Business Cycle Forecasting
Theoretical foundations and the application on macro and industry level

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PART 1
Executive summary

Today, businesses are facing increasingly fierce global competition and rapidly changing business conditions. Add to the picture financial instability and depressed economies, and it becomes difficult to accurately predict the future. The need for methods to improve forecasting of the future is rising. Business cycle forecasting was employed to address this issue. The objective of the thesis was to study the application of business cycle forecasting on both the macroeconomic and industry level. Forecasting on the industry level has not received much attention, whether academically or practically.

By conducting a comprehensive literature review, numerous sources to drivers of business and industry cycles were identified. It is recognized that there is no complete theory of the business cycle, and that in order to gain a complete view on cyclicity, knowledge must be pooled from all theories. The findings from business cycle theories were applicable for both levels of study.

Assessment of quantitative approaches revealed that the economic indicator approach had the best fit with the aim of the thesis. The review was guided by expert interviews. The selection of the indicator approach was based on a set of criteria advocating that the approach must be easy to understand and use by non-statistical expert, practical and effective in predicting business cycle turning points.

In order to use the economic indicator approach, the findings of the literature review is applied in the process of identifying potential leading indicators. Once selected, these indicators are tested in their ability to actually lead the business cycle. Indices of indicators have proven to be superior over individual indicators. 10 economic indicators were found for the macro level, and used to create a leading macroeconomic composite index. These 10 macroeconomic indicators were combined with 5 industry specific indicators for each of the three case industries.

Several important insights emerged from the empirical analysis. The leading macroeconomic composite index did a good job explaining cyclical movement in the three industry cases. Macroeconomic factors exert a large influence on most industries. However, the leading industry composite indices outperformed the leading macroeconomic composite index for all the industries. Thus, the indicator approach showed great potential for improving forecasting on the industry level.
# Table of Contents

1 - **Introduction** .................................................................................................................. 7

  - Motivation ........................................................................................................................... 7
  - Problem identification .......................................................................................................... 8
  - Problem statement .............................................................................................................. 9
  - Delimitations ....................................................................................................................... 10
  - Definitions ......................................................................................................................... 10
  - Thesis structure ................................................................................................................. 11

2- **Methodology** ................................................................................................................... 12

  2.1 Research philosophy ....................................................................................................... 12
      - 2.1.1 Positivism .............................................................................................................. 12
      - 2.1.2 Six categories of knowledge ................................................................................. 12
      - 2.1.3 The analytical approach ...................................................................................... 14
      - 2.1.4 The systems approach ....................................................................................... 14
  2.2 Research approach .......................................................................................................... 15
      - 2.2.1 Deduction, induction and abduction .................................................................. 15
  2.3 Research design .............................................................................................................. 16
      - 2.3.1 Multiple methods ................................................................................................. 16
      - 2.3.2 Secondary data ..................................................................................................... 16
      - 2.3.3 Explanatory research ........................................................................................... 17
      - 2.3.4 Case study ............................................................................................................ 17
      - 2.3.5 Meso- vs. micro-level ......................................................................................... 18
      - 2.3.6 Macro- vs. meso-level ....................................................................................... 18
      - 2.3.7 Multiple cases ...................................................................................................... 19
      - 2.3.8 Longitudinal study ............................................................................................... 20
      - 2.3.9 Reliability and validity ......................................................................................... 20
      - 2.3.10 Data accessibility ............................................................................................... 21
  2.4 Quantitative methods ...................................................................................................... 21
      - 2.4.1 Assessment of quantitative forecasting methods ................................................ 21
  2.5 Qualitative methods ....................................................................................................... 22
      - 2.5.1 Literature review ................................................................................................. 22
      - 2.5.2 Semi-structured expert interviews ..................................................................... 22
      - 2.5.3 Interview guide and interviewees ....................................................................... 23
3 – Review of business cycle theory

3.1 Introduction

3.2 Development of business cycle theory and different schools of thought

3.3 Early business cycle theories

3.3.1 Early agricultural theory

3.3.2 Early monetary theory

3.3.3 Underconsumption theory

3.3.4 Profit margin theories

3.3.5 Early investment theories

3.3.6 Long wave theories

3.3.7 Psychological theories

3.4 The Classical Model

3.5 Keynesian Economics

3.6 Neo-Keynesians

3.7 Monetarist theory

3.8 Rational expectations model

3.9 Real business cycle theory

3.10 New Keynesian models

3.11 Credit and financial instability

3.12 Austrian Business Cycle Theory (ABCT)

3.13 Discussion

4 - Assessment of quantitative forecasting methods

4.1 Econometric models

4.1.1 Regression analysis

4.1.2 Time-series analysis

4.2 Economic indicators

4.2.1 Composite index of economic indicators

4.2.2 The timing relationship between different types of economic indicators

4.3 Economic intuition

4.4 Selection of quantitative model

5 - Technical considerations

5.1 Rate of change with growth rates

5.2 Moving average
5.3 MACD .......................................................................................................................... 52
5.4 Graphical representation ............................................................................................... 53
5.5 Cross-Correlation Coefficient ..................................................................................... 53
5.6 Determining turning points .......................................................................................... 55

6- Identification of economic indicators ................................................................................. 56
   6.1. Real economic variables ........................................................................................... 56
   6.2 Wages, prices and labor ............................................................................................ 57
   6.3 Expectations and sentiments ...................................................................................... 57
   6.4 Monetary variables ..................................................................................................... 58
   6.5 Financial variables ..................................................................................................... 59
   6.6 Identified economic indicators .................................................................................. 59

7 - Empirical analysis ............................................................................................................. 61
   7.1 Introduction ................................................................................................................ 61
   7.2 Macroeconomic indicators ......................................................................................... 63
      7.2.1 The reference series for the U.S. economy ........................................................ 63
      7.2.2 Retail sales ............................................................................................................ 64
      7.2.3 Personal consumer expenditure ....................................................................... 65
      7.2.4 Total value of orders of manufacturing goods ............................................... 66
      7.2.5 Real hourly earnings .......................................................................................... 67
      7.2.6 The Employment Trend Index ........................................................................... 68
      7.2.7 Oil price ............................................................................................................... 69
      7.2.8 The Purchasing Managers Index .................................................................... 70
      7.2.9 S&P 500 ............................................................................................................. 71
      7.2.10 Consumer Confidence Index ........................................................................ 72
      7.2.11 Housing starts .................................................................................................. 73
      7.2.12 Real money supply (M2) ............................................................................... 74
      7.2.13 Yield curve ....................................................................................................... 75
   7.3 Creating a leading macroeconomic composite index ..................................................... 76
      7.3.1 Justification and procedure .............................................................................. 76
      7.3.2 Predictive abilities ............................................................................................. 78
   7.4 Industry economic indicators ....................................................................................... 81
      7.4.1 Introduction ......................................................................................................... 81
      7.4.2 Industry selections ............................................................................................. 81
1 - Introduction

Motivation

“Business, more than any occupation, is a continual dealing with the future; it is continual calculation, an instinctive exercise in foresight” (Henry R.Luce in Shim, 2000)

The above quotation captures the essence of why forecasting is extremely important for decision-makers such as business managers and investors. The ability to make good projections about the future enables managements to navigate in an unpredictable environment with the objective of outperforming competitors.

Foresight is becoming increasingly important, as businesses are facing more complex and volatile business conditions and a future filled with unpredictability and uncertainty. This trend is enhanced by a variety of developments including globalization, increased competition, resource scarcity and rapid technological development (Duus, 2013; Bartlett and Ghoshal, 1999). The recent financial crisis has reinforced the fact that globally integrated financial markets are incredibly vulnerable to regional market failures, and that spill-over effects from the financial market to the non-financial markets can be very significant (Knopp, 2010). This is in large part due to the increasing financialization of the general economy with ever more traded commodities, commercial papers and alike (Allen et al, 2009; Cohen-Cole et al, 2010).

Knowledge of cyclicality in output and other variables has existed for several hundred years, but on several occasions human overconfidence has led to the belief that cyclicality belonged to the past and not the future (Knopp, 2010). A good example of this overconfidence is found the 1960s, where many economists proclaimed the business cycle dead (Niemira and Klein, 1994). Recently this line of thought was repeated in the mid-2000s, where economists stated the belief that the upswing could continue for many years without resulting in a severe bubble burst and corresponding recession. In addition, the policy tools in place, was viewed as sufficient to prevent any future depression. This view was exemplified by Robert Lucas, Nobel Prize winner in Economics and professor at the University of Chicago, who in 2003 declared that “the central problem of depression-prevention has been solved for all practical purposes” (Krugman, p.9, 2009). Overall, it appears that the understanding and detection of business cycles still has room for improvement (Knopp, 2010).
Business cycle forecasting – Theoretical foundations and the application on macro and industry level

Policymakers often have to make the choice between intervening to reduce the volatility in the business cycle or simply letting the cycle run its course. The business manager always needs to make adjustments and navigate the company through the cycles in the best possible way. One of the most efficient tools available to limit the impact of volatility on the performance of a business is by improving the forecasting and identification of business cycle turning points (Ellis 2005). A better prediction of business cycle turning points can help create a strategic balance between a company’s internal resources and the external environment (Ansoff and McDonnell, 1990).

The observation of the first signs of expansion, recession or recovery is of great importance for businesses, as it enhances the possibilities for making adjustments that can reduce risk and create opportunities (Choi, 2003; Tan and Mathews, 2010; Bundgaard 22:30). A reduction of the business risk may come from improvements in resource allocation by making better investment choices, since strategic activities can be adjusted to benefit from the different stages of the business cycle (Mascharenhas and Aaker, 1989; Navarro, 2005). Too often this adjustment is a reaction to competitors’ actions and not an attempt to exploit superior knowledge created within the company, which means that potential opportunities to create an advantage are not seized (Mascharenhas and Aaker 1989; Bundgaard 56:40). Evidence suggests that business cycle turning points are possible to identify in advance, but despite obvious strategic advantages created by knowledge of the turning point, relatively few companies use forecasting as a tool in their strategic decisions (Duus, 1999; Printz 1992; Choi, 2003; Ellis, 2005; Jensen 9:50).

Problem identification

Although the potential gains from forecasting are numerous, there is a lack of application in businesses. A discrepancy between the models used in academia and in business (Knopp, 2010; Ellis, 2005). The thesis will address this problem by a practical method of analyzing business cycles with economic theory developed in the last several hundred years.

In the increasingly volatile business conditions, it is a puzzle why so few companies use forecasting to create a connection between their business and the uncertain future environment (Printz, 1992). The reason may be that managers fail to acknowledge that there might be a strong link between the general economy and their own industry, and therefore do not realize potential gains that can be achieved by exploiting knowledge of both macroeconomic and industry variables (Bundgaard 12:08; Jacobsen 10:09).
Overall there is support for the notion that industry cycles and business cycles should be distinguished, as some industries are more affected in recessions, while other industries experience turning points either prior to or later than the general economy (Berman and Pfieger, 1997; Bundgaard 06:05). Large amounts of literature regarding macroeconomic business cycles are available today, but most studies of cycles have focused on macroeconomic business cycles, whereas the focus on industry business cycles and especially their implications for strategic management have not been thoroughly explored (Niemira and Klein, 1994, Duus 1999, 2013; Printz 1992; Jacobsen 15:05). The potential value provided by knowledge of the business cycles has created a need for testing the dynamics of forecasting industry cycles, and thereby helping to provide a tool for companies within a given industry to better understand and act upon a volatile and complex future (Duus 1999, Duus 2000; Tan and Mathews, 2008). The ability to gather and apply information is considered a key competence for companies in terms of creating growth (Duus, 2000).

**Problem statement**

Based upon the above problem identification, a problem statement is created to investigate the following:

**Main research question** – *How and to what extent can business cycle forecasting be applied on the industry-level?*

To answer the main research question, the thesis is structured according to the sub-questions presented below:

1. *Can business cycle theory provide a theoretical basis for identifying economic variables that can explain business cycles on both the macro- and industry-level?*

2. *Which quantitative method is preferable for forecasting business cycle turning points on both the macro- and the industry-level?*

3. *Will including industry specific variables improve the forecasting of business cycle turning points in the specific industry, compared to using only macroeconomic variables?*
Delimitations

Predicting turning points is one of the main areas of focus in the thesis. As the prediction of turning points does not address the severity or amplitude of business cycles, it is not covered (Niemira and Klein, 1994). Focus is neither on what exact level of cyclicality is needed to constitute an actual classic business cycle.

An attempt to rank the usefulness of different business cycle theories is not done. Rather theories are used to illustrate their explanations of cyclicality, and find similarities for further application.

Quantitative forecasting methods are assessed qualitatively, and a final selection is made based on a number of qualitative criteria. Thereby, an actual performance comparison of these methods is not included. It is not the purpose to create a general forecasting model applicable for all industries, but the industry cases can serve as an a starting point for future research. The findings from the case industries are foremost suited for similar industries or businesses in those industries.

Definitions

Forecasting: is often regarded as the same as prediction. Although forecasting and prediction do not have exactly the same meaning, they will be regarded as similar. Forecasting is often described as a tool which purpose is not to accurately predict the future, but to set up some settings in which the future development will most likely take place given some level of uncertainty (Jain and Malehorn 2005).

Business cycle: is defined by Burns and Mitchell (1946) to express the following: “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” (Burns and Mitchell, 1946, p.3).

Business growth cycle: is measured in rate of change rather than level. Thus, all observations are the changes that have occurred since the last period or since same period last year. The peak of a growth cycle is when growth starts to level off again (Zarnowitz and Ozyildirim, 2002). The implication for using business growth cycles is that more business cycle turning points are identified, than compared to a traditional business cycle.
**Industry business cycle**: shares many similarities with the general business cycle, but an industry business cycle is measured for a particular industry rather than the economy. Hence, business cycle turning points can differ between the economy and industries.

**Thesis structure**

The thesis progresses in the following way: Section 2 presents the methodological considerations and choices made in order to answer the research question. Section 3 displays an overview of existing business cycle theory literature, and critically assesses what insights the literature can provide to the identification of likely causes of business cycles. Section 4 presents different approaches to quantitative analysis of the business cycle, and assess, which approach is most appropriate for this thesis. Section 5 reflects upon the technical considerations needed to do the empirical analysis, given the choice of quantitative forecasting method. Section 6 identifies relevant indicators from the insights of the literature review. The macro part of section 7 combines the knowledge from the previous three sections into a model for analyzing business cycles on a macro level. The industry part of section 7 presents the case industries, and uses the same approach as the first part for analyzing industry cycles. Section 8 concludes by summarizing the findings, discusses these findings in a larger context and suggests directions for future research.

**Figure 1.1: Thesis structure**

<table>
<thead>
<tr>
<th>1 - Introduction</th>
<th>Problem Statement</th>
</tr>
</thead>
<tbody>
<tr>
<td>Motivation</td>
<td>Problem identification</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>2 - Methodology</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Research philosophy</td>
<td>Research approach</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>3. Literature review</th>
<th>Sub-research question 1</th>
</tr>
</thead>
<tbody>
<tr>
<td>Business cycle theory</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>4- Assessment of quantitative forecasting methods</th>
<th>Sub-research question 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Econometric models</td>
<td>Regression</td>
</tr>
</tbody>
</table>

| 5 – Technical consideration                     |                    |

<table>
<thead>
<tr>
<th>6 - Identification of economic indicators</th>
<th>Sub-research question 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Macro indicators</td>
<td>Macro index</td>
</tr>
</tbody>
</table>

| 7 - Empirical analysis                          |                    |

<table>
<thead>
<tr>
<th>8 - Conclusion</th>
<th>Main research question</th>
</tr>
</thead>
</table>
2- Methodology

The following section outlines the methodology employed in the thesis. It is acknowledged that the results of the research are only as good as the quality of the data and the methodology applied (Gujarati and Porter, 2009).

2.1 Research philosophy

2.1.1 Positivism
In the thesis a systematic approach is applied, which identifies and forecasts business cycle turning points as laid out in the problem statement. In order to pursue this goal, a positivistic research philosophy is recommendable, since it provides the means to generalize by observing the reality (Saunders et al, 2009).

Positivism advocates that research is proven by empirical means (Saunders et al, 2009). The thesis uses empirical data to assess and explain the relationship between economic variables and industry cycles in order to predict turning points. The prediction of turning points is evaluated by relevant statistical analyses. Based on the results of the empirical analysis, new insight to the subject can be added. Another characterization of positivism is that it often leads to a well-structured methodology that facilitates replication (Gill and Johnson, 2002). Replication is an objective, which enables the findings to be applied in other industries or businesses, either as a starting point or used directly with the right adjustments being made.

Positivism assumes that the researcher is detached from the examined phenomena, meaning that the applied data cannot be altered (Saunders et al, 2009). The assumption is reasonable because a business cycle is a quantifiable phenomenon, where little can be done to alter the data that shows this phenomenon. A positivist research philosophy is foremost associated with quantitative data (Saunders et al, 2009). Although a positivistic research philosophy is followed, quantitative data is supplemented by qualitative data. This method is chosen because quantitative data are best understood combined with qualitative data such as expert interviews and insights from economic theory (Niemira and Klein, 1994).

2.1.2 Six categories of knowledge
Arbnor and Bjerke (2009) distinguish between six categories of knowledge, see figure 2.1.1, where the positivistic approach shares similarities with two of these.
Category one: *Reality as concrete and conformable to law, a structure that is independent of the observer*, perceives reality as tangible and concrete (Arnbor and Bjerke, 2009). Further, reality is independent of the observer, and can consequently be accurately measured and observed, which is in accordance with positivism. As this thesis pursues to identify and measure cyclical industry dynamics, the mentioned attributes of category one fits well. The empirical analysis of business cycle triggers applies quantitative methods. These quantitative methods are well suited to category one, due to the need for a practical systematic approach in the field (Duus, 1999, 2013). However, category one assumes strict ultimate presumptions, where variables are assumed to respond in a predictable and deterministic way to stimuli (Arnbor and Bjerke, 2009). This is not necessarily in agreement with the topic of the thesis because Niemira and Klein (1994) warn that one does often not find the expected relationship between theory and data, regarding the dynamics of business cycles. Category one is normally associated with controlled scientific experiments. In the thesis a controlled experiment is not conducted, instead real life statistical data and expert interviews are used to make analysis and conclusions. This means that the thesis cannot uniformly be characterized as knowledge creation from category one.

Category two, *Reality as a concrete determining process*, is well suited for the thesis, as the task of science becomes to combine concrete relations in a holistic view, which is concrete in its nature but ever-changing in its details (Arnbor and Bjerke, 2009). This fits well for business cycles where some parts, such as the sequence of events of a business cycle remains unchanged, but where the dynamics, amplitude and durations of the cycles often change because no business cycles are alike (Niemira and Klein, 1994, Ellis, 2005).

Category two regards the process of exchange between individual entities and society as a competitive situation, in which individual entities try to understand and exploit the environment in order to survive and thrive (Arnbor and Bjerke, 2009). In the context of industry cycles it can be regarded as making the best strategic choices given a particular state of a cycle for a particular industry or business in that industry. This category suffers from the fact that some relations are less clear-cut and stable than others. In accordance with the research of thesis, category two is related to the analysis of documented material like statistical data in order to explain the patterns observed over time. Thereby, category one and category two are combined to encompass the challenges of the research.

By using a combination of category one and category two, it is pursued to create explanatory knowledge, see figure 2.1.1. The figure shows that the chosen categories of knowledge constitute a blend of the analytical approach and the systems approach. Researchers often mention the methodological diversity in
the field of Strategic Forecasting (Business Cycle Forecasting), which means that no specific methodological
direction is offered (Duus, 2013). In this regard it makes sense to use a combination of approaches.

2.1.3 The analytical approach
This approach assumes that the whole is the sum of its parts and that reality is objective (Arbnor and
Bjerke, 2009). The analytical approach is often associated with quantitative data that can be analyzed using
statistical procedures. A significant amount of quantitative data is used, and this data will be analyzed
using statistical processes. The analytical approach provides the means to determine the likely causes of
business and industry cycles.

2.1.4 The systems approach
According to this approach the whole differs from the sum of its parts, which means that not only the parts
but also their relations are important (Arbnor and Bjerke, 2009). The systems approach denies the
usefulness of looking for causal relations, and look at forces that influence the system as a whole. In the
thesis a composite index of indicators is used to study the sum of causal relations and thereby not just
individual effects. Thus, the composite index differs from the sum of its parts, the indicators.

Figure 2.1.1: Methodology map

Source: Arbnor and Bjerke (2009)
The different dynamics of business cycles cannot be regarded individually but must be regarded in the context of the whole. However, for the sake of statistical analysis, cyclical dynamics are regarded individually, and then analyzed in the context of the whole, which is why a combination of the analytical and the systems approach is justified.

2.2 Research approach

2.2.1 Deduction, induction and abduction

Deduction, induction and abduction are the three main types of inference. Deduction involves inferences in which the conclusion is generally true from the premises, whereas both induction and abduction belongs to the class of “non-necessary inferences”. Since induction is only relevant when working with purely statistical data, abductive reasoning is used in the thesis for its non-necessary conclusions. Non-necessary means that the specific observation does not allow for a necessarily true general inference, but instead a most likely explanation based on theory (Magnani, 2001).

A combination of a deductive approach and an abductive approach is applied in the thesis. This is selected because a deductive approach is better suited for some sections of the thesis, while an abductive approach is more appropriate for other sections.

In relation to answering the problem statement and its research questions, a deductive research approach is well-suited because a deductive approach facilitates the research structure under which a researcher develops statements, based on previously developed theory that can be tested empirically, and hence rejected or confirmed according to scientific principles (Saunders et al, 2009). A deductive approach is pursued in using existing business cycle theory to identify possible drivers of cyclicality that can be used to predict industry cycle turning points, as suggested by Duus (1999). However, it is not a clear deductive approach because economic theory does not dictate how to find and use triggers of business cycles, but only serves as inspiration. Therefore, abductive reasoning is in fact used by looking at what others have done before. In that sense, it can be regarded as a mix of the abductive and deductive approach. Possible drivers of cyclicality will not be ignored if the drivers have never been mentioned by economic theory before. Functional business sources are reviewed to find additional inspiration.
The expert interviews help to provide guidance to the process of understanding business cycles on both the macro- and meso-level. Additionally, the expert interviews are used to develop a practical understanding of the most common forecasting methods and to select the most useful method to answer the problem statement. An objective of these interviews is to acquire general knowledge, and therefore the interviews are following an abductive approach.

The empirical analysis has traces of both deduction and abduction. The empirical analysis is following a deductive approach by investigating whether the identified possible triggers of business cycles actual can identify and predict business cycles on the industry level. The abductive trace comes from the fact that the analysis may identify new indicators and thereby contribute to future research on business and industry cycles.

It is advantageous to combine deductive reasoning with non-necessary reasoning, in this case abductive reasoning, as the two approaches supplement each other (Saunders et al, 2009). The degree of objectivity is high regarding secondary data, but it may decrease with the addition of personal interviews, where both the framing of the questions and the questions can be subjectively phrased (Saunders et al, 2009). However, it is regarded that the potential loss of objectivity is less than the valuable insights of the expert interviewees.

2.3 Research design

This section shows how the research questions are answered in the thesis (Saunders et al, 2009).

2.3.1 Multiple methods

The thesis, as already touched upon in the above sections, is combining both qualitative and quantitative data collecting techniques, and the thesis can as a result be characterized as using a multiple method. Tashakkori and Teddlie (1998) believe that a multiple method design is the best because it provides the researcher with better opportunities to answer the problem statement. Further, it makes it easier to evaluate research findings since qualitative and quantitative methods have specific strengths and weaknesses, and by applying both an optimal results can be achieved (Smith, 1981).

2.3.2 Secondary data

The data on economic variables are from secondary sources. It is very important that sufficient and reliable data can be gathered to be able to conduct the analysis. The data is gathered from reliable data bases such as Datastream, and from the direct sources like the U.S. Federal Reserve Bank. It is assumed that a
substantial amount of the needed economic data exists. However, for some of the variables it might be a problem that the time series are not far reaching enough or have undergone a change in statement, so that some past data cannot be compared with new data. A substantial amount of data on the macro-level is expected to exist and be easily available, but some problems might be encountered when gathering industry specific data.

Advantages of secondary time series data include is that it can be compared over time, is open to public scrutiny, often of high quality and it constitutes a potential large saving in resources and time compared to collecting the data yourself (Saunders, Lewis and Thornhill, 2009; Ghauri and Grønhaug, 2005). Disadvantages include that access might be difficult, different purpose and agendas of data collectors, and no real control over data quality. Given the advantages of secondary data compared to its weaknesses, it is believed that the substantial reliance on secondary data does not create any problems for the research. Secondary data is complemented by primary data gathered from the expert interviews.

2.3.3 Explanatory research

The main objective of the thesis is to identify and examine relationships between business- and industry cycle turning points and potential leading indicators. The overall research purpose can, as a consequence, be regarded as explanatory because it gives the researcher the possibility to explain such relationships (Saunders et al, 2009). However, in order to get there the different sections need to take on a number of different purposes in order to present the findings in a well-diversified way. The literature review needs to be descriptive in order for this thesis to present what is known and generally believed in this field, but it also needs to be explorative as we must critically review the main points of these theories. In the same vein, the review of quantitative methods has both descriptive and explorative elements. From then on, the thesis focuses on explaining our findings, and is mainly explanatory although there are explorative elements.

2.3.4 Case study

The case study is an in-depth empirical investigation of a contemporary phenomenon within its real life context (Saunders, Lewis and Thornhill, 2009; Yin, 2009). Experiments show what can happen under controlled circumstances, while case studies show what actually happens in real life (Maaløe, 2002). Therefore, to show what happens in real life a case study is appropriate, as this research design is both the most relevant and feasible in understanding complex real-life phenomena such as industry cycles. A case study is recommended when the goal is to understand the context affecting the cases, which is relevant for
this study in regard to explaining the relationship between the case industries and macro business cycles

The thesis pursues analytic generalization where previously developed theory, Strategic Business Cycle
Forecasting, is used as a kind of template that serves as the theoretical foundation for the thesis. If the
empirical results are useful and are in agreement with the theoretical foundation, then replication can be
done (Yin, 2009). Thereby, a case study can serve as a practical illustration of theory, which the thesis
strives to achieve (Maaløe, 2002).

A case study fits well with an explanatory study, though some researchers only find that case studies can
have an explorative nature (Saunders et al, 2009). Case studies are also criticized for being too
unsystematic and too biased (Yin, 2009). To address this criticism a clear systematic methodology is
followed and unbiased secondary data is employed.

When conducting a case study there is a need for triangulation, which means a need for different data
collection techniques (Saunders et al, 2009). The thesis deals with this by applying multiple research
methods with secondary data from reliable databases and primary data from expert interviews.

2.3.5 Meso- vs. micro-level
The rationale for choosing industries instead of individual businesses is that it will make the observed
trends clearer and more accurate by excluding the errors of observing individual businesses. Aggregating all
the individual business in an industry will reduce the volatility significantly and should produce a more
reliable and useful result (Shim, 2000). In addition an industry approach should all things equal be a more
valid forecasting starting point for other businesses or industries compared to an individual business
approach.

2.3.6 Macro- vs. meso-level
The reason for the substantial focus on the meso-level instead of the macro-level, is that aggregate
business cycles consist of significant changes in the underlying industries where some industries react
before, simultaneous or later than the aggregate cycle (Niemira and Klein, 1994; Berman and Pfleeger,
1997; Bundgaard 06:05). Some industries, like construction, are very vulnerable to business cycles while
others are practically immune, like the pharmaceuticals (Berman and Pfleeger, 1997; Bundgaard 07:15).
Further, in the 1980s and 1990s only 60 percent of American industries were in recession at the same time
as the aggregate business cycle (Tan and Matthews, 2009). Niemera and Klein (1994) advocates that studying business cycles on the meso-level has great potential as the possibilities for analyses of industry cycles for both public and private sectors are vast. When analyzing industry cycles, comparisons of the industry cycles with the aggregate macro cycle should be made as this shows timing relations between the specific industry and the general economy (Niemira and Klein, 1994; Tan and Mathews, 2009).

2.3.7 Multiple cases
A multiple case design with three industries is chosen to be able to compare the usefulness of forecasting of industry cycles in three different industries. Empirical analysis of several industries provide more reliable, compelling and robust results compared to just looking at one industry. Further, there is no single industry that can represent all other industries.

A multiple case study, compared to a single case study, is recommendable when the purpose of the study is explanatory in its nature as it enables generalization based on the cases (Yin, 2009). When doing a case study it might be difficult to generalize if the cases are very specific. Therefore, it should not be concluded that the findings of the thesis can be applied by every industry, but that it can serve as a starting point or inspiration for similar studies or practical application. Analytical applications start with the macro- and meso level and then move toward a more micro-level with the individual business level. Therefore, a multiple case study on the meso-level can serve as the basis of future single case projects which can best be designed from inspiration and replication of a multiple case study (Yin, 2009; Duus, 1995). A multiple case study can be thought of as method that ties qualitative and quantitative study since both kinds of data methods are necessary (Duus, 1995).

Many industries, mainly those with rapid consumer durables turnover, high levels of knowledge-intensity or high levels of capital-intensity, exhibit special dynamics moving through expansion and contraction that are not only related to the aggregate economic fluctuations (Carlsson and Eliasson, 2003; Duus, 2013). Almost all industries show cyclicality to some extent, which validates the multiple industry approach due to the specific cyclicality of industries (Choi, 2003; Niemira and Klein, 1994; Skousen, 1990; Duus, 1999; Carlsson, 1997).

The industries must be carefully selected based on one of two criteria (Yin, 2009). The first criterion suggests the selection of similar industries where the results of the industries are expected to be similar. The second criterion implies the selection of significantly different and often contradicting industries where the results of the industries are expected to be different. The second approach is chosen as it is believed
that it can offer the most interesting results by focusing on different industries, and the related implications.

2.3.8 Longitudinal study

A longitudinal study enables the researcher to study change and development over time in a controlled way (Adams and Schvaneveldt, 1991). Since business cycles are a repetitive event taking place again and again over a long period of time, a longitudinal study is most appropriate because it enables the researcher to evaluate whether the same factors can continually predict business cycles. Business cycles turning points (trough to trough or peak to peak) are in general occurring around every five years according to NBER (nber.org). To get a sample with several business cycle turning points a time period of more than 30 years is desired to be able to analyze at least six cycles. This is in regard to classical business cycles whereas growth cycles occur more often.

The quality of the data available will also decide the length as it is vital to have adequate data that can be compared. This consideration will most likely reduce the length of the chosen time period. This thesis selects a time period ranging from 1973 up until the present day based on multiple dilemmas. First, although it is wishful to have as long a period of observation as possible, the first 60 years of the 20th century was characterized by events very unlike the current economy. There is the two world wars, in between them a period of very little trade among countries, and after WW2 an economy adjusting back to normal circumstances. Second, there are a number of factors suggesting that businesses and the economy in general have become ever more advanced as the last decade progressed. The information technology revolution changed the way information was disseminated, and information can rapidly travel around the world as can investor’s money. This combination of technological advanced and financialization of the economy have had a number of effect on companies, which are now subject to global competition under constant scrutiny from global investors.

2.3.9 Reliability and validity

It is of great importance to obtain reliable and valid findings. Reliability and validity are the extent to which the findings are consistent with the applied data collection techniques, the analytical processes and the theory (Saunders et al, 2009). Reliability is assessed by whether the applied processes will yield the same results on other occasions, if similar observations will be reached by other observers and the level of transparency in how judgment was made from the data. To address these assessment criteria, the thesis is aspiring to have a clear and well-founded methodological approach that can be replicated. Since the majority of the applied data is from reliable sources and the empirical findings are measured statistically,
the results of the thesis should be considered reliable. However, if one investigates a different time period, different cases or a different country than the one used in the thesis, different results might be found.

The analytical approach, which is one of the two approaches that the thesis employs, regards reliability as high if there is high sensitivity and high precision (Arbnor and Bjerke, 2009). A high sensitivity can be obtained by using months instead of quarters when looking at time series. High precision can, for example, be achieved by changing the significance level of statistical analysis. Both high sensitivity and high precision will be prioritized in the thesis, if allowed by the constraints of data accessibility. In regard to the systematic approach, a systematic structure is used in the empirical analysis on both the macro and meso-level in order to achieve high consistency and reliability.

Validation is viewed as the quality of the findings in the research. High quality necessitates the right techniques as measured by the compatibility between theory, models and data (Arbnor and Bjerke, 2009). A useful test of whether measurements have been correctly applied is if a good forecast can be made, which is an obvious test of validity for the thesis. The conclusion of the thesis will answer whether satisfying results have been achieved.

2.3.10 Data accessibility
The thesis has employed a long diversified list of data sources to ensure validity and reliability, see appendix 4.3 and 5.3, 6.3 and 7.3 for lists of data sources (Maaløe, 2002; Yin, 2009; Saunders et al, 2009). The deductive approach states that the data samples need to be of a sufficient magnitude to ensure reliability and to enable generalization (Saunders et al, 2009). Consequently, the thesis strives to adhere with this criterion. It is important to acknowledge that case studies can be generalized to theoretical propositions, not to whole populations.

2.4 Quantitative methods

2.4.1 Assessment of quantitative forecasting methods
Many different economic quantitative models can predict business cycle turning points, but it can be difficult to find the best one, as this is very much dependent on the purpose of the analysis (Niemira and Klein, 1994). No method is explicitly right or wrong, but some methods are providing more insight than others, and are therefore more useful in the process of forecasting (Niemira and Klein, 1994). Duus (1999) addresses the need for a systematic forecasting approach for the meso-level that is easy to use and
understand, while still being effective. These criteria guide the selection of a quantitative forecasting method.

There exists heavy criticism of quantitative models, mostly due to too static assumptions of the models, which do not incorporate the dynamism of today’s world (Shim, 2000). However, each business cycle follows a predetermined pattern and in that sense the static models might work, as the same variables can possibly predict business cycles on a continuing basis (Burns and Mitchell, 1946).

Quantitative models work well when there is little or no systemic change in the environment of the entity being studied. When the environment changes the historical patterns become less useful (Shim, 2000). Consequently, it is necessary to complement with more qualitative reasoning in assessing what methods can be useful, which is why expert interviews are conducted to guide the process, as explained in section 2.5.2. To create a reasonable forecast, it is recommended to use both qualitative and quantitative techniques (Shim, 2000).

2.5 Qualitative methods

2.5.1 Literature review
The literature review is a review of business cycle theory. This review of business cycle theories are drawn from a number of different sources, but are mainly based on two books that are very thorough in their explanation. One is Niemara & Klein’s (1994) book “Forecasting financial and economic cycles”, which is appreciated for its very rounded discussion of business cycles in general. The other is the very recent “Recessions and Depressions – Understanding Business Cycles” by Todd A. Knopp (2010). This book does a very good job of linking together the different theories and it also presents a lot of useful sources on empirical evidence and alike. The review focuses on identifying the main points for each business cycle theory. These main points are used to derive potential explanations of business cycles that can be transferred to real life economic variables in order to predict business cycle turning points. The review of business cycle theory is regarded as a bridge between business cycle theory and practical forecasting.

2.5.2 Semi-structured expert interviews
The reason for using interviews is that it can help the researcher to gather relevant and reliable data (Saunders et al, 2009). The interviews conducted are done in accordance with the approach of semi-structured expert interviews. Semi-structured expert interviews are recommended when the purpose of the thesis is explanatory (Saunders et al, 2009). The use of semi-structured expert interviews is consistent
with the research strategy of the thesis since it provides the opportunity to explore the interviewees’ knowledge of the field of business cycle forecasting. The intention with the expert interviews is foremost to get real life practical knowledge on how to analyze and understand macroeconomic business cycles. Further, insight on how to go from the macro-level to the industry-level is targeted. The practical experience of the experts is used to address the benefits and disadvantages of selected quantitative forecasting methods. Additionally, insights on business cycle theory are addressed if possible given the interviewees’ knowledge. The insights provided by the expert interviews help to better understand business cycles in general and select the quantitative tools necessary for forecasting business cycle turning points on both the macro- and meso-level.

The interviewees’ answers reflect their experience and competences, and by following their advice, it can be regarded as a quality validation that an adequate quantitative approach is applied to the empirical data. This should ensure robust results from the empirical analysis.

2.5.3 Interview guide and interviewees

The template of the questions asked in the interviews is derived from the topics covered in the thesis. The template is based on the problem statement with focus on quantitative methods, business cycle theory and industry experience. The template is listed in appendix 1.2. Semi-structured interviews provides that the interview template is only an expression of the general topics of the interviews, as some questions might have been omitted or added in a particular interview, while some other questions might have been rephrased. Semi-structured interviews are not highly formalized or structured with standardized questions for all the interviewees. The interviews are not either completely informal or unstructured, but a thing in between these extremes (Saunders et al, 2009).

The list of themes and questions to be covered in the interview does not necessarily need to be covered in all the interviews because the experts being interviewed have different areas of expertise. Since Svend Jørgen Jensen and Tom Bundgaard have a practical understanding of business cycles, they were asked questions mostly covering this area. Claus Jacobsen on the other hand has a more theoretical based experience from his work at CBS. Thus, he was given more theoretical related questions. The interviewees have been chosen based on their expertise practical and theoretical knowledge of forecasting business cycles. Thus, it is expert interviews. As this thesis is foremost doing a quantitative study with very substantial amounts of statistical data, the amount of three interviewees have been selected. The large amount of quantitative data can make up for the rather low number of interviewees. More interviewees could have been added, but it is not believed that this would significantly improve the insights of the
interviews. It is important to mention that given semi-structured interviews’ non strict structure, the way the questions is asked, the questions included or omitted, will affect the data collected (Silverman, 2007).

All of the interviews have been recorded with permission from the interviewees, and the interviews are enclosed on a CD (appendix 1.3). Further, the main points of the interviews are transcribed and included in appendix 1.4. Lastly, appendix 1.1 contains a short description of the interviewees.
3 – Review of business cycle theory

3.1 Introduction

Business cycles have occurred throughout economic history, and business cycles have been described as early as the 18th century, but research centered on the phenomenon of business cycles did not start to appear before early 20th century. One of the earliest accounts of cyclicality in relation to output movement was made in 1837 by the British Lord Overstone:

“...subject to various conditions which are periodically returning; it revolved apparently in an established cycle. First we find it in a stage of quiescence, -next improvement, -growing confidence, -prosperity, -excitement, -overtrading, -convulsion, -pressure, -stagnation, -distress, -ending again in quiescence” (Lord Overstone, in Arnold, 2002).

Before delving into the different parts of business cycle theory, it’s appropriate to first define what is considered a business cycle. There are multiple definitions, but the most cited definition by Burns and Mitchell (1946) fits well:

“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; this sequence of changes is recurrent but not periodic; in duration business cycles vary from more than one year to ten or twelve years; they are not divisible into shorter cycles of similar character with amplitudes approximating their own” (Burns and Mitchell, 1946, p.3).

One important thing to note in the above quotation is that the expansions and contractions are occurring in many different measureable economic activities and not just a single or a few (Arnold, 2002). This is important, because it appears then there are certain relationships among variables, which can prove valuable in forecasting.

3.2 Development of business cycle theory and different schools of thought

In more than 100 years of research on business cycles, a number of different theories on the reasons for their occurrence have been developed. What is important to acknowledge is that business cycle research
have most of the time grown out of the more general economic theory considered relevant at the time, and larger factors often have been at play in determining, which theory dominated. For instance, at the height of the Great Depression there was a power struggle with the relatively laissez-faire Austrian School on one side, and the interventionist Keynesian School on the other side. At any other point in time, one may expect policymakers to be more open towards the do-nothing approach of the Austrians, but because of the dire circumstances, it just appeared too risky for policymakers to follow. Accordingly Keynesian economics dominated both in academic research and policymaking for the next couple of decades. Thus, it is important to remember that many factors are at play in determining which theories previously dominated, and which do so today (Skousen, 2009). Table 3.2.1 shows the structure of this section.

Table 3.2.1: List of business cycle theories reviewed

<table>
<thead>
<tr>
<th>Business Cycle Theories</th>
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<tbody>
<tr>
<td>Early business cycle theories</td>
</tr>
<tr>
<td>The Classical Model</td>
</tr>
<tr>
<td>Keynesian Economics</td>
</tr>
<tr>
<td>Neo-Keynesians</td>
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<tr>
<td>Monetarist theory</td>
</tr>
<tr>
<td>Rational expectations model</td>
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<tr>
<td>Real business cycle theory</td>
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<tr>
<td>New Keynesian models</td>
</tr>
<tr>
<td>Credit and financial instability</td>
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<tr>
<td>Austrian Business Cycle Theory</td>
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3.3 Early business cycle theories

Early theories on business cycles, which in general mean theories prior to the Great Depression, are mostly unicausal in their explanation of what causes business cycles. Therefore they are regarded as a bit naïve today. Nevertheless many of these theories provide the foundation for later developments within business cycle research, and therefore some of their main points shall briefly be considered (Knopp, 2010; Niemara and Klein, 1994).

3.3.1 Early agricultural theory

One of the most influential unicausal theories is W.S. Jevons Sunspot theory, in which he proposes that agricultural output, and therefore economic activity, is influenced by periods of varying sunlight. After it was clear that the length of business cycles and sunspot cycles actually did vary somewhat, Jevons attempted to salvage his work by saying that because farmers knew his theory so well, they altered their
behavior to the expectations, they had based on his theory. Thus expectations of less sunlight would lead to less output. Today no one believes sunspots can have this effect, but this is one of the earliest accounts of how expectations might affect behavior without any real changes having occurred (Knopp, 2010; Niemara and Klein, 1994).

Another influential theory based on agriculture is the Cobweb theory developed by American agrarian economist Mordekai Ezekial. It is a theory explaining how shocks to demand and supply can cause fluctuations in prices and output. Being an agricultural theory, it holds two assumptions that are based on agriculture, but in today’s economy it can be transferred to a number of markets and industries. First, goods are perishable, wherefore the farmer cannot store these and must sell them at the prevailing price. Second, the farmer plants this year’s seeds based on last year’s price. Thus, rather than being forward looking, his expectations are backward looking, or adaptive rather than rational (Knopp, 2010). If a temporary shock to supply causes prices to rise in the fall, farmers will respond in the spring by increasing output, which will then result in excess supply and a need to lower prices. Eventually, the price and output will close in on equilibrium, but the theory shows that this is an adaptive process. Criticism of the Cobweb theory mostly regards its two basic assumptions. If a product could be stored, producers would have a larger control over price formation, and consequently the adjustment process from a supply shock would be much faster. Secondly, the idea of adaptive expectations has also received much criticism although it later features in a number of other theories. The idea that people only form their expectations on past events is by many regarded as too naïve (Knopp, 2010; Niemara and Klein, 1994).

A third theory of the agricultural society is that developed by British political economist Thomas Robert Malthus. His view on cyclicality forms the basis for a later class of underconsumption theories (Niemara and Klein, 1994). Living in Britain during a period where there were no advancements in agricultural technology and a rising population, Malthus believed that there would soon be diminishing returns from agricultural output, due to a falling capital-to-labor ratio. Eventually, this would lead to mass starvation and poverty, and population would start to decrease. Returns and prosperity would then return until the entire cycle would repeat itself. Once again, this theory’s main assumption turns out to be its biggest flaw. Malthus assumes that there will be no technological advancements. However the industrial revolution that soon followed proved him wrong, and it also proves that technological development can maintain stability as well as cause cyclicality in itself (Knopp, 2010).
3.3.2 Early monetary theory

British economist Hawtrey is considered the most influential economist among early scholars of monetary theory. In Hawtrey’s theory, business cycles are caused by fluctuations in money supply (Knopp, 2010; Niemara and Klein, 1994). The theory was developed back when most countries were part of the gold standard. Their money supply was tied to their gold reserves, which in turn were tied to their trade balance. A trade surplus would result in an inflow of gold, necessitating an increase in money supply, which would lead to an increase in income and consequently also imports. Higher imports would then eventually lead to a trade deficit, causing an outflow of gold reserves and subsequently a decrease in the money supply. This cycle would then repeat itself. To eliminate the cyclicality, Hawtrey advocated dismissing the gold standard. Discrediting the overall hypothesis of his theory is the fact that cyclicality have not ceased after the gold standard had been abandoned. His work does, however, give important insights on the influence of monetary policy on cyclicality, something that receives a varying amount of focus in almost any subsequent theory (Knopp, 2010).

3.3.3 Underconsumption theory

This theory, highlighted through the work of English economist John A. Hobson, argues that rising income in an economy eventually will result in aggregate supply outgrowing aggregate demand. In Hobson’s theory, this happens because the marginal propensity to consume (MPC) falls as income rises. In other words, more wealthy people spend a lower fraction of their income on consumption than less wealthy people. Ultimately, cutting production is the only way to avoid this excess production, but as a consequence incomes will also fall and the MPC of the overall population will again rise, and this cycle will then repeat itself. As shown later, underconsumption theory was very influential in the development of Keynesian economics (Knopp, 2010; Niemara and Klein, 1994).

3.3.4 Profit margin theories

Some of the earliest empirical work on business cycles on a serious scale was undertaken by American economist Wesley Clair Mitchell. While his work does not include an elaborate theory, he did give his insights as to what caused business cycles. Mitchell maintained that theoretical explanations can only become known from studying empirical data of an economy covering a long period of time (Niemara and Klein, 1994). During an expansion in the economy, profit margins tend to rise for a variety of reasons. Most significantly because firms are able to empty their inventories, and also because expansions offers more potential for economies of scale, and is characterized by a higher level of capital utilization. This leads companies to initiate investments, but since new capacity does not immediately become available, the
cycle will peak beforehand, and this excess capacity will then worsen the following contraction. Two main insights are gained from this theory. First is the role of expectations, which as Knopp (2010) remarks play a part in every major theory. In the context of this profit margin theory, expectations can be seen as a quest for profits, and this quest being the driving force of business cycles (Niemara and Klein, 1994). Secondly, the influence imperfect competitive markets can have on cyclicality. This happens because the single producer fails to recognize that his competitors have the same quest for profit, and will act on this as well. This element of cyclicality has generally not been given much attention on its own, but research indicates that it is present in most industries. Tan and Matthews (2007) refer to this as a pinwheel cycle. Thus it is cyclicality that originates from within the industry itself. Both insights later came to play a large role in the development of Keynesian theory (Knopp, 2010).

### 3.3.5 Early investment theories

In many of the early business cycle theories, investments are only considered a secondary factor. Some does, however, go more into detail with the role of investments. Swedish economist Knut Wicksell formed a natural interest rate hypothesis that is the basis of overinvestment theory. If an unstable money supply or excessive bank credit leads to the market interest rate falling below the natural interest rate, firms will have an incentive to over-invest, and the opposite holds true if the market rate is at or above the natural rate (Knopp, 2010). The element leading to cyclicality here is, according to Wicksell, the banking system, which in its quest for profit will lower the market interest rate below the natural level. One of the main contributions of this early work of Wicksell was to separate the banking system from the real economy, allowing future students to see how cyclicality can arise in both systems. Another influential overinvestment theory is that by Austrian economist Friedrich Hayek, but the discussion of this theory is delayed to the section on Austrian business cycle theory, as it is mainly associated with this school of thought (Knopp, 2010; Niemara and Klein, 1994).

American economist John Maurice Clark is mostly remembered for his work on investment accelerators and multipliers. While his models do not explain why investments would rise in the first place, they did show how relatively small increases in investment can lead to larger subsequent increases in output and spending. This will then lead to another increase in investments, and this accelerated cycle will then continue. Later the accelerator concept becomes a cornerstone in Keynesian and New Keynesian economics (Knopp, 2010).
3.3.6 Long wave theories
Russian economist Nikolai Kondratieff argues that macroeconomic and microeconomic variables fluctuated in both short and long waves, and economists had been too focused on the short term. American economist Joseph Schumpeter goes more into detail with what causes these long waves. According to him it is technological advances. He identified a number of innovations throughout times that could account for these waves of growth. It all starts with a new invention, whose abilities are vastly superior to previous technologies. Once this new invention becomes acknowledged and implemented into society, it will fuel a steep incline in growth that will only decelerate once all benefits from the new technology is exhausted. Consequently, resources will initially be draw from established production processes into emerging processes, which for a while can cause a dip in economic growth (Knopp, 2010).

3.3.7 Psychological theories
While the influence of psychology is acknowledged early on there are no significant attempts at developing models in which these psychological factors is the sole factor of the business cycle. In fact, they are often assumed away, and it is only much later that they are formed into concepts such as adaptive expectations and rational expectations. In later theories, the importance of psychological factors becomes significant, and today no one doubts the effect that expectations and sentiment has on economic fluctuations and especially financial crises (Niemara and Klein, 1994).

3.4 The Classical Model
Classical economists of the mainstream school do not devout a lot of time to the study of business cycles; in fact they assume that there are no business cycles. Classical economics starts with the work of Adam Smith. Among his followers are French economist Jean-Baptiste Say, whose belief that increased output will lead to higher consumer spending was acknowledged by most other economists at the time (Skousen, 2009). This means that there can be no such thing as underconsumption, and fluctuations in output are simply part of life and as such without importance. In fact, they assume that when an outside force causes output to change level, it remains at this new level until hit by another force. Even if classical theory holds that there are no business cycles, and that the subject is without interest, classical theory is discussed, as many of its core assumptions have been what economists would disagree upon when proposing new theories. Classical economics are built on three crucial assumptions. First, perfect competition and flexibility is assumed to exist in all markets. Among other things, this implies that prices and wages are perfectly flexible, all actors in the market have perfect information, and there cannot be any excess supply or demand. Second, decisions are made for real values only. This means that monetary changes cannot have
any influences on decision making, and therefore should have no effect on real variables. When making
decisions, actors are assumed to factor in any changes in inflation, which they are capable of because they
are perfectly informed. Third, people have the same preferences and will all act alike. Combining the
assumptions of perfect competition and equal preferences leads to the actions of the economy being the
aggregate of all individuals. Consequently, classical economics make no distinction between
macroeconomics and microeconomics (Knopp, 2010).

In the classical model, changes in output are driven by three factors. The first factor affects the quantity of
labor. The second factor affects the quantity of capital, while the third factor affects technology. For all
three factors, government policy is seen as the most significant influence on these. Changes in taxation and
regulations will affect the marginal utility and cost of both capital and labor, and consequently it will also
affect real output. In the same way, changes in tax policies and regulation will also influence the incentive
to invest in technology. Because aggregate supply can only be affected by permanent shocks, and prices
have no influence on output, classical economists are essentially assuming a vertical supply curve. Classical
economics use the quantity theory of money to prove that monetary changes will only affect prices. The
quantity theory of money states that the money stock times the velocity of money equals the aggregate
price level times aggregate output. Since we already know that output is fixed by the vertical supply curve,
it becomes clear that any changes to the money supply or the velocity of money will be completely
absorbed by prices (Knopp, 2010).

In the last part of the 19th century and first part of the 20th century, the classical model came under heavy
criticism because economists started to doubt many of its assumptions. Some were also completely
invalidated by events in this period. The assumption that cyclicality could only occur from the supply side
and not the demand side were doubtful to many. Furthermore, as unemployment skyrocketed during the
Great Depression, it became clear that prices and wages were not perfectly flexible. Nor did it seem that
the financial system and therefore monetary influences, was without a role in at least exacerbating the
downturn (Knopp, 2010).

3.5 Keynesian Economics
British economist John Maynard Keynes is by many regarded as the most influential economist and policy
maker up until this day (Niemira and Klein, 1994). The theories he and his followers developed are more
complete than any previous theory. As mentioned earlier, classical economists generally assume that
macroeconomics is nothing but the aggregation of all microeconomics, or all individuals. Keynes was the
first to make a distinction between these now separately established branches of economic study, and his conclusions contrasts those of classical economists in many areas (Knopp, 2010). Keynes theories and Keynesian economics in general draws a lot from the under-consumptionists, but Keynesians are more successful in getting forward the message of why it is primarily aggregate demand that determines business cycles (Skousen, 2009). Keynesian theories are noticed in large part due to the Keynesian policy recommendations. Underconsumptionists state that the underconsumption problem is unavoidable and there is nothing anybody can do about it. This laissez-faire approach appeared economically questionable during the Great Depression, so when Keynes suggested that something could be done he gained a lot of attention (Niemara and Klein, 1994; Zarnowitz, 1992). Keynes does not believe that supply and demand are perfectly clearing, and that prices and wages will easily adjust. Thus, he proposes that unemployment can exist for other reasons than people not wanting to work, which was contrary to the belief held by most economists at the time. Wages can be sticky because the individual worker does not compare his wage to that of the general population, but rather to others in his vicinity. Consequently, wage adjustments will be slower than suggested by classical economists. Therefore a falling price level can result in unemployment before workers will accept reduction in their wages. Wage friction is a propagator of the business cycle in the eyes of Keynes, but not the initiator (Knopp, 2010).

Keynes agrees with classical economists that the potential output of a country is determined by its labor and capital stocks, and level of technological advancement. Therefore, he is able to accept the classical production function. He does formulate a different aggregate demand function, as the classical economists have relied on the quantity theory of money to explain aggregate demand. Also, Keynes is the first to look at aggregate demand from a purely macroeconomic perspective. In his demand function, aggregate demand is made up of aggregate consumption, aggregate investment spending, and aggregate government spending and net exports. According to Keynes, the main source of aggregate demand instability is investment demand fluctuations (Knopp, 2010). It is this instability in investment demand that keeps the economy from maintaining full employment, which in Keynes’ eyes is what initiates the slowing of the economy and as such the business cycle (Niemara and Klein, 1994; Arnold, 2002). Keynes proposal that savings need not equal investments is also his dismissal of Say’s Law. Keynes believed that once aggregate demand is satisfied, any additional savings will not be channeled into investments. Therefore it is possible for aggregate demand and aggregate supply to differ from each other, and expectations are more important for investment demand than savings (Arnold, 2002). However, Keynes is later criticized for his assessment of Say’s Law, and today it is widely accepted that he in fact misinterpreted it (Skousen, 2009).
Summing up, Keynes explanation of the business cycle is the following. First, a change in expectations leads to lower investment demands which will also lead to lower stock prices and prices on real assets. This set off what Keynes describes as a multiplier effect in which the expectations first leans to lower incomes, which then leads consumers to reduce their spending, and as a consequence it dampens investment demand even further. After a while this self-sustaining cycle will lead to a falling price level of goods. Keynes assumes that wages are sticky, and therefore the falling price level of products leads to higher real wages, and consequently employers have no other choice, but to lay off workers. This leads income to fall even further and the cycle may gain more momentum (Knopp, 2010). Keynes main proposition for dealing with these cycles is to stabilize and stimulate aggregate demand through government spending. This should restore confidence and counter the effects of the cycle. Unlike many classical economists Keynes does not believe that business cycles can be managed through monetary policy. This was in part due to the inefficiency of the policymakers that he had witnesses during the Great Depression, but also due to what he refers to as the “liquidity trap”. Keynes believes that investments are insensitive to changes in interest rates, and thus lowering of the interest rate through an increase in money supply will have no effect. The liquidity trap also occurs because during a recession both banks and consumers are more likely to hold on to any extra cash they are given, and thus an increase in money supply is unlikely to have any immediate impact on spending and therefore has little ability to restore confidence (Knopp, 2010).

3.6 Neo-Keynesians

Following Keynes original works, a group of scholars modified and refined his theories. They are grouped as Neo-Keynesians. Overall, their main aim is to integrate Keynes ideas into a foundation of microeconomic principles, which Keynes largely failed (Zarnowitz, 1992). Most famous is the IS-LM model developed by Hicks. In this model the concept of sticky prices that Keynes proposes is changed into fully fixed prices, wherefore the model only can be regarded as one of the very short run. This model shows how business cycles can arise from shocks to the aggregate demand function. Another important point separating Keynesian theories from the original work of Keynes is their focus on consumption volatility rather than just investment volatility. Keynes believes that volatility in business investment is the primary source of business cycles, but Keynesians downplays the role of business investments, and argues that consumer durable goods purchases are just as dependent on expectations for the future. The third major difference between Keynes and his Keynesian followers is the latter’s focus on monetary policy. Keynes does not believe in monetary policy as a tool for stabilizing the economy, but Neo-Keynesians have a more positive view on its abilities (Arnold, 2002). This belief is mainly brought about by the work of Arthur Philips, who...
proposes that there is a solid negative relationship between unemployment and inflation, meaning that inflation can be used to keep unemployment down (Knopp, 2010).

Empirical evidence on Keynes’ main theories mostly comes from The Great Depression. Back then, the macroeconomic crisis was preceded by a steep decline in the stock market, which caused expectations to drop very low and spill into other parts of the economy such as consumer spending. Despite the sharp drop and the following crisis that resulted in bank runs and alike panics, government and central bank policymakers failed to implement actions that could counter the tragic development, which was at least in part due to the laissez-faire policy that dominated the policymaking until it became clear that markets would not correct themselves in the short-run without governmental interference. In later crises, empirical support for Keynesians are somewhat mixed, but it still holds a strong position in economic theory despite many of its hallmark conclusions being at least partially dismissed (Knopp, 2010).

To sum up, what Keynes and his followers contribute with is mostly to put the demand side at the forefront of attention. Today, almost any theory proposing that business cycles arise from the demand side is labeled Keynesian (Arnold, 2002). His concepts of sticky prices and wages suggest that there is an adjustment process in which a large number of workers are involuntary unemployed and that there is a role for governments and central bankers in stabilizing these fluctuations of the aggregate demand.

3.7 Monetarist theory

Following the work of Philips and other Keynesians, monetary policy became the center of attention during the 1950s and 1960s. The monetarist school seeks to integrate some important concepts of classical theory with modern macroeconomic theory. These classical concepts were often modified, and therefore rarely proposed without the monetarists having implemented some significant changes to them. Furthermore, they are in opposition to many of the concept and theories that Keynes and to a lesser degree his followers proposes. As noted earlier, classical theory does not differentiate between macroeconomics and microeconomics and Keynes was practically the first to do so (Knopp, 2010). At first, monetarists believed that prices and wages are perfectly flexible. The observed adjustment process in these elements occurs from incorrect expectations as opposed to imperfect markets which Keynes proposes. Economist Milton Friedman uses the concept of adaptive expectations, which is already known from the early agricultural Cobweb theories, to show that disequilibria can occur from people forming false expectations (Knopp, 2010). Second, monetarists partially believe in what is called the natural rate hypothesis. Originally the natural rate hypothesis states that money is completely neutral and therefore cannot influence output in neither the short nor the long run. Monetarists believes this to hold true only in the long run, and that
money can influence output in the short run because of the role it has on price expectations. Third, they believe business cycles are driven by fluctuations in aggregate demand, which again is driven by fluctuations in the money supply. This leads monetarists to conclude that both the financial system and general expectations are merely propagators of the business cycle, but it is changes to the money supply that always is the initiator (Knopp, 2010). In the monetarist view, business cycles are initiated by unexpected changes to the money supply, and because people have adaptive expectations any change to the money supply will in effect be unanticipated. Changes in the money supply will fool both consumers, workers and manufacturers because they are all assumed to have adaptive and thus backward looking expectations. Without knowledge of the money supply and therefore the general price level, any changes in prices will be mistaken for a relative prices change, and therefore allowed to have influence on decision making. Thus, manufacturers will produce more and workers will work more, when they observe that product prices and wages increase (Knopp, 2010).

The most important finding of monetarist theory is the apparent role of monetary policy on business cycles (Niemara and Klein, 1994). In their research, Friedman and others finds that during most business cycles, the stock of money tends to move close with the cycles of aggregate output. Later research into the theory, however, finds that it is changes to the money supply rather than the level of money stock that appears to move more closely with the aggregate economic cycle (Belongia and Garfinkel, 1992). Empirical evidence is generally supporting the monetarist ideas, at least to some degree. Friedman and Schwartz (1963) argue that all recessions between 1867 and 1960 were preceded by a significant decline in money supply. Romer and Romer (1994) find that this also is the case in the postwar recessions that they have investigated.

A problem with monetarist theory is that it maintains that money demand will be stable, which is necessary if one wishes to control economic progress through regulation of the money supply. However, evidence have pointed to the fact that money demand is not always stable with examples of events like bank runs under the Great Depression and financial innovation in the 1990s that caused changes. Therefore at this point many economists recognize that attempts to control the money supply may be without much effect (Knopp, 2010).

3.8 Rational expectations model
Rational expectations go against the notion of adaptive expectations, which is increasingly regarded as unrealistic. Instead it is assumed that individuals are capable of forming their expectations being both backward looking and forward looking. Rational expectations generally mean that all available information
is taken into account. This is not the same as saying that individuals know everything, but that they are aware of all information publicly available and take this into account in their decision making (Knopp, 2010). By far the most used rational expectations model is that developed by Lucas (Knopp, 2010). His model is basically the same as Friedman’s model, which is based on the classical natural rate hypothesis. The only difference is that individuals in Lucas’ model are assumed to have rational expectations as opposed to Friedman’s model where they have adaptive expectations. Information imperfection is still the source of fluctuations in the end. When a change in the price of one’s own product is observed, it can be interpreted in two ways. First, individuals can assume that there has been no change in the relative demand for their product and that the entire change in price is a result of increased money supply. Second, individuals can instead assume that the entire change is a result of an increase in relative demand for their product, and that none of it is a result of inflation. The latter is the case for adaptive expectations, where all changes are interpreted as relative changes. Because individuals are rational, they will assume neither of these extremes, but instead some middle way. However, because it is rational to assume that some of the effect is from a relative increase in demand, even rational individuals can be fooled by monetary policy. (Knopp, 2010)

In today’s society, where practically all information is available it may seem puzzling that rational individuals can fail to anticipate a change or misinterpret information. However, it is only recently that central banks have begun to publish changes to the money supply. Previously, the public was without knowledge of even temporary changes to the money supply. The lag in publication is today for much economic data very small and insignificant (Knopp, 2010). Given that proponents of rational expectations argue that individuals are capable of realizing their own mistakes very quickly, it is surprising that they argue in favor of a noninterventionist (Knopp, 2010).

Empirical evidence of rational expectations is rather mixed. Some support come from a study of interwar hyperinflation in Germany and Poland. According to the Keynesian and Monetarist views, recessions would be inevitable in this case if government is again to gain control over money supply. However, the numbers show that this was not the case and that the public must have adjusted its price expectations rather quickly, which is in support of rational expectations (Sargent, 1986). More recently, studies attempting to separate anticipated and unanticipated demand shocks have found that in both cases these shocks had real economic effects, which casts doubt on the rational expectations hypothesis (Knopp, 2010).
3.9 Real business cycle theory

Real business cycle (RBC) models are a class of models that focuses entirely on the effect supply factors have on business cycles. These models adhere to many principles of classical economics and are regarded as one of the most extensive attempts to integrate microeconomic principles into macroeconomic phenomena. First, the models assume the natural rate hypothesis to hold true in both the short and long run. This actually means that output will never deviate from its natural level and therefore that any changes to output as the result of an outside shock are permanent. Second, real business cycle theorists also believe that there is perfect information and perfect competition in markets, wherefore they also consider aggregate demand to be without any influence and relevance in business cycles. Shocks to aggregate supply are the main initiator of business cycles and such shocks can come in many forms. It can be in the form of a change in government taxation or regulations, or in the form of a price shock to an essential input source like it was the case in the 1970s oil crisis. In the case of a shock to input prices, this can happen because a lot of the existing capital stock will be rendered inefficient by for instance an increase in oil prices. Furthermore, transportation costs will also rise, which especially hurts low-margin goods that rely on cheap transportation and consumers in general. Shocks to aggregate supply can also come from technology. RBC theorists are very inspired by Schumpeter’s long wave theory and believe that it is relevant not only in the long run, but also in the short run. The chain of events is the same as with an oil price shock. First, a new introduction of a technology will render much of the existing capital stock inefficient when its advantages become known. Subsequently, there will be a reduction in output, because all companies are now implementing and learning to use this new technology (Niemira and Klein, 1994, Knopp, 2010)

The fact that these shocks result in a new permanent level of output can lead one to believe that this is not truly a business cycle model. After all, the process itself does not suggest any cyclicality. The shocks are believed to be exogenous and unpredictable, wherefore they must occur at random. Experiments have, nevertheless, shown that even with this being the case outcomes still happens in clusters. It can be observed by flipping a coin, which also results in apparent patterns. Thus, the belief that shocks are permanent and unpredictable does not preclude cyclicality (Knopp, 2010).

Convincing empirical evidence for the RBC theory is hard to obtain. This has to do with the fact that it is difficult to measure productivity. Early attempts have focused a lot on what is referred to as the Solow growth residual. Without going into details, this concept assumes that any change in output that cannot be explained by change in inputs is a reflection of productivity. This is highly simplistic, as there may be a number of unaccounted variables that can just as well cause this change. Since real business cycle models
focus a lot on supply shock, it may also be relevant to look at input prices for significant sources of
cyclicality (Knopp, 2010).

3.10 New Keynesian models

New Keynesian models are a name given to models that gained popularity in the late 1980s. Up until this
point, most models had failed in being both internally and externally consistent. Internally consistent
means based on widely accepted concepts, most of which were classical and neo-classical microeconomic
concepts. This is not the case for traditional Keynesian theory, which in most people’s eyes lacks a
microeconomic base. On the other hand, Keynesian theory is believed to have a larger degree of empirical
support, where many other theories have failed to gain empirical support beyond the period in which they
originated. This is what is meant by external consistency. The idea of the New Keynesian models is to
develop models with both internal and external consistency which means combining classical
microeconomic concepts with the most important conclusions of traditional Keynesian theory (Knopp,
2010).

Therefore, New Keynesian models adopt concepts from many existing theories. It holds on to the Keynesian
cornerstones of market failure and price inflexibility, but it simultaneously agrees that expectations can be
rational and that money supply and monetary policy are important elements to incorporate. Since they are
referred to as “new” Keynesian models there obviously are some disagreements with the traditional
Keynesians. The first disagreement being that new Keynesians, like monetarists, believe that there is a
natural rate of output and employment which in the long run is determined by aggregate supply. Second,
they believe that savings can be good for an economy and that savings does not depress investments.
Third, new Keynesians also dismisses the traditional Keynesian hallmark, the Philips curve. Given that this
was in the 1980s, where the Philips curve had long been disproved by Monetarists, it is not surprising. A
fourth and final disagreement is that while traditional Keynesians and Keynes himself in particular believes
fiscal policy to be a more efficient influent than monetary policy, new Keynesians actually believe the
opposite to be true (Knopp, 2010).

Because of the acknowledgement of- and attempt to integrate many different theories, there need not be a
single cause of business cycles in the new Keynesian models. Business cycles can happen both from a
contraction in aggregate supply and aggregate demand. On the demand side this could origin from the
traditional Keynesian beliefs of a reduction in expectations. Such a decrease in expectations will decrease
aggregate demand and because of inflexible prices and wages result in unemployment and excess supply of
goods. The idea is then that there is a propagation effect, because the effect on aggregate demand spills into aggregate supply. As a consequence, producers will cut production below the new equilibrium level, further exacerbating the symptoms. On the supply side, it can be a contraction of the money supply lowering credit availability or another shock to supply which is similar to what real business cycle theories propose. An increase in input prices will result in excess supply, because of inflexible prices and wages, and the fact that much of the capital stock is now inefficient. However, this effect will also spill into aggregate demand, as people will lower their expectations and fell that risk has increased, which then causes output to fall even below the new equilibrium level that would have been suggested by a real business cycle model. The cycle will be reversed when over the long term prices and wages will adjust (Knopp, 2010).

Empirical support is more consistent for this new Keynesian theory, which is not surprising since it unifies other theories into one that lives up to the criteria of both internal and external consistency. As in other Keynesian theories, inflexibility of prices and wages are still at the forefront of attention. The fact that these variables may have different degrees of rigidity is why real wages can fluctuate over the business cycle. Studies by Basu and Taylor (1999) find real wages to exhibit both periods of pro-cyclicality and counter-cyclicality. One may therefore conclude that the theory exhibits a lot of empirical relevance, and that price and wage flexibility clearly plays a role in business cycles (Knopp, 2010).

3.11 Credit and financial instability

In most major models, financial markets are given some attention, but are never at the center of attention. Keynes probably gives the most attention, as financial market failure in his work is one of the main reasons why people lowered their expectations during the Great Depression. However, financial markets slipped more and more out of attention as many schools of thought believed, or at least assumed, markets to be perfectly flexible and perfectly informed and therefore without any influence on business cycles. However, evidence has shown that every major crisis since 1900 has been accompanied by a financial crisis. Therefore, it is of little surprise that interest in this subject has increased in recent decades (Knopp, 2010).

One of the cornerstones in this area of study is Irving Fischer’s debt-deflation theory. In his model, an economic expansion will cause people and companies to build up an increasing level of debt, which causes them to come near to or exceed their maximum debt capacity. It may not appear so because people are fooled to believe that the expansion will continue. Companies become very leveraged and sensitive to interest rate changes, and a minor shock is enough to push over the least financially solid. This starts a chain reaction where asset sale turns into asset dumping and previously solid individuals and companies suddenly find themselves in big problems. This causes banks to get overly anxious and refuse to lend to
anyone, which leads to a credit freeze. The economy may then appear locked for some time until all agents realize their overreaction and there is a partial recovery as interest rates decrease in the recession. In Fischer’s model, the debt burden is especially painful, because it is usually fixed and therefore becomes enlarged in real terms once the economy is hit by deflation. Another important insight of Fischer’s model is the notion that financial markets appears to overreact to both good and bad news, which inevitably causes a large part of the cyclicality (Knopp, 2010).

Another related theory is the “The Financial Instability Hypothesis”. Hymen Minsky, who is generally considered a Post-Keynesian, argues that financial strategies followed by firms will change over time. Many companies will start out in what he calls hedged finance, where their current level of debt causes no problems with repayments and interest rate payments. However, because good times allow them to repay easily, they find it appealing to take on more debt. This leveraging will then continue until firms become so leveraged that even slight changes in economic conditions causes them to become unable to repay. The conclusion is that rising leverage can fuel and carry growth, but because it has this “Ponzi scheme” element to it, the contracting economic conditions that will almost inevitably follow an expansion will be so much harder, and will in the end force companies to sell off perfectly good assets. As in Fischer’s theory, human errors or overreactions here also play the cause of what in the end becomes a bubble (Knopp, 2010).

These two cornerstone theories have led to the development of a number of models based on credit and finance within the post-Keynesian school. Here the most important are Bernanke’s Financial Accelerator model and the models of credit rationing. The Financial Accelerator model relies on the notion that financial intermediaries are less willing to lend during a downturn, because of adverse selection and moral hazard risks, which essentially deprives credit from the companies that need it the most. Thus, lenders overreact because it is difficult to disguise a good borrower from a bad one. In this way, financial intermediaries are exacerbating the effect of a downturn. The models of credit rationing argue that it is the supply of credit itself rather than the interest rate level that causes fluctuations. The rationale behind this is that a higher interest rate will not deter the moral hazard problem, but may in fact induce the borrower to take on even more risk than before, and therefore further reducing the likelihood that he will ever repay. Therefore the bank will choose not to lend at all. The conclusion of both these models is therefore that the level of supply of credit is a better predictor than interest rate level (Knopp, 2010).

Empirical support for these models comes in different form. First, it appears that credit volatility is larger for firms that are already financially vulnerable, which overall also tend to be smaller firms (Bernanke et al,
1996). Furthermore, lending conditions changes over the business cycle as both the size and number of loans issued falls during a recession (Lang and Nakamura, 1995). For this study it is most important whether these changing financing conditions alter the behavior of companies over the business cycle as well. Evidence for this is found in a number of studies, wherein ratios such as assets-to-loan ratio and interest-payment to cash-flow ratio are found to be strongly pro-cyclical (Stanca, 2002). Another study finds that the spread between investment grade corporate debt and the presumably default free treasury rate is a good predictor of real economic activity, because as expectations about the future worsens more financially troubled firms, those with a lower credit rating, is going to have a harder time repaying their debt (Friedman and Kuttner, 1993).

### 3.12 Austrian Business Cycle Theory (ABCT)

ABCT actually has a long history, and may itself be regarded a precursor to the Keynesian models developed on credit and financial instability. (Knopp 2010) The main difference is that the Keynesians are demand-side theories, while ABCT is a supply-side theory. As we mentioned in the beginning of this review, much of ABCT originates from Hayek’s overinvestment theory. (Keeler, 2001)

ABCT relies on concepts well-known from the theories that are previously discussed. First, it takes an outset in Wicksell’s concept of a natural rate of interest. (Keeler, 2001) More than being a cause of overinvestment per se, in the Austrian view the drop in the market interest rate below a natural level will lead to an incorrect resource allocation. Second, it also focuses on how a monetary shock can be misperceived for relative price change, which was also discussed by a number of other theories. The variable that ABCT focuses on is the term structure of interest. In equilibrium, which is when the market interest rate equals the natural rate, the term structure will be smoothly upward sloping, and this slope will represent the increased risk and reduced liquidity that comes with holding a security over longer periods.

The Austrian School differs from what is regarded mainstream economics in its explanation of the business cycle (Skousen, 2009). This is due to the fact that it focuses a lot on credit cycles which is considered the main explanatory factor of most business cycles. (Keeler, 2001) The theory is very specific in its proposition that it is only monetary shocks that causes cyclicality by its effect on the interest rate. The Austrian Business Cycle is initiated by a shock to the money supply, which causes a drop in interest rates, but the drop affects the short term interest rate more severely than the long term interest rate. This essentially happens because the long term rate is an average of the short term rates up to that point, and thus the effect will be moderated on the longer term. ABCT also emphasizes a vertical industry structure, which
ranges from higher-order industries to lower-order industries (Ebeling, 1996). Lower-order industries are the ones closest to the final consumer, whereas if one moves the other way up the value chain this is the higher-order industries. Since interest rates can be thought of as the price margin between different stages of production, it will lead to a surge of investment funds into longer states of production, or higher order of goods. This shift happens because actors in the market misperceive the events. The shift in interest rates is only due to a shock to the money supply and not a change in relative prices as people think. Eventually, the short term rates will again adjust, and actors will start to again move towards lower order industries, but because much of the investment cannot be reversed this overinvestment will cause a contraction and very likely a recession. (Keeler, 2001; Skousen, 2009)

So far, evidence of the ABCT has been mixed. Mishkin finds clear support for a negative relationship between the short term interest rate and inflation, which is in support of the liquidity effect that initiates the Austrian cycle (Keeler 2001). Zarnowitz (1992) also looked at this topic, but only finds limited support for a liquidity effect. Hayek and the Austrians initially lost the battle during the Great Depression to Keynesians. This was in most parts due to their policy recommendation rather than their explanation of what had caused the cycle (Skousen 2009). Subsequent research has shown much support for the hypotheses of causes to the Depression (Keeler 2001). Hughes (1997) finds support for the vertical production structure proposed in Austrian economics, which an analysis of the 1990-91 US recession. Prior to the crisis, credit primarily flew to capital intensive higher order industries, and it was only just prior to the recession that credit started flowing to less capital intensive lower order industries. (Hughes 1997)

3.13 Discussion

The previous section offered a more or less chronological presentation of developments within business cycle theory. As is evident, most early theories are commonly unicausal in their explaining of the business cycle and therefore highly unrealistic. Along with advancements in technical methodology as well as computer power, theories later become more and more elaborate in the attempt to explain all workings of the business cycle. Earlier theories are often too dependent on their own time for empirical support, and therefore can appear very subjective. Only later has there been a willingness to combine factors that previously have been held separate for mainly ideological reasons. Today, this has emerged into a number of facts that most theories agree on and that are the central themes in most recent theories.
First, it is accepted that both the supply side and the demand side can have a role in business cycles. Both sides have ample evidence to support their case, and no convincing argument to exclude their opponent. It is therefore important to select indicators representing both sides in our later analysis.

Second is the role of expectations. In almost any theory since the early theories, expectations have played a role in causing fluctuations. The early Cobweb theory and all other theories up until the Rational Expectations Theory state that people form adaptive expectations, which causes output and other variables to deviate from equilibrium. Later, the Rational Expectations Theory suggests that people in fact can form rational expectations, but that this rationality still results in deviations from equilibrium. What remains is that it is important to include variables that reflect the expectations formed in markets, when one is to do a study on forecasting.

Third, it is widely accepted today that wages and prices are not perfectly flexible, and that therefore not all unemployment is voluntary. Keynes was the first to break through with this notion, and although there have been several attempts to discredit much of his work, evidence still speak in favor of wage and price inflexibility. Most of this evidence comes in the form of non-constant real wage, which seem to have shifted between periods of pro- and counter-cyclicality. Consequently, the real wage appears to be an important indicator of cyclicality.

Fourth, while initially denied by many, today the most influential models recognize the effect of monetary policies and the money supply on economic output. The modified version of the initial natural rate hypothesis suggests that money supply only can influence output, and cause it to deviate from equilibrium in the short run.

Fifth, the role of the financial economy has become increasingly important with the creation of still more financial instruments. This coupled with the fact that most major crises in the last 100 years also have been accompanied with a financial crisis is sufficient to recognize that measures of the financial economy also must be included to get a complete picture of the business cycle.

To sum up, in order to understand the whole picture of the business cycle one needs to include variables from both the demand and supply side, and ideally these variables must include both nominal and real variables. Also, one must include variables to reflect the financial markets. This is both macroeconomic data in the form of money and more disaggregated data reflecting the lending and borrowing of financial
intermediaries. Lastly, one must acknowledge that not only quantitative variables play a role, but also variables formed on more qualitative measures such as expectations and sentiments.

Essentially, a complete theory of the business cycle should be able to explain all its mechanics. No theory can say that it has obtained that goal yet. It has been important to not only describe the more recent elaborate theories and the battles between them, but also describe from where these theories have emerged. The objective was not to search for a complete theory, but instead look for as many drivers of business cycles as possible. Including the more simple theories have enhanced the overall understanding. Examining a multitude of different theories in order to identify a sufficient range of drivers have also proved necessary given that most theories only receive partial support for their empirical evidence.

Many of the theories disagree on the movement of certain variables, which complicates the process of selecting how to incorporate the identified variables into the forecasting method. When facing this dilemma, one is best served by looking closely at empirical evidence. Beyond empirical evidence, it is crucial that the assumptions of the identified variables do not contradict the conditions of today’s world. It is imperative to remember that many of these theories were developed in an economic world of different structures than the one today. For instance, it may be conceivable that prices change faster today than they did when Keynes first proposed the notion of market friction, due to among others financialization, globalization and a rapid pace of technology.

In conclusion, the overall objective with the literature review was to get theoretical foundation for identifying economic variables that can explain the possible causes of business cycles on both the macro- and industry-level. This objective has been sufficiently achieved.
4 - Assessment of quantitative forecasting methods

This section is included to discuss the pros and cons of different quantitative models in order to select the most appropriate for the forecasting of business cycle turning points for both the macro and meso-level. It is important to acknowledge that forecasting is not an exact science, but more like an art, and therefore field experience tend to prove valuable (Duus, 1999; Shim, 2000).

To select and judge the capabilities of quantitative methods, certain criteria emphasized by Duus (1999, 2000) are applied. These criteria include that the forecasting models must be effective, easy to understand by non statistical experts and have practical value. In addition, Shim (2000) has listed some considerations that one must take into account when choosing a quantitative forecasting model, which includes assessing benefit-cost-trade-offs, level of complication, short-run or long-run application, level of accuracy, level of error, and availability of data. Insights from the expert interviews are included to guide this section, as these experts have great practical knowledge and experience on the subject.

Forecasting generally assumes that the past causal relationship will continue in the future based on historical data (Shim, 2000). This is in practice not always the case; therefore forecasts are almost never perfect. Thus, some inaccuracies can be expected (Shim, 2000; Niemira and Klein, 1994). Additionally, forecasts accuracy decreases as the time period of the forecast increases and forecasts for groups are more accurate than for individual entities. For example, industry forecasting is more accurate than individual business forecasting (Shim, 2000; Niemira and Klein, 1994).

A forecasting period of 3-5 years is advised regarding the field of strategic forecasting (Printz, 1992). However, no quantitative forecasting model can be expected to successfully predict 3-5 years into the future, which is why a much shorter time period is accepted (Bundgaard 26:50). Forecasting business cycle turning points is an ongoing process as leading indicators as well as econometric models must be updated from time to time (Niemira and Klein, 1994).

4.1 Econometric models

Econometrics can be described as the application of mathematical and statistical methods to economic data and it is regarded as the branch of economics that gives empirical content to economic relations (Gujarati and Porter, 2009). In other words, econometrics is "the quantitative analysis of actual economic phenomena based on the concurrent development of theory and observation, related by appropriate
methods of inference” (Samuelson et al, 1954). Thus, an econometric model investigates the statistical relationship that is believed to exist between the various economic variables and a particular economic phenomenon (Granger, 1991). Econometrics is the union of economics, statistics and mathematics and in union these parts produce more than the sum of the parts, in agreement with the systems approach (see methodology section 2.1.4). Since econometrics brings empirical data together with theory, it is useful for forecasting. A common characteristic of the econometric techniques is that they are rather unbiased and objective from computer based findings, though the data and setups are chosen by humans (Jørgensen, 2001).

A disadvantage of econometric models is that the models are rather complex, which necessitates that the researcher possess substantial statistical skills (Shim, 2000; Niemira and Klein, 1994). Thus, econometric models cannot be said to comply with the criterion of being easy to use and understand, as they often include several hundred variables. However, econometric models are viewed as effective in predicting and identifying turnings points if a set of simplistic assumptions hold (Shim, 2000). Often, these simplistic assumptions cannot capture the dynamism of the real world. This is exemplified with the fact that although the Federal Reserve Bank of the US, along with many other central banks and institutions, use complex econometric models, they could not predict the recent financial crisis. Even as late as in January 2008, where signs of a bubble burst were evident, chairman of The FED, Ben Bernanke, rejected that the FED would forecast a forthcoming recession (The Federal Reserve, 2012).

The most common tool of econometric models is regression analysis, and the data commonly employed in econometric models are time-series data, cross-sectional data and panel data. Time-series data are relevant in relation to the topic and will be looked upon whereas cross-sectional data and panel data is disregarded for this analysis. Though econometrics, regression analysis and time-series analysis overlap, the thesis will in the following sections try to distinguish between them. The weaknesses and benefits of regressions analysis and time series-analysis are rather identical to those of econometric models.

4.1.1 Regression analysis
Regression analysis includes techniques for analyzing variables where the focus is on the relationship between a dependent variable and one or more independent variables. Thereby, regression analysis tries to explain how the expected value of the dependent variable changes when one of the independent variables is changed, while the other independent variables are held fixed (Shim, 2000; Gujarati and Porter 2009). Thus, the researcher is able to determine which variable has the strongest relationship with for example
changes in GDP (Shim, 2000; Niemira and Klein, 1994). Regression analysis is founded on a set of assumptions. One of these assumptions necessitates a linear relationship between the independent and dependent variable. Also, the expected value of the error term must be zero, constant variance and homoscedasticity for the error terms must be fulfilled (Shim, 2000). Lastly, the error terms have to be normally distributed and have no auto-correlation. If these assumptions do not apply, the conclusions of the analysis cannot be trusted. The assumption of a linear relationship between variables is unfortunately often very unlikely in real life (Niemira and Klein, 1994). It is advised to make a scatter-plot of the data to look if there is a relationship before conducting the actual regression (Shim, 2000).

Regression analysis requires substantial statistical skills, which conflicts the criterion of a practicality and being easily understandable, but it can under certain, sometimes unrealistic, circumstances be rather accurate.

4.1.2 Time-series analysis
The purpose of time-series analysis is to create a pattern from historical data and use this pattern to predict the future. Time-series data have a natural time ordering. This makes time series analysis different from other common data analysis techniques that have no natural ordering of the observations. Regarding business cycles, time-series analysis is an obvious choice for analysis and forecasting given the sequence-like nature of the business cycle (Shim, 2000). The data needed to make time-series analysis must be reliable and stable (Jørgensen, 2001). The data series must be stationary, meaning no seasonality, no trend and constant variance (Shim, 2000). The possibility of auto-correlation must also be considered and adjusted for, if present.

Time-series analysis requires statistical skills which conflicts the criterion of a practical and easily understandable model, but it can under optimal circumstances be rather effective. Time series analysis assumes that past relations will continue to persist, which is plausible for some relations but certainly not for all. Therefore, it can be difficult to give a general conclusion on the effectiveness of time-series analysis. However, in general, time-series analysis is regarded as rather accurate in the short term (Jørgensen, 2001). It is a limitation that time-series analysis works best under stable environments and a lot of turbulence can render time-series analysis less useful (Jørgensen, 2001). This type of quantitative analysis is only suited for short-term planning, so it is not strategic. The method cannot be used for new markets with no history.
4.2 Economic indicators

The purpose of economic indicators is to predict the direction of the aggregate economy with a time perspective of 6 to 9 months (Shim, 2000; Jensen 36:10). The economic indicator approach is a popular forecasting tool and the approach has during the last decades increased its number of proponents, which is a testament of its usefulness (Niemira and Klein, 1994). Economic theory and business cycle theory is judged on its ability to predict the future and, as explained in the literature review few have been successful in giving comprehensive explanations. While interest in business cycle theories have come and gone, the interest and application of empirical economic indicators remain strong (Niemira and Klein, 1994). Of the, albeit sparse, work done on industries regarding business cycle turning points, several authors have used economic indicators to predict turning points (Choi, 2003; Liu, 2005).

In light of the last decade with all its turmoil, the superior performance of economic indicator models in comparison with econometric models may help to resurrect the perceived usefulness of economic indicators even though it is by opponents regarded as “measurement without theory” (Filardo, 2004; Drechsel and Scheufele 2010).

Researchers of the National Bureau of Economic Research (NBER) do not base their selection of economic indicators on theory, and thereby falls prey to the “measurement-without theory” accusation. However, it is possible to use economic theory, more specifically business cycle theory, to find useful indicators on both the macro- and meso-level as recommended by Duus (1999, 2013) and other scholars (Niemira and Klein, 1994).

Indices of economic indicators have since 1919 more or less successfully predicted every expansion and recession in the US (Niemira and Klein, 1994). The approach has not changed much, but the weightings of the indicators and selection of indicators are continuously subject to revision.

Three key strengths of economic indicators are that they are easy to interpret, easy to communicate and relatively inexpensive to formulate, which is very much in line with Duus’ (1999, 2000) criteria of selecting a forecasting tool. However, economic indicators needs to be constantly evaluated and developed in order not to make it too mechanical and systematical, which does take some time and resources (Duus 1999; Printz 1992). Leading indicators are, unlike econometric models, designed to forecast only the timing of cyclical turning points and thereby not predict the severity of an expansion or recession. This is not to say that this cannot be done if very deep knowledge of a great number of indicators is acquired. Economic indicators cannot either answer “what if” questions which are central to policy decisions (Dua, 2011).
What may be a good indicator for one particular industry will not necessarily work for another industry for either logical, conceptual or data reasons (Niemira and Klein, 1994; Printz, 1992). As a consequence, specific indicators for each industry must be selected, though some might be relevant for more than one industry.

4.2.1 Composite index of economic indicators
Burns (1961) provides the following rationale for using composite indicators, “Since the cyclical timing of single processes cannot be implicitly trusted, a measure of protection against surprises of the individual cases may be won by combining the indications of numerous series” (Burns, 1961, p.35). Using a composite index of indicators can greatly limit the potential misleading random shocks of individual indicators. Niemira and Fredman (1991) conclude that the value of composite indicators in relation to individual indicators can be summarized as the whole being greater than the sum of the individual indicators, which speaks for the merit of the approach and fits the systems approach, see section 2.1.

A further advantage of using several indicators together on is that the identified turning points are less sensitive to data revisions, which are a rather large benefit for analytical purposes (Niemira and Klein, 1994). Despite the security in using an index of indicators, the index can still present false signals due to random macro-economic shocks (Niemira and Klein, 1994; Vaccara and Zarnowitz, 1977).

Viewing a composite indicator model in relation to an econometric model, a composite index has no single dependent variable, which is relevant because a business cycle is impacting more than one variable (Niemira and Klein, 1994). Further, an econometric model assumes fixed timing between the variables, whereas the indicator approach makes it possible that the timing relationship between indicators changes over time and between different business cycle. Despite the differences of the two types of models, the two models are complementary and the combined advantages of the models can provide valuable insights (Niemira and Klein, 1994).

4.2.2 The timing relationship between different types of economic indicators
Economic indicators can be characterized as leading, coincident and lagging. Leading indicators are created to predict 6-9 months ahead of the economy (Shim, 2000; Jensen 36:10). Coincident indicators move up and down in line with the economy, and lagging indicators trail behind movements in the economy (Shim, 2000). Graph 5.1.2 shows clearly the idea behind leading, coincident and lagging indicators. The leading index (blue line) leads the coincident index (red line) 3-9 months and the lagging index (green line) more
than 12 months (Baumohl, 2008). By following the blue line one can predict what will happen to both the red and the green line. This is the value of leading indicators.

Graph 4.2.1: Timing relationship between the Conference Board’s composite indices of leading, lagging and coincident economic indicators

4.3 Economic intuition

It is recommended that every expected relationship between two variables is founded on economic intuition, also called judgmental forecasting (Ellis, 2005). This requirement screens out non useful variables, and is needed to judge whether the observed variables behave appropriately. Unexpected behavior might be due to technical oddities or miscalculations. By ensuring congruency between economic sense and output these mentioned miscalculations can be spotted.

4.4 Selection of quantitative model

The review of quantitative models shows that all the models assessed have potential, limitations and some similarities. Based on the criteria of the model being easy to understand, practical and effective to use, the economic indicator approach is best suited for the thesis. This is especially true, if replication is desired on the industry-level. The preferable quantitative method for forecasting business cycle turning points on both the macro- and the industry-level is the economic indicator approach. By using economic theory to find economic indicators, the criticism of the economic indicator approach for being “measurement without theory” is neutralized. The identified indicators can, through small alterations, be used on both the macro- and meso-level. The fact that the economic indicator approach can only predict business cycle turning points is no disadvantage because the focus of the thesis is only to predict turning points, not address
amplitude or duration of the business cycles. The choice of quantitative model is in agreement with Duus (1999), who proposes to use the same economic indicator approach, where the selection of the economic indicators is based on business cycle theory and practical considerations.
5 - Technical considerations

Before the empirical analysis begins, it is necessary to carefully address all the technical choices and the considerations behind the analytical tools used in the analysis, because these choices have large implications on the analysis. If the quantitative forecasting method was known in advance, then this section could have been included in the methodology section. The thesis prioritizes consistency instead of individual adjustment by using the same approach for all the analyzed data. Though these choices are foremost founded on theoretical arguments it should be acknowledged that the development and presentation of economic indicators is also a trial and error process (Niemira and Klein, 1994).

5.1 Rate of change with growth rates

The time series is adjusted according to the rate of change (RoC) approach, which measures change by comparing the value for that month to the value in the same month of the previous year. This is done to de-trend the data, and turn level data into growth rates. Elis (2005) stresses the need for the use of RoC instead of levels when working with economic indicators. Also, Ellis (2005) emphasizes the importance of using month versus same month last year growth rates instead of month versus previous month growth rates, as it creates better analytical understanding of the economic activity. Mathematically, growth rates improve the lead time of economic series or at least more clearly show fluctuations (Niemira and Klein, 1994). By using the rate of change procedure, seasonality is effectively removed from the time series.

5.2 Moving average

It is recommended not to jump to conclusions about the status of the economy based on just a single month of data (Baumohl, 2008). Instead it is recommended to use a moving average to lessen the effect of misleading data of a single month. This way, the research being conducted is affected much less from data errors. Moving averages are averages that are updated as new information is released (Shim, 2000). A moving average is better at showing the underlying trend of the data series by smoothing out random fluctuations and shocks (Baumohl, 2008; Ellis, 2005). A disadvantage of a moving average is that it has a natural lag versus the original series. This lag depends on the technique applied, but remedies can be put in place to limit the lag disadvantage.

5.3 MACD

The MACD method is a technical analysis indicator, capable of identifying changes to direction and trends in time series. The MACD approach is used as a smothering and filtering mechanism using exponential
smoothing moving averages (EWMA) where most recent data are given higher weight than distant data (Shim, 2000). The MACD approach is applied by taking the difference between two EWMA’s of different length (26 and 13 months) in accordance with the recommendations of Bundgaard and Jensen (Bundgaard part 3 25:08; Jensen 19:40). Then a EWMA of 9 months is taken on the difference between the two series. The thesis has not chosen to optimize the MACD for each indicator, because consistency and practical simplicity are given priority. Instead the thesis has chosen EWMA of 26 and 13 months. Longer EWMA values make the approach redundant in terms of identifying cycles because longer EWMAs will create a too long lag and too little focus on the present. The relative short EWMA is needed to be able to spot a change in direction in adequate time. A longer EWMA can potentially remove some of the false turning point signals and missed turning points. Though not employed in the thesis, but still important, one of the strengths of the MACD approach is that a signal mode is available to spot a change in direction. Once the growth in the short term EWMA is larger than the growth in the long term EWMA, it will create an upward movement in the different series, and vice versa.

5.4 Graphical representation
Charts are important in order to correctly understand the relationship between different indicators (Ellis, 2005). To the extent possible the thesis will follow Ellis’ (2005) advice for using only two series in a chart, a proposed cause and effect, to achieve optimal clarity and understanding. In some instances the fluctuation differences between the two series in the graph have been so large that two vertical (y-axis) have been used for better illustration.

5.5 Cross-Correlation Coefficient
The purpose of cross-correlation coefficients (CCCs) is to establish whether statistical significant cross-correlation coefficients between the single indicators and the reference series exist (Choi, 2003). By calculating CCCs, the thesis is able to accurately determine leads and lags by measuring the strength of the co-movement between the two series (Niemira and Klein, 1994). The correlation value ranges between -1 (perfectly negative) and 1 (perfectly positive) where high positive and negative numbers within this range signals a high cross-correlation with either movement in same or opposite direction. The highest CCC value, either positive or negative, is determined to be the most likely lead or lag. For example, if the highest CCC value is at $t_{-5}$, then on average the first series leads the second series with five periods. A major benefit of this approach is that it shows whether the results are statistically significant, which in itself does not prove anything but nonetheless suggests a definite relationship. One must not forget that high CCCs should never be thought of as suggesting causality (Niemira and Klein, 1994). Instead, it is plainly a measure of strength of co-movement between the time series.
While graphical representation of historical relationships between individual indicators and relevant reference series is useful for understanding, it is not an accurate way to assess relationships between variables. Combining visualization with CCC analysis will create a better and more conclusive understanding of the potential lead or lags between the time series (Choi, 2003). The fact that peaks often have longer leads than troughs can distort the CCC results by averaging the lead of peaks and troughs (Lahiri and Moore, 1991). This can confuse the researcher as CCCs will show shorter (longer) leads before peaks (troughs) than what is expected from graphical representation and economic intuition. However, CCC is still very useful and gives a good approximation of leads and lags.

One has to acknowledge that when identifying CCCs, it is crucial that the time series is stationary so that the mean and variance of the time series do not differ during the observed period (Shim, 2000; Choi, 2003; Gujarati and Porter, 2009). A traditional approach to be certain that the time series are stationary is to take the first differences. However, as both RoC and MACD are employed, any trend in the data is removed. To control this, a stationary test is performed, the Augmented Dickey-Fuller test, on selected time series. The tests show that the time series are stationary.

To calculate CCCs, the statistical program SPSS is used, which is recommended by Choi (2003). The program applies the following function in its calculation of CCCs of lag $v$:

$$
\hat{\rho}_{xy}(v) = \left\{ \frac{\sum_{t=1}^{n-v}(x(t) - \bar{x})(y(t+v) - \bar{y})}{\sqrt{\sum_{t=1}^{n}(x(t) - \bar{x})^2 \sum_{t=1}^{n}(y(t) - \bar{y})^2}} \right\}_{v = 0, \ldots, n-1} \left\{ \hat{\rho}_{yx}(-v), \right\}_{v = -(n-1), \ldots, 0}.
$$

In the calculation of CCC, a confidence interval of 95% is applied, illustrated in the graphs of appendix 4.3 by the upper and lower bound lines. These lines have values of around -0.1 and 0.1. However, due to the MACD method applied to the time series, high correlation among the variables is expected, which is why the thesis will only report the single highest CCC and CCC intervals with larger than 0.5 or -0.5 values. CCCs above +0.5 are considered to be high (Sutomo & Irawan, 2005). 30 months of potential lags and leads is chosen, because some indicators, like financial indicators, can have long lead times. Output from SPSS contains both a table of CCC values of the 30 lags and leads along with a graphical illustration.
5.6 Determining turning points

There exist a wide range of different methods to identify and date growth business cycles (Niemira and Klein, 1994; Christoffersen, 2000). To adjust for short business fluctuations it is necessary to adopt some guidelines to be certain that the business cycle fluctuations are significant enough to be classified as a growth business cycle. Many rules exist and the following guidelines are used: the series must alternate peaks and troughs, at least three consecutive up- or downward movements, at least 15 months duration of a cycle (peak to peak or trough to trough) (Niemira and Klein, 1994; Shim 2000; Choi, 2003; Christoffersen, 2000; NBER, 2012). These rules are applied to the MACD adjusted time series to identify turning points of the reference series for the general economy and for the three reference series for the cases. It is also applied to the leading composite indices.

The MACD and RoC approaches will by intuition identify turning point peaks and troughs before traditional measures since these approaches identify growth business cycle turning points where a drop in growth (while still being positive) will show a turning point peak, whereas only a drop in level will show a turning point peak for traditional business cycle identification. As an example consider when the growth of the economy falls from two to one percent, and then from one to two percent. This can be identified as a growth turning point but not a classical turning point.

A decision-rule system can be created to screen for fake signals. A simple and helpful rule for spotting and screening turning points in the economy and in industries is to look for two or more consecutive months of declines or increases of the composite index (Niemira and Klein, 1994). The level of accuracy in these predictions of turning points is increased when going from 2 to 3 months and when adding a threshold criterion (Niemira and Klein, 1994).
6- Identification of economic indicators

The literature review presents how a variety of factors are proposed as initiators and propagators of the business cycle (cf. section 3). From the outset, most of the factors being considered are macroeconomic in nature, and some of them have the ability to be made industry-specific (Niemira and Klein, 1994). In the conclusion of the literature review (cf. section 3.12), it is demonstrated that there are some well-established notions that most economists, independent of their school of thought, believe is true. These notions revolve about the broad categories of economic variables, and therefore they can serve as a means for grouping the proposed indicators. The three case industries are the auto industry, the construction sector and the semiconductor industry. The selection of case industries is elaborated upon in section 7.5.

6.1. Real economic variables

The number of variables that one can investigate within this section is numerous. The supply side concerns variables related to industries on the upstream from the target industry. Austrians refer to these as higher order industries (cf. section 3.11). These variables have to do with what is related to the target industries. There is little consensus on what variables to select from the upstream industries, as they all have their pros and cons. Investment activity along with new orders, undoubtedly, will have the longest lead, but is also the furthest removed from actual delivery to the target industry, while measures such as sales and shipping are more reliable but also closer. Also investments can be made on false assumptions, and therefore never turn into actual demand. Thus one faces a tradeoff between lead length and reliability. Ideally, as is the case for the coincident index, the reference series of the whole economy, the thesis would want a measure that could capture overall activity of the economy or the case industries (Laytan and Banerji, 2004). It is difficult to identify higher order variables on the macro level because the macro index encompasses the entire economy, and therefore there is no part of the supply side that is excluded. For the three cases, a leading index is identified that encompasses the activity in the primary metals and the steel industry, which are believed to be important for both the construction and the automobile industry. These variables will be employed for these two industries.

As Real Business Cycle theories explains, shock to an important input source can effectively alter the production of companies. The focus on oil stems from the oil crises in the 1970s, and the fact that oil continues to be an important factor in the economy. Therefore, it is argued that oil is still relevant as an indicator today. The price of oil will be analyzed if it can be used as a leading indicator.
The demand side affects all variables related to the downstream industries, which are industries that are buyers to the target industries. They are also referred to as lower order industries by the Austrian school (cf. section 3.11). Ellis (2005) finds that consumer spending often leads production of goods with around six months, and that production will lead capital spending by another six months, wherefore it altogether takes consumer spending around 12 months to reach capital spending. It would be preferable with data that covers the broad activity of the case industries. But since some of the case industries are at the final stage of production, one has to suffice with sales data on final consumers, which in the case of end consumers seems sufficient (Ellis, 2005). Downstream demand is relevant whether it is in the form of another industry or the end purchaser of the product. While Keynes initially focused on consumption volatility, his follower, the Neo- and Post-Keynesians are more willing to recognize that consumption volatility also played a significant role (Niemira and Klein, 1994). Based on this, retail sales and personal consumption expenditure (PCE) are identified as leading indicators of the overall economy, and furthermore the thesis is able to identify variables for these indicators in each of the three industries.

Another possible valuable measure on the macro level is new orders of manufactured goods that also deal with demand. Although it may seem contradictory that business cycles can be driven from both the supply side and the demand side, one must recognize that this is the consensus among many economists today, at least the ones that adhere to the New Keynesian school of thought (Knopp, 2010). Therefore, the earlier notion of adhering to only one of these sides can be disregarded as somewhat antiquated today.

6.2 Wages, prices and labor

Wages and prices are the source of respectively labor market and goods market frictions, and are therefore important variables in all Keynesian theories. Both real and nominal wages are argued to vary over the business cycle. Although the Keynesian notion is that countercyclical real wages leads to involuntary unemployment, subsequent evidence shows that in the entire post WW2 era, real wages have been slightly procyclical, which also is the stance the thesis adheres to in light of the evidence (cf. section 3.4).

Furthermore, costs play an important role in determining whether and how much a company chooses to produce (Knopp, 2010). Both nominal wages and average workweeks of employees can be considered short term measures of the demand for labor. First workers are asked to work more, and subsequently companies cave into their demands for a higher wage. A longer term measure, the Employment Trend Index, is available for the macro perspective, and is considered as a possible leading indicator.

6.3 Expectations and sentiments

These variables come in many different forms, and can be more or less tangible. Expectations are mostly important for their ability to steer managerial action (Baumohl, 2008). Just like the aforementioned real
variables, they can also concern either the supply side or the demand side (Knopp, 2010). Among the most used on the supply side is the Purchasing Managers Index, which is an index surveying the future procurement intentions of goods manufacturing companies. On the demand side, one can also identify indicators that measure the sentiment of consumers. Therefore the Consumer Confidence Index is included. Many actions by managers are driven by future profit expectations. If they expect profits to improve they may consider expanding, whereas if they expect profits to decline they may consider closing down some activities. This was described very early in the work of Mitchell (1946), who noted the procyclical nature of profit margins. It is however not only the expectations of managers themselves that determine their actions, but also the expectations of the markets in general, and the expectations of consumers. Keynes describes this very directly, and notes that it is expectations more than anything else that causes volatility in investment demand. He uses the stock market as an example, and today the stock market is perhaps even more influential than it was during the Great Depression. The stock market is one of the most used predictors of economic activity (Bodie et al, 2009). Today, indices are very closely followed, and a number of industry specific stock indices of a more or less official scale exist. While these indices are not traded in themselves, they are constituted of heavily traded stocks, which make these indices appropriate on the same level as for example the S&P 500 index.

6.4 Monetary variables

The most influential theories today recognize the importance of including money supply in an analysis of business cycles. Monetary variables are very applicable as they are mostly released by a single source, the central bank of a particular country. Empirical findings discussed in the literature review states that it is changes to the money supply rather than its actual level that is a good predictor of economic activity (Knopp, 2010). It is important to capture the money that is in circulation in the economy, and therefore the widely used M2 measure of the money supply is employed. This is also the measure applied by the conference board (see appendix 2, list of CB leading indicators).

Interest rates are the price of time. As with any price measure, it can reflect both supply and demand. The single level of the single interest rate may be a function of many factors, but the relationship between short term and longer term interest rates says more about financial markets’ expectations for the future. Longer terms interest rates are generally a reflection of what future short term interest rates are expected to be, and therefore the higher the longer term rates are relative to the shorter term rates, the better the economy is expected to become going forward (Ang et al 2003). From Wicksell’s natural rate hypothesis it is known, as well as the broader monetary overinvestment theory, that too low an interest rate causes
overinvestment (cf. section 3.3.5). This is also the main contention of Austrians scholars. Therefore, the yield curve is included as the indicator shows the influence of the interest rate on the economy, and expects it to be pro-cyclical in relation to the business cycle. Interest rates on a sector level are included when relevant.

6.5 Financial variables

The thesis separates the variables of financial intermediaries from the financial variables that concern the state, thus acknowledging the distinction that is also made in the newer Keynesian financial theories (cf. Section 3.10). As explained in the literature review, banks and other financial intermediaries do not always respond in the way monetary policymakers intend for them to do. If this is the case, there is no need for separating these groups of variables, but with the knowledge that they do in fact differ, it is appropriate to separate monetary and financial factors (Knopp, 2010).

While macroeconomic interest rates are generally thought of as a measure of the demand for money, interest rates offered by banks and finance companies can exhibit other properties. Companies often finance part or all of the consumers’ purchases when it comes to large purchases of durable goods, such as houses and automobiles. For these variables the thesis expects a negative relationship, as these finance companies become more worried that they will not be paid when the economy is in turmoil. Accordingly, these companies may raise their interest rates or alternatively not lend at all (cf. Section 3.10). In both the construction and the auto industry final customers often finance a large part of their purchase through lending. Thus, both the interest rate on auto loans and home mortgages are considered as leading indicators for the respective industries.

6.6 Identified economic indicators

Table 6.1 lists the identified economic indicators with inspiration from both the literature review and the Conference Board, as discussed above. A list of the full names of the economic indicators with additional info is found in appendix 4.1 for the macro-level and appendix 5.1, 6.1 and 7.1 for the meso-level.
### Table 6.1: List of economic indicators

<table>
<thead>
<tr>
<th>Economic Indicators</th>
<th>U.S. Economy</th>
<th>Auto</th>
<th>Construction</th>
<th>Semiconductor</th>
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<tr>
<td><strong>Real supply</strong></td>
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<td>Oil price</td>
<td>Steel/Primary metals</td>
<td>Steel/Primary metals</td>
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<td>Auto inventory to sales ratio</td>
<td>Sales of new One family houses</td>
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<td>PCE</td>
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<td>PCE computers</td>
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<td>New orders in manufacturing</td>
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<td><strong>Wages, prices, labor and costs</strong></td>
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<td>RHE in manufacturing</td>
<td>RHE in construction</td>
<td>RHE in manufacturing</td>
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<td>Employment trend</td>
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<td>AHE construction</td>
<td>AHE semiconductors</td>
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<td></td>
<td>AW auto</td>
<td>AW construction</td>
<td>AW semiconductors</td>
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<td>Semiconductor capacity utilization</td>
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<td>Output per employee in manufacturing</td>
<td>Output per employee in manufacturing</td>
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<td><strong>Expectations and sentiments</strong></td>
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<td>PMI</td>
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<tr>
<td>S&amp;P 500</td>
<td>Stock index for automobiles and parts companies</td>
<td>Stock index of construction supplies and materials companies</td>
<td>Stock index for semiconductor companies</td>
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<tr>
<td>Consumer Confidence Index</td>
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<td>Housing starts</td>
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<td>New home mortgages effective interest rates</td>
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7 - Empirical analysis

7.1 Introduction

The main purpose of this empirical analysis is to identify leading economic indicators based on economic theory for both the macro- and meso-level, and combine these indicators in leading composite indices. When selecting economic indicators according to business cycle theory one can achieve better results, also on an individual business- or industry-level (Duus, 1999; Niemira and Klein, 1994; Choi, 2003). When theory is combined with practical considerations in identifying economic indicators, the best results can be achieved (Niemira and Klein, 1994). Consequently, the identified economic indicators from business cycle theory, described in section 6, are analyzed in the light of inspiration from economic indicators used by institutions working with business cycle analysis such as The Conference Board with their Leading Economic Indicator Composite Index (LEI), Coincident Economic Indicator Composite Index (CEI) and Lagging Economic Indicator Composite Index.

It becomes clear that the indicators applied have a sound theoretical basis. Trial and error have to some extent been applied to separate useful and non-useful economic indicators. The reason that a trial and error process is necessary is that an indicator that theoretically should lead another series often does not (Niemira and Klein, 1994). Explanations for this includes poor quality of the data applied and flawed theory (Niemira and Klein, 1994). This is why it is often best to apply economic theory with some caution in the identification process as the theoretical links of causality can be difficult to prove (Niemira and Klein, 1994). A high degree of flexibility is needed in identifying and choosing economic indicators because no data series are perfect and compromises are often necessary (Niemira and Klein, 1994).

The identified indicators are analyzed in relation the effectiveness of the indicator. For an economic indicator to be considered effective and to be included in a leading composite index, the indicator must show capabilities of leading the economy or the particular industry. This is done in agreement with Choi (2003), who stresses the need for statistical accuracy in the selection process, which is why cross-correlation coefficient (CCC) analysis is included to measure the effectiveness of each indicator.

The thesis follows the recommendation by Ellis (2005) and Niemira and Klein (1994) that it is important to establish if each economic indicator has an expected timing relationship with the reference series rooted in economic sense, and that this relationship is proven over repeated cycles. This is assessed by historically graphing each individual indicator with the reference series. It is of great importance to determine the
relationship between the macro indicators and the reference series because lagging indicators can deceive the unaware if believed to be leading and distort the usefulness of a composite index (Ellis, 2005). A conclusion to each macro indicator will decide if the indicator is relevant enough to be included in the leading composite indices.

The empirical analysis is divided into two parts, a macroeconomic part and an industry part, see figure 7.1. In the macroeconomic part, macroeconomic indicators are analyzed with the goal of creating a leading macroeconomic composite index. A target of 10 useful macroeconomic indicators is pursued with inspiration from the Conference Board’s Leading Index. The industry part analyzes industry specific economic indicators in order to construct three leading industry indices containing both industry and macroeconomic indicators. Five industry indicators, for each of the three case industries, are to be selected. One can argue for using more or less than 10 macroeconomic indicators or more or less than five industry indicators, but the sum of 15 indicators can create well diversified indices that do not rely too much on one single indicator. Adding more indicators can distort the criteria of being easy to understand and practical to use.

Table 7.1: Empirical analysis overview

<table>
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<th>Empirical analysis</th>
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<td>Macro part</td>
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<td>Macroeconomic indicators</td>
<td>Creating a leading macroeconomic composite index</td>
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<td>Industry part</td>
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<td>Industry selection</td>
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<tr>
<td>Industry economic indicators</td>
<td>Creating leading industry composite indices</td>
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</table>
7.2 Macroeconomic indicators

7.2.1 The reference series for the U.S. economy

A reference series for the overall activity of the U.S. economy is needed to compare different economic series’ relationships with economic activity. A single series of economic activity like quarterly GDP is not a sufficient measure of economic activity (Laytan and Banerji, 2004). Instead an index of measurements like employment, sales and income has greater potential of capturing the swings of economic activity (Laytan and Banerji, 2004). Further, Boehm and Summers (1999) believe that an index is less affected by revisions or changes than a single series. Consequently, the thesis has chosen to use The Conference Board’s Composite U.S. Index of Coincident Economic Indicators (CEI). The index contains four data sets that are supposed to be very closely related to changes in economic activity, see appendix 2. The index is released on a monthly basis which fits well with the other time series of this thesis as the thesis generally focuses on monthly data. The CEI is an excellent benchmark for the current state of the aggregate economy and the current stage of the aggregate business cycle so when economic activity picks up then the CEI rises simultaneously (Bauhmohl, 2008).

To substantiate the above argument a strong correlation must be present between the two data sets. The CEI is published monthly while GDP is released quarterly, so to compare the two data sets the CEI has been adjusted to quarterly figures. A correlation between the two data series is found to be 0.92 which is sufficiently close to 1 to be considered a very good proxy. Graph 7.2.1 supports this since the two time series follow each other.

Graph 7.2.1: Real GDP, coincident index and official U.S. Recessions (nber.org)
7.2.2 Retail sales

This indicator measures the change in monthly retail sales. Retail sales are relevant because it represents one third of personal consumption expenditure (PCE) which accounts for two thirds of all economic activity (Baumohl, 2008). Retail sales have the disadvantages of only showing sales of goods, not services which accounts for two thirds of PCE and revisions can be substantial. Belongia and Garfunkel (1992) find that this indicator leads peaks with four months and troughs with two months, while other researchers find this indicator to be coinciding with the economy (Duus, 1999).

Graph 7.2.2 depicts the development of retail sales and the reference series of economic activity. The graph clearly shows that retail sales lead economic activity with some months both during peaks and troughs. CCC analysis is conducted to establish whether this observed pattern can be confirmed. CCC reveals that retail sales on average are likely to lead economic activity with 3 months, $t_{-3}$ (CCC of 0.901). 0.901 is a strong cross-correlation and the interval $t_{-5}$ to $t_{+11}$ has values above 0.5 (see appendix 4.3). (Upper bound, 0.901, -10 to 17 (0,1), 23 to 30 and -15 to -30 (-0,1)).

One might argue that the inclusion of retail sales is not necessary when PCE is also included. However, retail sales can improve diversification and have confirmative attributes. The presented evidence of retail sales’ forecasting abilities of economic activity does that the indicator will be included in the leading macro-index.

Graph 7.2.2: Timing relationship between the U.S. economy and retail sales
7.2.3 Personal consumer expenditure

This indicator measures the change in personal consumer expenditure (PCE) and it is a very important indicator as it drives two thirds of the U.S. economy (Ellis, 2005; Baumohl, 2008). PCE is the cornerstone of the economy and the key driver of the majority of other economic series (Ellis, 2005). PCE is a more comprehensive measure than retail sales since it includes services which accounts for 60 percent of spending (Baumohl, 2008).

As anticipated, graph 7.2.3 confirms that PCE leads the economy. The lead is clearest in terms of turning point peaks and the lead is less clear regarding troughs. The cross-correlation coefficient analysis backs this argument with an average lead-time of $t_{lag}$ (CCC of 0.874). A cross-correlation of 0.874 is a very high cross-correlation. Further, the interval $t_{lag}$ from $t_{lead}$ has cross-correlations values above 0.5 (see appendix 4.3). It is surprising that PCE only on average leads the economy with three months, given the findings of Ellis (2005), but it can be due to PCE’s strength in predicting peaks compared to troughs (cf. graph 7.2.3). The CCCs are averages of both peaks and troughs, and given that peaks normally have better predictive power than troughs, it can explain the surprising results (Niemira and Klein, 1994).

The empirical findings of the CCC, graphical representation and intuition support the inclusion of PCE in a leading macro-index. PCE will be included in thesis’ leading macro-index.

Graph 7.2.3: Timing relationship between the U.S. economy and PCE
7.2.4 Total value of orders of manufacturing goods

This indicator shows the development of new orders in the manufacturing industry, and can consequently give hints of the total production of manufactured goods in the coming months. This indicator is a popular indicator because manufacturing reacts fairly quickly to the ups and downs of the business cycle (Baumohl, 2008). Research by Belongia and Garfinkel (1992) assess that this indicator leads peaks with two months and troughs with zero months.

The expected graphical illustration of new orders in manufacturing and general economic activity is showing two rather coincident series, perhaps with manufacturing leading the economy with a few months, as shown in graph 7.2.4. This is confirmed by CCCs that establishes that new orders in manufacturing on average lead the economy with one month, t, (0.910). 0.910 is a very high cross-correlation coefficient, which is not surprising, since manufacturing production is a part of the reference series, the CEI. The interval between t, to t, has values above 0.5, which illustrates that new orders of manufacturing are a rather coincident indicator (see appendix 4.3). It is a bit unexpected that new orders in manufacturing do not lead the economy more because it takes time before the signing of a contract turns to actual production (Lahiri and Moore, 1991). If production managers tries to and succeeds at anticipating demand by setting production to their expectations, then the short lead is explained. The conclusions from economic intuition, graphical illustration and CCC analysis do not support to include new orders of manufacturing in the leading macro-index.

Graph 7.2.4: Timing relationship between the U.S. economy and new orders of total manufacturing

![Graph showing the timing relationship between the U.S. economy and new orders of total manufacturing.](image)
7.2.5 Real hourly earnings

This indicator measures the change in real hourly earnings (RHE) of American workers. Some people consider real hourly indicators as the best indicator to predict PCE because it is the largest single contributor to personal income (Ellis, 2005). Wages contribute to 56 percent of all personal income (Baumohl, 2008; Ellis, 2005). People need a constant reliable stream of income to be able to consume. If this stream of income increases (decreases) so will spending and thereby economic activity (Baumohl, 2008).

Graph 7.2.5 depicts the relationship between real hourly earnings and economic activity. The graph does not find a clear relationship for the whole period, but RHE do in some instances lead economic activity. CCCs are more conclusive than graphical representation, and find that on average the most likely lead time is eight months, $t_a (0.434)$ (see appendix 4.3). The CCC relationship between earnings and PCE is also investigated, and the results show that RHE leads PCE with four months, $t_a (0.451)$, which is expected in relation to PCE leading the economy with three months.

Although graphical representation does not clearly support including real hourly earnings in a leading macroeconomic index, the other parameters strongly support the presence of the indicator in the index.

**Graph 7.2.5: Timing relationship between the U.S Economy (left-axis) and real hourly earnings (right-axis)**
7.2.6 The Employment Trend Index

This indicator shows the trend of employment. It is very important for a country whether jobs are being created or destroyed, both politically and economically (Baumohl, 2008). The Employment Trend Index aggregates eight labor market indicators. For a list of the eight labor market indicators see appendix 2. The rationale behind The Conference Board’s index is to filter out noise of individual indicators and show the underlying unemployment trend more clearly (Conference Board, 2012).

Graph 7.2.6 shows that the Employment Trend Index moves in accordance with the economy. In some occasions the index leads the economy. The CCC analysis finds that the average lead time of the Employment Trend Index is two months, \( t_{-2} \) (0.865). The interval between \( t_{-6} \) to \( t_{+10} \) has values above 0.5 (see appendix 4.3). Regarding the discussion of general employment being a lagging indicator, CCCs prove this statement by finding that general employment on average lags the economy with two months, \( t_{-2} \) (0.944). The most significant cross-correlation coefficient between the Employment Trend Index and general employment is a four months lead, \( t_{+4} \) (0.881). The index has predictive power on both the economy and employment.

In response to the above mentioned empirical findings it is decided to include the Employment Trend Index in the leading macro-index in spite of the limited predictive power because a measure of the employment trend is economically important.

Graph 7.2.6: Timing relationship between the U.S. economy and the Employment Trend Index

![Graph 7.2.6: Timing relationship between the U.S. economy and the Employment Trend Index](image-url)
7.2.7 Oil price

Oil has transformed the economy, and today plays an important role both as fuel for transportation and as input into a number of goods and production processes (Renshaw, 1992). Research on the subject also seems to confirm that oil price have a significant impact on the economy, where Renshaw (1992) finds that in every year the US crude oil price has increased by more than 5%, the subsequent year’s GDP growth has been zero or negative. Consequently, a rise in the price of oil is expected to have a negative impact on economic activity. In order to analyze the oil price in relation to the U.S. economy, it has been necessary to inverse the indicator, so that decreases in oil price and increases in economic activity move in the same direction.

Examining the behavior of the oil price over the entire period, one cannot help to notice that there seems to be a change in the relationship between the oil price and economic activity somewhere in the 2000s, see graph 7.2.7. Several researchers have looked into this, and Fan and Xu (2010) find that there are two changes in the 2000s. One is caused by an inflow of cheap credit into the oil futures market in the beginning of the decade, and another change occurs at the onset of the financial crisis, in which all this credit was pulled out of the market again (Fan and Xu, 2010). CCCs find that the most likely lead of the oil price on economic activity is 19 months, $t_{19} (0.317)$. Based on the above evidence, it is decided not to include the oil price in the leading macro index, as the large distortions of the last decade can do more damage than good to the analysis. However it is acknowledged that the oil price has potential as a leading indicator in more stable markets with its impressive CCC lead of 19 months.

Graph 7.2.7: Timing relationship between the U.S. economy (left-axis) and the oil price (right-axis)
7.2.8 The Purchasing Managers Index

The index is based on surveys from purchasing managers in the manufacturing sector (Institute of Supply Management, 2012). Since manufacturing companies need a lot of supplies to have a steady production, the purchasing managers of those companies have a good understanding of how much is going to be needed in the coming months (Baumohl, 2008). Thus, purchasing managers are at the frontier of monitoring activity in the manufacturing sector. The indicator is believed to be the most influential statistic released by the private sector because of its predictive power, its early release and no revisions (Baumohl, 2008).

Graph 7.2.8 shows the visual relationship between PMI and the reference series, the U.S. economy. The graph illustrates clearly the likely predictive powers of PMI because PMI turns several months before the economy in both peaks and troughs. To confirm this visual relationship CCC analysis has been conducted, which unexpectedly finds that PMI on average lags the economy 13 months, $t_{13} (-0.692)$. This finding is unexpected considering that it is believed by financial markets that the indicator has predictive power (investopedia.com). However, a lead of seven months almost has a similar correlation, $t_{-7} (0.625)$. Further, interval values from $t_{+3}$ to $t_{+13}$ and from $t_{-18}$ to $t_{-8}$ are respectively higher and lower than 0.5 and -0.5 (see appendix 4.3). It seems unlikely given both intuition and graphical representation that PMI lags the economy 13 months.

Given the slightly contradicting findings from the graphical representation and CCC, PMI is included in the leading macro-index due to that the seven months lead is almost as significant as the lag. Further, the very high market sensitivity to the American PMI must indicate the usefulness of the indicator (Baumohl, 2008).

Graph 7.2.8: Timing relationship between the U.S. economy (left-axis) and PMI (right-axis)
7.2.9 S&P 500

The S&P 500 is a stock market index based on the stock prices of the top 500 publicly traded American companies. The index is one of the most followed indices and many believe it is one of the best representations of the American stock market and a good indicator of the wellbeing of the U.S. economy (Bodie et al, 2009). The American stock market is considered an efficient market that reacts almost instantaneously to news about anything that may affect the economy (Elton et al, 2011). The NBER classifies the stock market as a leading indicator of business cycles, and it is also used by The Conference Board in their leading index (NBER, 2012; Conference Board, 2012). Lahiri and Moore (1991) consider this indicator to be a long-leading indicator with a lead of more than 12 months at peaks and more than six months at troughs.

Graph 7.2.9 makes it clear that the S&P 500 can predict many of the peaks and troughs of the U.S. economy. This is supported by CCCs where the correlation between the S&P 500 and the U.S. economy is strongest at $t_{15}(0.555)$, meaning that the S&P 500 on average leads the economy with five months. It is not only at $t_{15}$ where there is a high and significant correlation, but also the interval from $t_{2}$ to $t_{8}$ has values above 0.5 (see appendix 4.3). This finding is not completely congruent with the findings of Lahiri and Moore (1991), who found a stronger lead, but it is not contradicting either. The reason for the incongruence is potentially the different data period used, and the averaging of peaks and troughs in CCC calculations.

The S&P 500 index is included as an indicator in the leading macro-index because it shows a good lead time according to graphical representation, CCC, other related studies and economic rationale.

Graph 7.2.9: Timing relationship between the U.S. economy (left-axis) and the S&P 500 (right-axis)
7.2.10 Consumer Confidence Index

The Consumer Confidence Index measures how the American consumer perceives the future, and the indicator is created from the idea that there is value in tracking the mind of a typical American consumer (Conference Board Consumer Confidence, 2012). The indicator has some obvious qualities, but also some disadvantages. The index consistently questions new people, which all things equal will increase volatility compared to recycling respondents (Baumohl, 2008). Additionally, history shows that the correlation between these surveys and consumer spending is not close to one, which might be because the respondents’ answers are rooted in their current situation rather than their future situation (Ellis, 2005). The Consumer Confidence Index is chosen over the Consumer Sentiment Index, as the latter have poorer data availability.

While the index does not have a strong historical record of predicting consumer spending, the index can still possess value in predicting economic activity (Ellis, 2005). Graph 7.2.10 indicates that this is the case, as Graph 7.2.10 shows that the index leads economic activity in both peaks and troughs. CCCs estimate the most likely lead time to be five months, $t_{15}$ (0.786). The interval $t_{1}$ to $t_{13}$ has values above 0.5 (cf. appendix 4.3).

The empirical findings that the Consumer Confidence Index leads economic activity proves the value of the indicator, and the indicator will consequently be included in the leading macroeconomic composite index.

Graph 7.2.10: Timing relationship between the U.S. economy (left-axis) and the Consumer Confidence Index (right-axis)
7.2.11 Housing starts

This indicator measures the amount of housing construction starts each month. Housing is very good predictor of economic activity and only once since World War II has housing been strong in a recession which was during the 2001 short-lived recession (Baumohl, 2008). This fact speaks for the merit and consistency of housing. Residential construction is among the first sectors to shut down when the economy nears recession, and it is the first to boom when the economy is in recession, due to the indicator’s sensitivity to interest rates (Baumohl, 2008). Residential construction accounts for only 5% of GDP, but its real impact on the economy is much larger due to the multiplication effect (Baumohl, 2008). The multiplication effect is, for example, that an increase in construction spending will lead to a larger increase in national income.

Lahiri and Moore (1991) consider this indicator to be a long-leading indicator with a lead of more than twelve months at peaks and more than six months at troughs. A study by Belongia and Garfinkel (1992) establish that housing starts lead peaks with 13 months and troughs with three months.

Graph 7.2.11 shows clearly the expected relationship with housing starts leading the economy series in both peaks and troughs. The CCCs support the graphical illustration by finding $t_{\alpha}$ (0.755) as the period with the most significant lag, meaning that housing starts on average leads the economy by eight months. An eight month lead is consistent with the findings of Lahiri and Moore (1991) since CCC analysis includes both leads and lags. As a result housing starts will be included in the leading macro-index.

Graph 7.2.11: Timing relationship between the U.S. economy (left-axis) and housing starts (right-axis)
7.2.12 Real money supply (M2)
This indicator tracks real money supply (m2). The real money supply is the nominal money supply adjusted for inflation. The Federal Reserve can by controlling the real money supply control the federal funds rate (discount rate) and thereby the borrowing possibilities in the economy (Baumohl, 2008). The federal funds rate is the rate at which banks borrow from The Fed. When the Fed feels that the federal funds rate needs to be lower, they buy bonds and push cash in the system (Bodie et al, 2009). Lahiri and Moore (1991) consider this indicator to be a long-leading indicator with a lead of more than twelve months at peaks and more than six months at troughs. A study by Belongia and Garfinkel (1992) confirm these results, and conclude that this indicator leads peaks with 16 months and troughs with three months.

Graph 7.2.12 clearly shows the expected relationship between economic activity and the real money supply from 1975 to approximately 1990 where money supply leads economic activity. From 1990 and onwards the relationship is less clear. CCC analysis calculates that the real money supply on average leads the economy with ten months, $t_{10}$ (0.351). A lead of ten months fits with the findings of Lahiri and Moore (1991) and Belongia and Garfinkel (1992) since both leads and lags are included in CCC.

The conclusions from economic intuition, charting and CCC analysis speak for the inclusion of the indicator in the leading macro-index.

Graph 7.2.12: Timing relationship between the U.S. economy and the real money supply
7.2.13 Yield curve

The yield curve, also known as the interest rate spread, shows the expectations of investors for the future short-term interest rates (Fed funds rate) compared to the long-term interest rates (10 year Treasury bonds) (Ang et al, 2003). A large (small) difference between short- and long-term interest rates will result in a high (low) yield curve value, and it suggests that short-term interest rates will increase (decrease) in the future (Ang et al, 2003). The yield curve is regarded as an excellent predictor of economic activity with a good historical track record (Baumohl, 2008; Ellis, 2005; Ang et al, 2003). A technical advantage of the yield curve is that it is not produced by any government bureau of private organization, but is directly taken from financial markets, which should reflect the collective knowledge of all investors (Bodie et al, 2009).

Graph 5.1.17 supports the claim that the yield curve has excellent predictive power of the U.S. economy with a significant lead time. Also, the claim is strongly justified by CCC where the most likely lead time of the yield curve is 16 months, $t_{16}$ (0.628, see appendix 4.3). The interval from $t_{-25}$ to $t_{-17}$ and from $t_{+9}$ to $t_{+24}$ has correspondingly lower and higher values than -0.5 and 0.5.

These findings recommend including the indicator in a leading macro-index.

Graph 7.2.13: Timing relationship between the U.S. economy (left-axis) and the yield curve (right-axis)
7.3 Creating a leading macroeconomic composite index

7.3.1 Justification and procedure
The reason for choosing to make a composite index instead of using a single indicator is that Burns (1961) discourages the use of a single indicator for prediction and identification of turning points. He encourages combining several indicators into a composite index. The index approach has proven to be more useful than the single indicator approach (Burns, 1961; Niemira and Klein, 1994). Further, individual indicators can be very sensitive to random short-lived shocks, but by using a composite index this disadvantage of individual indicators will be reduced considerably (Choi, 2003). The chosen indicators are considered to be well diversified and cover the most important aspects of the economy, as argued in the previous section. The more comprehensive and diversified included economic indicators, the more effective the composite index will be (McGuckin et al, 2003).

Having found the economic indicators to include in the leading macroeconomic composite index, the next step is to pick a method for creating the index. The Department of Commerce and The Conference Board apply the same approach for the creation of their composite indices (Conference Board Index, 2012). The same approach will be used in this thesis, just with some minor modifications, as emphasized in the following. The reason for choosing this approach is because it assigns weights to the time series based on volatility. Volatility adjustment is very important due to the fact that if this is not done, then too much weight will be put on series with high volatility relative to those series with low volatility (Filardo, 2004). Another benefit of this approach is that it is relatively simple to use, and it is easy to make adjustments and optimizations. Thus, the approach is viable for replication. Below in step 3, the modification is done by using the CCCs results to assign weight to the applied economic indicators. This is done by giving a higher weight to indicators with superior leading capabilities. It is rather common to assign weights according to a more subjective character, which is done in step 3 (Conference Board, 2012). What is done in step 3 has an objective nature in weighting from statistical analysis, but the selection of the three weight intervals is subjective. Step 3 covers this adjustment. The remaining steps are similar to the standard approach.

The complete employed approach is outlined below with inspiration from the Conference Board (Conference Board Index, 2012) and Niemeria & Klein (1994):

**Step 1: Month-to-month changes for each indicator.** If the indicator is not in percent change form, a symmetric alternative to the conventional percent change formula is used: \( x_t = 200 \times (X_t - X_{t-1})/(X_t + X_{t-1}) \).
If the indicator $X$ is in percent change form or an interest rate, simple arithmetic differences are calculated:

$$x_t = X_t - X_{t-1}.$$

**Step 2: The monthly contributions of the indicators are adjusted to the volatility of each indicator.**

Standard deviations $v_x$ of the changes in each indicator are computed. The volatilities are inverted ($w_x = 1/v_x$), the total sum of volatility is calculated ($k=\text{sum over } x\{w_x\}$), and they are restated so the index's indicators weights sum to one ($r_x=(1/k) \times w_x$).

**Step 3: The monthly contributions of the indicators are adjusted to each indicator's individual CCC.**

Indicators with an average CCC lead below five months are given a weight of 0.5. Indicators with an average CCC lead larger than five but lower than 10 are given a weight of 0.75. Finally, indicators with an average CCC lead above or equal to ten months are given a weight of 1. The total sum is calculated, and they are restated so the index's indicators combined weights sum to one ($r_x=(1/k) \times w_x$). The calculated final weights are multiplied with the monthly contributions.

**Step 4: Merge the weights of volatility and CCC.** The two weights are merged by multiplying the weights of each indicator, the total sum is calculated ($k=\text{sum over } x\{w_x\}$), and they are restated so the index's indicators weights sum to one ($r_x=(1/k) \times w_x$). The calculated final weights are multiplied with the monthly contributions.

**Step 5: Calculate the adjusted monthly contribution across the indicators for each month to acquire the growth rate of the indices.** The outcome of this step is the sum of the adjusted indicators ($i_t=\text{sum over } x\{m_{x,t}\}$) which is the monthly growth rate of the index.

**Step 6: The growth rates of the composite index are adjusted to equate the trend to the coincident index.** This is accomplished by adding an adjustment factor, $a$, to the growth rates of the index each month ($i_t'=i_t+a$). For example, the trend adjustment factor for the leading index is computed by subtracting its average monthly growth rate (sum over $[t]$ $i_t$/$T$ where $T$ is the number of observations in the sample) from the average monthly growth rate of the coincident index.

**Step 7: The level of the index is calculated applying the symmetric percent change formula.** The index is calculated starting from an initial value of 100 for the first month of the sample period (i.e. January 1974). The first month's value is $I_1=100$. The second month's value $I_2 = I_1 \times (200 + i_2)/(200 - i_2)$.
Step 8: The index is adjusted according to the MACD approach. This final step is carried out to achieve consistency and comparability with the other sections of the thesis. It is a necessary step to undertake in order to show the cyclical growth changes clearly.

Table 7.3.1 shows the economic indicators included in the Leading Macroeconomic Composite Index (LMCI). Relevant information is summarized in the table such as most significant CCC, standard deviation and the weights used to create the composite index. The large volatility differences assign very low weights to some volatile indicators, but it is deemed necessary.

Table 7.3.1: List of economic indicators in the leading macroeconomic composite index

<table>
<thead>
<tr>
<th>Indicator</th>
<th>CCC lead</th>
<th>CCC weight</th>
<th>Standard Deviation</th>
<th>Volatility weight</th>
<th>Total weight</th>
</tr>
</thead>
<tbody>
<tr>
<td>LEI</td>
<td>3</td>
<td>6.9%</td>
<td>0.76</td>
<td>11.0%</td>
<td>7.4%</td>
</tr>
<tr>
<td>Housing Starts</td>
<td>8</td>
<td>10.3%</td>
<td>7.96</td>
<td>1.0%</td>
<td>1.1%</td>
</tr>
<tr>
<td>Employment Trend Index</td>
<td>2</td>
<td>6.9%</td>
<td>1.13</td>
<td>7.4%</td>
<td>4.9%</td>
</tr>
<tr>
<td>PCE</td>
<td>3</td>
<td>6.9%</td>
<td>0.51</td>
<td>16.2%</td>
<td>10.9%</td>
</tr>
<tr>
<td>Consumer Confidence Index</td>
<td>5</td>
<td>10.3%</td>
<td>8.73</td>
<td>1.0%</td>
<td>1.0%</td>
</tr>
<tr>
<td>Real Hourly Earnings</td>
<td>8</td>
<td>10.3%</td>
<td>0.31</td>
<td>26.8%</td>
<td>27.0%</td>
</tr>
<tr>
<td>PMI</td>
<td>7</td>
<td>10.3%</td>
<td>4.87</td>
<td>1.7%</td>
<td>1.7%</td>
</tr>
<tr>
<td>S&amp;P 500</td>
<td>5</td>
<td>10.3%</td>
<td>4.59</td>
<td>1.8%</td>
<td>1.8%</td>
</tr>
<tr>
<td>Real Money Supply</td>
<td>10</td>
<td>13.8%</td>
<td>0.45</td>
<td>18.6%</td>
<td>24.9%</td>
</tr>
<tr>
<td>Yield Curve</td>
<td>16</td>
<td>13.8%</td>
<td>0.58</td>
<td>14.5%</td>
<td>19.4%</td>
</tr>
</tbody>
</table>

7.3.2 Predictive abilities

Graph 7.3.1 clearly shows that the Leading Macroeconomic Composite Index (LMCI) leads the economy with several months. Graphical representation suggests that the composite index works as planned. This is further proved by CCCs that find that the LMCI on average leads the economy with six months, $t_{-6} (0.883)$. A cross-correlation coefficient of 0.883 is satisfyingly high. The interval from -3 to 18 has values above 0.5 (see appendix 4.3). A lead of six months is indeed useful in relation to predicting business cycle turning points.

Table 7.3.2: CCCs performance comparison of the LMCI and the Conference Board’s LEI

<table>
<thead>
<tr>
<th></th>
<th>LMCI</th>
<th>CB’s LEI</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lead</td>
<td>6</td>
<td>3</td>
</tr>
<tr>
<td>CCC of lead</td>
<td>0.923</td>
<td>0.883</td>
</tr>
</tbody>
</table>
Knowledge of a business cycle turning point six months in advance can provide a company, government or investor with a significant advantage (Choi, 2003). However, to be certain that the turning points are not false signals, turning point criteria must be put in place (Niemira and Klein, 1994). Without engaging in a long discussion of turning point criteria, an example of such criteria can be that the turning point is followed by 2-3 consecutive months verifying this change in trend (cf. section 5.6). This reduces the lead from six months to 3-4 months. Therefore, it is crucial that the lead is at least a few months larger than the turning point criteria (Niemira and Klein, 1994).

In order to assess if a lead of six months is satisfying for a leading index, a comparison between the LMCI and the Conference Board’s Leading Index of Economic Indicators (LEI) is done in table 7.3.2. CCCs calculations show that the LEI leads the economy with three months, \( t_{3} \) (0.923, see appendix 4.3). A lead of three months is in the low band of what Baumohl (2008) finds, as he finds a lead of 3-9 months. As the same approach is employed in calculating CCCs for the LEI and the LMCI, the results of these two indices are well-suited for comparison. The LMCI outperforms the LEI by having a lead twice as large. In regard to cross-correlation coefficient values of the average leads, the LEI has a slightly higher coefficient with 0.923 against 0.883.

Graph 7.3.1: Timing relationship between the U.S. economy and the LMCI

A comparison of turning points in the leading macroeconomic composite index (LMCI) and the economy is done to show how effective the LMCI is to predict actual turning points in the economy as shown in table 7.3.3. It must be stressed that this is not a very accurate or statistical method of comparing turning points. Further, it is difficult to line up the same cycles, when there is a clear and significant timing relationship.
However, despite these shortcomings valuable information can be extracted such as average cycle duration, average lead for peaks and troughs, and to see when the LMCI gets false signals or miss a cycle. The main points from table 7.3.3 is that on average the LMCI leads the economy with approximately 6.4 months, distributed between 7.4 months for peaks and 5.4 months for troughs. The LMCI has one business cycle more than the economy in this period and some false signals are unfortunately spotted. The LMCI misses one business cycle of the economy. A few turning points are rejected on the basis of the turning points criteria (cf. section 5.6).

The average duration of business cycles of the LMCI is around three years (from peak to peak and from trough to trough). For the economy the average cycle is three years and nine months. The shorter duration of the LCMI is due to the index having two more growth cycles. The index is experiencing around a year later timing of the first turning point and a year earlier timing of the last turning point, which shortens the average duration.

Table 7.3.3: Turning point analysis of the U.S. economy and the LMCI

<table>
<thead>
<tr>
<th>Leading Macroeconomic Composite Index</th>
<th>U.S. economy</th>
<th>Lead (-), Lag (+) or false or miss</th>
</tr>
</thead>
<tbody>
<tr>
<td>Peaks</td>
<td>Troughs</td>
<td>Peaks</td>
</tr>
<tr>
<td>Aug-75</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Jul-76</td>
<td>Jul-80</td>
<td>Apr-77</td>
</tr>
<tr>
<td>Feb-82</td>
<td>Jun-82</td>
<td>Nov-81</td>
</tr>
<tr>
<td>Jan-84</td>
<td>Aug-85</td>
<td>Aug-84</td>
</tr>
<tr>
<td>Apr-87</td>
<td>Aug-89</td>
<td>Jan-89</td>
</tr>
<tr>
<td>Aug-90</td>
<td>May-91</td>
<td>Aug-91</td>
</tr>
<tr>
<td>Feb-93</td>
<td>Jan-94</td>
<td>Jun-93</td>
</tr>
<tr>
<td>Oct-94</td>
<td>Dec-95</td>
<td>Feb-95</td>
</tr>
<tr>
<td>Dec-96</td>
<td>Oct-97</td>
<td>Miss</td>
</tr>
<tr>
<td>Jul-98</td>
<td>Jun-01</td>
<td>Feb-99</td>
</tr>
<tr>
<td>Sep-02</td>
<td>Jun-03</td>
<td>False</td>
</tr>
<tr>
<td>Jul-04</td>
<td>Feb-06</td>
<td>May-05</td>
</tr>
<tr>
<td>Oct-07</td>
<td>Mar-09</td>
<td>Aug-09</td>
</tr>
<tr>
<td>Aug-10</td>
<td>Apr-11</td>
<td>-8</td>
</tr>
</tbody>
</table>

Average lead: -7.4, -5.4
7.4 Industry economic indicators

7.4.1 Introduction

The rationale for doing a forecasting study on the industry level is based on the fact that industry cycles often differ considerably from macroeconomic business cycles (Bundgaard, part 1 6:05). Bain & Company, a corporation of strategy consultants, uncovered that in any recession during the 1980s and the 1990s only around 60% of all industries were actually in a recession (Tan and Matthews 2009).

In the literature review a long list of possible explanations that can explain business cycle fluctuations is found, see table 6.1. In accordance with the recommendations of Niemira and Klein (1994) and Duus (1999), these indicators are made industry specific. To develop a comprehensive list of indicators for the case industries, some trial and error and information from related studies are taken into consideration. This section applies the same approach as employed in the macroeconomic section.

7.4.2 Industry selections

Forecasting is more applicable for cyclical industries than non-cyclical industries (Niemira and Klein, 1994). Durable goods industries are around three times more cyclical than non-durable goods industries in the U.S. (Petersen and Strongin, 1996). As cyclical industries are in greater need of prediction of industry turning points, the thesis concentrates its selection of case industries on durable goods manufacturing industries. The idea behind the case selection is to find three industries that have different characteristics in terms of cyclical movement with the economy. It is interesting to see if these characteristics improve or reduce the usefulness of business cycle forecasting. The objective is to find three industries that have similar relationships to the ones described in graph 4.2.1 with a leading, a coincident and a lagging industry. This approach is suggested by Bundgaard, as a possible way to segment the cases (Bundgaard, part 3 7:15)

It is expected that an industry that lags the economy is best suited to benefit from predicting business cycle turning points, while a leading industry is expected to benefit the least (Niemira and Klein, 1994). The three chosen industries are found by economic intuition and a process of trial and error.

It is difficult to find industries that are significantly leading or lagging as the vast majority of industries’ movement is similar to that of the overall U.S. economy. The auto industry is selected as the leading industry, the construction sector as the coincident industry and the semiconductor industry as the lagging.

The intuition behind selecting construction as the industry representing coincident movement with the economy can seem surprising, since construction both have lagging (non-residential construction) and
leading (residential construction) characteristics (Galegroup Construction, 2012). The argument is made that the two sectors of construction offset each other, which is supported by the fact that construction’s correlation with the economy is very high at 0.94. The selections of the auto industry and the semiconductor industry are based on a trial and error process. The semiconductor industry is slightly lagging the overall economy (cf. section 7.7). The semiconductor industry symbolizes the computer era, and is a crucial part of today’s world (Liu, 2005). The auto industry is leading the economy (cf. section 7.5). It is an interesting industry due to its historical and symbolic value. The auto industry is still indirectly an important part of the U.S economy and a symbol of old fashion production (OECD, 2012).

Reference series of activity are selected for each of the three case industries. The three reference series of the industries are needed to enable comparison of business cycles in the cases with the general economy, and with the industry indicators (Choi, 2003).
7.5 The auto industry

7.5.1 Introduction
The size of the automobile industry is small relative to overall economic activity, but because of the industry’s strong linkages with other parts of the economy, the final impact of the auto industry on the economy is significant (OECD, 2012). Normally, it is expected that the automobile industry moves in line with the business cycle of the general economy, but the industry actually leads the economy. The amplitude of the auto industry’s business cycles is significantly larger than in the economy and other manufacturing sectors (OECD, 2012). This enhances the need of and potential of forecasting in the auto industry (OECD 2012).

7.5.2 Reference series
The reference series of the auto industry is chosen to be industrial production of motor vehicles because it is a good representation of the auto industry and data availability is excellent. Other more obvious time series disappoint in regard to data accessibility and flexibility. As a precaution, it is checked if the auto industry’s reference series have similar cyclical fluctuations as other time series of the auto industry, which it does. Throughout the auto industry analysis, industrial production of motor vehicles is referred to as the auto industry in graphs, text and tables.

7.5.3 Relationship with the economy
The average duration of a business cycle in the auto industry is approximately three years and four months. Thus, there is a shorter average cycle in this industry than in the economy (three years and nine months), meaning that there are additional cycles in the auto industry. These cycles might be industry specific, which offers the possibility that industry indicators can improve forecasting abilities and correctly identify the specific industry cycles. Table 7.5.1 shows a comparison of the business cycles in the U.S. economy and in the auto industry. The table verifies the extra cycles in the auto industry. Combining the average lead of peaks and troughs, the average becomes a lead of 1.8 months. As explained in section 7.3.2, this is not a statistical method of analysis, so precision is not expected or a target. A few turning points are rejected on the basis of the turning points criteria (cf. section 5.6). A high correlation exists between car sales and private consumption in the U.S. and the correlation coefficient has increased significantly in the past decade in the U.S. (OECD, 2012). This can explain why the auto industry slightly leads the economy based on the fact that it was earlier found that consumption to leads economic activity (cf. section 7.2)

Table 7.5.1: Turning Point analysis of the auto industry and the U.S. economy
Automotive Products | U.S. Economy | Lead (-1) or Lag (+) or False or miss
---|---|---
Peaks | Troughs | Peaks | Troughs | Peaks | Troughs
Feb-75 | Aug-75 | - | -6
Aug-76 | May-77 | Apr-77 | -8 | False
Aug-77 | Dec-78 | False | False
Mar-79 | Aug-80 | Oct-80 | False | -2
Dec-81 | Dec-82 | Nov-81 | Dec-82 | 1 | 0
Apr-84 | Apr-86 | Aug-84 | Jul-86 | -4 | -3
Aug-87 | May-88 | False | False
May-89 | Jun-91 | Jan-89 | Aug-91 | 4 | -2
Feb-93 | Jun-93 | Feb-94 | -4 | Miss
May-98 | Dec-98 | Jun-96 | False | -1
Sep-99 | Jun-01 | Feb-99 | Feb-02 | 7 | -8
Feb-03 | May-05 | May-05 | -27 | False
Nov-07 | Jun-09 | Aug-09 | False | -2
Aug-10 | Oct-11 | Apr-11 | -8 | False
Average lead | -2.4 | -1.1

Graph 7.5.1 shows the lead of the auto industry. The argument is supported by CCCs that finds an average lead of 4 months, $t_{-4}$ (CCC of 0.762, see appendix 5.3). Correlation between the auto industry and the economy is 0.64, which suggests that the auto industry is not coinciding with the economy.

**Graph 7.5.1: Timing relationship between the U.S. economy (left axis) and the auto industry (right-axis)**
7.6 Construction

7.6.1 Introduction
The construction sector is notoriously cyclical (HVACR Distribution Business, 2012). The good thing is that the cyclicity of construction is relatively foreseeable (Galegroup Construction, 2012). It is this predictability that is crucial in providing building contractors with some guiding in managing their expectations for their businesses. Construction can be divided into residential construction and non-residential construction. The two markets have different cycles that can accelerate or dampen the overall construction cycle (HVACR Distribution Business, 2012). Normally, residential construction is considered an early industry that leads the economy, while the opposite is true of non-residential construction (HVACR Distribution Business, 2012). Graph 3.5 in appendix 3 illustrates the relationship between residential and non-residential construction, where residential construction leads non-residential. The residential construction industry is very sensitive to changes in economic conditions and financial markets. For example, there is a significant negative correlation between federal interest rates and the volume of new homes under construction (Galegroup Construction, 2012). When the interest rate on mortgages is low, it means that housing starts are high because of increased affordability. In a classic business cycle, residential construction moves upward for two to three years before turning downward as interest rates increase (Galegroup Construction, 2012). As interest rates rise, non-residential construction begins its journey up, and it peaks two years after the overall business cycle, at which point residential construction is starting to move up. Hence, residential and non-residential construction will in theory offset each other, and make total construction to coincide with the economy (Grebler and Burns, 1982). Unfortunately, reality is often much messier than theory. These cycles often heighten the ups and downs of the overall construction sector instead of offsetting each other, making construction output fluctuations very volatile (HVACR Distribution Business, 2012).

7.6.2 Reference series
The construction sector is affected by poor data availability, represented by graph 3.5 in appendix 3 with the starting date of March 1994. To conduct adequate business cycle analysis a more distant starting date is preferred. Therefore, Construction Supplies Production is selected as a proxy for construction because the monthly data of this time series begins in the early 1970s. Construction Supplies Production is the reference series for construction, and it adequately follows the swings in other construction time series. Throughout the thesis, Construction Supplies Production is mentioned as the construction sector.
7.6.3 Relationship with the economy

The average length of a business cycle in construction is two years and ten months. Thus, there is a shorter average cycle in this sector than in the economy. This means that there are additional cycles in the construction sector. Some of these additional cycles must be industry specific, which offers optimism that industry indicators can improve forecasting abilities for the case in question. Table 7.6.1 shows a comparison of the business cycles in both the U.S. economy and in the construction sector, and the table confirms the extra cycles in construction. Combining the average lags of the peaks and troughs, the average becomes a lag of 2.1 months. This is not exactly as expected, but the value is within a range that can be considered coincident (Niemira and Klein, 1994). Turning point analysis is not a statistical way of doing analysis so accuracy is not anticipated or a target, just an overview. A few turning points are rejected on the basis of the turning points criteria (cf. section 5.6).

Table 7.6.1: Turning Point analysis of the construction sector and the U.S. economy

<table>
<thead>
<tr>
<th>Construction Supplies</th>
<th>U.S. Economy</th>
<th>Lead (-1), Lag (+) or False or miss</th>
</tr>
</thead>
<tbody>
<tr>
<td>Peaks</td>
<td>Troughs</td>
<td>Peaks</td>
</tr>
<tr>
<td>Sep-75</td>
<td>Aug-75</td>
<td>-</td>
</tr>
<tr>
<td>Jul-77</td>
<td>Nov-80</td>
<td>Apr-77</td>
</tr>
<tr>
<td>Nov-81</td>
<td>Oct-82</td>
<td>Nov-81</td>
</tr>
<tr>
<td>May-84</td>
<td>Dec-86</td>
<td>Aug-84</td>
</tr>
<tr>
<td>Mar-88</td>
<td>Jan-90</td>
<td>False</td>
</tr>
<tr>
<td>Sep-90</td>
<td>Aug-91</td>
<td>Jan-91</td>
</tr>
<tr>
<td>Mar-93</td>
<td>Nov-93</td>
<td>Jun-93</td>
</tr>
<tr>
<td>Oct-94</td>
<td>Apr-96</td>
<td>Feb-95</td>
</tr>
<tr>
<td>May-97</td>
<td>Dec-99</td>
<td>Dec-96</td>
</tr>
<tr>
<td>Jul-00</td>
<td>Dec-01</td>
<td>Feb-99</td>
</tr>
<tr>
<td>Apr-03</td>
<td>Oct-03</td>
<td>False</td>
</tr>
<tr>
<td>Mar-06</td>
<td>Aug-07</td>
<td>May-05</td>
</tr>
<tr>
<td>Jan-08</td>
<td>Sep-09</td>
<td>False</td>
</tr>
<tr>
<td>Apr-11</td>
<td>Apr-11</td>
<td>0</td>
</tr>
</tbody>
</table>

Average lead: 4.3, -0.1

Graph 7.6.1 illustrates the historical relationship between Construction Supplies Production and the U.S. economy, and from observation it appears that the two time series coincide, and that construction supplies production is more volatile. CCCs support this observation and the most likely lead is at \(t_{0.9} \) (0.957), meaning that the two series strongly coincide. The interval from \(t_{0.8} \) to \(t_{0.9} \) has values above 0.5 (cf. appendix 6.3).
Correlation between construction and the economy is 0.96. The very high correlation supports the argument that construction is coinciding with economic activity.

**Graph 5.6.1: Timing relationship between the U.S. economy (left axis) and the construction sector (right-axis)**
7.7 The semiconductor industry

7.7.1 Introduction

Since its early years the semiconductor industry experienced continuous growth accompanied by significant cyclical swings (Tan and Mathews, 2009). The industry has during the last several decades gone from an insignificant part of the economy to an important part. Today, semiconductors are often referred to as “the crude oil of the information age” (Galegroup Semiconductor, 2012; Liu, 2005). The industry has a reputation of very volatile sales (Galegroup Semiconductor, 2012). An example of volatile sales can be the dot.com crash, which resulted in that semiconductors sales fell from $ 204 billion to $ 139 billion from 2000 to 2001 (Galegroup Semiconductor, 2012).

Historically, the semiconductor industry behaves cyclically as illustrated by graph 7.7.1 (Tan and Mathews, 2009). Both macroeconomic business cycles and industrial dynamics can cause cyclicality in a given industry. Tan and Mathews (2009) find that the cyclical dynamics in the semiconductor industry differ from both the business cycles at the macro-level and the lengthy industrial technology life cycle. Two factors of industry dynamics have increased the cyclicality of the semiconductor industry. The first factor being the short life cycles of many semiconductor products caused primarily by rapid technological innovations. The semiconductor industry is no longer fully dependent on computer sales as the rise of cell phones, tablets and digital televisions have helped diversify the demand (Galegroup Semiconductor 2012; Semiconductor Intelligence, 2012). The second factor for cyclicality in the industry is over-expansion of production facilities in times of strong demand (Tan and Mathews, 2009). Dearden et al (1997) provide a thoughtful reason to why competitive behavior of companies can lead to industry capacity cycles. In an expansion firms in the semiconductor industry tend to invest heavily in added capacity as they see their sales rise. Capacity investment takes time to plan and carry out, which often means that the opening of a new factory takes place when the expansion has halted. When all semiconductor firms have added excess capacity and sales are starting to stabilize or even decrease, then a fierce price competition is likely beginning in order to maintain economies of scale, which is very important in this industry (Tan and Mathews, 2009). This overexpansion of production and related price competition strongly amplifies the cyclicality of the semiconductor sector (Tan and Mathews, 2009). Capital investment in the semiconductor industry follows a pro-cyclical pattern, but firms that follow a counter-cyclical investment plan can reap large rewards (Tan and Mathews, 2009).

These industry dynamics make the semiconductor industry an interesting topic and a challenge in order to predict business cycles in the industry.
7.7.2 Reference series

Industrial production of semiconductors and related equipment is chosen to be the reference series for the semiconductor industry. Other relevant semiconductor time series suffered from not being available earlier than the 80s. Throughout the thesis, industrial production of semiconductors and related equipment is called the semiconductor industry for simplicity.

7.7.3 Relationship with the economy

The average length of a business cycle in the semiconductor industry is two years and ten months. Hence, there is a shorter average cycle in this industry than in the economy, meaning that there are extra cycles in the semiconductor industry. Some of these cycles must be industry specific. Table 7.7.1 shows a comparison of the business cycles in the U.S. economy and in the semiconductor industry. The table confirms the extra cycles in the construction sector. Combining the average lag of peaks and troughs, the average becomes a lag of 4.6 months. A few turning points are rejected on the basis of the turning points criteria.

Table 7.7.1: Turning Point analysis of the semiconductor industry and the U.S. economy

<table>
<thead>
<tr>
<th>Semiconductors Production</th>
<th>U.S. Economy</th>
<th>Lead (-1) or Lag (+) or False or Miss</th>
</tr>
</thead>
<tbody>
<tr>
<td>Peaks</td>
<td>Troughs</td>
<td>Peaks</td>
</tr>
<tr>
<td>Sep-75</td>
<td></td>
<td>Aug-75</td>
</tr>
<tr>
<td>May-77</td>
<td>Jan-79</td>
<td>Apr-77</td>
</tr>
<tr>
<td>Feb-80</td>
<td>May-81</td>
<td>Oct-80</td>
</tr>
<tr>
<td>Aug-82</td>
<td>May-83</td>
<td>Nov-81</td>
</tr>
<tr>
<td>Oct-84</td>
<td>Nov-86</td>
<td>Aug-84</td>
</tr>
<tr>
<td>Apr-88</td>
<td>Feb-90</td>
<td>False</td>
</tr>
<tr>
<td>Aug-90</td>
<td>Nov-91</td>
<td>Jan-89</td>
</tr>
<tr>
<td>Jan-93</td>
<td>Feb-94</td>
<td>Jun-93</td>
</tr>
<tr>
<td>Oct-95</td>
<td>Feb-95</td>
<td>Jun-96</td>
</tr>
<tr>
<td>Nov-98</td>
<td>Dec-96</td>
<td>Oct-97</td>
</tr>
<tr>
<td>Sep-99</td>
<td>Mar-02</td>
<td>Feb-99</td>
</tr>
<tr>
<td>Jan-04</td>
<td>May-05</td>
<td>False</td>
</tr>
<tr>
<td>Mar-06</td>
<td>Mar-07</td>
<td>May-05</td>
</tr>
<tr>
<td>Jun-08</td>
<td>Sep-09</td>
<td>Aug-09</td>
</tr>
<tr>
<td>Jan-11</td>
<td>Apr-11</td>
<td>-3</td>
</tr>
</tbody>
</table>

**Average lead:** 5.3, 3.9
Graphical representation of the semiconductor industry and economic activity, see graph 7.7.1, shows that the semiconductor slightly lags the economy. CCCs calculations find that semiconductors on average lag the economy with one month, \( t_1 \) (0.610), and that the interval from \( t_5 \) to \( t_{14} \) has values above 0.5 (see appendix 7.3). Correlation between the semiconductor industry and the economy is 0.61. The correlation is not high enough to make the argument that the industry coincides with the economy. Thus, it is likely that the semiconductor industry does lag the economy.

**Graph 7.7.1: Timing relationship between the U.S. economy (left axis) and the semiconductor industry (right-axis)**

![Graph 7.7.1: Timing relationship between the U.S. economy (left axis) and the semiconductor industry (right-axis)](image-url)
7.8 Auto industry indicators

7.8.1 Real hourly earnings in manufacturing

It is understood that real hourly earnings (RHE) have capabilities of leading economic series, due to its impact on consumer expenditure, as explained in the section 7.2. There is no reason why this should not be the case for RHE in manufacturing. Consequently, this indicator is believed to be able to predict turning points in the auto industry because the auto industry is a part, and at least historically a large part, of the manufacturing industry.

Graph 7.8.1 shows that RHE in manufacturing in some business cycles leads the auto industry with several months and in other cycles the indicator coincides with the auto industry. CCC analysis finds that the most likely timing relationship between this indicator and the auto industry is this indicator leading four months, $t_{-4}$ (0.538). The interval from 1 to 7 has values above 0.5 (see appendix 5.3). The findings from economic intuition, graphical illustration and CCCs present arguments to include the indicator in the leading auto industry index.

![Graph 7.8.1: The auto industry (left-axis) and real hourly earnings in manufacturing (right-axis)](image)

7.8.2 Stock Index for Automobiles and Auto Parts Companies

This indicator measures the price index of 16 publicly traded American auto and auto parts companies. In accordance with the findings of the S&P 500, economic intuition tells that the stock index of auto companies will lead the production of auto related goods.
Graphical visualization, see graph 7.8.2, shows that the stock index for automobiles and parts companies coincides with the auto industry. In some cycles the indicator slightly leads. It is evident from CCC that the average timing relationship between this indicator and the auto industry is a two months lead, \[ t_{12} (0.631) \]. The interval from -2 to 7 has values above 0.5 (see appendix 5.3). The results from economic logic, graphical representation and CCCs provide argumentation to include the indicator in the leading auto industry index.

**Graph 7.8.2: The auto industry (left-axis) and stock index for automobiles and parts companies (right-axis)**

### 7.8.3 Auto finance interest rates (inverse)

This indicator measures the change in the interest rate offered on auto finance loans. The purchase of an automobile is a significant decision for most households, and it involves a large amount of funding. To be able to obtain this large amount of funding, it is common practice to finance a car purchase. As with other financed purchases, the specific interest rate is of great importance to the overall costs of the purchase. An increase in the auto finance interest rate is expected to result in fewer sales of car. Since a positive relationship is necessary to create the graph and calculate CCCs and indices, the indicator has been inversed. It is anticipated that an increase in the auto finance interest rate will decrease the activity in the auto industry because the auto products become more expensive. Data for the United States suggests that the reduction in car sales in mid-2008, in the wake of the financial crisis, has been enhanced by the lack of access to credit, leading many consumers to postpone their car purchases (OECD 2012). Econometric calculations indicate that tight credit conditions could explain more than 80 percent of the decrease in car sales at the end of 2008 in the United States (OECD 2012). This example illustrates the importance of borrowing opportunities for the auto industry.
Graph 7.8.3 illustrates that the auto finance interest rate is a rather good predictor of changes in the auto industry as the indicator leads most cycles in the auto industry with several months. The highest CCC is found at eight months, meaning that this indicator leads the auto industry with eight months, $t_{\text{a}} (0.373$, see appendix 5.3). Economic intuition, graph 7.8.3 and CCCs all support the inclusion of the indicator in the leading auto industry index.

Graph 7.8.3: The auto industry (left-axis) and auto finance interest rate (right-axis)

7.8.4 Nominal hourly earnings for workers in auto metal stamping
The indicator determines the nominal hourly earnings for workers in auto metal stamping. While the indicator shares similarities with real hourly earnings, it differs in that real wages can rise even with nominal wages falling. Thus nominal wages is important to include getting a clear picture of demand for labor within the automobile industry.

Graph 7.8.4 shows that NHE for workers in auto metal stamping leads the auto industry in many business cycles. The amplitude of this lead seems to vary considerably from cycle to cycle, and the lead is not present for all cycles. The most likely timing relationship between this indicator and the auto industry is, according to CCC, that this indicator leads the auto industry with 13 months, $t_{\text{a}} (0.199$, see appendix 5.3). The outcome of the above criteria is positive, which is why the indicator will be incorporated in the leading auto industry index.
Graph 7.8.4: The auto industry (left-axis) and hourly earnings for workers in auto metal stamping (r-axis)

Graph 7.8.5: The auto industry (left-axis) and auto inventory to sales ratio (right-axis)

7.8.5 Inventory to auto sales ratio
This indicator measures the development in auto sales compared to the inventory of cars. It is a useful indicator because it is expected that the ratio is very high in troughs (large inventories and few car sales) and low in peaks (small inventories and large car sales). Since this ratio is made up of two opposing effect, it can be expected to be even more leading than sales alone. The ratio should have a negative relationship with output in the auto industry. Since a positive relationship is needed to create the graph and calculate CCCs and indices, the indicator has been inversed. A rise in the inverted time series is anticipated to result in an increase in the auto industry. It is rather clear from graphical representation, see graph 7.8.5, that the auto inventory to sales ratio leads the auto industry with a few months in both peaks and troughs. Results from CCC analysis show that the average lead between this indicator and the auto industry is three months, \( t_{13} \) (0.554). The interval from 1 to 6 has values above 0.5 (see appendix 5.3). These results provide incentive to include the indicator in the leading auto industry index.
7.9 Construction sector indicators

7.9.1 Steel industry leading index

The indicator shows the changes in the level of overall activity in the steel industry. This indicator is relevant for the construction sector because steel is an important part of the materials used in construction. It is expected that an increase in the leading steel index happens before an increase in construction. Therefore, it is anticipated that the indicator can be used to forecast movement in the construction sector.

Graphical visualization, see graph 7.9.1, supports this expectation, and shows clearly that the steel industry leading index leads the construction sector with some months. This is true for both peaks and troughs. It is evident from CCC that the average timing relationship between this indicator and the construction sector is a five months lead, $t_{c5}$ (0.805). The interval from -1 to 11 has values above 0.5 (see appendix 6.3). All three criteria support to include the indicator in the leading construction sector index.

Graph 7.9.1: Construction and steel industry leading index

7.9.2 Sales of new one family houses

This indicator shows the amount of new one family houses being sold. Whereas indicators like housing starts and building permits are regarded as production expectations for home builders, new home sales are a better reflection of consumers’ financial wellbeing and expectations for the future (Baumohl, 2008).

Though new home sales only contribute 15% to the real estate market, its impact on the economy is much larger. A lot of physical investment is involved in the construction of the house and a new home sale often results in a large spending spree in furniture and related goods in the following 12 to 18 months after the
purchace, which can explain that this indicator is also followed closely by the general economy (Baumohl, 2008).

Graph 7.9.2 illustrates that the sales of new one family houses are a good predictor of changes in the construction sector as the indicator leads most cycles in the construction sector with several months. The highest CCC is found at nine months, meaning that this indicator leads the construction sector on average with nine months, $t_{13} (0.775)$. The interval from 2 to 17 has values above 0.5 (see appendix 6.3). The advantages of this indicator speak for its inclusion in the leading construction sector index.

Graph 7.9.2: Construction (left-axis) and sales of new one family houses (right-axis)

7.9.3 Real hourly earnings for workers in construction

It is understood that real hourly earnings (RHE) have capabilities of leading economic series, due to its impact on consumer expenditure, as described in section 7.2. There is no reason why this should not be the case for RHE for workers in construction. Consequently, this indicator is believed to be able to predict turning points in the construction because a raise in wages corresponds to higher demand in the industry.

Graph 7.9.3 shows that RHE for workers in construction in a majority of business cycles leads the construction sector with several months. In a few other cycles the indicator lags or coincides with the construction sector. CCC analysis finds that the most likely timing relationship between this indicator and the construction sector, is a lead of 13 months, $t_{13} (0.188$, see appendix 6.3). The findings from economic intuition, graphical illustration and CCCs make the case to include the indicator in the leading construction sector index.
7.9.4 New home mortgages effective interest rate

The purchase of a new home is a very significant decision for most households, and it involves a large amount of funding. Since a positive relationship is necessary to create the graph and calculate CCCs and indices, the indicator has been inversed. It is anticipated that an increase in the indicator will decrease the activity in the construction supplies industry, because finance of new homes will become more expensive.

Graph 7.9.4 shows that the effective interest rate for new home mortgages quite strongly leads the construction sector in many business cycles. The amplitude of this lead seems to vary considerably from cycle to cycle, and the lead is not present for all cycles. The most likely timing relationship between this indicator and the construction sector, according to CCC, is that this indicator leads the construction sector with 14 months, $t_{-14}$ (0.422, see appendix 6.3). As a result of the strong argumentation of the predictive power of the indicator, the indicator is included in the leading construction sector index.
7.9.5 Stock index of construction supplies and materials companies

This indicator measures the price index of the 23 American companies within the construction supplies and materials industry. An increase in the indicator signals that the financial markets expect that the industry will improve its performance (Bodie et al., 2009). While this improvement in performances can be due to several different factors, it will on most occasions be associated with an increase in the industry’s activity. Thus, economic intuition tells that the stock index of construction companies will lead output in the construction industry.

Graphical representation, see graph 7.9.5, shows that this economic indicator leads the construction sector with a few months in both peaks and troughs with substantial deviations for a few cycles. Results from CCC analysis show that the average lead between this indicator and the construction industry is six months, $t_{16}$ (0.396, see appendix 6.3). These results from economic logic, graphical representation and CCCs provide enough evidence to incorporate the indicator in the leading construction sector index.

Graph 7.9.5: Construction (left-axis) and stock index of construction supplies and materials companies (right-axis)
7.10 Semiconductor industry indicators

7.10.1 Stock index for semiconductors companies
This indicator measures the price index of the 28 publicly traded American companies within semiconductors and related equipment. While several factors can influence stock prices it will most of the time be associated with the anticipation of increased activity in the industry (Bodie et al, 2009). As a result, this stock index of semiconductor companies is expected to lead output.

The graph provides no decisive picture of the relationship between the two variables. However, in several instances it seems like the index is leading production. The index appears to be more volatile and experience more cycles than the semiconductor industry, which is to be expected from the multitude of influences on the stock market. The highest cross-correlation coefficient (CCC) is found at four months, meaning that this indicator on average leads the semiconductor industry with four months, $t_{44} (0.775$, see appendix 7.3). Given economic intuition, graphical illustration and CCCs, the indicator will be included as one of the five industry specific economic indicators for the leading semiconductor industry index.

Graph 7.10.1: The semiconductor industry (left-axis) and stock index for semiconductor companies (right-axis)

7.10.2 Real hourly earnings in manufacturing
Section 7.2 finds that real hourly earnings (RHE) have the ability to lead the activity of the overall economy. There is no reason why this should not be the case for RHE in manufacturing. Consequently, this indicator is believed to be able to predict turning points in the semiconductor industry because semiconductor
production is a part of the manufacturing industry. An increase in the indicator is anticipated to lead an increase in semiconductor production.

Graph 7.10.2 depicts the relationship between semiconductor production and real hourly earnings in manufacturing. It appears that earnings often have risen earlier than semiconductor production, meaning that it has leading capabilities. It is evident from CCCs that the average timing relationship between this indicator and the semiconductor industry is a ten months lead, \( t_{10} = 0.274 \) (see appendix 7.3). The long lead time from CCC analysis, economic logic and graphical representation makes adequate argumentation that this indicator needs to be included in the leading semiconductor industry index.

Graph 7.10.2: The semiconductor industry (left-axis) and real hourly earnings in manufacturing (right-axis)

7.10.3 Output per employee in manufacturing

This indicator measures the change in output per employee in manufacturing, which can be regarded as a proxy for productivity in the manufacturing sector. In the literature review, the section on Real business cycle theories highlighted the difficulty in finding clear measures of productivity, but this variable is the best approximation. An increase in productivity reduces costs, and reduced costs can often spur a rise in sales, and thereby a rise in production (cf. section 3). However, such an increase does not necessarily lead to increased sales and production. While the effect on production of productivity increases is not certain, it is very doubtful that it can result in a fall in production.

Graphical representation, see graph 7.10.3, shows that output per employee in manufacturing frequently leads the production of semiconductors with some months. CCCs analysis finds that the most likely timing
relationship between this indicator and the semiconductor industry is a four months lead, t-4 (0.617). The graph and CCCs provide enough evidence, in spite of the weak economic intuition, to use the indicator in the leading semiconductor industry index.

**Graph 7.10.3: The semiconductor industry (left-axis) and output per employee in manufacturing (right-axis)**

![](image)

**7.10.4 Average workweek for workers in the semiconductor industry**

This indicator measures the average hourly workweek of workers in the semiconductor industry. The average workweek cannot increase indefinitely, and at some point the indicator reaches it maximum. This is when the companies start to hire new employees, and the effect spills into employment numbers (Baumohl, 2008). Thus, the workweek increases before new hiring is done. When the workweek increases, it means that demand is rising, and therefore production is also increasing (Ellis, 2005). This indicator has potential as a leading indicator of production.

Graph 7.10.4 shows the timing relationship between the average workweek for workers in the semiconductor industry and the semiconductor industry. It is apparent that the indicator leads the industry. This finding is supported by CCCs. The highest CCC is found at seven months, meaning that this indicator on average leads the semiconductor industry with seven months, t-7 (0.292, see appendix 7.3). These findings support including this indicator in the leading semiconductor industry index.
7.10.4 The semiconductor industry (left-axis) and average workweek for workers in the semiconductor Industry (right-axis)

Graph 7.10.5: The semiconductor industry (left-axis) and average workweek for workers in the semiconductor Industry (right-axis)

7.10.5 PCE computers

This indicator shows the development of personal consumption expenditure (PCE) on computers and related devices. As mentioned in the macro section, see section 7.2, PCE is a good predictor of economic activity. Given the technology related nature of semiconductors, the indicator is expected to be strongly related to the semiconductor industry (Tan and Mathews, 2009). However, there exist two different trends that distort this expectation. The first deals with the fact that computer spending has become very stable during the last one to two decades (Liu, 2005). The second trend is the fact that the semiconductor industry has become less dependent on personal computers in the same period, as a variety of other technological products use semiconductors as well (galegroup.com). Consequently, it is difficult to compare the periods from 1975 to 1990 and from 1991 to 2012. To overcome this problem two separate graphs are created. Graph 7.10.5 shows the period from 1975 to 1990. This period is characterized by very large fluctuations in the PCE on computers, and the indicator seems to be leading the semiconductor industry. The second period from 1991 to 2012 is depicted in graph 7.10.6, and it still appears that the indicator has some predictive power on the industry. The volatility of PCE on computers has in the second period decreased dramatically.

It is evident from CCCs that the average timing relationship between this indicator and the semiconductor industry is for the whole period a 19 months lead, τ_{19} (0.355, see appendix 7.3).

In spite of the changing trend of the indicator around 1990, the indicator still possess value for predicting business cycle turning points in the semiconductor industry. The reason being that economic intuition,
graphical representation and CCC analysis all provide arguments for the inclusion of the indicator in the leading semiconductor industry index.

Graph 7.10.5: The semiconductor industry (left-axis) and PCE computers (right-axis) (1975-1990)

Graph 5.4.X: The semiconductor industry (left-axis) and PCE computers (right-axis) (1991-2012)

7.10.6 Capacity utilization in the semiconductor industry
This indicator measures the production capacity utilization of semiconductor production. Related studies on the semiconductor industry by Tan and Mathews (2009) find that capacity utilization plays a very important role in determining business cycles in the industry. Lui (2005) confirms that capacity plays an important role in signaling the future state of the semiconductor industry. This is consistent with the industry practitioners such as McClean’s (2001) observations, who found that the semiconductor industry
cycles were primarily caused by overcapacity. However in this analysis, the predictive power of utilization seems to be very limited as it coincides with production.

Graph 7.10.6 confirms this suspicion because the graph shows that the indicator coincides with the semiconductor industry. CCC analysis finds that the most likely timing relationship between this indicator and the semiconductor industry is a one month lead, \( t_{-1} \) (0.669, see appendix 7.3). A lead of one month is considered to be basically coincident, and of little practical use.

These findings provide no reason for including the indicator in the leading semiconductor industry index, and it is left out.

**Graph 7.10.6: The semiconductor industry and semiconductor production capacity utilization**
7.11 Leading industry composite indices

The 10 economic indicators from the LMCI are combined with the five industry specific indicators for each industry. Having 10 macroeconomic indicators and only half as many industry indicators, puts more weight on the macro-level than the industry-level. While industry-specific indicator can provide valuable observations on the specific industry, it is still believed that the impact of changes in the economy will have a strong effect on almost every industry. The inclusion of industry specific indicators will hopefully fine tune the composite indices to better capture special industry dynamics.

To create these indices, the exact same steps have been performed as was performed when creating the LMCI. The only difference now is the reference series have changed from the economy to the respective industries. A comparison between each leading industry composite index and the LMCI are done, to show if the inclusion of industry specifics indicators will have any impact of the predictive power of the index in predicting the specific industry cycles. This comparison will be based upon CCCs. A turning point analysis is done to further evaluate the capabilities of the leading industry composite indices.

7.11.1 The auto industry

The results in table 7.11.1 show that the LMCI with auto industry specific economic indicators outperform the original LMCI in relation to predicting business cycle turning points in the auto industry. The industry specific index outperforms the LMCI with a better lead (1 vs. 0) and a more significant average lead (0.84 vs. 0.83). The longer lead represents that the industry specific index has better predictive abilities. The higher cross-correlation coefficient means that the industry index is more in tune with the reference series. Table 7.11.2 is an overview of the economic indicators included in the LMCI with auto industry specific indicators along with the weights, CCCs and standard deviation of the indicators.

Table 7.11.1: CCCs performance comparison of the LMCI and the leading auto composite index

<table>
<thead>
<tr>
<th></th>
<th>LMCI</th>
<th>Leading Auto Composite Index</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lead</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Lead CCC</td>
<td>0.83</td>
<td>0.84</td>
</tr>
</tbody>
</table>
Table 7.11.2: List of economic indicators included in the leading auto composite index

<table>
<thead>
<tr>
<th>Indicator</th>
<th>CCC lead</th>
<th>CCC weight</th>
<th>Std. Deviation</th>
<th>Std. Dev. weight</th>
<th>Total weight</th>
</tr>
</thead>
<tbody>
<tr>
<td>Auto Inventory/Sales Ratio (inverse)</td>
<td>3</td>
<td>4.8%</td>
<td>11.4</td>
<td>0.6%</td>
<td>0.4%</td>
</tr>
<tr>
<td>Nominal Hourly Earnings for Workers in Auto Metal Stamping</td>
<td>13</td>
<td>9.5%</td>
<td>1.7</td>
<td>4.1%</td>
<td>5.6%</td>
</tr>
<tr>
<td>Auto Finance Interest Rates (inverse)</td>
<td>8</td>
<td>7.1%</td>
<td>12.3</td>
<td>0.6%</td>
<td>0.6%</td>
</tr>
<tr>
<td>Stock Index for Automobiles and Parts Companies</td>
<td>2</td>
<td>4.8%</td>
<td>7.3</td>
<td>1.0%</td>
<td>0.7%</td>
</tr>
<tr>
<td>Real Hourly Earnings in Manufacturing</td>
<td>4</td>
<td>4.8%</td>
<td>0.6</td>
<td>11.8%</td>
<td>8.1%</td>
</tr>
<tr>
<td>Retail Sales</td>
<td>3</td>
<td>4.8%</td>
<td>1.2</td>
<td>5.8%</td>
<td>3.9%</td>
</tr>
<tr>
<td>Housing Starts</td>
<td>8</td>
<td>7.1%</td>
<td>8.0</td>
<td>0.9%</td>
<td>0.9%</td>
</tr>
<tr>
<td>Employment Trend Index</td>
<td>2</td>
<td>4.8%</td>
<td>1.1</td>
<td>6.3%</td>
<td>4.3%</td>
</tr>
<tr>
<td>PCE</td>
<td>3</td>
<td>4.8%</td>
<td>0.5</td>
<td>13.9%</td>
<td>9.5%</td>
</tr>
<tr>
<td>Consumer Confidence Index</td>
<td>5</td>
<td>7.1%</td>
<td>8.7</td>
<td>0.8%</td>
<td>0.8%</td>
</tr>
<tr>
<td>Real Hourly Earnings</td>
<td>8</td>
<td>7.1%</td>
<td>0.3</td>
<td>22.9%</td>
<td>23.5%</td>
</tr>
<tr>
<td>PMI</td>
<td>7</td>
<td>7.1%</td>
<td>4.9</td>
<td>1.5%</td>
<td>1.5%</td>
</tr>
<tr>
<td>S&amp;P 500</td>
<td>5</td>
<td>7.1%</td>
<td>4.6</td>
<td>1.6%</td>
<td>1.6%</td>
</tr>
<tr>
<td>Real Money Supply</td>
<td>10</td>
<td>9.5%</td>
<td>0.4</td>
<td>15.9%</td>
<td>21.7%</td>
</tr>
<tr>
<td>Yield Curve</td>
<td>16</td>
<td>9.5%</td>
<td>0.6</td>
<td>12.4%</td>
<td>16.9%</td>
</tr>
</tbody>
</table>

Graph 7.11.1 depicts the timing relationship between the auto industry and the leading auto composite index, and the two time series coincide in accordance with the results of the CCCs with a lead of one month. This might seem a bit disappointing, but one has to keep in mind that the auto industry is leading the economy. The main finding is that the index with auto industry indicators does outperform the index without. In regard to actually predicting a turning point in the auto industry, a lead of one month is not enough to be of any value.

Graph 7.11.1: Auto industry and the leading auto composite index
A turning point analysis compares the turning points in the auto industry with those of the leading auto composite index to show if the index captures all the cycles in the auto industry, or if the index provides false or missing signals. The analysis finds that the index leads the auto industry with five months in peaks and 1.7 months in troughs. The average lead is 3.4 months. The unexpected substantial lead of the leading auto composite index is untrustworthy given the results of CCCs and graphical representation. Further, turning point analysis identifies 2 false cycles, see table 7.11.3. A few turning points are rejected in both time series on the basis of the established turning points criteria (cf. section 5.6).

Table 7.11.3: Turning point analysis of the auto industry and the leading auto composite index

<table>
<thead>
<tr>
<th>Leading Auto Composite Index</th>
<th>Auto Industry</th>
<th>Lead (-) or lag (+) or false or miss</th>
</tr>
</thead>
<tbody>
<tr>
<td>Peaks</td>
<td>Troughs</td>
<td>Peaks</td>
</tr>
<tr>
<td>Jul-76</td>
<td>Jul-80</td>
<td>Aug-76</td>
</tr>
<tr>
<td>Oct-81</td>
<td>Jun-82</td>
<td>Dec-81</td>
</tr>
<tr>
<td>Dec-83</td>
<td>Jul-85</td>
<td>Apr-84</td>
</tr>
<tr>
<td>Feb-87</td>
<td>Aug-89</td>
<td>Aug-87</td>
</tr>
<tr>
<td>Aug-90</td>
<td>May-91</td>
<td>Oct-90</td>
</tr>
<tr>
<td>Aug-92</td>
<td>Oct-93</td>
<td>Feb-93</td>
</tr>
<tr>
<td>Aug-94</td>
<td>Oct-95</td>
<td>May-96</td>
</tr>
<tr>
<td>Mar-97</td>
<td>Sep-97</td>
<td>May-98</td>
</tr>
<tr>
<td>Jun-98</td>
<td>May-01</td>
<td>Sep-99</td>
</tr>
<tr>
<td>Sep-02</td>
<td>Jul-03</td>
<td>Feb-03</td>
</tr>
<tr>
<td>Jun-04</td>
<td>Feb-06</td>
<td>May-05</td>
</tr>
<tr>
<td>Oct-07</td>
<td>Mar-09</td>
<td>Nov-07</td>
</tr>
<tr>
<td>Jul-10</td>
<td>May-12</td>
<td>Aug-10</td>
</tr>
</tbody>
</table>

Average lead | -5.0 | -1.7 |
7.11.2 The construction sector

The outcomes in table 7.11.4 show that the LMCI with construction sector economic indicators outperform the pure LMCI in regard to forecasting business cycle turning points in the construction sector. The leading construction composite index outperforms the LMCI with a better lead (7 vs. 6) and a more significant average lead (0.825 vs. 0.806). The better lead represents that the sector specific index has better forecasting abilities. The higher cross-correlation coefficient means that the industry index is more in line with the construction sector than the LMCI. Table 7.11.5 provides an overview of the economic indicators included in the LMCI with construction sector specific indicators along with the weights, CCCs and standard deviation of these indicators.

Table 7.11.4: CCCs performance comparison of the LMCI and the leading construction composite index

<table>
<thead>
<tr>
<th></th>
<th>LMCI</th>
<th>Leading construction composite index</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lead</td>
<td>6</td>
<td>7</td>
</tr>
<tr>
<td>Lead CCC</td>
<td>0.806</td>
<td>0.825</td>
</tr>
</tbody>
</table>

Table 7.11.5: List of economic indicators included in the leading construction composite index

<table>
<thead>
<tr>
<th>Indicator</th>
<th>CCC lead</th>
<th>CCC weight</th>
<th>Std. Deviation</th>
<th>Std. Dev. weight</th>
<th>Total weight</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sales of New One Family Houses</td>
<td>9</td>
<td>6.5%</td>
<td>7.3</td>
<td>1.0%</td>
<td>0.9%</td>
</tr>
<tr>
<td>Real Hourly Earnings for Workers in Construction</td>
<td>13</td>
<td>8.7%</td>
<td>0.7</td>
<td>9.5%</td>
<td>12.1%</td>
</tr>
<tr>
<td>Stock Index of Construction Supplies and Materials Companies</td>
<td>6</td>
<td>6.5%</td>
<td>7.2</td>
<td>1.0%</td>
<td>0.9%</td>
</tr>
<tr>
<td>New Home Mortgages Effective Interest Rate</td>
<td>13</td>
<td>8.7%</td>
<td>2.4</td>
<td>2.9%</td>
<td>3.6%</td>
</tr>
<tr>
<td>Steel Industry Leading Index</td>
<td>5</td>
<td>6.5%</td>
<td>1.3</td>
<td>5.3%</td>
<td>5.1%</td>
</tr>
<tr>
<td>Retail Sales</td>
<td>3</td>
<td>4.3%</td>
<td>1.2</td>
<td>5.7%</td>
<td>3.6%</td>
</tr>
<tr>
<td>Housing Starts</td>
<td>8</td>
<td>6.5%</td>
<td>8.0</td>
<td>0.9%</td>
<td>0.8%</td>
</tr>
<tr>
<td>Employment Trend Index</td>
<td>2</td>
<td>4.3%</td>
<td>1.1</td>
<td>6.2%</td>
<td>3.9%</td>
</tr>
<tr>
<td>PCE</td>
<td>3</td>
<td>4.3%</td>
<td>0.5</td>
<td>13.6%</td>
<td>8.6%</td>
</tr>
<tr>
<td>Consumer Confidence Index</td>
<td>5</td>
<td>6.5%</td>
<td>8.7</td>
<td>0.8%</td>
<td>0.8%</td>
</tr>
<tr>
<td>Real Hourly Earnings</td>
<td>8</td>
<td>6.5%</td>
<td>0.3</td>
<td>22.5%</td>
<td>21.5%</td>
</tr>
<tr>
<td>PMI</td>
<td>7</td>
<td>6.5%</td>
<td>4.9</td>
<td>1.4%</td>
<td>1.4%</td>
</tr>
<tr>
<td>S&amp;P 500</td>
<td>5</td>
<td>6.5%</td>
<td>4.6</td>
<td>1.5%</td>
<td>1.5%</td>
</tr>
<tr>
<td>Real Money Supply</td>
<td>10</td>
<td>8.7%</td>
<td>0.4</td>
<td>15.6%</td>
<td>19.9%</td>
</tr>
<tr>
<td>Yield Curve</td>
<td>16</td>
<td>8.7%</td>
<td>0.6</td>
<td>12.1%</td>
<td>15.4%</td>
</tr>
</tbody>
</table>

Graph 7.11.2 depicts the timing relationship between the construction sector and the leading construction composite index, and it appears that the index clearly leads movements in the construction sector. This graphical representation supports the findings of the CCC analysis with a lead of seven months. A lead of
seven months is large enough in order to predict turning points in the construction sector. The satisfying lead is a direct consequence of the construction sector coinciding with the economy, which provides potential for a good lead. Further, the construction sector is blessed with high-quality sector specific indicators like sales of new one family houses and mortgage interest rates.

Graph 7.11.2: Construction sector and the leading construction composite index

A turning point analysis compares the turning points in the construction sector with those of the leading construction composite index to show if the index identifies all the cycles in the construction sector, or if the composite index obtains missing or false signals, see table 7.11.6. The analysis shows that the index leads the construction sector with six months in peaks and 6.5 months in troughs. The average lead is 6.3 months, which is close the findings of the CCCs that found a lead of seven months. The turning point analysis identifies zero false cycle, but misses one cycle, which is satisfactory. A few turning points are rejected in both the index and the construction sector on the basis of the established turning points criteria (cf. section 5.6).

Table 7.11.6: Turning point analysis of the construction sector and the leading construction composite index

<table>
<thead>
<tr>
<th>Leading Construction Composite Index</th>
<th>Construction Sector</th>
<th>Lead (-), Lag (+) or False or miss</th>
</tr>
</thead>
<tbody>
<tr>
<td>Peaks</td>
<td>Troughs</td>
<td>Peaks</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Jul-76</td>
<td>Jul-80</td>
<td>Jul-77</td>
</tr>
<tr>
<td>Sep-81</td>
<td>Jun-82</td>
<td>Nov-81</td>
</tr>
</tbody>
</table>
7.11.3 The semiconductor industry

The results in table 7.11.7 show that leading semiconductor composite index outperform the true LMCI in relation to predicting business cycle turning points in the industry. The industry index outperforms the LMCI with a better lead (9 vs. 8) and a more significant average lead (0.638 vs. 0.588). The longer lead represents that the industry specific index has better predictive abilities. The higher cross-correlation coefficient means that the industry index is more in tune with the reference series. Table 7.11.8 is an overview of the economic indicators included in the LMCI with auto industry specific indicators along with the weights, CCCs and standard deviation of the indicators.

Table 7.11.7: CCC performance comparison of the LMCI and the leading semiconductor composite index

<table>
<thead>
<tr>
<th></th>
<th>LMCI</th>
<th>Leading semiconductor composite index</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lead</td>
<td>8</td>
<td>9</td>
</tr>
<tr>
<td>Lead CCC</td>
<td>0.588</td>
<td>0.638</td>
</tr>
</tbody>
</table>

Table 7.11.8: List of economic indicators included in the leading semiconductor composite index

<table>
<thead>
<tr>
<th>Indicator</th>
<th>CCC lead</th>
<th>CCC weight</th>
<th>Std. Deviation</th>
<th>Std. Dev. weight</th>
<th>Total weight</th>
</tr>
</thead>
<tbody>
<tr>
<td>Stock Index for Semiconductor Companies</td>
<td>4</td>
<td>4.5%</td>
<td>10.71</td>
<td>0.6%</td>
<td>0.4%</td>
</tr>
<tr>
<td>Average Workweek for Workers in the Semiconductor Industry</td>
<td>7</td>
<td>6.8%</td>
<td>2.21</td>
<td>2.9%</td>
<td>2.9%</td>
</tr>
<tr>
<td>Output per Employee in Manufacturing</td>
<td>4</td>
<td>4.5%</td>
<td>0.64</td>
<td>10.1%</td>
<td>6.6%</td>
</tr>
<tr>
<td>PCE computers</td>
<td>19</td>
<td>9.1%</td>
<td>4.00</td>
<td>1.6%</td>
<td>2.1%</td>
</tr>
<tr>
<td>Real Hourly Earnings in Manufacturing</td>
<td>10</td>
<td>9.1%</td>
<td>0.60</td>
<td>10.7%</td>
<td>14.1%</td>
</tr>
<tr>
<td>Retail Sales</td>
<td>3</td>
<td>4.5%</td>
<td>1.23</td>
<td>5.2%</td>
<td>3.4%</td>
</tr>
</tbody>
</table>
Business cycle forecasting – Theoretical foundations and the application on macro and industry level

<table>
<thead>
<tr>
<th></th>
<th>8</th>
<th>6.8%</th>
<th>7.96</th>
<th>0.8%</th>
<th>0.8%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Housing Starts</td>
<td>8</td>
<td>6.8%</td>
<td>7.96</td>
<td>0.8%</td>
<td>0.8%</td>
</tr>
<tr>
<td>Employment Trend Index</td>
<td>2</td>
<td>4.5%</td>
<td>1.13</td>
<td>5.7%</td>
<td>3.7%</td>
</tr>
<tr>
<td>PCE</td>
<td>3</td>
<td>4.5%</td>
<td>0.51</td>
<td>12.5%</td>
<td>8.3%</td>
</tr>
<tr>
<td>Consumer Confidence Index</td>
<td>5</td>
<td>6.8%</td>
<td>8.73</td>
<td>0.7%</td>
<td>0.7%</td>
</tr>
<tr>
<td>Real Hourly Earnings</td>
<td>8</td>
<td>6.8%</td>
<td>0.31</td>
<td>20.8%</td>
<td>20.5%</td>
</tr>
<tr>
<td>PMI</td>
<td>7</td>
<td>6.8%</td>
<td>4.87</td>
<td>1.3%</td>
<td>1.3%</td>
</tr>
<tr>
<td>S&amp;P 500</td>
<td>5</td>
<td>6.8%</td>
<td>4.59</td>
<td>1.4%</td>
<td>1.4%</td>
</tr>
<tr>
<td>Real Money Supply</td>
<td>10</td>
<td>9.1%</td>
<td>0.45</td>
<td>14.4%</td>
<td>19.0%</td>
</tr>
<tr>
<td>Yield Curve</td>
<td>16</td>
<td>9.1%</td>
<td>0.58</td>
<td>11.2%</td>
<td>14.7%</td>
</tr>
</tbody>
</table>

Graph 7.11.3 depicts the timing relationship between the semiconductor industry and the leading semiconductor composite index, and the graph shows that the index clearly leads movements in the industry. This confirms the findings of the CCCs. A lead of nine months is adequate in forecasting turning points in the semiconductor industry in due time. The significant lead is a consequence of the industry lagging the U.S. economy. Thus, it is easier to find indicators with a good lead when the industry is lagging the economy.

Graph 7.11.3: Semiconductor Industry and the leading semiconductor composite index

A turning point analysis is conducted to compare the turning points in the semiconductor industry with those of the leading semiconductor composite index to show if the index finds all the cycles in the semiconductor industry, or if the index provides false or missing signals. The analysis finds that the index leads the semiconductor industry with 8.7 months in peaks and 8.7 months in troughs, see table 7.11.7. The lead of 8.7 months is very close to the CCCs lead of nine months, which shows that turning point analysis does possess value in assessing the performance of a leading composite index. The findings of table 7.11.8 are in support of graph 7.11.8. Further, turning point analysis identifies that the index provides two false
turning points, and misses four turning points. This is expected given many macroeconomic indicators because the fact remains that the industry experiences many internal cycles (Tan and Mathews, 2009).

Table 7.11.8: Turning point analysis of the semiconductor industry and the leading semiconductor composite index

<table>
<thead>
<tr>
<th>Leading Semiconductor Composite Index</th>
<th>Semiconductors Industry</th>
<th>Lead (-) or Lag (+) or False or miss</th>
</tr>
</thead>
<tbody>
<tr>
<td>Peaks</td>
<td>Troughs</td>
<td>Peaks</td>
</tr>
<tr>
<td>Sep-75</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Jul-76</td>
<td>May-77</td>
<td>Jan-79</td>
</tr>
<tr>
<td>Jul-80</td>
<td>Feb-80</td>
<td>May-81</td>
</tr>
<tr>
<td>Aug-82</td>
<td>May-83</td>
<td>Miss</td>
</tr>
<tr>
<td>Dec-83</td>
<td>Jul-85</td>
<td>Oct-84</td>
</tr>
<tr>
<td>Mar-87</td>
<td>Nov-89</td>
<td>Apr-88</td>
</tr>
<tr>
<td>Sep-90</td>
<td>Apr-91</td>
<td>Aug-90</td>
</tr>
<tr>
<td>Jul-92</td>
<td>Aug-93</td>
<td>Jan-93</td>
</tr>
<tr>
<td>Sep-94</td>
<td>Nov-95</td>
<td>Oct-95</td>
</tr>
<tr>
<td>Feb-98</td>
<td>May-99</td>
<td>Nov-98</td>
</tr>
<tr>
<td>Nov-99</td>
<td>Jul-01</td>
<td>Sep-99</td>
</tr>
<tr>
<td>Dec-02</td>
<td>Jun-03</td>
<td>Jan-04</td>
</tr>
<tr>
<td>May-04</td>
<td>Nov-05</td>
<td>Mar-06</td>
</tr>
<tr>
<td>Oct-07</td>
<td>May-09</td>
<td>Jun-08</td>
</tr>
<tr>
<td>Sep-10</td>
<td>Jan-11</td>
<td>-4</td>
</tr>
</tbody>
</table>

**Average lead** | **-8.7** | **-8.7** |
7.12 Discussion of the empirical results

The macroeconomic index exhibited a definite ability to lead the reference series of the general economy. Its lead of approximately 6 months is very useful for forecasting, and furthermore indicates that the variables included in the index also will be valuable in forecasting industries that are coincident with the economy or leads it slightly.

All the indices with industry specific indicators show results that are superior to the original LMCI. The addition of industry specific indicators improves the forecasting of business cycle turning points in the three case industries, compared to using only macroeconomic indicators. The superior performance is true for both the average lead and significance of cross-correlation coefficients. Graphical illustrations for each industry support these findings. Turning point analyses show mixed results. The analysis tool discovers similar average lead results like CCCs of the leading construction composite index and the leading semiconductor composite index, but results for the leading auto composite index are not in accordance with graphical representation or CCCs. However, turning point analyses demonstrate that the leading auto composite index and the leading construction composite index are experiencing few false signals and misses, while the leading semiconductor composite index is identifying a bit too many false signals and misses. Perhaps, some adjustment to the leading industry composite indices regarding indicator selection and weighting can yield better results.

The degree of success of the leading indices for the three cases depends on the timing relationship between the cases and the economy, where the best potential is for an industry lagging the economy, followed by one coinciding and lastly the potential is not great for a leading.

The lead of the leading auto composite index is not strong enough for actual forecasting. The leading composite indices for both the construction sector and the semiconductor industry are deemed strong enough for useful forecasting, based on their substantial leads. The usefulness of a leading composite index depends on the criteria one uses for determining turning points, like three consecutive months of a change in direction, before a turning point can be identified (cf. section 5.6). This requires a lead larger than three, which the indices of the semiconductor industry and the construction sector have. A more thorough discussion of turning point screening is the topic of another study.
8 - Conclusion

A literature review was conducted to see whether business cycle theory can give a theoretical basis for identifying variables that can explain business cycles. The review gave an understanding of the development in economic theory from basic and simplistic theories to the more elaborate theories of modern time. All theories reviewed are distinct in some way, but many of them share a number of different features. While there is not, and probably never will be, a complete theory of the business cycle, there is agreement among scholars of different schools of thought on a number of subjects. As identified in the literature review, these are: 1) both supply side and demand side variables are important for business cycles, 2) expectations are just as relevant as real variables, 3) prices and wages are not perfectly flexible, and their friction leads to cyclicality, 4) monetary policy and monetary variables have a role in explaining business cycles and 5) financial markets play a large role in business cycles. These subjects are generally accepted today, and are backed by substantial empirical support, wherefore they can be regarded as reliable and well-established findings. As evident in the first sub-research question, an objective of the thesis was to assess if business cycle theory can identify economic variables that can explain cyclicality. Throughout the literature review a theoretical base through which economic variables allow exploration of the business cycle was identified. The findings were applicable on both the macro and the meso-level. The section on economic indicators utilizes the findings of the literature review, and the results of that section supports that relevant economic indicators can be derived from business cycle theory. The identified economic variables were mainly macroeconomic, but several were available on a meso-level.

A review of quantitative methods was conducted to identify the best method for practically identifying business cycle turning points. In the review of quantitative methods, different forecasting methods are examined. The methods were judged on being effective, easy to understand and use by non-statistical experts, and having practical value. The findings of the review suggested that all methods have some potential and some limitations. Econometric models were primarily rejected on the basis of being too complex to use by non-statistical experts. The economic indicator approach was selected based upon being understandable and easy to apply in practice by non-statistical experts. The fact that economic indicators have successfully predicted recessions since the Great Depression is a tribute to its effectiveness. The approach can be employed on both the macro and the industry level. Selecting the economic indicator approach therefore provides this thesis with a preferable quantitative forecasting method to predict turning points on both the macro- and the industry level.
An empirical analysis is conducted to apply the selected economic indicators on both a macroeconomic and industry level. First, the identified macro indicators are tested for their individual ability to lead the economy. The result was that almost all indicators have some individual ability to lead, however with large differences in the length of the lead. Next, the indicators that lead the economy were gathered into a leading macroeconomic composite index (LMCI). With the knowledge that indices are superior to individual indicators, it was appropriate to test the combined performance of the selected indicators. Statistical results found that the index leads the economy with six months. This lead is longer than that of the Conference Board’s Leading Composite Index, and therefore it is of great practical value. However, the LMCI suffers from predicting some false turning point signals and some missed turning point signals, which indicates that the approach have some flaws as well.

The second part of the empirical analysis is the case analysis. For each of the cases, the macro indicators from the previous section are combined with five industry-specific indicators. After these individual indicators are tested for their ability to lead, all 15 indicators are combined into industry specific composite indices. For all cases, the results are very positive, as the three leading industry composite indices all show improved forecasting abilities compared to using the original LMCI on each industry (see table 8.1) The superior performance is supported by CCCs, graphical representations and turning point analyses. While this improvement might seem rather limited, the importance of increasing the lead with one month is actually valuable. Turning point analysis demonstrated few false turning point signals and turning point misses for the auto index and the construction index, while the semiconductor industry showed less promising results. This was to be expected given the knowledge of how the semiconductor industry follows the general economy less than the other case industries. Further index adjustment might prove useful to increase the lead of the index and reduce the amount of false signals.

The inclusion of industry specific variables has improved the forecasting of business cycle turning points for the case industries. Thus, the findings confirm the third sub-research question.

The success of the leading indices for the three cases depends on the timing relationship between the cases and the economy. The auto industry was leading the economy, the construction sector coinciding with the economy and the semiconductor industry lagging the economy. The highest potential of a leading economic indicator composite index is for an industry lagging the economy, followed by a coinciding industry and the potential is not great for a leading industry, which the results confirmed, see table 8.1.
Table 8.1: Empirical findings

<table>
<thead>
<tr>
<th></th>
<th>U.S. economy</th>
<th>Auto industry</th>
<th>Construction sector</th>
<th>Semiconductor industry</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>LMCI</td>
<td>CB’s LEI</td>
<td>LMCI</td>
<td>LMCI</td>
</tr>
<tr>
<td>Lead</td>
<td>6</td>
<td>3</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>CCC of lead</td>
<td>0.923</td>
<td>0.883</td>
<td>0.830</td>
<td>0.840</td>
</tr>
</tbody>
</table>

The overall objective of the thesis in the form of the main research question has through the sub-research questions been answered, as explained above. Business cycle theory was capable of providing a base for business cycle forecasting, and for a better understanding of the cyclicality affecting the economy and certain industries. Combined with an appropriate quantitative forecasting method, a forecasting system was developed, where the nuances and subtleties of specific industries were included to improve the forecasting of industry business cycle turning points.

Contributions

The thesis found that industry indicators are important for forecasting turning points in the industry cycle, but that paying attention to the macro economy is also very important for every single industry, because all industries are to different degrees driven by the same macroeconomic forces. This is important insight, and especially for industries where industry specific variables are hard to come by, gives an idea of how to use forecasting anyhow.

The thesis has furthermore contributed by linking many well-known indicators to theory, which will give practitioners a better understanding of these indicators, and hopefully realize why these indicators are also important for their business. Economic theories are a good way to learn about the dynamics of the economy, and when real life economic indicators can be linked to specific theories, it gives them substance.

Practitioners will also benefit from the knowledge that not all industries move in sync, and that some industries are leading or lagging the general economy, which can be important insight for managerial decision making. Understanding the relationship to the overall economy is therefore an important step in understanding an industry.

The empirical analysis conducted can also serve as inspiration for managers or academic researcher on how to develop an easy and practical industry forecasting model. The simplicity of the model ensures that there
is little need for statistical expert knowledge. Since relatively few empirical studies of industry cycles exist, the thesis can contribute to the field.

**Future research**

The case approach allowed us to observe some differences between industries, and insight into the different impact that some indicators have on certain industries were spotted. The objective was mainly to assess the potential of a leading composite index in different industries, but it might be interesting to study more thoroughly the influence of specific indicators on a large statistical sample of industries. This could provide more insight on why a specific indicator is important for some industries.

In the empirical analysis, it was observed how the lead of the indicators and indices exhibited different leads in peaks and troughs. Others might therefore find it interesting to experiment with indices where the indicators used in an expansive economy is different from the ones used in a contracting economy, or where the weights of the same indicators are allowed to change in these different scenarios. To our knowledge, there has been no research on this subject so far, but several have found that the lead potential of single indicators differ from peaks to troughs.

In the same vein, and in light of the economic turmoil in the last 5-6 years, it could be interesting to see a more in-depth analysis of which factors that are important for guiding industry activity in such a volatile economic environment.
Reference list

Books


Printz, Louis, 1992, ”Strategisk Varsling”, In John Parm Ulhøi (ed.) Virksomhedsledelse i International Belysning, Systime, Herning.


Academic articles and journals


Duus, Henrik J., 1995, ”Strategisk ledelse af innovationsprocesser - Et økonomisk studie i virksomheders fornyelse, markedsprocesser og samfundsudvikling” PhD Afhandling, 393 sider,


120


Grebler, Leo, and Burns, Leland S., 1982, “Construction Cycles in the United States since World War II”, American Real Estate and Urban Economics Association in its journal Real Estate Economics


Vaccara, B.N. and Zarnowitz, V. 1977, “How good are the leading indicators?”, Proceedings of the business and economic statistics section, American Statistical Association

Presentations


Working papers


Internet websites

Conference Board 2012(Accessed latest on November 28, 2012)
http://www.conference-board.org/data/eti.cfm

http://www.conference-board.org/data/consumerconfidence.cfm (on consumer confidence)

http://www.conference-board.org/data/bci/index.cfm?id=2154 (Steps in calculating an index)

http://www.federalreserve.gov/newsevents/testimony/bernanke20080117a.htm

http://hvacrdistributionbusiness.com/hot_topics/construction-industry-focus-0112/

http://www.ism.ws/ISMReport/MfgROB.cfm?navItemNumber=12942

http://nber.org/cycles/cyclesmain.html

http://go.galegroup.com/ps/retrieve.do?sgHitCountType=None&sort=RELEVANCE&inPS=true&prodlId=GVR&userGroupName=cbs&tabId=T003&searchId=R3&resultListType=RESULT_LIST&contentSegment=&searchType=BasicSearchForm&currentPosition=4&contentSet=GALE%7CCX3049900058&docId=GALE|CX3049900058&docType=GALE (automobiles and other motor vehicles)

http://go.galegroup.com/ps/retrieve.do?inPS=true&prodlId=GVR&userGroupName=cbs&tabId=T003&searchId=R1&searchType=AdvancedSearchForm&contentSet=GALE&docId=GALE|CX3049900376 (Construction)

http://go.galegroup.com/ps/retrieve.do?sgHitCountType=None&sort=RELEVANCE&inPS=true&prodlId=GVR&userGroupName=cbs&tabId=T003&searchId=R2&resultListType=RESULT_LIST&contentSegment=&search
Databases

Economagic (www.economagic.com), accessed through a personal fee paid. Economagic was mainly accessed in the earlier phases of the process, and just about all of its economic series are also available in Datastream.

Datastream.com, accessed through the CBS Library external resources

Oecd.com, accessed both through the OECD webpage and CBS Library external resources