My title*

My subtitle if needed

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March 23, 2024

First sentence. Second sentence. Third sentence. Fourth sentence.

Table of contents

*Code and data are available at: LINK.

1 Introduction

You can and should cross-reference sections and sub-sections. We use R Core Team (2023) and (**rohan?**).

The remainder of this paper is structured as follows. Section 2….

2 Data

2.1 Software and R-packages

We create this project using statistical software, `R` (R Core Team 2023). For cleaning and re-purposing the data, we used `tidyverse` (Wickham et al. 2019) package and graphs, we relied on `ggplot2` (Wickham 2016). The data used in this paper comes from (Boysel and Vaughan 2021) package. We further used `rstanarm` (Goodrich et al. 2022) for modelling. Lastly, we used `kableExtra` (Zhu 2021) and `viridis` (Garnier et al. 2024) for aesthetics purposes.

2.2 Incorporating FRED data

The data comes from FRED or Federal Reserve Economic Data, which is an online database, consisting of hundreds of thousands time series economic data on both US national level and international level. From the database, we incorporated six different datasets using `fredr` package. These were titled:

- Real personal consumption expenditure: Food
- Real disposable personal income
- Real personal consumption expenditure: Durable Goods
- Real personal consumption expenditure: Nondurable Goods
- Real personal consumption expenditure: Services
- Real personal consumption expenditure: Healthcare

A detailed description of what each of these datasets reports on can be found on Table 1. There are few key features that are present in all of the datasets. Firstly, we only incorporate data between 2007 and 2022 on a quarterly basis. We used as an 2007 as an anchor because data on durable/nondurable goods is only available from year and we wanted to model our data on 15 year period, hence 2022.

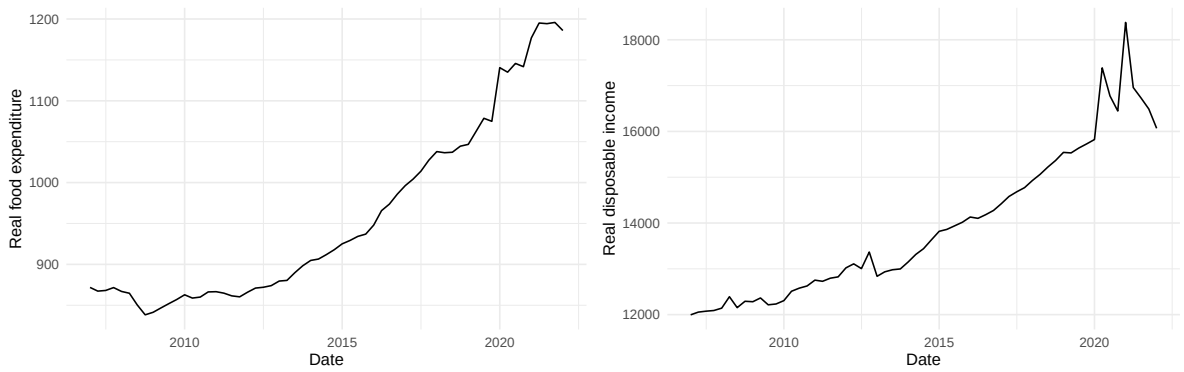
All the datasets are also seasonally adjusted and chained to 2017 dollars. Seasonally adjusted time series eliminates effect of seasonal influences. Seasonal influences like strikes, abnormal weather patterns, or events Boxing day sale, can distort the real underlying movements in the business cycle and adjusting for these variation, provides us with much clearer understanding of the dataset from period to period. The datasets used 2017 price level as reference point. This adjusts for inflation across time, allowing us to accurately compare economic data over multiple periods. We further adjust for inflation by using real economic data, as opposed to nominal data. This enables us to create valid comparison groups, allowing us to compare a category with another category across time.

2.3 Dataset characteristics

Each dataset contains five different columns, with key ones being date and value. The data variable reports on the specific day on which data was collected. With quarterly data, we only see data on the first day from the months of January, April, August and October. Although quarterly, FRED does not include data for quarter months of August, or indeed December. This is more due to convenience as some data becomes available only after end of the quarter and updating the database on before that is not productive. Lastly, value columns reports on expenditure in billions of US dollars. For a better understanding of how each category measure up against one another, please see Figure 2. Table 2 reports in cleaned data that is being used for modelling and analysis.

2.4 Measurement

FRED does not collect data itself but relies on public and private organizations to provide the database with data. Except for first and last observations of the month, FRED ignores missing value when it average, sum and end-of-period aggregation ("Getting to Know FRED" 2024). In this context, missing values often arise during statutory holidays, when federal offices are closed. On those weeks, FRED only reports data on 6 days of the week, excluding the holiday and end-of-period calculation will be conducted based whatever the corresponding days are in that month, minus one.



(a) Food expenditure (b) Income

Figure 1: Levels of real consumption expenditure and income expenditure, in billions of dollars, chained to 2017 prices

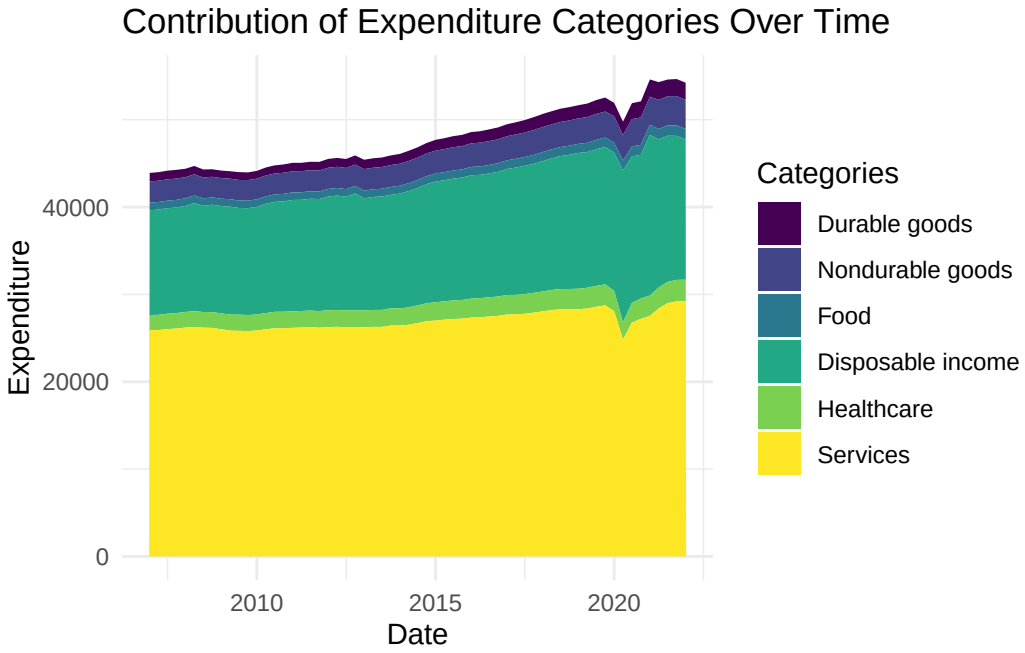


Figure 2: Expenditure for different categories, in billions of 2017 dollars

Table 1: Description of the data variables

Expenditure variable	Description
Date	Date of data collected
Durable goods	Durable goods are goods that are more for future consumption than immediate consumption. These types of goods provides utlity over a length of period. Examples include machinery, tools, appliances among others
Non-durable goods	Durable goods are anything that are generally consumed within a short period of time. Examples include food, clothing, cosmetics etc
Food	Expenditure in food by all Americans in a time period
Disposable income	Refers to total income that is availble to individuals for consumption after deducing taxes
Healthcare	The category reports on total expenditure on healthcare services, including medical treatments, medicine cost, physician services among other services
Services	This category encomapasses a variety of services, inluding education, transportation, utilities, hospitality and many others

3 Model

In this section, we briefly discuss Bayesian models that are being used in this analysis. Background details and model diagnostics can be found under Appendix B.

3.1 Model set-up

Using `rstanarm` library, we evaluated two Bayesian model, with one being simple linear regression, and another being multiple linear regression. The simple linear regression explores whether an increase in income leads to increase in expenditure in food. Multiple linear regression evaluates the same topic, however, controlling for various other predictors.

3.1.1 Simple linear regression

Define y_i as the expenditure in food in year i. Then $income_i$, is level of disposable income in year i, both in billions of US dollars.

$$
\begin{aligned}
y_i|\mu_i, \sigma &\sim \text{Normal}(\mu_i, \sigma) && (1)\\
\mu_i &= \beta_0 + \beta_1 \times \text{income}_i && (2)\\
\beta_0 &\sim \text{Normal}(0, 279) && (3)\\
\beta_1 &\sim \text{Normal}(0, 0.17) && (4)\\
\sigma &\sim \text{Exponential}(0.009) && (5)
\end{aligned}
$$

Table 2: Cleaned data showing real expenditure by different categories

Date	Durable goods	Non-durable goods	Food	Disposable income	Healthcare	Services
2007-01-01	969.90	2435.00	871.80	11995.90	1736.72	25900.00
2007-04-01	980.10	2429.90	867.30	12055.30	1745.91	25913.00
2007-07-01	992.10	2437.50	868.10	12075.60	1762.55	26024.00
2007-10-01	999.50	2435.50	871.60	12090.30	1770.73	26088.00
2008-01-01	967.20	2416.60	866.90	12141.60	1788.97	26202.00
2008-04-01	960.30	2420.40	864.70	12391.20	1793.99	26273.00
2008-07-01	927.90	2385.10	850.40	12152.80	1800.01	26186.00
2008-10-01	859.60	2362.30	838.30	12291.70	1804.94	26167.00
2009-01-01	861.10	2361.40	841.40	12282.00	1817.91	26012.00
2009-04-01	854.90	2347.30	846.70	12364.40	1838.01	25848.00
2009-07-01	896.40	2354.70	851.90	12214.70	1849.31	25830.00
2009-10-01	875.30	2362.30	857.00	12232.60	1840.44	25795.00

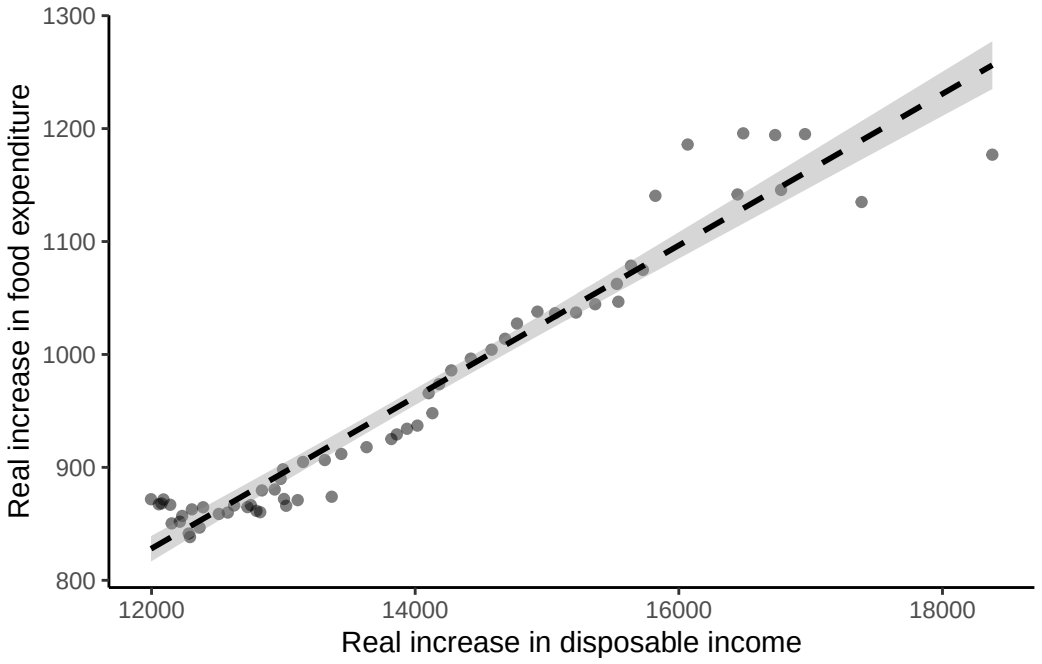


Figure 3: Relationship between increases in disposable income and increases in food expenditure, between 2007 and 2022.

Table 3: Summary results for both models

	Simple linear	Multiple linear
(Intercept)	24.07	−97.50
	(30.88)	(114.73)
income_expenditure	0.07	0.02
	(0.00)	(0.00)
durable_expenditure		−0.15
		(0.04)
nondurable_expenditure		0.47
		(0.04)
healthcare_expenditure		0.00
		(0.04)
services_expenditure		−0.01
		(0.01)
Num.Obs.	61	61
R2	0.936	0.992
R2 Adj.	0.933	0.990
Log.Lik.	−289.419	−224.943
ELPD	−292.9	−233.0
ELPD s.e.	8.0	8.0
LOOIC	585.7	466.0
LOOIC s.e.	16.0	16.0
WAIC	585.6	464.3
RMSE	27.49	10.36

3.1.2 Multiple linear regression

Define y_i as the expenditure in food in year i. Then $income_i$, is level of disposable income in year i. Model further controls for durable goods with $durable_i$, non-durable goods with $nondurable_i$, levels of health care expenditure with $healthcare_i$ and levels of expenditure in services with $services_i$. All the variables are in billions of US dollars.

$$y_i|\mu_i, \sigma \sim \text{Normal}(\mu_i, \sigma) \tag{6}$$
$$\mu_i = \beta_0 + \beta_1 \text{income}_i + \beta_2 \text{durable}_i + \beta_3 \text{nondurable}_i + \beta_4 \text{healthcare}_i + \beta_5 \text{services}_i \tag{7}$$
$$\beta_0 \sim \text{Normal}(0, 279) \tag{8}$$
$$\beta_1 \sim \text{Normal}(0, 0.17) \tag{9}$$
$$\beta_2 \sim \text{Normal}(0, 0.84) \tag{10}$$
$$\beta_3 \sim \text{Normal}(0, 0.95) \tag{11}$$
$$\beta_4 \sim \text{Normal}(0, 1.25) \tag{12}$$
$$\beta_5 \sim \text{Normal}(0, 0.27) \tag{13}$$
$$\sigma \sim \text{Exponential}(0.009) \tag{14}$$

3.2 Model justification

We expect a positive relationship between between income and food expenditure. Figure 3 shows that for an increase an disposable income, food expenditure increases by approximately equal amount. Further, Figure 1 compares both of these variables over time and we see similar patterns of growth, with steady exponential increase in between 2010 and 2020 and both measures veer off after 2020, presumably due to Covid-19 downturn. A paper by Parker and Wong (1997) looks at data from Mexico and finds that income and expenditure are correlated. In fact, lower income uninsured groups reduces cash expenditure on health care during economic crisis. Mahadea and Rawat (2008) further considers relationship between between happiness and incomes and finds that economic growth and increased income contributes to happiness. Therefore, based on exploratory data analysis and theories, we believe that there is posive relationship between food expenditure and income levels.

4 Results

Our results are summarized in **?@tbl-modelresults**.

5 Discussion

5.1 First discussion point

If my paper were 10 pages, then should be be at least 2.5 pages. The discussion is a chance to show off what you know and what you learnt from all this.

5.2 Second discussion point

5.3 Third discussion point

5.4 Weaknesses and next steps

Weaknesses and next steps should also be included.

Appendix

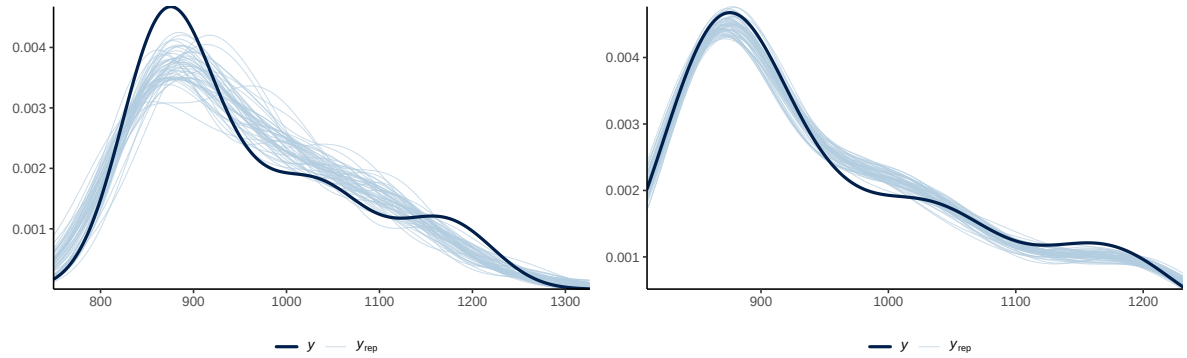
A Additional data details

B Model details

B.1 Posterior predictive check

In **?@fig-ppcheckandposteriorvsprior-1** we implement a posterior predictive check. This shows...

In **?@fig-ppcheckandposteriorvsprior-2** we compare the posterior with the prior. This shows...



(a) Posterior prediction check of simple linear regression

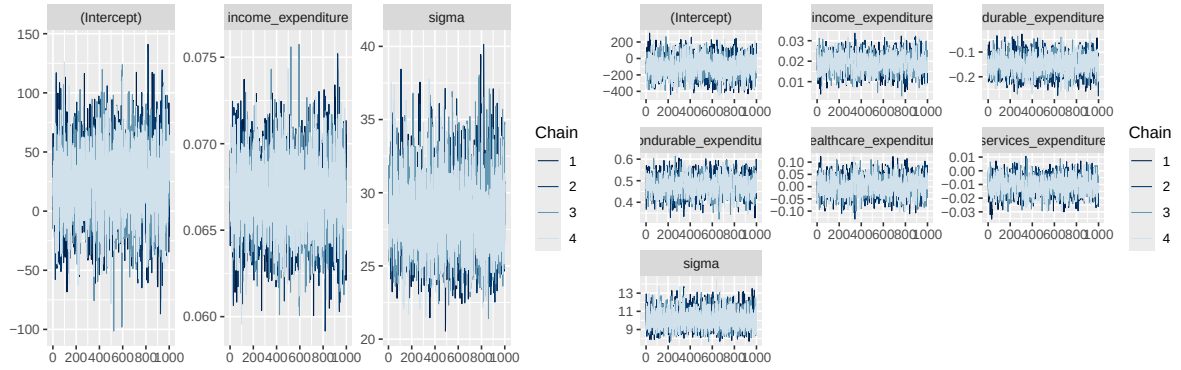
(b) Posterior prediction check of multiple linear regression

Figure 4: Examining how the model fits, and is affected by, the data

B.2 Diagnostics

?@fig-stanareyouokay-1 is a trace plot. It shows... This suggests...

?@fig-stanareyouokay-2 is a Rhat plot. It shows... This suggests...



(a) Trace plot of Model 1

(b) Trace plot of model 2

Figure 5: Checking the convergence of the MCMC algorithm

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