

# The Role Of The EU In Encouraging Sustainable Protein Consumption

An Agent-Based Model On The Effect Of Social Norms On Reducing Meat Consumption in the Netherlands

S.L.P.K. Timmers





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by

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# Preface

"Be the change you want to see in the world" - Gandhi. In a way, this quote is what started the journey of this thesis many years ago. Within my first year of university in the UK, I decided to follow a vegetarian diet. At the time, I was concerned about climate change, and as my understanding of the effect of dietary consumption - especially meat - on the environment grew I decided I would make a personal change. When discussing my dietary choices I found that the response over the years gradually changed, or maybe I found myself gravitating more towards bubbles where peers share similar perceptions. Something that always stuck by me was the response I received when I said I ate vegetarian for climate concerns compared to vegans who said they did it for animal welfare and ethical reasons. Where I was met with understanding, and people shared the little ways they tried making personal changes to reduce their personal 'carbon footprint', those who changed their diets for ethical reasons were attacked and met with defensive rhetoric. The end result is the same, then why is there an acceptance of one concern and pushback to the other concern? The reason, I know now, is social norms.

This thesis has indeed been a journey. One with many many ups and downs. In the extraordinary circumstances of writing a thesis during the midst of a global pandemic, I have been confronted with myself, my way of life, my habits and work ethics in more ways than I had expected or maybe even desired. I have reached a depth I was not sure I would get out of, feeling like I would never be able to climb the mountain of work and research I saw towering over me, and here I am now. Standing on the verge of delivering something I can be genuinely proud and happy of. As with any journey, it is more about the actual journey than the destination. I am eternally grateful to all those who have been part of this journey, who have provided me support, new insights, been there in my darkest hour, and made this lonely and daunting process far less lonely.

First of all I want to thank my supervisor, Natalie van der Wal, for her positive attitude, endless patience and belief in me, thorough and attentive feedback, and providing me the space and opportunity to reach this end. I was blessed with a supportive committee, and want to thank both Jill Slinger and Francis Brazier for their insights during the meetings, and helping me focus on what truly matters. I want to also thank my external supervisors and colleagues at the EPC, Stefan Sipka and Annika Hedberg, who have provided me with support and insights into the world of European policymaking which will be useful for my next journey.

My parents, as a beacon of light and support, have always been there for me. My love and appreciation for them is greater than words, and I want to thank them for both being an emotional, financial and knowledgeable support to me. I would not be where I am now without both Paul Timmers and Kizito Niemer, my dear parents. I gained renewed confidence and happiness from the weekly Skype calls and online games with them and my siblings: Nyanza, Victor, Paul, and Justus. At the start of my EPA journey my niece Fenna was born, who since then has provided me with so many smiles and proud uncle moments. Now at the end of this journey, my baby niece Yinte was born, and with this thesis process coming to an end I will be able to devote more time to her and my new baby niece Yinte.

In my EPA journey I have met friends who helped me grow as a person perhaps more than any lecture or course could. During this thesis they have also been there, in all the small and big ways. I want to especially thank Sahiti Sarva, for the deep conversations, making me think about everything in a more meaningful way, and your support when I most needed it. I want to thank Ashok Willis, for so many things but especially the cycling tour from Delft to Rome which has provided me with the knowledge that no matter the weather or challenge, perseverance will bring you further. I want to further thank Ignasi Cortes, for joining me on this journey from London, Jin Rui for the conversations and inspiration, and Gergely Boldizsar and Paula Goetz for being great friends. There are many others who I became close with, and I am so grateful for having made such good friends during these two years here. I made friends, and met my partner Julie during this journey, who has always provided support, care, understanding, macarons when I most needed them, and helped break through the stress and enjoy life, making the thesis period more rewarding.

Furthermore, I owe a huge debt of gratitude to my lovely housemates who have provided food when I was stressed, hugs and deep talks when my mind needed clearing, great conversations and laughs, and who are just overall incredible human beings. I'm lucky that a year ago they deemed me fun enough to welcome into their house and hearts. Thank you for everything, Jessie, Garazi, Simone, Irem, and Cameron. Finally, I want to thank you the reader, for opening this report and taking a glance at the culmination of the past six months of my life. I hope the destination of my journey, this thesis report, may inspire you on your own journey.

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Delft, August 2021*

# Executive Summary

There is an urgent need according to the International Panel on Climate Change to reduce greenhouse gas emissions in order to mitigate climate change and remain below 1.5°C warming above pre-industrial levels. Large-scale changes are required for this, both in policy and behaviour. An area where there is resistance and slow change is in meat consumption. The agricultural sector accounts for 25-35% of total global greenhouse gas emissions, while individual food consumption by households accounts for around 20% of household emissions. The agricultural industry is one of the most hard-to-decarbonize sectors, with the Farm to Fork Strategy developed by the European Commission providing a more holistic view on improving this sector but falling short of covering the elephant, or cow, in the room: meat consumption. This research found that social norms can be targeted to reduce meat consumption and associated emissions by up to 0.4-4%, while fiscal policies such as a 20% tax on meat are more effective and can reduce overall dietary emissions by over 10%.

Individual meat consumption is shaped by a range of factors, including social norms. These norms can play an important role, and are thus far underutilised as a lever for change in meat consumption as they are not well understood. Social norms play during the interaction of individuals, whereby individuals will consume more food, change their food consumption, or change their own beliefs and concerns based on their peers. Food consumption is further shaped by the food environment, including the prices of food and availability amongst others. This is seen in the Netherlands, where increased availability and reduced prices of meat substitutes have led to a growth in meat substitute consumption. Researchers found that without changing dietary consumption, and in particular meat consumption, even if all fossil fuel emissions stop today we will exceed 1.5 degrees warming by the end of the century. Reducing overall emissions, and reaching net zero emissions, is one of the main targets of the European Green Deal. As the Farm to Fork Strategy does not adequately address meat consumption, and the interaction between social norms and meat consumption is not well understood, this research aims to bridge this gap of understanding. The main research question this thesis addresses is: *How do social norms influence meat consumption and to what extent can European policy influence these to reduce meat consumption?*

To answer this question the Netherlands was taken as a case study, as here there is an availability of meat substitutes and increase in consumption of these, together with an increase in overall meat consumption. This makes it interesting to study what role social norms have played here, and whether these can be modelled and influenced by public policies. The Netherlands cannot be taken as fully representative of the rest of Europe, and thus in the discussion the findings of this research are discussed with regards to the various political, policy and socio-economic contexts, and findings in other studies.

An agent-based model was constructed, as this allows for the study of emergent behaviour, and interactions between individual agents who each have their own profiles, concerns and behaviour. The agent-based model is grounded in the Theory of Planned Behaviour. This is a theoretical framework which explains behaviour through the intention of individuals, which in itself is driven by the attitude toward the behaviour, subjective norm, and perceived behavioural control. A literature study and data analysis were conducted to determine and justify the assumptions and rules governing the agent-based model.

A literature study of the factors influencing meat consumption revealed that the three prevalent factors are health, environment and animal welfare concerns. As diets are complex structures, influenced by the food environment, habitual cues, price, taste, culinary tradition and habits amongst others, the model makes simplifications. The main components of behaviour investigated are the interaction of agents and social norms, where agents (i.e. individuals) will influence one another when sharing meal times together. The analysis of these social networks is based on work by Scalco et al. and Zhang et al.

Consumption of protein follows a complex behaviour, where people will typically eat different sources of protein and meat rather than stick to a single diet. In a similar fashion, people will not always choose between meat or no meat, but will rather eat different types of meat when they are changing their diet. This eating behaviour is modelled through an analysis of existing surveys by the Central Bureau for

Statistics, RIVM and LISS (Longitudinal Internet studies for the Social Sciences) Panel Data. From the LISS Panel database, as offered open-source by CentERdata, the following surveys were investigated: "Background variables", "Reasons to Eat Less Meat", "Health", "Politics and Values", "Personality", and "Hope Barometer". These surveys were combined and analysed through a correlation analysis to determine the factors of relevance to the frequency of meat consumption. The combined surveys were further analysed using a logistic regression to determine the likelihood to reduce meat consumption, and through a least-squares multiple linear regression to determine whether diets can be calculated from the relevant survey factors. The correlation analysis supported findings from the literature, that the factors of health, environmental and animal welfare concerns play a statistically significant role in determining diets. The regression analysis of these did not provide strong significant predictors, and were therefore used to gain insight into the system rather than being applied in the model specification.

The "Belevingen 2020" survey, similarly to the 'Reasons to Eat Less Meat' survey, included health, environment and animal welfare concerns as reasons individuals consume less meat, in addition to taste, household member influence, price, and other reasons. The responses of this survey were combined with the Dutch National Food Consumption survey by the RIVM, and analysed using a correlation analysis and a subsequent least squares multiple linear regression. The correlation analysis conducted as part of the data analysis in this research shows that consumers with higher environmental concerns are more likely to reduce their pork and beef consumption, and increase their poultry and meat substitute consumption. The least squares regression determined the relevance of factors to consumption for specific meat types: beef, pork, poultry, processed meat and meat substitutes. As the data availability of these combined sets was insufficient to incorporate all factors, the findings from the LISS Panel analysis together with findings from literature were combined to determine the three concerns as prime factors of interest.

The agent-based model was built to determine the likelihood of consuming each type of meat depending on an individual's health, and environmental concern, as determined by statistical survey data based on the individual's age, gender and level of education. The social norms were modelled through the interaction of agents in social networks, where they assess the level of concern of other agents and adjust their own based on the general prevailing norm in the network. Based on the literature review, there are several policies of interest which the EU can pursue to enhance the food environment and encourage social norm changes towards reducing meat consumption. Fiscal policy and social marketing campaigns were tested for three different scenarios, namely the base-case, a scenario where the population has high environmental awareness, and a scenario where the agents are highly susceptible to other influences. The model simulation indicates that social norms and social network interactions gradually results in increased health and environmental concern over time, with overall environmental concern on average increasing by around 6% over the span of 3 years.

The main findings from the model were that environmental social marketing campaigns can play a role in changing the consumption of individuals, when they are targeted towards specific population groups who initially have low concerns. This means that it is more beneficial to provide education and target campaigns at lower educated and less wealthy individuals. These normative changes, however, played a minor role compared to fiscal policies. A tax on all meat types was found to be an effective and robust policy to both reduce overall meat consumption and reduce emissions related to consumption. This tax may disproportionately affect less wealthy individuals, and therefore it is encouraged to supplement this kind of tax with subsidies for more environmentally sustainable consumption as meat substitutes. A tax on beef alone was found to reduce beef consumption more than a tax on all meats would, but it shows that individuals are more likely to substitute their reduced beef consumption with increased consumption of pork, poultry and processed meat. Especially processed meat sees a significant increase in consumption as people step away from consuming beef. This substitute effect indicates that overall meat consumption is redistributed rather than reduced.

From an emissions point of view, the redistribution of consumption does not result in significantly lower emissions, as the increase in consumption of other meat types offsets overall emissions gains from reduced meat consumption. This indicates that there is an overall change required in the food environment, with all meat types needing a price increase to encourage actual improvements. This finding is in line with other studies such as those conducted by CE Delft and TAPPC, who also call for an increase in meat prices. From analysing literature which deals with the political, socio-economic and policy contexts of meat consumption, it appears that there is mixed political will to pursue a fiscal tax on meat, that there is public acceptance depending on the utilisation of tax proceeds, and that the policy

should form part of a policy package and framed in a way which gains most public acceptance. This should be further analysed through an actor analysis, and impact assessment, and findings from this research should be investigated for more European countries to provide more support to the findings from this research.

In the face of the urgent need to reduce emissions, governments should aim to follow robust policies which reduce emissions. This research finds that the influence of governmental policy on social norms appears to be small, but still results in a notable change in consumption. Fiscal policies appear to have a more significant and immediate influence. In the light of achieving net zero emissions by 2050, the EU should therefore encourage sustainable food consumption through focusing on improving the food environment, through facilitating more sustainable consumption and taxing all meat consumption. This should be done in combination with social marketing campaigns targeted at those who are historically less concerned. However, this should be more than a carrot-and-stick approach, where one is taxed and the other is encouraged. Instead, Europe can take the role of a transformative leader where they overhaul the entire food environment to produce a more sustainable tomorrow.

*S.L.P.K. Timmers  
Delft, July 2021*



# Contents

<b>1</b>	<b>Introduction</b>	<b>1</b>
1.1	Objectives and Research Approach . . . . .	2
1.2	Research Question . . . . .	3
<b>2</b>	<b>Literature research</b>	<b>5</b>
2.1	Overview Research . . . . .	5
2.2	What is a sustainable diet? . . . . .	6
2.3	Main factors influencing meat consumption . . . . .	7
2.4	Social norms, social networks and meat consumption . . . . .	7
2.4.1	Use of social norms and meat consumption . . . . .	8
2.4.2	Spreading of social influence via networks . . . . .	8
2.5	Barriers to change . . . . .	9
2.5.1	Habits . . . . .	9
2.6	Behavioural Theories . . . . .	9
2.7	Theory of Planned Behaviour applied to meat consumption . . . . .	12
2.8	EU Policies influential to meat consumption . . . . .	14
2.8.1	Food pricing . . . . .	14
2.8.2	Campaigns . . . . .	15
2.8.3	Changing the food environment . . . . .	15
2.8.4	EU Policy mandate and contextualisation . . . . .	15
2.9	Choice of modelling paradigm . . . . .	16
2.10	Summary literature review . . . . .	19
<b>3</b>	<b>Methodology</b>	<b>21</b>
3.1	Case-Study: The Netherlands . . . . .	22
3.1.1	Population Demographics . . . . .	23
3.1.2	Parameters of importance - TPB . . . . .	23
3.1.3	Modelling specific meat consumption . . . . .	24
3.2	Choice of Key Performance Indicators . . . . .	25
3.3	Data analysis methods . . . . .	25
3.3.1	Correlations . . . . .	26
3.3.2	Logistic Regression . . . . .	26
3.3.3	Multiple Linear Regression . . . . .	27
3.4	Experimental Design . . . . .	27
3.4.1	Scenarios . . . . .	28
3.4.2	Policies . . . . .	28
3.4.3	Experimental Set-up . . . . .	30
<b>4</b>	<b>Data Analysis</b>	<b>33</b>
4.1	LISS Panel Data Analysis . . . . .	33
4.1.1	Survey data description . . . . .	33
4.1.2	Parameters of importance . . . . .	34
4.2	Belevingen 2020 and DNFCS . . . . .	40
4.2.1	Correlation analysis . . . . .	41
4.2.2	Least-Squares Regression: Likelihood to consume meat types . . . . .	42
4.3	Summary data analysis . . . . .	44

<b>5</b>	<b>Model specification</b>	<b>45</b>
5.1	Overview . . . . .	45
5.1.1	Purpose and overview . . . . .	45
5.1.2	Entities, state variables and scales . . . . .	46
5.1.3	Process overview and scheduling . . . . .	50
5.2	Design concept . . . . .	53
5.2.1	Theoretical and empirical background . . . . .	53
5.2.2	Individual decision-making . . . . .	53
5.2.3	Learning . . . . .	55
5.2.4	Interaction . . . . .	55
5.2.5	Collectives . . . . .	55
5.2.6	Heterogeneity . . . . .	55
5.2.7	Stochasticity . . . . .	56
5.2.8	Observation . . . . .	56
5.3	Details . . . . .	56
5.3.1	Implementation details . . . . .	56
5.3.2	Initialization/input . . . . .	57
5.3.3	Submodels . . . . .	58
<b>6</b>	<b>Model Verification and Validation</b>	<b>61</b>
6.1	Model Verification . . . . .	61
6.1.1	Population . . . . .	61
6.1.2	Model outputs . . . . .	62
6.1.3	Agent-tracking . . . . .	63
6.2	Model Validation . . . . .	63
6.2.1	Sensitivity Analysis . . . . .	63
6.2.2	Empirical Validation . . . . .	65
<b>7</b>	<b>Results</b>	<b>67</b>
7.1	Model Behaviour . . . . .	67
7.2	Policies influence on meat consumption . . . . .	69
7.3	Policies influence on emissions . . . . .	72
7.4	Summary of Results . . . . .	74
<b>8</b>	<b>Discussion</b>	<b>77</b>
8.1	Answering the research subquestions . . . . .	77
8.2	Strengths, limitations and future research . . . . .	79
8.3	Implications . . . . .	82
8.4	Conclusion . . . . .	84
<b>A</b>	<b>Appendix: Supplementary Research</b>	<b>97</b>
A.1	Supplementary research: Diets . . . . .	97
A.1.1	Current diet Netherlands . . . . .	99
A.1.2	Sustainable protein and meat substitutes . . . . .	100
A.2	Supplementary research: Impacts of meat consumption . . . . .	101
A.2.1	Health . . . . .	101
A.2.2	Environment . . . . .	101
<b>B</b>	<b>Appendix: Farm to Fork Strategy</b>	<b>103</b>
B.1	Farm to Fork Strategy . . . . .	103
B.1.1	Labelling . . . . .	103
<b>C</b>	<b>Appendix: Model</b>	<b>105</b>
C.1	Model . . . . .	105
C.1.1	Model interface . . . . .	105
C.2	Implementing main model processes . . . . .	108
<b>D</b>	<b>Appendix: Behavioural Theory</b>	<b>109</b>
D.1	Behavioural theories . . . . .	109
D.2	Extended Theory of Planned Behaviour . . . . .	109



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<b>E Appendix: Data</b>	<b>111</b>
E.1 Surveys . . . . .	.111
E.2 Multiple Linear Regression Analysis. . . . .	.112
E.3 The Netherlands . . . . .	.116



# List of Figures

2.1	Distribution of sources by year from the literature review, from 2006-2021 (Source: Author)	5
2.2	Prisma of Studies Screened with keywords "Meat consumption", "Behaviour", "Climate Change" and "Models" (Source: Author)	6
2.3	Venn diagram showing that the Theory of Planned Behaviour contains important aspects related to consumption behaviour, with the TRA, SCT, SNT, VBN, HBM and TTM covering parts of each aspect (Source: Author)	12
2.4	Theory of Planned Behaviour applied to meat consumption (Source: Author)	13
2.5	Stages of decision-making in the European Union, including the four key institutions: the European Commission (consulted by stakeholders), European Parliament, the Council and the European Court of Justice based on information from the official European Union website (European Union, 2016b). (Source: Author)	16
2.6	Factors included in the research with relation to meat consumption (green circle), and factors which did not fit in the scope and focus on this study (red circle) (Source: Author)	20
3.1	Conceptual diagram showing the components of this research and relation between these components, with the Theory of Planned Behaviour (Ajzen, 1991) theory used as theory lens (indicated by diamond) and software packages used including Python and NetLogo (in italics) (Source: Author)	21
3.2	Convergent and divergent analytical approach to the modelling cycle with the model as the focal point, taken from Slinger et al. (2008).	22
3.3	Results from the Dutch National Food Consumption Survey 2012-2016, for the various food types in the Netherlands by both time of consumption and place.	23
3.4	Illustration of meat consumption types (Source: Author)	24
3.5	Average of cumulative sums from 1000 model runs for the High Susceptibility scenario with no policies active (Source: Author)	30
4.1	Correlation matrix of variables with weak correlation to the frequency in meat consumption ('ch18k200'), using survey responses from the Hope Barometer and Health survey. (Source: Author)	35
4.2	Correlation matrix of the Background variables with highest correlation to the frequency of meat consumption, with 'geslacht' as gender, 'aantal hh' as number household members, 'partner' as partner, 'burgstat' as civil status, 'woonvorm' as living way, 'sted' as urbanisation, 'oplnmet' as highest education level obtained, and 'ch18k200' as frequency of meat consumption. Negative correlations to ch18k200 indicate it is correlated to a reduction in meat consumption. (Source: Author)	35
4.3	Correlation matrix of the Health Survey with highest correlation to the frequency of meat consumption, with ch18k001 as age, ch18k017 as 'how much do you weigh', ch18k200 as frequency of meat consumption, ch18k201 as 'what is your target weight', and ch18k246 as 'I pay health insurance premiums for my partner'. Negative correlations to ch18k200 indicate a correlation to a reduction in meat consumption (Source: Author).	36
4.4	Correlation matrix for the Politics and Values Survey with the frequency of meat consumption, with cv18j048 as 'political parties are not interested in my opinion', cv18j049 as 'people like me have no influence on government policy', cv18j116 and cv18j118 as positive views on foreigners, and cv18j120 and cv18j123 as negative views on foreigners, and ch18k200 as the frequency of meat consumption. Negative correlations to ch18k200 indicate a reduction in meat consumption (Source: Author)	36
4.5	Correlation matrix of 5 most important variables in relation to the frequency of meat consumption ('ch18k200'). All variables are part of the 'reasons to eat less meat' survey (oi18a002, oi18a006, oi18a008, oi18a010, oi18a012) (Source: Author)	36

4.6	Mean values of background variables for each category of frequency of meat consumption (ch18k200). The values correspond to: 1 = Never, 2 = 1-3 times per month, 3 = 1 time per week, 4 = 2-4 times per week, 5 = 5-6 times per week, 6 = every day (Source: Author) . . . . .	38
4.7	Mean values of background variables for each category of frequency of meat consumption (ch18k200) for 'geslacht' (gender), 'aantalki' (number of children), 'partner' (partner), 'woning' (living condition), 'sted' (urbanisation), 'nettoat' (income level), and 'oplmet' (education level). The values of ch18k200 respond to: 1 = Never, 2 = 1-3 times per month, 3 = 1 time per week, 4 = 2-4 times per week, 5 = 5-6 times per week, 6 = every day (Source: Author) . . . . .	38
4.8	Least-square regression analysis outcome of the LISS Panel Data, using the health, climate and animal welfare concern factors from the 'Reasons to Eat Less Meat' survey (code: oi18a), frequency of meat consumption (ch18k200), how much individuals weigh ('ch18k017') (Health Survey code: ch18k), ease of obtaining asylum (cv18j118), and background variables (gender, partner, income urbanisation, education, code: avars_201807) (Source: Author) . . . . .	39
4.9	Multinomial logistic regression results of the LISS Panel Data, using the health, climate and animal welfare concerns from the 'Reasons to Eat Less Meat' survey (code: oi18a), background variables (gender, partner, income urbanisation, education, code: avars_201807), and frequency of meat consumption ('ch18k200', Health Survey code: ch18k) (Source: Author) . . . . .	40
4.10	Correlation matrix between consumption per day of various food types, calculated using data from the Dutch National Food Consumption Survey (RIVM, 2020b). (Source: Author)	41
4.11	Correlation matrix between the reasons to reduce meat consumption from the Belevingen 2020 survey (CBS, 2021b) and probability of consuming specific meat types on any given day from the Dutch National Food Consumption Survey (RIVM, 2020b). (Source: Author) . . . . .	42
4.12	Logistic regression of the days of beef consumption taken from the DNFCS (RIVM, 2020b), with percentage of consumption days as dependent variable, and health and environment concerns as independent variables taken from the Belevingen 2020 survey (CBS, 2021b) (Source: Author) . . . . .	43
4.13	Summary of the surveys used to conduct the data analysis and outcomes of this analysis with regards to the analysis methods (Source: Author) . . . . .	44
5.1	Structure of model descriptions following the ODD protocol, taken from Grimm et al. (2020). . . . .	45
5.2	High-level overview of the model's components (Source: Author) . . . . .	46
5.3	Activity diagram overview for the Meat Consumption model (Source: Author) . . . . .	50
5.4	Flowchart of the population generation and order of specification of characteristics. Each step follows a probabilistic nature based on the CBS data (Source: Author) . . . . .	51
6.1	Population Setup Tests (Source: Author) . . . . .	61
6.2	Meat consumption likelihood of the model compared to the DNFCS (RIVM, 2020b) (Source: Author) . . . . .	62
6.3	Reporters for all concerns in the base-case scenario, showing values of all individual model runs (Source: Author) . . . . .	62
6.4	Concerns for a run from the NetLogo interface (Source: Author) . . . . .	63
6.5	Sensitivity of meat consumption per meat consumption type to a change in susceptibility to external influence of a population (Source: Author) . . . . .	63
6.6	Boxplots of the maximum concerns of agents when susceptibility is varied (Source: Author)	64
6.7	Sensitivity of meat consumption per meat type and concerns with respect to changes in the population size for experiments conducted in the base-case scenario (sizes include 100, 200, 500, 1000, 10,000) (Source: Author) . . . . .	64
6.8	Grams of meat eaten by agents in the model compared to grams eaten from the Dutch National Food Consumption Survey (RIVM, 2020b) (Source: Author) . . . . .	65

7.1	Results of the scenarios (1: base-case, 2: high environmental concern, 3: high susceptibility) without any active policy, with regards to the average agent concerns (health, environment, animal wellbeing), and average weekly consumption of each food type in grams (Beef, Pork, Poultry, Processed, and Substitutes) (Source: Author) . . . . .	67
7.2	Results of the scenarios (1: base-case, 2: high environmental concern, 3: high susceptibility) without any active policy, with regards to the average weekly meat consumption in grams (Beef, Pork, Poultry, Processed and Substitutes), and the emissions (gCO <sub>2</sub> eq, gSO <sub>2</sub> eq, gPeq, gNMVOC, gPM <sub>10</sub> eq, m <sub>2</sub> ) of each scenario (Source: Author) . . . . .	68
7.3	Average weekly environmental concern for each scenario with no policies active over the span of 3 years (156 observations), with each observation corresponding to 1 week (Source: Author) . . . . .	69
7.4	Visualization of the concerns (health, environment, animal wellbeing) and meat type consumption (beef, pork, poultry, processed, substitutes) for the various policies following the base-case scenario (Source: Author) . . . . .	70
7.5	Visualization of the concerns (health, environment, animal wellbeing) and meat type consumption (beef, pork, poultry, processed, substitutes) for the various policies following the high environmental concern and high susceptibility scenarios respectively (Source: Author) . . . . .	71
7.6	Average weekly emissions of the population for the population in the base case, high environmental concern and high external influence scenarios with all policies active (base-case policy = no policy active) (Source: Author) . . . . .	73
7.7	Score-card of the effect of policies on meat consumption and emissions with respect to the no-policy. (Scenario = Base-Case, green = positive change, red = negative change) (Source: Author) . . . . .	74
7.8	Score-card of the effect of policies on meat consumption and emissions with respect to the no-policy. (Scenario = High Environmental concern, green = positive change, red = negative change) (Source: Author) . . . . .	75
7.9	Score-card of the effect of policies on meat consumption and emissions with respect to the no-policy. (Scenario = High Susceptibility, green = positive change, red = negative change) (Source: Author) . . . . .	75
A.1	Scenarios demonstrating the environmental effects of implementing measures considered for reducing environmental effects of food production as shown in report by the EAT-Lancet Commission on healthy diets from sustainable food systems (Willett et al., 2019) . . . . .	98
A.2	Scientific targets for a 'planetary health diet', and their potential ranges, based on an intake of 2500 kcal/day as seen in the "Food Planet Health" report by the EAT-Lancet Commission (Willett et al., 2019) . . . . .	98
A.3	The Dutch Diet (2) . . . . .	99
A.4	The Dutch Diet (1) . . . . .	99
A.5	Conceptual framework of the components of sustainable diets as illustrated by Jones et al. (2016) . . . . .	100
A.6	Global greenhouse gas emissions from food production as reported on by Poore and Nemecek in Our World in Data (2020) . . . . .	102
A.7	Environmental effects distribution per serving of food type in terms of Greenhouse gases, Land use, Energy Use, Acidification potential and Eutrophication potential as shown in report by the EAT-Lancet Commission on healthy diets from sustainable food systems (Willett et al., 2019) . . . . .	102
C.1	Model interface of the Meat Consumption model, building on the MeatNet model by Scalco et al. (2019) . . . . .	105
C.2	Model interface parameters: Define and create networks . . . . .	106
C.3	Model interface parameters: Policies/Interventions . . . . .	106
C.4	Model interface parameters: Visualization . . . . .	107
C.5	Model interface parameters: Outputs . . . . .	107

C.6	Social-influence managing process, randomly managing what concern among the three will undergo a process of influence . . . . .	108
C.7	Social influence process for environmental concerns, where agents will look at the concerns of those around themselves, weigh the concerns of those more and less concerned than themselves, and accordingly based on their own susceptibility to influence ( $\alpha$ ) and the presence of a social-marketing campaign ( $\gamma$ ) adjust their own environmental concern	108
D.1	Extended Theory of Planned Behaviour as extension of the Theory of Planned Behaviour, taken from Tommasetti et al. (2018). . . . .	109
E.1	Reasons to Eat Less Meat Questionnaire (LISS Panel Survey from CentERdata) . . . . .	111
E.2	Multiple linear regression analysis for pork consumption, through combining the Belevingen 2020 Survey (CBS, 2021b) and Dutch National Food Consumption Survey (RIVM, 2020b). (Source: Author) . . . . .	112
E.3	Multiple linear regression analysis for poultry consumption, through combining the Belevingen 2020 Survey (CBS, 2021b) and Dutch National Food Consumption Survey (RIVM, 2020b). (Source: Author) . . . . .	113
E.4	Multiple linear regression analysis for processed meat consumption, through combining the Belevingen 2020 Survey (CBS, 2021b) and Dutch National Food Consumption Survey (RIVM, 2020b). (Source: Author) . . . . .	113
E.5	Multiple linear regression analysis for substitute meat consumption, through combining the Belevingen 2020 Survey (CBS, 2021b) and Dutch National Food Consumption Survey (RIVM, 2020b). (Source: Author) . . . . .	113
E.6	Multiple linear regression analysis for a Vegan diet, through combining the Belevingen 2020 Survey (CBS, 2021b) and Dutch National Food Consumption Survey (RIVM, 2020b). (Source: Author) . . . . .	114
E.7	Multiple linear regression analysis for a Vegetarian diet, through combining the Belevingen 2020 Survey (CBS, 2021b) and Dutch National Food Consumption Survey (RIVM, 2020b). (Source: Author) . . . . .	114
E.8	Multiple linear regression analysis for a Flexitarian diet, through combining the Belevingen 2020 Survey (CBS, 2021b) and Dutch National Food Consumption Survey (RIVM, 2020b). (Source: Author) . . . . .	115
E.9	Multiple linear regression analysis for a diet of 5-6 times eating meat per week, through combining the Belevingen 2020 Survey (CBS, 2021b) and Dutch National Food Consumption Survey (RIVM, 2020b). (Source: Author) . . . . .	115
E.10	Multiple linear regression analysis for a diet of eating meat every day, through combining the Belevingen 2020 Survey (CBS, 2021b) and Dutch National Food Consumption Survey (RIVM, 2020b). (Source: Author) . . . . .	116
E.11	Multiple linear regression analysis for a never eating meat, through combining the Belevingen 2020 Survey (CBS, 2021b) and Dutch National Food Consumption Survey (RIVM, 2020b). (Source: Author) . . . . .	116
E.12	Characteristics contributing to dietary make-up . . . . .	117
E.13	Meat consumption of the Dutch adult population aged 19-79 split by Gender (Male, Female), Education levels (low, intermediate, higher), and Urbanisation (strong, moderately, low) . . . . .	118
E.14	Meat and fish consumption of the adult population in the Netherlands . . . . .	118
E.15	Days of meat and fish consumption of the adult population in the Netherlands, from never to every day . . . . .	119
E.16	Percentages of no or limited meat consumption due to environmental reasons in the Netherlands . . . . .	119
E.17	Percentages of no or limited meat consumption due to environmental reasons in the Netherlands . . . . .	119
E.18	Correlation between meat consumption levels of various meats during 2005 to 2019 . . . . .	119
E.19	Meat consumption level between 2005 and 2019 (kgs) in the Netherlands . . . . .	119
E.20	Price level of meat between 2000 and 2018 (CPI) in the Netherlands . . . . .	120
E.21	Non-normalized meat consumption per meat type for the base case scenario per policy . . . . .	121

# List of Tables

1.1	Subquestions and types of questions to guide the research on spreading the norm of reduced meat-consumption . . . . .	4
2.1	Table of key search terms and their combination, with synonyms ("OR" searches) in the same column and additional ("AND" searches) terms in the row. (Source: Author) . . . .	5
2.2	Summary of behavioural theories (Source: Author) . . . . .	10
3.1	CBS and RIVM Datasets for population demographics . . . . .	23
3.2	LISS Panel Data surveys used to determine factors of importance to changing meat consumption. . . . .	24
3.3	Summary of scenarios including the current situation in the Netherlands (Base-case), a scenario where environmental concerns are heightened due to climate change concerns (High Environmental Concern) and a scenario where individuals are more susceptible to external influences (High Susceptibility) (Source: Author) . . . . .	28
3.4	Summary of policies (A-F) tested for each simulation scenario (1-3), and settings of parameters in the simulation experiments for each of the policies, with tax specified for the meat types and campaigns focused on population groups (Source: Author) . . . . .	29
3.5	Number of experimental runs ( $n$ ) with the associated mean ( $\mu$ ), standard deviation ( $\sigma$ ), coefficient of variation ( $C_v$ ) and change in this coefficient for subsequent run numbers ( $\Delta C_v$ ) for beef consumption in the "High Susceptibility" scenario (Source: Author) . . . . .	31
3.6	Number of experimental runs ( $n$ ) with the associated mean ( $\mu$ ), standard deviation ( $\sigma$ ), coefficient of variation ( $C_v$ ) and change in this coefficient for subsequent run numbers ( $\Delta C_v$ ) for beef consumption in the "High Environmental Concern" scenario (Source: Author) . . . . .	31
4.1	LISS Panel Data surveys used to determine factors of importance to changing meat consumption. . . . .	33
4.2	Hope Barometer variables with low correlation to the frequency of meat consumption (Source: Author) . . . . .	35
4.3	Summary of relevant variables from the CBS surveys analysed with respect to frequency of meat consumption, with surveys including the Health survey, Politics and Values Survey, Background Variables survey and Reasons to Eat Less Meat Survey (Source: Author) . . . . .	37
4.4	Multiple linear regression analysis coefficient for beef, pork, poultry, processed meat and meat substitutes for the factors of Health and Environmental concern (Source: Author) . . . . .	43
5.1	List and brief description of agent's attributes (Source: Author) . . . . .	47
5.2	Pseudo-code for construction of household and co-worker networks and implementation during runs following the procedure of Scalco et al. (2019) . . . . .	48
5.3	Setup pseudocode for the main model (Source: Author, based on Scalco et al. (2019) . . . . .	51
5.4	Pseudocode for the main running of the model (Source: Author, based on Scalco et al. (2019) . . . . .	52
5.5	Model observations and units of these observations (Source: Author) . . . . .	56
5.6	Demographics for the model outcomes (Source: Author) . . . . .	56
5.7	Inputs, sources and range of values (Source: Author) . . . . .	57
5.8	Emissions per food type (beef, pork, poultry, processed & substitute in terms of climate, acidification, toxicity, smog, particulate matter and land use (de Bruyn, Warringa, & Odegaard, 2018) . . . . .	58
5.9	Parameters determining the likelihood of consuming each food type based on the regression analysis performed on the surveys of Belevingen 2020 and the Dutch National Food Consumption Survey (CBS, 2021b; RIVM, 2020b) (Source: Author) . . . . .	58

5.10 Price and cross price elasticity of demand for each food type in the Netherlands, as determined by van Hoof (2019) . . . . .	59
7.1 Average weekly meat consumption in grams for each of the five meat types (Beef, pork, poultry, processed, substitute meat) (Source: Author) . . . . .	69
7.2 Average weekly emissions per agent for each of the emissions types: greenhouse gas (gCO <sub>2</sub> eq), acidification (gSO <sub>2</sub> eq), toxicity (gP <sub>eq</sub> ), smog (gNMVOC), particulate matter (gPM <sub>10</sub> eq), land use (m <sup>2</sup> ) (Source: Author) . . . . .	69
7.3 Values of consumption for beef, pork, poultry, processed meat and meat substitutes when each policy is in place individually for the Base-Case scenario (Source: Author) . . . . .	70
7.4 Average values of consumption for beef, pork, poultry, processed meat and meat substitutes when each policy is in place individually for the High Environmental Concern Scenario (Source: Author) . . . . .	72
7.5 Average values of consumption for beef, pork, poultry, processed meat and meat substitutes when each policy is in place individually for the High Susceptibility Scenario (Source: Author) . . . . .	72
7.6 Average values of emissions when each policy is in place individually for the Base-Case Scenario (Source: Author) . . . . .	74
E.1 Least-square multiple linear regression analysis results showing the regression coefficients for health, environment and animal welfare concerns with respect to the probability of consuming specific meat types . . . . .	112



# 1

## Introduction

The report published by the International panel for Climate Change (IPCC) in August 2021 called for a "code red for humanity", stating unequivocally that human activity is the cause of climate change, and that we will likely overshoot 1.5°C warming above pre-industrial levels by 2030 even if we start reducing emissions now (Masson-Delmotte et al., 2021). Ambitious changes are required in all sectors, especially in electricity and heat production, agriculture, forestry and other land use, transportation, and industry. Within these domains, individual consumers have a significant impact on the levels of emissions, as they are contributing to the demand for goods and services which are polluting the environment. The most effective actions an individual can take to reduce their personal emissions is through driving less, having fewer children, restricting flying, and changing diets (Wynes & Nicholas, 2017). Proscriptive regulations which would strictly regulate these behaviours are unconstitutional, against individual freedoms, do not fall under the EU mandate, and attempts to enforce behavioural control are likely to be faced with severe backlash and resistance (Sparkman, Howe, & Walton, 2020). However, any structural changes will require behavioural changes to succeed. Therefore, it is crucial to understand the way behaviours and attitudes are influenced.

This is even more important as regards to the demand for food, as research found that even if we would stop all fossil fuel emissions today, if we do not also change the world's diets then we will still overshoot the 1.5°C warming target by the end of the century (Clark et al., 2020). Exceeding this level of warming will exacerbate droughts, wildfires, extreme flooding events, and more (Masson-Delmotte et al., 2021). The role of the agricultural industry was highlighted in the IPCC report (Masson-Delmotte et al., 2021). The agricultural sector accounts for 25-35% of total global greenhouse gas (GHG) emissions (Sejian, Gaughan, Baumgard, & Prasad, 2015), and has been labelled as one of the most difficult-to-decarbonize sectors. Food consumption accounts for 18% for EU household emissions on average, and varies per region between 11%-32% (Ivanova et al., 2017). There is a large resistance to change in dietary consumption, most notably changing meat consumption (Apostolidis & McLeay, 2016). Efforts to reduce emissions in this sector and maintain the warming of the climate below 1.5 degrees will require large-scale changes both in policy and behaviour within Europe and globally (Hartmann & Siegrist, 2017).

The European Union, as response to the pressing urgency of climate action in the agricultural sector, has brought the Farm to Fork strategy to the table as part of the European Green Deal (European Commission, 2020). This strategy takes a holistic view on the supply chain of the agricultural industry, with targets set out to reduce pesticide use, fertilizer losses and use, antimicrobial use, and increase organic farming (European Commission, 2020). The main policy instrument used by the EU to influence the agricultural sector remains the Common Agricultural Policy, which incentivizes farmers to produce livestock, crops, and follow practices as the EU sees fit. The Farm to Fork Strategy mentions the need to shift to a more sustainable diet, and the CAP is being reformed, but both of these fall short of directly addressing a topic at the core of the agricultural industry: the livestock sector. The livestock sector contributes to 75% of agricultural emissions in the EU, while only accounting for 37% of protein and 18% of calorific intake (Hedberg, 2020; Times, 2020). The CAP not only fails to address the concerns from citizens with regards to sustainable farming, the environment, and climate change (Scown, Brady, & Nicholas, 2020), livestock farmers also receive up to 90% of their income through direct subsidies

from the EU (Hedberg, 2020). The elephant, or cow, in the room is meat, and the overconsumption of meat. In order to reach the targets set out by the IPCC, the agricultural industry will have to change, and there will have to be a significant shift in consumer behaviour regarding meat consumption (Hartmann & Siegrist, 2017).

Social norms can play an important role in shaping this meat consumption, and moving towards a more sustainable protein source, i.e. protein contributing to a sustainable diet, which are typically plant-based (Hartmann & Siegrist, 2017). Norms are the "practical prescriptions, permissions, or prohibitions, accepted by members of particular groups, organisations, or societies, and capable of guiding the actions of those individuals" (Zia, Saini, Muhammad, & Farooq, 2019). Behavioural challenges posed by climate change are fundamentally problems of social influence, meaning that if the consequences of behaviours are unclear, we look at others to infer how to act. However, this has thus far resulted in unsustainable behaviours, with driving fossil-fueled cars and eating meat predominantly being the norm. Such norms can also be a powerful lever for positive change (Sparkman et al., 2020).

Social norms have thus far been underutilised as a lever. This can be seen in the Farm to Fork Strategy, where the majority of policies focus on supply-side solutions, while the only demand-side policy influencing norms is based on food labelling (European Commission, 2020). A study by The European Consumer Organisation (BEUC) argued that consumers should be encouraged and supported in adopting more plant-based diets, and found that consumers expect governments to take leadership in promoting sustainable food production and consumption (BEUC, 2020). While policy can have an influence in many ways, it is not clear how policies will influence normative changes, and provide the shift in culture which is required to reach the sustainability targets. This is the case as dietary consumption can be seen as a complex adaptive system (Holland, 2006), where an individual's diet is influenced by emerging social norms (Zia et al., 2019), dependent on their socio-economic context and culture (Olstad & Kirkpatrick, 2021), and the self-organisation of the food system (White et al., 2020).

Normative changes are required throughout Europe. European countries may behave differently to normative changes, and have their own socio-economic and cultural contexts. A country of interest for investigating the role of EU policy on social norms is the Netherlands. This country has seen an apparent increase in the quantity of self-reported flexitarian and vegetarian consumers over the past years (Vegetariërsbond & de Waart, 2020). This self-reported change, however, has not materialised in a proportional behavioural change, as research shows that many individuals who now label themselves as some flexitarian on average continue to consume similar quantities of meat as self-reported meat consumers. Even when making changes, meat is often substituted by other animal produce, such as fish, cheese, and eggs, rather than sustainable plant-based alternatives (Vegetariërsbond & de Waart, 2020). Although the Netherlands has seen a large increase in substitute meat consumption, this has occurred in tandem with an increase in regular meat consumption. This makes it an interesting case study to see whether EU policy can provide support in influencing the social norms on meat consumption and result in an effective reduction.

The objectives and research approach taken within this thesis are discussed in Section 1.1, leading to the guiding research question in Section 1.2. This thesis will discuss the state-of-the-art literature in Chapter 2, provide a conceptualisation of the model in Chapter 3, provide an in-depth model description following the ODD Protocol in Chapter 5. This model is then verified and validated in Chapter 6, with the results provided in Chapter 7. These results are discussed in Chapter 8, together with the limitations, implications and conclusions.

## 1.1. Objectives and Research Approach

Currently there is insufficient understanding of how social norms can be used to influence meat consumption, and what role EU policy can play in this domain. Improving this understanding can support the transition towards a sustainable society and help address one of the many facets of the societal grand challenge of climate change (TU Delft, 2020). Human behaviour is complex, with individuals limited by their bounded rationality, and uncertainty regarding how individuals will respond to policies and external influences. Meat consumption further can be viewed as complex adaptive system (Holland, 2006), making the response of policies on emergent behaviours as social norms difficult to establish and understand (Scalco et al., 2019; Zia et al., 2019).

This research aims to address this lack of understanding of the functioning of the layered and interconnected socio-technical system which represents the interplay of EU policy on meat consumption

norms, and takes the Netherlands as an explorative case-study. There is an abundance of theory on behaviour, however, it is necessary to find and utilise a theory which can adequately explain how social norms influence consumption. There is still a lack in understanding how certain social norms develop and spread, and what influence institutional rules and policies are on these norms.

This topic, therefore, lends itself well to the explorative modelling of this complex socio-technical system, in order to quantify the impacts of system interventions such a public policy. The research approach most suitable for analysing this perspective is through constructing a simulation model. The model will be required to capture how norms are shaped and how policies influence these norms. Norms inherently are an emergent behaviour, and behavioural change is a result of interaction with peers and other sources of information (Sparkman et al., 2020). These norms emerge during interactions between individuals, where people tend to look at others around themselves, and while eating together certain group norms emerge (Higgs, 2015).

The focus of this study on these emergent social norms, the complex nature of dietary consumption, and presence of a heterogeneous population makes agent-based modelling a suitable modelling paradigm. Agent-based models are capable of capturing the emergent behaviour from individual interactions (Berry, Kiel, & Elliott, 2002). Through taking a bottom-up approach, the emergence of macroscopic societal regularities can be achieved, where feedback between agent interactions governs behaviour based on microspecifications, which then in turn generates macrophenomena as norms (Epstein, 2006). This view is the antithesis of a multi-layered governance hierarchy embodying a top-down approach. Accordingly, we will distinguish only individual agents and their broader environment, and will not distinguish national and international governance layers within the agents' environments. As such, this research approach mainly focuses on modelling the policies the EU has a mandate for and implement these as if they are a national actor, and will discuss the implications of this research with regards to the broader political, policy and socio-economic contexts which play a role in decision making in the EU.

A benefit of the agent-based simulation framework is that it can directly represent an agent without theoretical restrictions. This allows for dynamic situations and complex interactions to be modelled (Edmonds et al., 2019), which is required to observe phenomena as the formation of food norms. There is a risk involved through not being constrained by specific theory, as there are many possible ways of translating any observed phenomena into simulated code (Edmonds et al., 2019). Therefore, it is important that assumptions and heuristics behind norm formation are grounded in the literature and observed reality. The Theory of Planned Behaviour (TPB) will serve as a framework. This theory has been demonstrated to be an appropriate framework for understanding people's intentions to reduce meat consumption, and allows for correlations to be made between consumption, moral and pro-environmental considerations (Carfora, Conner, Caso, & Catellani, 2020; Çoker & van der Linden, 2020). The grounding in reality will be sought through analysing various surveys and by combining these to gain insights on stated preferences.

The main research question will be answered by analysing, describing and simulating the influence of individual preferences and awareness, social networks, social norms, prices and availability on protein consumption; which typically consists of the meal choice for breakfast, lunch and dinner. This modelling approach will be iterative, following an initial convergent analysis from problem description, conceptualisation, followed by model specification, and later a divergent analytical approach (Slinger et al., 2008).

## 1.2. Research Question

Meat consumption is an important contributor to climate change (Ritchie, Reay, & Higgins, 2018), and social norms play an important role in driving dietary changes (Muñoz & Marselis, 2016). There is insufficient understanding of how policies influence these social norms, and what the exact role is of social norms on consumption, and the magnitude of these norms on dietary changes.

Up until now dietary change has mainly been examined through life-cycle analysis, regression analysis, and surveys, with little focus on social norms and how these spread. Addressing the topic from a social norm perspective can yield new insights for decision makers, who in the coming years will have to support citizens in bringing about change in society. Understanding how social norms spread, and gaining insight into the effects of governmental policies on these norms is therefore an important step.

Knowledge of social norms influence on diets can help society in guiding governmental policy related

to individual behaviour, by taking into account the complexity of consumer behaviour, and combining this with the requirements for governance in modern, networked societies (Aiking, 2014). This is of particular interest in the field of public policy development and policy analysis, where behaviour adds to the complexity and uncertainty within multi-actor systems.

The European Union as governmental entity plays an active role in developing policy and providing strategies to reach their targets. Therefore, it is beneficial to further the understanding of European policy and social norms, whether European policy can influence social norms and to what extent this has an impact. Furthering scientific knowledge will also help understand the way social norms spread, and if we can measure influences on these. To explore the impact of European policy, the European country of the Netherlands will be used as case study, as this country has already seen some normative changes regarding meat consumption, has public data available on changing consumption and will provide a starting point. In translating from national to EU policy we must take into account that the EU may have a different mandate for certain types of policy intervention than an EU Member State. The knowledge gap to be addressed in the master's thesis can be summarised by the research question:

***How do social norms influence meat consumption and to what extent can European policy influence these to reduce meat consumption?***

This research question addresses two key parts of this research study. One part is the interplay between social norms and meat consumption. The other is the influence of policy, and in particular EU policy, on these. The main research question intends to assess how modelling of norms can assist governmental policy decision making. It is not clear yet whether these policies will actually have any influence on social norms, and therefore this research will be explorative in nature. This main research question is supported by various sub-questions, which each represent part of the puzzle which needs to be put together to form a clear picture. This includes an understanding of how social norms influence meat consumption, what behavioural policies can be applied, what policies the EU has a mandate over, what the main influencing factors and drivers around meat consumption are, which interventions can be modelled and how these can be modelled in a valid and coherent manner, how investigating this problem from a normative aspect relates to other research in this field, and how findings from this study could be used by decision makers. Several sub-questions have been designed to systematically go through this required understanding. These can be found in Table 1.1, where each sub-question is linked to a category of the research phases.

Table 1.1: Subquestions and types of questions to guide the research on spreading the norm of reduced meat-consumption

	Questions	Type
1	How do social norms influence meat consumption, and what policies can the EU implement to influence meat consumption?	Literature Review
2	How can agent-based modelling be used to model and simulate the influence of EU policy and social norms on meat consumption?	Modelling
3	What are the effects of EU policy and social norms on meat consumption?	Model results and use

The first subquestion covers the conceptualisation phase of the problem, an important step to provide a solid foundation in understanding the problem. This question is answered through a literature research, conducted as desk-research, with the findings outlined in Chapter 2. These findings are used to derive the Methodology, which is discussed in Chapter 3. The data gathering and analysis aspect of the project, which provides the parameterisation of the variables related to meat consumption and social norms, and provides further understanding of the problem, is provided in Chapter 4. The second subquestion is answered through combining the previous three aspects, the literature search, methodology, and data analysis, and feeding the findings into the construction of an agent-based model. The specification for this model is explained using the ODD (Overview, Design Concepts and Details) Protocol in Chapter 5. This model is verified and validated in Chapter 6. The third subquestion is answered through analysing the model, with model results provided in Chapter 7, and discussed in Chapter 8. This final Chapter 8 discusses the research questions, simulation results, highlights the strengths and limitations of this research, and provides implications for policymakers, future research and a conclusion to the report.

# 2

## Literature research

### 2.1. Overview Research

There is a significant body of literature on meat consumption, the effects of meat consumption on health, on the environment, and on the ethical aspects of it. This literature review will discuss the current state-of-the-art literature on the topic of meat consumption behaviour patterns, the relation of meat consumption to climate change, and the existence of models in the field. The literature research was based on searching for topics with the terms "meat consumption", "climate change", "behaviour", "sustainability", "policies" and "models", with the key questions in mind of 'how does meat consumption relate to climate change', 'how is dietary consumption behaviour influenced' and 'what is the state-of-the-art in researching influences on meat consumption'. This search was conducted within Scopus and Google Scholar. An overview of the search terms can be found in Table 2.1.

Table 2.1: Table of key search terms and their combination, with synonyms ("OR" searches) in the same column and additional ("AND" searches) terms in the row. (Source: Author)

Term	Meat	Climate Change	Sustainability	Models	Policies
	Meat-consumption			Agent-based	Behaviour
	Protein			Choice Behaviour	

Combinations of these search terms resulted in several hundred studies. These articles were systematically screened through the Covidence application, reducing from 397 studies to 133 studies, as seen in Figure 2.2. Of these studies, around 14 focused on policies, and 10 of these generated various models. The quantity of publications has seen a strong increase recently, as seen in Figure 2.1, indicating that this topic has become more widely discussed and researched.

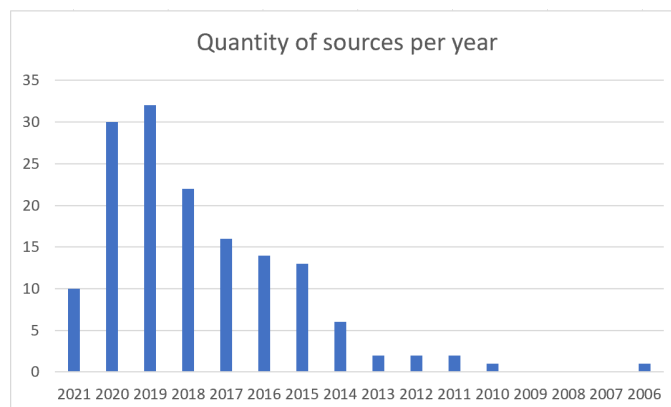


Figure 2.1: Distribution of sources by year from the literature review, from 2006-2021 (Source: Author)

A subset of these papers has been used to address the academic knowledge gap and gain a basic understanding of the problem at hand. In this Chapter we first discuss what a sustainable diet is in Section 2.2, the main factors influencing meat consumption in Section 2.3, the social norms, social networks and their relation to meat consumption in Section 2.4, and the barriers to change in Section 2.5. Furthermore, behavioural theories will be discussed in Section 2.6, with a focus on the Theory of Planned Behaviour and Extended Theory of Planned Behaviour as theoretical framework for behaviour that the model will be based on. The policy frameworks are discussed in Section 2.8, existing models in Section 2.9, and finally a summary of key literature findings is provided in Section 2.10.

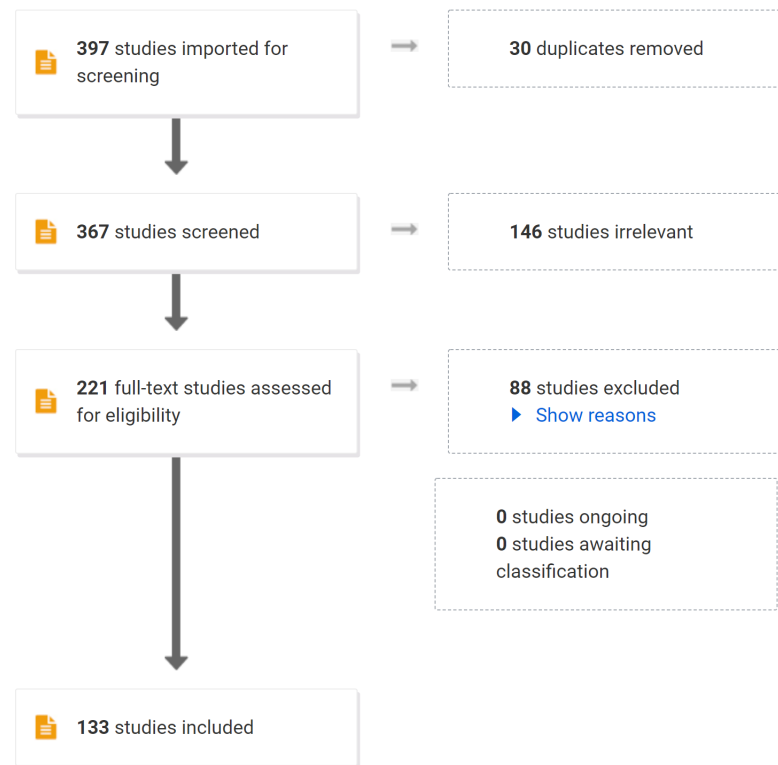


Figure 2.2: Prisma of Studies Screened with keywords "Meat consumption", "Behaviour", "Climate Change" and "Models" (Source: Author)

## 2.2. What is a sustainable diet?

A sustainable diet is defined by the FAO as "protective and respectful of biodiversity and ecosystems, culturally acceptable, accessible, economically fair and affordable, nutritionally adequate, safe and healthy, while optimizing natural and human resources" (Burlingame, 2012). In a literature review of how sustainability is measured, it was found that the most important components included the estimated greenhouse gas emissions, land use, and the consumption of animal-source foods (meat especially) (Jones et al., 2016).

Dietary changes could reduce dietary emissions by up to 50%-78% (Aleksandrowicz, Green, Joy, Smith, & Haines, 2016; Perignon, Vieux, Soler, Masset, & Darmon, 2017; Vieux, Perignon, Gazan, & Darmon, 2018). Reduced meat consumption is a key element of this, as livestock is associated with having the greatest environmental impacts. These impacts include climate change, land use, water use, and loss of biodiversity (Willett et al., 2019). The dietary changes required to achieve a sustainable diet differ per country and gender, however, all changes require a reduction in meat consumption and shift to more sustainable protein (Vieux et al., 2018). Sustainable protein consumption here is defined as protein derived from low carbon emitting sources as soy, legumes, beans, insects and fungi (Hartmann & Siegrist, 2017).

The EAT-Lancet Commission, a scientific commission constituting of Commissioners and authors from 16 countries who specialise in fields including human health, agriculture, political science and environmental sustainability (Willett et al., 2019), lays out specific targets to reach a food system transformation in line with the SDGs and Paris Agreement in their report "Food Planet Health" (Willett et al., 2019). This report recommends consuming no more than 200g of red meat per week, and consuming no processed meat. This is more stringent than other recommendations of authors as Micha et al. (2010), who recommend no more than 500g/week of red meat and little to no processed meat. Appendix A further expands on sustainable diets.

### **2.3. Main factors influencing meat consumption**

Dietary consumption is a complex behaviour, which is influenced by the food environment (price, availability), personal preferences, environmental triggers, contextual food cues, personal barriers and other motives and factors. It is important to understand which factors meat consumption, as these determine which policies and campaigns are more suitable. Three key factors were found to be health, environment, and ethical/animal welfare concerns (Hopwood, Bleidorn, Schwaba, & Chen, 2020).

Various instruments exist to distinguish the importance of different eating motives. The Food choice Questionnaire focuses on nine motives, while 'The Eating Motivations Survey' measures 15 different motives including habits, hunger, health, liking, convenience, pleasure, tradition, nature, sociability, price, visual appeal, weight control, affect regulation, social norms, and social image (Renner, Sproesser, Strohbach, & Schupp, 2012). These motives, while important to determine overall dietary choices and consumption, were determined to relate less strongly to meat consumption in Western Society than the three factors: health, environmental, and ethical concerns. This was found in the study by Hopwood et al. who created the 'Vegetarian Eating Motives Inventory' (VEMI), which measures the importance of the factors of health, environment and ethics (Hopwood et al., 2020).

### **2.4. Social norms, social networks and meat consumption**

Norms are defined as the "practical prescriptions, permissions, or prohibitions, accepted by members of particular groups, organizations, or societies, and capable of guiding the actions of those individuals" (Morrow & of Virginia, 2015). While norms describe the collective behaviour of groups, organisations and societies, these norms are an emergent property of individuals' cognition (Zia et al., 2019). Behaviour of individuals are capable of changing, creating and affection norms, which in turn can influence behaviour. These norms are central to the problem surrounding the shift towards more sustainable diets.

Research into norms includes dynamic norms, where information about changing norm trends can result in people conforming to the change even if the normative change is in opposition to current norms, and framing normative appeals where others are invited to join a common goal (Sparkman et al., 2020). Other normative research includes descriptive norms, where patterns of behaviour are linked to the expectation that people will follow this behaviour, and injunctive norms which are prescriptive rules which specify the type of behaviour individuals should or shouldn't follow (Savarimuthu, Purvis, & Verhagen, 2012).

According to researchers such as Higgs (2015), people will take on eating norms, where they subconsciously imitate those around them, as this can enhance the affiliation with a social group and being liked (Muñoz & Marselis, 2016). This reflects the findings by Cialdini, who found that people look at others to judge what behaviour is deemed correct, in a phenomenon coined 'social proofing' (Cialdini, 2007). People can be motivated to make dietary changes to alter their public image, and generate certain perceptions within others (Higgs, 2015). This can be seen within households, and within work situations where peer networks will have significant influences on an individuals' diet, and where typically a prevailing dietary norm exist (Scalco et al., 2019).

This is also seen in studies such as those by Herman (2015), who found that the quantity of meat consumed increases when eating with family members compared to eating alone or with other companions. Overall consumption also increases as the group size increases, and when people eat out.

### 2.4.1. Use of social norms and meat consumption

From the literature search, it was found that social norms are more frequently used as intervention for triggering behaviour changes surrounding food waste, but are scarcely used to influence food consumption (Reisch et al., 2021). Investigating the effects of interventions on the norms surrounding food consumption thus needs further exploration. Studies using the Theory of Planned Behaviour (TPB) indicate that attitudes, subjective norms and perceived control can provide some explanation on how people reduce their meat consumption (Alam, Ahmad, Ho, Omar, & Lin, 2020; Çoker & van der Linden, 2020).

Diets are complex social constructions, which are influenced by a variety of factors such as health, settings, contextual food cues, norms, triggers, taste preferences and barriers. Choices can be made in a deliberate fashion, based on the available information whereby an individual chooses the best option after performing a cost-benefit analysis (System 2), or through heuristics (System 1) (G. W. Horgan, Scalco, Craig, Whybrow, & Macdiarmid, 2019).

This is the principle of the dual processing theory, where people use two distinct systems to process information (Kahneman, 2011). System 1 relies on heuristics, which may lead to less optimal decisions, can produce rapid responses and use less cognitive resources (Cohen & Babey, 2012). This system is more active in out-of-home contexts, where decision-making is more spontaneous, faster and influenced by heuristic cues (Cohen & Babey, 2012). This in turn affects the type of food and quantity of food consumed.

Nudge theorists (Reisch et al., 2021) believe that poor lifestyle choices are commonly the result of System 1 type processes. Therefore, implementing nudges influencing choice heuristics (e.g. layout of food in supermarkets, portion sizes) are thought to be more beneficial at the point of choosing (Lin, Osman, & Ashcroft, 2017). However, these may be ineffective and short-term as they do not cause the decision maker to re-examine why they performed a particular behaviour (Lin et al., 2017). Longer lasting behavioural changes may require deliberate choices and awareness of these, which is a characteristic of System 2 and could be influenced through other methods as informational campaigns. While actual behaviour cannot be neatly separated into two systems, it is possible to distinguish nudges by their ability to cause one to re-evaluate information that informs better decisions, resulting in an alignment between choice behaviour and the new information (Lin et al., 2017). A combination may be required to achieve normative change, and they both have their merits.

Empirical studies, like those conducted by the University of Ghent, show the influence of contextual food cues through providing 'nudges' in the environment (Rubens & Vandenbroele, 2017a, 2017b, 2017c). That study indicates that through introducing smaller portion sizes of sausages they were able to stimulate consumers to alter their purchasing behaviour (Rubens & Vandenbroele, 2017b). The introduction of smaller portions led to 63% of consumers purchasing a smaller portion, reducing the total meat sold by weight with 18%. This shows the importance of social settings. However, studies on these impacts are not yet conclusive on the long-term effects.

### 2.4.2. Spreading of social influence via networks

It is important to gain an understanding of how social norms spread via networks. Work by Higgs et al. (2015) show that people are motivated to make changes when surrounded by others. Norms can morph and change over time in groups, following the multi-level theory of decision-making (Zhang, Giabbanelli, Arah, & Zimmerman, 2014). The social norms present in an individual's social network will influence their decision-making (Muñoz & Marselis, 2016).

Social networks exist at various levels; with the main groups being household members, peers, and co-workers. Studies show that family members are the main source of influence on food-related consumption choices (de Castro, 1994; Scalco et al., 2019). In a network, peers and members of your household can be represented as strong ties, while co-workers form weak ties in social network interactions (de Castro, 1994).

Social norms in networks can be targeted through campaigns. Campaigns which focus on both descriptive and injunctive norms can provide positive influences on social behaviour, and are used by organisations for social norm marketing (Savarimuthu et al., 2012).



## 2.5. Barriers to change

A number of barriers hamper consumers in reducing meat consumption. For instance, consumers tend to believe that not eating meat negatively compromises iron and protein intakes (Lea, Crawford, & Worsley, 2006). Eating meat is also viewed by many as being pleasurable, and an important part of traditional meal patterns or a meal being incomplete without meat as the central component. Many consider that humans have evolved to consume meat and that not doing so is unnatural, justifying meat consumption as being necessary, natural, normal and nice (Macdiarmid, Douglas, & Campbell, 2016; Piazza et al., 2015). Furthermore, price, lack of information, and the challenge of identifying sustainable food options combined with the limited availability of these options have been identified as the main perceived barriers to sustainable eating by The European Consumer Organisation (2020).

These barriers are important, as they can reduce the likelihood of consumers to change their behaviour. In the same vein, meat substitutes may experience lower barriers of consumption due to their increased similarity to meat, and once consumed there is a higher likelihood for consumers to try substitutes more often (International Food Information Council Foundation, 2019). However, these meat alternatives are still typically associated with the terms "tofu", "vegan and vegetarian" and "disgust", as well as being seen as similar to processed meat (Michel, Hartmann, & Siegrist, 2021). That study by Michel et al. (2021) also found that due to this perception, meat alternatives are more likely to succeed in replacing processed meats, and are most commonly eaten in informal situations such as those when eating alone or when being with friends or family. Such barriers may influence the likelihood for new habits to be formed.

### 2.5.1. Habits

Habitual food consumption comprises close to half of total food consumption (Naik & Moore, 1996). These habits are automatic behaviours, which provide responses to contextual food cues (Muñoz & Marselis, 2016). Habitual changes are best achieved through restructuring the environment and exposure to cues, which focuses on establishing new habits rather than deconstructing existing ones, with habit change taking between one and six months of repetition (Lally & Gardner, 2013; Muñoz & Marselis, 2016). Positive experiences can result in repeated behaviour, which can turn into habits. There are both internal and external factors influencing experiences and habits.

Internal factors include the person's reference level, as result of previous behaviour, their identity, beliefs and values as behaviour consistent with these will result in positive experiences. Furthermore, health and emotion at the time of the behaviour are influential factors, and contextual information as social, political, and religious, which can influence both food selection and taste (DeJesus, Shutts, & Kinzler, 2015; McFerran, Dahl, Fitzsimons, & Morales, 2010; Muñoz & Marselis, 2016).

External factors influencing habits and experiences are the affordability, availability, accessibility, attractiveness of behaviour and sense of loss (Muñoz & Marselis, 2016). Individuals may experience a higher sense of loss when they have more options, as they have to reject more options which in turn leads to lower satisfaction. This is known as the "Paradox of Choice" (Schwartz, 2004).

## 2.6. Behavioural Theories

Behavioural theories are useful for understanding the behaviour of individuals and what drives this behaviour. Assumptions during the modelling phase are grounded based on the behavioural theory. Therefore, the theory underpinning the model requires to be robust, be extensive and covers aspects which can be influenced through policies.

There are numerous behavioural theories, the main theories prevalent in the field of behavioural economics are explained in Table 2.2. These theories were chosen based on their relation to behaviour, health, and the normative aspect. The Theory of Planned Behaviour (TPB) (Ajzen, 1991) and Extended Theory of Planned Behaviour (ETPB) (Alam et al., 2020) appear to fit the desired characteristics well, as these models incorporate both social norms, as well as attitudes and behavioural control which are all deemed important as components influencing consumption (Alam et al., 2020; Macdiarmid et al., 2016; Çoker & van der Linden, 2020).

Table 2.2: Summary of behavioural theories (Source: Author)

Behavioural theory	Key assumptions
Theory of Reasoned Action (TRA)	Intention is the best predictor of behaviour (Fishbein & Ajzen, 1975). Intention is an outcome of the evaluation of attitudes towards a behaviour, its expected outcomes and subjective norms.
Theory of Planned Behaviour (TPB)	The TPB expands on the TRA, and explains behaviour through behavioural intention. Behavioural intention is influenced by the attitude about the likelihood that a behaviour will have the expected outcome, and the evaluation of risks and benefits of this outcome. Key constructs include: attitudes, behavioural intention, subjective norms, social norms, perceived power, and perceived behavioral control (Ajzen, 1991).
Extended Theory of Planned Behaviour (ETPB)	The ETPB further complements the TPB by including the perceived usefulness of the behaviour, and curiosity in performing this behaviour (Alam et al., 2020)
Social Cognitive Model (SCT)	The SCT expands the Social Learning Theory of Bandura (Bandura, 1989; LaMorte, 2019b). Learning occurs in a social context, with dynamic and reciprocal interaction of the person, environment, and behaviour. SCT incorporates the constructs of reciprocal determinism, behavioural capability, observational learning, reinforcements, expectations, and self-efficacy (LaMorte, 2019b)
Health Belief Model (HBM)	The HBM predicts adoption of behaviour through the person's belief in a personal threat combined with the person's belief in the effectiveness of the recommended health behaviour. Constructs include: perceived susceptibility, perceived severity, perceived benefits, perceived barriers, cue to action, self-efficacy (LaMorte, 2019a).
Transtheoretical model (TTM)	A model which dictates individuals move through six stages of change: precontemplation, contemplation, preparation, action, maintenance, and termination. Progress through stages occur through cognitive, affective and evaluative processes (LaMorte, 2019e).
Social Norms Theory (SNT)	Understanding environment and interpersonal influences (e.g. peers) to change behaviour. Peer influence is affected by perceived norms, rather than the actual norm. Behaviour is influenced by misperceptions of actions and thoughts by peers (LaMorte, 2019c).
Value Belief Norm Theory (VBN)	VBN theory is mainly applied in support of environmental movements. Individuals who accept the basic values of a movement and who believe that the objects they value are threatened, and who believe that they can engage in actions to restore the values will therefore feel obligated to conduct a pro-movement action according to their personal norms. The type of support depends on their capabilities and constraints. Five variables result in this causal chain: the New Environmental Paradigm (NEP), awareness of consequences (AC), ascription of responsibility (AR) to self-beliefs, and personal norms (Chen, 2015; Stern, Dietz, Abel, Guagnano, & Kalof, 1999).

Table 2.2 provide a brief overview of the key assumptions of each behavioural theory. The TRA, TPB and ETPB are closely related to one another and explain actions through the intention to perform an action, with each subsequent theory expanding the drivers of intention (Ajzen, 1991; Alam et al., 2020; Fishbein & Ajzen, 1975). The SCT focuses on learning through action (Bandura, 1989), HBM explains behaviour through the belief in threat and ability to mitigate this (LaMorte, 2019a). The TTM outlines the processes of change (LaMorte, 2019e), while the SNT explains behaviour through peer influence (LaMorte, 2019c), and the VBN explains actions through value alignment with environmental

movements (Chen, 2015; Stern et al., 1999). All these theories come with their own limitations.

The TRA explains action through intention, with this a product of attitudes and subjective norms (Fishbein & Ajzen, 1975). This does not account for the control individuals may have over their behaviour; whether they are capable of performing the action. This theory also does not cover aspects as past behaviour, nor capture the sets of beliefs which may play a role in determining behaviour, nor take environmental context into account (Hagger, 2019). This theory has been used to model meat consumption (Scalco et al., 2019),

The TPB improves upon the TRA and deals with some of the important limitations (Ajzen, 1991). Still, limitations include that the TPB assumes individuals always have the opportunities and resources to successfully perform the desired behaviour, independent of their intention to perform the behaviour. The TPB also does not account for other variables which may influence the behavioural intention and motivation, such as fear, threat, mood and past experiences (LaMorte, 2019d). However, the attitude indirectly captures multiple of these variables. Normative influences do not take environmental or economic factors into account, nor time frames between intent of behaviour and actual behavioural action (LaMorte, 2019d). Authors as Çoker and van der Linden effectively used the TPB to quantify the impact of environmental attitudes on behaviour, and found attitudes to be a strong indicator of actual behaviour (Çoker & van der Linden, 2020).

The ETPB expands on the TPB through taking the perceived usefulness of actions and curiosity into account, which the TPB does not (Alam et al., 2020). This expansion still does not take variables into account as fear, threat, mood, and past experiences. A concern of the ETPB is that curiosity is abstract and can be hard to quantify (Alam et al., 2020; LaMorte, 2019d). Alam et al. (2020) have used the ETPB to conduct a regression analysis on the impact of various factors on sustainable food consumption, and found that social norms, perceived value, perceived consumer effectiveness, and attitude have significant impact on the intention to consume sustainably (Alam et al., 2020). Perceived availability and effectiveness appear to play a role, although social norms and intention are stronger predictors of behaviour (Alam et al., 2020).

The SCT does not take intention into account, rather it assumes changes in environment will automatically lead to changes in the person (Bandura, 1989). This theory is loosely organised, and focuses strongly on the processes of learning. The theory does not focus on emotion or motivation, only past experiences, and as theory has been criticised to be broad-reaching (LaMorte, 2019b). The SCT has been used to investigate eating behaviour in studies by authors as Malan et al. (2020), who combined the SCT and TPB and found that through seminars promoting environmental sustainability and human health through improving dietary consumption were effective by improving knowledge of links between environmental sustainability and food systems (Malan et al., 2020).

The HBM does not account for the person's learning in a social context, attitudes, beliefs or other determinants which may influence a person's acceptance of certain behaviour (LaMorte, 2019a). The HBM explains behaviour primarily through threats, but does not take into account that behaviours are habitual, nor regards non-health related reasons as social acceptability, norms, environmental or economic factors, and assumes equal information about illnesses or diseases (LaMorte, 2019a). The HBM has been applied by researchers as Urbanovich et al. (2020) to examining dietary changes, with findings that the highest perceived benefits of plant-based diet adoption are health and well-being, with barrier breaking down eating habits. That study also regarded the Theory of Planned Behaviour, which showed that social norms was the most significant mediator between meat consumption and intention to adopt plant-based diets (Urbanovich & Bevan, 2020).

The TTM classifies individuals with regards to their readiness to change behaviour, and has been used to create strategies for nutritional interventions (Nakabayashi, Melo, & Toral, 2020). While successful, it has also received criticism for ignoring social contexts, such as social norms and income. The boundaries of stages can be arbitrary, with no existing determining criteria for individuals to move between stages. This model also assumes coherent, logical and rational plans in the decision-making process of individuals, which may not always be the case (LaMorte, 2019e).

The SNT describes the social norms, environment and interpersonal influences as driver of behaviour. Looking at the peer influence, and perceived norms, can be valuable. Limitations to this theory are that participants of intentions focused on social norms may question the messages presented due to their pre-existing misperceptions. Social norm messaging further requires adequate data collection, and the sources of social norm messaging need to be sufficiently credible to the target population. The frequency of messaging a target population need to be sufficient to make an impact, but can be

counterproductive if excessible (LaMorte, 2019c).

The VBN suggests the perception of adverse effects from climate change can promote mitigation behaviour. This theory does not take into account the contextual forces and an individual's characteristics and surroundings, which may constrain behaviour, and theorises that pro-environmental action can be driven by solely personal norms (Stern et al., 1999). Studies on the VBN and meat consumption found that besides pro-environmental drivers, health concerns also played an important role (Lai, Tiroto, Pagliaro, & Fornara, 2020). Therefore, the VBN alone does not provide the full picture of changes in meat consumption.

Studies in each of the theories, with regards to meat consumption, agreed that social norms play an important role. Many of the studies combined a specific theory with the Theory of Planned Behaviour (Malan et al., 2020; Urbanovich & Bevan, 2020; Çoker & van der Linden, 2020), which includes key aspects to explaining meat consumption; social norms, attitude and perceived behavioural control as drivers of intention and behaviour. Several studies agreed that the environmental and health concerns play an important role in influencing the attitudes of individuals (Lai et al., 2020; Urbanovich & Bevan, 2020; Çoker & van der Linden, 2020). The Theory of Planned Behaviour, covering important aspects related to behaviour as shown in Figure 2.3, will therefore be used within this research. The Extended Theory of Planned Behaviour also fulfills similar criteria, but lacks the empirical research to quantify aspects as curiosity, therefore this research will focus on the TPB (Ajzen, 1991).

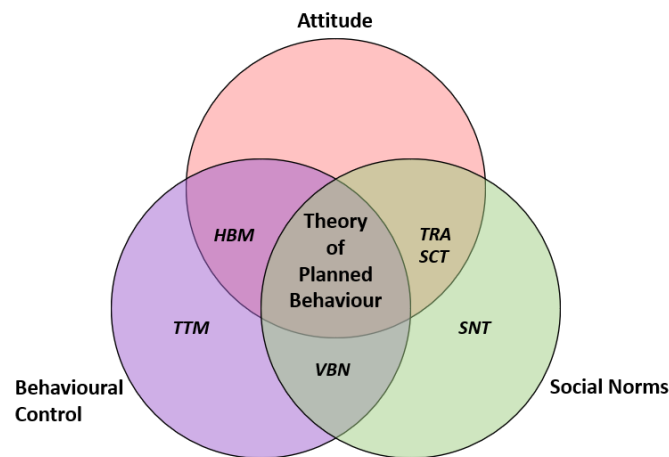


Figure 2.3: Venn diagram showing that the Theory of Planned Behaviour contains important aspects related to consumption behaviour, with the TRA, SCT, SNT, VBN, HBM and TTM covering parts of each aspect (Source: Author)

## 2.7. Theory of Planned Behaviour applied to meat consumption

The agent's behaviour within the model will follow the Theory of Planned Behaviour (TPB) (Ajzen, 1991). This social behaviour theory was chosen as this provides a practical analytical framework which has been effectively used to model aspects of meat consumption (Çoker & van der Linden, 2020). Models using TPB with regards to meat consumption include the modelling the impact of attitudes towards beef consumption in Ireland (McCarthy, de Boer, O'Reilly, & Cotter, 2003), predicting the intention to continue following certain diets (Povey, Wellens, & Conner, 2001), and modelling reduced meat consumption (Çoker & van der Linden, 2020). This is the first time the Theory of Planned Behaviour would be applied to an agent-based model to explain the influence of social norms on meat consumption of various types of meat. This model builds on the previous model by Scalco et al. (2019), which looked at meat consumption through the Theory of Reasoned Action.

The TPB was developed by Ajzen in 1991 (Ajzen, 1991), and implies behaviour of individuals are influenced by the individual's attitudes, subjective norms and perceived behavioural control. Research by Çoker and van der Linden (2020) found that attitudes, subjective norms and perceived control could explain around 60% of variations in the intention to reduce meat consumption, while habit did not provide additional predictive utility over the TPB (Çoker & van der Linden, 2020). In reducing meat consumption, the attitude, subjective norms and perceived behavioural control of the TPB play an important role (Osman & Thornton, 2019; Çoker & van der Linden, 2020).

The attitude towards a behaviour can be defined as the predisposition to interact either in a predictably positive or negative fashion towards a person, situation, object or behaviour (Tommasetti et al., 2018). When individuals perceive their actions as useful and beneficial, then they will have a positive attitude towards the behaviour. This has been shown to correlate to be linked to the awareness of links between meat consumption and climate change and/or health risks (Çoker & van der Linden, 2020). This can be modelled as the concerns that an individual has for the climate, health and animal welfare, as these concerns relate to the awareness of individuals and their attitude (Hopwood et al., 2020). Attitudes are the strongest predictor of intention for meat consumption (Çoker & van der Linden, 2020), together with subjective norms.

Subjective norms play a role when consumers interact with one another. The way this can be modelled is through generating social networks where agents interact during meal times. The influence of norms is not the same between all members of society. In networks, as in real life, some networks have strong ties while others have weaker ties. Studies have shown that households and family have a stronger influence on an individual, than co-workers in work-places. These represent strong and weak groups respectively (Hamill & Gilbert, 2010). Therefore, to incorporate this, the interactions between agents have to be modelled and agents need to be part of networks where peers exert influence on one another.

Perceived behavioural control can be related to the ability of individuals to change their behaviour. For changing behaviour, agents require a food environment which allows them to choose the diet they want to follow, and agents require the means to be able to afford this diet. This can be modelled as the expectation about the ease or difficulty of implementing certain behaviours (Tommasetti et al., 2018).

The parameters which influence meat consumption to be modelled were derived from the literature search in Chapter 2 and data analysis in Chapter 4. The summary of these parameters and their application within the Theory of Planned Behaviour can be seen in Figure 2.4.

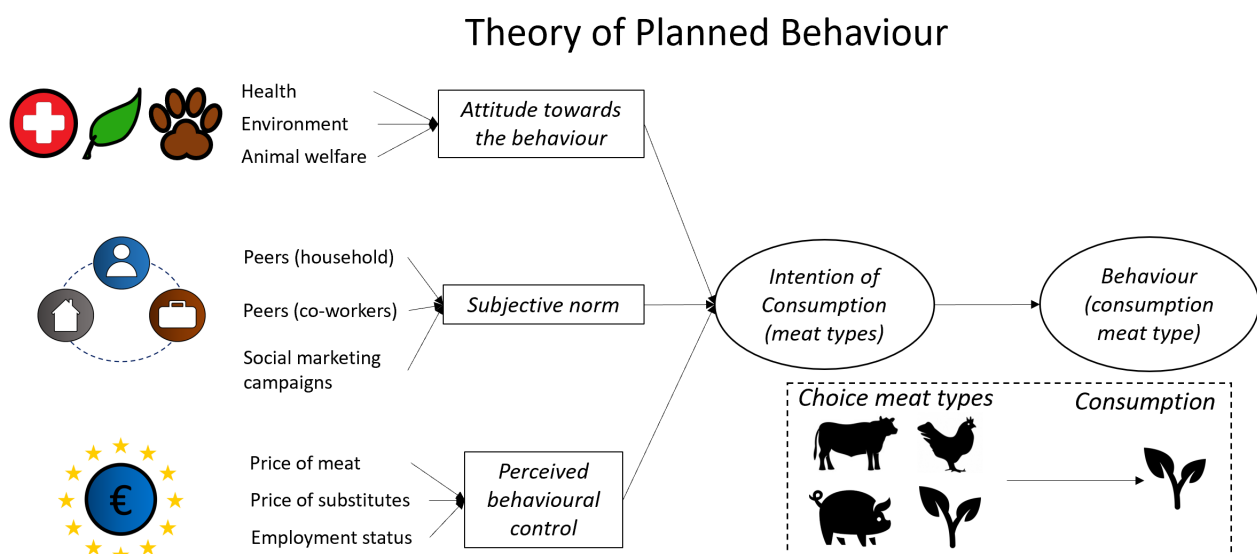


Figure 2.4: Theory of Planned Behaviour applied to meat consumption (Source: Author)

The attitude towards meat consumption is primarily influenced by the concerns for health, the climate and animal welfare (Hopwood et al., 2020). Subjective norms are based on these concerns within the population, where individuals adapt their behaviour when eating with others (Higgs, 2015), and are transferred through social networks of peers (Macdiarmid et al., 2016) within households and between co-workers (Scalco et al., 2019; Zhang et al., 2014). Norms and attitudes can be influenced by policies as social marketing campaigns (BEUC, 2020; Scalco et al., 2019). Finally, barriers to perceived behavioural include the price, lack of information, and challenge to identify sustainable foods (BEUC, 2020). Therefore, perceived control will be related to an individual's income and price of both meat and meat substitutes, which can be altered through changing the food environment (de Krom, Vonk, & Mulwijk, 2020; Kyriakopoulou, Dekkers, & van der Goot, 2019).

## 2.8. EU Policies influential to meat consumption

European Policies regarding agriculture and sustainable consumption can be implemented at various levels along the supply chain. The Farm to Fork strategy is part of the European Green Deal, and addresses core challenges to making the food system more sustainable (European Commission, 2020). The Farm to Fork strategy aim to ensure sustainable food production, ensure food security, stimulate sustainable food processing, reduce food loss and waste, and promote sustainable food consumption and facilitate the shift to healthy and sustainable diets (European Commission, 2020). This dietary shift is envisioned predominantly through the use of a labelling framework. However, this policy proposal has been criticised for not adequately addressing meat consumption (Hedberg, 2020).

This Section will investigate the potential role of policies such as food pricing in subsection 2.8.1, campaigns in subsection 2.8.2, and changing the food environment in subsection 2.8.3

### 2.8.1. Food pricing

The price of meat is heavily influenced by subsidies provided by the European Common Agricultural Policy. The supermarket price does not reflect the true price of meat, when taking into account these subsidies, and negative externalities as the damage to the climate, environment, health, animal well-being, particulate pollution, animal pest outbreaks and antibiotics resistance amongst others brought forth by intensive livestock rearing (de Bruyn et al., 2018; Sargant, 2014). The EU spends between 18-20% of the EU budget, around 30 billion euros, on subsidies for livestock farming, with 78% of direct income from livestock farmers coming from subsidies (Hedberg, 2020).

Governments can step in to influence consumption through fiscal measures. Price has been found to be an important influencing factor on people's consumption habits (Lally & Gardner, 2013). Several studies promote the idea of putting a tax on meat (de Bruyn et al., 2018; Funke et al., 2021; Katare et al., 2020; Klenert et al., 2018; TAPPC & DVJ Insights, 2020), and call for a Pigouvian tax whereby meat products are proportionately taxed according to their emissions (Säll & Gren, 2015). Others argue that these taxes on food are likely to fail, pointing to the case when Denmark passed a fat tax in 2011 and repealed it one year later as 48% of Danes crossed the border to buy meat and cheese (Fleischer, 2014). Excise duties are another option, also known as 'sin taxes', which levy taxes on certain products that are not considered healthy or wholesome (TAPPC & DVJ Insights, 2020). The True Animal Protein Price Coalition (TAPPC) calls for a fair meat excise tax in the EU, similar to excise taxes on alcohol, tobacco, fuel and aviation (TAPPC & DVJ Insights, 2020).

A change of food prices is supported by a majority of Western European consumers, according to a survey amongst consumers in France, Germany and the Netherlands (TAPPC & DVJ Insights, 2020). In this survey 70% of Western European respondents were in favour of altering the tax system to make meat products more expensive and reduce taxes on healthier products like vegetables and fruits. Dutch are reportedly willing to pay 10 eurocents per 100 grams of meat, if these revenues are utilised to support farmers in improving animal welfare standards, encourage CO2 reduction and improve salaries of workers in slaughterhouses. (TAPPC & DVJ Insights, 2020).

A study by CE Delft has found that price of meat within the Netherlands should be 53% higher for pork, 40% higher for beef and 26% higher for chicken when taking into account negative externalities previously mentioned and reducing subsidies (de Bruyn et al., 2018). These subsidies result in an artificially reduced price, inflating consumption and making meat more attractive than alternatives. However, a meta-analysis on price and income elasticities of food found that at high income levels the elasticity of demand will be lower, and demand responses are less to price changes for staple products (Femenia, 2019). Hence, the implications of taxes in the EU may differ.

Research on changing habits, and motivators for changing consumption have found that price can act as a facilitating or restricting factor (de Krom et al., 2020). In terms of organic food consumption, price, safety, taste, healthiness, appeal and convenience are considered as important factors (Vieux et al., 2018). Although, individual price perception may differ amongst consumers, and price nor taste are always the deciding factor (Dagevos, 2005).

Studies find that alternative meat sources are more price sensitive than regular meat consumption, which ranges from price inelastic to price elastic depending on the meat type (Ritchie et al., 2018). While food prices are an important determinant of consumption patterns, an excessively high food price may negatively impact health and nutritional status of poorer people (Green et al., 2013). Therefore, food policies require to be supported with evidence to indicate the consumer will benefit from these, as they

can both facilitate a change to a healthy or unhealthy diet.

### **2.8.2. Campaigns**

Awareness of the link between meat consumption and climate change, as well as the link between meat consumption and health risk, are important determinants of the attitude individuals have towards consuming meat substitutes (Çoker & van der Linden, 2020). The EU has recently faced backlash in the launch of their "become a beefatarian" campaign, and the 'Proud of EU Beef' campaign, where ads call for an increase in meat consumption (European Research Executive Agency, 2020). Public awareness campaigns can provide an important role in influencing the awareness and concerns of individuals (Zhang et al., 2014). These can also support clearing up misconceptions surrounding sustainable consumption, such as sustainable consumption being more expensive by default or that only those well-off can follow sustainable diets (BEUC, 2020).

### **2.8.3. Changing the food environment**

A change in consumption practices requires consumers to change existing routines and habits. Habits are not easily altered, as there is a complex infrastructure supporting these. The food environment can be shaped to facilitate changes in consumption. This includes the convenience of accessing items, the price, availability of substitutes, the shop layout and food offering (de Krom et al., 2020). Availability of meat substitutes is an important factor in supporting dietary changes (Kyriakopoulou et al., 2019), while high prices of substitutes are considered a barrier. This can be influenced through regulation of food prices, amongst others (TAPPC & DVJ Insights, 2020). The EU can also influence the product marketing of plant-based substitutes through influencing the labels and names that can be used for these substitutes. Action at several levels, including regulation, is required to alter the food environment (pricing, availability, marketing) to facilitate the adoption of sustainable diets (BEUC, 2020).

### **2.8.4. EU Policy mandate and contextualisation**

It is important to understand the political decision-making in the EU, as the mandate (power) for policy-setting at the European level differs from that at national level. The EU consists of 27 member states, with policymaking in the EU occurring across four key EU institutions; the European Commission, the European Parliament, the Council, and the European Court of Justice as laid down in the EU Treaties (European Union, 2016a). This creates a complex multi-actor system; where actors as member states may have different priorities, may not agree on the proposed solutions, and no single actor can impose their solution on the others (Enserink et al., 2010). Decision-making in the EU, as outlined in Figure 2.5 involves all European institutions. The heads of states and governments decide on general political priorities and objectives, the Commission submits legislative proposals to the EU Parliament, and the Parliament together with the Council of Ministers examines and adopts the proposed laws. The Commission, as executive branch of the EU, also checks whether member states follow the laws decided at EU level, and evaluate impacts of the EU laws, while the EU Court may settle disagreements.

Proposals go through up to three readings in the EU Parliament and Council before they are adopted and become official. Legislation can be classified as regulation/directive, decision or recommendation. Regulations are legislative decisions which must be implemented the same manner by each Member State, directives are EU laws that are transposed into national law, decisions are aimed at specific organisations or individuals, while recommendations are non-binding policies (also known as soft laws) (European Union, 2016b).

Actions by the EU are founded on the Treaties, which have been approved by all EU member countries (European Union, 2016a). Policy areas have to be cited in the Treaties for the Commission to propose laws in this area. Under these Treaties, the EU is able to adopt legislation, which the member countries then implement (European Union, 2016a). Regarding meat pricing, for example, under the Treaties the EU can mandate or facilitate a tax on meat consumption through excise duties similar to those on alcohol, tobacco or fuels. The EU can mandate a minimum excise duty to harmonise taxes in Member States. The EU can also use VAT as a tax tool, change the level of subsidies provided to meat production (TAPPC & DVJ Insights, 2020), conduct campaigns or harmonise food labelling practices. The EU can support coordination of national taxation. The EU can do studies, impact assessment, evidence gathering, to support EU and coordinate national interventions (European Union, 2016b). These types of policies would each have to go through the decision-making mechanism as shown in Figure 2.5, with a multitude of stakeholders and actors which are required to be involved and consulted.

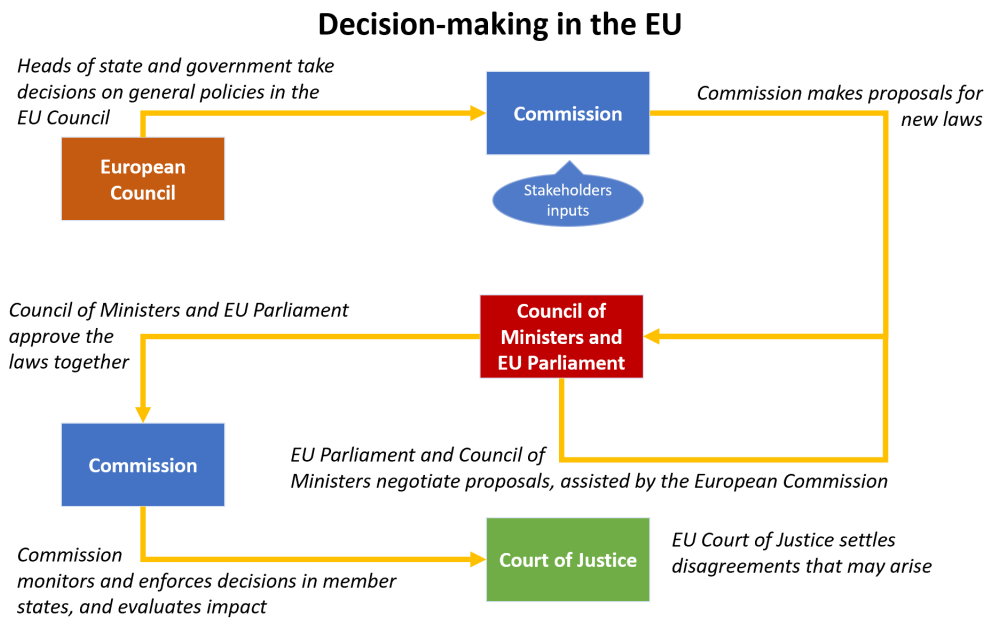


Figure 2.5: Stages of decision-making in the European Union, including the four key institutions: the European Commission (consulted by stakeholders), European Parliament, the Council and the European Court of Justice based on information from the official European Union website (European Union, 2016b). (Source: Author)

These complex multi-level actor decision-making arenas will not be investigated in this study, however, they will be reflected upon in the light of the policy implications derived from this research (Enserink et al., 2010). This research will focus on the nature of the policies that the EU can be implemented to influence social norms and meat consumption, and does not go in-depth into an actor analysis. This requires the assumption that policies can be directly implemented by national governments, which flattens the multi-level organisational decision-making aspect of the European Union. Therefore, in choosing the modelling paradigm, the various actors present at the various national levels do not have to be considered.

## 2.9. Choice of modelling paradigm

The modelling paradigm chosen to simulate a system has an influence on the results derived from this model (Diallo, Lynch, Padilla, & Gore, 2016), and governs the method a system is described in terms of available input parameters. The modeling paradigm thereby reflects the various ways a system can be represented (Lynch & Diallo, 2015), functions as the driving "mindset for modeling" supporting the model design (Hardebolle & Boulanger, 2009), and embodies the assumptions of communities, concepts practices and underlying values for each paradigm (Diallo et al., 2016). Therefore, the choice of modelling paradigm is important as it not solely is a tool which lends itself to the task at hand, but also shapes the narration and thought process behind model construction. Meat consumption has been modelled in several ways.

The majority of models on the topic of food consumption are integrated assessment models, which have found that the social norm effect and self-efficacy are the main drivers of widespread dietary changes (Eker, Reese, & Obersteiner, 2019). Several models use economic demand elasticity models (Green et al., 2013), such as the model by Ritchie et al. (2018) which demonstrates that meat substitutes can help reduce GHG emissions (Ritchie et al., 2018). Other modelling techniques include Life Cycle Assessments (Broeks et al., 2020; Moberg, Walker Andersson, Säll, Hansson, & Rööb, 2019), multinomial logistic regression models (Malek, Umberger, & Goddard, 2018; Pachucki, Jacques, & Christakis, 2011), stage-based models of consumer behaviour change (Klößner, 2017), dynamic models (Broeks et al., 2020), and linear optimisation models (G. Horgan, Perrin, Whybrow, & Macdiarmid, 2016).

An important aspect which these modelling techniques do not take into account is that meat consumption can be viewed through the lens of Complex Adaptive Systems (Holland, 2006). Diets are



governed by a multitude of factors, including a person's age, gender, socio-economic status, beliefs, religion, environment, social norms, peer group and more (Renner et al., 2012). As such, dietary consumption can be viewed as a Complex Adaptive System (CAS); where social norms and dietary choices are the result of the interaction of many agents and their environment (Holland, 2006). One of the emergent behaviours which arises from the interaction of networks of agents in society are social norms (Scalco et al., 2019), which in turn influence the dietary choices of individuals, both consciously and subconsciously. Important relevant properties of Complex Adaptive Systems to meat consumption are emergent behaviour, context dependency and self-organisation.

Firstly, emergent behaviour is a property of meat consumption, which occurs where the behaviour of a complex adaptive system as a whole contains new characteristics as outputs which cannot be attributed to individual components (Holland, 2006). There is no linear causal relation between individual psychological determinants and consumption behaviour. Patterns of food consumption can be viewed as a collective practice, influenced by factors at several socio-ecological levels (Olstad & Kirkpatrick, 2021). Eating patterns, therefore, are an emergent property. This emergent behaviour is also observed in commercial food systems, where the drive for continuous growth and profits leads to an emergence of aggressive marketing, regulation avoidance through lobbying, and the generation of large external, social, health and environmental costs (White et al., 2020).

Secondly, the context dependency is important in meat consumption. In many complex systems there is an elaborate hierarchical organisation, where the upper levels constrain the actions of the lower levels (Holland, 2006). Individuals are complex social actors, who are influenced by their social context (Olstad & Kirkpatrick, 2021). Individuals may not consume food based on weighing risks and benefits, but may be influenced more by the context they are situated in. Contextual barriers may exist, based on an individual's socio-economic position, and the social, cultural, political, and economic dimensions of their food environment (Delormier, Frohlich, & Potvin, 2009; Olstad & Kirkpatrick, 2021; WHO, 2010). This context dependency influences the impact of social network interventions, as individuals may be more susceptible to their peers (Tommasetti et al., 2018), may care more about health, environment or ethical concerns (Hopwood et al., 2020), or may be driven by external factors.

Finally, food systems exhibit another characteristic of complex adaptive systems; self-organisation. Food systems incorporate large and complex interdependent networks of entities within agriculture, fisheries, food processing and production, storage and distribution, wholesale and retail, preparation and marketing of raw, processed and ready to consume foods. These networks are supported by national and global logistics, financial systems, and agreements on trade and regulatory frameworks (White et al., 2020). In the EU, the food chain involves 13 million enterprises and 29 million workers (Rachele, 2020). These food systems both influence and are influenced by consumption choices of individuals. The food system also adapts to rules and regulations, thereby making it possible to implement policy interventions, such as fiscal policies, which act as levers to change the structure of the whole system (White et al., 2020).

These characteristics, the emergence of social norms (Zia et al., 2019), context dependency (Olstad & Kirkpatrick, 2021) and self organisation (White et al., 2020), make meat consumption a complex adaptive system. The model is required to capture this emergence, and to allow for a heterogeneity in the population which is responsible for the emergence of the social norms. This makes agent-based modelling a suitable technique to model these characteristics.

Agent-based modelling is a modelling technique which simulates the actions and interactions of autonomous agents, with the goal of observing the individual impacts of their behaviour on the system as a whole (Reynolds, 1987). Social norms, as previously discussed, are an emergent behaviour which arises from interactions within social networks. This phenomenon has been researched through agent-based models and social-anthropological studies, a modelling technique which focuses on situations where individual actions by agents have an impact on the overall system behaviour. This research will primarily build on the models of Scalco et al. (2019) and findings by Thomopoulos et al. (2019) and Zia et al. (2019).

The model by Scalco et al., simulates the meat consumption of people in the UK and looks at the influence of eating networks on consumption (Scalco et al., 2019). Here, agents were represented as individual consumers, with variables investigated including sex, age, monthly income, perception of living cost, concerns about the impact of meat on the environment, health, and animal welfare. The mean weekly meat consumption and likelihood of eating meat were investigated in this study. This provides a useful baseline model to calculate the likelihood to consume meat, based on the results of

a regression model (Scalco et al., 2019).

The second model by Thomopoulos et al. (2019) investigates the impact of messaging types on the choice to change food diets at an individual level. Networks of arguments surrounding vegetarian diets were modeled, with each argument formalized as a node and connected with other arguments. This model helps explore the interplay of individual values and external influences as social pressure, communication campaigns, and sanitary, environmental and ethical crises (Thomopoulos et al., 2019).

Finally, the agent-based model of Zia et al. (2019) investigates the resistance against unpopular norms. Currently, in society going against meat-consumption can be seen as promoting an unpopular norm. While resisting certain unpopular norms can be beneficial, as is the case in unjust societies, there can also be a resistance to unpopular norms which are beneficial to society such as reducing flying and reducing meat consumption. Throughout society there is an unpopular norm aversion, which needs to be addressed. These models form a solid foundation to build research on, and look at how governments can play a role in spreading beneficial norms using public policy; a crucial aspect which has not been covered by these models.

## 2.10. Summary literature review

The literature review has covered important aspects to meat consumption, including defining what a sustainable diet is (Burlingame, 2012; Willett et al., 2019), discussing the main factors influencing meat consumption (Hopwood et al., 2020), role of social norms and social networks (Scalco et al., 2019; Zhang et al., 2014), behavioural theories with a focus on the Theory of Planned Behaviour (Ajzen, 1991), and EU policies (European Union, 2016a). The main findings from each Section and take-aways are discussed in this summary.

A sustainable diet is "protective and respectful of biodiversity and ecosystems, culturally acceptable, accessible, economically fair and affordable, nutritionally adequate, safe and healthy, while optimizing natural and human resources" (Burlingame, 2012). Current diets are not sustainable, with dietary changes capable of reducing dietary emissions by 50%-78% (Perignon et al., 2017), with changes in all instances requiring reducing meat consumption (Vieux et al., 2018). Changing towards a more sustainable diet requires individuals to change their meat consumption. The three main factors influencing meat consumption are: health, environment and ethical/animal welfare concerns (Hopwood et al., 2020). Other important factors include price, social norms, social image, habits, hunger, liking, convenience, pleasure, tradition, nature, sociability, visual appeal, weight control and affect regulation (Renner et al., 2012).

The social eating norms will cause individuals to subconsciously imitate those around them (Muñoz & Marselis, 2016), with norms spreading within social networks. Peer networks in households have a more significant impact on individuals than co-workers (Macdiarmid et al., 2016). Social norms are currently underutilised as policy lever. They can be implemented through nudges influencing choice heuristics (e.g. layout of food in supermarkets and portion sizes), or through targeting norms in networks through campaigns (Savarimuthu et al., 2012). The main perceived barriers to sustainable consumption include price, lack of information, and availability of substitutes (BEUC, 2020). Other important barriers include the perception of meat and meat substitutes (Michel et al., 2021). Habitual food consumption comprises close to half of total food consumption (Naik & Moore, 1996), with habitual change being influenced by positive experiences. Internal factors influencing experience include previous behaviour, identity, beliefs and values (DeJesus et al., 2015), while external factors include affordability, availability, accessibility and attractiveness (Muñoz & Marselis, 2016).

There are several promising behavioural theories to explain the important consumption aspects, including the Theory of Planned Behaviour (TPB) (Ajzen, 1991), Extended Theory of Planned Behaviour (ETPB) (Alam et al., 2020), and Value-Belief Norm Theory (VBN) (Stern et al., 1999). Research showed that awareness of the links between meat consumption and climate change and health risks are significant determinants of attitudes (Çoker & van der Linden, 2020), which influences intention and behaviour. This research follows the TPB, which explains behaviour through attitude towards the behaviour, subjective norm, and perceived behavioural control (Ajzen, 1991).

To influence the meat consumption, several EU policies were found to be of relevance, including food pricing (de Bruyn et al., 2018; TAPPC & DVJ Insights, 2020), campaigns (Çoker & van der Linden, 2020), and changing the food environment (BEUC, 2020; Kyriakopoulou et al., 2019; TAPPC & DVJ Insights, 2020). Meat consumption can be viewed as a Complex Adaptive System (Holland, 2006), with the main properties being emergent behaviour (Olstad & Kirkpatrick, 2021), context dependency (Olstad & Kirkpatrick, 2021), and self organisation (White et al., 2020). The presence of emergence and heterogeneity in the population, which determines social norms and consumption, makes agent-based modelling an appropriate modelling tool.

An agent-based modelling approach was chosen as an appropriate method to model the problem at hand. Social norms are not embedded in the system, but are dynamic and emerge based on the interactions between agents and spread through social networks (Macdiarmid et al., 2016; Savarimuthu et al., 2012). While interactions occur, in reality each person is also different and has their own identity. To come closer to modelling the individual aspect of it, agent-based modelling offers the possibility to generate individuals who all have their own agent profile. The model in the present study is based on the Theory of Planned Behaviour (Ajzen, 1991), and should at least take the factors of health, the environment and ethics into consideration (Hopwood et al., 2020). Other important factors include the social norms surrounding meat consumption (Higgs, 2015; Muñoz & Marselis, 2016), and price (Renner et al., 2012). The policies to be investigated are to include changing the food environment, food pricing, and implementing campaigns. Figure 2.6 indicates the factors which will be included and focused on in this research, and highlights those that will not be considered. The literature review indicates that

the included factors, and aim to capture the complex essence of this problem, but it is important to recognise that results and findings of this research will be influenced and limited by these choices.

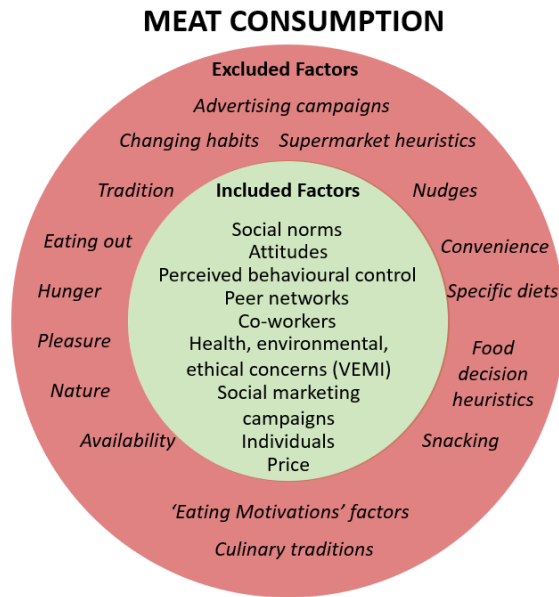


Figure 2.6: Factors included in the research with relation to meat consumption (green circle), and factors which did not fit in the scope and focus on this study (red circle) (Source: Author)

# 3

## Methodology

The literature research provided the theoretical lens through which this research will be conducted. The Theory of Planned Behaviour (TPB) (Ajzen, 1991) will be used as behavioural theory to determine the intention of individuals to consume meat and substitutes. The parameterisation of meat consumption is conducted through the Data Analysis using Python, as described in Chapter 4. This analysis includes the data gathering for constructing a representative population, and an analysis of various surveys using logistical regression to determine the likelihood to consume meat. The findings from this analysis are used for the model specification in NetLogo, which includes defining a model rule for meat consumption and providing the input for population generation, and is described using the ODD Protocol in Chapter 5. This model is validated in Chapter 6, and used to run experiments which for which the results are analysed in Python, and provided and discussed in Chapters 7 and 8 respectively. The outline of this method is shown in Figure 3.1.

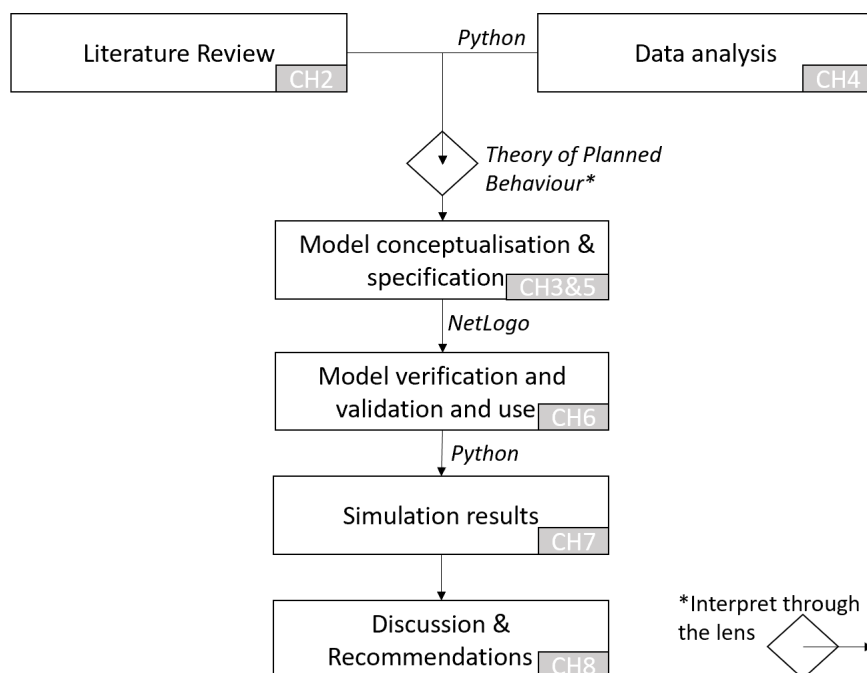


Figure 3.1: Conceptual diagram showing the components of this research and relation between these components, with the Theory of Planned Behaviour (Ajzen, 1991) theory used as theory lens (indicated by diamond) and software packages used including Python and NetLogo (in italics) (Source: Author)

This chapter will discuss the steps taken to synthesise the findings from literature, and expand upon the methods of data collection, and modelling. The modelling approach follows the iterative modelling cycle of Slinger et al. (2008), as seen in Figure 3.2. This approach highlights the steps taken in the

modelling process: a convergent analysis from the problem description, conceptualisation, followed by model specification, and alter a divergent analytical approach. This iterative process allows for reflecting on choices made during the modelling process, and served to improve the model throughout (Slinger et al., 2008).

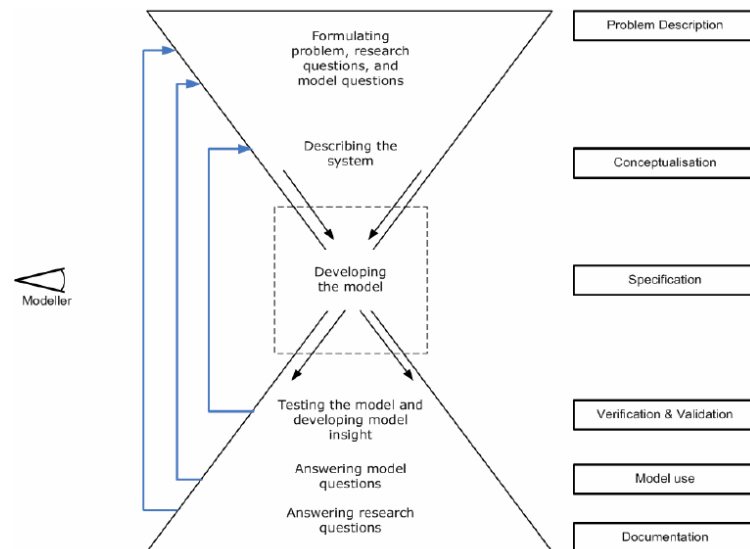


Figure 3.2: Convergent and divergent analytical approach to the modelling cycle with the model as the focal point, taken from Slinger et al. (2008).

The literature reveal of Chapter 2 revealed important gaps in the understanding; namely the way and extent to which social norms influence meat consumption. This resulted in the problem formulation "How do social norms influence meat consumption and to what extent can European policy influence these to reduce meat consumption?".

The key findings from the literature which need to be considered are: (a) Meat consumption can be viewed as a complex adaptive system (Olstad & Kirkpatrick, 2021; White et al., 2020), (b) the main factors influencing meat consumption are health, environment and ethical concerns, (c) other important aspects include price, and social norms, (d) social norms play an important role and spread through networks.

These findings have motivated this research to develop an Agent-Based model based on the model of Scalco et al. (Scalco et al., 2019), with a focus on the spreading of social norms through networks (Tommasetti et al., 2018; Zhang et al., 2014). The model will be grounded in the Theory of Planned Behaviour (Ajzen, 1991), which was chosen as it takes the influence of social norms into account, and includes factors which can be derived from the surveys utilised in this study.

This research will investigate the influence of EU policy on social norms and meat consumption through an agent-based model. The EU as a whole consists of 27 countries, with each their heterogeneous populations, traditions, cultures, and dietary consumption. As it is not feasible within the scope of this study to investigate each EU country, a case-study approach is taken where one country is focused on. The model conceptualisation, parameterisation and results will be based on the case-study, with the utility of this being reflected on in the discussion.

### 3.1. Case-Study: The Netherlands

The Netherlands has been chosen as a case-study for this research. The reasons for this are threefold: (1) it is a European country, (2) substitute meat consumption is more widespread here, (3) regular meat consumption recently increased. Individuals in the model, therefore, are required to follow the population demographics for the Netherlands.

Data specific to the Dutch population is required for this case-study. This requires the following types of data: population demographics, information about the Dutch population with regards to the Theory of Planned Behaviour, and actual protein consumption by the Dutch population.

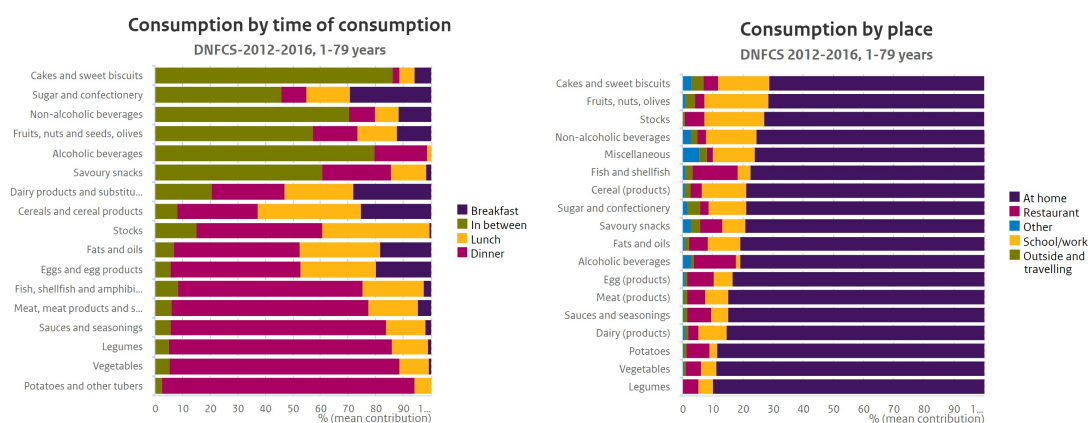
### 3.1.1. Population Demographics

The population demographics for the Netherlands are based on survey findings from the Central Bureau for Statistics (CBS). This database provides information on the Dutch population based on their sex, age, and level of education amongst others. The StatLine database combines survey data and metadata from the CBS and the 'Rijksinstituut voor Volksgezondheid en Milieu' (RIVM). Here, data on the Dutch National Food Consumption Survey (DNFCS) 2012-2016 provides information related to the actual protein consumption by the Dutch population (RIVM, 2020a, 2020b). An overview of the surveys used can be found in Table 3.1.

Table 3.1: CBS and RIVM Datasets for population demographics

Name of survey	Code	Source
Consumer Price Index 1996-2015	71311ENG	CBS
Population; education level; gender; age and migration	82275NED	CBS
Households; size and composition	82905NED	CBS
DNFCS 2012 - 2016: Mean contribution (%) of moment to a food group	50070NED	RIVM
DNFCS 2012 - 2016; consumption	50038NED	RIVM

The DNFCS shows that the Dutch population consumes the 93.9% of meat during either breakfast (4.6%), lunch (18%) or dinner (71.3%). The location of this consumption is primarily at home (84.7%) or at the workplace (7.5%), with these accounting for 92.2% of total meat consumption. This consumption distribution can be found in Figure 3.3a and Figure 3.3b for consumption by time and place respectively.



(a) Consumption for various food types in the Netherlands by time of consumption (breakfast, lunch, dinner or in-between), as taken from the Dutch National Food Consumption Survey (RIVM, 2020a). (b) Consumption for various food types in the Netherlands by place (at home, work, restaurant, while travelling or other), as taken from the Dutch National Food Consumption Survey (RIVM, 2020b).

Figure 3.3: Results from the Dutch National Food Consumption Survey 2012-2016, for the various food types in the Netherlands by both time of consumption and place.

Given these findings of the Dutch population, the model will focus on meat consumption during these three meal times, and look at consumption within households and at work. This assumption thereby disregards consumption in-between meals, accounting for 6.2% of meat consumption, and consumption at restaurants (5.9%) (RIVM, 2020a). This focus gives individuals more control over their meal choice.

### 3.1.2. Parameters of importance - TPB

The parameters of importance related to meat consumption and the Theory of Planned Behaviour (Ajzen, 1991) for Dutch consumers was determined through analysing various surveys. This research makes use of the data of the LISS (Longitudinal Internet studies for the Social Sciences) panel administered by CentERdata (Tilburg University, The Netherlands). The main survey sources include the 'Reasons to Eat Less Meat' LISS Panel survey, and the Belevingen 2020 survey from the CBS (CBS, 2021b).

The 'Reasons to Eat Less Meat' survey, consisting of 5742 adult respondents, includes questions as "I want to be healthy", "Plant-Based diets are better for the environment", and "Animal rights are important to me". These questions all fall into either the category of health, environment, or animal welfare, with each category containing five questions each phrased differently. The responses of this survey were combined with other LISS Panel datasets, through using the encrypted personal identifiers. The LISS Panel Surveys used are seen in Table 3.2.

Table 3.2: LISS Panel Data surveys used to determine factors of importance to changing meat consumption.

Name of Survey	Code	Type	Year
Reasons to Eat Less Meat	oi18a	Single Wave	2018
Background variables	avars_201807	Single Wave	2018
Health	ch18k	Longitudinal	2018
Personality	cp18j	Longitudinal	2018
Politics and Values	cv18j	Longitudinal	2018
Hope Barometer	nq18a	Longitudinal	2018

This combined dataset was analysed to determine the importance of various parameters to an individual's frequency in meat consumption. The factors which were found to be correlated to changes in diets were taken from the surveys, and used in a logistical regression. This regression analysis determines the importance and relevance of each factor with regards to reducing meat consumption, where reduced consumption is defined as consuming meat less than 4 days per week. The logistical regression on these diets indicate that environmental, ethical and health factors are statistically significant predictors ( $p < 0.05$ ) for dietary consumption, along with age, gender, education, income level and occupation. An in-depth analysis of this data can be found in Chapter 4.

### 3.1.3. Modelling specific meat consumption

The main protein sources consumed in the Netherlands were identified from the Dutch National Food Consumption Survey (DNFCS), and are classified as: Beef, pork, poultry, processed meat, and meat substitutes. These make up on average 92.2% of daily meat consumption for the total Dutch adult population (RIVM, 2020b). As individuals typically won't stop eating meat directly based on individual concerns, but are more likely to change the type of meat they consume, it was chosen to model the likelihood to consume each type of meat which is calculated through a least-squares multiple linear regression model (James, Witten, Hastie, & Tibshirani, 2013).

The likelihood to consume specific meat types uses the parameters of importance; health, climate and environmental concern. During meal times, individuals will have a probability to consume specific meat types and based on this will randomly consume one of these. The dis-aggregation of meat consumption in meat types means there is a distinct chance of consumption for each meat type. This is conceptualised in Figure 3.4.

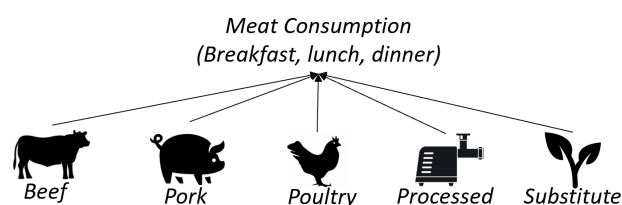


Figure 3.4: Illustration of meat consumption types (Source: Author)

This assumes that individuals, when consuming meat, will always consume one of beef, pork, poultry, processed meat or meat substitutes. The likelihood to consume a specific meat type follows a similar principle used by Scalco et al. (2019), who calculated the likelihood to consume meat through a logistical regression on the British Food Survey. This research project uses the Belevingen 2020 CBS survey (CBS, 2021b), along with the Dutch National Food Consumption Survey (RIVM, 2020b).

The Belevingen 2020 survey (CBS, 2021b) provides how important individuals find specific reasons to reduce meat consumption (e.g. climate, health, animal welfare, taste, meat being too expensive,



housemate influence or other reasons). This dataset is aggregated for various populations groups; age groups, gender, education level and level of urbanisation. The DNFCs (RIVM, 2020b) uses the same population groups as the Belevingen 2020 survey (CBS, 2021b), and provides the actual consumption of each meat type per population group, and per meal time. Combining these datasets at this level allows for using a multiple linear regression (James et al., 2013) model to calculate the likelihood to consume meat types based on health, environmental, and animal welfare concerns. This in-depth calculation is performed in Chapter 4.

These three factors were chosen as according to both studies in literature and a data analysis conducted for this study they are the most important (Hopwood et al., 2020), and are statistically significant. While this does not provide a full picture of all aspects influencing consumption, these factors depend on the individual profiles (age, sex, education), and are factors which exist in more European countries.

### 3.2. Choice of Key Performance Indicators

The primary concern of this study is to evaluate the influence of social norms on meat consumption, and the role of the EU in influencing meat consumption, to reduce the environmental impact of individuals. Therefore, it is not sufficient to solely investigate the quantity of meat consumed, but also determine which type of meat is consumed and what the emissions associated with this consumption are. This results in the two KPIs: Meat consumption, and environmental emissions.

Meat consumption is dis-aggregated into the main types of meat consumption. These include beef, pork, poultry, processed meat and meat substitutes, which combined account for 92.2% of total meat consumption (RIVM, 2020b).

The environmental emissions related to meat consumption encompass more than solely the CO<sub>2</sub> emissions. While these are an important aspect, as greenhouse gas emissions directly contribute to Climate Change (International Panel on Climate Change, 2019), other environmental emissions related to meat consumption are also of importance. The emissions related to meat consumption which will be tracked are: greenhouse gas emissions ( $gCO_2eq$ ), acidification ( $gSO_2eq$ ), toxicity ( $gPeq$ ), smog ( $gNMVOC$ ), particulate matter ( $PM_{10}eq$ ). Average agricultural land use ( $m^2/kg$ ) is also tracked. These values are determined based on the calculations from the report from CE Delft (2018) following Equation 3.1. The grams of meat per individual is tracked, and multiplied by the respective emissions per each emissions type.

$$Emissions.gCO_2eq = \sum_{i=1}^5 gMeat_i * EmissionsCO_2eq.gMeat_i \quad (3.1)$$

Equation 3.1 calculates the individual emissions of CO<sub>2</sub> as the product of the grams of meat eaten from each meat type ( $i$ ) and the CO<sub>2</sub> emissions per grams of this meat type. The five meat types include: beef, pork, poultry, processed meat and meat substitutes. The example Equation 3.1 shows the example for CO<sub>2</sub>. The equations for  $gSO_2eq$ ,  $gPeq$ ,  $gNMVOC$ , and  $PM_{10}eq$  follow the same logic, while the agricultural land is divided by 1000 to match the units ( $m^2/kg$ ). The total emissions of a specific type is calculated using Equation 3.2, where total emissions are the sum of individual emissions based on their consumption as calculated in Equation 3.1. Here  $n$  is the total number of individuals in the population.

$$TotalEmissions.gCO_2eq = \sum_{i=1}^n Emissions.gCO_2eq_i \quad (3.2)$$

Policies are successful if they not only manage to reduce the overall meat consumption, but also cause the greatest reduction in environmental emissions. Governments may have a preference for reducing a particular type of emissions, therefore these KPIs allow for the tailoring of policy to the needs of actors.

### 3.3. Data analysis methods

The extensive data analysis is conducted in Chapter 4. This analysis combines the data from various surveys, and was used to determine the likelihood to consume meat at each time step of the model. This

likelihood is based on the health, climate and animal welfare concerns of the individual. The influence of these concerns were computed using a logistical regression. This section provides justification for these methods.

### 3.3.1. Correlations

Correlation research is a useful method to gather information about variables when researchers are unable to perform an experiment (Schober, Boer, & Schwarte, 2018). As it was not the focus of this experiment to conduct experiments which determine the relation between various factors and meat consumption, these relations were investigated using correlation research. This research is conducted both on surveys from the LISS panel administered by CentERdata (Tilburg University, The Netherlands), the Belevingen 2020 survey (CBS, 2021b), and Dutch National Food Consumption Survey (RIVM, 2020b).

The surveys used from the LISS Panel include the 'Reasons to Eat Less Meat', 'Health', 'Personality', 'Politics and Values', 'Hope Barometer' and 'Background variables' surveys. These were all conducted in 2018. These surveys can be combined on the unique identifier "nomem\_encr" which each survey contains. Using the opensource pandas package in Python, a dataframe containing all relevant surveys can be combined, cleaned and processed to determine correlations between variables (Wes McKinney, 2010). The Pearson (product-moment) correlation coefficient was investigated for this study using the pandas software (Wes McKinney, 2010), which measures the linear relationship between two variables (Schober et al., 2018). The Pearson correlation coefficient is the ratio of covariance of  $x$  and  $y$  to the product of their standard deviations, which can be expressed through Equation 3.3. The correlation coefficient takes a value between -1 and 1, with values greater than 0 indicating a positive correlation and smaller than 0 indicating a negative correlation (Schober et al., 2018).

$$r = \frac{\sum_i ((x_i - \bar{x})(y_i - \bar{y}))}{\sqrt{\sum_i (x_i - \bar{x})^2 \sum_i (y_i - \bar{y})^2}} \quad (3.3)$$

For this study, as correlations between individual variables and complex behaviour as meat consumption are likely to be small, any variable with a correlation greater than 0.1 was further investigated. Correlations smaller than 0.1 are typically defined as negligible by researchers, while above 0.1 would be "weak", and above 0.4 "moderate" (Schober et al., 2018). For the LISS Panel surveys, correlations were investigated with regards to the frequency of meat consumption, which has the identifier of 'ch18k200' in the 'Health' survey. The Belevingen 2020 survey (CBS, 2021b) and Dutch National Food Consumption Survey (RIVM, 2020b) were also investigated and combined at an aggregate level, in terms of age, gender, level of education, income, and urbanisation. The correlations between variables in these surveys were also investigated using the pandas software in Python (Wes McKinney, 2010). This correlation analysis is further elaborated on in Chapter 4.

### 3.3.2. Logistic Regression

Logistic regression is a method used to determine the probability of an event occurring in the face of more than a singular explanatory variable (Sperandei, 2014). This is similar to multiple linear regression, with the important distinction that the response, or dependent, variable is binomial. In the case of meat consumption, an individual will either consume meat, or they will not consume it, as consumption is dichotomous.

The logistic regression allows for the impact of each variable to on the dependent variable to be calculated, with the result being the odds ratio of an event of interest occurring (Sperandei, 2014). Through analysing all these variables together, the logistic regression has the benefit of avoiding confounding effects (Sperandei, 2014).

The logistic regression is a chance ratio, which is modelled following Equation 3.4.

$$\log\left(\frac{\pi}{1-\pi}\right) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots \beta_m x_m \quad (3.4)$$

In Equation 3.4,  $\pi$  indicates the probability that an event will occur (e.g. meat consumption), while  $\beta_i$  are the coefficients of the regression, and  $x_i$  are explanatory variables (Sperandei, 2014). The coefficients  $\beta_i$  cannot be taken as stand-alone values and used directly outside of the logistical regression, as they are only applicable when taken with respect to the reference group; the constant  $\beta_0$ .

The responses of frequency of meat consumption (ch18k200) as part of the Health survey (LISS Panel) provides the values: 1 = Never, 2 = 1-3 times per month, 3 = 1 time per week, 4 = 2-4 times per week, 5 = 5-6 times per week, 6 = every day. The logistic regression requires the dependent variable to be binary (reduce or not reduce consumption). The binary range is acquired by labelling any frequency of consumption over 5 times per week as a non-reduction, while labelling responses below 2-4 times per week as reduction. This is seen in Equation 3.5. Here 0 signifies reduction, and 1 signifies no change.

$$ch18k200 = \begin{cases} 0, & \text{if } ch18k200 \leq 4 \\ 1, & \text{if } ch18k200 \geq 5 \end{cases} \quad (3.5)$$

The logistic regression is applied in the Data Analysis (Chapter 4) to formulate the likelihood to consume specific meat types based on an individual's concerns for health, the environment and animal welfare. This builds on the formulation used by Scalco et al. (2019), who also determined the likelihood to reduce meat consumption based on a logistic regression.

### 3.3.3. Multiple Linear Regression

The multiple linear regression predicts the outcome of a dependent variable based on multiple independent predictors (James et al., 2013). This is done through providing a separate slope coefficient to each predictor in a single model. This allows the linear regression model to take the form of Equation 3.6. Here  $X_j$  represents the  $j$ th predictor, and  $\beta_j$  quantifies the relation between the variable and the response (James et al., 2013).

$$\hat{y} = \hat{\beta}_0 + \hat{\beta}_1 X_1 + \hat{\beta}_2 X_2 + \dots + \hat{\beta}_p X_p \quad (3.6)$$

In the multiple linear regression, the parameters are estimated using the least squares approach, where  $\beta_0, \beta_1, \dots$  are chosen to minimize the sum of squared residuals (James et al., 2013). This follows equation 3.7. The multiple least squares regression coefficient estimates are calculated using the 'ordinary least squares (OLS)' package in Python.

$$RSS = \sum_{i=1}^n (y_i - \hat{y}_i)^2 = \sum_{i=1}^n (y_i - \hat{\beta}_0 - \hat{\beta}_1 x_{i1} - \hat{\beta}_2 x_{i2} - \dots - \hat{\beta}_p x_{ip}^2) \quad (3.7)$$

The multiple linear regression was chosen to determine the likelihood of consuming each meat type. Consumption of the meat types follows a certain probability, which is determined using the survey data from the Dutch National Food Consumption Survey (RIVM, 2020b) and Belevingen 2020 survey (CBS, 2021b). The DNFCS provides the probability of consuming meat types as a percentage. This results in a continuous factor, which cannot be calculated using logistic regression as this required binary outputs of the dependent variable. This differs from the formulation by Scalco et al. (2019), who used a logistic regression to determine the overall likelihood to consume meat. In this research, we are interested in quantifying the impact of each meat type, and changes in consumption.

Combining the Dutch National Food Consumption Survey (RIVM, 2020b) and Belevingen 2020 survey (CBS, 2021b) allows us to use multiple linear regression and split meat consumption into five different categories which account for over 90% of meat consumption: beef, pork, poultry, processed meat and meat substitutes (RIVM, 2020b). The regression coefficients determine the importance of factors in the Belevingen 2020 survey on the probability of consuming each meat type taken from the DNFCS survey (RIVM, 2020b), These are then used in the agent-based model to calculate the likelihood to consume each meat type at each eating moment.

## 3.4. Experimental Design

The generation of scenarios and policies depends on the purpose of the model, and the processes that are investigated. The purpose of this model is to better understand the influence of social norms on meat consumption, and the role policy can play in influencing meat consumption.

### 3.4.1. Scenarios

Agent-based models allow for analyzing various scenarios (Lempert, 2002). These scenarios are based on different concepts on the current state of affairs in the world. Three different scenarios were envisioned to be explored in this model. The first is the base-case scenario, where the population is generated to be representative of the Dutch population and their concerns. The second scenario envisions a climate crisis, which results in heightened environmental concern within the general public in the Netherlands. Higher environmental awareness is a likely scenario, as consumers are already becoming more and more concerned about the environment (CBS, 2021b). However, meat consumption has also seen a slight rise in recent years (WUR, 2019), therefore it is interesting to gauge how important concern is by itself. The third scenario is one where consumers are highly susceptible to influence by factors in their daily lives. This represents the over-consumption and influence of social media, reading news articles, and changing lives and opinions more readily. These scenarios are summarized in Table 3.3.

Table 3.3: Summary of scenarios including the current situation in the Netherlands (Base-case), a scenario where environmental concerns are heightened due to climate change concerns (High Environmental Concern) and a scenario where individuals are more susceptible to external influences (High Susceptibility) (Source: Author)

Scenario	Description
Base-Case	An agent population based on the population of the Netherlands, following population demographics data taken from CBS, the DNFCS, Belevingen 2020 and StatLine
High Environmental Concern	The base-case scenario with the Environmental concern following a distribution with a mean of 20 points higher
High Susceptibility	The base-case scenario with the p.ext.max.source being 5 rather than 0.5 as in the base-case.

The base-case scenario uses values determined and specified in the model specifications of Chapter 5. The High Environmental concern scenario, when generating the population, shifts the distribution of environmental concerns in the population by 20 points. This shift is based on the difference found between meat eaters and vegetarians from the Reasons to Eat Less Meat survey, as outlined in 4. The High Susceptibility scenario increases the susceptibility to external influences (p.ext.max.source), which has been investigated as part of a sensitivity analysis in 6. The base-case uses a value of 0.5, while the high susceptibility uses 5, which reflects a population which is more susceptible to external influences than to peers.

### 3.4.2. Policies

The behaviour of meat consumption is driven by the intention to consume specific meat types, according to the TPB (Ajzen, 1991). This intention is influenced by the attitude, social norms and perceived control. Policies targeting the reduction in meat consumption can, therefore, focus on one or more of these aspects. There are many different policies which could be performed at national and at the European level, such as improving public awareness on the impact of meat consumption through social marketing campaigns (BEUC, 2020; Çoker & van der Linden, 2020), implementing food labelling (European Commission, 2020), changing the food environment through taxation of meat (de Bruyn et al., 2018; TAPPC & DVJ Insights, 2020), improving price and/or availability of substitutes (de Krom et al., 2020; Kyriakopoulou et al., 2019), subsidising sustainable foods (Kyriakopoulou et al., 2019), implementing regulations on marketing (BEUC, 2020), fixing portion sizes in supermarkets (Rubens & Vandenbroe, 2017a), amongst others.

This study focuses on two key policies: social marketing campaigns, and food pricing. These two policies were chosen as they directly relate to the factors found to be relevant through the literature search, applying the Theory of Planned Behaviour and data analysis.

Social marketing campaigns can focus either on promoting the health aspect, environmental concerns, animal welfare concerns, or a combination of these. This is modelled following the approach of Zhang et al. (2014). These influence of these campaigns decay over time (Scalco et al., 2019), and will have a certain level of success. This is further elaborated on in the ODD Protocol in Chapter 5.

Concerns appear to be strongly correlated to the level of education of individuals, where a large disparity can be seen both in meat consumption and environmental awareness (CBS, 2021b; RIVM,

2020b). The environmental concern for highly educated individuals is up to 60%, while the environmental concern for the lower educated population is between 10-20%. Therefore, social marketing campaigns may have a different level of success depending on what section of the population is targeted (Scalco et al., 2019), which will be investigated in this project through running experiments targeting either the general or lower educated population.

Food pricing is a policy which can be implemented either through taxing specific meat types, taxing all meat, or subsidising meat substitutes. Meat types are not all equally polluting, therefore it is interesting to see how individuals will change their consumption based on taxation policies. One of the characteristics of sustainable diets are that they are 'economically fair and affordable' (Burlingame, 2012). Excessive taxation of all meats without providing any alternatives thus does not promote a sustainable diet.

To determine the effect of taxation on food consumption, it is required to understand the price elasticity of demand of meat types. Price will both influence the behavioural control (Ajzen, 1991), and change consumption. This is further elaborated on in the ODD Protocol in Chapter 5. The policies investigated are applied individually to each scenario. There are six distinct runs per scenario. These policies are compared to 'no policy', which takes the settings as initialised in the scenario without any policy active. The policies to be compared are one where beef is taxed with 20%, where beef is taxed by 20% and meat substitutes are subsidised by 20%, a generic tax of 20% on all meat excluding substitute, and the social marketing campaigns. The 20% tax rate was used to compare this study to findings of other studies, and increase the VAT of meat which is at 6% to above the current 21% of other food products (Broeks et al., 2020). A summary of the policies are provided in Table 3.4.

Table 3.4: Summary of policies (A-F) tested for each simulation scenario (1-3), and settings of parameters in the simulation experiments for each of the policies, with tax specified for the meat types and campaigns focused on population groups (Source: Author)

<i>Factors</i>		<i>Policy Model Settings</i>		
<i>Simulation scenarios</i>	<i>Policies</i>	<i>Tax (price)</i>	<i>Campaigns</i>	<i>Policy</i>
1. Base-Case	A. No Policy	Off	Off	A
2. High Env. Concern	B. Tax on beef	On (+20% beef)	Off	B
3. High Susceptibility	C. Tax beef, Sub substitutes	On (+20% beef, -20% substitutes)	Off	C
	D. Tax on meat	On (+20% all meat)	Off	D
	E. Env. social marketing campaign: general audience	Off	On (Env, $\gamma = 0.75$ )	E
	F: Env. social marketing campaign: lower educated	Off	On (Env, $\gamma = 0.75$ )	F

### 3.4.3. Experimental Set-up

The experimental set-up includes determining the number of repetitions, outcomes to be investigated and initial conditions of the experiments.

The required number of repetitions was calculated following the methodology used by Van der Wal et al. (2017) and Lee et al. (2015). The number of repetitions for each combination of policies and scenarios are determined by running the scenario combination with most variability 1000 times. In this case, the combination consists of the 'high susceptibility' scenario with no policy active showed most variability when visually inspected. The cumulative averages and variances in beef consumption and environmental concern are inspected to determine the threshold number of repetitions at which these samples stabilise (Van der Wal et al., 2017). This is achieved through both a visual inspection of the average cumulative sum of beef consumption and health concerns, as shown in Figure 3.5 for which the average of the cumulative sum is calculated using Equation 3.8.

$$y_k = \frac{\sum_{i=1}^k x_i}{k} \quad (3.8)$$

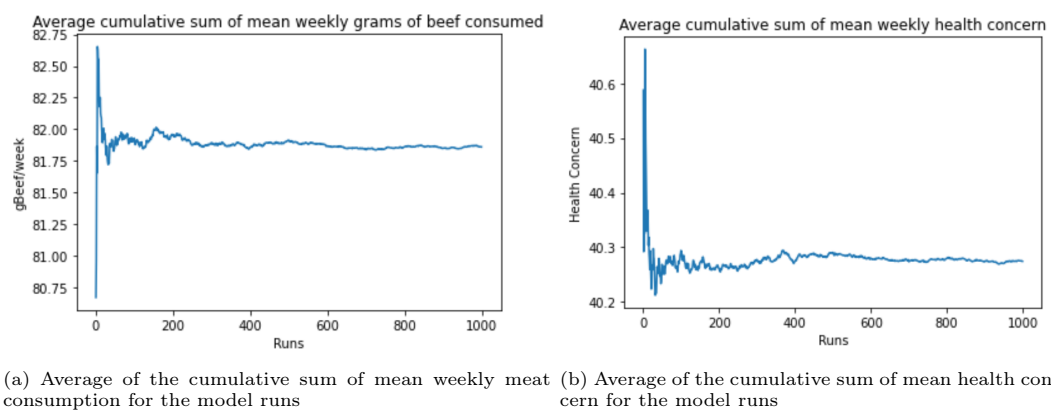


Figure 3.5: Average of cumulative sums from 1000 model runs for the High Susceptibility scenario with no policies active (Source: Author)

Figure 3.5 shows that variability reduces with increasing the number of runs. This variability, however, does not appear to stabilise until around 500 runs. However, it should be noted that the range of outcomes does not vary significantly, with outcomes varying between 3.6% for beef consumption and 1.5% for health concerns. The minimum sample size can be mathematically determined following the methods of Law and Kelton (2007), and Lorscheid et al. (2012) as described by Lee et al. (2015). The method to determine the minimum number of runs is determined through determining at what point the coefficient of variation ( $c_v$ ) remains within a fixed criterion, epsilon ( $E$ ). The coefficient of variation is the ratio of the standard deviation of the sample ( $\sigma$ ) and its mean ( $\mu$ ), as shown in Equation 3.9 (Lee et al., 2015).

$$c_v = \frac{\sigma}{\mu} \quad (3.9)$$

The coefficient of variation is compared for different length model runs, to determine the point at which the consecutive  $c_v$ 's fall to below the criterion  $E$  (Lee et al., 2015). The minimum number of runs, therefore, following the method by Lorscheid et al. (2012) is calculated using Equation 3.10.

$$n_{min} = \operatorname{argmax}_n |c_v^{x,n} - c_v^{x,m}| < E, \forall x \text{ and } \forall m > n \quad (3.10)$$

This has been tested for various sample sizes ( $n \in \{10, 30, 50, 100, 200, 500, 1000\}$ ). The outcomes for the coefficients of variation and absolute difference between these for consecutive sample tests are outlined in Table 3.5. This results in a minimum sample size of over 1000 for the High Susceptibility scenario.

Table 3.5: Number of experimental runs ( $n$ ) with the associated mean ( $\mu$ ), standard deviation ( $\sigma$ ), coefficient of variation ( $C_v$ ) and change in this coefficient for subsequent run numbers ( $\Delta C_v$ ) for beef consumption in the "High Susceptibility" scenario (Source: Author)

$n$	$\mu$	$\sigma$	$C_v$	$\Delta C_v$
10	82.18	1.91	43.01	-
30	81.81	1.78	55.34	12.3
50	81.91	1.46	56.24	0.91
100	81.93	1.41	58.29	2.1
200	81.95	1.50	54.80	3.5
500	81.91	1.51	54.38	0.41
1000	81.86	1.54	53.16	1.2

This similar analysis was conducted for the 'high environmental concern' scenario, where stability also was not obtained after 1000 runs, as seen in Table 3.6. Variance stability, therefore, is not achieved within the model runs. However, a clear drop in variance is observed when running more than 50 runs. It appears as if stability is reached at 500 runs, however, the change of coefficient of variation does not continue to decline after 500 runs. Therefore, while variance stability is not achieved, running experiments with 50 runs is sufficient to achieve results with values for the mean and std being within 1% of 1000 runs.

Table 3.6: Number of experimental runs ( $n$ ) with the associated mean ( $\mu$ ), standard deviation ( $\sigma$ ), coefficient of variation ( $C_v$ ) and change in this coefficient for subsequent run numbers ( $\Delta C_v$ ) for beef consumption in the "High Environmental Concern" scenario (Source: Author)

$n$	$\sigma$	$\mu$	$C_v$	$\Delta C_v$
10	82.57	0.89	92.63	-
30	82.75	1.23	67.03	25.6
50	82.86	1.19	69.67	2.64
100	82.99	1.15	72.03	2.36
200	83.10	1.21	68.68	3.35
500	83.03	1.21	68.43	0.25
750	83.04	1.19	69.92	1.49
1000	83.05	1.16	71.86	1.94

The outcome measures are based on the KPIs which, as discussed in Section 3.2, are meat consumption and emissions. Meat consumption is split up in beef, pork, poultry, processed meat and meat substitutes. Emissions are split into greenhouse gas emissions ( $gCO_2eq$ ), acidification ( $gSO_2eq$ ), toxicity ( $gPeq$ ), smog ( $gNMVOC$ ), particulate matter ( $PM_{10}eq$ ), and average agricultural land use ( $m^2/kg$ ). The consumption of each meat type is the sum over all individuals of meat consumption per meal per individual. Outcomes are measured and recorded for each different population subgroup, which allows for investigating how specific groups are influenced and allow for the targeting of policies on subgroups. These subgroups include age, gender, and education. Age groups are split between young (18-30), and adults (31-65). The gender is split between male and female. Education levels are split between low educated, middle educated and highly educated.

The experiments were run using the NetLogo 6.2.2. software, which allows for the construction of agent-based models. Experiments were run for each of the different scenarios (base-case, high environmental concern, high susceptibility) and each policy respectively from Table 3.4. These policies were all tested for 50 runs, with 900 runs in total (3 scenarios x 6 policies x 50 runs). The scenarios were run over the duration of 3 years, between 2016 and 2019, which was the time of available data and matched the length of the model runs by Scalco et al. (2019), allowing for comparisons to be drawn.





# 4

## Data Analysis

The data analysis is used to formulate the rules and guide decision-making in the agent-based model. This analysis looks at results from multiple online surveys through the lens of the Theory of Planned Behaviour to understand which parameters are important and correlate to determining meat consumption. The significant parameters are based on the findings from literature and from correlations found within this research, and are analysed using logistic regression within the Python software. The outcome of this logistic regression is used to create a function in the agent-based model through which the likelihood to consume meat per meat type for agents is determined.

This Chapter is split up in several sections, each covering a different aspect of the data analysis process. Section 4.1 covers the analysis of the LISS Panel Data to determine the parameters of importance, Section 4.2 covers the analysis of the DNFCS and Belevingen 2020 Surveys which were used to determine the likelihood to consume specific meat types through a logistical regression, and Section ?? covers the calculation of the price elasticity's of demand.

### 4.1. LISS Panel Data Analysis

The LISS panel is a representative sample of Dutch individuals who participate in monthly Internet surveys, collected by CentERdata (Tilburg University, The Netherlands). The panel is based on a true probability sample of households drawn from the population register. Households that could not otherwise participate are provided with a computer and Internet connection. A longitudinal survey is fielded in the panel every year, covering a large variety of domains including health, work, education, income, housing, time use, political views, values and personality. This database contains longitudinal studies, which are repeated yearly, and single-wave studies. Through providing encrypted personal identifier numbers, this database allows for the combination of survey responses with the same respondents.

#### 4.1.1. Survey data description

Surveys were chosen based on their relation to the Theory of Planned Behaviour, this includes searching for surveys which may influence the attitude towards meat consumption for individuals. The surveys used are summarized in Table 4.1. The 'Reasons to Eat Less Meat' survey was conducted in 2018, therefore, all other surveys were taken from the same year to minimize the changes in attitudes which may have occurred over the years.

Table 4.1: LISS Panel Data surveys used to determine factors of importance to changing meat consumption.

Name of Survey	Code	Type	Year	Respondents
Reasons to Eat Less Meat	oi18a	Single Wave	2018	5,742
Background variables	avars_201807	Single Wave	2018	10,702
Health	ch18k	Longitudinal	2018	5,500
Personality	cp18j	Longitudinal	2018	5,800
Politics and Values	cv18j	Longitudinal	2018	6,263
Hope Barometer	nq18a	Longitudinal	2018	1599

The 'Reasons to Eat Less Meat' survey investigates the importance individuals attribute concerns on health, the environment and animal welfare as reasons to reduce meat consumption based on a 7-point Likert Scale. Each of these three factors are investigated through five questions. Questions on health include "I want to be healthy" and "My health is important to me". Questions surrounding the environment include "plant-based diets are better for the environment", and "plant-based diets are more sustainable". Questions surrounding animal welfare include "animals do not have to suffer", and "animal rights are important to me". More details are found in Appendix E.

All surveys make use of the 'Background variables' survey, which provides monthly updates on background variables of individuals. This includes gathering personal information related to the respondents' age, gender, household, income, education, origin, occupation, urbanisation, and civil status. The health survey was included as this includes important dietary information as the frequency of meat consumption. Other variables included in this survey related to health, the individuals' physical activity, physical well-being, problems related to health, and habits as smoking, drinking, drug use, may have an influence on meat. This survey was part of the LISS Core Study.

Two other LISS Core Study surveys included are the personality survey and politics and values survey. The personality survey, which focuses on social information, which may be important to determine attitudes surrounding dietary consumption. This includes concepts as happiness, life satisfaction, Big Five personality, mood, value orientation, amongst others. The politics and values survey was used to see whether specific values are important in determining meat consumption. This includes political information as party membership, government policy satisfaction and political interest, and values as gender role attitudes and conservatism. Finally, the 'Hope Barometer' was selected as survey to convey whether specific beliefs and hopes are directly related to consumption. This survey was conducted in 2018 by the Erasmus Happiness Economics Research Organisation (EHERO) as part of the "Hope as Motive" project (Pleeging & CentERdata, 2021).

#### 4.1.2. Parameters of importance

In determining the parameters of importance and their influence on dietary consumption, the datasets were first combined, then factors which showed an absolute correlation over 0.1 were taken to be analysed in a least squares analysis and logistical regression analysis. The least-squares analysis is used to determine whether factors can be used to determine the specific diets of individuals. Logistical regression analysis require outcomes to be binary, and are useful to provide the probability that either an action is taken or not taken. This allows us to classify meat consumption as either 'reduction in consumption' or 'no reduction in consumption', and thereby determine the likelihood that individuals will reduce meat consumption based on the relevant parameters.

The datasets were combined using the encrypted personal identifiers. As the 'Hope Barometer' contained far fewer data-points, this was analysed separately to determine whether any parameter is correlated to the frequency of meat consumption. This frequency of meat consumption was taken from the 'Health' survey, with identifier 'ch18k200'. The other surveys were combined to determine

#### Correlation analysis of the Hope Barometer survey

The Hope Barometer survey, combined with the health survey, was analysed separately. This provides interesting findings, where the variables most strongly correlated to the frequency of meat consumption ( $r > 0.1$ ). Variables with significance over 0.1 were taken, as meat consumption is a complex behaviour and therefore any single variable is not expected to be strongly correlated to consumption, and low correlations ( $r = 0.1$ ) can be meaningful. The Hope Barometer, after cleaning the data by removing columns with missing over half of respondents, contains 91 variables. There were 5 variables found to be weakly correlated ( $r > 0.1$ ) to the frequency in meat consumption ('ch18k200'), as seen in Figure 4.1.

	nq18a054	nq18a074	nq18a082	nq18a083	nq18a084	ch18k200
nq18a054	1.000000	-0.022632	-0.017434	-0.020745	-0.029864	-0.119761
nq18a074	-0.022632	1.000000	0.909841	0.908266	0.905279	-0.120047
nq18a082	-0.017434	0.909841	1.000000	0.934733	0.945936	-0.110169
nq18a083	-0.020745	0.908266	0.934733	1.000000	0.952075	-0.100432
nq18a084	-0.029864	0.905279	0.945936	0.952075	1.000000	-0.100585
ch18k200	-0.119761	-0.120047	-0.110169	-0.100432	-0.100585	1.000000

Figure 4.1: Correlation matrix of variables with weak correlation to the frequency in meat consumption ('ch18k200'), using survey responses from the Hope Barometer and Health survey. (Source: Author)

The variables and their meaning are provided in Table 4.2. An interesting finding is that the expectation regarding the deterioration of the climate emerged as being related to meat consumption ( $r = -0.12$ ), together with spiritual beliefs ( $r < -0.1$ ). This reinforces findings by Hopwood et al. (2020), who found concerns about the climate (and health/animal welfare) are an important aspect to changes in diets. It should be noted that the variables related to spiritual belief are all strongly correlated to one another, as also shown in Figure 4.1.

Table 4.2: Hope Barometer variables with low correlation to the frequency of meat consumption (Source: Author)

Variable	Explanation
nq18a054	Expectations regarding deterioration of the climate
nq18a074	My spiritual beliefs help my success in life
nq18a082	I find comfort in my spiritual beliefs
nq18a083	In crisis, I stay calm thanks to spiritual belief
nq18a084	My spiritual beliefs give sense of security

### Multiple Survey Analysis

The 'Reasons to Eat Less Meat', 'Health', 'Background variables', 'Politics and Values', and 'Personality' surveys were combined for this analysis. The combined dataset of the surveys, after removing missing values and columns missing over 50% of respondents, consisted of 4385 rows  $\times$  379 columns. Variables with a correlation over  $r > 0.1$  with the frequency of meat consumption ('ch18k200' in the Health Survey) were calculated using a correlation matrix in Python. The results for the background variables, health survey, and politics and values can be found in Figures 4.2, 4.3 and 4.4 respectively. The personality survey did not provide any factors with correlation coefficients  $r$  greater than 0.1.

	geslacht	aantalhh	partner	burgstat	woonvorm	sted	opmet	ch18k200
geslacht	1.000000	-0.030696	-0.059316	0.025343	-0.000630	-0.020513	-0.027347	-0.133003
aantalhh	-0.030696	1.000000	0.561558	-0.310773	0.731714	0.168363	0.088811	0.103750
partner	-0.059316	0.561558	1.000000	-0.552845	0.375647	0.171226	0.016116	0.115279
burgstat	0.025343	-0.310773	-0.552845	1.000000	-0.233339	-0.237264	0.135514	-0.142533
woonvorm	-0.000630	0.731714	0.375647	-0.233339	1.000000	0.158046	0.010847	0.102154
sted	-0.020513	0.168363	0.171226	-0.237264	0.158046	1.000000	-0.163663	0.155720
opmet	-0.027347	0.088811	0.016116	0.135514	0.010847	-0.163663	1.000000	-0.145951
ch18k200	-0.133003	0.103750	0.115279	-0.142533	0.102154	0.155720	-0.145951	1.000000

Figure 4.2: Correlation matrix of the Background variables with highest correlation to the frequency of meat consumption, with 'geslacht' as gender, 'aantal hh' as number household members, 'partner' as partner, 'burgstat' as civil status, 'woonvorm' as living way, 'sted' as urbanisation, 'opmet' as highest education level obtained, and 'ch18k200' as frequency of meat consumption. Negative correlations to ch18k200 indicate it is correlated to a reduction in meat consumption. (Source: Author)

The correlation matrix of the background variables shows that the frequency of meat consumption (ch18k200) is correlated with gender ( $r = -0.13$ ), your partner ( $r = 0.12$ ), civil status ( $r = 0.14$ ), living type ( $r = 0.1$ ), urbanisation ( $r = 0.16$ ), and education ( $r = -0.15$ ).

	ch18k001	ch18k017	ch18k200	ch18k201	ch18k246
ch18k001	1.000000	-0.425055	-0.133003	-0.577284	-0.127071
ch18k017	-0.425055	1.000000	0.158157	0.851823	0.151113
ch18k200	-0.133003	0.158157	1.000000	0.167600	0.135924
ch18k201	-0.577284	0.851823	0.167600	1.000000	0.150265
ch18k246	-0.127071	0.151113	0.135924	0.150265	1.000000

Figure 4.3: Correlation matrix of the Health Survey with highest correlation to the frequency of meat consumption, with ch18k001 as age, ch18k017 as 'how much do you weigh', ch18k200 as frequency of meat consumption, ch18k201 as 'what is your target weight', and ch18k246 as 'I pay health insurance premiums for my partner'. Negative correlations to ch18k200 indicate a correlation to a reduction in meat consumption (Source: Author).

The correlation matrix of the Health survey in Figure 4.3 shows that the frequency of meat consumption (ch8k200) is correlated with age (ch18k001,  $r = -0.13$ ), weight (ch18k017  $r = 0.16$ ), target weight (ch18k201,  $r = 0.17$ ), and paying health insurance for your partner (ch18k246,  $r = 0.14$ ). Figure 4.4 shows the correlations with frequency of meat consumption (ch18k200) and the Politics and Values survey, where meat consumption is weakly correlated to variables related to how much influence individuals have on their government (cv18j048 and cv18j049,  $r = -0.12$ ), cultural and foreigner acceptance (cv18j116, cv18j118, cv18j120, cv18j123)

	cv18j048	cv18j049	cv18j116	cv18j118	cv18j120	cv18j123	ch18k200
cv18j048	1.000000	0.495455	0.211919	0.184367	-0.279686	-0.193348	-0.113782
cv18j049	0.495455	1.000000	0.204030	0.149159	-0.243870	-0.153823	-0.121000
cv18j116	0.211919	0.204030	1.000000	0.406522	-0.542022	-0.416364	-0.118734
cv18j118	0.184367	0.149159	0.406522	1.000000	-0.562188	-0.455383	-0.160338
cv18j120	-0.279686	-0.243870	-0.542022	-0.562188	1.000000	0.587470	0.159523
cv18j123	-0.193348	-0.153823	-0.416364	-0.455383	0.587470	1.000000	0.129066
ch18k200	-0.113782	-0.121000	-0.118734	-0.160338	0.159523	0.129066	1.000000

Figure 4.4: Correlation matrix for the Politics and Values Survey with the frequency of meat consumption, with cv18j048 as 'political parties are not interested in my opinion', cv18j049 as 'people like me have no influence on government policy', cv18j116 and cv18j118 as positive views on foreigners, and cv18j120 and cv18j123 as negative views on foreigners, and ch18k200 as the frequency of meat consumption. Negative correlations to ch18k200 indicate a reduction in meat consumption (Source: Author)

The five factors most strongly correlated to a change in diet are seen in Figure 4.5, which are all variables from the 'Reasons to Eat Less Meat' survey, and are all related to environmental reasons for reducing meat consumption ( $r = -0.25$  to  $r = -0.33$ ).

	oi18a002	oi18a006	oi18a008	oi18a010	oi18a012	ch18k200
oi18a002	1.000000	0.793942	0.682463	0.780065	0.666421	-0.282251
oi18a006	0.793942	1.000000	0.658006	0.799047	0.671741	-0.265840
oi18a008	0.682463	0.658006	1.000000	0.695649	0.645024	-0.326100
oi18a010	0.780065	0.799047	0.695649	1.000000	0.692448	-0.266999
oi18a012	0.666421	0.671741	0.645024	0.692448	1.000000	-0.252074
ch18k200	-0.282251	-0.265840	-0.326100	-0.266999	-0.252074	1.000000

Figure 4.5: Correlation matrix of 5 most important variables in relation to the frequency of meat consumption ('ch18k200'). All variables are part of the 'reasons to eat less meat' survey (oi18a002, oi18a006, oi18a008, oi18a010, oi18a012) (Source: Author)

These results clearly show that as individual variables, the health, environment, and animal welfare concerns have a stronger direct correlation to the frequency of meat consumption than any other vari-

able. This is in-line with findings from Hopwood et al. (2020). The VEMI found health to be a more important variable, whereas the correlations appear to indicate that animal welfare and climate concerns are more strongly correlated. However, correlation does not mean causation, and a regression analysis is required to verify the impact of each variable on the frequency of meat consumption. The full correlation matrix can be seen in Appendix E.

A notable result of the health survey is that the frequency of fish consumption ('ch18k199'), did not appear to be correlated to the frequency of meat consumption ( $r < 0.1$ ). This provides further justification for the choice to solely focus on meat consumption during this research, however, further research should be done to more accurately determine the interplay between these types of consumption. The relevant variables and their explanations from the surveys are summarised in Table 4.3. This paints a complex picture, where meat consumption is correlated to factors ranging from concerns to political viewpoints.

Table 4.3: Summary of relevant variables from the CBS surveys analysed with respect to frequency of meat consumption, with surveys including the Health survey, Politics and Values Survey, Background Variables survey and Reasons to Eat Less Meat Survey (Source: Author)

<i>Background variables</i>				
<i>Variable</i>	geslacht	aantalhh	partner	oplnmet
<i>Explanation</i>	Gender (male = 1, female = 2)	Number of household members	Relationship status (0 = single, 1 = with partner)	Education level
<i>Health Survey</i>				
<i>Variable</i>	ch18k017	ch18k200	ch18k201	ch18k246
<i>Explanation</i>	How much do you weigh?	Frequency of meat consumption (1 = Never, 2 = 1-3 times per month, 3 = 1 time per week, 4 = 2-4 times per week, 5 = 5-6 times per week, 6 = Daily)	What is your target weight?	I pay health insurance for my partner
<i>Politics and Values Survey</i>				
<i>Variable</i>	cv18j048	cv18j049	cv18j116	cv18j118
<i>Explanation</i>	Political parties are not interested in my opinion	People like me have no influence on policy	It is good if society consists of people from different cultures	It should be easier to obtain asylum in NL
<i>Reasons to Eat Less Meat Survey</i>				
<i>Variable</i>	oi18a002	oi18a006	oi18a008	oi18a010
<i>Explanation</i>	Plant-based diets are better for the environment	Plant-based diets are more sustainable	Eating meat is bad for the planet	Plant-based diets are environmentally friendly

Further investigation on the mean values of background variables with respect to the frequency of meat consumption can be seen in Figure 4.6. This figure shows a clear trend, where on average individuals who never or rarely consume meat compared to every day meat eaters tend to be female (1.805 vs 1.5, with 1 being male and 2 being female), have fewer children (0.69 vs 1.12), tend to be live alone (0.47 vs 0.72), have higher wages (4.7 vs 3.5) and are more highly educated (4.5 vs 3.8). It should be noted that the distinction between individuals who eat meat every day, or 5-6 times a week is insignificant. Meat consumption of 5-6 times per week is typically not considered as reducing meat consumption (Neff et al., 2018).

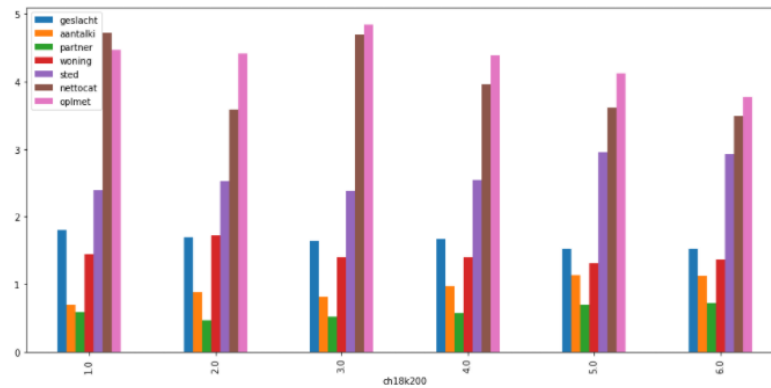


Figure 4.6: Mean values of background variables for each category of frequency of meat consumption (ch18k200). The values correspond to: 1 = Never, 2 = 1-3 times per month, 3 = 1 time per week, 4 = 2-4 times per week, 5 = 5-6 times per week, 6 = every day (Source: Author)

The values for this graph can be seen in Figure 4.7.

	geslacht	aantalki	partner	woning	sted	nettocat	oplmet
ch18k200							
1.0	1.805556	0.694444	0.583333	1.444444	2.388889	4.722222	4.472222
2.0	1.694444	0.888889	0.472222	1.722222	2.527778	3.583333	4.416667
3.0	1.650000	0.816667	0.516667	1.400000	2.383333	4.700000	4.850000
4.0	1.675497	0.973510	0.576159	1.410596	2.536424	3.966887	4.390728
5.0	1.528736	1.132184	0.701149	1.316092	2.954023	3.609195	4.126437
6.0	1.526786	1.125000	0.723214	1.366071	2.928571	3.491071	3.767857

Figure 4.7: Mean values of background variables for each category of frequency of meat consumption (ch18k200) for 'geslacht' (gender), 'aantalki' (number of children), 'partner' (partner), 'woning' (living condition), 'sted' (urbanisation), 'nettocat' (income level), and 'oplmet' (education level). The values of ch18k200 respond to: 1 = Never, 2 = 1-3 times per month, 3 = 1 time per week, 4 = 2-4 times per week, 5 = 5-6 times per week, 6 = every day (Source: Author)

This analysis of variables indicates that the most important factors related to meat consumption are: health, environment and ethical concerns, combined with background factors as gender, age, income and level of education. The importance and influence of each of these factors on frequency of meat consumption is investigated through a least-squares analysis. The importance and influence of these factors on the probability of reducing meat consumption is investigated through a logistical regression.

#### Least-Squares Analysis: Determine dietary consumption

The Least-Squares analysis is a regression analysis which determines the influence of independent variables on a continuous dependent variable. This requires the dependent variable to be continuous in a non-binary range, and the independent variables to also vary. The regression analysis was conducted using the sklearn package in Python.

First the variables of relevance were taken from the analysis conducted previously. These include all factors which correlate to the frequency of meat consumption from the various surveys. An iterative

process is followed, where the factors which are not statistically significant are removed one by one, until all remaining factors are statistically significant. The result can be seen in Figure 4.8.

OLS Regression Results						
Dep. Variable:	ch18k200	R-squared:	0.130			
Model:	OLS	Adj. R-squared:	0.129			
Method:	Least Squares	F-statistic:	82.00			
Date:	Thu, 19 Aug 2021	Prob (F-statistic):	7.18e-127			
Time:	11:54:18	Log-Likelihood:	-7023.3			
No. Observations:	4385	AIC:	1.406e+04			
Df Residuals:	4376	BIC:	1.412e+04			
Df Model:	8					
Covariance Type:	nonrobust					
	coef	std err	t	P> t	[0.025	0.975]
const	5.9981	0.143	42.018	0.000	5.718	6.278
geschlecht	-0.2859	0.037	-7.721	0.000	-0.359	-0.213
partner	0.1964	0.048	4.091	0.000	0.102	0.291
burgstat	-0.0478	0.013	-3.759	0.000	-0.073	-0.023
sted	0.0735	0.014	5.088	0.000	0.045	0.102
oplmet	-0.0901	0.012	-7.386	0.000	-0.114	-0.066
env	-0.1900	0.014	-13.160	0.000	-0.218	-0.162
awe	-0.0710	0.013	-5.404	0.000	-0.097	-0.045
hlt	0.0563	0.017	3.250	0.001	0.022	0.090
Omnibus:	251.010	Durbin-Watson:	1.965			
Prob(Omnibus):	0.000	Jarque-Bera (JB):	294.639			
Skew:	-0.630	Prob(JB):	1.05e-64			
Kurtosis:	3.155	Cond. No.	87.9			

Figure 4.8: Least-square regression analysis outcome of the LISS Panel Data, using the health, climate and animal welfare concern factors from the 'Reasons to Eat Less Meat' survey (code: oi18a), frequency of meat consumption (ch18k200), how much individuals weigh ('ch18k017') (Health Survey code: ch18k), ease of obtaining asylum (cv18j118), and background variables (gender, partner, income urbanisation, education, code: avars\_201807) (Source: Author)

The least-square analysis of the LISS Panel data indicates that the most important factors in determining the diet of an individual are the gender ('geschlecht'), whether they had a partner, their level of urbanisation ('sted'), level of education ('oplmet'), environmental ('env'), health ('hlt') and animal welfare concerns ('awe'). Of the large initial sweep of parameters from the multiple surveys, these remain as statistically significant  $p < 0.05$ . This multiple linear regression shows that most factors have a negative correlation with the frequency of meat consumption. Being female, having a high education, high environmental and animal welfare concerns will result in lower frequency of meat consumption. Health, as only concern, was found to be positively correlated with meat consumption, indicating that those concerned about their health may consume meat more frequently. The reason for this cannot be derived from this analysis.

#### Logistic Regression: Likelihood to Reduce Meat Consumption

The logistic regression analysis is a regression analysis which determines the odds ratio of an event occurring (Sperandei, 2014). This requires the dependent variable to be binary (reduce or not reduce consumption). The binary range is acquired by labelling any frequency of consumption over 5 times per week as a non-reduction, while labelling responses below 2-4 times per week as reduction, following the methodology of Equation 3.5. The regression analysis for LISS Panel surveys, with only the statistically significant factors remaining, is shown in Figure 4.9.

Figure 4.9 shows that only the variables which are part of the background variables, and the two of the three concerns remain statistically significant. Similarly to the other findings from the correlation analysis and data analysis of LISS Panel surveys, health concerns were not directly found to be correlated or statistically significant. There is a weak to negligible correlation of health concerns, which is a surprising findings. The weighting ( $\beta$ ) of health concerns compared to environment concerns is far lower (0.0434 vs -0.2503) and appears to be positively correlated with meat consumption rather than negatively correlated. This analysis indicates that there is no general correlation for individuals that all meat is bad for your health. While individuals may find their health important in general, with health reasons being cited as more important than animal welfare to reduce meat consumption in the "Reasons to Eat Less Meat Survey" for meat eaters, there is a negligible correlation between health concerns and actual changes in diets. This hints at a cognitive dissonance, but should be compared to other literature and discussed to make any meaningful interpretations of the data.

While initially multiple surveys were combined, and a broad sweep of possible parameters was investigated, there appear to be few parameters which are statistically significant in determining whether

MNLogit Regression Results						
Dep. Variable:	ch18k200	No. Observations:	2979			
Model:	MNLogit	Df Residuals:	2970			
Method:	MLE	Df Model:	8			
Date:	Sat, 14 Aug 2021	Pseudo R-squ.:	0.05428			
Time:	18:25:08	Log-Likelihood:	-1943.7			
converged:	True	LL-Null:	-2055.3			
Covariance Type:	nonrobust	LLR p-value:	8.425e-44			
ch18k200=1	coef	std err	z	P> z	[0.025	0.975]
const	1.8171	0.295	6.166	0.000	1.239	2.395
geslacht	-0.4090	0.084	-4.871	0.000	-0.574	-0.244
partner	0.4514	0.083	5.410	0.000	0.288	0.615
nettocat	-0.0372	0.025	-1.509	0.131	-0.085	0.011
sted	0.1024	0.030	3.400	0.001	0.043	0.161
oplmet	-0.1617	0.049	-3.308	0.001	-0.257	-0.066
env	-0.2441	0.031	-7.750	0.000	-0.306	-0.182
hlt	0.0271	0.036	0.743	0.457	-0.044	0.099
awe	-0.0520	0.028	-1.855	0.064	-0.107	0.003

Figure 4.9: Multinomial logistic regression results of the LISS Panel Data, using the health, climate and animal welfare concerns from the 'Reasons to Eat Less Meat' survey (code: oi18a), background variables (gender, partner, income urbanisation, education, code: avars\_201807), and frequency of meat consumption ('ch18k200', Health Survey code: ch18k) (Source: Author)

individuals reduce their overall meat consumption. The R-square value of this model is only 0.06, and therefore it was deemed too inaccurate to adequately be used in the model specification. This regression analysis, therefore, provides insight into the difficulty of predicting the frequency of meat consumption based on various background characteristics. Meat consumption in itself may be too broad to be defined by these variables, and therefore will be dis-aggregated to derive more meaningful insights.

### Summary LISS Panel

The LISS Panel data provided a useful understanding of which factors influence the frequency of meat consumption in the Netherlands. This correlation analysis supports findings from the literature, which indicates that health, environment and animal welfare concerns are important in shaping consumer demand. Health, however, was found to have a more negligible influence on consumption than found from other studies in the literature (Hopwood et al., 2020). The difference between stated concerns in the LISS Panel Reasons to Eat Less Meat Survey, and the actual frequency of consumption in the LISS Panel Health survey, indicate there may be cognitive dissonance where thoughts do not reflect actions. However, this cannot be determined by this sole analysis. The correlation analysis, and subsequent least-squares and logistic regression analysis, indicate that environmental concerns play a more significant role in determining the frequency of meat consumption. While remaining factors are predominantly statistically significant, the R-square value of these regressions is below 0.1, and therefore this analysis was only used to gain understanding in the underlying system, and to discuss and reflect on the findings. The frequency of meat consumption as a whole may be too broadly defined to be determined by these variables, as each of these variables may influence specific consumption of different meat types differently.

The present study is not solely interested in meat consumption, but more importantly in investigating methods of reducing meat consumption to reduce emissions related to this consumption. To determine the emissions, and combine this with the findings from CE Delft (de Bruyn et al., 2018), consumption per meat type is required. This study will focus on the main meat types: beef, pork, poultry, processed meat and meat substitutes. These account for 92.2% of overall meat consumption (RIVM, 2020b). Therefore, the Belevingen 2020 (CBS, 2021b) and DNFCS (RIVM, 2020b) will be investigated in light of the findings from the LISS Panel analysis.

## 4.2. Belevingen 2020 and DNFCS

The Belevingen 2020 survey (CBS, 2021b) focuses on climate change and the energy transition, and the experiences adults in the Netherlands have with regards to various themes related to climate change. These include living, mobility, climate conscious lifestyles, and meat consumption, amongst others. The meat consumption data (H6 Maatwerktafel Vleesconsumptie 2020) was used in the present study (CBS, 2021b).



The Belevingen 2020 survey provides responses on the importance of various attributes to meat consumption of individuals, which include: health, climate, animal welfare concerns, taste, housemate influence, price of meat being too expensive, and 'other'. This survey further includes the diets of individuals, and individual perceptions whether they should reduce meat and whether they want to. For this research, access to the raw metadata and individual responses of the 3500 participants was not granted, therefore, the public data of the H6 Maatwerktabel was used (CBS, 2021b). This data is provided at the same level of aggregation that the Central Bureau for Statistics uses (by gender, age groups, education level, income and urbanisation).

The Dutch National Food Consumption Survey 2012-2016, conducted by the RIVM, provides the information required on both food consumption moments and food consumption. The moments relate to the percentage of a food type consumed during a meal time (breakfast, lunch, dinner or in-between) based on sex, age, or other characteristics as education. The consumption survey provides quantities of a food type consumed on average, per day, as well as the percentage of days that certain food types are consumed. These sources thereby give an overview of the consumption within the Netherlands (RIVM, 2020b).

The Dutch National Food Consumption Survey gives extensive information about the quantity of meat consumed per meat type, per aggregation category (RIVM, 2020b). This allows us to combine both surveys at this aggregation level, to derive insights into the importance of health, climate and animal welfare on the consumption of specific meat types.

### 4.2.1. Correlation analysis

The combined datasets of the Belevingen 2020 Survey (CBS, 2021b) and DNFCS (RIVM, 2020b) were first analysed through a correlation analysis. This provides some useful initial insights. Two correlations will be discussed here: the correlation between consumption days of various food types, and the correlation between important factors of Belevingen 2020 and the consumption days of various food types.

The correlation between consumption days of various food types is shown in Figure 4.10. This correlation matrix clearly shows that there is a strong negative correlation between beef and poultry ( $r$ ), pork and poultry ( $r$ ), and all meat types with meat substitutes ( $r$ ) (except poultry). A strong positive correlation is found between beef consumption and pork consumption ( $r$ ), and beef and processed meat consumption ( $r$ ). This indicates that there is an interchange between consumption of various meat types, supporting the decision to investigate consumption of each of these types separately. Poultry and meat substitutes appear to be in direct competition with consumption of beef ( $r = -0.83$  and  $r = -0.46$ ), pork ( $r = -0.56$  and  $r = -0.80$ ) and processed meat ( $r = -0.13$  and  $r = -0.59$ ), indicating individuals may swap out beef/pork for poultry/substitutes.

	Beef_Day	Pork_Day	Poultry_Day	Processed_Day	Sub_Day
Beef_Day	1.000000	0.895344	-0.833130	0.581075	-0.458790
Pork_Day	0.895344	1.000000	-0.557242	0.670478	-0.800356
Poultry_Day	-0.833130	-0.557242	1.000000	-0.134156	0.026865
Processed_Day	0.581075	0.670478	-0.134156	1.000000	-0.595307
Sub_Day	-0.458790	-0.800356	0.026865	-0.595307	1.000000

Figure 4.10: Correlation matrix between consumption per day of various food types, calculated using data from the Dutch National Food Consumption Survey (RIVM, 2020b). (Source: Author)

The correlation between the importance of factors to individuals for reducing meat consumption, taken from the Belevingen 2020 Survey (CBS, 2021b), and the probability to consume specific meat types from the DNFCS (RIVM, 2020b), is shown in Figure 4.11. This figure provides interesting findings.

Figure 4.11 shows that environmental and animal welfare concerns are strongly correlated ( $r > 0.9$ ). Furthermore, these concerns appear to strongly correlate with eating more meat substitutes ( $r > 0.8$ ), more poultry ( $r > 0.6$ ), and strongly negatively correlated with pork ( $r < -0.8$ ) and processed meat ( $r < -0.6$ ) consumption. There is also a (weak to moderate) negative correlation between beef consumption and environmental/animal welfare concerns ( $r = -0.28$ ). Interestingly, health concerns are positively

correlated with beef ( $r = 0.18$ ) and poultry consumption ( $r = 0.25$ ), negatively correlated with pork ( $r = -0.29$ ) and processed meat ( $r = -0.21$ ) consumption, and moderately positively correlated to substitutes ( $r = 0.61$ ).

	Environment	Animal	Health	Taste	Housemate	Too expensive	Beef_Day	Pork_Day	Poultry_Day	Processed_Day	Sub_Day
Environment	1.000000	0.959885	0.743115	-0.065603	0.482250	0.369749	-0.280488	-0.812810	0.676655	-0.652381	0.871585
Animal	0.959885	1.000000	0.692413	0.034689	0.534270	0.316899	-0.358897	-0.810433	0.696614	-0.704537	0.854308
Health	0.743115	0.692413	1.000000	-0.545361	0.048780	-0.031165	0.182025	-0.291320	0.247224	-0.206751	0.608940
Taste	-0.065603	0.034689	-0.545361	1.000000	0.218299	0.436584	-0.681338	-0.458224	0.087906	-0.511111	-0.011480
Housemate	0.482250	0.534270	0.048780	0.218299	1.000000	0.299918	-0.454228	-0.604845	0.674079	-0.208346	0.504023
Too expensive	0.369749	0.316899	-0.031165	0.436584	0.299918	1.000000	-0.730677	-0.670210	0.520746	-0.340996	0.052678
Beef_Day	-0.280488	-0.358897	0.182025	-0.681338	-0.454228	-0.730677	1.000000	0.637804	-0.617999	0.383924	-0.060868
Pork_Day	-0.812810	-0.810433	-0.291320	-0.458224	-0.604845	-0.670210	0.637804	1.000000	-0.701585	0.780939	-0.733936
Poultry_Day	0.676655	0.696614	0.247224	0.087906	0.674079	0.520746	-0.617999	-0.701585	1.000000	-0.410857	0.479241
Processed_Day	-0.652381	-0.704537	-0.206751	-0.511111	-0.208346	-0.340996	0.383924	0.780939	-0.410857	1.000000	-0.670799
Sub_Day	0.871585	0.854308	0.608940	-0.011480	0.504023	0.052678	-0.060868	-0.733936	0.479241	-0.670799	1.000000

Figure 4.11: Correlation matrix between the reasons to reduce meat consumption from the Belevingen 2020 survey (CBS, 2021b) and probability of consuming specific meat types on any given day from the Dutch National Food Consumption Survey (RIVM, 2020b). (Source: Author)

Other important findings from Figure 4.11 include the presence of a moderate negative correlation between beef consumption and taste ( $r = -0.68$ ) and price ( $r = -0.73$ ). The notion that meat is too expensive appears to result in reduced beef and pork consumption, and increased poultry consumption. Individuals who don't enjoy the taste of meat seem to generally decrease all meat types ( $r < -0.4$ ), although this has a negligible effect on poultry ( $r = 0.09$ ). Finally, housemate influence is moderately negatively correlated to beef ( $r = -0.45$ ), pork ( $r = -0.61$ ) and processed meat consumption ( $r = -0.21$ ), while it is positively correlated to poultry and meat substitute consumption.

#### 4.2.2. Least-Squares Regression: Likelihood to consume meat types

The multiple linear regression combines the estimated importance of health, climate and animal welfare concerns to the days each meat type is consumed. These consumption days are given in percentage of days the meat type is consumed, and therefore are better suited for a multiple linear regression than logistic regression. Both the Belevingen 2020 survey (CBS, 2021b) and DNFCS (RIVM, 2020b) use the same population divisions; by age, gender, education and urbanisation. Combining these datasets at this level of education reduces the quantity of data point available, compared to using raw survey data. This data was requested, but permission was not granted for this study. Therefore, the quantity of parameters that can be explained by the data also reduces (Harrell, 2015).

According to the Regression Modeling Strategies book by Frank Harrell, to determine reasonable-size effects with reasonable power, 10-20 observations are required per parameter (co-variate) estimated (Harrell, 2015). This provides a dilemma with the data at hand, either all factors (health, climate, animal welfare, price, housemates, taste, other) are used in the model, which will result in over-fitting the model, or a reduction in dimensions should be applied. Both options were investigated, and this research focuses on the reduction in dimensions where the significant variables are considered.

The logistic regression for consumption of each of the meat types was conducted, with one example of this analysis provided in Figure 4.12. This is the result of a systematic reduction in the quantity of variables. The two remaining factors are health and environmental concerns. These remain, as they provide both statistically significant behaviour for most meat types, and there are sufficient observations to support this (Harrell, 2015).

```

OLS Regression Results
=====
Dep. Variable:      Beef_Day      R-squared:          0.419
Model:             OLS           Adj. R-squared:     0.322
Method:           Least Squares  F-statistic:        4.330
Date:             Fri, 20 Aug 2021 Prob (F-statistic):  0.0384
Time:             11:20:32       Log-Likelihood:     -25.110
No. Observations: 15           AIC:                56.22
Df Residuals:     12           BIC:                58.34
Df Model:         2
Covariance Type:  nonrobust
=====
                    coef      std err      t      P>|t|      [0.025      0.975]
-----
const              7.0965      4.179      1.698      0.115      -2.009      16.202
Environment        -0.1732      0.061     -2.824      0.015      -0.307      -0.040
Health              0.3781      0.143      2.652      0.021      0.067      0.689
=====
Omnibus:           1.286      Durbin-Watson:      2.408
Prob(Omnibus):    0.526      Jarque-Bera (JB):   1.054
Skew:             0.474      Prob(JB):           0.590
Kurtosis:         2.112      Cond. No.           550.
=====

```

Figure 4.12: Logistic regression of the days of beef consumption taken from the DNFCS (RIVM, 2020b), with percentage of consumption days as dependent variable, and health and environment concerns as independent variables taken from the Belevingen 2020 survey (CBS, 2021b) (Source: Author)

The parameters of health and environmental concerns were used in the multiple linear regression analysis. While this does not provide a full picture of all factors, these factors were found to be the most important from both literature and this research (Hopwood et al., 2020; Scalco et al., 2019), can be applied to the Theory of Planned Behaviour, are determined by the individual profiles (age, sex, and education), and can be supported by the available data. Thereby, these parameters indirectly include the age, sex and education. Table 4.4 summarises the findings for each regression analysis.

Table 4.4: Multiple linear regression analysis coefficient for beef, pork, poultry, processed meat and meat substitutes for the factors of Health and Environmental concern (Source: Author)

Type	Factors			R – squared
	coeff.	Health	Environment	
Beef	7.10 +- 4.18 (p = 0.115)	0.378 +- 0.143 (p = 0.021)	-0.173 +- 0.061 (p = 0.015)	0.419
Pork	10.51 +- 2.18 (p = 0.00)	0.346 +- 0.074 (p = 0.001)	-0.2841 +- 0.032 (p = 0.00)	0.879
Poultry	24.12 +- 2.99 (p = 0.00)	-0.215 +- 0.102 (p = 0.057)	0.178 +- 0.044 (p = 0.002)	0.604
Processed	61.88 +- 5.53 (p = 0.00)	0.428 +- 0.189 (p = 0.042)	-0.331 +- 0.081 (p = 0.002)	0.598
Substitute	0.483 +- 1.10 (p = 0.669)	-0.016 +- 0.038 (p = 0.688)	0.072 +- 0.016 (p = 0.001)	0.763

As meat consumption is a complex adaptive system, there are many factors which will have unforeseen influences on meat consumption which will not be directly incorporated through the logistic regression. This will be reflected upon in the discussion in Chapter 8.

### 4.3. Summary data analysis

This data analysis chapter has covered the steps taken to derive the likelihood to eat less meat functions, which are used in the model to calculate the likelihood in terms of a percentage that each meat type is consumed per eating episode. The analysis of the various surveys showed that certain findings from the literature are also relevant within the Netherlands. These findings include that health, environment and animal welfare concerns are the most important factors in determining the frequency of meat consumption, which was demonstrated both through the correlation analysis and regression analysis (Hopwood et al., 2020). The important background variables which matter for determining meat consumption include the age, gender, income, education level, and household situation (number of kids and partner) of an individual. On average, those who consume meat less frequently tend to be female, have fewer children, live alone, have higher wages, and are more highly educated.

Concerns related to health, the environment and animal welfare have a different influence on the likelihood to different meat types. Therefore, it was important to split meat consumption and perform a multiple linear regression analysis on each of the five meat types investigated. Factors correlated to meat consumption regarding the climate were also found in the Hope Barometer Survey, while factors as target weight are related to health concerns (found in the Health Survey). Environmental concern was found to have the strongest correlation in actual reduced meat consumption, while health concerns were more often cited as important but had a weak to negligible correlation to actual changes in the frequency of meat consumption.

The multiple linear regression regression does incorporates the most important factors, which are health, the environment and animal welfare concerns. While health was not found to be statistically significant in predicting overall frequency of meat consumption (LISS Panel analysis), health concerns were found to be statistically significant and play an important role in determining specific meat type consumption. The regression does not take all factors from the Belevingen 2020 survey into account, as doing so would overfit the model with regards to the amount of datapoints available (Harrell, 2015) which provide information both on factors and specific consumption (CBS, 2021b; RIVM, 2020b). The summary of the analysis conducted on this chapter is displayed in Figure 4.13, showing that the multiple linear regression model is used to define a model rule in the agent-based model, while the other analysis provides us more insight into the complex nature of the problem at hand.

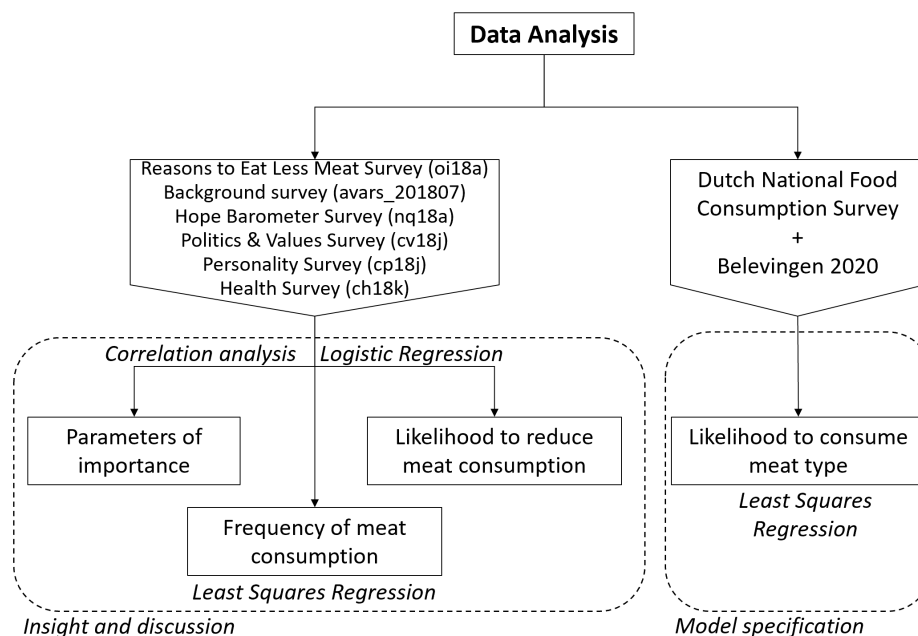


Figure 4.13: Summary of the surveys used to conduct the data analysis and outcomes of this analysis with regards to the analysis methods (Source: Author)

# 5

## Model specification

The model specification takes the findings of the literature review, conceptualisation and data analysis and applies this to the agent-based model grounded in the Theory of Planned Behaviour. The model specification will be described following the ODD Protocol (Grimm et al., 2020). The ODD Protocol is designed to facilitate the writing and reading of agent-based model descriptions, and facilitate model replication (Grimm et al., 2020). This protocol is conceptually divided into three categories; "Overview", "Design concepts" and "Details". These categories give an overview, explain the way relevant design concepts for ABM have been used, and explain the details of the model workings. The components of the overview include the purpose and patterns, entities, state variables and scales, and a process overview and the scheduling. The details include the initialization, input data, and submodels. Figure 5.1 provides an overview of these categories.

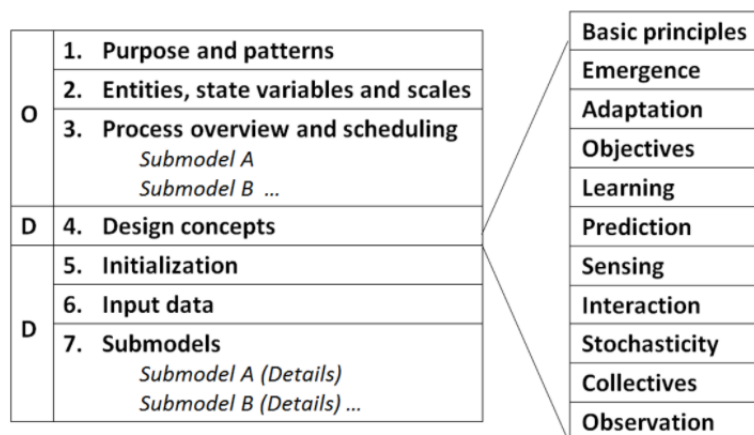


Figure 5.1: Structure of model descriptions following the ODD protocol, taken from Grimm et al. (2020).

### 5.1. Overview

#### 5.1.1. Purpose and overview

This agent-based model aims to reproduce the behaviour of the Dutch population in relation to meat consumption through replication of the personal preferences and peer influence among consumers. This is built with the goal to observe behavioural changes under influence of various European policies such as information campaigns and fiscal policies. This will thereby investigate the influence of EU policy on social norms surrounding meat consumption.

This model takes a complementary approach to other research on consumption of shifting diets, to demonstrate the influence of social norms on meat consumption for various meat types. Regarding other models, this model breaks down meat consumption in the main consumption groups of beef, pork,

poultry, processed meat and meat substitutes. Measuring each of these consumption groups offers a richer picture of the processes which lead to reduction of meat consumption, where it is often more likely for consumers to switch the type of protein they tend to eat than completely stop eating meat.

This document, ODD (Overview, Design concepts, and Details) describes the agent-based model underlying the Meat Consumption model. The standardized ODD protocol is followed as described by Grimm et al. (2020). There are a number of elements which influence the agents' behaviour. Figure 5.2 shows a general overview of these elements, which will be described in subsequent subsections.

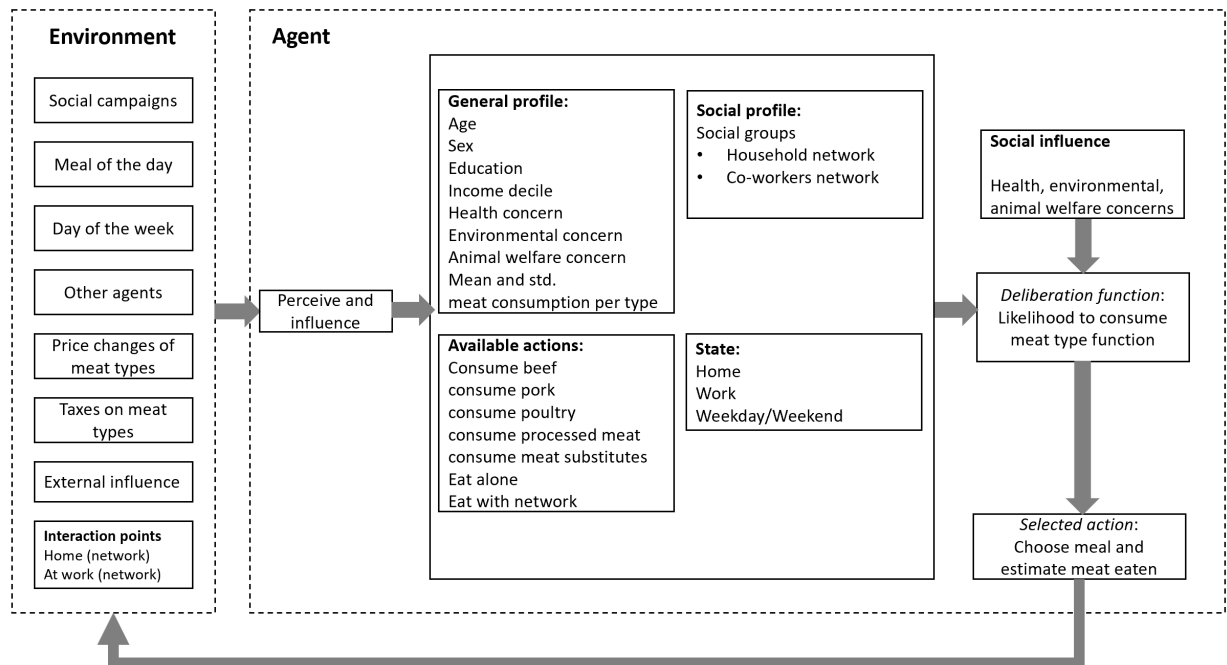


Figure 5.2: High-level overview of the model's components (Source: Author)

### 5.1.2. Entities, state variables and scales

#### Agents

Agents in this model represent adult consumers in the Netherlands. The characteristics of these agents include sex, age, income, employment status, education, living cost and what diet they are following. These characteristics are assumed to be constant over the duration of the simulation. In initialising the agents, each agent has a personal concern regarding the impact of meat consumption on the environment, health, and animal welfare, which can vary over the course of the simulation due to a process of social influence. Each agent has a probability of consuming a meat type based on their personal concerns. These types include beef, pork, poultry, processed meat and meat substitutes.

The agents interact through and are part of networks. All agents are part of an eating network which comprises household members, while only the agents which are workers will be part of the second eating network which connects agents to co-workers at the workplace. In the network there is always a possibility of eating alone, where agents are not influenced by other agents.

Table 5.1: List and brief description of agent's attributes (Source: Author)

Attribute	Description
Network related variables	
Family ID	Identify agent's family
Employment status	Define agents as workers or non-workers
Work team ID	Identify agent's work team
Individual variables	
Sex	Sex of the agent
Age	Age of the agent
Environmental concern	Agent personal concern related to meat and the environment
Health concern	Agent personal concern related to meat and health
Animal welfare concern	Agent personal concern related to meat and animal welfare
Income class	Agent's income class
Education level	Agent's education level
Susceptibility to influence	Personal susceptibility towards family members/co-workers
Eating related variables	
Diet	Meat-free diet or meat-eater
Beef consumed	Amount of beef eaten per single meal (grams)
Pork consumed	Amount of pork eaten per single meal (grams)
Poultry consumed	Amount of poultry eaten per single meal (grams)
Processed consumed	Amount of processed meat eaten per single meal (grams)
Substitute consumed	Amount of substitute meal eaten per single meal (grams)
Eating beef intention	Likelihood of eating beef at time t
Eating pork intention	Likelihood of eating pork at time t
Eating poultry intention	Likelihood of eating poultry at time t
Eating processed intention	Likelihood of eating processed meat at time t
Eating subs intention	Likelihood of eating substitute meat at time t
Emissions related variables	
CO2 emissions	Agent grams CO <sub>2</sub> eq emission from consumption
Acidification	Agent grams SO <sub>2</sub> eq from consumption
Toxicity	Agent grams of Peq from consumption
Smog	Agent grams of NMVOC from consumption
Particulate	Agent grams PM <sub>10</sub> eq emission from consumption
Agricultural land	Agent m <sup>2</sup> related to consumption

## Networks

The model contains two networks, namely the household network and work network. These networks partially overlap simulating relationships among household members and co-workers. All agents are part of a household network, including single-size households, while not all agents are part of co-worker networks. Only agents who are workers are part of the work network. The links between agents in both household and co-worker networks are assumed to be unidirectional, which means two agents exercise the same power of influence on each other. These links of networks are implemented in NetLogo as two different breeds. Households are represented in the model as cliques.

The model generated these networks, as agents are randomly generated at the beginning of the simulation and there is no information about the actual network. The distribution of adults per household follows the household composition data from the Central Bureau of Statistics in The Netherlands (CBS, 2021a; StatLine, 2021). The co-worker network gathers together agents who are marked as workers, with a chance of these worker networks interlinking. The average number of co-workers eating together was fixed based on a study by Bell and Pliner (2003).

Social influence in relation to meat related concerns is spread through the links in the simulation. The links between agents become activated when two agents consume a meal together. The household network has a higher weighting in the links, as research demonstrates that family members exercise the greatest social facilitation of food intake, thereby influencing eating behaviour and food choice,

compared to other companions (de Castro, 1994).

Table 5.2: Pseudo-code for construction of household and co-worker networks and implementation during runs following the procedure of Scalco et al. (2019)

<p>HOUSEHOLD MEMBERS NETWORK SETUP</p> <p>Begin</p> <ol style="list-style-type: none"> <li>1: Set household-ID to 1</li> <li>2: While there are agents without a household ID           <ul style="list-style-type: none"> <li># Create a household with homogeneous consumption behaviour</li> <li>1: Draw a number of household members &lt;- household size</li> <li>2: Repeat household size               <ol style="list-style-type: none"> <li>1: Find the agent among those without a household ID with the maximum likelihood of consuming meat</li> <li>2: Assign household-ID to the agent</li> </ol> </li> <li>3: Create a link between each agent with the same household-ID</li> <li>4: Set household-ID household-ID + 1</li> </ul> </li> </ol> <p>End</p>
<p>CO-WORKERS NETWORK SETUP</p> <p>Begin</p> <ol style="list-style-type: none"> <li>1: Set team-ID to 1</li> <li>2: While there are agents among workers and without a team ID           <ul style="list-style-type: none"> <li># Create a single work team</li> <li>1: Draw a number of team members &lt;- team-size</li> <li>2: Repeat team-size               <ol style="list-style-type: none"> <li>1: Find the agent among those without a team ID</li> <li>2: Assign team-ID to the agent</li> </ol> </li> <li>3: Create a link between each agent with the same team-ID</li> <li>4: Set team-ID team-ID + 1</li> </ul> </li> <li># Create bridges among work teams</li> <li>3: Set index to 1</li> <li>4: While index &lt; max(team-ID)           <ul style="list-style-type: none"> <li>Ask to a proportion (decided from the interface) of agents with team-ID equal to index to create a link with another agent with a team-ID different from index</li> <li>Set index index + 1</li> </ul> </li> </ol> <p>End</p>
<p>MAIN SCHEDULE</p> <p>Begin</p> <ul style="list-style-type: none"> <li># Define context based on day and phases of the day</li> <li>1: If the current meal is equal to breakfast or dinner           <ul style="list-style-type: none"> <li># All agents eat at home</li> <li>1: If a household campaign is active, compute effects of campaign on the target agents</li> <li>2: For each agent, find the associated household members eating at home and compute peer influence</li> <li>3: Compute likelihood of eating meat</li> <li>4: Compute meat intake if meat-based meal</li> </ul> </li> <li>2: If the current meal is equal to lunch           <ul style="list-style-type: none"> <li>If the current day is a weekday               <ul style="list-style-type: none"> <li># Workers eat at the workplace</li> <li>1: If a workplace campaign is active, compute the effects of campaign on target workers</li> <li>2: For each workers, find the associated co-workers in the workplace network that are eating at the same time and compute peer influence</li> </ul> </li> <li># Non-workers eat at home</li> <li>3: If a household campaign is active, compute effects of campaign on agents eating at home</li> <li>4: For each agent, find the associated household members eating at home and compute peer influence</li> <li>5: Compute likelihood of eating meat for each agent</li> </ul> </li> </ul> <p>End</p>



The pseudo-code for constructing the household and co-worker networks, and the implementation of these during the runs is shown in Table 5.2.

### **Temporal framework**

This model utilises a time management subroutine. Each tick in the simulation corresponds to an eating episode. Days are broken up into three ticks, with each tick corresponding to either breakfast, lunch or dinner as eating episode. These series of eating episodes remain constant over the simulation. The model tracks daily consumption of meat types, and stores values in both a daily and weekly time-frame. Weeks correspond to 7 days, which take 21 ticks. The simulation lasts for a period of 3 years, which is the timeframe where data used overlaps.

The eating episode influences the agents in three ways. Firstly, agents can only take part in the co-worker network, i.e. eat with co-workers, during lunchtimes and if they are workers. During breakfast and dinner times the agent will always eat at home, where they can either eat alone or as part of the household network. Secondly, agents will always eat at home during the weekends. Therefore, the model tracks the eating episode/meal time, days, what day of the week it is, when a week has passed and when a year has passed. Finally, depending on the week, there will be a different price of the meat types based on historical data and tax policies.

### **Spatial resolution**

The agents' position is displayed in 3D space according to their concerns. The X-axis corresponds to the agents' health concern, Y-axis to the environmental concern, and Z-axis to the animal welfare concerns. The position of agents reflects the changes in concerns, and is updated per tick. This spatial model does not influence the agents' decision making, and only serves as visual support to the mapping networks and simulation behaviour.

### **Exogenous factors**

The exogenous factors symbolise specific policies/interventions that can be taken by governments. These can be adjusted in the interface of the model. Two intervention types exist in the model, namely: fiscal policy/price increases and social-norm interventions (based on social marketing campaigns). The fiscal policy is a tax that can be placed on meat types. This tax can either be placed on all meat types, or be varied for each individual meat type (beef, pork, poultry, processed meat, meat substitutes). The price of meat can be increased by up to 200%, in increments of 5%. These can be controlled as sliders on the model interface. Meat substitute prices can also drop below 100%, symbolising a subsidy on meat substitutes rather than a tax.

The marketing campaigns can combine various factors. Primarily, the content of campaigns can be changed to reflect whether the campaign focuses on the health, environmental or animal welfare related to meat consumption. Secondly, the target population of the campaigns can be specified. The options for specification include general population, age (young, old), sex (male, female) existing concerns (low, high), and education (low, medium, high). Thirdly, the context of the campaigns can be decided: focusing on households, on the workplace, or both. Finally, the hypothetical success of campaigns can be varied, being either low, medium or high. The level of success of a campaign affects the impact of campaigns on targeted agents.

### 5.1.3. Process overview and scheduling

The model was implemented in the multi-agent language NetLogo. A synthetic population is first generated and initialised based on the population statistics of the Netherlands, as reported by the Central Bureau for Statistics in their StatLine database (CBS, 2021e). This ensures a representative population is generated. The statistical data and probabilities can be found in Appendix E.

Each time-step of the model represents an eating episode. In the weekends all agents will eat at home, while during weekdays agents who are workers will eat at home. Those eating at home will be influenced by their housemate peer network, depending on whether they are eating alone or not. Similarly, those eating at work will be influenced by their co-workers. The strength of influence varies depending on the network, and the concern to be influenced is randomly decided. Each agents calculates their likelihood to consume each meat type (beef, pork, poultry, processed and meat substitutes), and goes through a process to choose which type to consume. The quantity eaten is estimated based on a normal distribution, with mean and standard deviation based on the agent's level of education. The emissions with regards to the consumption is calculated, and the model moves one day further. The influence functions occur within the social network and depend on the agent's environment. The activity diagram of the simulation can be seen in Figure 5.3. The activity diagram for the agents in the simulation is provided in Figure 5.3. The pseudocode for the running of this model is found in Table 5.4

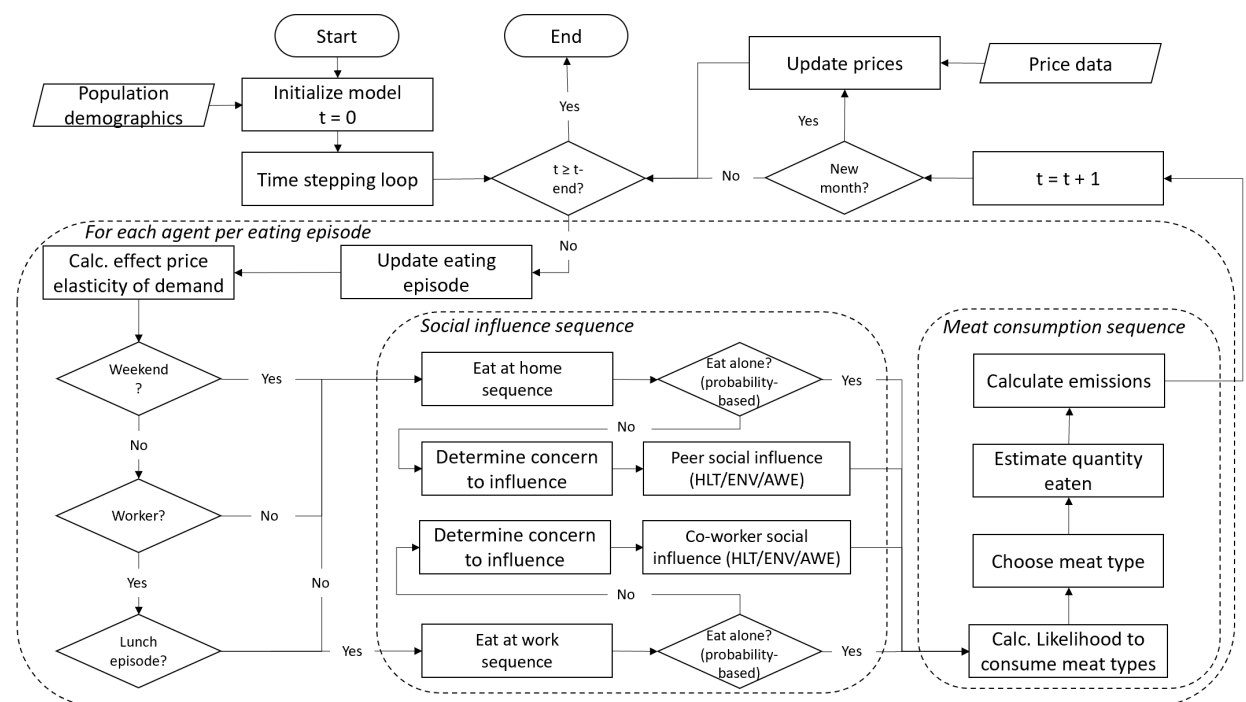


Figure 5.3: Activity diagram overview for the Meat Consumption model (Source: Author)

The setup procedure first generates a synthetic population based on the population statistics of the Netherlands, as reported by the Central Bureau for Statistics in their StatLine database (CBS, 2021e). This ensures a representative population is generated. The statistical data and probabilities can be found in Appendix E. The pseudocode for the setup is outlined in Table 5.3.

Table 5.3: Setup pseudocode for the main model (Source: Author, based on Scalco et al. (2019))

```

SETUP
Begin
1: Create-Agents
2: Initialise parameters
3: Setup-population / Create-Networks
4: Create-Layouts
5: Initialise-Time
6: Read data and initialise prices
7: Calculate Price Elasticity of Demand effects
8: Initialise reporters
End

```

The flowchart of the population initialisation can be seen in Figure 5.4. This shows the agents' sex is first determined based on probability, followed by their age and subsequent level of education. These characteristics determine the concerns, diet and income decile of the agent. Once all agents are fully initialised, a network structure is built, and the time framework is initialised.

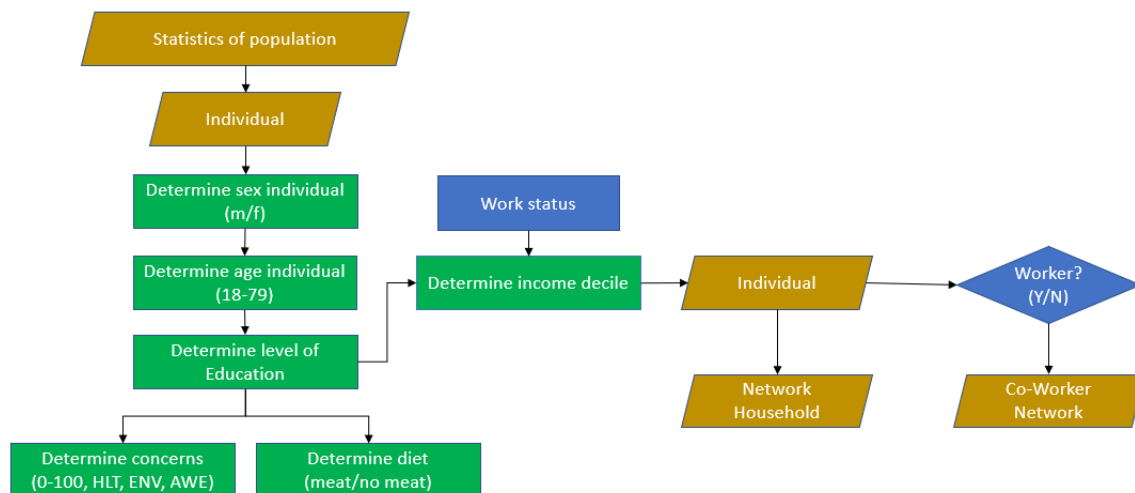


Figure 5.4: Flowchart of the population generation and order of specification of characteristics. Each step follows a probabilistic nature based on the CBS data (Source: Author)

In the main code, the time is moved forward and prices of meat are updated. These are read from a CSV file containing Consumer Price Index (CPI) for each meat type from 2015 - 2019, with 2015 being the base year (CPI 2015 = 100). The price of meat is updated once per month, corresponding to the Consumer Price Index data from the StatLine database (83131ENG) of the Central Bureau for Statistics (CBS, 2021d).

Table 5.4: Pseudocode for the main running of the model (Source: Author, based on Scalco et al. (2019))

```

MAIN CODE
Begin
1: Move-Forward-Time
2: Update-Meat-Prices-Index
3: Calculate the Price Elasticity of Demand effect
4: # Define context based on the day and phases of the day
5: # During breakfast and dinner every agent will eat at home.
6: If ((current-meal = breakfast) OR (current-meal = dinner))
7:   [ask agents
8:     Eat-At-Home
9:     If (campaign? = TRUE) [Campaign-Influence]
10:    Household-Peer-Influence
11:    Eating-Behaviour
12: # During weekdays workers will eat at the workplace,
13: # while non-workers will eat at home during this period.
14: # During weekends all agents will eat at home
15: If (current-meal = lunch)
16:   [ifelse (current-day weekdays)
17:     [ask agents
18:       ifelse (worker? = TRUE)
19:         [Eat-At-Work
20:         If (campaign? = TRUE) [Campaign-Influence]
21:         Workplace-Peer-Influence
22:         Eating-Behaviour
23:         [Eat-At-Home
24:         If (campaign? = TRUE) [Campaign-Influence]
25:         Household-Peer-Influence
26:         Eating-Behaviour
27:       [ask agents
28:         Eat-At-Home
29:         If (campaign? = TRUE) [Campaign-Influence]
30:         Household-Peer-Influence
31:         Eating-Behaviour]
32: # Other sources of influences.
33: Ask agents
34:   External-Influence
35: # Updates plots, monitors, etc.
36: Outputs-Update
37: # Define the current day with words
38: define-current.day.of.week
End

```

The model will behave differently depending on the eating episode. If the eating episode corresponds to either breakfast or dinner, then it is assumed the agent will eat at home. The simulation then activates the household network, calculates the effects of the social marketing campaigns which are in effect, and runs the process of peer-influence between household members. The days of the week are tracked, regulating where agents will eat. During the weekend, it is assumed that all agents will eat all meals (breakfast, lunch and dinner) at home. During weekdays, workers will eat lunch at work, while non-workers will eat lunch at home. Breakfast and dinner are eaten at home regardless of the day.

Agents who are eating at work will spread peer influence through the co-worker network and only influence their co-workers and not household members. Subsequently, the effect of other potential external sources of influence other than peer influence are calculated for the agents' concerns. Finally, the outputs, plots and agent positions in 3D space are updated.

## 5.2. Design concept

### 5.2.1. Theoretical and empirical background

The model utilises various principles of scientific theories. The agents' behaviour is grounded in the Theory of Planned Behaviour (TPB) (Ajzen, 1991). Based on the TPB, the individual antecedents of intention were modelled separately from the social ones. Eating behaviour is influenced by social factors, and attitudes and habits develop through the interaction with other people (Zhang et al., 2014). This model thereby creates a link between personal attitudes and the those of other people around them (Scalco et al., 2019).

Intention is assumed to be the best predictor as proxy for the actual behaviour, and is computed via a linear regression. This linear regression is conducted based on survey data from the CBS Belevingen 2020 report (CBS, 2021b) and the Dutch National Food Consumption Survey (RIVM, 2020b).

For the design of social networks, the ABM model of Scalco et al. (Scalco et al., 2019) was built upon, which utilises the concepts of social design of social networks in ABM as laid out by Hamill & Gilbert (Hamill & Gilbert, 2010). These concepts were used to design and join two distinct eating networks, namely the household and co-worker networks. Using networks facilitates the formalisation of social influence (Scalco et al., 2019), and allows for this influence to be regulated at specific eating episodes and days. Following the principle of homophily (McPherson, Smith-Lovin, & Cook, 2001; Scalco et al., 2019) the households are homogeneous within them and heterogeneous between them with respect to their maximum probability of eating meat. This is an assumption which follows research where homogeneity within households with regards to food consumption has been observed (Pachucki et al., 2011; Scalco et al., 2019).

The interventions based on social influence are grounded in empirical evidence, where it is shown that social campaigns can both promote fruit and vegetable intake, reduce alcohol intake, promote pro-environmental behaviour amongst others. The translation of social media marketing campaigns effecting concerns are based on the model of the ABM by Zhang et al. (2014).

Finally, the susceptibility of agents towards the influence of household members and colleagues is based on the model of Scalco et al. (Scalco et al., 2019) and the previous work on food choice networks (de Castro, 1994; Pachucki et al., 2011).

The influence of prices on consumption is well established (Green et al., 2013). Price elasticity of demand is based on the work of (van Hoof, 2019) and looks both at the own and cross price elasticity of demand. Price elasticity of demand for meat substitutes was modelled after research performed in the US, as proxy for price elasticity for meat substitutes in the Netherlands (Ritchie et al., 2018).

### 5.2.2. Individual decision-making

#### Subjects and objects of decision

In the model each agent represents a consumer in the Netherlands. These agents will have a chance to eat a specific type of meat protein (beef, pork, poultry, processed meat or meat substitutes) at each eating episode. This chance is a calculated probability based on their concerns and the product price, which are initialised based on their profiles and influenced by other agents and campaigns. Each agent decides what meal they will consume three times a day; for breakfast, lunch and dinner. Agent's have a certain probability to eat alone, during which they will not be influenced by other agents.

This model does not consider snacking in-between meals, which accounts for around 6.2% of daily meat consumption. For simplicity, the agents will always eat a meat type during a meal, which includes meat substitutes, and will not skip any meals or eat at restaurants. The quantity of meat consumption per meat moment is dependent on the individual profile, and the moment of consumption, which both draw upon the Dutch National Food Consumption Survey (DNFCS).

#### Decision rules

The agent evaluates the individual likelihood to consume a certain meal type based on their own environmental, health and animal welfare concerns, and the price. These concerns are initialised based on the agent's sex, age, and education. This likelihood is calculated for all meat types at every time step, i.e. for beef, pork, poultry, processed meat and meat substitutes. When choosing which meal to eat, a random probability is generated for each of the meat types. The agent then iterates through their options, until a choice is made by the agent where the likelihood to eat that meat type is higher than the random probability. The variables and their associated weights are selected on the analysis

conducted on the responses of the "Belevingen 2020: klimaatverandering en energietransitie" (Experiences 2020: climate change and energy transition) conducted by the Central Bureau for Statistics in the Netherlands (CBS, 2021b)

This survey shows the importance of environmental, health and animal welfare concerns, as well as taste, influence of housemates, price and other reasons for reducing meat consumption. This survey provides an aggregate for the population demographics used in the model. These are coupled to a survey of the actual meat consumption of food types in the Netherlands to determine the correlation and importance between these parameters and likelihood to consume a certain meat type. As this dataset is limited, three main factors were chosen: environmental, animal welfare and health concerns. These three factors were found to be important from the literature, such as the LISS Panel study "Reasons to Eat Less Meat" and subsequent research published by Hopwood et al. (Hopwood et al., 2020).

### Social influence and effects of social marketing campaigns

The influence of social marketing campaigns follows the approach by Zhang et al. (2014). As seen in Equation 5.1, the influence is calculated as a weighted average depending on the weight  $\gamma$  and the relative concerns of an agent  $i$  compared to its peers. These peers are either household members or co-workers, depending on the eating episode, day, and whether the agent is a worker. When the social marketing campaign weight  $\gamma$  is equal to zero then the peer influence occurs without any effect of the social marketing campaign.

$$c_{i,t} = (1 - \alpha_i)C_{i,t-1} + \alpha_i \frac{\sum_{C_{j,t-1} > C_{i,t-1}}^{j \in \text{peers}(i)} (1 + \gamma)C_{j,t-1} + \sum_{C_{j,t-1} \leq C_{i,t-1}}^{j \in \text{peers}(i)} (1 - \gamma)C_{j,t-1}}{\sum_{C_{j,t-1} > C_{i,t-1}}^{j \in \text{peers}(i)} (1 + \gamma) + \sum_{C_{j,t-1} \leq C_{i,t-1}}^{j \in \text{peers}(i)} (1 - \gamma)} \quad (5.1)$$

In Equation 5.1,  $C$  represents the value of the agent's concern regarding a specific aspect of meat consumption (i.e. environment, health or animal welfare) at a time  $t$ . The parameter  $\gamma$  reflects the degree of success of a social marketing campaign, while  $\alpha$  indicates how susceptible an agent is towards a peer in their household network or co-worker network. This process occurs separately for each of the agent's concerns. This allows for agents to be simultaneously be influenced by certain agents in relation to animal welfare, while influenced by others related to health (Scalco et al., 2019). Gamma ( $\gamma$ ) is used to bias the agents' attention to agents in their network which have higher concerns than themselves (Zhang et al., 2014).

The  $\gamma$  parameter can be varied in the model for each of the health, environment and animal welfare campaigns within the model interface. As the  $\gamma$  value influences the agent's attention to campaigns, it is used as a proxy for the campaign success. Therefore, varying this can be used to simulate the hypothetical cases of a low, medium or high campaign success. As agents pay less attention to campaigns over time, the value of gamma will also decay over time.

The  $\alpha$  parameter represents the strength of influence that other agents will exert over agent  $i$ . In other words, the susceptibility of an agent to other agents. As agents are more influenced by members of their family, according to social modelling of eating behaviour (de Castro, 1994), the  $\alpha$  value for agent influence towards household members is higher than that for co-workers. This is modelled following the model by Scalco et al. (Scalco et al., 2019), where a normal distribution is assumed based on the suggestion by Bruch & Atwell (2015). This assumption was made as there is no specific data on the probability distribution of consumer susceptibility towards peers, and it can be assumed that some agents/people will be more susceptible than others.

### Decay of the effects of social marketing campaigns

The influence of the social marketing campaign, symbolised by the gamma  $\gamma$  parameter, decays over time through a time-decay function seen in Equation 5.2:

$$\gamma_t = \gamma_0 * e^{(-\lambda t)} \quad (5.2)$$

Here,  $\gamma$  reflects the influence of the marketing campaign on the concerns of the agent. The lambda  $\lambda$  parameter represents the exponential decay constant, and the time  $t$  signifies the current month in the simulation (Scalco et al., 2019). The  $\lambda$  value was chosen based on literature about the 'persistence' of social marketing campaign effect which are utilise norm-based messaging (Allcott & Rogers, 2012; Robinson, Fleming, & Higgs, 2014). The rate of decay can be set differently for each agent concern (health, environment and animal welfare), however, these have been assumed to be the same for each

intervention to maintain simplicity. The decay of the social marketing campaigns during the simulation can be seen in Figure ?? for campaigns which have low, medium or high success.

### 5.2.3. Learning

This model does not apply individual or collective learning.

### 5.2.4. Interaction

The interaction between agents is modelled through network interactions (Scalco et al., 2019). During these interactions, there is an exchange of influence (Zhang et al., 2014) between agents with regards to their concerns on meat consumption. Agents can only interact if they are part of the same network, and when the network is activated. Therefore, only agents within the same household network can interact when they are both having a meal at home, and agents within the co-worker network can only interact during lunchtimes if agents are workers. The co-worker network cannot be used for interactions during the weekend, or by agents who are not workers.

For simplicity, agents who are workers are assumed to remain workers during the simulation, and agents who are non-workers are assumed to remain non-workers. Therefore, agents will only interact with other agents which are part of their network. Between co-worker networks, it is possible to have an interconnection (Scalco et al., 2019).

### 5.2.5. Collectives

Two collectives exist within the simulation, namely households and work teams. These are both social groups, and are specified during the setup phase of the simulation. These social groups remain constant throughout the simulation. The formation of a household represents a clique, where each agent who is part of the household is connected to all other agents within this household. This household network allows agents to influence one another when sharing eating moments at home. In a similar way, the co-worker network allows workers within the same work team to influence one another. Within the work team, agents are connected to every other member of the same work team. Work teams are interconnected, representing the hypothetical structure of an organisation.

### 5.2.6. Heterogeneity

Heterogeneity in the population takes shape the shape of varied population profiles, susceptibility of influence to other agents, concerns, food consumption behaviour and quantities of food eaten. In the setup phase agent profiles are initialised based on the population demographics from the Central Bureau of Statistics of the Netherlands CBS (2021e). Agent profiles consist of their own age, sex, education level, income decile, their diets and whether they are workers. Diets are used to determine which workers are vegetarian, thereby only eating non-meat products, and who are meat-eaters.

The most important source of heterogeneity in the population influencing model outcomes is the level of concern each agent has for the environment, animal welfare and health. These are part of the agent profiles and assumed to follow a normal distribution. These probability density functions vary based on the agent's education level, which was assessed to be an important differentiating factor. This education level is in turn based on the agents' age and gender. The probability distribution of concerns are based on the survey "Belevingen 2020: klimaatverandering en energietransitie" (CBS, 2021b), where 3000 individuals were asked about their gender, age, education level, the level of urbanisation they live in, their diet, and reasons for reducing their meat consumption.

Heterogeneity exists at the level of social influence in the model, where agents' have an individual susceptibility to the social influence effect of other agents. Furthermore, agents each have a probability of eating alone depending on whether they are a worker and the time of the day. Finally, the mean and standard deviation of meat consumption during eating episodes varies for the agents based on their gender, age, and level of education. This is different for each type of meat, and follows probabilities derived from the Dutch National Food Consumption Survey (DNFCS) conducted between 2012 and 2016 (RIVM, 2020b). The quantity of meat eaten is therefore differs per agent. This quantity is further influenced by the time of day, as agents will eat a different proportion meat depending on the moment according to the DNFCS: Meal moments (RIVM, 2020a). The meal moment only contains data for meat as an umbrella term, therefore it is assumed that each type of meat consumption follows the probability based on the agents' age, gender and level of education (with the majority of meat consumption

occurring during dinner).

It should be noted that the consumption survey on mean contribution (%) of moments to food groups indicates that meat consumption in moments in-between meals accounts for 5-10% of daily meat consumption for different population groups (6.2% overall) (RIVM, 2020a). For simplicity of the model, this was not taken into account during the model and factored in when looking at the validity of the model. All agents are also assumed to consume one type of meat or meat substitute during each meal.

### 5.2.7. Stochasticity

Stochasticity is modelled as an external sources of influence. This model assumes that peer influence during meals is not the only factor influencing the concerns of the agents, and that external influences exist. This works as a proxy for the exposure to various sources of information, social media, and other experiences that may affect the personal concern for the environment, health, and animal welfare. This external influence is modelled as random oscillations which are equally distributed over time and take effect at the end of the day. This external influence was subjected to both a sensitivity analysis and parameter sweep, to select a reasonable value during the validation phase.

### 5.2.8. Observation

The observations collected in this model included are outlined in Table 5.5, and include the meat eaten per individual, likelihood to consume meat types, weekly emissions and agent concerns.

Table 5.5: Model observations and units of these observations (Source: Author)

Observation	Units
Meat eaten per meat type (beef, pork, poultry, processed, substitute)	g/week
Likelihood to consume meat type (beef, pork, poultry, processed, substitute)	%
Average Weekly emissions by agents	
Climate	gCO <sub>2</sub> eq
Acidification	(gSO <sub>2</sub> eq)
Toxicity	gPeq
Smog	gNMVOC
Particulate matter	gPM <sub>10</sub> eq
Agri. land use	m <sup>2</sup>
Agent concerns (health, environment, animal welfare)	%

These model outcomes are recorded for the overall population, and split per demographic group. These demographics are outlined in Table 5.6.

Table 5.6: Demographics for the model outcomes (Source: Author)

Type	Demographics
Income	Low/Mid/High
Age	Young (18-29)/Adults (30-60)
Gender	Males/Females
Occupation	Workers/Non-workers
Education	Low/Mid/High

## 5.3. Details

### 5.3.1. Implementation details

The model is implemented in NetLogo 6.1.1. The model input data was gathered from online databases as StatLine from the Central Bureau of Statistics through the open-source API "cbsodata" in Python. Python was used to determine correlations, significance of data, and conduct the regression analysis. The output data of the model is also processed in Python.



### 5.3.2. Initialization/input

In the model setup, the agent profiles are initialised. The model reads monthly price information of each meat type from an input file, based on the Consumer Price Index of food types (CBS 83131ENG) (CBS, 2021d). The sex, age and education (CBS 82275NED) are taken from the StatLine database of the Central Bureau of Statistics (CBS, 2021c, 2021e). The Central Bureau for Statistics collects information on population demographics of the Netherlands. The consumption behaviour is calculated from the Belevingen 2020 survey by the CBS (CBS, 2021b), combined with the information on food consumption of the population from the Dutch National Food Consumption Survey (RIVM, 2020b). The input, their source, and range of values are reported in Table 5.7.

Table 5.7: Inputs, sources and range of values (Source: Author)

Input	Dynamic*	Source	Range
Sex	No	CBS	{0; 1}
Age	No	CBS	{18, 79}
Education	No	CBS	[0-4]
Employment status	No	CBS	{true; false}
Income class	No	CBS	[0,10]
Meat-free diet	No	Belevingen	{0; 1}
Health concern	Yes	Belevingen	[0, 100]
Environment concern	Yes	Belevingen	[0, 100]
Animal welfare concern	Yes	Belevingen	[0, 100]
Susceptibility to influence ( $\alpha$ )	No	Endogenous	[0, 0.30] w.r.t. household members [0, 0.15] w.r.t. co-workers
Likelihood to eat meat type (Beef, Pork Poultry, Processed, Substitute)	Yes	Endogenous	[0, 1]
Quantity of meat consumed per type	Yes	Endogenous	[0, ]
Contribution (%) moment to consumption	No	DNFCS	[1, ]
Food related emissions	No	CE Delft	[0, ]
Probability of eating alone	Yes	RIVM	[0, 1]
Average work size team	No	CBS	4
Average family size	No	CBS	2
Price Elasticity of Demand	No	CE Delft	[0, ]
Social marketing campaign success ( $\gamma$ )	No	Endogenous	{0; 0.25; 0.5; 0.75}
Consumer Price Index meat (2015 = 100)	Yes	CBS	[90, 110]

\* Dynamic variables are those whose value can change during the simulation run. Certain variables are classified as "Endogenous" variables, which indicates that the value for this is determined within the model. 'Belevingen' refers to the 'Belevingen 2020' survey (CBS, 2021b), while DNFCS is the Dutch National Food Consumption Survey (RIVM, 2020a), and RIVM here refers to the Background report on Dutch food consumption (Geurts, 2016).

To determine the efficacy of measures in terms of reducing emissions from food consumption, not only was the food consumption per type reported, but also the related emissions throughout the simulation. The emissions per food type can be broken down into climate related emissions (gSO<sub>2</sub>eq), acidification (gSO<sub>2</sub>eq), toxicity (gPeq), Smog (gNMVOC), particulate matter (gPM<sub>10</sub>eq) and land use ( $m^2/kg$ ), amongst others. The values of these are based on the calculations from a report from CE Delft (de Bruyn et al., 2018). Emissions from meat substitutes were based on the emissions from tofu. It should be noted that emissions from beef consumption are calculated at weighted average from beef derived from dairy cows (75%), calves (8%) and beef cows (17%). Emissions from beef cows are significantly higher than dairy cows, however, to replicate consumption emissions more accurately the combined value was taken as reported on in the CE Delft study (de Bruyn et al., 2018). Similarly, poultry emissions are taken to be those from egg laying hens (20%) and chicken raised for meat consumption (80%).

Table 5.8: Emissions per food type (beef, pork, poultry, processed & substitute in terms of climate, acidification, toxicity, smog, particulate matter and land use (de Bruyn et al., 2018)

Emission type	Beef	Pork	Poultry	Processed	Substitute
Climate (gCO <sub>2</sub> eq)	13.629	11.309	6.556	11.309	2.4
Acidification (gSO <sub>2</sub> eq)	0.153	0.162	0.0387	0.162	0.007
Toxicity (gP <sub>eq</sub> )	0.00176	0.0014	0.00098	0.0014	0.000327
Smog (gNMVOC)	0.00411	0.0272	0.0116	0.0272	0.0129
Particulate (gPM <sub>10</sub> eq)	0.02832	0.0294	0.0087	0.0294	0.0029
Land use (m <sup>2</sup> /kg)	16.72	8.38	4.79	8.38	1.47

### 5.3.3. Submodels

#### Meal Selection

The modelling of the meal selection occurred in various phases, to determine which factors to include. A logistical regression analysis of the LISS Panel "Reasons to Eat Less Meat" survey, combined with the profile of the respondents, allowed for the identification of various factors as significant predictors for meat reduction behaviour. This behaviour was determined by the self-reported diets of consumers, being either vegan, vegetarian, flexitarian, pescatarian, eating meat 5-6 times a week or eating meat every day. The significant variables include environmental, health and animal welfare concerns, the agent's age, gender, and education level. This analysis provides an indication for consumption behaviour, but do not specify which type of meat was eaten.

The type of meat eaten was derived from another regression analysis, performed on the CBS "Belevingen 2020: klimaatverandering en energietransitie" survey (CBS, 2021b). This dataset provides the importance of factors including environment, health, animal welfare, taste, housemates, price and others reasons for respondents to reduce their consumption. This data is provided as aggregate per population identifier (gender, age intervals, education, urbanisation). To determine the influence of factors on specific meat type consumption, the Belevingen 2020 data was combined with statistics of actual meat consumption of each meat type provided by the Dutch National Food Consumption Survey (RIVM, 2020b). The quantity of data can only be used to explain a number of parameters, as utilising all parameters in a regression will result in an over-fit for the model. Therefore, based on the previous regression on LISS Panel data, the three parameters of interest were chosen as environment, health and animal welfare concerns. These parameters are important parameters in relation to meat consumption (Hopwood et al., 2020; Renner et al., 2012).

A regression analysis performed using the survey data and consumption data provides a likelihood to eat each meat type per day. The agent uses this function at each time step to evaluate their own likelihood to consume a specific meat type (beef, pork, poultry, processed meat or meat substitutes) based on their environmental, health and animal welfare concerns as seen in Equation 5.3.

$$y_i = (b_0 + b_1(env_{i,t}) + b_2(hlt_{i,t}) + b_3(awe_{i,t})) * ped.meat.type * veg? \quad (5.3)$$

The resulting parameters of the analysis for each meat type can be found in Table 5.9. The price elasticity of demand effect (ped.meat.type) is further discussed in the Price elasticity section. If an agent is vegetarian (veg? = 0), then the likelihood to consume meat for beef, pork, poultry and processed meat will be 0, while the likelihood to consume meat substitutes will be 100.

Table 5.9: Parameters determining the likelihood of consuming each food type based on the regression analysis performed on the surveys of Belevingen 2020 and the Dutch National Food Consumption Survey (CBS, 2021b; RIVM, 2020b) (Source: Author)

Parameter	Beef	Pork	Poultry	Processed	Substitute
Constant (b <sub>0</sub> )	9.098	11.007	23.268	64.791	0.300
Environment concern (b <sub>1</sub> )	-0.003	-0.241	0.105	-0.082	0.057
Animal welfare concern (b <sub>2</sub> )	-0.221	-0.055	0.094	-0.322	0.020
Health concern (b <sub>3</sub> )	0.360	0.342	-0.207	0.401	-0.014

### Estimate quantity of meat consumed per consumer

A submodel is used to estimate the quantity of meat eaten by each agent during each eating episode for each type of meat. The model assumes the agent can only choose one type of meat per meal for simplicity. The meat intake for each meat type follows a normal distribution based on the agents' sex, age level of education and time of day. Mean consumption per meat type is taken from the Dutch National Food Consumption Survey (RIVM, 2020b), with the standard deviation based on the mean, 5th and 95th percentiles.

The time of day corrects the meat consumed by the agent by a factor dependent on the moment, following data from the DNFCs on contribution (%) of moments to a food type (RIVM, 2020a). This moment correction factor is agent-dependent, as it is based on the age, sex and education level of the agent. These distributions thereby all approximately follow empirical data.

The type of meat eaten during an eating episode is decided per agent based on the calculated likelihood to eat a meat type. If an agent is vegetarian then they will always consume meat substitutes. If the agent is not vegetarian then they will have to choose between the different meat types. A random parameter is generated, and if this parameter exceeds the likelihood to consume a meat type then a meal is chosen. The agent iterates through the meal types until a meal is chosen. All agents are assumed to eat a type of meat during each meal.

### Price elasticity and quantity consumed

The probability of eating a certain meat type is influenced both by changes in agents' concerns and changes in the price level. The likelihood to eat a specific meat type is altered both by the own price elasticity of demand, as well as the cross price elasticity of demand between products. The price elasticity of demand relates to the percentage change in consumption when the price changes by 1%. This will result in reduced likelihood to consume a meat type when prices rise, and increased likelihood as prices fall. Studies showed that the own price elasticity of beef is high (Mangen & Burrell, 2003), that the elasticity of beef is typically higher than that of pork or chicken (Gallet, 2010; Wirsenius, Hedenus, & Mohlin, 2011). The price elasticity of demand for various meat types was based on an average of studies in the Netherlands (van Hoof, 2019; Vergeer et al., 2020).

The price elasticity of demand for meat substitutes is based on a recent report on the impact of plant-based protein alternatives on beef demand in the U.S, and assumed to have a similar influence in the Netherlands (Tonsor, Lusk, & Schroeder, n.d.). Values greater than 1 signify the product is price elastic, while values below 1 indicate price inelastic products. These values are given in Table 5.10.

Table 5.10: Price and cross price elasticity of demand for each food type in the Netherlands, as determined by van Hoof (2019)

	Beef	Pork	Poultry	Processed	Substitute
Beef	-1.05	0.15	0.14	0.15	-0.429
Pork	0.06	-0.85	-0.094	-0.85	-0.055
Poultry	0.36	0.07	-0.96	0.07	0.306
Processed	0.06	-0.85	-0.094	-0.85	-0.055
Substitute	0.542	0.085	0.047	0.085	-2.368

Within the model fiscal policies are modelled as a slider, which can alter the price changes. Price changes for beef, pork, poultry and processed meat can be increased by 100% in increments of 5%. Substitute meat consumption can be both increased and decreased, with a decrease related to subsidies rather than a tax.



## Model Verification and Validation

### 6.1. Model Verification

Several model verification tests were conducted. These include running verifying whether all agents receive values for their personal profile, following an agent to ensure they are going through all the steps, writing agent outputs and extreme value testing.

#### 6.1.1. Population

In the model set-up, extensive care was taken to ensure the population followed specified population demographics. The population taken was that of the Netherlands, for which the population data is retrieved from the Central Bureau for Statistics of the Netherlands (CBS, 2021c, 2021e; StatLine, 2021).

As the generation of the population was built up, the key variables of quantity of men, women, age groups, level of education and dietary composition were all checked at each step. When comparing the population from Figure 6.1 to the distributions seen from the CBS (CBS, 2021e), the generated population closely resembles the actual population. Similarly, the likelihood to consume meat per day is similar to the average of the Dutch population from the Dutch National Food Consumption Survey (RIVM, 2020b) in Figure 6.2.

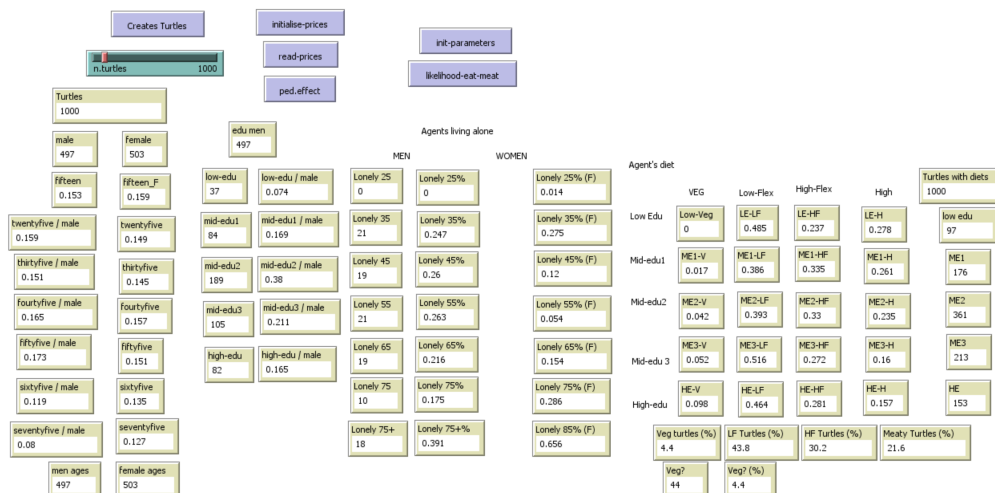


Figure 6.1: Population Setup Tests (Source: Author)

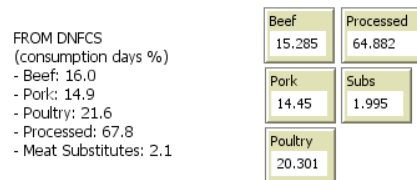


Figure 6.2: Meat consumption likelihood of the model compared to the DNFCs (RIVM, 2020b) (Source: Author)

During the model setup, all members of the population had an age, gender, level of education, income and personal levels of concerns for health, the environment and animal welfare assigned to them.

### 6.1.2. Model outputs

The model outputs of experiments were tracked using reporter variables. These reporter variables track the weekly average values of variables of interest. These include the KPIs, namely meat consumption per meat type and emissions, and the average concerns of individuals. These outputs are recorded once per week, which enhances the running time of the model and provides more meaningful statistics as normative change is slow. In the model, each time tick represents one meal, with three ticks per day, and 21 per week. The outcomes have to be verified. Figure 6.3 shows each concern, and their max and minimum values.

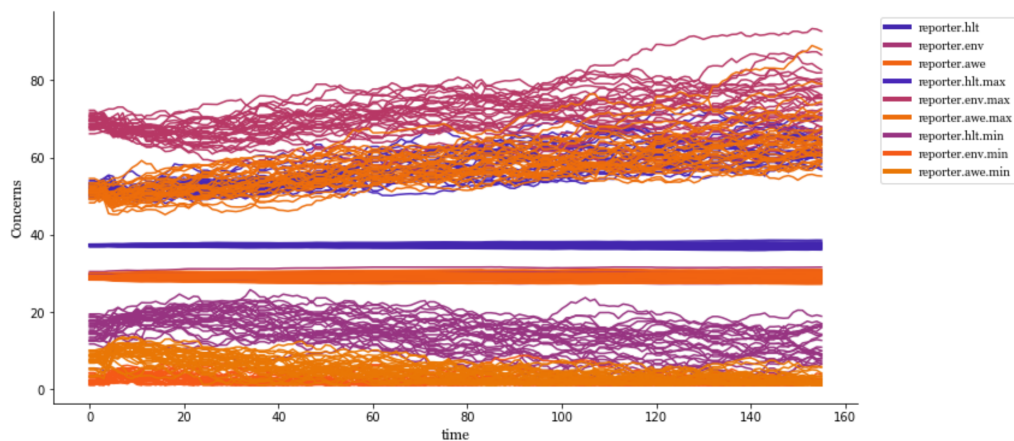


Figure 6.3: Reporters for all concerns in the base-case scenario, showing values of all individual model runs (Source: Author)

From Figure 6.3, we can see that the sampled outcomes are continuous. The behaviour of the reported model outputs follows the same behaviour as seen in Figure 6.4, which shows the model interface in NetLogo. This indicates that the weekly values capture model behaviour, and that values are recorded correctly. From Figure 6.4 it is visible that the model does not show sudden large changes.

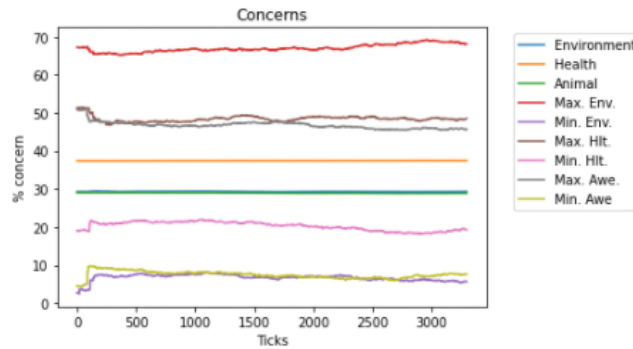


Figure 6.4: Concerns for a run from the NetLogo interface (Source: Author)

### 6.1.3. Agent-tracking

One agent was tracked throughout the whole simulation, which showed that each day the agent ate 3 meals, 1 meal corresponding to each time interval. The total amount of meals corresponds to the total amount of ticks for each of the agents. Furthermore, it was observed that agents strictly ate positive values of meat, and only ate one type of meat per meal. This is a model assumption.

## 6.2. Model Validation

"All models are wrong, but some are useful" (Box & Draper, 1987). While this is true, for models to be useful they also have to be valid. Validation tests are described by Forrester (1970) as tools to gain confidence in the model behaviour.

### 6.2.1. Sensitivity Analysis

A sensitivity analysis was conducted both on the external influence parameter ('par.ext.source.max'), which is a stochastic variable that represents random changes in consumer's concerns as result of experiences that are not explicitly modelled in the simulation (e.g. media influence, negative food experiences, etc. ), and on the population size. This sensitivity test is both a qualitative assessment in terms of the directions of outputs, and a quantitative measure to ensure the orders of magnitude makes sense. The sensitivity to the external influence is discussed first.

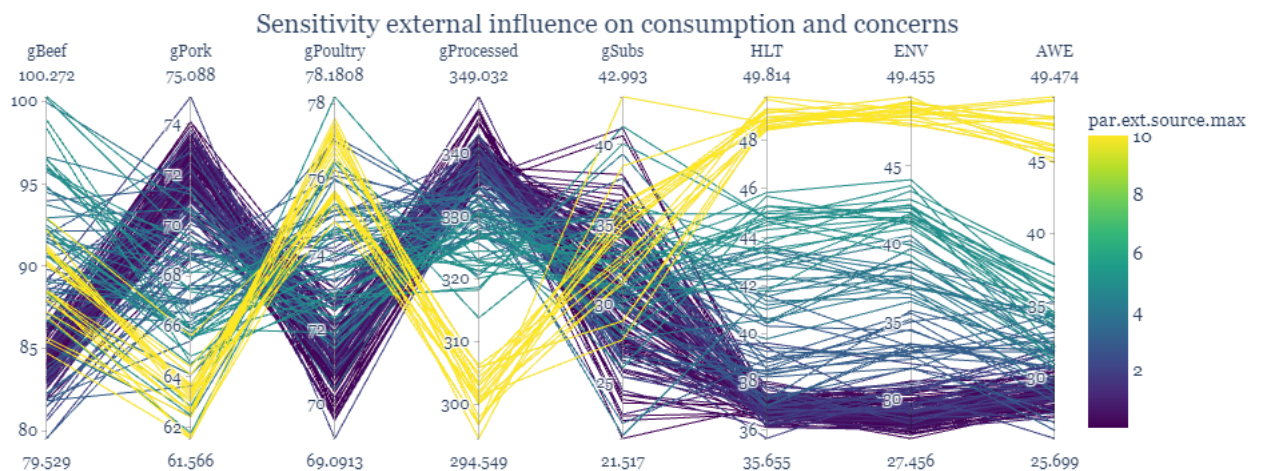


Figure 6.5: Sensitivity of meat consumption per meat consumption type to a change in susceptibility to external influence of a population (Source: Author)

Figure 6.5 shows the sensitivity of the external influence on meat consumption and concerns. This analysis was run for a range of values (0, 0.1, 0.5, 1, 5, and 10). This analysis shows that the external

influence will result in a more stochastic model at higher values. At values below 1, the model behaviour is stable. The model behaviour becomes less stable when the sensitivity is around 5, and becomes stable again at extremely high values. For the base-case scenario, a population is taken with a value of 0.5, representing a scenario with a relatively stable population. The High Susceptibility scenario looks at the model when the `par.ext.source.max` value is 5. For all values provided, the model behaviour remains similar. This is seen in the relationship between health, environmental concerns and animal welfare concerns, where high concerns result in higher substitute consumption, lower processed meat consumption, higher poultry consumption, higher pork consumption and lower beef consumption. The inverse is the case when concerns are relatively low.

This external influence was found to have a more significant value on the maximum and minimum values of the concerns, as seen from the boxplots in Figure 6.6. This is the case as without the external influence there tends to be a regression to the mean of the population of the norms of individuals over time. When there is a high external influence, individuals with high concerns may increase in their concern.

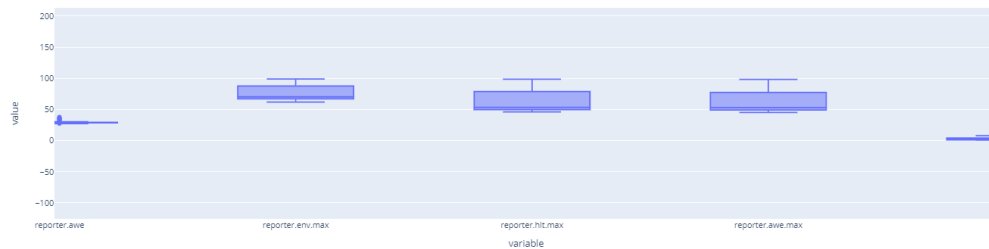


Figure 6.6: Boxplots of the maximum concerns of agents when susceptibility is varied (Source: Author)

The sensitivity analysis of the population was run for population sizes ranging from 100 to 10,000. The analysis of populations which are orders of magnitude higher was not considered in this sensitivity analysis, as the influence of population size on meat consumption was found to be stable past 1000. In Figure 6.7, it can be seen that the runs with a population of 10,000 closely overlap with the experiments where with a population of 1,000. As trade-off between run-time and accuracy, the sensitivity analysis indicates that experiments should be sufficiently representative when run with 1000 individuals.

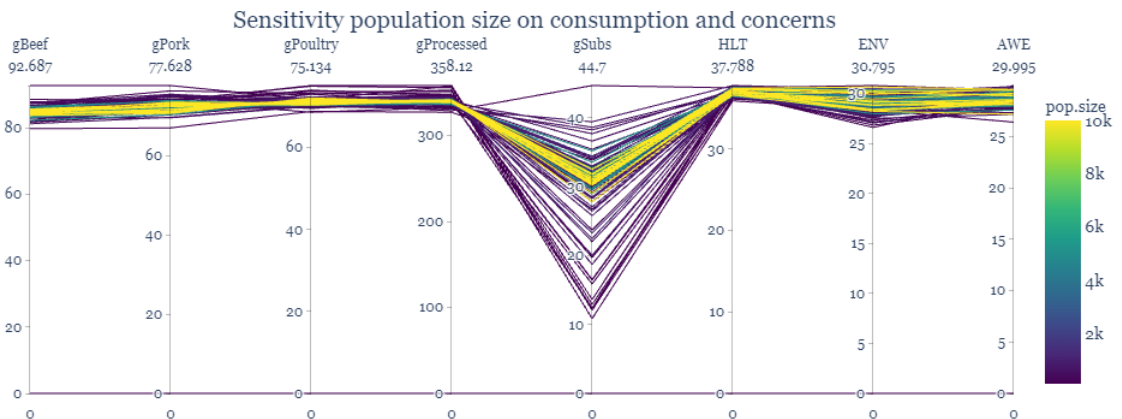


Figure 6.7: Sensitivity of meat consumption per meat type and concerns with respect to changes in the population size for experiments conducted in the base-case scenario (sizes include 100, 200, 500, 1000, 10,000) (Source: Author)



### 6.2.2. Empirical Validation

The model was empirically validated through comparing the model outputs with the empirical data from the CBS and the Dutch National Food Consumption survey in terms of overall meat consumption, reasonable yearly changes in meat consumption, and emissions related to dietary consumption. This can be seen in Figure 6.8.

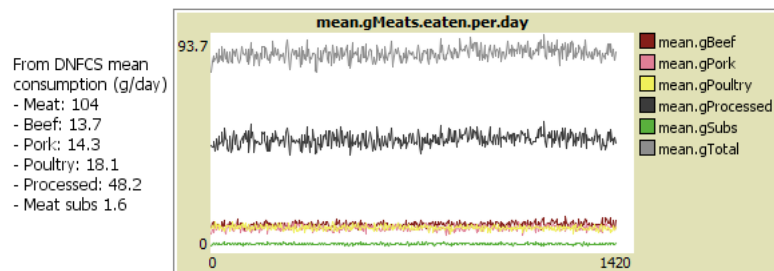


Figure 6.8: Grams of meat eaten by agents in the model compared to grams eaten from the Dutch National Food Consumption Survey (RIVM, 2020b) (Source: Author)

The total daily consumption of meat in the model amounts fluctuates around 89 grams per day for the base-case scenario. The average grams of meat consumed from the DNFCS is 104 grams of meat (RIVM, 2020b). This model does not consider the eating of food in-between meals, as during meal times on average 92.7% of food is eaten (RIVM, 2020a). This would mean agents should eat around 96 grams of meat per day. This is within 10% of the predicted meat consumption of the model.



# 7

## Results

The model, as specified in Chapter 5, was investigated for the three scenarios and six policies outlined in Chapter 3. These three scenarios represent the base-case Dutch population, a highly environmentally concerned population, and highly susceptible Dutch population. The policies were applied to each respective scenario, to determine the effects of these on the KPIs. These policies include the environmental social marketing campaign, targeting the general population and lower educated population respectively, and fiscal policies which include: taxing beef, taxing beef and subsidising substitutes, and taxing all meat. These are compared to the the scenarios with no active policy. Each combination was run for 50 experiments.

These experiments were run using the BehaviourSpace tool in NetLogo. Reporter variables were calculated to provide a snapshot of the average value of each variable per week. The model outputs were then processed and visualized in Python. This Chapter covers the most important results of the experiments run on the model. Section 7.1 provides results for each of the base case scenarios with regard to meat consumption, and changes in individual concerns. Section 7.2 focuses on the impact of policies on one KPI of interest, namely average meat consumption per type. Finally, Section 7.3 looks at the emissions related to each scenario and policy.

### 7.1. Model Behaviour

The model behaviour is observed in three different scenarios. These scenarios are run without any policies in place, for the duration of 3 years, to determine the model range of model responses. Scenario 1 represents the base-case, scenario 2 represents the highly environmentally concerned population and scenario 3 represents the highly susceptible population.

Visualizing average concerns and weekly meat consumption for each scenario

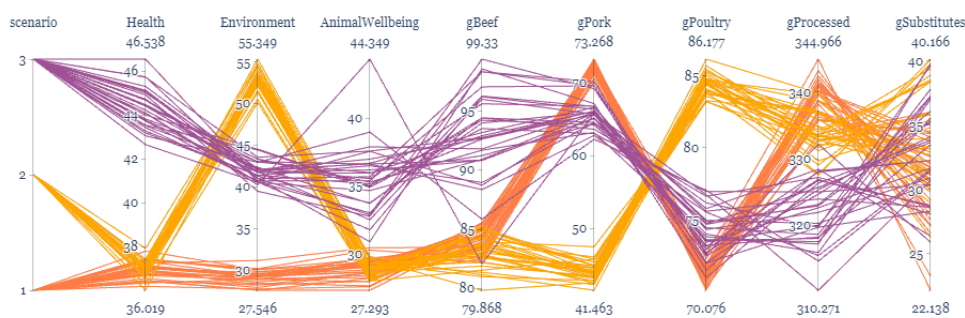


Figure 7.1: Results of the scenarios (1: base-case, 2: high environmental concern, 3: high susceptibility) without any active policy, with regards to the average agent concerns (health, environment, animal wellbeing), and average weekly consumption of each food type in grams (Beef, Pork, Poultry, Processed, and Substitutes) (Source: Author)

Figure 7.1 gives an insight in the relation between the various concerns and meat consumption. Each line represents a model run. It was expected that individuals with high environmental concern would consume meat sources with lower emissions. In the case of the highly environmentally concerned population, beef and processed meat consumption is reduced, and pork consumption is significantly reduced, while the consumption of poultry and meat substitutes has increased. This indicates there is a positive relation between environmental concerns and poultry/meat substitute consumption, and a negative relation between environmental concerns and beef and pork/processed meat consumption.

Processed meat in the Netherlands has the highest consumption (>300g per week), while overall there is little substitute meat consumption (25g per week). The highly susceptible population has higher health and environmental concerns than other scenarios, which results in a >10% decrease in processed meat consumption, and an increase in beef consumption. These results indicate that there is typically a trade-off between meat consumption types. The highly susceptible population has more varied consumption between model runs, due to the increased stochasticity of the model parameters, therefore the results of this may be important to investigate how robust policies are. The model results for meat consumption and emissions per emissions type are provided in Figure 7.2. It was expected that runs with high beef consumption would show the highest emissions.

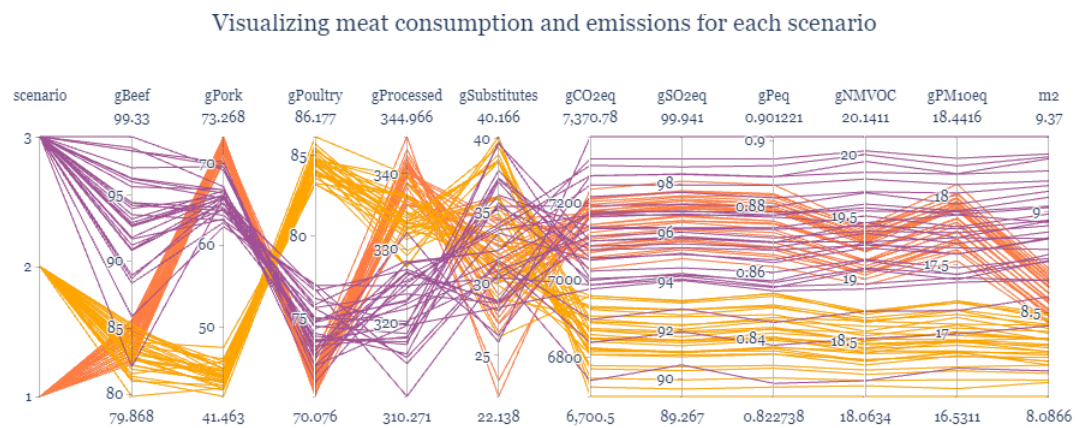


Figure 7.2: Results of the scenarios (1: base-case, 2: high environmental concern, 3: high susceptibility) without any active policy, with regards to the average weekly meat consumption in grams (Beef, Pork, Poultry, Processed and Substitutes), and the emissions (gCO<sub>2</sub>eq, gSO<sub>2</sub>eq, gPeq, gNMVOC, gPM<sub>10</sub>eq, m<sub>2</sub>) of each scenario (Source: Author)

Figure 7.2 shows the emissions per emission type for each of the three scenarios with no policy active. This figure shows that average emissions for all emission types are lower in the 'highly environmentally concerned' scenario by 4-5% on average than the base-case scenario. The highly susceptible population may be influenced in ways which increase or decrease the overall consumption, indicating that it may not be possible to ascertain whether individuals will increase or decrease their emissions based on the external sources. While beef consumption in the third scenario is almost always higher than in the base-case (scenario 1), the emissions of scenario 3 are not always higher than in scenario 1. This indicates that only high beef consumption does not always lead to the highest observed emissions. The summary of the model findings for the various base cases in terms of weekly meat consumption can be found in Table 7.1, and for average weekly emissions per agent in Table 7.2

Table 7.1: Average weekly meat consumption in grams for each of the five meat types (Beef, pork, poultry, processed, substitute meat) (Source: Author)

	<i>gBeef</i>	<i>gPork</i>	<i>gPoultry</i>	<i>gProcessed</i>	<i>gSubstitutes</i>
Scenario 1: Base-case	84.1	72.0	71.3	339.2	30.6
Scenario 2: High Env. Concern	83.2	44.0	84.5	333.9	34.2
Scenario 3: High Sus.	93.0	65.8	74.1	322.2	32.7

Table 7.2: Average weekly emissions per agent for each of the emissions types: greenhouse gas (gCO<sub>2</sub>eq), acidification (gSO<sub>2</sub>eq), toxicity (gPeq), smog (gNMVOC), particulate matter (gPM<sub>10</sub>eq), land use (m<sup>2</sup>) (Source: Author)

	<i>gCO<sub>2</sub>eq</i>	<i>gSO<sub>2</sub>eq</i>	<i>gPeq</i>	<i>gNMVOC</i>	<i>gPM<sub>10</sub>eq</i>	<i>m<sup>2</sup></i>
Scenario 1: Base-case	7141.9	96.6	0.88	19.2	17.8	8.6
Scenario 2: High Env. Concern	6853.3	91.6	0.84	18.47	16.9	8.3
Scenario 3: High Sus.	7106.1	95.9	0.87	19.4	17.7	8.9

The change of environmental concerns over time is shown in Figure 7.3. This shows 156 results, representing the duration of 1 year, with each time tick representing 1 week. It can be seen in both the base case and high environmental concern scenario that concerns remain relatively stable over time, with concerns being more sensitive to a change in the stochasticity. This indicates that without any active policies, the average concerns of individuals will change due to peer interactions and external influences, but at a slow pace with an average change of 6% over the 3 years with respect to the initial value.

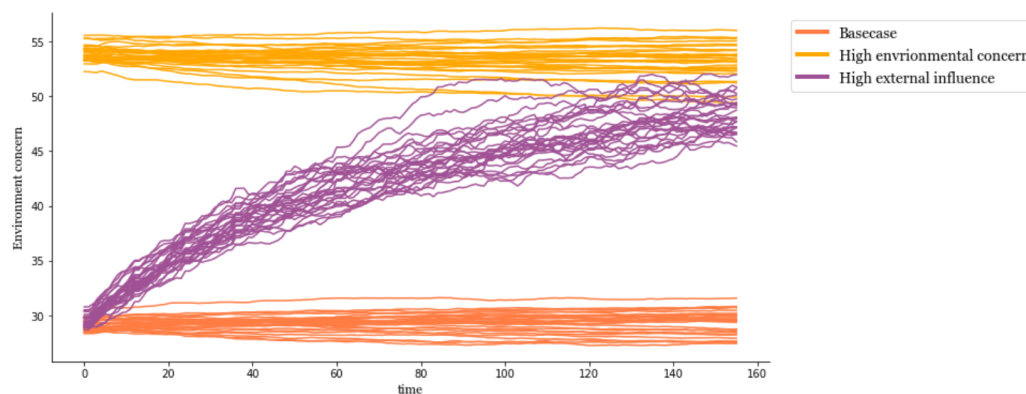


Figure 7.3: Average weekly environmental concern for each scenario with no policies active over the span of 3 years (156 observations), with each observation corresponding to 1 week (Source: Author)

## 7.2. Policies influence on meat consumption

The effect of policies on the KPI meat consumption is investigated through comparing the outcomes of policies in each scenario with the 'base-case' where no policy is active. Five different policies, and one 'no-policy' case, were tested out on the three scenarios. Three of these policies are fiscally related, and two social marketing campaigns. The fiscal policies include a 20% tax on all meat products (excluding

meat substitutes), a 20% tax on beef, and a 20% tax on beef combined with a 20% subsidy on meat substitutes. The campaigns are both environmental awareness campaigns, with one of the campaigns focusing on the general population, and the other focusing on the lower educated population.

The influence of these policies on meat consumption types in the base-case scenario is depicted in Figure 7.4.

Visualizing average concerns and weekly meat consumption for each policy (Base-Case)

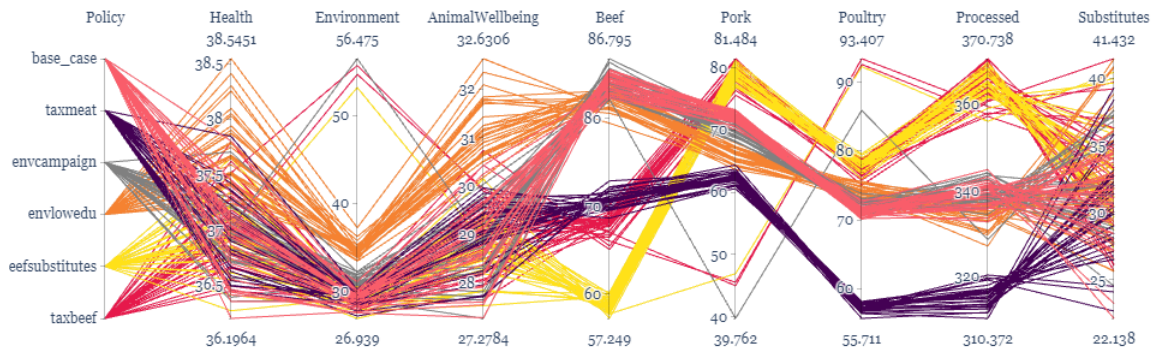


Figure 7.4: Visualization of the concerns (health, environment, animal wellbeing) and meat type consumption (beef, pork, poultry, processed, substitutes) for the various policies following the base-case scenario (Source: Author)

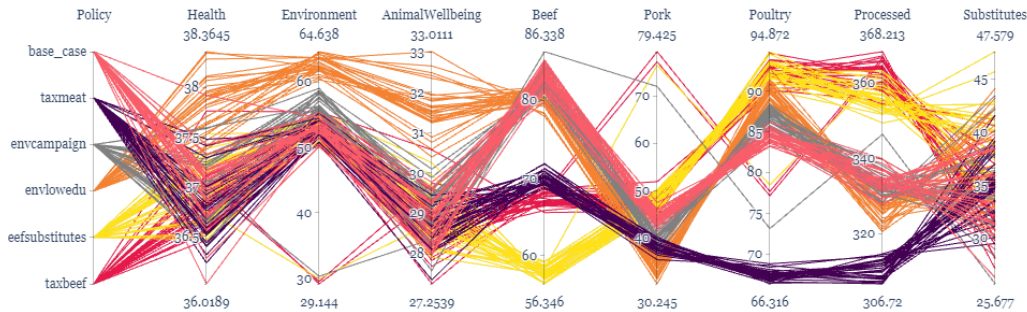
Figure 7.4 shows that beef consumption is significantly lower when beef is taxed, and lowest when both beef is taxed and substitutes are subsidised. Beef consumption sees a minor decrease when there is an environmental campaign targeting the lower educated population. The tax on beef increases the consumption of all other meat types with respect to the base-case, with the highest increases occurring in processed meat (10%) and pork (10%). The tax on all meat caused a similar decrease in beef consumption as the tax on beef, with an additional decrease in the consumption of all other meat types with respect to the base-case. Table 7.3

Table 7.3: Values of consumption for beef, pork, poultry, processed meat and meat substitutes when each policy is in place individually for the Base-Case scenario (Source: Author)

<i>Scenario 1 : Base – Case</i>	<i>Beef</i>	<i>Pork</i>	<i>Poultry</i>	<i>Processed</i>	<i>Substitutes</i>
No-policy	84.1	72.0	71.3	339.2	30.6
Env. Campaign (General public)	84.3	68.9	72.6	339.0	31.8
Env. Campaign (Low educated)	82.3	66.0	74.1	334.5	32.8
Tax beef	67.9	76.5	78.3	365.5	32.2
Tax beef, sub substitutes	58.9	77.8	78.4	365.0	32.9
Tax meat	70.8	62.4	57.3	315.4	30.4

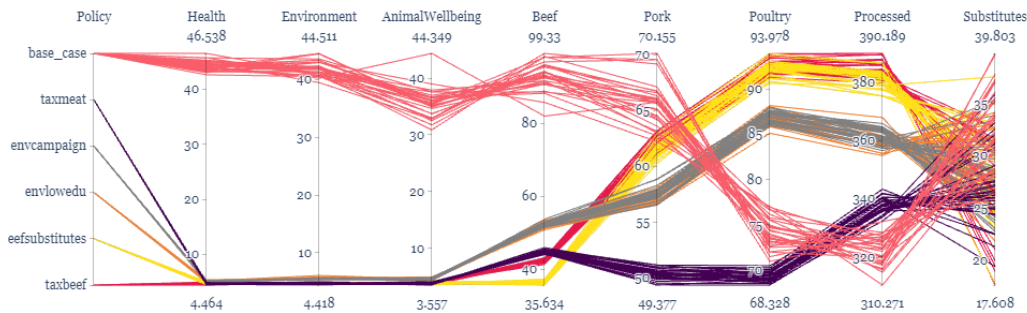
Figures 7.5a and 7.5b show the parallel coordinates plot for the policies on the high environmental and high susceptibility scenarios respectively. Figures 7.5a and 7.5b both show that the tax on beef and subsidy on substitutes causes the most significant decrease in beef consumption, and increase in poultry and substitute meat consumption.

Visualizing average concerns and weekly meat consumption for each policy (High Env. Concern)



(a) Scenario 2: High Environmental concern scenario

Visualizing average concerns and weekly meat consumption for each policy (High Susceptibility)



(b) Scenario 3: High susceptibility scenario

Figure 7.5: Visualization of the concerns (health, environment, animal wellbeing) and meat type consumption (beef, pork, poultry, processed, substitutes) for the various policies following the high environmental concern and high susceptibility scenarios respectively (Source: Author)

This shows that beef consumption is the lowest when beef is taxed and when substitutes are given subsidies, and the highest during the base case and the general environmental campaign. For all other meat types, the consumption per type is the highest when beef is taxed, and the lowest when all meat types are taxed. In all scenarios, the meat tax results in the lowest consumption for meat types, with the beef tax resulting in lowest beef consumption, while providing highest pork, processed meat and poultry consumption. The levels of average consumption per food type for all policies per scenario are provided in Tables 7.4 and 7.5 for the high environmental concern and high susceptibility scenarios respectively.



Table 7.4: Average values of consumption for beef, pork, poultry, processed meat and meat substitutes when each policy is in place individually for the High Environmental Concern Scenario (Source: Author)

<i>Scenario 2 : High Env. Concern</i>	<i>Beef</i>	<i>Pork</i>	<i>Poultry</i>	<i>Processed</i>	<i>Substitutes</i>
No-policy	83.2	44.0	84.5	333.9	34.2
Env. Campaign (General public)	82.9	40.5	86.3	333.1	34.3
Env. Campaign (Low educated)	80.6	33.5	89.9	326.0	37.3
Tax beef	69.3	50.0	91.1	362.4	33.2
Tax beef, sub substitutes	57.8	48.6	92.0	355.9	38.8
Tax meat	70.0	38.0	67.3	310.6	35.2

In both scenarios, processed meat consumption accounts for the highest single meat type consumption. This increases by around 10% when beef is taxed, and decreases by around 7% when all meat is taxed. The subsidy for meat substitutes boosts substitute meat consumption by 13.5% compared to having no policy in the high environmental concern scenario.

Table 7.5: Average values of consumption for beef, pork, poultry, processed meat and meat substitutes when each policy is in place individually for the High Susceptibility Scenario (Source: Author)

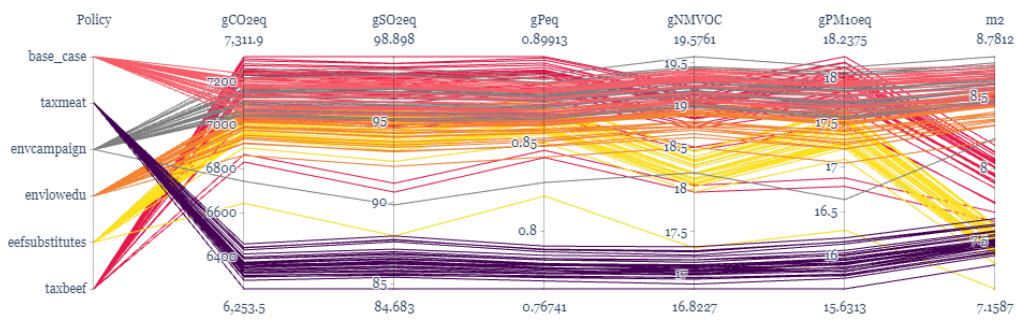
<i>Scenario 3 : High Susceptibility</i>	<i>Beef</i>	<i>Pork</i>	<i>Poultry</i>	<i>Processed</i>	<i>Substitutes</i>
No-policy	93.0	65.8	74.1	322.2	32.7
Env. Campaign (General public)	52.4	57.5	87.0	361.5	27.5
Env. Campaign (Low educated)	52.1	57.2	86.9	360.6	28.7
Tax beef	42.3	62.2	92.5	384.7	26.5
Tax beef, sub substitutes	36.5	61.6	92.3	381.3	28.1
Tax meat	44.8	50.4	69.3	337.7	26.9

### 7.3. Policies influence on emissions

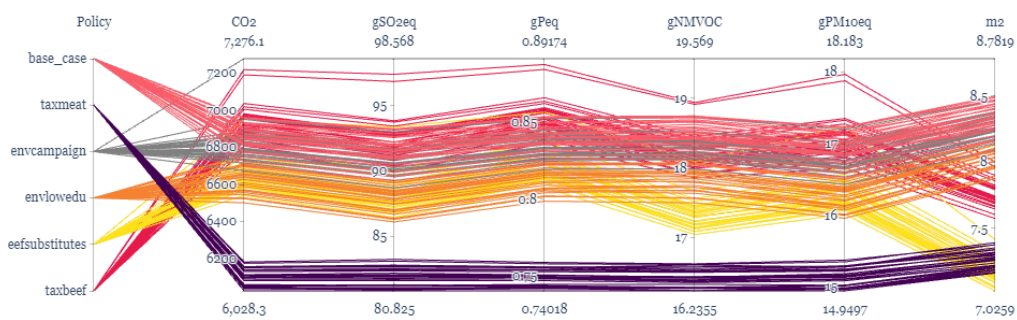
The problem associated with meat consumption, and reason why governments would want to encourage meat consumption, is related to the emissions of the types of meat consumed. The average weekly emissions in terms of greenhouse gases (CO<sub>2</sub>eq), acidification (gSO<sub>2</sub>eq), toxicity (gPeq), smog (gN-MVOC), particulate matter (PM<sub>10</sub>eq) and agricultural land use (m<sup>2</sup>) associated with meat consumption. The visual representation of the results for the three scenarios can be seen in Figures 7.6a, 7.6b, and 7.6c for the base-case, high environmental concern and high susceptibility scenarios.



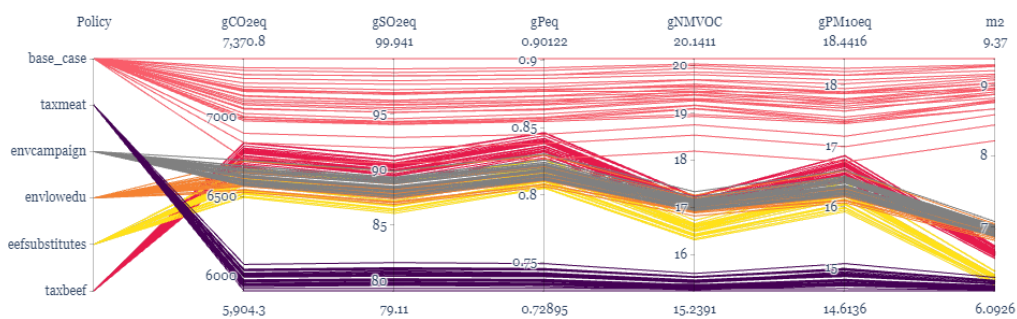
Visualizing average weekly emissions for each policy (Base-Case)



(a) Scenario 1: Average weekly emissions profile for the Base-Case scenario



(b) Scenario 2: Average Weekly emissions profile for the High Environmental Concerns  
Visualizing average weekly emissions for each policy (High Susceptibility)



(c) Scenario 3: Average weekly emissions profile for the High Susceptibility scenario

Figure 7.6: Average weekly emissions of the population for the population in the base case, high environmental concern and high external influence scenarios with all policies active (base-case policy = no policy active) (Source: Author)

In each of the three scenarios the policy with the most influence on emissions is the tax on all meat types. All policies perform either similarly or better than the base case in all scenarios. Environmental emissions are fairly similar for the base case scenarios, with the High Environmental concern scenario resulting in lower emissions for all measured metrics. The average weekly emissions per policy and scenario can be seen in Table 7.6 for the base-case scenario.

Table 7.6: Average values of emissions when each policy is in place individually for the Base-Case Scenario (Source: Author)

<i>Scenario 1: Base – Case</i>	<i>gCO2eq</i>	<i>gSO2eq</i>	<i>gPeq</i>	<i>gNMVOC</i>	<i>gPM10eq</i>	<i>m2</i>
No-policy	7141.9	96.63	0.88	19.2	17.8	8.6
Env. Campaign (General public)	7121.4	96.2	0.87	19.2	17.8	8.6
Env. Campaign (Low educated)	7007	94.5	0.86	18.9	17.4	8.4
Tax beef	7183.8	96.8	0.88	18.9	17.9	8.0
Tax beef, sub substitutes	6994.9	94.0	0.96	18.2	17.4	7.5
Tax meat	6360.3	86.4	0.78	17.1	15.9	7.5

Table 7.6 shows that CO2 emissions decrease by around 100 grams per week for the environmental campaign targeting less educated individuals, while the tax on beef actually on average results in a 40g increase in emissions, and the tax on all meat results in a decrease of 780 grams of CO2 per week.

## 7.4. Summary of Results

The results of model experiments, where each scenario was tested in combination with each policy, can be summarised in a score-card illustrated in Figures 7.7, 7.8 and 7.9 for the three respective scenarios. These score-cards give an indication of how well the policies fare with respect to the no-policy case in terms of meat consumption and emissions by normalizing each outcome with the no-policy outcome. In these score-cards, an increase in substitute meat consumption is seen as positive.

<i>Scenario: Base-Case</i>											
Policy	Beef	Pork	Poultry	Processed	Subs	gCO2eq	gSO2eq	gPeq	gNMVOC	gPM10eq	m2
base-case/ no-policy	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
env campaign	1.003	0.957	1.019	0.999	1.037	0.997	0.996	0.997	0.998	0.996	0.999
env lowedu	0.979	0.917	1.04	0.986	1.067	0.981	0.977	0.982	0.981	0.978	0.98
taxbeef	0.807	1.063	1.098	1.077	1.052	1.006	1.001	1.010	0.982	1.001	0.928
taxbeef sub substitutes	0.700	1.081	1.101	1.076	1.074	0.979	0.973	0.985	0.946	0.973	0.870
taxmeat	0.842	0.867	0.803	0.930	0.991	0.891	0.894	0.891	0.888	0.893	0.872

Figure 7.7: Score-card of the effect of policies on meat consumption and emissions with respect to the no-policy. (Scenario = Base-Case, green = positive change, red = negative change) (Source: Author)

The model results suggest that taxing beef can result in a decrease of 20% of beef consumption, with an increase of up to 10% in all other consumption types, leading to increases in emissions compared to no policy being active. This is the case for the base-case and high environmental concern scenario, as seen in Figures 7.7 and 7.8 respectively. Combining a tax on beef with a subsidy on substitutes results in decreased overall emissions. The most consistent result is obtained by the environmental social marketing campaigns campaigns, which all result in decreased emissions, but have an impact of 0.3-3% of emission reductions compared to no policy. The most effective result is achieved from the tax of 20% on all meat, which for the base-case reduces beef consumption by 16%, pork by 13%, poultry by 20%, and processed meat consumption by 7%. These emission reduction lead to a reduction in greenhouse gas emissions by 10.9%, acidification by 10.6%, toxicity by 10.9%, smog by 11.2%, particulate matter by 10.7% and land use by 12.8%.

<i>Scenario: High Environmental Concern</i>											
Policy	Beef	Pork	Poultry	Processed	Subs	gCO <sub>2</sub> eq	gSO <sub>2</sub> eq	gPeq	gNMVOC	gPM10eq	m2
base-case/ no-policy	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
env campaign	0.996	0.922	1.02	0.998	1.004	0.994	0.992	0.994	0.994	0.993	0.995
env lowedu	0.969	0.761	1.064	0.976	1.091	0.968	0.961	0.969	0.968	0.963	0.968
taxbeef	0.809	1.136	1.078	1.085	0.972	1.012	1.009	1.016	0.986	1.009	0.931
taxbeef sub substitutes	0.695	1.104	1.088	1.066	1.135	0.971	0.963	0.976	0.938	0.963	0.860
taxmeat	0.841	0.863	0.797	0.930	1.030	0.890	0.894	0.890	0.888	0.893	0.871

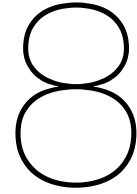
Figure 7.8: Score-card of the effect of policies on meat consumption and emissions with respect to the no-policy. (Scenario = High Environmental concern, green = positive change, red = negative change) (Source: Author)

The scorecards in Figure 7.9 indicate that all policies would have a positive effect compared to no policies being active. In all scenarios, when only beef is taxed, there is an increase in all other meat type consumption. If the drop in beef consumption is sufficient compared to the increase in all other meat consumption, as is the case in Figure 7.9, then overall emissions will drop.

<i>Scenario: High Susceptibility</i>											
Policy	Beef	Pork	Poultry	Processed	Subs	gCO <sub>2</sub> eq	gSO <sub>2</sub> eq	gPeq	gNMVOC	gPM10eq	m2
base-case/ no-policy	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
env campaign	0.563	0.874	1.174	1.122	0.841	0.933	0.922	0.941	0.881	0.923	0.778
env lowedu	0.560	0.870	1.173	1.119	0.875	0.931	0.920	0.939	0.879	0.920	0.776
taxbeef	0.455	0.945	1.248	1.194	0.808	0.952	0.939	0.962	0.882	0.939	0.744
taxbeef sub substitutes	0.392	0.936	1.245	1.183	0.857	0.927	0.912	0.938	0.853	0.913	0.703
taxmeat	0.482	0.766	0.935	1.048	0.821	0.841	0.837	0.848	0.794	0.836	0.691

Figure 7.9: Score-card of the effect of policies on meat consumption and emissions with respect to the no-policy. (Scenario = High Susceptibility, green = positive change, red = negative change) (Source: Author)





# Discussion

This chapter brings together the findings from the previous chapters, and discusses these with regards to the broader literature and policy field regarding meat consumption. This research addresses the question "How do social norms influence meat consumption and to what extent can European policy influence these to reduce meat consumption?". This question was answered by modelling social norms in relation to meat consumption in an agent-based model, for which the theoretical framework is based on literature. Agent-based modelling allowed for the emergent behaviour, which social norms can be classified as according to the emergent norm theory (Arthur, 2013). The rules of the agent-based model were based on previous models by Scalco et al. (Scalco et al., 2019), Zhang et al. (Zhang et al., 2014), and an analysis of various surveys in the Netherlands, which was taken as case-study. This chapter discusses the findings for each of the subquestions in Section 8.1, regards the strengths, limitations and future research in Section 8.2, provides implications to decision-makers with regards to the policy, political and socio-economic contexts regarding meat consumption in the EU in Section 8.3, and provides a conclusion in Section 8.4.

## 8.1. Answering the research subquestions

The first research subquestion investigated in this research is "how do social norms influence meat consumption, and what policies can the EU implement to influence meat consumption?". This research found that there is a general consensus that social norms play a role in consumption, following the literature review, as the concerns and behaviours of others will influence the behaviour of an individual (Cheah, Sadat Shimul, Liang, & Phau, 2020; Klöckner, 2017; Malek et al., 2018; Reisch et al., 2021; Ritchie et al., 2018; Scalco et al., 2019). These social norms are spread through social networks (Scalco et al., 2019; Wansink & Sobal, 2007; Zhang et al., 2014), where individuals are influenced strongly by their peers and weakly by their co-workers (de Castro, 1994). From the literature review, three factors were found to be the most important: concerns of health, environment and animal welfare (Hopwood et al., 2020; Lai et al., 2020). The data analysis conducted for this research supports these findings, as analysing the various surveys showed that health, environment and animal welfare concerns are more strongly correlated to the frequency of meat consumption than other factors (0.3 vs 0.1 for other factors following the LISS Panel Surveys, and 0.8 following the Belevingen 2020 and DNFCS), and were statistically significant ( $p < 0.05$ ) in predicting meat consumption. Meat consumption, however, can be defined as complex adaptive system (Holland, 2006), and consumption patterns are complex. While Hopwood et al. (2020) found health concerns the most important, this research found environmental concerns appeared to be more significant which is also the case in research by Lai et al. (2020). Meanwhile, other research shows that individuals may be more affected by price (Huizinga & Kruse, 2016; Sanchez-Sabate & Sabaté, 2019), while others state consumption behaviour is the results of over 15 (Renner et al., 2012), or that it is the primarily the result of environmental cues (Cohen & Babey, 2012; G. W. Horgan et al., 2019; Reisch et al., 2021), and that consumption is the result of 200 daily food decisions (Wansink & Sobal, 2007).

The EU can play a role in influencing meat consumption through supply-side policies, such as the Common Agricultural Policy (CAP) (European Commission, 2020), or they can influence the demand-

side. Demand-side policies through which the EU can influencing social norms include social marketing campaigns (BEUC, 2020; Scalco et al., 2019), fiscal policies (TAPPC & DVJ Insights, 2020), or changing the food environment by supporting access to items, improving availability of substitutes, and offering subsidies on substitutes (de Krom et al., 2020; Kyriakopoulou et al., 2019). The EU policy can only implement policies after they have been through the various stages of decision-making, which include the writing of proposals by the commission, the iterative negotiation of proposals by the Council of Ministers and European Parliament (assisted by the European Commission), and subsequent monitoring and enforcing of decisions in member states by the European Commission (European Union, 2016b). Therefore, the EU is not able to directly implement any policy to influence meat consumption, as political decision-making will require these stages to be passed. Once passed, the EU can implement regulations for which they have a mandate under the European Treaties, which includes a tax on meat consumption through excise duties, conducting campaigns and harmonising food labelling practices amongst others (European Union, 2016a).

The second subquestion addressed in this research is: "How can agent-based modelling be used to model and simulate the influence of EU policy and social norms on meat consumption?". This research decided to use agent-based modelling to construct social networks through which social norms can spread (Scalco et al., 2019; Zhang et al., 2014). Each individual was represented by an agent, who is linked together with other agents as part of a household and co-worker network (Scalco et al., 2019; Zhang et al., 2014). Through these networks of agents, normative transfer can occur when agents interact during eating episodes (Zhang et al., 2014), where agents observe the concerns of other individuals and will adjust their own concerns accordingly depending on the strength of the network (de Castro, 1994; Scalco et al., 2019). This is modelled following the model by Scalco et al. (2019) and Zhang et al. (2014). This assumes that individuals are able to observe the concerns of others and are influenced by all peers, which may not be the case as individuals may be more influenced by specific individuals in their network.

The influence of social norms on meat consumption is grounded in the Theory of Planned Behaviour (Ajzen, 1991). The Theory of Planned Behaviour was followed to model the intention to consume meat, which views social norms as one of the main drivers to determine behaviour together with attitudes and perceived behavioural control (Ajzen, 1991). This theory has been used in other studies, which indicated that attitude towards beef eating was the strongest predictor of behaviour (McCarthy et al., 2003), and that factors from the TPB predicted around 57% of the variations in intention to reduce meat consumption (Çoker & van der Linden, 2020). While the spreading of norms occurs through networks (Scalco et al., 2019; Zhang et al., 2014), the intention to consume meat was derived from a multiple linear regression using the Belevingen 2020 survey (CBS, 2021b) and Dutch National Food Consumption Survey (RIVM, 2020b). These surveys allowed splitting the meat consumption into the prominent meat types: beef, pork, poultry, processed meat and meat substitutes, which account for 92% of meat consumption in the Netherlands (RIVM, 2020b).

Separating these types of consumption has not been done before in an agent-based model. Therefore, this method requires some verification. The method applied in this study is based on the method used by Scalco et al. (2019) who modelled intention to reduce meat consumption on a logistic regression. In the research by Scalco et al. (2019), they predicted the likelihood to reduce meat consumption based on the health, environmental, with the model having an R-squared value of 0.67. The data analysis in this research also investigated the likelihood to reduce meat consumption, where the same variables were found to be statistically significant ( $p < 0.05$ ), but offered a far lower R-squared value of 0.06-0.13. The multiple linear regression for the various meat types provided an R-squared value between 0.42 - 0.88, with all meat types statistically significant ( $p < 0.05$ ) except, for meat substitutes. The perceived behavioural control in this model followed a more established method, using price elasticity of demand (Gallet, 2010; van Hoof, 2019; ?). Separating meat consumption per type allowed this model to provide more nuanced insight into policy effects, but in doing so reduced the quantity of factors used compared to other research (Scalco et al., 2019).

In answering the second part of this subquestion, this research used agent-based modelling to investigate various experiments with policies in place. The influence of the EU was based on policies for which the EU has a mandate (European Union, 2016a), with the policies either influencing the concerns of agents through a social marketing campaign (BEUC, 2020; Scalco et al., 2019) or through fiscal policies (BEUC, 2020; TAPPC & DVJ Insights, 2020). The EU is interested in the reduction of emissions related to the agricultural industry, therefore both the specific meat consumption and their

related emissions were tracked as KPIs. Policies which were investigated influenced a tax on beef, a tax on beef and subsidy on substitutes, a tax on all meat, and environmental social marketing campaigns directed at the general population and low educated population respectively.

The results of these model runs answer the third and final subquestion posed in this research: "What are the effects of EU policy and social norms on meat consumption?". The results of this research indicate that social marketing campaigns have a positive influence on reducing overall emissions, but that this reduction is minimal (between 0.3-3% of dietary greenhouse gas emissions for successful campaigns). An environmental campaign targeted at the lower educated population appeared to be more successful than that targeted at the general population, which was similar to findings by Scalco et al. (2019). Investigating the surveys showed that higher educated individuals have higher levels of concerns and lower levels of meat consumption compared to lower educated individuals (CBS, 2021b; RIVM, 2020b). Therefore, targeting lower educated individuals can have a more significant impact as their concerns will revert closer to the mean of the population (which is higher than their own concerns).

The fiscal policies in this research appear to have a significant impact on meat consumption, which agrees with the findings of other studies (Lykkeskov & Gjerris, 2017; Scalco et al., 2019). The tax on beef consumption caused a drop in beef consumption (20%), but an overall slight increase in four emission types (gCO<sub>2</sub>eq, gSO<sub>2</sub>eq, gP<sub>eq</sub>, and gPM<sub>10</sub>eq). This is a surprising find, as it was expected that taxing beef would decrease overall emissions (Lykkeskov & Gjerris, 2017). The model shows that average consumption will shift away from beef consumption in such quantities towards processed meat, pork, poultry and substitute meat consumption that overall emissions increase. This is not entirely in-line with findings from other studies, which indicate that substituting ruminant meat by monogastric meat as poultry or pork should result in reducing emissions (Hallström, Carlsson-Kanyama, & Börjesson, 2015; Lykkeskov & Gjerris, 2017). This discrepancy can be explained in various ways. As the emissions profile for each meat type was taken from the CE Delft's report on emissions in the Netherlands (de Bruyn et al., 2018), where emissions from beef is taken as average from both meat from cattle and from dairy cows (which are less emission-intense), the results may be sensitive to a country's emissions profile and specific use of emission figures. The results may also be sensitive to the price elasticity of demand, and the initial consumption of a country. This research saw a large shift to pork and processed meat consumption, which currently already accounts for the majority of consumption (RIVM, 2020b). Therefore, while this research indicates a tax on beef may not be as effective as other research indicates, these results are inconclusive, may be country dependent, and should be further investigated.

This research found that a tax on all meat products appears to be a robust policy for reducing emissions and reducing meat consumption. A meat tax can reduce overall meat consumption, with a 20% tax on all meat in this study resulting in a 10% decrease in meat consumption and greenhouse gas emissions from protein consumption. Other studies, such as an econometric analysis on meat consumption and emissions in Sweden, found similar results where taxing all meat products could reduce pollutants by up to 12.1%. The study by Scalco et al. (2019) found even more pronounced effects, with consumption decreasing by 20% when meat is taxed by 20%. These results of this model indicate that taxing all meat products will remove the leakage of emissions from consumption of beef to other meat types, and encourage an overall reduction in meat consumption and thereby reducing emissions (de Bruyn et al., 2018). Therefore, the EU can play a far more significant role pursuing fiscal measures and harmonizing these throughout the EU than pursuing policies solely focused on social norms through social marketing campaigns. However, these policies were still found to be beneficial, and as social norms are a complex in nature, these norms are required to change to reduce emissions beyond the reductions achieved through fiscal measures.

## 8.2. Strengths, limitations and future research

The main strength of this model is that it investigates meat consumption at a more granular level, splitting meat consumption into beef, pork, poultry, processed meat and meat substitutes. By splitting up these types and combining them with their emission profiles (de Bruyn et al., 2018), this model provides visual-analytical characteristics between key trade-offs of policies and their influences on dietary change. Showing the interplay between various types of consumption has not previously been done at this level for an agent-based model. This research has verified whether the findings of literature, that health, environmental and animal welfare concerns are the most important to determine meat con-

sumption (Hopwood et al., 2020; Lai et al., 2020), were applicable to the Netherlands through the data analysis. This model looks both at the meat consumption and associated dietary changes, which provides more insight into effective policies for decision-makers to follow. This model can further provide results and findings for populations as a whole, or focus on the influence of specific policies on specific groups of consumers. This allows for targeted policies to be investigated, to see which population subsection should be targeted, as well as determining how 'just' policies are based on their influence on specific groups (Lykkeskov & Gjerris, 2017).

There are several important limitations to the model which need to be taken into account. These limitations relate to the diets of consumers, theoretical framework, the compositions of social networks, the scope of this model, data availability and applicability of this model to studying EU behaviour as a whole. The current model focuses on concerns, which are important determinants (Hopwood et al., 2020), but these do not capture the 15-200 other aspects which may influence food decisions (Renner et al., 2012). This is seen back in the results of the regression models, where for the LISS Panel Data the  $R^2$  value did not exceed 0.1, and the multiple linear regression model based on the Belevingen 2020 survey (CBS, 2021b) and DNFCs (RIVM, 2020b) may have over fitted the data resulting in a high  $R^2$  value of over 0.8. The diets category in this model is fixed, meaning that consumers will not make complete dietary changes (e.g. meat eater to vegetarian), but will only make dietary changes based their concerns. In the real world, dietary changes are complex and may require a strong food environment to change these (Lally & Gardner, 2013; Rööös, Karlsson, Witthöft, & Sundberg, 2015), or they may follow a vegan diet, vegetarian, pescatarian, flexitarian or meat diet, or may simply dislike certain meat types for reasons as taste which this model does not capture (CBS, 2021b).

The modelling of meat consumption was based on the Theory of Planned Behaviour (Ajzen, 1991). While there is a general consensus that social norms play a role in meat consumption (Cheah et al., 2020; Klöckner, 2017; Malek et al., 2018; Reisch et al., 2021; Ritchie et al., 2018; Scalco et al., 2019), and the factors from the TPB were found to predict around 57% of variation in intentions to reduce meat consumption (McCarthy et al., 2003), the TPB still faces criticism worth considering. The TPB has been criticised for focusing exclusively on rational reasoning, where unconscious influences on behaviour are excluded (Sheeran, Gollwitzer, & Bargh, 2013). There are also concerns about the validity of the theory, with the sufficiency hypothesis of this theory being falsified (Sniehotta, Presseau, & Araújo-Soares, 2014), and other factors such as habit strength, self-determination, skills to perform new activities, and anticipated regret also playing an important role (Sniehotta et al., 2014), although other studies show attitudes of the TPB matter more than habits for meat consumption (Çoker & van der Linden, 2020). This theory also does not take factors as curiosity into account, which in the US according to the 2020 Food & Health survey (International Food Information Council Foundation, 2019) was the reason given by the majority of respondents for trying out meat substitutes. This factor falls under the Extended Theory of Planned Behaviour (Alam et al., 2020), but was not considered in this study. A theoretical model of behaviour will always have limitations, as human behaviour is complex and cannot fully be captured by behavioural theories or mathematical expressions due to the bounded rationality of agents (Enserink et al., 2010).

In this study, households are modelled following the principle of homophily, where similar people tend to have contact at higher rates than dissimilar people (McPherson et al., 2001; Scalco et al., 2019). Homophily is a limitation in the social interactions of individuals, as people form their attitudes and social norms based on the interactions with others (McPherson et al., 2001). This is a simplification, and limitation of the model, as individuals may live with household members who hold different views and follow different diets more often than according to this theory (McPherson et al., 2001). The Belevingen 2020 survey found that 5% of individuals reduced their meat consumption due to a housemate either consuming limited or no meat (CBS, 2021b).

The model is further limited by the various meat types it investigates. It covers the most important meat types, which covers 92% of meat consumption (RIVM, 2020b). However, this does not include the other protein sources as eggs, dairy and fish. The data analysis in this research indicated that fish consumption has a negligible correlation to meat consumption, while other studies looking at flexitarian diets suggest that there may be a hierarchy of meat replacements which range from fish, to eggs, to cheese or directly to meat substitutes (Schösler, Boer, & Boersema, 2012). Including these protein sources, together with pulses which are important according to the Eat-LANCET report (Willett et al., 2019), may provide a more in-depth understanding of how consumption changes. In the Netherlands, for example, there is a high dairy consumption and some research suggests that individuals may sub-



stitute meat consumption for consumption of dairy products as cheese (Schösler et al., 2012), which is associated with higher emissions than poultry and meat substitutes. Therefore, the scope of the research and policies investigated does not capture the scope of sustainable protein consumption in its entirety. Both meat and dairy consumption is required to reduce to meet climate change targets (Hedenus, Wirsenius, & Johansson, 2014).

An important limitation of this model is the data availability and the level at which the data analysis and regression is done on meat consumption. On the one hand, combining the Belevingen 2020 survey (CBS, 2021b) and DNFCs survey (RIVM, 2020b) provided a break-down of consumption per meat type. On the other hand, the aggregation of these datasets meant there were an insufficient amount of datapoints to meaningfully include factors other than health, concern and animal welfare (James et al., 2013). While the LISS Panel data provides useful insight into the frequency of meat consumption, however, this does not provide data on the type of meat consumption. Therefore, only a subset of the factors which influence meat consumption (Renner et al., 2012; Wansink & Sobal, 2007) have been included in this regression analysis. Factors as curiosity, which are part of the Extended Theory of Planned Behaviour (Alam et al., 2020), were not considered and could provide useful additional insights.

Finally, translating the findings for the model implications across European countries may be limited, as they may experience different barriers, perceived behavioural control, attitudes, availability of substitutes, and concerns. Furthermore, this model does not show the complex stages of decision-making which occur at EU level and involve many stakeholders. However, it does show the importance of interventions at a governmental level to encourage consumption, as even in the Netherlands there is no natural tendency for meat consumption to reduce to levels required to meet the Eat-LANCET recommendations (Willett et al., 2019) and IPCC targets (International Panel on Climate Change, 2019).

This brings us to the future research which can be conducted. This model offers a strong backbone for the influence of social norms and meat consumption. This allows it to integrate other aspects, which are part of the Theory of Planned Behaviour (Ajzen, 1991). This could be supplemented by the Value Belief Norm Theory, which can provide more insight into internal normative changes of individuals (Stern et al., 1999), or could be expanded to the Extended Theory of Planned Behaviour (Alam et al., 2020). In the ETPB, the perceived behavioural control could be integrated through modelling the individual perception of living cost and availability of meat substitutes (Alam et al., 2020). Curiosity could be influenced by viewing others perform a specific behaviour, and through marketing campaigns surrounding meat substitutes (Zhang et al., 2014). Therefore, an internal level of curiosity for agents can be modelled, with agents trying a specific behaviour if they see it often enough. Modelling the curiosity of agents can allow for the investigation of other policies which are targeted to social norms and food environment, such as increasing the availability of meat substitutes and introducing food labelling (BEUC, 2020). Higher availability of meat substitutes has been related to the increased meat substitute consumption seen in the Netherlands in recent years (Geurts, 2016; Ritchie et al., 2018). Curiosity may also influence agent networks, as not only the norms are passed but also the type of food consumed may be influenced. Curiosity may be influenced more when people eat out. Furthermore, when eating out and eating in groups this also influences the quantity of meat eaten and type of meat eaten (Herman, 2015). As investigating specific meat consumption and normative changes through agent-based modelling is a novel approach, more research will be required to expand on this method and further validate it.

An important future research step would be to conduct a more extensive survey on personal profiles (age, gender, education, urbanisation), their concerns (health, environment, animal welfare), other attributes (price, household influence, availability of substitutes, and actual consumption of each individual in terms of meat types, dairy types, eggs, fish, and pulses and plant-based substitutes). This would allow for a more comprehensive view of which factors matter for protein consumption, and can provide a more robust statistical analysis (James et al., 2013). Making the model and model findings suitable for European countries, it would be useful to make a more general model, where standardized population data from various European countries can be fed in the model, with country-specific food environments which influence the perceived behavioural control, usefulness and curiosity of agents. Due to the focus of the study and data availability, many of these aspects discussed were not integrated.

In summary, the main model strengths are the ability to display interaction between agents, this influence on social norms, and the variations in different types of meat consumption as a result of normative changes. The main model limitations are the quantity of parameters currently investigated

based on the limited data availability. Future research can focus on three aspects. Firstly, the research can be done on how to make the model more comprehensive to incorporate perceived behavioural control, perceived usefulness, and curiosity. Secondly, an area of focus can be the gathering additional data to support the relations between parameters and specific meat type consumption. Thirdly, to extend the validation of this model for other European countries, the model should be made more generalized and tested on data from different countries based on their populations, which will also require research on how different European countries approach consumption.

### 8.3. Implications

The European Commission has set out their pathway to reach net zero emissions by 2050 through the European Green Deal. The findings from this report suggest that an effective measure for the EU to reduce emissions and meat consumption would be to impose a tax on all meat products. This is in line with other research as done by CE Delft (de Bruyn et al., 2018), who have also called for a tax on meat in the EU, and others who discussed meat taxation in various EU countries (Broeks et al., 2020; Douenne & Fabre, 2020; Funke et al., 2021; Hedenus et al., 2014; Lykkeskov & Gjerris, 2017; Ritchie et al., 2018; Säll & Gren, 2015). The recommendations for policymakers requires this study to be placed in the wider EU policy context, and reflect on the implications of these policies to both policymakers, stakeholders, and complex socio-economic context. Policymakers should not only pursue policies which result in achieving their key objective, but also take the trade-offs of policies into account and reflect on the implications and feasibilities of these policies. The implications of this research will be discussed according to the policy context, the political context, socio-economic context, in light of other research done in the field.

**The policy context.** The current strategy in the EU focused on making the agricultural sector more sustainable, as part of the European Green Deal, is the Farm to Fork Strategy which addresses on the supply chain as a whole (European Commission, 2020). The policies outlined in the Farm to Fork Strategy make no mention of meat taxes, nor address the meat aspect of consumption, but focus on the labelling of food products as demand-side policy (European Commission, 2020). To reduce emissions, and head towards net zero carbon emissions, is not feasible without addressing meat consumption (TAPPC & DVJ Insights, 2020). Both supply and demand-side policies may be required to address the negative externalities from livestock production and consumption. Meat can be taxed at the source, through negative externality correcting instruments as optimal carbon pricing, nitrogen regulation and ecosystem valuation (Funke et al., 2021). However, this may result in carbon leakage, as other countries with lower environmental regulations may incur lower costs and thereby meat imports may increase (Matthews, 2019). A carbon border adjustment mechanism (CBAM), as proposed by the European Commission, would be required as additional policy to mitigate this (Remeur, 2020).

Complementary policies would also be required to transform the livestock sector, which include reforming direct and indirect subsidies as under the EU's Common Agricultural Policy (Hedberg, 2020). Supply-side policies may require additional monitoring of the many small farms present in the EU, which may result in high monitoring costs of up to 2.5% of the CAP budget to determine if pollution conditions are met (Geijzendorffer et al., 2015). Research by Schmutzler and Goulder (1997) found that when there are high monitoring costs then consumption taxes may be more efficient Schmutzler and Goulder (1997). An excise tax on meat consumption may not incur carbon leakage, and reduce competitive concerns, as meat from all domestic and foreign sources would be taxed (Funke et al., 2021). Research further shows that there are constraints to efficiency gains to mitigate climate externalities from the production side, thus in the light of net-zero requirements this will require a shift from the demand-side (Clark et al., 2020; Funke et al., 2021). However, consumption taxes do not incentivize efficiency gains, and the agricultural sector requires transformations which need supply-side policies. Therefore, from a policy perspective, an excise duty on meat consumption is effective, and following this study and research from CE Delft should be implemented on all meat products (de Bruyn et al., 2018; TAPPC & DVJ Insights, 2020), but should be done in combination with other supply-side policies. For these policies, including how the policy would fit in a policy package, the European Commission would have to conduct an impact assessment to determine the consequences, with more research and cross comparisons required in multiple European countries.

**The political context.** Policymaking in the EU occurs through an iterative process, with many stakeholders and actors involved (European Union, 2016b). In the EU member states may view meat

taxes difference, and there is a strong livestock industry in the EU, with a lot of vested interest and influence (Neslen, 2020). Findings from this study recommend policies that can be taken at EU level, but do not indicate whether there is political will to develop these policies. This will need to come both at a public and political level. In December of 2020, the European Commission launched the 'Beefatarian' campaign as part of the 'Proud of EU Beef' initiative, promoting an increase in meat consumption and attempting to disassociate climate worries from meat consumption; effectively undermining the EU's goals to reduce emissions (Neslen, 2020). A critical response was sent out by numerous MEPs, who accused the European Commission of being fearful to let down the meat and dairy industry (Neslen, 2020). When questioned about whether the campaign was consistent with the Farm to Fork Strategy, the response by the Agriculture Commissioner Janusz Wojciechowski was that "there is no Commission idea to stop meat consumption or to reduce meat consumption and to order consumers' behavior or diets" (Neslen, 2020). This indicates there is currently a political division whether to pursue these necessary policies.

Public opinion will vary in EU countries. In the Netherlands 58% of consumers are in favour of a tax on meat products (TAPPC & DVJ Insights, 2020), while in France only 17% of consumers are in favour of such a tax (Douenne & Fabre, 2020). A survey on willingness to pay tax on meat by TAPPC showed that 80% of German, 63% of Dutch and 67% of French participants were willing to pay taxes on meat if revenues are used to pay for farmers for improved animal welfare and CO<sub>2</sub> reductions, and higher salaries for workers in slaughterhouses (TAPPC & DVJ Insights, 2020). This indicates that the framing of the policy, and recycling of revenues from meat taxation will be important (Funke et al., 2021), with multiple researchers calling for a Pigouvian tax (Katare et al., 2020; Klenert et al., 2018) on meat consumption, where consumption prices increase corresponding to their marginal damage to decrease the negative externalities (Säll & Gren, 2015).

This current research indicates that a tax on all meat types will be required, as such a Pigouvian tax would have to be used to increase a baseline tax rate, which is supported by studies as CE Delft (de Bruyn et al., 2018). This current research also indicates that raising awareness of climate change and the environmental link to meat consumption may result in higher environmental concerns and changes in meat consumption and emissions. Social marketing campaigns may also further improve social attitudes around climate policies, especially when signalling to the public why actions are taken (Douenne & Fabre, 2020). However, the investigation of both the high environmental concern and high susceptibility scenario indicate that even with higher environmental concerns, this is insufficient by itself to cause the change in meat consumption required.

**Socio-economic context.** Livestock farming and meat consumption play an important role in economic development and culinary traditions. They are an important source of protein, and in the EU account for around 40% of daily protein consumption (Westhoek et al., 2014). Consumer elasticities for food and other livestock products are personally and culturally derived (Funke et al., 2021), therefore more research is required to determine how policies affect different European countries.

The proposed meat tax on all meat products, has with it the concern that it may face backlash, as it goes against culinary traditions in various EU member states, and it may disproportionately affect low-income households (Funke et al., 2021). The Belevingen 2020 survey showed that individuals who have lower education and income are more likely to cite the price as reason for not eating meat (CBS, 2021b). Further taxing meat may therefore have a disproportionate effect on these individuals. In the past, taxation has occasionally led to tax revolts, as occurred in France when there was a tax on petroleum products which triggered the 'gilets-jaunes' movement (Boyer, Delemotte, Gauthier, Rollet, & Schmutz, 2020). Therefore, the design and framing of the policy and ensuring the benefits of the policy are understood and communicated is important.

Designing a meat taxation policy can be construed such that public support is increased (Funke et al., 2021). Research shows that the framing of pricing and the use of revenues are decisive determinants to get the public on board (Klenert et al., 2018). A study by Fesenfeld et al. (2020) showed that policy packaging can increase support for meat taxes, as they found public support for meat taxation is highest when they are moderate and in combination with more popular policies such as animal welfare standards, discounts on vegetarian meals and information campaigns. This current research, and those of CE Delft among others (de Bruyn et al., 2018), call for more ambitious meat taxes. According to Fesenfeld et al. (2020), more ambitious meat taxation can be made more acceptable when combined with lowering agricultural subsidies to meat farmers, introducing stricter farming standards, and when tax revenues are used to support low-income households (Fesenfeld et al., 2020).

**Summary of implications.** This current research indicates that a tax on all meat products is necessary to reduce greenhouse gas emissions and support the shift towards a sustainable diet. This policy should not stand alone, yet is a necessary part of a policy package. The policy can be written as a Pigouvian tax, where the tax level depends on emission profiles of meat types, however, this research indicates that such a tax should be done in addition to a general tax on all meat types as emissions otherwise will be redistributed rather than reduced. The precise tax rate and avenues for revenue recycling should be further investigated. The results of this study further show that changing the social norms surrounding meat consumption are not easy, and will take time. Addressing the social norms, and promoting awareness of the environmental aspect of meat consumption is a necessary aspect to reduce consumption, and may increase public acceptance of other policies, but is insufficient in itself to adequately reduce emissions. One thing is certain, even if individuals become more concerned about the climate, without governmental action and policies to support reducing meat consumption, emissions will not decrease sufficiently.

## 8.4. Conclusion

This research set out to answer the research question "how do social norms influence meat consumption and to what extent can European policy influence these to reduce meat consumption?". This research question is the result of a literature search, where there was a gap found in the understanding of the interaction between social norms, meat consumption, and the role of governmental bodies as the EU. The answer to the research question depends on the theoretical view of the world a researcher takes, on the boundary of the system, and on the various policy, political, and socio-economic contexts that are taken into consideration. As such, this research does not provide a definite answer, but provides insights into the problem, which is of importance to policy makers and to shaping society. From the literature review, it emerged that meat consumption can be seen as a complex system, where there is an emergence of social norms (Zhang et al., 2014), context dependency (Olstad & Kirkpatrick, 2021), and self-organisation (White et al., 2020). There is a general consensus in the literature that social norms play a role in affecting meat consumption (Muñoz & Marselis, 2016), with the influence being quantified and investigated through various methods. This research takes the view of the complex adaptive system (Holland, 2006), using an explorative agent-based modelling approach based, building on the model constructed by Scalco et al. (2019) to determine the influences of social norms, grounded in the Theory of Planned Behaviour (Ajzen, 1991) and supported by findings from surveys from LISS Panel data, the Belevingen 2020 survey (CBS, 2021b) and Dutch National Food Consumption Survey (RIVM, 2020b).

The literature review indicated that the main factors influencing consumption are the concerns for health, the environment and animal welfare (Hopwood et al., 2020). These findings were supported by the correlation analysis conducted in this study of the LISS Panel surveys 'Reasons to Eat Less Meat', Background variables, Health, Politics and Values, and Personality, where these three concerns showed a moderate correlation with the frequency of meat consumption in the Netherlands. Social norms, according to the literature, are spread through social networks and can influence these concerns. In this research, the influence of social norms was mapped using social networks in an agent-based model, where agents interact with one another and depending on the strength of agent links (families and households), they will influence the concerns of other agents. This follows the model of Scalco et al. (2019), and findings from Zia et al. (2019). This is a simplified model of real world interactions, as social norm spreading may occur in different contexts, and also influence other factors. This research has followed the Theory of Planned Behaviour, which provides useful insights into the workings of social norms, but does not fully incorporate other aspects as curiosity, value changes and skills.

The European policies considered in this research are based on the policy mandate of the EU, whereby they can promote social norms through social marketing campaigns, and have a mandate to develop fiscal policy in collaboration with member states (European Union, 2016a). This research indicates that fiscal policies are far more effective than policies targeting social norms. This is in line with findings by Scalco et al. (2019), and CE Delft (de Bruyn et al., 2018). The social norm policies are modelled as social marketing campaigns, which may achieve a certain degree of success. This research does not go into the nature of what a campaign would look like, but finds that successful social marketing campaigns targeting lower educated individuals is more effective than targeting the general

public, and could achieve a reduction of up to 3% of dietary greenhouse gas emissions. This research indicates that fiscal policies appear to be more effective, with a tax on all meat types by 20% resulting in a potential decrease of emissions by around 10%. These findings are similar to other research on fiscal policies and meat consumption in various European countries (Klenert et al., 2018; Mårtensson, 2014).

Taxing all meat appears to be the most effective and robust policy, and through these policies it appears that the EU can have a tangible influence on consumer behaviour. When viewing a tax on meat through the various contexts, it is not as easy to implement. From the political context, there does not appear to be unanimous and strong political will to implement a tax on meat, as the agricultural commissioner once stated that the European Commission is not interested in reducing meat consumption (Neslen, 2020). From the policy context, a tax may be more effective than other supply-side policies which require significant monitoring and large-scale changes (Fesenfeld et al., 2020; Klenert et al., 2018). A tax targeting the negative externalities of consumption to health and nature is not unprecedented. However, more research and an impact assessment would be required to determine the actual impacts throughout Europe. It appears to be effective in the Netherlands, however, the Netherlands may have higher a price elasticity of demand for meat, and has a high availability of substitutes. This research shows that taxing all meat is more robust than solely taxing beef, as individuals may change their beef consumption for other meat consumption and thereby emissions are not reduced. While this research shows emissions may be redistributed, other studies view a tax on beef as more beneficial. The findings in this study are based on the assumptions made in this research and the elasticity of demand and emission profiles used for the Netherlands. More research will be required to accurately determine the effect in other countries.

From a socio-economic context, taxing beef may be seen as a more fair policy, as it has the highest emission profile, and following Pigouvian taxation it would be more fair to tax the product which has the highest emissions (Douenne & Fabre, 2020). Individuals who are poorer are typically hit harder by taxation, which will be the case in the Netherlands following the correlation analysis of the Belevingen 2020 survey (CBS, 2021b) and Dutch National Food Consumption survey (RIVM, 2020b). This correlation analysis showed a negative correlation between price and beef consumption, with this being the highest for lower educated individuals who also tend to be poorer. A tax on meat is also culturally sensitive, as there is a strong culinary tradition in many European countries. The various actors and member states would have to be analysed and considered to determine whether a tax on meat is in the interest of the public, and at what rate this should be applied. This research does not provide further insight on this, but in investigating the social context found that there is more public acceptance of such a tax if proceeds are recycled into making other food cheaper and farms more sustainable (Funke et al., 2021).

The answer to the research question thus raises additional questions, on how social marketing campaigns should be designed, how a tax on meat can be made fair, and how it can be made more acceptable. While this model provides a simplification of the spread of social norms, this explorative analysis of changes in meat consumption of various meat types does show that norms spreading will have an impact on consumption of individuals. The challenge of climate change is such that governments should aim to reduce emissions at all levels and support consumers in changing to a more sustainable lifestyle. This is especially the case for diets. The model shows that there is a risk that when prices of beef alone are increased, meat consumption becomes redistributed rather than reduced. We do not want to redistribute our problems, but reduce them. Facilitating consumers to change their behaviour through fiscal policies and incentives appears to be more feasible and effective for governments to achieve rapid emission reductions than changing the social norms within societies. Therefore, governments should focus on improving the food environment such that changes are easy to make and encouraged. This research indicates a tax on all meat is beneficial in the Netherlands, and may be beneficial to be developed at the EU level. The development, policy packaging, framing, and rate of taxation should depend on further investigation done by the European Commission. While social norms are less effective and more difficult to address, they are clearly possible to address and will also help reduce overall emissions. In the path to reaching net zero by 2050, and in the light of the IPCC report published in 2021, this research indicates that it is in the interest of the European Commission to expand the European Green Deal and Farm to Fork Strategy by exploring fiscal and normative policies focused on reducing meat consumption and spreading environmental awareness.



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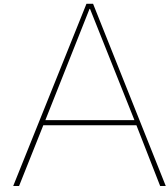
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## Appendix: Supplementary Research

### A.1. Supplementary research: Diets

Dietary consumption plays an important role in the health of ourselves and our planet. Over the past 50 years, dietary consumption has seen significant changes. Increased crop yield and reliable production have helped reduce hunger, improved life expectancy and supported the decline in global poverty. However, on the flip side of the coin, unhealthy diets which are high in calories, heavily-processed foods and animal sourced foods have all contributed to a decline in health globally (Willett et al., 2019).

Furthermore, food production also is one of the largest causes of global environmental change. It is estimated that food production is responsible for around 26% of global greenhouse gas emissions, 70% of freshwater use and occupying around 50% of global land inhabitable land (Ritchie & Roser, 2017).

The effect of dietary changes have been widely researched. In the field of dietary consumption, the EAT-Lancet Commission is a well-regarded scientific body which "combines expertise from the fields of human health, agriculture, political science and environmental sustainability to develop global scientific targets based on the best evidence available for healthy diets and sustainable food production". In this sense, the Commission fulfills a similar role to the International Panel on Climate Change (IPCC) in the field of climate science. This Commission has called for a substantial dietary shift, which requires over a 50% reduction in global consumption of unhealthy foods such as red meat. They have researched the impacts of various diets, as shown in Figure A.1

It is clear from Figure A.1 that to stay within a safe operating food system, both a combination of dietary changes and an improvement to production and management related measures are required. Dietary change has significant mitigation potential for climate change through reducing greenhouse-gas emissions, and can improve environmental conditions, but is not a silver bullet to solve all issues related to agriculture. It is an important cog in the wheel of change that needs to be turned.

			Greenhouse-gas emissions (Gt CO <sub>2</sub> -eq/yr)	Cropland use (M km <sup>2</sup> )	Water use (M km <sup>3</sup> )	Nitrogen application (Tg)	Phosphorus application (Tg)	OPTM biodiversity loss (E/MSY)	MAN biodiversity loss (E/MSY)	OPTN biodiversity loss (E/MSY)	NAT biodiversity loss (E/MSY)
Food production boundary			5.0 (4.7-5.4)	13 (11.0-15.0)	2.5 (1.0-4.0)	90 (65.0-140.0)	8 (6.0-16.0)	10 (1-80)	10 (1-80)	10 (1-80)	10 (1-80)
Baseline in 2010			5.2	12.6	1.8	131.8	17.9	100	100	100	100
Production (2050)	Waste (2050)	Diet (2050)	..	..	..	..	..	..	..	..	..
(1)											
BAU	full waste	BAU	9.8	21.1	3.0	199.5	27.5	2	36	153	1067
BAU	full waste	reference	5.0	21.1	3.0	191.4	25.5	2	45	120	1309
BAU	full waste	pescatarian	3.2	20.6	3.0	189.7	25.3	2	46	118	1313
BAU	full waste	vegetarian	3.2	20.8	3.1	186.9	24.7	2	48	122	1374
BAU	full waste	vegan	2.1	20.7	3.3	184.1	24.4	2	50	128	1431
(2)											
BAU	halve waste	BAU	9.2	18.2	2.6	171.0	23.2	1	24	105	716
BAU	halve waste	reference	4.5	18.1	2.6	162.6	21.2	2	32	81	940
BAU	halve waste	pescatarian	2.7	17.6	2.6	160.0	20.8	2	33	78	940
BAU	halve waste	vegetarian	2.7	17.8	2.7	158.5	20.5	2	35	83	1000
BAU	halve waste	vegan	1.7	17.7	2.8	155.0	20.0	2	36	90	1051
(3)											
PROD	full waste	BAU	8.9	14.8	2.2	187.3	25.5	1	7	68	237
PROD	full waste	reference	4.5	14.8	2.2	179.5	24.1	1	14	54	414
PROD	full waste	pescatarian	2.9	14.6	2.2	178.2	24.0	1	15	54	426
PROD	full waste	vegetarian	2.9	14.6	2.2	175.5	23.6	1	15	56	462
PROD	full waste	vegan	2.0	14.4	2.3	172.8	23.4	1	17	59	507
(4)											
PROD	halve waste	BAU	8.3	12.7	1.9	160.1	21.5	0	3	41	103
PROD	halve waste	reference	4.1	12.7	1.9	151.7	20.0	1	9	33	270
PROD	halve waste	pescatarian	2.5	12.4	1.9	149.3	19.8	1	9	34	281
PROD	halve waste	vegetarian	2.5	12.5	1.9	148.0	19.5	1	10	36	317
PROD	halve waste	vegan	1.6	12.3	2.0	144.6	19.2	1	12	40	358
(5)											
PROD+	full waste	BAU	8.7	13.1	2.2	147.6	16.5	1	10	61	292
PROD+	full waste	reference	4.4	12.8	2.1	140.8	15.4	1	14	47	414
PROD+	full waste	pescatarian	2.8	12.4	2.2	139.3	15.3	1	15	46	424
PROD+	full waste	vegetarian	2.8	12.5	2.2	136.6	14.8	1	16	47	456
PROD+	full waste	vegan	1.9	12.3	2.3	133.5	14.4	1	17	49	494
(6)											
PROD+	halve waste	BAU	8.1	11.3	1.9	128.2	14.2	0	7	38	196
PROD+	halve waste	reference	4.0	11.0	1.9	121.3	13.1	0	10	28	290
PROD+	halve waste	pescatarian	2.4	10.6	1.9	118.8	12.9	0	10	27	298
PROD+	halve waste	vegetarian	2.4	10.7	1.9	117.6	12.6	0	11	29	330
PROD+	halve waste	vegan	1.5	10.5	2.0	113.9	12.1	0	12	33	366

Figure A.1: Scenarios demonstrating the environmental effects of implementing measures considered for reducing environmental effects of food production as shown in report by the EAT-Lancet Commission on healthy diets from sustainable food systems (Willett et al., 2019)

In terms of dietary consumption, the EAT-Lancet Commission recommends a diet rich in grains, legumes and nuts. The recommended macro-nutrient intakes in grams per day, and range of these recommendations can be found in Figure A.2.









		Macronutrient intake grams per day (possible range)	Caloric intake kcal per day
	Whole grains Rice, wheat, corn and other	232	811
	Tubers or starchy vegetables Potatoes and cassava	50 (0-100)	39
	Vegetables All vegetables	300 (200-600)	78
	Fruits All fruits	200 (100-300)	126
	Dairy foods Whole milk or equivalents	250 (0-500)	153
	Protein sources Beef, lamb and pork Chicken and other poultry Eggs Fish Legumes Nuts	14 (0-28) 29 (0-58) 13 (0-25) 28 (0-100) 75 (0-100) 50 (0-75)	30 62 19 40 284 291
	Added fats Unsaturated oils Saturated oils	40 (20-80) 11.8 (0-11.8)	354 96
	Added sugars All sugars	31 (0-31)	120

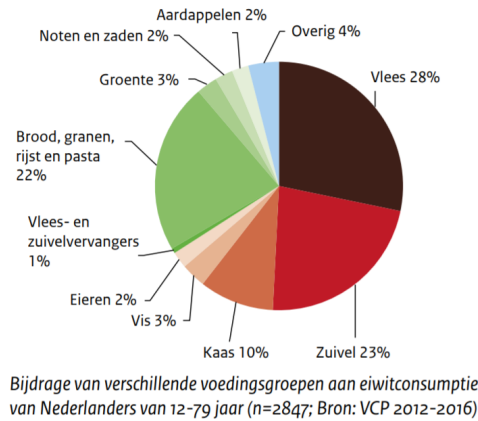
Figure A.2: Scientific targets for a 'planetary health diet', and their potential ranges, based on an intake of 2500 kcal/day as seen in the "Food Planet Health" report by the EAT-Lancet Commission (Willett et al., 2019)

### A.1.1. Current diet Netherlands

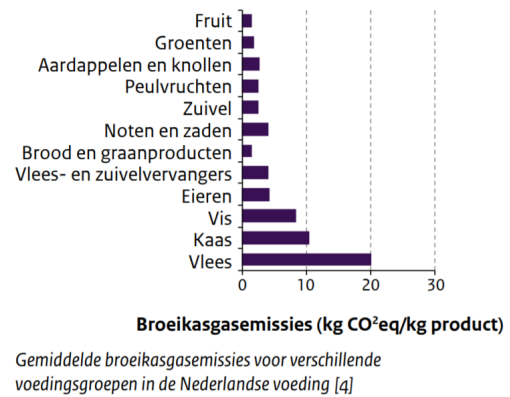
The Netherlands conducts a Dutch National Food Consumption Survey (DNFCS) every four years. The results of the latest survey indicate that the diet followed by Dutch citizens is unsustainable in its current form (). The Dutch average meat consumption totals around 77 kilos per year, exceeding the National Nutrition Centre recommendations by 50%. Furthermore, dairy consumption also exceeds the daily recommended intake by 30%, while consumption of pulses and nuts are only 15% of the recommended quantity. This is far below advised.

Protein consumption as a whole exceeds the daily recommended intake, with an average consumption of 80 grams per day compared to an average of 60 grams which would be closer to what is recommended (de Bruyn et al., 2018).

**Vlees levert helft van het dierlijke eiwit**



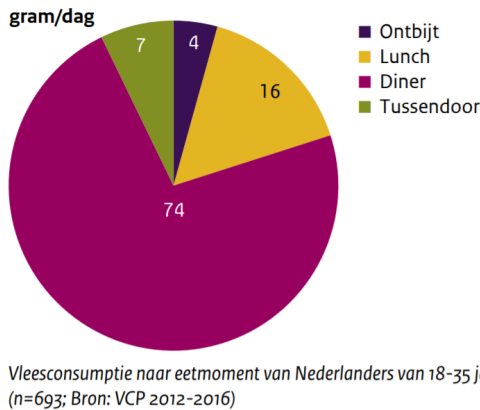
(a) Protein consumption in the Netherlands



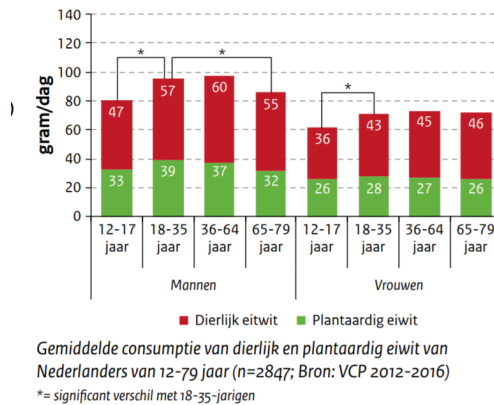
(b) Emissions consumption in the Netherlands

Figure A.3: The Dutch Diet (2)

Text here



(a) Distribution of meat consumption spread over the Time of day of meat consumption in the Netherlands



(b) Proportion of animal protein consumption versus plant-based protein consumption

Figure A.4: The Dutch Diet (1)

### A.1.2. Sustainable protein and meat substitutes

It is clear that meat consumption, and the livestock industry, has a detrimental impact on global health and the environment. Further details on this can be found in Appendix A.2. Then, the question arises what constitutes as sustainable protein, and what can be consumed as substitute for meat. Sustainable diets should not just be less polluting, but should also taste good and be appropriate within each country to follow. The diets currently followed by modern Europeans or North Americans cannot be labelled as sustainable, given that there are insufficient resources available for this to be followed (Burlingame, 2012).

The Food and Agriculture Organisation proposes the definition for sustainable diets as "those diets with low environmental impacts which contribute to food and nutritional security and to healthy life for present and future generations. Sustainable diets are protective and respectful of biodiversity and ecosystems, culturally acceptable, accessible, economically fair and affordable; nutritionally adequate, safe and healthy; while optimizing natural and human resources" (Burlingame, 2012). This is illustrated by Jones et al. in Figure A.5.

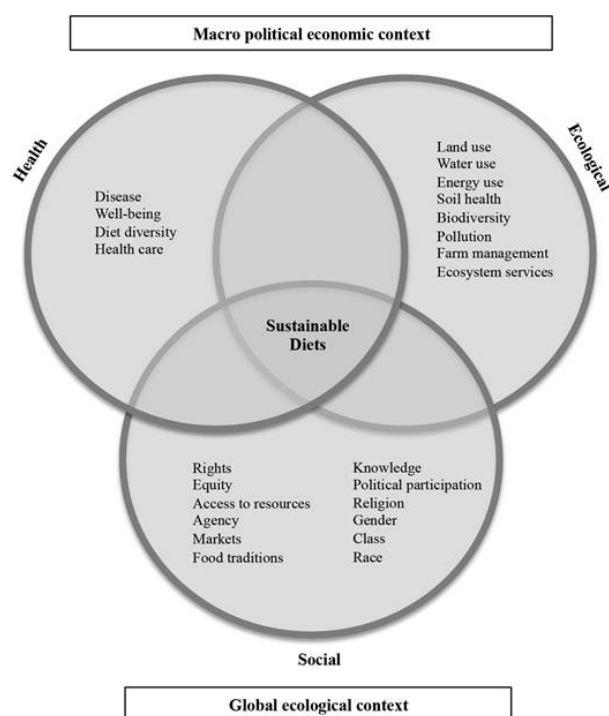


Figure A.5: Conceptual framework of the components of sustainable diets as illustrated by Jones et al. (2016)

This shows that there is no single universal diet which can and should be followed. However, it is still possible to use this as guidelines to determine what constitutes as sustainable protein. Several studies have been conducted using mathematical optimization functions to determine the optimal diet (Wilson, Cleghorn, Cobiac, Mizdrak, & Nghiem, 2019). Wilson et al. have conducted a systematic literature review of 12 studies optimizing diets, which all find that diets optimized for sustainability and nutrition are more plant-based, requiring reductions particularly in ruminant meat consumption as beef and lamb. Dairy consumption also require reduced consumption (Wilson et al., 2019).

Adults require an average of 0.8 grams of protein per kilogram of bodyweight, resulting in an average of 56g / day for a 70 kg individual (Willett et al., 2019).

## **A.2. Supplementary research: Impacts of meat consumption**

### **A.2.1. Health**

Unhealthy diets have contributed to the explosive growth in adults who are overweight, obese, and have diabetes, with diabetes almost doubling in the past decades and the number of overweight adults exceeding 2 billion (Smith & Smith, 2016). This ubiquity of unhealthy diets therefore poses a serious threat to health, constituting a greater threat to morbidity and mortality than tobacco, drug, and alcohol uses combined (Willett et al., 2019).

Meat consumption can provide important nutrients, such as iron, zinc and vitamin B12 (G. W. Horgan et al., 2019). The consumption of processed meat, however, is associated with increased risk of coronary heart diseases, type 2 diabetes, and colon cancer and other cancers (G. W. Horgan et al., 2019; Micha et al., 2010; Smith & Smith, 2016). While these links are known, there appears to be contradictions between the awareness of negative impacts on health, the environment, and animal welfare, and the reluctance to reduce meat consumption (G. W. Horgan et al., 2019; Macdiarmid et al., 2016). This was shown in a UK study, which showed that despite 31% of consumers being aware of the environmental impacts of a diet high in meat, only 19% of those interviewed had reduced their meat consumption in the following years (G. W. Horgan et al., 2019).

There is a belief that reducing meat consumption will have a negative influence on the intake of iron and protein (Sanchez-Sabate & Sabaté, 2019). In relation to meat, there appears to be a paradox between the awareness of negative impacts on health, environment, and animal welfare and the reluctance to reduce meat consumption (Macdiarmid et al., 2016). A recent survey carried out in 2017 reported that more UK consumers are aware of the environmental issues related to a diet high in meat compared to 2014 (31% vs 28%) (YouGov & Eating Better, 2017). Nonetheless, only 19% in 2017 report they had reduced the amount of meat eaten in the past year.

### **A.2.2. Environment**

One of the grand challenges facing humanity is climate change (Beniston, 2013). This challenge is rising to the forefront of policy-making and discussions, given its potentially devastating impact on the current and future generations through extreme weather conditions, rising sea levels, droughts, and food insecurity amongst others (International Panel on Climate Change, 2019). In 1973 the Club of Rome published the Limits to Growth report, where the environmental impact of humans on the natural environment was brought to attention ("The Limits to Growth", 2013). The report determined that there are five principal factors which in their interplay limit growth in the planet, namely: population increase, agricultural production, nonrenewable resource depletion, industrial output, and pollution generation.

The main contributor to climate change is Greenhouse Gas (GHG) emissions, with the agricultural sector accounting for over a quarter of global GHG emissions (Burlingame, 2012; Willett et al., 2019), as seen in Figure A.6. Globally livestock-related emissions from enteric fermentation and manure contributed to nearly two-thirds of total agricultural GHG emissions (Ritchie & Roser, 2020).

The emissions from the livestock industry are derived from biological processes, which are difficult to optimize or manage, such as methane from the digestion process of ruminants and NO<sub>x</sub> emissions from land-use (Röös et al., 2015). The EAT-Lancet Commission has outlined various environmental effects caused by the various food types, clearly demonstrating in Figure A.7 that the livestock industry is at the core of many environmental issues.

Livestock rearing, in particular of ruminants as cows, is a major contributor not only to Greenhouse gas emissions, but also to land use, energy use, acidification potential, and eutrophication potential. On the other hand, vegetables and pulses contribute minimally to these.

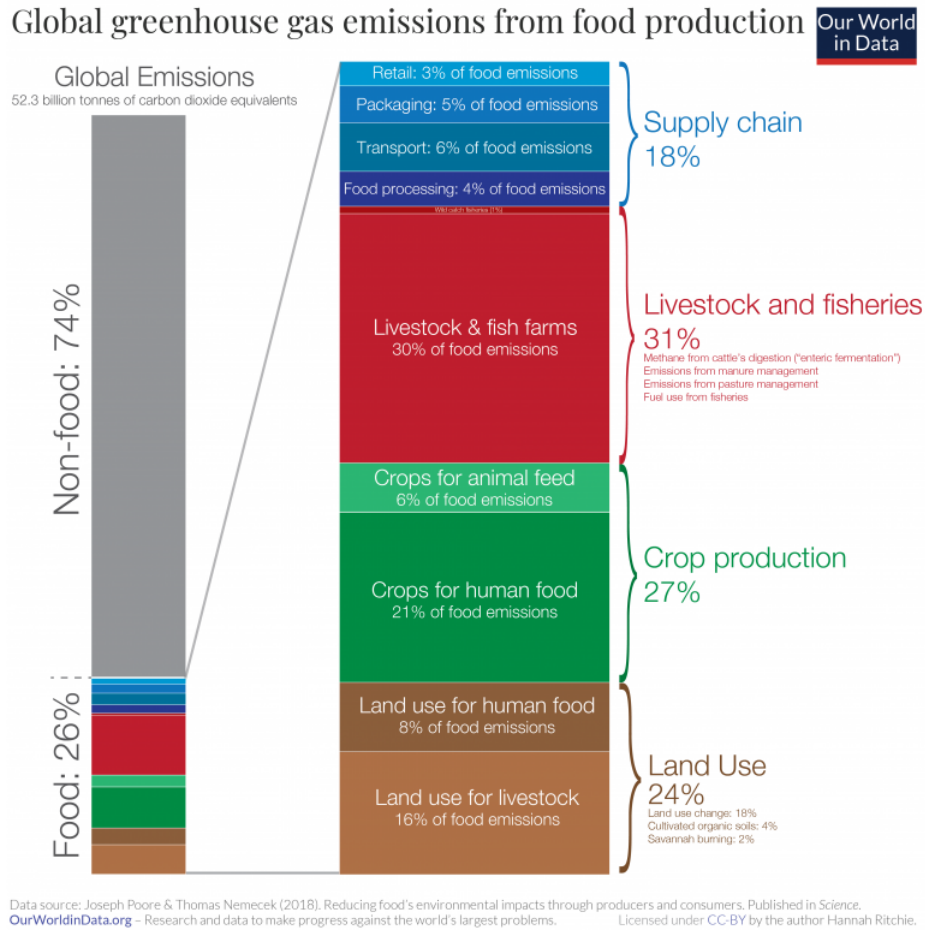


Figure A.6: Global greenhouse gas emissions from food production as reported on by Poore and Nemecek in Our World in Data (2020)

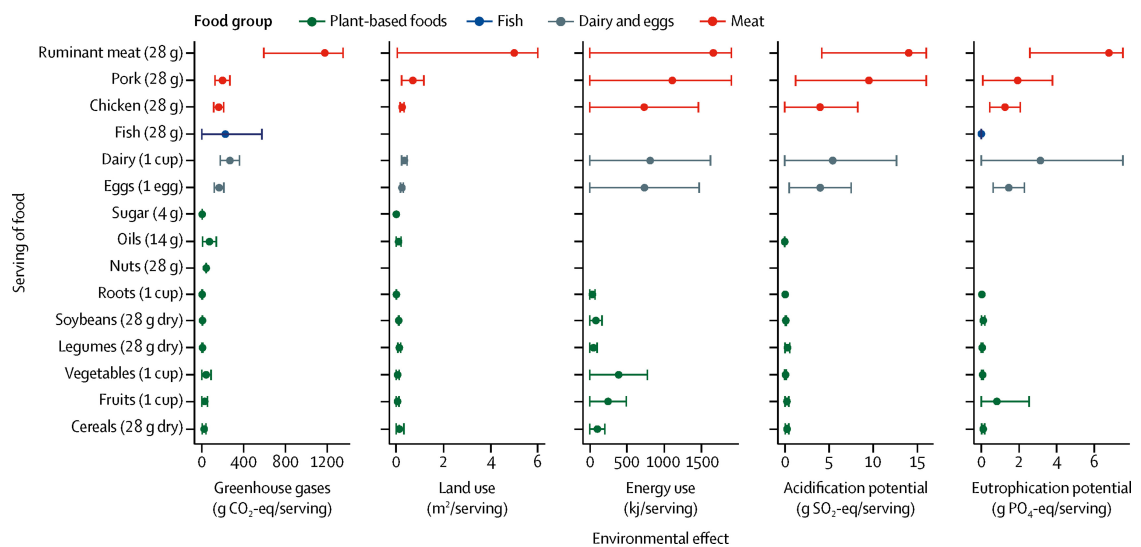
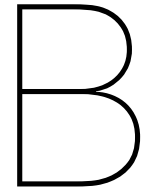


Figure A.7: Environmental effects distribution per serving of food type in terms of Greenhouse gases, Land use, Energy Use, Acidification potential and Eutrophication potential as shown in report by the EAT-Lancet Commission on healthy diets from sustainable food systems (Willett et al., 2019)



# Appendix: Farm to Fork Strategy

## **B.1. Farm to Fork Strategy**

### **B.1.1. Labelling**

Given the broad definition of sustainable diets, and the complex interplay of factors defining sustainability, it is difficult for consumers to discern what a sustainable diet is (Burlingame, 2012). Labelling can play an important role to educate and empower consumers in their consumption.

An area where the EU has seen success through labelling is in the energy industry. Energy efficiency labels were introduced in 2010 and have since seen widespread use in electrical appliances ranging from light-bulbs to refrigerators and washing machines (Yilmaz et al., 2019). An econometric analysis on the impact of EU's energy labelling policy found that the sale of high-efficiency appliances rose by 55% at the label announcement, and further increased by sales by 42% at the implementation of the label. Furthermore, sale of low energy-efficiency appliances declined by 45% at the label implementation (Bjerregaard & Møller, 2019). The implementation of these labels by the EU helps set EU-wide minimum standards, and get rid of the worst performing products in the market. According to the Special Eurobarometer 492, 93% of consumers recognised the label and 79% of consumers considered it when buying energy efficient products (European Commission, 2021)

Labelling is one of the key policies considered within the Farm to Fork strategy to support consumers in adopting a more sustainable diet (European Commission, 2020). The European Commission considers certification and labelling on the sustainability performance of food products, together with setting incentives, to raise sustainability standards and have these become the norm for food products within the EU market (2020). Additional animal welfare and front-of-pack nutrition labels are also considered by the EU. Each of these respective labels targets one of the areas of concern for consumers; front-of-pack nutrition labels enable consumers to make health conscious decisions, sustainability labels empower environmentally sustainable food choices and animal welfare labels targets raising ethical standards.

Several studies have been conducted on the potential impact of labels on food consumption. It was found that one of the reasons why consumers do not readily change their food habits when targeting sustainability issues is due to being unaware of the significant impact of their personal food choices, as red meat consumption, on increasing greenhouse gas emissions (Feucht & Zander, 2018; Macdiarmid et al., 2016). Consumers typically believe that changing their behaviour would have limited influence on reducing greenhouse gas emissions (Eker et al., 2019; Graham & Abrahamse, 2017; Van Loo, Hoefkens, & Verbeke, 2017). Sustainability is generally treated as a less salient factor than other factors as healthy eating, taste, price, availability or social trends (Osman & Thornton, 2019).

A green food labelling system has been used in place in the UK, namely the 'Carbon Footprint' label. This label gives an indication of the total greenhouse gas emissions produced during a product's lifecycle in tonnes of carbon dioxide equivalent. However, while consumers are aware of the label, it was found to have had limited impact on actual consumption behaviour changes (Grunert, Hieke, & Wills, 2014). In certain cases, labels which use negative framing and appeal to human fear and negative consequences, may result in boomerang effects where consumers take choices which go against the intention of the message (Hart & Nisbet, 2012).

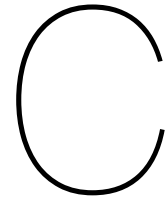
A more promising type of food labelling appears to be the traffic light index. This has been explored in several studies, which have shown that nutrition labelling encourages healthier food choices (Cecchini & Warin, 2016; VanEpps, Downs, & Loewenstein, 2016). This result is also reflected on greener food choices when applying traffic light labelling to carbon emissions Spaargaren, Koppen, Janssen, Hendriksen, and Kolfshoten (2013). Researchers as Spaargaren (2013) found that traffic light labels depicting carbon emissions on food products contributed to minor reduction of 3% in carbon emission levels.

Studies by Feucht and Zander (2018) also indicate that the use of traffic light carbon labels over more verbal claims can be beneficial. This study also highlights that carbon labels may have limited contribution to more climate-friendly consumption, as they found consumers favour local production over climate-friendly indicators (Feucht & Zander, 2018). Consumers also tend to group claims of climate-friendliness with local and organic production, and think these fall under terms as 'eco-friendly' or 'ethical'.

An empirical study by Slapø and Karevold (2019) found that placing traffic light labelling in cafeteria settings results in a minor effect, and that labelling of eco-friendliest food choices didn't change food choices in an environmentally friendly direction. However, labels still can be useful to reduce consumer doubt (Muñoz & Marselis, 2016), and changes in habitual purchasing practices requires an ability to recognise changing behaviour has a genuine impact which labels can provide (Vittersø & Tangeland, 2014).

Most studies indicate that traffic light index is the preferred type of label, but highlight that this as a sole method will not result in adequate change. It is also not clear how long the effect of this measure would last, and the design appears to be highly important. More empirical studies are required to fully assess the impact of traffic light labels indicating carbon emissions. Other methods these researchers advocate for are taxes on foods with high carbon footprints, and other behavioural economics interventions such as nudges in the form of creating a dedicated space for climate-friendly food in supermarkets, or positioning climate-friendly food on eye level.





# Appendix: Model

## C.1. Model

### C.1.1. Model interface

- Add table here with interface variables from the meat consumption
- Add image here of the model interface

The model interface allows for the user to define and create the networks, set the policies and interventions, and monitor the model outcomes and outputs. The model interface is shown in Figure C.1.

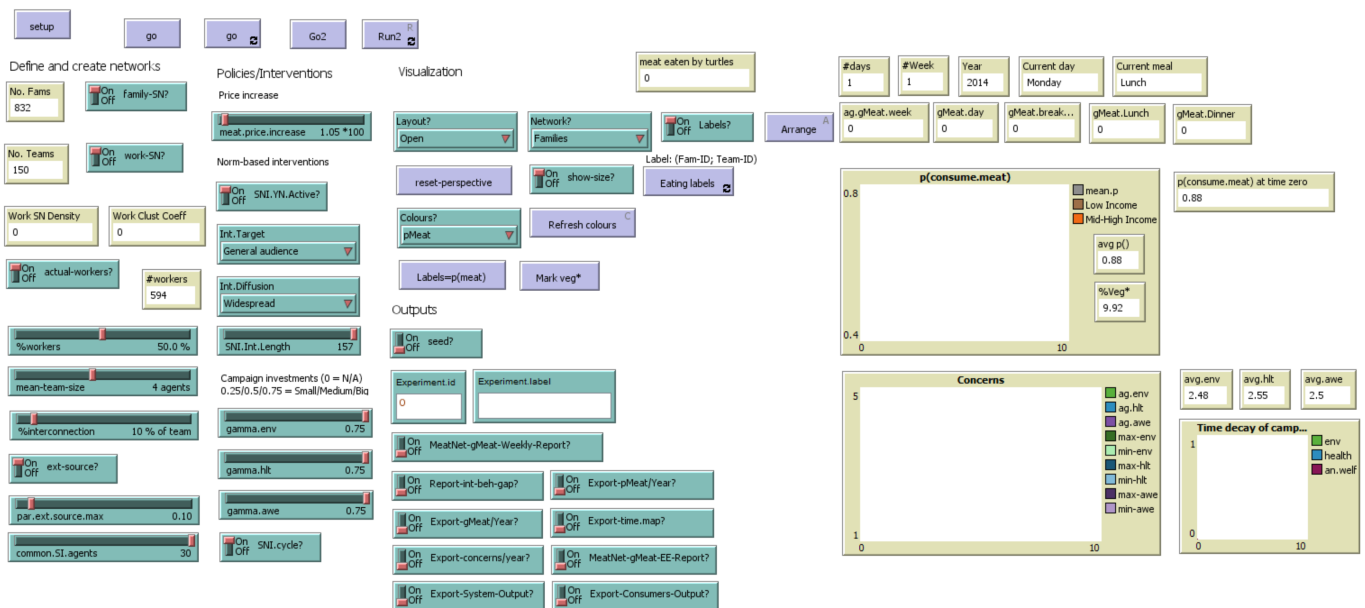


Figure C.1: Model interface of the Meat Consumption model, building on the MeatNet model by Scalco et al. (2019)

Each button on the model interface is elaborated on in Tables C.2, C.3, C.4, and C.5.

	Type	Range/Units	Definition
<b>Define and create networks</b>			
<u>N.families</u>	Monitor		Number of families
<u>N.teams</u>	Monitor		Number of teams
<u>family-SN?</u>	Switch	On/Off	Create social network family
<u>work-SN?</u>	Switch	On/Off	Create social network work
<u>work-SN-density</u>	Monitor		Social network density work
<u>actual-workers</u>	Switch	On/Off	Workers?
<u>%workers</u>	Slider	0-100%	Percentage of workers
<u>mean-team-size</u>	Slider	0-9 agents	Mean team size
<u>%interconnection</u>	Slider	0-100 % of team	Connection between percentage of teams
<u>ext-source?</u>	Switch	On/Off	External source of influence (change consumers' Concerns due to not explicitly modelled by The simulation (e.g. influences by media, Bad food experiences, etc.)
<u>common.Sl.agents</u>	Slider	2-30	Number of agents an individual will have a Random process of social interaction with
<u>par_ext_source_max</u>	Slider	0-1	Replicate consumer's susceptibility to external Sources of influence

Figure C.2: Model interface parameters: Define and create networks

	Type	Range/Units	Definition
<b>Policies</b>			
<u>meat_price.increase</u>	Slider		Increase in meat price
<u>SNI.YN.Active?</u>	Switch		Social Network Intervention active
<u>Int.Target</u>	Chooser		Intervention target ("N/A", "General audience", "Young 18-30", "Adults 30-65", "Elders 65+", "Env concerned", "Env unconcerned", "Health concerned", "Health unconcerned", "Awe unconcerned", "Only females", "Only males", "Flexitarians")
<u>Int.Diffusion</u>	Chooser		Intervention diffusion ("N/A", "Widespread", "Only workplaces", "Households")
<u>SNI.Int.Length</u>	Slider	0 - 157 (weeks)	Weeks active of Social Network Intervention
<i>Campaign investments</i>			
<u>gamma.env</u>	Slider	0 - 0.75	Campaign investments (0 = N/A, 0.25/0.5/0.75 = Small/Medium/Big)
<u>gamma.hlt</u>	Slider	0 - 0.75	Campaign investments (0 = N/A, 0.25/0.5/0.75 = Small/Medium/Big)
<u>gamma.awe</u>	Slider	0 - 0.75	Campaign investments (0 = N/A, 0.25/0.5/0.75 = Small/Medium/Big)
<u>SNI.cycle?</u>	Switch	On/Off	Social Network intervention cycling?

Figure C.3: Model interface parameters: Policies/Interventions

	Type	Range/Units	Definition
<b>Visualization</b>			
Layout?	Switch	On/Off	Show layout
Network?	Switch	On/Off	Show network
Labels?	Switch	On/Off	Show labels
show-size?	Switch	On/Off	Show size (likelihood to consume meat)
reset-perspective	Button		Reset perspective of 3D visualisation
Eating labels	Button		Activate eating labels for agents in 3D visualisation
Colours?	Chooser		Set 3D agents to colour according to: " <u>pMeat</u> ", " <u>ag.eny</u> ", " <u>ag.hlt</u> ", " <u>ag.awe</u> "
Refresh colours	Button		Refresh colours in 3D visualization
Labels=p(meat)	Button		Activate probability meat consumption labels in 3D visualization
Mark veg*	Button		Mark vegetarians in 3D visualization

Figure C.4: Model interface parameters: Visualization

<b>Outputs</b>			
seed?	Switch	On/Off	Fix seed?
Experiment.id	Input	Number	Give the experiment an ID number
<u>Experiment.label</u>	Input	String	Label the experiment
<u>MeatNet.gMeat-Weekly-Report?</u>	Switch	On/Off	Record in an external txt file the amount of meat eaten weekly by agents
Report-int- <u>beh-gap?</u>	Switch	On/Off	Record in an external txt file the behaviour Of agents with respect to their intention
Export- <u>pMeat/year?</u>	Switch	On/Off	Write the yearly probability of meat consumption
Export- <u>gMeat/Year?</u>	Switch	On/Off	Write the yearly meat consumption in grams
Export- <u>time_map?</u>	Switch	On/Off	Record in an external txt file agents' concerns and average consumption and likelihood of eating meat for the last 3 months
Export-concerns/year?	Switch	On/Off	Record in an external txt file yearly consumption of meat by subgroups, agents' concerns
<u>MeatNet-gMeat-EE-Report?</u>	Switch	On/Off	Record in an external txt file the amount of meat eaten during each meal
Export-System-Output?	Switch	On/Off	Record temporarily agents' variables to be written in the txt files at the end of each run of the simulation
Export-Consumers-Output?	Switch	On/Off	Record in an external txt file yearly consumption of meat by subgroups, agents' concerns, and likelihood of eating meat Also, record individual agents' variables at the end of each simulation.

Figure C.5: Model interface parameters: Outputs

## C.2. Implementing main model processes

The main model processes include the social influence function, the likelihood to consume meat function, and the meat consumption function.

There is a social influence process for environmental, health, and animal welfare concerns. At each eating episode there is a random chance for the agent to activate one of these three processes. This is determined by the 'social-influence-manage-function', where randomly one of the three social influence functions is chosen. This managing function can be seen in Figure C.6.

```
;; Manage what concerns among the three ones will undergo a process of influence
to social-influence-manage-function [temp.locals]
  let random.p1 (random-float 1)
  let random.p2 (random-float 2)
  ifelse random.p1 > random.p2
  [
    let random.p3 (random-float 1)
    let random.p4 (random-float 1)
    ifelse random.p3 > random.p4
    [ social-influence-env (temp.locals) ]
    [ social-influence-ht (temp.locals) ]
  ]
  [social-influence-awe (temp.locals) ]
end
```

Figure C.6: Social-influence managing process, randomly managing what concern among the three will undergo a process of influence

The process for influencing the environmental concern of agents can be seen in Figure C.7. This makes use of the social influence equation by Zhang et al. (2014). Here the alpha ( $\alpha$ ) indicates how susceptible an agent is towards a peer in their household network or co-worker network. Household networks have an alpha of 0.30, while co-worker networks have an alpha of 0.15. This difference represents the strong links between household members and weaker links between co-worker networks (Scalco et al., 2019). The gamma indicates the additional influence as result of the social marketing campaign. This ranges from not active (0) to highly successful (0.75), and decays following the social marketing campaign decay function. The agents will look at the other agents in their network, calculate the weighted concerns of those more and less concerned than themselves, and adjust their own concern accordingly.

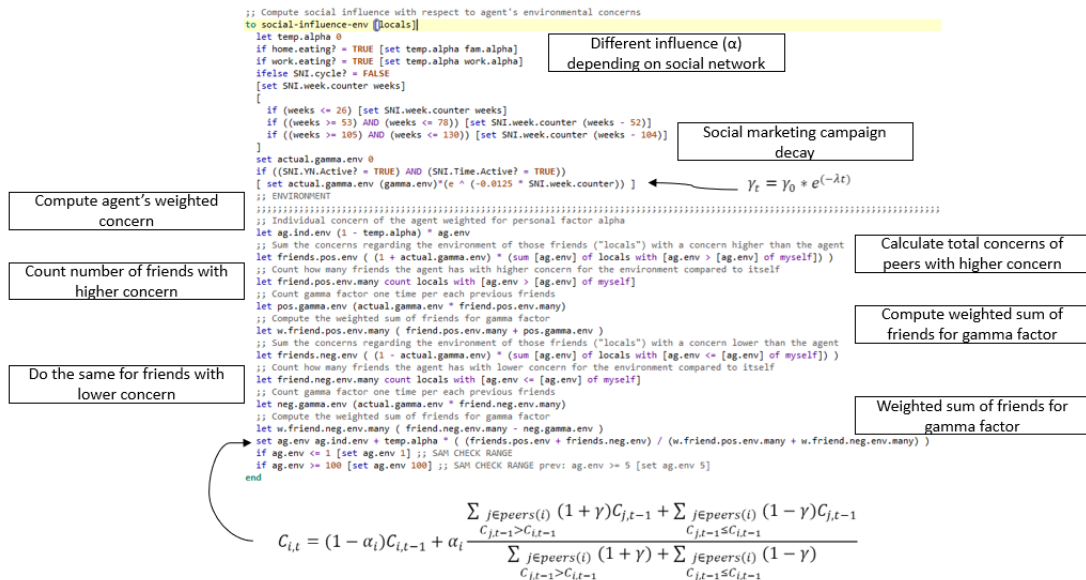
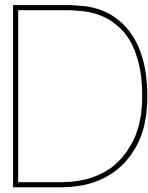


Figure C.7: Social influence process for environmental concerns, where agents will look at the concerns of those around themselves, weigh the concerns of those more and less concerned than themselves, and accordingly based on their own susceptibility to influence ( $\alpha$ ) and the presence of a social-marketing campaign ( $\gamma$ ) adjust their own environmental concern



# Appendix: Behavioural Theory

## D.1. Behavioural theories

Other theories of importance related to social norms and meat consumption are the Extended Theory of Planned Behaviour and the Value-Belief Norm theory. The ETPB is further conceptualised for the case of meat consumption here, and may be used for future research.

## D.2. Extended Theory of Planned Behaviour

An additional theoretical framework which was considered in the Extended Theory of Planned Behaviour. The Extended Theory of Planned Behaviour is a behavioural theory which aims to explain and predict behaviour, and is an extension of the Theory of Planned Behaviour (TPB). The TPB is based on attitudes, norms, intentions and people's perception of the power they have over their behaviour. The motivation to comply are subjective norms; the perception of social norms or what peers' beliefs are about the behaviour (Tommasetti et al., 2018). The ETPB includes the perceived usefulness of the behaviour, and the curiosity in performing this behaviour (Alam et al., 2020; Tommasetti et al., 2018). This can be seen back in Figure D.1.

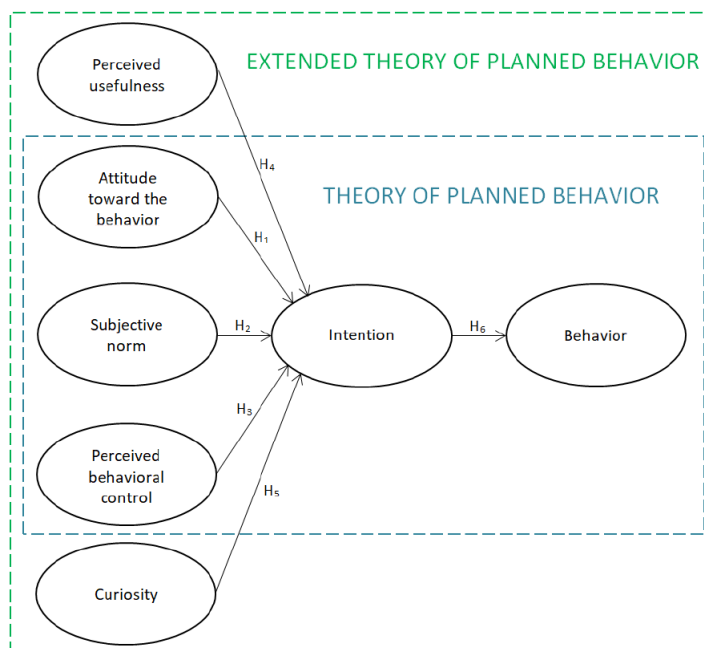
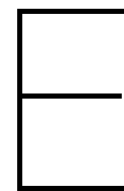


Figure D.1: Extended Theory of Planned Behaviour as extension of the Theory of Planned Behaviour, taken from Tommasetti et al. (2018).

The Extended Theory of Planned Behaviour provides a theoretical practical framework for policy-makers to define strategies directed at influencing individual behaviour through environmental, economic and social policy (Tommasetti et al., 2018). Formal instruments, as taxation and subsidies, typically are used for influencing behaviour indirectly. To determine the influence of other policies, it can be beneficial to use a framework as the ETPB. This has previously been applied to sustainable food consumption by researchers as Alam et al. (2020). This study showed that social norms and perceived consumer effectiveness both have a strong influence on the consumer's intention towards sustainable food consumption. These both have a stronger influence than attitude Alam et al. (2020). As the Theory of Reasoned Action, which is used in the model of Scalco et al. (2019), does not take consumer perceptions and curiosity into account, including this in a model would be beneficial. According to Çoker et al. (2020), attitudes, subjective norms, and perceived control explain 57% of variations in intentions to reduce meat consumption.

- *Perceived usefulness*: Changing meat consumption will require for the alternative to meat consumption to be sufficiently useful to be consumed. Currently, many individuals still find meat important due to its nutritional value (Verbeke, Pérez-Cueto, Barcellos, Krystallis, & Grunert, 2010), taste and other aspects (Van Wezemael, Caputo, Nayga, Chryssochoidis, & Verbeke, 2014). However, meat consumption also results in significant health issues as cancer, heart disease, diabetes and more (G. W. Horgan et al., 2019; Micha et al., 2010; Smith & Smith, 2016). These findings can increase the perceived usefulness of switching diets from a health-aspect, as there are benefits to diets which remove red meats or are meat-free (Hopwood et al., 2020; Walker, Gibney, Mathers, & Hellweg, 2019).
- *Attitude toward the behaviour*: Behavioural change requires the individual to have a positive attitude towards new behaviour. Studies show that for meat consumption, the awareness of the problem and link between meat consumption and climate change, or meat consumption and health risks, are a significant determinant of attitudes (Çoker & van der Linden, 2020). Attitudes in turn are the strongest predictor of intentions for meat consumption following a study by Çoker et al. (2020). Ignorance between these links may make individuals less likely to reduce their meat consumption.
- *Subjective norm*: individuals take subjective sociocultural considerations into account, making it difficult to change food behaviour (Muñoz & Marselis, 2016). Norms play an active role in meat consumption, where individuals will change their behaviour when eating with others (Higgs, 2015) to alter their public image, especially within peer networks (Macdiarmid et al., 2016).
- *Perceived behavioural control*: perceived barriers to sustainable eating include the price, lack of information, the challenge to identify sustainable foods and limited availability of these foods (BEUC, 2020).
- *Curiosity*: The International Food Information Council Foundation found that curiosity was the primary reason for consumers to try plant-based meat alternatives, ranking higher than both environmental or health concerns (International Food Information Council Foundation, 2019).

This theory was not used as there is insufficient data to link the characteristics of the ETPB to specific food consumption per food type. This theory still appears to be valuable, and should aim to be implemented in future research.



# Appendix: Data

## E.1. Surveys



### **oi18a001 – oi18a010**

Please rate the importance of each of the following reasons for you to eat less meat or animal products. Please rate these items even if you don't intend to change your diet.

*Question type:* Table

*Answer type:* Radiobuttons

*Subquestions:*

- oi18a001** I want to be healthy
- oi18a002** Plant-based diets are better for the environment
- oi18a003** Animals do not have to suffer
- oi18a004** Animals' rights are respected
- oi18a005** I want to live a long time
- oi18a006** Plant-based diets are more sustainable
- oi18a007** I care about my body
- oi18a008** Eating meat is bad for the planet
- oi18a009** Animal rights are important to me
- oi18a010** Plant-based diets are environmentally-friendly

*Categories:*

- 1. 1 not important
- 2. 2
- 3. 3
- 4. 4
- 5. 5
- 6. 6
- 7. 7 very important

### **oi18a011 – oi18a015**

And please rate the importance of each of the following reasons for you to eat less meat or animal products. Please rate these items even if you don't intend to change your diet.

*Question type:* Table

*Answer type:* Radiobuttons

*Subquestions:*

- oi18a011** It does not seem right to exploit animals
- oi18a012** Plants have less of an impact on the environment than animal products
- oi18a013** I am concerned about animal rights
- oi18a014** My health is important to me
- oi18a015** I don't want animals to suffer

- 1. 1 not important
- 2. 2
- 3. 3
- 4. 4

Figure E.1: Reasons to Eat Less Meat Questionnaire (LISS Panel Survey from CentERdata)

## E.2. Multiple Linear Regression Analysis

A multiple linear regression was also conducted using the DNFCS (RIVM, 2020b) and Belevingen 2020 survey (CBS, 2021b), which includes the three independent variables: Health, Environment and Animal Welfare concerns. These three concerns, given the data available and strong correlation between Environmental and Animal welfare concerns, did not provide statistically significant results for some of the meat types. The strong correlation between environment and animal welfare concerns mean that within this study they do not provide additional benefit when used together. Therefore, in the study itself the animal welfare concern was left behind.

Table E.1: Least-square multiple linear regression analysis results showing the regression coefficients for health, environment and animal welfare concerns with respect to the probability of consuming specific meat types

Type	Factors				R – square
	coeff.	Health	Environment	Animal	
Beef	9.10 +- 4.44 (p = 0.065)	0.360 +- 0.141 (p = 0.027)	-0.0025 +- 0.156 (p = 0.988)	-0.221 +- 0.187 (p = 0.261)	0.485
Pork	11.01 +- 2.43 (p = 0.001)	0.3416 +- 0.077 (p = 0.001)	-0.2414 +- 0.085 (p = 0.017)	-0.0554 +- 0.102 (p = 0.598)	0.882
Poultry	23.27 +- 3.31 (p = 0.00)	-0.2067 +- 0.105 (p = 0.075)	0.1052 +- 0.116 (p = 0.385)	0.0944 +- 0.139 (p = 0.511)	0.620
Processed	64.79 +- 5.8 (p = 0.00)	0.401 +- 0.184 (p = 0.052)	-0.08 +- 0.204 (p = 0.695)	-0.322 +- 0.244 (p = 0.213)	0.653
Substitute	0.299 +- 1.24 (p = 0.814)	-0.014 +- 0.039 (p = 0.732)	0.0565 +- 0.044 (p = 0.221)	0.020 +- 0.052 (p = 0.703)	0.766

The multiple linear regression analysis conducted for the various meat types are found in Figure E.2 for pork, Figure E.3 for poultry, Figure E.4 for processed meat, and Figure E.5 for substitutes

```

=====
                        OLS Regression Results
=====
Dep. Variable:          Pork_Day      R-squared:                0.879
Model:                  OLS           Adj. R-squared:           0.859
Method:                 Least Squares  F-statistic:              43.59
Date:                   Fri, 20 Aug 2021  Prob (F-statistic):       3.14e-06
Time:                   11:21:39      Log-Likelihood:          -15.354
No. Observations:      15            AIC:                     36.71
Df Residuals:          12            BIC:                     38.83
Df Model:               2
Covariance Type:       nonrobust
=====
                        coef      std err      t      P>|t|      [0.025      0.975]
-----
const                10.5060      2.181      4.818      0.000      5.755      15.258
Environment          -0.2841      0.032     -8.875      0.000     -0.354     -0.214
Health                0.3463      0.074      4.654      0.001      0.184      0.508
=====
Omnibus:              1.257      Durbin-Watson:           1.369
Prob(Omnibus):        0.533      Jarque-Bera (JB):        0.793
Skew:                 0.541      Prob(JB):                0.673
Kurtosis:             2.688      Cond. No.                 550.
=====

```

Figure E.2: Multiple linear regression analysis for pork consumption, through combining the Belevingen 2020 Survey (CBS, 2021b) and Dutch National Food Consumption Survey (RIVM, 2020b). (Source: Author)



```

=====
                    OLS Regression Results
=====
Dep. Variable:          Poultry_Day      R-squared:                0.604
Model:                  OLS              Adj. R-squared:           0.538
Method:                 Least Squares    F-statistic:              9.143
Date:                   Fri, 20 Aug 2021  Prob (F-statistic):      0.00387
Time:                   11:21:59         Log-Likelihood:           -20.100
No. Observations:      15              AIC:                      46.20
Df Residuals:          12              BIC:                      48.32
Df Model:               2
Covariance Type:       nonrobust
=====
                    coef    std err          t      P>|t|      [0.025    0.975]
-----+-----
const                24.1221    2.992         8.061    0.000     17.602    30.642
Environment           0.1781    0.044         4.054    0.002      0.082     0.274
Health               -0.2146    0.102        -2.102    0.057     -0.437     0.008
=====
Omnibus:                 1.642    Durbin-Watson:           2.928
Prob(Omnibus):           0.440    Jarque-Bera (JB):        0.318
Skew:                    -0.270    Prob(JB):                0.853
Kurtosis:                3.466    Cond. No.                550.
=====

```

Figure E.3: Multiple linear regression analysis for poultry consumption, through combining the Belevingen 2020 Survey (CBS, 2021b) and Dutch National Food Consumption Survey (RIVM, 2020b). (Source: Author)

```

=====
                    OLS Regression Results
=====
Dep. Variable:          Processed_Day    R-squared:                0.598
Model:                  OLS              Adj. R-squared:           0.531
Method:                 Least Squares    F-statistic:              8.935
Date:                   Fri, 20 Aug 2021  Prob (F-statistic):      0.00420
Time:                   11:22:20         Log-Likelihood:           -29.309
No. Observations:      15              AIC:                      64.62
Df Residuals:          12              BIC:                      66.74
Df Model:               2
Covariance Type:       nonrobust
=====
                    coef    std err          t      P>|t|      [0.025    0.975]
-----+-----
const                61.8781    5.529        11.192    0.000     49.832     73.924
Environment          -0.3306    0.081        -4.073    0.002     -0.507     -0.154
Health               0.4283    0.189         2.271    0.042      0.017     0.839
=====
Omnibus:                 5.400    Durbin-Watson:           3.030
Prob(Omnibus):           0.067    Jarque-Bera (JB):        2.955
Skew:                    -0.308    Prob(JB):                0.228
Kurtosis:                5.086    Cond. No.                550.
=====

```

Figure E.4: Multiple linear regression analysis for processed meat consumption, through combining the Belevingen 2020 Survey (CBS, 2021b) and Dutch National Food Consumption Survey (RIVM, 2020b). (Source: Author)

```

=====
                    OLS Regression Results
=====
Dep. Variable:          Sub_Day          R-squared:                0.763
Model:                  OLS              Adj. R-squared:           0.724
Method:                 Least Squares    F-statistic:              19.32
Date:                   Fri, 20 Aug 2021  Prob (F-statistic):      0.000177
Time:                   11:22:50         Log-Likelihood:           -5.1484
No. Observations:      15              AIC:                      16.30
Df Residuals:          12              BIC:                      18.42
Df Model:               2
Covariance Type:       nonrobust
=====
                    coef    std err          t      P>|t|      [0.025    0.975]
-----+-----
const                0.4832    1.104         0.438    0.669     -1.923     2.889
Environment           0.0722    0.016         4.456    0.001      0.037     0.108
Health               -0.0155    0.038        -0.412    0.688     -0.098     0.067
=====
Omnibus:                 2.466    Durbin-Watson:           2.478
Prob(Omnibus):           0.291    Jarque-Bera (JB):        1.048
Skew:                    0.095    Prob(JB):                0.592
Kurtosis:                1.719    Cond. No.                550.
=====

```

Figure E.5: Multiple linear regression analysis for substitute meat consumption, through combining the Belevingen 2020 Survey (CBS, 2021b) and Dutch National Food Consumption Survey (RIVM, 2020b). (Source: Author)

A multiple linear regression analysis was also conducted for the different types of diets, to determine whether it was possible to correlate the findings. With the available data and low significance this was not further implemented in the model, but may be useful for future research and considerations. These are provided in Figures E.6 for vegan diets, E.7 for vegetarian diet, E.8 for flexitarian diet, E.9 for 5-6 times per week, E.10 for everyday and E.11 for never meat consumption.

OLS Regression Results						
Dep. Variable:	Vegan	R-squared:	0.769			
Model:	OLS	Adj. R-squared:	0.662			
Method:	Least Squares	F-statistic:	7.144			
Date:	Tue, 06 Jul 2021	Prob (F-statistic):	0.000738			
Time:	15:16:35	Log-Likelihood:	6.0853			
No. Observations:	23	AIC:	3.829			
Df Residuals:	15	BIC:	12.91			
Df Model:	7					
Covariance Type:	nonrobust					
	coef	std err	t	P> t	[0.025	0.975]
const	4.4096	1.539	2.866	0.012	1.130	7.689
Environment	0.0675	0.014	4.836	0.000	0.038	0.097
Animal	-0.0085	0.024	-0.358	0.726	-0.059	0.042
Health	-0.1123	0.034	-3.350	0.004	-0.184	-0.041
Taste	-0.0440	0.020	-2.166	0.047	-0.087	-0.001
Housemate	-0.0880	0.038	-2.294	0.037	-0.170	-0.006
Too expensive	0.0287	0.020	1.461	0.165	-0.013	0.070
Other reason	0.0075	0.023	0.333	0.744	-0.041	0.056
Omnibus:	2.976	Durbin-Watson:	3.008			
Prob(Omnibus):	0.226	Jarque-Bera (JB):	1.699			
Skew:	-0.651	Prob(JB):	0.428			
Kurtosis:	3.280	Cond. No.	2.15e+03			

Figure E.6: Multiple linear regression analysis for a Vegan diet, through combining the Belevingen 2020 Survey (CBS, 2021b) and Dutch National Food Consumption Survey (RIVM, 2020b). (Source: Author)

OLS Regression Results						
Dep. Variable:	Vegetarian	R-squared:	0.651			
Model:	OLS	Adj. R-squared:	0.488			
Method:	Least Squares	F-statistic:	3.994			
Date:	Tue, 06 Jul 2021	Prob (F-statistic):	0.0116			
Time:	15:05:57	Log-Likelihood:	-12.134			
No. Observations:	23	AIC:	40.27			
Df Residuals:	15	BIC:	49.35			
Df Model:	7					
Covariance Type:	nonrobust					
	coef	std err	t	P> t	[0.025	0.975]
const	-3.0321	3.398	-0.892	0.386	-10.274	4.210
Environment	0.0444	0.031	1.442	0.170	-0.021	0.110
Animal	0.0413	0.052	0.790	0.442	-0.070	0.153
Health	0.0057	0.074	0.077	0.940	-0.152	0.163
Taste	0.0587	0.045	1.307	0.211	-0.037	0.154
Housemate	-0.1083	0.085	-1.279	0.220	-0.289	0.072
Too expensive	-0.0410	0.043	-0.947	0.359	-0.133	0.051
Other reason	0.0645	0.050	1.288	0.217	-0.042	0.171
Omnibus:	0.530	Durbin-Watson:	1.995			
Prob(Omnibus):	0.767	Jarque-Bera (JB):	0.477			
Skew:	-0.308	Prob(JB):	0.788			
Kurtosis:	2.657	Cond. No.	2.15e+03			

Figure E.7: Multiple linear regression analysis for a Vegetarian diet, through combining the Belevingen 2020 Survey (CBS, 2021b) and Dutch National Food Consumption Survey (RIVM, 2020b). (Source: Author)

```

=====
                        OLS Regression Results
=====
Dep. Variable:          Flex      R-squared:                0.553
Model:                 OLS      Adj. R-squared:           0.345
Method:                Least Squares  F-statistic:              2.653
Date:                  Tue, 06 Jul 2021  Prob (F-statistic):       0.0534
Time:                  15:17:04    Log-Likelihood:           -56.272
No. Observations:     23         AIC:                      128.5
Df Residuals:         15         BIC:                      137.6
Df Model:              7
Covariance Type:      nonrobust
=====
                        coef      std err          t      P>|t|      [0.025      0.975]
-----
const                45.3182    23.153         1.957    0.069     -4.030     94.667
Environment          -0.1294     0.210        -0.616    0.547     -0.577     0.318
Animal               0.3130     0.356         0.879    0.393     -0.446     1.072
Health               0.0509     0.504         0.101    0.921     -1.024     1.126
Taste                0.1998     0.306         0.653    0.524     -0.452     0.852
Housemate           -1.2558     0.577        -2.175    0.046     -2.486     -0.025
Too expensive        0.1252     0.295         0.424    0.677     -0.504     0.754
Other reason        -0.8467     0.341        -2.484    0.025     -1.573     -0.120
=====
Omnibus:              0.421    Durbin-Watson:           1.805
Prob(Omnibus):        0.810    Jarque-Bera (JB):        0.216
Skew:                 0.225    Prob(JB):                0.897
Kurtosis:             2.849    Cond. No.                 2.15e+03
=====

```

Figure E.8: Multiple linear regression analysis for a Flexitarian diet, through combining the Belevingen 2020 Survey (CBS, 2021b) and Dutch National Food Consumption Survey (RIVM, 2020b). (Source: Author)

```

=====
                        OLS Regression Results
=====
Dep. Variable:          5-6 days meat  R-squared:                0.451
Model:                 OLS      Adj. R-squared:           0.195
Method:                Least Squares  F-statistic:              1.763
Date:                  Tue, 06 Jul 2021  Prob (F-statistic):       0.169
Time:                  15:17:23    Log-Likelihood:           -50.652
No. Observations:     23         AIC:                      117.3
Df Residuals:         15         BIC:                      126.4
Df Model:              7
Covariance Type:      nonrobust
=====
                        coef      std err          t      P>|t|      [0.025      0.975]
-----
const                53.6410    18.134         2.958    0.010     14.990     92.292
Environment          0.2777     0.164         1.688    0.112     -0.073     0.628
Animal              -0.4166     0.279        -1.494    0.156     -1.011     0.178
Health              -0.2964     0.395        -0.750    0.465     -1.138     0.546
Taste               -0.2553     0.240        -1.066    0.303     -0.766     0.255
Housemate           0.0817     0.452         0.181    0.859     -0.882     1.046
Too expensive       -0.0685     0.231        -0.296    0.771     -0.561     0.424
Other reason        0.0499     0.267         0.187    0.854     -0.519     0.619
=====
Omnibus:              3.105    Durbin-Watson:           1.889
Prob(Omnibus):        0.212    Jarque-Bera (JB):        2.376
Skew:                 -0.780    Prob(JB):                0.305
Kurtosis:             2.787    Cond. No.                 2.15e+03
=====

```

Figure E.9: Multiple linear regression analysis for a diet of 5-6 times eating meat per week, through combining the Belevingen 2020 Survey (CBS, 2021b) and Dutch National Food Consumption Survey (RIVM, 2020b). (Source: Author)

```

OLS Regression Results
=====
Dep. Variable:      Every day meat    R-squared:          0.807
Model:              OLS                Adj. R-squared:    0.717
Method:             Least Squares      F-statistic:       8.947
Date:               Tue, 06 Jul 2021    Prob (F-statistic): 0.000216
Time:               15:18:10           Log-Likelihood:    -44.431
No. Observations:  23                  AIC:               104.9
Df Residuals:      15                  BIC:               113.9
Df Model:          7
Covariance Type:   nonrobust
=====
                    coef    std err          t      P>|t|      [0.025    0.975]
-----+-----
const             -10.3547    13.836     -0.748    0.466    -39.846    19.137
Environment       -0.3826     0.125    -3.049    0.008    -0.650    -0.115
Animal            0.0450     0.213     0.211    0.835    -0.409    0.499
Health            0.5403     0.301     1.793    0.093    -0.102    1.183
Taste             0.1396     0.183     0.764    0.457    -0.250    0.529
Housemate         1.7103     0.345     4.957    0.000    0.975    2.446
Too expensive     -0.4252     0.176    -2.410    0.029    -0.801    -0.049
Other reason      0.9543     0.204     4.684    0.000    0.520    1.389
=====
Omnibus:          0.384    Durbin-Watson:     2.384
Prob(Omnibus):   0.825    Jarque-Bera (JB):  0.531
Skew:            -0.148   Prob(JB):          0.767
Kurtosis:        2.317    Cond. No.          2.15e+03
=====

```

Figure E.10: Multiple linear regression analysis for a diet of eating meat every day, through combining the Belevingen 2020 Survey (CBS, 2021b) and Dutch National Food Consumption Survey (RIVM, 2020b). (Source: Author)

```

OLS Regression Results
=====
Dep. Variable:      Never meat        R-squared:          0.761
Model:              OLS                Adj. R-squared:    0.650
Method:             Least Squares      F-statistic:       6.829
Date:               Tue, 06 Jul 2021    Prob (F-statistic): 0.000935
Time:               15:18:36           Log-Likelihood:    -30.955
No. Observations:  23                  AIC:               77.91
Df Residuals:      15                  BIC:               86.99
Df Model:          7
Covariance Type:   nonrobust
=====
                    coef    std err          t      P>|t|      [0.025    0.975]
-----+-----
const             7.1316     7.701     0.926    0.369    -9.283    23.546
Environment       0.1881     0.070     2.694    0.017    0.039    0.337
Animal            0.1403     0.118     1.185    0.255    -0.112    0.393
Health            -0.2619    0.168    -1.562    0.139    -0.619    0.096
Taste             -0.0304     0.102    -0.299    0.769    -0.247    0.186
Housemate        -0.5848     0.192    -3.045    0.008    -0.994    -0.175
Too expensive     0.0568     0.098     0.579    0.571    -0.152    0.266
Other reason      0.0728     0.113     0.642    0.530    -0.169    0.315
=====
Omnibus:          0.774    Durbin-Watson:     1.985
Prob(Omnibus):   0.679    Jarque-Bera (JB):  0.760
Skew:            -0.214   Prob(JB):          0.684
Kurtosis:        2.218    Cond. No.          2.15e+03
=====

```

Figure E.11: Multiple linear regression analysis for a never eating meat, through combining the Belevingen 2020 Survey (CBS, 2021b) and Dutch National Food Consumption Survey (RIVM, 2020b). (Source: Author)

### E.3. The Netherlands

	OtherCharacteristics	Vegan	Vegetarian	Pesco	Flex	5-6 days meat	Every day meat	Never meat
0	Mannen	0.4	1.0	1.9	41.1	29.7	25.9	3.3
1	Vrouwen	0.4	2.3	3.2	48.3	31.2	14.6	5.9
2	18 tot 25 jaar	0.6	2.7	2.4	38.3	29.8	25.8	5.7
3	25 tot 35 jaar	0.9	1.7	3.4	41.1	32.1	17.8	6.1
4	35 tot 45 jaar	0.1	1.0	1.6	44.2	28.5	23.9	2.7
5	45 tot 55 jaar	0.5	1.6	2.7	42.4	33.2	20.1	4.7
6	55 tot 65 jaar	0.3	2.1	2.4	48.4	30.7	16.9	4.8
7	65 tot 75 jaar	0.1	1.3	2.8	48.1	31.0	18.0	4.2
8	75 jaar of ouder	0.1	1.3	2.4	52.0	25.5	20.9	3.9
9	Basisonderwijs	0.2	-0.2	0.5	44.4	32.0	19.8	0.5
10	Vmbo, avo onderbouw, mbo 1	0.1	0.8	1.4	41.7	32.0	23.1	2.3
11	Mbo 2,3,4, havo, vwo	0.2	1.3	1.8	42.6	31.1	24.0	3.3
12	Hbo-, wo-bachelor	0.2	2.4	3.6	47.5	28.6	18.2	6.3
13	Wo-master, doctor#	1.8	2.5	4.8	47.5	30.8	11.3	9.1
14	Eerste 25 procent (lage welvaart)	0.1	2.5	3.7	51.3	24.6	17.2	6.3
15	Tweede 25 procent	0.4	1.2	3.1	43.6	29.5	23.3	4.7
16	Derde 25 procent	0.8	1.1	2.0	42.2	33.3	21.6	3.9
17	Vierde 25 procent (hoge welvaart)	0.1	2.0	1.6	42.8	33.1	19.3	3.7
18	Zeer sterk stedelijk	0.7	2.4	4.5	53.1	24.6	13.6	7.6
19	Sterk stedelijk	0.4	1.8	2.7	45.2	29.0	21.2	4.9
20	Matig stedelijk	0.0	0.8	1.1	41.3	35.1	21.4	1.9
21	Weinig stedelijk	0.1	1.3	1.0	39.2	34.3	24.7	2.4
22	Niet stedelijk	0.5	1.7	2.5	38.2	35.9	22.9	4.8

Figure E.12: Characteristics contributing to dietary make-up

ID	Sex	Age	OtherCharacteristics	FoodGroups	MeanConsumption_1	P5_2	P50_3	P95_4	N_5
0 21795	Male	19 to 79 years	Education: lower	07. Meat, meat products and substit.	129.1	42.4	121.3	258.8	242.0
1 40066	Female	19 to 79 years	Education: lower	07. Meat, meat products and substit.	90.6	17.2	82.4	185.9	360.0
2 21946	Male	19 to 79 years	Education: intermediate	07. Meat, meat products and substit.	127.3	34.8	113.5	261.1	406.0
3 40217	Female	19 to 79 years	Education: intermediate	07. Meat, meat products and substit.	85.3	5.5	80.0	178.0	383.0
4 22097	Male	19 to 79 years	Education: higher	07. Meat, meat products and substit.	112.2	11.0	97.0	250.1	395.0
5 40368	Female	19 to 79 years	Education: higher	07. Meat, meat products and substit.	78.1	0.0	69.9	178.3	292.0
0 22852	Male	19 to 79 years	Urbanisation: strong or extremely	07. Meat, meat products and substit.	119.7	31.3	108.0	258.8	494.0
1 41123	Female	19 to 79 years	Urbanisation: strong or extremely	07. Meat, meat products and substit.	82.3	0.0	75.0	178.3	484.0
2 23003	Male	19 to 79 years	Urbanisation: moderately	07. Meat, meat products and substit.	128.2	34.8	120.7	255.9	200.0

Figure E.13: Meat consumption of the Dutch adult population aged 19-79 split by Gender (Male, Female), Education levels (low, intermediate, higher), and Urbanisation (strong, moderately, low)

	Vlees- en visconsumptie, bevolking van 18 jaar of ouder, 2020	Schatting	Ondergrens	Bovengrens
0	Volledig plantaardig (vegetariër, volledig pla...	0.4	0.2	0.7
1	Nooit vlees en nooit vis (vegetariër, niet vol...	1.7	1.3	2.2
2	Nooit vlees, wel vis (pescotariër)	2.6	2	3.2
3	Maximaal 4 dagen per week vlees (flexitariër)	44.8	43	46.5
4	5 of 6 dagen per week vlees	30.5	28.9	32.1
5	Iedere dag vlees	20.2	18.8	21.6
6	Totaal personen die geen vlees eten (vegetaris...	4.6	3.9	5.4
7	Totaal personen die geen of beperkt vlees eten...	49.4	47.6	51.1

Figure E.14: Meat and fish consumption of the adult population in the Netherlands

Vlees- en visconsumptie, bevolking van 18 jaar of ouder, 2020		Schatting	Ondergrens	Bovengrens
12	Nooit vlees en nooit vis	2.1	1.6	2.7
13	(Minder dan) 1 of 2 dagen vlees of vis	8.8	7.8	9.9
14	3 of 4 dagen vlees of vis	20.5	19.1	22
15	5 of 6 dagen vlees of vis	33.4	31.8	35.1
16	Iedere dag vlees of vis	35.2	33.5	36.9

Figure E.15: Days of meat and fish consumption of the adult population in the Netherlands, from never to every day

Vlees- en visconsumptie, bevolking van 18 jaar of ouder, 2020		Schatting	Ondergrens	Bovengrens
8	Geen (vegetarisch of pescotarisch) of beperkt ...	16.2	14.9	17.6
9	Geen (vegetarisch of pescotarisch) of beperkt ...	7.5	6.6	8.5
10	Beperkt vlees eten (flexitarisch) met klimaat ...	6.6	5.8	7.5
11	Geen vlees eten (vegetarisch of pescotarisch) ...	0.9	0.6	1.3

Figure E.16: Percentages of no or limited meat consumption due to environmental reasons in the Netherlands

Vlees- en visconsumptie, bevolking van 18 jaar of ouder, 2020		Schatting	Ondergrens	Bovengrens
8	Geen (vegetarisch of pescotarisch) of beperkt ...	16.2	14.9	17.6
9	Geen (vegetarisch of pescotarisch) of beperkt ...	7.5	6.6	8.5
10	Beperkt vlees eten (flexitarisch) met klimaat ...	6.6	5.8	7.5
11	Geen vlees eten (vegetarisch of pescotarisch) ...	0.9	0.6	1.3

Figure E.17: Percentages of no or limited meat consumption due to environmental reasons in the Netherlands

Periods	Beef	Pork	Chicken	Calf	Goat	Horse	Total	
Periods	1.000000	-0.839652	-0.798143	0.764193	-0.317744	0.919755	-0.643441	-0.298851
Beef	-0.839652	1.000000	0.940665	-0.371305	0.527312	-0.779779	0.305886	0.729059
Pork	-0.798143	0.940665	1.000000	-0.322816	0.497026	-0.728584	0.162420	0.756029
Chicken	0.764193	-0.371305	-0.322816	1.000000	0.019425	0.787215	-0.860498	0.341616
Calf	-0.317744	0.527312	0.497026	0.019425	1.000000	-0.135535	-0.170375	0.530079
Goat	0.919755	-0.779779	-0.728584	0.787215	-0.135535	1.000000	-0.712957	-0.235724
Horse	-0.643441	0.305886	0.162420	-0.860498	-0.170375	-0.712957	1.000000	-0.327166
Total	-0.298851	0.729059	0.756029	0.341616	0.530079	-0.235724	-0.327166	1.000000

Figure E.18: Correlation between meat consumption levels of various meats during 2005 to 2019

**Tabel 3.1** Vleesverbruik a) per hoofd van de bevolking in Nederland, 2005-2019 (kg)

	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Varkensvlees	37,2	37,4	37,6	37,8	37,7	37,7	37,7	37,3	37,1	36,7	36,6	36,5	36,6	36,6	36,7
Pluimveevlees	20,7	20,8	21,5	21,6	22,5	22,5	22,1	22,0	22,3	22,5	22,1	22,2	22,1	22,5	22,9
Rundvlees	15,9	16,1	16,1	16,1	16,3	16,2	15,9	15,7	15,7	15,5	15,4	15,4	15,4	15,5	15,5
Kalfsvlees	1,3	1,3	1,3	1,4	1,4	1,3	1,3	1,3	1,3	1,3	1,3	1,3	1,3	1,3	1,3
Schape- en geitenvlees	1,0	1,0	1,0	1,1	1,1	1,1	1,1	1,1	1,2	1,2	1,2	1,2	1,2	1,2	1,2
Paardenvlees	0,6	0,5	0,2	0,1	0,1	0,1	0,1	0,1	0,1	0,1	0,1	0,1	0,1	0,1	0,1
Totaal vlees	76,7	77,1	77,8	78,1	79,1	79,0	78,2	77,6	77,5	77,3	76,7	76,6	76,6	77,2	77,8

a) Op basis van karkasgewicht (gewicht met been).

Bron: CBS, berekening Wageningen Economic Research.

Figure E.19: Meat consumption level between 2005 and 2019 (kgs) in the Netherlands

	<b>Butter_3</b>	<b>Cheese_4</b>	<b>Eggs_6</b>	<b>Milk_8</b>	<b>PorkSteak_9</b>	<b>StewingSteak_12</b>
<b>200</b>	1.09	7.01	1.40	0.51	7.63	8.65
<b>201</b>	1.11	7.34	1.40	0.57	8.81	9.27
<b>202</b>	1.12	7.58	1.40	0.61	8.12	9.40
<b>203</b>	1.09	7.67	1.90	0.62	8.00	9.01
<b>204</b>	1.05	7.34	1.60	0.60	7.75	8.59
<b>205</b>	1.01	7.18	1.40	0.60	7.55	8.60
<b>206</b>	1.01	7.24	1.40	0.60	7.93	9.00
<b>207</b>	1.08	7.11	1.40	0.58	7.73	9.02
<b>208</b>	1.22	8.39	1.50	0.70	7.84	9.19
<b>209</b>	1.15	8.15	1.50	0.71	8.29	9.29
<b>210</b>	1.04	8.80	1.60	0.64	7.44	7.91
<b>211</b>	1.16	9.30	1.60	0.67	8.18	8.57
<b>212</b>	1.12	8.63	1.70	0.71	7.68	8.94
<b>213</b>	1.19	8.89	1.89	0.76	7.41	8.64
<b>214</b>	1.33	9.24	1.84	0.80	6.86	8.80
<b>215</b>	1.28	7.19	1.96	0.77	7.00	9.50
<b>216</b>	1.26	6.94	2.07	0.76	7.10	9.45
<b>217</b>	1.69	10.22	2.24	0.90	7.61	9.79
<b>218</b>	2.04	10.98	2.47	0.90	7.26	9.32

Figure E.20: Price level of meat between 2000 and 2018 (CPI) in the Netherlands



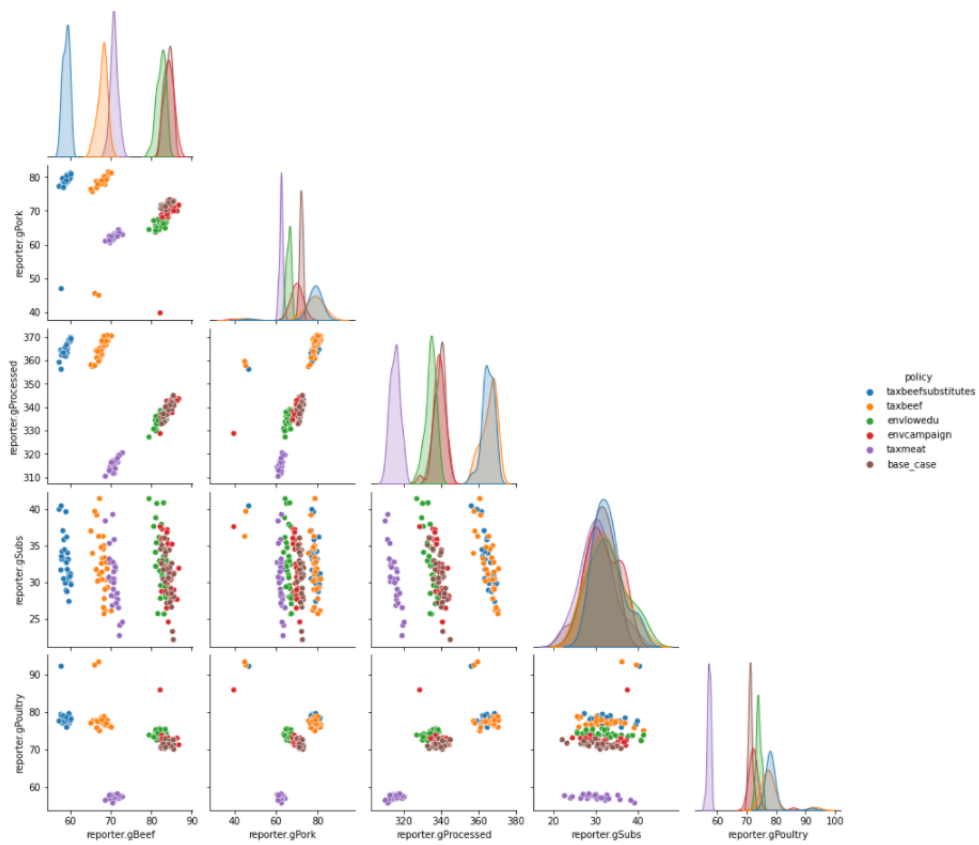


Figure E.21: Non-normalized meat consumption per meat type for the base case scenario per policy