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Investment Risk Modeling and Forecasting of the Property Cycle

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by

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Investment Risk Modeling and Forecasting of the Property Cycle

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ABSTRACT

In the last ten years the available information and used technology has massively increased in financial markets. [16] Besides, stocks this trend has also infected the real estate market. In light of the financial meltdown of 2007, cyclical research has become an important topic again, even though bubbles are somehow seen as normality of the system. [1] Hence, national banks have taken the monitoring of financial markets much more seriously and expanded their repertoire of statistical variables. [2]

Using the assumptions of cyclicality is often done passively by bankers and property developers in their investment decision, even though historical numbers hint these relationships. The reason for this is that more experienced market participant already have seen the *patterns* and recognize them compared to novices. However, besides having expectations on the future market behavior no further research is often done. However, as other studies show [101] investing or lending within the right timing can be an important determinant of success.

This thesis, is split into two large parts. On the one hand, we will show chronologically the cyclical research, which has been done in the past and pointing out the methodology of each paper. Further, we will also investigate current trends in the property market and show the rise of technology. On the other hand, we will present a comprehensive methodology, which uses several time-series models to forecast the property cycle. Our research will focus on Austria. All inputs, will be selected by an extensive variable selection process, which will be outlined. As a second part we will view these forecasts as cyclical sensitivities and simulate each model result, on a synthetic real estate portfolio to show the effects of the cycle. The forecasts will be evaluated by their accuracy to assess the *usefulness* of our prediction models. Several accuracy measures have been picked to support a comparable view among all time-series models.

Our results, suggest that forecasting the property cycle helps to identify valuable lending and investment opportunities for bankers and property developers. Our final results suggest that the most accurate model results for our time series model are yielded by the ARIMA and exponential smoothing methods. This goes inline with the final simulation results of DSCR and LTV, which are the most reasonable for these two models. Still the other methods are accurate in terms of their measurements. However, the vector auto-regression method and simple regression does not yield proper results in the simulation engine. The reason for this are the model's reactions to sensitivity.

[1] See the recent Chinese stock bubble, Bloomberg 9th July 2015 - `http://www.bloomberg.com/news/articles/2015-07-09/who-blew-up-china-s-stock-bubble-`.

[2] For further information see the press announcement on December 22th, 2014 by the Austrian National Bank - `https://www.oenb.at/en/Monetary-Policy/real-estate-market-analysis/pressreleases.html`.

Kurzfassung

In den letzten zehn Jahren kam es zu einem regelrechten Wettruesten an Technologie und verfuegbarer Information an den Finanzmaerkten. [16] Neben den Aktienmaerkten ist auch der Immobilienmarkt von diesem Fortschritt betroffen.

Vor dem Hintergrund der Finanzkrise im Jahre 2007 ist die zyklische Forschung ein wichtiges Thema geworden, obwohl Blasen von vielen Investoren als *Normalitaet im System* gesehen werden [3] Aus diesem Grund haben Nationalbanken die UEberwachung der Finanz und vor allem Immobilienmaerkte in eigene Hand genommen und ihr Repertoire an statistischen Variablen erweitert, welche in regelmaeßsigen Abstaenden ueberwacht und interpretiert werden. [4]

Banken und Bautraeger treffen oftmals unter den Annahmen des Marktzyklus ihre Anlage- und Projektentscheidungen. Historische Zahlen ueber Mieten zeigen deutlichen den zyklischen Marktzusammenhang. Getrieben ist diese Vorgehensweise oft durch erfahrene Marktteilnehmer aus Banken und Immobilienbueros, welche *die Zeichen* des Marktes im Gegensatz zu Branchen Novizen deuten koennen. Jedoch werden diese Annahmen oft in keinen weiteren Analysen miteinbezogen und abgebildet. Andere Studien zeigen, dass das Timing der Investitions- oder Kreditvergabe Entscheidung ein wichtiger Erfolgsfaktor sein kann. [101]

Diese These, ist in zwei große Teile aufgeteilt. Auf der einen Seite werden wir chronologisch die Entwicklung des Wirtschaftszyklus aufzeigen und auf die dahinterliegende Methodik einzelner wichtiger Papier eingehen. Ferner werden wir auch aktuelle Trends auf dem Immobilienmarkt untersuchen und zeigen die Wichtigkeit des technologischen Fortschritt im Zusammenhang mit statistischen Vorhersagemethoden. Auf der anderen Seite, werden wir eine umfassende Methodik, welche ein tiefergehendes Variablenauswahlverfahren und schließlich mehrere Zeitreihenmodelle umfasst, vorstellen. Unsere Forschung wird sich auf den oesterreichischen Immobilienmarkt konzentrieren. In einem zweiten Teil werden wir diese Prognosen als zyklische Sensitivitaeten sehen und die Ergebnisse durch eine Simulationsengine auf ein synthetisches Immobilienportfolio projizieren, welches die Auswirkungen des Zyklus zeigt.

Unsere Researchprognosen werden einerseits durch ihre Genauigkeit, jedoch letztendlich durch ihre *Vorhesagekraft* ausgewertet. Aus diesem Grund wurden eine Reihe von statistischen Genauigkeitskennzahlen ausgewaehlt, um eine vergleichbare Ansicht unter allen Zeitreihenmod-

[3] Siehe die juengsten chinesische Aktienblase, Bloomberg 9. Juli 2015 - `http :. //www.bloomberg.com/news/articles/2015-07-09/who-blew-up-china-s-stock-bubble-`.

[4] Weitere Informationen entnehmen Sie der Pressemitteilung der Oesterreichischen Nationalbank am 22. Dezember 2014 - `https://www.oenb.at/en/Monetary-Policy/real -estate-Markt-Analyse / pressreleases.html`.

elle zu gewaehrleisten.

Unsere Ergebnisse legen nahe, dass statistische Prognose des Immobilienzyklus, ein wertvolles Tool fuer Kredit- und Investitionsmoeglichkeiten einerseits fuer Banken und Bautraeger darstellt. Unsere endgueltigen Ergebnisse legen nahe, dass die genauesten Modellergebnisse fuer unsere Zeitreihenmodell ist ARIMA und Exponential Smoothing. Verglichen mit den Resultaten der DSCR und LTV in der Simulations Engine, liefern Beide Modelle die Besten Resultate. Jedoch gilt dies nicht fuer alle Modell Outputs, wie Simple Regression und Vector Auto-Regression. Der Grund dafuer liegt darin, dass die Model-Sensitivitaeten sehr stark beeinflusst werden.

Dedication and acknowledgements

This PhD thesis was started in March 2015 after proposing my thesis to my supervisor at the Institute of Statistics and Mathematical Methods in Economics at the Vienna University of Technology. I am grateful to the department for providing excellent research opportunities and an inspiring environment. There are a number of people I wish to thank. First and foremost, I thank my supervisor Dr. Hardy Hanappi for encouraging and supporting me during my time as a PhD student. He always gave me very constructive and helpful comments during our regular meetings. I really feel truly privileged to have worked and learned from such an inspiring professor.

I dedicate this thesis to my beautiful wife Teresa. Thanks for supporting me through the ups- and downs of the researching and writing process. I love you!

Furthermore, I want to thank my dear friend Dipl. Ing. Alexander Kiennast, who helped me to finalize and correct my thesis. In addition to that, I would like to thank my family specifically Prof. Mag. Magdalena Kadnar for having a watchful eye on potential mathematical and syntactical errors.

During my research period I have read and studied lots of inspiring ideas, however one idea that followed me through the whole writing process is summarized in the quote below:

"Truth, more precisely, an accurate understanding of reality, is the essential foundation for producing good outcomes." Principles by Ray Dalio [45]

Author's declaration

I declare that the work in this dissertation was carried out in accordance with the requirements of the University's Regulations and Code of Practice for Research Degree Programmes and that it has not been submitted for any other academic award. Except where indicated by specific reference in the text, the work is the candidate's own work. Work done in collaboration with, or with the assistance of, others, is indicated as such. Any views expressed in the dissertation are those of the author.

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Table of Contents

List of Tables

Table **Page**

List of Figures

Figure **Page**

Chapter 1

Introduction

Property Cycles have been recorded throughout the history. [12] Serious discussions of the subject have started to emerge during the early twentieth century [104] and are still subject of academic research today. [12] [101] [93] Economic cycles, such as the property cycle, are long-term recurring waves, which tend to follow the mean reversion principal.[63] Asset prices move up and down around a dynamic equilibrium during economic growth and stagnation, measured by fluctuation. Through the history economist have observed these cycles through different industries, such as real estate. Recent events, such as the 2008 subprime mortgage crises shed new light on the importance to measure property cycles. The following sections will introduce the **Background of the research 1.1**, **Research Problems 1.2**, **Aims and research objectives 1.3**, **Methodological considerations 1.4** and a brief **Outline 1.5** of this thesis.

1.1 Background for the Research

Recent events such as the financial crisis of 2008 [1] and the European Debt Crisis [2] shed new light on the theory of deterministic cycles in economics, which was introduced by Kalecki (1935) [109], Kaldor (1940) [108], Hicks (1950) [82] and Goodwin (1951) [68]. Business cycles happen in regular intervals, often influenced by the factor that creditors lend too much money to debtors and the fragile economic system overbalances, so that the economical outcome is inflation and outright default of many debtors. These mass defaults cause a chain reaction, which, when looking at

[1] See "Five Years After Crisis, No Normal Recovery" - http://www.bloomberg.com/news/articles/2012-04-02/five-years-after-crisis-no-normal-recovery and "Why not to expect recovery anytime soon" - http://www.economist.com/blogs/freeexchange/2012/09/financial-crisis

[2] See Debt, morality and the cycle - http://www.economist.com/blogs/buttonwood/2015/02/euro-crisis.

the whole economic picture, forms parts of the re-occurring property cycle. In his famous, but oversimplified video and essays [44], Ray Dalio[3] tries to explain the cyclical dependence of our economy. Recent events such as the housing bubble of 2008 show the importance of the property market. In fear of another burst of a housing bubble, which might accelerate the business depth cycle and form an economic recession, countries are trying to monitor and measure the much shorter property cycle, compared to longer economic waves, such as the business cycle. [4]

The real estate sector is of great importance to an economy. In 2011 a count has been done by Statistik Austria, where more than 2,191,280 buildings and 4,441,408 flats were recognized in Austria.[5] A little less than four-fifths of all buildings in Austria are one- and two-family houses, every ninth is a residential building with three or more dwellings and 9.9% fall into the category of other building, such as building for communities and non-residential. Compared to these numbers, only 45.3% of all homes are one- and two-family dwellings, 21.6% of homes in smaller and multi-story buildings with three to ten apartments and 29.9% in those from eleven apartments. 2.9% of homes are located in buildings which are mainly for other purposes.

From the counting statistic it can be seen that housing is fundamental for many people in Austria, either as a necessary object for living or as an investment good and object of wealth. Furthermore, it is one of the most important forms of collateral in borrowing a loan. Hence, changes in real estate and property prices can have large effects on the debt situation and credit-bearing capacity of households and thus on the banking sector. On the other hand, the construction industry is a very important employer for many people. From this arguments the analysis and the monitoring of the property cycle is a very valuable topic from an economic social perspective. Recently researchers, such as Hui and Want[93] or Bracke[26] tried to model the property cycle for certain cities. This thesis will on one hand create a property cycle forecasting model for the Austrian property market and will push one step further and use the insights, which are gained from the theoretical state of the art model and make them usable for real estate stakeholders.

[3] See How The Economic Machine Works by Ray Dalio - `https://www.youtube.com/watch?v=PHe0bXAIuk0`

[4] See the Deutsche Bank Report [83], which shows the importance of the property market segments for our economy.

[5] See Statistik Austria - `http://www.statistik.at/web_de/statistiken/wohnen_und_gebaeude/bestand_an_gebaeuden_und_wohnungen/index.html`

1.2 Research Problems

My research problem is split up into two different parts. The first part is **Modeling and Forecasting** and the second part is **Simulation and Risk Measurement**. Each of the two parts, with its research questions will be described below:

1.2.1 Modeling and Forecasting

The first challenge is the creation of a robust model for the Austrian property market. The goal is to create a predictive model based on statistical modeling techniques, to forecast the property cycle. The sub-problems can be formulated as following:

- Which state of the art methods can be used to model and forecast the property cycle and accordingly derive a theoretical model of such a market?
- Which state of the art methods can be used to validate the model‘s accuracy?

1.2.2 Simulation and Risk Measurement

The second challenge is to provide a simulation and risk measurement application. During this thesis the common statistical framework R[6] will be used. As there are different stakeholders in the market, such as REITs, banks, developers or construction companies, which have different interests in the property cycle, we will only focus for the case of simplicity on banks and their counterparts, property developers. However, the presented approach could also be easily adapted by other stakeholders. The subproblem can more precisely formulated as the following question:

- How to create a simulation and risk measurement application, which uses the output from the property cycle model and translates it into specific risk parameters of a banks property project portfolio?

As shown in the upcoming literature section 2, several studies were conducted, with the goal of measuring and showing the impact of the property cycle in different markets. However, stakeholders in the real estate market want to know, at which point their portfolio is in the cycle and how their project portfolio might evolve during future cyclical behavior. A prototypical implementation will tackle this problem and show the consequences based on different scenarios, covering the best, medium and worst cases.

[6]For further information see `http://cran.r-project.org/`.

1.3 Aims and Research Objectives

This research project aims to forecast the real estate market of Austria. Further, we will make the risk in the market visible to market dependent parties, such as financial institutions by a portfolio simulation framework. The prototypical implementation will simulate the results of the predictive model on a synthetic real estate project portfolio. By combining these two project challenges, investors will be able to use the results in their actual real estate project portfolio. Hence, to complete this aim successfully, the following research objectives are set:

1. Examine the historical implications and effects of property cycles in Europe and the US. Draw relevant connections to cyclical research and other cycles, such as the business cycle and the credit cycle.

2. Conduct an in depth literature review of currently state-of-the-art modeling techniques of property cycles in academics. Based on this, we will independently interview and question property cycle experts on the thesis subjects. This will give us a holistic view on modeling techniques.

3. An assessment of the currently used scenario stress testing practices of property market participants on their portfolio. Based on this, we will create a wire-frame and through experts opinion and literature review, we will incrementally create the foundation of our later prototypical simulator implementation.

4. Collect data from different sources and assess it‘s practicability and it‘s properties as dependent or independent variable of the forecasting model.

5. Evaluate the created model and assess its accuracy whether the chosen methodology can correctly forecast Austria’s property cycle.

6. Draw conclusions from the simulation framework and run the property cycle forecasting model in the prototypical portfolio simulator implementation. Furthermore, our results will be aligned with the insights, which we gained on the one hand from the extensive literature analysis and on the other hand from expert opinions.

7. Identification of practical use-cases for businesses, financial institutions and local authorities for the property cycle model and the portfolio simulator.

1.4 Methodological Considerations

Before we start to develop a methodology, we focus on researching cyclical literature throughoutly. Even tough the property cycle is our main topic, we also try to focus on other cyclical swings and the forecasting practices behind them. This will be the foundation for our further research project.

The final project consists of two parts. In the first part we focus on the forecast of the Austrian rental index, which is provided on a quaterly basis by the Austrian National bank. Before we start the prediction process, we will extensively focus on the selection of variables. Hence, we will employ a wide range of methods to get a final robust data sample.

In the following step we will use several forecastin methods, such as variations of exponential smoothing, with simple, trend and seasonal smoothing, simple and multiple regression, vector auto-regression and ARIMA modeling. All methods will provide forecasting estimates, which will be used in the final part of our research project.

The last part of this multi-stranded approach is the cyclical simulation engine. The engine will be completely programmed in Microsoft Excel, as this tool is widely used by stakeholders in the real estate market. Further, we will simulate the effects of the property cycle and show the behavior of a synthetic asset portfolio through the next five years.

1.5 Outline

The following outline will show, which themes will accompany each chapter.

Chapter 2 will give an extensive literature review on either property cycles and property market modeling and forecasting techniques. We will start from the roots of property cycle research and show the long history of its development. We will show the components of a property cycle and give a theoretical background on the dependence of the property cycle on business and credit cycle. Next we will show the structure of a real estate market and its components. After showing the different phases of a property cycle, explaining why a cycle fluctuates, we will assess research on property market forecasting models. An in-depth literature review will show relevant forecasting models and the used factors within the model. As our further research will use a combination of such models, we will compare the most recently used and show their accuracy based on previously done scientific research. To validate our model extensive literature research will be done going through accuracy validation techniques. Finally, we will give a background on risk management and portfolio management in banks, which will be conducted both by interviewing experts and literature review, and explain the strategic importance of the property cycle on the view of a financial institution. As for the simulator we will point out a clear risk management tool specification.

Chapter 3 discusses our used scientific methodology to properly forecast and simulate property cycle risk. In the first step we will describe our chosen modeling approach theoretically. Further we will show the strengths of R[7] and a clear process for implementing our used model. In the next step we will describe each model from the chapter 2 theoretically and assess its strengths and weaknesses. In the next step, we will show our used modeling and forecasting approach. After explaining our model we will assess our simulation component. First we will start by showing risk management systems in the real estate industry and their use cases from stakeholders of the property market. Finally, we will show our simulation framework, which we have assessed through expert interviews from various real estate market participants. This subsection will show wire-frames and several scenario use cases.

Chapter 4 will take a deep look on the used data during this research project. In the first step we will assess the data quality and completeness of the used economic values, which we will later feed in our model. Eventually, we will show data cleansing techniques, which are used to create a homogeneous data set. Further, we will describe the independent variable and reason our final decision. Finally, we will describe the independent variables and their meaning related to our forecasting model of the Austrian real estate market.

[7] See `http://www.r-project.org/` for further information about the statistical programming language.

Chapter 5 will show our final forecasting and simulator results. We will present the final model and assess its accuracy through selected statistical validation techniques. Further we will show three different scenarios in our build simulation framework and show the effects of cyclical risk for each scenario.

Chapter 6 draws conclusions of the research body and presents a short outlook into future research. In this chapter, we will also show possible limitations and presents the implications of our gained results for property market participants in Austria. Finally, we will judge critical the use of the property forecasting model and the project portfolio simulator.

Chapter 2

Literature Review

This chapter will review the relevant literature, which is concerned with the roots of the property cycle and its dependencies, the real estate market and how it works, property cycle forecasting models and its indicators, methods and tools to measure risk in the property markets. Section 2.1 will give an introduction to cyclical research. We will review the different types of cycles cited in the literature, especially the business- and credit cycle, which influence the property cycle heavily. Furthermore, we will show a long research body of cyclical theory and explain the reasons and impact factors why cyclical fluctuations occur. Finally, we will cover the main economic theories, which explain the up- and down-movement in cycles. In section 2.2, we will show an abstract structure of the real estate market and explain the importance of property as an investment medium from a socioeconomic perspective. As our thesis especially focuses on financial institutions, we will examine the interaction between banks and property developers. In section 2.3 we start with defining the term property cycle. As there is a long body of literature concerned with the efficient market hypothesis[1] and the property cycle, we will give a brief introduction about the EMH and why the property cycle only party fulfills it. In the following we will show a brief history of selected historical papers within the area of property cycle research. Finally, we will show the investors perspective and *WHY* property cycle research is important either for public and private real estate participants. In the section 2.4, first we categorize predictive property models either by diving into the literature and also by proposing our own classification structure. In the following step we show the general problems of qualitative and quantitative forecasting, which are mainly the two most common ways of forecasting. Furthermore, we will give an extensive overview, summarized by a table about forecasting techniques, which are used in the literature. We also show in particular the input factors of forecasting models,

[1] EMH is the short form of efficient market hypothesis, which will be used in the thesis.

separating indicators into two different time-frames, long and short term. Finally, an overview of accuracy measures will be proposed, from which we will select the most important to validate the first part of our research challenge. In section 2.5 our focus will be on the component of risk in the real estate market. First, we have to define important analogues, which are used within the thesis. As the development of a portfolio strategy is important for banks, we outline a potential process and show opportunities for risk managers. In the next step, we show methods to estimate portfolio risk and actual risk measurements. In the last two sections, we examine the tooling side of risk management in real estate. As we create a simulator system, we show the advantages and review literature regarding the specification. Finally, we show ways to use property cycle research actively in a company, by pointing out strategic, behavioral and organizational considerations.

2.1 Cyclical Theory

The following section, we will give a general introduction about cyclical theory. At first we will show the anatomy of a cycle, which will also propose a general terminology for cyclical research, followed by an overview of different types of cycles. As pointed out, the business and the credit cycle influence the property cycle heavily. In the next section, we will give a historical overview of cyclical theory. As one of the most interesting aspects of cycles is its fluctuations, we will explain the most important theories, which approach this problem from several economic points of view.

2.1.1 Anatomy of a cycle

In coming up with new theories and ideas economists have often taken nature as an example and observed regular occurring patterns. The most obvious pattern in our nature are the seasons, which brought routine in our lives and helped us to adapt through the history.[91] For example, people seed their corn in spring and hope that some months later in summer, they can harvest their grown fruits. This forward looking thinking and the ability to forecast certain future conditions has helped our society in becoming fruitful and prosperous. In our economy, finding regularities or simply said patterns gives our society the ability to forecast and predict the economic market environment and therefore influences our economic future. A pattern can roughly be defined as a sequence of events that happen repeatedly. [86] As Hofstadter (1995) argued, finding a pattern in a noisy environment is close to the core, if not even the core, of intelligent observation and therefore often very hard to analyze and model.[86]

In economics, one of the most interesting class of patterns are cyclical waves. Cycles occur in our economy in various forms and lengths. Through history cycles, were a common pattern in our economy. For example, when looking in the bible one can find indications of cycles, which influenced ancient economy, *"And so the seven good years in Egypt came to an end. Then came the first of the seven years of need as Joseph had said ..." (Genesis 41:53,54.)*[22]

As we will continue to use the term cycle through this thesis, the following definition explains the used terminology:

Definition 2.1. *A cycle can be defined as, "... a series of events that are regularly repeated. In terms of a business or property cycle, the sinusoidal waves pass through a series of peaks and troughs, where the economic activity moves from boom phase to bust and back to boom repeatedly."* [2]

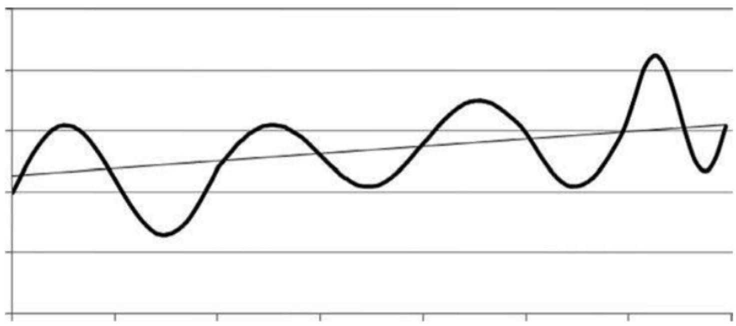


Figure 2.1: Economic trend-line with abstract cyclical fluctuations. [76]

Figure 2.1 shows an abstract visualization of the ups and downs of a cycle, which follows a clear uptrend as indicated by the drawn trend line. It can be seen, that the length and the duration when cyclical peaks or valleys occur can differ. This suggests that there are exogenous drivers responsible for the cyclical fluctuations. [76] Examples of such drivers are, production and innovation, which also occurs during the dales of the cycle and can drive the fluctuation upward. [76] [44] On the other hand, the peak of the cycle is entered, when the *"growth potential"* of the market, in which the pattern occurs, is fully reached.

The foundation of fluctuating patterns was laid out in mathematics, physics, engineering and signal processing, which observed these patterns either through theoretical studies or through real world experiments. [141] Figure 2.2 shows a typical sine wave, which gives a simple mathematical abstraction of a cycle. As shown, a cycle can have a specific phase length, which goes from one inflection point to the next. During a phase, there can be one peak or valley. The amplitude shows the heights or depth of the valley. A full cycle is characterized by the occurrence of one single peak and valley. Hence, it can be said, that two *different* phases form a

[2]See Grover (2013)[76]

[3]See Pyhrrn (1999) [141]

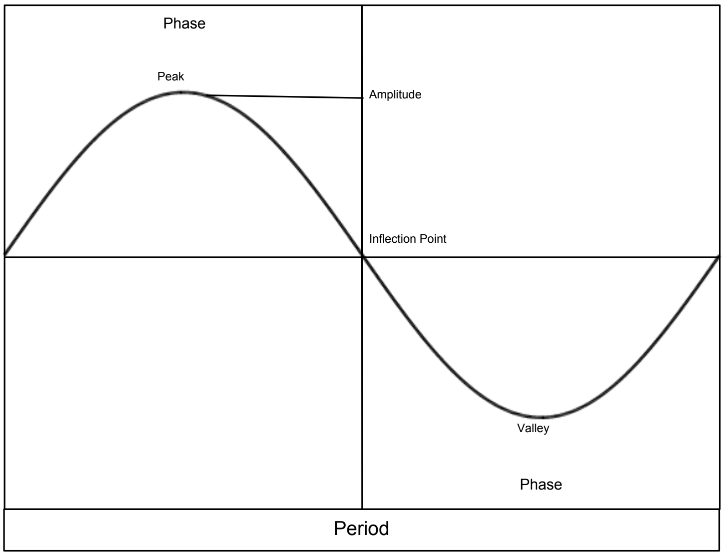


Figure 2.2: Sine Wave with description of characteristics.[3]

cyclical period. Born, Roulac and Pyhrrn (1999) [141] recommend to use this universal pattern definition specifically in property cycle research, because of its time-tested, widely adopted and clear character. Furthermore, a common terminology among researchers strengthens the general scientific understanding and output in this important research field.

Grover and Grover (2013) [76] point out that, if a cycle is not regular it is more appropriate to use the term *"wave"* instead of *"cycle"*. [76] However, through this thesis no differentiation will be made by the terms *"wave"* or *"cycle"*.

2.1.2 Types of Cycles

In 1890, French economist Clement Juglar laid the groundwork for the identification of economic cycles in his publications [4]. [22] He identified the Juglar cycle, which are, according to his definition around 7 to 11 years long, but do not have to occur in regular patterns. In the late 20th Schumpeter used Juglar's cyclical idea and grouped it into a four step stage process, which naturally occur in a cycle:[22]

1. **Expansion:** Typically, production and prices increase, as a result there are low interest rates in the economy.

2. **Crisis:** The highest point in a cycle. Stock exchanges crash and firms go bankrupt. Chaotic economic behavior happens during this phase. Often this point is also referred to as *"the burst of a bubble"*.

[4]One of Juglar's most famouse relevant publications is, "Des Crises commerciales et leur retour periodique en France, en Angleterre, et aux Etats-Unis" [107].

3. **Recession:** After prices fall and production decreases, interest rates rise and the economy is in a recession. This represents the valley of the cycle.

4. **Recovery:** Because of the fall in prices and income, demand start to rise and the economy recovers. Often this happens slowly put continuously.

Scientific Economic Waves	
Cycle	*Length*
Kitchin inventory	3 to 5
Juglar fixed investment	7 to 11
Property Cycles [154]	7.5
Kuznets infrastructural investment	15 to 25
Kondratiev wave	45 to 60

Table 2.1: Types of Economic Cycles.[5]

Table 2.1 shows an overview of economic waves, which are widely accepted within the scientific community. The longest detected cycle is the Kondratiev wave also known as supercycle, which is believed to have a periodic length of 45 to 60 years. [58] Driving factors of Kondratiev waves are investment and innovation. [104] Figure 2.3 shows the Kondratiev wave through time linked to the different historic ages. Another shorter cycle are Kuznet swings [117] observed by Simon Kuznet in 1930. Kuznet believes that the fluctuations occur because of population changes, such as migration. [168] In a study Scott and Judge (2000) [154] tried to measure the commercial property cycle in the UK and came to the conclusion of a cyclical length of 7.8 years. Hence, it can be considered that the cycle overlaps with the Kuznets infrastructural investment cycle. Much shorter cycles are the Juglar cycle and the Kitchin inventory cycle, which fluctuations are believed occur either from investment into fixed capital or information lags inside the economy. [107] [114]

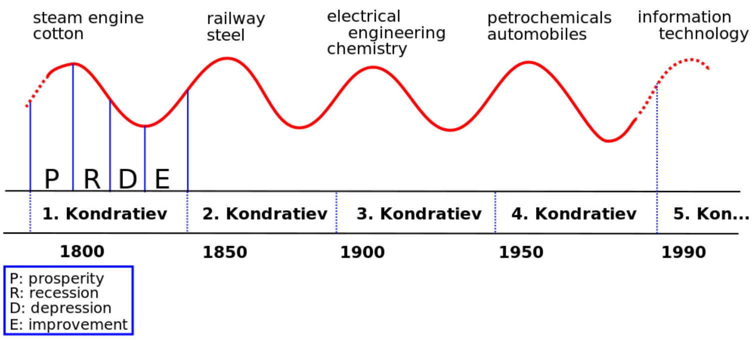


Figure 2.3: Kondratiev wave through time.[6]

[5]For a more comprehensive overview see Jadevicius, Sloan and Brown (2010) [104] p. 117.
[6]Picture was taken from `http://commons.wikimedia.org/wiki/File:Kondratieff_Wave.svg`

2.1.3 Business Cycle and Credit Cycle: Influencer's of the property cycle

Besides that this thesis is about the property cycle, we will pick out two extremely important cycles, the **business cycle** and the **credit cycle**, which influence the property cycle to a large extent. Furthermore, these two cycles have been investigated extensively and are an important part of cyclical theory.

Business Cycle

Under business cycle the definition from Burns and Mitchell, from their book *Measuring Business Cycles* [32] is widely understood:

Definition 2.2. *Business cycles are a type of fluctuation found in the aggregate economic activity of nations that organize their work mainly in business enterprises: a cycle consists of expansions occurring at about the same time in many economic activities, followed by similarly general recessions, contractions, and revivals which merge into the expansion phase of the next cycle; in duration, business cycles vary from more than one year to ten or twelve years; they are not divisible into shorter cycles of similar characteristics with amplitudes approximating their own. Burns and Mitchell (1946) [32]*

A business cycle can lasts from ten up to twelve years and cannot be cut into shorter cycles. [32] According to Diebold and Rudebusch (1996) [50], Burns and Mitchell‘s business cycle definition has two components, one is **a cycle has the same movement as other economic variables** and the other is that the cycle can be **divided into certain periods**. The first component is described as a centerpiece method by Burns and Mitchell [32]. As Diebold and Rudebusch (1996) [50] point out, Burns and Mitchell considered several hundreds of economic series. For each series, they calculated the monthly turning points, to examine the cumulative turning point of the business cycle. The second component, was also clearly shown in Burns and Mitchell [32] study. Typical for their research era, they thread the expansion phase separately from the contraction phase. [50] They also, categorized certain variables as leading and lagging. [50] Reed and Hao (2008) [144] point out that the business cycle can generally be found in economies with a free market and usually not in purely planned systems, such as communistic dominated economies.

The importance of the business cycle to the whole economic environment shows itself in parameters and indicators of an economy. The easy to grasp concept of a wave can be understood and indicates a clear representation of the abstract mechanisms, which happen in an economy. A comparison can be drawn to human emotions, sometimes we are quite happy and appreciate our situation, in other times we are depressed. Often these *states* come in continuous waves. Generally it can be said, that growth, development and innovation are extremely healthy factors of an economy, whereas decline and slowdown are considered as deterioration. However, one does not work without the other. Governments use cyclical analysis tools to plan their monetary and fiscal policies ahead, but also financial institutions use such tools to make scenario predictions and strategic valuable management decisions about investments.

Credit Cycle

The credit cycle is the second important wave, which we want to cover within this thesis. Generally, we can define it like the following:

Definition 2.3. The credit cycle describes the periodic expansion and contraction of **access to credit** over a time period.

As Keynes (1931) stated, *"...A sound banker, alas, is not one who foresees danger and avoids it, but one who, when he is ruined, is ruined in a conventional and orthodox way with his fellows, so that no one can really blame him."* [112] Therefore, this shows the importance of this cycle to the banking systems and financial institutions.

Lown and Morgan (2006) [121] stated that the credit cycle can influence the course of the business cycle. Borgy et al. (2009) argued that the recent financial crisis showed the effect that can be generated when the credit cycle becomes unstable, through endogenous credit booms. On the other hand, Schularick and Taylor (2009) [151] pointed out, that economic crises have a higher probability, when the funding investment booms. Haldane (2010) [2] shows in his study that the credit cycle might show well defined regularities and has also been largely influenced by the business cycle. Further drivers are *financial liberalization* and *competition*. [2] In his analysis he shows that the frequency of the credit cycle is five times higher than the frequency of the business cycle. [2] This explains the vast influence of the credit cycle on the business cycle.

Importance to the Property Cycle

The most obvious signs of cycles are exogenous shocks, which are reflected in the market. Grover and Grover (2013) [76] propose that such shocks might link the business cycle to the property cycle, because it affects the economy as a whole. Further, as housing is strongly linked to suppliers of capital goods, its demand is connected with investment factors. Hence a cyclical pattern in the property market, *"might suggest that the cyclical pattern was just a reflection of a wider business cycle."* [76]

During the real estate cycle, credit is often a driving factor, because it is very common in a lot of countries that property or land transactions are financed by debt. [48] Allen and Gale (2000) show in their study, that banks shift their lending behavior, because their business is indirectly influenced by the property cycle. The credit cycle influences banks directly, because they hand out loans to their clients, which eventually invest in the property market. Therefore, one might say that there is a large impact from the credit cycle to the property cycle, because banks do the lending business to large extent.

2.1.4 Cyclical Fluctuation

There are many explanations of the source of cyclical fluctuations. Most scientific theories approach this question axiomatic. [156] The following subsection, will give first an overview of empirical explanations and then show the most important theories, to explain waves in our economic system.

2.1.4.1 Empirical Explanation of Cyclical Fluctuation

There are different economic schools of thoughts. Every school, for example Keynesian, Austrian or Neo-Classic has their own concepts, why economic cycles fluctuates.[22]

Economic school	***Drivers***
Classical	Goverment interfers, market regulates itself
Keynesians	Spending is low
New classical	Exogenous shocks, large crisis
Austrian	Central banks intervent with monetary policies
Endogenous	Innovation and new technology
Others	Some examples are, political cycle, pork cycle, seasons, sun and moon phases or biological cycle

Table 2.2: Brief overview of all economic schools and their understanding of cyclical drivers.[22]

Table 2.2 gives a brief overview of the different economic schools and their explanations of their cyclical drivers. Before picking out the most important theories of economic schools(see section 2.1.4.2), we show general factors, which influence the cycle. [167]

Technological crisis

As shown in figure 2.3, new technologies often herald the beginning of a new era. After the industrial revolution, lots of people had no work. However, on the other hand productivity rose. Nowadays, in the era of information technology, lots of jobs get replaced by intelligent algorithms, processes and computer programs. These shocks occur regularly through the history, but often do not happen smoothly. It is believed that the self-driving car technology, which is pushed by the search and technology company google, will cause a similar change in our economy. [7]

Natural disasters

Lot's of cyclical industries depend on the weather in term of their productivity output. The most classic examples are the agricultural industry and the tourism industry. Even though our weather forecasts have become much more accurate as in the past, many countries struggle with certain conditions. For example the US, where hurricanes are meanwhile a standard event, which occur

[7] For further information please see the official website - `https://plus.google.com/u/0/+SelfDrivingCar/videos`

regularly every year. It is the case, that usually not the disaster itself, but the aftereffects have a tremendous effect on the industry and its segments.

Monetary shocks

Nowadays, monetary shocks occur regularly. Even if central banks try to intervene with a new monetary policy, still financial crisis happen periodically. In general the effects of monetary shocks are inflation and rising interest rates.

Political disasters

Besides the central bank, also a government has large influence on a countrie's economy and its companies. The power of a political leader effects a countries system directly, for example by changing tax laws or setting up new regulations. One problem that has specifically being pointed out is corruption in governmental positions. The corruption perception index is a great example of showing numerically, how strongly influenced a political system is by corruption. [8] One of the most prominent examples is Greece, where corruption was and also is a large topic in their country.[9]

Sticky prices

Price adjustments happen, when in a market economy negative productivity lowers the real wages workers get. However, if wages are fixed and therefore inflexible, this adjustment cannot happen and a shock occurs. As a result, many of these workers lose their jobs and the production output slows further down. This downward cycle results into a crisis. [100] [38]

Financial crisis

Banks can be seen as the nervous system of an economy, because they manage large amounts of credit or other financial products of citizens. Hence, if a bank goes bankrupt lots of other companies are affected and cannot meet their obligations. Even though the government insures deposits of a certain value.[10] Serious economic crisis often have the breakdown of the banking system as an amplifier. The recent crisis of 2008 showed the importance of banks for the government, which resulted into several bail-outs. [11]

[8] The corruption and perception index was launched in 1995 by the organization transparency international. For further information, please visit http://www.transparency.org/research/cpi/overview.

[9] See bloomberg, February 3, 2014, http://www.bloomberg.com/news/articles/2014-02-03/greeks-united-on-view-their-country-is-corrupt-eu-survey-shows.

[10] In Austria the deposit insurance is up to 100.000 EUR. For further information see §93, §93a, §93b, §93c, §103h and §103k of the Austrian Banking Act, https://www.ris.bka.gv.at/GeltendeFassung.wxe?Abfrage=Bundesnormen&Gesetzesnummer=10004827

[11] See bloomberg, October 13, 2008, "EU Nations Commit 1.3 Trillion Euros to Bank Bailouts (Update3)", http://www.bloomberg.com/apps/news?pid=newsarchive&sid=abDNqy86viis&refer=home

2.1.4.2 Theoretical Explanation of Cyclical Fluctuation

As shown in table 2.2, several theories have been introduced to explain fluctuations of economic waves. The main theories focus on the business cycle. Even though, there are similarities between the theoretical mechanisms for other cycles. There are a large number of heterodox economic theories, which challenge the dominance of the Keynesian theory. These schools can be considered as a further explanation to gain a much deeper understanding of cyclical movements.

Keynesian Theory

In his book *"General Theory of Employment, Interest and Money"*[111], Keynes explained his view of business cycle drivers. In Keynes theory demand and supply play an extremely important role. His theoretical concept can be best shown by an example. Let‘s consider a company that can produce as much as the market demands. Therefore, a company will produce as many goods as it can sell with profit. The driver for this behavior is the available market demand. So if the demand for the companies' product rises, the business will sell more to satisfy the market conditions and immediately stop, if it cannot sell their products profitably. To produce more, the company needs more resources, such as machines and manpower. As a result there will be higher employment, higher income and higher profitability in the company. On the other hand if the demand is low there will be lower employment, lower income and lower profitability in the company. As the company cannot reduce jobs or buy machines overnight, there will be a company lag to adapted to market demand fluctuations. Hence, if in our example a company represents a national economy, the same principals and mechanics will occur and cyclical fluctuations can be observed. Furthermore, also other sectors and industries will be affected by the cycle. However, when does demand expand in the Keynesian theory? Going through the business cycle and starting in the expansion phase there are two factors that cause investments to fall. If demand increases for capital, prices of capital goods rises. This raises the costs of investment projects and reduces the effectiveness of the capital in the economy. As a second component, as interest rates rise the return on investment becomes lesser and projects can even become unprofitable. Hence, speculators will try to find ways to still make money in the markets and will raise false expectations with pessimistic investors. Under these assumptions the stock prices cause a bubble, which will burst by a sudden collapse, because the efficiency of capital has decreased. During the expansion phase, the demand for capital good raises and the capital efficiency goes up. The growing scarcity of products will bring new investors in the market, which will fund their investments by low interest rates. As new projects are done in an economy, wages will go up and unemployment will go down. Hence, the pessimistic opinion will change into an optimistic opinion and the cycle will go up. The two most important contributions to business cycle analysis are:

1. Fluctuations in investment, cause changes in demand and further in economic activities.

2. Fluctuations in demand for investment are caused by the future expectations of business men, in profit expectations.

Real Business Cycle Theory (RBC)
The Keynesian model got heavily criticized by economists. [12] Important points include that it leaves aside the microfoundations, the Lucas critique [13] and since there are no utility functions in the Keynesian model normative questions cannot be asked. The Real Business Cycle Theory (RBC) started by Nelson and Plosser in 1982, tries to find solutions for these problems.

The structure of the typical RBC model is: [14]

- An agent framework is used.
- Every company- and every household-agent has a specific utility function. The goal for them is to maximize this function.
- Cycle are generally created by exogenous productivity shocks. The basic assumptions for an economic environment are rational investor expectations, competitive market and perfectly available information.

One of the most important papers in RBC literature is from Kydland and Prescott (1982). [118] The RBC theory follows two principles:

1. Money is not the most important factor for business cycles.
2. The most prominent cause in RBC models are technological shocks, but also governmental changes, interest rates and demographic changes.

Economists, who prefer the RBC model to explain business cycles, argue that there are three drivers that account for fluctuations: [162] [160] 14

1. Cycles usually happen over a certain period of time and are not instantly happening.
2. Different sectors and industries experience the cyclical behavior and effects concurrently.
3. Significant changes in the labor market.

[12] For example, Mankiw (1989) [126] presents a confrontation of the two business cycle theories.
[13] Is the model is useful for policy changes? Lucas critique argues that it is if a model only takes historical data into consideration then it is not useful for economic policy making. [56]
[14] For further information see `http://economics.wikia.com/wiki/Real_Business_Cycles_theory`.

Austrian Business Cycle Theory (ABCT)

The two Austrian School economists Mises and Hayek, introduced Austrian Business Cycle theory. It was build on the business cycle view of the Swedish economist Wicksell. Generally, ABCT is not different from other theories in regards to its structure, such as expansion and contradiction. It tries to answer the following questions: [132]

- Why is there a group of business errors that happen so rapidly?
- Why is the fluctuation in capital goods industries larger than in consumer goods industries and prices?
- Why does the quantity of money increase during an economic book phase and why does the quantity not decrease during the bust phase?

In the ABCT, one can say that the two main factors are, sustainable and unsustainable growth. [64]

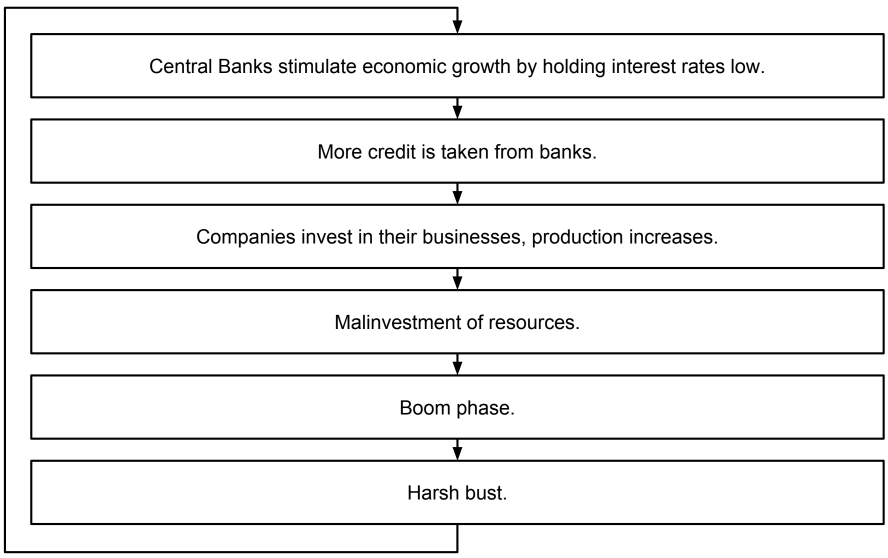


Figure 2.4: Simplification of the Austrian Business Cycle Theory. [132]

Figure 2.4 shows a simplification of the complex ABCT. We provide this abstraction to focus on the fluctuation generation part of the theory. As this flow diagram can be seen as a cyclical process, several steps have to be taken to build a wave. In the first step central banks usually start to lower the interest rates, to influence the economic machinery. Their reasons for this are that they want people to borrow money from banks. In the following steps businesses start to lend money from banks and invest into their businesses. This behavior raises production. [15] However, in the following stage malinvestment, the misallocation of resources, happens. Hayek describes this process in his work, *"Human Action"* by an example. [170] A builder is planning a house. He orders some bricks and other materials and hires people from different professions to start building. During the process, he realizes, that he does not have enough resources to finish building the house. As the last brick is laid, the house is still not finished and the project stops. [170] This example, represents the peak of the cycle, the bust. As this phase occurs so abruptly the cycle goes down again and as figure 2.4 indicates, the central banks arrive at the problem of economic stimulation.

[15]The Hayekian Triangle shows the different stages of firm production. All the different stages are driven by their time horizon, as farther stages prepare for consumption in a wider horizon, whereas nearer stages are for consumption in the near future. [80]

2.2 Real Estate Economy

The real estate economy plays for private investors an extremely important role, industrial-, commercial- and service companies, institutional investors, such as banks and funds and also for the public sector, [16] either as a production factor or as investment medium. [152] Furthermore, real estate and property ownership is one of the most important asset components of households. Further, expenditure on housing and rent takes up a large chunk of Austrians household spending. [150] With the recent happened financial crisis of 2008, property bubbles came back again into focus of financial institutions and the public sectors. Economists agree, that real estate price bubbles represent a serious threat to the stability of an economies financial system. [150] The following chapter will give an introduction to a real estate economy, starting from defining real estate, the structure of a real estate economy and finally describing property as an investment medium and the life cycle of a property investment, with a specific focus on banks.

2.2.1 The real estate market

As stated by Herath and Maier (2009) [122], the term "real estate market", can mean different things to different stakeholders. [122] The reason for this is, on the one hand the different segmentation of properties, for example by use types, and on the other hand the different interests stakeholders have in real estate markets. In economic terms the definition of the real estate market comes from the general market definition[17]:

Definition 2.4. A real estate market is a market, where supply of and demand for real estate meet and where real estate is traded. [122]

This general definition leaves a lot of open questions, starting with the term *"real estate"*. Hence, we define under the term *"real estate"*:

Definition 2.5. Real estate is a name given to land, buildings and legal rights over immovable property, especially when they can be priced for possible sale in an actual or potential market. [140]

As previously stated above, the real estate market is very segmented in terms of different use types. One of its main value performance drivers are the different use types a property can have. The type of property is decided in Austria by each municipality, which has a long term zoning plan. This view might differ from the current usage. One reason, why such considerations are made is, that the land use plan acts as a major instrument of regional planning, either spatially or functionally organized, to meet the requirements of the proper settlement, economic

[16] In Austria the "Bundesimmobiliengesellschaft" (`http://www.big.at/ueber-uns/` is the largest public investor with fixed assets of nine billion euros and approximately 2.200 properties.

[17] See Herath and Maier (2009)[122] for further information on this definition.

development, tourism, recreation and the needs of the municipalities financial nature and landscape protection. [18] Some examples for commonly referred use types are *land*, *office*, *retail*, *hotel* or *shopping center*. Each of these special types, can have a substantial impact on the later price development of a property. An office building in Silicon Valley today does definitely not have the same value as an office building in the first district of Vienna, because of the different market developments. Hence, further factors such as market momentum, such as demand and supply, specific location and the timing of the transaction also have to be considered. [122] Many property speculators play with one of these factors to gain profits from their gambles. [19] Hence, this shows that into the final valuation of a property, many different factors have to be considered.

As Ray Dalio (1991)[44] points out, a market is the sum of all its transactions. In Austria each real estate transaction can be seen in the national land registry[20]. The land registry is kept by the district courts. It is a public directory, where all registered land and the existing rights on a real estate have to be entered. The following rights require an entry into the land registry[21]:

- property ownership
- residential property
- right of lien
- construction law
- easements and land charges

Hence, buying a property mainly means to buy the title or right on the property.

The basis for each entry in the Austrian land registry is the so called, *Kataster*. A *Kataster* defines a certain land area and the Austrian land surveying offices(BEV)[22] collects all needed data for each land area, such as the specific location, land area, assigned use type. The Austrian BEV, also defines the land borders and makes reports if there are claims from property owners. In Austria all these rules can be found in the *Liegenschaftsteilungsgesetz*[23].

The Austrian land registry consists of three main parts:

[18] For further Information see help.gv, Flaechenwidmungs- und Bebauungsplaene ,https://www.help.gv.at/Portal.Node/hlpd/public/content/20/Seite.200030.html.

[19] Property speculation is a serious problem in the property markets, see http://www.ots.at/presseaussendung/OTS_20140801_OTS0134/der-standard-kommentar-immobilienspekulation-von-rosa-winkler-hermaden.

[20] See https://www.help.gv.at/Portal.Node/hlpd/public/content/60/Seite.600000.html for more information.

[21] See https://www.help.gv.at/Portal.Node/hlpd/public/content/60/Seite.600500.html for further information.

[22] For further information, see http://www.bev.gv.at.

[23] For further information, see https://www.ris.bka.gv.at/GeltendeFassung.wxe?Abfrage=Bundesnormen&Gesetzesnummer=10001787.

1. **General ledger:** The general ledger is intended to receive the land registration.[24]

2. **List of deleted records:** This is where the question of the deletion of entries in the general ledger (supported by automation) are transmitted.[25]

3. **Auxiliary directories:** This directory provides search possibilities from the land database, to find the *Kataster* and the deposit number of the searched property.[26]

Besides these main parts, the land registry includes also a collection of deeds and a land registry folder. The collection of deeds is a physical repository, where deeds, such the purchase agreement or the acquisition of land ownership, were printed and stored in order of a diary number. These bound volumes could only be looked into at a district court, which carried out the land registration. The land registry, contains also the land registry folder. This is a map that shows each *Kataster*, stating the plot number and its borders.

Having a detailed look into the land registry is possible for everybody [27]. Access is granted both in the **general ledger** as well as in the **collection of deeds**. At the following places one can access the land registry:

1. Inspection and queries in court.

2. Inspection at notaries.

3. Inspection and queries over the Internet.

1. Inspection and queries in court

Generally, you can inspect the land registry at every district court. There you get insights into the general ledger, the auxiliary directories and in the directory of the deleted entries, as well as in the current land registry folder, the digital cadastral map. Before you get the desired data you have to admit your request either written or during the office hours. One Land Registry extract from the general ledger and excerpts from the auxiliary directories cost 13,70 EUR.

2. Inspection at notaries:

Every notary can grant access, request land registry excerpts or create new land registry entries in his right as court commissioner. Notaries are entitled to grant access against a fee, which are required by the court for land register excerpts.

[24]For more information, see https://www.help.gv.at/Portal.Node/hlpd/public/content/60/Seite.600110.html.

[25]For more information, see https://www.help.gv.at/Portal.Node/hlpd/public/content/60/Seite.600120.html.

[26]For more information, see https://www.help.gv.at/Portal.Node/hlpd/public/content/60/Seite.600130.html.

[27]See General information on the land registry, https://www.help.gv.at/Portal.Node/hlpd/public/content/60/Seite.600210.html#Allgemein.

3. Inspection and queries over the Internet:
The land registry can also be accessed via the internet. Since May 2012 the land database was renewed and received an entirely new querying solution.

Type of query	**Fees in EUR**
Current Deed (full query a register number)	3.36
Current portion of extract (query of the A-, B- or C-sheet insert a number)	1.79
Query the last diary number (seal)	1.68
Query the collection of documents (each document polled)	1.05
Interrogation of persons directory (per person polled)	1.68
Query the historical register number (list of deleted entries) for the last five years	1.68
Query the historical register number (list of deleted entries) without any time limit	3.99
Deed on a specific date (depending polled insert number)	3.99
Land Registry-part excerpt on a specific date (depending interrogated sheet)	2.31
Query the last diary number (seal) on a specific date	2
Query the information about a journal number (additional information)	1.68
Search for purchase contracts per cadastral	1.68
Information on a property group in the group directory	1.68
Query from the digital cadastral (DKM graphics) (up to 500 m)	3.36
Query from the digital cadastral (DKM graphics) (up to 1,000 m)	11.60
Query from the digital cadastral (DKM graphics) (up to 2,000 m)	44
Excerpt from the land register without land address (for up to ten plots)	3.36
Excerpt from the land register without land address (for 11-100 Land)	11.60
Excerpt from the land register with Land address (for up to ten plots)	3.57
Excerpt from the land register with Land address (for 11 up to 100 plots)	13.70
Search plot addresses in Address Directory - address search (for up to 10 hits)	1.05
Search plot addresses in Address Directory - address search (up to 100 hits)	3.36
Search plot addresses in Address Directory - address search (for up to 1,000 hits)	34
Querying public corporations	1.58

Table 2.3: Fee overview to access land registry.[28]

Table 2.3 gives a general overview over the fees for a land registry entry. As it can be seen there are several different price categories to access the land registry.

The Federal Ministry of Justice also allows other vendors to access their directory online. Similar billing standards have been made for authorized vendors.

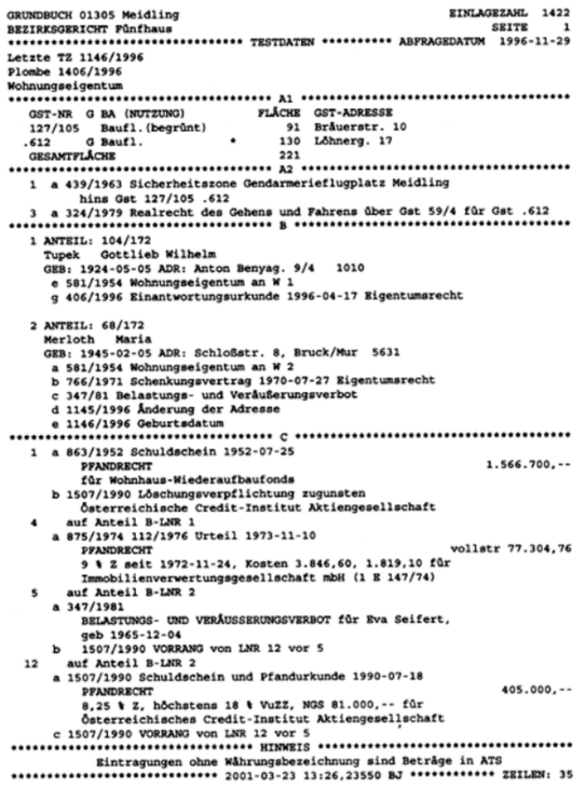
The main advantage of, these often privately held companies is that they, make searching and querying the official land registry much more comfortable. One of their largest disadvantages are the higher costs for one entry. The most well known vendors are Checkimmo[29] for around 15,00

[28]Table 2.3 was taken from `https://www.help.gv.at/Portal.Node/hlpd/public/content/60/Seite.600340.html` on June, 1st 2015.

[29]See `https://www.checkimmo.com`.

Euro, Jusline[30] for 12,00 Euro, A1[31] for around 20,00 Euro and through the software package Advokat[32].

A land registry entry consists of several sheets. The A1-sheet, A2-sheet, B-sheet and the C-sheet. The A1-sheet includes the lot number, the belonging to the cadastral boundary, the surface extent and the address of the land. The A2-sheet contains changes to the land registry body, public service obligations and rem permissions. The B-sheet consists of co-ownership and information about the assigned owner, such as the date of birth and address. The C-sheet comprises charges and legally significant facts. Figure 2.5 shows an example entry from the land registry.



```
GRUNDBUCH 01305 Meidling                                    EINLAGEZAHL  1422
BEZIRKSGERICHT Fünfhaus                                           SEITE     1
******************************** TESTDATEN ********** ABFRAGEDATUM  1996-11-29
Letzte TZ 1146/1996
Plombe 1406/1996
Wohnungseigentum
************************************ A1 **************************************
   GST-NR  G BA (NUTZUNG)          FLÄCHE  GST-ADRESSE
   127/105   Baufl.(begrünt)           91  Bräuerstr. 10
  .612     G Baufl.           *       130  Löhnerg. 17
   GESAMTFLÄCHE                       221
************************************ A2 **************************************
   1  a 439/1963 Sicherheitszone Gendarmerieflugplatz Meidling
         hins Gst 127/105 .612
   3  a 324/1979 Realrecht des Gehens und Fahrens über Gst 59/4 für Gst .612
************************************ B ***************************************
   1 ANTEIL: 104/172
     Tupek   Gottlieb Wilhelm
     GEB: 1924-05-05 ADR: Anton Benyag. 9/4   1010
      e 581/1954 Wohnungseigentum an W 1
      g 406/1996 Einantwortungsurkunde 1996-04-17 Eigentumsrecht

   2 ANTEIL: 68/172
     Merloth   Maria
     GEB: 1945-02-05 ADR: Schloßstr. 8, Bruck/Mur  5631
      a 581/1954 Wohnungseigentum an W 2
      b 766/1971 Schenkungsvertrag 1970-07-27 Eigentumsrecht
      c 347/81 Belastungs- und Veräußerungsverbot
      d 1145/1996 Änderung der Adresse
      e 1146/1996 Geburtsdatum
************************************ C ***************************************
   1  a 863/1952 Schuldschein 1952-07-25
         PFANDRECHT                                               1.566.700,--
         für Wohnhaus-Wiederaufbaufonds
      b 1507/1990 Löschungsverpflichtung zugunsten
         Österreichische Credit-Institut Aktiengesellschaft
   4    auf Anteil B-LNR 1
      a 875/1974 112/1976 Urteil 1973-11-10
         PFANDRECHT                                          vollstr 77.304,76
         9 % Z seit 1972-11-24, Kosten 3.846,60, 1.819,10 für
         Immobilienverwertungsgesellschaft mbH (1 E 147/74)
   5    auf Anteil B-LNR 2
      a 347/1981
         BELASTUNGS- UND VERÄUSSERUNGSVERBOT für Eva Seifert,
         geb 1965-12-04
      b   1507/1990 VORRANG von LNR 12 vor 5
  12    auf Anteil B-LNR 2
      a 1507/1990 Schuldschein und Pfandurkunde 1990-07-18
         PFANDRECHT                                                 405.000,--
         8,25 % Z, höchstens 18 % VuZZ, NGS 81.000,-- für
         Österreichisches Credit-Institut Aktiengesellschaft
      c 1507/1990 VORRANG von LNR 12 vor 5
********************************* HINWEIS ************************************
          Eintragungen ohne Währungsbezeichnung sind Beträge in ATS
**************************** 2001-03-23 13:26,23550 BJ ************ ZEILEN: 35
```

Figure 2.5: Example entry of the land registry.[33]

As indicated above, a real estate economy can be seen as the sum of its transactions. On the one hand, it may be argued that if we have all land registry entries, we could make a clear forecast on the real estate market. Knowing all closed real estate deals, would give as the current

[30] See https://www.jusline.at/.

[31] See http://www.a1.net/business/produkte-loesungen/grundstuecksdatenbank.

[32] See http://www.advokat.at/.

[33] This example of a land registry entry was taken from https://www.help.gv.at/Portal.Node/hlpd/public/resources/images/gbauszug.gif.

market state, but might not be a good indicator for giving a specific and clear market forecast for the property cycle, as the current state does not include any market drivers. For example, lots of real estate transactions are done in a bulk format and the price of the transactions are influenced either by the transaction volume, but also by the financial situation of the seller. A recent example that shows this, is the large deal between General Electric Co. and the alternative financial service company Blackstone Group, where Blackstone did a deal of over $23 billions in assets.[34] This deal was one of the largest real estate deals after the US housing crisis of 2008. When considering this large transaction standalone, different standpoints of the future state of the real estate market might be argued. For example, one might say that prices will go up in the future, because of growing demand, resulting from further investments that Blackstone might take. Others might say that, this transaction will have a negative effect on the market, because of well known speculations that hedge funds are doing. Hence, to gain a clearer view on real estate market drivers, we have to identify a clear structure of a property market.

2.2.2 Structure of the Real Estate Economy

Compared with Europe, studying real estate economy is much more popular and deeper seeded in the United States. The reason might be, that as part of a positive economic development, the real estate industry plays an important role in construction or modernization of property buildings. Furthermore, the *house movement* was much deeper seeded in the US compared to Europe. [94] As stated by Schulte (2008), [152] lots of studies from the US include the relationships between the overall economic development and the real estate cycle. When figuring out the general structure of a real estate market, the primary focus is often on macroeconomic components. According to Schulte (2008)[152] real estate decisions are influenced to a considerable extent from macroeconomic variables. The main and easiest indicators to measure such an analysis are the gross domestic product(GDP), gross value added, final consumption expenditure, aggregate investment, the labor market and the price level. The reason for this is the indicator data availability. Other, more negative macroeconomic factors are unemployment and inflation.

Figure 2.6 shows a real estate economy from the view of banks, inspired by Schulte‘s (2008) house of real estate. There are four main aspects, which have to be considered, as of Schulte (2008)[152]. On the top there are the management aspects, as two pillars the institutional aspect and the typological aspect and as a foundation the interdisciplinary aspect. The interdisciplinary aspect refer to general professions, which are involved in the real estate market. During our research, talks with industry experts have shown that the main disciplines are computer scientists, economics, law, architecture and engineering. [35] The typological aspect describe the different

[34]For more information, see "Blackstone Cements Its Dominance With Real Estate Deals", 15. April.2015, `http://www.bloomberg.com/news/articles/2015-04-15/schwarzman-s-blackstone-cements-dominance-with-real-estate-deals`.

[35]When looking at the real estate market different sectors have come up, ranging from data collection services, such as Zoomsquare `http://www.zoomsquare.com/` to actual investing and developing, for example Signa Capital [**?**

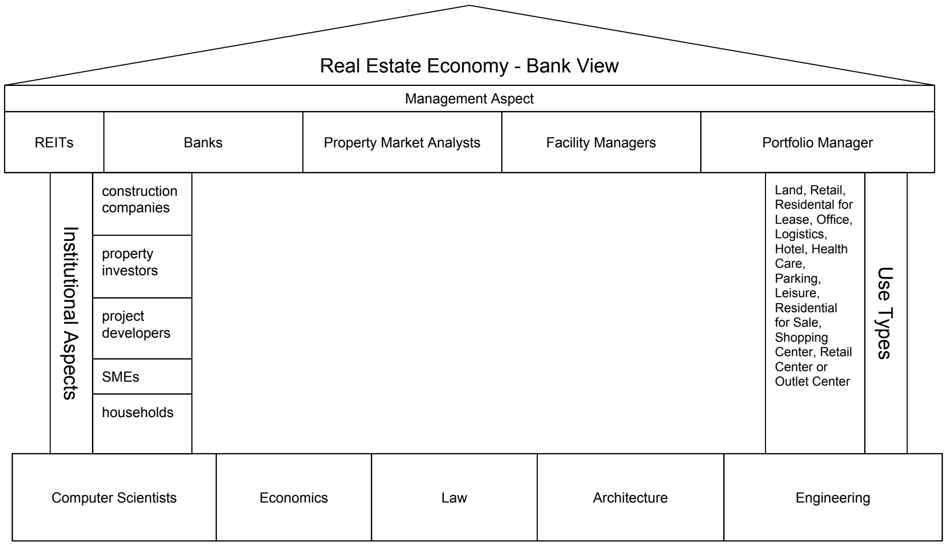


Figure 2.6: Real Estate Economy Banks View. An adaption of Schlute (2008) real estate economy house. [152]

use types a property can have, for example Land, Retail, Residential for Lease, Office, Logistics, Hotel, Health Care, Parking, Leisure, Residential for Sale, Shopping Center, Retail Center or Outlet Center.[36] The institutional aspect show the different stakeholders, which are part of the real estate economy and often operate with banks, such as construction companies, property investors, project developers small and medium-sized enterprises or households. The roof of the house is built by the aspects of management, such as REIT [37], real estate analysts or facility managers, which are mostly part on *"transaction"* level of a real estate economy.[38] These parties are not directly involved with the real estate market in terms of construction, planning or using the property, but often share valuable reports or financing strategies with banks.

2.2.3 Property as an Investment Medium

Real estate is an important part of an economy, either for institutional investors and also for private investors. As shown in section 2.2.2 there are several stakeholders, which are interested in property either as an investment medium, or as financier for investing into property.

Figure 2.7 shows an abstract structural view of project financing for banks and developers. There are several components a project that is in *the pipeline* to be financed includes: On the top, there is the customer. This can be a single person or a company. On the next level, we have the projects, a customer can have. If the customer manages his projects well, the bank, will have

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[36]Retail sub-categorizes Shopping Center, Retail Center or Outlet Center.

[37]Real Estate Investment Trusts.

[38]For more information please see chapter 2.2.1.

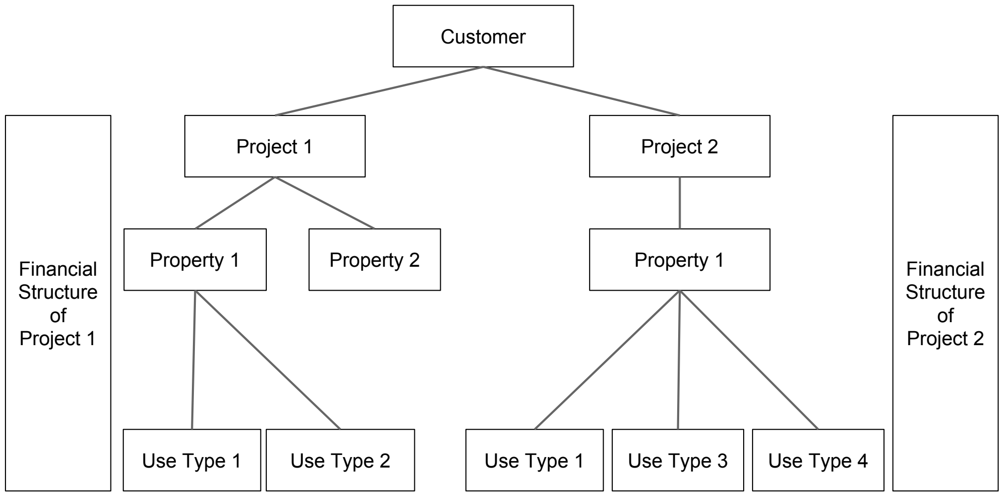

Figure 2.7: Structure of property financing for banks.

several projects with the customer. Each project can have 1 to *n* properties, depending on the complexity of the project. Finally, each property can have several use types. In fact, there are no use type restrictions, but a usual property will have 1 to 2 use types. However, there can also be properties with more use types. Each project has a financial structure. This usually includes the loan amount, interest rate and a repayment schedule and further information, such as the currency the customer is paying or if the loan is fixed or floating.

As stated by Barras (2009) [12], investing into real estate serves a two-fold purpose. On the one hand, there is people's need for housing, hence actually using the property for itself. On the other hand, there are speculators and financiers, which try to earn a good amount of money from property investments. As Barras (2009) [12] argued, *"...land and buildings also act as a repository of wealth; they form the largest component of the tangible assets which constitute the wealth of nations."* This contradiction, between speculator and housing, is the source of an interest conflict in the real estate markets. The investors perspective is to increase his ROI[39], on the other hand the occupier wants to minimize his housing costs. [12] If prices rise, existing owners and house investors benefit, because of their rising ROI, but tenants and house owners lose, because of rising rents and less accommodation services. Banks are in the middle of this conflict and have to guess and estimate the future profitability of their counter-parties. Barras (2009) states that this conflict of interest is a large influencer of the market environment. [12]

[39]ROI defined as the return of investment, a performance measure for the monetary gain in a property investment.

2.2.4 Project Development Phases: Banks and Developers

There are several stakeholder in a real estate economy, for example REITs(real estate investment trusts), developers and banks, as shown in Figure 2.6. As stated in the introduction, this thesis will focus more extensively on banks and developers, because they often have a direct relationship to each other. Even though home owners also lend money from banks, developers have usually larger loans and hence a higher amount of money is at risk. Furthermore, even though forecasts of the property cycle are important for many stakeholders, our built simulation model will focus exclusively on the investment view of banks and developers.

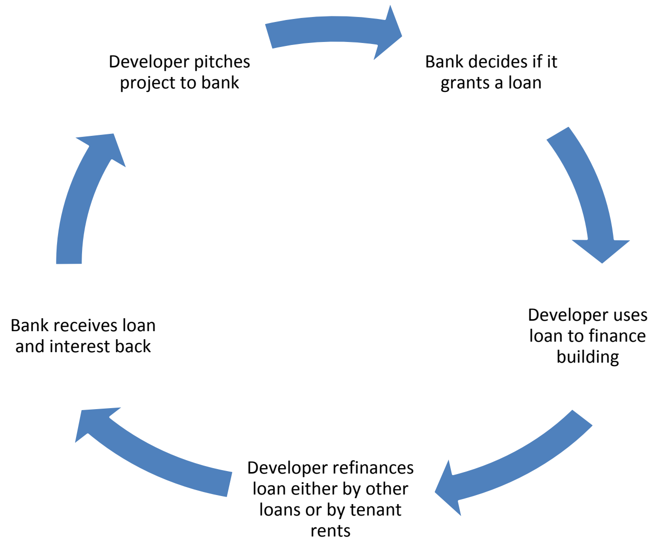

Figure 2.8: Investment phases of banks and real estate developers.

Figure 2.8 shows the investment cycle of banks and developers. During our expert talks, we outlined this clear process of the interaction of banks and developers. At first a developer pitches a project to a bank and asks for a loan, according to his capital need. The bank decides if it grants the loan or not. The banks try to estimate the risk on the project and often the final decision is made by higher level management positions, depending on the amount of the loan in a specific committee. In the next step, the developer uses the loan to finance the property project. Before signing the loan contract, the bank has made a fixed payment schedule agreement with the developer, so that it gets the borrowed money back with a certain interest rate amount. If the developer, cannot pay the loan amount back, the bank has to work out another agreement with the developer. The 'Workout' department is responsible for negotiations with the counterpart in this case. Usually later in a successful project development phase, developers might refinance the loan either by their free cash flow, such as rents or the sale of the property, or by taking a *"cheaper"* loan, with better conditions, from another bank. After the bank received their outstanding commitment, the project is closed from the view of the bank. Further, the cycle starts again by presenting the bank a new property investment project.

2.2.5 Cyclical Steering

There exists a clear linkage between house prices, private lending and the underlying economy. [67] Goodhart and Hofmann (2008) [67] show this by analyzing VAR estimates of over 17 industrialized countries in the time period from 1970 until 2006. Their analysis concludes that there exists a strong link between monetary variables and property prices. Further, they find that the link is even stronger during cyclical peak phases. Such asset price booms have attracted a long list of research, because of their relation to current events such as the financial market meltdown or the European debt crisis.

Detken and Smets (2003) [49] define *asset price boom* in relation to house prices as the following:

Definition 2.6. Asset price booms are a *"[...]period in which aggregate real asset prices are more than* 10 *percent above their recursively estimated Hodrick Prescott trend.[...]"* [49]

The Hodrick Perscott trend is a filter to remove the cyclical component of time series. [85] It falls under time series decomposition techniques. In our economy asset price booms, such as the rise of property prices, are quite common and occur on a regular basis as shown by Borio and Lowe (2001) [21], Bordo and Jeanne (2002) [20] or Roubini (2006) [146]. However, on the peak of this boom the unstable balance can crash extremely easily. Hence, monetary policy makers prevent this by putting regulations in place. Eickmeier and Hofmann (2010) [53] analyze private sector balance sheets by using a factor-augmented vector autoregressive model (FAVAR) to investigate the effect of monetary policies. They show that policies have a clear effects on real estate wealth, house prices and risk spreads in lending markets. [53] One might argue, that the crisis of 2008 hence might be prevented beforehand and that regulators might not have seen predictive signals. Taylor (2009) [165] investigates the effects of government intervention and shows that it had worsen the effects of the crisis. Still the large research body that followed after the crisis has made policy makers aware of the dangers of asset price booms.

One of the main stakeholders in the real estate markets are banks, which contribute by lending to finance the housing boom. This natural behavior can be seen in an economic critical situation to amplify and distribute the effects of the crisis. [133] The results of overleveraging have become one of the main influencers of the crisis of 2007 and 2008. [155] Schleer, Semmler and Illner (2014) [155] present a measure for overleveraging, which is defined as the actual versus the sustainable economic debt, whereas the latter can be broken down into an optimal allocation of return, interest rate and risk. Their study is based on 40 European banks, which models the bank's exposure and credit contradictions. [155]

[40] The plots was taken from Schleer, Semmler and Illner (2014) [155].

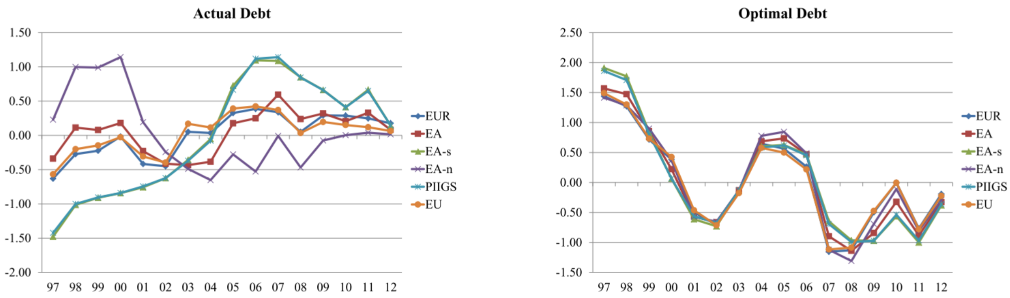

Figure 2.9: Actual and sustainable debt grouped by country from 1997 until 2012. [155][40]

Figure 2.9 shows on the left hand side the actual debt development and on the right hand side the optimal debt development. It can be seen that, since 2004 the spread among the sustainable path grew in the other direction, which indicates overleveraging. [155] Schleer, Semmler and Illner (2014) [155] show that after a shock occurs to bank lending, different reactions are triggered, which depend on the overall regime the macroeconomic environment is currently in. An example for such triggers might be the response to credit or the gross domestic product.

This asymmetric effect is also shown by Mittnik and Semmler (2011) [133]. They conclude that the impact of the shock is reflected either by the frequency and not only that policy actions are taken in a timely manner. Further, they also find that the impact of the shock is of high importance, which implicates the cyclical regime the economy is currently in. [133] This argument has also been recently presented by critics of Basel 3 [42]. Atkinson and Blundell-Wignall (2010) [17] point out the weaknesses of Basel 3 and show potential for corrections. Speculations about the rumoring Basel 4 implementation might already be in the pipeline by the BIS [41] committee. [116] Procyclicality is one of the main disadvantages of the currently implemented framework. [17] As financial institutions calculate their risk weighted assets on a rating scale basis, banks have to hold more capital in bad times than in good times. However, as banks are part of the macroeconomic environment, they tend to suffer as much as other companies from an economic downturn. This effect rather amplifies the cycle than dampens it. [17]

From the perspective of banks cyclical effects have a large influence on their loan portfolio and influences largely the final investment decision. [65] Glen and Mondragon-Velez [65] measure loan performance by bank's loan loss provision. [42] Beck, Jakubik and Piloiu (2013) [15] point out that the affecting variables for non-performing loans are *"[...]real GDP growth, share prices, the exchange rate, and the lending interest rate.[...]"* [15]. They also find that monetary policy makers should act cautiously to prevent to input negative economic feedback loops.

[41]BIS describes the Bank of International Settlement. Further information can be found at `http://bis.org/`.
[42]Loan loss provision can be described as costs that are set a side for potential non performing loans. [62]

These high level decisions cannot be influenced by banks, and hence we conclude that the essence is to carefully select loans based on their cyclical regime they are in, before taking this risky exposure on their own books. Cyclical steering of a housing portfolio might be a solution for the worsening of bank's loan portfolios during bad times. The premise is counter-intuitive: Banks should lend money in bad times to see higher and much more secured returns in economically good times.

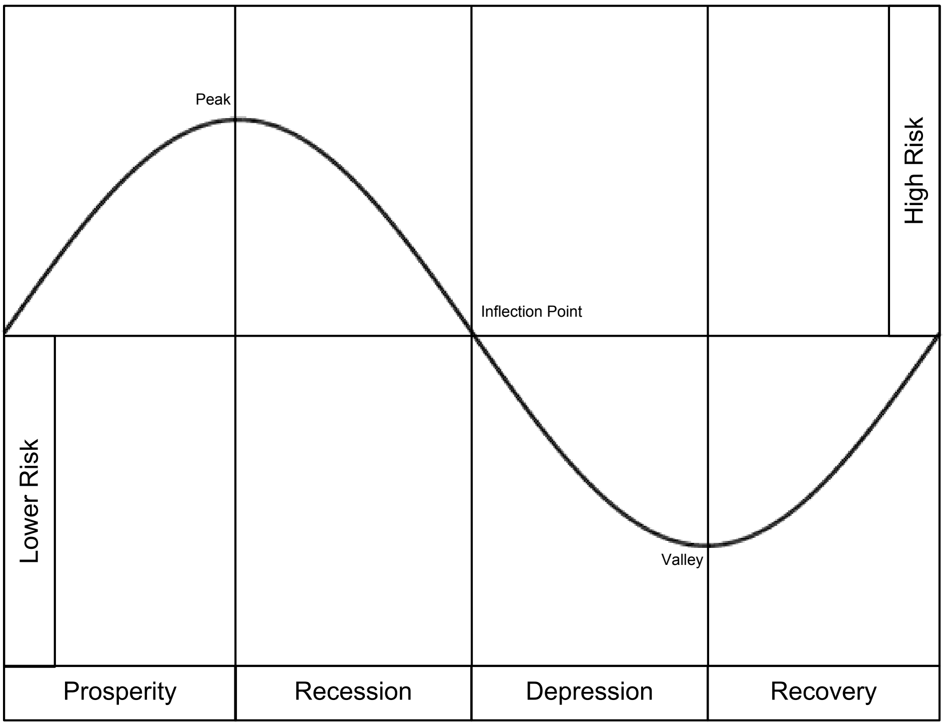

Figure 2.10: Cyclical Steering through different cyclical phases.

Figure 2.10 shows the different regimes the property cycle might go through. A deeper description can be found in section 2.3. Hence, even though a bank property loan might look exceptionally well structured, the future of the loan performance depends on cyclical movements. Hence, when starting to finance a loan during depression or recovery the total loan performance might be higher, as when the economy is having a difficult time ahead after the peak. We have pointed out that financing a loan during bad economic times, might be of lower risk to a bank than during prosperous times. However, this requires strategic considerations by banks, which are outlined in section 2.5.5.

2.3 Property Cycles

The following section will show the most important contexts of literature research in connection with the property cycle. First, we will give a definition of the property cycle and showing each cyclical phase in detail. Next, as the efficient market hypothesis is a cornerstone of economic market theory, we will introduce it's meaning and show extensive research about the efficiency of the property cycle. Furthermore, we will give a historical overview of property cycle research and finish the section by showing the investors perspective and its interest in real estate market fluctuations.

2.3.1 Definition

The definition of the property cycles consists of two aspects, first we can consider the general cyclical definition.[43] Another aspect is, as this definition does not distinguish the property cycle from other cycles, the property cycle can also be described through its unique cyclical development in the real estate market. In academic literature, there are a lot of synonyms for the term property cycle, such as real estate cycle, housing cycle or building cycle[12]. However, during this thesis the definition of the term property cycle will be equivalently used for the term real estate cycle, housing cycle and building cycle.

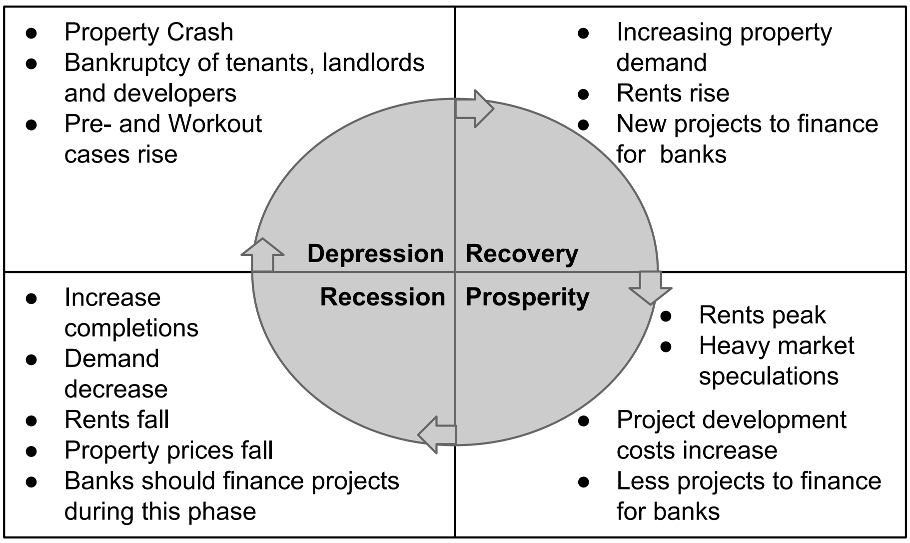

Figure 2.11: Description of the property cycle and its phases from a bank's perspective.[44]

Figure 2.11 describes each cyclical phase in the view of banks. A similar figure, but more generalized, can be found in Grover and Grover (2013) [76]. The property cycle consists of four

[43]For further information see Chapter 2.1.1

[44]This model is an extension from a more generalized model by Grover and Grover (2013). [76]

phases: *depression*, *recovery*, *prosperity* and *recession*. When demand for real estate rises, more investors get into property investment and often slowly the market starts to peak as no more demand is available to be fulfilled. During this process rents start to rise and new projects are started. Banks often close a lot of loan contracts for such projects and an optimistic mood dominates the real estate market. After the peak prices fall immediately, rents go down and speculators acquire failed projects in the market. Banks face bankrupt investors, which cannot pay their loan money back. Many of these cases are then passed into their workout department, where failed real estate projects are tried to be restructured. The economy goes into a recession with low demand, tightening credit conditions and falling rents and land prices. As described in chapter 2.1.4.2 there are several theories and factors which influence the rise and fall of cycles. Therefore, being in the recession is no permanent state for an economy. Hence, in the next phase the cycle starts again.

2.3.2 Efficient market hypothesis and the property cycle

Eugene F. Fama introduced the term *"Efficient Market Hypothesis"* in his 1970 paper *"Efficient Capital Markets: A Review of Theory and Empirical Work"*. [55] This terms has been discussed in various forms in economic literature. As it is one of the fundamental building blocks of markets, the hypothesis is also closely related to the property market. Even though it was originally presented by Fama for the securities market. [55] An efficient market can be defined as: [55]

Definition 2.7. *" ...a market in which firms can make productive-investment decisions, and investors can choose among the securities that represent ownership of firms' activities under the assumption that security prices at any time "fully reflect" all available information." [55]*

Under *"fully reflected information"* Fama (1970) [55] understands, that all information is available to investors in a market. He further categorizes the efficient market hypothesis into three forms: *Weak*, *Semi-Weak* and *Strong* form efficient market hypothesis.

Strong Form Efficient Market Hypotheses

The strong form efficient market hypotheses fully reflects Fama's definition of an efficient market. All information, either public and private, is available to everyone in a market. [55] However, this form can only just be reached in a theoretical market, because information asymmetries make it nearly impossible that all investors have equal access to information.

Semi-Weak Form Efficient Market Hypotheses

As the restrictive corset of the strong form cannot be aligned with real world markets, Fama has changed the underlying assumption of information availability. Hence, in the semi-weak form, all *publicly available information* has to be included in a companies stock price and every investor can easily inform himself through regular news channels. Through academic literature, many refer to the semi-strong form as the semi-weak form, because reducing the information availability assumption makes it closer to the weak form. However, it is widely accepted that under each of these names the semi-weak form efficient market hypothesis is meant. [106] For most economists this form is the closest to the real world.

Weak Form Efficient Market Hypotheses
The weak form efficient market hypothesis breaks up the split of public and private information and solely focuses on historic information. [106] Hence, historic information is reflected in the companies stock price. Further the weak form also explains, why certain trade analysis techniques such as technical analysis or charting work, because past information is fully reflected in the markets and certain historic information will arise again. [125]

The basis of the efficient market hypothesis are random walk movements in prices. In his 1970 study, Fama picked stocks to represent a market and calculated their auto-correlation, which results close to zero. That means, that past prices cannot predict future price movements. [55] [113] Shiller (2014), who recently received the nobel price in 2014 for his work on the predictability of stock prices,[45] mentioned in his nobel price lecture that even though Fama shows with his efficient market hypothesis that theoretically a market might be efficient, however in reality stock prices can be predicted over a certain period of time. Man and Chau (2006) argue that Fama initially focused on the asset class of stocks, rather than real estate, hence they argue that further conclusions, even though there might be a certain dependence on these two markets, cannot be drawn. In addition to that, various effects, for example the value [136] [10] and the size effect [142] [13], which where empirically found in the stock market, seem to show Fama's [55] strong form efficient market hypothesis as misleading. Shiller pointed out in his nobel price lecture that for real estate market other conditions are met: *"And yet, when I first joined with Karl Case to do joint work on real estate prices, in the 1980s, we found that hardly any scholarly research had been done on the efficiency of real estate markets. The state of knowledge about these markets was abysmal. Under the influence then of a widely-held presumption at that time that all markets must be efficient, many economists, at least in their popular pronouncements, seemed to assume that real estate markets must be efficient too. This presumption appeared to us as quite possibly wrong, based on anecdotal evidence suggesting that real estate prices are not at all well approximated by a random walk, as is the case for stocks, but often tend to go in the same direction, whether up or down, again and again for years and years."* [157] What Shiller means, is that the information flow in the real estate market is rather slow and has lags. Therefore, to make fast and *"easy money"*, compared to stock markets, is nearly impossible. [101] The general scientific understanding is that the real estate market is *weak form efficient* at most. [113] There are two

[45] For further information see http://www.nobelprize.org/nobel_prizes/economic-sciences/laureates/2013/shiller-facts.html.

reasons, for that *information flow* and *price volatility*. [101] The latter can be observed in cyclical analysis. [101]

2.3.3 A brief history of property cycle research

Property Cycle research has a long history starting with general research about fluctuations. Cyclical research started with *"Nouveaux Principes d'economie politique"* by Jean Charles Leonard de Sismondi written in 1827. [159] 100 years later Hoyt (1933) [92] examined the real estate cycle for Chicago, in the time-frame from 1830-1933. By the time he was aware of the cycle, but his understanding was that a series of independent forces influenced the market and generate a cycle. The drivers Hoyt (1933) identified were: population growth, level of rents and costs of operation(OPEX[46]) of existing buildings, newly created constructions, value of lands, and land parcels. [76] In the UK, Cairncross (1934) [33] analyzed the building industry in Chicago from 1870 to 1914. He showed that there were periodic fluctuations in building demolitions, construction values and rents. [33] [76] Compared to Chicago by this time the city of Glasgow had a lot of immigrants, which is reflected in the underlying data. [76] [33] Jadevicius (2010) [104] argued in his paper, *"Is 100 years of research on property cycles enough to predict the future of UK property market performance with accuracy?"*, that the first serious discussions about the property cycle started in the late nineteenth century. The three most important studies in this era are Lewis (1965) [120], Abramowitz (1964) [1] and Gottlieb (1976) [69].

Lewis (1965) published an important survey paper, which showed the growth in the UK economy from 1700 to 1950. Through this paper he found that, the building cycle had to be 18 to 20 years in length. As Hoyt (1933) [92], also Lewis tried to explain the cycle with several factors, such as production level, population, income, level of migration, availability of credit and level of rent and also the *economic mood* in which they occurred. [104] He especially emphasized population and credit in his survey.. [120]

In 1964 Abramowitz [1] published a large survey paper, where he analyzed 37 time series and identified in construction several long term cycles, which range from 15 to 25 years. Even though Abramowitz admits that the data quality might be bad, his results still remain very impressive. Further he also roots the cause of the cycle in lags, such as unsatisfied demand and postponed construction plans, because of the ongoing war. Jadevicius (2010) [104] argues, that Gottlieb (1976) [69] study was probably the most comprehensive survey in the post war era. Gottlieb, analyzed over 200 time series of different countries for example Australia, Canada, France, Germany, Italy, Japan, Netherlands, UK and the United States, within different data categories, such as financial, economic, demographic, construction and real estate. He showed, that the property cycle has either on the national and local level the same duration, which he estimated around 20 years. Gottlieb (1976) [69] also found a dependence between changes in demography and the property cycle, which suggests the change in housing at the time.

[46] OPEX are the operating expenses, the costs of running a property project.

After 1990, property cycles came into new light. Academics and professional consultants blamed the inaccuracy of data, that they could not detect the degree of the ongoing property crash. [104] Hence, lots of important studies where started. New forecasting techniques, where tried out such as McGough and Tsolacos (1995) [129], who used different ARIMA models to provide predictions for the office and retail sector. They found a relationship between certain economic indicators and commercial property. Furthermore, their concept of "stylized facts", the search for established patterns, was another important result of their study.

Renaud (1995) [143] analyzed the global phenomenon of the property cycle from 1985 to 1994. He identified that careless lending has a large impact. As this happened before the important introduction of Basel 3, he suggested that local authorities should monitor and supervise changes in the structure of the capital markets. [143] Furthermore, he proposes that more transparent banks might recover better from a property cycle shock. Renaud (1995) found structural changes in the global real estate markets and argues, that it is difficult to differentiate between cyclical factors and structural indicators.

Recently the trend in property cycle research and real estate price forecasting goes to the use of new forecasting models and better, often more granular, data sources. Hui and Wang (2015) [93] took a deep look into the cyclicality of securitized property markets. Their study includes global property market such as Australia, Hong Kong, Japan, Singapore, UK and the United States. Hui and Wang (2015) [93] findings show, that a co-integration relationship exists between markets and during bullish times it becomes stronger. Further, the cyclical pattern is different when comparing developed and undeveloped markets. Another study, done by Brown, Jadevicius and Sloan [103] investigates the property cycle in the UK from 1963 to 2010. Using combination forecasting as a modeling technique they found it as an excellent complementary prediction method. During their research, they investigated several different modeling techniques, such as ARIMA/ARIMAX, Exponential Smoothing, Multiple Regression, Simple Regression and Vector Autoregression. As a conclusion, they found out that simple time series models are more accurate in prediction and than larger, more complex, models.

Another quite interesting approach, in terms of data usage is from Zuo, Zhang and Zhou (2015) [164]. They believe that a large factor which is underestimated by many price prediction studies is the impact of human behavior. For their three different models, SVR, RBFNN and BPNN, they used Google search engine query data. To evaluate the model they calculated three different validation values, such as Root Mean Square Error, Mean Absolute Error and Relative Absolute Error. Their data included, crawled news articles from "Sina Real Estate News" and the Chinese House Price Index (HPI). Their results for the four Chinese cities, Beijing, Shanghai, Hangzhou and Chengdu, they show that their model provides valuable results on a city level, which perform better with news sentiments and search engine data.

The studies presented above, give a brief overview on the importance of the real estate cycle through history. Starting with Sismondi in 1827 [159], there exists a long body of research until today. As data will become much more accurate and more sources will become available to the academic community, we believe that studies will become much more accurate to predict the property cycle.

2.3.4 Investor Perspective

When doing large real estate deals the property cycle influences lots of stakeholders in the market and is therefore very relevant in daily business. Large real estate transactions have huge market influence and can, if they are not executed with the right timing, cost millions more in transaction costs. One example to mention, is the large deal of the Blackstone's[47] group, an asset management and alternative financial service cooperation, with General Electrics[48], a multinational energy company, which operates in several different segments starting from car production to energy. General Electrics announced on April, 10th 2015, to sell a $14 billion chunk of its real estate assets to the Blackstone group, because of restructuring of the financial aspect of the company.[49] Furthermore, besides large alternative investment groups such as Blackstone, we identified two of the most important stakeholders, which generally have a large interest in the property market, such as developers and banks. The latter will play a large part in the risk simulation framework.

Real Estate Market Stakeholders: Banks

Real Estate plays an extremely important role for banks in terms of daily business. [150] [48] For the commercial real estate sector banks are inevitable, because they provide continuous project financing. Furthermore, as shown in Figure 2.8 there is close cooperation between these banks and developers. Even though since the financial crisis many things changed for banks. Some of them started to question the profitability of their business model. However, many banks stuck to the proven simplicity of their credit business model, which is also used as of today. [18] In the real estate sector, banks are lending to finance real estate and secure their exposure by using the real estate as collateral. The attitude how banks are lending money to their counterparts has a large influence on the real estate market. [48] Breaking down these arguments there are several components, which influence a bank as a stakeholder:

1. **Volume of credit:** The most obvious influencer is the is the volume of credit a bank has in the real estate market. It is also often referred to the exposure, the value that is not secured by a collateral, within the bank. Property prices affect the credit volume of a bank for several reasons: The borrower has a limited amount of money, therefore if property prices change, this has a large effect on his profit margin and his borrowing capacity. Hence, he will try to change his repayment plan, which will affect the credit volume of banks. [48]

[47] Company web page, May, 15th 2015, http://www.blackstone.com/
[48] Company web page, May, 15th 2015, http://www.ge.com/.
[49] See WSJ, 9th, April 2015, `http://www.wsj.com/articles/ge-close-to-selling-real-estate-holdings-1428600831`.

2. **Real Estate as collateral:** As indicated above banks use the value of the borrower's property as collateral to secure the value of their loan. Hence, a change in the property price can often end with the result, that the bank owns the property, because the borrower is unable to pay. [48]

3. **Liquidity effect:** Bank lending can also have a large effect on liquidity in the real estate market, which further result in changes of the property price. [48]

4. **Non performing loans:** Since the financial crisis of 2008, many banks still have a reasonable amount of non-performing loans, which are related to the real estate sector. Hence, many banks want to clean their portfolio as a result. Therefore, one important goal is to ensure, that future property transactions will be funded at the dale of the cycle to ensure that the client still can sell as a profit at the cycle's peak and the bank gets its money back. This best case scenario, has not yet been adapted by many banks. Furthermore, the bank also owns in many cases the collateral, which value is in the face of a crisis less worth than before.

5. **Financial accelerator:** There is evidence in the market, that increasing property prices make banks sell more loans. [76]

Real Estate Market Stakeholders: Property Developers
Land and property developers can be seen in game theory as a group of individuals, where social interaction is one of the most important aspects. [148] Barras (2009) [12] argues that developers treat every product differently, which results in time lags and different lead times. He concludes that, there is a factor of uncertainty within each to each investment decision a property developer makes. Breaking down these arguments there are several components, which influence a developer as a stakeholder:

1. **Market Timing:** Prices are dependent on supply and demand, hence if a developer buys a property and he can expect that the price of the property might rise, he has a successful foundation to *develop* the property. However, on the other hand, if the property cycle might be at its peak, it is extremely dangerous for a developer to set up a project, because he would develop to an overvalued price and sell, when property prices come down. Therefore, the most important interest of any developer in the property cycle might be to figure out the right timing of when to buy or start a new project.

2. **Property Portfolio:** Large Real Estate Developers often have large project portfolios. In contrast to banks, their portfolio consist of real properties and it highly depends on the developer's business model, where the company puts its focus. Either on reselling properties or generating profits through re-renting their space. Hence, the core interest could be, to know how the real estate portfolio might perform in the future. The building cycle has

a large influence on the portfolio's behavior, because it also influences the valuation of a certain property.

3. **Investment Opportunities:** As shown in the subsection 2.1.1 investors want to buy properties low and eventually sell them high on the real estate market. Hence, one of their largest interests is to buy at the valley of the cycle, because usually at this point prices of real estate tend to be undervalued.

4. **Information Advantage:** Property Developers often operate for years in the same market and know the ins and outs. At best they are aware of the real estate cycle in their home market and have a feeling at which point of the cycle the market is. [12] This information advantage provides a competitive advantage against other companies in their industry.

5. **Adjustment processes:** Antwi and Henneberry (1995) [5] showed in their research that developers lag a response to price signals in the real estate market. They reason that market participants have become comfortable with the current situation and therefore the adaption process occurs rather slowly. This lagging process, leads to oversupply in the market, which amplify cyclical fluctuations. Such adjustment processes are early signals to investors and only experienced enough developers react to them.

2.4 Property Market Forecasting

As shown in section 2.3.3 there is a long tradition of property market forecasting. The need for researchers using data sets to create models and forecast conditions has grown in academics as well as the private sector, where the job data scientist is becoming increasingly popular. Armstrong (1985) indicates in his book, that even though times have become increasingly turbulent, our forecasting models have suffered. [6] Often forecasting is confused with long term planning by organizational leaders. [6] However, the purpose of predicting in case of the property cycle is to provide a specific market view, where people in a company can act in advance and shield the company against these consequences. [6] The following section will give an introduction into property market forecasting starting with different forecasting categories from the literature and introducing our own view on such classifications. Further, we will show the different issues with the two main forecasting paths, qualitative and quantitative forecasting. In the next subsection, we will present variables and indicators used in forecasting models. We will group these into long-run and short-run factors. Along these groupings we will provide specific research studies from the literature and create an extensive survey among the most important forecasting variables and techniques. Finally, we will show accuracy mechanisms used by academic researchers to validate property forecasting models.

2.4.1 Forecasting Categories

Caminiti (2004) [34] considers models as *"invaluable tools"*. In his view, a model can help to *"...develop a shared conceptual understanding of complex natural systems, allow testing of management scenarios, predict outcomes of high risk and high cost environmental manipulations, and set priorities."*[34] Indeed, modeling and forecasting has become, with the age of information technology, new impetus. We believe that, one of the main reasons is, that for well predicted results a significant amount of data is needed.

There are many different forecasting model methodologies. In this subsection, we will shed light on the different modeling categories, which have been presented by several authors.

The highest possible classification of forecasting models are *simple* versus *complex* models. In academics there exists several understandings of these high level categories. [104] One of the most interesting tests is presented by Zellner (2001). [173] To define if a model is simple or complex, he asks the actual user of the model if he understands it or not. [173] Furthermore, Zellner goes into a structured interview with the user and tries to find out if the user of the model has a full understanding of the forecast mechanics. He has summarized his questions in a survey, *Forecasting Simplicity Questionnaire* [50]. Zellner provides all his resources, which he uses publicly

[50] The full survey can be accessed via `http://www.kestencgreen.com/Questionnaire-Simplicity.pdf`.

on his website. [51]. Green and Armstrong (2015)[72] did a survey study on simple versus complex models and came to the conclusion that *"...complexity harms accuracy."*[72] Hence, as of them *"...complexity beyond the sophisticated simple, fails to improve accuracy..."*[72] It can be concluded, that simple models are much more efficient than unnecessary complexities in a forecasting model. Even though this high level perspective gives a rough understanding of a structural direction of models, many researchers have provided more granular specifications of property forecasting models.

As shown in chapter 2.3.3 property cycle research is now going on for around 100 years starting with Hoyt [92] in 1933. Barras (2009) [12] identified in his book three modeling approaches: *stock adjustment process*, *rent adjustment process* and *multi-equation modeling*. Below we will describe each of the modeling categories:

Stock adjustment process

As pointed out in subsection 2.3.3 capital stock is one of the main drivers in real estate, specifically the amplifier that changes the demand of occupation into investment. [12] Barras (2009) [12] states, that there are two factors in this model that are responsible for the cyclical swings. On the one hand there is a lag, which is caused by newly created buildings, which take time to get constructed, on the other hand there is the "*durability of built structures*", which means that once if a building is created, it satisfies a certain demand level.

Rent adjustment process

Barras (2009) [12] states that rent, occupancy and vacancy are large influencers in real estate projects. Occupier demand is driven by vacant building on the market. If the demand is settled then rents and prices increase, during a certain lag, developers start to become aware of the market signals and start new projects, followed by a decreasing demand. The oversupply of new space leads then to a downward spiral of rent and prices, which go to equilibrium. Barras (2009) [12] argues in his book an empirical rule of real estate markets that, *"...the higher the elasticity of occupier demand for space, the higher the equilibrium vacancy rate needs to be, because economic shocks will generate a greater change in turnover."* [12] On the other hand the higher the elasticity of the demand to occupy space, the higher the vacancy rate needs to be, because a property bubbles usually creates a large change in market turnover. [12] [149]

Multi-equation modeling

The last modeling category, as of Barras (2009) [12], are multi-equation models. These models are basically a combination of stock-adjustment and rental-adjustment models. The three core behavioral equations are *development supply*, *occupier demand* and *rental change*. [12] One of the main advantages of this model category is the modeling of the cyclical lags, which can occur

[51] An actual description can be found on `http://simple-forecasting.com/`. `http://www.kestencgreen.com/Questionnaire-Simplicity.pdf`

at any stage in the model and are able to *"...capture the disequilibrium behavior of property markets"*. [12] Barras (2009) [12] states that the factors that are responsible for this behavior are, the period of construction, capital stock delays and the interest rate. [12]

Brooks (2010) [27] takes a much higher level approach and groups models by their qualitative and statistical properties.

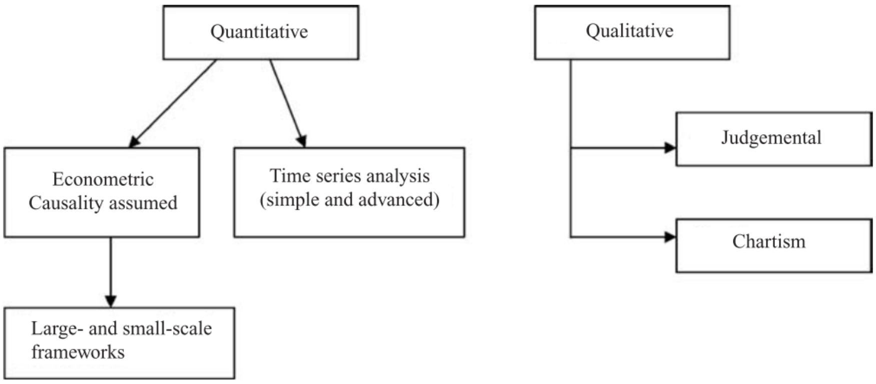

Figure 2.12: Categorization of forecasting models by Brooks (2010). [27]

Figure 2.12 shows Brooks (2010) [27] categorization. On the one hand he considers a quantitative modeling approach, using econometric and a large and small-scale framework or time series analysis techniques. On the other hand he splits up the modeling part into a qualitative approach, which can either be judgmental or charting.

Jadevicius (2014) [101] summarized several forecasting models from literature into one classification system.

In figure 2.13 he classifies models into formal and informal. Further he splits the quantitative into informal and quantitative part. Next he splits formal into a qualitative and quantitative section. Finally, Jadevicius (2014) [101] stops at the methodological level and groups each method into multivariate and univariate.

Taken the above classifications as   Figure 2.14 shows our view on forecasting categories. As the previous categorizations, were mostly driven by the classification of methodology, we suggest a much more holistic view on forecasting and leaving the method level aside. However, it also takes important parts of the previous organization approaches from above into account. [101] [27] [12] Our view is that the there are mainly two different categories in which forecasting can fall, **qualitative** and **quantitative** forecasting. Qualitative forecasting is mainly characterized by experts opinion, which includes for example, industry consultancies and specific reports and technical analysis, using specific charting methods to gain more insights about a time series. On the other hand there is quantitative forecasting, which includes *economically focused methods*

[52] All approaches from section 2.4.1 have been taken into account. See Jadevicius (2014) [101], Brooks (2010) [27] and Barras (2009) [12].

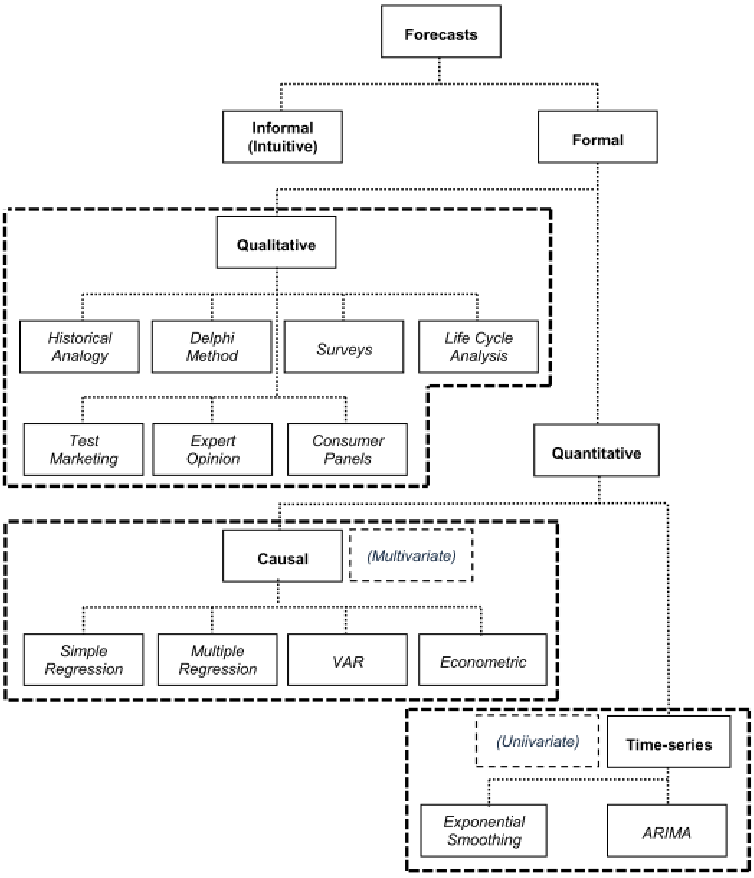

Figure 2.13: Categorization as of Jadevicius (2014). [101]

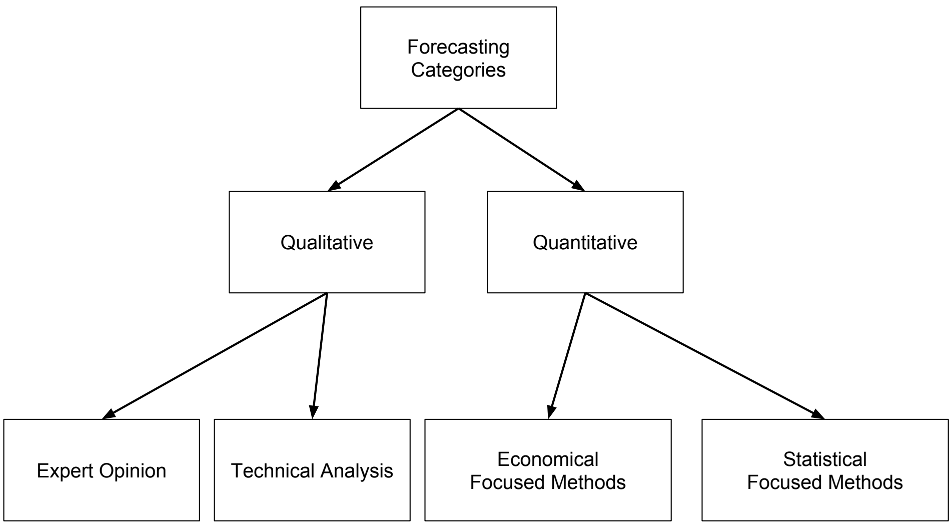

Figure 2.14: Categorization of forecasting approaches.[52]

and *statistically focused methods*. All above shown categorizations go into a method level, when broken down further. [101] [27] [12] However, our view is that actual methods used at the moment approach forecasting from either a higher level perspective or a lower, more methodological, perspective, such as forecasting a certain market index. [102] Each perspective is either more statically focused or economically driven. In reviewing the literature, we examined that the use of new data sources and in general more data has led researchers towards using more statistical approaches rather than looking from the *"30.000 feet view"*. Furthermore, as the method level will advance, our classification can also be used by future researchers using more sophisticated methods.

2.4.2 Issues with qualitative or quantitative forecasting

There are two categories to approach forecasting. On the one hand you can do *quantitative* forecasting and on the other hand you can forecast *qualitatively*. Quantitative forecasting can be defined as:

Definition 2.8. *Quantitative forecasting uses statistical modeling techniques to forecast a future view.*

On the other hand qualitative forecasting can be defined as the following.

Definition 2.9. *Qualitative forecasting uses an industry expert's opinion or reports to gain a glimpse of probable future events.*

As well as the qualitative as the quantitative approach has its disadvantages.
The following list will show issues with qualitative forecasting:

1. **Experts may overvalue real market impacts:** Brooks (2010) [27] states that using judgmental forecasting, a rapidly changing market or insignificant market signals can be seen as exaggeration of market behavior.

2. **Double Counting:** Brooks (2010). [27] argues that experts use similar variables more than once, even though the information is already inside their intuitive forecast. For example, productivity might be on the one hand shown by low economic output, on the other hand also included in the GDP of a country. [27] p. 445

3. **Opinionated:** Experts may be influenced by some sources, and therefore do not have the open mind that is needed to fully understand a situation. [27]

4. **Careless:** Experts have to weight certain events by their experience and determine the impact on the market. Brooks (2010) [27] states that it is often the case, that the information that is available in the market is not efficiently used.

5. **Historic data:** An experts opinion is highly dependent on his past experience. Hence, the expert's age and industry experience play an important role in regards to their credibility. [27]

6. **Overconfidence:** Brooks (2010). [27] states that, in order to forecast real estate market activity, experts often use besides their past experience also different information sources to strengthen their view. However, it is often the case, that experts have overconfidence in their opinion and assume that they have complete information.

The following list will show problems with quantitative forecasting:

1. **Historic data:** When basing a predictive model on historic data, the output may reflect past events, but does not imply new crisis conditions. Hence it is extremely important to have a representative data sample.

2. **Model selection:** Finding the optimal model is more of an art, than an actual science. Often forecasters use models that are based on their peers research.

3. **Representation of non-numeric factors:** Representing a representative factor for *"market mood"* in a quantitative model is extremely hard, if not impossible. Hence, not all variables can be represented by a numeric factor and have to be substituted by others.

4. **Quality data:** A predictive forecast is highly dependent on its underlying data. As this is also a problem during this research project, see section 4 for further information.

5. **Data Quantity:** Compared to other data collections, many real estate are under-supplied with data, because real estate data collection for many countries only started in the end of the last century. For example, in Austria collecting representative data started in the late 80s. [53]

2.4.3 Variables and Indicators

To create a proper forecast we focus on three types of indicators:

Definition 2.10. Leading: A leading indicator has the ability to indicate the future of an event.

Definition 2.11. Coincidental: The coincidental indicator occurs at the same time, when the actual event is happening.

Definition 2.12. Lagging: A lagging indicator shows that an actual event has happened. Its ability is to actually confirm that the happened.

In table 2.4 a list of indicator classified variables can be seen.

[53] See oenb.at, "Residential property index" of the Austrian National Bank - `http://www.oenb.at/en/Statistics/Standardized-Tables/Prices--Competitiveness/Sectoral-Price-Development/residential-property-price-index.html`.

Indicator	Source	Type
Dividend Yield	Brooks, Tsolacos and Lee (2000) [28]	Leading
Short-term interest rates	Brooks, Tsolacos and Lee (2000) [28]	Leading
slope of the yield curve	Brooks, Tsolacos and Lee (2000) [28]	Leading
interest rate spread(difference between the long-term and short-term interest rate)	Brooks, Tsolacos and Lee (2000) [28]	Leading
Property Rents	Brooks, Tsolacos and Lee (2000) [28]	Leading
property yields	Brooks, Tsolacos and Lee (2000) [28]	Leading
GDP	Brooks, Tsolacos and Lee (2000) [28]	Lagging
varEmployment and money supply	Brooks, Tsolacos and Lee (2000) [28]	Leading
the three month Treasury Bill rate (TBIL)	Brooks, Tsolacos and Lee (2000) [28]	Leading
the yield on 20-year gilts (GY20)	Brooks, Tsolacos and Lee (2000) [28]	Leading
narrow money supply (M0)	Brooks, Tsolacos and Lee (2000) [28]	Leading
broad money supply (M4) and the price on the FTSE 100 share index (SP100)	Brooks, Tsolacos and Lee (2000) [28]	Leading
car registrations (CAR)	Brooks, Tsolacos and Lee (2000) [28]	Leading
volume of retail sales (RS) and jobs vacancies (JOBV).	Brooks, Tsolacos and Lee (2000) [28]	Leading
Space market index	Cowley (2007) [43]	Leading
exports/import	Cowley (2007) [43]	Leading
metropolitan area leading economic index	Cowley (2007) [43]	Leading

Indicator	Source	Type
job advertisements	Cowley (2007) [43]	Leading
the yield curve	Cowley (2007) [43]	Leading
trade internationally currency exchange	Cowley (2007) [43]	Leading
house starts	Cowley (2007) [43]	Leading
average weekly	Cowley (2007) [43]	Leading
hours in manufacturing	Cowley (2007) [43]	Leading
construction costs	Cowley (2007) [43]	Leading
construction activity	Cowley (2007) [43]	Leading
Gilt yields	Kyrstaloyianni, Matysiak and Tsolacos (2004) [119]	Leading
Car registrations	Kyrstaloyianni, Matysiak and Tsolacos (2004) [119]	Leading
Net lending to consumers	Kyrstaloyianni, Matysiak and Tsolacos (2004) [119]	Leading
Export orders	Kyrstaloyianni, Matysiak and Tsolacos (2004) [119]	Leading
Volume of expected output	Kyrstaloyianni, Matysiak and Tsolacos (2004) [119]	Leading
Financial Surplus Deficit	Kyrstaloyianni, Matysiak and Tsolacos (2004) [119]	Leading
Consumer confidence	Kyrstaloyianni, Matysiak and Tsolacos (2004) [119]	Leading
Stock of finished goods	Kyrstaloyianni, Matysiak and Tsolacos (2004) [119]	Leading
Real money supply	Kyrstaloyianni, Matysiak and Tsolacos (2004) [119]	Leading

Indicator	Source	Type
Changes in inventories	Kyrstaloyianni, Matysiak and Tsolacos (2004) [119]	Leading
Consumer credit	Kyrstaloyianni, Matysiak and Tsolacos (2004) [119]	Leading
Personal disposable income	Kyrstaloyianni, Matysiak and Tsolacos (2004) [119]	Leading
Industrial production	Kyrstaloyianni, Matysiak and Tsolacos (2004) [119]	Leading
Unit labour costs	Kyrstaloyianni, Matysiak and Tsolacos (2004) [119]	Leading
Gross trading profits	Kyrstaloyianni, Matysiak and Tsolacos (2004) [119]	Leading
House building starts	Kyrstaloyianni, Matysiak and Tsolacos (2004) [119]	Leading
Yield curve	Kyrstaloyianni, Matysiak and Tsolacos (2004) [119]	Leading
Manufacturing investment	Kyrstaloyianni, Matysiak and Tsolacos (2004) [119]	Leading
Real money supply	Kyrstaloyianni, Matysiak and Tsolacos (2004) [119]	Leading
Press recruitment ads.	Kyrstaloyianni, Matysiak and Tsolacos (2004) [119]	Leading
Private to total credit	Kyrstaloyianni, Matysiak and Tsolacos (2004) [119]	Leading

Indicator	**Source**	**Type**
New orders in manufacturing	Kyrstaloyianni, Matysiak and Tsolacos (2004) [119]	Leading
FT All Share price Index	Kyrstaloyianni, Matysiak and Tsolacos (2004) [119]	Leading
Manufacturing employment	Kyrstaloyianni, Matysiak and Tsolacos (2004) [119]	Leading
Retail sales	Kyrstaloyianni, Matysiak and Tsolacos (2004) [119]	Leading
Sales Volume	Miller and Sklarz (1986) [131]	Leading
Percentage of Listings Sold	Miller and Sklarz (1986) [131]	Leading
Mean Time on Market	Miller and Sklarz (1986) [131]	Leading
Mean Percentage of LIsting Price Received	Miller and Sklarz (1986) [131]	Leading
Months Remaining of Inventory	Miller and Sklarz (1986) [131]	Leading

Table 2.4: Leading, Lagging and Coincidental Indicators from the literature.

Most of the indicators presented in table 2.4 are leading indicators. The reason for this is, that the research problem of looking into the future is still the most interesting one. Hence, scientists have focused on this much more, compared to the other indicator types. We use table 2.4 as a reference point in the variable selection section 4.2.

2.4.4 Accuracy Measurements

Today exist a variety of toolboxes and techniques to create a forecasting model. Even though researchers have with this new possibilities, undiscovered opportunities at their hand, the accuracy of the final model has to be measured. Jadevicius (2014) [101] points out that in property cycle research, there still remains a difference between the actual model output and how the property market behaves. Hence, it is extremely important to look at a property forecasting model from different sites, to show its *precision* and *trueness*. The following section, will first show the definition of accuracy and then give a short introduction of the used accuracy measures. A much more detailed overview can be found in section 5.3.

Accuracy can be defined as of *ISO 5725-1:1994*[54]. The following definition describes accuracy.

Definition 2.13. *The closeness of agreement between a test result and the accepted reference value.*[54] *Accuracy consists of trueness and precision. "Trueness" refers to the closeness of agreement between the arithmetic mean of a large number of test results and the true or accepted reference value. "Precision" refers to the closeness of agreement between test results.* [55]

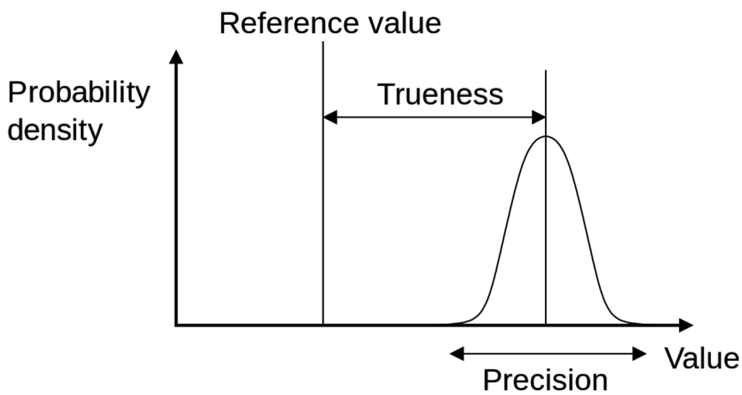

Figure 2.15: Typical measurement to assess forecasting accuracy of a predictive model.[56]

Figure 2.15 shows a graphical representation of the accuracy definition. As it can be seen, there is a reference value, that shows the real trueness and the precision of the forecast value. Once these two sub definitions align, the value can be shown as accurate or not.

As pointed out earlier, there are many different forecasting techniques. However, one might ask, how accurate are these techniques? Several error measuring methods have been created to give a hint on the accuracy of a prediction model.

Mean Forecast Error (MFE)

$$MFE = \frac{\sum_{i=1}^{n} e_i}{n} \tag{2.1}$$

$$e_i = A_t - F_t \tag{2.2}$$

[54] The full standard, can be found at `https://www.iso.org/obp/ui/#iso:std:iso:5725:-1:ed-1:v1:en`.

[55] See ISO 5725-1:1994(en) section 0.1.,`https://www.iso.org/obp/ui/#iso:std:11833:en` for the full definition and further information about trueness and precision.

[56] This picture was taken from `http://commons.wikimedia.org/wiki/File%3AAccuracy_and_precision.svg`.

The mean forecast error (MFE) measures the mean difference between A_t the actual value and F_t the forecasting value. Whereas n is the number of forecasting values. If $MFE > 0$ then the forecasting model has further potential in terms of accuracy on the other side, if $MFE < 0$ then the model might be over-fitted. If MFE is exactly 0 ($MFE = 0$) then, the predictive model is ideal.

Mean Absolute Error (MAE)

(2.3)
$$MAD = \frac{\sum_{i=1}^{n} |e_i|}{n}$$

The mean absolute deviation measures the absolute forecasting error of a predictive model. Hence, MAD extends the MFE, by precisely showing how much the forecast is inaccurate.

Coefficient of determination (R^2)

The coefficient of determination measures, how well a model fits its underlying data. R^2 is a standard method used in regression analysis to measure its accuracy.

(2.4)
$$R^2 = \left\{ \frac{\frac{1}{N} \times \sum[(x_i - \bar{x}) \times (y_i - \bar{y})]}{(\sigma_x \times \sigma_y)} \right\}^2$$

Equation 2.4 shows the coefficient of determination for a linear regression. N are the number of observations and x_i denotes the observations made for x and y_i denotes the observations made for y. Furthermore, $\bar{x}$ and $\bar{y}$ are the mean of x and y. σ_x and σ_y are the respective standard deviations of x and y.

The above shown accuracy measures only represent partly the actually used measures. Hence, for a detailed overview we refer to subsection 5.3.

2.5 Property Market Risk

This section, will focus on the risk side of the property market from a banking sector view. As shown in section 2.3.4, studying cycles in the real estate market provides on the one hand large advantages for investors. On the other hand, it also reveals potential risk in the markets. With the introduction of Basel 3 [57] in the year 2013[58], banks had to fulfill many new regulations, such as new capital requirements and intense monitoring standards. For many banks, commercial property loans are a viable part of their business model to generate profits. [7] In this section, we will first define the term *risk* and *portfolio management*. In a following subsection, we will show how real estate portfolio managers develop strategies to manage their portfolio. Furthermore, we will point out several aspects of the cycle as an investment medium. As risk management uses a lot of methodologies and tools, we will show how to measure risk and give a clear specification for risk management tools. Finally, as using cyclical research in a bank's portfolio department is not trivial, we will show a possible way to implement real estate cycle strategies.

2.5.1 Risk in the Property Market

Risk

The word risk comes from the Latin, *reseco*, and described the risk to get in danger on the sea. [7] The most popular definition is from Frank Knight (1921) [115], who wrote this characterization of risk in his famous book *Risk, Uncertainty, and Profit*.

Definition 2.14. *"...Uncertainty must be taken in a sense radically distinct from the familiar notion of Risk, from which it has never been properly separated.[...]The essential fact is that "risk" means in some cases a quantity susceptible of measurement, while at other times it is something distinctly not of this character; and there are far-reaching and crucial differences in the bearings of the phenomena depending on which of the two is really present and operating. It will appear that a measurable uncertainty, or "risk" proper, as we shall use the term, is so far different from an un-measurable one that it is not in effect an uncertainty at all."* [115]

Knights definition 2.14 of risk is based on the assumption of *"quantifiable uncertainty"* [46] He illustrates this concept by the example of two people drawing red and black balls from an urn. The first participant just draws randomly, thinking about a fair chance of outcome. In Knights eyes he is ignorant. The second participant thinks about the outcome and determines the correct probability, based on the number of total balls, for getting a red or a black ball. In Knights opinion, even though the first participant is exposed to the risk, he does not measure the risk correctly. The second participant is aware of the risk and also measures it correctly. [46] This quite general definition gives a feeling about risk and can be used as a first starting point, because it only

[57] For further information about base 3 please have a look at `http://www.bis.org/bcbs/basel3.htm`.

[58] There is a clear time schedule within the Basel Banking Committee of Supervision the Basel III phase-in arrangements - `http://www.bis.org/bcbs/basel3/basel3_phase_in_arrangements.pdf`.

includes the causal component of risk, which is uncertainty. [90] The definition of Knight has been revised by Holton (2004) [89]. He defines risk as:

Definition 2.15. *Risk requires both exposure and uncertainty.*

Holton [89] describes *uncertainty* as, *"...a state of not knowing whether a proposition is true or false."* [89] On the other site, Holton defines *exposure* as a component, if we see the value, to which the risk is exposed, as important or not. This implies the condition, that if we care about uncertainty, then we will find ways to prevent them. Exposure is taken as an assumption in our research and therefore, we stay at a more mathematical and widely more practically accepted definition:

Definition 2.16. *Risk is the value, that is different from the expected value.*

Risk Management

As indicated in the introduction of this section, risk management became an extremely popular topic since the financial market meltdown of 2007. [7] It enhances the theoretical definition of risk in 2.5.1 defining specific actions for *"managing"* risk. *ISO 31000:2009* states the following definition of risk management:

Definition 2.17. *Risk management provides principles, guidelines and a process for managing risk. It can be used by any organization regardless of its size, activity or sector. It can help organizations increase the likelihood of achieving objectives, improve the identification of opportunities and threats and effectively allocate and use resources for risk treatment.* [59]

Importance for banks

Today banks operate in a tight corset of regulations and requirements. [60]Since the financial meltdown of 2008 monitoring of a countries banking sector has tightened even more. With the current implementation of the Basel 3 [61]framework higher capital requirements have to be fulfilled. The objectives of these regulations are often said to improve the stability of the sector by the following:

- Economic and systemic risk reduction, because banks play an extremely important role in our economy.
- Banks used for criminal purposes, for example money laundering.
- Through the crisis the trust in banks has dropped tremendously, regulations should bring back this trust in the sector.

[59] See iso.org, 31.May.2015, "ISO 31000 - Risk management", `http://www.iso.org/iso/home/standards/iso31000.htm` for further information.

[60] For further information see 57.

[61] For further information see 57.

- Credit portfolio management becomes more efficient, because banks have more data, in which sectors they are good at and in which not.
- Knowing the customer's risk, banking products are more fairly priced, which leads to treating customers adequately.

However, one might argue that the over-regulation of the banking sector might lead to much larger *regulatory* made risk factors. Hence, in our data driven society the trend of modern banking goes to the quantification of data to get a clear view on the current financial situation. In modern Banks risk management departments provide these kinds of tools. Taken the regulatory requirements into consideration, we can conclude that risk management has become an extremely important field in the banking sector.

2.5.2 Real Estate Portfolio Management

Banks often have more than one real estate project that is financed at the same time. Usually a whole portfolio of real estate loans consist of different use types and has a variety of *qualitative* factors. There exist several different views on portfolio management, often depending on the researcher. [14] [169] To sum up all these somewhat different definitions, *portfolio management* is defined as:

Definition 2.18. *Managing real estate projects or properties and reducing risk in terms of reward gains through looking at all assets from a high level perspective. Portfolio Management should also provide leading cooperate stakeholders a basis for further strategic decisions.*

Portfolio management can be summarized as, *"...take a big-picture view and manage the risk of the portfolio in its entirety."* [23]

2.5.2.1 Portfolio Strategy Development

Baum (2009), compared portfolio management to developing a business plan. [14] In his book, *"Commercial Real Estate Investment"* [14] he outlines a clear process for developing a portfolio and further strategies:

1. **Define and outline portfolio objectives:** Buying and selling assets brings new risk into a bank or development firm. Furthermore, objectives should be defined, which give a rough outline of a strategy. In the next step, also clear measurements should be defined, to assess if the assets in the portfolio are good or not. [14]
2. **Portfolio analysis:** In a portfolio analysis the predefined objectives are checked with the actual real estate portfolio. Strengths, weaknesses, opportunities and threats (SWOT analysis) are listed up and aligned with the portfolio objectives. [14]

3. **Strategic statement:** This is a general plan of a portfolio. It includes the "how" and "when", the overall goals will be reached. [14]

4. **Performance reviews:** In the strategic statement performance review dates are considered. During such a review the current state of the portfolio is assessed. Possible benchmarks are competitor performance, market index or clearly stated portfolio objectives. It depends on the craft of the portfolio manager, which next strategic steps he wants to take, to align the portfolio with its objectives. [14]

2.5.3 Risk Analysis

There are various forms of risks when doing a real estate investment. Analyzing each risk aspect will benefit future strategic decisions. Goddard and Marcum (2013) [66] point out several risk aspects, which should be considered before investing into real estate:

Business Risk

Business risk can be seen on the balance sheet of a property investment. Hence, it is highly dependent to the cyclical fluctuations, which occur in our economy. For example, investing only into one area, the risk of business is that prices in this region may drop and the whole portfolio gets devaluated. [66]

Management Risk

Portfolio managers or single property investors rely on their experience to successfully run a property investment. Hence, if the manager is quite new to this field lots of fine mechanisms between the market stakeholders may not be clear to him. Therefore, it is best practice in many companies, before managing large real estate investments inexperienced managers get an extensive practical experience and support from their more experienced peers. Furthermore, in times when bonus systems are quite popular, there may be a conflict of interest for a manager and the proper risk handling of his portfolio. [66]

Liquidity Risk

In running a real estate project, lots of money is needed beforehand, for example for buying a property or improving its state. Developers are faced with money claims from all sides, such as banks, who wants their borrowed loan back or the tenants, who should pay their installments. If a property developer runs out of liquidity, he has to sell the property too early, which results in a loss or even bankruptcy. On the other hand, banks are also aware of the risk that their counter-party cannot stay solvent to finance its loan. Hence, a strategic plan should be made in the beginning of each property project. [66]

Legislative Risk
A changing law in a country can mean that property prices rise or even fall. Furthermore, some countries go even that far, that they expropriate property holders. The political stability of a government and the ruling, plays an extremely important role in evaluating the location to invest in property beforehand. [66]

Interest Rate Risk
Interest rates are a large economic influence in our economy. They usually come into play, when financing a property project. It can be generally said that when interest rates rise, property developers pay more for their loan, hence they have to rearrange their costs in a property investment, if they still want to have a stable return of investment, when interest rates were low. [66]

Environmental Risk
Earthquakes, floats and fire damage are all risk factors, which a property can potentially face. However, today there are special reports about the dangers in an area where managers can inform themselves about, before they invest. In Austria for example, one can have a look at `http://www.hora.gv.at/` to get further information if the area is vulnerable to distasters or not. [66]

Financial Risk
Financing a property on debt can only work if the investor can sell the property later at a higher price. However, if this plan does not work, because property prices changed in another direction in the meantime, the investor faces large financial risk. As of Goddard and Marcum (2013) [66], financial risk is concerned with the amount of leverage for a property one can make. [66] This type of risk is often associated with developers, who finance projects. However, much more seldom also banks can run into this issue.

2.5.3.1 Methods for measuring risk

Quantifying risk has several challenges. In the first step it should be decided, which risk should be quantified. Secondly, the right method has to be chosen to quantify risk. Goddard and Marcum (2013) [66] point out that stress testing and due diligence analysis the two most common methods.

Stress-testing
As indicated in the thesis introduction the portfolio risk simulation framework will incooperate three different scenarios, a base case, a best case and a worst case scenario for each project in a property portfolio. This will show the manager, how the property will perform under which potential future view. Basel 3 [42] demonstrates the importance of such a framework, which should

be used in a bank. Even though measuring the property cycle is not mandatory for financial institutions, Basel 3 points out the importance of stress testing extensively:

"...bank must have in place sound stress testing processes for use in the assessment of capital adequacy. Stress testing must involve identifying possible events or future changes in economic conditions that could have unfavorable effects on a bank's credit exposures and assessment of the bank's ability to withstand such changes." [42]

Some reasons for this are that stress-testing overcomes limitations of historical data analysis, by assuming different scenarios, supports communication through the organization and helps to develop risk mitigation plans and policies. [42] Under stress-testing a certain value is used and scenarios are defined, where the tester thinks, that the value might move. Often these scenarios cover a wide range of possible futures. In the next step the parameters are changed, as defined by the scenarios and the stressed values results are observed.

Due Diligence Analysis

The second risk measuring method is the due diligence analysis. Goddard and Marcum (2013)[66] define due diligence analysis as *"...the process of discovering information needed to assess whether an investment risk is suitable given the objectives of the investor and the lender."* [66] In fact, every aspect of an investment is screened. In terms of property investment this includes, financial documents, such as tenancy lists, buying or selling price, property valuation, the property's title and further market documents. Goddard and Marcum (2013)[66] state, that it is also quite possible before conducting a transaction, that the seller party has to fill out a survey regarding physical property risk. After checking the financial transactions, each party will have a clear view about its counter-party and can decide fact based, if they want to do the deal or not.

2.5.4 Risk Management Tools

Effective risk management tools benefit internal decision processes, but also auditors and public authorities. The advantages of risk management systems can be divided into internal and external benefits:

Internal Benefits

There are several internal benefits of risk management systems, starting with historic information. Besides having systems to analyze and quantify market data, there also have to be databases to store this data. Hence, risk management systems improve the company's infrastructure in general. When having more information, available risk managers can gain deeper market knowledge. Furthermore, best practices, documentation and knowledge is shared within the department, which spreads in the culture of a bank.

External Benefits
Authorities and regulators demand that risk management systems have to be included into a banks operation. Measuring the property cycle brings banks a step further to fully understand the risk of their portfolio. As banks have quite a bad reputation nowadays, investors seek confidence, a save investment and prove of a bank's strategic decisions. By basing their decisions on extensive real estate market research, banks are more appealing to cautious investors and thereby indirectly profit from the external benefit.

2.5.4.1 Risk Management Tools Specification

Before creating our simulation engine, we will specify our need through a requirement analysis:

- **User friendly Interface:** Users should easily access the tool through an intuitive and structured Graphical User Interface (GUI).
- **Decision-making process:** The concept of the tool should be easily integrated into existing company processes and other systems.
- **Prototyping:** The simulation engine should be created on a platform, that is on one hand available to the risk managers and on the other hand easy for them to install or integrate.
- **Performance:** As portfolio information is often time critical, for example a large transaction has to be valuated. The application should perform really well also with large data sets.
- **Measurements:** The main advantage of the tool should be to have a clear overview on project basis for the predicted risk in the cycle. Hence, all shown measurement should be clearly selected and of great interest to the risk manager.

We outline the tools mock-ups in section 3.6.1 and a full implementation can be seen in section 5.4.

2.5.5 Strategic Consideration and Implementation for Analysts

In giving portfolio managers the right risk assessment tools to estimate cyclical risk on their portfolio, this information can be used further in the strategic planning and property selection process. As Pyhrrn, Roulac and Born (1999) [141] stated, property cycle and especially its predictability is a key subject real estate stakeholders are interested in. This subsection will show either the strategic implications for the investment side, which include for example developers and REITs [62] and risk managers, such as in banks. However, these two views can also be used in one entity interchangeable.

[62] REITs are real estate investment trusts. These are large real estate funds, which manage an extensive property amount.

2.5.5.1 Strategic Implications for Investors

As stated in section 2.2.4 the basic cyclical assumption, which is interesting to property market stakeholders, is to buy when the real estate cycle has its lowest point and sell at the peak of the cycle. Hence, the investor's ROI[63] will be the price difference he earns between the lowest and the highest point in the cycle. As Pyhrrn, Roulac and Born (1999)[141] explained, the cyclical impact of the performance of real estate is very dramatic to an investor and can be one determining factor from the beginning of an investment. Factors such as the acquisition and disposition of property and the time frame a property should stay in the portfolio are highly dependent on the market the investor is operating in. [141] Many investors act through their long market experience. Intuitively they believe to know, when the property cycle might be down and when it might be up. However, even though the gut feeling approach might help small investors, which often phase, because of their portfolio size, smaller risk, large investors need to quantify their assumptions, show market reports and justify their decision in front of higher-level management positions, on the question WHY they want to do a certain investment. Pyhrrn, Roulac and Born (1999)[141] point out, that it is also very important in which part of the cycle an investor is. Depending if the price of the property is on its peak, an investor might wait or buy if the price reaches the cycle's valley. However, if the price is on the way up, the investor might decide to still buy the property, but change the lease structure, capital spending plan or operating policy. [141] Hence, one might conclude that for every state in the cycle investors can find an optimal strategy to steer their portfolio through it. It may be argued, that nowadays many investors still follow the herd, do not identify the rise and the fall of trends and often start new investments out of a feeling. Quantifying the risk in which their portfolio is, can help them to understand the current state and to develop an optimal strategy for their portfolio.

2.5.5.2 Strategic Implications for Portfolio Managers

Portfolio managers operate in a tight corset of rules and regulations within their portfolio. However, as investors their goal is to generate the highest possible returns for their assets. Hence, they definitely should adapt and understand the same concepts and viewpoints that go for investors. [141] Pyhrrn, Roulac and Born (1999) [141] point out several important strategic implication, which go for real estate portfolio managers:

- **New criteria for portfolio diversification:** Including the cyclical component of the property market in their portfolio, can lead to new strategies to earn higher returns by using lower risk.

- **Future orientation:** As property market data is extremely sparse and very expensive, portfolio managers use their internal data sources to optimize and structure their portfolio.

[63]ROI is Return of investment.

However, this data only includes historic events and is not very useful to take future decisions. The knowledge of the property cycle, helps a portfolio manager to plan for future events.

- **More sophisticated forecasting techniques and data:** In cyclical research there are many different models used to predict the portfolio cycle. [64] Hence, portfolio managers will have to create several property cycle models, to gain a better understanding on the market. This "forced" model creation helps portfolio managers to better understand the risk in the market.
- **More time and deeper research:** Property cycle research is just one component and often the beginning to understand market behavior. However, if considering the property cycle component important in portfolio research, managers will naturally start to ask further questions. Hence more time and research is needed to answer these, which should result into better strategies and a deeper market understanding.

2.5.5.3 Implementing Real Estate Cycle Strategies: Organizational Considerations

Using knowledge of real estate in creating a strategy has also implications on the behavior of portfolio managers and its organization. For example, one problem is that the property cycle is forward looking and besides looking at the herd behavior of a current market, many investment decisions can be counter-intuitive. Pyhrrn, Roulac and Born (1999) [141] point out that there are three important themes, which need to be considered before using cyclical research in an organization such as *Detachment*, *Persuasion* and *Flexibility*. [141] These three themes can be seen as process to in-cooperate property cycle research. A portfolio manager should be **detached** to his decision, and look from a high level perspective at it. After marking a clear decision about the investment the portfolio manager needs to **persuade** other authorities in his company. It is very important that the concept of the property cycle is clear within the whole organization. Furthermore, a certain resource allocation strategy should be outlined during this step. Finally, when implementing the strategy, **flexibility** in terms of resource allocation is needed. Therefore, if the cyclical predictions change the portfolio manager needs to react and adapt. The biggest advantage of using cyclical research within an organization is, that all strategies have a clear and understandable foundational view on the real estate market.

[64] For further information see section 2.4.

2.6 Summary

Chapter 2 examines the used literature in this thesis. The following sections are part of this chapter, Cyclical Theory 2.1, Real Estate Economy 2.2, Property Cycles 2.3, Property Market Forecasting 2.4 and the risk in real estate markets 2.5.

Section 2.1 we show a definition of a cycle, the anatomy of a cycle and present a general taxonomy, which is abstracted from a sine wave. [65] Further we show the different cyclical phases and other economic waves. [66] In the next subsection we show two important cycles that are closely related to the property cycle, the *business* and *credit cycle*. As these two cycles also suffer from fluctuations we point down these factors in subsection 2.1.4.2, where we show 3 different economic theories, which have a different view on cyclical developments.

In section 2.2 we define the term *real estate market*. Furthermore, we show how the Austrian real estate market is managed and where the most important information is stored. In subsection 2.2.2 we show a general real estate economy model from the view of banks and developers. [67] Figure 2.8 shows the investment phases of project development between banks and real estate developers.

In section 2.3 the property cycle is defined and explains its effects to the economy, banks and property developers. Furthermore, figure 2.11 shows the four cyclical phases and its effects to the banking and property development sector. In subsection 2.3.2 we examine the efficient market hypothesis with its three forms and suggest that the real estate market is *semi-weak efficient*. The following subsection gives an overview on property cycle research starting with Hoyt (1933) [92]. Finally, we conclude this section by pointing out the investor's interest in the property cycle, showing the specific motivations of banks and property development firms.

Section 2.4 examines the forecasting part of property cycles. First we show the literature in classifying property forecasting models and then propose our own categorization of predictive real estate market models. [68] As the two main categories are quantitative versus qualitative forecasting, we point out the issues with each forecasting category. Subsection 2.4.3 gives and overview on the used variables, which are divided into leading and lagging indicators. Table 2.4 gives an overview of relevant forecasting studies, with a classification of their indicators. Finally, we present accuracy methods, which are widely used in the literature.

[65] See figure 2.2.
[66] See table 2.1.
[67] See figure 2.6.
[68] See figure 2.14.

Section 2.5 examines property cycle risk and focuses on the simulation and risk perspective of the second part of our research, the simulation engine. In the first sections we define *risk*, *risk management* and *portfolio management*. Furthermore, we point out the different risk factors in the real estate market and show risk analysis methods, such as stress-testing and due diligence analysis. Furthermore, we examine internal and external benefits of risk management for banks and lay out specific requirements for risk management tools. As there are a lot of strategic considerations before using property cycle research, we show the importance to use such research in a company for the *investment* and for the *portfolio management* side. Finally, we point out organizational considerations to successfully implement steering over the property cycle in an institution.

Chapter 3

Methodology and Research Design

The following chapter describes the used methodology and the research design of our project. Miller and Sklarz (2012) [130] hit the nail on the head by pointing out that, *"Housing market analysis and the forecasting of prices is both an art and a science. The art comes from good economic theory and from the selection and integration of variables that capture the behavior component of the market. The science comes from using appropriate statistical modeling approaches."* [130] As shown in the previous chapter, housing market analysis can be approached from a lot of different angles. Hence, we start this chapter by examining an abstract framework of the used research method 3.1. Next, we will show the tools and challenges 3.2, which makes real estate market analysis an actual *art*. The *science*, which we apply is outlined in the forecasting technique section 3.4 and the challenges, which we faced are examined in 3.3. We employ exponential smoothing 3.4.1, simple and multiple regression modeling 3.4.2, vector-auto regression 5.2.4 and ARIMA modeling 3.4.4. To validate the used techniques we evaluate our methods by accuracy measures, which are shown in section 3.5. Finally, we describe the property simulator engine 3.6, which is constructed by the inputs from literature research and by interviews with professionals.

3.1 Research Method

Deciding on the method of research is crucial for defining our objectives as well as the output we can expect. Therefore we will present here on the one hand a general framework, which will describe our research method and on the other hand show our specific research methodology and the built design artifacts.

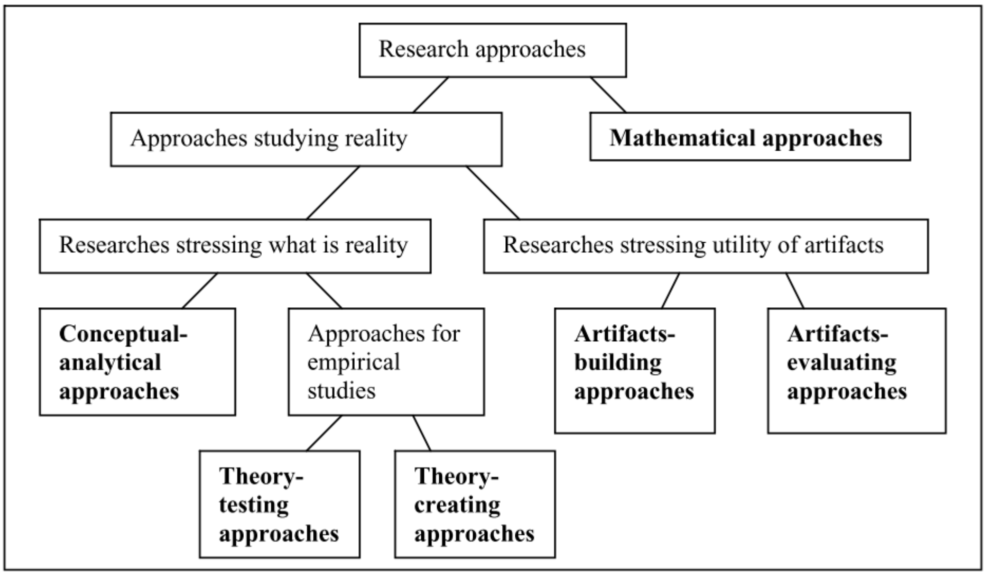

Figure 3.1: Järvinen's research methods taxonomy. [105]

Figure 3.1 shows Järvinen (2000) [105] taxonomy of research approaches. He starts with two different categories, on the one hand a mathematical approach and on the other hand a *"reality based"* approach. As we will try to stress reality, we will focus on a *conceptual analytics approach*.

Figure 3.2 shows a high level overview of our used research methodology, which is linked to the produced design artifact. Note that our research approach is iterative and the output of each step influences later process steps. In the first step we start with *designing* our process. Design involves the *Conceptual Model* and *Experimental Design*, which proves the chosen methodology. During this step we define the used property cycle forecasting methods, the measurement of the cycle and an evaluation scheme to test the validity of our results. Next, we conduct an extensive literature survey, which lead us into other research fields such as time series analysis, economic- and cyclical modeling, applied economics or forecasting, interviewing industry experts and to test various forecasting methods beforehand. Furthermore, we also investigate potential sources of economic time series data for Austria, which can be used together with our forecasting terminology. Finally, we come up with a mechanism to test the accuracy of the used approach, by defining an evaluation scheme. The selection and design of the input data and the output evaluation of the model is influenced by a deep literature analysis and domain knowledge, which is linked to experts. In the next phase, we implement the forecasting model and the simulation engine. Through this phase, our research methodology is *implementation* and *development driven*. The output of this phase is an understanding of the behavior of the future property cycle and a simulation engine, that can be used by bankers or developers, who are in the real estate market to make decisions, which are based on the cyclical phase they are currently operating in. Finally,

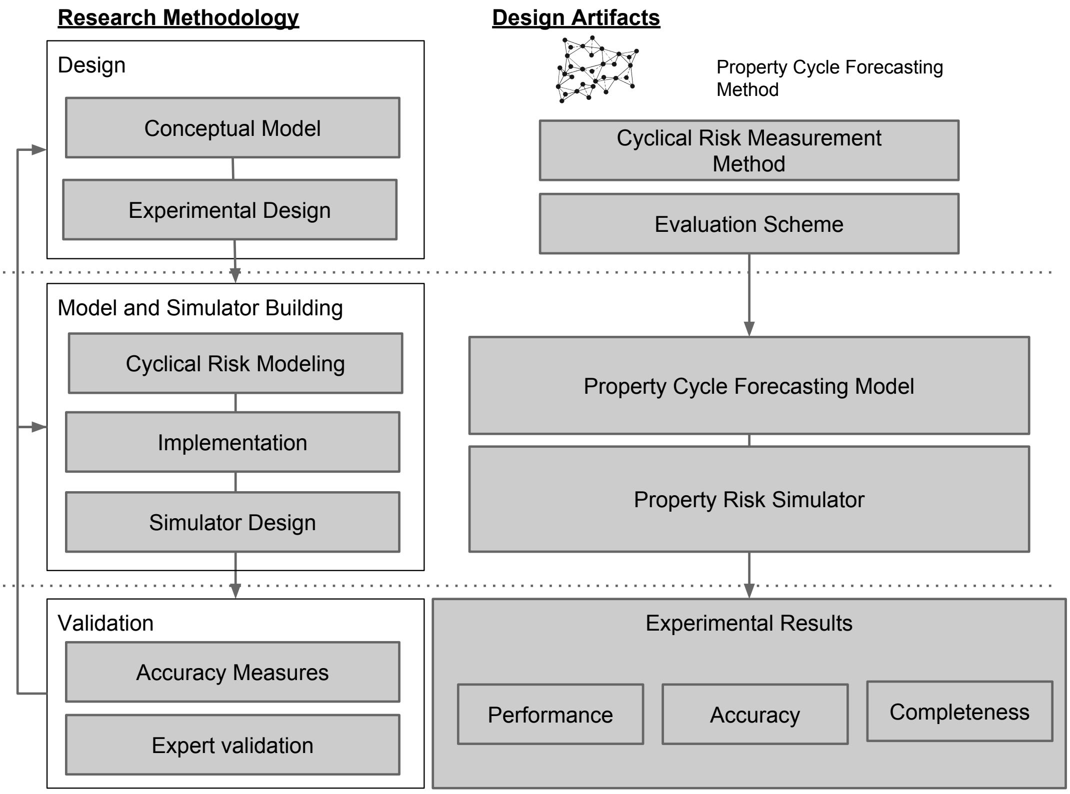

Figure 3.2: Research method linked to design artifacts.

we validate our the model and assess the usefulness of the simulator by expert judgment and standard statistical accuracy measures. On the design side, we will judge our experimental results by its *performance*, *accuracy* and *completeness*.

3.2 Research Process and Tools

Within our high level overview of the used research method in figure 3.2, we break down the specific model building process into 4 separate steps as shown in figure 3.3. We process through the following steps:

1. **Data collection and preparation:** During this step, we determine important leading variables from the literature, identify potential data sources, for example ERIX from CBRE [1], and prepare each data set for further processing, by either adjusting the time-span or cleaning it up for not-available values.

[1]Erix is a payed global research application for real estate professionals, which can be accessed via `http://erixlogin.cbre.eu/`. Further information about potential data sources can be found in subsection 4.1.2.

2. **Pre-Analysis in R and Excel:** After collecting potential time series, we use several techniques to select a sub-sample, which will be used in the modeling process. Besides experts judgment and literature research, we employ several statistical methods of *variable selection*. A clear break up of the used methods can be found in subsection 4.2.

3. **Model creation and evaluation in R:** In the third step, we use several modeling techniques to forecast the cyclical swings in the dependent time series variable. All used methods are employed by other researchers within the field of cyclical research and extended via ideas and best-practices from the field of statistical modeling and prediction.

4. **Results processing in R and Excel:** During our research we use R for performance expensive calculations. Even though there are a lot of packages, which can for example create beautiful graphs, we try to stay if possible with the R *base* package. In contrast excel also provides a wide toolbox to process the csv outputs from R. We use both tools to show our final results in chapter 5.

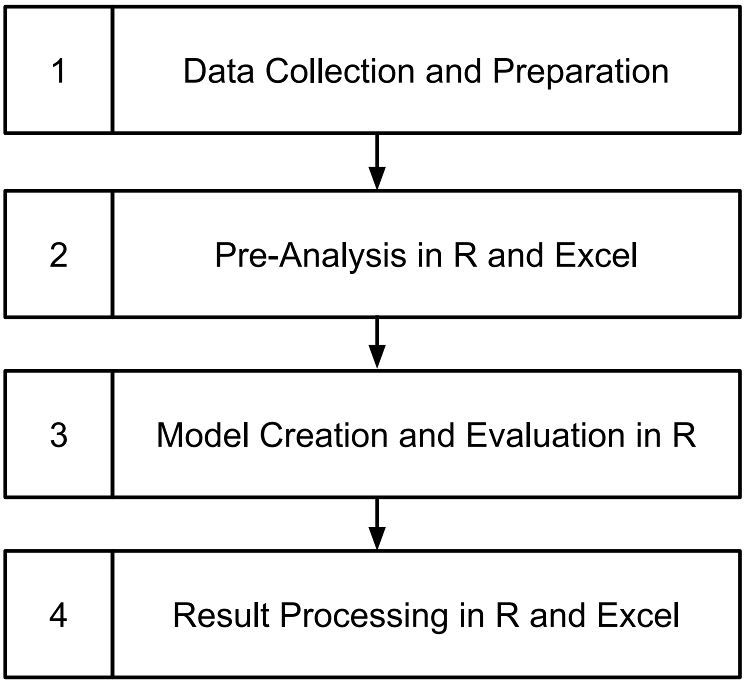

Figure 3.3: Research steps and modeling tools for the forecasting model.

In the first part of our research process, we show the creation of the forecasting model. In figure 3.4 we expand the modeling part by our simulation engine, which is the second step in our research project as pointed out in 3.1.

5. **Requirement Analysis of Simulator:** After obtaining the modeling results, we will focus on the Simulator, which uses a discounted cash flow analysis model to incooperate the

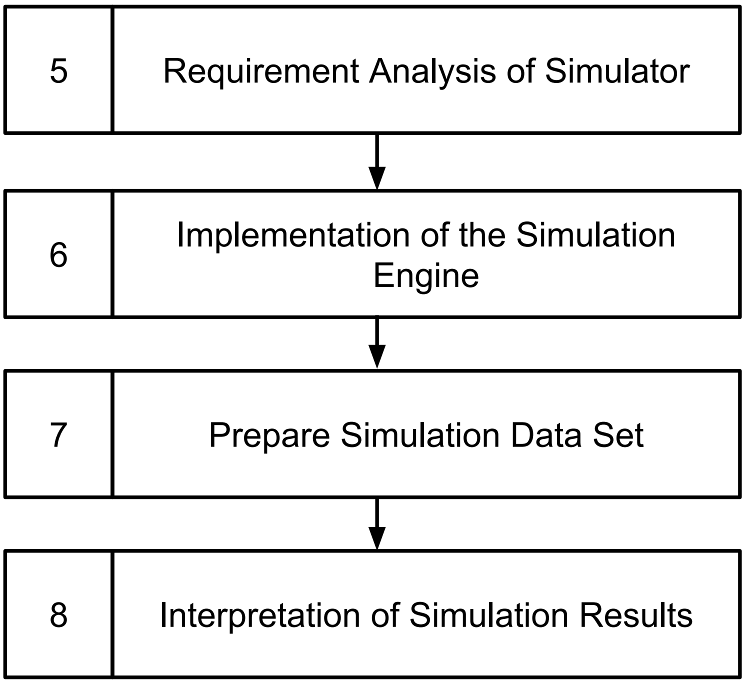

Figure 3.4: Research steps and simulation tools for the simulation engine.

sensitivities from our prediction model. Thus, we will analyses the specific requirement, either by literature research, expert opinion and using ideas from leading real estate market software, such as Argus. [2]

6. **Implementation of the Simulation Engine:** After defining the requirements for our software tool, we will chose a specific platform to develop the tool. During this step we will focus on the implementation aspects of our research project. Note that this step also includes to test our software thoroughly for bugs and potential errors.

7. **Prepare Simulation Data Set:** To run our sensitivities with the simulation engine, we will generate a test data set of several projects. Each project, will have different properties than the project before, which will result in a portfolio, which is representable for our approach.

8. **Interpretation of Simulation Results:** Finally, we will obtain our results, which will be interpreted and conclusions will be drawn based on our used methodology. All results are presented in chapter 5.

[2] Further information can be obtained through the website `http://www.argussoftware.com/argus-enterprise/`.

3.3 Model Implementation Risk and Tools

As shown in the previous chapter we have defined a structured research process, which has already been used and validated by other researchers. However, even though the process has been defined smoothly, this does not fully exclude risk from our challenges during our research project. As a general fact problems occur, when working out the *nitty-gritty* details of a forecasting model, which can have a rather large impact. The following section will show the difficulties and the tool side of implementing a predictive property cycle forecasting model.

3.3.1 Difficulties in choosing appropriate forecasting methods

As shown in chapter 2 there are different methodologies to forecast the property cycle. The main difference is that, on the one hand there are "*statistical methods*", which use techniques ranging from time-series modeling to machine learning and on the other hand "*simulation methods*", which are characterized by modeling the mechanics of a property cycle of a certain area in a holistic model. [3]

Each of the two methodologies has its advantages and disadvantages. Statistical models usually rely on more technical aspects, because their key is to use and extend the currently available forecasting methodologies properly. The main aspects of simulation methods is, that they rely on a lot of market assumptions and are much easier to fit to certain market conditions, by changing the underlying parameters. Barras (2009) showed in his book an example of such a model using multiple-equations. [12]

This variety of available methods makes it hard for modelers to choose the single best method, which yields the best predictions for a certain market state. In recent years statistical methods experienced a renaissance in science. The reasons for this phenomenon are on the one hand the rising availability of data points and the accuracy of the measured data. Many companies publish their data to the public under the concept of *open data*. Besides these initiatives, national banks and public institutions have started to recognize the need for open data of the general public and publish their measured economic data on their websites. As shown in subsection 2.3.2 publicly available information is one important aspect of influencing an efficient market. Hence, the Austrian National Bank has started an initiative to publish a publicly available residential property price index for Austria each quarter. [4] This property index is created by a group of real estate researchers, such as TU Vienna Professor Feilmayr and is based on several data sets, such as a large quantity of REMAX offer data.

[3] For an example of a simulation model, see Barras (2009) [12].

[4] For further information visit, `https://www.oenb.at/Geldpolitik/immobilienmarktanalyse/daten-und-analysen.html`.

Besides choosing the right data input for the modeling terminology, some researchers point out the problems of using predictive models. Makridakis (1998) shows that, using different models yields also different forecasting results. [123]

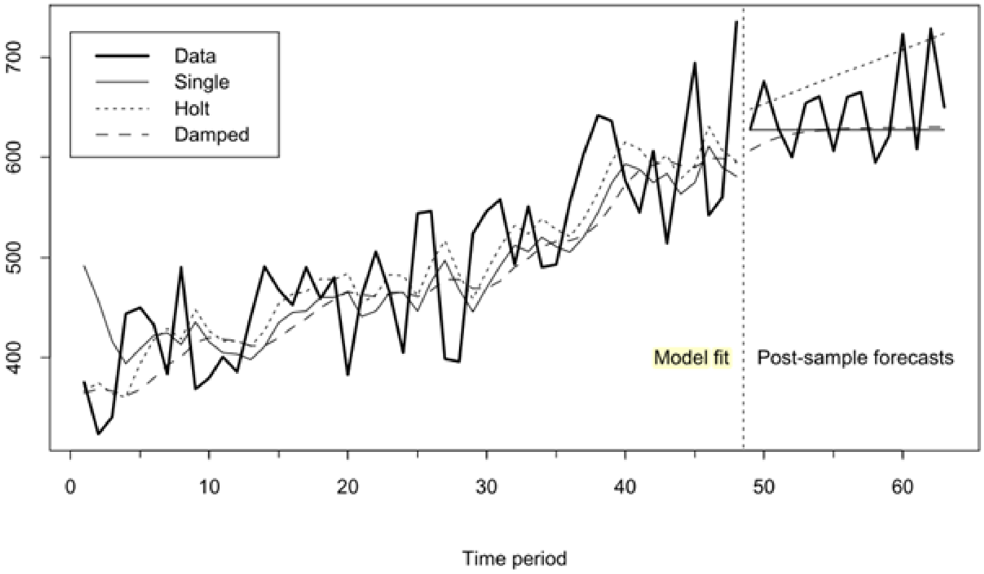

Figure 3.5: Makridakis (1998) post sample forecast for Single, Holt and Damped Exponential Smoothing. [123]

As figure 3.5 demonstrates, using different methods of exponential smoothing yields different forecasting results for future predictions, even though the data shows a clear upward trend. This *"modeling bias"* is another hot topic among researchers, which point out the vast variations, which can happen if a simple or more complex model is used.

Green and Armstrong (2015) [72] compared in their study 32 papers in which they identified 97 occurrences of simple and complex methods. They split their findings into four method types: *judgmental*, *extrapolative*, *causal* and *combined*. Their results show that simpler models perform much better than complex ones. In particular, there are two areas where simple models advance, such as predicting unusual events and its output accuracy. If complexity is needed, then the best way, as stated by Green and Armstrong (2015) [72], is to add it gradually and test the model accuracy after each step.

Fildes and Petropoulos (2014) [57] concentrate in their study on the evaluation of model accuracy in comparison to aggregated, more complex, model selections. Further, they examine the use of combined forecast and show that its accurate results outperform the single use of simple versus complex methods. To validate their results, Fildes and Petropoulos (2014) [57] segment their dataset into several subsets by using predictability, trend and seasonality as segmentation-parameters. Finally, they test the subsamples on the popular M3-Competition dataset. Fildes and Petropoulos (2014) [57] include the following forecasting methods in their experiment.

Forecasting methods included in the experiment.

#	Method	Short name	Applied to
1	Naive	Naive	Raw data
2	Naive 2	DNaive	Deseasonalized data
3	SES	Expsmoo	Raw data
4	SES 2	DExpsmoo	Deseasonalized data
5	Holt	Holt	Raw data
6	Holt 2	DHolt	Deseasonalized data
7	Holt–Winters	HoltWint	Raw data
8	Damped	Damp	Raw data
9	Damped 2	DDamp	Deseasonalized data
10	Damped with multiplicative seasonality	DampMult	Raw data
11	Theta	Theta	Deseasonalized data
12	ARIMA	ARIMA	Raw data

Figure 3.6: Prediction methods used in the experiment by Fildes and Petropoulos (2014) [57].

From their final results they show that simple model selection, as using a single method, performs far better than complex models. Another large forecasting issue, which is identified by them is the survivorship bias. The bias can simply be explained as following:

Definition 3.1. *When creating a new model, researchers tend to focus on the variables that worked, or survived, and use these further in their studies. However, the other variables, which did not work are often overlooked and put aside. This can lead to the problem of drawing wrong conclusions after applying further methods on the data set.*

Ioannidis (2005) [99] points out that many research studies face this problem. She shows that a study has a higher probability of delivering accurate results, when more similar studies are conducted in the field, when there are a higher number of complementary studies, which deepen the research in the field, when there are clear definitions, research designs, results and methodologies and when the field is financially strong supported and also has industrial partners, who are interested in the research outcome. Cyclical research fulfills most of these criteria. We outline all specifically taken actions during this research project in section 4.2.

As pointed out, there are a lot of difficulties in creating a good forecasting model. It has become more an *art* than an actual *science*. Therefore, we also believe that the choice of the actual used tools is extremely important for implementing a well performing predictive model.

3.3.2 Strength of using R as Modeling Tool

There are many mathematical and statistical programming languages, which are used by researchers. For example, Jadevicius (2014) [101] uses SPSS for implementing property cycle models. Other researchers use Matlab [5] or also Python [6]. We decided to use the statistical programming language *R*. This statistical language started as an experiment, to create a number of functions, which could be used as a test bed for an abstract concept of how a statistical programming language could look like. The earliest versions were programmed in *LISP* and it was decided that the language syntax would be similar to the programming language *S*. [98] Later R was released as free software, also known as open source, and many developers and statisticians joined and added further functionality in form of packages to the language. To store this wide range of packages an archiving mechanism was needed, which was provided by Professor Kurt Hornik at the Vienna University of Technology. Since then the master site stayed in Austria, with several mirror sites in other countries. [98] As we write this thesis, R is running in version 3 and many scientists, developers and researchers are using it on a day-to-day basis to calculate their statistical models. In the following list, we will point out the strengths of using R in forecasting and building property cycle models and conclude from that, why we chose it primarily for our research.

- **Community:** As pointed out R has an extremely large and solid community. Most of the researchers are either on the official R Mailing List, R forums or on `stackoverflow.com` a question and answer community.

- **Packages:** As the community is extremely active, there are currently several sites, where packages can be downloaded. You can use either the official R package library, `bioconductor.org`, which is a small independent packaging site or even load your R package directly via the repository `github.com`.

- **Professionalism:** As R grew mature, many companies have been founded around the language. Products and services rang from providing an IDE, such as `rstudio.com` to consulting services, for example `revolutionanalytics.com` to large conferences like the *r-finance* conference.

- **Performance:** Compared to high level programming languages like Java or C++, R is less performant. The reason for this is that it is layered on other languages such as C++. However, this weakness has been addressed by some packages, for example the *data.tables* package, which provide a new faster data structure or the *dplyr* package, which uses faster operators to speed up calculations. Last but not least, our experiments show that even

[5] For further information see `http://de.mathworks.com/products/matlab/`.
[6] For further information see `https://www.python.org/`.

when using fast packages, the actual implementation of the forecasting algorithms tends to be the most important influence on the execution speed of the program.

- **Language Flexibility:** R is using typical concepts of statistical languages such as vectorization, which makes the programming process extremely convenient. For example, in R you one can use *apply functions* instead of simple *for-loops*, which are on the one hand faster than *for-loops* and on the other hand, make the code more robust and easier to understand.

Finally we want to point out that, through our literature research we have seen that, the use of R is rising in economic research and lots of useful packages, which include common economic methods have already been released.

3.4 Forecasting Techniques

As shown in the literature section, there exist a lot of models, which are used by other researchers to predict the dynamics of the property cycle. Using many different models, delivers a wide range of forecasting possibilities, because different models have different useful features. In the hand of property developers and banks, real estate is not seen as a rather liquid asset. Hence, the decision to invest is carefully considered. Choosing many different forecasting models is essential to deliver a wide range of possible model *opinions*. Taking the literature into account, we use a wide range of methods, such as *exponential smoothing*, with simple, trend and seasonal smoothing, *simple and multiple regression*, *vector auto-regression* and *ARIMA* modeling. In the following subsections, we describe each modeling technique shortly, which is used in our research project. All final results are demonstrated in chapter 5.

3.4.1 Exponential Smoothing

Exponential Smoothing was proposed by the three key pioneers Brown (1959) [30], Holt (1957) [88] and Winters (1960) [172] and has been used and inspired many forecasting techniques, which are used today. [96] The key idea of exponential smoothing is that the method weights each observation exponentially as a function of time. That means, older observation have a *smaller weight* than more recent observations. The simplicity of this method, makes it applicable for a wide range of time series and can be used to generate predictions rather quickly, which was a great advantage by the time of its invention. The following subsections, will introduce each smoothing method separately.

3.4.1.1 Simple Exponential Smoothing

Simple exponential smoothing is the naive method for applying the general principles of exponential smoothing. Athanasopoulos and Hyndman (2014) [96] show the formula for exponential smoothing as the following:

$$\hat{y}_{T+1|T} = \alpha y_T + \alpha(1-\alpha)y_{T-1} + \alpha(1-\alpha)2y_{T-2} + ... \tag{3.1}$$

The parameter α describes the smoothing parameter and $0 \leq \alpha \leq 1$. Forecasting the time series one step ahead, is the weighted average of all observations $y_1, ..., y_T$, which is influenced by the weight α.

There are three forms to derive the equation 3.1: *Component form*, *Error correction form* and *Multi-horizon forecasts*. To describe each form would go beyond the scope, which is why we refer to an in-depth description in the book of Athanasopoulos and Hyndman (2014) [96].
Before making a forecast the smoothing process has to be started, by setting the level ℓ_t. Level can also be described as the *smoothed value*. [96] A widely used method is to set the level parameter to the first observation, $\ell_0 = y_1$. Another way to set ℓ_t, is to find this parameter by optimization. Another model requirement is the smoothing parameter α. Often a regression model is used, which minimizes the sum of squared errors (SSE).α can also be set by using expert judgment, which is not as commonly used as other methods. Further information about all three forms can be found in the book Athanasopoulos and Hyndman (2014) [96].

3.4.1.2 Holt's Linear Trend Model

In 1957 Holt extended the simple version of exponential smoothing by a *trend component*. [88] He noticed that simple exponential smoothing does not work well, when the data is trending. In the literature some researchers refer to Holt's Linear Trend Method as *Holt-Winters double exponential smoothing* or *double exponential smoothing*. The method uses three equations, a forecasting and two smoothing equations, whereas one is the level equation and the other is Holt's trend equation. [96]

$$\text{Forecasting equation: } \hat{y}t + ht = \ell_t + hb_t \tag{3.2}$$

$$\text{Smoothing equation 1 - Level equation: } \ell_t = \alpha y_t + (1-\alpha)(\ell_{t-1} + b_{t-1}) \tag{3.3}$$

$$\text{Smoothing equation 2 - Trend equation: } b_t = \beta^*(\ell_t - \ell_{t-1}) + (1-\beta^*)b_{t-1} \tag{3.4}$$

The parameter ℓ_t is the level of the time series. b_t estimates the trend, in specific the slope, of the series. As in the previous section α describes the smoothing parameter and is $0 \leq \alpha \leq 1$. For the trend a second smoothing parameter can be found in the model, which is β^* and is bounded by $0 \leq \beta^* \leq 1$. [7]

3.4.1.3 Damped Trend Model

In subsection 3.4.1.2, we showed that exponential smoothing can be extended by a trend component. The problem is that usually time series do not infinitely trend in the future. For example, it is widely known that stocks tend to trend for a certain amount of time, but change direction when the market corrects the move. This criticism lead Gardner and McKenzie (1985) [61] to create a model, which *dampens* the trend in the future. [96]

$$\text{Forecasting equation: } \hat{y}t + ht = \ell_t + (\phi + \phi^2 + \cdots + \phi^h) b_t \tag{3.5}$$

$$\text{Smoothing equation 1 - Level equation: } \ell_t = \alpha y_t + (1-\alpha)(\ell_{t-1} + \phi b_{t-1}) \tag{3.6}$$

$$\text{Smoothing equation 2 - Trend equation: } b_t = \beta^*(\ell_t - \ell_{t-1}) + (1-\beta^*)\phi b_{t-1} \tag{3.7}$$

Each equation above includes the dampening parameter ϕ, which is bound by $0 < \phi < 1$. If $\phi = 1$, then the method is the same as in subsection 3.4.1.2. For values below 1 the trend dampens to a constant. This results into the effect, that short term forecasts are trended and long term forecast become constant. [96]

Taylor (2003) [166] points out an alternative dampening parameter, which improves the additive version.

$$\hat{y}t + ht = \ell_t b_t^{(\phi+\phi^2+\cdots+\phi^h)} \tag{3.8}$$

$$\ell_t = \alpha y_t + (1-\alpha)\ell_{t-1} b_{t-1}^{\phi} \tag{3.9}$$

$$b_t = \beta^* \frac{\ell_t}{\ell_{t-1}} + (1-\beta^*) b_{t-1}^{\phi} \tag{3.10}$$

This method will yield a more conservative forecast. Hence, when creating the final results, we will stick to this more advanced trend model than the Holt's Linear Trend Model. For further information about this specific method subset we recommend the book of Athanasopoulos and Hyndman (2014). [96]

[7] Compared to the smoothing parameter α, the trend parameter is β^* instead of β, because of the concept of *state space models*, which show the underlying concept of, why exponential smoothing works. For further information we refer to the book of Athanasopoulos and Hyndman (2014) [96].

3.4.1.4 Holt-Winters Seasonal Method

The Holt-Winters seasonal method uses Holt's model as a basis and extends it by a seasonal component. [39] The model comprises of four equations, and extends the Holt's Linear Trend model from section 3.4.1.2 with a seasonal component s_t. There are two methods, which can be used for the Holt-Winter's seasonal trend model, either can the seasonal component be expressed as a percentage, within the *multiplicative method* or via the *additive method*, the component is expressed in absolute terms. [96] Hence, the additive method is preferred when the seasonal factor is rather constant, whereas the multiplicative component is used when the seasonal component changes over time and should rather be modeled as ratio. For sake of simplicity, the following equations will only show the additive method of the Holt-Winters seasonal method: [96]

$$\text{Forecasting equation: } \hat{y}t + ht = \ell_t + hb_t + s_{t-m+h_m^+} \tag{3.11}$$

$$\text{Smoothing equation 1 - Level equation: } \ell_t = \alpha(y_t - s_{t-m}) + (1-\alpha)(\ell_{t-1} + b_{t-1}) \tag{3.12}$$

$$\text{Smoothing equation 2 - Trend equation: } b_t = \beta^*(\ell_t - \ell_{t-1}) + (1-\beta^*)b_{t-1} \tag{3.13}$$

$$\text{Smoothing equation 3 - Season equation: } s_t = \gamma(y_t - \ell_{t-1} - b_{t-1}) + (1-\gamma)s_{t-m} \tag{3.14}$$

The complex indices $h_m^+ = \lfloor (h-1) \mod m \rfloor + 1$ ensures, that only the last observations are taken for the estimation of the seasonal indices. As in the previous section 3.4.1.2, the trend equation stays the same. The newly added equation, the seasonal equation, expresses a weighted average between the current year's season m and the same season m last year.

3.4.2 Simple / Multiple Regression

Simple Linear Regression is characterized by the following equation:

$$y = \beta_0 + \beta_1 x + \varepsilon \tag{3.15}$$

ε specifies the error term of the equation and β are the coefficients, or the intercept or slopes, in the model.

The basic assumptions for the errors ε of linear regression are:

1. Mean is 0.
2. ε is not auto-correlated.
3. Independent of the predictor variable.

Multiple Linear Regression extends the general model of simple regression by coefficients. The generalized model looks like the following:

$$y = \beta_0 + \beta_1 x + \varepsilon \tag{3.16}$$

$$y_i = \beta_0 + \beta_1 x_{1,i} + \beta_2 x_{2,i} + \cdots + \beta_k x_{k,i} + \varepsilon_i \tag{3.17}$$

x_k specifies the k predictor variables, β_k, the coefficients for each predictor k. Hence, the coefficients measure the minor effects of the predictors k.

Similar to linear regression the assumptions for multiple regression are:

1. Mean is 0.
2. The errors ε are not correlated with each other.
3. The errors ε are not correlated with k.

In versions of regression the coefficients have to be estimated. A common method is to estimate the minimum sum of squares of the error terms ε. For the coefficients $\beta_0, \ldots, \beta_k$ we get:

$$\sum_{i=1}^{N} e_i^2 = \sum_{i=1}^{N} (y_i - \beta_0 - \beta_1 x_{1,i} - \cdots - \beta_k x_{k,i})^2 \tag{3.18}$$

As this is a rather calculation intensive task, computerized calculations are used rather than *"calculating the problem in written form"*. In R regression is part of the core of the R framework, the *base* package.

3.4.3 Vector Auto-Regression (VAR)

The previously shown forecasting models, which have been explained so far, focus on a dependent variable, which is influenced by independent variables. [96] This unidirectional relationship is sometimes far from reality. For example, figure 3.7 shows the change in percentage of consumption and disposable income. [96] These two variables, influence each other bidirectionally. As it is shown in the graph, when the disposable income rises, consumption will rise and vice versa.

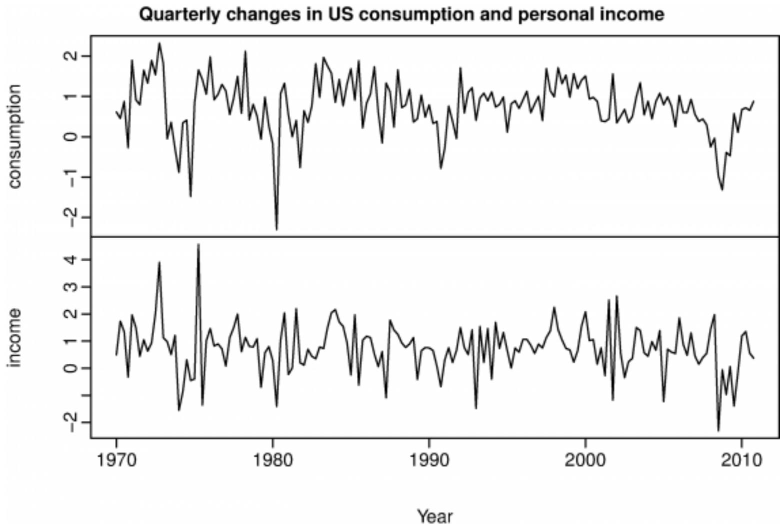

Figure 3.7: Quarterly change in us consumption and personal income. A clear bidirectional relationship can be seen in the graph. [96]

Vector autoregressive models (VAR) handle such feedback induced relationships, by treating every variable as *endogenous*. [96] In the next section 3.4.4 we will describe the components of the ARIMA model, whereas a vector autoregressive model is basically just a generalization of an univariate autoregressive model, to predict a set of variables. [96]

To show the specification of a vector autoregressive model, we will show a two dimensional *VAR(1)* model, which has a constant lag: [96]

$$\hat{y}_{1,T+2|T} = \hat{c}_1 + \hat{\phi}_{11,1}\hat{y}_{1,T+1} + \hat{\phi}_{12,1}\hat{y}_{2,T+1} \quad (3.19)$$

$$\hat{y}_{2,T+2|T} = \hat{c}_2 + \hat{\phi}_{21,1}\hat{y}_{1,T+1} + \hat{\phi}_{22,1}\hat{y}_{2,T+1} \quad (3.20)$$

$e_{1,t}$ and $e_{2,t}$ are the error terms and can also be interpreted as white noise. Often these two factors correlate with each other. The coefficients $\phi_{ii,\ell}$ capture the lag ℓ of variable y_i. [96]

When using a vector autoregressive model the modeler has to decide, how many variables O and how many lags l, he wants to include in the equation system. The number of coefficients can be easily found via: $O + l \times O^2$. As a rule of thumb it can be said, the more coefficients there are in the model, the larger the forecasting estimation error. [96] This shows the importance of a clear data selection process, which will be further explained in subsection 4.2.

Secondly, a modeler has to test his variables for stationarity before using the vector autoregressive framework. Our process for doing this is described in section 4.2.2.3.

3.4.4 ARIMA

ARIMA is the abbreviation for *Auto Regressive Integrated Moving Average*. The method consists of either using a combination of an Autoregressive model and Moving Average model. The following two paragraphs will give a short explanation of each component of an ARIMA model.

Autoregressive model

An Autoregressive model uses *past values* to forecast future observations by regressing its variables against themselves.

$$y_t = c + \phi_1 y_{t-1} + \phi_2 y_{t-2} + \cdots + \phi_p y_{t-p} + e_t \tag{3.21}$$

When using more than one variable, an AR model can have a larger order, which is similar to multiple regression. Hence, we say $AR(q)$ for a model, of the order q.

Moving Average model

Moving Average models use *past errors* as an estimate to forecast future observations. As Autoregressive models, it uses regression to create a model of the data series.

$$y_t = c + e_t + \theta_1 e_{t-1} + \theta_2 e_{t-2} + \cdots + \theta_q e_{t-q}, \tag{3.22}$$

The error term e_t specifies white noise in the model. Similar to the Autoregressive Models, Moving Average model depend on the order of lagged variables. So we say $MA(q)$ for a model, of the order q.

Combining AR and MA gives an ARIMA model.

$$y'_t = c + \phi_1 y'_{t-1} + \cdots + \phi_p y'_{t-p} + \theta_1 e_{t-1} + \cdots + \theta_q e_{t-q} + e_t \tag{3.23}$$

Whereas y'_t is the difference adjusted series. An ARIMA model consists of p, q and d and we say $ARIMA(p,d,q)$:

- p is the order of the AR.
- d is the degree of the first difference.
- q is the order of the MA.

Furthermore, the condition of stationarity is also used for ARIMA as for AR and MA. As these three degrees of freedom make the model quite flexible, it is quite hard to select optimal values for p, q and d. Hence, we use the *auto.arima* function from the R *forecast* package, which helps tremendously in selecting the optimal values.

3.5 Forecasting Accuracy

As pointed out in section 3.1, we evaluate all predictions by their accuracy. Hence, we have picked a wide range of potential measures. The reason for that is, that the used prediction models have different strengths and weaknesses and by using a wide range of accuracy measures, we try to cover as much of this diversity as possible. In the following, all accuracy measures are presented.

Mean error	$\text{ME} = \frac{1}{n}\sum_{t=1}^{n} e_t$
Mean percentage error	$\text{MPE} = \frac{100\%}{n}\sum_{t=1}^{n} \frac{e_t}{y_t}$
Mean squared error	$\text{MSE} = \frac{1}{n}\sum_{t=1}^{n} e_t^2$
Root mean squared error	$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{t=1}^{n} e_t^2}$
Mean absolute error	$\text{MAE} = \frac{1}{n}\sum_{t=1}^{n} \lvert e_t \rvert$
Mean absolute percentage error	$\text{MAPE} = \frac{100\%}{n}\sum_{t=1}^{n} \left\lvert \frac{e_t}{y_t} \right\rvert$
Mean absolute scaled error	$\text{MASE} = \frac{\sum_{t=1}^{n} \lvert e_t \rvert}{\frac{n}{n-1}\sum_{t=2}^{n} \lvert y_i - y_{i-1} \rvert}$
Auto-correlation of errors at lag 1	ACF1

Whereas n is the number of observations i, e_t is the forecast value f_t subtracted by the actual value y_t, $e_t = y_t - f_t$. All errors presented in 3.5 are part of the R forecasting package. [8] Further, Koehler and Hyndman (2006) [97] described each error in their paper. The main principle is that the accuracy measures the difference to the actual model. We will use all the above errors through evaluating our predictions in section 5.3.

[8] For further information please visit the official documentation - `https://cran.r-project.org/web/packages/forecast/forecast.pdf`.

3.6 Property Simulator

The following section will describe the property simulator. Goal of the engine is to use the cyclical risk sensitivities from the property cycle forecasting models and make it useful for day to day operations in real estate development firms or banks. In subsection 3.6.1 we will show the requirement analysis, which was conducted before the property cycle simulation engine was developed. In the following section 3.6.2, we will show the use of the discounted cash flow analysis method and outline each step, which will be used in the simulation engine. Further, as our chosen development platform will be *Microsoft Excel*, we will show the strengths of this platform in subsection 3.6.3. Finally, as our results are aggregated in the simulation engine to indicators, we show in subsection 3.6.4 all calculation of the result parameters.

3.6.1 Property Cycle Simulator Requirement Analysis

Before starting to implement the property cycle simulation engine, we researched on current concepts and applications, which are used by real estate agents and partly by banks. Hence, we collected the requirements for our future concept. The following necessities have been collected by either using literature, modeling from current applications or interviewing and showing previous sample mock-ups to experts. The previously done literature research is outlined in chapter 2.

- **Flexibility:** In day to day operations, decisions can change with new incoming data. Therefore, the simulation engine has to be designed as flexible as possible, so that for example the underlying data or parameters can be adjusted or changed extremely easy. Furthermore, for a portfolio manager it is also quite interesting to look at the single deal level or to select his portfolio by his needs and get an aggregated output.

- **User-Friendly:** As the program is designed for everyday use, the simulation engine has to be user-friendly. Therefore, in designing the graphical user interface(GUI), we choose typical colors and GUI Elements, so that the user feels comfortable. Further, the simulation engine cannot consist of a rather simple script, from the standpoint of a computer scientist, that can be run via the command line, because not many real estate managers are used to complicated technology. Creating a simple to use application also saves a lot of time in the long run for the operating user.

- **Performance:** One of the main requirements is that the application has to be performant. Hence, optimizing the back-end code is a must before the engine can be used by property managers. The simulation engine should also handle large data amounts rather quickly as large property firms can have for example lots of tenants in one property. One solution for this problem is to either choose a platform, which supports to handling these large amounts of data, or to bulk or process the data in phases, like calculating each deal separately and aggregate the results on the portfolio level later.

- **Platform independent:** In lots of banks and property development firms *Windows* from Microsoft is the dominating operating system. However, there exist also firms, which use *Linux* or *MAC OS*. Hence, it is important that our developed software can be used on other platforms without having large migration issues. Therefore, we have to choose a platform independent framework.

For our prototyping platform we chose *Microsoft Excel 2010*, which is in fact not currently the latest version of excel [9], but still widespread in use by banks or real estate development firms. The reason for this is, that the license costs for Microsoft office products are immense and the technological advantage of changing to the latest software version are rather thin. This can be shown by an example, Excel has had its last major feature changes in the 2010 version by changing its navigation.

Figure 3.8 shows the output of the literature research, unstructured interviews and comparisons of real estate software, which is currently used by companies. [10]

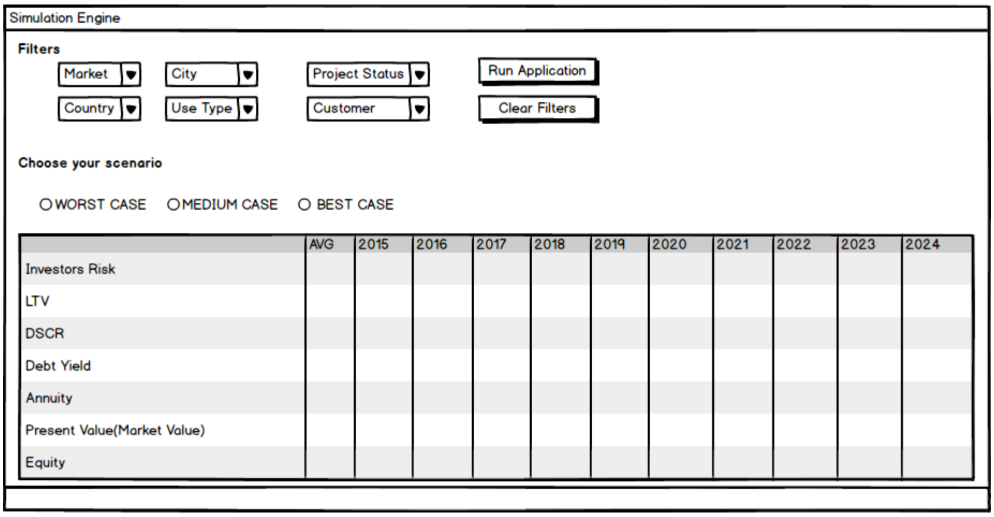

Figure 3.8: Research Mock-up of the Simulation Engine.

Our research prototype comprises of three sections. In the first section, the user can filter the underlying properties by *market*, *country*, *city*, *use type*, *project status* and *customer*. The filter customer was in particular mentioned by portfolio managers, because they structure their loans on a customer basis. Property developers are much more interested in the other five filters, because these provide them a useful overview of their portfolio and can easy show them the parameters of their sub-portfolios. After selecting his desired single customer or portfolio, the

[9]The latest version the spreadsheet program of Microsoft is Excel 2016. Further information can be found here `https://products.office.com/en/excel`.

[10]The previously done research is outlined in chapter 2.

user can choose between three scenarios, which represent cyclical outcomes. When pressing the *run* button the portfolio manager will be presented by a ten year forecast of the investment risk, which is based on cyclical assumptions, the *loan to value ratio (LTV)*, the *debt service coverage ratio (DSCR)*, the *debt yield*, the *annuity payments*, the used *equity amount* and the *market value*.

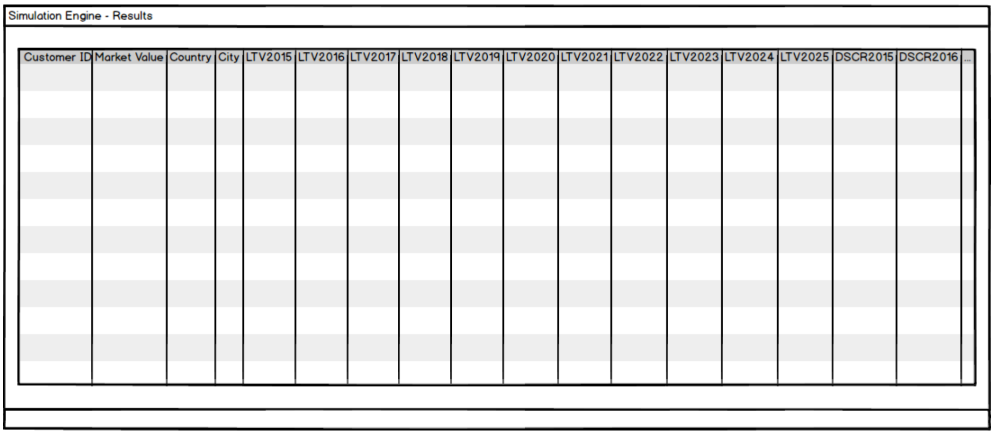

Figure 3.9: Result Page of the Simulation Engine.

In figure 3.9 the user will get all the results on a single deal basis. All indicators are presented here for several years in the future. A clear explanation of the used indicators is presented in subsection 3.6.4. Each parameter will be either implemented in *visual basic (vba)* or with already implemented excel functions. Section 5.4 shows the actual implementation of the mock-up to excel.

3.6.2 Discount Cash Flow Analysis

In real estate development firms and banks, the discounted cash flow analysis method is widely used. Keck (1998) [110] points out in his survey that 95% of their participant use some form of discounted cash flow analysis method. Corley, Green and Worley (2015) [71] did a survey of over 64 people, who were involved in financial services. Out of this sample size, 19 use the discounted cash flow analysis to determine the present value of a financial asset. Cowley (2007) [43] shows in a survey that the discounted cash flow method is the dominant technique to value properties and base further investment decisions on it. Hence, the discounted cash flow method is one of the prevalent methods in dealing with financial assets. Besides real estate the abstract concept of the discount cash flow method can also be used for other assets in a similar way.

The idea of the discounted cash flow method is, when taking each cash flow c for a property at time t and summing all cash flows up, the present value for time t of the real estate can be determined. [60] Usually, the period t is one year for an income producing property. [60] The most interesting value for a bank is the net present value, which can be derived out of the sum of present values p for year $t_1...t_n$, where n are the number of years. Usually, an initial cash investment in form of equity is also used in t_1, which can be subtracted from the net present value. Gallinelli (2004) [60] defines the net present value as following:

Definition 3.2. *NPV is the difference between the PV of all future cash flows and the amount of cash you invest to purchase those cash flows.*

Hence, in mathematical terms the DCF method can be expressed like in equation 3.24:

$$DCF = \frac{CF_1}{(1+r)^1} + \frac{CF_2}{(1+r)^2} + ... + \frac{CF_n}{(1+r)^n} \tag{3.24}$$

Equation 3.24 shows the discounted cash flow as a sum of the future cash flows under the time value of money. [60]

Excel provides useful functionality to perform this rather complex analysis in extremely simple manner. As a pre-condition, if all cash flows are structured clearly, using the $PV()$ and the $NPV()$ function, gives the present value for year t and the net present value for the entire valuation period.

3.6.3 Strength of using Excel as Simulation Tool

In subsection 3.6.1 we analyzed the use for banks and developer firms for their need of incorporating property cycles in their daily built models. We concluded that we will use Excel as a development platform. As shown in a survey conduced by Cowley (2007), nine of ten firms use Microsoft Excel as their primary modeling tool in their daily operations. [43] The reasons for this are that Excel provides strengths that a programming language has not. The following list, shows the strengths of Excel as a simulation tool.

- **Feature rich:** Microsoft Excel comes with a large set of formulas and statistical functions out of the box. It has to be said, that even though many of these functions are not as sophisticated as within frameworks such as R, they cover a large part of the every day needed functionality toolbox of a banker or property developer.

- **Widespread:** The first version of excel was released in 1993. [24] Since then many firms have used excel in their day to day operations and a lot of company processes are accomplished with the help of Microsoft Excel. Hence, learning the functionality of excel is extremely important for every white-collar worker.

- **Rapid development cycle:** As pointed out, Excel comes already with a lot of functionality. A simple excel file consists of several sheets, which can easily be used to create complex Excel models. Even when the required functionality does not exist, Visual Basic (vba) provides a simple programming framework to add the desired function to the spreadsheet.

- **Transparency:** Excel Models are extremely transparent. Every variable change can be tracked within the model itself. Excel provides out of the box an extremely useful audit tool, to check if all calculations are done correctly. However, sometimes extremely complex models are built and operated by users, who do not fully understand the underlying concepts. Therefore during development, best-practices have to be applied, such as color marking input for calculations and output cells and writing a comprehensive documentation.

- **Minimal training time:** As Excel is used by lots of white-collar workers, there exists a lot of expertise about this application in companies. Hence, upcoming problems can be solved fast. However, if the problem cannot be solved, there is a wealth of online resources, which provide tutorials and solutions to similar problems.

- **Easy sharing of results and data:** Microsoft Excel makes sharing data extremely easy. The most common way to share an *"excel program"* is simply by sending it via mail. Furthermore, if you want to add your own data or create a further model all the data can be copied to another excel sheet to provide the information. This process, which can be related to the general concept of *"agile implementation"*, helps companies to change fast and adapt their data to the current business situation. [41]

- **Compatibility:** Microsoft Excel fits perfectly into the landscape of other Microsoft products, such as Power Point, Access and Word. The standard company's email programs support to send an excel sheet directly within your spreadsheet. Examples for this are the popular mail clients, such as Lotus Notes or Microsoft Office. Furthermore, excel can also load data that gets updated externally, for example from a Sharepoint Server. This makes excel extremely flexible and a good fit for users, who already use Microsoft products regularly in their operation.

The above listed strengths make excel clearly the first choice to implement our simulation engine. Some might argue that a custom implementation, like in java or python, might be better in the long run, we think our implementation should focus on the needs of the end customer. Microsoft Excel provides a large advanced formula toolbox, is used by lots of development firms regularly and can be fitted in the currently available application landscape of a company extremely well.

3.6.4 Simulation Results

As shown in subsection 3.6.1 there are several pre-result and result parameters, which will be calculated in the simulation engine. The following section will describe each result value in particular:

Investors Risk: The first parameter is Investors Risk, which is represented by sensitivities in the property cycle model.

Loan-to-value (LTV): The loan-to-value ratio represents the ratio of the *loan* a lender has gotten from the bank and the actual *value* of the property. Usually, the value is the appraisal value of the asset, which is determined by external evaluation. However, there can also be other forms of *values* used in calculating the LTV, such as the present value, which determines the market value on a cash flow basis. Hence, this shows the art in evaluating property projects and explains why the result of these estimations can vary from time to time.

$$\text{LTV} = \frac{\text{Loan Amount}}{\text{Value of the property}} \tag{3.25}$$

Equation 3.25 shows the calculation approach of the LTV. In our simulation engine, we will use the loan amount and the market value at time t and therefore calculate the LTV for each period.

Debt-Service Coverage Ratio (DSCR): The debt-service coverage ratio, is the second ratio, which we use in our result table. It can be calculated as follows:

$$\text{DSCR} = \frac{\text{Net Operating Income}}{\text{Total Debt Service}} \tag{3.26}$$

Equation 3.26 shows as the nominator the factor *net operating income*, which can be different for various use types. For example, a hotel can be under a lease or management agreement. That means that the hotel itself must not be owned by the property owner and is operated by a sub-firm. Examples for such an ownership structure are the companies Hilton [11] or Jurys Inn [12]. Furthermore a property can be split by several use types, which all contribute to the final net operating income of the property. One rather complex case are shopping centers, which have several tenants, who also can quite often change. Hence, estimating the net operating income is often a tedious task. On the other hand, the debt service is rather easy to calculate. Usually it comprises of the outstanding loan amount and the interest payment. However, facility details can be different for more complex property projects.

Annuity: When paying back a loan, annuity payments are charged. Annuity can simply be defined as a steady payback cash flow. Usually, developers will pay back after some time a large amount of the loan, which is the balloon payment. The reason for this is often motivated to spare interest payments. Hence, it highly depends on the loan facility, how the annuity payments are

[11] For further information see `https://www.hilton.com`.

[12] For further information see `https://www.jurysinns.com`.

structured. Annuity is needed to determine the debt service for a loan repayment, which is used by the DSCR.

Market Value: In the simulation engine, the market value is determined by calculating the present value of the cash flow for each year. As appraisal values are not available steadily, this rather cash flow focused method, gives the possibility to evaluate a property quick and easy. Furthermore, the cyclical sensitivities, will be used on the market value, which will show the largest effects on properties then. We calculate final value of the property under the assumption that the property developer will sell the property in the end. Furthermore, our assumption is, based on historic yields from CBRE [13].

3.7 Summary

Chapter 3 examines the used research method and the research design. The following sections are part of this chapter research method 3.1, the used research process and tools 3.2, the challenges of modeling the property cycle 3.3, forecasting techniques 3.4, the measure of the forecasting accuracy 3.5 and the description of the property simulator 3.6.

In section 3.1, we outline our research approach. First, we start by showing the applied method in a flow chart. Next we outline for each phase the deliverables and the artifacts, which we produced.

Implementing a cyclical forecasting models implies difficulties, which came up during our research phase. Section 3.3 describes each challenge and the risks, which we faced during this research project. Further, as we use *R*, the statistical modeling language, we explain its usefulness and importance.

As we use several forecasting techniques to get multiple sensitivities for our simulation engine, section 3.4 explains each technique in depth. The methods we employ are: exponential smoothing 3.4.1, simple and multiple regression 3.4.2, vector-auto regression 5.2.4 and ARIMA 3.4.4 modeling.

To compare each modeling technique we use the measure of forecasting accuracy in subsection 3.5, to gain a homogeneous understanding of the methods accuracy.

[13] See `http://www.cbre.com/erix`.

Finally, we describe the property simulator in subsection 3.6. Beforehand, we use requirement analysis techniques to gain an understanding of the usefulness of the simulation engine application. The subsection 3.6.1 also shows wire-frames, of the presented application in the result chapter 5. In the following subsection 3.6.2, we describe the used discounted cash flow analysis terminology and in subsection 3.6.3 the strengths of implementing the simulation engine on the Microsoft excel platform. Finally, we present in subsection 3.6.4 the output of our simulation project, by showing the precise calculations of the *Loan-to-Value*, the *Debt-Service Coverage Ratio*, *Annuity* and the *Market Value*.

Chapter 4

Data

Data is the first building block of our model. In chapter 2, we showed the importance of data in property cycle models by using leading indicators. During this chapter we will show the importance of the chosen variables in detail. We will start by a comprehensive discussion about the variable selection process in subsection 4.2. At first, we will explain the used data sources 4.1.1 and then point out the challenges during the data collection procedure in subsection 4.1.2. In the next section, we will show the variable selection techniques 4.2, which we use to determine our final data set. We start with cluster analysis 4.2.1 and then describe the importance of unit root testing in subsection 4.2.2, by showing the Augmented Dick-Fuller test 4.2.2.1 and the Kwiatkowski-Phillips-Schmidt-Shin test 4.2.2.2. Furthermore, we will detail stepwise regression 4.2.3 and the Granger Causality test 4.2.4. Finally, we conclude the variable selection technique section by pointing out lasso regression 4.2.5. In the next section 4.3, we show the model variables. On the one hand, we show the independent variable 4.3.1 and on the other hand describe each dependent variable 4.3.2 and detail its importance to our predictive model. Finally, we explain the test data for our simulation engine in subsection 4.4. At first we describe the data generation process 4.4.1 and then show the synthetic project data 4.4.2.

4.1 Variable Collection Process

Before starting with the statistical process of variable selection, which aims to identify the best forecasting model, we have to collect variables from several data sources. Figure 4.1 shows the four steps which are taken in the *variable collection process*. In the first step we identify sources and gather data. Secondly, the assembled data has to be evaluated and from the vast amount of variables only specific indicators are selected. Our selection criteria are in this stage mostly expert views and comprehensive literature research. The third step in our process visualizes the compilation of a data set, which is ready for the final step. At last, we sub-select our data set by statistical variable selection techniques.

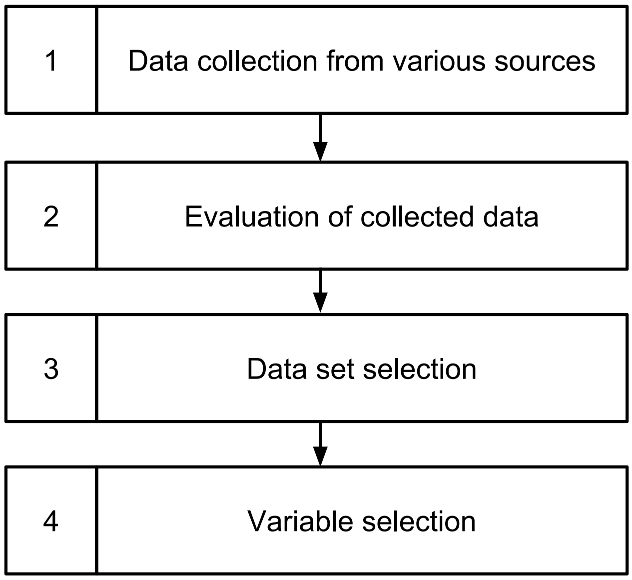

Figure 4.1: Steps taken in collecting data.

The following subsections, show on the one hand the data sources, which we found relevant during the collection phase. In subsection 4.1.2, we show the availability and data quality of observations regarding the Austrian real estate market. During this subsection, we will also include problems, which we encountered during the data collection phase.

4.1.1 Data Sources

Table 4.1 shows all data sources, which were used during the data collection phase. Following the table, a list will describe them in more detail:

- **AMECO:** The Annual macro-economic database is the official economic data base of the European Commission's Directorate General for Economic and Financial Affairs (DG ECFIN). It is widely used in economic publications.

- **BIS:** The Bank of International Settlement provides a wide range of statistical indicators based on the global and local financial system.

- **Bloomberg:** Bloomberg is a paid service, which provides excellent data quality on various time frames. The shortest time frame that can be used is tick data, which can be understood as *real time data*.

Source	Free Access	Provider url
AMECO	Yes	www.ec.europa.eu/economy_finance/db_indicators/ameco/index_en.htm
BIS	Yes	www.bis.org/
Bloomberg	No	findata.org/rbloomberg/
DataMarket	Yes	datamarket.com/
Datastream	No	www.forms.thomsonreuters.com/datastream/
Deutsche Bundesbank Data Repository	Yes	https://www.bundesbank.de/Navigation/EN/Statistics/statistics.html
ERIX	No	cbre.com
EuroStat	Yes	www.ec.europa.eu/eurostat
FRED	Yes	www.research.stlouisfed.org/fred2/
Interactive Broker	No	www.interactivebrokers.com/en/main.php
OECD	Yes	www.oecd.org/
OENB	Yes	oenb.at
Penn World Table	Yes	pwt.sas.upenn.edu/
Quandl	Yes	www.quandl.com
REMAX	No	www.remax.at/
Statistik Austria	Partly	www.statistik.at
ThinkNum	Yes	thinknum.com/
Yahoo Finance	Yes	finance.yahoo.com/

Table 4.1: Table of relevant data sources.

- **Data Market:** Data Market is a data aggregator and provides different kinds of data on a country level. Some of the provided data is free, however the business model of the market place is to trade with data, so a lot of the data needs to be paid for.

- **Datastream:** Datastream is a tool provided by Thomson Reuters. The tool is based on Excel and therefore can easily be used in collecting data. Thomson Reuters provides a huge database of economic indicators. The negative aspect is that the data is not free and can only be accessed via specific registered terminals.

- **Data repository of Deutsche Bundesbank:** As an open public repository, the Deutsche Bundesbank data repository is completely free and has no restrictions in usage. It provides monetary, financial and economic statistics, as well as other indicators.

- **ERIX:** This database is provided by CBRE and is paid only. CBRE is a real estate development agency with a research department, which provides interesting indicators based on their own property development activities, such as yield, rent or capitalization, on a country or market level.

- **EuroStat:** The statistical office of the European commission provides several indicators based on a macro and micro level. The data is publicly available and nearly all time series are complete.
- **FRED:** The Federal Reserve Economic Data is the official and publicly available data provider of the United States. Besides tracking their own economic development, detailed statistical variable and indicators of a lot of other countries can also be found.
- **Interactive Broker:** This broker provides through its excellent interface stock, currency and bond data. The data is free as long as you have an active trading account via the broker.
- **OECD:** The OECD data repository provides freely available data, to the financial community. There is a wide range of indicators and variables available on the website.
- **OeNB:** The Austrian National Bank, has its own statistical and economic data repository. Via an interface, the user can select the data he is interested in and can then download it via several file formats.
- **Penn World Table:** The University of California, University of Davis and the University of Groningen have developed a set of panels to measure the real GDP across different countries over a long period. They added several other indicators such as capital, employment, population and productivity.
- **Quandl:** Quandl is an extremely large and useful data aggregation search engine. It has a vast amount of external data sources and searching quandl provides instant access to many other different data sources. During our research phase we used quandl extensively, because it also groups data into free and paid.
- **REMAX:** REMAX [1] does not have any official data sources. Thankfully, Professor Feilmayr provided us with offer data from REMAX.
- **Statistik Austria:** The official statistical department of Austria has lots of data publicly available. However, some of the data is incomplete and hence a lot of time series could not be used for our models.
- **ThinkNum:** ThinkNum is not the classical data provider. Still, lots of data can be imported via an R interface. The variables, which are available are mostly specific data on companies, such as their balance sheet or stock price.

[1] REMAX stands for *"Real Estate Maximums"* and is a real estate company that connects buyers and sellers in the real estate market. Further information can be found on `https://www.remax.at`.

- **Yahoo Finance:** Yahoo Finance provides basically data on stocks. The freely available data can be downloaded with a 15 minute lag. However, considering our quarterly time frame, this was not a problem during our research phase.

4.1.2 Data Quality and Availability

One of the most important aspects of predictive model building is to have high quality data which is easy to access and in the best case also free of charge. During our research project several problems occurred during this process, such as:

- **Incomplete time series:** The most common problem, when getting a time series is that it is incomplete. Either the economic series monitoring started too late or the surveiller of the series stopped for some years, which makes the whole series not as valuable as if the series were complete and contained no missing data points. During our research, several series provided by Statistik Austria [2] were incomplete.

- **No historic data:** Another issue is that institutions often have started time series monitoring only recently. Hence, if the monitoring stared later than 2000, we had to reject the series. There are several techniques to lengthen a time series. One is to combine two time series, based on the correlation coefficient of the two series. [104] The challenge with this technique is, to find another time series, which correlates well with the base time series.

- **Length of time series:** Several researchers argue that a time series has to have a certain length to make a robust forecast. Holden et al. (1991) [87] and McGough and Tsolacos (1995) [129] argue that the time series has to have at least 50 data points to be sufficient. Weiss and Andersen (1984) [171] argue that around 30 observations are enough. Several other researchers use other lengths to achieve good results, such as Mouzakis and Richards' (2004) [134] data with 22 points, Stevenson and McGarth (2003) [163] employee 39 data points and D'Arcy et al. (1999) [47] use around 28 observations. All these studies achieve good forecasting results. Hence, one might argue that a time series has to have more than 30 to 40 observations.

- **Time frame availability:** Estimating a cycle is often done on a yearly basis, for example Jadevicius (2014) [101]. However, to lengthen a time series and increase its predictability as shown in the bullet point before one has to extend the series. We split the time frame up and use quarterly data for estimating the cycle. This step helps us to create a reliable and accurate model, which we would not get if we focus rather on a shorter yearly based time frame.

[2] See the statscube for accessing data from Statistik Austria, `http://www.statistik.at/web_de/services/datenbank_superstar/index.html`

- **Free / Open data:** Lots of data is still not publicly available and only certain data sources can then be used. There are lots of large companies such as CBRE, which have real estate projects in important European cities, such as Vienna or Berlin, and share their rent data with others by paying a monthly subscription fee. Luckily, we got an access to also use such kind of data in our forecasting model.

Overall the historic data quality for Austria is extremely bad, when considering real estate. Still there are many standard data points available as of now. As indicated by the Austrian National Bank [3] as long as the data collection effort is continued, then also model accuracy of the presented methodology will rise.

4.2 Variable Selection Techniques

"Correlation does not imply causation", is a common phrase in statistics. The definition of causation is an age old question and many philosophers came up with different definitions over time. According to Granger (1969) [161], a cause, in contrast to correlation, is a *"[...]deeply defined relationship and potentially useful[...]"*. [4] This is especially the case, when selecting variables, which are used for prediction. Our base sample should consist of data, that has the highest predictive value. Hence, we initially "*test*" our selected data, and pick unique variables, which contain the respective features.
Variable selection has been pointed out as a rather ineffective practice by statisticians. The reasons for this view is grounded in the *art of variable selection* and is definitely true, if feature selection is *"done wrong"*. The reason for that can be shown by some examples: using selection techniques yields models that have coefficients, which are biased away from zero, its standard errors are often too small and confidence intervals are too narrow to show any significance to the modeler. [78] As a result, the model output is over-fitted and the test statistics and p-value outcomes cannot be interpreted correctly. [78] Even though these limitations exist, the author strongly believes that a pre-analysis and clear variable selection methodology has to be used to order and pre-study the amount of economic data and present a comprehensible path for the reader, which starts at the initial variable selection and ends at the final model creation. [78]
The following subsections, describe each *selection procedure*, which our initial sample runs through to gain the final data set. We will start with the explanation of a cluster analysis in section 4.2.1. Further we will examine stationarity in subsection 4.2.2.3 and its importance to test it via two outlined approaches. Further, we will point out regression based variable selection by showing forward and backward regression 4.2.3 and the use of the LASSO method in section 4.2.5. Next, we will describe the modeling variables in section 4.3, starting with our independent

[3] See `https://www.oenb.at/en/Statistics.html` for further information about the available data of the Austrian National Bank.

[4] See `http://www.scholarpedia.org/article/Granger_causality`.

variable 4.3.1 and explain the dependent variables 4.3.2. Finally, we will present the data which will be used in the simulator engine in section 4.4, pointing out the use of synthetic data 4.4.2 and provide an explanation of the data itself in 4.4.1.

4.2.1 Cluster Analysis

Before starting to select variable for the forecasting model, we start with a cluster analysis. This method is a technique to show similarities between variables by grouping them. [8] We use a *hierarchical cluster* to show the different groupings of each variable, which is used in the model. [5] Hierarchical clustering can roughly be described as using a set of dissimilarities for the number of objects and joining the two most similar objects into one cluster at each iteration stage. The hierarchical clustering algorithm ends, when only one single cluster exists. To compute similarity a distance metric is defined. Figure 4.2 shows a dendrogram of the hierarchical cluster.

The tree diagram in figure 4.2 shows the similarity among the variables. The approach which we use is hierarchical clustering, specifically agglomerative clustering [6] and shows, similarity and hierarchy of the underlying data. The upper nodes show the hierarchy and the length of the arrow shows its similarity. It can be seen in figure 4.2 there are mainly three clusters and several sub-clusters. In appendix B table B.1 describes the variable order of the taken cluster approach.

4.2.2 Unit Root

Testing for stationarity is one of the standard testing methods before implementing a meaningful model. The problem of stationarity is that if we have a time-series of data $X_1,...,X_n$, we want to assume that X_n is independent. Having independent data points is a necessary property, which applies for a lot of models, such as ARMA, and also for basic modeling theorems, such as the law of large numbers and the central limit theorem [75] [11]. There are several ways to turn a non-stationary sequence into a stationary sequence, such as de-trending a series, seasonal adjustment and taking the logarithmic difference of a sequence. [96] In the next three subsections, we will show the two statistical tests, the Adjustment Dick Fuller Test 4.2.2.1 and the Kwiatkowski-Phillips -Schmidt-Shin Test 4.2.2.2, which we will use for checking if our time series are stationary or not and finally describe a specific stationarity adjustment routing in subsection 4.2.2.3.

[5] We use the *hclust* R method for performing hierarchical clustering. Further information can be found at, `https://stat.ethz.ch/R-manual/R-patched/library/stats/html/hclust.html`

[6] Further information can be found at, `https://stat.ethz.ch/R-manual/R-patched/library/stats/html/hclust.html`

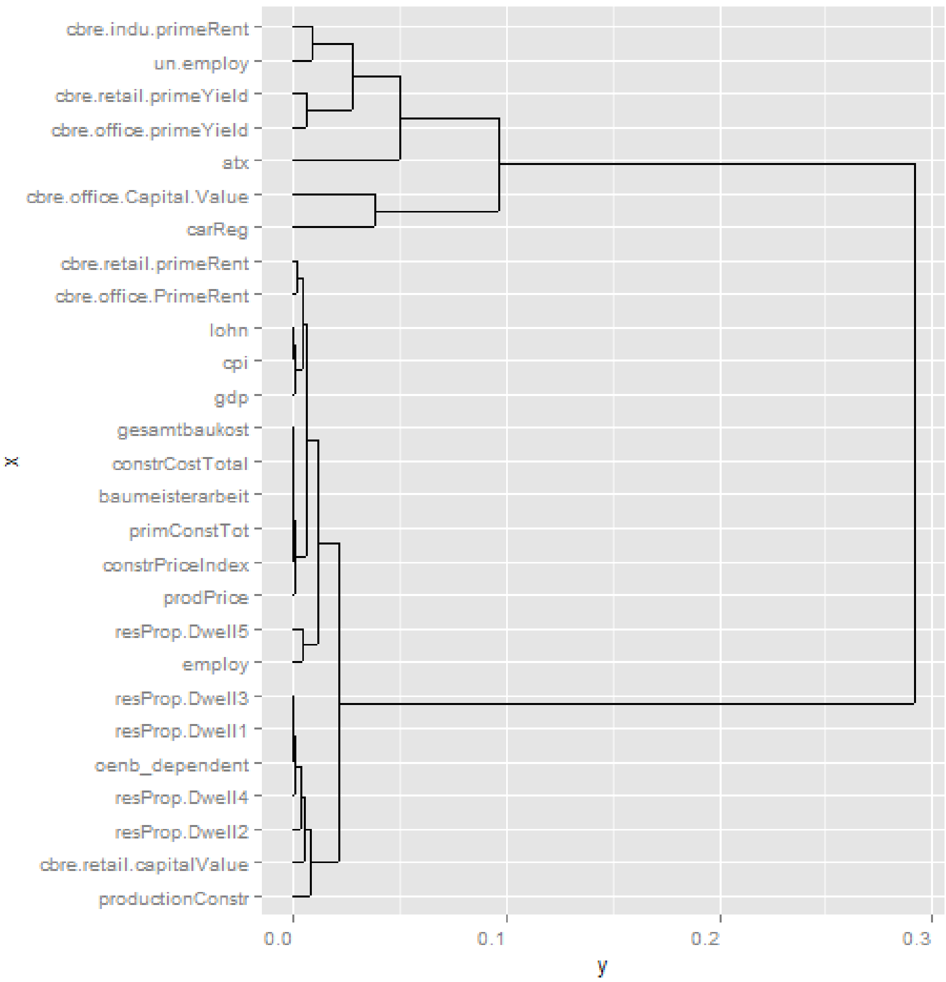

Figure 4.2: Hierarchical clustering

4.2.2.1 Augmented Dick-Fuller Test

The augmented Dick-Fuller Test is a unit root test for time series. The testing procedure is applied to an *AR(n)* model. [73] [147]

$$\Delta y_t = \alpha + \beta t + \gamma y_{t-1} + \delta_1 \Delta y_{t-1} + \cdots + \delta_{p-1} \Delta y_{t-p+1} + \varepsilon_t \tag{4.1}$$

Equation 4.1 shows the augmented Dick-Fuller Test, whereas α is a constant, β the regression coefficient and the lag order p of the *autoregressive (AR(n)) process*. [73] [147] Using the lag p in the equation allows the use of higher order autoregressive processes.

The final unit root testing is then done under the assumption of H_0 that $H_0 : \gamma = 0$, whereas the alternative hypothesis is to assume that $H_1 : \gamma < 0$. After computing the test statistics value, the interpretation is, if the computed value is less than the critical value, H_0 is rejected and no unit root exists, otherwise H_1 is accepted. For testing our time series, we use the R function *adf.test()* of the package *tseries*.

4.2.2.2 Kwiatkowski Phillips Schmidt Shin Test

The *Kwiatkowski Phillips Schmidt Shin Test (KPSS)* is a *complementary* unit root test, which supplements the previously done Dick Fuller Test. [158] Nelson and Ploser (1982) show in their study that common unit root tests, such as the Dick Fuller Test have a chance to reject their null hypotheses of stationarity. Kwiatkowski et al. (1992) [158] argue that the problem relies, that the null hypothesis of the standard unit root tests state that economic series are *non-stationary*, whereas the latter is more often the case. Hence, the KPSS test assumes as a null hypothesis that the tested time series is *stationary*. [158] Furthermore, the KPSS test complements classic stationarity test by also testing for a deterministic trend. [135] We choose this test, because it is complementary to the Augmented Dick-Fuller test, presented in subsection 4.2.2.1.

$$X_t = c + \mu t + k \sum_{i=1}^{t} \xi_i + \eta_t \tag{4.2}$$

In equation 4.2 a regression model is shown, with η_t shows the stationarity and ξ_t has an expected value of 0 and a variance of 1. The alternative hypothesis is, if $H_1 : k \neq 0$ and the null hypothesis is, if $H_0 : k = 0$. Compared to the Adjustment Dick-Fuller Test, the H_0 hypothesis is that the time series is *stationary*. [158]

4.2.2.3 Stationarity Adjustment Routine

"A stationary time series is one whose properties do not depend on the time at which the series is observed.[...]" [96] When talking about stationarity, the topic itself can be best presented by an example. If we assume that we have a series of data, $x_1,...,x_n$, we want to assume that the data points are independent among each other. The reason for this is, that we do not want during the modeling process that the mean and the variance change over time and we can derive a forecasting pattern. Hence, we have to check our data for stationarity. [96]
There are several ways to adjust a time series for stationarity. Differencing a time series is a common approach. [96] To change the unit root of a seasonal series, we use the following R code, which was inspired by Athanasopoulos and Hyndman (2013). [96]

```
ser <- nsdiffs(x)
if(ser > 0) {
  finSer <- diff(x,lag=frequency(x),differences=ser)
} else {
  finSer <- x
```

```
}
nd <- ndiffs(finSer)
if(nd > 0) {
  finSer <- diff(finSer,differences=sernd)
}
```

In the method code above the function *ndiffs()* and *nsdiffs()* is used. The first function, determines the needed number of first differences required for a data series. The second function, checks if seasonal differencing is required. In the subsection 4.2.2, we present two test statistics, which exclude each others null hypothesis to test our time series for stationarity, the Adjustment Dick Fuller Test 4.2.2.1 and the Kwiatkowski-Phillips-Schmidt-Shin Test 4.2.2.2.

4.2.3 Stepwise Regression

The main idea of stepwise regression is based on a greedy algorithm. Basically, the core principal of stepwise regression is to either add or remove a variable, which depends on the form of stepwise regression, from a data set and after each iteration it is decided by the model algorithm, based on a termination criteria, for example an F-Test, to change the number of predictors or to terminate the variable selection process. [52] [84] [51] [77] It has to be made clear that, besides the F-Test, also other *"selection"* measures can be used such as R-square, Akaike information criterion (AIC) [3] or Bayesian information criterion (BIC) [153].

The procedure of a stepwise regression using an F-Test works as follows:

1. In the first step, the modeler has to make the decision, if he wants to remove (backward) or add (forward) variables to the regression.
2. In the next step, the modeler selects an alpha to test the predictors on, f.ex.: $\alpha = 0.15$
3. Each x_1 to x_n is regressed on the independent variable, y. The first variable that is put into the stepwise regression has the minimum p-value, hence is below stated α.
4. If for example, x_1, was the best predictor, the model is *"stepwise"* regressed with the other available variables.
5. The procedure is stopped, when adding/removing new variables does not yield the defined α.

This automated method of variable selection has also its limitations. [145] [127] [95] Stepwise regression yields a single predictive data selection, however usually there are more possible models, which can be used. Furthermore, the automated methodology can include or exclude some important or unimportant predictors, which fit the used threshold, in the example above α, incidentally. Compared to other automatic selection methods, stepwise regression performs rather well, which is shown for example by Olejnik, Mills, and Keselman (2000) [138] However, besides the useful technical selection process, the authors showed, that stepwise regression often does not yield the *correct* model. Hence, we decided to also use a further method, the causality test by Granger (1969), which is presented in subsection 4.2.4. [161]

Stepwise regression results
As shown in appendix B we conduct three different experiments, forward regression, backward regression and a combination of both types.

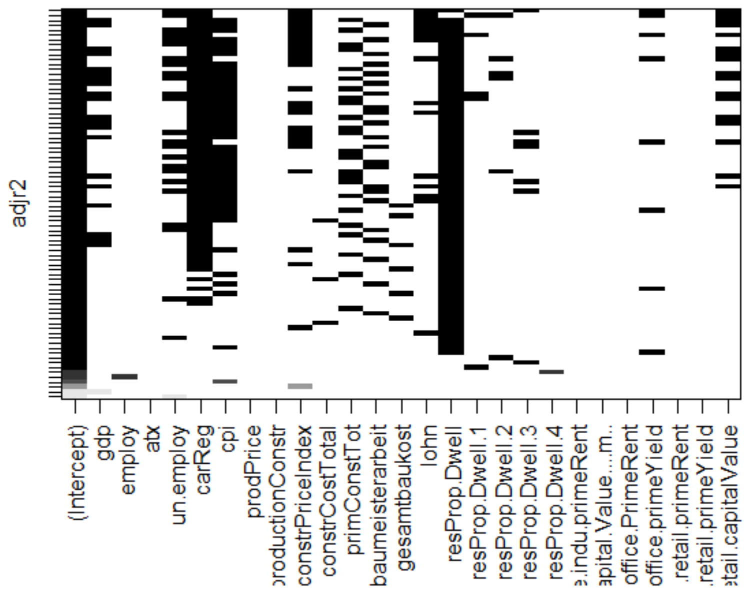

Figure 4.3: Adjusted R^2 of the property cycle data set.

Figure 4.3 and 4.4 show the adjusted R^2 and the Bayes Information Criteria plotted for the data set. The plot shows all combinations the best models by visual indication. When looking at the AIC results of the selected data, according to forward regression the best model includes: *car registrations, consumer price index, primary construction index and the residential property index for dwellings*. For backward regression the result is, *carReg, constrPriceIndex, resProp.Dwell1, resProp.Dwell3, resProp.Dwell4, cbre.office.primeYield and cbre.retail.capitalValue*. For forward and backward, the best result is, *carReg, cpi, primConstTot and resProp.Dwell*. A mapping of all variables can be found in table 4.2. All results of stepwise regressions are included in the appendix B.

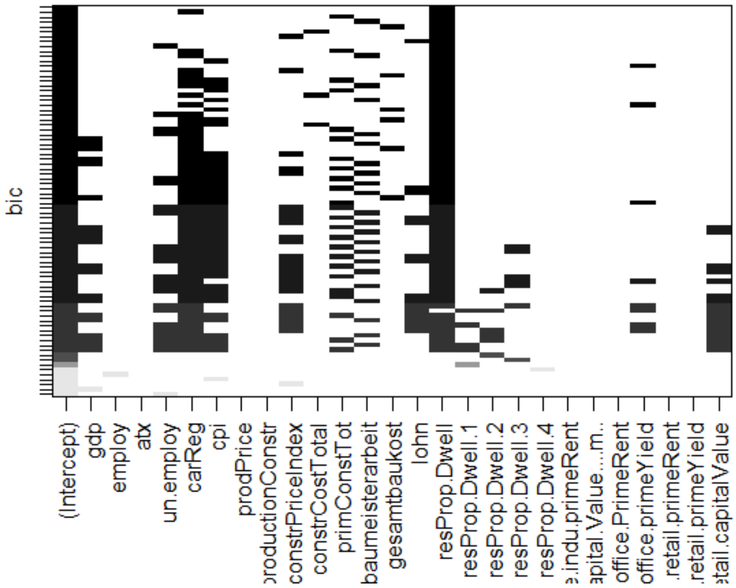

Figure 4.4: Bayes information criteria (BIC) of the property cycle data set. [153]

4.2.4 Granger Causality Test

The Granger Causality Test (or G-causality) was developed in 1969 by Professor Clive W.J. Granger, when he investigated a causal relationship of two related stochastic processes. [7] [161] Granger Causality can be defined as the following: When given two time-series x and y, Granger Causality Test is useful in choosing if one time series should be more preferably used in prediction models than the other, because a causal relationship exists. The method is based on linear regression modeling using stochastic processes. [161] Basically, the test is taking different lags of one of the series, which is used to model changes in the other series. [70] The definition of the test relies heavily on the idea, that each observed effect is preceded and induced by a distinct cause. [8]

Mathematical formulation

$$X_1(t) = \sum_{j=1}^{p} A_{11,j} X_1(t-j) + \sum_{j=1}^{p} A_{12,j} X_2(t-j) + E_1(t) \tag{4.3}$$

[7] For further information see, `http://www.scholarpedia.org/article/Granger_causality`.

[8] For further information see, `http://www.scholarpedia.org/article/Granger_causality`.

$$X_2(t) = \sum_{j=1}^{p} A_{21,j} X_1(t-j) + \sum_{j=1}^{p} A_{22,j} X_2(t-j) + E_2(t) \quad (4.4)$$

Let‘s consider two variables X_1 and X_2 in the context of linear regression, where p describes the model order, the maximum number of lags in terms of observations that are in the model. The model order can be determined by using AIC (Akaike Information Criterion) [3] or BIC (Bayesian Information Criterion) [153]. The matrix A_{11},A_{12}, A_{21} and A_{22} have the model coefficients and the residuals, representing the prediction errors, of the model are E_1 and E_2. In causality test of Granger X_1 causes X_2, when the variance of E_1 or E_2 are reduced by including X_2. This relationship can be tested by an F-Test, by saying that $A_{12} = 0$ under the assumption that the covariance of X_1 and X_2 is stationary, therefore, the time series mean and variance do not change during their time frame. [9] Furthermore, the second assumption is that the objective of the data can be described using a linear model. Like Granger, other researchers argue, that this is not *true* [10] causality, therefore it is named Granger-causality. [11] Hence, there are mainly three limitations using Granger causality.

Linearity

As stated above, the original Granger Causality test relies heavily on linear explanations, and therefore can only show causality within linear features. Of course there exist extensions, such as approaches by Freiwald et al. (1999) [59], Brovelli et al. 2004 [29] and Ancona et al. (2004) [4] [12], which try to show a causal relationship on non-linear variables.

Stationarity

An assumption of the Granger Causality Test is that the covariance is stationary. Hence, the test cannot be used on non-stationary features. However, solving the problem for non-stationarity signals, the windowing technique from Hesse et al. (2003) [81] can be used.

Observed variable dependence

As with other statistical modeling techniques, Granger Causality depends on the initial data selection, which the test is calculated on. Hence, if in the data no cause is used for an output, it cannot be used by the test. As stated by Professor Granger, it is advised to not interpret the test as physical cause chain. [13]

[9] For further information please visit: http://www.scholarpedia.org/article/Granger_causality#Mathematical_formulation

[10] Which is currently an unsolved problem to be described in mathematics and statistics.

[11] For further information please visit: http://www.scholarpedia.org/article/Granger_causality#Mathematical_formulation

[12] For further information please see the respective papers.

[13] For further information please visit: http://www.scholarpedia.org/article/Granger_causality#Mathematical_formulation

Granger Causality Test Results
All results of the Granger Causality test can be found in table B.2.3. A clear explanation of the entire test can be found in section 4.2.4.

4.2.5 Lasso Regression

In our variable choosing process, we also use the LASSO (Least Absolute Shrinkage and Selection Operator) as a variable selection method. This regression method uses a penalty to shrink the size of the regression coefficients. [79] The LASSO algorithm constraints minimize the sum of the absolute value estimations. By using this method, some parameter estimates will be 0. When using this method, as long as no parameter estimates are 0, LASSO regression outputs an *optimal model*. [79] LASSO is extremely useful, when the features are highly correlated. [79]

Lasso Regression Results
All results of the conducted Lasso regression can be found in subsection B.2.4.

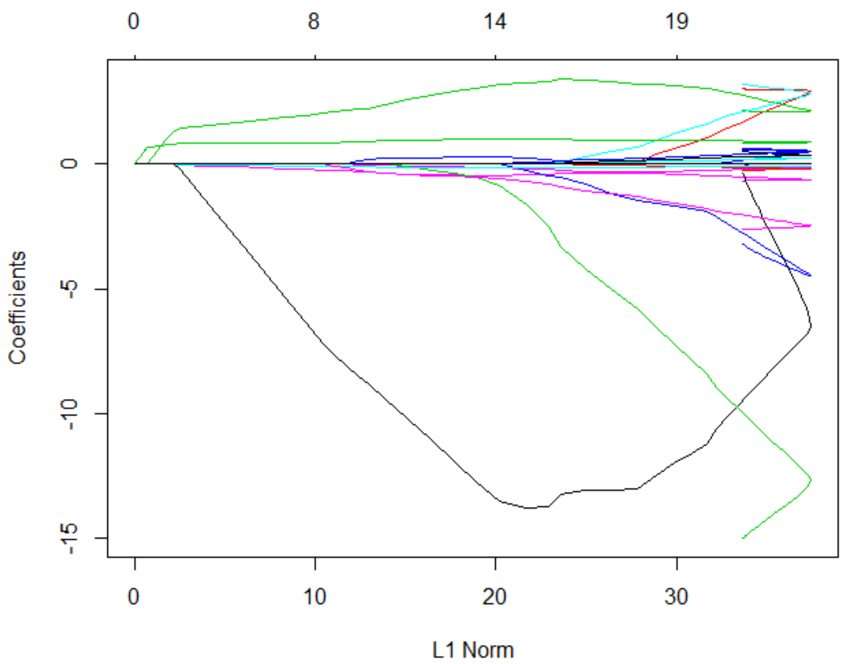

Figure 4.5: Coefficients and L1 Norm of the lasso model.

Figure 4.5 shows the coefficients of the conducted LASSO model and figure 4.6 shows the mean squared error of the LASSO iterations selecting lambda using cross-validation. Even though using two different methods the results are quite similar, with 0,8007937 for the cross-validation

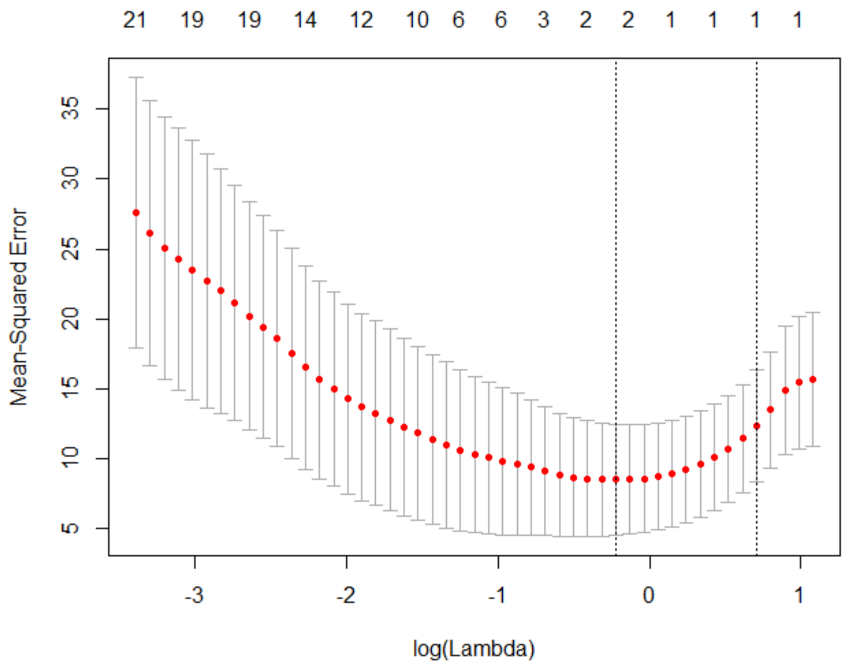

Figure 4.6: Mean Squared Error of Lasso Regression Model.

method and 0,7699665 for the lasso regression method using the R package *glmnet* [14]. Both figures 4.5 and 4.6 show using the boundaries and the iterative approach of penalties of the lasso method.

4.3 Modeling Variables

As presented in subsection 4.1.1 we used several free and paid sources to collect relevant data for our model. Table 4.2 shows the pre-selected variables, which we used for starting the variable selection process. All variables, which are marked *gray* in the below table were selected through our extensive variable selection method. The table shows the earliest possible year the variable is available, the final period, the available time frame, a description of the variable itself and the source, where the variable was taken from.

Start	***End***	***Time-frame***	***Variable***	***Source***	***Variable Model Name***
1992	2015	Quarterly	ATX Quarterly Adjusted-Close	Yahoo Finance	atx

[14]For further information see `https://cran.r-project.org/web/packages/glmnet/glmnet.pdf`.

1947	2014	Quarterly	Austria GDP	FRED	gdp
1990	2015	Quarterly	Basic primary construction total,residential buildings	WIFO, Statistics Austria, OeNB	primConstTot
1957	2015	Quarterly	Car registration	FRED	carReg
1990	2015	Quarterly	Construction costs total, residential buildings	WIFO, Statistics Austria, OeNB	constrCostTotal
1996	2015	Quarterly	Construction price index total	WIFO, Statistics Austria, OeNB	constrPriceIndex
1989	2015	Quarterly	Construction wages with underground delivery	Statistik Austria	const.wages.with.und
1989	2015	Quarterly	Construction wages without underground delivery	Statistik Austria	const.wages.without.und
1989	2014	Quarterly	Construction work index with underground delivery	Statistik Austria	const.work.with.und
1989	2014	Quarterly	Construction work index without underground delivery	Statistik Austria	const.work.without.und
1999	2015	Quarterly	Employment Rate	OECD	employ
1996	2015	Quarterly	Industrial - Prime Rent	CBRE	cbre.indu.primeRent
1991	2015	Quarterly	Office - Capital Value	CBRE	cbre.office.CapitalValue
1991	2015	Quarterly	Office - Prime Rent	CBRE	cbre.office.PrimeRent
1991	2015	Quarterly	Office Prime Yield	CBRE	cbre.office.primeYield
1989	2015	Quarterly	Other construction costs with underground delivery	Statistik Austria	const.costs.oth.with.und
1989	2015	Quarterly	Other construction costs without underground delivery	Statistik Austria	const.costs.oth.without.und

1996	2015	Quarterly	Production of Total Construction in Austria	FRED	productionConstr
2000	2014	Quarterly	Rental Index	OeNB	oenb_dependent
2000	2014	Quarterly	Residential Property Prices, all flats ex. Vienna	BIS	resProp.Dwell3
2000	2014	Quarterly	Land Prices, dwellings ex. Vienna	BIS	resProp.Dwell1
2000	2014	Quarterly	Residential Property Prices, existing flats ex. Vienna	BIS	resProp.Dwell4
2000	2014	Quarterly	Residential Property Prices, family houses ex. Vienna	BIS	resProp.Dwell2
2000	2014	Quarterly	Residential Property Prices, new flats ex. Vienna	BIS	resProp.Dwell5
1998	2015	Quarterly	Retail Capital Value	CBRE	cbre.retail.capitalValue
1998	2015	Quarterly	Retail Prime Rent	CBRE	cbre.retail.primeRent
1998	2015	Quarterly	Retail Prime Yield	CBRE	cbre.retail.primeYield
1996	2015	Quarterly	Consumer Price Index	Eurostat	cpi
1995	2015	Monthly	Producer Price Index	Eurostat	prodPrice
1989	2014	Quarterly	Total construction costs with underground delivery	Statistik Austria	baumeisterarbeit
1989	2014	Quarterly	Total construction costs without underground delivery	Statistik Austria	gesamtbaukost
1969	2015	Quarterly	Unemployment Rate	OECD	un-employ

Table 4.2: Output of pre-selected and finally chosen variables of the variable selection process.

The following subsections 4.3.1 and 4.3.2 examines our finally selected variables and explain it in further detail.

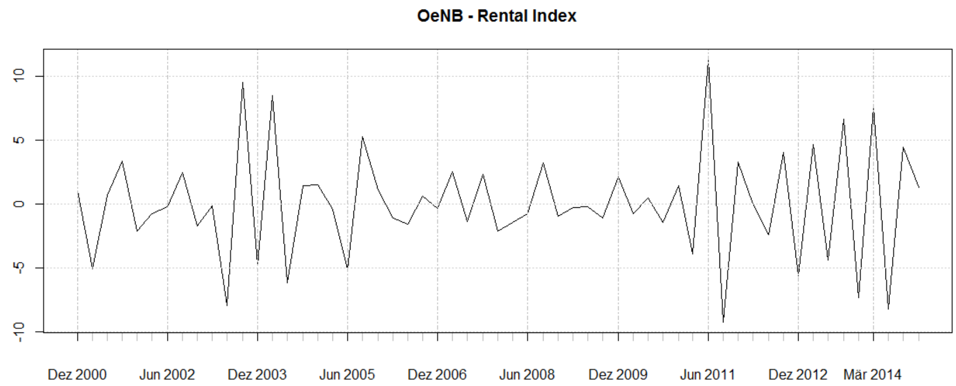

Figure 4.7: Austrian rental index

4.3.1 Independent Variable

Our independent variable is shown in figure 4.7. The initial data is stationary, hence we use our stationary routine to adjust the data points. [15] The rental index is based on several data sets. A large part are price offers of different rental use types, which are provided by REMAX [16]. [150] [31] The index is available on a regional breakdown, which is divided into two parts, including Vienna or excluding Vienna. The current calculation methodology is also split into two parts, for family homes and condominiums it is based on an *imputation index* and for single-family house, building plots and condominiums a dummy index is available. [31] A detailed description of the used methodology can be found in Brunauer, Feilmayr and Wagner (2012). [31]

4.3.2 Dependent Variables

The following subsections show the dependent variables, which are marked grayly in table 4.2. Our final data set of dependent variables comprises of five variables, which are Car Registration 4.3.2.1, Consumer Price Index 4.3.2.2, Primary Construction Costs 4.3.2.3, Prime Yield 4.3.2.4, Capital Value 4.3.2.5 and Land Price Index 4.4.1. The underlying data behind each plot is also shown in appendix A as a result table.

4.3.2.1 Car Registration

Figure 4.3.2.1 shows passenger car registrations in Austria. The data is taken from the FRED, which is described in subsection 4.1.1. Car registrations is described as a leading indicator by Matysiak and Tsolacos (2003) [128]. Furthermore, the indicator variable was also recently used by Jadevicius (2014) [101].

[15] Further information about the specific procedure can be found in subsection 4.2.2.3.
[16] For more information about REMAX visit `www.remax.at/`.

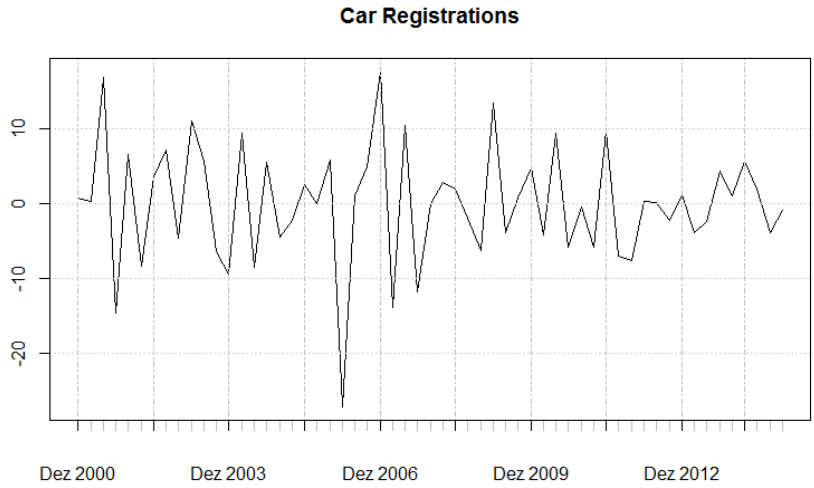

Figure 4.8: Car Registrations in Austria

4.3.2.2 Consumer Price Index

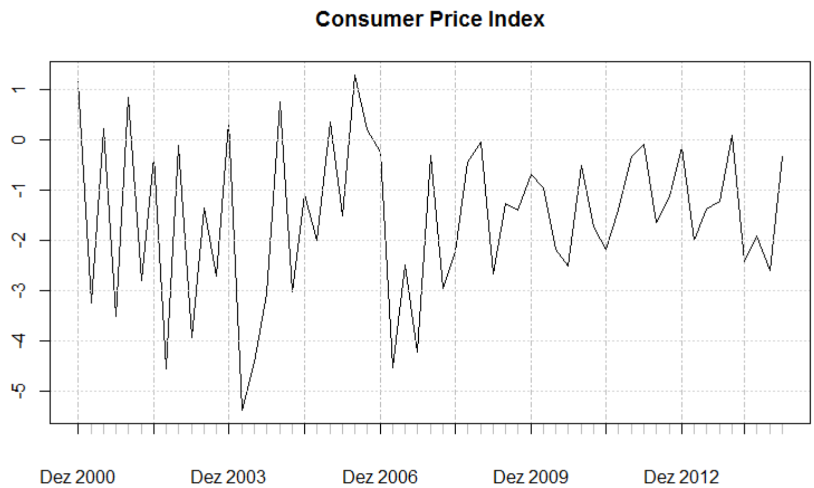

Figure 4.9: Consumer Price Index

In figure 4.9 the harmonized consumer price index is shown. The initial indicator is in a raw format and not seasonal and working day adjusted. Furthermore, we also adjusted the indicator for stationarity.

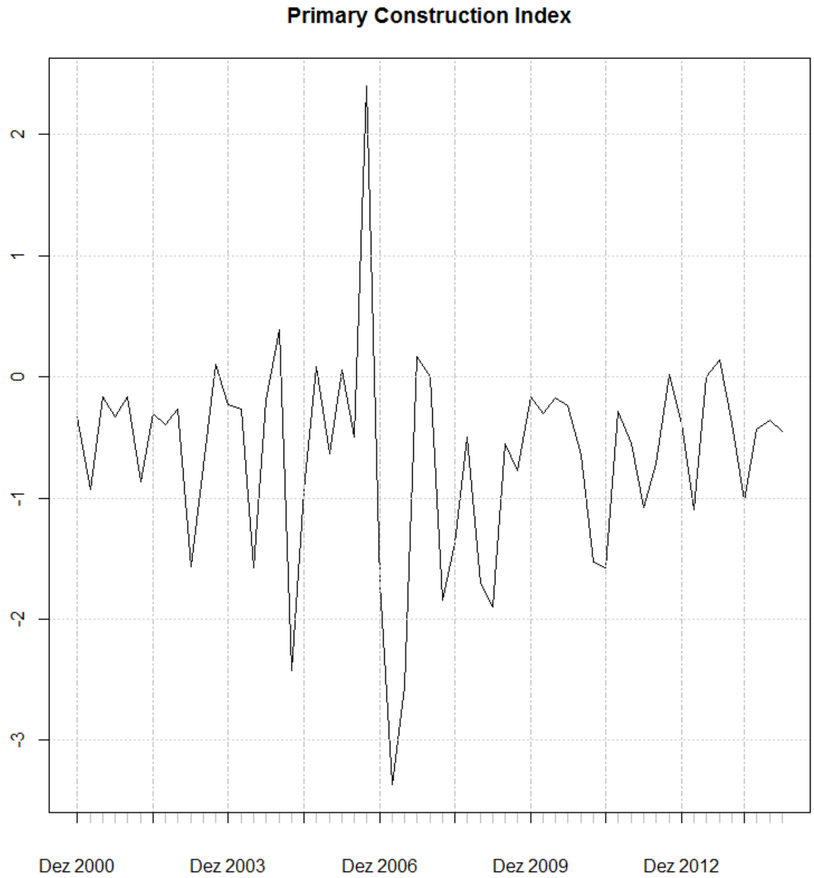

Figure 4.10: Primary Construction Costs.

4.3.2.3 Primary Construction Costs

As shown in Jadevicius (2014) [101], construction costs are a great leading indicator to predict the property cycle. Many variables, which are related to real estate have been monitored since the late 90s. Therefore, the quality and availability of the time series are extremely good. Similar to the consumer price index 4.3.2.2, we also adjusted the primary construction costs for seasonality and made the series stationary.

4.3.2.4 Prime Yield

As in some discussions with industry experts, we noticed that yields tend to be an extremely important indicator for a property developer to decide if a project is worthwhile or not. Figure 4.11 shows the prime yield for office buildings. The series was seasonality adjusted and hence we only had to adjust it for stationarity. The figure also indicates a large break in 2007, however the reason for this is that we adjusted the variable for stationarity. In fact, the initial series only had

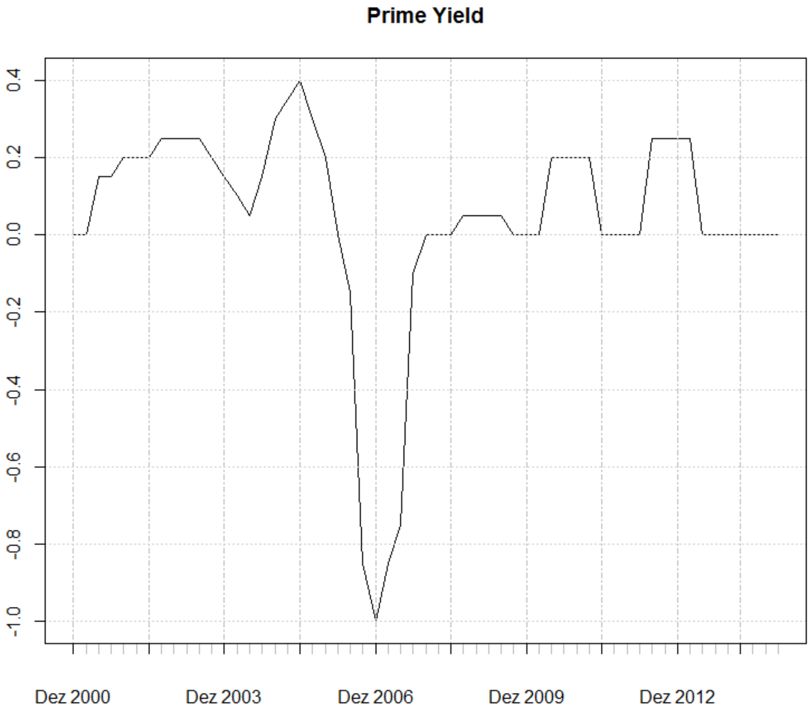

Figure 4.11: Prime Yield

a small break during this time.

4.3.2.5 Capital Value

The CBRE [17] Capital Value Index shows the relative value of capital for a certain city or area. The index is constructed using a sector index, region index value and an IPD region weight, which is a mirror of a standardized property portfolio by CBRE. [18] Figure 4.12 shows the capital value index for Austria.

4.3.2.6 Land Price Index

As one of our best performing variables in the selection process, we choose a land price index. The variable was taken from the *Bank of International settlement* (BIS) and comprises data from its member central banks and the BIS Residential Property Price database. [19] The methodology is based on the handbook of *"Handbook on Residential Property Price Indices"* published by Eurostat. [9]

[17] See `http://www.cbre.at` for further information.
[18] A detailed description and a mathematical formulation of the index can be found on `http://www.cbre.at`.
[19] For further information please visit `http://www.bis.org/statistics/pp.htm`.

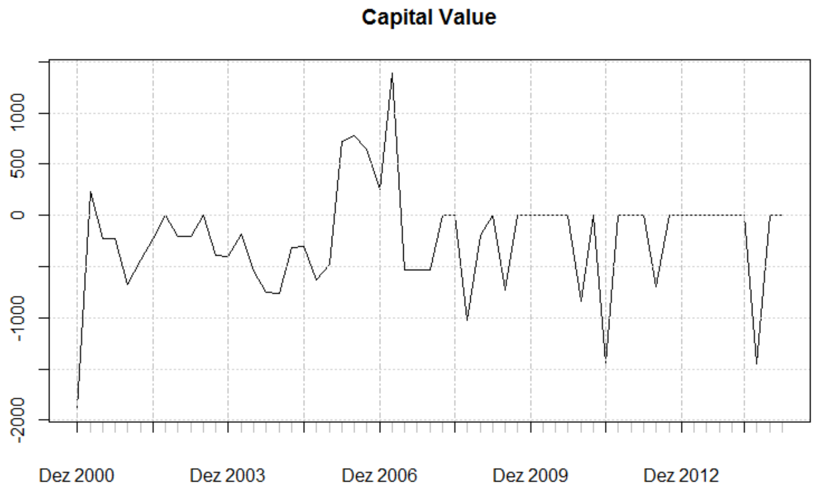

Figure 4.12: Residential Capital Value

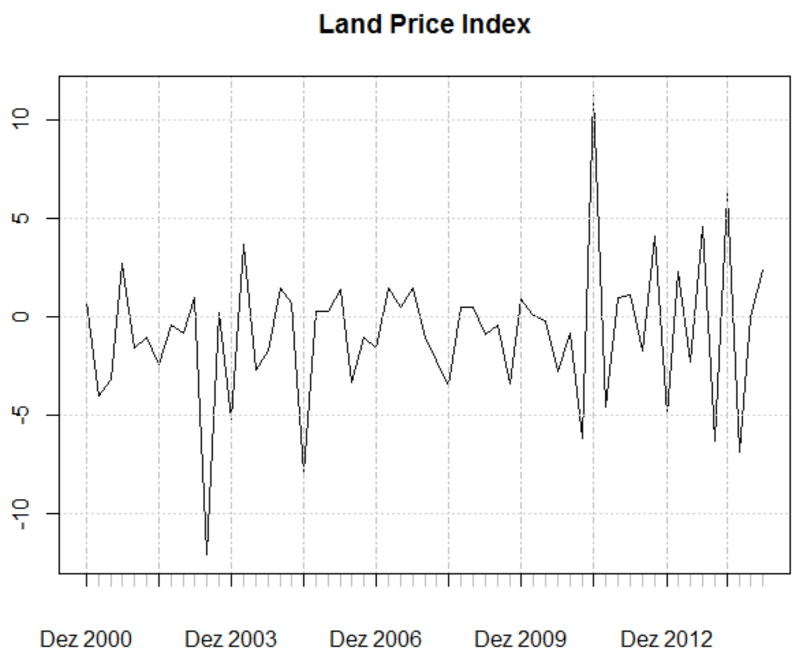

Figure 4.13: Land Prices Dwellings

4.4 Simulator

To show the cyclical effects on a portfolio of properties, we use a simulation engine. During our literature review, not many sources were uncovered, which show a structured approach to set up an underlying data set of a simulation engine. Hence, we select our sample based on expert judgment. As Griliches (198) puts it, *"[...]If the data were perfect, collected from well designed randomized experiments, there would be hardly room for a separate field of econometrics.[...]"* [74] This oversimplification shows the importance of using a transparent data generation process and relevant assumptions for our processing engine.

In the sections above we described the data, which is used in the forecasting model. In this second part, we will show on the one hand the data generation process 4.4.1 and on the other hand examine samples of the projects data 4.4.2.

4.4.1 Data Generation Process

As in section 4.1, we also have a data generation process for simulation data. Figure 4.14 reflects the steps we took to come up with *synthetic data* for our simulation engine.

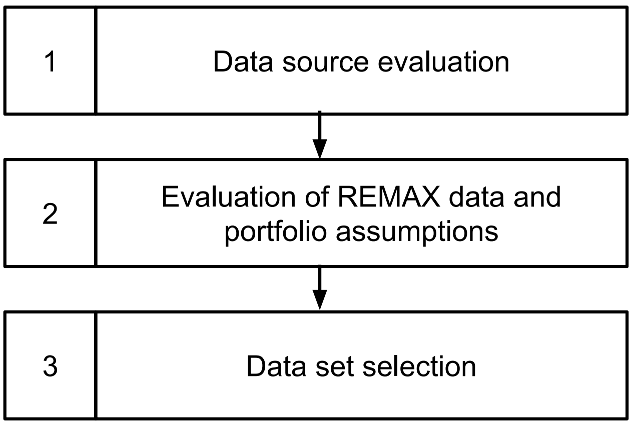

Figure 4.14: Simulation Data Process.

In the first step, we did a comprehensive literature research and interviews, clarifying the questions regarding a typical portfolio of a developer or a bank. However, our evaluation shows that the size is usually dependable on the risk appetite and the size of the company. Hence, we choose in our evaluation in the second step real world properties from REMAX and model our data set. All taken assumptions are provided in subsection 4.4.2. After checking the consistency of the data, we select our data set in the final step.

4.4.2 Synthetic Projects Data

To test the effects of cyclicality we run through our simulation engine a *synthetic* data set. As shown by Cowley 2007 [43] the portfolio should consist of buildings with different ages and market values. Our finally used data set is outlined in C. As our portfolio consists only of the loan financials of a property, we have to outline some assumptions for our used data:

- **Balloon payment:** As we do not have the exact maturity date of our properties and only take rough assumptions, based on the age and the average loan maturity length of properties, which can be from five to twenty years, we take balloon payments out to simplify our assumptions. [20] Furthermore, showing cyclicality, based on the LTV and the DSCR, in a portfolio is not based on the balloon payment, which just shortens the loan.

- **Separate Evaluation:** We group our property financials into *large*, *medium* and *small*. As our simulation engine evaluates each loan separately, we show the risk of the property cycle for differently sized developer projects.

- **Currency:** Property developers and banks often face the problem of financing or issuing a loan in another currency. As our property cycle research focuses on Austria, we assume the Euro as base currency for our financials. The unwanted option of hedging a portfolio against cyclical risk is therefore taken out.

- **Portfolio size:** We generate a portfolio of around five properties, to simulate a small to medium real estate development firm. As we evaluate each property on a single level, the number of properties is only partly relevant to our final conclusions.

- **Maturity date:** To make homogeneous assumptions about each loan we just lengthen the maturity date for each of the five loans for one year in the future. The reason for this is that we want to show the effect of the property cycle on a linearly distributed portfolio.

A clear outline of the used data can be found in the appendix section C.1 in table C.1.

4.5 Summary

This chapter examines the data used in the cyclical research project. The following sections are part of this chapter: variable collection process 4.1, variable selection techniques 4.2, modeling variables 4.3 and a description of the simulation data set in section 4.4.

In the starting section 4.2, we outline our process for collecting variables. In the first subsection, we examine data sources and their availability. In subsection 4.1.2, we show challenges,

[20] Further information was provided by `http://www.cbre.com/erix`.

which occurred through our collection of data and explain the *why* of arriving at the final modeling data set.

We select several potential variables and use variable selection techniques to reduce the number of relevant variables. To get an overview of the variable's similarity, we start with *hierarchical clustering* in section 4.2.1. As we use comprehensive modeling techniques, outlined in section 3.4, we check our data for a unit root using the adjusted dick fuller test and the KPSS test [21]. In the next step, we use stepwise regression to reduce our data sample. As also used in the literature, we focus on applying the Granger Causality to potentially filter out causal data variables. Finally, we apply lasso regression 4.2.5 as a variable selection technique. Using these techniques gives us the final data set, which is used in our forecasting models. All results are outlined in appendix B.

Section 4.3 describes the data set, where our selection techniques are applied to. Table 4.2 shows all used data and marked in gray is the finally used selection data. The following sections, describe each variable such as the independent variable in subsection 4.3.1 and the dependent variables in subsection 4.3.2. Each final variables in plotted and its importance is explained.

In the last section of chapter 4, the simulator data set is explained. In the first subsection 4.4.1, the data generation process, which is used for the final simulator data set is outlined and in the following section, the synthetic project data is described. Appendix C examines the used simulator data set and outlines it in table C.1.

[21]Both tests are outlined in section 4.2.2.1 and 4.2.2.2.

Chapter 5

Empirical Results

According to CBRE [1] EUR 586mn was invested in the Austrian Real Estate market in 2015. [36] Compared to the first quarter, this was an uplift of 62%. [37][37][35] According to CBRE, the office sector was the largest part of this transactions with over 63%, residential building investments account for 14%. The whole transaction volume is according to OeNB [2] around 21,6 billion and the total number of transactions are 18,1 thousand for the last year.[137] Even though interest rates are at the same level as in 2009, house loans are stagnating.[137] Furthermore, the *ability to repay loans* [3] is on an all-time low. Developers fight with these rising market conditions as the Vienna housing market seems to *overheat* in the long run. [137]

Hence, forecasting cyclical sensitivities is becoming an extremely important topic as it determines the point, when it might be the time to invest into the property market. However, according to Leibnitz, *"[...]One of the secrets of analysis consists... in the art of skillful employment of available signs.[...]"* [19] During our research project, we used a wide range of forecasting techniques. Employed correctly we believe that the outcome will yield reasonable prediction sensitivities, which can be used in the cyclical simulator. The following sections will be part of this chapter: We will start by examine a descriptive statistics 5.1 about the forecasting variables. In the following section we will explain the forecasts 5.2, starting with exponential smoothing methods 5.2.1, simple and multiple regression methods in section 5.2.2 and 5.2.3, vector autoregression methods 5.2.4 and an ARIMA model 5.2.5. Furthermore, we will evaluate the accuracy of our taken methods in section 5.3. In the second part of this chapter we will explain the cyclical simulation engine 5.5 and the final simulation results for each scenario in subsection 5.5.1, 5.5.2

[1] See `http://www.cbre.com/` for further information.
[2] See `https://www.oenb.at` for further information.
[3] See oenb fact-sheet for further information.

and 5.5.3.

5.1 Descriptive Statistics

As shown in table 5.1 we used seven variables for our forecasting models. As described in chapter 4.2 all input variables, were selected through a comprehensive selection process.

A quarterly time-frame is used for all variables starting in the second quarter of 2000 and ending in the final quarter of 2014. The reason for this is, on the one hand that our overall sample of observations is larger when using a more granular observation period, which as a result influences the accuracy of our model and on the other hand using quarterly observations helps to better identify the granularity of cyclical swings in the simulation engine.

Overall our dataset consists of 57 observations, whereas no data points are missing. The minimum of the dependent variable is $-9,23$ and the maximum is $11,26$. All selected variables are adjusted for stationarity. *Cbre.retail.capitalValue* has much higher values compared to the other variables, the reason for this is that it is measured in EUR per square meter.

However, the range of the variables is from $0,40$ to around 18, when leaving *Cbre.retail.capitalValue* aside. Hence, the ranges are similar to each other. Furthermore, when comparing the sum of all observations, we can see that the final calculation is often negative, which suggests more cyclical downturns in recent years. When comparing these results to the last economic events from 2000 onward, we can roughly agree with these results interpretations.

The statistical variables, such as the median and the mean reflect the statements from above. Another interesting parameter is the standard deviation of the mean, which shows that all seven parameters do not differentiate highly from the mean. Furthermore, the 95% confidence interval of the mean suggest that all variables are lying within our wanted range.

Even though the standard deviation of the mean does not deviate much, we can see that the overall standard deviation is much higher. However, the reason for this is, that through adjusting our data for stationarity, such higher variances and standard deviations are present.

Finally, we also compute the coefficient of variation, which shows a measure for the dispersion of a statistical distribution. [54] It is calculated by dividing the standard deviation through the mean. [139] The results show that the highest dispersion is present in the dependent variable *oenb_dependent* and the independent variable *carReg*.

Descriptive Statistics	**oenb_dependent**	**carReg**	**cpi**	**primConstTot**	**resProp.Dwell**	**cbre.office.primeYield**	**cbre.retail.capitalValue**
Number of Values	57,00	57,00	57,00	57,00	57,00	57,00	57,00
Number of Missing Values	0,00	0,00	0,00	0,00	0,00	0,00	0,00
Min	-9,23	-27,11	-5,38	-3,36	-12,10	-1,00	-1882,35
Max	11,26	17,55	1,28	2,40	11,30	0,40	1386,67
Range	20,49	44,66	6,66	5,76	23,40	1,40	3269,02
Sum	0,77	-2,53	-88,41	-37,13	-45,90	2,40	-12800,35
Median	-0,22	0,24	-1,40	-0,43	-0,40	0,05	0,00
Mean	0,01	-0,04	-1,55	-0,65	-0,81	0,04	-224,57
SE of Mean	0,57	1,05	0,21	0,11	0,48	0,04	69,92
95% CI of Mean	1,13	2,09	0,42	0,23	0,96	0,07	140,08
Variance	18,25	62,31	2,49	0,74	13,06	0,08	278697,92
Std. Dev.	4,27	7,89	1,58	0,86	3,61	0,28	527,92
Coef. Var.	317,97	-177,59	-1,02	-1,32	-4,49	6,64	-2,35

Table 5.1: Descriptive statistics of the forecasting variables.

5.2 Forecasting Estimates

The following subsection will give an overview of all forecasting estimates. We have also included graphics and pre-results of our predictive calculations. First, we will start by presenting the result of *exponential smoothing 5.2.1* and present each of the three models, *simple exponential smoothing 5.2.1.1*, the *damped trend model 5.2.1.2* and the *Holt Winter‘s Seasonal Model 5.2.1.3*. In the next steps we will focus on *simple - 5.2.2* and *multiple regression 5.2.3*. Finally, we will present the outcome of the *vector autoregressive model 5.2.4* and *ARIMA 5.2.5 model*.

5.2.1 Exponential Smoothing

The first technique we have used to estimate the dependent variable, *oenb_dependent* is exponential smoothing. The principles of this method are the use of weights for each observations, whereas there are different methods to cope with several properties a time series can have, such as simple exponential smoothing 5.2.1.1, damped trend model 5.2.1.2 and the Holt-Winters seasonal method 5.2.1.2. Before, we dive into each method, we present in figure 5.1 STL decomposition of the time series, *oenb_dependent*. STL was developed by Cleveland et al. (1990) [40] and is the abbreviation for *Seasonal and Trend decomposition using Loess*. The advantages of the STL method is that it can handle any type of seasonality on several data length levels, also if the seasonal property changes over time. Further, the impact of the trend itself can be adjusted and controlled by the modeler and it is a method that produces results that is robust to outliers. [96]

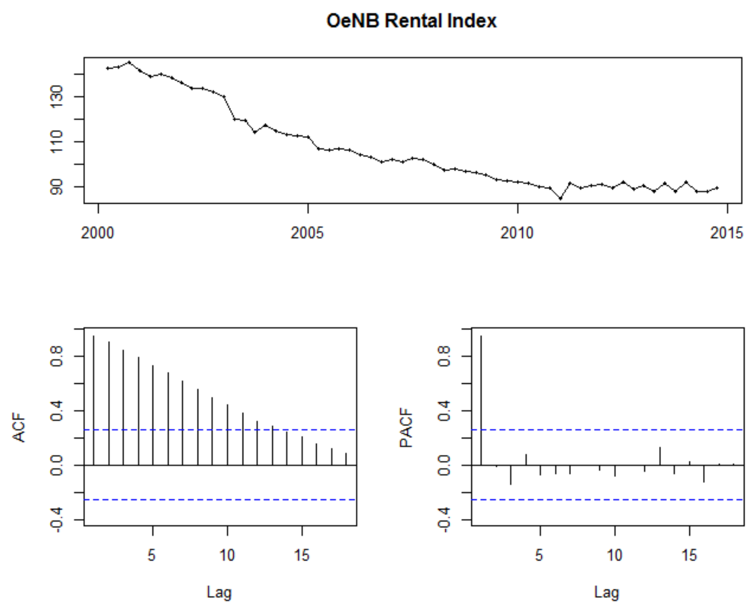

Figure 5.1: STL decomposition of the OeNB rental index.

Figure 5.2 shows the seasonal decomposition of the time series. The observations *oenb_dependent* are seasons and the trend is clearly downwards. Furthermore, the remainder columns confirms the downward trend.

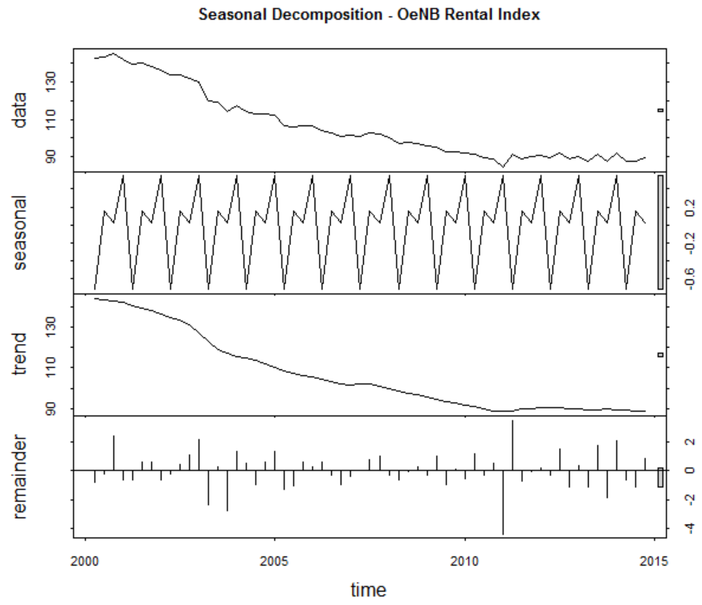

Figure 5.2: Seasonal Decomposition of the OeNB Rental Index.

Figure 5.1 shows on the top the plain time series. To have accurate results, there should be no correlations between the observations. We show this by plotting in the left corner, a correlogram of the dependent variable. The ACF plot of the series, shows that the auto-correlation for earlier values exists. The PACF plot indicates an *AR(1)* process as the order of auto-correlation within the time series.

In the next subsections we will present the results of the used exponential smoothing forecasting methods.

5.2.1.1 Simple Exponential Smoothing

As seen from the figure 5.2 the time series *oenb_dependent* has several properties such as *trending* or *seasonality*. Hence, simple exponential smoothing can be seen as a rather *naive* method in forecasting the OeNB rental index. Still, we use this method to show the differences in results for different models, which will be presented later in section 5.4.

Figure 5.3, shows the results of the forecast. It can be seen that the output is linear in its behavior even though the accuracy band around the predictions widens. If we have a closer look at the data we can see that there are no real differences to figure 5.3, because the point forecast stays constant. The reason for this is that when simple exponential smoothing is used naively, all future observations equal the weight of the last seen observation. A detailed view of all results,

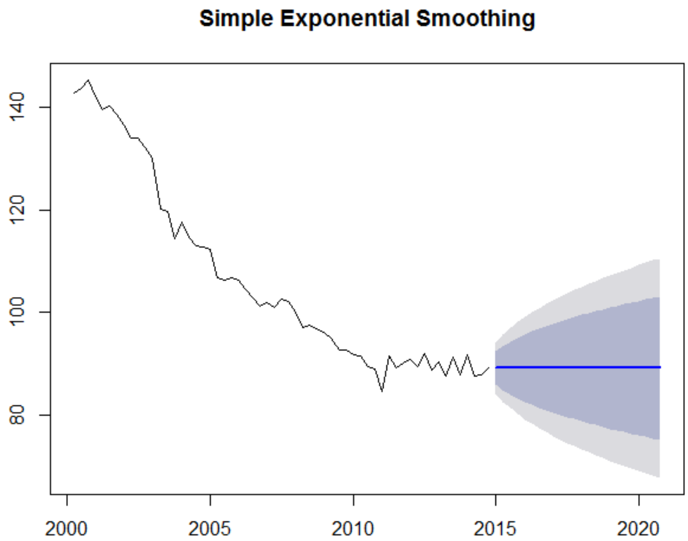

Figure 5.3: Simple Exponential Smoothing.

which we calculate using simple exponential smoothing can be found in table A.1 under the appendix section A.1.

5.2.1.2 Damped Trend Model

One of our exponential smoothing forecasting models is the damped trend model, which we prefer against Holt‚Äôs Linear Trend Model as pointed out in subsection 3.4.1.3. As also shown in figure 5.2 the time series *oenb_dependent* is trending, hence to dampen the trending component and get more accurate predictions, we use the damped trend method by Holt.

Figure 5.4 show the initial series and the predicted series in blue and indicates a forecast that goes into the downward direction. The reason for this outcome is that a strong trend is already the output from the past. This result can be explained by the fact that, even though the damped trend method by Holt smoothens the trend, the line still trends downwards, which can also be shown by decomposing the forecasting time series and comparing its slope against Holt‘s linear method. Figure 5.5 presents a *composition* of the trend and the slope. Clearly, the slope component strengthens over time and the trend seems to go sidewards. Hence, the series has a strong tendency to follow this side-ward path that it started around the year 2010.

We present a detailed view of all obtained results in appendix A under section A.2.

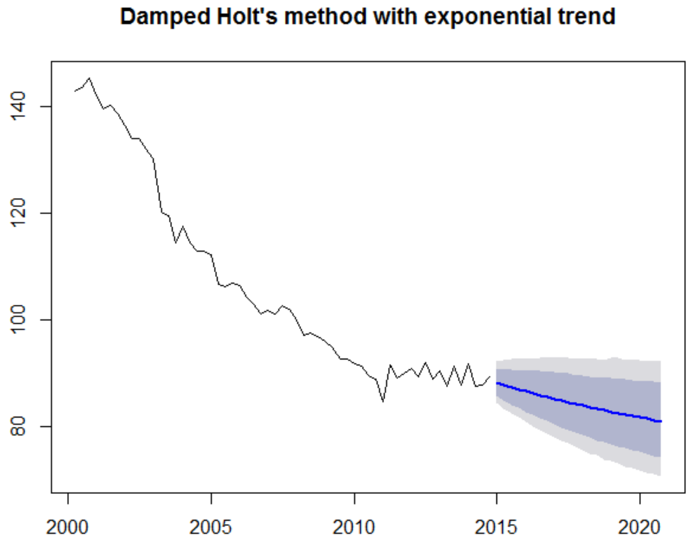

Figure 5.4: Damped Exponential Smoothing Method.

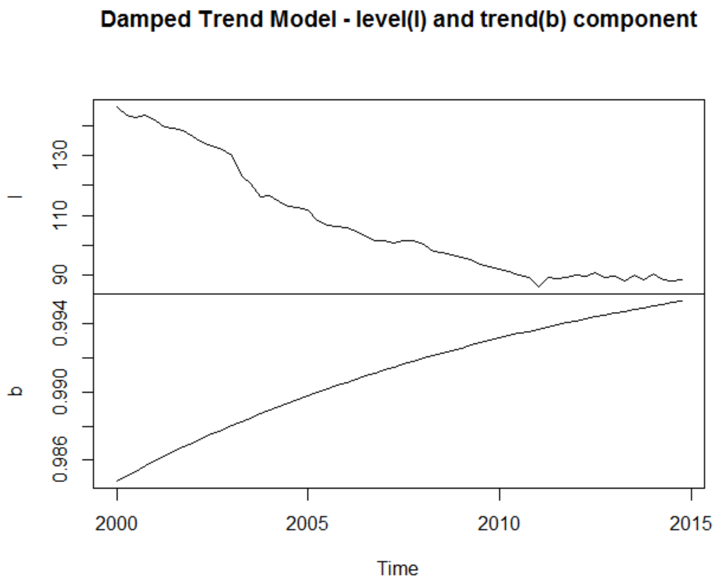

Figure 5.5: Damped Trend Model showing the level component under l and the trend component under b.

5.2.1.3 Holt-Winters Seasonal Method

The final exponential smoothing method we use is the Holt-Winters Seasonal Method. Compared to the other two methods this method before it also captures *seasonality*, which is apparently as of figure 5.2 the case for the dependent observations.

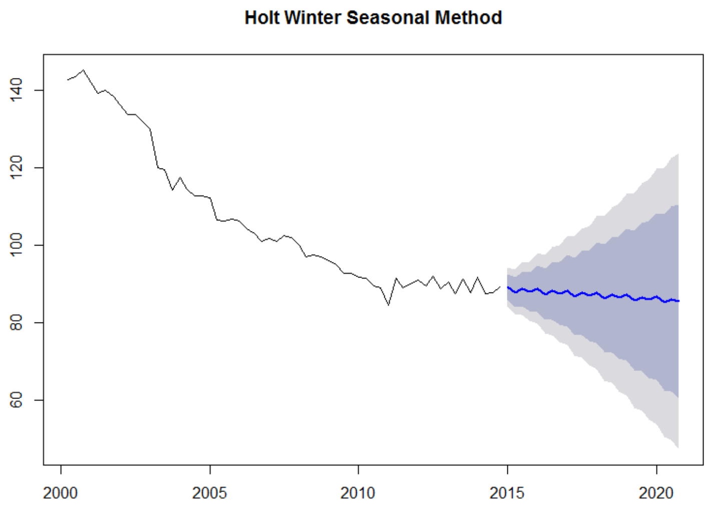

Figure 5.6: Holt Winter Seasonal Method.

Figure 5.6 shows the output of the Holt-Winters seasonal model. It is interesting to note that on the one hand the forecasting interval widens much larger, than compared to the other two exponential smoothing methods. Further, even though the trend seems to go downward, the small swings continue to reflect the seasonality of the approach. Figure 5.7 shows the impact of the seasonality component by the trend. It is clear that the trend will continue further as the seasonality effects the series.

A detailed table of all results, which are presented in table 5.7 can be found in appendix A in table A.3.

5.2.2 Simple Regression

In the literature regression models are, compared to our other predictive models, less used to forecast the property cycle. [101] We are using a simple and multiple regression model, which is presented in the following section 5.2.3.

Before, we present the forecast we show in figures 5.8, 5.9, 5.10 and 5.10 regression diagnostics plots to explain the background of the forecast.

Figure 5.9 shows a Q-Q Plot of the residuals. As typical for regression models the plot makes nearly a straight line. On the tail sections, some residuals are much higher than expected.

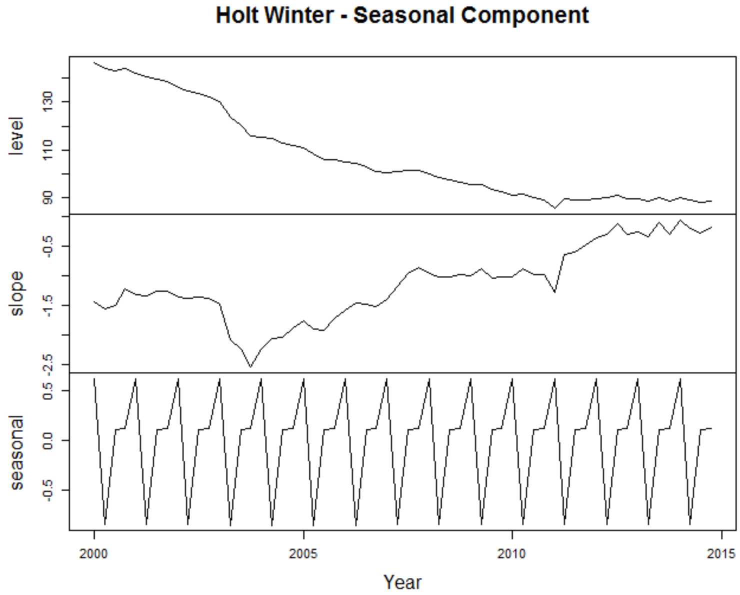

Figure 5.7: Holt Winter Seasonal Component.

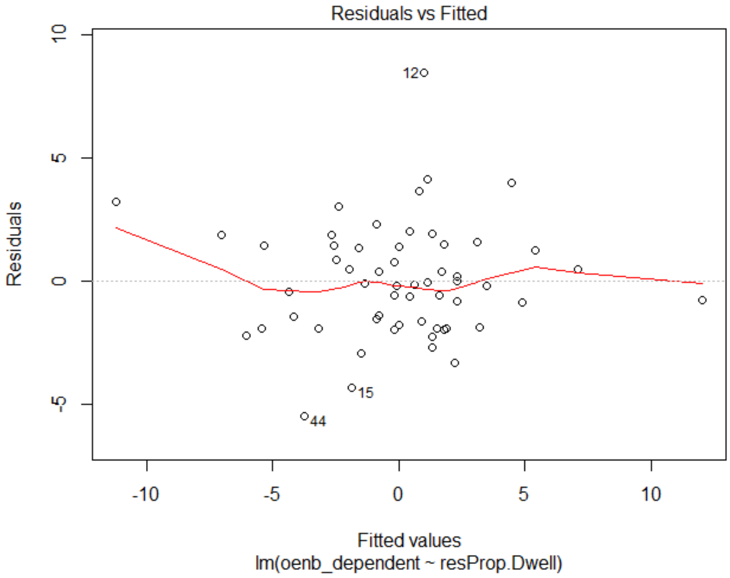

Figure 5.8: Residual fit.

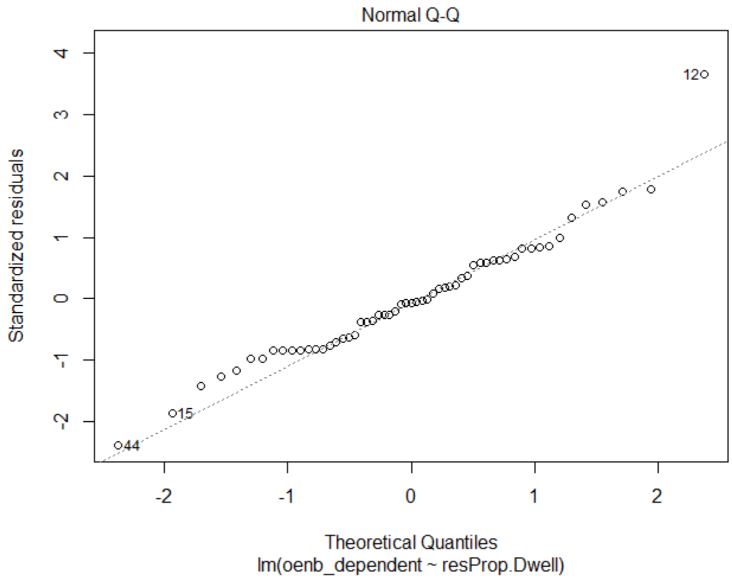

Figure 5.9: Normal Q-Q Plot.

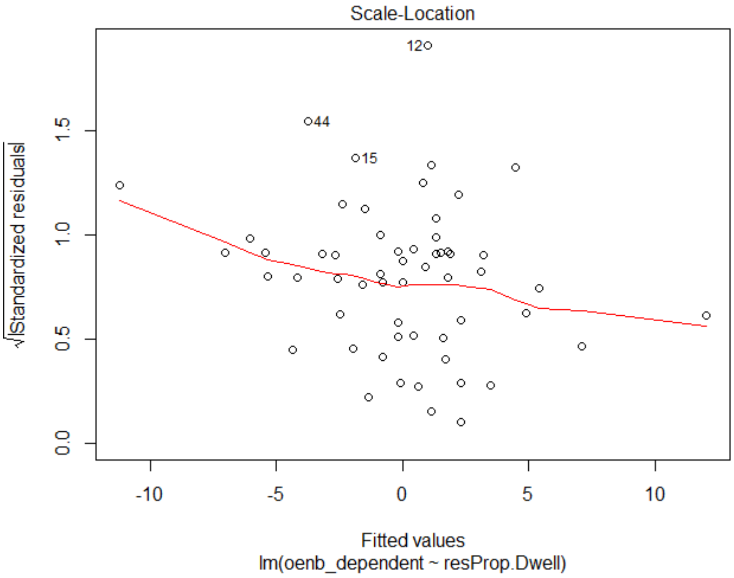

Figure 5.10: Standardized Residuals.

In figure 5.10 and 5.10 we standartize the residuals. The procedure to obtain this plot is to divide the residuals by their standard deviations. Further, the cooks distance shows the influence of the observations when a least square regression is performed. In figure 5.10 on the one hand it can be seen that the residuals, besides one or two outlier, are all in the same place. Furthermore, their influence, in figure 5.10 the cook distance, is within the two red boundaries.

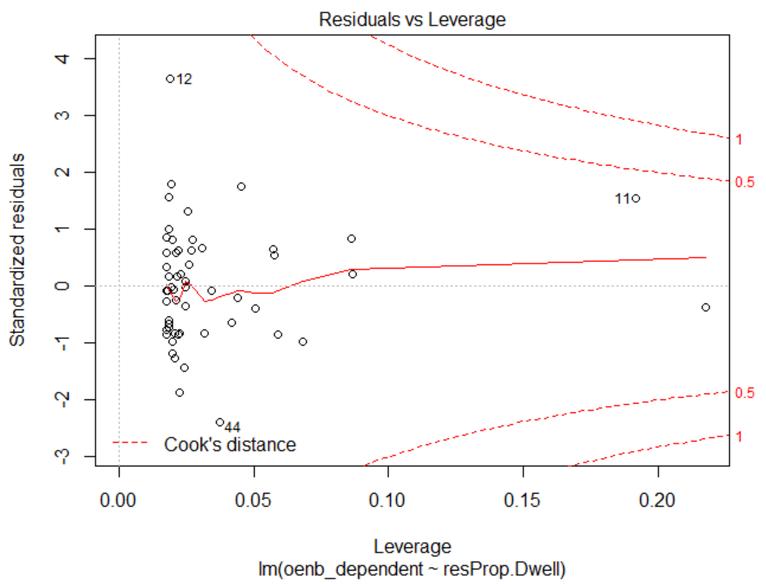

Figure 5.11: Standardization of residuals and cook distance.

Finally, we show the forecast of our observation variables in figure 5.12. The model itself regresses *oenb_dependent* with *resProp.Dwell*, as this is the most influential variable as shown in chapter 4. The intercept is 0.813 and for *resProp.Dwell* 0.993. All accuracy parameters are shown in section 5.3.

All forecasting results can be found in the appendix section in table A.4.

5.2.3 Multiple Regression

Figure 5.13 shows the regression diagnostics, which were done in the section 5.2.2 on the multiple regression. The qqplot clearly indicates the regression relationship. Further, the standardized residuals are spread as before and also the outliers are within the cook distance.

The model itself includes the following variables: *carReg* + *cpi* + *primConstTot* + *resProp.Dwell* + *cbre.office.primeYield* + *cbre.retail.capitalValue*. We further conduct a check of the relative importance of each variable. The result is shown in figure 5.14. It can be seen that the most important variable is *resProp.Dwell*. Hence, this fact explains the similarity of our forecasting

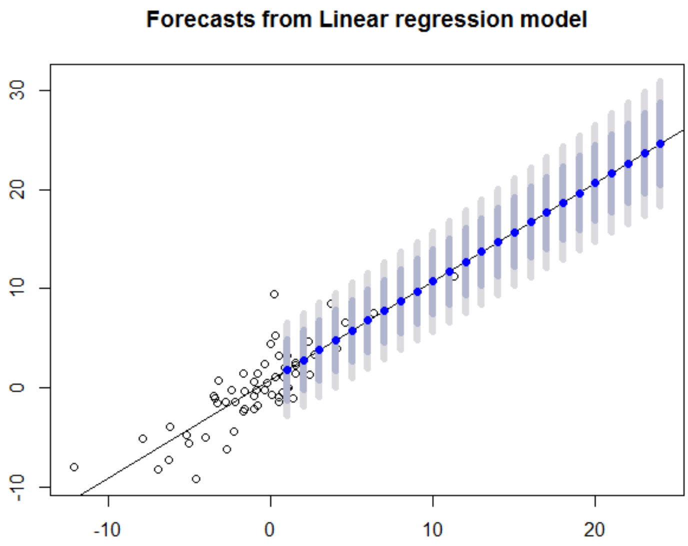

Figure 5.12: Forecast of simple regression model.

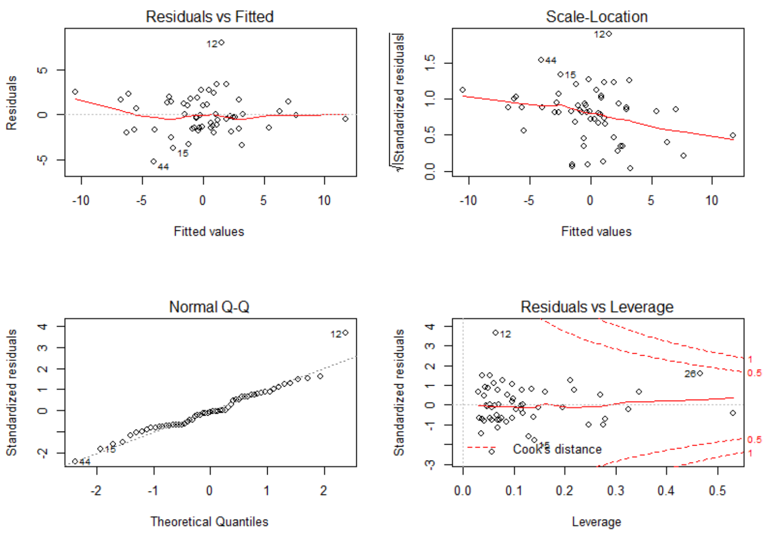

Figure 5.13: Regression diagnostics for multiple regression.

results to simple regression as shown in section 5.2.2 Hence, we will continue to use the results from the simple regression in the simulation engine.

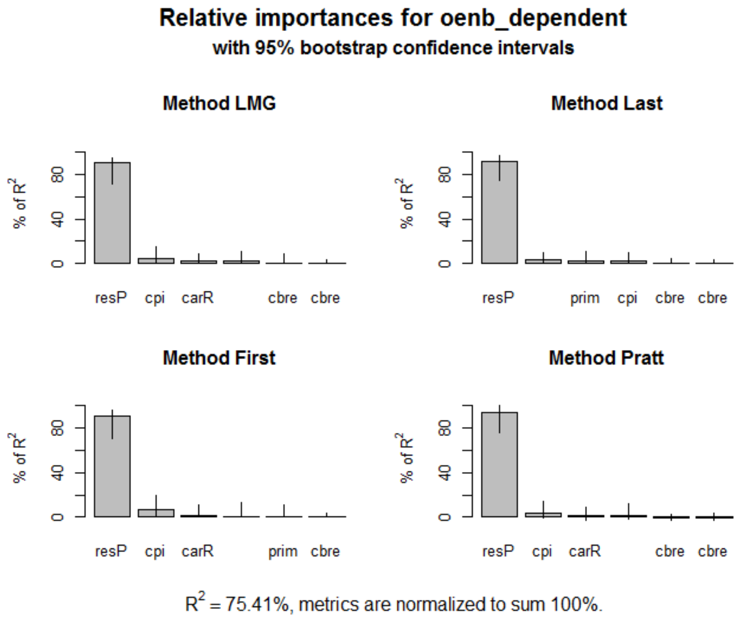

Figure 5.14: Relative importance of variable for the multiple regression model.

5.2.4 Vector Auto-Regression(VAR)

Vector auto-regression is another model we use to forecast the property cycle. It is performed as described in section 5.2.4. Figure 5.15 shows the forecast for all seven previously selected variables. For the var model we used a maximum lag of 8, as the AIC is 8. Further, the p-value of the asymptotic portmanteau test is extremely small with $2.2e^{16}$. [25] The accuracy results show that the prediction is compared to the other models not as accurate, but still acceptable. [4]

A clear list of the results for the OeNB rental index can be found in A.5 in the table A.5.

5.2.5 ARIMA

For the ARIMA model we use a stationary data set, which consists of all predictor variables. The gray line, the observed variables, of figure 5.16 indicates the stationarity of the data set.

Figure 5.16 shows the prediction for the next five years of the rental index from an *ARIMA(3,0,1)* model with zero mean. As the time series moves further into the future, the Arima model flattens and a constant forecast can be seen.

[4]For further information see section 5.3.

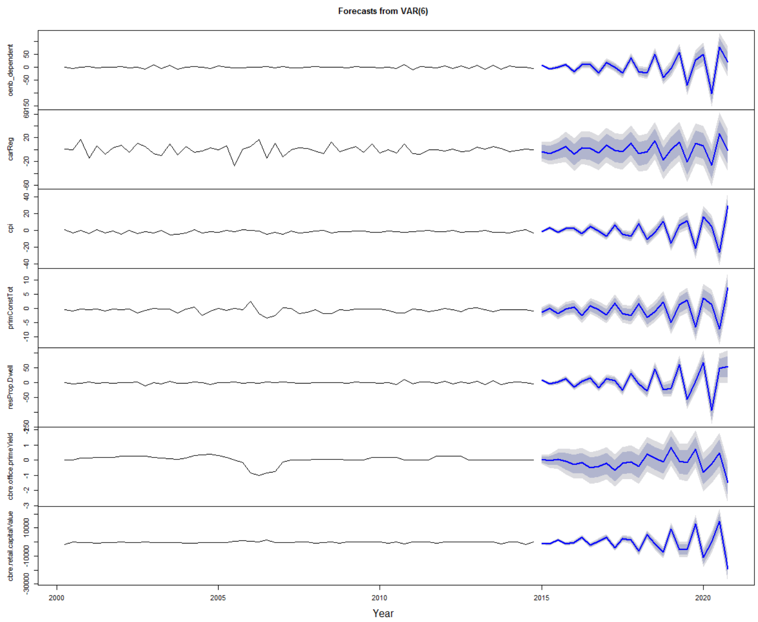

Figure 5.15: Vector Auto-Regression Results of OeNB Rental Index

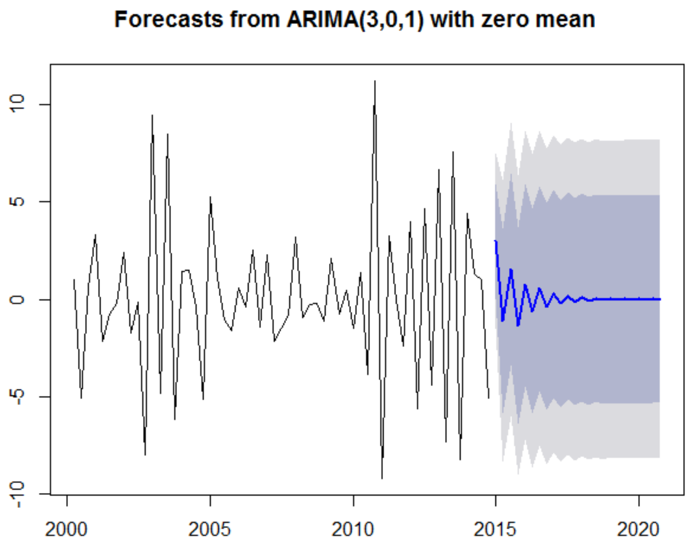

Figure 5.16: Forecast of Arima Model

Even though we used an automated method to obtain an *ARIMA(3,0,1)* model, the reason for the *AR(3)* and *MA(1)* that can be seen in figure 5.17. The ACF and PACF plot indicate auto-correlation, however our choice was to clear the series by log-adjusting, hence the auto-correlation does not have much influence on the output results.

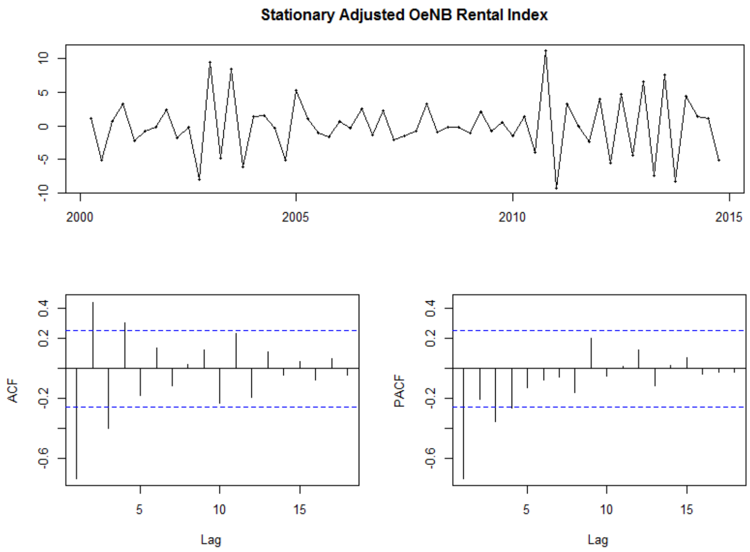

Figure 5.17: OenB rental index stationary adjusted

The graph 5.17 shows that the PACF indicates an AR(3) model. Other possible candidates might be ARIMA(4,0,1), ARIMA(2,0,1) and ARIMA(3,0,1). The algorithm chose correctly the best fitted model: *ARIMA(3,0,1)*. As in the previous sections, we have included all ARIMA model results in the appendix in section A.6 in table A.6.

5.3 Accuracy Results

In our research process 3.1, we have outlined that accuracy measures are part of our *validation* procedure. Table 5.2 presents each accuracy measure, which we outlined in section 3.5. For evaluation we are using the following accuracy measures: *ME, RMSE, MAE, MPE, MAPE, MASE* and *ACF1*. The model columns indicate the used forecasting methodology. Compared to the other methods, we have included all forecasted variables of the vector auto-regressive model, to show the uniform accuracy of each variable. The following columns present the accuracy measures and the final column indicates the variable, of the accuracy output. If there is only a model output, then the cell is marked with −. We have also marked for the simple regression model the *ACF1* column with −, as there exists no comparable value.

Model	***ME***	***RMSE***	***MAE***	***MPE***	***MAPE***	***MASE***	***ACF1***	***Variables***
ARIMA	0,0707	2,3062	1,7394	-3 468,43	3 627,25	0,4683	0,0035	-
VAR	2,63e-18	0,7463	0,5851	-873,57	937,13	0,0989	0,2809	oenb_dep.
VAR	-5,76e-17	3,752	2,5567	170,846	351,263	0,2558	0,1583	carReg
VAR	-3,82e-17	0,3566	0,2815	3,6706	53,97	0,1388	0,1694	cpi
VAR	-2,14e-17	0,3821	0,3052	Inf	Inf	0,3843	0,2687	primConstTot
VAR	-1,30e-17	0,9977	0,7787	-Inf	Inf	0,173	0,1196	resProp.Dwell
VAR	1,33e-18	0,0654	0,0507	NaN	Inf	0,6999	-0,0524	cbre.off.primYi
VAR	4,95e-15	178,11	144,07	NaN	Inf	0,2984	0,0674	cbre.ret.capVal
Damped Exponential Smoothing	0,042	2,2852	1,6296	0,0279	1,564	0,365	-0,0525	-
Holt-Winters Seasonal Method	0,2543	2,5488	1,9637	0,3216	1,8661	0,4189	0,0366	-
Simple Exponential Smoothing	-1,0427	2,6867	2,0189	-0,8855	1,9216	0,4467	-0,24	-
Simple Regression	1,13e-16	2,2954	1,752	1 927,05	1 983,93	0,5553	-	-

Table 5.2: Accuracy Measures for each forecasting model.[5]

Table 5.2 presents the outputs of all accuracy measures. The mean error (ME) is extremely small for all available models, which means that the average error is not far from the actual model. Similarly, the mean absolute error (MAE) and the root mean squared error (RMSE) does not variate much from the actual model. Still, the ARIMA and vector auto regression model present small outliers, when compared to the other models. As shown in column MPE, also the mean absolute percentage error (MPE) has the disadvantage of showing Inf or -Inf as output. Furthermore, the mean absolute scaled error (MASE) does not show any great outliers compared among the models. Finally, the auto-correlation function at lag 1 (ACF1) is showing minor auto-correlation for the exponential smoothing methods and the ARIMA methods. Compared to the other model the vector auto-regression has the highest auto-correlation at lag 1.

When summarizing table 5.2 the best models are clearly the ARIMA and exponential smoothing methods in terms of accuracy. The vector auto-regression and simple regression model also

[5]All variable names where shorten, however their semantic still stays the same, because of the column lengths.

shows quite promising results.

5.4 Cyclical Scenario Simulator

In the first part of the project, we obtain the cyclical sensitivities. To make these results usable for bankers and property developers, we employ a discount cash-flow model, which computes the cyclical sensitivities on single project level aggregated on portfolio level for three scenarios. In chapter 3 we showed mock-ups for the cyclical scenario simulation application. The actual implemented Excel prototype, consist of the simulation engine, which puts out the final outputs for each result variable and a *net present value matrix*, which shows for a certain rent level and a yield threshold, sustainable values for the net present value. Figure 5.18 shows the net present value matrix in the Excel application.

NPV			Exit Yield							
		99 201 503,46	7,5%	8,0%	8,5%	9,0%	9,5%	10,0%	10,5%	11,0%
AVG Rental	-40%	-	-24 482 029	-28 971 112	-32 924 728	-36 432 397	-39 564 782	-42 378 401	-44 919 000	-47 223 995
	-30%	-	-13 154 762	-18 392 026	-23 004 578	-27 096 858	-30 751 307	-34 033 863	-36 997 895	-39 687 055
	-20%	-	-1 827 495	-7 812 940	-13 084 427	-17 761 319	-21 937 832	-25 689 325	-29 076 789	-32 150 116
	-10%	-	9 499 772	2 766 147	-3 164 277	-8 425 780	-13 124 357	-17 344 787	-21 155 684	-24 613 177
		-	20 827 039	13 345 233	**6 755 873**	909 759	-4 310 883	-9 000 249	-13 234 579	-17 076 238
	10%	-	32 154 306	23 924 319	16 676 024	10 245 298	4 502 592	-655 710	-5 313 474	-9 539 298
	15%	-	37 817 939	29 213 862	21 636 099	14 913 067	8 909 330	3 516 559	-1 352 922	-5 770 829
	20%	-	43 481 573	34 503 405	26 596 174	19 580 836	13 316 067	7 688 828	2 607 631	-2 002 359
	25%	-	49 145 206	39 792 949	31 556 249	24 248 606	17 722 804	11 861 097	6 568 183	1 766 110
	30%	-	54 808 840	45 082 492	36 516 325	28 916 375	22 129 542	16 033 366	10 528 736	5 534 580

		Avg Net Rent Incl.sqm(year)	Exit Yield/DF
Estimated Value	99 201 503,46		
NPV	6 755 873,46	1 000,00	8,5%

Figure 5.18: Net present value sensitivity matrix. Inputs are the average monthly rent per sqm and the corresponding yield.

Figure 5.19 shows the three panels of the simulation engine. Compared to the previously designed mock-ups in 3.6.1 slight changes were made. In the first panel, the user can filter by customer and model. Further, he can start the application right away or clear all set filters. In the row *yearly model sensitivities*, the user can see the respective model results. In the following panel, one of three different scenarios can be chosen. Finally, the user can see a preview of the results on a single customer level. All results go five year in the future and the respective customer results, as outlined in section 4.4.2, can be seen.

Figure 5.20 shows an example output of the final results sheet for the simulation engine. When pressing the *Calculate* button *DSCR* and *LTV* for all properties is automatically calculated and the output is printed on the result worksheet.

In the following we will present the results for each forecasting model on single project level and aggregated portfolio level. A clear overview of the synthetic project data can be seen in appendix C under section C.1.

5.4.1 Simulation Assumptions

All values can be changed in the Excel application. However, before running our results, we implied several assumptions.

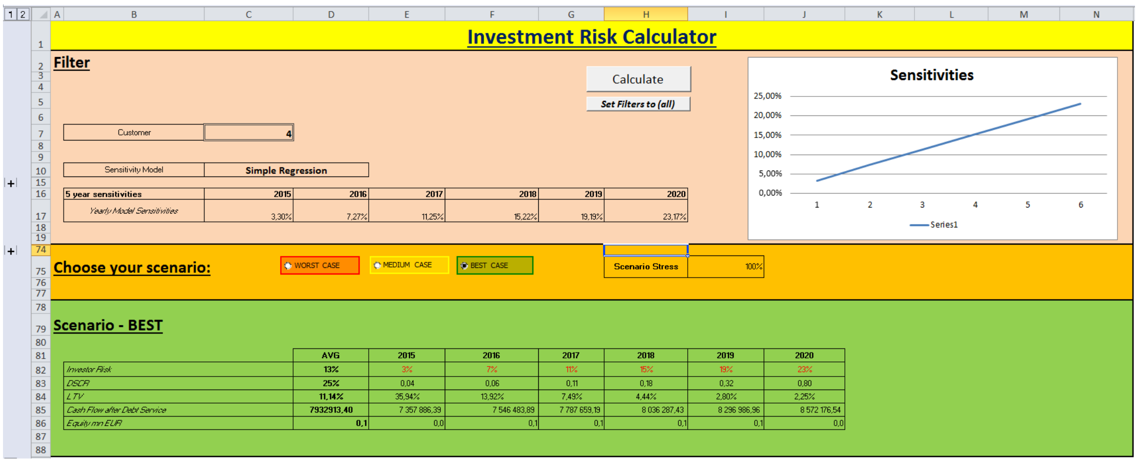

Figure 5.19: Investment Risk Calculation user interface.

Customer Id	Cyclical Risk Mar	DSCR 2015	DSCR 2016	DSCR 2017	DSCR 2018	DSCR 2019	DSCR 2020	LTV 2015	LTV 2016	LTV 2017	LTV 2018	LTV 2019	LTV 2020	Cash Flow after Debt Service 2015
1	29,773%	0,10	0,20	0,80	1,11	1,44	1,79	14,71%	3,59%	2,26%	1,62%	1,25%	1,00%	7361068,24
2	29,773%	0,10	0,15	0,37	1,11	1,44	1,79	15,54%	5,06%	2,26%	1,62%	1,25%	1,00%	7358542,34
3	30%	0,09	0,14	0,27	0,55	1,44	1,79	0,16	0,06	0,03	2%	1%	1%	735770105%
4	30%	0,09	0,14	0,25	0,41	0,73	1,79	0,16	0,06	0,03	2%	1%	1%	735728090%

Figure 5.20: Simulation engine results sheet.

- **Scenario Cases:** Upon the cyclical sensitivities we strengthen the cycle by raising its impact. We use three scenarios to show different versions of the property cycle. The base case scenario is 100%, the medium case is 120% and the worst case is 150%.

- **Data:** As shown in section 4.4.2 we use the underlying data with the outlined data assumptions. The specific data can be viewed in appendix C in section C.1.

- **Model results:** We have normalized the ARIMA model results, because the output is based on stationary input value. Hence, using the exponential function all forecasting values have been normalized.

- **Value and Income:** Explicitly, we are stressing the income (net operating income) and the projected market value of the asset. By stressing these values, different results in the DSCR and LTV are obtained.

- **Interpretation of results:** A DSCR of over 1 can be interpreted so that the borrower has enough net rental income to pay back the loan. Usually, an LTV below 75% is required by financial institutions to approve a loan. The interpretation of the LTV is, that the loan amount should cover the value of the building.

5.5 Simulation

The following subsections will examine the results, which are obtained from the cyclical simulation engine. In the first step we will present each scenario case results for its respective scenarios, such as *best*, *medium* and *worst* case. Through each section, we will interpret the results and draw implications for the underlying portfolio data. If necessary, we will point out literature research. Further, our obtained simulation results is either validated by expert judgment and comprehensive literature research. The reason for this is that discounted cash flow models do not provide statistical indicators and in practice the model results are judged by comparing them to other similar projects.

5.5.1 Scenario - Normal Case

The normal case scenario does not strengthen the impact of the cycle. Hence, we take 100% of the cyclical sensitivities to stress the assets value.

When we aggregate each of the five loans we get the following results for the DSCR in table 5.3 and LTV in overview 5.4.

DSCR Average	**DSCR 2015**	**DSCR 2016**	**DSCR 2017**	**DSCR 2018**	**DSCR 2019**	**DSCR 2020**
ARIMA	83,46%	77,77%	153,65%	225,88%	289,07%	342,17%
Damped Trend Model	113,35%	83,19%	141,94%	193,99%	241,22%	279,86%
Holt Winter	114,51%	85,00%	146,48%	201,94%	253,00%	295,42%
Simple Exponential Smoothing	115,33%	86,11%	149,27%	207,02%	260,92%	306,51%
Simple Regression	4,27%	7,02%	18,83%	35,35%	56,19%	79,67%
Vector Auto-Regression	3,88%	-4,92%	11,77%	-16,29%	4,97%	39,94%
Total	72,47%	55,69%	103,66%	141,32%	184,23%	223,93%

Table 5.3: Best Case Scenario - DSCR Portfolio Average.

It can be seen in table 5.3 that the ARIMA and all exponential smoothing models output useful results. However, the deb service coverage ratio for the simple regression and the vector auto-regression model is too low. This problem can be reasoned that the sensitivity output for the simple regression model are rather linear and the vector auto-regression outputs extremely volatile values.

LTV Average	**LTV 2015**	**LTV 2016**	**LTV 2017**	**LTV 2018**	**LTV 2019**	**LTV 2020**
ARIMA	1,78%	1,05%	0,74%	0,60%	0,54%	0,52%
Damped Trend Model	1,31%	0,98%	0,80%	0,70%	0,65%	0,64%
Holt Winter	1,30%	0,96%	0,78%	0,67%	0,62%	0,61%
Simple Exponential Smoothing	1,29%	0,95%	0,76%	0,65%	0,60%	0,59%
Simple Regression	34,88%	11,61%	6,03%	3,84%	2,80%	2,25%
Vector Auto-Regression	38,38%	-16,56%	9,65%	-8,33%	31,69%	4,50%
Total	13,16%	-0,17%	3,13%	-0,31%	6,15%	1,52%

Table 5.4: Best Case Scenario - LTV Portfolio Average.

Table 5.4 shows the results for the loan-to-value ratio on portfolio level. As shown above the outputs for the simple regression and vector auto-regression model are unreasonable. This results can be traced down due to the cyclical sensitivities. Furthermore, table 5.4 shows that the longer the loan portfolio goes the better the LTV gets. During our expert interviews a LTV of 75% is often demanded by bankers to hand out a loan.

5.5.2 Scenario - Medium Case

During the medium scenario case the strength of the impact is raised to 120%. Hence, the cyclical sensitivities go 20% upwards, which reflects the strengthening of the cyclical high. The following two tables show the DSCR 5.5 and LTV 5.6 average.

In table 5.5 it can be seen that the average DSCR is extremely good for financing this portfolio. In the ARIMA and all exponential smoothing cases the client is able to repay his loan in the next years, even though a small cyclical low impacts in 2016 the property market.

DSCR Average	DSCR 2015	DSCR 2016	DSCR 2017	DSCR 2018	DSCR 2019	DSCR 2020
ARIMA	120,18%	111,99%	221,26%	325,26%	416,27%	492,72%
Damped Trend Model	163,23%	119,79%	204,39%	279,35%	347,35%	403,00%
Holt Winter	164,90%	122,40%	210,92%	290,80%	364,32%	425,41%
Simple Exponential Smoothing	166,08%	124,00%	214,95%	298,11%	375,72%	441,38%
Simple Regression	6,14%	10,12%	27,12%	50,90%	80,91%	114,73%
Vector Auto-Regression	5,58%	-7,09%	16,95%	-23,45%	7,16%	57,52%
Total	104,35%	80,20%	149,27%	203,50%	265,29%	322,46%

Table 5.5: Medium Case Scenario - DSCR Portfolio Average.

Table 5.6 shows the loan to value ratio of the medium case scenario. From a bank point of view, the ratios, do not look promising in the first year. However, after the cyclical high has passed the loan-to-value ratio falls into an acceptable band. This observation is confirmed by the exponential smoothing and ARIMA models. Furthermore, the longer the cycle moves, the better the LTV gets from a banker's viewpoint. So a bank might hedge this loan by having much larger interest rate in the first year and lower them substantially in the following years.

LTV Average	LTV 2015	LTV 2016	LTV 2017	LTV 2018	LTV 2019	LTV 2020
ARIMA	1,24%	0,73%	0,51%	0,42%	0,38%	0,36%
Damped Trend Model	0,91%	0,68%	0,56%	0,49%	0,45%	0,45%
Holt Winter	0,90%	0,67%	0,54%	0,47%	0,43%	0,42%
Simple Exponential Smoothing	0,90%	0,66%	0,53%	0,45%	0,42%	0,41%
Simple Regression	24,22%	8,06%	4,19%	2,66%	1,95%	1,57%
Vector Auto-Regression	26,65%	-11,50%	6,70%	-5,78%	22,00%	3,12%

Total	9,14%	-0,12%	2,17%	-0,22%	4,27%	1,05%

Table 5.6: Medium Case Scenario - LTV Portfolio Average.

5.5.3 Scenario - Worst Case

In the worst scenario the cyclical sensitivities are influenced by 150%. As the loan portfolio already has a good financial starting point, the deb-service coverage ratio is already in place from the beginning as seen in table 5.7. The cyclical sensitivities show that the fall of the cycle is in the beginning of 2015. Hence, the results strengthen over time for the asset portfolio. However, as indicated the simple regression and vector auto-regression do not deliver reasonable results, which are inline with the cyclical developments.

DSCR Average	**DSCR 2015**	**DSCR 2016**	**DSCR 2017**	**DSCR 2018**	**DSCR 2019**	**DSCR 2020**
ARIMA	187,78%	174,98%	345,72%	508,23%	650,42%	769,88%
Damped Trend Model	255,04%	187,17%	319,36%	436,48%	542,74%	629,69%
Holt Winter	257,66%	191,24%	329,57%	454,37%	569,24%	664,70%
Simple Exponential Smoothing	259,49%	193,74%	335,86%	465,80%	587,06%	689,65%
Simple Regression	9,60%	15,81%	42,37%	79,54%	126,42%	179,26%
Vector Auto-Regression	8,72%	-11,08%	26,48%	-36,65%	11,18%	89,88%
Total	163,05%	125,31%	233,23%	317,96%	414,51%	503,84%

Table 5.7: Worst Case Scenario - DSCR Portfolio Average.

Table 5.8 shows that a loan under the assumptions of the ARIMA model, would not have a chance to get approved. However, the exponential smoothing methods clearly show a low LTV from the start. In the following years the ARIMA model clearly follows the path of the exponential smoothing methods and it can be seen that the asset would have a high chance to turn into a successful property project.

LTV Average	LTV 2015	LTV 2016	LTV 2017	LTV 2018	LTV 2019	LTV 2020
ARIMA	0,79%	0,47%	0,33%	0,27%	0,24%	0,23%
Damped Trend Model	0,58%	0,44%	0,36%	0,31%	0,29%	0,29%
Holt Winter	0,58%	0,43%	0,34%	0,30%	0,28%	0,27%
Simple Exponential Smoothing	0,57%	0,42%	0,34%	0,29%	0,27%	0,26%
Simple Regression	15,50%	5,16%	2,68%	1,70%	1,25%	1,00%
Vector Auto-Regression	17,06%	-7,36%	4,29%	-3,70%	14,08%	2,00%
Total	5,85%	-0,08%	1,39%	-0,14%	2,73%	0,67%

Table 5.8: Worst Case Scenario - LTV Portfolio Average.

5.6 Summary

In chapter 5 we presented and interpreted the final results. We started by pointing out a descriptive statistic in section 5.1 of our forecasting dataset, which gave a general overview of the underlying data which is used.

In the following section 5.2 we present the forecasting estimates. We started by pointing out the result of exponential smoothing 5.2.1. In the next steps we focused on simple- 5.2.2 and multiple regression 5.2.3. Finally, we examined the outcome of the vector autoregressive model 5.2.4 and ARIMA 5.2.5 model. All these forecasting results, were comprehensively presented and supported with other intermediary outputs whenever necessary.

Further, we present an overall overview of the models forecasting accuracy 5.3. From this standpoint all models have promising starting criteria for the second part of this research project.

In the following section we present the cyclical scenario simulator 5.5. We describe the built engine in detail and point out the specifics of the user interface.

Finally, we show the results of applying the cyclical sensitivities to a synthetic loan portfolio. As we are running three scenarios, we group them into Scenario - Normal Case 5.5.1, Scenario - Medium Case 5.5.2 and Scenario - Worst Case 5.5.3. The results show that the forecasting models of exponential smoothing 5.2.1 and ARIMA 5.2.5 provide reasonable output results. However, the simple regression model 5.2.2 and vector autoregressive model 5.2.4 does not yield reasonable results and therefore have to be excluded.

Chapter 6

Conclusion

Since the property bubble burst in 2008, the focus felt on the importance of the property market. In Austria property prices have heightened and rumors are that the Viennese market is on the rise to a new property bubble. Our study has pointed out that real estate cycles are a natural economic phenomenon and one way to prevent this risk is to use properly predicted sensitivities in an investment decision. In the previous chapters we outlined each part of our thesis. In the final section of this research study we will focus on the summarizing the main concepts 6.1 and showing the limitations of the research 6.2 and the future work 6.3.

6.1 Summary of the Main Findings

The extreme effects of the housing bubble had major implications over the next years. Banks went bust and governments had to step in to save on the one hand the banks and their retail money and on the other hand the depositor, who feared to lose his money. *"Too big to fail"* was a term that was shaped during this time and is still used, when media talks about upcoming bubbles. Hence, central banks realized the need to analyze and forecast property cycles. However still, banks and property developers make their project decisions on fancy financial forecasts and economic sensitivities have only played an outside role. We believe that using the forecasts in investment decisions will strengthen the foundation a property project is planned by the developer and has better chances to get the desired financing approved by the bank.

The research project starts by pointing out the literature about the theory of cycles. Generally a cycle has a certain anatomy and starts with a rise to a peak, which is characterized as a prosperous phase for the economy. After the peak declined the cycle overcomes its inflection point and meets its valley. During this phase the economy is depressed and the media reports lots of negative economic effects during this time. However, usually the cycle recovers and the new economic and structural change leads to another peak. This up and down swing is the general characteristic of economic cycles. We also showed the similarity to a sine wave and pointed out that the mathematical terminology can be used to explain the phenomenon of a property cycle in detail. Furthermore, we pointed out other important cycles such as the Kitchin inventory-, Juglar fixed investment-, Kuznets infrastructural investment- and Kondratiev waves.

Literature points out that other cyclical phenomenons have an effect on the property cycle. Two of these effects are the business- and the credit cycle. The business cycle is usually driven by a certain economic theme, such as the information technological era. The credit cycle is driven by the banks and the availability of credit. Usually banks are able to give credit if interest rates are high. However, in economic downturns interest rates usually fall, because there is less need to invest in the open markets. The reason for this can be broken down into a greater fear to lose its invested money. We further pointed out the theory behind cycles and picked three main themes, such as the Keynesian Theory, Real Business Cycle Theory (RBC) and the Austrian Business Cycle Theory (ABCT).

After pointing out the cyclical phenomena, we show the structure of the property market in Austria. First we clearly define the term real estate market as these are the boundaries our further research will be conducted. In the next step, we show how the market is structured and which steps have to be taken to own a property. Each real estate market has several participants, which are examined in a diagram. The plot is inspired by Schulte's (2008) [152] house of real estate. As our study focuses on the investment process of real estate, we show the complex parts of a real estate project from the viewpoint of banks and real estate developers.

Previously we reviewed the cyclical literature and had a general focus on the behavior of cycles. However, section 2.3 explains the property cycle in detail. Many studies try to show inefficiencies of the real estate market, hence we briefly explain its implications to the efficient market hypothesis. [124] Furthermore, we examine a historical overview of cyclical research. Section 2.4 points out the principals of different prediction approaches. During our study we focus on a quantitative approach. Hence, we point out the advantages and disadvantages of such a method.

As we focus on investment risk we give a general definition of risk and explain the characteristics of a real estate portfolio. The main advantages for real estate market participants are the strategic considerations that using cyclical sensitivities in-cooperates. The groundwork for this often lies in changes in the organization and can provide a better decision making process of projects that are held in the pipeline.

In chapter 3 we point out the methodology and research design of our study. First we explain that we are focusing on the subgroup of a *reality based* approach and within the group on a conceptual analytical approach. Furthermore, we point out for our research project the clear stages and the design artifacts, which we built. During our project we follow a generally defined process, which has proven to be successful with other researchers. Still, within this process we have the required flexibility to change according to our research results.

In the first step our research focuses on the implementation of a statistical model. During our building phase we had some difficulties of choosing the appropriate forecasting method and tools. However, we decided to implement all our methods with the statistical framework R. Furthermore, we use several forecasting techniques such as exponential smoothing, simple exponential smoothing, Holt's linear trend model and the damped trend model and Holt-Winters seasonal method, simple and multiple regression, Vector Auto-Regression (VAR) and ARIMA modeling. Furthermore, we employ specific set of measures to validate the forecasting accuracy.

The second step of our research project is the simulation engine. At first we analyzed the wanted requirements and created mock-ups of the engine. These rough prototypical pictures were shown to experts and further changed until we arrived at the final implementation stage. Next, we point out the discounted cash flow method. The simulation engine is implemented in Microsoft Excel and therefore all simulation results will be presented in a separate spreadsheet. To check the final output we are using a set of well defined measures such as the debt-to-service coverage ratio (DSCR) and the loan-to-value ratio (LTV).

In chapter 4 we examine the underlying data that we use in our research project. We process through clear data collection steps and review in the first step the data quality of available data sources for Austria. Our conclusion is that Austria lacks many variables for the real estate market, which are publicly available for example in the UK. As a first step we are using variable selection techniques such as cluster analysis to group all available variables. Further, we test our variable with the Augmented Dick-Fuller Test and the Kwiatkowski Phillips Schmidt Shin Test for stationarity. These two tests exclude each other in terms of the null hypotheses, hence they perfectly complement each other and provide clear results. Further, we employ stepwise regression and show the causality of our data with the routine from Granger. Finally, we use lasso regression to shrink size of the regression coefficients. Each method serves as a criterion to choose our final variables. Our final data set consists of seven variables, such as the OeNB rental index, car registration, consumer price index, primary construction costs, prime yield and capital value and land price index. For the simulation engine we use synthetic project data as we do not have access to property project data. Hence, we base our data on assumptions which are checked with property experts.

In chapter 5 we present our research results. In the first part of our research project, we present the forecasts for each model in a graphical way. The accuracy results suggest that the all models provide useful results, however clearly the best results can be found within the exponential smoothing methods and the ARIMA method. This goes also inline with other studies such as Jadevicius (2014) [101]. During our tests within the cyclical simulation engine we used the forecasting sensitivities of our models to generate DSCR and LTV measures on a portfolio level for three different scenario cases, the normal-, medium- and worst case. In all three cases the forecasting results for the exponential methods and the ARIMA methods yield the best results. The results for regression and vector auto regression were only partly of interest.

6.2 Limitations of the Research

The research project was conducted carefully and inline with the standards of other similar academic studies. However, still there are some limitations which leave room for future research. First, we use R as a modeling language, which is a package rich software suite and used by many other researchers. In specific, as discussed in section 3.3.2, R has a lot of strengths and flexibility. However, still packages provided in the R universe focus on model generalizations and are not specifically targeted to the real estate market and its data structure. Furthermore, a more holistic approach would allow researchers to experiment and optimize input variables and get a better fit for each model, which would, as a result, improve the model accuracy.

As of now, there are no extensive studies about the cyclical behavior of the Austrian property market. Still, in 2015 lot's of studies focus on economic models, which try to fit a certain viewpoint on the market to project cyclical behavior. [1] Hence, we can only compare our study to others outside of Austria. However, the comparability of these is limited, since other data standards are available. [2]

Besides standardizing the forecasting terminology we focused in the simulation part on a widely recognized version of the discounted cash flow model. However, there are different versions and assumptions, which can be incorporated into modeling future cash flows, which are based on assumptions of the present. Furthermore, we used a synthetic property portfolio as we do not have access to real estate asset data.

Finally, as pointed out in section 4.1.2 Austria's data quality is limited. The Austrian National Bank tries to fill gaps with its real estate index backwards, however, still many other variables

[1] A comprehensive example of such a model can be seen in Barras (2009) [12].

[2] For example in the UK Jadevicius (2014) [101] used a time series from 1963 to 2010.

are incomplete or too short for a time series analysis. Hence, we decided to focus on a quarterly basis since this lengthens our input.

6.3 Future Work

During the research study lots of further questions came up, which were only partly or not answered at all. These questions provide an opportunity for aspiring researchers to clarify and to explain certain relationships. The author is aware that during the research project some questions had to be skipped, still the provided research project is a holistic approach to tackle the property cycle and to use it on a real estate asset portfolio.

In chapter 2, we discussed the research body of papers around the property cycle. Even though during our research we did not come across many survey papers about the different methods of the discounted cash flow analysis, we think that there is still room for improvement. Further, in the industry the discounted cash flow analysis method is a popular tool to show the present value for future cash flows, it is differently used among property project and mostly an art form than an actual science.

We employed eight different models, such as three exponential smoothing methods, simple- and multiple regression, vector autoregressive model and ARIMA model. All this models are strictly based on insights we got from our literature research. Furthermore, as the property cycle in Austria has not yet been analyzed properly we believe that taking proven models from literature was a good starting point. However, in recent years machine learning methods are on the rise. The reason for this is that compared to some years ago more data is collected on lower costs. Hence, using machine learning such as supported vector machines, random forest or even the quite promising rising method of deep learning could potentially provide more insights into the property cycle.

Another possible way to forecast the property cycle would be a pre-study to check for leading indicators of a specific property market, such as Austria. During our research we held on the assessment of already done studies and expert opinions. However, checking the input data for its characteristics would help to understand certain underlying principals of the property market, such as its greatest influencers.

Finally, we see room for research in the property engine simulation tool. Currently we implemented, as wished by industry experts, the tool in an Excel environment. However, further research can be done when implementing the environment in a much stabler setting such as a Java application or a web application. A good starting point for such a project, would be to check for already popular software, such as Argus. [3] Many real estate agents are on the one hand looking for flexibility, this is the reason why a lot of *tools* are created in Excel, and on the other hand for correctness of their property investment models. We think that it is a pity that nowadays lots of firms still operate on an *"Excel basis"*, because the technological progress has gone extremely far in the recent years. We further believe that the use of technology will bring real estate agents and banks the competitive advantage to decide on property investment decisions.

[3] See `http://www.argussoftware.com/` for further information.

APPENDIX A

Appendix A

A.1 Exponential Smoothing

Year	Quarter	Point.Forecast	Lo.80	Hi.80	Lo.95	Hi.95
2015	Q1	89,13	85,93	92,33	84,24	94,03
2015	Q2	89,13	84,85	93,41	82,59	95,68
2015	Q3	89,13	83,99	94,27	81,27	96,99
2015	Q4	89,13	83,26	95,00	80,15	98,11
2016	Q1	89,13	82,61	95,65	79,16	99,11
2016	Q2	89,13	82,02	96,25	78,25	100,01
2016	Q3	89,13	81,47	96,79	77,41	100,85
2016	Q4	89,13	80,96	97,30	76,63	101,63
2017	Q1	89,13	80,48	97,78	75,90	102,36
2017	Q2	89,13	80,03	98,24	75,21	103,06
2017	Q3	89,13	79,59	98,67	74,54	103,72
2017	Q4	89,13	79,18	99,08	73,91	104,35
2018	Q1	89,13	78,78	99,48	73,30	104,96
2018	Q2	89,13	78,40	99,87	72,72	105,55
2018	Q3	89,13	78,03	100,24	72,15	106,11
2018	Q4	89,13	77,67	100,59	71,60	106,66
2019	Q1	89,13	77,32	100,94	71,07	107,19
2019	Q2	89,13	76,99	101,28	70,56	107,71
2019	Q3	89,13	76,66	101,61	70,05	108,21

2019	Q4	89,13	76,34	101,92	69,57	108,70
2020	Q1	89,13	76,03	102,24	69,09	109,17
2020	Q2	89,13	75,72	102,54	68,62	109,64
2020	Q3	89,13	75,42	102,84	68,17	110,09
2020	Q4	89,13	75,13	103,13	67,72	110,54

Table A.1: Results of simple exponential smoothing.

A.2 Damped Trend Model

Year	Quarter	Point.Forecast	Lo.80	Hi.80	Lo.95	Hi.95
2015	Q1	88,20	85,73	90,67	84,40	92,16
2015	Q2	87,79	84,89	90,73	83,40	92,45
2015	Q3	87,40	84,10	90,65	82,53	92,60
2015	Q4	87,02	83,52	90,54	81,89	92,60
2016	Q1	86,65	82,82	90,50	80,89	92,63
2016	Q2	86,28	82,19	90,54	80,13	92,65
2016	Q3	85,93	81,69	90,44	79,37	92,96
2016	Q4	85,58	81,07	90,29	78,75	92,91
2017	Q1	85,24	80,48	90,21	78,15	92,91
2017	Q2	84,91	79,87	90,06	77,32	93,20
2017	Q3	84,59	79,42	89,93	76,94	92,91
2017	Q4	84,27	78,95	89,69	76,18	92,80
2018	Q1	83,97	78,49	89,64	75,61	92,75
2018	Q2	83,66	77,97	89,48	74,94	92,74
2018	Q3	83,37	77,47	89,19	74,69	92,62
2018	Q4	83,08	77,13	89,26	73,95	92,47
2019	Q1	82,80	76,75	89,10	73,59	92,84
2019	Q2	82,53	76,36	88,91	73,13	92,83
2019	Q3	82,26	76,11	88,86	72,58	92,45
2019	Q4	82,00	75,71	88,70	72,33	92,57
2020	Q1	81,75	75,40	88,56	71,94	92,50
2020	Q2	81,50	74,89	88,65	71,36	92,31
2020	Q3	81,26	74,50	88,44	71,18	92,33
2020	Q4	81,02	74,20	88,35	70,71	92,46

Table A.2: Results of Holt‘s method of dampening trend.

A.3 Holt-Winters Seasonal Model

Year	Quarter	Point.Forecast	Lo.80	Hi.80	Lo.95	Hi.95
2015	Q1	89,34	86,06	92,62	84,32	94,35
2015	Q2	87,86	84,07	91,66	82,05	93,67
2015	Q3	88,71	84,33	93,08	82,01	95,40
2015	Q4	88,09	83,09	93,10	80,44	95,75
2016	Q1	88,82	82,83	94,80	79,66	97,97
2016	Q2	87,35	80,67	94,02	77,14	97,55
2016	Q3	88,19	80,79	95,59	76,87	99,50
2016	Q4	87,58	79,41	95,75	75,08	100,07
2017	Q1	88,30	79,06	97,54	74,17	102,42
2017	Q2	86,83	76,77	96,88	71,45	102,20
2017	Q3	87,67	76,76	98,58	70,98	104,35
2017	Q4	87,06	75,26	98,85	69,02	105,09
2018	Q1	87,78	74,83	100,73	67,98	107,58
2018	Q2	86,31	72,43	100,19	65,08	107,53
2018	Q3	87,15	72,31	102,00	64,45	109,85
2018	Q4	86,54	70,70	102,38	62,32	110,75
2019	Q1	87,26	70,19	104,33	61,16	113,36
2019	Q2	85,79	67,69	103,89	58,10	113,47
2019	Q3	86,63	67,47	105,80	57,32	115,94
2019	Q4	86,02	65,77	106,27	55,05	116,99
2020	Q1	86,74	65,18	108,30	53,77	119,71
2020	Q2	85,27	62,59	107,96	50,58	119,96
2020	Q3	86,11	62,28	109,95	49,66	122,56
2020	Q4	85,50	60,49	110,51	47,25	123,75

Table A.3: Results of Holt-Winters Seasonal Model.

A.4 Simple Regression Model

Year	Quarter	Point.Forecast	Lo.80	Hi.80	Lo.95	Hi.95
2015	Q1	1,81	-1,26	4,87	-2,93	6,54

2015	Q2	2,80	-0,27	5,87	-1,95	7,55
2015	Q3	3,79	0,71	6,88	-0,98	8,56
2015	Q4	4,79	1,68	7,89	-0,01	9,58
2016	Q1	5,78	2,66	8,91	0,95	10,61
2016	Q2	6,77	3,62	9,93	1,91	11,64
2016	Q3	7,77	4,59	10,95	2,85	12,68
2016	Q4	8,76	5,55	11,97	3,80	13,73
2017	Q1	9,76	6,51	13,00	4,74	14,77
2017	Q2	10,75	7,46	14,04	5,67	15,83
2017	Q3	11,74	8,41	15,07	6,60	16,89
2017	Q4	12,74	9,36	16,11	7,52	17,95
2018	Q1	13,73	10,30	17,16	8,44	19,02
2018	Q2	14,72	11,24	18,20	9,35	20,10
2018	Q3	15,72	12,18	19,25	10,26	21,18
2018	Q4	16,71	13,12	20,30	11,16	22,26
2019	Q1	17,70	14,05	21,35	12,06	23,34
2019	Q2	18,70	14,98	22,41	12,96	24,43
2019	Q3	19,69	15,91	23,47	13,85	25,53
2019	Q4	20,68	16,84	24,53	14,74	26,62
2020	Q1	21,68	17,76	25,59	15,63	27,73
2020	Q2	22,67	18,69	26,66	16,51	28,83
2020	Q3	23,66	19,61	27,72	17,40	29,93
2020	Q4	24,66	20,53	28,79	18,27	31,04

Table A.4: Results of simple regression model.

A.5 Vector Auto-Regression Model

Year	Quarter	Point Forecast	Lo 80	Hi 80	Lo 95	Hi 95
2015	Q1	8,40	6,20	10,60	5,03	11,77
2015	Q2	-6,64	-10,88	-2,41	-13,12	-0,17
2015	Q3	0,25	-4,83	5,34	-7,53	8,04
2015	Q4	9,98	4,28	15,67	1,26	18,69
2016	Q1	-18,02	-25,81	-10,24	-29,93	-6,12
2016	Q2	9,13	0,31	17,95	-4,36	22,62

2016	Q3	9,77	-0,03	19,56	-5,21	24,75
2016	Q4	-21,26	-32,14	-10,38	-37,91	-4,62
2017	Q1	16,99	5,84	28,13	-0,06	34,04
2017	Q2	-0,04	-11,70	11,62	-17,87	17,79
2017	Q3	-23,26	-35,71	-10,80	-42,30	-4,21
2017	Q4	34,42	21,52	47,33	14,68	54,16
2018	Q1	-16,00	-29,59	-2,42	-36,78	4,77
2018	Q2	-21,41	-36,22	-6,60	-44,06	1,24
2018	Q3	48,76	31,93	65,60	23,01	74,51
2018	Q4	-39,40	-57,43	-21,37	-66,97	-11,82
2019	Q1	-5,93	-25,57	13,72	-35,97	24,12
2019	Q2	56,56	34,24	78,88	22,42	90,69
2019	Q3	-70,55	-94,95	-46,16	-107,86	-33,25
2019	Q4	26,71	0,95	52,48	-12,69	66,12
2020	Q1	50,34	21,40	79,27	6,09	94,59
2020	Q2	-102,38	-135,03	-69,73	-152,31	-52,44
2020	Q3	78,06	43,35	112,77	24,98	131,14
2020	Q4	20,44	-17,72	58,61	-37,93	78,82

Table A.5: Results of vector auto-regression.

A.6 ARIMA Model

Year	Quarter	Point.Forecast	Lo.80	Hi.80	Lo.95	Hi.95
2015	Q1	3,00	0,05	5,96	-1,52	7,52
2015	Q2	-1,13	-5,88	3,62	-8,39	6,13
2015	Q3	1,55	-3,38	6,49	-5,99	9,10
2015	Q4	-1,35	-6,40	3,69	-9,06	6,36
2016	Q1	0,75	-4,46	5,95	-7,22	8,71
2016	Q2	-0,61	-5,88	4,66	-8,67	7,45
2016	Q3	0,55	-4,74	5,85	-7,55	8,65
2016	Q4	-0,38	-5,70	4,94	-8,51	7,75
2017	Q1	0,28	-5,06	5,61	-7,88	8,43
2017	Q2	-0,23	-5,57	5,11	-8,39	7,93
2017	Q3	0,17	-5,17	5,52	-7,99	8,34
2017	Q4	-0,13	-5,47	5,22	-8,30	8,05

2018	Q1	0,10	-5,25	5,45	-8,08	8,28
2018	Q2	-0,08	-5,42	5,27	-8,25	8,10
2018	Q3	0,06	-5,29	5,41	-8,12	8,24
2018	Q4	-0,04	-5,39	5,30	-8,22	8,13
2019	Q1	0,03	-5,31	5,38	-8,14	8,21
2019	Q2	-0,03	-5,37	5,32	-8,20	8,15
2019	Q3	0,02	-5,33	5,37	-8,16	8,20
2019	Q4	-0,02	-5,36	5,33	-8,19	8,16
2020	Q1	0,01	-5,34	5,36	-8,17	8,19
2020	Q2	-0,01	-5,36	5,34	-8,19	8,17
2020	Q3	0,01	-5,34	5,35	-8,17	8,19
2020	Q4	-0,01	-5,35	5,34	-8,18	8,17

Table A.6: Results of ARIMA.

APPENDIX B

APPENDIX B

B.1 Cluster Analysis

The table B.1 shows the order of the hierarchical clustering method used in section 4.2.1.

Order	Variable
1	oenb_dependent
2	resProp.Dwell
3	resProp.Dwell.2
4	resProp.Dwell.3
5	resProp.Dwell.1
6	carReg
7	productionConstr
8	cpi
9	resProp.Dwell.4
10	constrPriceIndex
11	primConstTot
12	baumeisterarbeit
13	constrCostTotal
14	gesamtbaukost
15	cbre.retail.capitalValue
16	employ
17	un.employ
18	atx

19	cbre.indu.primeRent
20	lohn
21	cbre.retail.primeRent
22	cbre.retail.primeYield
23	prodPrice
24	cbre.office.Capital.Value....m..
25	cbre.office.PrimeRent
26	gdp
27	cbre.office.primeYield

Table B.1: Variables order of hierarchical clustering

B.2 Forward regression

```
Start:  AIC=345.41
datSel$oenb_dependent ~ 1

                             Df Sum of Sq     RSS    AIC
+ resProp.Dwell3              1   19682.0   209.0  78.61
+ cpi                         1   18299.4  1591.6 198.40
+ constrPriceIndex            1   18259.5  1631.5 199.86
+ resProp.Dwell2              1   18148.0  1743.0 203.76
+ cbre.office.PrimeRent       1   17777.3  2113.6 215.14
+ cbre.retail.primeRent       1   17487.7  2403.3 222.72
+ gesamtbaukost               1   16651.4  3239.6 240.33
+ constrCostTotal             1   16639.5  3251.5 240.55
+ primConstTot                1   16620.3  3270.7 240.90
+ baumeisterarbeit            1   16614.4  3276.5 241.00
+ gdp                         1   16468.6  3422.4 243.57
+ prodPrice                   1   16308.8  3582.2 246.27
+ cbre.office.Capital.Value   1   15429.3  4461.7 259.22
+ employ                      1   13194.0  6696.9 283.18
+ resProp.Dwell5              1    9096.9 10794.0 311.34
+ productionConstr            1    7815.9 12075.0 317.96
+ cbre.indu.primeRent         1    6725.6 13165.3 323.06
+ un.employ                   1    3823.4 16067.5 334.81
```

```
+ cbre.office.primeYield      1       888.6  19002.3  344.71
<none>                                       19891.0  345.41
+ stat.resProp.Dwell.1        1       402.3  19488.7  346.20
+ atx                         1       270.3  19620.7  346.60
+ stat.resProp.Dwell.4        1       166.9  19724.1  346.91
+ stat.carReg                 1        65.5  19825.5  347.21
+ stat.lohn                   1        39.8  19851.2  347.29

Step:  AIC=78.61
datSel$oenb_dependent ~ resProp.Dwell3

                             Df Sum of Sq    RSS    AIC
+ resProp.Dwell2              1    94.452 114.51 45.122
+ constrPriceIndex            1    61.487 147.47 60.049
+ cbre.office.PrimeRent       1    61.063 147.89 60.218
+ cpi                         1    45.595 163.36 66.087
+ baumeisterarbeit            1    38.410 170.55 68.627
+ primConstTot                1    38.370 170.59 68.641
+ gesamtbaukost               1    37.296 171.66 69.011
+ constrCostTotal             1    37.225 171.73 69.035
+ cbre.retail.primeRent       1    34.751 174.21 69.879
+ gdp                         1    26.206 182.75 72.705
+ prodPrice                   1    25.818 183.14 72.830
+ employ                      1    17.989 190.97 75.300
+ cbre.office.Capital.Value   1    16.055 192.90 75.894
+ cbre.indu.primeRent         1     7.932 201.03 78.328
<none>                                    208.96 78.611
+ productionConstr            1     4.541 204.42 79.315
+ stat.resProp.Dwell.4        1     3.998 204.96 79.471
+ resProp.Dwell5              1     2.923 206.03 79.780
+ cbre.office.primeYield      1     1.277 207.68 80.249
+ atx                         1     0.924 208.03 80.349
+ stat.carReg                 1     0.702 208.25 80.412
+ stat.lohn                   1     0.700 208.26 80.413
+ stat.resProp.Dwell.1        1     0.086 208.87 80.587
+ un.employ                   1     0.008 208.95 80.609

Step:  AIC=45.12
```

```
datSel$oenb_dependent ~ resProp.Dwell3 + resProp.Dwell2

                           Df Sum of Sq     RSS    AIC
+ stat.resProp.Dwell.1      1   30.2538  84.252 29.020
+ constrPriceIndex          1   26.6626  87.843 31.483
+ cbre.office.PrimeRent     1   25.4160  89.090 32.314
+ cpi                       1   22.1667  92.339 34.428
+ cbre.retail.primeRent     1   16.9608  97.545 37.664
+ stat.resProp.Dwell.4      1   15.6701  98.835 38.439
+ baumeisterarbeit          1   13.7112 100.794 39.597
+ primConstTot              1   13.6985 100.807 39.605
+ gesamtbaukost             1   13.3580 101.148 39.804
+ constrCostTotal           1   13.2985 101.207 39.838
+ prodPrice                 1   11.6311 102.874 40.802
+ gdp                       1    8.8179 105.688 42.394
+ cbre.office.Capital.Value 1    6.2794 108.226 43.794
<none>                                  114.506 45.122
+ productionConstr          1    1.8135 112.692 46.180
+ employ                    1    1.5964 112.909 46.294
+ un.employ                 1    1.0579 113.448 46.574
+ stat.lohn                 1    0.8895 113.616 46.662
+ cbre.indu.primeRent       1    0.7715 113.734 46.723
+ stat.carReg               1    0.2893 114.216 46.973
+ cbre.office.primeYield    1    0.2847 114.221 46.975
+ atx                       1    0.1177 114.388 47.061
+ resProp.Dwell5            1    0.0952 114.410 47.073

Step:  AIC=29.02
datSel$oenb_dependent ~ resProp.Dwell3 + resProp.Dwell2 + stat.resProp.Dwell.1

                           Df Sum of Sq    RSS    AIC
+ constrPriceIndex          1   13.0944 71.157 21.054
+ cpi                       1   10.9721 73.280 22.788
+ cbre.office.PrimeRent     1   10.0157 74.236 23.553
+ stat.resProp.Dwell.4      1    7.8905 76.361 25.218
+ cbre.retail.primeRent     1    7.2713 76.980 25.695
+ baumeisterarbeit          1    6.0815 78.170 26.600
+ primConstTot              1    6.0743 78.177 26.605
```

```
+ gesamtbaukost                  1      6.0507  78.201  26.623
+ constrCostTotal                1      6.0148  78.237  26.650
+ prodPrice                      1      5.2007  79.051  27.261
+ gdp                            1      3.9188  80.333  28.210
<none>                                          84.252  29.020
+ productionConstr               1      2.0032  82.249  29.600
+ cbre.office.Capital.Value      1      1.4997  82.752  29.960
+ un.employ                      1      1.2299  83.022  30.152
+ resProp.Dwell5                 1      0.7502  83.502  30.492
+ cbre.office.primeYield         1      0.2620  83.990  30.836
+ atx                            1      0.1529  84.099  30.913
+ cbre.indu.primeRent            1      0.1167  84.135  30.938
+ employ                         1      0.0538  84.198  30.982
+ stat.carReg                    1      0.0385  84.213  30.993
+ stat.lohn                      1      0.0339  84.218  30.996

Step:  AIC=21.05
datSel$oenb_dependent ~ resProp.Dwell3 + resProp.Dwell2 + stat.resProp.Dwell.1 +
    constrPriceIndex

                               Df Sum of Sq    RSS     AIC
+ resProp.Dwell5                 1    17.8516  53.306   6.0119
+ stat.resProp.Dwell.4           1     6.1573  65.000  17.7142
+ cbre.office.Capital.Value      1     5.8987  65.259  17.9484
+ primConstTot                   1     4.5730  66.584  19.1350
+ baumeisterarbeit               1     4.5589  66.598  19.1475
+ constrCostTotal                1     4.3258  66.832  19.3536
+ gesamtbaukost                  1     4.2954  66.862  19.3804
+ cbre.office.PrimeRent          1     3.4205  67.737  20.1474
+ prodPrice                      1     3.3237  67.834  20.2318
+ employ                         1     2.8895  68.268  20.6082
<none>                                         71.157  21.0540
+ atx                            1     1.8664  69.291  21.4858
+ cbre.indu.primeRent            1     1.8655  69.292  21.4866
+ cbre.office.primeYield         1     1.7306  69.427  21.6013
+ productionConstr               1     0.6651  70.492  22.4999
+ gdp                            1     0.4193  70.738  22.7053
+ stat.lohn                      1     0.2406  70.917  22.8541
```

```
+ un.employ                  1      0.2201  70.937  22.8712
+ cpi                        1      0.1373  71.020  22.9400
+ cbre.retail.primeRent      1      0.0889  71.068  22.9802
+ stat.carReg                1      0.0004  71.157  23.0536

Step:  AIC=6.01
datSel$oenb_dependent ~ resProp.Dwell3 + resProp.Dwell2 + stat.resProp.Dwell.1 +
    constrPriceIndex + resProp.Dwell5

                            Df Sum of Sq     RSS     AIC
+ cbre.office.PrimeRent      1     3.8963  49.409  3.5336
+ cbre.office.Capital.Value  1     3.4562  49.850  4.0568
+ primConstTot               1     2.3823  50.923  5.3144
+ baumeisterarbeit           1     2.3563  50.949  5.3445
+ constrCostTotal            1     1.9319  51.374  5.8339
+ gesamtbaukost              1     1.9151  51.391  5.8531
<none>                                     53.306  6.0119
+ cbre.retail.primeRent      1     1.5682  51.738  6.2501
+ gdp                        1     0.7746  52.531  7.1483
+ stat.lohn                  1     0.7322  52.573  7.1958
+ un.employ                  1     0.6063  52.699  7.3369
+ cbre.office.primeYield     1     0.5714  52.734  7.3760
+ productionConstr           1     0.4126  52.893  7.5534
+ atx                        1     0.2695  53.036  7.7128
+ cpi                        1     0.2425  53.063  7.7429
+ stat.resProp.Dwell.4       1     0.0981  53.208  7.9032
+ employ                     1     0.0743  53.231  7.9296
+ cbre.indu.primeRent        1     0.0165  53.289  7.9936
+ stat.carReg                1     0.0004  53.305  8.0114
+ prodPrice                  1     0.0001  53.306  8.0117

Step:  AIC=3.53
datSel$oenb_dependent ~ resProp.Dwell3 + resProp.Dwell2 + stat.resProp.Dwell.1 +
    constrPriceIndex + resProp.Dwell5 + cbre.office.PrimeRent

                            Df Sum of Sq     RSS     AIC
+ cbre.retail.primeRent      1    3.15793  46.251  1.6368
+ cbre.indu.primeRent        1    2.41120  46.998  2.5817
```

```
+ cbre.office.Capital.Value  1   1.67867 47.731 3.4942
<none>                                   49.409 3.5336
+ cbre.office.primeYield     1   1.54622 47.863 3.6577
+ primConstTot               1   0.97700 48.432 4.3553
+ baumeisterarbeit           1   0.96059 48.449 4.3753
+ stat.lohn                  1   0.60017 48.809 4.8125
+ un.employ                  1   0.55972 48.850 4.8614
+ employ                     1   0.54113 48.868 4.8839
+ constrCostTotal            1   0.52791 48.881 4.8998
+ gesamtbaukost              1   0.52230 48.887 4.9066
+ atx                        1   0.35487 49.055 5.1083
+ prodPrice                  1   0.10835 49.301 5.4041
+ productionConstr           1   0.04250 49.367 5.4828
+ stat.carReg                1   0.02903 49.380 5.4989
+ gdp                        1   0.00398 49.405 5.5288
+ cpi                        1   0.00002 49.409 5.5336
+ stat.resProp.Dwell.4       1   0.00000 49.409 5.5336

Step:  AIC=1.64
datSel$oenb_dependent ~ resProp.Dwell3 + resProp.Dwell2 + stat.resProp.Dwell.1 +
    constrPriceIndex + resProp.Dwell5 + cbre.office.PrimeRent +
    cbre.retail.primeRent

                            Df Sum of Sq    RSS     AIC
+ primConstTot               1    6.8684 39.383 -5.8478
+ baumeisterarbeit           1    6.8435 39.408 -5.8106
+ gesamtbaukost              1    6.6054 39.646 -5.4551
+ constrCostTotal            1    6.5856 39.666 -5.4257
+ prodPrice                  1    4.4209 41.831 -2.2907
+ gdp                        1    3.2377 43.014 -0.6449
+ cbre.indu.primeRent        1    2.9741 43.277 -0.2845
+ productionConstr           1    2.9318 43.320 -0.2269
+ atx                        1    1.6661 44.585  1.4723
<none>                                   46.251  1.6368
+ cpi                        1    1.1793 45.072  2.1129
+ employ                     1    0.6676 45.584  2.7790
+ stat.lohn                  1    0.2646 45.987  3.2984
+ un.employ                  1    0.1725 46.079  3.4164
```

```
+ stat.carReg                  1    0.0637 46.188   3.5555
+ cbre.office.Capital.Value    1    0.0437 46.208   3.5810
+ cbre.office.primeYield       1    0.0158 46.236   3.6166
+ stat.resProp.Dwell.4         1    0.0026 46.249   3.6335

Step:  AIC=-5.85
datSel$oenb_dependent ~ resProp.Dwell3 + resProp.Dwell2 + stat.resProp.Dwell.1 +
    constrPriceIndex + resProp.Dwell5 + cbre.office.PrimeRent +
    cbre.retail.primeRent + primConstTot

                             Df Sum of Sq    RSS      AIC
+ prodPrice                   1    7.4602 31.923 -16.2385
+ un.employ                   1    4.7642 34.619 -11.4552
+ cbre.office.Capital.Value   1    3.7339 35.649  -9.7249
+ cbre.office.primeYield      1    2.7481 36.635  -8.1155
+ cpi                         1    2.5929 36.790  -7.8661
+ employ                      1    1.4859 37.897  -6.1170
<none>                                    39.383  -5.8478
+ gdp                         1    0.7825 38.601  -5.0320
+ baumeisterarbeit            1    0.7022 38.681  -4.9093
+ stat.lohn                   1    0.3833 39.000  -4.4249
+ productionConstr            1    0.0915 39.292  -3.9851
+ atx                         1    0.0495 39.334  -3.9221
+ stat.carReg                 1    0.0326 39.351  -3.8966
+ cbre.indu.primeRent         1    0.0067 39.376  -3.8578
+ constrCostTotal             1    0.0066 39.376  -3.8578
+ gesamtbaukost               1    0.0040 39.379  -3.8538
+ stat.resProp.Dwell.4        1    0.0003 39.383  -3.8483

Step:  AIC=-16.24
datSel$oenb_dependent ~ resProp.Dwell3 + resProp.Dwell2 + stat.resProp.Dwell.1 +
    constrPriceIndex + resProp.Dwell5 + cbre.office.PrimeRent +
    cbre.retail.primeRent + primConstTot + prodPrice

                             Df Sum of Sq    RSS     AIC
+ cbre.office.Capital.Value   1    6.3341 25.589 -27.288
+ cbre.office.primeYield      1    6.1451 25.778 -26.853
+ cpi                         1    2.7672 29.156 -19.588
```

```
+ gdp                       1     2.1037  29.819  -18.261
+ un.employ                 1     1.3341  30.589  -16.757
+ gesamtbaukost             1     1.0983  30.825  -16.304
+ constrCostTotal           1     1.0858  30.837  -16.280
<none>                                    31.923  -16.238
+ employ                    1     1.0552  30.868  -16.222
+ cbre.indu.primeRent       1     0.7385  31.184  -15.619
+ atx                       1     0.5997  31.323  -15.357
+ stat.lohn                 1     0.1918  31.731  -14.594
+ stat.carReg               1     0.1196  31.803  -14.460
+ baumeisterarbeit          1     0.1127  31.810  -14.447
+ stat.resProp.Dwell.4      1     0.0602  31.863  -14.350
+ productionConstr          1     0.0466  31.876  -14.325

Step:  AIC=-27.29
datSel$oenb_dependent ~ resProp.Dwell3 + resProp.Dwell2 + stat.resProp.Dwell.1 +
    constrPriceIndex + resProp.Dwell5 + cbre.office.PrimeRent +
    cbre.retail.primeRent + primConstTot + prodPrice + cbre.office.Capital.Value

                        Df Sum of Sq    RSS     AIC
+ stat.lohn              1   1.19163 24.397 -28.101
+ un.employ              1   1.09501 24.494 -27.868
<none>                               25.589 -27.288
+ baumeisterarbeit       1   0.43646 25.152 -26.302
+ cbre.indu.primeRent    1   0.40627 25.183 -26.232
+ employ                 1   0.31572 25.273 -26.020
+ constrCostTotal        1   0.31388 25.275 -26.016
+ atx                    1   0.24640 25.342 -25.858
+ gesamtbaukost          1   0.24514 25.344 -25.855
+ productionConstr       1   0.16344 25.425 -25.666
+ stat.resProp.Dwell.4   1   0.14993 25.439 -25.634
+ cbre.office.primeYield 1   0.08626 25.503 -25.487
+ cpi                    1   0.02740 25.561 -25.351
+ gdp                    1   0.02459 25.564 -25.344
+ stat.carReg            1   0.00006 25.589 -25.288

Step:  AIC=-28.1
datSel$oenb_dependent ~ resProp.Dwell3 + resProp.Dwell2 + stat.resProp.Dwell.1 +
```

```
    constrPriceIndex + resProp.Dwell5 + cbre.office.PrimeRent +
    cbre.retail.primeRent + primConstTot + prodPrice + cbre.office.Capital.Value +
    stat.lohn

                          Df Sum of Sq    RSS     AIC
+ un.employ                1   1.40612 22.991 -29.603
+ constrCostTotal          1   0.82415 23.573 -28.129
<none>                                 24.397 -28.101
+ gesamtbaukost            1   0.75640 23.641 -27.959
+ baumeisterarbeit         1   0.47513 23.922 -27.261
+ employ                   1   0.45744 23.940 -27.218
+ productionConstr         1   0.37869 24.018 -27.024
+ cbre.indu.primeRent      1   0.24294 24.154 -26.692
+ cbre.office.primeYield   1   0.12950 24.268 -26.415
+ atx                      1   0.09826 24.299 -26.339
+ stat.resProp.Dwell.4     1   0.07571 24.322 -26.284
+ gdp                      1   0.05937 24.338 -26.245
+ cpi                      1   0.04835 24.349 -26.218
+ stat.carReg              1   0.00655 24.391 -26.117

Step:  AIC=-29.6
datSel$oenb_dependent ~ resProp.Dwell3 + resProp.Dwell2 + stat.resProp.Dwell.1 +
    constrPriceIndex + resProp.Dwell5 + cbre.office.PrimeRent +
    cbre.retail.primeRent + primConstTot + prodPrice + cbre.office.Capital.Value +
    stat.lohn + un.employ

                          Df Sum of Sq    RSS     AIC
<none>                                 22.991 -29.603
+ baumeisterarbeit         1   0.66770 22.323 -29.342
+ cbre.indu.primeRent      1   0.49017 22.501 -28.875
+ constrCostTotal          1   0.37899 22.612 -28.584
+ productionConstr         1   0.32178 22.669 -28.435
+ gesamtbaukost            1   0.28659 22.704 -28.343
+ atx                      1   0.22726 22.764 -28.189
+ stat.resProp.Dwell.4     1   0.22546 22.766 -28.185
+ employ                   1   0.09558 22.895 -27.849
+ cbre.office.primeYield   1   0.06845 22.923 -27.779
+ gdp                      1   0.04860 22.942 -27.728
```

```
+ cpi                        1    0.03956  22.951  -27.705
+ stat.carReg                1    0.00087  22.990  -27.606
> # AIC table
> (fwd$anova$AIC)
 [1] 345.408540  78.610909  45.122062  29.020041  21.053993   6.011880   3.533596
1.636802  -5.847835 -16.238540 -27.287487 -28.101059 -29.603414
```

B.2.1 Backward regression

```
Start:  AIC=-16.09
datSel$oenb_dependent ~ gdp + employ + atx + un.employ + cpi +
    prodPrice + productionConstr + constrPriceIndex + constrCostTotal +
    primConstTot + baumeisterarbeit + gesamtbaukost + resProp.Dwell2 +
    resProp.Dwell3 + resProp.Dwell5 + stat.resProp.Dwell.4 +
    stat.lohn + stat.resProp.Dwell.1 + stat.carReg + cbre.indu.primeRent +
    cbre.office.Capital.Value + cbre.office.PrimeRent + cbre.office.primeYield +
    cbre.retail.primeRent

                              Df Sum of Sq    RSS     AIC
- cbre.office.Capital.Value   1     0.002  19.249  -18.084
- cpi                         1     0.028  19.276  -18.003
- cbre.office.PrimeRent       1     0.032  19.279  -17.992
- stat.resProp.Dwell.4        1     0.049  19.296  -17.939
- cbre.office.primeYield      1     0.076  19.323  -17.857
- atx                         1     0.079  19.327  -17.847
- stat.resProp.Dwell.1        1     0.128  19.375  -17.699
- employ                      1     0.134  Quarterly19.382  -17.679
- baumeisterarbeit            1     0.138  19.385  -17.668
- primConstTot                1     0.186  19.433  -17.523
- stat.carReg                 1     0.228  19.475  -17.395
- productionConstr            1     0.318  19.565  -17.122
- stat.lohn                   1     0.440  19.687  -16.756
- gesamtbaukost               1     0.483  19.730  -16.627
- cbre.indu.primeRent         1     0.510  19.758  -16.546
- gdp                         1     0.515  19.763  -16.531
- resProp.Dwell5              1     0.597  19.845  -16.286
<none>                                     19.247  -16.089
- constrCostTotal             1     0.691  19.938  -16.009
- prodPrice                   1     1.372  20.619  -14.028
```

```
- un.employ                  1      1.548   20.795  -13.527
- cbre.retail.primeRent      1      4.000   23.248   -6.948
- resProp.Dwell2             1      8.495   27.743    3.480
- constrPriceIndex           1     11.228   30.476    9.025
- resProp.Dwell3             1    103.133  122.381   91.046

Step:  AIC=-18.08
datSel$oenb_dependent ~ gdp + employ + atx + un.employ + cpi +
    prodPrice + productionConstr + constrPriceIndex + constrCostTotal +
    primConstTot + baumeisterarbeit + gesamtbaukost + resProp.Dwell2 +
    resProp.Dwell3 + resProp.Dwell5 + stat.resProp.Dwell.4 +
    stat.lohn + stat.resProp.Dwell.1 + stat.carReg + cbre.indu.primeRent +
    cbre.office.PrimeRent + cbre.office.primeYield + cbre.retail.primeRent

                          Df Sum of Sq    RSS     AIC
- cpi                     1     0.030  19.279 -19.992
- stat.resProp.Dwell.4    1     0.048  19.297 -19.938
- atx                     1     0.083  19.332 -19.829
- employ                  1     0.134  19.383 -19.676
- baumeisterarbeit        1     0.146  19.395 -19.639
- stat.resProp.Dwell.1    1     0.174  19.424 -19.552
- primConstTot            1     0.197  19.446 -19.485
- stat.carReg             1     0.232  19.481 -19.376
- productionConstr        1     0.345  19.594 -19.037
- stat.lohn               1     0.439  19.688 -18.753
- gesamtbaukost           1     0.482  19.731 -18.625
- gdp                     1     0.525  19.774 -18.497
- resProp.Dwell5          1     0.639  19.888 -18.159
<none>                                 19.249 -18.084
- constrCostTotal         1     0.691  19.940 -18.004
- cbre.indu.primeRent     1     0.736  19.985 -17.870
- un.employ               1     1.552  20.801 -15.509
- cbre.office.PrimeRent   1     1.762  21.011 -14.917
- prodPrice               1     2.383  21.632 -13.198
- cbre.retail.primeRent   1     4.006  23.255  -8.929
- cbre.office.primeYield  1     6.711  25.960  -2.437
- resProp.Dwell2          1    11.331  30.580   7.225
- constrPriceIndex        1    11.876  31.125   8.268
```

```
- resProp.Dwell3          1    105.886 125.135   90.359

Step:  AIC=-19.99
datSel$oenb_dependent ~ gdp + employ + atx + un.employ + prodPrice +
    productionConstr + constrPriceIndex + constrCostTotal + primConstTot +
    baumeisterarbeit + gesamtbaukost + resProp.Dwell2 + resProp.Dwell3 +
    resProp.Dwell5 + stat.resProp.Dwell.4 + stat.lohn + stat.resProp.Dwell.1 +
    stat.carReg + cbre.indu.primeRent + cbre.office.PrimeRent +
    cbre.office.primeYield + cbre.retail.primeRent

                           Df Sum of Sq     RSS     AIC
- stat.resProp.Dwell.4      1     0.079  19.358 -21.752
- baumeisterarbeit          1     0.121  19.401 -21.622
- employ                    1     0.129  19.409 -21.598
- atx                       1     0.143  19.422 -21.557
- stat.resProp.Dwell.1      1     0.147  19.426 -21.543
- primConstTot              1     0.169  19.448 -21.477
- stat.carReg               1     0.259  19.538 -21.205
- productionConstr          1     0.327  19.606 -21.000
- stat.lohn                 1     0.450  19.729 -20.631
- gesamtbaukost             1     0.565  19.844 -20.289
- gdp                       1     0.595  19.874 -20.199
- resProp.Dwell5            1     0.620  19.899 -20.125
<none>                                   19.279 -19.992
- cbre.indu.primeRent       1     0.728  20.007 -19.806
- constrCostTotal           1     0.764  20.043 -19.699
- un.employ                 1     1.654  20.934 -17.135
- cbre.office.PrimeRent     1     1.890  21.170 -16.473
- prodPrice                 1     2.375  21.654 -15.138
- cbre.retail.primeRent     1     4.152  23.432 -10.484
- cbre.office.primeYield    1     7.255  26.534  -3.148
- resProp.Dwell2            1    12.710  31.989   7.884
- constrPriceIndex          1    15.415  34.695  12.674
- resProp.Dwell3            1   106.161 125.440  88.503

Step:  AIC=-21.75
datSel$oenb_dependent ~ gdp + employ + atx + un.employ + prodPrice +
    productionConstr + constrPriceIndex + constrCostTotal + primConstTot +
```

```
    baumeisterarbeit + gesamtbaukost + resProp.Dwell2 + resProp.Dwell3 +
    resProp.Dwell5 + stat.lohn + stat.resProp.Dwell.1 + stat.carReg +
    cbre.indu.primeRent + cbre.office.PrimeRent + cbre.office.primeYield +
    cbre.retail.primeRent

                         Df Sum of Sq     RSS     AIC
- baumeisterarbeit        1     0.111  19.469 -23.415
- atx                     1     0.120  19.478 -23.386
- primConstTot            1     0.157  19.515 -23.274
- stat.resProp.Dwell.1    1     0.163  19.521 -23.257
- employ                  1     0.232  19.589 -23.051
- stat.carReg             1     0.300  19.658 -22.844
- productionConstr        1     0.338  19.696 -22.730
- stat.lohn               1     0.457  19.815 -22.374
- gesamtbaukost           1     0.571  19.928 -22.038
<none>                                 19.358 -21.752
- cbre.indu.primeRent     1     0.718  20.076 -21.604
- gdp                     1     0.736  20.094 -21.551
- constrCostTotal         1     0.781  20.138 -21.420
- resProp.Dwell5          1     1.223  20.581 -20.138
- un.employ               1     1.891  21.249 -18.252
- cbre.office.PrimeRent   1     1.997  21.354 -17.960
- prodPrice               1     2.306  21.664 -17.111
- cbre.retail.primeRent   1     4.075  23.433 -12.480
- cbre.office.primeYield  1     7.660  27.017  -4.082
- resProp.Dwell2          1    12.668  32.026   5.952
- constrPriceIndex        1    15.337  34.695  10.674
- resProp.Dwell3          1   106.588 125.946  86.741

Step:  AIC=-23.41
datSel$oenb_dependent ~ gdp + employ + atx + un.employ + prodPrice +
    productionConstr + constrPriceIndex + constrCostTotal + primConstTot +
    gesamtbaukost + resProp.Dwell2 + resProp.Dwell3 + resProp.Dwell5 +
    stat.lohn + stat.resProp.Dwell.1 + stat.carReg + cbre.indu.primeRent +
    cbre.office.PrimeRent + cbre.office.primeYield + cbre.retail.primeRent

                         Df Sum of Sq     RSS     AIC
- stat.resProp.Dwell.1    1     0.181  19.650 -24.868
```

```
- atx                       1      0.201  19.670 -24.807
- employ                    1      0.228  19.697 -24.728
- stat.carReg               1      0.297  19.766 -24.521
- productionConstr          1      0.406  19.874 -24.198
- stat.lohn                 1      0.491  19.959 -23.946
- gesamtbaukost             1      0.615  20.083 -23.581
- gdp                       1      0.636  20.104 -23.519
<none>                                    19.469 -23.415
- constrCostTotal           1      0.849  20.318 -22.896
- cbre.indu.primeRent       1      1.112  20.581 -22.138
- resProp.Dwell5            1      1.113  20.582 -22.134
- un.employ                 1      1.809  21.278 -20.172
- cbre.office.PrimeRent     1      1.892  21.361 -19.942
- prodPrice                 1      2.622  22.091 -17.961
- primConstTot              1      3.053  22.522 -16.820
- cbre.retail.primeRent     1      5.202  24.671 -11.443
- cbre.office.primeYield    1      7.612  27.080  -5.945
- resProp.Dwell2            1     12.653  32.122   4.128
- constrPriceIndex          1     20.107  39.576  16.441
- resProp.Dwell3            1    116.810 136.279  89.393

Step:  AIC=-24.87
datSel$oenb_dependent ~ gdp + employ + atx + un.employ + prodPrice +
    productionConstr + constrPriceIndex + constrCostTotal + primConstTot +
    gesamtbaukost + resProp.Dwell2 + resProp.Dwell3 + resProp.Dwell5 +
    stat.lohn + stat.carReg + cbre.indu.primeRent + cbre.office.PrimeRent +
    cbre.office.primeYield + cbre.retail.primeRent

                           Df Sum of Sq    RSS     AIC
- atx                       1      0.187  19.837 -26.310
- employ                    1      0.288  19.938 -26.008
- productionConstr          1      0.302  19.952 -25.969
- stat.carReg               1      0.323  19.973 -25.907
- gdp                       1      0.570  20.220 -25.181
- stat.lohn                 1      0.656  20.306 -24.932
<none>                                    19.650 -24.868
- gesamtbaukost             1      0.732  20.382 -24.710
- constrCostTotal           1      0.984  20.634 -23.986
```

```
- cbre.indu.primeRent        1      1.019  20.669 -23.884
- resProp.Dwell5             1      1.034  20.684 -23.843
- un.employ                  1      2.007  21.657 -21.129
- cbre.office.PrimeRent      1      2.379  22.029 -20.126
- prodPrice                  1      2.853  22.503 -18.869
- primConstTot               1      2.991  22.641 -18.508
- cbre.retail.primeRent      1      5.583  25.233 -12.113
- cbre.office.primeYield     1      7.916  27.566  -6.897
- resProp.Dwell2             1     19.850  39.500  14.326
- constrPriceIndex           1     22.150  41.800  17.666
- resProp.Dwell3             1    125.803 145.453  91.237

Step:  AIC=-26.31
datSel$oenb_dependent ~ gdp + employ + un.employ + prodPrice +
    productionConstr + constrPriceIndex + constrCostTotal + primConstTot +
    gesamtbaukost + resProp.Dwell2 + resProp.Dwell3 + resProp.Dwell5 +
    stat.lohn + stat.carReg + cbre.indu.primeRent + cbre.office.PrimeRent +
    cbre.office.primeYield + cbre.retail.primeRent

                         Df Sum of Sq     RSS     AIC
- employ                  1     0.209  20.046 -27.691
- stat.carReg             1     0.335  20.171 -27.323
- productionConstr        1     0.376  20.213 -27.202
- stat.lohn               1     0.638  20.474 -26.443
<none>                                 19.837 -26.310
- gesamtbaukost           1     0.829  20.666 -25.893
- cbre.indu.primeRent     1     0.910  20.747 -25.664
- gdp                     1     1.080  20.917 -25.182
- constrCostTotal         1     1.093  20.930 -25.146
- resProp.Dwell5          1     1.493  21.329 -24.030
- un.employ               1     1.916  21.753 -22.869
- primConstTot            1     2.819  22.656 -20.470
- prodPrice               1     2.962  22.798 -20.100
- cbre.office.PrimeRent   1     3.597  23.434 -18.478
- cbre.retail.primeRent   1     5.651  25.488 -13.521
- cbre.office.primeYield  1     7.742  27.579  -8.869
- resProp.Dwell2          1    19.664  39.501  12.329
- constrPriceIndex        1    22.001  41.838  15.720
```

```
- resProp.Dwell3           1   145.240 165.076  96.703

Step:  AIC=-27.69
datSel$oenb_dependent ~ gdp + un.employ + prodPrice + productionConstr +
    constrPriceIndex + constrCostTotal + primConstTot + gesamtbaukost +
    resProp.Dwell2 + resProp.Dwell3 + resProp.Dwell5 + stat.lohn +
    stat.carReg + cbre.indu.primeRent + cbre.office.PrimeRent +
    cbre.office.primeYield + cbre.retail.primeRent

                          Df Sum of Sq     RSS     AIC
- stat.carReg              1     0.331  20.377 -28.725
<none>                                  20.046 -27.691
- productionConstr         1     0.719  20.765 -27.613
- stat.lohn                1     0.828  20.874 -27.302
- gdp                      1     0.871  20.917 -27.181
- gesamtbaukost            1     0.893  20.939 -27.119
- cbre.indu.primeRent      1     0.975  21.021 -26.889
- constrCostTotal          1     1.122  21.168 -26.478
- resProp.Dwell5           1     1.314  21.360 -25.945
- primConstTot             1     2.612  22.658 -22.465
- un.employ                1     2.684  22.730 -22.278
- cbre.office.PrimeRent    1     3.489  23.535 -20.224
- prodPrice                1     3.689  23.735 -19.726
- cbre.retail.primeRent    1     5.863  25.909 -14.553
- cbre.office.primeYield   1     7.729  27.775 -10.451
- resProp.Dwell2           1    19.477  39.523  10.361
- constrPriceIndex         1    26.075  46.121  19.470
- resProp.Dwell3           1   148.559 168.605  95.951

Step:  AIC=-28.72
datSel$oenb_dependent ~ gdp + un.employ + prodPrice + productionConstr +
    constrPriceIndex + constrCostTotal + primConstTot + gesamtbaukost +
    resProp.Dwell2 + resProp.Dwell3 + resProp.Dwell5 + stat.lohn +
    cbre.indu.primeRent + cbre.office.PrimeRent + cbre.office.primeYield +
    cbre.retail.primeRent

                          Df Sum of Sq     RSS     AIC
- gesamtbaukost            1     0.652  21.029 -28.866
```

```
<none>                                      20.377  -28.725
- gdp                          1     0.719  21.096  -28.679
- cbre.indu.primeRent          1     0.746  21.123  -28.603
- productionConstr             1     0.758  21.135  -28.571
- constrCostTotal              1     0.858  21.235  -28.291
- stat.lohn                    1     1.187  21.564  -27.384
- resProp.Dwell5               1     1.250  21.627  -27.212
- un.employ                    1     2.360  22.737  -24.259
- primConstTot                 1     2.688  23.065  -23.413
- cbre.office.PrimeRent        1     3.777  24.154  -20.691
- prodPrice                    1     4.959  25.336  -17.873
- cbre.retail.primeRent        1     5.958  26.335  -15.591
- cbre.office.primeYield       1     7.514  27.891  -12.204
- resProp.Dwell2               1    19.156  39.533    8.376
- constrPriceIndex             1    25.756  46.133   17.486
- resProp.Dwell3               1   148.285 168.662   93.971

Step:  AIC=-28.87
datSel$oenb_dependent ~ gdp + un.employ + prodPrice + productionConstr +
    constrPriceIndex + constrCostTotal + primConstTot + resProp.Dwell2 +
    resProp.Dwell3 + resProp.Dwell5 + stat.lohn + cbre.indu.primeRent +
    cbre.office.PrimeRent + cbre.office.primeYield + cbre.retail.primeRent

                              Df Sum of Sq     RSS      AIC
- productionConstr             1     0.712  21.741  -28.902
<none>                                      21.029  -28.866
- cbre.indu.primeRent          1     0.761  21.791  -28.767
- gdp                          1     0.806  21.835  -28.648
- constrCostTotal              1     1.132  22.162  -27.772
- resProp.Dwell5               1     1.695  22.724  -26.292
- un.employ                    1     1.778  22.807  -26.078
- stat.lohn                    1     1.813  22.842  -25.987
- cbre.office.PrimeRent        1     3.454  24.483  -21.894
- primConstTot                 1     4.003  25.032  -20.586
- cbre.retail.primeRent        1     5.627  26.656  -16.877
- prodPrice                    1     6.636  27.665  -14.684
- cbre.office.primeYield       1     7.085  28.115  -13.733
- resProp.Dwell2               1    19.332  40.361    7.600
```

```
- constrPriceIndex          1     25.206  46.236   15.617
- resProp.Dwell3            1    155.630 176.659   94.704

Step:  AIC=-28.9
datSel$oenb_dependent ~ gdp + un.employ + prodPrice + constrPriceIndex +
    constrCostTotal + primConstTot + resProp.Dwell2 + resProp.Dwell3 +
    resProp.Dwell5 + stat.lohn + cbre.indu.primeRent + cbre.office.PrimeRent +
    cbre.office.primeYield + cbre.retail.primeRent

                         Df Sum of Sq     RSS     AIC
- gdp                     1     0.418  22.159 -29.779
- cbre.indu.primeRent     1     0.727  22.468 -28.962
<none>                                 21.741 -28.902
- constrCostTotal         1     0.795  22.536 -28.783
- stat.lohn               1     1.489  23.231 -26.992
- un.employ               1     1.630  23.371 -26.635
- resProp.Dwell5          1     1.969  23.710 -25.786
- cbre.office.PrimeRent   1     2.955  24.697 -23.381
- primConstTot            1     3.332  25.073 -22.489
- prodPrice               1     6.348  28.089 -15.788
- cbre.office.primeYield  1     6.375  28.116 -15.731
- cbre.retail.primeRent   1     9.773  31.514  -8.999
- resProp.Dwell2          1    18.626  40.368   5.609
- constrPriceIndex        1    24.980  46.721  14.233
- resProp.Dwell3          1   165.678 187.419  96.193

Step:  AIC=-29.78
datSel$oenb_dependent ~ un.employ + prodPrice + constrPriceIndex +
    constrCostTotal + primConstTot + resProp.Dwell2 + resProp.Dwell3 +
    resProp.Dwell5 + stat.lohn + cbre.indu.primeRent + cbre.office.PrimeRent +
    cbre.office.primeYield + cbre.retail.primeRent

                         Df Sum of Sq     RSS     AIC
- constrCostTotal         1     0.413  22.572 -30.689
- cbre.indu.primeRent     1     0.603  22.762 -30.194
<none>                                 22.159 -29.779
- un.employ               1     1.284  23.443 -28.454
- resProp.Dwell5          1     1.558  23.717 -27.770
```

```
- stat.lohn                1     1.924  24.082 -26.867
- primConstTot             1     2.916  25.075 -24.485
- cbre.office.PrimeRent    1     3.129  25.288 -23.985
- prodPrice                1     6.269  28.428 -17.079
- cbre.office.primeYield   1     7.446  29.605 -14.686
- cbre.retail.primeRent    1     9.497  31.656 -10.733
- resProp.Dwell2           1    18.216  40.375   3.620
- constrPriceIndex         1    25.725  47.884  13.683
- resProp.Dwell3           1   172.197 194.356  96.337

Step:  AIC=-30.69
datSel$oenb_dependent ~ un.employ + prodPrice + constrPriceIndex +
    primConstTot + resProp.Dwell2 + resProp.Dwell3 + resProp.Dwell5 +
    stat.lohn + cbre.indu.primeRent + cbre.office.PrimeRent +
    cbre.office.primeYield + cbre.retail.primeRent

                          Df Sum of Sq     RSS     AIC
- cbre.indu.primeRent      1     0.686  23.257 -30.924
<none>                                  22.572 -30.689
- resProp.Dwell5           1     1.372  23.944 -29.207
- stat.lohn                1     1.587  24.159 -28.680
- un.employ                1     1.868  24.440 -27.998
- cbre.office.PrimeRent    1     2.738  25.310 -25.935
- prodPrice                1     5.971  28.543 -18.841
- cbre.office.primeYield   1     8.166  30.738 -14.470
- cbre.retail.primeRent    1    11.261  33.833  -8.810
- primConstTot             1    12.165  34.737  -7.255
- resProp.Dwell2           1    19.246  41.818   3.691
- constrPriceIndex         1    28.368  50.940  15.334
- resProp.Dwell3           1   173.991 196.562  95.003

Step:  AIC=-30.92
datSel$oenb_dependent ~ un.employ + prodPrice + constrPriceIndex +
    primConstTot + resProp.Dwell2 + resProp.Dwell3 + resProp.Dwell5 +
    stat.lohn + cbre.office.PrimeRent + cbre.office.primeYield +
    cbre.retail.primeRent

                          Df Sum of Sq     RSS     AIC
```

```
<none>                                        23.257  -30.924
- resProp.Dwell5              1      1.127   24.385  -30.132
- un.employ                   1      1.525   24.783  -29.176
- stat.lohn                   1      1.795   25.053  -28.537
- prodPrice                   1      6.994   30.251  -17.412
- cbre.office.primeYield      1      8.967   32.224  -13.684
- cbre.office.PrimeRent       1     10.294   33.551  -11.303
- cbre.retail.primeRent       1     10.980   34.238  -10.108
- resProp.Dwell2              1     18.827   42.085    2.067
- primConstTot                1     20.648   43.905    4.565
- constrPriceIndex            1     35.925   59.183   22.183
- resProp.Dwell3              1    178.133  201.390   94.435
> # AIC table
> (bwd$anova$AIC)
 [1] -16.08931 -18.08425 -19.99218 -21.75233 -23.41474 -24.86808 -26.30983 -27.69079 -28
```

B.2.2 Forward and Backward regression

```
Start:  AIC=345.41
datSel$oenb_dependent ~ 1

                             Df Sum of Sq     RSS    AIC
+ resProp.Dwell3              1   19682.0   209.0  78.61
+ cpi                         1   18299.4  1591.6 198.40
+ constrPriceIndex            1   18259.5  1631.5 199.86
+ resProp.Dwell2              1   18148.0  1743.0 203.76
+ cbre.office.PrimeRent       1   17777.3  2113.6 215.14
+ cbre.retail.primeRent       1   17487.7  2403.3 222.72
+ gesamtbaukost               1   16651.4  3239.6 240.33
+ constrCostTotal             1   16639.5  3251.5 240.55
+ primConstTot                1   16620.3  3270.7 240.90
+ baumeisterarbeit            1   16614.4  3276.5 241.00
+ gdp                         1   16468.6  3422.4 243.57
+ prodPrice                   1   16308.8  3582.2 246.27
+ cbre.office.Capital.Value   1   15429.3  4461.7 259.22
+ employ                      1   13194.0  6696.9 283.18
+ resProp.Dwell5              1    9096.9 10794.0 311.34
+ productionConstr            1    7815.9 12075.0 317.96
+ cbre.indu.primeRent         1    6725.6 13165.3 323.06
```

```
+ un.employ                  1     3823.4  16067.5  334.81
+ cbre.office.primeYield     1      888.6  19002.3  344.71
<none>                                     19891.0  345.41
+ stat.resProp.Dwell.1       1      402.3  19488.7  346.20
+ atx                        1      270.3  19620.7  346.60
+ stat.resProp.Dwell.4       1      166.9  19724.1  346.91
+ stat.carReg                1       65.5  19825.5  347.21
+ stat.lohn                  1       39.8  19851.2  347.29

Step:  AIC=78.61
datSel$oenb_dependent ~ resProp.Dwell3

                            Df Sum of Sq      RSS     AIC
+ resProp.Dwell2             1       94.5    114.5   45.12
+ constrPriceIndex           1       61.5    147.5   60.05
+ cbre.office.PrimeRent      1       61.1    147.9   60.22
+ cpi                        1       45.6    163.4   66.09
+ baumeisterarbeit           1       38.4    170.5   68.63
+ primConstTot               1       38.4    170.6   68.64
+ gesamtbaukost              1       37.3    171.7   69.01
+ constrCostTotal            1       37.2    171.7   69.04
+ cbre.retail.primeRent      1       34.8    174.2   69.88
+ gdp                        1       26.2    182.8   72.70
+ prodPrice                  1       25.8    183.1   72.83
+ employ                     1       18.0    191.0   75.30
+ cbre.office.Capital.Value  1       16.1    192.9   75.89
+ cbre.indu.primeRent        1        7.9    201.0   78.33
<none>                                       209.0   78.61
+ productionConstr           1        4.5    204.4   79.31
+ stat.resProp.Dwell.4       1        4.0    205.0   79.47
+ resProp.Dwell5             1        2.9    206.0   79.78
+ cbre.office.primeYield     1        1.3    207.7   80.25
+ atx                        1        0.9    208.0   80.35
+ stat.carReg                1        0.7    208.3   80.41
+ stat.lohn                  1        0.7    208.3   80.41
+ stat.resProp.Dwell.1       1        0.1    208.9   80.59
+ un.employ                  1        0.0    208.9   80.61
- resProp.Dwell3             1    19682.0  19891.0  345.41
```

```
Step:  AIC=45.12
datSel$oenb_dependent ~ resProp.Dwell3 + resProp.Dwell2

                           Df Sum of Sq     RSS     AIC
+ stat.resProp.Dwell.1      1     30.25   84.25  29.020
+ constrPriceIndex          1     26.66   87.84  31.483
+ cbre.office.PrimeRent     1     25.42   89.09  32.314
+ cpi                       1     22.17   92.34  34.428
+ cbre.retail.primeRent     1     16.96   97.54  37.664
+ stat.resProp.Dwell.4      1     15.67   98.84  38.439
+ baumeisterarbeit          1     13.71  100.79  39.597
+ primConstTot              1     13.70  100.81  39.605
+ gesamtbaukost             1     13.36  101.15  39.804
+ constrCostTotal           1     13.30  101.21  39.838
+ prodPrice                 1     11.63  102.87  40.802
+ gdp                       1      8.82  105.69  42.394
+ cbre.office.Capital.Value 1      6.28  108.23  43.794
<none>                                   114.51  45.122
+ productionConstr          1      1.81  112.69  46.180
+ employ                    1      1.60  112.91  46.294
+ un.employ                 1      1.06  113.45  46.574
+ stat.lohn                 1      0.89  113.62  46.662
+ cbre.indu.primeRent       1      0.77  113.73  46.723
+ stat.carReg               1      0.29  114.22  46.973
+ cbre.office.primeYield    1      0.28  114.22  46.975
+ atx                       1      0.12  114.39  47.061
+ resProp.Dwell5            1      0.10  114.41  47.073
- resProp.Dwell2            1     94.45  208.96  78.611
- resProp.Dwell3            1   1628.45 1742.96 203.762

Step:  AIC=29.02
datSel$oenb_dependent ~ resProp.Dwell3 + resProp.Dwell2 + stat.resProp.Dwell.1

                           Df Sum of Sq     RSS     AIC
+ constrPriceIndex          1     13.09   71.16  21.054
+ cpi                       1     10.97   73.28  22.788
+ cbre.office.PrimeRent     1     10.02   74.24  23.553
```

```
+ stat.resProp.Dwell.4       1       7.89   76.36  25.218
+ cbre.retail.primeRent      1       7.27   76.98  25.695
+ baumeisterarbeit           1       6.08   78.17  26.600
+ primConstTot               1       6.07   78.18  26.605
+ gesamtbaukost              1       6.05   78.20  26.623
+ constrCostTotal            1       6.01   78.24  26.650
+ prodPrice                  1       5.20   79.05  27.261
+ gdp                        1       3.92   80.33  28.210
<none>                                      84.25  29.020
+ productionConstr           1       2.00   82.25  29.600
+ cbre.office.Capital.Value  1       1.50   82.75  29.960
+ un.employ                  1       1.23   83.02  30.152
+ resProp.Dwell5             1       0.75   83.50  30.492
+ cbre.office.primeYield     1       0.26   83.99  30.836
+ atx                        1       0.15   84.10  30.913
+ cbre.indu.primeRent        1       0.12   84.14  30.938
+ employ                     1       0.05   84.20  30.982
+ stat.carReg                1       0.04   84.21  30.993
+ stat.lohn                  1       0.03   84.22  30.996
- stat.resProp.Dwell.1       1      30.25  114.51  45.122
- resProp.Dwell2             1     124.62  208.87  80.587
- resProp.Dwell3             1    1206.67 1290.92 188.049

Step:  AIC=21.05
datSel$oenb_dependent ~ resProp.Dwell3 + resProp.Dwell2 + stat.resProp.Dwell.1 +
    constrPriceIndex

                            Df Sum of Sq   RSS    AIC
+ resProp.Dwell5             1     17.85 53.31  6.012
+ stat.resProp.Dwell.4       1      6.16 65.00 17.714
+ cbre.office.Capital.Value  1      5.90 65.26 17.948
+ primConstTot               1      4.57 66.58 19.135
+ baumeisterarbeit           1      4.56 66.60 19.147
+ constrCostTotal            1      4.33 66.83 19.354
+ gesamtbaukost              1      4.30 66.86 19.380
+ cbre.office.PrimeRent      1      3.42 67.74 20.147
+ prodPrice                  1      3.32 67.83 20.232
+ employ                     1      2.89 68.27 20.608
```

```
<none>                                           71.16   21.054
+ atx                        1          1.87    69.29   21.486
+ cbre.indu.primeRent        1          1.87    69.29   21.487
+ cbre.office.primeYield     1          1.73    69.43   21.601
+ productionConstr           1          0.67    70.49   22.500
+ gdp                        1          0.42    70.74   22.705
+ stat.lohn                  1          0.24    70.92   22.854
+ un.employ                  1          0.22    70.94   22.871
+ cpi                        1          0.14    71.02   22.940
+ cbre.retail.primeRent      1          0.09    71.07   22.980
+ stat.carReg                1          0.00    71.16   23.054
- constrPriceIndex           1         13.09    84.25   29.020
- stat.resProp.Dwell.1       1         16.69    87.84   31.483
- resProp.Dwell2             1         75.85   147.00   61.863
- resProp.Dwell3             1        769.90   841.06  164.771

Step:  AIC=6.01
datSel$oenb_dependent ~ resProp.Dwell3 + resProp.Dwell2 + stat.resProp.Dwell.1 +
    constrPriceIndex + resProp.Dwell5

                            Df  Sum of Sq     RSS     AIC
+ cbre.office.PrimeRent      1       3.90    49.41   3.534
+ cbre.office.Capital.Value  1       3.46    49.85   4.057
+ primConstTot               1       2.38    50.92   5.314
+ baumeisterarbeit           1       2.36    50.95   5.344
+ constrCostTotal            1       1.93    51.37   5.834
+ gesamtbaukost              1       1.92    51.39   5.853
<none>                                       53.31   6.012
+ cbre.retail.primeRent      1       1.57    51.74   6.250
+ gdp                        1       0.77    52.53   7.148
+ stat.lohn                  1       0.73    52.57   7.196
+ un.employ                  1       0.61    52.70   7.337
+ cbre.office.primeYield     1       0.57    52.73   7.376
+ productionConstr           1       0.41    52.89   7.553
+ atx                        1       0.27    53.04   7.713
+ cpi                        1       0.24    53.06   7.743
+ stat.resProp.Dwell.4       1       0.10    53.21   7.903
+ employ                     1       0.07    53.23   7.930
```

```
+ cbre.indu.primeRent            1      0.02  53.29   7.994
+ stat.carReg                    1      0.00  53.31   8.011
+ prodPrice                      1      0.00  53.31   8.012
- stat.resProp.Dwell.1           1     11.91  65.21  15.908
- resProp.Dwell5                 1     17.85  71.16  21.054
- constrPriceIndex               1     30.20  83.50  30.492
- resProp.Dwell2                 1     70.72 124.02  53.833
- resProp.Dwell3                 1    609.71 663.01 152.736

Step:  AIC=3.53
datSel$oenb_dependent ~ resProp.Dwell3 + resProp.Dwell2 + stat.resProp.Dwell.1 +
    constrPriceIndex + resProp.Dwell5 + cbre.office.PrimeRent

                               Df Sum of Sq    RSS     AIC
+ cbre.retail.primeRent         1      3.16  46.25   1.637
+ cbre.indu.primeRent           1      2.41  47.00   2.582
+ cbre.office.Capital.Value     1      1.68  47.73   3.494
<none>                                       49.41   3.534
+ cbre.office.primeYield        1      1.55  47.86   3.658
+ primConstTot                  1      0.98  48.43   4.355
+ baumeisterarbeit              1      0.96  48.45   4.375
+ stat.lohn                     1      0.60  48.81   4.813
+ un.employ                     1      0.56  48.85   4.861
+ employ                        1      0.54  48.87   4.884
+ constrCostTotal               1      0.53  48.88   4.900
+ gesamtbaukost                 1      0.52  48.89   4.907
+ atx                           1      0.35  49.05   5.108
+ prodPrice                     1      0.11  49.30   5.404
+ productionConstr              1      0.04  49.37   5.483
+ stat.carReg                   1      0.03  49.38   5.499
+ gdp                           1      0.00  49.41   5.529
+ cpi                           1      0.00  49.41   5.534
+ stat.resProp.Dwell.4          1      0.00  49.41   5.534
- cbre.office.PrimeRent         1      3.90  53.31   6.012
- stat.resProp.Dwell.1          1      7.56  56.97   9.934
- resProp.Dwell5                1     18.33  67.74  20.147
- constrPriceIndex              1     21.42  70.83  22.784
- resProp.Dwell2                1     54.39 103.80  45.333
```

```
- resProp.Dwell3                 1    569.58 618.99 150.683

Step:  AIC=1.64
datSel$oenb_dependent ~ resProp.Dwell3 + resProp.Dwell2 + stat.resProp.Dwell.1 +
    constrPriceIndex + resProp.Dwell5 + cbre.office.PrimeRent +
    cbre.retail.primeRent

                              Df Sum of Sq    RSS     AIC
+ primConstTot                 1      6.87  39.38  -5.848
+ baumeisterarbeit             1      6.84  39.41  -5.811
+ gesamtbaukost                1      6.61  39.65  -5.455
+ constrCostTotal              1      6.59  39.67  -5.426
+ prodPrice                    1      4.42  41.83  -2.291
+ gdp                          1      3.24  43.01  -0.645
+ cbre.indu.primeRent          1      2.97  43.28  -0.284
+ productionConstr             1      2.93  43.32  -0.227
+ atx                          1      1.67  44.59   1.472
<none>                                      46.25   1.637
+ cpi                          1      1.18  45.07   2.113
+ employ                       1      0.67  45.58   2.779
+ stat.lohn                    1      0.26  45.99   3.298
+ un.employ                    1      0.17  46.08   3.416
- cbre.retail.primeRent        1      3.16  49.41   3.534
+ stat.carReg                  1      0.06  46.19   3.556
+ cbre.office.Capital.Value    1      0.04  46.21   3.581
+ cbre.office.primeYield       1      0.02  46.24   3.617
+ stat.resProp.Dwell.4         1      0.00  46.25   3.633
- cbre.office.PrimeRent        1      5.49  51.74   6.250
- stat.resProp.Dwell.1         1      6.96  53.21   7.904
- constrPriceIndex             1     19.88  66.13  20.734
- resProp.Dwell5               1     20.94  67.19  21.671
- resProp.Dwell2               1     49.24  95.49  42.408
- resProp.Dwell3               1    566.69 612.94 152.103

Step:  AIC=-5.85
datSel$oenb_dependent ~ resProp.Dwell3 + resProp.Dwell2 + stat.resProp.Dwell.1 +
    constrPriceIndex + resProp.Dwell5 + cbre.office.PrimeRent +
    cbre.retail.primeRent + primConstTot
```

```
                            Df Sum of Sq    RSS     AIC
+ prodPrice                  1      7.46  31.92 -16.239
+ un.employ                  1      4.76  34.62 -11.455
+ cbre.office.Capital.Value  1      3.73  35.65  -9.725
+ cbre.office.primeYield     1      2.75  36.63  -8.115
+ cpi                        1      2.59  36.79  -7.866
+ employ                     1      1.49  37.90  -6.117
<none>                                    39.38  -5.848
+ gdp                        1      0.78  38.60  -5.032
+ baumeisterarbeit           1      0.70  38.68  -4.909
+ stat.lohn                  1      0.38  39.00  -4.425
+ productionConstr           1      0.09  39.29  -3.985
+ atx                        1      0.05  39.33  -3.922
+ stat.carReg                1      0.03  39.35  -3.897
+ cbre.indu.primeRent        1      0.01  39.38  -3.858
+ constrCostTotal            1      0.01  39.38  -3.858
+ gesamtbaukost              1      0.00  39.38  -3.854
+ stat.resProp.Dwell.4       1      0.00  39.38  -3.848
- cbre.office.PrimeRent      1      3.10  42.48  -3.382
- stat.resProp.Dwell.1       1      5.81  45.19   0.269
- primConstTot               1      6.87  46.25   1.637
- cbre.retail.primeRent      1      9.05  48.43   4.355
- constrPriceIndex           1     18.39  57.77  14.760
- resProp.Dwell5             1     20.42  59.80  16.798
- resProp.Dwell2             1     45.33  84.71  37.342
- resProp.Dwell3             1    446.49 485.87 140.396

Step:  AIC=-16.24
datSel$oenb_dependent ~ resProp.Dwell3 + resProp.Dwell2 + stat.resProp.Dwell.1 +
    constrPriceIndex + resProp.Dwell5 + cbre.office.PrimeRent +
    cbre.retail.primeRent + primConstTot + prodPrice

                            Df Sum of Sq    RSS     AIC
+ cbre.office.Capital.Value  1      6.33  25.59 -27.287
+ cbre.office.primeYield     1      6.15  25.78 -26.853
+ cpi                        1      2.77  29.16 -19.588
+ gdp                        1      2.10  29.82 -18.261
```

```
+ un.employ                  1     1.33   30.59  -16.757
+ gesamtbaukost              1     1.10   30.82  -16.304
+ constrCostTotal            1     1.09   30.84  -16.280
<none>                                    31.92  -16.239
+ employ                     1     1.06   30.87  -16.222
+ cbre.indu.primeRent        1     0.74   31.18  -15.619
+ atx                        1     0.60   31.32  -15.357
+ stat.lohn                  1     0.19   31.73  -14.594
+ stat.carReg                1     0.12   31.80  -14.460
+ baumeisterarbeit           1     0.11   31.81  -14.447
+ stat.resProp.Dwell.4       1     0.06   31.86  -14.350
+ productionConstr           1     0.05   31.88  -14.325
- stat.resProp.Dwell.1       1     2.77   34.70  -13.321
- cbre.office.PrimeRent      1     7.08   39.00   -6.420
- prodPrice                  1     7.46   39.38   -5.848
- resProp.Dwell5             1     9.18   41.10   -3.327
- primConstTot               1     9.91   41.83   -2.291
- cbre.retail.primeRent      1    16.51   48.43    6.353
- resProp.Dwell2             1    21.25   53.18   11.868
- constrPriceIndex           1    24.85   56.78   15.733
- resProp.Dwell3             1   406.23  438.15  136.297

Step:  AIC=-27.29
datSel$oenb_dependent ~ resProp.Dwell3 + resProp.Dwell2 + stat.resProp.Dwell.1 +
    constrPriceIndex + resProp.Dwell5 + cbre.office.PrimeRent +
    cbre.retail.primeRent + primConstTot + prodPrice + cbre.office.Capital.Value

                            Df Sum of Sq     RSS     AIC
- stat.resProp.Dwell.1       1     0.381  25.970  -28.415
- cbre.office.PrimeRent      1     0.428  26.017  -28.309
+ stat.lohn                  1     1.192  24.397  -28.101
+ un.employ                  1     1.095  24.494  -27.868
<none>                                    25.589  -27.287
+ baumeisterarbeit           1     0.436  25.152  -26.303
+ cbre.indu.primeRent        1     0.406  25.183  -26.232
+ employ                     1     0.316  25.273  -26.020
+ constrCostTotal            1     0.314  25.275  -26.016
+ atx                        1     0.246  25.342  -25.858
```

```
+ gesamtbaukost               1       0.245   25.344  −25.855
+ productionConstr            1       0.163   25.425  −25.666
+ stat.resProp.Dwell.4        1       0.150   25.439  −25.634
+ cbre.office.primeYield      1       0.086   25.503  −25.487
+ cpi                         1       0.027   25.561  −25.351
+ gdp                         1       0.025   25.564  −25.344
+ stat.carReg                 1       0.000   25.589  −25.288
− resProp.Dwell5              1       2.262   27.851  −24.290
− cbre.office.Capital.Value   1       6.334   31.923  −16.239
− prodPrice                   1      10.060   35.649   −9.725
− resProp.Dwell2              1      11.622   37.211   −7.195
− cbre.retail.primeRent       1      12.999   38.588   −5.051
− primConstTot                1      16.150   41.739   −0.421
− constrPriceIndex            1      31.042   56.631   17.582
− resProp.Dwell3              1     207.259  232.848  100.998

Step:  AIC=−28.42
datSel$oenb_dependent ~ resProp.Dwell3 + resProp.Dwell2 + constrPriceIndex +
    resProp.Dwell5 + cbre.office.PrimeRent + cbre.retail.primeRent +
    primConstTot + prodPrice + cbre.office.Capital.Value

                             Df Sum of Sq     RSS      AIC
+ stat.lohn                   1       1.499   24.471  −29.923
− cbre.office.PrimeRent       1       0.452   26.422  −29.397
+ un.employ                   1       1.156   24.813  −29.103
<none>                                        25.970  −28.415
+ baumeisterarbeit            1       0.447   25.523  −27.439
+ stat.resProp.Dwell.1        1       0.381   25.589  −27.287
+ cbre.indu.primeRent         1       0.355   25.615  −27.227
+ constrCostTotal             1       0.295   25.675  −27.088
+ employ                      1       0.282   25.688  −27.060
+ gesamtbaukost               1       0.218   25.752  −26.913
+ atx                         1       0.212   25.758  −26.898
+ stat.resProp.Dwell.4        1       0.207   25.763  −26.887
+ cbre.office.primeYield      1       0.198   25.772  −26.867
+ productionConstr            1       0.073   25.897  −26.582
+ gdp                         1       0.019   25.951  −26.458
+ cpi                         1       0.008   25.961  −26.435
```

```
+ stat.carReg                  1       0.003   25.967  -26.421
- resProp.Dwell5               1       2.044   28.014  -25.945
- cbre.office.Capital.Value    1       8.728   34.698  -13.321
- prodPrice                    1      12.336   38.306   -7.485
- cbre.retail.primeRent        1      14.040   40.010   -4.916
- resProp.Dwell2               1      16.118   42.088   -1.929
- primConstTot                 1      19.601   45.571    2.762
- constrPriceIndex             1      39.526   65.496   24.162
- resProp.Dwell3               1     217.077  243.047  101.527

Step:  AIC=-29.92
datSel$oenb_dependent ~ resProp.Dwell3 + resProp.Dwell2 + constrPriceIndex +
    resProp.Dwell5 + cbre.office.PrimeRent + cbre.retail.primeRent +
    primConstTot + prodPrice + cbre.office.Capital.Value + stat.lohn

                              Df Sum of Sq      RSS      AIC
- cbre.office.PrimeRent        1       0.141   24.612  -31.584
+ un.employ                    1       1.450   23.021  -31.527
+ constrCostTotal              1       0.850   23.620  -30.010
<none>                                         24.471  -29.923
+ gesamtbaukost                1       0.778   23.693  -29.829
+ baumeisterarbeit             1       0.482   23.988  -29.098
+ employ                       1       0.451   24.020  -29.021
+ productionConstr             1       0.324   24.147  -28.710
+ cbre.indu.primeRent          1       0.214   24.257  -28.441
- stat.lohn                    1       1.499   25.970  -28.415
+ cbre.office.primeYield       1       0.176   24.295  -28.349
+ stat.resProp.Dwell.4         1       0.087   24.383  -28.135
+ atx                          1       0.080   24.391  -28.117
+ gdp                          1       0.078   24.393  -28.112
+ stat.resProp.Dwell.1         1       0.074   24.397  -28.101
+ cpi                          1       0.037   24.434  -28.013
+ stat.carReg                  1       0.005   24.466  -27.935
- resProp.Dwell5               1       2.010   26.481  -27.266
- cbre.office.Capital.Value    1       9.608   34.079  -12.383
- prodPrice                    1      11.288   35.759   -9.544
- cbre.retail.primeRent        1      11.793   36.264   -8.716
- resProp.Dwell2               1      16.566   41.037   -1.421
```

```
- primConstTot                1    20.269  44.739   3.676
- constrPriceIndex            1    39.031  63.502  24.338
- resProp.Dwell3              1   211.202 235.673 101.710

Step:  AIC=-31.58
datSel$oenb_dependent ~ resProp.Dwell3 + resProp.Dwell2 + constrPriceIndex +
    resProp.Dwell5 + cbre.retail.primeRent + primConstTot + prodPrice +
    cbre.office.Capital.Value + stat.lohn

                            Df Sum of Sq     RSS     AIC
<none>                                    24.612 -31.584
+ un.employ                  1     0.751  23.861 -31.413
+ baumeisterarbeit           1     0.571  24.041 -30.970
+ constrCostTotal            1     0.390  24.221 -30.528
+ gesamtbaukost              1     0.336  24.276 -30.396
+ cbre.indu.primeRent        1     0.328  24.284 -30.376
+ productionConstr           1     0.249  24.363 -30.183
+ employ                     1     0.219  24.392 -30.113
+ atx                        1     0.213  24.399 -30.096
+ cbre.office.primeYield     1     0.187  24.425 -30.034
+ cbre.office.PrimeRent      1     0.141  24.471 -29.923
+ stat.resProp.Dwell.4       1     0.110  24.502 -29.849
+ stat.resProp.Dwell.1       1     0.065  24.546 -29.742
+ stat.carReg                1     0.003  24.609 -29.592
+ gdp                        1     0.002  24.610 -29.589
+ cpi                        1     0.001  24.610 -29.588
- stat.lohn                  1     1.810  26.422 -29.397
- resProp.Dwell5             1     1.873  26.485 -29.257
- prodPrice                  1    11.240  35.852 -11.391
- cbre.retail.primeRent      1    12.489  37.100  -9.371
- resProp.Dwell2             1    17.284  41.896  -2.198
- cbre.office.Capital.Value  1    19.755  44.367   1.182
- primConstTot               1    26.882  51.493   9.971
- constrPriceIndex           1    40.564  65.176  23.874
- resProp.Dwell3             1   226.971 251.583 103.564
> # AIC table
> (fwdAndbwd$anova$AIC)
 [1] 345.408540  78.610909  45.122062  29.020041  21.053993   6.011880   3.533596
```

1.636802 −5.847835 −16.238540 −27.287487 −28.415492 −29.923456
−31.584499

B.2.3 Granger Causality Test

The table B.2 shows variable 1, which is influenced, or causal under granger causality, by variable 2.

Variable 1	***Variable 2***
un.employ	oenb_dependent
cbre.office.PrimeRent	gdp
gdp	atx
constrCostTotal	atx
gesamtbaukost	atx
cbre.office.Capital.Value....m..	atx
cbre.office.primeYield	atx
cbre.retail.primeYield	atx
prodPrice	un.employ
atx	cpi
prodPrice	cpi
constrPriceIndex	cpi
resProp.Dwell.3	cpi
gdp	constrPriceIndex
atx	constrPriceIndex
constrCostTotal	constrPriceIndex
primConstTot	constrPriceIndex
baumeisterarbeit	constrPriceIndex
gesamtbaukost	constrPriceIndex
gdp	primConstTot
carReg	primConstTot
constrPriceIndex	primConstTot
cbre.indu.primeRent	primConstTot
cbre.office.primeYield	primConstTot
gdp	baumeisterarbeit
carReg	baumeisterarbeit
constrPriceIndex	baumeisterarbeit
cbre.indu.primeRent	baumeisterarbeit
cbre.office.primeYield	baumeisterarbeit
employ	lohn

resProp.Dwell	lohn
resProp.Dwell.2	lohn
resProp.Dwell.3	lohn
cbre.retail.primeYield	lohn
un.employ	resProp.Dwell
un.employ	resProp.Dwell.1
cpi	resProp.Dwell.1
gdp	cbre.indu.primeRent
atx	cbre.indu.primeRent
carReg	cbre.indu.primeRent
cpi	cbre.indu.primeRent
cbre.office.Capital.Value....m..	cbre.indu.primeRent
cbre.office.PrimeRent	cbre.indu.primeRent
cbre.office.primeYield	cbre.indu.primeRent
cbre.retail.primeYield	cbre.indu.primeRent
cbre.retail.capitalValue	cbre.indu.primeRent
cbre.office.PrimeRent	cbre.office.Capital.Value....m..
gdp	cbre.office.primeYield
atx	cbre.office.primeYield
carReg	cbre.office.primeYield
cbre.office.Capital.Value....m..	cbre.office.primeYield
cbre.office.PrimeRent	cbre.office.primeYield
gdp	cbre.retail.primeRent
cbre.office.primeYield	cbre.retail.primeRent
un.employ	cbre.retail.primeYield
prodPrice	cbre.retail.primeYield
cbre.office.Capital.Value....m..	cbre.retail.primeYield
cbre.office.PrimeRent	cbre.retail.primeYield
prodPrice	cbre.retail.capitalValue
cbre.office.Capital.Value....m..	cbre.retail.capitalValue

Table B.2: Results of the conducted Granger Causality Test.

B.2.4 Lasso Regression

Below you can find the coefficients of the conducted lasso regression:

```
> lasso.coef
```

```
      (Intercept)                gdp             employ                atx
un.employ             carReg                 cpi          prodPrice
        0.6334623          0.0000000          0.0000000          0.0000000
0.0000000          0.0000000          0.0000000          0.0000000
productionConstr  constrPriceIndex   constrCostTotal       primConstTot  baumeisterarbeit
gesamtbaukost                  lohn       resProp.Dwell
        0.0000000          0.0000000          0.0000000          0.0000000
0.0000000          0.0000000          0.0000000          0.7699665
  resProp.Dwell.1    resProp.Dwell.2    resProp.Dwell.3    resProp.Dwell.4
        0.0000000          0.0000000          0.0000000          0.0000000
```

Furthermore, in the R code below all results of the lasso regression can be found, which are also shown in figure 4.5.

```
> lasso.mod

Call:  glmnet(x = x[train, ], y = y[train], alpha = 1)

      Df   %Dev    Lambda
 [1,]  0 0.0000 2.9460000
 [2,]  1 0.1006 2.6840000
 [3,]  1 0.1841 2.4460000
 [4,]  1 0.2535 2.2280000
 [5,]  1 0.3110 2.0300000
 [6,]  1 0.3588 1.8500000
 [7,]  1 0.3985 1.6860000
 [8,]  1 0.4314 1.5360000
 [9,]  1 0.4588 1.3990000
[10,]  1 0.4815 1.2750000
[11,]  1 0.5003 1.1620000
[12,]  1 0.5160 1.0590000
[13,]  1 0.5290 0.9646000
[14,]  2 0.5399 0.8789000
[15,]  2 0.5604 0.8008000
[16,]  2 0.5774 0.7297000
[17,]  2 0.5914 0.6648000
[18,]  3 0.6035 0.6058000
[19,]  3 0.6140 0.5520000
[20,]  3 0.6227 0.5029000
[21,]  6 0.6373 0.4582000
```

```
[22,]   6 0.6542  0.4175000
[23,]   6 0.6681  0.3804000
[24,]   6 0.6798  0.3466000
[25,]   6 0.6894  0.3158000
[26,]   6 0.6974  0.2878000
[27,]   8 0.7044  0.2622000
[28,]   8 0.7117  0.2389000
[29,]  10 0.7197  0.2177000
[30,]  10 0.7281  0.1984000
[31,]  10 0.7353  0.1807000
[32,]  11 0.7455  0.1647000
[33,]  12 0.7568  0.1501000
[34,]  13 0.7666  0.1367000
[35,]  13 0.7754  0.1246000
[36,]  14 0.7830  0.1135000
[37,]  14 0.7919  0.1034000
[38,]  16 0.8064  0.0942400
[39,]  17 0.8210  0.0858700
[40,]  19 0.8344  0.0782400
[41,]  19 0.8478  0.0712900
[42,]  18 0.8587  0.0649500
[43,]  19 0.8683  0.0591800
[44,]  19 0.8773  0.0539300
[45,]  19 0.8848  0.0491400
[46,]  19 0.8909  0.0447700
[47,]  20 0.8960  0.0407900
[48,]  20 0.9006  0.0371700
[49,]  21 0.9045  0.0338700
[50,]  21 0.9077  0.0308600
[51,]  21 0.9104  0.0281200
[52,]  21 0.9126  0.0256200
[53,]  21 0.9145  0.0233400
[54,]  21 0.9160  0.0212700
[55,]  21 0.9173  0.0193800
[56,]  21 0.9184  0.0176600
[57,]  21 0.9192  0.0160900
[58,]  21 0.9200  0.0146600
[59,]  21 0.9206  0.0133600
```

```
[60,] 21 0.9211 0.0121700
[61,] 21 0.9215 0.0110900
[62,] 22 0.9219 0.0101000
[63,] 22 0.9223 0.0092070
[64,] 22 0.9226 0.0083890
[65,] 22 0.9228 0.0076440
[66,] 22 0.9230 0.0069650
[67,] 22 0.9232 0.0063460
[68,] 22 0.9233 0.0057820
[69,] 22 0.9234 0.0052690
[70,] 22 0.9235 0.0048010
[71,] 22 0.9236 0.0043740
[72,] 22 0.9237 0.0039860
[73,] 22 0.9237 0.0036320
[74,] 22 0.9238 0.0033090
[75,] 22 0.9238 0.0030150
[76,] 22 0.9239 0.0027470
[77,] 22 0.9239 0.0025030
[78,] 22 0.9239 0.0022810
[79,] 22 0.9239 0.0020780
[80,] 22 0.9239 0.0018930
[81,] 23 0.9240 0.0017250
[82,] 24 0.9240 0.0015720
[83,] 24 0.9240 0.0014320
[84,] 24 0.9240 0.0013050
[85,] 24 0.9240 0.0011890
[86,] 24 0.9240 0.0010840
[87,] 24 0.9240 0.0009873
[88,] 24 0.9240 0.0008996
```

APPENDIX C

APPENDIX C

C.1 Synthetic Simulation Data

Variables	**Loan 1**	**Loan 2**	**Loan 3**	**Loan 4**	**Loan 5**
Committed Amount	1 000 000,00	1 000 000,00	1 000 000,00	1 000 000,00	1 000 000,00
Balloon	500 000,00	500 000,00	500 000,00	500 000,00	500 000,00
Project Currency	EUR	EUR	EUR	EUR	EUR
Final Maturity Date	23.10.2016	23.10.2017	23.10.2018	23.10.2019	22.10.2020
Interest	4,00%	4,00%	4,00%	4,00%	4,00%
Bullet	0	0	0	0	0
Tenor	20	20	20	20	20
Net Leasable Area	10000	10000	10000	10000	10000
Avg Net Rent Inc/sqm(month)	83,3	83,3	83,3	83,3	83,3
OPEX	0,05	0,05	0,05	0,05	0,05
CAPEX	0,05	0,05	0,05	0,05	0,05

Nominal Collateral Value	1 500 000,00	1 500 000,00	1 500 000,00	1 500 000,00	1 500 000,00
Repayment Source	rent	rent	rent	rent	rent
Refi Rate	0,01	0,01	0,01	0,01	0,01
Margin (%)	5%	5%	5%	5%	5%
Refi Type	EURIBOR	EURIBOR	EURIBOR	EURIBOR	EURIBOR

Table C.1: Synthetic simulation data.

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