An Agent-Based Model of (Food) Consumption: Accounting for the Intention-Behaviour-Gap on Three Dimensions of Characteristics with Limited Knowledge

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Abstract

We propose an agent-based model to study purchase diffusion. We conceive goods with 3 dimensions of characteristics, price premiums and limited knowledge on the part of consumers. Despite purchase intention for each characteristic being high, only a reduced number of consumers are initially able to acquire them. The model thus reproduces the Intention-Behaviour-Gap often identified in sustainable food consumption, by exploring two of its known sources: price premiums on the presence of extra characteristics, and lacks in consumers' knowledge as to which goods contain them. We analyse the extent to which knowledge of characteristics diffuses throughout the population and purchases of them are adopted. By testing how different parameters affect these evolutions, we offer insights as to how wider adoption of desirable purchase behaviours can be encouraged. Results show that all parameters have significant effects on knowledge availability and purchase behaviour, and that the ensuing increased knowledge particularly affects purchases of combined characteristics—an interesting and unexpected result. Modifying network parameters (average network degree and knowledge spillovers) produces effects comparable to those of external ones (initial knowledge availability and price premiums), an interesting feature in terms of policy recommendations since the former can arguably imply less costly interventions than the latter.

Keywords: Intention-Behaviour-Gap, Agent-based modelling, Innovation diffusion, Lancaster goods.

1 Introduction

1.1 Motivation for the model

In many respects, the health, environmental and social impacts of the contemporary globalised food system are deemed negative [Tscharntke et al., 2012, Lamine, 2015]. Recommendations at all levels [United Nations General Assembly, 2015, IPES-Food, 2017] promote a higher consideration of health, environment and society across the food industry. While the production and distribution sides of the issue have been the subject of a relatively large body of research and policy recommendations, consumption remains somewhat understudied [Carroll and Fahy, 2015, Keller et al., 2016].

Consumers' general awareness and interest in these issues have increased over the past few years, although actual purchases of goods that can qualify as healthy, environmentally sustainable and socially optimal remain lower than declared intentions. Studies find price premiums and lack of knowledge on the part of consumers as to which goods contain the said characteristics to be amongst the reasons for this intention-behaviour gap (IBG) [Joshi and Rahman, 2015].

1.2 Theoretical approach

We conceive goods as (binarily) satisfying or not the characteristics of being healthy, good for the environment and good for society. In this, we follow the seminal work of Lancaster (1966), who introduced the notion of goods as collections of characteristics that consumers seek to satisfy.

Evidence shows that each of our three dimensions of analysis (*i.e.* health, environment, society) have in the past few years been increasingly adopted by [French] consumers [IPSOS, 2016, 2019]. The innovation-diffusion approach thus appears as an appropriate framework to describe current trends and study possible evolutions, since it was conceived to study how groups of consumers move from low to high adoption. For this, we draw from an agent-based model (ABM) presented by Leite and Teixeira [2012].

Our work, however, expands theirs in two different ways: first, by using Lancaster-type goods we allow for multiple dimensions of innovations to run in parallel and—to some extent—in competition (as consumers may have to make trade-offs between them). Second, we study intention-behaviour gaps generated by price differences and lack of knowledge on the part of consumers, thus accounting for a typical finding of sustainability studies (and of the aforementioned surveys): that of discrepancies between intention and action.

Two dimensions of diffusion are present in our analysis: knowledge and purchase. The former is a direct output of social interaction, whereby individual consumers can gain knowledge from one another as to what goods contain which characteristic. The second is indirect, since the acquisition of knowledge will permit consumers to assess whether they are able or not to buy the good they want, and so purchase is not an immediate result of interaction.

1.3 Working hypotheses, objectives and main findings

In order to proceed with our modelling work, we establish two main working hypotheses, thus far impossible to verify in the literature:

> **H1:** The level of interest on a given characteristic determines whether or not a consumer will initially have the knowledge of which goods contain it.
> **H2:** Individuals with knowledge of a characteristic and the ability to purchase it can influence others' knowledge and thus drive diffusion.

H1 is derived from the intuition that the higher the interest in a given dimension (*e.g.* environmental sustainability), the more a consumer will seek information as to how to satisfy it, thus increasing his or her chances of gaining knowledge. **H2** is derived from a common element in innovation diffusion studies, whereby experience of earlier adopters trickles down and can influence others' adoption, as well as from the fact that individuals largely seek information on their social networks [Rogers, 2002]. These hypotheses are worth discussing further, and we'll get back them at the end of the article.

Other than these, our model is built under a specific economic assumption: goods objectively have the quality of containing or not a given characteristic, and there is no subjectivity in identifying them, nor an evolution over time of what constitutes healthy, sustainable or socially fair food.

With regards to our subject-matter (food), there is reason to think that the process of knowledge diffusion for each of the characteristics is in the early stages of diffusion, with some 80% of respondents declaring they lack information as to how to identify them on products they purchase [IPSOS, 2016, 2019]. We thus calibrate the model so that about 20% of consumers have *knowledge* for each of the characteristics from the beginning. Conversely, preferences are preset so that 60% of consumers have the *intention* of buying each characteristic.

The model recreates a situation in which consumers with experience buying each dimension disseminate knowledge of them and in turn can influence adoption over time. Although goods containing extra dimensions are pricier than their more basic counterparts[1], sufficiently interested consumers will pay the

[1] Data on price premiums for healthy, sustainable and socially fair goods is scarce. As something of an *educated guess* we add a 33% premium on the presence of one dimension, an

price premium on condition of knowing where they can be found. Those who do not adopt a given dimension are either uninterested in it, do not have the knowledge of where to find it, or are unable to pay for it—these last two being behind the aforementioned IBG.

When studying this model, we seek to observe the relationship between purchases, knowledge and price premiums for networked consumers. We look at the extent to which knowledge is a source of IBG and how its diffusion throughout the simulation can reduce the said gap. More particularly, we seek to find emerging properties in the relationship between knowledge diffusion and IBG for *combined* characteristics.

2 Model description

Consumers

We initialise 400 agents ("consumers") each of whom is randomly linked to s_i others, $s_i \sim U(1, 2S)$. The average number of links per consumer is thus S.

Each consumer is endowed with an individual budget $w_i \sim U(\$1, W)$.

They have a randomly-assigned individual preference for each of the dimensions $p_{i,a} \sim U(0, 1)$, $a = \{1, 2, 3\}$. With regards to these preferences:

- A common intention-threshold H ($0 < H < 1$) determines the point above which preference becomes intention:
  $p_{i,a} > H \rightarrow h_{i,a} = 1$
- A common knowledge-threshold K ($H < K < 1$) determines the point above which preference is associated with knowledge of a dimension:
  $p_{i,a} > K \rightarrow k_{i,a} = 1$

Goods

We create a space of 8 types of goods, depending on whether each of the dimensions is present or not (2^3). Types of goods thus range from $[0 \quad 0 \quad 0]$ (a basic good) to $[1 \quad 1 \quad 1]$ (a complete one).

The presence of a dimension in a good comes with a price premium. We set x, $x{+}10\%$ and $x{+}15\%$ as the premium for the presence of one, two and three characteristics on a given good. The price of a basic good being set at \$1, that of a complete one will then be $\$(1{+}x + 10\% + 5\%)$. The supply for each type of good is fully elastic (there is no limit to the quantity that can be supplied at the price of a good, and consumers are price-takers).

extra 10% on the second, and a further 5% on the third, resulting in a 48% premium on a good containing all three characteristics.

Time-dynamics

At each time-step consumers have to purchase one unit of a type of good (which can be pictured as a weekly basket). They will aim for their most preferred good according to $p_{i,a}$ and $k_{i,a}$.

A consumer unable to purchase their preferred good due to an insufficient budget will settle for a sub-optimal one. For this, they will drop the dimension(s) for which they have the lowest preference and aim to buy the next relevant good.

Consumers who are able to purchase a given dimension accumulate experience following the rule of Leite and Teixeira [2012] :

$$E^t_{i,a} = \begin{cases} 1 - (t - \bar{t}_{i,a})^{-1}, & \text{if} \quad t > \bar{t}_{i,a} \\ 0, & \text{otherwise} \end{cases} \tag{1}$$

Where $E^t_{i,a}$ is the amount of experience on characteristic a accumulated by consumer i up to the t-th time-step, and $\bar{t}_{i,a}$ is the time-step at which he or she first knowingly bought it.

Consumers interested in a given dimension but without knowledge of it ($H < p_{i,a} < K$) are unable to knowingly buy it[2]. They thus seek it from other consumers in their immediate network who have been able to purchase it, following:

$$Pr(k^t_{i,a} = 1) = \begin{cases} l \sum_{j_1}^{j_n} E^t_{j,a}, & \text{if} \quad l \sum_{j_1}^{j_n} E^t_{j,a} < 1 \\ 1, & \text{otherwise} \end{cases} \tag{2}$$

Where $j_1, ..., j_n$ represent each of the nodes in i's immediate network, and l is an *experience spillover* parameter. Equations 1 and 2 imply that the more experience i's network gains on a given characteristic, the likelier it will be for i to gain knowledge of which goods contain it.

The reader will notice that preferences are fixed throughout the simulation. This means that all through our runs, only consumers whose preference on a given dimension was initially sufficiently high ($p_{i,a} > H$) will have the intention to buy, and that whether they do or not will depend on budget and knowledge considerations only. In this, the model can be seen as a snapshot in which neither preferences nor prices evolve, and diffusion takes place only through knowledge spreading[3].

[2]The model allows for the possibility of unknowing pickups, whereby a sufficiently wealthy consumer buys a characteristic he or she has no knowledge of, in which case no experience is accumulated. In this, we do not restrict purchases of goods only to consumers with intention and knowledge of them.

[3]A possible extension of our proposed framework would be to relax this assumption. A

2.1 Initial setup

We initially parametrise our model in the following way[4].

Fixed parameters

– $W = \$2$	(Consumers are endowed with between 1 and 2 dollars for their food purchases per unit of time)
– $H = 0.4$	(For any given dimension, 60% of consumers have the intention of purchasing it, whereas 40% don't)

Variable parameters

– $l = 0.42$	(The knowledge spillover per time-step is of 42% of the experience accumulated by agents on a consumers' network
– $S = 6$	(Consumers are connected on average to 6 others)
– $K = 0.81$	(81% of consumers do not have spontaneous knowledge of the goods containing each dimension. Only 19%—those with a very high preference of a dimension—do)
– $x = +33\%$	(Price premiums are of 33, 43 and 48% for the presence of 1, 2 and 3 characteristics in a good)

We run our model under this *baseline* setup in order to study the evolution of a number of indicators described in section 2.3.

2.2 Parameter modification

After testing our model under the baseline setup described above, we look at how variations in our chosen parameters affect its evolution. We modify each parameter individually by $\pm 1/3^{rd}$ ($\pm 33.3\%$), starting from the baseline situation. The direction chosen for each parameter is that which increases knowledge circulation and adoption: $+33.3\%$ for l and S, -33.3% for K and x.

The parameters we test allow us to assess how our model reacts to higher or lower knowledge circulation (l), larger or smaller networks (S), modifications in the price premiums (x), and a higher or lower knowledge threshold (K). In doing so, we study how *network-related* parameters (l and S) affect the model's dynamics, as opposed to *external* ones (x and K). With this, we seek to gain insight into how an increased social interaction impacts purchases and the intention-behaviour gap, and compare it to the related effects of having external interventions such as subsidies, better labelling of characteristics or

rich literature uses ABM to study the evolution of opinion (preference), and has the potential of producing interesting results when combined with our approach. See Deffuant et al. [2005], Huet et al. [2019], Butler et al. [2019], Barbet [2019].

[4] The reader should be informed that the choice of values, which may seem strange at first sight, was done in order to facilitate manipulation. Therefore, we choose \$1 as a base price instead of the more common \$0 since it allows for a better grasping of percentual variations of price premiums. Likewise, choosing 0.42 or 0.81 for two of the parameters gives round values for our $1/3^{rd}$ variations.

communication campaigns. Table 1 below sums up the different modifications tested. The full detail of results is shown on Table 6 in the Appendix 5.

		Parameters modified			
	Baseline	l	S	K	x
l	0.42	0.56	-	-	-
S	6	-	8	-	-
K	0.81	-	-	0.54	-
x	0.33	-	-	-	0.22

Table 1: Different parameters' modifications ($\pm 33.3\%$ variations from baseline listed). Each parameter is modified either positively or negatively in the direction that favours knowledge circulation and purchases.

2.3 Observed Indicators

When studying the evolution of the model, we pay attention to a number of indicators, described in Table 2 below.

Indicator	Description
%know1D **%know2D** **%know3D**	the average percentage of consumers with knowledge of one, two or three of the dimensions
%buy1D **%buy2D** **%buy3D**	the average percentage of consumers actually purchasing one, two or three of the dimensions
%IKG	the average intention-knowledge gap per dimension
%IBG	the average intention-behaviour gap per dimension
%KBG	the average knowledge-behaviour gap per dimension

Table 2: Indicators used to analyse simulations.

IBG refers to the consumers (as a proportion of the total population) who have the intention to buy a dimension, yet fail to do so because of knowledge or budget limitations. IKG refers to how many have intention but do not have knowledge of a dimension, and KBG to how many have knowledge (and thus intention) but fail to buy because of budget limitations only. Other than IBG, these concepts are not drawn from the existing literature and can thus be seen as an addition. IKG, IBG and KBG are normalised to 100% to account for the fact that there are three dimensions.

There is a trivial relationship between the last three indicators, since the IBG is caused either by knowledge or by budget limitations (or both). Note however that KBG + IKG does not necessarily equate IBG because of the unknowing pickups we spoke about earlier.

For each configuration of parameters, we run the model 25 times during 80 time-steps (the time it normally takes for evolving indicators to stabilise). We look at indicators at time-steps 1 and 80.

3 Simulation results

3.1 Baseline setup

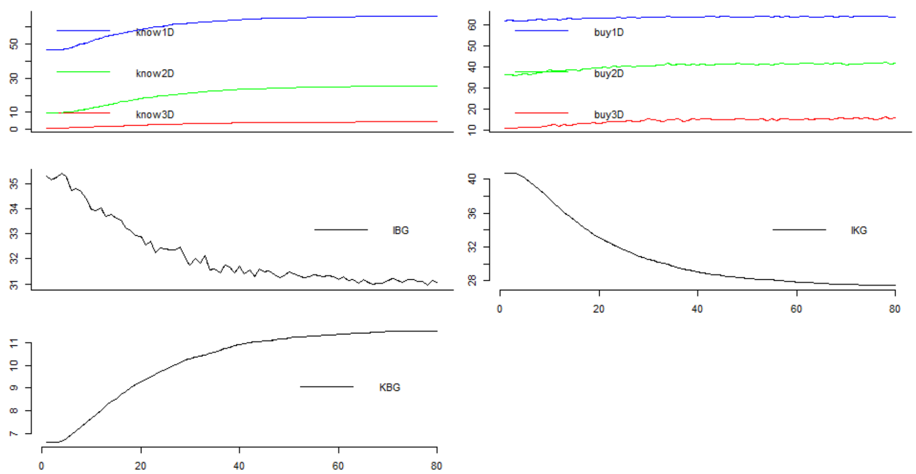

Figure 1: Evolution of main indicators (25 runs). The evolution of all indicators is S-shaped.

We first run the model on the basic setup we propose. Figure 1 above and Table 3 below synthesise the evolution of the main indicators of our virtual world. Left to itself, each indicator evolves towards a certain equilibrium, the main observations being:

– The evolution of indicators for knowledge, IBG, IKG and KBG, as well as (albeit less visibly) purchases shows an evolution producing S-shaped curves—a usual finding in innovation diffusion studies. This is not entirely unexpected since we built our model on the basis of a preexisting one that already showed these features. Still, since the majority of indicators (IBG, IKG, KBG) are new constructions, this is a relevant finding.

– Both knowledge and purchases of one (blue), two (green) and three (red) dimensions increase. Since neither prices nor preferences vary, this means that *word-of-mouth*-type information is circulated and helps consumers identify the dimensions they look for. Increases in actual purchases are purely the result of knowledge gains.

– Knowledge of at least one dimension moves from being available to less than 46.51% of the population initially, to 66.55% by $t = 80$, an increase of 20.04%. This means that two-thirds of our consumers are able to identify at least one characteristic in a product containing it by the time the simulations

	$t = 1$	$t = 80$ ($\Delta_{t=1}$)
%know1D	46.51	66.55 (20.04)
%buy1D	61.59	63.58 (1.99)
%know2D	9.41	25.50 (16.90)
%buy2D	36.19	41.63 (5.44)
%know3D	0.72	4.39 (3.67)
%buy3D	10.88	15.71 (4.83)
%IKG	40.70	27.44 (-13.26)
%IBG	35.28	31.08 (-4.21)
%KBG	6.6	11.52 (4.92)

Table 3: Indicators on baseline setup, 25 runs (in brackets, change from $t = 1$). Knowledge availability increases for 1, 2 and 3 dimensions, as do purchases. IKG and IBG go down, KBG goes up.

stabilise. Knowledge of two and three dimensions also increase, the proportion of consumers able to identify all three dimensions reaching 4,39% by the end of baseline simulations.

– Purchases also evolve, as can be gathered from inspecting Figure 1 and Table 3. Since neither prices nor preferences evolve, all increases in purchases can be attributed to knowledge gains, and they are more pronounced for consumers buying 2 or 3 dimensions than for those buying one alone.

– The IKG drops from 40.60% to 27.44% over the course of the simulations.

– The IBG also drops, though its fall is more moderate, moving from 35.28% to 31.07%.

– The KBG nearly doubles, to 11.52%. This, because gains in knowledge place an increasing number of consumers in a situation of incapacity due to price premiums.

These initial results open up a number of issues. As stated earlier, we know that consumers currently declare lack of knowledge as an important limiting factor in their food purchases. In the reality of our model, we expect knowledge to disseminate by itself to an important proportion of the population (a result already observed, under certain circumstances in earlier works by Rouchier et al. [2014]). We'll see however, that certain parameter modifications produce stronger knowledge gains.

The observed increase in knowledge translates as changes in purchases in what is perhaps the most interesting finding of the model: **the proportion of consumers buying one of the dimensions shows little change, whereas that of consumers buying two or three increases more perceptibly**. The increase in the percetage of consumers buying 1 characteristic is of 1.99%, compared to about 5% for 2 and 3 characteristics. This, despite the fact that increases in knowledge are *decreasing* in the number of dimensions (20.04% for 1, 16.90% for 2 and 3.67% for 3). This is possibly explained by both probabilities and by a trickling effect as described in Section 4. At any rate, it is not something we expected *ex ante* when building the model, and provides with an interesting emergent property of the model. We get back to this in the next sections.

The last three indicators provide with more aggregate information. What we see is an important shift from high to low IKG, and a corresponding inverse for KBG. This means that our model has an important proportion of consumers moving from intention-without-knowledge to knowledge-without-budget situations. Nonetheless, the reduction seen for the IBG indicates that a relevant part of the gains in knowledge translate as gains in consumption.

3.2 Parameter modification

We look in some detail at the values of our different indicators. Table 6 in the Appendix 5, shows that:

- All parameters modified (l, S, K, x) have an impact on knowledge indicators (**%know1D**, **%know2D**, **%know3D**) when compared to initial baseline results.

- Parameters' influence on purchase indicators (**%buy1D**, **%buy2D**, **%buy3D**) is also important, **particularly when purchases of more than one characteristic are considered**, thus providing a confirmation of the result described above.

- All gap indicators (**IKG**, **IBG**, **KBG**) are substantially modified for all parameters, implying that:

  $\Longrightarrow$ Knowledge of characteristics effectively circulates reaching a wider proportion of individuals who seek it (thus reducing the intention-knowledge gap).

  $\Longrightarrow$ Higher knowledge availability increases both the number of people with knowledge who are able to buy (thus reducing the intention-behaviour gap) *and* of those who are unable to (increasing the knowledge-behaviour gap). This, since the extra knowledge will favour purchases only of those with sufficient budget.

- Variations in l and S do not imply a significant difference at time-step 1 when compared with the baseline, meaning that differences in final results are the result of time-based dynamics. Variations in K and x —which create important differences in initial knowledge and purchase capacity—significantly alter indicators at $t = 1$ making comparison of results at $t = 80$ more complex. In the next subsections we look at these in more detail.

3.3 Network-relevant parameters (l and S).

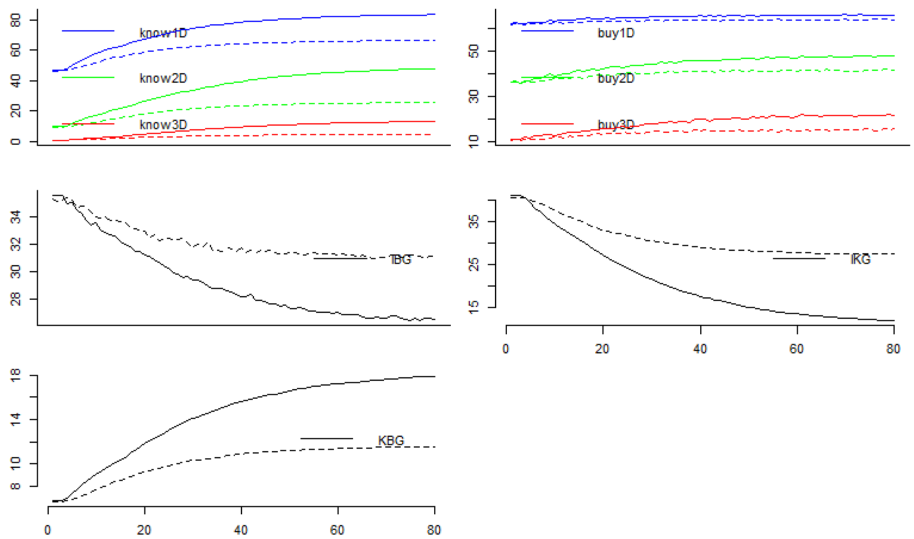

Figure 2: Evolution of main indicators (25 runs). Dashed lines correspond to baseline setup, continuous ones to the parameter l modified by +33%.

The modification of each l and S —which we have called *network-relevant*—produce significant results, although knowledge of dimensions by time-step 80 is higher for changes in l, thus giving it a lower intention-knowledge gap. This increased knowledge when l is modified translates also as better results for each of the different indicators, including purchases, intention-behaviour and knowledge-behaviour gap. For purposes of illustration, Figure 2 shows the difference between baseline and a modified l.The results for l and S at $t = 80$ are shown on Table 4.

Table 4 confirms what we had discussed above: gains in purchases increase as more dimensions are considered, overproportionately to the knowledge gains.

3.4 Knowledge threshold and price premiums.

Giving easier initial access to knowledge of the dimensions as well as reducing the price premium distorts the departure point of simulations. This is summarised on the left side of Table 5, where we see that a modified K greatly increases initial knowledge *and* purchases, and that x increases initial purchases. The

	$t = 80$ (Δ_{baseline})		
	base	l	S
%know1D	66.55	83.64 (17.09)	80.52 (13.97)
%buy1D	63.58	65.88 (2.30)	64.81 (1.23)
%know2D	25.50	47.95 (22.45)	43.10 (17.60)
%buy2D	41.63	47.61 (5.98)	45.43 (3.80)
%know3D	4.39	13.03 (8.64)	10.81 (6.42)
%buy3D	15.71	21.54 (5.83)	19.62 (3.91)
%IKG	27.44	11.96 (-15.48)	14.87 (-12.57)
%IBG	31.07	26.48 (-4.59)	27.70 (-3.37)
%KBG	11.52	17.88 (6.36)	16.99 (5.47)

Table 4: Indicators at $t = 80$ for +33% modifications of parameters l and S (in brackets, changes from baseline). Compared to baseline, both parameters have a significant impact on all indicators studied.

results at $t = 80$ are reinforced. The shift is also visible in Figure 3. Also of interest is that the IKG and KBG reach their most extreme values when modifying K, and that purchases of three dimensions seem to depend more on knowledge than on price premiums—meaning that complete goods will be favoured by information more than prices. This is much in line with results for l and S on Subsection 3.3.

Lower price premiums also affect the baseline situation from the start, by facilitating purchases at $t = 1$, although their effect on initial knowledge is minimal. Nonetheless, by $t = 80$ the higher purchases have strongly encouraged knowledge diffusion—and in turn purchase—thus improving all indicators when compared to baseline.

4 Concluding remarks

Our work is an effort to use the innovation diffusion framework to study sustainable consumption of (food) products. For this, we have expanded an existing model to include a measure of intention-behaviour gap (caused by price premiums and lacks of knowledge) and the multi-dimensionality that characterises food consumption. We work on three dimensions of characteristics, which can

	$t = 1$ (Δ_{baseline})			$t = 80$ (Δ_{baseline})		
	base	K	x	base	K	x
%know1D	46.51	84.36 (37.85)	47.09 (0.58)	66.55	91.49 (24.94)	78.97 (12.42)
%buy1D	61.59	65.53 (3.94)	72.80 (11.21)	63.58	66.32 (2.74)	76.5 (12.92)
%know2D	9.41	43.49 (34.08)	10.07 (0.66)	25.5	59.44 (33.94)	40.27 (14.77)
%buy2D	36.19	46.29 (10.10)	43.72 (7.53)	41.63	49.50 (7.87)	54.65 (13.02)
%know3D	0.72	9.6 (8.88)	0.78 (0.06)	4.39	18.12 (13.73)	9.07 (4.68)
%buy3D	10.88	20.61 (9.73)	13.16 (2.28)	15.71	24.87 (9.16)	23.39 (7.68)
%IKG	40.70	14.12 (-26.58)	41 (0.30)	27.44	3.58 (-23.86)	17.54 (-9.90)
%IBG	35.28	27.22 (-8.06)	31.10 (-4.18)	31.07	24.04 (-7.03)	22.21 (-8.86)
%KBG	6.60	16.96 (10.36)	4.59 (-2.01)	11.52	21.52 (10.00)	10.8 (-0.72)

Table 5: Indicators at $t = 1$ & $t = 80$ for -33% modifications of parameters K and s (in brackets, changes from baseline). Indicators at $t = 1$ are strongly modified, making comparisons at $t = 80$ more complex.

be interpreted as being how healthy, environmentally sustainable and socially fair food purchases are.

We first observe that knowledge of characteristics diffuse throughout the simulations regardless of the parameter setup chosen, and that this causes an increase in purchases of sustainable goods and a reduction in the intention-behaviour gap faced by individuals. In other words, the accumulation of experience and knowledge of sustainable consumption by certain agents creates a shift towards a larger adoption of such practices in the society, and social interaction can be behind reductions in the observed intention-behaviour gap. As it has been noted that "cultural factors are perhaps the most powerful determinants of which food we consume" [Prescott & Graham-Bell, 1995, p. 201], cited in Béné et al. [2019])], this feature of the model is interesting in terms of its relationship to a real-world phenomenon.

We also see that the modification of certain parameters that affect the dynamics of the network (knowledge spillovers and network density) further reinforce the diffusion of knowledge, the increase in purchases and the reduction of the intention-behaviour gap. This means that societies where interaction on the topic of sustainable consumption is more prevalent, should move quicker towards a widespread adoption of sustainable practices. Conversely, external

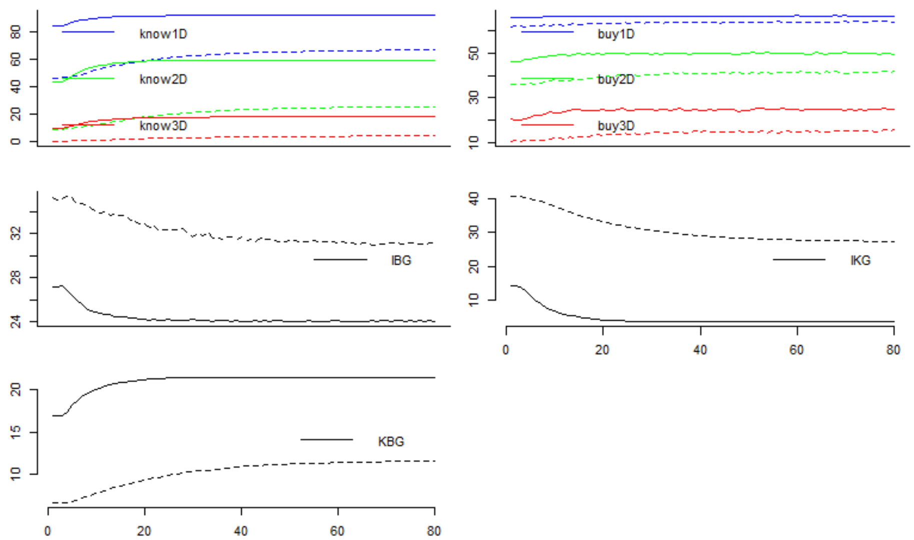

Figure 3: Evolution of main indicators (25 runs). Dashed lines correspond to baseline setup, continuous ones to the parameter K modified by +33%. The process is shifted right from the beginning.

interventions (modifying the price premiums or the level of knowledge available) tend to produce shifts in the dynamics right from the start, though their effect on the evolution of indicators is lesser.

The most interesting result in our view is that the increase in purchases of additional characteristics is directly proportional to the number of characteristics considered, whereas the increase in knowledge is inversely proportional. In other words, gains in knowledge of characteristics translates into higher purchases when more dimensions are considered. The implications of this are substantial: social interaction and the exchange of knowledge is a more strong determinant of purchases for increasingly complex goods—such as is the case with sustainable food. Given the inherent complexity of sustainable food products, their adoption by a larger proportion of the population will be strongly dependent on how social interaction is exploited in that sense. As Carroll and Fahy has put it, contemporary shopping practices are socially situated activities, to which we add that the more complex the practice, the more socially dependent it will be. Reductions in the intention-behaviour gap will benefit from interaction when an increasing number of dimensions are considered.

Although we did not *ex ante* expect this result, we have identified one reasons why it may appear, which we attribute to probabilities: the chances of unknowingly purchasing a good will be lower for consumers seeking a larger number of characteristics. Purchases of several dimensions of sustainability will thus be more dependent on the information consumers can gather from their social networks than for those seeking to buy only one (or none).

When modifying parameters, we get further insights into these dynamics. What we see is, first and foremost, a process in which parameters' variations can have important effects on the resulting values of our indicators. We observe that the effect of higher knowledge spillovers and of network degree is, in some respects, as important as that of initial knowledge availability and price premiums. This is an encouraging result, since it can be argued that *network-relevant* parameters relate to cheaper interventions (creation of discussion forums, other forms of gatherings around food issues) than their knowledge and price premium counterparts (which can be conceived of as messages in the sense proposed by Rogers [2002] or production subsidies). The policy implications of this are important.

In terms of future work, the first avenue we identify is the need to validate our working hypotheses (**H1-H2**, Section 1.3), to better understand how knowledge of health, environmental and social dimensions in food is held by different actors, and how to more realistically describe its dissemination. It would be welcome to see surveys and field work to put these hypotheses to test and understand how interest is related to knowledge of dimensions, how this knowledge circulates within social groups influencing purchases, and the extent to which we can claim that mental representations of each of these characteristics is common to all individuals. Moreover, empirical work on our model's results, in particular with respect to social interaction being a stronger determinant of purchases of increasingly complex goods would be an interesting endeavour. From a modelling point of view, it would be interesting to explore these results analytically, as well as to generalise to n dimensions of characteristics. Our emerging property of a disproportional influence of knowledge dissemination for a higher number of dimensions is worth further exploration and a generalisation to more dimensions. The model also contains a number of assumptions that could be relaxed in order to increase its *descriptive* realism, such as fixed preferences throughout the simulations, absence of contrarians or negative influencers, fixed price premiums, etc. Checking how it responds to modifications in these would also be a welcome effort.

The main conclusion our model seems to bring forward is that creating instances of reflection and sharing around the topic of food can be *per se* a driving force towards a consumption that is respectful of environment, society and health. This, we believe, is a notion worth exploring further.

5 Appendix: Full table of results

			Modified parameters (Δ_{baseline})			
		baseline	l	S	K	x
$t = 1$	**%know1D**	46.51	46.76 (0.25)	45.62 (−0.89)	84.36 (37.85)	47.09 (0.58)
	%buy1D	61.59	62.16 (0.57)	61.61 (0.02)	65.53 (3.94)	72.80 (11.21)
	%know2D	9.41	9.56 (0.15)	9.42 (0.01)	43.49 (34.08)	10.07 (0.66)
	%buy2D	36.19	36.49 (0.30)	35.84 (-0.35)	46.29 (10.10)	43.72 (7.53)
	%know3D	0.72	0.72 (0)	0.54 (0.18)	9.60 (8.88)	0.78 (0.06)
	%buy3D	10.88	11.35 (0.47)	10.58 (-0.3)	20.61 (9.73)	13.16 (2.28)
	%IKG	40.70	41.15 (0.45)	41.14 (0.44)	14.12 (-26.58)	41.00 (0.30)
	%IBG	35.28	35.55 (0.27)	35.40 (0.12)	27.22 (-8.06)	31.10 (-4.18)
	%KBG	6.60	6.67 (0.07)	6.37 (-0.23)	16.96 (10.36)	4.59 (-2.01)
$t = 80$	**%know1D**	66.55	83.64 (17.09)	80.52 (13.97)	91.49 (24.94)	78.97 (12.42)
	%buy1D	63.58	65.88 (2.30)	64.81 (1.23)	66.32 (2.74)	76.5 (12.92)
	%know2D	25.5	47.95 (22.45)	43.1 (17.60)	59.44 (33.94)	40.27 (14.77)
	%buy2D	41.63	47.61 (5.98)	45.43 (3.80)	49.50 (7.87)	54.65 (13.12)
	%know3D	4.39	13.03 (8.64)	10.81 (6.42)	18.12 (13.73)	9.07 (4.68)
	%buy3D	15.71	21.54 (5.83)	19.62 (3.91)	24.87 (9.16)	23.39 (7.68)
	%IKG	27.44	11.96 (-15.48)	14.87 (-12.57)	3.58 (-23.86)	17.54 (-9.90)
	%IBG	31.07	26.48 (-4.59)	27.7 (-3.37)	24.04 (-7.03)	22.21 (-8.86)
	%KBG	11.52	17.88 (6.36)	16.99 (5.47)	21.52 (10.00)	10.8 (-0.72)

Table 6: Baseline results and different parameters modified by 33.3% at $t = 1$ & $t = 80$, 25 runs per setup (in brackets, change from baseline).

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