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# RESEARCH ON THE NORWEGIAN CONSUMPTION FUNCTION

## Consumer Confidence

MASTER THESIS

by

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MSc in Finance and MSc in Business with Major in Finance

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Abstract

This paper examines the link between consumer confidence and consumption expenditures in Norway. We first tested the predictive ability of consumer confidence in a linear regression with macroeconomic fundamentals as controls. The model shows how confidence brings additional information to explain consumption growth beyond fundamentals. Inclusion of consumer confidence for the EU in the model reveals a possible confidence channel from the EU to Norway. The relationship between the Norwegian consumer confidence and Norwegian fundamentals is investigated further through vector autoregressions (VAR). Impulse response functions reveal an increased consumption response to confidence shocks in times of uncertainty. Consumers seem to maintain a long memory of the impact of confidence during these uncertain times relative to regular times. We also discovered the increasing importance of confidence shock during the last three decades. Our findings suggest that consumer confidence should be included when assessing consumption growth.

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# 1.0 Introduction and Motivation

In the last two years, from 2020 to 2022, the Covid pandemic has ravaged many of the world's financial markets. The pandemic was a worldwide health disaster with few historical parallels. We must go back 100 years to the Spanish flu to find a corresponding epidemic. Several countries operated with lockdowns and, as a result, consumption dropped. Situations like the pandemic impact consumers' trust in the country's financial situation. Reports from Finans Norge tell that the population's expectation for the economic future has been at historically low levels since the crisis arrived. It has not yet recovered (Håkonsen and Moen, 2023).

Earlier this spring, Ine Oftedahl, the Director of Data Transformation at DNB Bank, observed a clear shift in consumer spending patterns. According to her reports, there has been a noticeable decrease in the use of cards among Norwegians (Giske, 2023).

Reports like these suggests that understanding consumer confidence and how it relates to the consumption function is essential.

The consumption function provides a framework for understanding and analyzing the relationship between income, consumption, saving, investment, and overall economic activity. Consumption levels affect policymakers, business owners, and the overall economy in a country. It plays a crucial role in macroeconomic analysis, policy formulation, and understanding consumer behavior.

Earlier studies on consumer confidence have shown that consumer confidence can be a useful tool for predicting consumption patterns. Dées and Brinca (2013) find that consumer confidence is a valuable predictor of consumption, especially when there are notable fluctuations in household indicators. While Carroll et al. (1994) find that consumer confidence has predictive power in forecasting future spending patterns. Consumer confidence reflects people's outlook on the economy and their personal finances, influencing their spending choices. Incorporating consumer confidence into the consumption function could potentially provide valuable insights into the Norwegian consumption function.

This master thesis will investigate whether the consumer confidence index is valuable in predicting consumption expenditure. We follow an exercise from Dées and Brinca (2013), starting with a simple estimation model of consumption growth as dependent variables, and change in consumer confidence as explanatory variable. We then include different sets of fundamental macroeconomic variables. When building the consumption model with fundamentals, we take inspiration from earlier work on the consumption function. Disposable income and wealth are well-known determinants of consumption growth. Later research, including Erlandsen and Nymoen (2008), has discussed the involvement of the real interest rate, unemployment rate, and age distribution. While these variables are proven to impact consumption expenditure in some way, the involvement of the consumer confidence index still needs to be settled. Studies outside of Norway have come to different conclusions when involving the variable. Some of these research articles are reviewed later in this thesis. This paper introduces consumer confidence to Norwegian consumption.

The results show that including consumer confidence to different sets of fundamentals, increases the fit of the model. We use VAR modeling to look at impulse response functions (IRF) and variance decomposition. We notice that consumption expenditure has a negative response initially but change direction after the first period. The positive response implies increased consumption spending when confidence increases. Plots of IRF for different sub-periods, reveals an increasing trend of the response to confidence shock on consumption. The sub-periods include events as the financial crisis, the price drop in oil and the pandemic. Our findings suggests that consumer confidence is valuable when assessing consumption patterns in Norway.

# 2.0 Literature Review

This literature review aims to analyze the existing body of research on the consumption function, shedding light on the key factors influencing consumer spending patterns and their implications for economic outcomes. Additionally, it helps understand the consumption function's dynamics and uncover new insights into its complexities by examining a wide range of empirical studies, theoretical frameworks, and methodological approaches.

Our thesis focusses on household consumption in Norway and how consumer confidence affects household consumption. We will start with discussing literature on the consumption function, including research on the Norwegian consumption function. We will move over to discussing the benefits and consequences of using macro data when looking at the consumption function. Finally, we will discuss literature that has used consumer confidence as a variable when explaining consumption behaviors.

## 2.1 The Consumption Function

The consumption function was introduced by Keynes (1936) and has since been reviewed, adjusted, and renewed. Keynes developed a consumption function to explain the relationship between income and consumption. He proposed that consumption is a function of income, and when income increases, households tend to spend a portion of the additional income.

Later, Modigliani and Brumberg (1954) and Friedman (1957) re-defined the consumption function. Modigliani and Brumberg (1954) proposed the life-cycle hypothesis (LCH), which states that individuals plan their consumption and saving patterns over their lifetime, considering their expected lifetime income. Friedman (1957) introduced the permanent income hypothesis (PIH) and highlighted that consumption is primarily determined by individuals' long-term income.

Hall (1978) expanded the LCH and the PIH. The research explores the stochastic implications of these hypotheses by incorporating income uncertainty and borrowing constraints into the analysis. Hall introduced the concept of Euler equations, which are dynamic equations that express the intertemporal trade-offs individuals make between current and future consumption. By formulating and analyzing Euler equations, Hall (1978) examines how individuals make consumption decisions in the face of income volatility and borrowing constraints. The equations show the relationship between income, consumption, and saving over an individual's lifetime.

The models proposed by Keynes, Modigliani and Friedman were later criticized for not being able to capture the complexity and dynamics of consumer behavior. Common arguments were the lack of variables, especially wealth components (Muellbauer and Lattimore, 1995). Considering the historical changes to financial and economic markets since Keynes paper in 1936, it is not surprising that new empirical analysis has entered the space. One such event is the credit liberalization in the 1980s. (Krogh, 2010)

Over the years, economists have tried to develop the consumption function to enhance the understanding of consumption patterns. Research has incorporated factors such as consumer confidence, wealth effects, interest rates, and credit availability into the analysis of the consumption function. One example is Carroll (2001), where Hall (1978) is challenged by an alternative perspective on the consumption function. Carroll (2001) introduces the concept of liquidity constraints and argues that they significantly influence individuals' consumption decisions. By incorporating liquidity constraints into the analysis, Carroll provides a more realistic understanding of consumer behavior and highlights the importance of credit availability and borrowing limits. Carrol (2001) analyzed U.S. data and concluded that income and wealth significantly influence consumption.  His work offers an alternative perspective on the theory of the consumption function and contributes to a deeper understanding of household consumption choices.

Our thesis examines household consumption in Norway, and it is crucial to incorporate Norwegian studies. Norwegian researchers have made significant contributions to the study of the consumption model, providing valuable insight into consumer behavior in the Norwegian context.

Eilev Jansen has contributed significantly to economic research and analysis for the Norwegian consumption function. His work has provided insights into how various factors influence economic activity and contribute to shaping economic forecasts and policies. Jansen (2013) examines the impact of the financial crisis on the consumption function, focusing on the role of wealth effects. The study investigates how changes in household wealth during the financial crisis affected household wealth. Jansen (2013) uses Norwegian data to explore the relationship between wealth and consumption. The research highlights the importance of considering both short and long-run wealth effects in the consumption function, showcasing their impact on the savings rate and their ability to balance the effects of low-interest rates. Additionally, the study acknowledges the ongoing debate regarding the measurement of housing prices and the potential interaction effects between housing wealth and credit availability. These findings contribute to understanding consumption dynamics and lay the groundwork for future research to refine the Norwegian consumption function.

Landsem (2016) investigates the Norwegian long-run consumption function, and start of by replicating some of the results of Jansen (2013). The study aimed to understand the determinants of household consumption in Norway by examining various economic factors. Through empirical analysis, Jørgen Landsem explored the relationship between consumption and variables such as income, wealth, interest rates, and demographic variables while trying to improve the function. He tested two hypotheses, one concerning the impact of income distribution after the financial crisis and the other capturing the effect of splitting wealth into three components based on liquidity levels. The inclusion of wealth component is based on Brodin and Nymoen's (1992), and the income distribution is measured through an adjusted Gini coefficient and wage share of the country. The findings of Landsem (2016) suggests that financial wealth had a greater impact on consumption compared to housing wealth, while income distribution measures could not explain consumption at a significant level. The author argues that the findings could be the result of the variables not capturing real changes in the income distribution, the changes being too small to impact consumption, or income inequality not influencing consumption as expected. Regarding wealth components, financial wealth had a greater impact on consumption compared to housing wealth in the long run equation (Landsem, 2016).

Fagereng and Halvorsen's (2016) research delved into the Norwegian homeowner market and its impact on the prevailing consensus regarding high levels of private debt. During the period of 2000-2011, the authors observed diverse reactions among Norwegian households to income shocks, which were contingent upon their preferences for spending versus saving ratios and their ability to accumulate financial reserves. They identified a significant proportion of leveraged households with inadequate buffers against income shocks, alongside others possessing sufficient reserves to withstand such shocks. The former group, characterized as low buffer households, was projected to reduce consumption in response to negative income shocks at a one-to-one ratio. Conversely, the highly leveraged households with ample buffers exhibited pronounced responsiveness to changing economic conditions, particularly during the financial crisis. Additionally, the study revealed a consistent tendency for households' consumption levels to be relatively lower in periods after investments in durable goods financed through debt. According to the findings in the article, we would expect that in the event of a crisis, leveraged homeowners would be inclined to lower their consumption level, due to increase in precautionary saving and delayed expenditures in durable goods.

## 2.2 Micro versus Macro Data

An interesting study on situation-affected consumption was published by Mian et al. (2013). The paper investigates the consumption consequences of the housing collapse during the financial crisis. The research includes microdata from the United States and focus on credit growth and consumption. The authors use the geographic distribution of wealth losses across the United States to capture the consequences to consumption. The findings show that there is an effect of housing net worth shocks on consumption. The results also show that the marginal propensity to consume (MPC) differ across the ZIP codes in the United States. This implies that wealth shocks depend both on the total wealth loss and how the losses in wealth are distributed among the population in the United States.

However, using micro data can be difficult. Li and Zhang (2021) utilizes macro data to examine the impact of changes in housing wealth on household consumption patterns, with main focus on the implications for China. The authors investigate the role of housing wealth as a determinant of consumer behavior at the macroeconomic level. They analyze data from China, considering the fluctuations in housing prices and the corresponding effects on household consumption. The study examines how changes in housing wealth influence consumer spending and whether there are variations in consumption patterns based on different economic conditions. Using macro data, the authors can provide a broader perspective on the relationship between housing wealth and consumption. They offer insights into how housing market dynamics, such as fluctuations in housing prices, can impact household consumption decisions.

Li and Zhang (2021) also discuss the difficulties using microdata when studying consumption. They argue that obtaining representative and comprehensive micro-level data for a large population can be expensive and time-consuming. Secondly, ensuring data quality and accuracy can be complex, as it requires careful sampling, cleaning, and validation procedures. Additionally, they argue that microdata may face issues related to non-response and attrition rates, which can introduce biases in the analysis.

In summary, micro data offers valuable insight to individual behavior, but challenges related to cost, data quality, representativeness, and privacy make its acquisition and analysis difficult.

## 2.3 Literature on Consumer Confidence

Consumer confidence is a diverse topic, where some researchers claim that the variable is useful for predicting consumption expenditure and others claim it has little effect. Carroll et al. (1994) found that consumer confidence is a key factor contributing to the onset of the U.S. recession in 1990-91. Using data from the Michigan Survey of Consumer Confidence, the authors found that changes in consumer confidence can predict future consumption behavior. Even after considering other economic factors, consumer confidence provides valuable information for forecasting spending patterns. The study suggests that consumer confidence captures subjective factors influencing consumer decision-making, such as expectations, beliefs, and emotions.

Dées and Brinca (2013) builds on the findings of Carroll et. all (1994). They examine the relationship between consumer confidence and consumer spending in the United States and the euro area. The authors investigate whether changes in consumer confidence can be used as a predictor of future consumption behavior. The study utilizes a vector autoregression (VAR) model to analyze the dynamic interactions between consumer confidence and consumption spending. It uses data from the United States and the euro area to capture the relationship in different economic areas. The findings indicate that consumer confidence can be valuable when forecasting consumption expenditure, particularly when there are substantial fluctations in household indicators. Additionally, there is evidence of a "confidence channel", as U.S. confidence can assist in forecasting consumption in the euro area. Overall, the study underscores the potential significance of consumer confidence indicators in predicting and understanding consumption patterns. We adopt the same approach for our thesis, using a VAR framework to discover the significance of consumer confidence in Norway.

Al-Eyd et al. (2008) concludes differently. The research do not find that consumer confidence is provides valuable forecasting traits for consumption. The research examine the predictive role of consumer confidence for consumption expenditure across five major OECD countries. The findings suggest that while correlations and Granger causality results may indicate a relationship between consumer confidence and consumption, the actual predictive power of confidence indicators is weak when other key determinants of consumption, such as income and wealth, are considered. They argue that other variables like share prices, house prices, and earnings may provide more useful information than confidence indicators.

The research of Dées and Brinca (2013) argue that there are two primary aspects of the literature on consumer confidence. The first being its position within modern consumption theories and the second being its ability to provide additional predictive information beyond traditional economic variables. The next two paragraphs explain these aspects.

The theoretical understanding of confidence and its significance within modern consumption theories, particularly concerning the Permanent Income Hypothesis (PIH), is essential in the literature. The PIH suggests that long-term income rather than short-term fluctuations influence consumer choices, but deviations can occur due to liquidity constraints or uncertainty about future income. Consumer confidence indices are perceived as valuable tools for capturing information about expected income and consumer behavior. Consumption expenditure is also argued to be impacted by non-economic factors, including political conflicts or wars driven by increased uncertainty and affecting households' willingness to consume. Researchers like Katona (1975) and Acemoglu and Scott (1994) have examined these non-economic factors.

The other aspect of literature is whether consumer confidence provides additional predictive information beyond fundamental variables such as income, wealth, unemployment, and interest rates. While findings vary, many studies find a statistically significant association between confidence indicators and expected economic outcomes. Confidence measures are particularly useful in predicting economic fluctuations, recessions, recoveries, and during sizable economic or political shocks. Researchers such as Haugh (2005) and Garner (2002) highlight the significance of confidence indicators in understanding and predicting these economic dynamics.

# 3.0 Theory

Understanding how individuals and households allocate their income to purchasing goods and services is crucial for gaining insights into broader economic trends and formulating effective policy decisions. Over the years, various theories and frameworks have been developed to explain and analyze consumption patterns. In the following section, we will review the relevant theories on consumption.

We start by explaining the influential Keynes (1936), which emphasized income and expectations in shaping consumption behavior. He introduced the concept of the marginal propensity to consume (MPC), which is often defined as the proportion of an increase in income spent on consumption, highlighting the role of aggregate demand and the need for government intervention.

Keynes' consumption model, which was influential for a significant period, faced criticism in the 1960s. Attanasio and Weber (2010) discuss the implications of this model and highlight its shortcomings. According to the critiques, the model does not recognize the significance of forward-looking behavior, neglecting expectations and future income in decision-making. It also failed to consider the impact of wealth on consumption choices, disregarding changes in asset values and housing prices. Additionally, the assumption of homogeneous consumer behavior limited its ability to account for diverse preferences, income levels, and access to credit among individuals.

Subsequently, attention shifted to alternative models such as the life-cycle hypothesis (LCH) in Modigliani and Brumberg (1954) and the permanent income hypothesis (PIH) in Friedman (1957), which emerged as responses to the limitations of the Keynesian model. The LCH and PIH considered forward-looking behavior, incorporated wealth effects, and acknowledged the heterogeneity in consumer behavior. These alternative models provided a more comprehensive framework for analyzing intertemporal consumption and saving decisions, leading to improved understanding in the field (Attanasio and Weber, 2010).

We will explain each of these models later in this chapter when reviewing the theory of consumer confidence.

## 3.1 Keynes Consumption Model

Keynes (1936) was considered a macroeconomics revolution and introduced the consumption function theory. The book challenged classical economic theories and presented a new understanding of the relationship between income and consumption.

According to Keynes's consumption model, individuals spending decisions are primarily determined by current disposable income. As income increases, the consumption increases. However, Keynes recognizes that individuals do not spend their entire additional income but tend to save a portion. This concept is captured by the marginal propensity to consume (MPC) (Drakopoulos, 2021, p. 233-267). We find the MPC by dividing the change in consumption by the change in income (or wealth).

$$MPC = \frac{\Delta Consumption}{\Delta Income} \qquad MPC = \frac{\Delta Consumption}{\Delta Wealth} \tag{3.1}$$

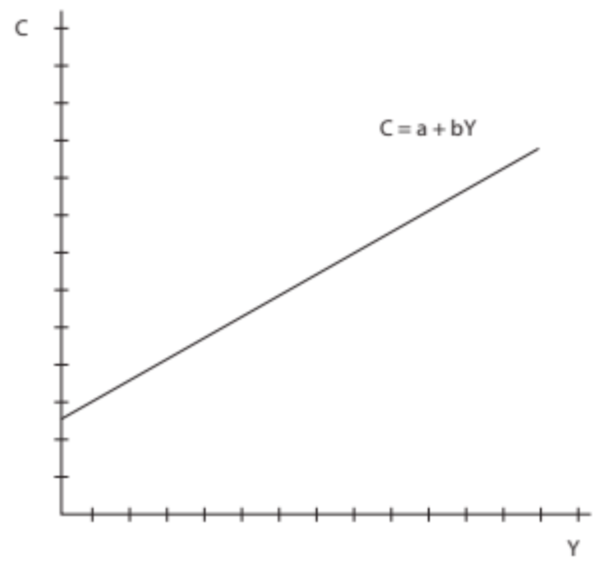
The Keynesian consumption function can be represented as follows. We use Drakopoulos's (2021) notation:

$$\mathrm{C} = a + b \times Y \tag{3.2}$$

where C represents consumer spending, $a$ is the autonomous consumption which refers to consumption that does not depend on income, such as basic necessities. $Y$ is the disposable income and $b$ represents the MPC which is between zero and one (Drakopoulos, 2021, p. 233-267).

Keynes assumes that consumption follows a linear relationship, as illustrated in Figure 3.1. The equation suggests that consumption is determined by autonomous consumption and income level (Drakopoulos, 2021, p. 233-267).

**Figure 3.1** Graph of the linear relationship between consumption (C) and income (Y)




Keynes (1936) proposed a consumption function that considers objective and subjective factors influencing consumer spending. Objective factors include measurable economic variables such as income distribution, wealth, and interest rates. According to Keynes (1936), income distribution plays a crucial role in determining the propensity to consume. His theory suggests that individuals with lower incomes tend to have a higher propensity to consume than those with higher incomes. This is because low-income households tend to devote most of their income to consumption, while high-income households satisfy their needs more quickly. Furthermore, changes in wealth and interest rates impact consumer behavior, as an increase in wealth tends to lead to higher consumption levels, while higher interest rates may discourage borrowing and result in decreased consumer spending (Chakraborty, 2010, p.27-39).

In addition to objective factors, Keynes (1936) recognized the importance of subjective factors in the consumption function. According to Keynes (1936), these subjective factors could include the desire for saving buffers, individuals level of frugality, enjoyment of financial independence, wanting to leave a legacy, anticipating future needs, and prioritizing liquidity and financial considerations (Chakraborty, 2010, p.27-39). These factors can be hard to measure and would require microdata on households. However, for aggregated data, consumer confidence index could be a near measurement of the population’s subjective consumption decisions. The index quantifies subjective opinions on several aspects in the current economy.

Keynes emphasized that both objective and subjective factors should be considered when analyzing consumption patterns and their impact on the overall economy. By recognizing individuals' diverse motivations and attitudes toward saving and spending, Keynes (1936) provided a more comprehensive understanding of consumer behavior and its implications for macroeconomic dynamics (Chakraborty, 2010, p. 27-39).

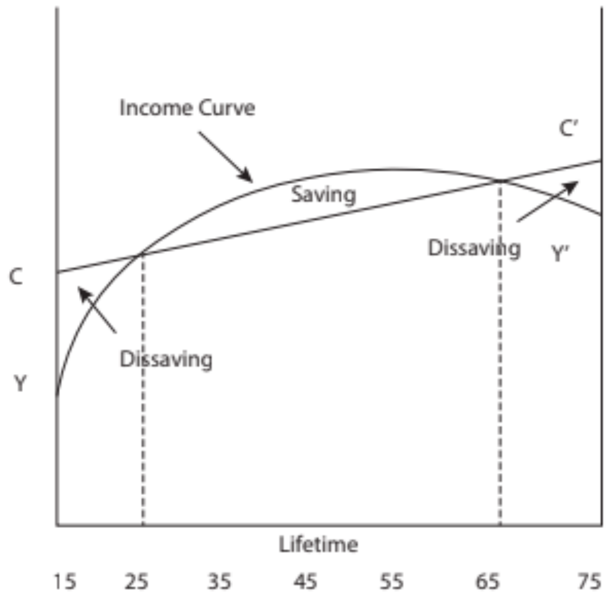
### 3.1.1 Life Cycle Hypothesis

Modigliani and Brumberg (1954) introduce the life cycle hypothesis (LCH), which suggests that individuals plan their saving and consumption patterns based on their expected lifetime income. According to this theory, individuals tend to save during their working years to accumulate wealth and finance their consumption needs during retirement when their earning potential decreases. The LCH emphasizes the importance of income fluctuations over an individual's lifetime and the need for adequate savings to maintain a desired standard of living.

The hypothesis can be extended to make predictions for consumption patterns. Following the logic of LCH, we should expect that the population would borrow prior to employment, save during the years they are in work, and then utilize their savings after they retire (Doppelhofer, 2009). This concept is illustrated in Figure 3.2.

Additionally, the LCH suggests that temporary changes in income would have minimal impact on consumption. The focus should therefore be on expected and permanent fluctuations in income as this would result in a proportional adjustment in consumption level (Doppelhofer, 2009).

**Figure 3.2** Illustration of the Life Cycle Hypothesis




Using the notation of Doppelhofer (2009), we assume a population of individuals with a lifespan of $t$ periods. In each period $t$, these individuals encounter a budget constraint that governs their financial limitations:

$$y_t + b_{t-1}(1 + r) = c_t + b_t \tag{3.3}$$

In this equation, $y_t$ represents the income available to the individual in period $t$, $b_{t-1}$ represents the savings or wealth carried over from the previous period, r represents the interest rate, $c_t$ represents the consumption in period $t$, and $b_t$ represents the savings or wealth accumulated in period $t$ (Doppelhofer, 2009).

The next formula of LCH is the intertemporal budget constraint. This is a budget constraint, where the decision maker is considering the present value of current and future cash flows. The constraining part is that this value must be equal the present value of lifetime spending. Still using the notation of Doppelhofer (2009), the intertemporal budget constraint can be expressed as:

$$y_1 + \frac{y_2}{1 + r} + \ldots + \frac{y_T}{(1 + r)^{T-1}} + b_0(1 + r) =$$

$$c_1 + \frac{c_2}{1+r} + \ldots + \frac{c_T}{(1+r)^{T-1}} + \frac{b_T}{(1+r)^{T-1}} \tag{3.4}$$

In this hypothesis, individuals view their time horizon as limited and do not leave behind any assets as legacy for future generations. Consequently, we can assume they set their final period's asset value $b_t$ to zero. To simplify it, we assume that individuals earn a constant labor income $\bar{y}$ until they retire at $R$ years. After retirement, there is no labor income until the expected end of life at time $T$. Further, we assume that individuals prefer a steady and consistent consumption pattern throughout their lifetime (Doppelhofer, 2009).

A review of the theory is done in Modigliani (1986), which points out the several assumptions underlying the LCH that does not hold as firmly as initially presumed. In this paper, Modigliani acknowledges that consumption must vary at different stages of life and highlights the importance of understanding individual and aggregate saving and wealth-holding behavior. Young individuals with lower incomes but higher consumption may need to borrow or use savings from previous periods to support their consumption. As they progress in their careers and experience higher salaries, they tend to save more to accumulate wealth for retirement. Modigliani's work and considers several of the subjective factors that were introduced in Keynes (1936) as motives for saving and spending habits at different phases of life.

While the basic version of the LCH has proven useful in understanding consumption behavior, Modigliani (1986) acknowledges that certain assumptions, such as a deterministic length of life and the absence of a bequest motive, may not align with empirical evidence. The paper proposes that an enhanced version of the LCH, which considers uncertain lifespans and the desire to leave an inheritance, can provide a better understanding of how people accumulate wealth and make savings decisions (Modigliani ,1986).

### 3.1.2 Permanent Income Hypothesis

Another theory that tries to explain long-term consumer behavior is the Permanent Income Hypothesis (PIH). This theory was developed by Milton Friedman in 1957, and states that individuals' long-term average income determines consumer spending. According to PIH, consumers adjust their spending patterns to align with their expected permanent income, which is a weighted average of their expected future income.

What differentiates PIH from LCH is their time horizons. While the LCH analyzes consumption and saving patterns over an individual's lifetime with a fixed timeline, the PIH examines consumption behavior beyond an individual lifetime.

To describe the mathematical process behind PIH, we will use the notation from Doppelhofer's (2009). We start by assuming that a generation is equally as concerned about its own utility and as in the next generation. The utility of a generation born in time $t$ can be expressed as:

$$t = 1\colon U_1 = u(c_1) + \beta u(c_2)$$

$$t = 2\colon U_2 = u(c_2) + \beta u(c_3) \tag{3.5}$$

$$\dots$$

After recursive substitution, we arrive to the lifetime utility of the first generation:

$$U_t = u(c_1) + \beta u(c_2) + \beta^2 u(c_3) + \dots = \sum_{t=1}^{\infty} \beta^{t-1} u\,(c_t) \tag{3.6}$$

where $U_t$ is the total utility for a generation born in time $t$, $u$ is the utility for own consumption, and $\beta$ is a discount factor for future utility. As we notice, the total utility of a generation is expressed as a function of its own utility, as well as past and future generations utility. This relationship indicates that the welfare of prior and future generations impacts the welfare of the current generation. Given that each generation cares about the next generation, they will behave like they have an unlimited time horizon when making consumption decisions.

Further, we can merge the budget constraints of each generation into an intertemporal budget constraint. The intertemporal budget constraint is explained in Doppelhofer (2009) as:

$$\sum_{t=1}^{\infty} \frac{y_t}{(1+r)^{t-1}} + b_0(1+r) = \sum_{t=1}^{\cup} \frac{c_t}{(1+r)^{t-1}} + \lim_{T\to\infty} + \frac{b_T}{(1+r)^{T-1}} \tag{3.7}$$

Similar to the LCH, the intertemporal budget constrain represents the present value of the current and future income, which includes initial assets, against the present value of consumer spending and the present value of wealth. In PIH, we are using an infinite time horizon, which stands in contrast to the limited time horizon in LCH.

The constraint on the right-hand side, $\lim_{T\to\infty} \frac{b_T}{(1+r)^{T-1}} \geq 0$, ensures that the discounted present value of assets remains positive, or equal to zero, and that the change in debt level does not exceed change in interest rate. As a result of this constraint, consumers can not sustain infinite consumption by continuously borrowing larger sums. Their savings are also constrained to the interest rate, as a faster savings rate would result in an unlimited present value of savings. Therefore, we have that

$$\lim_{T\to\infty} \frac{b_T}{(1+r)^{T-1}} = 0 \tag{3.8}$$

We now have a simpler intertemporal budget constraint:

$$\sum_{t=1}^{\infty} \frac{y_t}{(1+r)^{t-1}} + b_0(1+r) = \sum_{t=1}^{\infty} \frac{c_t}{(1+r)^{t-1}} \tag{3.9}$$

Solving the optimization problem by maximizing utility in equation (3.6) and considering the budget constraint equation (3.9), we receive the Euler equation:

$$u'(c_t) \ = (1+r)\beta u'(c_{t+1}) \tag{3.10}$$

If we consider the simple case of $\beta = \frac{1}{(1+r)}$, the Euler equation will be:

$$u'(c_t) \ = u'(c_{t+1}) \tag{3.11}$$

This implies a constant consumption over time, $c_t = c_{t+1} = \bar{c}$, which we can substitute in the intertemporal budget constraint:

$$\sum_{t=1}^{\infty} \frac{\underline{c}}{(1+r)^{t-1}} = \sum_{t=1}^{\infty} \frac{y_t}{(1+r)^{t-1}} + b_0(1+r) \tag{3.12}$$

From this we can read that individuals will use or spend the equivalent value of their total wealth as if it were an annuity. In other words, instead of consuming their wealth all at once, individuals will distribute their consumption over a period of time as if they were receiving regular payments or income from their wealth, similar to an annuity. According to Friedman (1957) this annuity is the permanent income $y^P$, and we can derive the following:

$$c_t = {y_t}^P = \frac{r}{1+r}\left(\sum_{s=0}^{\infty} \frac{y_{t+s}}{(1+r)^s} + b_{t-1}(1+r)\right) \tag{3.13}$$

According to Friedman, income $y$ can be divided into permanent income $y^P$ and transitory income $y^T$, where transitory income is the difference between income and permanent income. According to PIH, the transitory income rarely influence consumer demand, at least not as dominantly as changes in permanent income (Doppelhofer, 2009).

The PIH suggests that the average propensity to consume and save is the same across different income levels, as individuals allocate a fixed fraction of their permanent income to consumption. However, this theory has been criticized. First, it fails to align with real-life observations, as lower-income households tend to have a higher MPC compared to higher-income households. This contradicts the idea that all income groups save proportionately. Second, the PIH assumes that changes in transitory income do not affect consumption levels, leading to a zero marginal propensity to consume out of transitory income. However, empirical evidence shows that unexpected income increases current consumption and income loss result in reduced consumption. Lastly, the PIH overlooks the distinction between human and non-human wealth by combining them in its analysis. This simplification ignores the influence of different types of wealth on consumption behavior. (Chakraborty, 2010, p.40-56)

Despite these weaknesses, the PIH has influenced research on the consumption function.

## 3.2 Consumer Confidence

Consumer confidence is a measure that reveals the level of optimism or pessimism that households have about the overall economy and their personal financial situation. It encounters consumers' perceptions of the current economic situation and expectations for the future (OECD, 2023). The measure was first introduced in the U.S. during the second world war, and Norway got its own measure in 1992 (Kirkedam, 2023).

Consumer confidence is typically assessed through surveys by market research firms or government agencies. The Norwegian index is carried out by Kantar Public, and published by Finans Norge. The objective of the surveys is to understand the consumer's view on various aspects, such as their past, current and future financial situation, job prospects, and willingness to make major purchases.

The responses are aggregated and quantified to form an index or a confidence indicator (OECD, 2023).

Several factors can influence consumer confidence. Economic indicators such as GDP growth, unemployment rates, inflation levels, and stock market performance play a significant role. Additionally, factors like political stability, government policies, global economic conditions, and media coverage of economic news can impact consumer confidence (European Commission, 2020).

A high consumer confidence level indicates consumers are more optimistic about the economy and their financial well-being. This optimism tends to show through increased consumer spending, as people are more willing to make purchases and take on debt. On the other hand, lower consumer confidence can lead to decreased spending as consumers become more cautious and reluctant to spend money other than on necessities (OECD, 2023).

The use of consumer confidence in the consumption function is a topic of debate among economists. Some argue that consumer confidence can provide valuable insights into consumer behavior and be useful in explaining consumption decisions. An argument is that the confidence measure captures psychological factors that may impact consumer spendings, such as expectations about future income, employment, and overall economic conditions.

On the other hand, the indicator may be too subjective and possibly not provide significant additional explanatory power beyond what is already captured by fundamental economic variables, such as income, interest rates, and wealth. Counterarguments for including consumer confidence in the consumption function is that it adds noise and measurement error, leading to less reliable and robust results.

In Chapter 3.2, we will examine research that supports and challenges the inclusion of consumer confidence in the consumption function.

# 4.0 Methodology

This chapter presents the methods used in our analysis to explore our hypothesis that consumer confidence is a valuable variable when forecasting consumption. We start by explaining the type of data series we use and how we prepare it for analysis before explaining the models and concepts we use in our empirical analysis.

Section 4.1 introduces time series analysis and its validity assumptions. The section also includes one essential time series analysis concept: stationarity. We describe how we deal with non-stationary variables in our data.

Section 4.2 explains VAR modeling and the concepts of Granger causality, impulse response functions, and variance decomposition. These features can evaluate the predictive power of specified variables on the dependent variable.

The techniques introduced in this chapter encompass widely recognized statistical and econometric principles. Two textbooks that explain these concepts well and that we have used thoroughly are Brooks (2014) and Wooldridge (2015). The analysis is programmed using R language in the integrated development environment, RStudio.

Our methodology is carefully chosen to help us analyze our data and reveal whether consumer confidence can help forecast consumption growth.

## 4.1 Time Series Analysis

It is essential to be familiar with the characteristic of the data and variables when doing empirical analysis. One of the most distinctive characteristics of time series is its temporal ordering. This trait allows for predictive investigation of the variables, as observations are collected and recorded over regular intervals (Brooks, 2014).

For the time series models to be valid and the results to be reliable, the models must contain some properties. Several assumptions must be satisfied and may vary depending on the model used. In a time series model with lagged variables as predicting variables, assumptions regarding linearity in parameters, autocorrelation, multicollinearity, homoscedasticity, and normality are crucial.

Violations of these assumptions can affect the accuracy of the model's estimates and predictions (Brooks, 2014). We will briefly go through autocorrelation and homoscedasticity as these are arguably some of the most crucial.

Times series are assumed to have no autocorrelation, which means that the model's residuals are uncorrelated with residuals in earlier periods. As we will never know the true residuals $u_t$ , we must use the estimated residuals $\hat{u}_t$. If there are patterns in the estimated residuals, they are autocorrelated. Consequences that follow if we do not adequately attend to the autocorrelation is inefficient coefficient estimates and inappropriate goodness of fit measures (Wooldridge (2015) To test for autocorrelation, we have used the Breusch-Godfrey test.

Time series are assumed to have homoscedastic error terms, which means that the variance of the error terms is constant over time and independent of the explanatory variables. If we detect heteroscedasticity in our series without dealing with it, our standard errors could be inappropriate and could lead to misleading inferences (Wooldridge (2015). We use notation from Wooldridge (2015) to show the formula for homoscedasticity.

$$Var(u_t|\mathbb{x}_t) = \sigma^2, \text{ where } \mathbb{x}_t = (x_{t1}, x_{t2}, \ldots, x_{tk}) \quad (4.1)$$

$u_t$ is the error term, $x_t = (x_{t1}, x_{t2}, \ldots, x_{tk})$ is the explanatory variables, and $\sigma^2$ is a constant. We use Whites test to check for heteroscedasticity.

Using series that violate any of these assumptions may lead to imprecise results, incorrect inferences, and inaccurate and unreliable statistical analysis. Time series data may also be subject to non-stationarity, and we will explain this in the next sub-chapter.

### 4.1.1 Stationarity

Checking for stationarity is essential in time series analysis for several reasons. If a series is stationary it can show behavior and properties that are not accurate, and checking for stationarity is essential for understanding the underlying patterns, ensuring accurate trend analysis, and forecasting, facilitating valid statistical analysis, and applying appropriate time series modeling techniques. In addition, the standard assumptions for asymptotic analysis might not be valid if the variables are non-stationary (Brooks, 2014).

There are different levels of stationarity, and the strictly stationary process is one where the distribution of $\gamma$ remains unchanged over time. A time series is known as weakly stationary if its mean and variance is constant and if it is time-invariant. For a series to be time-invariant, the covariance between two observations must not depend on the point of time we measure them but only depend on the difference. This is referred to as the autocovariance (Brooks, 2014). A weakly stationary series satisfies the following three equations. We follow the notation of Brooks (2014):

Constant mean:

$$E(\gamma_t) = \mu \qquad\qquad t = 1,2,\ldots,\infty \tag{4.2}$$

Constant variance:

$$Var(\gamma_t) = E[(\gamma_t - E(\gamma_t))(\gamma_t - E(\gamma_t))] = \sigma^2 < \infty \tag{4.3}$$

Constant autocovariance

$$E\left[\left(\gamma_{t_1} - E(\gamma_{t_1})\right)\left(\gamma_{t_2} - E(\gamma_{t_2})\right)\right] = \gamma_{t_2 - t_1} \quad \forall t_1, t_2 \tag{4.4}$$

Non-stationary variables should often be modified to use them in different models. One common strategy is to difference the variables by the number of unit roots. If we must difference a series $d$ times for it to become stationary, it is integrated of order $d$ and has $d$ unit roots. A non-stationary series can be written as I(1), which implies that it contains one unit root and needs to be differenced once. The same logic goes for a non-stationary I(2) series, which has two unit roots and requires to be differenced twice to become stationary I(0) (Brooks, 2014).

When plotting an I(0) series, we should see that it crosses the mean frequently, while I(1) and I(2) would rarely cross it. Economic and financial series typically contain one unit root, making them non-stationary. An example is consumption, which is subject to economic growth, inflation, policy decisions and other factors. See Figure 5.1 for a plotted graph of consumption. As we can observe, the series wander a long way from its mean.

Various statistical tests, such as unit root tests like the Augmented Dickey-Fuller (ADF) test, are used to check for stationarity. These tests help identify whether a time series is stationary or non-stationary and guide the appropriate modeling and analysis techniques.

#### 4.1.1.1 Unit Root Test

Dickey and Fuller introduced unit root testing in 1979 (Dickey and Fuller, 1979). The intention is to test the null hypothesis that the series contains a unit root ($\phi = 1$) against the one-sided alternative that the series is stationary ($\phi < 1$). The notation from this section is from Brooks (2014). We test the following equation for unit root.

$$\gamma_t = \phi \, \gamma_{t-1} + u_t \tag{4.5}$$

where $u_t$ is a random disturbance with zero mean and a constant variance $\sigma^2$. If we are not able to reject the null, the series contains a unit root and is a random walk. To check that it is non-stationary, we look at the variance. So, if we assume that $\phi = 1$ and $\gamma_0 = 0$, then by repeated substitution of

$$\gamma_1 = u_1$$

$$\gamma_2 = \gamma_1 + u_2 = u_1 + u_2$$

$$\gamma_3 = \gamma_2 + u_3 = u_1 + u_2 + u_3$$

we will get:

$$\gamma_t = \textstyle\sum_{j=1}^{t} u_j \tag{4.6}$$

with the variance:

$$var(\gamma_t) = t\sigma_u^2 \tag{4.7}$$

This equation makes it easy detect that the variance is not constant. If we set the time component to infinity ($t \rightarrow \infty$), we would notice that the variance also would go to infinity ($var(y_t) \rightarrow \infty$). Since it is not possible to test $\phi = 1$ directly, we take the first difference of $y_t$. Testing $\phi = 1$ is equivalent to testing $\psi = 0$ (due to $\psi = \phi - 1$), so now, the function looks like this:

$$\Delta\gamma_t = \psi\gamma_{t-1} + u_t \tag{4.8}$$

For the test, we use the critical values that David Dickey and Wayne Fuller created (Dickey and Fuller, 1976).

The Dickey-Fuller test assumes no autocorrelation, but this is often not the reality. The solution is to use the Augmented Dickey-Fuller (ADF) test, where we "augment" the test using lagged variables. This makes the residuals uncorrelated over time, removing the previous issue of correlation. To conduct the test, we need to know how many lags to include, and the optimal lag length can be found by information criteria. The critical values of the test will differ based on the inclusion of a constant term and/or deterministic trend, and we should therefore determine this before running the test (Brooks, 2014).

The main criticism of ADF is that the power of the tests is low if a stationary series has a root close to the non-stationary boundary. An example could be if $\varphi$=1 or $\varphi$=0.95, which would lead to poor results (Konermann, 2022b). We approach this by including a stationarity test in addition to the unit root test. We used the KPSS test (Kwaitowski et al., 1992). We will not explain this test in the thesis.

## 4.2 Granger Causality

After making sure that our data is not violating any assumptions or is non-stationary, we can move on to test for predictability. Granger causality is a statistical concept that measures the predictive power of one time series variable on the future values of another. It was first introduced by Granger (1969) and is a great tool for understanding the relationships among our variables. We use Granger causality to establish whether any of our variables has a causing relationship with consumption.

If it is proven that a variable Granger-causes another, it means that the inclusion of lagged values of the time series leads to a significant improvement in the prediction beyond what can be achieved using only the past values of that variable itself. The concept provides insights into the direction and strength of the causal relationship between the variables (Wooldridge, 2015).

For the Granger Causality test, the null hypothesis assumes that the lagged values of X do not explain, or Granger-cause, the variance in Y. If we are able to reject the null, there is evidence to suggest that X has a significant impact on predicting the future values of Y. Notice that Granger causality does not imply a direct cause-and-effect relationship or the absence of reverse causality.

Granger and Newbold (1977) claimed that the test implies a "temporally related" relationship, rather than X causing Y. It only indicates whether one variable provides additional predictive power for another variable. Granger causality tests are commonly used in econometrics and time series analysis to explore relationships and dependencies between variables over time.

## 4.3 VAR Modeling

As we want to explore the dynamic relationship between the variables, we build a VAR model. Impulse response functions and variance decompositions makes it is easier to interpret the dynamics of the VAR, as this can be difficult on its own. This section will review these concepts to understand better how our analysis is conducted.

### 4.3.1 Impulse Response Function and Variance Decomposition

A great tool to analyze the dynamic relationship between variables in a system is use impulse response functions (IRF). The function reveals the response of a variable to a shock in another variable while holding all other variables in the system constant. By using IRF, we can understand how a unit shock in the impulse variable affects the response variable and how the response variable will adapt to a steady state after the shock. (Konermann, 2022a)

The IRF can be displayed through plots, and by interpreting the plots, we can better understand the interdependencies and dynamic relationships between variables in our system. Positive values indicate an increase in the response variable, while negative values indicate a decrease. We can look at the shape and duration of the response curve to gain insight on the dynamics and persistence of the shocks. (Konermann, 2022a)

Another alternative to examine the dynamics in our VAR model is though variance decompositions plots. The purpose of the method is to detect what proportion of the response from the IRF is due to the dependent variable's "own" shocks. We can compare this to shocks to the explanatory variables. The key takeaway from variance decomposition is the relative importance of each shock to the variables in the model. (Konermann, 2022a)

When calculating impulse responses and variance decompositions, the ordering of the variables is important. The main reason is that we assumed no autocorrelation; that the error terms in the model are statistically independent. In reality, error terms will typically be correlated to some degree and examining the effect of the innovations separately will not be useful as they have a common component. The solution is to “orthogonalize” the innovations, turning them uncorrelated. In a bivariate VAR, this problem would be approached by attributing all the effects of the common component to the first of the two variables in the VAR. The situation is more complex when there are multiple variables, yet the interpretation is the same (Brooks, 2014).

# 5.0 Data

When gathering data, our intention was to collect a set of fundamental variables perceived as good consumption predictors to compare the results when adding consumer confidence. Our final dataset covers household consumption, income, and two wealth measures: financial and housing. In addition, we include the real interest rate, unemployment rate, and age distribution. Finally, we will also present the additional variable, consumer confidence.

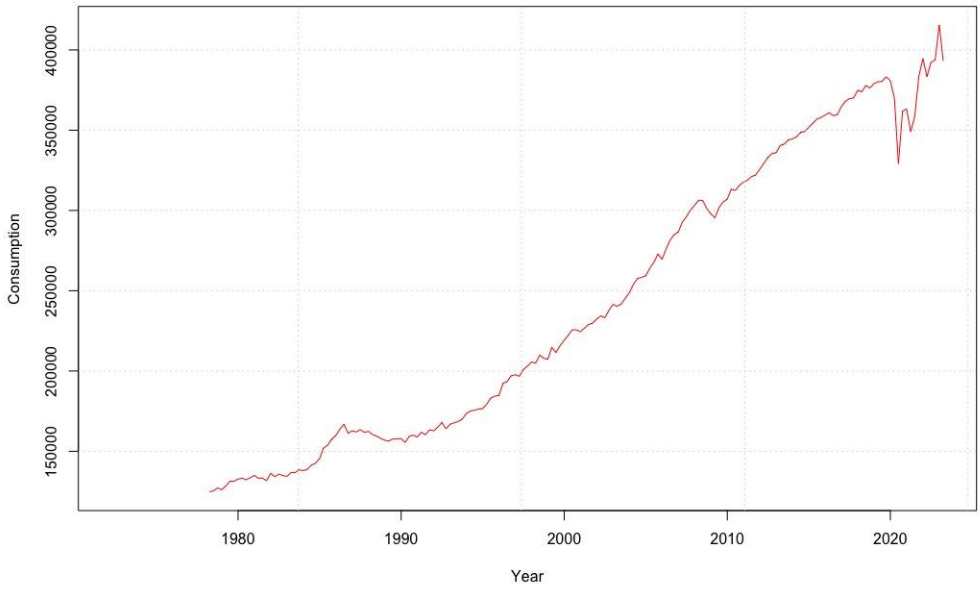
We gather information from several registers, which will be announced with the specific data. The variables and sources are listed in Appendix A.1. The timespan of our data is from the second quarter of 1992 to the last quarter of 2022, and the frequency of the data is quarterly. We use the real values for the variables and make sure that the series is deflated using the consumer price index (CPI), where this is suitable. In addition, we log-transform the series for consumption, income, and wealth measurements. We have kept interest rates, age variable, unemployment rate, and consumer confidence indicators in levels.

## 5.1 Household-Specific Data

### 5.1.1 Consumption

The primary focus of this thesis is the consumption variable. As discussed in Chapter 2.2, it can be challenging to obtain micro-level data as measures of consumption is typically available at an aggregate level. It is also common with self-reported surveys on consumption, but these are often categorized by measurement issues. We use aggregated macro data for total consumption as this is what is available for the household sector. The frequency of the data is quarterly and is collected from the national accounts provided by Statistics Norway. Figure 5.1 displays a graph of consumption. As we can see, consumption has increased over the years, with some falls. Recognize these drops around the 2008 financial crisis and the 2020 pandemic.

**Figure 5.1** Graph of the total household consumption




## 5.1.2 Income

Income as a predictive variable has appeared regularly in literature and financial theory and as early as in Keynes's theory from 1936. Most of the literature reviewed in Chapter 2.0, includes income as a predictive variable, and it makes sense to include it in our analysis.

Statistics Norway has long been collecting income data from registers. The *Income and capital accounts of the national accounts* are categorized into sectors, revealing transactions occurring within and between the sectors. The statistic provides a range of elements, such as interest and dividend payments, taxes, and benefits. We have extracted real household disposable income from the accounts, available quarterly from 1999 to 2023. Data on household income before this is available at an annual frequency. To account for the years before 1999, we used an approximation technique using the yearly and quarterly data growth rates.

## 5.1.3 Wealth

Another variable often considered a standard variable in economic analysis is wealth. We include wealth as a predicting variable as it often interferes with people's consumption choices. According to Statistics Norway, 76,4% of the Norwegian population owns housing and has high private debt. We want to split the wealth into financial and housing wealth, as done in Landsem (2016).

Following is a description of wealth, and the next two sub-chapters describe financial and housing wealth.

We use the definition of net household wealth from Brodin and Nymoen (1992):

$$W_t = (L_{t-1} + ML_{t-1} + NL_{t-1} + (PH/PC)_t \times K_{t-1} - CR_{t-1}) \qquad (5.1)$$

where $L_t$, $ML_t$, and $NL_t$ is household sector liquid, medium liquid, and illiquid assets. These three variables account for the financial wealth. The housing wealth $PH_t$ is housing prices, $PC_t$ is the price deflator and $K_t$is the volume of the residential housing stock. The loans to households from banks and financial institutions, $CR_t$, is subtracted from the wealth to have net household wealth.

As we only have the total debt, we have to suitably split it between financial and housing wealth to obtain the net value. There is no clear way to do this, as no measure is available for assigning the relative debt to each component. We are using the same method as Landsem (2016), who assigned portions according to the average relative size of the components. The average long-term relative size of housing wealth is 65%, leaving 35% to financial wealth. This split seems reasonable considering the high leverage ratio of households.

#### 5.1.3.1 Financial Wealth

Our measure of financial wealth is based on the calculations in Landsem (2016) and includes two distinct sources of data regarding households' financial balances, FINDATR and FINSE. The first database, FINDATR, was maintained by Norges Bank and covered quarterly data from 1975 until the first quarter of 2003. At this point, the quarterly financial sector accounts underwent revisions, and the database was replaced by FINSE. The new database contains data from the fourth quarter of 1995 until today and is maintained by Statistics Norway. The essence of the financial wealth measure is to connect these to datasets in a suitable manner. For further explanation of the databases and the construction of the final dataset, see Landsem (2016).

The net financial wealth variable is derived from Equation 5.1

$$Net\ FW_t = L_{t-1} + ML_{t-1} + NL_{t-1} - CR * d_f \qquad (5.2)$$

where $CR * d_f$ is the proportion of the total debt assigned to financial wealth. There are three levels of liquidity, where the most liquid category include cash and bank deposits. The second category includes stocks, bonds, and other financial assets and is less liquid. The last category encompasses insurance claims and is considered the least liquid.

#### 5.1.3.2 Housing Wealth

It can be challenging to obtain accurate data for housing wealth, as it is difficult to account for the actual value of housing. A close approach is to use a house price index, a common measure in several studies. It reflects the movements in the market, and as argued in Peltonen et al. (2012), "when real estate prices rise, the wealth of homeowners increases, and household consumption can rise even when labor income remains."

We estimate housing wealth as done in Brodin and Nymoen (1992):

$$Net\ HW = PH/PC_t \times K_{t-1} - CR * d_h \tag{5.3}$$

where $PH$ is housing prices, $PC$ is consumer price deflator and $K$ is the volume of residential housing stock. The house price index is obtained from FRED database, while the housing stock is obtained from Statistics Norway. To find the average house prices, we used the latest available average house price from Real Estate Norway together with the house price index.

We know the variable may not reflect market value, but obtaining a better data series available for the entire sample period is difficult. What is important is that it tells the movements in the market, even though it is lower than the market value.

## 5.2 Other Variables

In addition to fundamental variables mentioned in the previous sub-chapters, we decided to include variables that might impact consumption expenditure, even though they are not backed up as direct fundamentals in financial theory.

The first is the after-tax real interest rate from Erlandsen and Nymoen (2008). It takes the following calculation:

$$Real\ Interest\ Rate = Nominal\ Rate \times (1 - Tax) - Inflation \tag{5.4}$$

where the $Nominal\ Rate$ is the average interest rate on house loans, and $Tax$ is the average tax rate, and $Inflation$ is the inflation rate for the corresponding time.

The second variable, also from Erlandsen and Nymoen (2008), is the variable for the age composition. We have collected the distribution of "prime savers" in the population. Erlandsen and Nymoen (2008) define "prime savers" as 50 to 66 years old, as this group has a less average propensity to consume. The rationale is that in periods with a high ratio of this age group, one could experience less spending and higher saving. For further readings, see Erlandsen and Nymoen (2008). This variable is calculated as follows.

$$AGE = \frac{People\ aged\ 50-66}{People\ aged\ 20-49 + People\ aged\ 67\ and\ up} \tag{5.5}$$

As the age distribution is only available at an annual frequency, we interpolated the yearly data with quarterly data from the population series. We did this in R, using an approximation formula.

The last variable is the unemployment rate. A consequence of high unemployment rates is decreased disposable income for affected individuals, which can result in reduced consumer spending. Several articles, including Dées and Brinca (2013), use the unemployment rate as a predicting variable for consumption growth. Statistics Norway reports quarterly data on the unemployment rate.

## 5.3 Consumer Confidence

As explained in section 3.4, consumer confidence is a variable that can potentially improve the consumption function. The Norwegian consumer confidence index is available at Finans Norge, and the available sample is from the second quarter of 1992 until the last quarter of 2022. The barometer is a collaborative project between Finans Norge and Kantar Public. Finans Norge also reports the consumer confidence index for the EU. We have collected the quarterly index for the EU as well. Both indicators are graphed in Figure 5.2 and 5.3.

The expectations barometer is a survey that measures Norwegian households' expectations of their own and the country's economy. The survey is carried out by Kantar TNS, with the same questions each quarter. The first survey was done in 1992.

We use the main indicator, which consists of a combination of five sub-indicators, "the country's economy last year", "the country's economy next year", "own finances last year", "own finances next year", and "major acquisitions". Kirkedam defines the main indicator as “the difference between the percentage of optimistic and pessimistic answers for each question and divide it by five” (Kirkedam, 2021) (own translation).

From the graphs in Figure 5.2 and 5.3, we see that confidence was at its lowest in 2022. This could be the result of war in Ukraine, inflationary pressure and increasing policy rate. The confidence is also clearly affected by the financial crisis in 2008, where we see that both graphs drop. For Norway, there is also a substantial drop in the confidence around 2016, which might be the result of the 2016 price drop in oil.

Comparing the confidence in Norway to the EU, we recognize that the EU typically have a more pessimistic outlook, with exception of the 2016 drop and the first quarters of 2023.

**Figure 5.2** Norwegian consumer confidence

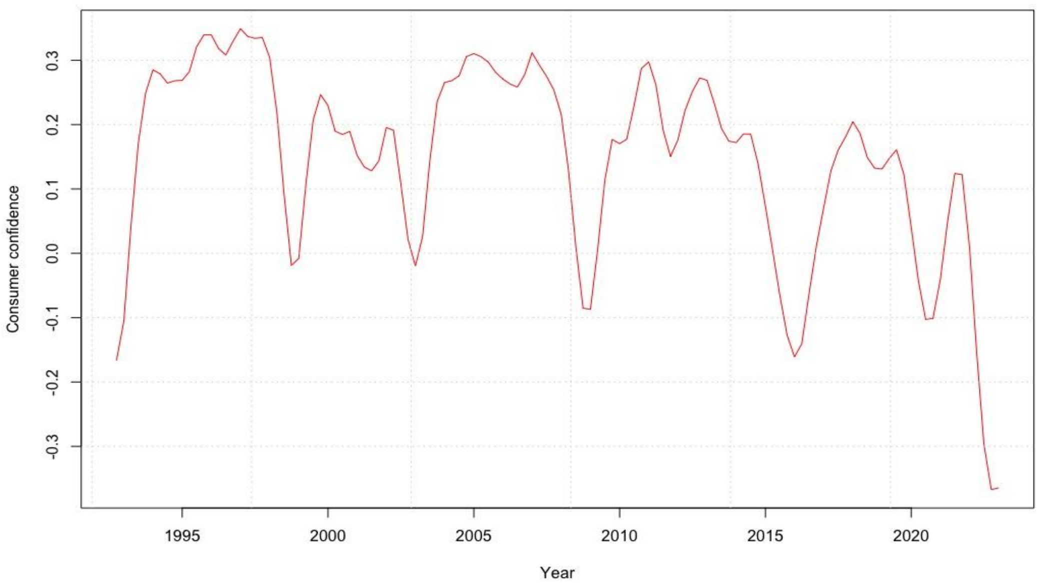
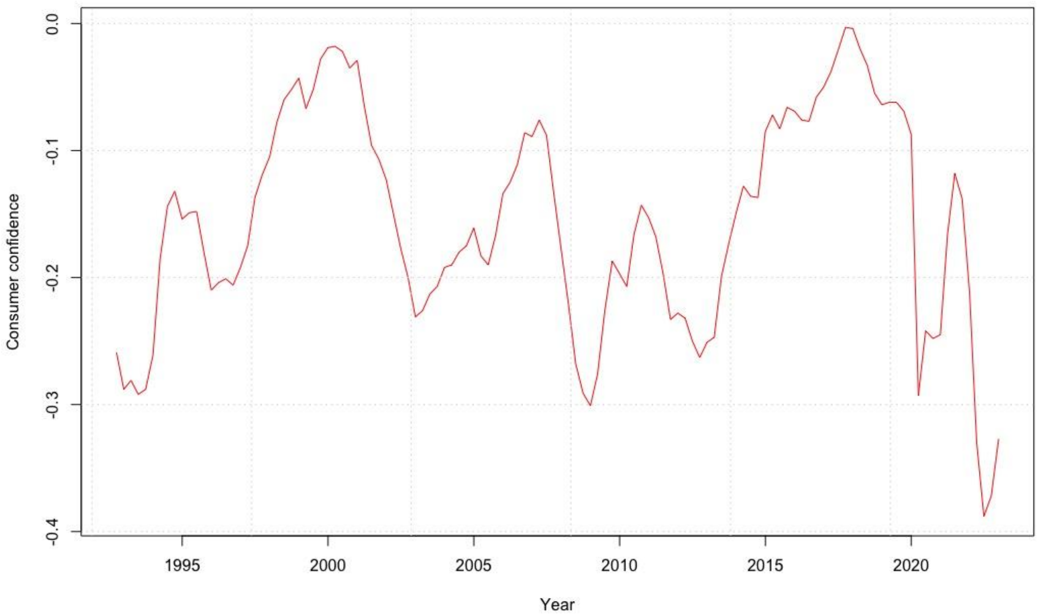


**Figure 5.3** EU consumer confidence



# 6.0 Analysis and Results

To explore our hypothesis, we follow an exercise from Dées and Brinca (2013). In their research, they explore the effect of consumer confidence in the U.S. and the euro area. The essence of the exercise is to build a model that can tell us whether it makes sense to add consumer confidence to the fundamental variables for predicting consumption growth.

We start our empirical analysis by running a unit root test, which enables us to verify the stationarity of the variables, ensuring that they possess stable statistical characteristics suitable for subsequent analysis.

After that, we run causality tests to determine whether the explanatory variables can be considered causal factors in predicting consumption growth over time. It gives us an indicator of the relationship between the variables. However, note that a variable's lack of Granger causality is not an automatic reason to exclude it for further analysis.

By this point, we have a good base for estimating models. We start with a simple consumption equation where the past values of the confidence indicator are the only explanatory variable for consumption expenditure. After that, we divide the standard variables into three sets of fundamental variables. They are introduced to the simple model at an increasing magnitude. Finally, we estimate a VAR model to derive impulse response functions and variance decomposition. Plots of these functions help us consider how shocks in the explanatory variables affect consumption growth and which variables affect the consumption response most. We look at four sub-periods to see whether the effects differ according to the economic situation.

## 6.1 Unit Root Test

As discussed in Chapter 4, testing for stationarity in the variables is necessary. We use the Augmented Dickey-Fuller (ADF) test for this purpose. According to the tests, all variables were I(1), meaning that they contain one unit root. The result is not surprising, as we are dealing with economic time series subject to economic growth, business cycles, policy interventions, and other external shocks. By taking the first difference of the variables, they become stationary. With all variables being stationary, we can use them for VAR modeling.

## 6.2 Granger Causality

Next step is to study Granger causality among the variables. Table 6.1 presents the results of the Granger causality analysis. We used the optimal lag length for each variable. Rejections of the null hypothesis for a 5% significance level are in bold.

The test results show that consumption growth is Granger-caused by the change in net financial and net housing wealth, real interest rate, and consumer confidence in the EU. The change in domestic consumer confidence, income, unemployment, and age distribution does not support Granger causality on consumption expenditure. We also performed the Granger causality tests for Norwegian confidence. The results from the test did not give us any indication to believe that any of the variables Granger causes Norwegian consumer confidence, except for income.

**Table 6.1** P-values from Granger Causality tests[1]

| | $\Delta c$ | $\Delta CCI$ |
|---|---|---|
| $\Delta CCI$ | 0.12 | - |
| $\Delta c$ | - | 0.13 |
| $\Delta y$ | 0.48 | **0.05** |
| $\Delta w$ | **0.02** | 0.77 |
| $\Delta w^f$ | **0.00** | 0.10 |
| $\Delta w^h$ | **0.00** | 0.82 |
| $\Delta RR$ | **0.04** | 0.60 |
| $\Delta AGE$ | 0.12 | 0.46 |
| $\Delta unemp$ | 0.49 | 0.08 |
| $\Delta CCI*$ | **0.00** | 0.16 |

[1] The table reports the p-values from Granger causality tests of each variable in the first column on change in consumption and change in consumer confidence. P-values in bold means that the variable in the row Granger cause the dependent variable in the second or third column.

The results of the Granger causality tests confirm that there might be some wealth effects on consumption, as all the wealth measures are significant. In addition, confidence in the EU seems to influence consumption expenditure in Norway. This finding could, however, be driven by a positive association between fundamentals in the EU and positive EU consumer confidence. In Dées and Brinca (2013) a similar finding was displayed. Their findings indicated a confidence linkage between their economic areas, suggesting that U.S. confidence influences the EU consumption expenditure. Estimating consumption models and dynamic analysis is necessary to understand the relationships found in this section.

## 6.3 Estimation of a Simple Model for Consumption

It is time to estimate a model that can tell us about the predictive power of our explanatory variables on consumption expenditure. As done in Dées and Brinca (2013), we start with a model where the change in consumer confidence ($\Delta CCI_t$) is the only explanatory variable for consumption expenditure ($\Delta c_t$). We adopt most of the notation from Dées and Brinca (2013) for this exercise.

$$\Delta c = \alpha + \sum_{i=1}^{q} \beta_i \Delta CCI_{t-q} + \epsilon_t \tag{6.1}$$

where $\epsilon_t$ is the error term. We have considered several tests for optimal lag length, including AIC, SBIC, and by looking at the adjusted R squared. We found variations in optimal lag length for the models, so for the sake of comparability and consistency, we decided to use the same lag order for each model. All the models are built at a lag order of 2.

The test results of Equation 6.1 showed a small $\underline{R}^2$ of 1%. This indicates that past changes in consumer confidence can explain 1% of the linear variation in consumption growth alone.

We add to the model three separate sets of fundamental variables. We split the standard variables into similar sets as Dées and Brinca (2013), where the first set ($Z^1$) only includes past changes in consumption ($\Delta c$) and in real disposable income ($\Delta y$). The second set ($Z^2$) adds changes in financial wealth ($\Delta fw$) and housing wealth ($\Delta hw$) to $Z^1$. The third set ($Z^3$) also includes changes in the real interest rate ($\Delta RR$), age distribution ($\Delta AGE$), and unemployment rate ($\Delta unemp$).

Equation 6.2 is the linear model of changes in each set of fundamentals, while Equation 6.3 includes the change in consumer confidence. The objective is to compare the $\underline{R}^2$ between equations 6.2 and 6.3 to see if it increases with the increasing number of variables.

$$\Delta c = \alpha + \sum_{i=1}^{q} \gamma_i Z_{t-i}^{k} + \epsilon_t, \text{ for } k = 1,2,3 \quad (6.2)$$

$$\Delta c = \alpha + \sum_{i=1}^{q} \beta_i \Delta CCI_{t-q} + \sum_{i=1}^{q} \gamma_i Z_{t-i}^{k} + \epsilon_t, \quad (6.3)$$
$$\text{for } k = 1,2,3$$

Table 6.2 presents $\underline{R}^2$ for each model. From the table, we see that the models with only fundamental variables (Eq. 6.2), increase for each set. The first set, $Z^1$, explains 5% and increases to 8% with $Z^2$ and 11% with $Z^3$. When adding the confidence indicator, all the models increase the fit measure. The model with the highest $\underline{R}^2$ is the one including confidence indicator and the most extensive set of fundamentals, $Z^3$. This model explains almost 12% of the linear variation in consumption expenditure changes, and is so far the best model.

The $\underline{R}^2$ may seem low considering the number of variables involved, but this is not surprising. Compared to the results for the euro area in Dées and Brinca (2013), our results are not too far off. As they pointed out in the article, the low $\underline{R}^2$ results from there being no contemporaneous variables in the estimates.

The final model we want to estimate is one with the change in foreign consumer confidence ($\Delta CCI'$) added to Equation 6.3.

$$\Delta c = \alpha + \sum_{i=1}^{2} \beta_i \Delta CCI_{t-q} + \sum_{i=1}^{2} \beta_i \Delta CCI'_{t-q} + \sum_{i=1}^{2} \gamma_i Z_{t-i}^{3} + \epsilon_t \quad (6.4)$$

By adding the consumer confidence of the EU to the model, we see that it can explain more of the linear variance of consumption changes. The $\underline{R}^2$ is now at 42%, suggesting that there is a "confidence channel". This result aligns with research by Fei (2011), who finds empirical evidence that a confidence channel exists between larger and smaller countries. The confidence channel reflects that news in the EU spreads quickly to Norway, which is not surprising. Dées and Brinca (2013) also found a confidence channel from the U.S. to the euro area, underlining that confidence from bigger economic areas influences the smaller areas. However, the increase is substantial, and might be a result of missing control variables. The effect could be driven by a positive association between fundamentals in the EU and positive EU consumer confidence. This is not tested in our thesis but could be interesting for further research.

**Table 6.2** Adjusted R squared for simple models

| EQ. | MODEL | $\underline{R}^2$ |
|---|---|---|
| 6.1 | $\Delta c = \alpha + \sum_{i=1}^{2} \beta_i \Delta CCI_{t-q} + \epsilon_t$ | 0.009 |
| 6.2 | $\Delta c = \alpha + \sum_{i=1}^{2} \gamma_i Z^1_{t-i} + \epsilon_t$ | 0.045 |
| 6.3 | $\Delta c = \alpha + \sum_{i=1}^{2} \beta_i \Delta CCI_{t-q} + \sum_{i=1}^{2} \gamma_i Z^1_{t-i} + \epsilon_t$ | 0.082 |
| 6.2 | $\Delta c = \alpha + \sum_{i=1}^{2} \gamma_i Z^2_{t-i} + \epsilon_t$ | 0.082 |
| 6.3 | $\Delta c = \alpha + \sum_{i=1}^{2} \beta_i \Delta CCI_{t-q} + \sum_{i=1}^{2} \gamma_i Z^2_{t-i} + \epsilon_t$ | 0.112 |
| 6.2 | $\Delta c = \alpha + \sum_{i=1}^{2} \gamma_i Z^3_{t-i} + \epsilon_t$ | 0.104 |
| 6.3 | $\Delta c = \alpha + \sum_{i=1}^{2} \beta_i \Delta CCI_{t-q} + \sum_{i=1}^{2} \gamma_i Z^3_{t-i} + \epsilon_t$ | 0.115 |
| 6.4 | $\Delta c = \alpha + \sum_{i=1}^{2} \beta_i \Delta CCI_{t-q} + \sum_{i=1}^{2} \beta_i \Delta CCI'_{t-q} + \sum_{i=1}^{2} \gamma_i Z^3_{t-i} + \epsilon_t$ | 0.417 |

Consumer confidence seems to improve all the models from Equation 6.3. There are also suggestions for a confidence channel between the EU and Norway. This finding implies that past changes in the EU confidence influence the current changes in consumption in Norway. However, this might be due to the omitted variable bias, as we have not included any control variables for the standard economic variables in the EU.

Although this analysis is simple, it does contribute to drawing preliminary conclusions that can guide further research.

## 6.4 VAR Analysis

For the next part of the analysis, we want to use a VAR system to help us analyze the dynamic relationship between our variables. We examine the impact of a positive shock to confidence on consumption through impulse response functions (IRF). After this, we compute variance decomposition to graph the contribution of confidence shocks compared to the proportion of the movements in consumption due to its own shocks.

For the VAR modeling, we decided to exclude the unemployment rate and age distribution as we noticed that a simpler model was more suitable. We removed these variables to simplify the model and considered that none of the variables passed the Granger causality test when making the decision. Following the notation of Brooks (2014), our VAR model is the following:

$$\gamma_t = \sum_{i=1}^{q} A_i \gamma_{t-1} + Bu_i \tag{6.5}$$

where

$$\gamma = \begin{cases} \Delta c_t \\ \Delta CCI_t \\ \Delta Z^3{}_t \end{cases}$$

and

$$B = \begin{matrix} b_{11} & 0 & 0 \\ b_{12} & b_{21} & 0 \\ b_{13} & b_{22} & b_{33} \end{matrix}$$

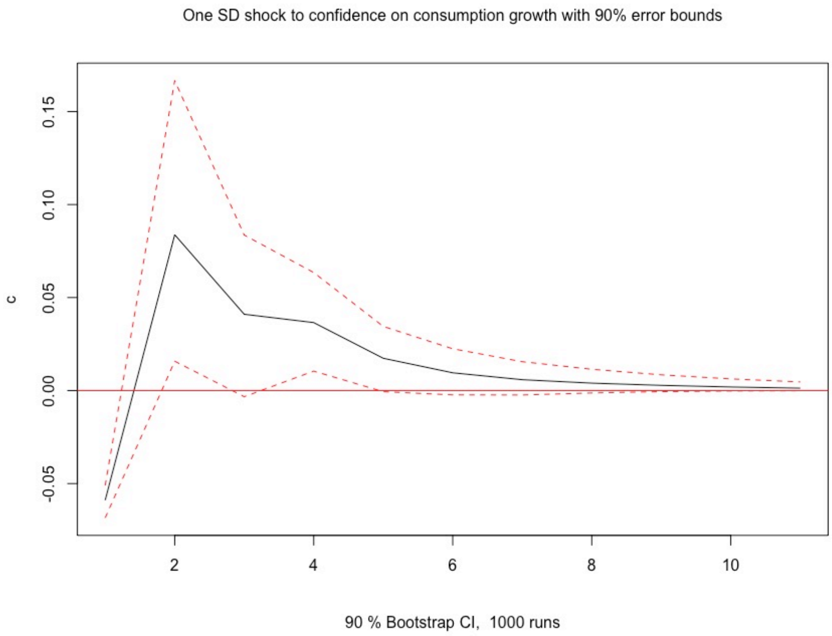
where $Bu_i$ is a vector of orthogonalized shocks. Using the Choleski decomposition, the ordering of the variables is essential and should preferably follow financial theory. The ordering of our VAR is inspired by Dées and Brinca (2013), and is the following: domestic confidence, financial wealth, housing wealth, real interest rate, income, and consumption. Using SBIC, we found that the optimal lag length (q) is 1.

Figure 6.1 displays the graph of the impulse response functions of a shock to change confidence on consumption. The y-axis represents the response of the consumption growth, and the x-axis represents the time after the shock. Each period represents one quarter of a year. The dotted lines around the responses are the 90% error bands, and the function is bootstrapped 1000 times by the Monte Carlo approach. The function shows the standard deviation response to a positive one standard deviation shock to consumer confidence.

The plot in Figure 6.1 shows that the IRF starts below zero and moves above zero before the second quarter. It suggests that the variable initially responds negatively to the shock but eventually rebounds and shows a positive response. There could be several reasons as to why the response shows negative in the first period, despite the positive shock to consumer confidence. Households may implement precautionary spending, experience delayed spending decisions, uncertain income/wealth expectations or experiencing different transaction costs as an initiate response. With precautionary savings, they might want to set up a buffer by increasing their savings or reducing their consumption, or with delayed consumption, they might need time to process the new information and adjust their spending decisions. Even though there is an optimistic view on the future, households might not receive an increase in income or wealth immediately, they might not be able to respond with increased consumption. Different transaction costs could be expenses regarding buying objects, negotiation, finding trading partners, enforcing contracts or other logistical issues. This behavior can result in a temporary negative response in consumption immediately after the shock followed by a recovery or adjustment.

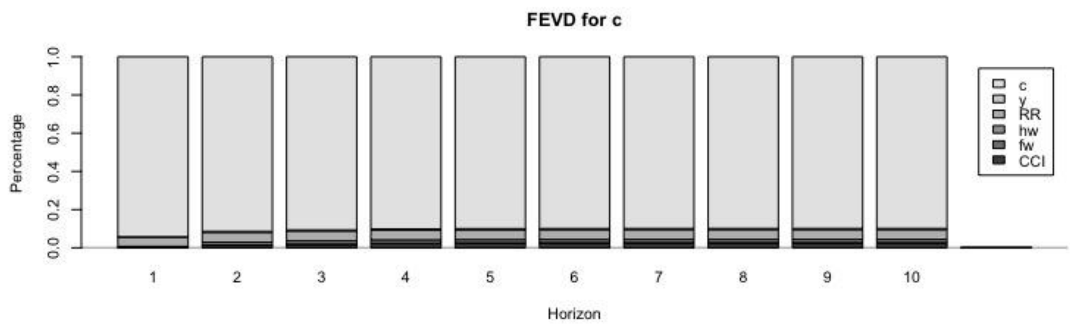
A one-standard-deviation shock to consumer confidence causes a positive response in consumption after the first period, after which the effect dissipates after the second quarter. The response is significant from the second quarter. As the plot suggests, the effect adjusts slowly and is around 0.00 at the 10th quarter. At its highest point in the second quarter, the response is at approximately 0.08 standard deviations, which is a relatively strong response compared to the findings in Dées and Brinca (2013). They found the biggest response to be 0.0008 and 0.001. From the analysis of IRF, shocks to consumer confidence seem to play a role in consumption determination.

**Figure 6.1** IRF for the shock to CCI on consumption expenditure




The variance decomposition in Figure 6.2 also shows some effect of confidence shocks on consumption expenditure. In correspondence to the findings of Dées and Brinca (2013), most of the variance in consumption growth is driven by fundamentals and lags of consumption.

**Figure 6.2** Variance decomposition




Next, we have extracted four sub-periods from our dataset, considering historical happenings. We want to look at the consumption response to shocks in consumer confidence during crises compared to "normal" times. The first sub-period is from the third quarter of 1992 until the fourth quarter of 1999. The next sub-period is from 2007 (1) until 2012 (4), capturing the financial crises. The third sub-period is from 2014(1) until 2018(4), capturing the price drop in oil, and the last sub-period is capturing the pandemic from 2019(1)-2022(4). Plots of the IRFs are in Figure 6.3 to Figure 6.6. We use error bounds of 68%, which is common in macroeconomics, even though it is not a commonly used confidence level for hypothesis testing.

These graphs show a positive consumption response to consumer confidence shocks in all four subperiods. For the pre-crises/pre-pandemic sub-periods, the response seems to be subsiding in the 6th quarter, while for the other two sub-periods, we can not see that it settles within the frame. Notice the increasing reaction of consumption to confidence shocks over time. The response is relatively weak in the first sub-period and increases substantially by the financial crises sub-period. It seems like confidence indicators have become more impactful on consumption growth after the financial crisis, as we see an increased response in the third sub-period capturing the price drop in oil. The sub-period representing the pandemic has the most vigorous response. While it seems strong compared to the other plots, we can compare it to findings in the U.S. from 2021, where the response was nearly at 2.0. The research was done by Abosedra, Laopodis, and Fakih and used monthly data from 2016 until 2021 (Abosedra et al, 2021).

**Figure 6.3** IRF plot of sub-period 1992(3) - 2006(4)

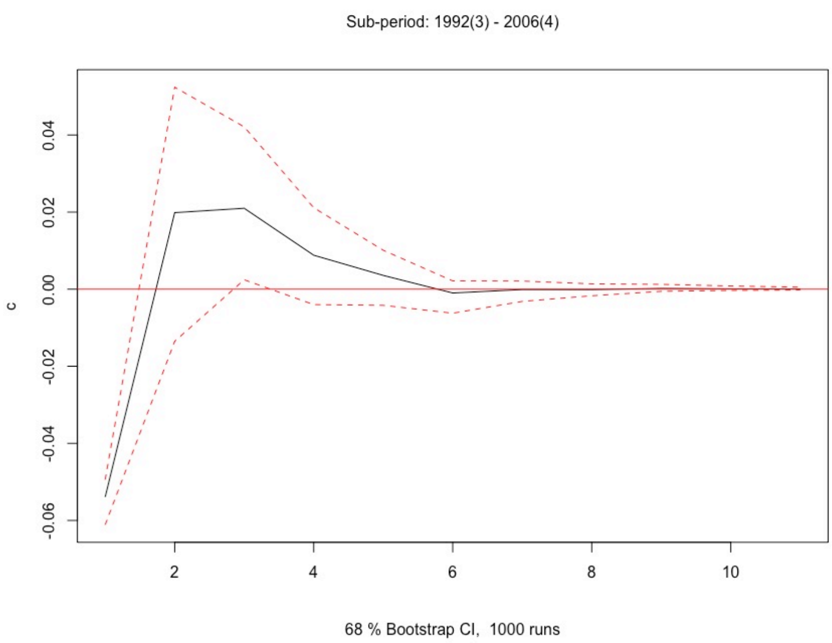


**Figure 6.4** IRF plot of sub-period 2007(1) - 2014(4)

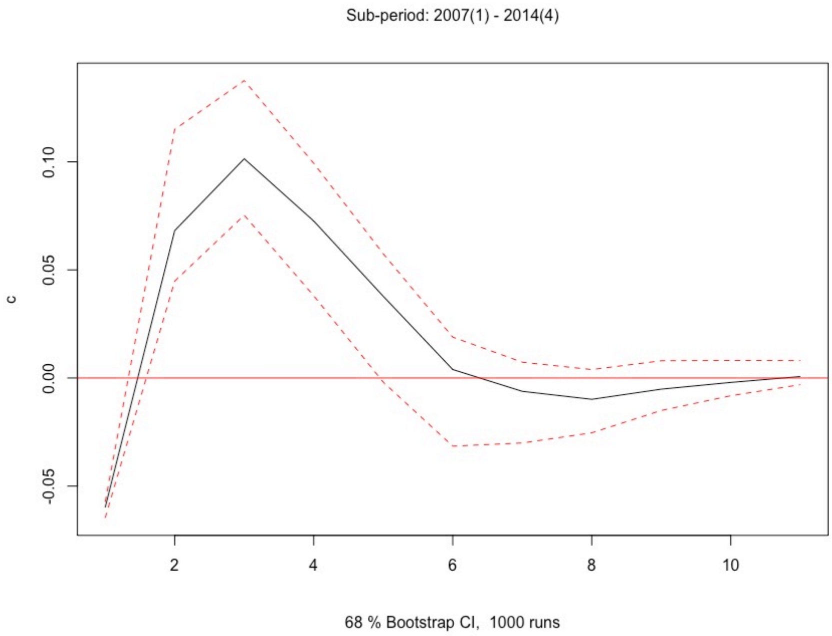



**Figure 6.5** IRF plot of sub-period 2012(1) - 2018(4)

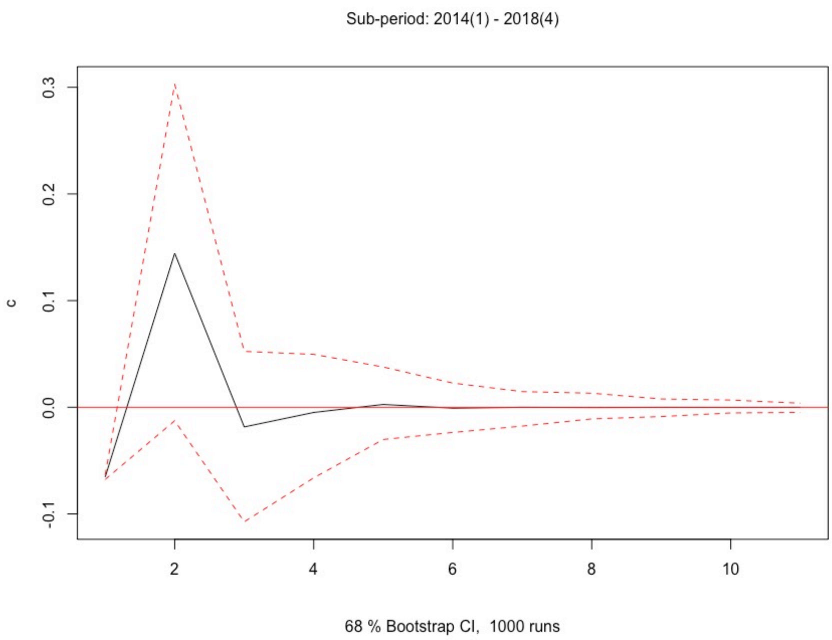
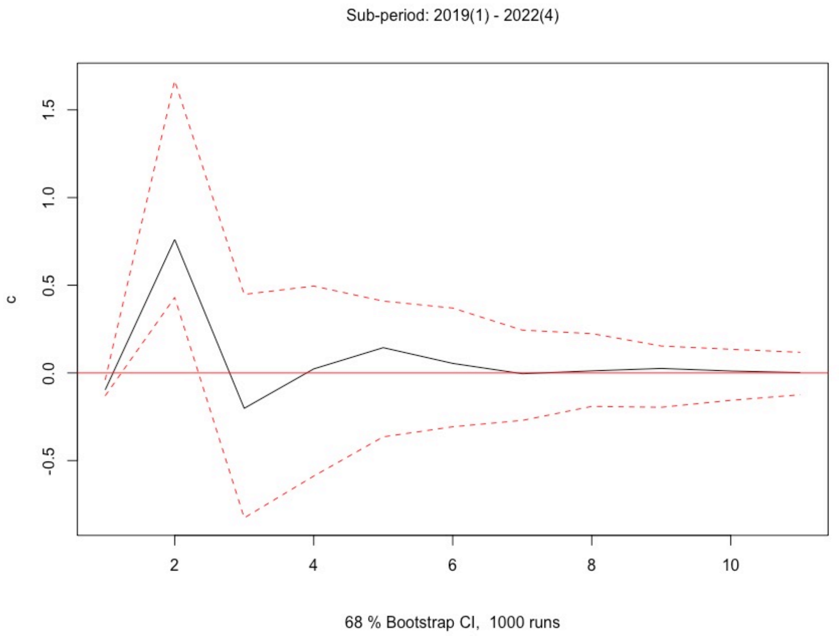


**Figure 6.6** IRF plot of sub-period 2019(1) - 2022(4)




We also split the data into longer sub-periods, the first being 1992(3) - 2012(4) and the second being 2015(1) - 2022(4). The plots display the same patterns as the four-split. From 1992 to 2012, the impact seems negative at the first lag before it stays positive until it adjusts. The second split displays a stronger reaction to the shock and a quicker drop in the positive response. Both response functions have 85% error bands and show significance at periods two until five in Figure 6.7 and the first two periods in Figure 6.8.

**Figure 6.7** IRF plot of sub-period 1992(3) - 2012(4)

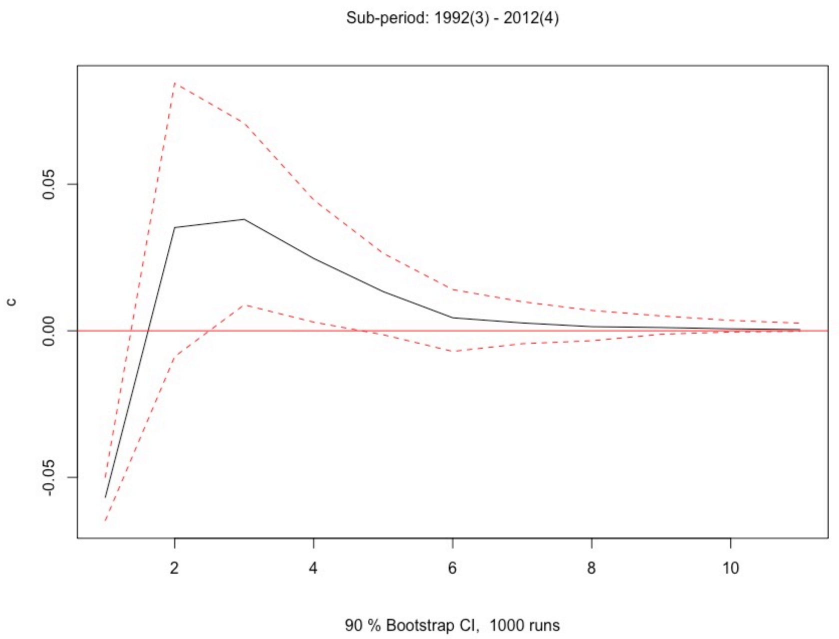
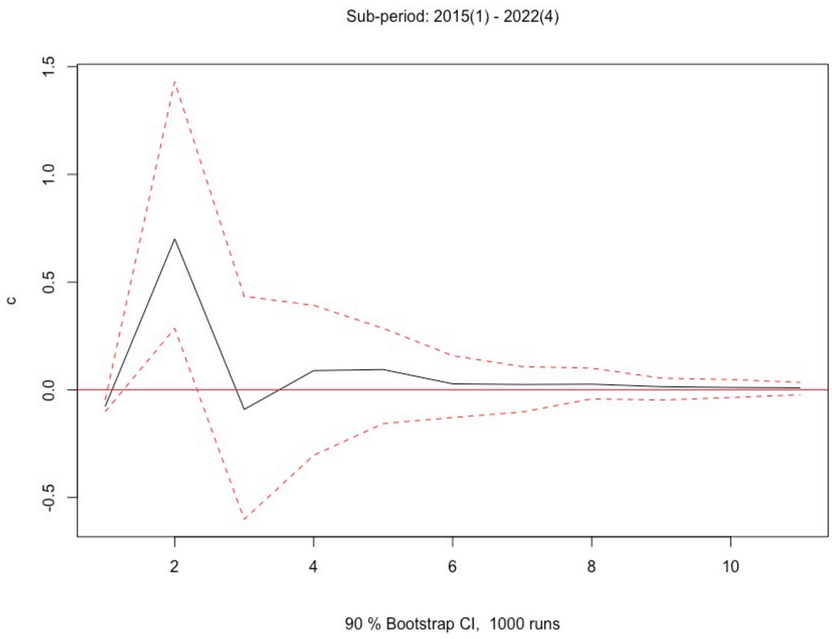


**Figure 6.8** IRF plot of sub-period 2015(1) - 2022(4)




These functions indicate that consumer confidence holds value when analyzing consumption expenditure. The long settlement time during crises suggests consumers maintain a long memory of the impact of confidence relative to regular times. In addition, we observe that the impact of the confidence shock on consumption is greater during uncertain times, and it has become stronger during the last 30 years. These factors indicate that consumer confidence is related to consumption expenditure and could be a valuable variable for predicting consumption growth.

# 7.0 Conclusion

This research aims to empirically assess the relationship between consumer confidence and consumption growth in Norway. The simple model analysis showed that consumer confidence could be a valuable predictor of consumption and that a confidence channel from the EU might exist. The adjusted R squared was at its greatest, with a measure of 11.5%, when including consumer confidence and the most extensive set of fundamentals. By adding foreign consumer confidence to the model, the fit increased to 41.7%. This could, however, be the result of omitted variable bias, as we are not including any control variables for the EU. This would be interesting to dig deeper into in further research.

The impulse response function shows that consumption expenditure initially has a negative response to positive confidence shock. The response is positive after the first period, indicating that with sudden increase in confidence, the consumption will increase. The initiate response could be a result of precautionary savings, information delays, variating income and wealth expectations or adjustment costs.

When looking at different sub-periods representing times of economic uncertainty, we can see an increased effect of shocks to consumer confidence on consumption growth compared to regular times. This indicates that the index does contain some value when analyzing consumption growth and concludes that the consumer confidence index has some predictive power for consumption growth in Norway.

Finally, our research and findings could serve as a preliminary study for future research. The paper presents an important implication for policymakers, business owners, and other stakeholders who depend on anticipating future market trends. An investigation of a confidence channel between Norway and related countries or economic areas could be interesting. Another angle could be to investigate the corona crisis in terms of confidence indicators and pandemic-specific variables. Some phases of the crisis to investigate could be initial spread, the local restrictions, the second wave of the pandemic, and the vaccination process. Further examination of confidence linkage and a thorough analysis of the crisis could be the direction for future research.

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# Appendices

## A.1 Data Definitions and Sources

| | |
|---|---|
| AGE | Age distribution. A ratio of the people between 50 to 66 years compared to the rest of the population aged 20 and up.<br>Source: Statistics Norway |
| C | Consumption expenditure in households.<br>Source: Statistics Norway |
| CCI | Consumer Confidence Index for Norway<br>Source: Finans Norge |
| CCI’ | Consumer Confidence Index for the EU<br>Source: Finans Norge |
| CPI | Consumer Price Index<br>Source: Statistics Norway |
| i | Average interest rate on house loans.<br>Source: Norges Bank |
| INF | Inflation rate<br>Source: Statistics Norway |
| Net FW | Net financial wealth<br>$Net\ FW_t = L_{t-1} + ML_{t-1} + NL_{t-1} - CR * d_f$<br>Source: Statstics Norway |
| Net HW | Net housing wealth<br>$Net\ HW = PH/PC_t \times K_{t-1} - CR * d_h$<br>Source: FRED, Real Estate Norway, Statistics Norway |
| PC | Price deflator based on total consumption expenditure. Used for nominal values of wealth, income and consumption.<br>Source: Statistics Norway |
| RR | Marginal after-tax real interest rate.<br>$RR = i * (1 - Tax) - Inflation$<br>Source: Statistics Norway |
| W | Net total wealth<br>$W_t = (L_{t-1} + ML_{t-1} + NL_{t-1} + (PH/PC)_t \times K_{t-1} - CR_{t-1})$<br>Source: Statistics Norway |
| Y | Household disposable income.<br>Source: Statistics Norway. |