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What Characterizes Cycles with Crashes versus Corrections in the House Market?

An Empirical Test on Price Behaviour Based on Economic Key Indicators

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Abstract

This thesis aims to examine and compare the cycles characterized by crashes and corrections in the Norwegian house market, by focusing on crucial economic indicators. By employing descriptive analysis and time-series Ordinary Least Squares (OLS) regression, we examine two periods characterized by crashes and corrections.

Subsequently, we shall delve into crisis theory and the dynamics between supply and demand. Contrary to previous studies, which primarily focused on the outcomes of bubbles and crashes in the house market, our thesis will focus on the differences between cycles with crash and correction.

To examine the differences, our paper deploys Hodrick-Prescott filtering to monitor real house prices and observe how they deviate from the long-term trend. We discuss the economic indicators such as GDP, nominal income, nominal interest rate, Price/Rent (P/R) ratio, house stock, unemployment rate, money supply, and credit volume, and analyse how they affect house prices.

The outcome from our analysis illustrates that during both crashes and corrections, house prices were significantly influenced by changes in credit volume and money supply. In scenarios with crashes, these factors contribute to the inflation of house prices and bubble tendencies, eventually leading to a bubble burst and subsequent market collapse. The findings further reveal that unemployment rate and house stock significantly influence the market during crashes, whereas their importance diminishes during corrections. The P/R ratio considerably impacted the model for both types of market cycles. However, in periods with crashes, it increases more over time. Conversely, nominal interest rate, GDP, or nominal income did not significantly influence the model.

Preface

This thesis marks the completion of our master's degree in Business Analytics and Financial Economics at the Norwegian School of Economics. During our master studies, we have discussed various topics our research question was determined after realising we both share the same interest in the real estate market. Together with our supervisor, we came up with a topic to examine.

Although writing our thesis has been challenging, we are sure that the educational knowledge and insight we have obtained will be beneficial in our future careers.

We want to thank our supervisor Professor Ola Honningdal Grytten for his support throughout the whole semester. His knowledge and constructive feedback have been necessary in executing this project. Furthermore, we want to thank Director in Norges Bank, Øyvind Eitrheim, and Dag Kolsrud from SSB, for providing us with data for our research.

Lastly, we want to thank our lecturers and fellow students at NHH for the great time during our studies.

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1. Introduction

Although the world has become more globalized and unreliable in recent decades due to a pandemic, energy crisis, oil crisis, and more attention to climate change, the Norwegian house market has been on the rise since 1993. Due to high loan rates and rising inflation, the house market is currently experiencing a decline in the purchasing power of households (Ogre, 2023). This thesis initiates an empirical investigation into the distinctive characteristics that distinguish between house market cycles that end in crashes aside from those that end in corrections.

Modern economic studies are quite interested in the cyclical variations of the house market, characterized by cycles of expansion followed by downturns. This is mostly due to their significant effects on individuals and overall financial stability. Due to their distinct socioeconomic effects, it is necessary to distinguish between crashes and corrections. Corrections are seen as an essential component of a market that is operating efficiently as they help to reduce speculative excesses and restore equilibrium. Contrarily, crashes have the potential to result in serious consequences such as financial crises, economic recessions, and household financial losses. Despite their critical importance, more in-depth research must be conducted to understand the factors differentiating these two occurrences (Shiller, 2015).

Based on our delimitation, we selected two price crash periods and two correction periods. The Kristiania Crash (1899–1905) and the Banking Crisis (1988–1993) will be the crashes we explore, whereas the Long Depression (1878–1844) and the Financial Crisis (2007–2010) will be the price corrections.

1.1 Research Question

In our thesis, we will examine the following research question:

What Characterizes Cycles with Crashes versus Corrections in the House Market?

Furthermore, we will conduct an empirical test on price behaviour based on economic key indicators.

1.2 Background and Motivation

Our thesis was motivated by the FIE431 Crashes and Crises course and the desire to write about a subject that is now being widely discussed. The news environment over the last year has been dominated by rising house prices, rising interest rates, increasing inflation, the energy crisis, and the war in Ukraine. Due to our shared interest in economic history, especially regarding the house market, we decided to write about the historical house market in Norway by focusing on periods with crashes and corrections. Over the past few decades, the Norwegian house market has experienced substantial growth, and it has been widely speculated whether a crash or correction is imminent.

1.3 Limitations

The thesis will concentrate on the period from 1836 to 2021 in the Norwegian house market. The restriction is based on our defined periods as well as the limited data available in the previous. On the demand side, we will concentrate on key economic indicators like GDP, interest rates, unemployment, income, money supply, and credit volume. This will be explored along with supply-side factors like interest rates and house stock. Due to Norway's small size and open economy, price drops and adjustments will frequently be correlated with global business cycles and therefore, distinctions may have an impact on the results.

1.4 Definitions of Crash and Correction

Crash

For this study, the term “crash” refers to a substantial decrease in house prices which happens when a bubble bursts. A definition of an asset bubble, as given by Grytten is *"the trading of assets in large volume, at prices with significant deviation from fundamental values"* (Grytten & Hunnes, 2016, p. 76). This can result in a collapse of asset prices because the supply-side is larger than the demand side. Prices drop rapidly, making it difficult to restore the market's buyer's side due to panic selling which also causes creditors to be more cautious in lending due to the fear of losses. If credit stops, it strangles the source of financing and ultimately harms the economy. In our thesis, we defined a crash as a decrease in real house prices of around 20 percent over 2 years.

Correction

A correction in the house market refers to the decline in house prices after rapid growth. This is a natural part of a house market cycle. Corrections can occur due to various factors, such as an increase in interest rates, a decline in demand, oversupply, or changes in the economy. The purpose of a correction is to bring house prices back in line with fundamental values, which can help make houses more affordable and sustainable for buyers in the long run. However, corrections can also negatively impact homeowners, particularly those who have recently purchased a home or have high levels of debt (Shiller, 2015). In our thesis, we have defined a correction as a decrease in real house prices of 5-15 percent over 2-5 years.

1.5 Outline

In Chapter 2, we will start by describing the purpose of our thesis and present previous research on the field of our study.

We will then present the selected theory that applies to our study in Chapter 3 which will begin with a review of house market theory before moving on to a presentation of crisis theory, including the seven-step dynamic crisis model and the anatomy of a crisis. A summary of the Norwegian house market from 1836 to the present will then be given in Chapter 4, where the periods identified as crashes and corrections will be examined in more detail.

The thesis will then present the applied data sources in Chapter 5 which consist of evaluating the reliability and validity and describing each data source used in our study. Furthermore, we will describe the study's methodology in Chapter 6 with a description of how market cycles are identified in the house market and then discuss the techniques for comparing data time series and how regression analysis is performed.

Chapter 7 will give an empirical analysis of the Norwegian house market. Additionally, stationarity and correlation analysis will be performed, as well as presenting cycle plots for each variable. In Chapter 8, we will give our regression models, our results, and a discussion of the outcomes for each variable.

And finally, chapter 9 will present our concluding remarks where we also provide our recommendations for future research.

2. Historiography

It has previously been written about the anatomy of house crashes and the build-up of financial bubbles resulting in asset crashes. Furthermore, there is a lot of research on the house market and how economic factors contribute to fluctuations in the market.

Høeg & Stenvaagnes (2013) wrote a master thesis on "*What macroeconomic variables can predict financial crises in Norway?*". The thesis is a time-series analysis, and they look at the relationship between GDP and other macroeconomic variables between 1880 - 2011. Their results were that nominal money- and credit volume were the variables that stood out to notice an impending crisis. Their methodology has been an inspiration for our thesis. Aksnes & Kessel (2021) have also inspired our analysis on which variables we should include to understand the property market in Norway.

In the following sections, we will present previous research relevant to our study's purpose and conclude with why we have decided to write about the current topic.

2.1 Previous Research

Malpezzi (1999) refers to a study that confirmed that changes in housing prices are partly predictable and not random. A simple two-equation model for housing prices was used. It showed that the equilibrium relationship between housing prices and income is well modelled, and regulation within the housing market is a strong factor in the equilibrium relationship. If the equilibrium deviated, it would lead to significant proportional changes in price. However, it is found that higher growth rates in population and income can be associated with higher conditional price changes, although higher mortgage rates lower price changes.

Karl E. Case & Robert J. Shiller (2003) analysed the characteristics of a bubble in the American housing market. Case & Shiller (2003) used surveys to examine what home buyers expected in terms of future price increases in the market. They looked at the American housing market and focused on seven criteria that are important drivers of price and potential bubble tendencies. In 2013, Robert J. Shiller won the Nobel Prize in economics for his book *Irrational Exuberance*. In the book, Shiller (2015) examines the psychological and social factors that drive bubbles and subsequent crashes in the stock and house markets. Shiller

(2015) discusses what happens when the market crashes and when the market experiences a correction.

Jacobsen & Naug (2004) analysed what drives house prices in Norway. They used an empirical model to analyse the strong growth that had been ongoing from 1992 until the 2000s. The study results showed that interest rates, new construction, unemployment, and household income were the most important factors affecting house prices. No solid evidence was found that house prices are overvalued relative to the fundamental value determined by interest rates, income, unemployment, and new construction. We have used this article to get inspiration on which variables to use in our regression of the house market, as well as gaining a broader understanding of how the property market works.

Anundsen (2019) investigates the drivers of cycles of the house market by employing a combination of theoretical modelling and empirical analysis. He uses time-series data from different countries to analyse the impact of economic factors on the house market. Furthermore, the analysis highlights factors that contribute to the boom-bust cycle. The article provides valuable insight into the cyclical nature of house markets which is an essential understanding when analysing price cycles with crashes and corrections.

In the thesis, we have also used the article by (Jacobsen, Solberg-Johansen, and Haugland, 2006) to explain the various shifts in supply and demand in the long and short term in the house market. The article addresses house investments and the changes between demand and supply in the long and short term. Among other things, they find a connection that the increase in house investments in 2004 was due to a period of low-interest rates and high house prices. Inspiration has also been drawn from (Grytten & Hunnes, 2016), who published the book *Crashes and Crises in a Historical Perspective*. The book deals with historical events involving crashes and crises dating back to the 17th century up to recent times. The book is also relevant because to map out how economic crises occur; one must understand how previous crises unfolded. We also use (Grytten O. H., 2008) to map the economic development in Norway.

Duca, Muelbauer & Murphy (2021) presented research on price drivers in the housing market and how the housing market affects the economy. The research also refers to how closely the housing market is linked to the credit market. The research highlights the importance of financial stability and the role of houses in the economic accelerator, and an overhang of housing supply can dramatically reduce economic activity in periods.

To find out how the HP-filter works and how to use it, we have used the article by Koilo & Grytten, *Maritime financial instability and supply chain management effects* (Koilo & Grytten, 2019). We have also used Hamilton (2018) on the downsides of using the HP-filter and Phillips & Shi (2021) and their solution to the problem by applying machine learning techniques to the filtering.

2.2 Purpose of Thesis

In this section, we will examine the objectives of our thesis. Although numerous research articles and master theses have been written on the house market and its historical aspects, we found a gap in the research explicitly focusing on comparing cycle periods involving crashes versus corrections in the Norwegian house market.

To address our research question, we incorporated the supply and demand theory and their interplay bolstered by crisis theory. We examined the impact of variables such as Price/Rent, house stock, unemployment, nominal interest rate, money supply, credit volume, nominal income, and GDP on house prices. Our research is narrowed to Norway, with the periods chosen based on historical data and fluctuations of the chosen variables during those times.

Consequently, this thesis aims to compare the economic characteristics during cycles with corrections and crashes in the house market.

3. Theory

In this chapter, we will present the theoretical framework to be used when analysing the characteristics of the house market in periods with crashes and corrections. The theory will help in determining the selection of variables to include in our analysis. We will start by presenting house market theory which includes how prices are determined in the house market and in the second part of the chapter, the crisis theory will be presented. A fundamental part is understanding how periods with economic crises tend to develop as significant decreases in house prices tend to be around financial crises. Hence, we will present a theory regarding crisis anatomy and the seven-step dynamic crisis model.

3.1 House Market Theory

Understanding how to put value on a house is essential and is determined by a combination of objective and subjective variables. The objective factor is the technical value or the cost of building a comparable home in the present market while the market value, or the price a market puts on the home, is the subjective factor. As a result, the market price of a home will represent the price at which it can be sold. The price emphasized in this thesis will be the market price, which will reflect the equilibrium created when supply and demand meet (SSB, 2004). Therefore, the supply and demand relationships are fundamental for comprehending the house market. In the following sections, we will briefly discuss both the supply and demand sides of the market and how they interact.

3.1.1 Supply Side

The house supply refers to the total house stock available in the market. An increase in supply would imply new houses being built from one period to another. Total house stock in time-period, t, can be defined from the equation from Kenny (1998):

$$H_t = (1-\delta)H_{t-1} + A_t, \tag{1}$$

where,

$Ht = Total\ house\ stock$

$At = Houses\ built$

$\delta = Depreciation\ factor$

Total house stock today (H_t) is related to the total stock in the previous period (H_{t-1}) adjusted by a depreciation factor *(δ)* and the increase in houses built *(A_t)* (Kenny, 1998).

3.1.2 Demand Side

The demand side of the house market is a more complex process; hence, we will examine the demand model constructed by Jacobsen & Naug (2004) to explain underlying demand factors in the house market. The model is presented in Equation (2):

$$H^D = f\left(\frac{V}{P}, \frac{V}{HL}, Y, X\right), \qquad f_1 < 0,\ f_2 < 0,\ f_3 > 0, \tag{2}$$

where,

$H^D\ = Total\ demand\ for\ houses$

$V\ = Owner's\ house\ costs$

$P\ = Prices\ of\ goods\ and\ services\ not\ related\ to\ houses$

$HL\ = House\ costs\ for\ a\ tenant, also\ known\ as\ rent$

$Y\ = Disposable\ income$

$X\ = Parameter\ capturing\ other\ fundamental\ factors\ affecting\ house\ demand$

$f_i\ = derivative\ of\ f\ with\ respect\ to\ i$

Equation (2) indicates that the demand for houses on the left side increases when households' income rises and decreases if house costs increase (Jacobsen & Naug, 2004).

3.1.3 The Interplay between Supply and Demand

House prices are driven by supply and demand factors as well as the framework conditions, which can have short-, medium-, or long-term effects. The table below illustrates the most crucial price determinants in the house market, looking both recently and historically (Grytten O. H., 2018, pp. 77; 79-80).

Demand factors	Supply factors	Framework conditions
Disposable Income	Housing Construction	Regulatory Regimes
Business Cycles	Access to Land	Tax Rules
Unemployment	Business Cycles	Building Standards and-Requirements
Population Growth	Construction Costs	Monetary and Credit Policies
Urbanization	Access to Capital	Public Housing
Wealth Distribution	Access to Loans	Land Areas
Access to Loans	Market Returns	Infrastructure
Interest Rates	Alternative Investment Opportunities	
Alternative Investment Opportunities	Taxation	
Taxation	Interest Rates	
Market Returns	Expectations	
Rental Market	History	
Expectations		
History		

Table 3. 1: *Supply and Demand Factors, and Framework Conditions*

Mathematically, the model of demand-side- and supply-side factors, as well as the framework conditions can be derived as functions.

$$House\ demand\ = f\ (X) \tag{3}$$

$$House\ supply\ = f\ (Y) \tag{4}$$

$$Framework\ conditions\ = f\ (Z) \tag{5}$$

where,

$X\ = Demand - side\ factors$

$Y\ = Supply - side\ factors$

$Z\ = Framework\ conditions$

Assuming that the framework conditions remain constant and equal to zero, we will compare equation (3) and (4) and derive the relationship to house prices. This represents the market equilibrium and can be presented as follows:

$$f\ (X) = f\ (Y),\ \ \Delta Z = 0 \tag{6}$$

As mentioned above, the time horizon determines the effects of shock on supply and demand. Figure 3.1, presents an example of how the short-term- and long-term equilibrium prices shift where the interplay between house prices on the y-axis and house stock on the x-axis is graphically presented:

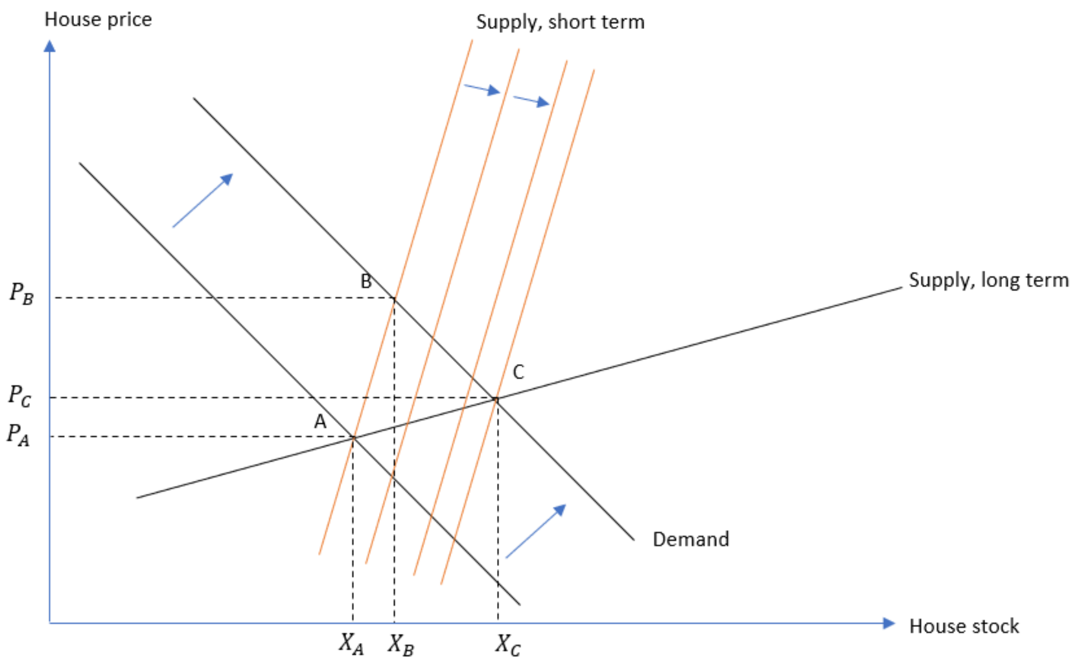


Figure 3. 1: *Supply and Demand in the Short and Long Term* (Jacobsen, Solberg-Johansen, & Haugland, 2006, p. 236)

Starting from the left in the above figure, we start at an equilibrium point, A where a significant increase in house stock leads to a new short-term adjustment at point B, representing a substantial increase in house prices from P_A to P_B. The market's supply side is particularly sensitive to the time horizon, as building new houses will be time-consuming. Due to capacity constraints in the construction industry, the short-term supply curve will be considerably steeper than the long-term supply curve. Due to a lag in adaptation, the house stock will not be able to meet the increased demand in the short term, and prices will increase as supply does not change quickly enough. Hence, will no longer be in a long-term equilibrium (Boug & Dyvi, 2008). A market price increase will cause more projects to be realized, leading to an increase in house stock, hence a shift upward in the short-term supply. The house stock will grow until it hits long-term equilibrium at point C (Jacobsen, Solberg-Johansen, & Haugland, 2006, p. 236).

3.2 Crisis Theory

3.2.1 Crisis Anatomy

From the previous empirical evidence, a financial crisis has some common characteristics. The chronological four-step build-up is a typical component of a financial crisis, called crisis anatomy as listed below:

1) Loss of financial stability
2) Inflation of money and credit
3) Bubble tendencies
4) Crisis

Loss of financial stability involves deviations in supply and demand from long-term equilibrium in the market. Credit becomes more accessible through low-interest rates and credit market liberalization thus, leading to a new phase of money and credit expansion. When activity in the market increases, it results in an increased demand for money and credit. Eventually, the activity will become so high that asset prices will exceed their fundamental value, leading to bubble tendencies. When there has been a prolonged period of excessive economic activity, it leads to over-investment and, eventually, significant losses; and if this happens, the last step in the crisis anatomy is a crisis which may involve market crashes, pessimism among actors, or a lack of investment ability or willingness (Grytten & Hunnes, 2016, pp. 37-38).

3.2.2 Seven-Step Dynamic Crisis Model

The seven-step dynamic crisis model is based on existing crisis theory and empirical data from historical crises. The model explains crises through seven phases while being synthetic and built on elements from other crisis researchers, particularly Kindleberger, Minsky, Eichengreen, and further empirical crisis research. An important note is that this is a dynamic model, and a crisis may only include some phases, which may occur differently.

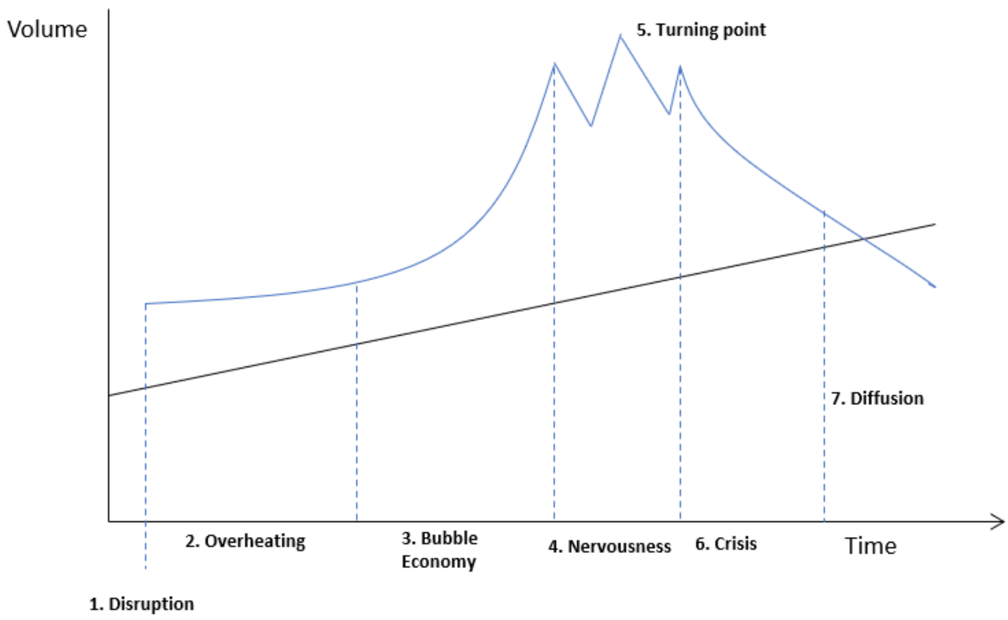


Figure 3. 2: *Graphical declaration of the seven-step dynamical crisis model*
(Grytten & Hunnes, 2016)

Phase 1: Disruption

The road to a crisis often begins with exogenous factors that change, leading to instability in the market. This phase is called "displacement" and can cause a loss of stability in the market due to increased economic activity; hence, instability on both the supply and demand sides of the market (Grytten & Hunnes, 2016, pp. 46-47).

Phase 2: Overheating

After a macroeconomic shock and subsequent increased economic activity, market actors generally believe the market will continue in that direction. This phase is also characterized by speculation, where actors invest heavily in speculative finance, and the amount of credit increases (Grytten & Hunnes, 2016, p. 47).

Phase 3: Bubble Economy

In phase three, it becomes evident that the economy is growing too quickly, however, there is still positivity regarding future returns, and the investment activity remains high. Asset prices have increased to a level much higher than their fundamental value, and investments are no longer economically rational. However, if actors believe that someone will be willing to buy at a higher price later, they will continue to invest (Grytten & Hunnes, 2016, p. 48).

Phase 4: Nervousness

As the market continues to grow to artificial values, nervousness spreads throughout the market due to fear of a correction. Banks begin to hold back credit due to fear that borrowers will not be able to repay their loans, which dampens the expansion of money in the market and gives actors further fears of losing their assets (Grytten & Hunnes, 2016, p. 49).

Phase 5: Turning Point

The turning point is when the market begins to decline, where negative expectations take over. Several investors and participants will withdraw from the market due to panic selling, causing the supply side to be larger than the demand side in the market, which causes prices to fall. There are three reasons why investment ability is weakened. In the first place, access to raising money and credit will be difficult. Secondly, investors will wait for the market to turn in a direction where it is possible to profit. Thirdly, investors will invest when the price decline has reached its "bottom" to secure their assets at the lowest possible cost. This contributes to stopping economic activity, and the volume of money and credit will either be reduced or stopped entirely or partially, which is often the beginning of a crisis or a mild correction (Grytten & Hunnes, 2016, pp. 49-50).

Phase 6: Crisis

At this phase, the market is driven by overly pessimistic expectations. Several actors will experience losses on assets as prices fall and the likelihood of actor bankruptcy increases. Due to the amount of credit in the market and the price fall in assets, credit institutions will incur significant losses, leading to credit institutions being more cautious in lending credit. This affects the actors who desperately need capital to survive, and the crisis will therefore worsen. Businesses have reduced income, demand is falling, and they must begin to downsize internally. What was previously a rising spiral has now become a negative one. Investors will wait to invest until they believe the market has reached the bottom, and most investors will not return until they see this opportunity unless they have a vested interest or are large enough to influence the market by investing. Even though the market has fallen significantly, there will always be actors out there who believe it will fall further, so one will end up in negative speculation (Grytten & Hunnes, 2016, p. 50).

Phase 7: Diffusion

Since markets are highly integrated, a financial crisis can often spread to the real economy. A stock market crash does not necessarily have to affect the economy. However, the real economy can be affected if losses to banks and credit institutions become so great that the market cannot recover. This is because businesses lose money, which affects the banks that have lent money to them, which in turn leads to a halt in credit access from the banks to the businesses, likely resulting in downsizing and affecting employees. Due to increased globalization and international trade, national crises can spread internationally (Grytten & Hunnes, 2016, pp. 50-51).

4. History of the Norwegian House Market

This section will give an overview of the Norwegian house market over the past 200 years. We will introduce the whole period before we take a briefer view of the periods defined as periods with crashes and corrections, respectively.

When looking at the historical events of crashes and corrections, it is important to be aware of the consequences of the definitions. For instance, the differences between a period with a minor crash and a significant correction may not be huge due to the definitions. However, there are typical differences in duration and scale. A minor crash often occurs quickly, while a significant correction occurs over an extended period. In addition, crashes typically occur when the price level has exceeded the long-term trend, ultimately resulting in a decline under its long-term trend. On the other hand, corrections tend to make prices return to their long-term trend instead of a fall way under the trend.

As there are no formal definitions of the terms, reasonable definitions of crashes and corrections may differ for other analytical purposes. This is important when we later use our generalized definitions and draw conclusions.

4.1.1 The Norwegian House Market from 1836 to 2021

The period from 1836 to 1898 represents a long economic upswing due to strong economic growth, strong population growth, increased household purchasing power, and increased exports in Norwegian businesses. A liberalizing economic and political policy is pursued, and monetary policy, on its part, contributes to a fixed exchange rate policy, safer framework conditions, and lower interest rates to make credit available.

At the end of the 19th century, there was an upswing in prices in the house market. Norway was in a boom that led to money and credit volume growth. The outcome was an overheating of the economy in the major cities of Norway, and in 1899, the bubble burst, sending Norway into a financial crisis that spread to the real economy (Grytten O. H., 2018, pp. 78-79).

When the First World War later started in August 1914, monetary policy was liberalised, and there was growth in the quantity of money and credit. At this time, there was a shortage of goods due to the growth in money and credit, which resulted in strong inflation and stock speculation (Hodne & Grytten, 2002). There was no speculation in real estate, but since other goods increased significantly, it resulted in weaker growth in house prices, which later turned into a significant fall in real house prices. House prices increased substantially less during this period because investments tend to be long-term in the house market. After the First World War, the global economy was sent into a recession, where strong inflation turned into deflation. The situation in Norway was that the Norwegian central bank pursued a tight monetary policy in the form of high-interest rates and reduced money and credit volume. The purpose was to get the Norwegian krone to return to its par value, but instead, there was a fall in demand, and deflation was strengthened. Between 1920 and 1935, the price level fell, and due to high-interest rates and a recession, there was almost no new house construction. The reduction in house construction affected the supply side of the economy, which led to house prices staying up, hence delaying the decline in house prices. If we summarise the interwar period for the Norwegian economy, which can be seen as one of the worst periods in the Norwegian economy with a halving of general prices, there is a solid growth in real house prices (Grytten O. H., 2008; Grytten O. H., 2018, pp. 78-81).

The post-war period until the 1980s was influenced by strong state control of the economy. Norway experienced regulations in the house market, and the government pursued a policy with a low-interest level. The goal was to increase investments and for a large part of the Norwegian population to own their own homes. In the cities, apartment buildings that were previously rental properties were converted into co-operative house[1]. Politicians took control of the interest rate policy to ensure large-scale house construction. In addition to large-scale house construction and setting low-interest rates, there were very favourable tax deductions on interest payments. However, the new vision led to increased credit demand. The Norwegian government continued the credit rationing introduced in the post-war years to prevent monetary inflation and high inflation from getting out of proportion. In summary, from 1940 until the 1980s, real house prices were relatively stable while prices for goods and services increased. From 1940-1950, there was a decline in house prices, followed by a moderate increase until the 1980s (Grytten O.H., 2008; Grytten O.H., 2018, pp. 80-83).

[1] A housing cooperative is a cooperative that provides those who own a share the right to use (occupy) their housing unit within the cooperative's property. It is a type of housing company, and the company form is defined and regulated in the 'Housing Cooperatives Act.' (Anderssen, 2020).

There was a need for a more liberalizing credit policy, as the country moved from the 1970s to the 1980s. Many believed Norway had to deregulate the credit market to keep up with the international market. The credit rationing that had been in place since World War II was discarded, and credit institutions had more freedom to issue loans. There were still favourable tax deductions on interest payments, which led to a negative real interest rate after taxes (Lie, 2012). With an accessible credit market, Norway had a strong upturn in the economy from the mid-1980s due to easily accessible credit. In practice, rent control was abolished, leading to increased demand for houses, and prices rose significantly and rapidly. Between 1978 and 1987, real house prices doubled in value even though interest rates rose. In addition to this, households' debt ratios were significantly higher. Overheating in the market led to the banking crisis, and real house prices fell by over 40 percent by 1993 (Grytten, Bjørsvik, & Nilsen, 2013, pp. 325-350; Grytten O.H., 2008; Grytten O.H., 2018, pp. 83-84) argues that this is one of the most significant price drops in the Norwegian house market (Grytten & Hunnes, 2016, pp. 236-237). Since the 1990s, prices have mainly increased, with an exception in the period between August 2007 to December 2008, when real prices fell by 18 percent. There are almost no such price drops in other quarters (Grytten O. H., 2018).

In recent times, there have been other crises, such as the coronavirus crisis and the energy crisis, where the former was a global pandemic that choked the economy’s supply side. Society was shut down to prevent the spread of the virus among the population, many businesses were partially or fully shut down, and the government provided support measures to prevent a wave of bankruptcies among companies. An expansionary fiscal and monetary policy was implemented, setting the policy rate to zero in Norway. For Norway, the crisis went surprisingly well due to the state’s good injection of capital into businesses and high savings among the population during the crisis. The economy recovered well after the infection control measures were removed. However, this led to increased demand, and hence Norway entering a boom. In February 2022, Russia invaded Ukraine. The invasion contributed to disruption and created a scarcity in supply chains, which increased energy and commodity costs in Norway (Norges Bank, 2023). Despite the circumstances, the house market continues to grow, but the market has the lowest new home sales since the financial crisis. The challenge identified is that either house prices must increase, or construction costs must decrease to increase sales (Eiendom Norge, 2023).

4.1.2 Crashes

The Kristiania Crash (1899-1905)

The Kristiania Crash, also known as the Kristiania Crisis, was a real estate and financial crisis that occurred at the end of the 19th century. The crisis was most severe in the capital, Kristiania, but other cities, such as Bergen, were also greatly affected. At the end of the 19th century, Norway was experiencing a boom period with easy access to credit. Due to urbanization in the major cities, there was an increasing demand for new houses, which drove up demand for the construction industry (Grytten & Hunnes, 2016, pp. 161-162).

From 1873, Norway had been on the gold standard, which meant that the Norwegian currency was valued in relation to gold. In 1892, Norway switched to a new monetary system, which meant moving from a quota system to a differential system. The quota system was set up so that the Norwegian Central Bank always had gold reserves equal to 40 percent of the money supply. By switching to the differential system, Norway became freer, i.e., unimpeded as it could increase the money supply without backing it with gold. This led to an inflation of money and credit through low-interest rates and increased money supply (Grytten & Hunnes, 2016, pp. 166-168; Grytten, Bjørsvik, & Nilsen, 2013, p. 78).

The credit expansion and access to credit were used to speculate in asset markets, leading to further house and stock price increases. Between 1895-1899, six new commercial banks were also established in Kristiania. Expectations of further price increases and speculation led to a bubble in the stock- and house market. During the fall of 1898, the Norwegian Central Bank was forced to raise interest rates, making debt more expensive and banks more cautious about whom they lent to. However, the stock market did not correct itself. It took two more interest rate hikes before speculators and banks became uncertain, and many began to sell off their securities at this point (Grytten, Bjørsvik, & Nilsen, 2013, pp. 77-83; Grytten & Hunnes, 2016, pp. 166-168).

Rumours began to spread that a company named Christophersen was facing significant financial problems. Christophersen was a large producer and exporter in the pulp and paper industry, with domestic and abroad operations. Likely, the debt burden was already far higher than the company's fundamental value as early as 1897. However, the company operated as usual due to easy access to credit and broad public trust. In 1899, the company went bankrupt, and this was a triggering factor for the crisis. The real house price index fell by about 27 percent, with the biggest fall between 1898 and 1900 by 18 percent. The stock market also fell significantly, with individual stocks experiencing declines from 16 percent to 31 percent in 1899 (Grytten & Hunnes, 2016, pp. 170-171); Hence, the period is defined as a crash.

Banking Crisis (1988-1993)

The banking crisis was an international financial crisis in the late 1980s. The crisis was particularly severe in the Nordic countries. After the stagflation of the 1970s, there was a paradigm shift in economic policy. A low-interest rate policy was to be pursued, which helped to liberalize the credit market. The strong credit growth and a negative real interest rate due to favourable interest deductions led to monetary and credit inflation (Grytten O.H., 2008; Grytten & Hunnes, 2016, pp. 227-229).

From 1983, economic upswing and money supply growth stimulated the stock and house market. Economic overheating led to a credit bubble, which resulted from the belief that one "could and should" borrow money to buy a home and invest in speculative assets. There was also a large discrepancy between credit and interest rate policies. Since Norway had to compete internationally, it had to follow the international interest rate level, which meant that it was possible to have low-interest rates in good times and high-interest rates in bad times (Grytten & Hunnes, 2016, pp. 229-236).

In late 1985, there was a fall in oil prices, which greatly affected the Norwegian economy, and as a result, the decision was made to devalue the Norwegian kroner. It was influential in the short term since Norwegian exports became cheaper than international prices. Still, trust in the Norwegian kroner was weakened simultaneously, leading to inflation. As a result, interest rates had to be raised. In 1987, several banks reported losses, with savings banks being the first to be affected, and in 1987, the stock market crashed with a 20 percent drop in one day. The house market also fell drastically, with real house prices falling by 43 percent from 1987 to 1993. The most significant decline was between 1988 and 1990 by 24 percent, thus a period defined as a crash. Consequently, Norwegian authorities had to inject capital to prevent the bankruptcy of several major commercial banks (Grytten & Hunnes, 2016).

4.1.3 Corrections

Long Depression (1873-1887)

Three features are usually central to The Long Depression: 1) development trends in the Norwegian economy, 2) changes in the monetary policy regime - the introduction of the gold standard, and 3) the transition from sailing ships to steamships in Norway's most important export industry (Grytten & Hunnes, 2016, pp. 144-145).

From 1876, we experienced a negative development in GDP, which reached bottom in 1878. The economic growth remained stagnant until 1887. One can see from the number of bankruptcies among companies between 1874 and 1894 that they can be linked to the downward trend in GDP and negative development in consumer prices. The bankruptcies in Norway are due to a closer connection to the international economy and increased industrialization domestically. Agriculture became more mechanised, thus, increasing efficiency and production, and the farmers produced more than necessary for their self-consumption, causing prices to go down. Railways and steamships also made it possible to trade over greater distances (Grytten & Hunnes, 2016, pp. 144-145; Grytten, 2008).

As mentioned earlier, introducing the gold standard impacted how monetary policy was managed. A shortage of gold arose after several countries switched simultaneously. The demand for gold exceeded the supply, leading to a drastic increase in gold prices. Due to the price increase, several countries could not obtain the gold reserves they would have preferred. Since the money supply had to be in line with the gold reserve, the money supply had to be reduced (Grytten & Hunnes, 2016, pp. 149-153; Grytten, 2008). The last factor affecting the economy was the long transition from sailing to a steamship in Norway compared to other countries. Ships were also crucial for the export industry in Norway. Part of the reason for the delay in the transition was the competition aspect (Hodne & Grytten, 2000, pp. 268-269). Steamships eventually became cheaper, more energy-efficient, and required less labour, but also Norway's late entry weakened competitiveness. When the United Kingdom began to adopt newer ships and technology, Norway could purchase used steamships, which was advantageous considering Norway's shortage of capital (Grytten & Hunnes, 2016, pp. 153-155).

To sum it up, real house prices were relatively stable in the 1800s, but Norway experienced a 12 percent decline in real house prices between 1878 and 1883, meeting the correction criteria.

Financial Crisis (2007-2010)

The financial crisis between 2007-2010 started as a house crash in the United States and spread to the stock market. Since 1993, low-interest rates, economic growth, and credit growth have dominated the economy. Before this crisis, a significant increase in money and credit markets resulted in credit bubbles. Getting a mortgage was also easy when the requirements were increasingly liberalized. Households that did not have a strong ability to pay were granted loans. In addition, interest-free periods were used to a greater extent, which made the repayment time longer. The trend in the American house market began to reverse in 2006, leading to an economic downturn that impacted employment rates. Consequently, affected households were unable to service their debts. Banks were left with properties they could not sell as the market was downward. The outcome in 2008 was a house crash, resulting in substantial losses for banks and causing several of the largest investment and commercial banks to collapse (NOU, 2011, pp. 49-52; Grytten & Hunnes, 2016).

In Norway, the house market witnessed a contraction of 14 percent between 2007 and 2008; and when adjusted for inflation, the decline amounted to 18 percent. Nevertheless, the downturn was considered modest owing to the continuous expansion of the house market since 1993. Concurrently, the Norwegian stock market underwent significant volatility because of oil price fluctuations. The crisis in Norway was moderate due to the provision of liquidity to banks through rescue packages, the rapid rise in oil prices, and the proactive monetary policy of Norges Bank (Grytten & Hunnes, 2016, pp. 243-257).

In conclusion, real house prices have witnessed a nearly consistent upward trajectory since 1993. However, a contraction of 18 percent is noticeable when examining monthly data. Annual data shows a decline of around 5 percent in real house prices between 2007 and 2009. Hence, this period is appropriately characterized as a correction.

5. Data

5.1 Introduction of Data Sources

Our primary, secondary data source is *Historical Monetary and Financial Statistics for Norway* from the central bank, called Norges Bank (NB). We use this data source for house price indices and other economic figures later presented. To further supply our thesis, we have used some data table extractions from Statistics Norway (SN) and the unemployment rate from the Norwegian welfare agency, called NAV. In the following sections, we will describe the time series of data extracted and consider their validity and reliability.

5.2 Validity

Validity in quantitative research examines whether the data used measures a causal relationship. Within validity, a distinction is made between internal and external validity. In this context, internal validity means whether the data used measures what it is supposed to measure. External validity concerns whether our data can be generalized (Wooldridge, 2016). If there are weaknesses or errors in our time series, it will lead to incorrect results that affect the conclusion of the thesis; thus, it is essential to ensure high validity in the data used.

We have mainly collected data from public sources, i.e., Norges Bank, NAV, and SSB, which can be considered to have high validity. However, due to gaps in some of the time series we originally wanted to use, we had to make some simplifications that may have affected the validity. For spliced time series, we will comment on the approach and how we assess the validity of each variable and source. We also ran simulations on OLS assumptions to see if there were any violations. These simulations strengthen the integrity of our internal validity, and the results can be found in the Appendix.

5.3 Reliability

The concept of reliability refers to the dependability and credibility of the data. In our context, this refers to the accuracy of our variables utilized for analysis and whether our results are consistent (Johannesen, Christoffersen, & Tufte, 2016). Determining the reliability of the data is an essential aspect when interpreting results, although it is not a fundamental condition for concluding (Dahlum, 2021). An important part that might influence reliability is use of annual data. This results in a limited number of observations for the periods investigated, implying that reliability might have been enhanced if quarterly data had been available for all variables.

For all time-series, we collected data from secure and reliable sources. All the data collected originates from public entities, available to all. In addition, the data collected has been used for research purposes by established researchers.

5.4 Norges Bank

This thesis uses the *Historical Monetary and Financial Statistics for Norway* database provided by Norges Bank when extracting annual house price indices, consumer price indices, gross domestic product, interest rate, credit volume, money supply, and nominal wages. In the following sections, we will comment on the validity and reliability of each data source used in this thesis.

5.4.1 House Price Indices

The database comprises composite house price indices for four out of the five most prominent cities in Norway, namely Oslo, Bergen, Trondheim, and Kristiansand, supplemented by an aggregate index (Eitrheim & Erlandsen, 2004). Until 1897, the data did not contain information for all mentioned cities. For instance, the data from 1719 to 1840 includes data from Bergen exclusively. Therefore, the aggregated index only reflects house prices from Bergen during this time (Eitrheim & Erlandsen, 2004).

The data set is derived from various sources due to variations in data collection methods over the years, and the different methods may introduce inconsistency that could affect the reliability. Nevertheless, Norges Bank has a strong reputation for reliability as it is the Norwegian central bank. With solid acceptance in the research community in Norway and well-documented data, Norges Bank is considered a reliable source. Therefore, we find it reasonable to conclude that the data exhibits high validity and reliability. It is worth mentioning that Eiendom Norge constructs a monthly house price index spanning from 2003 until today. This has been widely used the last years, but to avoid splicing of data, we have decided to use Norges Bank as a data source for the whole period.

5.4.2 Consumer Price Indices

Historical consumer price indices (CPI) between 1492 and 2021 are documented in *Historical Monetary and Financial Statistics for Norway* (Eitrheim, Klovland, & Qvigstad, 2022, pp. 523-562). The index was initially published by Grytten (2004) and later revised, resulting in increased data precision. The revisions have resulted in a significant improvement in terms of reliability and validity (Grytten O. H., 2022, p. 549). Statistics Norway describes the CPI as the development of prices of various goods and services purchased by Norwegian residents. Hence, the CPI is often used as a target for inflation (Tuv, 2019). This thesis uses the CPI to deflate house prices to provide real measures and strengthen the study's validity.

5.4.3 Gross Domestic Product

The historical indices for the gross domestic product (GDP) spanning the period between 1816-2021 were provided by Professor Ola Grytten. These data are documented in Chapter 8 of *Historical Monetary and Financial Statistics for Norway* (Eitrheim, Klovland, & Qvigstad, 2022, pp. 425-466). The calculation of the total GDP is based on 17 industries and 78 sub-industries. In the paper, Grytten concludes that the GDP series "*seems fairly consistent, valid, and reliable.*" (Eitrheim, Klovland, & Qvigstad, 2022, p. 446).

5.4.4 Interest Rate

The historical nominal interest rates between 1820 and 1999 are extracted from Norges Bank (Holter, 2000; Eitrheim, Klovland, & Qvigstad, 2022). From 2000 to 2021, we got data for banks' lending rates from Statistic Norway. As the data is in different formats, we need to splice the data. The construction of the time series will be presented in Chapter 6.4.1. Note that the interest rate is an annual average, not a complete time series. Still, we consider the data reliable as its data was retrieved from Norges Bank. However, our validity may be affected due to the splicing of data.

5.4.5 Credit Volume

The historical level of total credit in the period between 1817 and 2021 is documented in Chapter 4 of *Historical Monetary and Financial Statistics for Norway* (Eitrheim, Klovland, & Qvigstad, 2022). The total credit is calculated using total loans from Norges Bank, private banks, state institutions, credit companies, and financial companies. As Norges Bank is considered a trustworthy source, we consider the data to exhibit high reliability and validity.

5.4.6 Money Supply

Norway's money supply has been calculated by using various methods, with key variables M0, M1, and M2. M0 is considered the base money supply and comprises the aggregated cash and deposits held by banks and money-holding sectors in Norges Bank. M1 is defined as the narrow money supply and includes M0 and deposits in both business- and savings banks. M2, is defined as the broad money supply term, including M1 and other deposits held by the money-holding sectors, such as bank certificates and shares in money market funds (SSB, 2015). M2 is considered the representative variable for this thesis, as it includes a broader set of components than M0 and M1 that we consider appropriate to include in our analysis. Historical data for M2 from 1813 to 2022 were collected from the *Historical Monetary and Financial Statistics for Norway* (Eitrheim, Klovland, & Qvigstad, 2022). The degree of reliability and validity is considered high as Norges Bank is considered a reliable source.

5.4.7 Wages

Historical data on Norwegian wages is documented in Chapter 14 in *Historical Monetary Statistics for Norway* (Eitrheim, Klovland, & Qvigstad, 2022). This includes annual nominal wages from 1726 to 2021. Ideally, our analysis should have employed data on disposable income as it provides a better understanding of the impact of income on house prices as it accounts for tax and savings. However, the availability of such data is limited from 1978 until today, and we are therefore using nominal annual wages as a proxy for income in Norway. Despite the limitations in data availability, we consider a high degree of reliability and validity for the annual wage data.

5.5 Other

5.5.1 House Stock

For data on the total house stock in Norway, we have employed data from Dag Kolsrud, researcher at SSB. This is the same data Anundsen (2019) utilizes in his research on Norwegian house prices; hence, the data is considered highly reliable. The data set consists of quarterly figures from 1978 to 2021. Given the reputation of SSB as a reliable source, we consider our data to exhibit a high degree of validity.

5.5.2 Unemployment Rate

We have used data published from NAV on the historical unemployment rate in Norway. The data includes the population of fully unemployed individuals in Norway from 1948 to 2021. As NAV is a public organization and the data is available for all, we consider the data to exhibit high reliability. The data set does not include spliced variables and is considered valid.

5.5.3 Price/Rent Ratio

The Price-to-Rent, i.e., the P/R-ratio, is a modified version of the more commonly used P/E-ratio, or Price-to-Earnings ratio, typically used when analysing the stock market. However, within a study of the house market, the price (P) represents the price of a house, typically a house price index, and the earnings (E) represent a house's rental price. For our analysing purposes, we are employing the terms Price (P) and Rent (R). A significant ratio increase over time could indicate a house price bubble (Grytten O. H., 2009).

Professor Ola Honningdal Grytten provided us with the P/R data. The series from 1871-2009 have been published in the journal Samfunnsøkonomen (2009). Samfunnsøkonomen is a professional journal that disseminates economic research within the social science field in Norway. The series from 2009 to 2021 is updated by Ola Honningdal Grytten; hence we consider the data reliable and valid (Grytten O. H., 2009a).

6. Methodology

This chapter will examine some of the techniques for determining whether the short-term equilibrium of house prices differs from the fundamental price over the long term. The first section will discuss the techniques for estimating cycles and trends, and the second will discuss the techniques for examining trend deviation, such as the Hodrick-Prescott filter (HP-filter). We additionally present regression analysis and the methods for comparing various time series of data.

6.1 Determining Cycles

6.1.1 Structural Time Series

We employ structural time series analysis to examine cycles and trends in the house market. In this analysis, we separate an observed time series, x_t, into a trend component, g_t, a cycle component, c_t, a seasonal component, s_t, and an irregular component, i_t. Grytten & Koilo (2019) explains it mathematically as equation (7):

$$x_t = f(g_t, c, s, i). \tag{7}$$

Expressing the equation using an arithmetic approach yields the subsequent relationship:

$$x_t = g_t + c_t + s_t + i_t, \tag{8}$$

Where it is reasonable to view it as the residual in this context:

$$i_t = x_t - (g_t + c_t + s_t). \tag{9}$$

For our analysis, it is reasonable to see the irregular component and the seasonal component s_t as parts of the cycle component C_t. Equation (9) can therefore be presented in a simplified form:

$$x_t = g_t + c_t. \tag{10}$$

Equation (10) separates the time series into a trend component, g_t, and a cycle component, c_t. There are different methods of estimating deviation from trend based on time series, and the HP-filter is one of the most used techniques.

6.1.2 Hodrick-Prescott filter

The HP-filter measures business cycles and can help to separate the cycle and trend components in time series (Hodrick & Prescott, 1997). One advantage of using the HP-filter is that it is easy to understand and use and is also implemented in several statistical programs.

The HP-filter divides an observed time series into a trend component, g_t, and a cyclical component, c_t. Equation (11), which mathematically represents the HP-filter, finds the trend component value that minimizes the cycle component's variance, c_t, denoted by the expression x_t - g_t.

$$\min_{g_t} \sum_{t=1}^{T}(x_t - g_t)^2 + \lambda \sum_{t=2}^{T-1}[(g_{t-1} - g_t) - (g_t - g_{t-1})]^2 \qquad (11)$$

The initial component of the equation denotes the deviation from the trend, whereas the subsequent component measures the change in the growth rate of the trend from time *t* to time *t+1*. Additionally, the equation incorporates a smoothing parameter, λ, which governs the degree of smoothness of the trend line (Grytten & Hunnes, 2016, p. 60). When using a smoothing parameter in the HP-filter, we can control how much variance we want in our estimated trend component. When λ is set to zero, the resulting analysis will disregard the cyclical component resulting in a function that follows the actual observations. On the other hand, increasing λ to infinity would imply a situation with no changes in trend, in other words, a linear trend function. In almost all cases, these extreme points will have no explanatory value. The optimal λ value varies depending on the length of the time series.

This minimization problem has one unique solution denoted as:

$$g = Sx, \qquad (12)$$

Where $S = (I_n - \lambda F)^{-1}$, and I_n denotes a n x n identity matrix, that is a square matrix with only and the main diagonal and 0 elsewhere. The *F* represent a linear algebraic penta-diagonal n x n matrix, meaning a matrix with non-zero entries only on the main diagonal, the two upper diagonals, and the two lower.

$$F = \begin{pmatrix} f & 0 & 0 & & 0 & 0 & 0 \\ 0 & f & 0 & \cdots & 0 & 0 & 0 \\ 0 & 0 & f & & 0 & 0 & 0 \\ & \vdots & & \ddots & & \vdots & \\ 0 & 0 & 0 & & f & 0 & 0 \\ 0 & 0 & 0 & \cdots & 0 & f & 0 \\ 0 & 0 & 0 & & 0 & 0 & f \end{pmatrix},$$

$$F = \begin{pmatrix} 1 & -2 & 1 & & 0 & 0 & 0 \\ -2 & 5 & 4 & \cdots & 0 & 0 & 0 \\ 1 & -4 & 6 & & 0 & 0 & 0 \\ & \vdots & & \ddots & & \vdots & \\ 0 & 0 & 0 & & 6 & -4 & 1 \\ 0 & 0 & 0 & \cdots & 4 & 5 & -2 \\ 0 & 0 & 0 & & 1 & -2 & 1 \end{pmatrix} \quad (13)$$

(Grytten & Koilo, 2019)

The estimated cycle component is denoted by using the observed time series and subtracting the trend component:

$$c_t = x_t - g_t = (I_n - S)x \quad (14)$$

Choose Value of Smoothing Parameter

The behaviour of the HP-filter will change heavily when changing the smoothing parameter. Hodrick & Prescott (1997) established a standard of 1600 for quarterly data. Previous studies have established a rule of thumb setting λ values of 100 and 14.400 as the annual and monthly data standards, respectively. However, these λ values are not necessarily the best fit for the Norwegian data. SSB has concluded that a λ equal to 40 000 for quarterly data is a good fit when analysing business cycles in Norway, such as development in the gross domestic product (Benedictow & Johansen, 2005). This represents a λ value of 2500 for yearly data. A higher value λ is recommended for data used for analysing bubbles and possible corrections and crashes to avoid problems regarding endpoints. We have established a standard of 40 000 as a λ value when detrending variables are used in such analysis. This represents the variables for house prices. However, using the HP-filter is heavily discussed as it has weaknesses. One of those weaknesses is the difficulty in choosing the optimal value of λ.

Weaknesses of the HP-filter

There are a few drawbacks when using the HP-filter, and the most mentioned critics are that it is hard to tell what the appropriate value of the smoothing parameter should be. Although there have been established standards for the value of λ, the optimal value depends on the time series being studied and, therefore, may be a source for manipulating the data.

Another problem is the so-called endpoint problem, where the filter can create cycles at the start and end of the time series without having data to support this. There is an endpoint problem because the two-side-filtering method uses observed data from both the front and the back to estimate the output. In the front and back, the filter will gradually move towards a one-sided filter (Bjørnland, Brubakk, & Jore, 2005). A higher value of λ could reduce the endpoint problem.

Hamilton (2018) criticized the HP-filter and strongly argued against its use in several circumstances. Some arguments are against the "golden standard" of the smoothing parameter as it is argued to be too rigid. The article argues: "*The HP-filter produces series with spurious dynamic relations that have no basis in the underlying data-generating process.*" (Hamilton, 2018). However, recent research implies that there is a better way to use the HP-filter, using machine learning techniques.

Boosted HP-filter (bHP)

Phillips & Shi (2021) applied machine learning techniques, more specifically a boosting technique, to improve the performance of the HP-filter on time series of data. Boosting is a powerful machine-learning technique that creates more accurate and robust models. The technique uses weak learners and machine learning algorithms that perform slightly better than random guessing when predicting outcomes. They are not very powerful alone, but when using techniques such as boosting, we train the weak learners on the data, where the next weak learner tries to fix the mistakes of the previous one.

Phillips & Shi (2021) describe the Boosted HP-filter; the bHP-method. The main idea behind a machine learning approach is that the method will investigate the cyclical component after applying the first HP-filter. If the component still exhibits trending behaviour, the bHP will continue to apply the HP-filter to remove the rest of the trending behaviour (Phillips & Shi, 2021). The cyclical component can be expressed as follows in the second HP-filter fitting:

$$c^{(2)} = (I_n - S)c = (I_n - S)^2 x, \tag{15}$$

Where (2) indicates the second fitting of the HP-filter. The estimated trend component will correspondingly be written as:

$$g^{(2)} = x - c^{(2)} = (I_n - (I_n - S)^2)x \tag{16}$$

The bHP-filtering technique will continue to look for the remaining trend behaviour, and the filter may progress to a third time and further to m repeated times. After the bHP has repeated the process m times, the trend and cycle components are denoted as:

$$c^{(m)} = (I_n - S)c^{m-1} = (I_n - S)^m x, \tag{17}$$

$$g^{(m)} = x - c^{(m)} \tag{18}$$

It is recommended to still use the same rules for the tuning parameter, λ, while the new parameter, m, will be a tuning parameter. The tuning parameter will be set by a stopping criterion where Phillips & Shi (2021) suggest that the ADF test or Bayesian Information Criterion (BIC) stops the number of iterations. In our case, ADF will be used as a stopping criterion and described later in this chapter.

The reason why bHP-filter is a better way of determining the trend of time series is that the original HP-filter may be too weak to capture all the underlying trends. When having the flexibility to tune several iterations based on an underlying trend, the method can consistently estimate the trend and cycle (Phillips & Shi, 2021). As mentioned, Hamilton (2018) argues that the HP-filter induces spurious cycles. However, Phillips & Shi (2021) conclude in their article that the boosted HP-filter removes the validity of the above argument. They argue that the boosted HP-filter consistently estimates the trend function, and that the smoothing parameter will now lead to consistent estimates of the trend functions. Based on these results, we use the boosted HP-filter to detrend our variables in future analyses.

6.2 Comparison of Time-Series

6.2.1 Correlation Analysis

Correlation analysis is used in macroeconomic analysis to determine the relationship between two variables. Specifically, the coefficient of correlation, denoted by p, quantifies the relationship between two-time series, x and c, and provides a measure of the strength of their relationship. The coefficient of correlation ranges between 1 and -1 percent, with a value close to 1 percent indicating a strong positive correlation between the time series, where a 1 percent increase in *x* corresponds to a 1 percent increase in *c*. Conversely, a value of *p* equal, or close to, 0 suggests no systematic relationship between the variables (Sørensen & Whitta-Jacobsen, 2010, p. 369). The coefficient of correlation is defined as:

$$\rho(x_t, c_t) = \frac{\sum_{t=1}^{T}(x_t - \bar{x})(c_t - \bar{c})}{\sqrt{\sum_{t=1}^{T}(x_t - \bar{x})^2} * \sqrt{\sum_{t=1}^{T}(c_t - \bar{c})^2}} \tag{19}$$

In equation (19), x_t is a chosen economic variable. In our analysis, the dependent variable, c_t, will be the house price. $\bar{x}$ and $\bar{c}$ indicate the average value of *x* and *c*. In the context of our analysis, where the cyclical variable is represented by house prices, a *p* greater than 0 implies that the economic variable *x* is moving in a procyclical manner. On the other hand, a *p* less than 0, suggests that *x* is moving in a countercyclical manner.

It is important to note that variables may not always be synchronized, meaning the economic variables may be leading or lagging variables. To investigate this, we examine *x* in the period before, x_{n-1}, and after, x_{n+1}, to determine whether it is a leading or lagging indicator. A situation where *x* is a leading indicator would imply that $p(x_{t-n}, c_t)$ is significantly different from 0, and numerically different from $p(x_t, c_t)$. A situation where *x* is a leading indicator would mean that a change in *x*, *n* periods earlier, tends to be related to a change in house prices in the current period. Conversely, *x* being a lagging indicator would imply a situation where $p(x_{t+n}, c_t)$ is significantly different from 0 and numerically different from $p(x_t, c_t)$. This implies a situation where *x* tends to change *n* periods later than the change in house price (Sørensen & Whitta-Jacobsen, 2010, p. 370).

For our study, the correlation analysis will determine whether a variable should be a leading, lagging, or a synchronized variable in the regression analysis.

6.3 Regression Analyses

In this section, we will introduce the mechanism behind multiple regression, and Ordinary Least Squares (OLS) and its assumptions.

6.3.1 Multiple Regression with OLS estimates

Regression analysis is a statistical method used for determining the effects of a dependent variable using independent variables. In a simple linear regression model, the formula is explicitly known as:

$$Y_t = \beta_0 + \beta_1 X_{t,1} + u_t \tag{20}$$

where,

$Y_t = Dependent\ variable\ in\ time\ t$

$X_{t,k} = Independent\ variable\ k\ in\ time\ t$

$\beta_k = Coefficient\ for\ independent\ variable\ k$

$u_t = Error\ term\ int\ time\ t$

In multiple regression, we add more independent variables, *i,* to explain the dependent variable *Y.* The multiple regression model is explicitly known as:

$$Y_t = \beta_0 + \beta_1 X_{t,1} + \beta_2 X_{t,2} + \cdots + \beta_k X_{t,k} + u_t \tag{21}$$

The coefficients β_i will be estimated using the OLS-method, whereas the estimated coefficients β_0 to $\beta_{\substack{i\\k}}$ will be known as $\hat{\beta}_0$ and $\hat{\beta}_k$. An OLS method aims to minimize the sum of squared residuals and determine the optimal fit for linear regression as explicitly shown in equation (22):

$$\hat{\beta}_i = \frac{\sum_{k=0}^{n}(X_i - \bar{X})(Y - \bar{Y})}{\sum_{k=0}^{n}(X_i - \bar{X})^{\,2}} \tag{22}$$

When,

$$\hat{\beta}_0 = \bar{Y} - \hat{\beta}_k \bar{X} \tag{23}$$

where,

$\bar{X} = Average\ of\ X$

$\bar{Y} = Average\ of\ Y$

The interpretation of $\hat{\beta}_k$ is how much Y_t changes by a one-unit change in $X_{t,k}$ (Stock & Watson, 2014; Wooldridge 2016).

For a better interpretation of our variables, we will log-transform all variables. This will make our regression models log-log regressions with log variables on both sides of the equal sign:

$$\log(Y_t) = B_0 + \beta_1 \log(X_{t,1}) + \beta_2 \log(X_{t,2}) + \cdots + \beta_k \log(X_{t,k}) + u_t \tag{24}$$

In the log-log regression, a 1 percent change in the independent variable X_1 will result in a 1 percent change in the dependent variable.

Furthermore, we will use lags in our regression models. Lags are used when the effect of a dependent variable on an independent variable is not immediate but over different periods. Equation (25) is a description of a regression model where the independent variable affects the dependent one with a one-period lag:

$$\log(Y_t) = B_0 + \beta_1 \log(X_1)_{t-1} + u_t, \tag{25}$$

where,

$\log(X_1)_{t-1} = Logged\ variable\ X\ in\ period\ t-1$

Wooldridge (2016) points to the importance of choosing the correct number of lags to include in the regression model. A typical selection method is to choose the number of lags using Akaike Information Criteria (AIC) (Liew, 2004).

Furthermore, different methods exist to determine which independent variables to include in the multiple regression model. One method is the backward elimination, as explained in Kutner et al. (2005). In the backward elimination method, one starts with a full regression model, including all variables. Then, it searches for the variable with the highest p-value and removes it if the p-value is above the predetermined limit. The process will continue until all variables have a p-value below a predetermined level (Kutner et al., 2005, p. 368).

6.3.2 Ordinary Least Squares – Assumptions

When performing an OLS time series regression, our data series needs to fulfil some assumptions to tell the causal effects of our independent variables on the dependent variables. The premises will be presented in the following section.

Linear in Parameters

This assumption builds on the fact that our model needs to be linear in its parameters. Thus, the relationship between the regression coefficients $\beta_0 \dots . \beta_k$ and the dependent variable Y needs to be linear (Wooldridge, 2016).

Linear parameters are essential to ensure that OLS is the correct regression model to use when estimating the parameters in the model. If the relationship is not linear, one should investigate possible relationships using other regression estimation methods.

No perfect multicollinearity

When one regressor can be described as an exact linear combination of the other regressors in the model, this is known as perfect multicollinearity. The OLS estimator cannot be computed if there is perfect multicollinearity. It is induced mathematically by the fact that division on zero is produced by perfect multicollinearity in the OLS formulas. However, multicollinearity that is not perfect is acceptable. According to Stock & Watson (2014), imperfect multicollinearity occurs when there is a strong correlation between the regressors. We can use volatility inflation estimation (VIF) to determine whether our model has a multicollinearity issue. The VIF test can be expressed mathematically as follows:

$$VIF_j = \frac{1}{(1-R_j^2)}, \tag{26}$$

where R_j^2 refers to the explanatory power of the explanatory variables on the variable j.

As a rule of thumb, a VIF value greater than 10 indicates multicollinearity. One approach to solve this problem is to remove variables from the model, and another is to increase the number of observations (Wooldridge, 2016).

Zero conditional mean

In time series analysis, it is essential to note that the anticipated value of the error term u at any given time t is zero when considering the explanatory variable across all periods. This implies:

$$E(u_t|X_1, X_2, \dots, X_k) = 0, \qquad t = 1,2, \dots ., n, \tag{27}$$

where u_t is the error term for a given time, and X_i is the i independent variable in the multiple-regression.

The idea behind the zero conditional mean assumption is that the error term should not be systematically related to the independent variables in the model. When controlling for all independent variables, the error term should capture all remaining variations in the dependent variable, and the variation should be random.

If the equation above does not hold, this will result in a biased estimation of regression coefficients. The estimation could lead to incorrect inferences about the relationship between the dependent and the independent variables. However, if u_t is independent of X_i and $E(u_t) = 0$ the assumption automatically holds (Wooldridge, 2016).

Homoscedasticity

Homoscedasticity is an OLS regression assumption that refers to equal variance. The assumption holds when the error term remains constant across all values of the independent variables. Mathematically:

$$Var(u_t|X) = Var(u_t) = \sigma^2, \qquad t = 1,2, \ldots\ldots, n \tag{28}$$

An important note is that a violation of the model does not affect the coefficient, but the preciseness of our model can change and become less accurate and less efficient in its results. In other words, larger standard errors, and less reliable hypothesis tests (Wooldridge, 2016).

To test whether our model exhibits heteroscedasticity, we use graphical tests to visually look for patterns and use formal tests. To visually investigate our model, we create a scatter plot of our predicted values and absolute residuals. For the assumption of homoscedasticity to hold, we should not see any clear patterns in the points. To further test the assumption, and more formally, we are using the Breusch-Pagan test, which detects the presence of heteroscedasticity in a regression model. The process of the Breusch-Pagan test is explained in Wooldridge (2016):

To start the Breusch-Pagan test we estimate the original regression model:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_k x_k + u. \tag{29}$$

Then, we regress the squared OLS residual $\hat{u}^2$ for each observation.

$$\hat{u}^2 = \delta_0 + \delta_1 x_1 + \delta_2 x_2 + \cdots + \delta_k x_k + error_t, \tag{30}$$

where,

$$error_t = E(u_t|X_k) = 0 \tag{31}$$

We also keep the R-squared $R^2_{\hat{u}_t^2}$ from the regression and use this to calculate the F statistic:

$$F = \frac{R^2_{\hat{u}_t^2}/k}{(1-R^2_{\hat{u}_t^2})/(n-k-1)}, \tag{32}$$

where,

$F = F\ statistic$

$R^2_{\hat{u}_t^2} = R - squared\ of\ equation\ (32)$

$k = Number\ of\ regressors$

$n = Number\ of\ observations$

The Breusch-Pagan test will result in a p-value where a p-value below chosen significance level, in our case 0.05 percent, will imply that the assumption is violated. If the assumption is violated, we can use the Newey-West Standard Error to adjust the standard errors to make the hypothesis test more reliable.

No Autocorrelation

The assumption states that the error terms must be uncorrelated over different observations and periods. The mathematical expression of the assumption (Wooldridge, 2016):

$$Corr(u_t, u_s) = 0 \text{ for all } t \neq s, \tag{33}$$

where u_t and u_s are the error term in periods t and s.

In other words, an error term for one observation should not be related to an error term for another observation and this implies that the error term should be independently and identically distributed across observations. If there is autocorrelation, it violates the assumption of zero covariance between error terms in the OLS regression. Violations in autocorrelation will cause standard errors to be underestimated, making our coefficients to be less sufficient. Variables that are not necessarily significant can become significant and potentially result in a wrong conclusion.

A common test is the Durbin-Watson test (DW-test) to check whether autocorrelation is present in a model. The DW-test is commonly used for detecting autocorrelation in the error terms u and can be mathematically expressed as follows:

$$DW = (\sum_{t=2}^{T}(u_t - u_{t-1})^2 \,/\, \sum_{t=1}^{T}(u_t)^2, \tag{34}$$

where u_t is the error term in period t.

The test result varies between 0 and 4, where 2 indicates no autocorrelation. A number significantly lower than 2 will indicate positive autocorrelation, and a number significantly higher than 2 suggests negative autocorrelation.

As for the assumption of homoscedasticity, Newey West Standard Error can be a solution to autocorrelation to obtain valid standard errors and hypothesis results (Wooldridge, 2016).

Normality

This proposition asserts that the error term, u_t, follows a normal distribution. The error terms are normally distributed when symmetric around a mean of zero. Deviation from normal distribution would result in unreliable standard error estimates and confidence intervals that are either excessively wide or narrow (Wooldridge, 2016). Mathematically the assumption can be written as follows:

$$u|X_1, X_2, \dots, X_k \sim N(0, \sigma^2), \tag{35}$$

where u is the error term of the independent variable X_k and the σ^2 is the variance of the error.

We examine both graphical and formal tests to test the assumption of normality. The visual examination is done by Quantile-Quantile plots (QQ-plot) and histograms. If the data follow a straight line in the QQ plot, it indicates normality. The histogram should show if the residuals are normally distributed around a mean of zero. In addition to the graphical test, we use the Shapiro-Wilk test.

The Shapiro-Wilk test is a commonly used test for testing the normality of data. It is a test based on a null hypothesis of the data being from a normal distribution. A p-value less than chosen significance level will indicate that the normality assumption is violated. It is important to note that the test is sensitive to the sample size of the data. A small sample size may result in a low p-value and reject the null hypothesis even when the data does not significantly deviate from normality.

Stationarity

When applying ordinary least squares (OLS) to time series data, another requirement is that the time series is stationary. A time series is a stochastic process where the variables are indexed by time *t*. For a time-series to be stationary, it implies that the probability distribution of the process remains stable over time. Explicitly, a stationary time series is characterized by constant meaning and variance over time. In addition, the covariance between the values at different time points, *t,* and *t+i,* is dependent only on the time lag, *i*, not the actual time, *t*, at which the values are observed (Wooldridge, 2016). However, economic time-series data tends to be non-stationary due to underlying economic trends.

According to (Stock & Watson, 2014), the presence of non-stationary time series may lead to spurious regressions. The trend is an important form of non-stationarity in time series and refers to data where a variable persistently moves in one direction over an extended period. Trends can be split into two different types, deterministic and stochastic trends. A deterministic trend refers to a situation where the data is moving with a fixed rate, for instance, a 1 percent movement a year, whereby a stochastic trend is a trend that varies over time.

It is essential to determine the type of stochastic trend our time series exhibits to transform a nonstationary time series into stationary time series. The different types of nonstationary processes in time series are listed in the equation (36-38) below:

Random walk:

$$Y_t = Y_{t-1} + u_t \tag{36}$$

The simplest random walk implies a process where y_t is dependent on the previous y_{t-1} in addition to noise, u_t. Random walk implies that the best prediction of tomorrow's value is today's value in addition to unpredictable noise. If the variable in time t is dependent on the previous variable, the variance of the random walk will increase over time. Hence, the time series is non-stationary.

Random walk with drift:

$$Y_t = \beta_0 + Y_{t-1} + u_t \tag{37}$$

The next process, random walk with drift, is almost the same as the previous process except including a constant β_0. The drift term results in a time series declining or growing around a constant which results in y_t failing to obtain the constant mean and hence it violates the stationarity of the time series.

Random walk with drift and deterministic trend:

$$Y_t = \beta_0 + \beta_1 t + Y_{t-1} + u_t \tag{38}$$

The third type also includes a stochastic trend. The trend component $\beta_1 t$ will result in y moving around the long-term trend. The trend component depends on the time, t, and thus, is non-stationary.

Detecting Stochastic Trends

Time series analysis involves the inspection of potential trends in the data over period of time. An initial approach to observe non-stationarity in a time series will be visually inspecting a time series plot. If a potential trend is observed, the Augmented Dickey-Fuller (ADF) test can determine whether the data exhibits a stochastic trend. The ADF-test checks unit roots, or stochastic trends, in a time series. A stochastic trend in the time series would imply that the time series is nonstationary. This can result in spurious regressions in OLS, as spurious regression occurs when two unrelated time series are mistakenly classified as correlated (Stock & Watson, 2014). The null hypothesis for the test is that a unit root is present in the series, meaning nonstationary data. On the other hand, the alternative hypothesis is that the time series is stationary. We will perform a test with a constant and a test with a constant and trend. By computing both tests, we can determine which type of non-stationary process our data exhibits.

An additional advantage of ADF-testing is that it effectively removes autocorrelation from the residuals by adding lagged changes to the regression models. An important note is that the result depends on the number of lags added. Too many lags may result in a loss of initial observations, while too few lags may lead to a situation where we need to remove all autocorrelation in the residuals (Wooldridge, 2016). There has yet to be a consensus in previous research on choosing the correct lag length, although Stock & Watson (2014) suggests minimizing the Akaike Information Criterion (AIC). The AIC is specified mathematically in equation (39):

$$AIC(p) = ln\left[\frac{SSR(p)}{T}\right] + (p+1)\frac{2}{T}, \tag{39}$$

where SSR(p) is the sum of squared residuals, p is the choice of number of lags, and T is the number of observations (Stock & Watson, 2014).

An important note is that failing to reject the null hypothesis does not confirm a unit root being present in the time series. However, it makes it reasonable to adjust for trend in the time series (Stock & Watson, 2014).

Transformation of series with non-stationary data
We will apply the HP-filter to remove the trend component from our series for series exhibiting both a stochastic and a deterministic trend as in equation (38). HP-filter is a good fit when removing deterministic trends from time series. However, we may need additional transformation to remove linear trends from the series.

For a series following a random walk with or without a drift, equation (36-37), we will transform our data using the first-difference transformation of the series. First-difference transformation using consecutive observations in the series to calculate the difference between them. The calculation first-difference transformation is shown in equation (40):

$$\Delta Y_t = Y_t - Y_{t-1} \tag{40}$$

6.4 Summary of the Data Transformation

The present section summarizes the process required for transforming variables into the proper form prior to analysis. Except for the variables “interest rate” and “real house price,” we have taken the original data supplied in Chapter 5 as our basis for the applied variables. Additional splicing and modification were required for the interest rate and real house price, where the interest rate will be presented in the section below. As real house price plays an important role in our study, the construction will be presented along with the analysis of the variable in Chapter 7.

With all variables in the format wanted, we proceed to the ADF-test that is used to check for stationarity across all our variables. We apply the boosted HP-filter to remove the trend component of the variables for those that show non-stationarity. We use the first difference modification after applying the HP-filter to variables that still don't display stationary behaviour. Only the cycle component of our variables will be used for further analysis.

6.4.1 Construction of Interest Rate

The nominal interest rate and lending rate in 1999 is used to adjust the nominal interest rate in time, *t*. To adjust the data before 2000 to the same format as the banks' lending rate, we used the following formula:

$$Nominal\ Interest\ Rate_t^* = \frac{Bank\ lending\ rate_{1999}}{Nominal\ Interest\ Rate_{1999}} * Nominal\ Interest\ Rate_t \qquad (41)$$

where,

$$Nominal\ Interest\ Rate_t^* = Spliced\ interest\ \ rate \text{ in period t}$$

$$Nominal\ Interest\ Rate_t = Nominal\ interest\ rate\ in\ period\ t$$

$$Bank\ lending\ rate_{1999} = The\ banks\ lending\ rate\ in\ 1999$$

The spliced nominal interest rate serves as a basis before additional transformation using the HP-filter.

7. Empirical Analysis

In this chapter, we will start by presenting how we have constructed the house price in real terms and give a historical analysis of its trends and cycles. Furthermore, we will present the results from the stationarity and how we have solved the problem with non-stationary time series. In the end, we will present the results from the correlation analysis and how this has affected the time lag of our selected variables.

7.1 Constructing of Real House Prices 1836-2021

The house price indices are collected from Norges Bank. Statistics Norway and Eiendom Norge also produce house price indices but do not have data from 1836. We only use Norges Banks house price indices to have a complete data set for yearly data for the whole analysis period. The index is constructed by specifying a house price starting point (ex 1900 = 100). An increase in the index from 100 to 101 from one period to another will represent a 1 percent increase in prices ([101-100] / 100 = 1 percent).

The house price index contains the development of nominal house prices. However, looking at nominal rates can be misleading. A useful approach is to transform house price indices into real terms. When looking at house markets, we have two different deflators that can be used for this purpose, the GDP or CPI. The application of a deflator depends on the analysis you want to do. GDP is the appropriate deflator when studying the production side, while CPI is the best when looking at house prices regarding house owners' purchasing power (Grytten O. H., 2018). Hence, we use CPI as a deflator when constructing real house prices.

We are also adjusting real house prices to have the price in the year 1900 equal to 100. The calculation of real house prices is presented in equation (42):

$$rHousePrice_t = \frac{\frac{nHousePrice_t}{CPI_t}}{\frac{nHousePrice_{1900}}{100}}, \qquad (42)$$

where,

$rHousePrice_t = Real\ House\ Price\ in\ time\ t$

$nHousePrice_t = Nominal\ House\ Price\ in\ time\ t$

$CPI_t = Consumer\ Price\ in\ time\ t$

When transforming the house price index to real measures, the new index will present the development in house prices relative to other economic prices. It represents a better comparison of prices to other economic measures. A period of rapid increases in real house prices may indicate a house bubble where house prices are above their fundamental value (Grytten O. H., 2009). Whether the market is due to a correction or crash, or able to establish the prices at a higher level without price fall, depends on other factors discussed later in the analysis. A bubble can signal that a correction or a crash is imminent. However, it is challenging to identify bubbles in markets today. This is due to difficulties in determining fundamental economic prices in real-time.

7.2 Historical Analysis of Real House Prices

In Chapter 4, we have discussed the development in house prices considering historical corrections and crashes. In this section, we will further investigate the deviations between observations of real house prices and their long-term trend.

7.2.1 Historical Trend in the House Market

In Figure 7.1 we depict the constructed real house prices between 1836 and 2021. The light grey areas represent periods defined as corrections in the house market, and the dark grey represents the crashes. As we can see, after the Kristiania Crash in early 1900, real house prices were at the same level for about 100 years. However, after the Banking Crisis in the early 1990s, a drastic increase in real house prices has characterized Norway. From the bottom in 1992, with a value equal to 79 percent, to a value in 2021 equal to 366 percent, the real house prices have almost increased by 400 percent.

The substantial increase also results in a strong increase in the estimated trend. This may also result from the endpoint problem in the HP-filter discussed in Chapter 6. At the end of the data set, the estimated trend follows the actual data substantially. The endpoint problem makes it difficult to define the trend line in the last years and, hence, challenging to observe bubble tendencies. Therefore, we use different λ values to make diverse smoothing variations to reduce the endpoint problem.

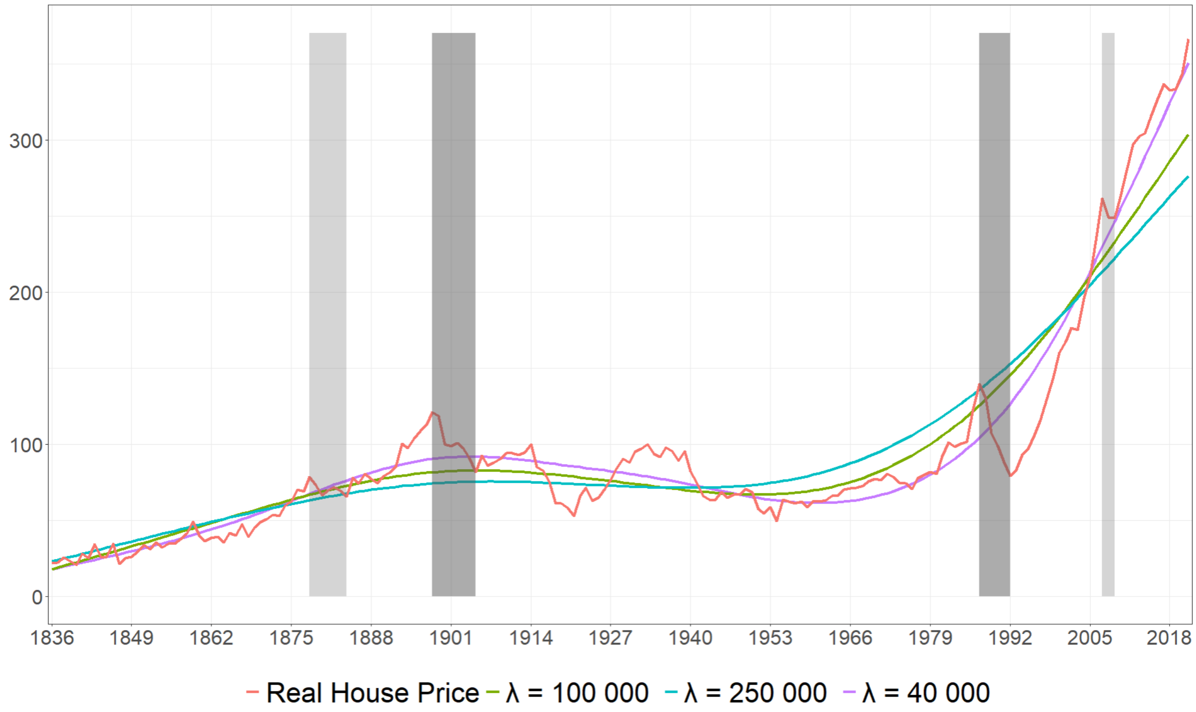


Figure 7. 1: *Real house price indices 1836-2021 (1900 = 100)*

For all crashes, the period before is characterized by significant deviation in real house prices over the estimated trend, followed by a fall below the estimated trend. During the Kristiania Crash (1899-1905), real house prices declined by around 30 percent, but as Figure 7.1 visualizes, prices barely dipped below the estimated long-term trend. The situation was different during the Banking Crisis (1987-1992), where the prices dropped by about 43 percent from the top in 1987 to the bottom in 1992. From Figure 7.1, we can see that the prices fell significantly lower than the estimated trend. The period after the crisis is characterized by a rapid increase, although the real house prices weren't back at the same level, 12 years later in 1999.

The price variation is not as easy to see for the corrections at first sight. The first period we have defined as a correction is during the Long Depression (1873-1887). For the period before the Long Depression, we had over a decade with prices below the long-term trend, but the prices started to increase during the 1870s. The market peaked in 1878 before the prices began to fall, and the correction from the top in 1878 to the bottom in 1884 was about 16 percent. However, it only took a few years before the prices stabilized at the previous level. We also experienced a correction in house prices during the Financial Crisis (2007-2009). The difference between this period and the periods we discussed above is that real house prices had risen significantly before the crisis. During the Financial Crisis, real house prices fell by around 5 percent on an annual basis but quickly recovered in the period after the crisis.

From the plot, we can also see other periods with high real house price variations. One example is the substantial negative deviation from the trend in the period during the First World War. The reason is that in periods of war, inflation tends to increase dramatically, and real house prices will decrease. Something similar happened during the Second World War but not as dramatically as during the First World War.

7.2.2 Historical Cycles in the House Market

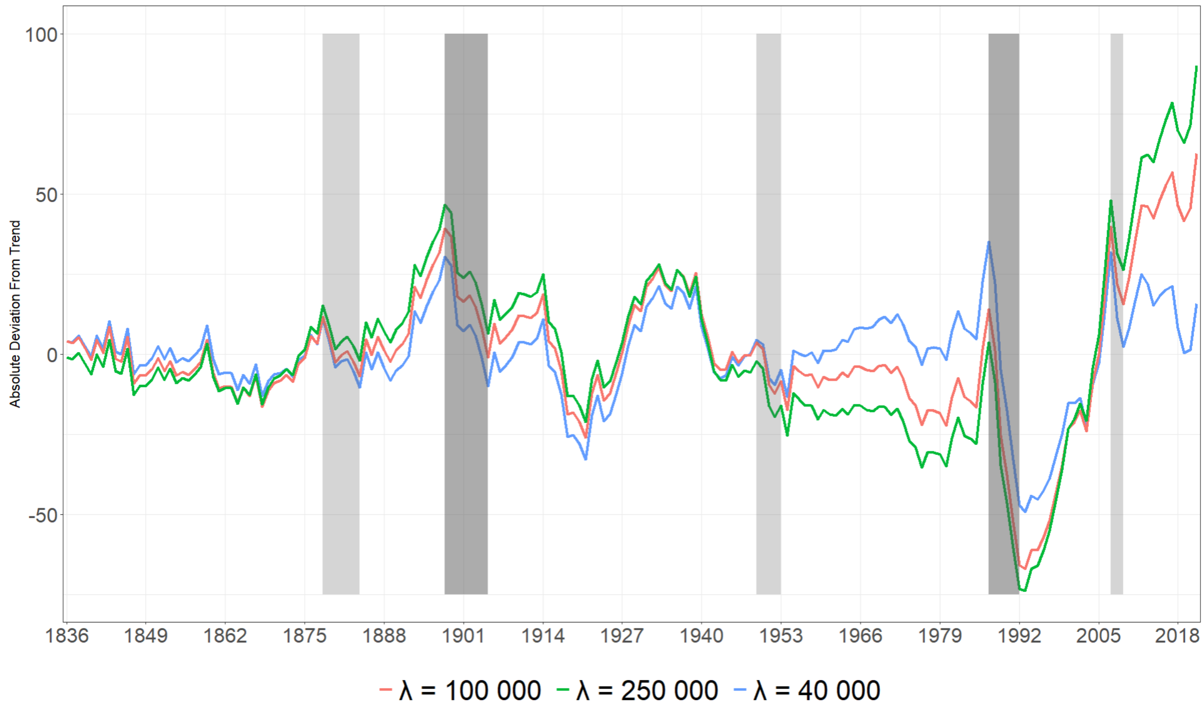


Figure 7. 2: *Cycles in real house prices during corrections and crashes*

Figure 7.2 visualizes the volatility in real house prices, with different value of λ, with the y-axis representing the absolute deviation of the trend. The graph shows that the price formation differs from 1836 to 1890 and from 1900 to today. The period before the Kristiania Crash in 1899 is characterized by smaller price cycles, where we do not see many variations. However, under the Long Depression (1873-1887), we have identified a period with correction. There are three reasons leading up to hard times around the 1880s. In the first place, the Norwegian economy was strongly correlated and dependent on Great Britain's economy. Secondly, there was a change in monetary politics when Norway started using a gold standard in 1874. Some declines were due to the introduction of the gold standard in 1874. This was mainly aimed at strengthening confidence and stability in the Norwegian currency. However, the result was that Norway had to pursue a more contractionary monetary policy. The third and last reason is that Norway spent more time than other countries transitioning from sailing ships to steamships (Grytten O. H., 2008).

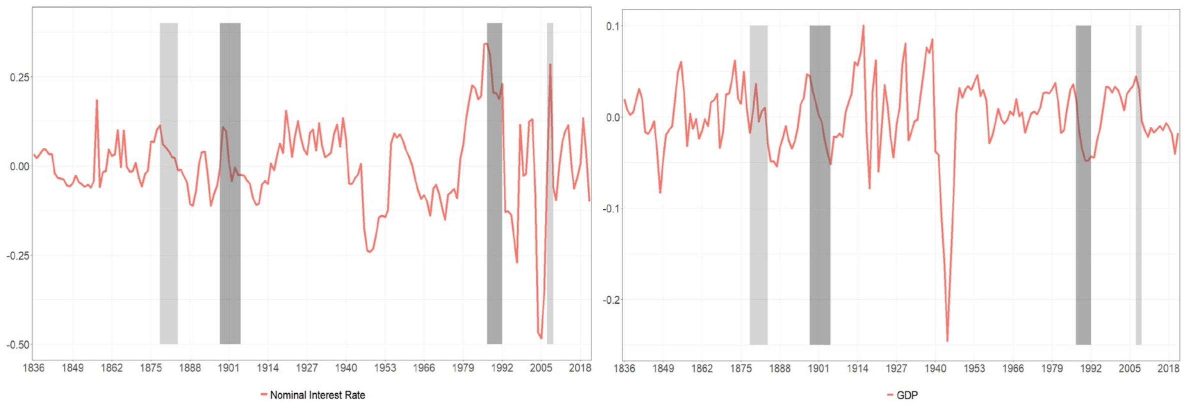
The most significant cycle deviations are represented during the Kristiania Crash, between the World Wars and the Banking Crisis. What characterizes these periods is a significant increase in money and credit. In addition to the increase in money and credit, interest rates are relatively low, incentivizing businesses and households to take on more credit. However, this leads to an overheating of the economy. Due to the overheating, credit bubbles are formed that grow so large that they eventually burst and lead to a crash.

Real house prices give a good intuition into how house prices develop compared to other economic prices. However, the variable will only be used for descriptive analysis and intuition and excluded from the regression analysis. The reason for this is due to the difficulties in getting intuitive results in regression analysis using house prices in real terms.

7.3 Cycles in Independent Variables

This section will discuss the independent variable's ability to indicate whether a crash or correction is imminent. In the discussion, we will use the historical economic situation from Chapter 4 while focusing on our independent variable's deviation from trend cycles.

Figure 7. 3: *Cycle plots for all independent variables*



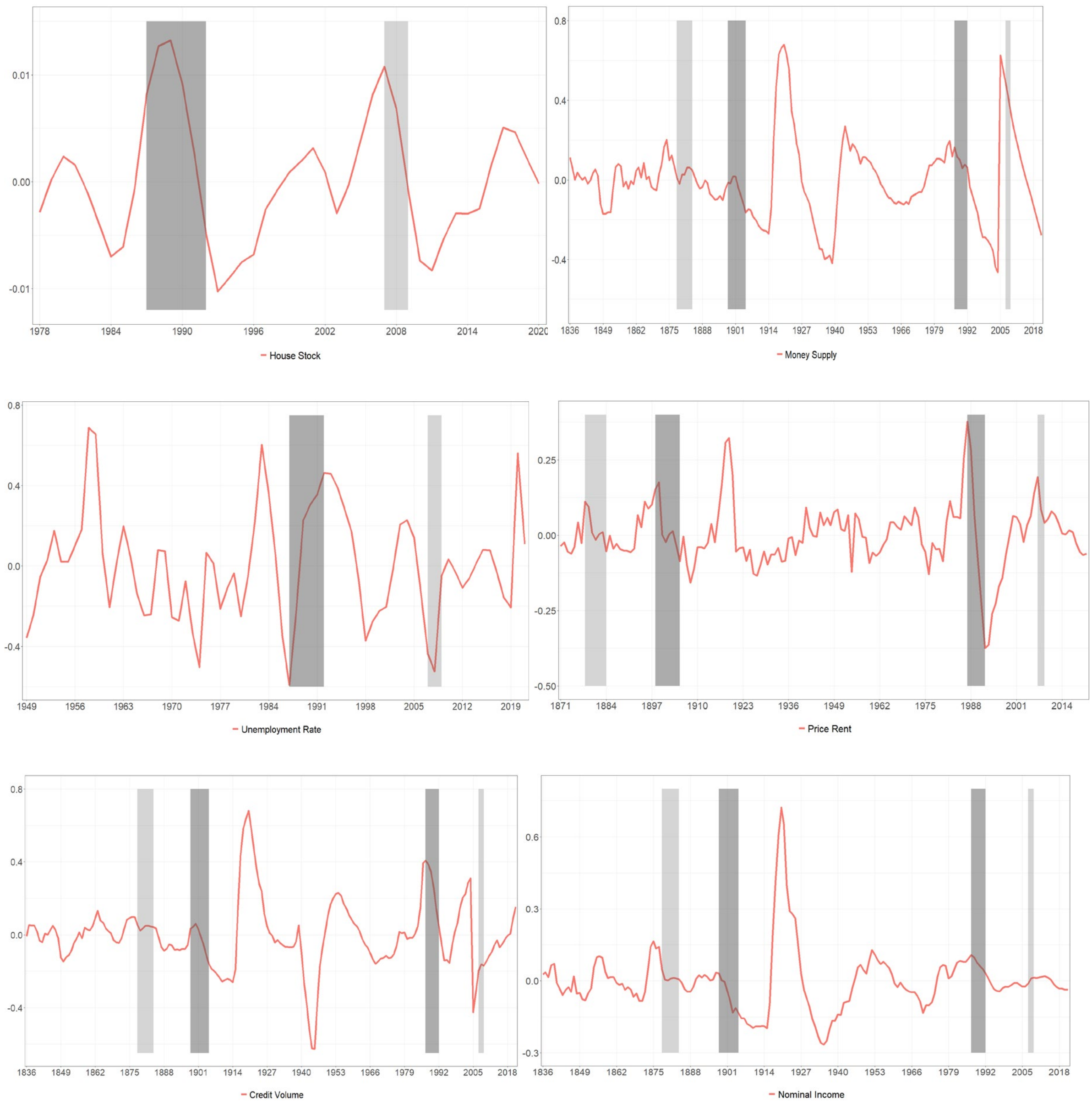


Figure 7.3 depicts the cyclical variations for all our log-transformed variables, with the y-axis representing the absolute deviation of the trend. A slight trend might be observed from the nominal income and nominal interest rate cycles, with the nominal interest rate being the most prominent. Here we observe an upward trend and a top right before crashes and corrections. The cyclical behaviour of nominal income and interest rates reveals a range of inflations before the periods. Before crashes and corrections, signs of rising inflation can be observed, and increasing inflation leads to a rising nominal interest rate, in line with the Fischer equation (Jones, 2017). During the crashes, there was also high speculation in the house market. On top of that, there were very favourable tax deductions on interest rates, and in some cases, the real interest rates were negative. These deductions stimulated the demand side of the market.

However, one of the limitations of nominal income as an explanatory variable is that it is pre-tax and does not account for other financial obligations. Thus, it may not offer as insightful perspective as disposable income, which is representing the net income households retain post fiscal deductions, inclusive tax. Moreover, nominal income is susceptible to inflation, distorting real purchasing power. We note periods of elevated inflation before the beginning of the crisis, which might explain some of the peaks observed in the nominal income cycle.

Cyclical variations peak in sync with all identified corrections and crashes for GDP and P/R, with the latter being the most significant. The positive correlation we discern between the P/R-ratio and house prices may indicate an overvalued house market, where house prices are inflated relative to the potential rental income they could generate. Consequently, the house market is more prone to corrections or crashes if the high valuations in the house market lack support from the underlying fundamental value.

As measured by GDP, economic activity displays variations, particularly around financial instabilities. However, the variables do not seem reasonable when predicting a crash or correction, as the variation does not seem very different from other historical periods. On the other hand, the end of all periods seems to reach a bottom point. Economic downturn trends usually point to an overly active economy before a significant decrease during the crisis. This tendency is consistent with the literature's assertion that difficult times generally follow slowdowns in economic growth.

P/R are notable in cycles during the Banking Crisis and the Kristiania Crash, where houses were treated as speculative investment assets, leading to an inflation of their perceived value. This implies an imbalance in the supply outstrips demand, causing a rising P/R-ratio. Thus, a crash occurs when the market becomes unstable due to a difference between market value and inherent fundamental value. While corrections undergo, a tight fiscal and monetary policy and technological paradigms resulting in considerable economic overcapacity, making the market correct itself to an equilibrium.

House stock peaks midway through the period of the Banking Crisis, while it peaks at the start of the Financial Crisis. The pattern during the Banking Crisis can be interpreted as a pre-crisis surge in house stock. The increase in house stock can be attributed to heightened demand, fostering an expectation of perpetual price escalation. This expectation prompts the execution of new construction projects during the economic boom. However, a decline becomes inevitable once it is acknowledged that the supply has outpaced demand. This trend indicates the complex interplay between demand and supply in the house market, highlighting the potential for market corrections when supply significantly exceeds demand. It is noteworthy that speculative behaviours characterized the house market around the 1980s and during the banking crisis, with houses widely perceived as "risk-free" investments.

Speculative demand necessitated further augmentation of supply. However, as the crisis takes hold, the house stock displays a negative trend. Furthermore, the house stock cycle's curve shape suggests the possibility of a period of low construction costs, which, when coupled with favourable interest rates, facilitates new construction projects. This observation underscores the influence of construction costs and interest rates on the realization of new projects, ultimately affecting the house stock and prices. During the Financial Crisis, the sudden decrease in house stock could be explained by the fear of starting a new project, as the origin of the crisis was a house crash in the United States.

The cyclical nature of unemployment exhibits noticeable fluctuations where it reaches its bottom just before the crash and correction, where the bottom can signal an overheated economy resulting in a crisis. Subsequently, unemployment rates increase during the period of falling house prices as these financial downturns materialize. Interestingly, unemployment exhibits a downward trend once the correction or crash phase concludes, with a stronger trend in the period with a crash.

The trend underlines the strong correlation between unemployment and economic expectations, with rising unemployment often signalling impending economic challenges among households. However, it is noteworthy that unemployment fluctuations during the crash are more significant than during correction, with correction associated with quicker recoveries. For instance, unemployment substantially impacted house prices more during the Banking Crisis than during the Financial Crisis. These matters could be attributed to the broader economic impact of the Banking Crisis, which led to a notable increase in unemployment during the crash. Unemployment rates, firmly tied to the demand side of the economy, tend to drive corresponding changes in demand and, consequently, house prices. An increase in unemployment is typically associated with reduced demand and a subsequent reduction in house prices.

The cyclical pattern of the money supply reveals a consistent trend of inflation preceding both crashes and corrections. In the context of the Long Depression, the period was characterized by monetary inflation. The reduction in the money supply before our observed correction resulted from the transition from the silver standard to the gold standard, resulting in contraction of money supply due to the high value of gold. An increase in the money supply typically stokes inflation, enhances consumption among businesses and households, and increases interest rates. If the growth in the money supply does not exceed consumption, the economy is unlikely to experience overheating, which otherwise could lead to speculative bubble formation and subsequent crashes.

The money supply cycle reveals indications of monetary inflation resulting from the liberalization of credit regulations. The aim was to promote homeownership among Norwegians, which eventually led to an overheated economy, giving rise to speculative bubbles and crashes. The cycle plot during the Financial Crisis presents an intriguing observation where we observe a sudden surge in the money supply starting from 2006. This can be attributed to the start of the house market crisis in the United States and its rapid international spread. To prevent the house market and banks from collapsing, Norway pursued a highly expansive monetary policy by printing money and injecting the reserves into the banks so they could lend to businesses and households (Grytten & Hunnes, 2016).

The cyclical behaviour of credit volume demonstrates a tendency towards expansion preceding a crisis. This is evident during both periods of crashes in the house market, with the Banking Crisis being the most prominent. A downward trend during the crash follows the increase in credit volume. During the Kristiania Crash, the credit supply contracted. The contraction can be attributed to the transition from the silver to the gold standard, resulting in deflation and a contraction in the money supply, consequently reducing the volume of credit (Grytten & Hunnes, 2016).

A positive relationship between credit volume and house prices is evident for crash periods. This behaviour aligns with crisis anatomy, where low borrowing costs and attractive tax deductions on interest payments drive credit expansion. The peak of the credit volume coincides with the start of the banking crisis. Credit accessibility is governed by supply and demand forces within the economy. Banks, as credit providers, interact with the demand for credit from businesses and households. Given the favourable tax deductions on interest payments, more households were incentivized to borrow, driving inflation upwards. This, in turn, led to an increase in loan defaults, forcing banks to dispose of their collateral security, typically homes or properties, often at a loss. Consequently, the credit volume cycle, i.e., the leverage cycle, is critical to understanding the dynamics of financial crises and the interplay between credit supply, house prices, and financial stability.

As for periods with corrections, it is more difficult to observe credit volumes' effect on house prices. However, we observe a dramatic fall in credit volume in the period before the Financial Crisis. In contrast to the increase in money supply before the crisis, due to rescue packages to banks to avoid bank collapse, banks became more restrictive in giving credit as the fear of a financial crisis increased (NOU, 2011, p. 84).

7.4 Stationarity Analysis

In this section, we present the results from the stationarity analysis. As discussed in Chapter 6, an essential factor in OLS regression is to have stationary data series. Before running our multiple regression models, non-stationary data series must be transformed into stationary data. ADF-tests will be used to determine which non-stationary process our data exhibits, and which results from the test will be used when determining which transformations need to be done before moving on with our regression analysis.

The first run with the ADF-test is with variables without transformations. The results are presented in Table A.11 in the Appendix. As we can see from the test, every time series indicates non-stationary data with a deterministic trend. We are transforming our time series by applying the boosted HP-filter for the series following a deterministic trend. We use the filter for all non-stationarity series as this gives consistent data series. We will only keep the cycle component for all variables. The results are presented in Table A.12 in the Appendix.

As seen from the test results, we successfully removed the deterministic trend in all our series of data. However, nominal income and house stock still exhibit a constant or a linear trend. We apply the first difference to remove the linear trend from the series.

7.5 Correlation Analysis

Correlation analysis can help determine which economic variables to include in the regression analysis and identifies whether the variables are leading, lagging, or concurred. Therefore, the findings of the correlation analysis will be used to determine whether each variable should have a lag or a lead in the regression analysis.

To determine the state of the variables, we are time-shifting the variables three periods before and after and pick the time shift with the highest correlation with house prices. We only consider statistically significant correlations at a 5 percent or lower level. The variables are distributed across different time intervals due to a lack of data in some periods. Table 7.1 and Table 7.2 show the results from the correlation analysis.

Variables	Lag indicators (-)				Lead indicators (+)		
	-3	-2	-1	0	1	2	3
Interest rate (1836 - 2021)	0,2346***	0,261***	0,2215***	0,1179	-0,1875***	-0,1797**	-0,1963***
House stock (1978 - 2021)	-0,306*	-0,1032	0,2018	0,4923***	0,6231***	0,5542***	0,3773**
Unemployment (1948 - 2021)	0,34***	0,0965	-0,2465**	-0,3124***	-0,1871	-0,0297	0,0323
Money Supply (1836 - 2021)	-0,2884***	-0,3007***	-0,3115***	-0,2975***	-0,2419***	-0,1681**	-0,0713
Credit volume (1836 - 2021)	-0,2948***	-0,2993***	-0,2601***	-0,193***	-0,1392*	-0,0796	-0,0629
Nominal Income (1836 - 2021)	-0,2481***	-0,3143***	-0,3825***	-0,4299***	-0,3853***	-0,3338***	-0,2581***
GDP (1836 - 2021)	0,1824**	0,2455***	0,283***	0,323***	0,2433***	0,1107	-0,0031
Nominal House price (1836 - 2021)	0,0502	0,1190	0,1708**	0,4684***	0,2606***	0,2284***	0,14*
P/R (1871 - 2021)	-0,0402	0,0755	0,2363***	0,4612***	0,4023***	0,3451***	0,2636***

$* p < 0.10, ** p < 0.05, *** p < 0.01.$ *Dependent variable: Real House Price*

Table 7. 1: *Correlation matrices with real house price*

Variables	Lag indicators (-)				Lead indicators (+)		
	-3	-2	-1	0	1	2	3
Nominal Interest rate (1836 - 2021)	0,1577**	0,2937***	0,4155***	0,5223***	0,552***	0,5042***	0,4452***
House stock (1978 - 2021)	-0,2219	-0,0138	0,2650	0,5118***	0,6046***	0,5165***	0,342**
Unemployment (1948 - 2021)	-0,0379	-0,1702	-0,2958**	-0,2534**	-0,0962	0,0662	0,1904
Money Supply (1836 - 2021)	0,2529***	0,3599***	0,4258***	0,4479***	0,4387***	0,3962***	0,3488***
Credit volume (1836 - 2021)	0,1725**	0,283***	0,3889***	0,4612***	0,4626***	0,4317***	0,3478***
Nominal Income (1836 - 2021)	0,3068***	0,4043***	0,4875***	0,5222***	0,5271***	0,4431***	0,3391***
GDP (1836 - 2021)	0,2894***	0,2802***	0,2245***	0,1464**	0,0134	-0,0960	-0,1651**
Real House price (1836 - 2021)	0,1413*	0,2236***	0,2612***	0,4684***	0,1746**	0,1314*	0,0494
P/R (1871 - 2021)	0,3652***	0,5167***	0,6521***	0,7711***	0,5555***	0,3318***	0,1087

$* p < 0.10, ** p < 0.05, *** p < 0.01.$ *Dependent variable: Nominal House Price*

Table 7. 2: *Correlation matrices with nominal house price*

Tables 7.1 and 7.2 comprehensively describe the results of the correlation analysis for real and nominal house prices. We use nominal house prices as the dependent variable in our regression analysis, so we focus on Table 7.2. The results from the correlation analysis are primarily in line with our expectations. However, nominal interest rate and house stock exhibit a positive correlation in *t=0* and will be discussed in Chapter 8.

An important note is that when conducting a lead-lag correlation with annual data, a variable designated as a lead could, in essence, be classified as a concurrent variable. To determine the appropriate variable selection, consideration is given to their originating sign and economic behaviour.

8. Regression Analyses and Results

The present chapter discusses results from the regression analyses. We depart by giving flagging our expectations of the regression coefficient directions before we explicitly present our models, run the regressions, and finally, discuss the results.

8.1 Coefficient Expectations for Regression Models

Table 8.1 presents our expected signs of estimated coefficients in each period. The estimations are based on empirical theory and our understanding of the Norwegian house market. The explanatory variables we want to estimate are the nominal interest rate, GDP, house stock, unemployment rate, money supply, credit volume, nominal income, and the P/R ratio. All the variables to be included in the regression are log-transformed.

	Excpected Sign of Estimated Coefficients in Regression Analysis			
	CRASHES		CORRECTIONS	
	Kristiania Crash (1892-1907)	*Banking Crisis (1981-1995)*	*Long Depression (1871-1886)*	*Financial Crisis (1999-2013)*
Interest Rate	-		-	
GDP	+		+	
House Stock	-		-	
Unemployment Rate	-		-	
Money Supply	+		+	
Credit Volume	+		+	
Nominal Income	+		+	
P/R	+		+	

Table 8. 1: *Expected signs of estimated coefficients*

8.2 Regression Models

This section presents our regression models and our results. For periods with correction and crash, respectively, we constructed a simple regression model on each variable. The dependent variable in our regression model is the nominal house price index on a logarithmic scale and transformed with an HP-filter. We are using nominal house prices instead of real terms as these return more intuitive results.

The independent variables are the ones presented in the section below. The variables are in lagged form to reflect the independent variables' natural effect on prices, and the lag or lead on each variable is chosen based on the results from the correlation analysis in Chapter 7. The OLS assumptions are tested, and the results are presented in the Appendix. For models indicating heteroscedasticity or autocorrelation, we apply Newey-West standard errors to reduce the problem.

The regression results from the simple models determine which variables to include in the multi-regression models. As a threshold, all variables with a significance level at 0.5 in one of the periods should be included in both multiple regression models due to the low number of observations in each period. Since we are using yearly data, we found it necessary to include more years than the specific period to include more data in our regression models, which will be specified in each regression model. However, we require a significance level of 0.1 to interpret the regression coefficients causally.

8.2.1 Regression Estimates for Nominal Interest Rate

This section will examine the relationship between nominal interest rates and house prices. In general, interest rate affects both the supply and demand side of house prices. On the supply side, it raises the prices of goods and materials; on the demand side, it raises the pricing of loans and decreases purchasing power of the consumer. Hence, we expect that the relationship is negative and that house prices will decrease when the interest rate increases.

To make estimations of the relationship, we perform an OLS regression for each period. The correlation analysis suggests the variable to be in period *t*, and the OLS assumptions are tested and presented in the Appendix. We used Newey-West standard errors because the test in the Appendix highlighted the possibility of autocorrelation. The OLS regression is presented in equation (43):

$$cP_t = \beta_0 + \beta_1 cNomIntRate_t + \varepsilon_t, \tag{43}$$

where,

$$cP_t = Cyclical\ component\ of\ logged\ house\ prices$$

$$NomIntRate_t = Cyclical\ component\ of\ logged\ nominal\ interest\ rate$$

	Dependent variable: Cycle component of logged house prices	
	CRASHES	CORRECTIONS
	Kristiania Crash (1892-1907) *Banking Crisis (1981-1995)*	*Long Depression (1871-1886)* *Financial Crisis (1999-2013)*
Interest Rate	0,847***	0,09.
	(0,174)	(0,094)
Intercept	-0,018	0,048***
	(0,028)	(0,015)
Observations	31	31
R-squared	0,51	0,05
Adj R-squared	0,50	0,01
Residual Standard Error	0,132	0,082
F-statistic	23,59***	0,91.
Significance level:		$.p < 0{,}5, *\, p < 0.10, **\, p < 0.05, ***\, p < 0.01.$

Table 8. 2: *Regression estimates for Nominal Interest Rate*

Table 8.2 represents the regression estimate for the nominal interest rate. The model indicates that during the period with crashes and corrections, a 1 percent increase in nominal interest rate will represent an increase in house price of 0.85 and 0.09 percent, respectively, with only the period of crashes being significant at a level of 0.1. This is not in line with our expectations, as an increase in interest rate is expected to reduce house prices.

However, there could be several factors for this result. High inflation is expected during crashes, which drives the nominal interest rate up. Also, there are loose credit conditions and riskier lending behaviour, which means banks are willing to lend more at a higher interest rate. This will increase demand in the house market, thus resulting in increasing house prices. We suggest including the variable in our multi-regression model based on the results.

8.2.2 Regression Estimates for Gross Domestic Product

In this section, we examine the relationship between GDP and house prices. We expect that the relationship is positive since an increase in GDP indicates a growing economy with stronger financial conditions for consumers. Hence, the demand side will be expected to increase, and house prices will increase.

To examine the relationship, we perform an OLS regression for each period. The correlations analysis suggests a lag of 3 periods, and the OLS assumptions are tested and presented in the Appendix. We applied Newey-West standard errors as the test in the Appendix indicated a possibility of autocorrelation. The OLS regression is presented in equation (44):

$$cP_t = \beta_0 + \beta_1 \mathrm{c}GDP_{t-3} + \varepsilon_t, \tag{44}$$

where,

$$\mathrm{c}GDP_{t-3} = Lagged\ cyclical\ component\ of\ logged\ gross\ domestic\ product$$

The results are presented in the table below:

	Dependent variable: Cycle component of logged house prices	
	CRASHES	**CORRECTIONS**
	Kristiania Crash (1892-1907) / *Banking Crisis (1981-1995)*	*Long Depression (1871-1886)* / *Financial Crisis (1999-2013)*
GDP	3,661***	1,656**
	(0,961)	(0,638)
Intercept	0,05*	0,016.
	(0,028)	(0,018)
Observations	31	31
R-squared	0,33	0,19
Adj R-squared	0,31	0,16
Residual Standard Error	0,154	0,075
F-statistic	14,52***	6,751**
Significance level:		. $p < 0{,}5$, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 8. 3: *Regression estimate for Gross Domestic Product (GDP)*

From the regression estimates in Table 8.3, the model indicates that during the period with crashes and corrections, a 1 percent increase in GDP will represent an increase in house prices of 3.66 percent and 1.66 percent, respectively. The crash period significant at a level of 0.01, and the correction significant at a level of 0.05. This result aligns with our expectations as economic growth stimulates the demand side of the house market. We suggest including the variable in our multi-regression model based on the results.

8.2.3 Regression Estimates for House Stock

This section examines the relationship between house prices and the house stock. We expect that the relationship is negative since an increase in house stock will strengthen the supply side of the house market. With an increased supply side, house prices will be expected to decrease.

To examine the relationship, we perform an OLS regression for each period. The correlations analysis suggests a lead of 1 period, and the OLS assumptions are tested and presented in the Appendix. We used Newey-West standard errors since the test in the Appendix highlighted the possibility of autocorrelation. The OLS regression is presented in equation (45):

$$cP_t = \beta_0 + \beta_1 cHouseStock_{t+1} + \varepsilon_t, \tag{45}$$

where,

$$cHouseStock_{t+1} = Leaded\ \ cyclical\ component\ of\ logged\ house\ stock$$

The results are presented in the table below:

	Dependent variable: Cycle component of logged house prices	
	CRASH *(1978-2000)*	**CORRECTION** *(1996-2018)*
House Stock	22,609***	3,424.
	(4,985)	(3,277)
Intercept	0,03.	0,007
	(0,032)	(0,015)
Observations	31	31
R-squared	0,50	0,05
Adj R-squared	0,47	0,00
Residual Standard Error	0,153	0,073
F-statistic	20,57***	1,091.
Significance level:		$.p < 0.5, * p < 0.10, ** p < 0.05, *** p < 0.01.$

Table 8. 4: *Regression estimates for House Stock*

From the results in Table 8.4, we observe a positive relationship for both periods. We only have estimates for two periods because we only have data on house stock from 1978-2021. The model indicates that during the period with crashes and corrections, a 1 percent increase in house stock will represent an increase in house price of 22.61 percent and 3.42 percent, respectively, with only the period with crashes being significant at a level of 0.1.

The direction of the coefficient is not in line with our expectations. However, the strong demand side could explain the positive relationship during the Banking Crisis. Increasing house prices stimulates construction activity leading to more house stock in the future. Also, if investors expect future growth in house prices, they may build more, and house stock increases. We may also see the result of the lag in the prices' ability to reach their new equilibrium, as presented in Figure 3.1, and our lead of 1 period failing to fix this in the model. However, we have decided to keep the lead of 1 period to keep consistency in the model estimates. We should have included the variable in the multiple regression model based on the results. However, due to data limitations before 1978, we cannot include the variable.

8.2.4 Regression Estimates for Unemployment Rate

This section examines the relationship between house prices and the unemployment rate. We expect that the relationship is negative since an increase in the unemployment rate will affect consumers' financial power as their income is reduced. This will weaken the demand side of the house market and decrease house prices.

To examine the relationship, we perform an OLS regression for each period. The correlation analysis suggests a lag of 1 period, and the OLS assumptions are tested and presented in the Appendix. We utilized Newey-West standard errors because the test in the Appendix highlighted the potential of heteroscedasticity and autocorrelation. The OLS regression is presented in equation (46):

$$cP_t = \beta_0 + \beta_1 cUnemployment_{t-1} + \varepsilon_t, \tag{46}$$

where,

$$cUnemployment_{t-1} = Lagged\ cyclical\ component\ of\ logged\ unemployment\ rate$$

The results are presented in the table below:

	Dependent variable: Cycle component of logged house prices	
	CRASH *(1978-2000)*	CORRECTION *(1996-2018)*
Unemployment Rate	-0,248*	-0,117.
	(0,127)	(0,071)
Intercept	0,031.	0,002
	(0,041)	(0,015)
Observations	31	31
R-squared	0,15	0,11
Adj R-squared	0,11	0,07
Residual Standard Error	0,197	0,071
F-statistic	3,793*	2,669.
Significance level:		$.p < 0{,}5, * p < 0.10, ** p < 0.05, *** p < 0.01.$

Table 8. 5: *Regression estimates for Unemployment Rate*

From the regression estimates from Table 8.5, the model indicates that during the period with crashes and corrections, a 1 percent increase in the unemployment rate will represent a decrease in house price of 0.25 percent and 0.12 percent, respectively, with the only period with crashes being significant at a level of 0.1. The sign of the coefficient is in line with our expectations as an increased unemployment rate leads to reduced demand for houses as economic uncertainty causes individuals to delay house purchases. We should have included the variable in the multiple regression model based on the results. However, due to limitations in data prior to 1948, we are not able to include the variable.

8.2.5 Regression Estimates for Money Supply

In this section, the relationship between money supply and house prices will be examined. The money supply represents the total amount of money available in the economy. The expectation is for the money supply to have a positive relationship with house prices since an increase in money supply can lead to a liquidity increase in the economy and, thus, increase the demand and house prices.

To examine the relationship, we perform an OLS regression for each period. The correlation analysis suggests the variable to be in period t, and the OLS assumptions are tested and presented in the Appendix. We used Newey-West standard errors as the test in the Appendix highlighted the possibility of autocorrelation. The OLS regression is presented in equation (47):

$$cP_t = \beta_0 + \beta_1 cMoneySupply_t + \varepsilon_t, \tag{47}$$

where,

$$cMoneySupply_t = Cyclical\ component\ of\ logged\ money\ supply$$

The results are presented in the table below:

	Dependent variable: Cycle component of logged house prices			
	CRASHES		CORRECTIONS	
	Kristiania Crash (1892-1907)	*Banking Crisis (1981-1995)*	*Long Depression (1871-1886)*	*Financial Crisis (1999-2013)*
Money Supply	1,121***		0,089.	
	(0,251)		(0,054)	
Intercept	0,048*		0,041***	
	(0,026)		(0,015)	
Observations	31		31	
R-squared	0,41		0,09	
Adj R-squared	0,39		0,05	
Residual Standard Error	0,145		0,080	
F-statistic	19,94***		2,739.	
Significance level:			$.p < 0{,}5, * p < 0.10, ** p < 0.05, *** p < 0.01.$	

Table 8. 6: *Regression estimates for Money supply*

Table 8.6 represents the regression estimate for money supply. The model indicates that during the period with crashes and corrections, a 1 percent increase in money supply will represent an increase in house price of 1.20 percent and 0.09 percent, respectively, with only the period with crashes being significant at a level of 0.1. The sign of the coefficient is in line with our expectations as an increased amount of money generally leads to increased demand for houses. We suggest including the variable in our multi-regression model based on the results.

8.2.6 Regression Estimates for Credit Volume

In this section, the relationship between credit volume and house prices will be examined. Credit volume represents the total amount of loans and credits offered by financial institutions in the economy. The expectation is for the money supply to have a positive relationship with house prices since a higher availability of credit and loans can lead to a liquidity increase in the economy and increase the demand and house prices.

To examine the relationship, we perform an OLS regression for each period. The correlations analysis suggests the variable to be in period t, and the OLS assumptions are tested and presented in the Appendix. We applied Newey-West standard errors because the test in the Appendix highlighted the chance of autocorrelation. The OLS regression is presented in equation (48):

$$cP_t = \beta_0 + \beta_1 cCreditVolume_t + \varepsilon_t, \tag{48}$$

where,

$$cCreditVolume_t = Cyclical\ component\ of\ logged\ credit\ volume$$

The results are presented in the table below:

	Dependent variable: Cycle component of logged house prices			
	CRASHES		CORRECTIONS	
	Kristiania Crash (1892-1907)	*Banking Crisis (1981-1995)*	*Long Depression (1871-1886)*	*Financial Crisis (1999-2013)*
Credit Volume	0,755***		-0,032	
	(0,144)		(0,095)	
Intercept	0,025.		0,047***	
	(0,025)		(0,015)	
Observations	31		31	
R-squared	0,49		<0,01	
Adj R-squared	0,47		<0,01	
Residual Standard Error	0,135		0,083	
F-statistic	27,53***		0,11	
Significance level:			$.p < 0{,}5, * p < 0.10, ** p < 0.05, *** p < 0.01.$	

Table 8. 7: *Regression estimates for Credit Volume*

Table 8.7 represents the regression estimate for the credit volume. The model indicates that during periods with crashes, a 1 percent increase in credit volume will represent an increase in house price of 0.76 percent and is significant at a level of 0.01. The sign of the coefficient is in line with our expectations that house prices also increase when credit increases. The coefficient in correction periods is not significant at a level of 0.5. We suggest including the variable in our multi-regression model based on the results.

8.2.7 Regression Estimates for Nominal Income

This section examines the relationship between nominal income and house prices. We expect that the relationship is positive since an increase in income will increase the purchasing power of consumers. Hence, the demand side will be expected to increase, and house prices will increase.

To examine the relationship, we perform an OLS regression for each period. The correlations analysis suggests a lead of 1 period, and the OLS assumptions are tested and presented in the Appendix. We employed Newey-West standard errors as the test in the Appendix suggested the potential of autocorrelation. The OLS regression is presented in equation (49):

$$cP_t = \beta_0 + \beta_1 cNominalIncome_{t+1} + \varepsilon_t, \tag{49}$$

where,

$$cNominalIncome_{t+1} = Leaded\ cyclical\ component\ of\ logged\ nominal\ income$$

The results are presented in the table below:

	Dependent variable: Cycle component of logged house prices			
	CRASHES		CORRECTIONS	
	Kristiania Crash (1892-1907)	*Banking Crisis (1981-1995)*	*Long Depression (1871-1886)*	*Financial Crisis (1999-2013)*
Nominal Income	2,721.		-0,675.	
	(1,724)		(0,44)	
Intercept	0,07*		0,048***	
	(0,036)		(0,014)	
Observations	31		31	
R-squared	0,08		0,08	
Adj R-squared	0,05		0,04	
Residual Standard Error	0,181		0,080	
F-statistic	2,492.		2,357.	
Significance level:			$.p < 0,5, {*}p < 0.10, {**}p < 0.05, {***}p < 0.01.$	

Table 8. 8: *Regression estimates for Nominal Income*

Table 8.8 represents the regression estimate for the nominal income. The model indicates that during crashes and corrections, a 1 percent increase in income will represent an increase in house prices of 2.72 and a decrease of 0.68 percent, respectively. Both models are only significant at a level of 0.5, so we cannot causally determine the relationship. However, the significance level indicates that the variable should be included in our multiple regression model.

8.2.8 Regression Estimates for Price/Rent Ratio

This present section examines the relationship between P/R-ratios and house prices. We expect the relationship to be positive since an increase in P/R indicates that house prices have increased more than the renting costs. Increasing house prices will increase the equation and therefore imply a positive relationship.

To examine the relationship, we perform an OLS regression for each period. The correlation analysis suggests the variable to be in period t, and the OLS assumptions are tested and presented in the Appendix. We used Newey-West standard errors as the test in the Appendix suggested a possibility of autocorrelation. The OLS regression is presented in equation (50):

$$cP_t = \beta_0 + \beta_1 cP/R_t + \varepsilon_t, \tag{50}$$

where,

$$cP/R_t = Lagged\ \ cyclical\ component\ of\ logged\ P/R\ Ratio$$

The results are presented in the table below:

	Dependent variable: Cycle component of logged house prices	
	CRASHES	**CORRECTIONS**
	Kristiania Crash (1892-1907) *Banking Crisis (1981-1995)*	*Long Depression (1871-1886)* *Financial Crisis (1999-2013)*
Price/Rent	1,005***	0,607**
	(0,075)	(0,223)
Intercept	0,037***	0,03*
	(0,013)	(0,015)
Observations	31	31
R-squared	0,86	0,20
Adj R-squared	0,86	0,18
Residual Standard Error	0,070	0,075
F-statistic	181,4***	7,436**
Significance level:		$. p < 0.5, * p < 0.10, ** p < 0.05, *** p < 0.01.$

Table 8. 9: *Regression estimates for P/R-coefficients*

Table 8.9 represents the regression estimate for the P/R-ratio. The model indicates that during crashes and corrections, a 1 percent increase in P/R will represent an increase in house prices of 1.01 and 0.61 percent, respectively. Both coefficients are significant at a level of 0.05 or less. The positive relationship can be explained through market expectations. When market participants expect future house prices to increase, they might be willing to pay more for a house today, even if the rent that could be earned from that house is relatively low. This would increase the P/R-ratio and house prices. However, if house prices rise relatively higher than rent prices over time, it could indicate a bubble in the house market (Grytten & Hunnes, 2016, pp. 83-84). We suggest including the variable in our multi-regression model based on the results.

8.3 Regression Estimates for Multi-Regression Model

In this section, we will examine the results from our multiple regression. We have the interpretation for our model mathematically illustrated in equation (51) for crashes and equation (52) for corrections. To finally choose which variables to be included in the multiple regression model, we apply the backward elimination method explained in Chapter 6.3.1. We remove variables until all variables are significant at a level of 0.5. Table 8.10 presents our final multiple regression model.

To examine the relationship, we perform an OLS regression for each period. The correlation analysis suggests our lag or leads for the periods, and the OLS assumptions are tested and presented in the Appendix. We used Newey-West standard errors since the test in the Appendix highlighted the possibility of autocorrelation. The multiple regression model is presented in equations (51) and (52) for crashes and corrections, respectively:

$$cP_{t(crashes)} = \beta_0 + \beta_1 cGDP_{t-3} + \beta_2 cMoneySupply_t + \beta_3 cCreditVolume_t + \beta_4 \, cNominalIncome_{t+1} + \beta_5 cP/R_t + \varepsilon_t \tag{51}$$

$$cP_{t(corrections)} = \beta_0 + \beta_1 cMoneySupply_t + \beta_2 cCreditVolume_t + \beta_3 NominalIncome_{t+1} + \beta_4 cP/R_t + \varepsilon_t \tag{52}$$

Dependent variable: Cycle component of logged house prices		
	CRASHES	CORRECTIONS
	Kristiania Crash (1892-1907) *Banking Crisis (1981-1995)*	*Long Depression (1871-1886)* *Financial Crisis (1999-2013)*
Interest Rate		
GDP	0,199.	
	(0,262)	
Money Supply	0,484***	0,483***
	(0,097)	(0,082)
Credit Volume	0,11*	0,83***
	(0,06)	(0,146)
Nominal Income	0,273.	-0,476*
	(0,354)	(0,277)
Price/Rent	0,824***	0,797***
	(0,046)	(0,167)
Intercept	0,04***	-0,011.
	(0,006)	(0,012)
Observations	31	31
R-squared	0,98	0,69
Adj R-squared	0,98	0,64
Residual Standard Error	0,030	0,049
F-statistic	230,3***	14,36***

Significance level: . $p < 0{,}5$, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 8. 10: *Multiple regression estimates for crashes and corrections*

Table 8.10 shows an adjusted R-squared equal to 0.98 in periods with crashes. The high adjusted R-squared is significantly influenced by the variable Price/Rent, as this includes house prices. It is important to be aware of these variables' influence on the results. Running the multiple regression without the variable would result in an adjusted R-squared equal to 0.71. However, we suggest including the variable to include this ratio's effect on house prices. The F-statistic for both periods is significant at a level of 0.01, both with and without including the variable Price/Rent, implying that our predictors are statistically significant.

When running the multiple regression model for all variables from the simple models, nominal interest rates were not significant at a level of 0.5 for both crashes and corrections. In addition, GDP was not significant in periods with correction. Due to this, these variables are excluded in the multiple regression presented in Table 8.10. As we can see from the table, all remaining variables are significant at a level of 0.5 or less.

For crashes, the interpretation of the model aligns with our expectations. However, nominal income and GDP are only statistically significant at a level of 0.5 and will not be further interpreted. Our model shows that a 1 percent increase in credit volume and money supply increase house prices by 0.48 percent and 0.11 percent, respectively. This corresponds to the literature and theory showing that during the Banking Crisis and Kristiania Crash, the economy experienced overheating with a substantial increase in money and credit.

When the pace of growth in house prices outstrips rental prices, a significant rise in the P/R is observed. As this trend progresses, it becomes increasingly unsustainable, creating conditions conducive to a house bubble's formation and subsequent collapse. In our multiple regression, the P/R-ratio is significant at a level of 0.01, where a 1 percent increase in the P/R-ratio corresponds to a 0.82 percent rise in house prices. This correlation resonates with our theoretical expectations, as an inflated P/R-ratio can signal that houses might be overvalued. Our findings suggest a significant association between the P/R-ratio and an escalation in house prices during the period. This aligns with the general understanding that a steadily inflating P/R-ratio can potentially foreshadow an impending market crash (Grytten O. H., 2009).

As for corrections, all our variables are statistically significant at a level of 0.1 and, for the most part, align with our expectations except nominal income. The coefficient is negative, and a 1 percent increase suggests a reduction in house prices of 0.48 percent. There could be several reasons for this result, and one reasonable explanation is that nominal income does not account for inflation. During both periods, inflation was at a reasonably high level. Even if nominal income increases, real purchasing power could decrease, and during periods of uncertainty, households may save more or pay off debt rather than invest in a house.

Money supply and credit volume are both significant at a level of 0.01, and a 1 percent increase suggests a 0.48 percent and 0.83 percent rise in house prices, respectively. During the periods for corrections, loose credit policy resulted in more people affording mortgages, leading to increased demand. Increasing the money supply will lead to lower interest rates and eventually make borrowing cheaper.

A 1 percent increase in the P/R-ratio corresponds to a 0.80 percent rise in house prices during the correction period. An escalation in the P/R-ratio with rising house prices during a correction phase might suggest a market normalization. As house prices rebound, buying becomes more attractive than renting, which is reflected in the P/R-ratio. However, a swift increase might be a cautionary signal of the impending formation of another house bubble.

9. Conclusions

The present master thesis examines empirical price behaviour with a focus on key economic indicators within the Norwegian house market, guided by the following research question:

What characterizes cycles with crashes versus corrections in the house market?

The thesis focuses on two crash periods and two correction periods investigating a variety of variables. The Kristiania Crash (1899–1905) and the Banking Crisis (1988–1993) are defined as cycles with crash, and the Long Depression (1873–1887) and the Financial Crisis (2007–2010) are defined as cycles with correction. We applied annual data for variables relevant to the Norwegian house market, in the period between 1836 and 2021.

We apply different quantitative techniques for analytical purposes. We use a descriptive analysis when constructing and plotting real house prices and discussed them in context of the history of the Norwegian house market. Prior to the regression analyses, we determine the lags of our variables by conducting a correlation test on the applied variables' relationship with nominal house price. Furthermore, a stationarity analysis was carried out by using ADF-tests to determine the state of our variables, and the need of adjusting for trend components. Furthermore, real house prices and their deviance from the long-term trend were examined using a HP-filter analysis. In addition, we used OLS regression for time series supplied with cycle plots to analyse the periods and investigate the link between our variables and the price of houses.

The results basically confirm our initial expectations. We conclude that during crashes and corrections, credit volume and money supply have significant influence on house prices. They have a considerable impact on how consumers' purchasing power and economic activities are directly affected. In cycles ending in crashes, boosts in money supply and credit volumes fuel demand for properties and, thus, house prices. Bubble tendencies typically arise during such market states. Bubbles eventually bursts when prices continue to rise at unsustainable rates, and an excessive amount of credits is given. However, when corrections occur, the market attempts to find its natural equilibrium by itself. The results imply that increasing credit volumes during these times boost economic activity and increase house prices.

Additionally, throughout the period of crashes, we obtained insights into corresponding unemployment rates and house stock. However, the estimated relationships were insignificant during periods of correction. As more households' experience unemployment, it seems reasonable that house prices will decline, as this will decrease economic activity and investment in the house market.

Our findings on the house stock during crashes also make logical sense since during a house boom, constructures may respond to high prices by building more homes, boosting the supply. Additionally, our model reveals some interesting data on the role of the P/R-ratio. House prices were significantly impacted by the ratio during both crashes and corrections. Thus, the ratio's increase over time might provide clues about possible bubble creation.

Contrarily, our model is not significantly influenced by the nominal interest rate, nominal income, or GDP. Within the multiple regression model, we expected that GDP would have a more substantial influence. Given that GDP is a general indicator for the economy at large and might not be able to reflect dynamics specific to the house market, this could be ascribed to the influence of other variables on house prices. Due to their lack of significance in the multiple regression and the absence of intuitive economic behaviour in the conducted OLS regression, nominal interest rate and nominal income were also omitted in our model.

In conclusion, we believe our findings provide useful insight into understanding the differences in cycles with crashes and corrections in the house market, with findings mostly in line with initial expectations. When comparing periods with crashes, with periods with corrections, the variables P/R, house stock, credit volume, and unemployment rate show a greater explanatory component in times before crashes. On the other hand, when examining house prices directly, the variables nominal interest rate, nominal income, and GDP seem to have minimal explanatory significance. House prices are undoubtedly influenced by the money supply and credit volumes, but it is challenging to distinguish across various periods.

Future studies might consider utilizing quarterly data focusing on the house market in more recent times. Since quarterly data were lacking, we had to use annual data sets in our analysis. Understanding the implications of the selected definition of periods is essential given that the classification of periods has a substantial influence on the outcome. Future research might therefore try to choose and focus on alternative time periods and look for different outcomes. Finally, it would be interesting to examine the findings in different markets or regions.

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Appendix

Testing OLS Assumptions

In the appendix we will present the results from various tests of the validity of our data. In our analysis, we have used multiple regression with OLS estimation. Thus, we have tested the OLS assumptions described in chapter 6.

To test for linearity and zero conditional mean we have used graphical analysis of residual plots. Multicollinearity is tested by VIF-test. Homoscedasticity is tested by plotting absolute residuals against predicted values, as well as a Breusch-Pagan test. Autocorrelation is tested by the Durbin-Watson test. Normality is tested by the Shapiro-Wilk test, combined with a graphical test with histogram and Q-Q plots of residuals.

We will only comment on the results of the test for model 8.3. The tests for the remaining models, model 8.2.1 to 8.2.8, will be presented without comments in the last part of the section.

Linearity and Zero-Conditional Mean

A residual plot against predicted values is shown in Figure A.1. In the plot, we look for patterns that can violate the assumption of linearity and zero conditional mean. As we can see from the plot, there are no clear patterns for the points. This reduces the risk of the assumptions being violated.

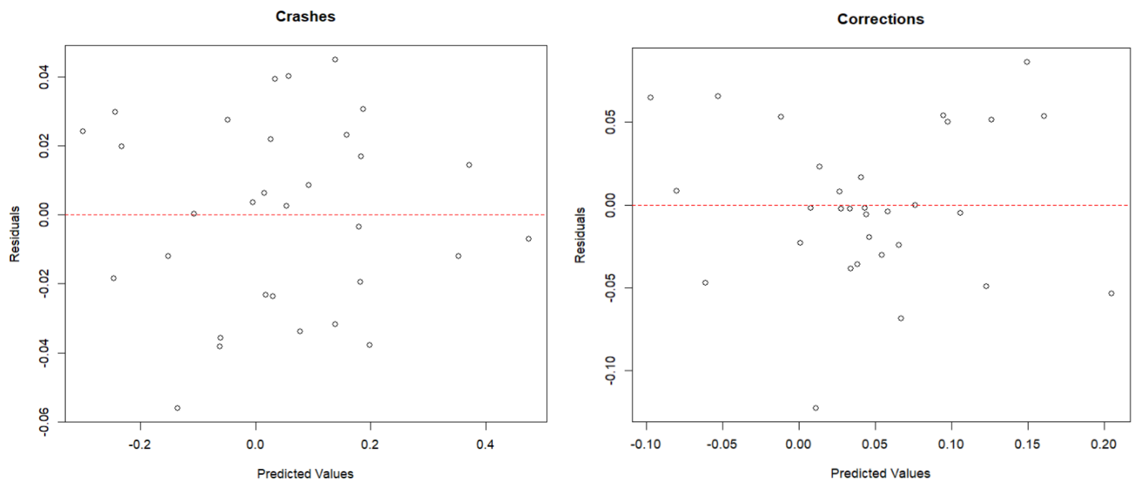

Figure A. 1: *Residual Plots for Model 8.3 (Equation 51 and 52 for details).*

Multicollinearity

We test against multicollinearity using a VIF-test explained in Chapter 6. As we can see from Table A.1 no variables have a VIF coefficient close to the value 10 and we can conclude that there is no presence of multicollinearity in the dataset.

Variance Inflation Factor (VIF)

	CRASHES *Kristiania Crash (1892-1907)* / *Banking Crisis (1981-1995)*	CORRECTIONS *Long Depression (1871-1886)* / *Financial Crisis (1999-2013)*
Credit Volume	3,604	6,688
Money Supply	3,596	6,065
Nominal Income	1,575	1,052
Price/Rent	2,126	1,292
GDP	2,007	

Table A. 1: *VIF-test for model 8.3*

Homoscedasticity

We are plotting the absolute residuals against the predicted values to look for any pattern of the residuals. From the plot in Figure A.2, there are no clear patterns in the residuals.

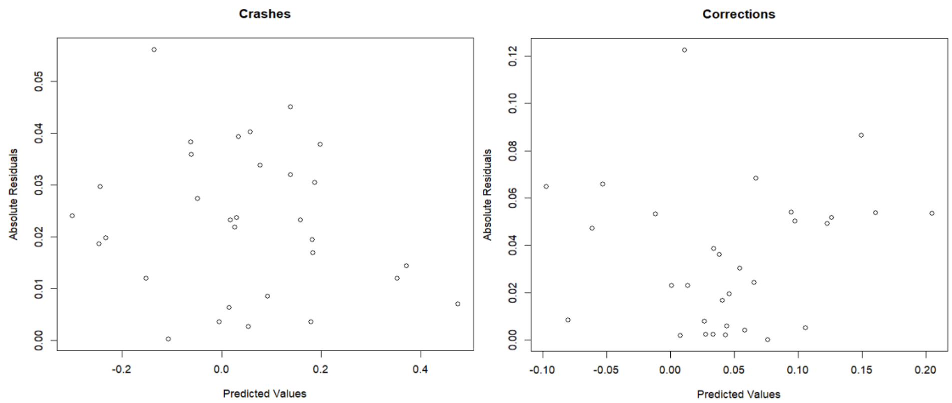

Figure A. 2: *Absolute Residual Plots for Model 8.3*

From Table A.2 we can see the results of the Breusch-Pagan test. We observe that the p-value from the tests is well above the significance level of 0.05 and we conclude that no heteroscedasticity is present.

Autocorrelation

From Table A.2, we can see the results of the Durbin Watson test. The Durbin Watson test is performed to examine whether autocorrelation is present. From the results we cannot conclude that no autocorrelation is present. Thus, the assumption may be violated. Newey-West standard errors can be applied to reduce the problem of autocorrelation.

Normality

When testing for the assumption of normality, we have plotted normal Q-Q plots and residual histograms. From the plots, we cannot conclude that the assumption for normality holds as the histograms are not evenly distributed around a mean of zero. We can also observe some outliers from the normal Q-Q plots.

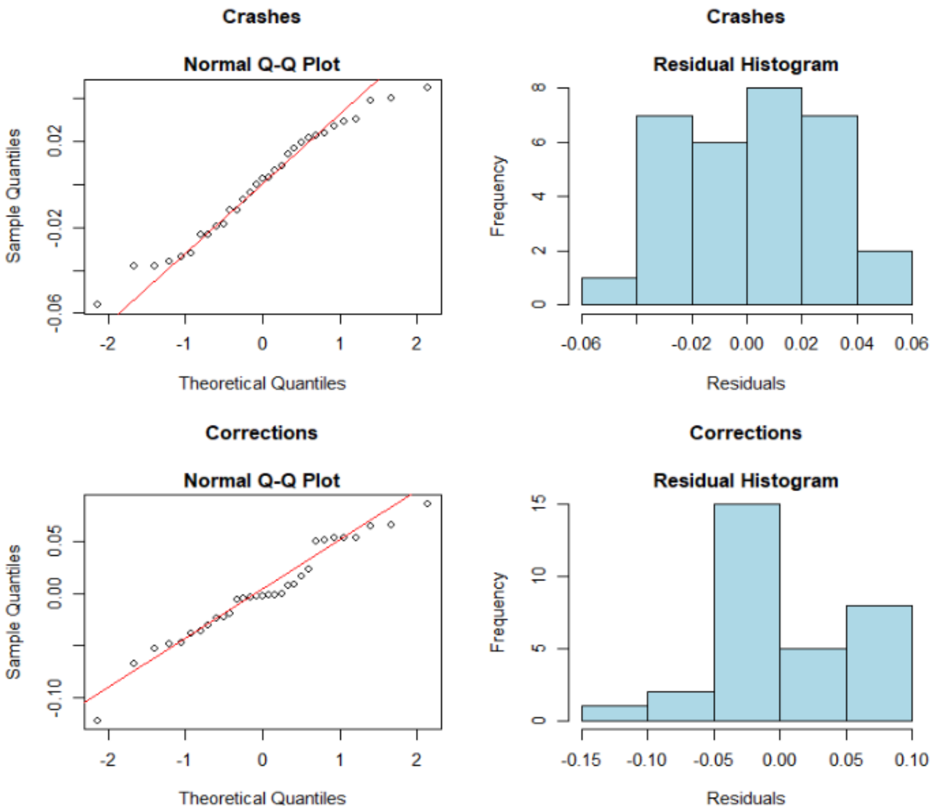

Figure A. 3: *Normal Q-Q Plots and Residual Histograms for Model 8.3*

From Table A.2, we can see the results of the Shapiro-Wilk tests. We observe that the p-value from the tests is well above the significance level of 0.05. As a result, we accept the null hypothesis of normality and can conclude that the data is normally distributed.

	CRASHES		CORRECTIONS	
	Kristiania Crash (1892-1907)	*Banking Crisis (1981-1995)*	*Long Depression (1871-1886)*	*Financial Crisis (1999-2013)*
Homoscedasticity				
Breuch-Pagan test	0,161		0,542	
Serial correlation				
Durbin Watson	1,296		1,037	
Normality				
Shapiro-Wilk	0,453		0,384	

Table A. 2: *Tests for Model 8.3*

Figures of Tests for Model 8.2.1 - 8.2.8

	CRASHES		CORRECTIONS	
	Kristiania Crash (1892-1907)	*Banking Crisis (1981-1995)*	*Long Depression (1871-1886)*	*Financial Crisis (1999-2013)*
Homoscedasticity				
Breuch-Pagan test	0,324		0,473	
Serial correlation				
Durbin Watson	0,814		0,714	
Normality				
Shapiro-Wilk	0,397		0,251	

Table A. 3: *Tests for Model 8.2.1*

	CRASHES		CORRECTIONS	
	Kristiania Crash (1892-1907)	*Banking Crisis (1981-1995)*	*Long Depression (1871-1886)*	*Financial Crisis (1999-2013)*
Homoscedasticity				
Breuch-Pagan test	0,823		0,959	
Serial correlation				
Durbin Watson	0,392		0,972	
Normality				
Shapiro-Wilk	0,139		0,510	

Table A. 4: *Tests for Model 8.2.2*

	CRASH *(1978-2000)*	CORRECTION *(1996-2018)*
Homoscedasticity		
Breuch-Pagan test	0,065	0,189
Serial correlation		
Durbin Watson	0,301	0,861
Normality		
Shapiro-Wilk	0,046	0,697

Table A. 5: *Tests for Model 8.2.3*

	CRASH *(1978-2000)*	CORRECTION *(1996-2018)*
Homoscedasticity		
Breuch-Pagan test	0,013	0,113
Serial correlation		
Durbin Watson	0,510	0,913
Normality		
Shapiro-Wilk	0,726	0,316

Table A. 6: *Tests for Model 8.2.4*

	CRASHES		CORRECTIONS	
	Kristiania Crash (1892-1907)	*Banking Crisis (1981-1995)*	*Long Depression (1871-1886)*	*Financial Crisis (1999-2013)*
Homoscedasticity				
Breuch-Pagan test	0,220		0,951	
Serial correlation				
Durbin Watson	0,514		0,799	
Normality				
Shapiro-Wilk	0,294		0,149	

Table A. 7: *Tests for Model 8.2.5*

	CRASHES		CORRECTIONS	
	Kristiania Crash (1892-1907)	*Banking Crisis (1981-1995)*	*Long Depression (1871-1886)*	*Financial Crisis (1999-2013)*
Homoscedasticity				
Breuch-Pagan test	0,669		0,486	
Serial correlation				
Durbin Watson	0,382		0,703	
Normality				
Shapiro-Wilk	0,080		0,078	

Table A. 8: *Tests for Model 8.2.6*

	CRASHES		CORRECTIONS	
	Kristiania Crash (1892-1907)	*Banking Crisis (1981-1995)*	*Long Depression (1871-1886)*	*Financial Crisis (1999-2013)*
Homoscedasticity				
Breuch-Pagan test	0,346		0,324	
Serial correlation				
Durbin Watson	0,374		0,814	
Normality				
Shapiro-Wilk	0,458		0,397	

Table A. 9: *Tests for Model 8.2.7*

	CRASHES		CORRECTIONS	
	Kristiania Crash (1892-1907)	*Banking Crisis (1981-1995)*	*Long Depression (1871-1886)*	*Financial Crisis (1999-2013)*
Homoscedasticity				
Breuch-Pagan test	0,383		0,064	
Serial correlation				
Durbin Watson	0,291		0,496	
Normality				
Shapiro-Wilk	0,094		<0,001	

Table A. 10: *Tests for Model 8.2.8*

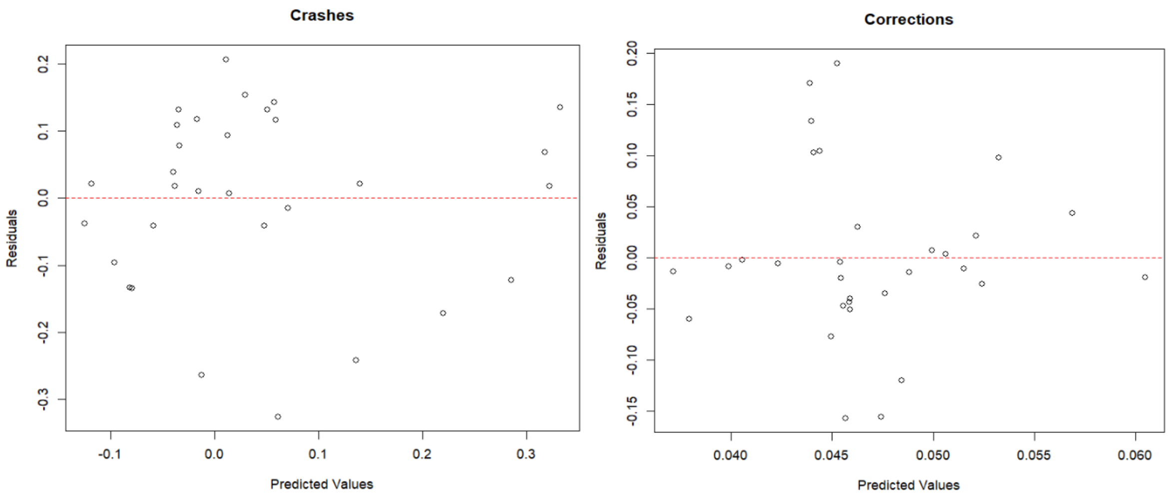

Figure A. 4: *Residuals vs Predicted values for Model 8.2.1 (Equation 43 for details)*

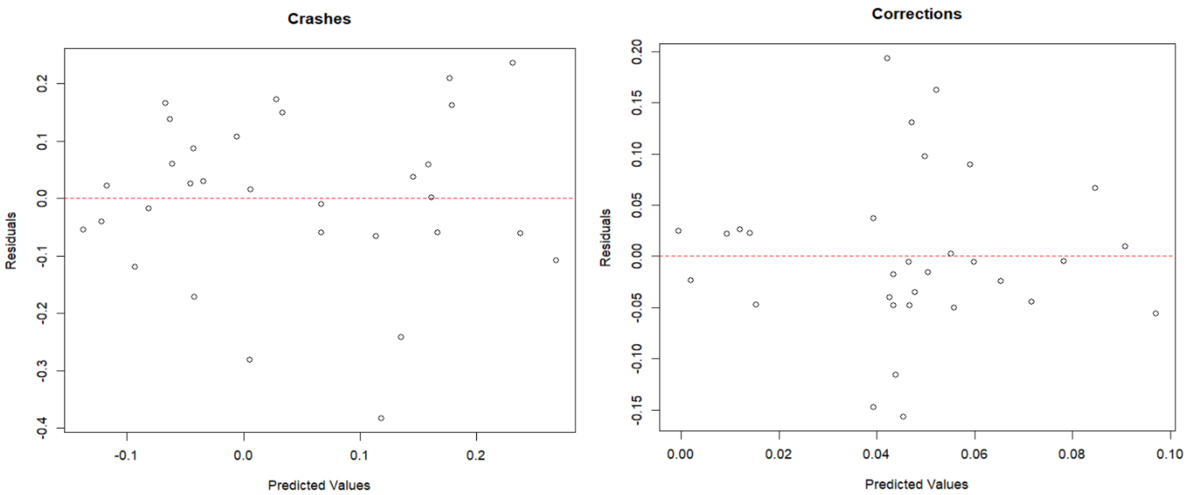

Figure A. 5: *Residuals vs Predicted values for Model 8.2.2 (Equation 44 for details)*

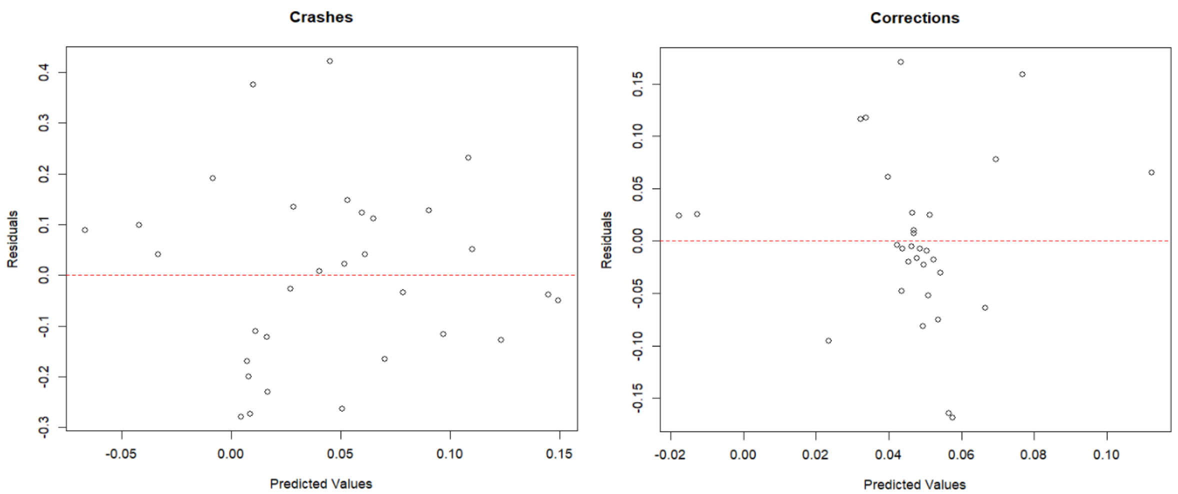

Figure A. 6: *Residuals vs Predicted values for Model 8.2.3 (Equation 45 for details)*

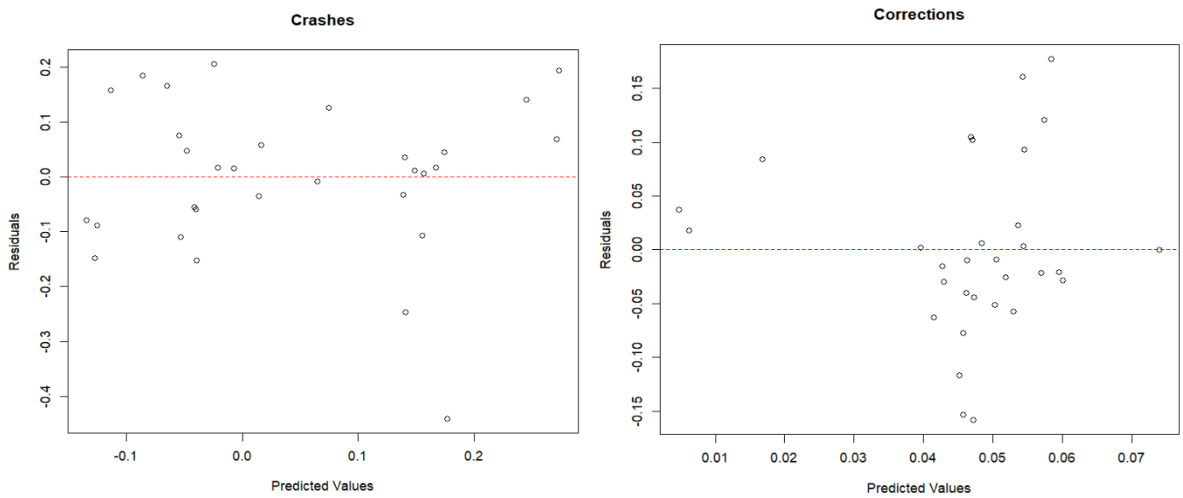

Figure A. 7: *Residuals vs Predicted values for Model 8.2.4 (Equation 46 for details)*

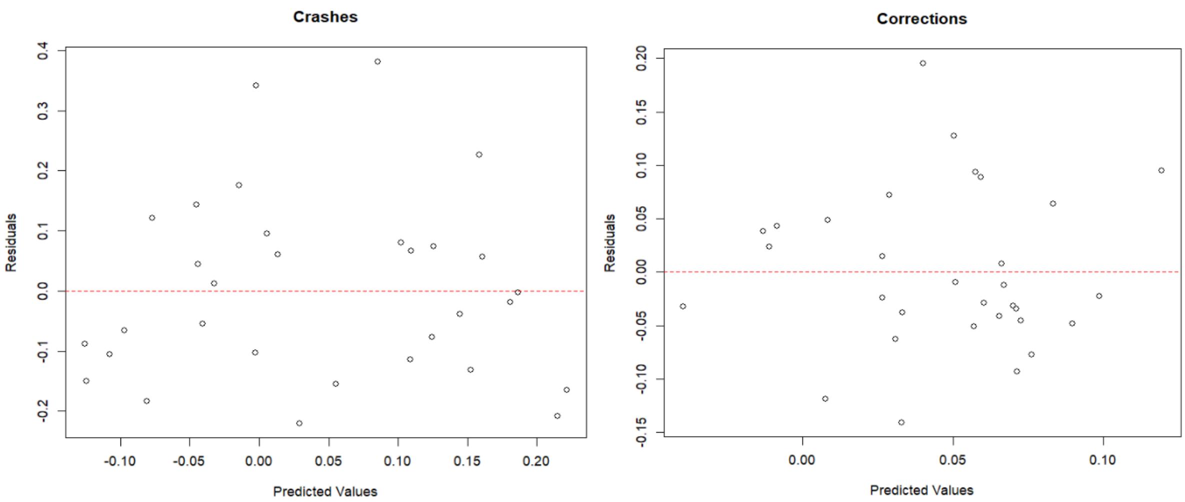

Figure A. 8: *Residuals vs Predicted values for Model 8.2.5 (Equation 47 for details)*

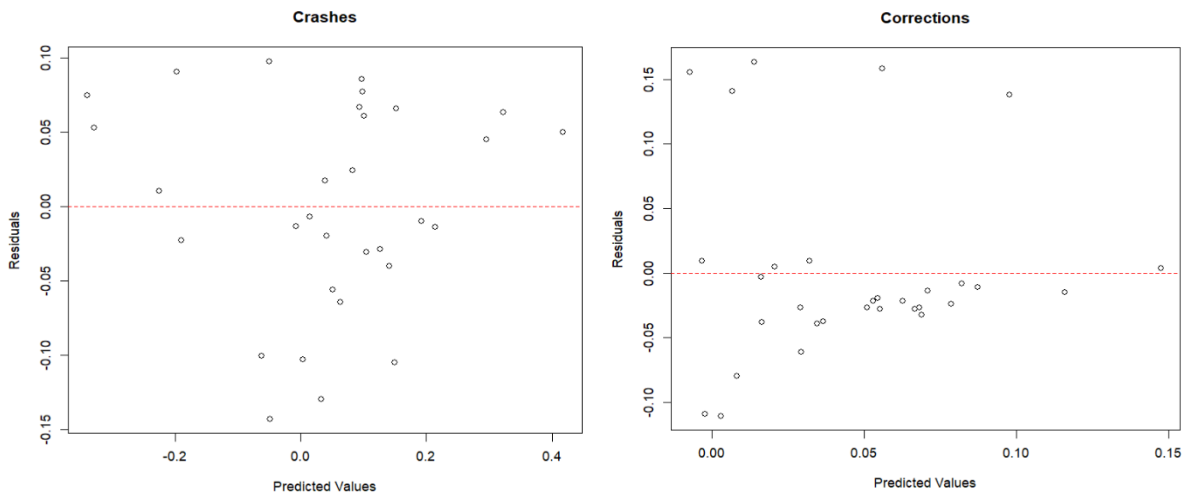

Figure A. 9: *Residuals vs Predicted values for Model 8.2.6 (Equation 48 for details)*

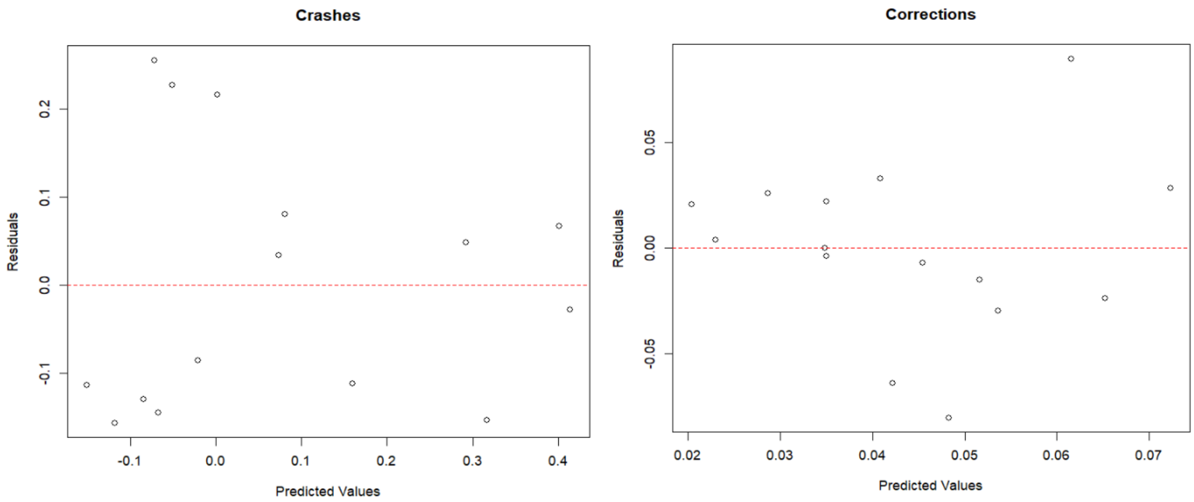

Figure A. 10: *Residuals vs Predicted values for Model 8.2.7 (Equation 49 for details)*

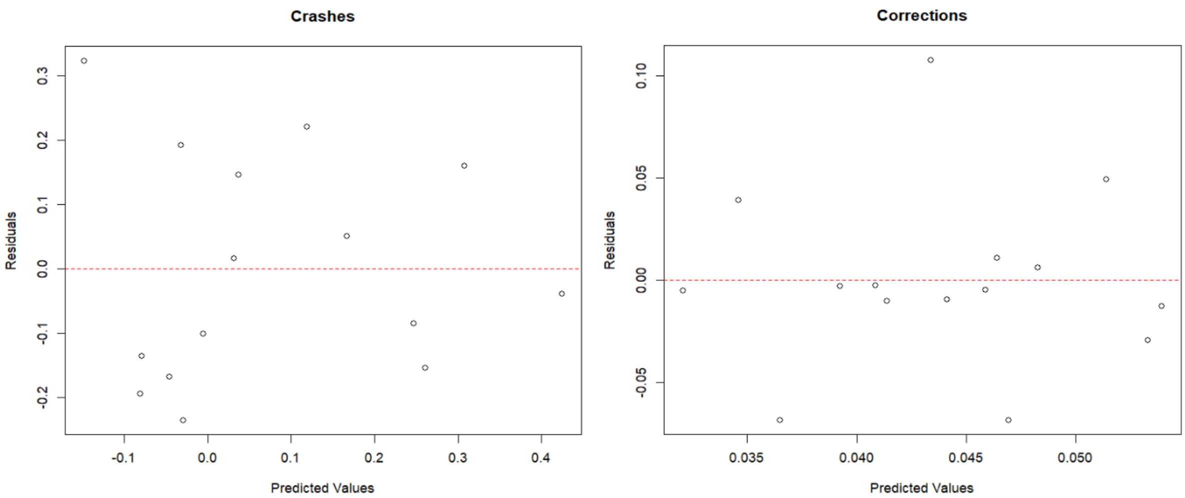

Figure A. 11: *Residuals vs Predicted values for Model 8.2.8 (Equation 50 for details)*

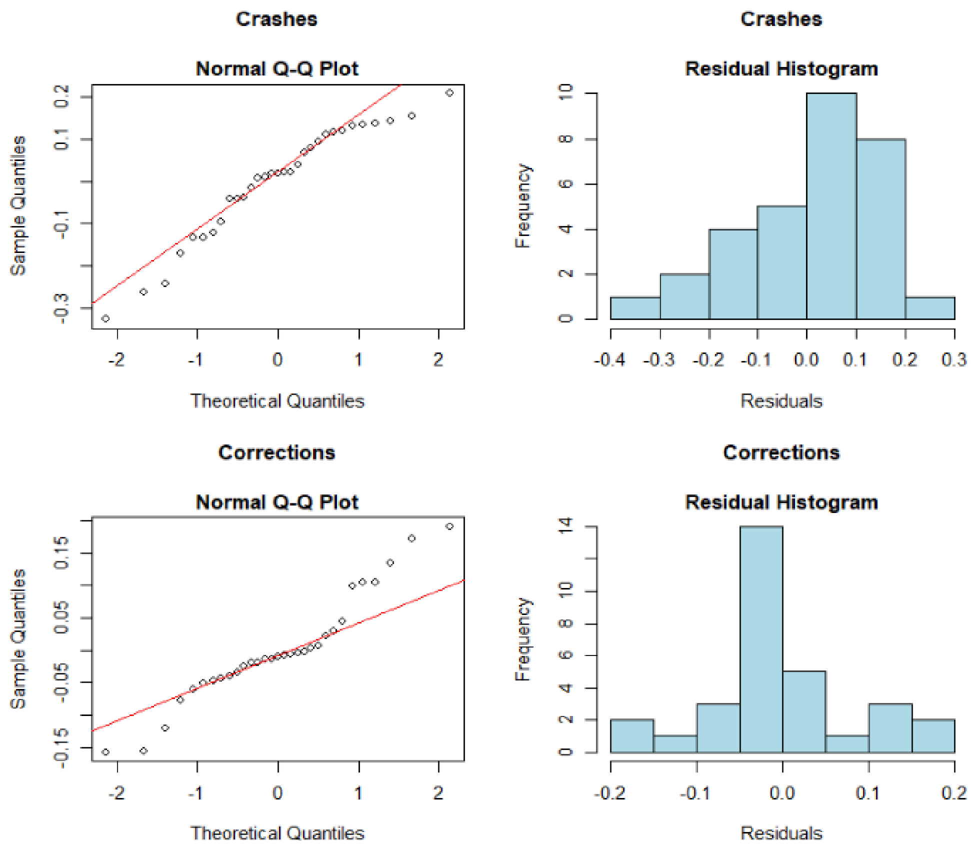

Figure A. 12: *Normal Q-Q Plots and Residual Histograms for Model 8.2.1*

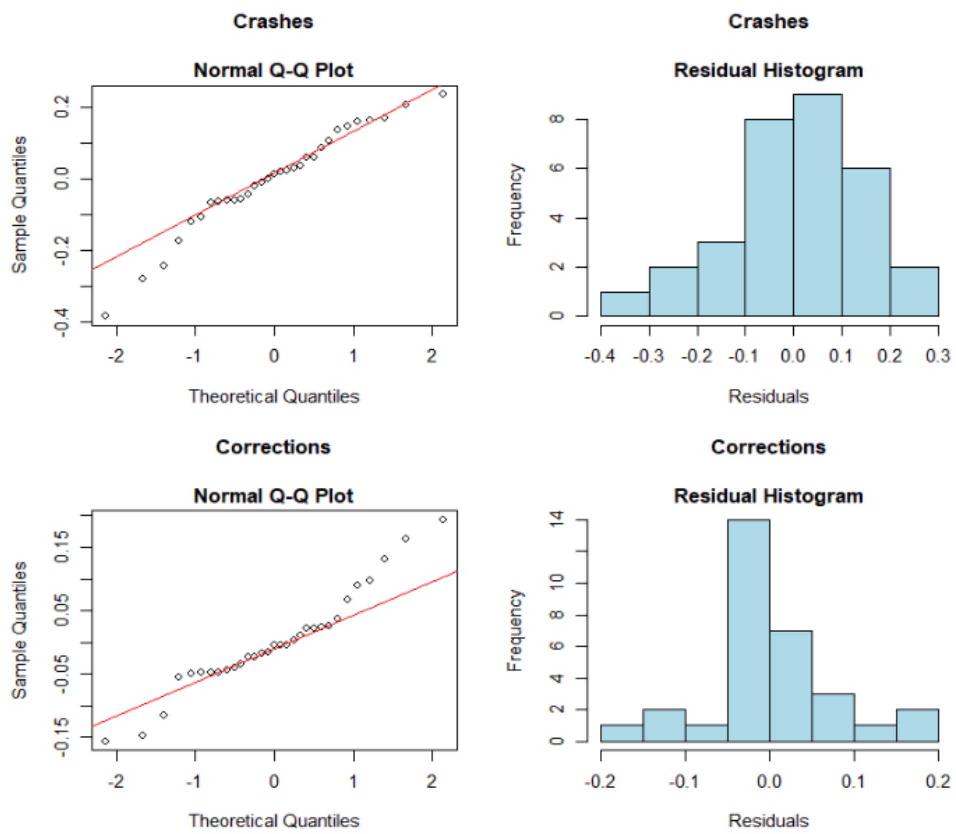

Figure A. 13: *Normal Q-Q Plots and Residual Histograms for Model 8.2.3*

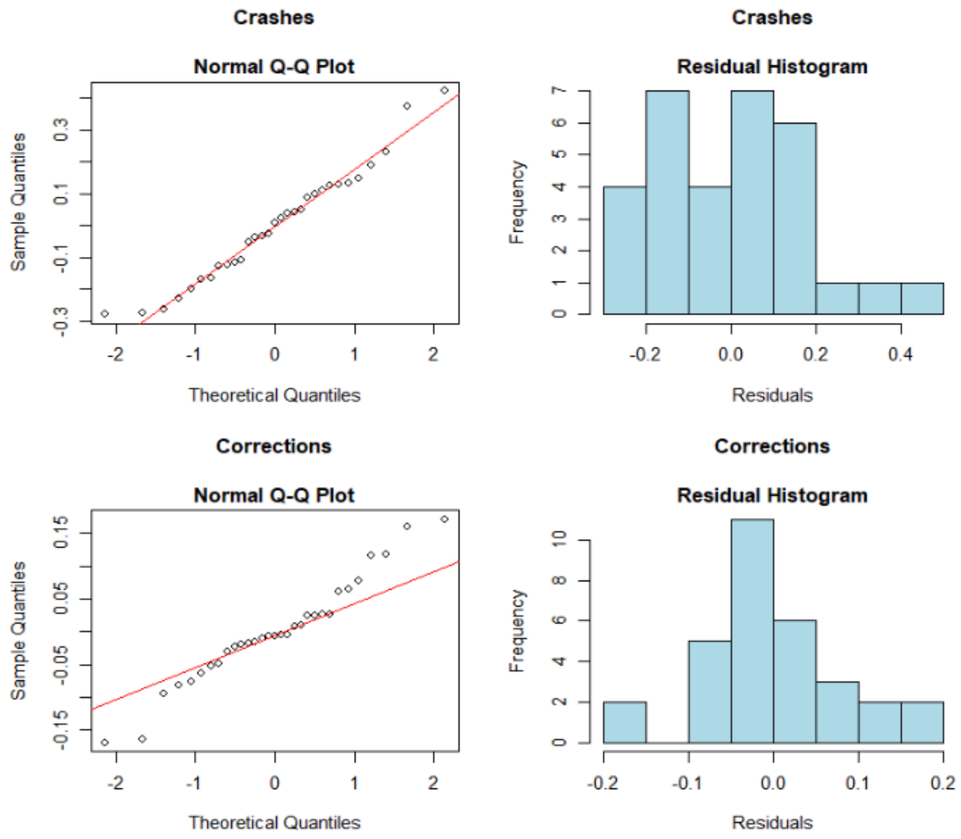

Figure A. 14: *Normal Q-Q Plots and Residual Histograms for Model 8.2.2*

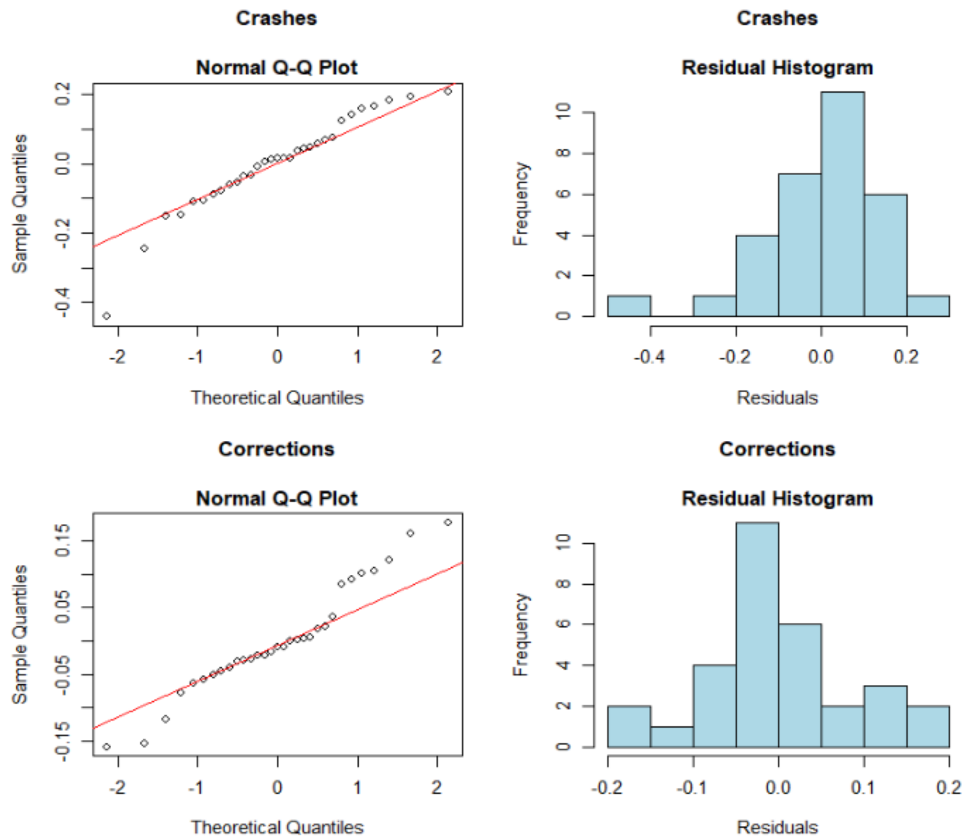

Figure A. 15: *Normal Q-Q Plots and Residual Histograms for Model 8.2.4*

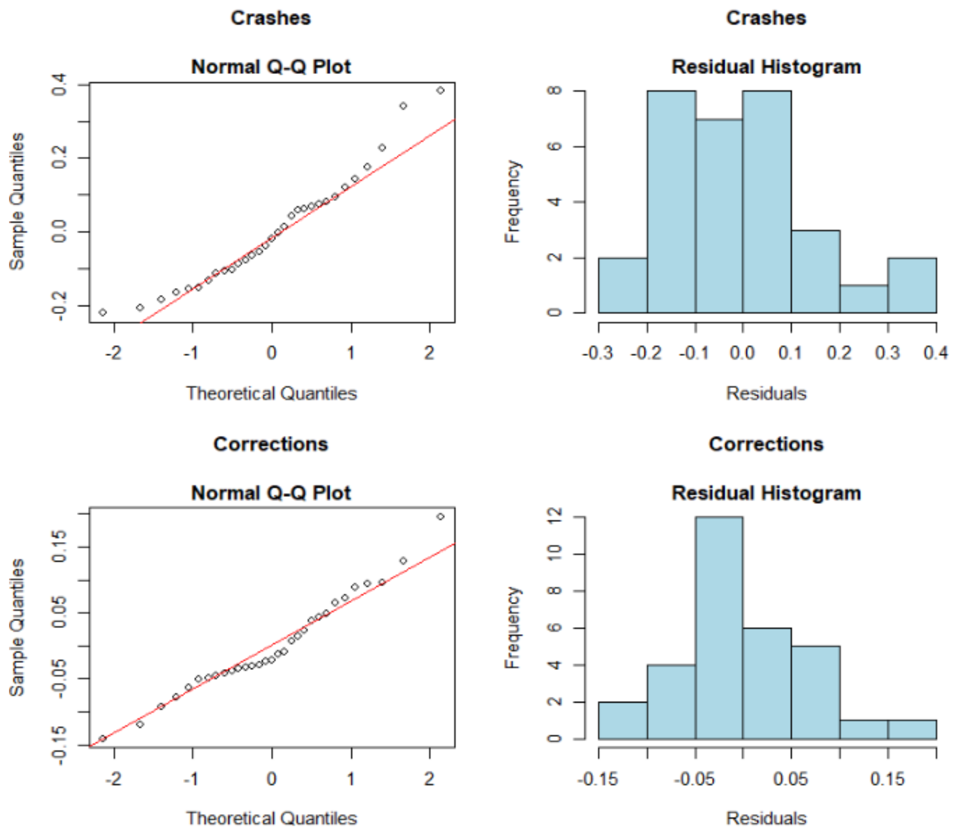

Figure A. 16: *Normal Q-Q Plots and Residual Histograms for Model 8.2.5*

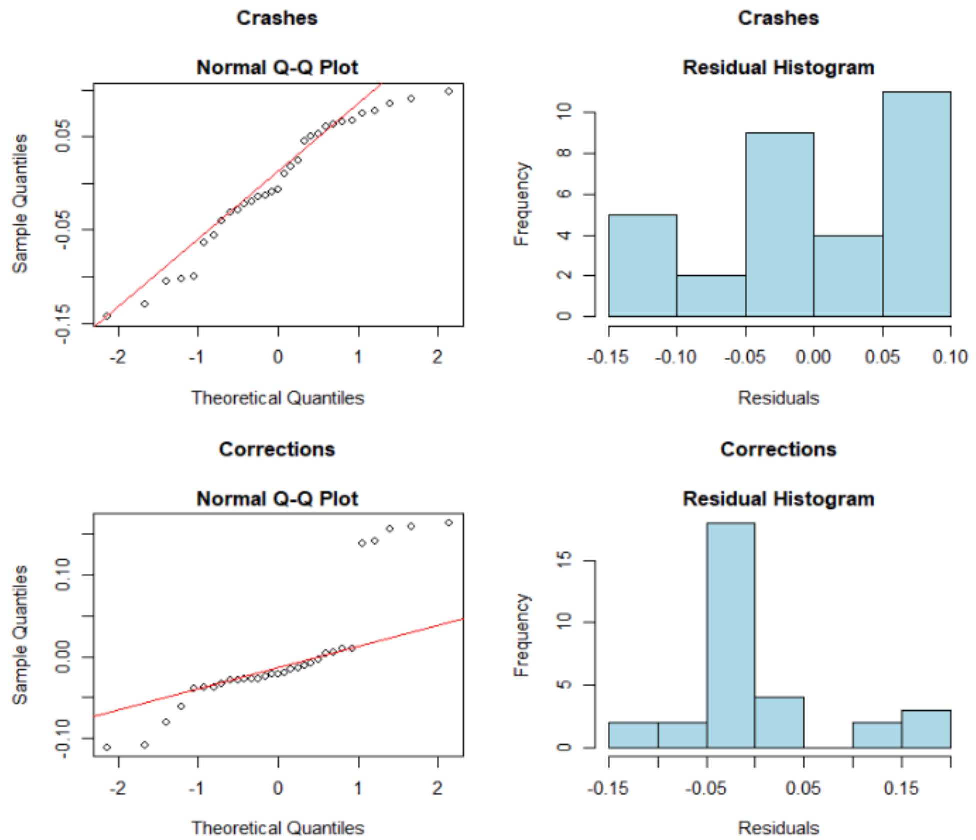

Figure A. 17: *Normal Q-Q Plots and Residual Histograms for Model 8.2.6*

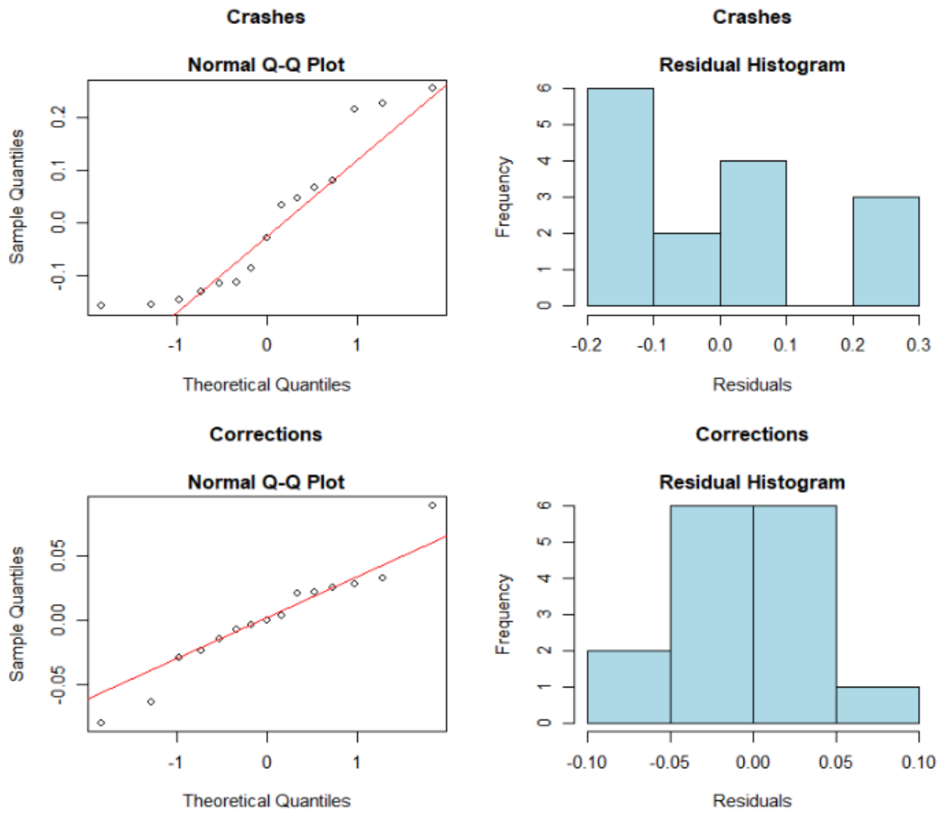

Figure A. 18: *Normal Q-Q Plots and Residual Histograms for Model 8.2.7*

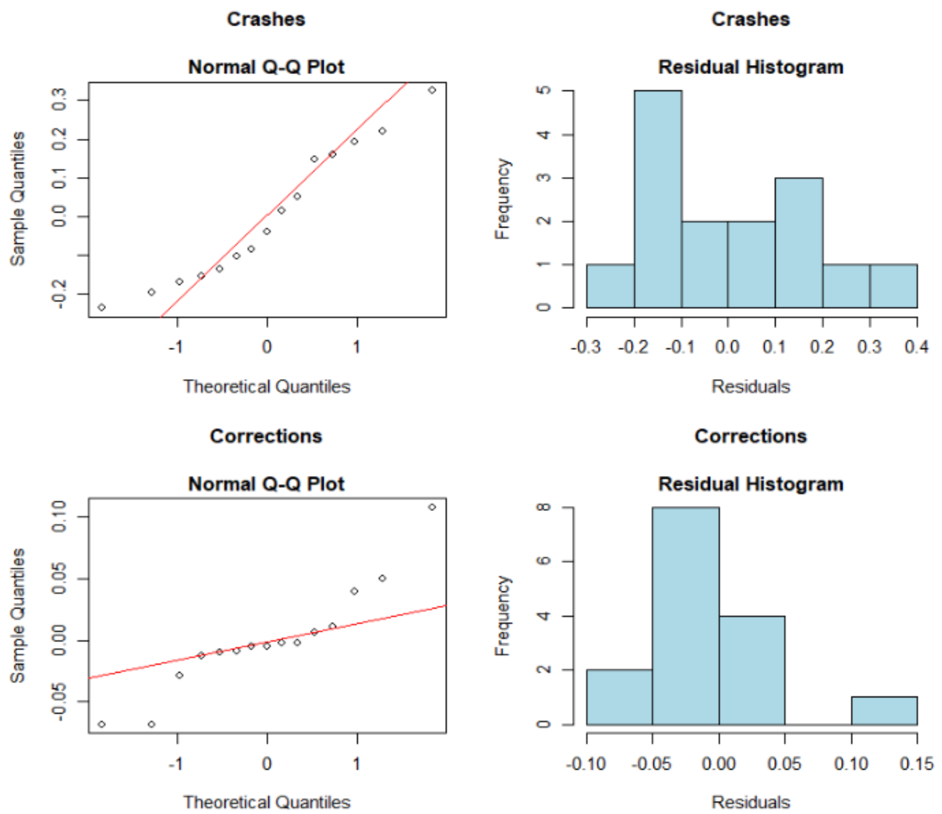

Figure A. 19: *Normal Q-Q Plots and Residual Histograms for Model 8.2.8*

Variables	Lags	Trend	Constant	p-value	Results
Nominal House Price	2	Yes	Yes	>0,99	Keep H0
Real House Price	1	Yes	Yes	>0,99	Keep H0
Credit Volume	0	Yes	Yes	>0,99	Keep H0
Money Supply	0	Yes	Yes	>0,99	Keep H0
Nominal Income	3	Yes	Yes	>0,99	Keep H0
GDP	1	Yes	Yes	>0,99	Keep H0
House Stock	3	Yes	Yes	>0,99	Keep H0
Unemployment Rate	0	Yes	Yes	0,29	Keep H0
Nominal Interest Rate	0	Yes	Yes	0,90	Keep H0
P/R	2	Yes	Yes	>0,99	Keep H0

Table A. 11: *ADF-test without transformations*

Variables	Lags	Trend	Constant	p-value	Results
Nominal House price	3	No	No	<0,01	Reject H0
Real House price	3	No	No	<0,01	Reject H0
Credit volume	3	No	No	<0,01	Reject H0
Money supply	3	No	No	<0,01	Reject H0
Nominal Income	3	No	Yes	<0,01	Reject H0
GDP	3	No	No	<0,01	Reject H0
House stock	3	No	Yes	<0,05	Reject H0
Unemployment rate	1	No	No	<0,01	Reject H0
Nominal Interest rate	1	No	No	<0,01	Reject H0
P/R	2	No	No	<0,01	Reject H0

Table A. 12: *ADF-test with transformations*