_changing:AvgBeta2Adopter_convergence:MedianAlphaAdopter_convergence]</td></tr>
<tr><td colspan="2">[maxBeta2Adopter_convergence|Ptech:v_1L:pstar3:AvgBeta2Adopter_convergence:MedianAlphaAdopter_convergence]</td></tr>
<tr><td colspan="2">[epsilon1|pstar3:MedianGammaAdopter_convergence:maxBeta2Adopter_convergence:tauhat3_tmax:Num_sim]</td></tr>
<tr><td colspan="2">[minGammaAdopter_convergence|epsilon1:MedianBeta2Adopter_convergence:MedianGammaAdopter_convergence]</td></tr>
<tr><td colspan="2">[tauhat3_achievedAtTime|P_Link:pstar3:epsilon1:AvgBeta1Adopter_convergence:MedianAlphaAdopter_convergence]</td></tr>
<tr><td colspan="2">[tauhatALL_achieved|tauhat3_achievedAtTime]</td></tr>
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[tauhatALL_tmax|Ptrans1:tau-hat3_achievedAtTime:tauhat3_tmax]	
nodes:	63
arcs:	192
undirected arcs:	0
directed arcs:	192
average markov blanket size:	9.27
average neighbourhood size:	6.10
average branching factor:	3.05
Consumer	
Bayesian network learned via Score-based methods	
model:	
[num_motivations][tmax][d][num_action_affecting_waste][scale_frequencies][type]	
[Sa_min_out_Taste.preferences][Sa_min_out_Time][Sa_min_out_Provision.and.sta-tus]	
[Sa_min_out_Price][Sa_min_out_FW.Proper][Sa_max_out_Health]	
[Sa_max_out_Taste.preferences][Sa_max_out_Time][Sa_max_out_Provi-sion.and.status]	
[Sa_max_out_Price][Sa_max_out_FW.Proper][nu|d][Pevo|d:nu][num_types|Pevo]	
[countsim|tmax:d:nu:Pevo][mu|d:nu:Pevo:countsim]	
[Sa_min_out_Health|num_types:Sa_min_out_Price][Util-ityAlpha|d:mu:nu:Pevo:countsim]	
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nodes:	38
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