Quantifying the greenhouse gas emissions of New Zealand households' food purchases: An analysis by socio-demographics

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Abstract

According to its most recent Nationally Determined Contribution (NDC) to the Paris Climate Agreement, New Zealand has committed to reducing its greenhouse gas emissions (GHGEs) by 50% from its 2005 levels by 2030. Dietary changes within New Zealand could simultaneously enhance public health and contribute sizably towards the nation's emissions reduction target, as food production is estimated to account for around a quarter to a third of global GHGEs. This research aims to identify the population groups within New Zealand which are best positioned for dietary emissions reductions by evaluating whether various socio-demographic variables are associated with per capita dietary emissions within households.

Differences in households' dietary emissions were appraised using food purchasing data collected from a large sample of households within New Zealand (N=1,775) over the course of a year. The sample was nationally representative in key demographic and geographic characteristics. Carbon emissions estimates were assigned to 1,908,485 total purchases using a process-based Life Cycle Assessment (LCA) dataset initially constructed in the UK and recently adapted for New Zealand. Per capita dietary emissions within each household were then calculated by dividing the household's total emissions ascribed to their food purchases by the household's size (i.e., the total number of adults and children living in the household). The results showed that the age group of the primary household shopper as well as household size were predictors of per capita dietary emissions — households with older primary shoppers had higher per capita dietary emissions, and larger households had lower per capita dietary emissions. Though past research has shown similar findings, it is unclear why older shoppers are associated with higher per capita dietary emissions. Diet composition and frequency of eating foods outside the home are possible explanations. The association observed between household size and per capita dietary emissions is also consistent with past studies showing increasing energy efficiencies and reduced food waste in larger households. In conclusion, to support New Zealand's pursuit of its emissions reduction goal, policies should be implemented that encourage older shoppers to purchase lower-emitting foods and, specifically, less meat and dairy, which account for the highest GHGEs.

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1. Introduction

Climate change is one of the defining challenges of our time. Failing to respond to it adequately will produce increasingly devastating effects on human health outcomes worldwide. The harmful impacts of unchecked climate change are no longer distant projections of the future; rather, they are already occurring and take a myriad of forms. Most directly, the intensification of heat waves and other extreme weather events, as well as rising levels of temperature-related air pollution, threatens the immediate physical health of global populations (McMichael, 2013). On a secondary level, climate change's disruption of natural systems results in food and water supply issues and elevated communicable disease risks (McMichael, 2013). Furthermore, mental health challenges are exacerbated due to mass displacement, growing conflict driven by natural resource scarcity, and escalating inequities (McMichael, 2013). Climate change's impact on human health is so substantial that the 2015 Lancet Commission on Health and Climate Change ventured that "tackling climate change could be the greatest global health opportunity of the 21st century" (Watts et al., 2015, p. 1861).

Food production and distribution is known to be a primary contributor towards anthropogenic greenhouse gas emissions (GHGEs). Greenhouse gas emissions are generated throughout the life cycle of a given food product; they reflect the cumulative carbon footprint stemming from the preparation (i.e., soil-management practices), cultivation, processing, packaging, storage, refrigeration, and transportation of each food. Taking these numerous stages into account, Vermeulen et al. (2012) estimate that dietary GHGEs account for 19-29% of total global GHGEs, while Crippa et al. (2021) assert that the number is as high as 34%. Furthermore, according to Springmann et al. (2018), by 2050:

> …as a result of expected changes in population and income levels, the environmental effects of the food system could increase by 50-90% in the absence of technological changes and dedicated mitigation measures, reaching levels that are beyond the planetary boundaries that define a safe operating space for humanity (p. 519)

The environmental effects referenced in the above quote refer not only to GHGEs, but also to cropland use, bluewater use, and nitrogen and phosphorous application (Springmann et al., 2018).

Due to the global food system's sizable environmental footprint, widespread changes in dietary habits have the potential to significantly reduce the deleterious effects of climate change. A systematic review of research on the environmental impacts of dietary change done by Hallström et al. (2015) suggests that up to 50% reductions in food-related GHGEs and land use could be achieved by dietary changes implemented only within affluent countries. This reduction potential appears largely dependent on the amount and type of meat and other animal products incorporated in newly adopted diets; red and ruminant meat production is responsible for the highest GHGEs, and diets that feature no animal products (vegan) or just no meat (lacto-ovo vegetarian) emit the least GHGEs (Hallström et al., 2015). Underscoring the extent to which animal products account for higher GHGEs, a study by Scarborough et al. (2014) estimated that the dietary emissions of meat eaters are approximately twice as high as those of vegans.

A worldwide reduction in meat consumption is necessary to shrink the global food system's environmental footprint substantially. Though there are nutritional benefits and risks associated with vegan (Craig, 2009) and vegetarian diets (Rocha et al., 2019), minimal intake of meat is considered conducive to a healthy diet. The EAT-Lancet Commission, utilizing extensive research on dietary patterns and health outcomes, proposes a "universal healthy reference diet" designed to provide healthy nutrition for an estimated global population of roughly 10 billion people by 2050 while keeping the global food system within an environmentally "safe operating space":

> This healthy reference diet largely consists of vegetables, fruits, whole grains, legumes, nuts, and unsaturated oils, includes a low to moderate amount of seafood and poultry, and includes no or a low quantity of red meat, processed meat, added sugar, refined grains, and starchy vegetables. (Willett et al., 2019, p. 447)

Other studies have also indicated that dietary changes can concurrently provide substantial nutritional and environmental health benefits primarily via an emphasis on plant-based food intake and the restriction of animal-based foods (Aleksandrowicz et al., 2016) (Drew et al., 2020). Furthermore, Springmann et al. (2016) estimate that, compared to a reference diet projected for the year 2050 by the Food and Agriculture Organization of the United Nations (FAO) (Alexandratos & Bruinsma, 2012), the widespread adoption of plant-based diets aligned with standard dietary guidelines could result in a 6-10% decrease in global mortality as well as a 29-70% decrease in dietary GHGEs by 2050.

New Zealand finds itself in a complex situation with regards to food-related emissions. For one, as a relatively small nation in terms of population, any dietary changes enacted in New Zealand alone that reduce GHGEs will not make a significant difference in combatting climate change globally. This not a reason for inaction, however, as preventing the most harmful effects of global warming will require serious commitment from all nations. Moreover, a sizable portion of the New Zealand economy is based on international exports of its own food, and some of its largest agricultural exports (dairy, sheep meat, and cow meat) are the very foods that the abovementioned literature indicates must be minimised in global diets to ensure the food system's sustainability. Agricultural production and dietary consumption can be distinguished in theory, but the dissonance between large economic interests and public and environmental health considerations complicates these matters within New Zealand. Nevertheless, New Zealand ratified the Paris Climate Agreement in 2016; according to its recently revised Nationally Determined Contribution (NDC) towards the agreement's goal of capping global warming at 1.5 degrees above pre-industrial levels, the country has committed to reducing its net GHGEs by 50% from its 2005 levels by 2030 (The New Zealand Government, 2021). Dietary changes have the potential to play a substantial role in this effort while simultaneously improving nutritional outcomes, as evidenced by Drew et al. (2020), who find that population-level adoption of diets (in New Zealand) conforming to the New Zealand Dietary Guidelines (NZDGs) could result in national emissions savings of 4-42%. To effectively direct resources towards promoting such changes, it is essential to identify the demographic factors and population subgroups that are associated with higher dietary GHGEs.

The first objective of this dissertation is to review the academic literature which has investigated the association between various socio-demographic variables and households' or individuals' estimated total dietary GHGEs. In doing so, methodological patterns and broad themes in the research's findings may be identified that facilitate contextualised analysis of the data examined in this study. Next, this dissertation aims to quantify the dietary emissions stemming from the food purchases of a large, representative sample of New Zealand households over the course of a year. First, total GHGEs will be calculated for each household, and the GHGEs of the household purchases will be described. Subsequently, this study aims to answer the question of whether New Zealand households' dietary GHGEs differ significantly by the socio-demographic factors of sex of the primary shopper, household income, age of the primary shopper, household life stage, and household size. The results of this analysis could provide stakeholders with actionable information on which populations are best positioned to contribute substantially towards food-related emissions reductions. More broadly, the research will inform and advance future efforts to promote sustainable dietary choices within New Zealand.

2. Literature Review

2.1 Objectives

The objective of this literature review is to evaluate the research which has measured individuals' or households' dietary GHGEs and assessed their possible associations with various socio-demographic variables. Detailed examination of patterns in methodological strategies and research findings provides important context for this dissertation, allowing its own methods and results to be interpreted within the broader framework of existing literature.

2.2 Methods

In collaboration with a University of Auckland research librarian, a search strategy was devised by establishing key search terms and syntax (see Appendix I for details) and then identifying suitable academic literature databases. Scopus as well as the "Agricultural and Environmental Science" and "Health Research Premium" collections of ProQuest Central were selected as the most relevant databases for the research topic. In Scopus, the search strategy was executed within article titles, abstracts, and keywords; in ProQuest, the search strategy was executed within "Anywhere except full text".

2.2.1 Inclusion and exclusion criteria

The search strategy and subsequent literature screening were guided by the following inclusion and exclusion criteria:

- *Source type*: Peer-reviewed academic journal publications were included, while grey literature, technical reports, and all other source types were excluded.
- *Countries*: To maximize relevance to the New Zealand dietary context, only studies conducted in affluent countries with diets broadly similar to those in New Zealand (i.e., Canada, the United States, all European nations, Australia, and New Zealand) in terms of their relatively high quantities of animal products and processed foods were included in the literature review. All other countries were excluded.
- *Year of publication*: Literature published from 2000 onwards was included. Studies undertaken before then were excluded due to the fact that data that old was likely to be crude and less relevant to modern conditions.
- *Full text sources*: Research with its full text made available was included. All other studies were excluded.

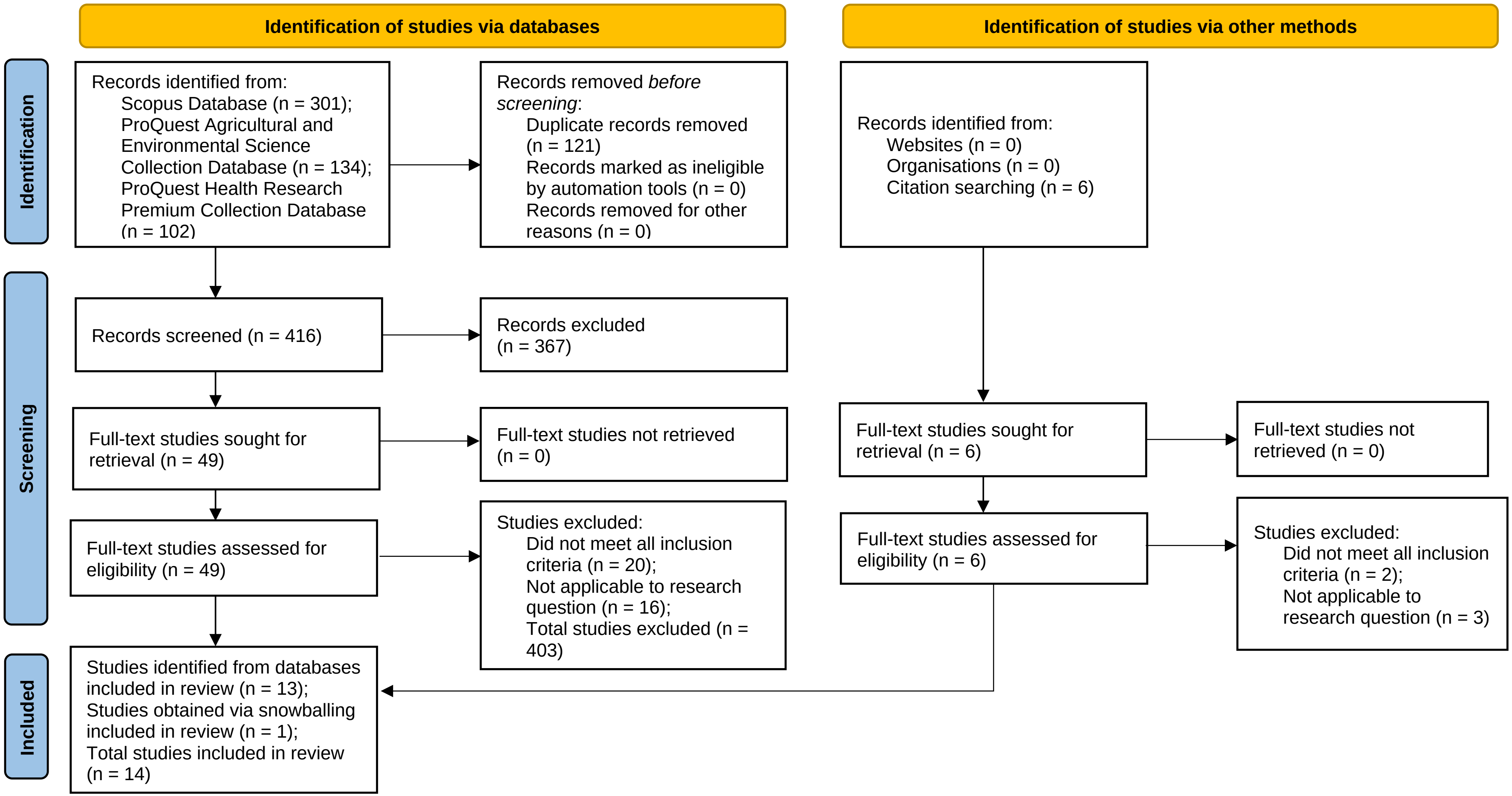
- *Measures of environmental impact*: Only those studies that measured the environmental impact of food consumption in terms of greenhouse gas emissions were included because the focus of this dissertation is on households' environmental outputs solely in terms of GHGEs.
- *Modelling versus purchasing or consumption data*: Research utilizing households' or individuals' actual food purchasing or consumption data was included. Studies that modelled the potential environmental impacts of suggested dietary scenarios were excluded.
- *Within country analysis versus between country analysis*: Studies that compared dietary GHGEs amongst households or individuals within a given country were included. Those studies that examined such differences between countries were excluded. Between country comparisons were deemed irrelevant for this dissertation due to the significant national variations in food production processes, food availability, and economic interdependencies.
- *Geographic comparisons of dietary emissions within countries*: For the studies that examined within country differences in dietary GHGEs amongst individuals or households, only geographic comparisons between urban and rural sampling units were included. Research that made geographic comparisons based on other regional distinctions were excluded, as these may be less generalisable due to the pertinence of specific characteristics of the locations.

2.3 Results

As outlined in the PRISMA Diagram on page 12, the literature search identified a total of 537 results of which 121 were duplicates. After removing the duplicates, 416 distinct studies remained. Of these remaining studies, titles were first scanned for relevance, and those that appeared pertinent were then selected for abstract reviewal (N=109). After reviewing the abstracts, 49 studies were selected for full text review. Finally, 14 studies were selected for data extraction in accordance with the inclusion and exclusion criteria previously explicated. The reviewed research was conducted primarily in various countries within Europe: Sweden (Nordström et al., 2020) (Strid et al., 2019) (Bälter et al., 2017), the United Kingdom (Reynolds et al., 2019) (Wrieden et al., 2019), Denmark (Lund et al., 2017) (Mertens et al., 2019), Finland (Salo et al., 2021), Germany (Meier & Christen, 2012), France (Mertens et al., 2019), Italy (Mertens et al., 2019), the Czech Republic (Mertens et al., 2019), Switzerland (Frehner et al., 2021), and Ireland (Hyland et al., 2017). Outside of Europe, two studies were conducted in the United States (Boehm et al., 2018) (Rose et al., 2019) and one took place in Australia (Reynolds et al., 2015).

Previous studies examining the possible associations between dietary greenhouse gas emissions (GHGEs) and socio-demographic variables have largely featured observational, cross-sectional research designs (Bälter et al., 2017) (Nordström et al., 2020) (Salo et al., 2021) (Meier & Christen, 2012) (Lund et al., 2017) (Reynolds et al., 2019) (Boehm et al., 2018) (Rose et al., 2019) (Frehner et al., 2021) (Wrieden et al., 2019) (Mertens et al., 2019) (Strid et al., 2019) (Hyland et al., 2017) (Reynolds et al., 2015). In order to estimate participants' dietary GHGEs, each study collected food consumption or purchasing data for its sample and then assigned emissions values to the food products before comparing total GHGEs by various demographic variables. For each of these steps, researchers have used a variety of methods and data sources which are outlined in Table 1 (page 16) and described in detail below.

Figure 1: Literature review PRISMA diagram



Template From: Page MJ, McKenzie JE, Bossuyt PM, Boutron I, Hoffmann TC, Mulrow CD, et al. The PRISMA 2020 statement: an updated guideline for reporting systematic reviews. BMJ 2021;372:n71. doi: 10.1136/bmj.n71.

2.3.1 Food consumption and purchasing data

Food consumption habits of households (Nordström et al., 2020) (Salo et al., 2021) (Reynolds et al., 2019) (Boehm et al., 2018) (Wrieden et al., 2019) (Reynolds et al., 2015) and individuals (Meier & Christen, 2012) (Rose et al., 2019) (Frehner et al., 2021) (Mertens et al., 2019) (Strid et al., 2019) (Hyland et al., 2017) (Bälter et al., 2017) have been explored in the literature. One study collected food consumption data for both households and individuals within each household in order to corroborate the accuracy of both sets of data (Lund et al., 2017).

For households, some studies have utilized food purchasing data recorded by participants to estimate representative dietary patterns (Reynolds et al., 2019) (Boehm et al., 2018) (Wrieden et al., 2019) (Lund et al., 2017). The time frames for collecting such data ranged widely from a single 7-day period (Boehm et al., 2018) to a single 14-day period (Wrieden et al., 2019) (Reynolds et al., 2019) to an entire year (Lund et al., 2017). Others have estimated household food consumption using data collected from expenditure surveys (Nordström et al., 2020) (Salo et al., 2021) (Reynolds et al., 2015) measuring household spending over the course of a week (Reynolds et al., 2015) or an entire year (Nordström et al., 2020); the time frame for expenditure data collection was not clear in the study done by Salo et al. (2021).

As for individuals' food intake, methods of data collection have included a single 24-hour dietary recall (Rose et al., 2019) or multiple 24-hour dietary recalls (Meier & Christen, 2012) (Frehner et al., 2021) (Mertens et al., 2019); food diaries and other forms of dietary records (Mertens et al., 2019) (Hyland et al., 2017) generated over the course of three (Mertens et al., 2019), four (Hyland et al., 2017) or seven consecutive days (Mertens et al., 2019); food frequency questionnaires (FFQs) (Lund et al., 2017) (Strid et al., 2019) (Bälter et al., 2017); and dietary history interviews (Meier & Christen, 2012). Accurately identifying food consumption patterns that are typical for a given household or individual is challenging, and all of the aforementioned methods of collecting representative dietary data have well-known limitations. First and foremost, self-reported dietary intake is prone to under-reporting (Gemming et al., 2014) most likely due to a combination of factors such as recall error and social-desirability bias. Therefore, those studies utilizing food diaries and other dietary records, 24-hour dietary recalls, food frequency questionnaires, and dietary history interviews may feature significant inaccuracies, although this risk was minimized by Lund et al. (2017), who combined multiple types of consumption data to validate participants' self-reported intake. Dietary patterns derived from household expenditure data may be susceptible to similar errors depending on the extent to which they rely exclusively on individuals' estimates and are not corroborated with actual purchasing records. Moreover, expenditure data can lead to misleading estimates of the quantities of food items purchased due to regional or inter-item (e.g., organic versus non-organic) variations in the prices of the same foods. Research employing purchasing data eliminates the potential for recall errors, but this method has limitations as well. Food purchasing data may develop inaccuracies stemming from the failure of participants to reliably or correctly record every purchase. Additionally, social-desirability bias may affect participants' consistency in recording each item purchased.

Setting aside questions regarding the validity of the various consumption reporting methods, the relatively short duration of most of these methods renders their ability to capture representative dietary patterns questionable. Even if households are able to provide fully accurate data over the course of multiple 24-hour dietary recalls or 14-days of recording food purchases, for example, it is always possible that this period of consumption may be unusual in the quantity or composition of the foods eaten. Dietary data tracked over the course of many months or, ideally, an entire year is better suited to account for variations in seasonal household intake, which can be significant (Shahar et al., 2001).

2.3.2 Environmental impact assessments

In order to evaluate the GHGEs resulting from households' dietary consumption, all of the reviewed studies have employed one of two forms of Life Cycle Assessments (LCAs) to evaluate the inputs, outputs, and environmental impacts of food products throughout their life cycle: "process-based" LCAs or Economic Input-Output LCAs (EIO-LCA). Most research in this area has employed the "process-based" LCA methodology, which estimates the environmental costs incurred at a given step in the production or distribution process (Nordström et al., 2020) (Meier & Christen, 2012) (Lund et al., 2017) (Reynolds et al., 2019) (Rose et al., 2019) (Frehner et al., 2021) (Wrieden et al., 2019) (Mertens et al., 2019) (Strid et al., 2019) (Hyland et al., 2017) (Bälter et al., 2017). This method can be applied to all stages of a food's life cycle — agricultural production, processing, packaging, transport, storage, preparation, and waste — and requires thorough analysis of the materials and resources expended (inputs) as well as the emissions and wastes (outputs) generated. The high level of detail needed for this approach is both a strength and a limitation. On the one hand, meticulous accounting of each stage in a food's life cycle yields increasingly accurate and comprehensive emissions estimates. However, the significant level of detail that this "bottom-up" approach requires makes it difficult to undertake. This leads to what is known as the truncation error, referring to the fact that inevitably, for the purposes of feasibility, LCAs must set boundaries for their analyses (i.e., decide which life stages will be included and excluded). Consequently, researchers are constrained by the scope of the LCA data that is available and relevant to the country where dietary emissions are being examined. As a result, many studies have combined numerous LCA datasets in order to expand the research's scope (Lund et al., 2017) (Rose et al., 2019) (Frehner et al., 2021) (Wrieden et al., 2019) (Strid et al., 2019) (Hyland et al., 2017) (Reynolds et al., 2015) (Bälter et al., 2017), and the boundaries of each study's LCA data vary. For example, one study measured dietary emissions only from "from cradle to farm gate" (including only the agricultural production stage) (Rose et al., 2019). Another incorporated the agricultural and transport stages up to the point of the regional distribution centre (RDC), thus excluding the processing, retail, preparation, and waste stages (Reynolds et al., 2019). More commonly, though, previous research has utilized LCAs with the boundaries of "cradle to store" (including agricultural production, processing, transport, and packaging) (Meier & Christen, 2012) (Frehner et al., 2021) or even "cradle to plate" (including agricultural production, processing, transport, packaging, retail, and preparation) (Wrieden et al., 2019) (Hyland et al., 2017).

Process-based LCAs that do not account for every stage of a food's life cycle often leave significant gaps in their estimates of foods' emissions, as is demonstrated in the work of Audsley et al. (2009), whose LCA data was employed by several of the studies cited in this review (Lund et al., 2017) (Reynolds et al., 2019) (Wrieden et al., 2019). Audsley et al. (2009) calculated foods' emissions only up to the point of the RDC (which they defined as the boundary point for the "primary production" life cycle phase), and they estimated that only 56% of emissions are generated in this stage. This indicates that both the production and post-production phases of a food's life cycle contribute appreciably to its total GHGEs.

Table 1: Literature review summary

Author, year	Country	Study design, sample size and sampling units	Food consumption data	Method of estimating dietary GHGEs	Boundaries of analysis for process-based LCAs	Total average/median household or individual emissions	Sociodemographic variables examined in relation to dietary GHGEs
Nordström et al., 2020	Sweden	Cross-sectional; N=2,692 households	Household expenditure survey	Process-based LCA	Unknown	2,287.74 kg CO_2 equivalents per household per year (mean)	Income, age, household composition
Salo et al., 2021	Finland	Cross-sectional; N=3,490 households	Household expenditure survey	EIO-LCA	Not applicable	3,689.54 kg CO_2 equivalents per household per year (mean)	Income, age, geography
Meier & Christen, 2012	Germany	Cross-sectional; N=13,000 individuals aged 14-80	Multiple 24-hour dietary recalls; dietary history interviews	Process-based LCA	"Cradle to store" — includes agricultural production, processing, transport/trade, and packaging stages	2,201 kg CO_2 equivalents per man per year (mean); 1,533 kg CO_2 equivalents per woman per year (mean)	Gender
Lund et al., 2017	Denmark	Cross-sectional; N=1,350 households; questionnaires were also issued to an individual from each household to enhance the validity of the food purchasing data	Food purchasing data for households; Food Frequency Questionnaires for individuals; both datasets were combined to validate one another's accuracy	Process-based LCAs	Used multiple different LCA datasets whose exact sources and boundaries are unclear	1,200 kg CO_2 equivalents per person per year (mean); household emissions were converted to average individual emissions based on household composition; results were standardised by the average adult Dane's daily energy intake	Income, educational level

Reynolds et al., 2019	United Kingdom	Cross-sectional; N=5,144 households	Food purchasing data	Process-based LCA	Production stage up to the point of the Regional Distribution Centre (RDC) — excludes processing, retail, household use, and waste	2.79 kg CO_2 equivalents per person in a given household per day (mean); the authors of this study did not provide this value themselves — total mean dietary GHGEs per person was calculated using the means and sample sizes of different household income quintile groups provided in the study; household dietary GHGEs were converted to emissions per person in each household by the authors of the study based on household composition	Income
Boehm et al., 2018	United States	Cross-sectional; N=4,826 households	Food purchasing data	EIO-LCA	Not applicable	71.8 kg CO_2 equivalents per standard adult equivalent in a given household per week (mean); household dietary GHGEs were converted to emissions per person in each household based on household composition	Income, educational level, race, ethnicity (race and ethnicity were distinguished as two separate concepts)

Rose et al., 2019	United States	Cross-sectional; N=16,800 individuals aged 18 and older	One 24-hour dietary recall	Process-based LCAs	Used several different LCA datasets; only the production, and in some cases the processing, stage of foods' life cycles were included; retail, household use, and waste stages were excluded	4.72 kg CO_2 equivalents per person per day (mean); 2.21 kg CO_2 equivalents per person per 1000 kcal	Income, educational level, age, gender, “race-ethnicity”
Frehner et al., 2021	Switzerland	Cross-sectional; N=2,057 individuals aged 18-75	Two 24-hour dietary recalls	Process-based LCAs	"Cradle to store" — includes agricultural production, processing, transport/trade, and packaging stages	3.25 kg CO_2 equivalents per person per day (median)	Income, educational level, gender
Wrieden et al., 2019	United Kingdom	Cross-sectional; N=12,434 households	Food purchasing data	Process-based LCAs	"Cradle to plate" — includes agricultural production, processing, transport, and packaging, retail, and preparation stages	24.14 kg CO_2 equivalents per person in a given household per week (median); household dietary GHGEs were converted to emissions per person in each household based on household composition	Income, gender, household composition

Mertens et al., 2019	Denmark, Italy, France, and the Czech Republic	Cross-sectional; N=1,739 individuals aged 18-64 in Denmark; N=1,666 individuals aged 18-64 in the Czech Republic; N=2,313 individuals aged 18-64 in Italy; N=2,276 individuals aged 18-64 in France	Two separate 24-hour dietary recalls in Czech Republic; 7-day diet records in France and Denmark; 3-day diet records in Italy	Process-based LCAs	Includes agricultural production, use of primary packaging, transport to retail, food losses and waste, and food preparation; excludes industrial food processing, storage, and transport from retail to home	**Denmark:** 5.4 kg CO_2 equivalents per person per day (mean) or 5.0 kg CO_2 equivalents per person per day per 2,000kcal (mean); **Czech Republic:** 5.6 kg CO_2 equivalents per person per day (mean) or 4.4 kg CO_2 equivalents per person per day per 2,000kcal (mean); **Italy:** 5.2 kg CO_2 equivalents per person per day (mean) or 4.9 kg CO_2 equivalents per person per day per 2,000 kcal (mean); **France:** 6.0 kg CO_2 equivalents per person per day (mean) or 6.4 kg CO_2 per person per day per 2,000 kcal (mean)	Educational level, age, gender, BMI
Strid et al., 2019	Sweden	Cross-sectional; N=46,893 women aged 18-75; N=45,766 men aged 18-63	Food Frequency Questionnaires	Process-based LCAs	Used numerous different sources with varying boundaries	Women: 2.9 kg CO_2 equivalents per person per day (median); men: 3.6 kg CO_2 equivalents per person per day (median)	Educational level, age, geography, BMI

Hyland et al., 2017	Ireland	Cross-sectional; N=1500 individuals aged 18-87	Food diaries for four consecutive days	Process-based LCAs	"Cradle to plate" — includes agricultural production, processing, transport, and packaging, retail, and preparation stages	6.532 kg CO_2 equivalents per person per day (mean)	Educational level, age, gender, geography
Reynolds et al., 2015	Australia	Cross-sectional; N=6,957 households consisting of 13,748 individuals over the aged 15 and older	Household expenditure survey	EIO-LCA	Not applicable	80 kg CO_2 equivalents per household per week (mean)	Income
Bälter et al., 2017	Sweden	Cross-sectional; N=5,364 individuals aged 18-45	Food Frequency Questionnaires	Process-based LCAs	Used multiple different LCA datasets whose exact sources and boundaries are unclear	4.7 kg of CO_2 equivalents per person per day (median)	Age, gender

Compounding the limitations resulting from the truncation error, process-based LCAs are unable to comprehensively account for the complex interdependencies of all products in modern economies. For instance, beyond the emissions generated by ruminant animals on farms, one must also consider the emissions generated by the trucks that transport meat to retail markets. Those trucks not only emit carbon from petrol usage (which many process-based LCAs do account for), they are also made from steel (as well as countless other items), which requires inputs and generates outputs in the process of its own production. The materials and resources used in the production of steel have their own requisite components — including machines made from more steel, which produces circularity effects —, and the analysis can go on indefinitely. Most process-based LCAs do not account for these indirect emissions arising from food production.

In light of these limitations, some researchers have utilized LCA data derived from Economic Input-Output (EIO) models, resulting in tools known as Environmentally Extended Input-Output (EEIO) models or EIO-LCAs (Salo et al., 2021) (Boehm et al., 2018) (Reynolds et al., 2015). EIO models are "top-down", macroeconomic representations of the monetary flows (i.e., transactions) between the various sectors within an economy. Accordingly, they measure what products or services (outputs) are consumed by other industries as inputs, thus quantifying the interdependence of products within complex economies. These datasets can be extended to include international transactions between economies (known as Multi-Regional Input-Output, or MRIO, models) to account for the varying inputs and outputs associated with domestic versus imported products. In order to derive GHGE estimates for products in each industry, monetary transaction data is multiplied by "GHG intensity coefficients" (Salo et al., 2021) or "emissions intensity factors" (EIFs) measured in kilograms of carbon dioxide equivalents (kgCO2e) per unit of monetary output (Boehm et al., 2018). For example, Reynolds et al. (2015) took raw spending on various foods and simply multiplied these numbers by assigned values for each food item's GHGEs generated per unit of currency output.

Utilizing an EIO-LCA approach in research on dietary emissions helps to minimize the truncation error as well as circularity effects. Also known as self-sector transactions, circularity effects refer to when an industry uses its own good as an input to produce more of that good. EIO-LCA models account for this phenomenon, thus enabling comprehensive estimations of environmental impacts (both direct and indirect) generated across an entire economy. However, much like with process-based LCAs, the primary strength of EIO models — their broad scope in linking products within an economy — is also their most significant limitation, as it is dependent upon a high level of aggregation. With regards to food, diverse products with significantly different environmental implications are often combined. For example, one study using an EIO-LCA approach grouped all food products into 15 categories (Salo et al., 2021); another aggregated food products into 26 categories (Boehm et al., 2018). This level of aggregation does not allow for precise accounting of notable differences in GHGEs generated by the distinct food items belonging to the same category. Consequently, it constrains researchers' ability to detect disparities in households' dietary emissions stemming from variations in diet composition, as opposed to the quantity consumed. Therefore, the detail intensive process-based LCAs are better suited to capture differences in households' GHGEs resulting from disparate dietary patterns, though they are less effective in accounting for far-reaching indirect and direct environmental impacts of food production across an entire economy.

Finally, regardless of which type of LCA was utilized, the standard time frame for quantifying carbon emissions in the reviewed literature was 100-years. Though global warming potential (GWP) can also be measured in a 20-year time frame to better account for greenhouse gases with shorter lifespans (such as methane), the 100-year horizon is most commonly used, as it is more suitable for gases like carbon dioxide that can remain in the atmosphere for hundreds of years once emitted.

2.3.3 Total average household or individual dietary emissions

The lack of methodological uniformity in the reviewed literature makes it difficult to compare the studies' findings with regards to averages of total household or individual dietary emissions. As outlined in previous sections and Table 1, past research has employed differing sampling units, units of measurement, environmental assessment approaches, and boundaries of analysis for such approaches. Even when multiple studies utilize the same sampling unit (i.e., households or individuals) and measurement unit (e.g., kg CO_2 equivalents per person per day), like-for-like comparisons of results derived from process-based LCAs are complicated by important differences in studies' boundaries of analysis. These disparities arise due to the immense challenge of gathering comprehensive, country-specific, and up-to-date emissions data for every stage of a food's life cycle.

The reviewed literature's results are summarised in Table 1. When examining households, total average dietary emissions were calculated per household per year [ranging from 2,287 kg CO_2 equivalents per year in Sweden (Nordström et al., 2020) to 3,689.54

kgCO_2 equivalents per year in Finland (Salo et al., 2021)]; per household per week [80 kg CO_2 equivalents per week in Australia (Reynolds et al., 2015)]; per standard adult equivalent in a given household per week [71.8 kg CO_2 equivalents per week in the US (Boehm et al., 2018)]; or per person in a given household per day [2.79 kg CO_2 equivalents per day in the UK (Reynolds et al., 2019)]. As for individuals, average emissions were largely estimated per person per day [ranging from 4.72 kg CO_2 equivalents per day in the US (Rose et al., 2019) to 6.532 kg CO_2 equivalents per day in Ireland (Hyland et al., 2017)] or per person per year [ranging from 1,200 kg CO_2 equivalents per person in Denmark (men and women) (Lund et al., 2017) to 1,533 kg CO_2 equivalents per year for women and 2,201 kg CO_2 equivalents per year for men in Germany (Meier & Christen, 2012)].

2.3.4 Relationships between socio-demographic variables and dietary emissions

Previous research has examined the possible associations between dietary emissions and a variety of socio-demographic variables. Most commonly, studies have focused on the demographic characteristics of income (Nordström et al., 2020) (Salo et al., 2021) (Lund et al., 2017) (Reynolds et al., 2019) (Boehm et al., 2018) (Rose et al., 2019) (Frehner et al., 2021) (Wrieden et al., 2019) (Reynolds et al., 2015), educational level (Lund et al., 2017) (Boehm et al., 2018) (Rose et al., 2019) (Frehner et al., 2021) (Mertens et al., 2019) (Strid et al., 2019) (Hyland et al., 2017), age (Nordström et al., 2020) (Salo et al., 2021) (Rose et al., 2019) (Mertens et al., 2019) (Strid et al., 2019) (Hyland et al., 2017) (Bälter et al., 2017), and gender (Meier & Christen, 2012) (Rose et al., 2019) (Frehner et al., 2021) (Mertens et al., 2019) (Hyland et al., 2017) (Bälter et al., 2017) (Wrieden et al., 2019).

With regards to income, the reviewed studies' findings were mixed. Several studies found a positive relationship between household income and dietary emissions (Nordström et al., 2020) (Lund et al., 2017) (Boehm et al., 2018) (Reynolds et al., 2015), although Boehm et al. (2018) also found that there was no relationship between participation in SNAP (Supplemental Nutritional Assistance Program), an indicator of low income, and dietary GHGEs. Similarly, Wrieden et al. (2019) observed that in the UK, though the highest income quintile group was significantly more likely to exhibit a "less sustainable" diet purchasing pattern, the other four income quintile groups were not significantly more likely to have either the "more sustainable" or "less sustainable" purchasing pattern. Other research found no clear association between income and dietary emissions (Salo et al., 2021) (Reynolds et al., 2019) (Rose et al., 2019) (Frehner et al., 2021).

Evidence for the possible association between dietary emissions and educational levels was similarly mixed. Three studies found a positive relationship between the two variables (Lund et al., 2017) (Boehm et al., 2018) (Strid et al., 2019). Mertens et al. (2019) examined data collected in four different European countries; their results showed a positive association between “GHGE density” (referring to energy-standardized dietary emissions) and educational levels in the Czech Republic, a negative correlation in France, and no correlation in Italy or Denmark. Likewise, no clear association was observed in studies done by Rose et al. (2019), Frehner et al. (2021), and Hyland et al. (2017). It is unclear why the abovementioned studies examining income and education’s possible associations with dietary emissions yield such disparate results. However, these contrasting findings may indicate that the existence (or lack thereof) and direction of the relationship between the two variables is mediated by country-specific factors.

In terms of age, previous research’s findings have been more consistent. Most studies have found a positive relationship between age of the respondent (for studies of individuals) or primary shopper (for studies of households) — or, in the case of Nordström et al. (2020), the age of the oldest member of households that do not include any retirees — and dietary emissions (Nordström et al., 2020) (Salo et al., 2021) (Rose et al., 2019) (Mertens et al., 2019). However, Mertens et al. (2019) only observed this association within Denmark and France, and not within the Czech Republic or Italy, where no association was observed. The results of a study done by Bälter et al. (2017) also showed no clear association between age and dietary emissions. On the other hand, Strid et al. (2019) found a negative association between the two variables, and Hyland et al. (2017) observed that the youngest age group (those aged 18-35 years old) had significantly higher dietary emissions than the older age groups. However, this was largely due to the younger participants’ consumption of greater quantities of food (Hyland et al., 2017).

The comparison of dietary emissions between men and women can be complicated for the same reason, as men consume greater quantities of food on average than women. Therefore, most of the studies examining differences between genders have been energy adjusted to reflect the amount of GHGEs embodied per some standard amount of caloric intake (Meier & Christen, 2012) (Rose et al., 2019) (Hyland et al., 2017) (Bälter et al., 2017) (Mertens et al., 2019). Even after standardizing for energy consumption, most of these studies still found that men’s dietary emissions were significantly higher than women’s (Meier & Christen, 2012) (Rose et al., 2019) (Hyland et al., 2017) (Bälter et al., 2017). Conversely, Mertens et al. (2019) found that women had higher energy-adjusted dietary emissions than men, though this was only the case in the Czech Republic and France, and not in Italy or Denmark. Moreover, two studies' results indicated there was not a significant difference in dietary emissions between men and women despite the fact that their data was not energy-adjusted (Frehner et al., 2021) (Wrieden et al., 2019).

In addition to income, education, age, and gender, previous research has examined the relationship between dietary emissions and various other socio-demographic variables. Regarding population density, Strid et al. (2019) found that living in an urban area was strongly associated with higher dietary emissions for individuals in Sweden. Similarly, Salo et al. (2021) observed that households in certain "dense rural" areas of Finland exhibited significantly lower carbon footprints from food consumption compared to the "inner urban" reference group. Hyland et al. (2017), on the other hand, found that differences in dietary emissions were not significant between individuals living in urban or rural areas of Ireland. Differences in dietary emissions were also examined between ethnicities in the United States by Boehm et al. (2018) and Rose et al. (2019) as well as between nationalities in Switzerland by Frehner et al. (2021). Interestingly, race and ethnicity were distinguished as two separate concepts by Boehm et al. (2018), while Rose et al. (2019) listed "race-ethnicity" as one variable. The studies in the United States were difficult to interpret because, rather than directly comparing individuals' or households' total dietary emissions, they tested the likelihood of group membership in GHGE quintile groups (Boehm et al., 2018) (Rose et al., 2019). The results of those studies indicated that African-American individuals were more likely to consume "low-emitting diets" than individuals of white, Latino, or "other" race-ethnicities (Rose et al, 2019); white households were more likely to be in higher dietary GHGE quintiles than black or Asian households (Boehm et al., 2018); and "non-Hispanic" (pertaining to ethnicity rather than race) households were more likely to be in a higher dietary GHGE quintile than Hispanic households (Boehm et al., 2018). In Switzerland, Frehner et al. (2021) found that participants of the "African/Eastern Mediterranean" nationality had significantly higher dietary emissions than the reference group (Swiss).

As for less commonly examined predictor variables, Body Mass Index (BMI) was found to be positively associated with energy-adjusted dietary emissions in Denmark and France (but not Italy or the Czech Republic) (Mertens et al., 2019) as well as in Sweden (Strid et al., 2019). Married participants showed significantly higher dietary emissions than divorced participants or those with "other" civil statuses according to Frehner et al. (2021). Nordström et al. (2020) observed a relationship between household composition (i.e., the number of adults and children in the household) and dietary emissions such that adults with children accounted for 42% higher dietary emissions than childless adults. However, no relationship between household composition and dietary emissions was found by Wrieden et al. (2019) after standardising total household dietary GHGEs per household member per week.

2.4 Conclusions

In summary, the reviewed literature (N=14 studies) revealed a range of methodological approaches to examining dietary GHGEs. Table 1 illustrates these patterns further. Studies were nearly split evenly between investigating households (N=7) and individuals (N=8); Lund et al. (2017) examined data provided by both sets of sampling units. Studies investigating households estimated household dietary intake primarily using food purchasing data and expenditure surveys. On the other hand, studies of individuals' food consumption relied on 24-hour dietary recalls, food diaries and other dietary records, FFQs, and dietary history interviews. With regards to the calculation of dietary GHGEs, the vast majority of studies employed process-based LCAs (N=11), although a few studies (N=3) utilized EIO-LCAs instead. Total average household or individual emissions was calculated in most of the research, yet like-to-like comparisons of these values are hindered by varying sampling units, measurement units, and boundaries of analysis (for those studies which employed process-based LCAs). Analyses of the possible relationship between various sociodemographic variables and food-related emissions yielded mixed results with the exception of gender and age, which were fairly consistent predictors of dietary GHGEs — age predominantly had a positive association with dietary emissions, and men tended to be higher emitters than women even when standardizing for total energy intake. The diverse findings on associations of other socio-demographic variables' (especially income and education) with dietary emissions is perhaps indicative of country-specific mediating factors such as distinctive culinary traditions.

3. Methods

3.1 Food purchasing data

Data on New Zealand households' dietary purchases were derived from the 2019 Nielsen Homescan® panel, a unique dataset consisting of an entire year's (8 October 2018 through 6 October 2019) worth of food purchases collected from 2,500 households. To maintain the target sample size of 2,500 households, participants were recruited throughout the data collection period to replace households that dropped out, scanned food purchases inconsistently, or were otherwise unable to provide useable data (Ni Mhurchu et al., 2017). Nevertheless, only those households that participated in the panel for at least 27 weeks of the year and who met Nielsen's quality criteria (N=1,800) were included in the final dataset furnished by Nielsen. During Nielsen's quality control procedures, households are removed from the dataset if they scan items inconsistently, exhibit abrupt changes in scanning behaviour that cannot be explained (e.g., by holidays or vacations), or do not meet the minimum spend criteria (adjusted by household size and number of purchase weeks) (Zorbas et al, 2020, p. 2).

The Nielsen Homescan® panel is representative of New Zealand households in several key demographic characteristics: household life stage, household size, and household income. The dataset is also representative of New Zealand households in terms of geography (Upper North Island, Lower North Island, and South Island). Panellists are sampled primarily from major urban and secondary urban locations, which account for 92% of the New Zealand population. To record food purchases, panellists are supplied with barcode scanners and asked to scan the barcodes of all food and beverage items (fresh and packaged) purchased following each shopping trip. Foods that do not have barcodes (e.g., fresh fruit and vegetables, fresh meats, bulk bin items, and delicatessen items) are also accounted for with a supplemental scanning guide that provides instructions specifically for recording the purchases of these goods. Scanned purchases include foods and beverages acquired in supermarkets, bakeries, petrol stations, fruit and vegetable stores, convenience stores, specialty stores, and online stores.

The 2019 Nielsen Homescan® panel provides the following demographic information for each household: life stage category (i.e., young families, mixed families, older families, older singles and couples, or adult households), income level (less than $12,000, $12,000-$22,000, $22,000-$30,000, $30,000-$40,000, $40,000-$50,000, $50,000-$70,000, $70,000-$90,000, $90,000-$110,000, $110,000-$140,000, $140,000 and above), age group of the primary household shopper (under 25 years, 25-29 years, 30-34 years, 35-39 years, 40-49 years, 50-65 years, over 65 years), sex of the primary household shopper, number of adults in the household, number of children in the household, household size (combining the numbers of adult and children in a given household), and postcode. Further details on the demographic information furnished by the 2019 Nielsen Homescan® panel and how it was used in statistical analyses are provided in Appendix II. Moreover, the dataset includes specific information on the products purchased by each household — barcode, barcode description (i.e., product name and description), food/market department, product category (e.g., frozen vegetables, packaged nuts, eggs, etc.), size, size unit (e.g., grams, millilitres, etc.), brand, date purchased, name of store, quantity purchased, and price.

3.2 Cleaning the food purchasing data

A number of alterations were made to the 2019 Nielsen Homescan® data in preparation for data analyses using RStudio software, Version 1.2.1335. First, households that did not record a purchase either within the first five weeks or the last five weeks of the year-long panel period were excluded (N=25). The intention of these exclusions was to remove those households that, despite meeting Nielsen's quality criteria, presumably did not participate in the panel throughout the entire year, which could be due to dropping out early or being recruited into the panel after the data collection period had already begun. Additionally, six product categories were excluded altogether from the Nielsen Homescan® dataset because their constituent products were either not food items consumed by participants (home brew accessories, baking cups, coffee filters, and pet foods) or did not have a suitable emissions estimate (artificial sweeteners and home brew concentrates) in the accompanying LCA emissions dataset.

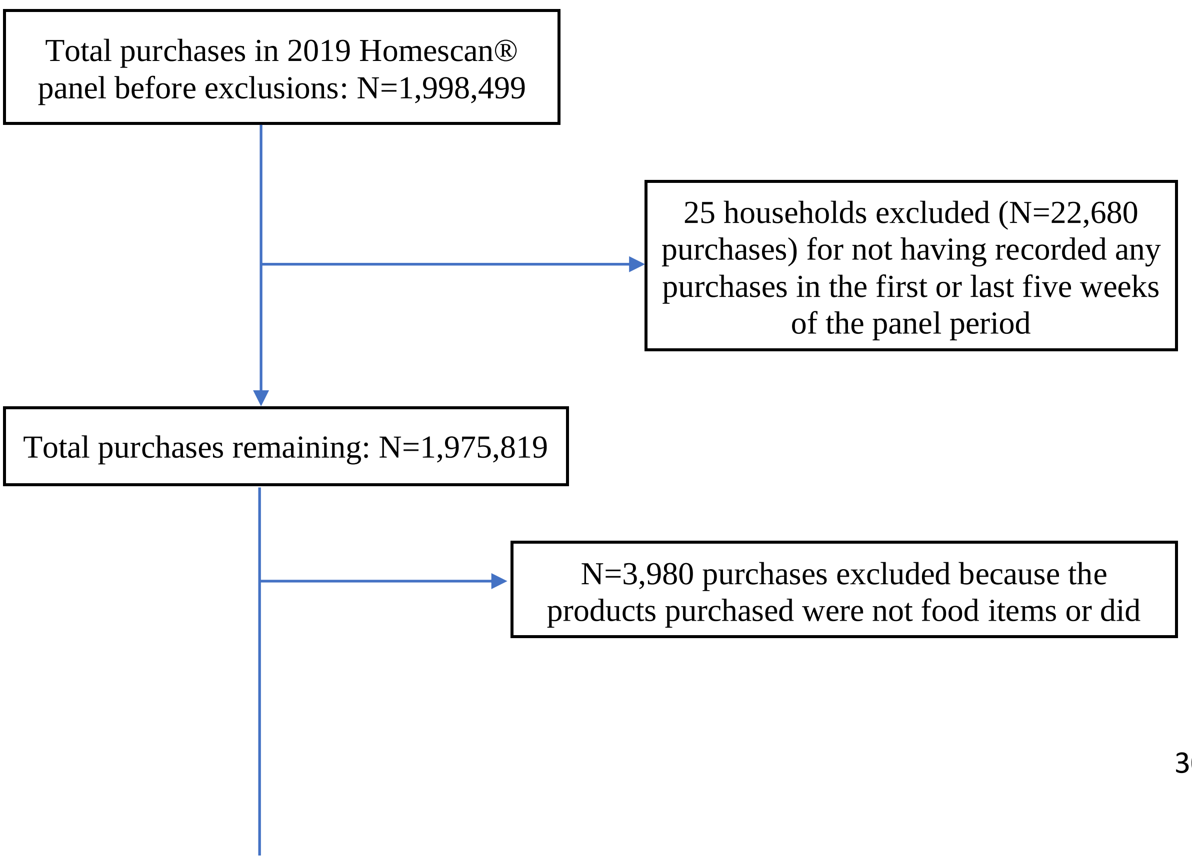
Subsequently, food purchases were identified that listed ambiguous size and unit values such as "1 PCK" or "1 UN". These products for which an exact size was not enumerated and that were purchased fewer than 12 times in total (an average of once per month) over the course of the year-long panel were excluded first. The barcode descriptions of the remaining food products without usable size or unit values were then reviewed for indications of their size. For example, many egg products' size and unit values were listed as one package or unit, but the exact quantity of eggs in each product's carton was listed in their barcode description. In those situations the egg product's size value was calculated by multiplying the number of eggs specified in the barcode description by 51 grams per egg; this reference weight was sourced from the New Zealand Food Composition Database website (New Zealand Institute for Plant and Food Research Limited & New Zealand Ministry of Health, 2018). Similar methods were used to estimate the size of various other food products that were listed in units or packages rather than grams. When their barcode descriptions did not provide indications of size, some products' sizes were identified and adjusted accordingly by searching for the exact product on the online shopping websites for Countdown, PAK'nSAVE, and New World. This method was particularly relevant for processed food products such as packaged bakery items and biscuits. Similarly, when an exact brand and product match was not found on the supermarkets' websites, equivalent products' details were utilized to estimate a size value when possible. For instance, though a supermarket own-brand mince purchased for $10 was not listed on the online shopping websites, its size was estimated as 690 grams by dividing $10 by the price per kilogram ($14.49) of an equivalently priced brand of minced meat.

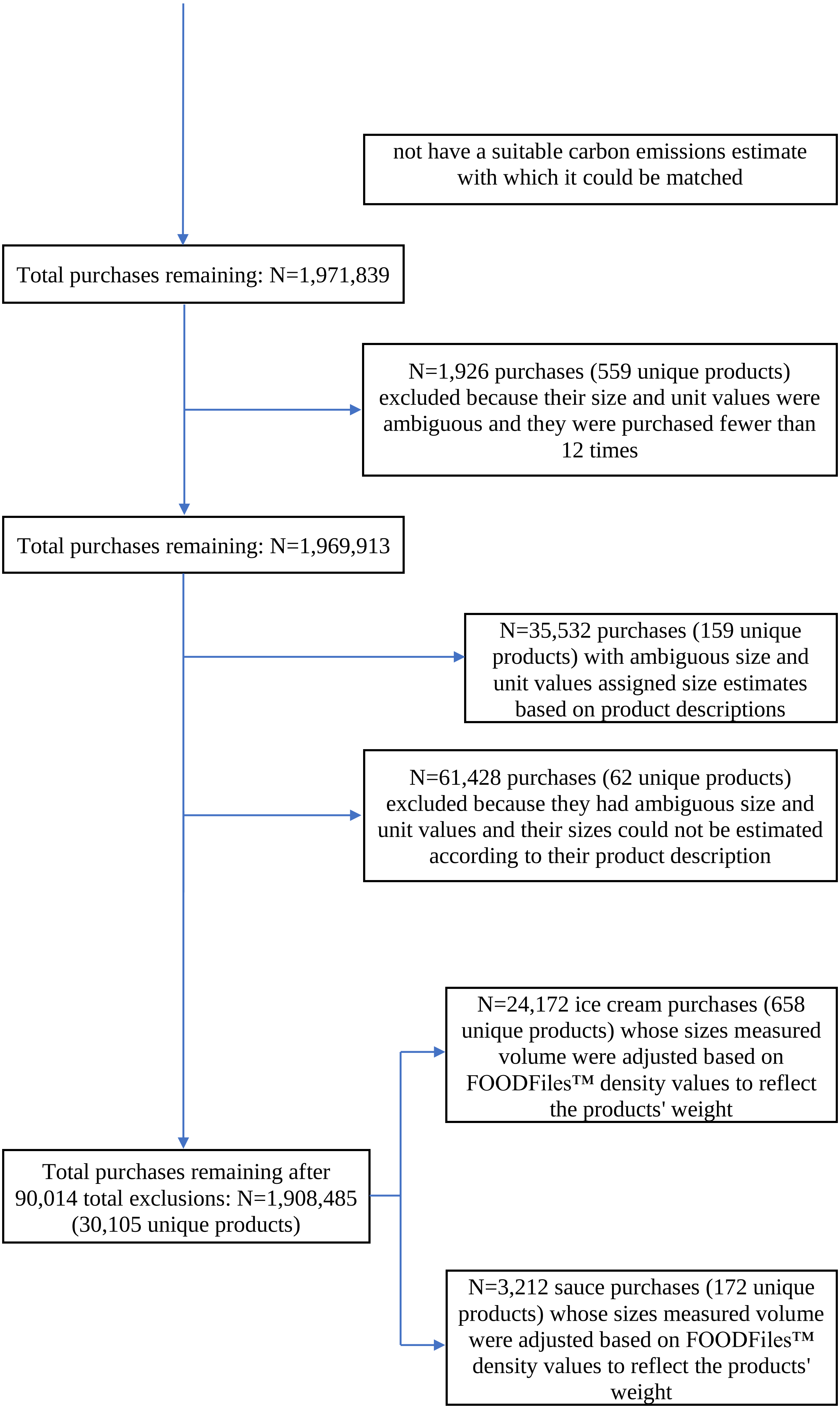
For other products, in cases where the quantity (but not the size) of a product was indicated in its barcode description (e.g., packaged vegetables), I estimated the food's individual unit size and then multiplied the estimate by the quantity of the product suggested. The unit size approximations were reviewed and approved by Dr. Kathryn Bradbury (PhD in Human Nutrition); they are listed in Appendix III. In rare occasions when both the size and unit values of a purchase were unusable and the barcode description for packaged vegetables did not indicate a quantity, the size of the entire packaged vegetable product (e.g., packaged kale, spinach, herbs, etc.) was estimated based on similar products catalogued on the aforementioned websites. These estimates are also provided in Appendix III. The remaining products that did not have usable size or unit values, that were not found on markets' websites, whose barcode descriptions did not provide indications of their size, whose sizes could not be estimated by equivalent products, and, therefore, whose sizes could not be estimated with reasonable confidence of accuracy were excluded. Altogether, 63,354 purchases (3% of total purchases) of 621 unique products were excluded for having ambiguous size and unit values, and 35,532 purchases (2% of total purchases) of 159 unique products were assigned size estimates. The entirety of the purchase exclusions and size estimates described above are summarized in Figure 2 below.

Finally, certain products' size and unit values were adjusted to convert their original size value from a measure of volume to a measure of weight. While most products' sizes in the Nielsen Homescan® dataset denoted their weight in grams, other products' (such as alcohol, ice cream, sauces, and cooking oils) sizes indicated their volume in millilitres or litres. Any food or beverage whose size was measured in millilitres or litres and whose density [as listed in the New Zealand FOODFiles™ 2018 Version 1 (New Zealand Institute for Plant and Food Research Limited & New Zealand Ministry of Health, 2019)] was less than 0.9 g/ml or greater than 1.1 g/ml was assigned a new size value indicating its weight. The average density for each food category was calculated by taking the mean (or median when the two measures were considerably different to account for outliers) of all corresponding entries in the FOODFiles™. For example, the document included 24 different entries for various types of ice creams, and their mean density was 0.69 g/cm^3 (New Zealand Institute for Plant and Food Research Limited & New Zealand Ministry of Health, 2019). Therefore, the weight in grams of each ice cream product listed in millilitres or litres in the Nielsen Homescan® panel was calculated by multiplying its volume by 0.69.

Only ice cream and sauces had a corresponding entry or entries in the FOODFiles™ 2018 whose mean or median value met the criteria. Consequently, the sizes of 27,384 purchases (1% of total purchases) of 830 unique ice cream and sauce products were adjusted to reflect weight based on density estimates. Apart from those adjustments, all products whose sizes were listed in millilitres or litres were assumed to have an equivalent weight in grams. The conversion of measures of volume to measures of weight was necessary in order to calculate the carbon emissions output for each unique food purchase, which is expressed per kilogram of food product, as detailed in the following sections.

Figure 2: Exclusions and adjustments made to the Nielsen Homescan® panel dataset




not have a suitable carbon emissions estimate with which it could be matched
Total purchases remaining: N=1,971,839
N=1,926 purchases (559 unique products) excluded because their size and unit values were ambiguous and they were purchased fewer than 12 times
Total purchases remaining: N=1,969,913
N=35,532 purchases (159 unique products) with ambiguous size and unit values assigned size estimates based on product descriptions
N=61,428 purchases (62 unique products) excluded because they had ambiguous size and unit values and their sizes could not be estimated according to their product description
N=24,172 ice cream purchases (658 unique products) whose sizes measured volume were adjusted based on FOODFiles™ density values to reflect the products' weight
Total purchases remaining after 90,014 total exclusions: N=1,908,485 (30,105 unique products)
N=3,212 sauce purchases (172 unique products) whose sizes measured volume were adjusted based on FOODFiles™ density values to reflect the products' weight

3.3 Environmental impact data

Foods in the Nielsen Homescan® panel dataset were combined with process-based LCA estimates to assign carbon emissions values to each product purchased. The LCA dataset utilized in this research was largely constructed by Drew et al. (2020), who adapted dietary emission estimates originally compiled in the UK by Hoolohan et al. (2013) to the New Zealand context. The original LCA dataset established by Hoolohan et al. (2013) approximates the carbon footprint — measured in kilograms of carbon dioxide equivalents per kilogram of food product (kg CO_2-e/kg) — of 66 food categories in the UK. Its boundaries of analysis are "cradle to point-of-sale", which includes seven life cycle stages: farming and processing, transit packaging, transportation, consumer packaging, warehouse and distribution, refrigeration, and retail overheads.

Drew et al. (2020) modified this reference dataset in several ways to enhance its applicability to New Zealand (NZ). These alterations focused primarily on utilizing NZ-specific values for domestically produced foods' highest emitting life cycle stage (farming and processing) and modifying the life cycle stages for both imported and NZ-produced foods that were expected to be most dissimilar to the reference UK values: emissions resulting from transportation and electricity usage (Drew et al., 2020). The domestically produced foods for which NZ-specific LCA values were not available received proxy farming and processing emissions estimates. These estimates were calculated by averaging the LCA figures for similar food products in NZ (Drew et al., 2020). Exclusively imported foods were not assigned NZ-specific farming and processing emissions values (Drew et al., 2020); instead, the estimates originally provided by Hoolohan et al. (2013) were employed for those products. For the foods that are partly imported and partly produced domestically, Drew et al. (2020) utilized a combination of NZ-specific emissions values (where available) and figures from the Hoolohan et al. (2013) reference database in proportion to the relative quantities of those foods that are imported versus domestically produced.

To modify Hoolohan et al.'s (2013) transportation data for New Zealand, Drew et al. (2020, p. 17007-3) estimated the distances travelled by imported food items based on the routes travelled either by air or sea, depending on the mode of transport. Drew et al. (2020) then multiplied these numbers by the "emissions factors" — the average carbon emissions associated with shipping one kilogram of a given food item (kg CO2-e/kg) by various modes of transport — provided by Hoolohan et al. (2013), which account for direct emissions generated by transport vehicles as well as indirect emissions stemming from the fuel supply chain. All foods produced domestically within New Zealand, on the other hand, were given the same transportation footprint of 0.13 kg CO_2-e/kg (Drew et al., 2020). The calculation of this figure was predicated on the work done by Saunders & Zellman (2007), who estimated the average road distance between coastal ports and farms within New Zealand to be 250 kilometres. Drew et al. (2020) took this average road distance figure and multiplied it by the emissions factor for land transportation by truck (measured in kgCO_2-e/km) to derive the transportation footprint of 0.13 kg CO_2-e/kg.

Furthermore, Drew et al. (2020, p. 17007-3) adjusted the electricity values from the Hoolohan et al. (2013) reference database for the New Zealand context according to the differences in non-renewable electricity usage between NZ and the UK during “downstream” life cycle stages: warehouse and distribution, refrigeration, and overheads. Non-renewable electricity usage differences were calculated using statistics reported by the UK’s Department of Energy and Climate Change (2014) and New Zealand’s Ministry of Business, Innovation & Employment (2017).

Lastly, Drew et al. (2020) supplemented the dataset constructed by Hoolohan et al. (2013) by adding 20-year total emissions estimates. The original dataset only included 100-year total emissions estimates for each food category because it is the standard time frame used in most studies on dietary emissions. However, the 100-year horizon does not account for greenhouse gases that have shorter life spans. For example, while carbon dioxide remains in the atmosphere for hundreds of years once emitted, methane and some hydrofluorocarbons (HFCs) are more short-lived, only staying in the atmosphere for anywhere from months to a few decades.

Following the amendments made by Drew et al. (2020) to the original dataset constructed by Hoolohan et al. (2013), Dr. Kathryn Bradbury created five new food categories based on New Zealand-specific LCA data. Additionally, based on a targeted search of recent literature, she updated the values in eight categories used by Drew et al. (2020) with newer LCA data that had been recently published. As seen in Appendix IV, the LCA dataset utilized in this study ultimately consisted of 51 categories used by Drew et al. (2020), 12 categories established by Hoolohan et al. (2013) but not utilized by Drew et al. (2020), and 13 categories either created or updated by Dr. Bradbury. For the purposes of comparing total emissions amongst overarching food groups in the 2019 Nielsen Homescan® panel, Dr. Bradbury also aggregated the 76 total categories in the LCA dataset into 15 major food categories, as detailed in Appendix IV.

3.4 Data linkage

The present research linking New Zealand households' food purchasing data with carbon emissions data builds upon the foundational work of others. My supervisor on this dissertation, Dr. Kathryn Bradbury (PhD in Human Nutrition), and a research assistant undertook the task of manually matching the 333 product categories in the Nielsen Homescan® panel with the most relevant food category within the LCA dataset constructed by Drew et al. (2020). For example, the Nielsen product category of "SOUR CREAM" — encompassing 27 unique products purchased a total of 5,837 times — was matched with the LCA category of "Cream". In instances where Nielsen's product categories encompassed a wide array of heterogenous foods that did not fit neatly in one LCA category, Dr. Bradbury and her research assistant matched a total of 2,138 unique products with the most appropriate category within the LCA dataset. Matching to this level of specificity was particularly relevant for the wide array of fruit and vegetable products purchased throughout the panel period, all of which were grouped together broadly in Nielsen's product categories of "FRESH FRUIT" and "FRESH VEGETABLES." The unique product matching done by Dr. Bradbury and her research assistant allowed for peaches and apples, for example, to be assigned the distinct LCA categories of "Stone fruit & grapes" and "Apples and pears", respectively. Together, the product category and unique product matching decisions were compiled in Excel documents which I used as the basis for merging the Nielsen Homescan® panel with the LCA data, as detailed below. As far as possible, unique products and product categories that are reconstituted at home were assigned to an LCA category that reflected the product 'as purchased'. For example, yoghurt powder sachets, which are comprised of milk powder combined with lactic acid bacteria, were matched with the powdered milk LCA category rather than the yoghurt category to reflect the product as purchased, not their end product after purchase and preparation.

For the purposes of this research, each unique purchase in the 2019 Nielsen Homescan® panel was first merged with the relevant LCA data in RStudio according to the product category matches made by Dr. Bradbury and her research assistant. Subsequently, the remaining food purchases in the dataset which were not matched according to their product category were instead merged with the appropriate LCA data based on the unique product matches designated by Dr. Bradbury and her research assistant. Once all food purchases (N=1,908,485 remaining after exclusions) had been merged with the relevant LCA data in RStudio, the carbon emissions value (measured in kgCO_2 equivalents) of each purchase was calculated by multiplying the emissions factor for each food (measured in kgCO_2-e/kg of food) by the quantity (kilograms) of the food purchased. Next, the dietary emissions totals (measured in both 20-year and 100-year time spans to account for greenhouse gases with lifetimes of varying lengths) were calculated for each household by summing the emissions values attached to their individual purchases over the course of the panel period. Finally, 20-year and 100-year per capita emissions were calculated by dividing the total emissions by the number of people (adults and children) in each household.

3.5 Statistical analyses

Statistical analysis procedures were established following multiple consultations with two biostatisticians, Dr. Yannan Jiang and Dr. Alana Cavadino, within the University of Auckland's School of Population Health, in the Faculty of Medical and Health Sciences. The data analyses were completed using RStudio software, Version 1.2.1335.

Firstly, the greenhouse gas emissions associated with the panel purchases were calculated by life cycle stage and categorised into 15 major food groups. Next, for the main analysis, certain categories within the age group and income group demographic variables were collapsed to reduce the sample size disparities between comparison groups. For example, with income groups, there were very few households (N=13) in the category of "$12,000 or less per year"; therefore, those households were combined with those in the income group "$12,001 - $22,000" (N=141), and the new category was labelled "$22,000 or less" (N=154). Similarly, because the number of households in the age groups of "Under 25 years" (N=2), "25-29 years" (N=32), and "30-34 years" (N=66) was small, they were combined into one category labelled "34 years and under" (N=100). Further details on the demographic variable group categories utilized in statistical analyses of the 2019 Nielsen Homescan® panel dataset can be found in Appendix II.

Once the aforementioned variable groups were collapsed, data exploration was undertaken. Histograms, kernel density plots, and Q-Q plots were generated to review the distribution of 20-year and 100-year per capita emissions for the households remaining in the Nielsen dataset (N=1,775) following the aforementioned exclusions. Boxplots as well as scatterplots (for household size) were generated for data visualization.

Bivariate analyses were undertaken on each independent variable and both outcome variables (20-year and 100-year per capita dietary emissions). Two Sample t Tests were conducted for the variable of sex, and ANOVA tests were run for the independent variables with three or more groups: income group, age group, and life stage. Household size, on the other hand, was treated as a continuous variable and, therefore, its possible relationship with dietary emissions was explored using simple linear regression. However, the assumption of homoscedasticity was violated and therefore weighted least squares regression was used in place of simple linear regression, as discussed below. Finally, multiple linear regression analyses were conducted to evaluate the impact of each independent variable on the dependent variables (20-year and 100-year per capita dietary emissions) while adjusting for the other independent variables.

Prior to completing statistical analyses, the underlying assumptions of each individual test were checked. The assumptions, which were reviewed from a biostatistical textbook (Motulsky, 2018), are summarized below:

Two Samples t Tests: Random or representative samples; independent observations; accurate data; data sampled from populations that approximate a normal distribution; equality of variances between variable groups

ANOVA: Random or representative samples; independent observations; data sampled from populations that approximate a normal distribution; equality of variance between variable groups

Simple linear regression: Linear relationship between a continuous independent variable and the dependent variable; residuals (scatter of data around the trend line) follow a normal distribution; homogeneity of variance around the trend line (i.e., homoscedasticity); data points are independent

Multiple linear regression: Linear effects only between continuous independent variables and the dependent variable; no interaction between independent variables beyond what is examined in the model; independent observations; residuals of the model are normally distributed

Data exploration revealed that the dependent variables of 20-year and 100-year per capita dietary emissions did not follow a normal distribution – they were right skewed. Furthermore, the distributions of residuals in the multiple linear regression models were skewed, so the dependent variables were log transformed for all bivariate analyses and the multiple linear regression. When reporting the results of weighted least squares regression modelling and multiple linear regression modelling, the coefficients were exponentiated for ease of interpretation. In the case of categorical variables, the exponentiated coefficient can be interpreted as the ratio of the geometric mean of the independent variable group to the geometric mean of its reference group. The exponentiated coefficient for a continuous variable (e.g., household size), on the other hand, can be understood as the ratio of the geometric mean of one independent variable value (e.g., household size = 1) to the geometric mean of each successive unit increase in the independent variable value (e.g., household size = 2). In general, the geometric mean is used as the primary measure of central tendency in this study because it is considered a more accurate estimation of central tendency for log-transformed data than the more commonly used arithmetic mean, otherwise known simply as the mean or average.

The equality of variances assumption for the Two Samples t Tests and ANOVA tests was examined by running Levene's test for equality of variances on each discrete independent variable group. For those variables in which the assumption of equal variances was violated, bivariate tests were run with the assumption of equal variances relaxed. Similarly, weighted least squares regression was utilized instead of simple linear regression to assess the possible relationship between household size and per capita dietary emissions because the assumption of homogenous variances was violated according to the Breusch-Pagan test.

Sensitivity analysis was undertaken to observe the impact of outliers on the results of multiple linear regression. This was done by removing the extreme outliers whose per capita dietary emissions were either greater than the third quartile value plus 1.5 times the interquartile range (q_3 + 1.5*IQR) or less than the first quartile value minus 1.5 times the interquartile range (q_1 – 1.5*IQR), then rerunning the multiple linear regression models to see if the results were materially different.

4. Results

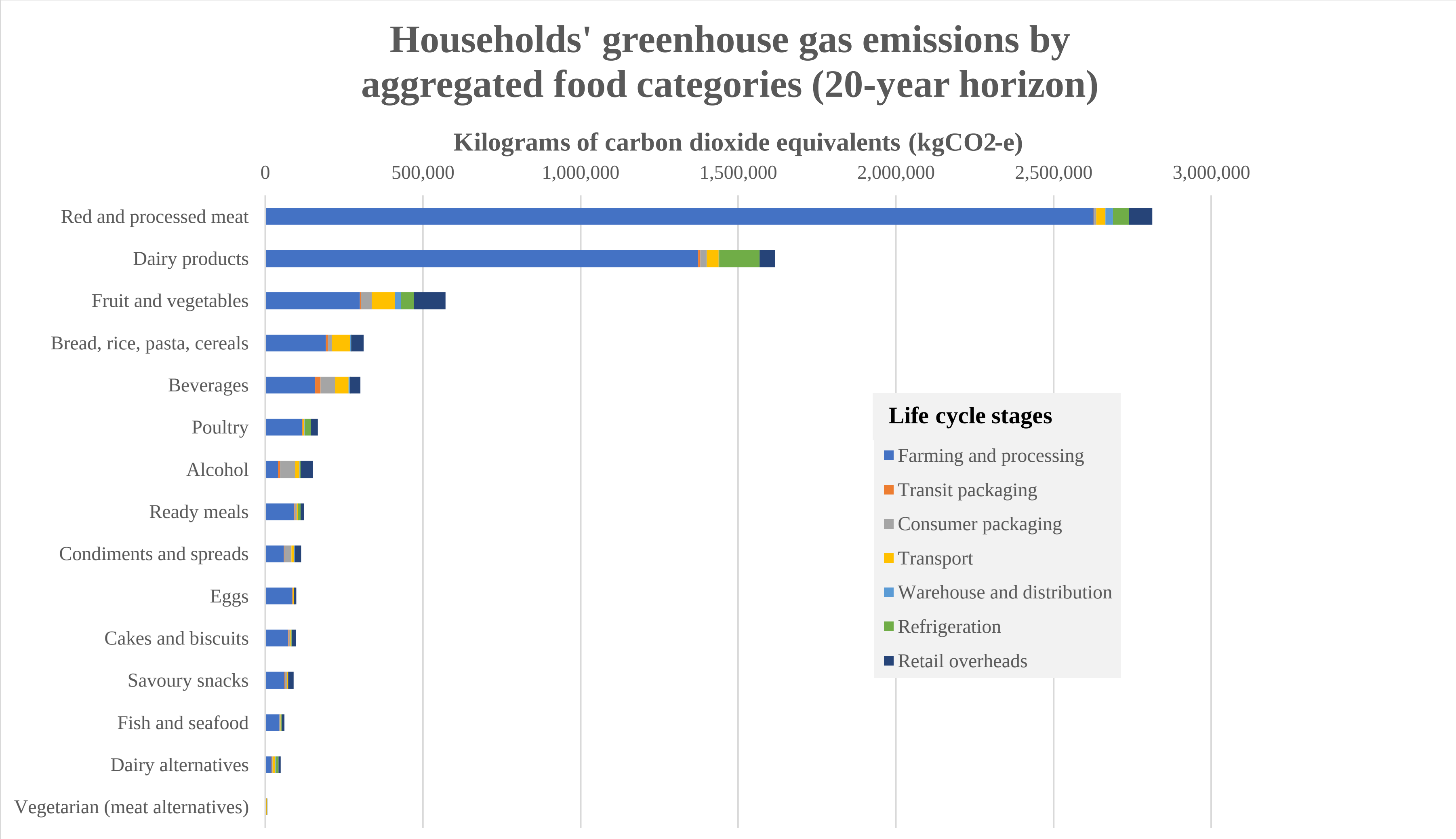
The 2019 Nielsen Homescan® dataset, following the exclusion of households that did not meet Nielsen's quality criteria, consisted of 1,800 households. For the purposes of the present research, a further 25 households were excluded from analysis due to the fact they did not record any purchases during either the first five or last five weeks of the year-long panel period. The sample size of the remaining households was 1,775.

4.1 Dietary emissions from all households' purchases over the year-long panel period

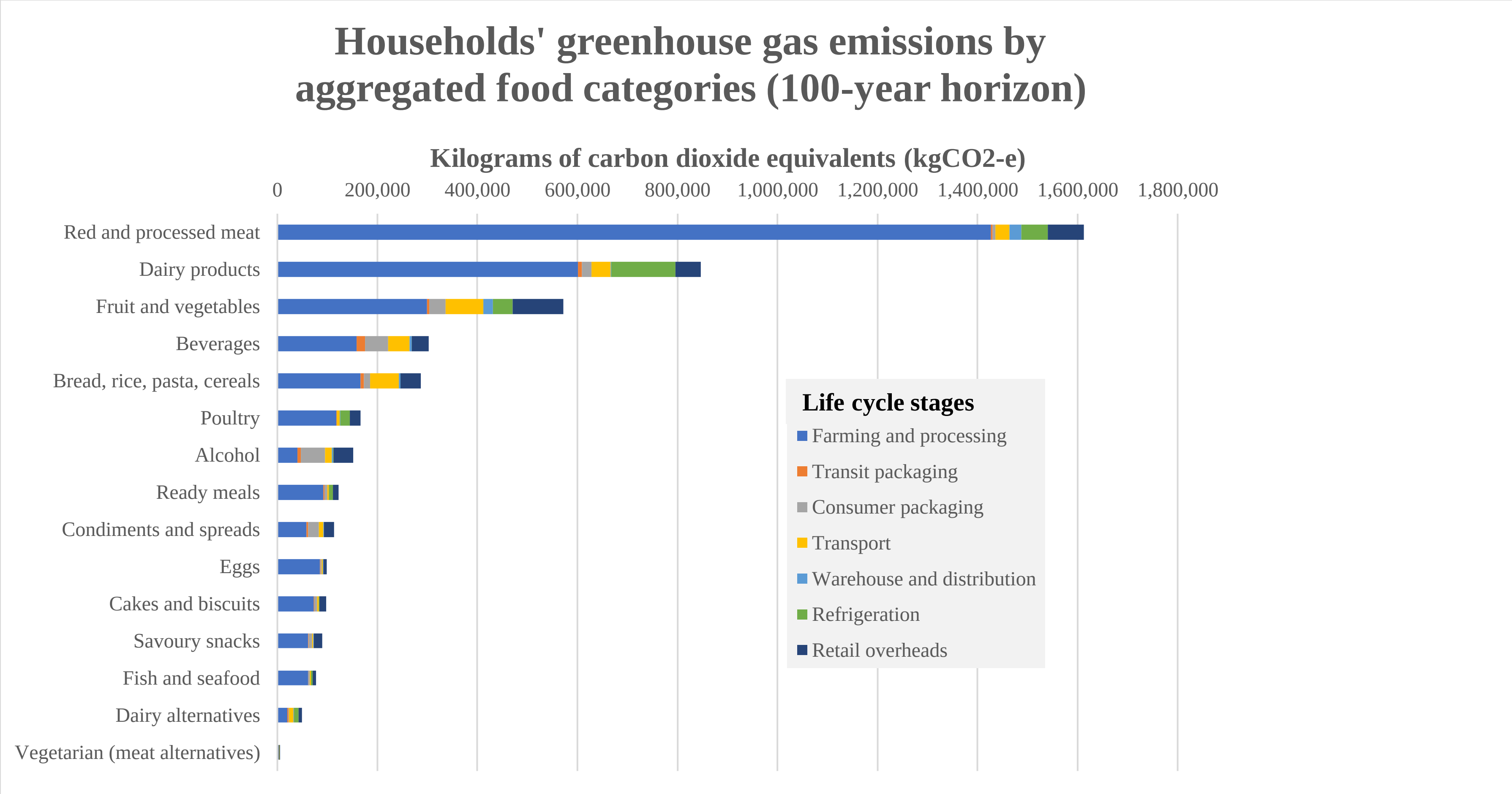
Overall, the unadjusted geometric mean of New Zealand households' per capita dietary emissions over the course of the year-long panel period was 1,438 kilograms of carbon dioxide equivalents in the 20-year horizon and 1,019 kilograms of carbon dioxide equivalents in the 100-year horizon. As for total household emissions (i.e., not adjusting for household size), the unadjusted geometric mean of dietary emissions was 3,218 kilograms of carbon dioxide equivalents in the 20-year horizon and 2,280 kilograms of carbon dioxide equivalents in the 100-year horizon.

Comparing aggregated food categories, red and processed meats and dairy products accounted for the highest amounts of total emissions from all households' purchases over the year-long panel period by large margins, followed by fruit and vegetables; bread, rice, pasta, and cereals; and beverages. Figures 3 and 4 below display the emissions totals for all 15 designated major food categories (listed alongside their constituent Life Cycle Assessment categories in Appendix IV) broken down by life cycle stage. As the figures show, the farming and processing stage comprises by far the greatest amount of greenhouse gas emissions compared to other life cycle stages.

Figure 3: Total emissions associated with all households' purchases in the 2019 Nielsen Homescan® panel by major food categories (20-year horizon)



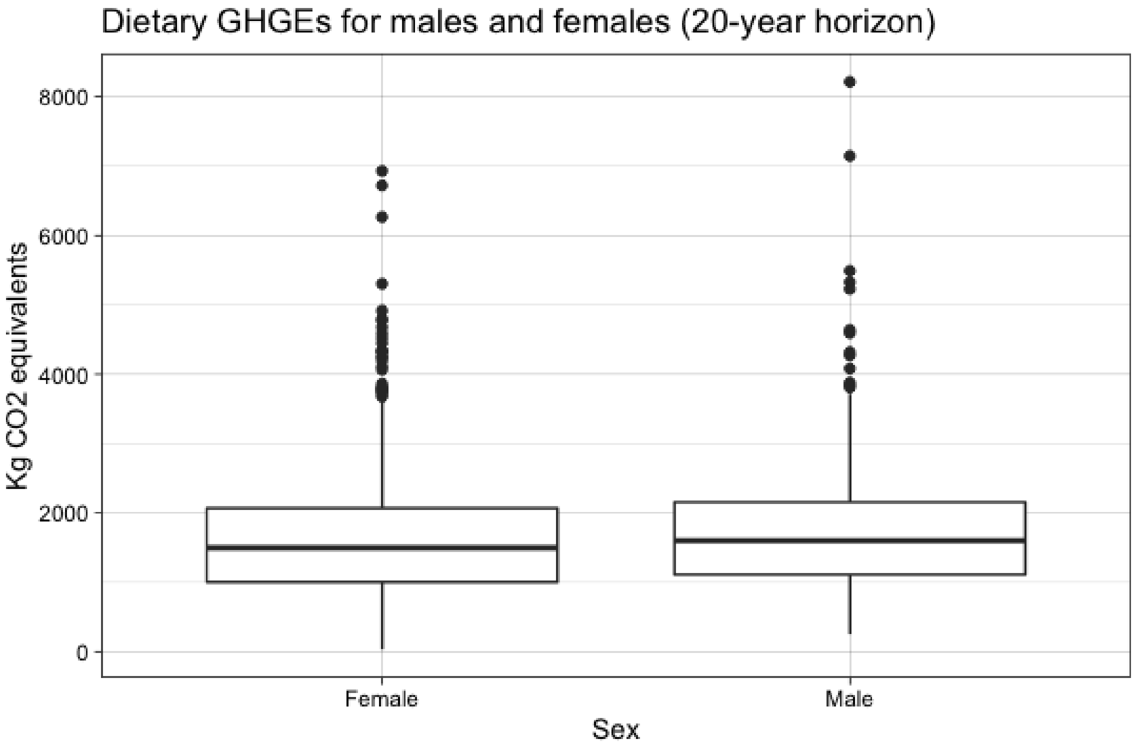
<u>Figure 4: Total emissions associated with all households' purchases in the 2019 Nielsen Homescan® panel by major food categories (100-year horizon)</u>



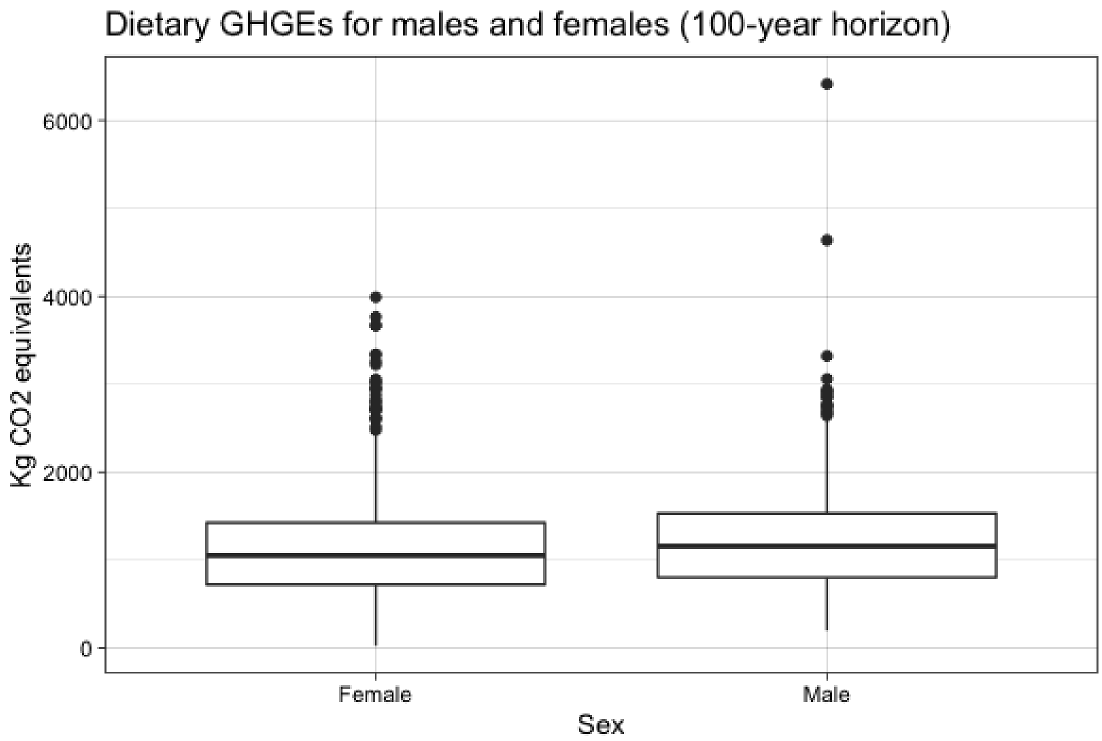
4.2. Bivariate analyses between household characteristics and per capita dietary emissions

Bivariate analyses of each independent variable's association with dietary emissions are detailed below. Per capita dietary emissions by sex of a household's primary shopper are summarised in Figure 5 (20-year horizon) and Figure 6 (100-year horizon).

Figure 5: Per capita dietary emissions (20-year horizon) by sex



<u>Figure 6: Per capita dietary emissions (100-year horizon) by sex</u>



Males (mean=1758, SD=964 in the 20-year horizon; mean=1240, SD=651 in the 100-year horizon) had significantly higher per capita dietary emissions than females (mean=1615, SD=835 in the 20-year horizon; mean=1128, SD=550 in the 100-year horizon).

Per capita dietary emissions by household income are summarised in Figure 7 (20-year horizon) and Figure 8 (100-year horizon).

Figure 7: Per capita dietary emissions (20-year horizon) by household income

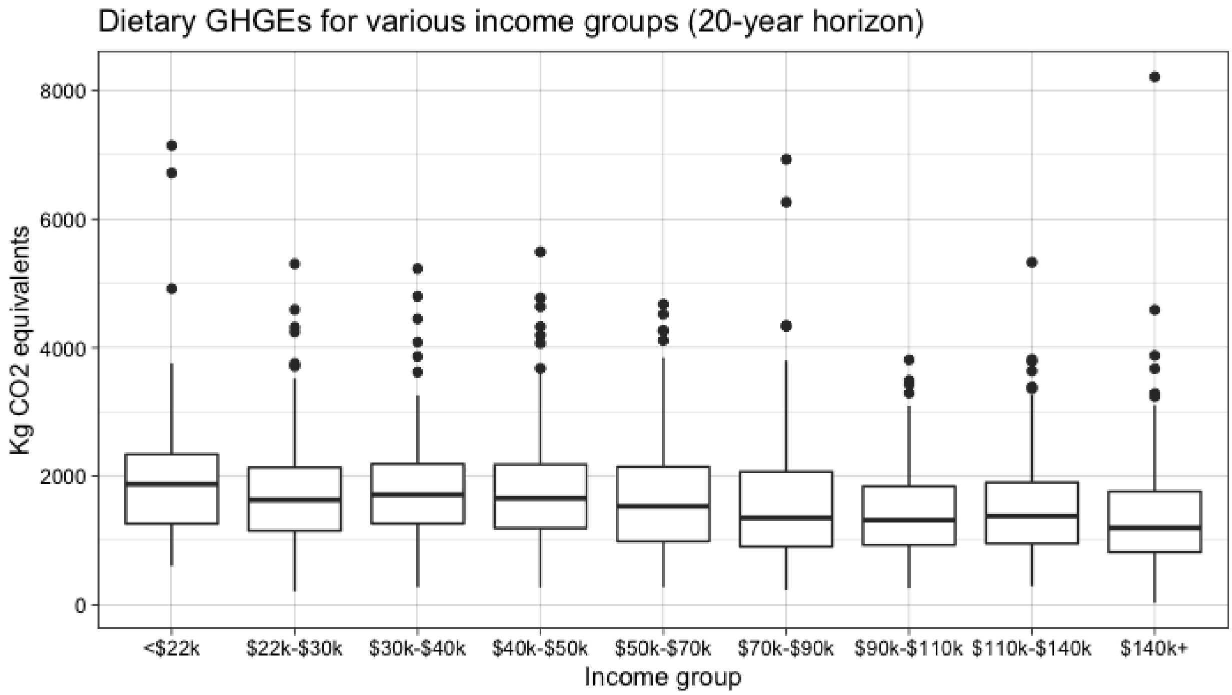
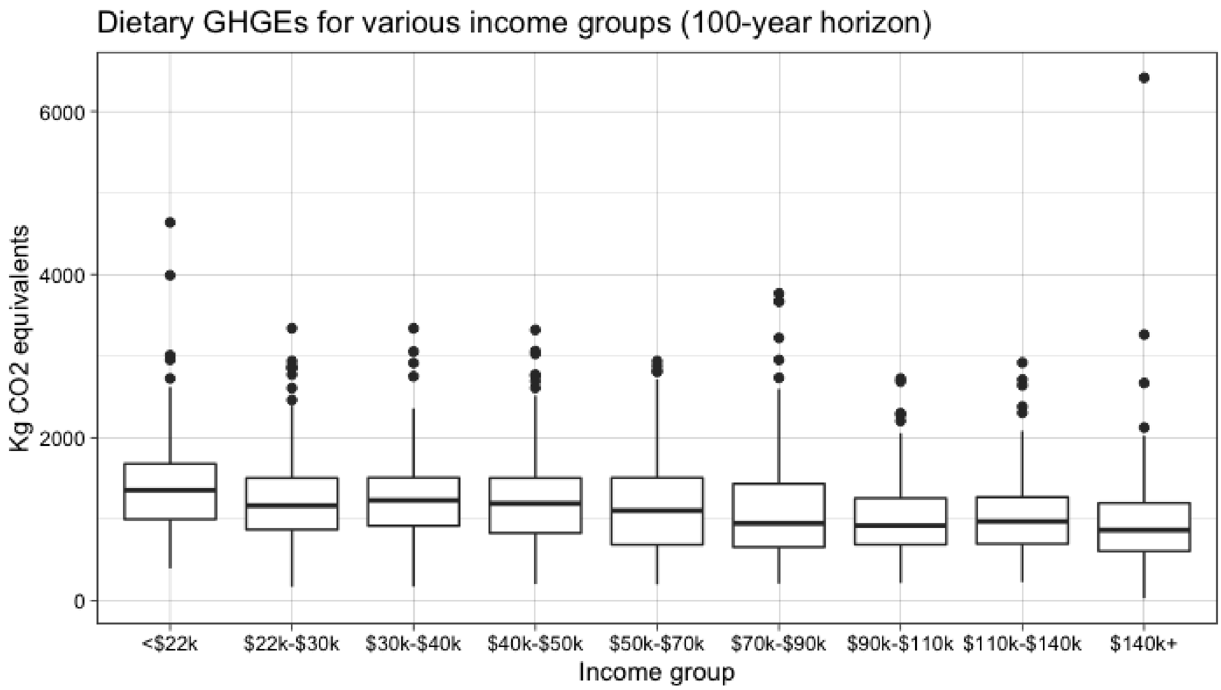


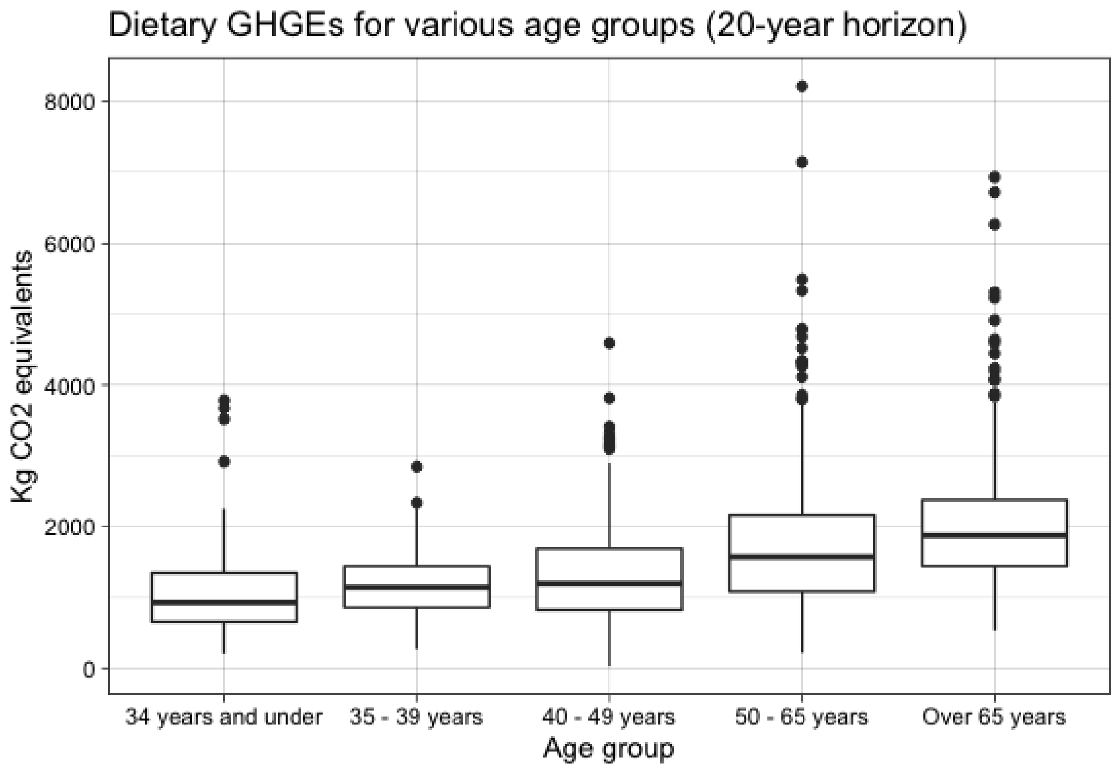
Figure 8: Per capita dietary emissions (100-year horizon) by household income



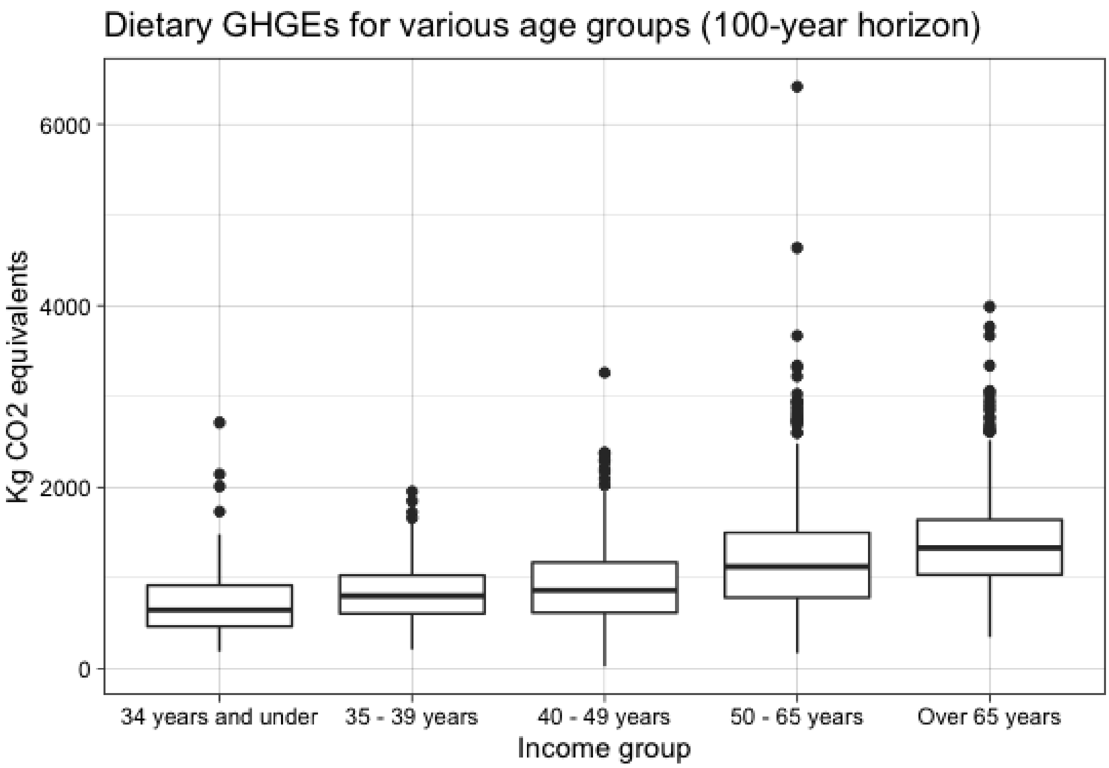
Household income was a significant predictor of per capita dietary emissions in both the 20-year and 100-year horizons. Post-hoc tests were not undertaken to determine which income groups differed significantly from one another because multiple linear regression analysis was to be conducted following each independent variable's bivariate analysis.

Per capita dietary emissions by age of a household's primary shopper are summarised in Figure 9 (20-year horizon) and Figure 10 (100-year horizon).

<u>Figure 9: Per capita dietary emissions (20-year horizon) by age of a household's primary shopper</u>



<u>Figure 10: Per capita dietary emissions (100-year horizon) by age of a household's primary shopper</u>



Age of the primary household shopper was a significant predictor of per capita dietary emissions in both the 20-year and 100-year horizons. As above, post-hoc tests were not undertaken to determine which age groups differed significantly from one another because multiple linear regression analysis was to be conducted following each independent variable's bivariate analysis.

Per capita dietary emissions by household life stage are summarised in Figure 11 (20-year horizon) and Figure 12 (100-year horizon).

Figure 11: Per capita dietary emissions (20-year horizon) by household life stage

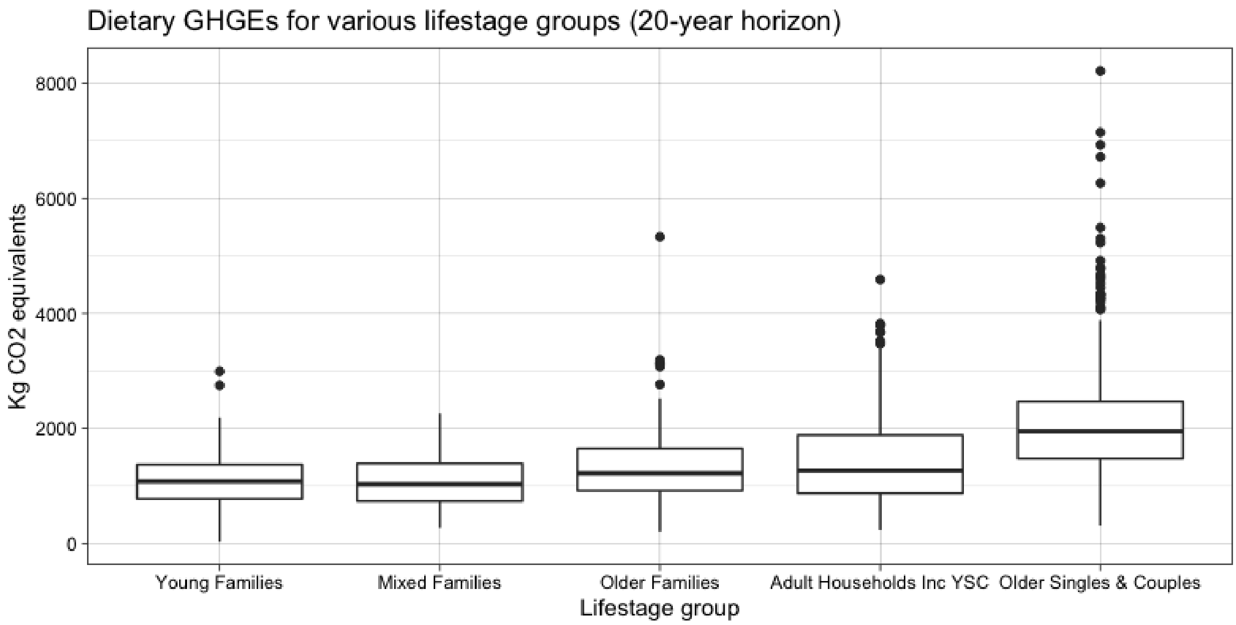
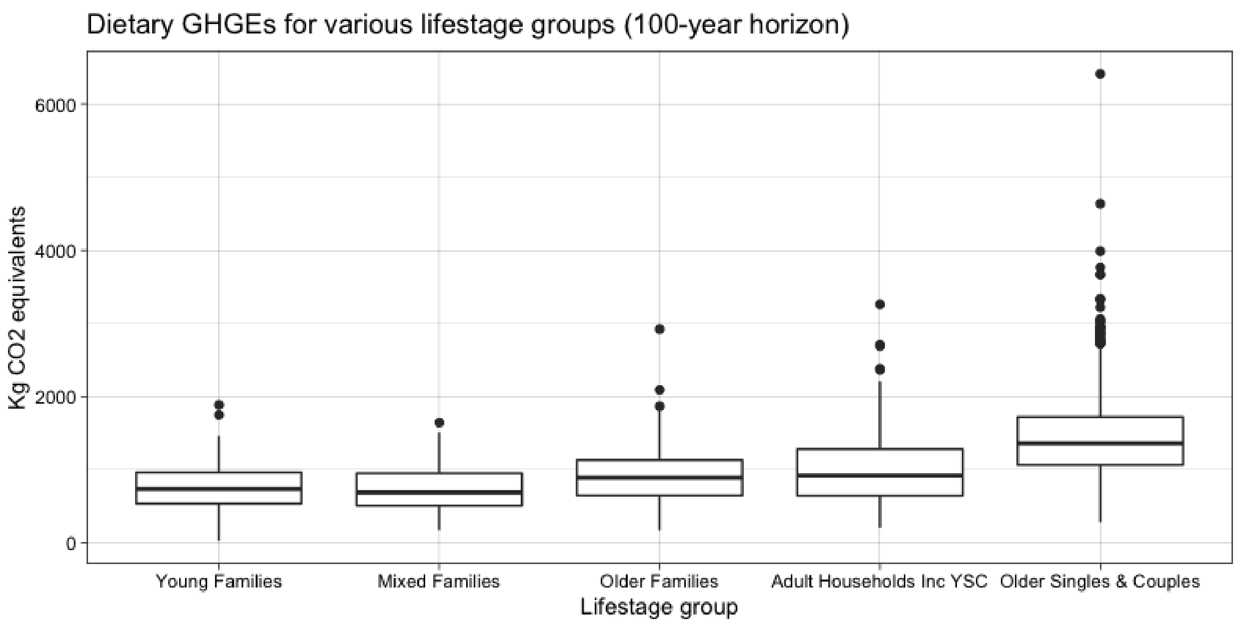


Figure 12: Per capita dietary emissions (100-year horizon) by household life stage



Household life stage was a significant predictor of per capita dietary emissions in the 20-year and 100-year horizons. As above, post-hoc tests were not undertaken to determine which life stage groups differed significantly from one another because multiple linear regression analysis was to be conducted following each independent variable's bivariate analysis.

Per capita dietary emissions by household size are summarised in Figure 13 (20-year horizon) and Figure 14 (100-year horizon).

<u>Figure 13: Per capita dietary emissions (20-year horizon) by household size</u>

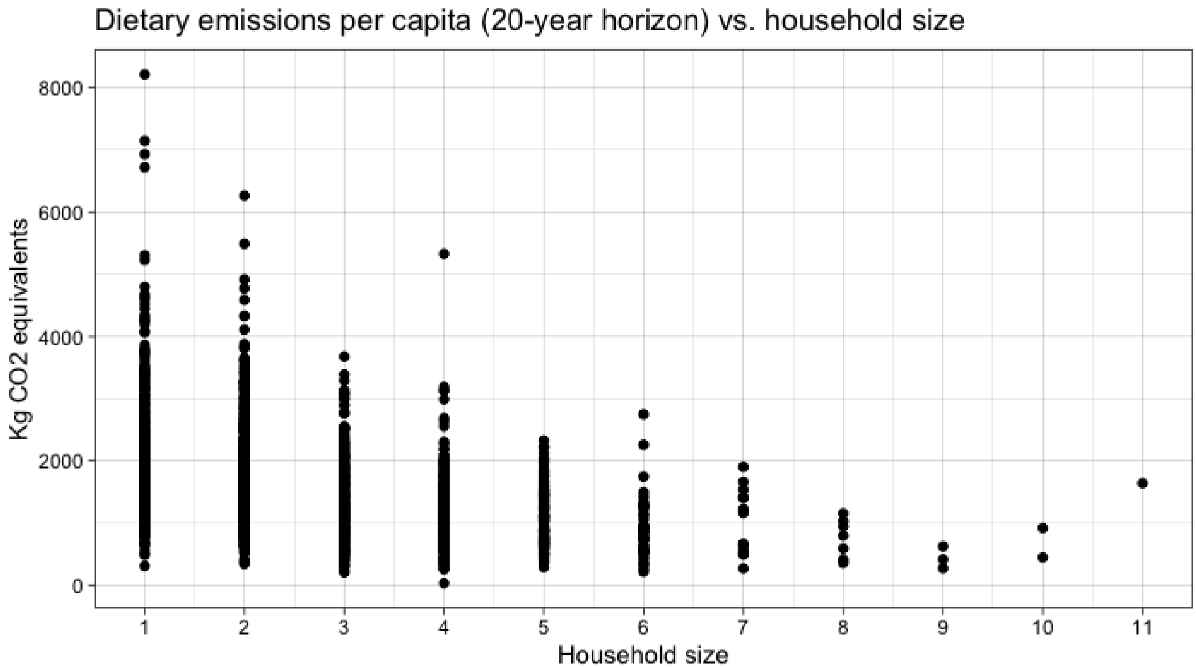
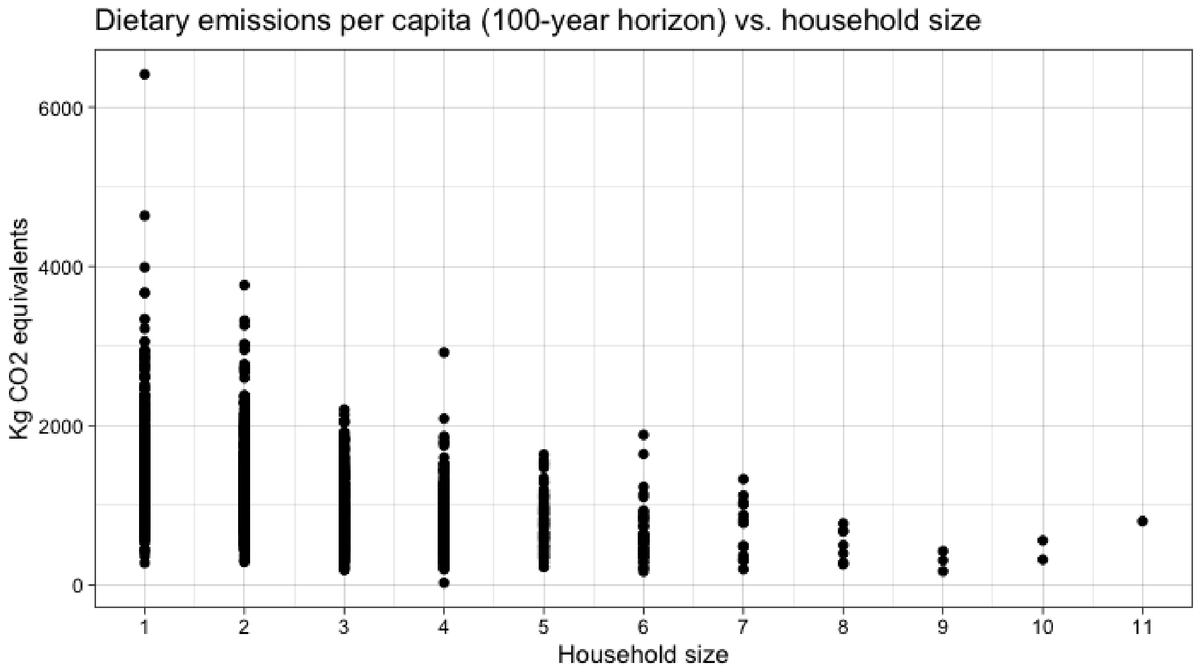


Figure 14: Per capita dietary emissions (100-year horizon) by household size



The best fit weighted least squares (WLS) regression lines are shown in the scatterplots of the log-transformed data below:

Figure 15: Log-transformed per capita dietary emissions (20-year horizon) by household size

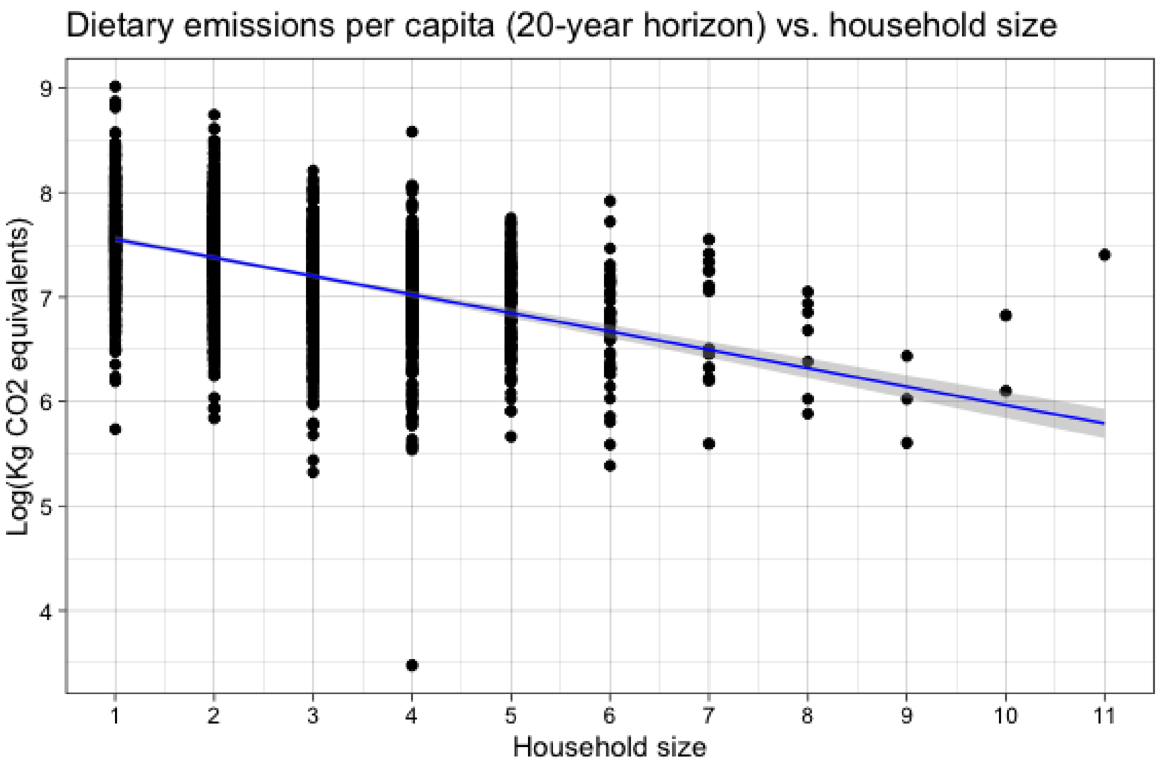


Figure 16: Log-transformed per capita dietary emissions (100-year horizon) by household size

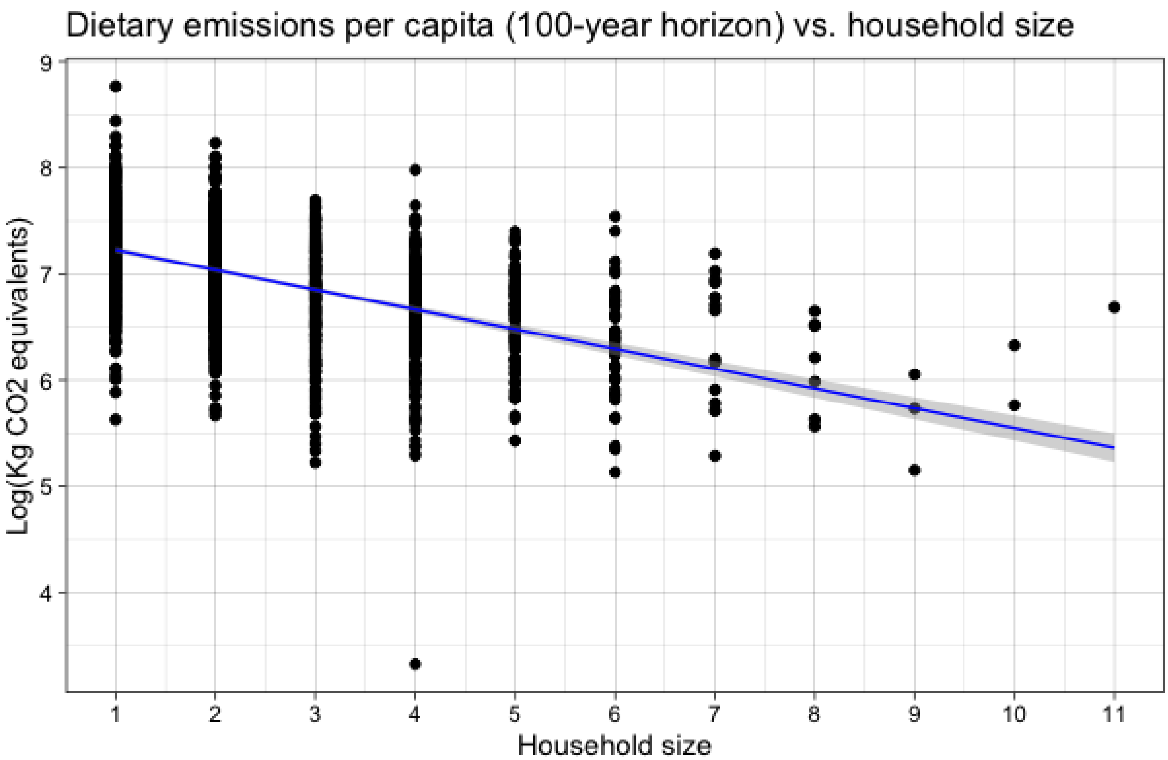


Table 2: Weighted least squares regression model results (20-year horizon)

	Per Capita Dietary Emissions (20-year horizon)		
Variable	*Ratio (95% CI)[1]*	*t-value*	*p-value*
Household size	0.84 (0.82 to 0.85)	-21.17	**<0.001**
Observations	1775		
R^2 / R^2 adjusted	0.202 / 0.201		

1. Ratio of the geometric mean. In this case, a ratio of 0.84 for every one-person increase in household size indicates that, on average, each additional person is associated with a 16% [(1-0.84)*100] decrease in per capita dietary emissions.

Table 3: Weighted least squares regression model results (100-year horizon)

	Per Capita Dietary Emissions (100-year horizon)		
Variable	*Ratio (95% CI)*[1]	*t-value*	*p-value*
Household size	0.83 (0.82 to 0.84)	-23.72	**<0.001**
Observations	1775		
R^2 / R^2 adjusted	0.241 / 0.240		

1. Ratio of the geometric mean. In this case, a ratio of 0.83 for every one-person increase in household size indicates that, on average, each additional person is associated with a 17% [(1-0.83)*100] decrease in per capita dietary emissions.

The results indicated that there was a statistically significant inverse relationship between household size and per capita dietary emissions such that an increase in the number of people in a household predicted a decrease in the household's per capita dietary emissions.

4.3 Multiple linear regression of household characteristics and per capita dietary emissions

Multiple linear regression was undertaken to quantify the impact of each independent variable on per capita dietary emissions while controlling for all other independent variables. The results of the analyses are presented below:

Table 4: Associations of household variables with per capita dietary emissions (20-year horizon)

		Per Capita Dietary Emissions (20-year horizon)		
Variable	*N*	*Ratio (95% CI)*[1]	*p-value*	*p-value of categorical variables*[2]
Sex of the primary shopper				0.769
Female	1343	1.00 (ref)		
Male	432	1.01 (0.96 to 1.06)	0.769	
Household Income				**0.012**
$22,000 or less	154	1.00 (ref)		
$22,001 - $30,000	204	0.92 (0.84 to 1.02)	0.102	
$30,001 - $40,000	207	1.03 (0.94 to 1.14)	0.532	
$40,001 - $50,000	167	1.09 (0.98 to 1.21)	0.104	
$50,001 - $70,000	269	1.05 (0.95 to 1.15)	0.326	
$70,001 - $90,000	242	1.03 (0.93 to 1.14)	0.542	
$90,001 - $110,000	191	0.98 (0.88 to 1.08)	0.671	
$110,001 - $140,000	183	1.03 (0.93 to 1.15)	0.531	
More than $140,000	158	0.94 (0.85 to 1.05)	0.282	
Age of the primary shopper				**<0.001**
34 years and under	100	1.0 (ref)		
35 - 39 years	129	1.17 (1.03 to 1.32)	**0.015**	
40 - 49 years	352	1.16 (1.04 to 1.29)	**0.006**	
50 - 65 years	701	1.29 (1.16 to 1.43)	**<0.001**	
Over 65 years	493	1.37 (1.22 to 1.54)	**<0.001**	
Household life stage				**<0.001**
Young Families	216	1.0 (ref)		
Mixed Families	105	1.06 (0.94 to 1.18)	0.332	

Older Families	191	1.12 (1.02 to 1.24)	**0.017**	
Adult Households Inc YSC	426	1.05 (0.96 to 1.15)	0.264	
Older Singles & Couples	837	1.33 (1.19 to 1.49)	**<0.001**	
Household size	1775	0.91 (0.88 to 0.93)	**<0.001**	

Observations: 1775

R^2 / R^2 adjusted: 0.285 / 0.278

1. Ratio of the geometric mean. For example, a ratio of 1.37 for the age group "Over 65 years" indicates that, on average, this group has a 37% higher geometric mean of per capita dietary emissions than the reference group "34 years and under".
2. Calculated using an F-test

Table 5: Associations of household variables with per capita dietary emissions (100-year horizon)

		Per Capita Dietary Emissions (100-year horizon)		
Variable	*N*	*Ratio (95% CI)*[1]	*p-value*	*p-value of categorical variables*[2]
Sex of the primary shopper				0.486
Female	1343	1.00 (ref)		
Male	432	1.02 (0.97 to 1.07)	0.486	
Household income				**0.011**
$22,000 or less	154	1.00 (ref)		
$22,001 - $30,000	204	0.92 (0.84 to 1.01)	0.073	
$30,001 - $40,000	207	1.01 (0.92 to 1.10)	0.866	
$40,001 - $50,000	167	1.07 (0.97 to 1.18)	0.177	
$50,001 - $70,000	269	1.03 (0.94 to 1.12)	0.545	
$70,001 - $90,000	242	1.01 (0.92 to 1.11)	0.778	
$90,001 - $110,000	191	0.96 (0.87 to 1.05)	0.379	
$110,001 - $140,000	183	1.01 (0.92 to 1.12)	0.787	
More than $140,000	158	0.92 (0.83 to 1.02)	0.120	
Age of the primary shopper				**<0.001**
34 years and under	100	1.00 (ref)		
35 - 39 years	129	1.18 (1.05 to 1.32)	**0.005**	
40 - 49 years	352	1.17 (1.06 to 1.30)	**0.002**	
50 - 65 years	701	1.28 (1.16 to 1.42)	**<0.001**	
Over 65 years	493	1.33 (1.20 to 1.49)	**<0.001**	
Household life stage				**<0.001**
Young families	216	1.00 (ref)		
Mixed Families	105	1.06 (0.96 to 1.18)	0.241	

Older Families	191	1.12 (1.03 to 1.23)	**0.012**
Adult Households Inc YSC	426	1.04 (0.96 to 1.13)	0.326
Older Singles & Couples	837	1.30 (1.17 to 1.44)	**<0.001**
Household size	1775	0.89 (0.87 to 0.91)	**<0.001**

Observations: 1775

R^2 / R^2 adjusted: 0.323 / 0.316

1. Ratio of the geometric mean.
2. Calculated using an F-test

After controlling for the effects of all other independent variables, age and household size were statistically significant predictors of per capita dietary emissions. The relationship between age group of the primary shopper and per capita dietary emissions is positive — older age groups are associated with higher per capita dietary emissions —, while the relationship between household size and per capita dietary emissions is negative, such that larger households are associated with lower per capita emissions. Household income and life stage were also significant predictors of per capita dietary emissions, but they displayed no clear pattern of association with per capita dietary emissions. For example, per capita dietary emissions were not consistently higher or lower across increasing income groups. Finally, sex of the primary shopper was not a significant predictor of per capita dietary emissions.

4.4 Sensitivity Analysis

Sensitivity analyses were conducted to evaluate the possible effect of extreme outliers on the results of multiple linear regression. 41 households were removed as high outliers and no households were removed as low outliers in the 20-year horizon. Similarly, 46 households were removed as high outliers in the 100-year horizon, and no households were removed as low outliers. The results of the sensitivity analyses are shown in Appendices V and VI. They reveal no material differences from the multiple regression models generated with outlier households included. Therefore, the multiple regression results reported earlier are considered robust to the effects of outliers.

5. Discussion

In this large sample of 1,775 New Zealand households that recorded their food purchases over the course of a year, the unadjusted geometric mean of households' per capita dietary emissions was 1,438 kilograms of carbon dioxide equivalents (kgCO_2-e) in the 20-year horizon and 1,019 kgCO_2-e in the 100-year horizon. The unadjusted geometric mean of total household dietary emissions was 3,218 kgCO_2-e in the 20-year horizon and 2,280 kgCO_2-e in the 100-year horizon. Amongst major food categories, red and processed meats followed by dairy products accounted for the highest amounts of total emissions from all purchases within the Nielsen Homescan® panel by far. The farming and processing life cycle stage encompassed the largest amount of greenhouse gas emissions by a wide margin compared to the other six life cycle stages included in the process-based LCA estimates. With regards to demographic variables, households where the primary shopper was older had higher per capita dietary emissions associated with purchased foods in the 2019 Nielsen Homescan® panel. In addition, households with more members had lower per capita dietary emissions. As discussed previously in the literature review, comparing the results of research on dietary emissions is complicated by the field's lack of methodological uniformity. Sampling units, units of measurement for environmental impact, environmental assessment approaches, and boundaries of analysis for such approaches vary widely in the literature. In light of these disparities it is important to contextualize the present research's findings cautiously.

In comparison to other studies that have examined total household emissions — with arithmetic means ranging from 2,287 kgCO_2-e per household in Sweden (Nordström et al., 2020) to 3,689.54 kgCO_2-e in Finland (Salo et al., 2021) and 4,160 kgCO_2-e [80 kgCO_2-e per week * 52 weeks] in Australia (Reynolds et al., 2015) — New Zealand households appear to fall on the lower end of the spectrum with an unadjusted geometric mean of 2,280 kgCO_2-e (100-year horizon) and an arithmetic mean of 2,618 kgCO_2-e (100-year horizon). The same pattern appears to be true when looking at per capita emissions. New Zealand households' year-long per capita dietary emissions in the 100-year horizon, as measured by both the unadjusted geometric mean (1,019 kgCO_2-e) and arithmetic mean (1,155 kgCO_2-e), appear to be lower than those found in most other studies: arithmetic mean=1,018 kgCO_2-e [2.79 kgCO_2-e per person per day * 365 days] in the UK (Reynolds et al., 2015); arithmetic mean=1,200 kgCO_2-e in Denmark (Lund et al., 2017); arithmetic mean=1,723 kgCO_2-e [4.72 kgCO_2-e per person per day * 365 days] in the US (Rose et al., 2019); arithmetic mean=1,898 kgCO_2-e [5.2 kgCO_2-e per person per day * 365 days] in Italy (Mertens et al., 2019);

arithmetic mean=1,971 kgCO_2-e [5.4 kgCO_2-e per person per day * 365 days] in Denmark (Mertens et al., 2019); arithmetic mean=2,044 kgCO_2-e [5.6 kgCO_2-e per person per day * 365 days] in the Czech Republic (Mertens et al., 2019); arithmetic mean=2,190 kgCO_2-e [6.0 kgCO_2-e per person per day * 365 days] in France (Mertens et al., 2019); and arithmetic mean=2,384 kgCO_2-e [6.532 kgCO_2-e per person per day * 365 days] in Ireland (Hyland et al., 2017). Due to the fact that carbon emissions are conventionally measured in 100-year time spans, the reviewed literature does not provide comparable figures for the 20-year horizon.

The observation that New Zealand households' food purchases account for fewer dietary emissions, both in total and when standardized per capita, than households in most other high-income economies is surprising for a nation which produces a great deal of meat and dairy. Theoretically, differences in average household size between New Zealand and other affluent countries could lead to disparities in total household dietary emissions. Nevertheless, even if true, this would not explain the differences observed in per capita emissions. Substantial disparities in total dietary consumption, on the other hand, between New Zealand and other countries could conceivably account for the differences in total household and per capita dietary emissions if New Zealanders were found to have a significantly lower average caloric intake, but this is highly improbable. The most likely explanation for the observed disparities is methodological heterogeneity, although it is difficult to determine which aspects of the methodology specifically may have led to lower GHGE estimates in the current study.

With regards to possible associations between socio-demographic variables and dietary emissions, bivariate analyses indicated that all demographic variables examined in this study were predictors of per capita dietary emissions. After the other demographic variables were adjusted for in multiple linear regression, age of the primary shopper and household size remained as significant predictors of per capita dietary emissions that also showed clear patterns of association. The positive association observed between age of the primary household shopper and per capita dietary emissions is consistent with the results of previous studies (Nordström et al., 2020) (Salo et al., 2021) (Rose et al., 2019) (Mertens et al., 2019), although Mertens et al. (2019) observed this association in only two (Denmark and France) of four countries examined. In the absence of evidence suggesting that older people eat significantly higher quantities of food, dietary preferences may be viewed as a more likely cause of higher dietary emissions. It is plausible that older people on average, especially in New Zealand, might consume more traditional diets comprised largely of meat and dairy products, which account for the highest amounts of carbon dioxide equivalents per kilogram of food. No clear positive association between age and meat consumption was found, however, in a secondary analysis of New Zealand's 2008/09 Adult Nutrition Survey (ANS) examining beef and lamb intake (Parnell et al. 2012). As for dairy, ANS results suggest that milk, "dairy products", and "butter and margarine" do comprise higher percentages of daily energy intake for older New Zealanders (University of Otago & Ministry of Health, 2011). For example, on average milk constitutes 5.8% of the daily energy intake for males aged 71-years or older, but only 3.7% of the daily energy intake for males aged 19-30 years-old (University of Otago & Ministry of Health, 2011). However, males aged 71-years and older only consume an average of 8,067 kilojoules per day, while the mean daily energy consumption for males aged 19-30 years-old is 11,940 kilojoules (University of Otago & Ministry of Health, 2011). The actual quantity of meat and dairy consumed, rather than the percentage of daily energy intake comprised by meat and dairy, is most relevant for the purposes of this discussion. It is difficult to ascertain with certainty from the ANS results whether meat and dairy intakes (in grams) were higher in older adults and, therefore, whether this would be responsible for higher per capita dietary emissions. Moreover, findings from the ANS suggest that older age groups may be more likely to eat the recommended three or more servings of vegetables per day and the recommended two or more servings of fruit per day than younger age groups (University of Otago & Ministry of Health, 2011). Vegetables and fruits account for some of the lowest emissions according to LCA values, so diets featuring higher amounts of these foods would likely have smaller carbon footprints if the total quantity of food consumed was held constant. Alternatively, the higher per capita dietary emissions observed in households with older primary shoppers could be a result of households' with younger primary shoppers propensities to eating out; the food consumed in these occasions would not be captured in the Nielsen dataset. Older shoppers might consume more home-cooked meals than younger shoppers and, thus, purchase greater quantities of foods for consumption at home. Findings from the 2008/09 ANS support this notion: "Adults aged 15–30 years were more likely to report eating fast food or takeaways three or more times a week compared to other age groups" (University of Otago & Ministry of Health, 2011, p. 251). However, previous studies which examined individuals' dietary intake (and would, therefore, capture out of home consumption) also found that older adults had higher dietary emissions (Rose et al., 2019) (Mertens et al., 2019).

The inverse relationship observed between household size and per capita dietary emissions differs from the literature review's findings — Nordström et al. (2020) estimate that adults without children in the household account for 42% fewer dietary emissions than adults with children, and Wrieden et al. (2019) find no association between household size and per capita dietary emissions. However, the inverse relationship observed in the present research is affirmed by other studies which were not encountered in the literature review. Fremstad et al. (2018) estimate that per capita emissions (including, but not limited to, dietary emissions) are reduced by about 6% for each additional member added to a given household. Similarly, Underwood & Zahran (2015) find that, on average, a person cohabitating with others has a carbon footprint that is 23% less than it would be if that person lived alone. These environmental benefits of larger households are typically attributed to the sharing of goods such as housing and appliances. Intuitively, one might expect per capita food expenditure to be unaffected by household size. Deaton & Paxson (1998) suggest that just the opposite is true: examining data from both affluent and low-income countries, they find that per capita expenditure on food decreases as household size increases. Interestingly, this relationship is strongest in low-income countries where, presumably, there would be less potential for spending money that would otherwise have been spent on shared household goods.

Perhaps the best explanation for this inverse relationship between household size and dietary expenditure (and, by extension, dietary emissions) is that, according to research on the topic, larger households waste less food per capita (Yu & Jaenicke, 2020) (Giordano et al., 2019) (Smith & Landry, 2021) (Herzberg et al., 2020). Household size probably does not influence the quantity of food consumed by each household member, but it may be that larger households cook and share more food collectively in ways that reduce food waste. With each household member wasting less food, per person food expenditure would decrease and, consequently, per capita dietary emissions would be lower in larger households. Another possible reason for the observed association between household size and dietary emissions is that, as household size increases, each household member's actual consumption is reflected less in the entire household's expenditure. It could very well be that in large households there is a higher frequency of household members eating foods that were not purchased by the household's primary shopper. In this study, though panellists were supposed to scan foods purchased by all members of the household, scanning may be more inconsistent for purchases made by household members other than the primary shopper. Finally, the present research's finding of an inverse relationship between household size and per capita dietary emissions could be confounded by the number of young children in larger households. Adults and children were counted equally when quantifying household size for the purposes of this study because, although small children might consume significantly less food than adults, older adolescents often consume just as much or more (University of Otago and Ministry of Health, 2011). However, it is possible that the children in larger households within the 2019 Nielsen Homescan® panel tended to be younger. If so, those younger children could have lowered the average per capita dietary emissions of that household.

Altogether, the various explanations for why household size would have an inverse relationship with dietary emissions raise the question (as discussed previously in the literature review) of how well household expenditures reflect the individual diets consumed by household members. Household purchasing data, no matter how reliably purchases are recorded, fails to capture all that happens between the time a food is bought and the time it is eaten. The frequencies with which household members eat outside the home, provide food for non-household members, and waste food may very well have substantial impacts on estimates of dietary emissions, and the 2019 Nielsen Homescan® panel does not provide any information on these factors. Without complementary data provided by dietary intake assessment methods such as food diaries, dietary recalls, or food frequency questionnaires, extrapolating individuals' consumption from household purchases is problematic, perhaps especially for larger households. Overall, this lack of information on individual household members' dietary habits following food purchasing constitutes a primary limitation of the present research.

Additionally, using a process-based Life Cycle Assessment (LCA) to estimate the carbon emissions associated with each food in the Nielsen Homescan® panel presents limitations. Though process-based LCAs are better suited than Environmental Input-Output (EIO) LCAs to capture differences in emissions amongst wide varieties of foods, which was an essential consideration in this study, their ability to accurately quantify carbon footprint is constrained by the truncation error. The boundaries of analysis for the process-based LCA utilized in this study were "cradle to point-of-sale." Seven important life cycle stages were captured in each food's dietary estimate — farming and processing, transit packaging, transportation, consumer packaging, warehouse and distribution, refrigeration, and retail overheads —, but the stages of home storage, food preparation, and waste were unaccounted for. Furthermore, although it aggregates foods less than EIO-LCAs typically do, the process-based LCA employed here still does combine some relatively disparate food groups for the purposes of feasibility, resulting in just 76 total food categories. Of course, the broad spectrum of foods available in New Zealand cannot be precisely sorted into only 76 categories, nor can those 76 categories provide fully accurate emissions estimates for all foods. It is important to qualify the research's findings with the acknowledgement that the results are broad estimates, not exact measurements. Additionally, the present study is limited by the fact that the food purchasing data upon which it is based was collected by a third party. Nielsen had full control over recruitment strategies, data collection, biases, and incentives for participants. As a result, some household demographic data that would have been quite useful for the purposes of this research were not collected. In particular, the possible association between household ethnicity and per capita dietary emissions would have been relevant to examine. The exact age of each household's primary shopper, rather than their age group, would also have been preferable for the purposes of enabling trend analysis.

The primary strength of this study is the comprehensiveness of the household purchasing data. The 1,800 households included in the 2019 Nielsen Homescan® panel (1,775 after exclusions) are not only representative of the New Zealand population in key demographic characteristics (household life stage, household size, and household income), and broad geographical regions (upper North Island, lower North Island, South Island), but they also yield a ratio of sample to population size that is unusually large. Furthermore, the data collection method of household shoppers scanning all foods purchased over the course of an entire year results in deeper, more reliable insights into households' dietary habits than would otherwise be available, for example, from expenditure surveys, or even other forms of participant-recorded food purchase data, which do not often span an entire year. And although it may not be possible to determine every household member's consumption using household purchasing data, it is more objective and less subject to recall errors or reporting biases than individuals' consumption data collected via 24-hour dietary recalls, food diaries, food frequency questionnaires, or dietary history interviews. It is possible, however, that households did not scan all food and beverage items brought back into the home.

Further underscoring the comprehensiveness of the Nielsen Homescan® panel data, scanned purchases included foods and beverages obtained from a wide range of retailers — supermarkets, bakeries, petrol stations, fruit and vegetable stores, convenience stores, specialty stores, and online stores. Such expansive coverage of potential food vendors provides additional confidence in the data's ability to capture diverse household dietary habits. On the other hand, as discussed above, foods purchased and consumed out of home (in cafes and restaurants, for example) are not captured in the dataset, and it is plausible that the proportion of food and beverages bought and consumed outside the home differs by household characteristics. For instance, the 2008/09 Adult Nutrition Survey found that 20.3% of males aged 19-30 years-old ate fast food or takeaways three or more times a week, compared to only 6.1% of males aged 31-50, 1.6% of males aged 51-70, and 0.4% of males aged 71 and older (University of Otago and Ministry of Health, 2011).

With regards to emissions estimates, this study's findings are made more robust by the inclusion of the 20-year time frame for greenhouse gas measurements in addition to the standard 100-year horizon that most research in the field is limited to. The 20-year timeframe is important to consider because it captures the sizable contributions of methane to global warming, while the 100-year horizon does not. Moreover, employing both horizons helps to validate the study's results. The findings for both time frames were nearly identical in this case.

Future research should focus on combining household purchasing data with household members' individual dietary records in New Zealand to corroborate the associations found between age of the primary shopper and per capita dietary emissions, as well as household size and per capita dietary emissions. Specifically, the combination of purchasing data and dietary records could provide indications of inter-household variability in food waste and intra-household variability in consuming foods purchased by the primary shopper. The positive association observed between age of a household's primary shopper and per capita dietary emissions could also be explored further by examining Nielsen panel data collected during the 2020 and 2021 COVID-19 Alert Level 4 time periods in New Zealand, when takeaways, restaurants and cafes were closed. Such analysis would help determine the extent to which the frequency of eating takeaway foods or foods outside the home may or may not mediate differences in per capita dietary emissions amongst various age groups, though diets and food purchases might differ in many ways during lockdowns to control an infectious disease pandemic. Finally, additional analysis of the 2019 Nielsen Homescan® panel could produce valuable new insights which account for differences in the quantity of food consumed by estimating per capita dietary emissions standardized per calorie purchased. Recent research conducted by Tawfiq et al. (2021) used a similar methodology to assess whether the healthiness of food and beverage purchases vary by retail store type, linking the 2019 Nielsen Homescan® panel dataset with two food composition databases that include energy measures. With enhanced understanding of the observed association between age of a household's primary shopper and per capita dietary emissions, interventions may be devised that encourage older shoppers to purchase lower-emitting foods and, particularly, less meat and dairy. This could take the form of a universal environmental impact score label akin to New Zealand’s Health Star Ratings, for example.

6. Conclusions

Already, climate change is having significant, harmful effects on human health worldwide which will become increasingly damaging over time in the absence of serious international interventions. The New Zealand government recently announced a revised Nationally Determined Contribution (NDC) towards the Paris Climate Agreement's goal of capping global warming at 1.5 degrees above pre-industrial levels. The new NDC targets a 50% reduction in 2005 levels of net greenhouse gas emissions by 2030 (The New Zealand Government, 2021). While New Zealand's food exports (meat and dairy products in particular) will continue to account for substantial emissions, encouraging New Zealanders to purchase foods with lower carbon footprints could feasibly help the country reach its emissions reduction goal, as food production is estimated to account for 19-29% (Vermeulen et al., 2012) or even 34% (Crippa et al., 2021) of total global emissions. Significant public health benefits could be derived concurrently by emphasizing reductions in meat and dairy intake alongside increases in fruit and vegetable intake.

In order to identify the populations which are best positioned to contribute towards food-related emissions reductions, this study's primary aim was to evaluate whether New Zealand households' per capita dietary emissions differed significantly by the socio-demographic variables of sex of the primary shopper, household income, age of the primary shopper, household life stage, and household size. Extensive data on the food and beverage purchases of 1,775 nationally representative households over the course of a year were linked with process-based Life Cycle Assessment estimates of each product's carbon footprint. Multiple linear regression modelling revealed that age of the primary shopper and household size were significant predictors of per capita dietary emissions. Possible explanations for the positive association observed between age of the primary shopper and per capita dietary emissions included diet composition (higher consumption of meat and dairy) and lower frequency of eating takeaway foods. The observed inverse relationship between household size and per capita dietary emissions was explained most plausibly by larger households' tendency to waste less food per household member (and hence purchase less), as evidenced in the literature, or by the possibility of larger households recording food purchases more inconsistently. Lastly, future research is recommended to further corroborate these possible explanations and inform the development of interventions aimed at encouraging older shoppers to purchase lower-emitting foods. Reductions in meat and dairy purchases, in particular, should be pursued because they account for the highest greenhouse gas emissions.

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Appendix I: Literature Review Search Terms

TITLE-ABS-KEY (("diet*") OR ("nutrition*") OR ("food consum*") OR ("dietary consum*") OR ("food purchas*") OR ("household spending") OR ("household expenditure*") OR ("eat*") OR ("food intake") OR ("food choice*") OR ("food expenditure*") AND ("carbon footprint") OR ("greenhouse gas") OR ("gas emission*") OR ("environment* impact") OR ("climat* impact") AND ("demographic*") OR ("socio-demographic*") OR ("sociodemographic*") OR ("household*") AND NOT ("cattle*") OR ("cow*") OR ("livestock") OR ("farm*"))

Appendix II: Demographic Variable Groups Table

Household Feature	Variable names and levels as defined by 2019 Nielsen Homescan® panel	Variable names and levels used for statistical analysis
Sex of the primary household shopper	*Female* *Male*	*Female* *Male*
Household's yearly income: Households' total annual income in terms of New Zealand dollars	*$12,000 or less per year* *$12,001 - $22,000*	*$22,000 or less*
	$22,001 - $30,000 *$30,001 - $40,000* *$40,001 - $50,000* *$50,001 - $70,000* *$70,001 - $90,000* *$90,001 - $110,000* *$110,001 - $140,000* *More than $140,000*	*$22,001 - $30,000* *$30,001 - $40,000* *$40,001 - $50,000* *$50,001 - $70,000* *$70,001 - $90,000* *$90,001 - $110,000* *$110,001 - $140,000* *More than $140,000*
Age of the primary household shopper at the onset of the panel period:	*Under 25 years* *25 – 29 years* *30 – 34 years*	*34 years and under*

	35 – 39 years *40 – 49 years* *50 – 65 years* *Over 65 years*	*35 – 39 years* *40 – 49 years* *50 – 65 years* *Over 65 years*
Household life stage: These variables reflect the number and ages of adults and children living in the household. Children are defined as individuals who are less than 18-years-old	*Young families:* Adults any age, children under 11-years-old only *Mixed families:* Adults any age, 1 or more children under 11 years-old and 1 or more children aged 11 - 18-years-old *Older families:* Adults any age, children aged 11 - 17-years-old only *Older Singles & Couples:* Adults over 45-years-old, 1 - 2 member households *"Adult Households Inc YSC":* All members of household aged 18 years or older, no household size limits (excludes all other life stage groups); "Inc YSC" = Including young singles and couples	*Young families:* Adults any age, children under 11-years-old only *Mixed families:* Adults any age, 1 or more children under 11 years-old and 1 or more children aged 11 - 18-years-old *Older families:* Adults any age, children aged 11 - 17-years-old only *Older Singles & Couples:* Adults over 45-years-old, 1 - 2 member households *"Adult Households Inc YSC":* All members of household aged 18 years or older, no household size limits (excludes all other life stage groups); "Inc YSC" = Including young singles and couples
Household size:		

These variables reflect the total number of individual people that reside in the household; children and adults both count equally	*1 - 11*	*1 - 11*

Appendix III: Food Unit Size and Density Estimates

Food	Weight Estimate
1 apple	133 grams
1 bunch asparagus	250 grams
1 avocado	170 grams
1 bunch baby carrot	15 grams
1 package of greens (kale, spinach or silverbeet)	120 grams
1 loaf of bread	700 grams
1 cabbage	900 grams
1 capsicum	270 grams
1 cauliflower	600 grams
1 head of celery	450 grams
1 courgette	200 grams
1 cucumber	200 grams
1 dragon fruit	600 grams
1 chicken drumstick	100 grams
1 egg	51 grams
1 fennel bulb	234 grams
1 head of garlic	50 grams
1 head of lettuce	300 grams
1 package of potted herbs (e.g., parsley, coriander, etc.)	40 grams
1 mango	175 grams
1 medium tomato	120 grams
1 onion (brown, red, or white)	160 grams
1 oyster	50 grams
1 package of fresh herbs (not potted)	25 grams
1 peach	150 grams
1 pineapple	1000 grams
1 pumpkin	1200 grams
1 punnet radishes	100 grams
1 bunch spring onion	100 grams

Food	Density Used for Converting Volume Measure to Weight Measure
Ice cream	0.69 g/ml
Sauces	1.11 g/ml

Appendix IV: LCA Reference Table

Aggregated categories for comparison	Hoolohan et al. (2013) category	Updated from Drew et al. (2020) by Dr. Bradbury? (Y/N)	Farming & processing (GWP100; kgCO2e per kg)	Farming & processing (GWP20; kgCO2e per kg)	Transit packaging (kgCO2e/kg)	Consumer packaging (kgCO2e/kg)	Transport (kgCO2e/kg)	Warehouse & distribution (kgCO2e/kg)	Refrigeration (kgCO2e/kg)	Overheads (kgCO2e/kg)	Total lifecycle emissions (100-year GWP: kgCO2e/kg)	Total lifecycle emissions (20-year GWP: kgCO2e/kg)	Source of farming and processing data	Original source utilised by Hoolohan et al. (2013)
Alcohol	Wines	N	0.65	0.65	0.07	0.51	0.13	0.03	0.03	0.61	2.03	2.03	Greenhaigh et al. (2011)	
Alcohol	Spirits and liqueurs	N	0.65	0.65	0.07	0.49	0.33	0.03	0.00	1.46	3.03	3.03	Hoolohan et al. (2013)	Garnett (2007)
Alcohol	Beer and cider	N	0.28	0.28	0.07	0.56	0.13	0.02	0.00	0.21	1.28	1.28	Hoolohan et al. (2013)	Garnett (2007)
Beverages	Soft drinks	N	0.19	0.19	0.08	0.23	0.23	0.02	0.00	0.10	0.84	0.84	Hoolohan et al. (2013)	
Beverages	Juice	N	0.71	0.71	0.08	0.11	0.13	0.02	0.00	0.13	1.18	1.18	Hoolohan et al. (2013)	
Beverages	Water	Not used in Drew et al. (2020)	0.03	0.03	0.08	0.29	0.13	0.02	0.00	0.03	0.58	0.58	Hoolohan et al. (2013)	Bespoke calculation based on Foster et al. (2006)

Fruit and vegetables	Apples and pears	Y	0.28	0.28	0.00	0.01	0.13	0.00	0.03	0.19	0.64	0.64	Calculated by averaging the Goossen (2018) estimate with the Saunders et al. (2006) estimate as well as the average of the two Milà i Canals et al. (2006) estimates (i.e. (0.05 +0.06 +(0.48+0.96)/2))/3)	
Fruit and vegetables	Citrus	N	0.33	0.33	0.00	0.01	0.28	0.00	0.00	0.27	0.89	0.89	Hoolohan et al. (2013)	Ribal et al. (2009)
Fruit and vegetables	Bananas	N	0.23	0.23	0.00	0.00	0.35	0.00	0.00	0.10	0.69	0.69	Average of: Iriate et al. (2014): 'On-farm' + 'Post-harvest fruit fandling' (0.27); Roibas (2016): 'farm stage' (0.28); Lescot (2012): 'farm practices' (0.14) (Hoolohan assumed similar as citrus to farm-gate)	
Fruit and vegetables	Berries	N	0.47	0.47	0.00	0.05	0.13	0.00	0.09	0.73	1.47	1.47	Hume et al. (2009)	
Fruit and vegetables	Stone fruit & grapes	N	0.52	0.52	0.00	0.09	0.13	0.00	0.09	0.46	1.29	1.29	Hume et al. (2009)	
Fruit and vegetables	Melons	Not used in Drew et al. (2020)	0.33	0.33	0.00	0.01	1.22	0.00	0.00	0.55	2.11	2.11	Hoolohan et al. (2013)	
Fruit and vegetables	Kiwifruit	Not used in Drew et al. (2020)	0.27	0.27	0.00	0.01	0.13	0.00	0.03	0.19	0.63	0.63	Averaged the four estimates from Müller et al. (2014) and then averaged with the estimate from Mithraratne et al. (2008), i.e. (((0.135+0.146+0.204+0.217)/4)+0.217)/2. Used emissions for apples and pears for other stages.	

Fruit and vegetables	Exotic fruit	N	0.33	0.33	0.00	0.03	1.22	0.00	0.23	0.55	2.36	2.36	Hoolohan et al. (2013)	
Fruit and vegetables	Dried fruit and vegetables, nuts and seeds	N	2.66	2.66	0.07	0.08	0.47	0.02	0.00	0.72	4.01	4.01	Hoolohan et al. (2013)	
Fruit and vegetables	Frozen fruit	Not used in Drew et al. (2020)	0.71	0.71	0.00	0.22	0.13	0.52	0.46	0.45	2.48	2.48	Hoolohan et al. (2013)	
Fruit and vegetables	Prepared fruit	Not used in Drew et al. (2020)	0.47	0.47	0.03	0.05	0.13	0.01	0.46	0.74	1.89	1.89	Hoolohan et al. (2013)	
Fruit and vegetables	Tinned fruit	Not used in Drew et al. (2020)	0.60	0.60	0.07	0.22	0.13	0.02	0.00	0.25	1.29	1.29	Hoolohan et al. (2013)	
Fruit and vegetables	Potatoes	N	0.23	0.23	0.00	0.01	0.13	0.00	0.00	0.10	0.48	0.48	Hoolohan et al. (2013)	Williams & Audsley (2008)
Fruit and vegetables	Other roots	N	0.06	0.06	0.00	0.01	0.13	0.00	0.07	0.11	0.39	0.67	Saunders et al. (2006)	
Fruit and vegetables	Salad	N	0.39	0.39	0.08	0.78	0.13	0.02	0.46	1.15	3.01	3.01	Hoolohan et al. (2013)	Hospido et al. (2009)
Fruit and vegetables	Tomatoes	N	2.48	2.48	0.00	0.18	0.13	0.00	0.00	0.38	3.18	3.18	Barber & Pellow (2008)	
Fruit and vegetables	Other vegetables	N	1.15	1.15	0.00	0.12	0.13	0.00	0.23	0.32	1.95	1.95	Hoolohan et al. (2013)	

Fruit and vegetables	Capsicum	Not used in Drew et al. (2020)	3.71	3.71	0.00	0.18	0.13	0.00	0.00	0.38	4.41	4.41	Barber & Pellow (2008); used emissions from tomatoes for the other stages.
Fruit and vegetables	Mushrooms	N	3.40	3.40	0.00	0.40	0.13	0.00	0.00	0.39	0.39	4.32	Hoolohan et al. (2013)
Fruit and vegetables	Frozen vegetables	Not used in Drew et al. (2020)	1.51	1.51	0.00	0.04	0.13	0.49	0.46	0.20	2.83	2.83	Hoolohan et al. (2013)
Fruit and vegetables	Prepared vegetables	Not used in Drew et al. (2020)	1.26	1.26	0.03	0.07	0.13	0.01	0.46	0.56	2.52	2.52	Hoolohan et al. (2013)
Fruit and vegetables	Tinned vegetables	Not used in Drew et al. (2020)	1.39	1.39	0.07	0.27	0.13	0.02	0.00	0.18	2.07	2.07	Hoolohan et al. (2013)
Dairy products	Milk	Y	0.78	1.96	0.00	0.05	0.13	0.00	0.46	0.07	1.49	2.67	Ledgard et al. (2020)
Dairy products	Cheese	N	9.00	16.94	0.08	0.08	0.13	0.02	0.46	0.58	10.34	18.28	Basset-Mens et al. (2007)
Dairy products	Cream	Y	3.67	9.21	0.08	0.16	0.13	0.02	0.46	0.34	4.85	10.40	Milk conversion calculation using milk estimate from Ledgard et al. (2020)

Dairy products	Yoghurt	Y	2.16	5.44	0.08	0.10	0.13	0.02	0.46	0.29	3.24	6.51	Milk conversion calculation using milk estimate from Ledgard et al. (2020)	
Dairy products	Butter	Y	9.91	24.89	0.08	0.02	0.13	0.02	0.46	0.52	11.13	26.11	Milk conversion calculation using milk estimate from Ledgard et al. (2020)	
Dairy alternatives	Margarine	N	1.16	1.16	0.08	0.08	0.55	0.02	0.46	0.32	2.67	2.67	Hoolohan et al. (2013)	
Dairy alternatives	Soya	N	0.19	0.19	0.08	0.07	0.21	0.02	0.46	0.16	1.18	1.18	Hoolohan et al. (2013)	90% water, 10% Soyabean from Williams et al. (2006)
Dairy products	Ice cream	Y	0.89	2.23	0.08	0.15	0.13	0.02	0.46	0.26	1.99	3.33	Milk conversion calculation using milk estimate from Ledgard et al. (2020)	
Dairy products	Powdered milk	N	10.58	29.87	0.07	0.26	0.13	0.02	0.00	0.55	11.61	30.89	Saunders et al. (2007)	
Eggs	Eggs	N	4.25	4.25	0.08	0.10	0.13	0.02	0.00	0.35	4.93	4.93	Hoolohan et al. (2013)	Williams et al. (2006). .

Red and processed meat	Beef	Y	19.79	49.40	0.01	0.01	0.13	0.02	0.46	0.47	20.89	50.50	Average of Lieffering (20.33) and Payen (19.24). Payen is 10.39 kg of liveweight beef cattle CO2eq (middle of range reported). Used the Muir conversion from live weight to carcass weight (54%) References: Lieffering et al. (2012); Payen et al. (2020); Muir & Thomson (2008)	
Red and processed meat	Lamb	N	15.77	41.91	0.01	0.00	0.13	0.02	0.46	0.67	17.06	43.20	Ledgard et al. (2010)	
Poultry	Poultry	N	2.82	2.82	0.01	0.02	0.13	0.02	0.46	0.52	3.97	3.97	Hoolohan et al. (2013)	Williams & Audsley (2008)
Red and processed meat	Pork, bacon & sausages	N	9.07	9.07	0.01	0.01	0.55	0.02	0.46	0.50	10.61	10.61	Hoolohan et al. (2013)	Williams et al. (2006)
Red and processed meat	Processed & cooked meat	Not used in Drew et al. (2020)	10.46	10.46	0.08	0.12	0.17	0.74	0.46	1.14	13.17	13.17	Hoolohan et al. (2013)	
Red and processed meat	Tinned meat	Not used in Drew et al. (2020)	10.59	10.59	0.07	0.39	0.13	0.02	0.00	0.58	11.79	11.79	Hoolohan et al. (2013)	
Fish and seafood	Fresh fish	N	4.58	4.58	0.01	0.06	0.13	0.02	0.46	0.68	5.94	5.94	Hilborn & Tellier (2012)	

Fish and seafood	Tinned fish	Not used in Drew et al. (2020)	5.47	1.34	0.07	0.68	0.30	0.02	0.00	0.79	3.21	3.21	Applied the ratio of fresh and tinned fish from Hoolohan et al. (2013) to the fresh fish estimate from Hilborn & Tellier (2012) to get the tinned fish estimate	Nielsen et al. (2003)
Vegetarian (meat alternatives)	Vegetarian (meat alternatives)	N	3.09	3.09	0.07	0.27	0.88	0.02	0.46	0.64	5.42	5.42	Hoolohan et al. (2013)	Williams et al. (2006)
Red and processed meat	Frozen meat and fish	Not used in Drew et al. (2020)	9.91	9.91	0.00	0.17	0.13	0.67	0.52	0.80	12.20	12.20	Hoolohan et al. (2013)	
Red and processed meat	Other meat and fish	Not used in Drew et al. (2020)	8.49	8.49	0.00	0.01	0.13	0.00	0.46	0.38	9.47	9.47	Hoolohan et al. (2013)	
Bread, rice, pasta, cereals	Sandwiches	N	6.28	6.28	0.00	0.11	0.13	0.02	0.46	0.86	7.85	7.85	Hoolohan et al. (2013)	
Red and processed meat	Pies	N	2.76	2.76	0.07	0.06	0.13	0.02	0.46	0.53	4.03	4.03	Hoolohan et al. (2013)	
Ready meals	Ready meals, pizza, fresh pasta	N	4.58	4.58	0.07	0.19	0.13	0.02	0.46	0.58	6.02	6.02	Hoolohan et al. (2013)	
Cakes, biscuits	Desserts	N	1.80	1.80	0.07	0.25	0.13	0.00	0.46	0.52	3.23	3.23	Hoolohan et al. (2013)	
Bread, rice, pasta, cereals	Bread	N	0.84	0.84	0.00	0.03	0.33	0.02	0.00	0.24	1.45	1.45	Hoolohan et al. (2013)	
Bread, rice, pasta, cereals	Rice	N	2.93	5.85	0.07	0.16	0.56	0.02	0.00	0.36	4.10	7.02	Hoolohan et al. (2013)	

Bread, rice, pasta, cereals	Pasta	N	1.01	1.01	0.07	0.09	0.33	0.02	0.00	0.23	1.74	1.74	Hoolohan et al. (2013)	Williams et al. (2006)
Cakes, biscuits	Cake	N	3.24	3.24	0.07	0.20	0.13	0.02	0.00	0.62	4.28	4.28	Hoolohan et al. (2013)	
Cakes, biscuits	Biscuits	N	3.35	3.35	0.07	0.24	0.13	0.02	0.00	0.53	4.34	4.34	Hoolohan et al. (2013)	
Bread, rice, pasta, cereals	Cereals	N	0.89	0.89	0.07	0.20	0.22	0.02	0.00	0.38	1.77	1.77	Hoolohan et al. (2013)	
Savoury snacks	Crisps & snacks	N	2.61	2.61	0.07	0.25	0.13	0.02	0.00	0.73	3.81	3.81	Hoolohan et al. (2013)	Nilsson et al. (2011)
Bread, rice, pasta, cereals	Home baking (exc. Eggs)	Not used in Drew et al. (2020)	0.82	0.82	0.07	0.03	0.40	0.02	0.00	0.07	1.41	1.41	Flour 45% [Williams et al. (2006)]; sugar 55%	
Condiments and spreads	Jam, honey, marmalade	N	1.15	1.15	0.07	0.61	0.13	0.03	0.00	0.47	2.47	2.47	Hoolohan et al. (2013)	
Ready meals	Soup	N	2.11	2.11	0.07	0.46	0.13	0.02	0.00	0.26	3.06	3.06	Hoolohan et al. (2013)	
Condiments and spreads	Condiments	N	1.19	1.19	0.07	0.51	0.13	0.02	0.00	0.47	2.40	2.40	Hoolohan et al. (2013)	
Confection-ary	Confection-ary	N	2.71	2.71	0.07	0.39	0.97	0.02	0.00	0.86	5.02	5.02	Hoolohan et al. (2013)	

Beverages	Coffee powder and tea bags	Y	10.08	10.08	0.07	0.42	0.47	0.10	0.00	1.33	12.47	12.47	Used 'beverages' category from Hoolohan et al. (2013) but transport value from Drew et al. (2020) (adjusted to raw product not ready to drink beverage).	Büsser & Jungbluth (2009)
Fruit and vegetables	Coconut	N	1.00	1.00	0.07	0.08	0.47	0.02	0.00	0.72	2.35	2.35	Dumelin (2009)	
Fish and seafood	Mussels	N	9.33	9.33	0.01	0.06	0.13	0.02	0.46	0.68	10.69	10.69	Clune et al. (2017)	
Fish and seafood	Prawns	N	2.48	2.48	0.01	0.06	0.13	0.02	0.46	0.68	3.84	3.84	Hilborn & Tellier (2012)	
Red and processed meat	Beef dripping	N	2.02	2.02	0.01	0.19	0.38	0.02	0.00	0.03	2.65	2.65	Schmidt (2015)	
Condiments and spreads	Coconut oil	N	1.00	1.00	0.01	0.19	0.38	0.02	0.00	0.03	1.63	1.63	Dumelin (2009)	
Dairy alternatives	Coconut creams	N	2.66	2.66	0.07	0.08	0.47	0.02	0.00	0.72	4.01	4.01	Dumelin (2009)	
Dairy products	Butter and margarine blends		5.53	13.026	0.08	0.05	0.34	0.02	0.46	0.42	6.90	14.39	50:50 ratio of butter and margarine	
Condiments and spreads	Vegetable oils	N	1.25	1.25	0.01	0.19	0.38	0.02	0.00	0.03	1.88	1.88	Schmidt (2015)	
Condiments and spreads	Peanut butter	N	1.29	1.29	0.07	0.08	0.47	0.02	0.00	0.72	2.64	2.64	McCarty et al. (2014)	

Beverages	RTD coffee and tea	N	0.30	0.30	0.00	0.00	0.00	0.00	0.00	0.01	0.31	0.31	Hoolohan et al. (2013)	Büsser & Jungbluth (2009); Doublet & Jungbluth (2010)

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Appendix V: Sensitivity analysis (with outliers removed) of associations of household variables with per capita dietary emissions (20-year horizon)

Variable	*N*	Per Capita Dietary Emissions (20-year horizon) *Ratio (95% CI)*[1]	*p-value*	*p-value of categorical variables*[2]
Sex of the primary shopper				0.927
Female	1316	1.00 (ref)		
Male	418	1.00 (0.95 to 1.05)	0.927	
Household income				**0.013**
$22,000 or less	150	1.00 (ref)		
$22,001 - $30,000	197	0.92 (0.83 to 1.01)	0.075	
$30,001 - $40,000	202	1.03 (0.94 to 1.13)	0.519	
$40,001 - $50,000	160	1.07 (0.96 to 1.18)	0.215	
$50,001 - $70,000	263	1.04 (0.95 to 1.14)	0.383	
$70,001 - $90,000	237	1.02 (0.93 to 1.12)	0.696	
$90,001 - $110,000	190	0.98 (0.88 to 1.08)	0.670	
$110,001 - $140,000	180	1.02 (0.92 to 1.13)	0.708	
More than $140,000	155	0.93 (0.83 to 1.03)	0.155	
Age of the primary shopper				**<0.001**
34 years and under	99	1.00 (ref)		
35 - 39 years	129	1.18 (1.05 to 1.33)	**0.006**	
40 - 49 years	350	1.17 (1.06 to 1.30)	**0.003**	
50 - 65 years	681	1.28 (1.15 to 1.42)	**<0.001**	
Over 65 years	475	1.37 (1.22 to 1.53)	**<0.001**	
Household life stage				**<0.001**
Young families	216	1.00 (ref group)		
Mixed Families	105	1.04 (0.94 to 1.16)	0.440	
Older Families	190	1.12 (1.02 to 1.23)	**0.015**	

Adult Households Inc YSC	421	1.06 (0.97 to 1.16)	0.189
Older Singles & Couples	802	1.32 (1.19 to 1.47)	**<0.001**
Household size	1734	0.92 (0.89 to 0.94)	**<0.001**

Observations: 1734

R^2 / R^2 adjusted: 0.277 / 0.269

1. Ratio of the geometric mean
2. Calculated using an F-test

Appendix VI: Sensitivity analysis (with outliers removed) of associations of household variables with per capita dietary emissions (100-year horizon)

		Per Capita Dietary Emissions (100-year horizon)		
Variable	*N*	*Ratio (95% CI)*[1]	*p-value*	*p-value of categorical variables*[2]
Sex of the primary shopper				0.989
Female	1316	1.00 (ref)		
Male	413	1.00 (0.95 to 1.05)	0.989	
Household Income				**0.009**
$22,000 or less	147	1.00 (ref)		
$22,001 - $30,000	197	0.93 (0.85 to 1.01)	0.100	
$30,001 - $40,000	203	1.02 (0.94 to 1.12)	0.596	
$40,001 - $50,000	159	1.06 (0.96 to 1.17)	0.229	
$50,001 - $70,000	264	1.04 (0.95 to 1.13)	0.403	
$70,001 - $90,000	235	1.01 (0.92 to 1.10)	0.877	
$90,001 - $110,000	189	0.96 (0.88 to 1.06)	0.456	
$110,001 - $140,000	180	1.01 (0.92 to 1.12)	0.760	
More than $140,000	155	0.92 (0.83 to 1.01)	0.084	
Age of the primary shopper				**<0.001**
34 years and under	99	1.00 (ref)		
35 - 39 years	129	1.19 (1.07 to 1.33)	**0.002**	
40 - 49 years	351	1.19 (1.08 to 1.31)	**<0.001**	
50 - 65 years	677	1.28 (1.16 to 1.41)	**<0.001**	
Over 65 years	473	1.34 (1.21 to 1.49)	**<0.001**	
Household life stage				**<0.001**
Young families	216	1.00 (ref)		
Mixed Families	105	1.05 (0.95 to 1.16)	0.360	
Older Families	190	1.12 (1.03 to 1.22)	**0.010**	

Adult Households Inc YSC	423	1.06 (0.97 to 1.14)	0.192	
Older Singles & Couples	795	1.29 (1.17 to 1.43)	**<0.001**	
Household size	1729	0.90 (0.88 to 0.92)	**<0.001**	

Observations: 1729

R^2 / R^2 adjusted: 0.311 / 0.304

1. Ratio of the geometric mean
2. Calculated using an F-test