AMERICAN UNIVERSITY OF BEIRUT

ASSESSMENT OF THE ABILITY OF BUSINESS TENDENCY SURVEY, TO MONITOR AND PREDICT ECONOMIC ACTIVITY IN LEBANON

by
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ABSTRACT
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In this thesis, we examine and forecast the growth cycle in Lebanon through business survey indicators. Survey indicators are combined into a composite index named "Confidence" in each sector to replicate current business conditions on a sectoral level. These indicators are then aggregated into a single composite indicator referred to as ESI to match the reference series and reflect overall economic activity in Lebanon.

On the basis of the quarterly approximation of the Bry and Boschan algorithm, the ESI dating chronology was closely able to match that of the reference series with high degree of concordance between phases.
For more robust findings, short-term forecasts of quarterly economic growth(CI) are compared between time series models incorporating the ESI against their corresponding benchmark (AR, ARIMA) by adopting a pseudo out-of-sample forecasting technique. The results show more than 30% improvement in forecast accuracy across the different horizons, for the AR augmented model compared to its benchmark.

In conclusion , business survey indicators presented by the ESI were able to monitor past economic development of the CI as well as performing short-term forecast for different horizons.

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ABBREVIATIONS

BDL	Banque Due Liban
BTS	Business Tendency Survey
BO	Balance of Opinion
CI	The BDL-Coincident Indicator
Q.o.Q	Quarter on quarter growth rates i.e. annualized quarterly growth rate
GDP	Gross Domestic Product
EU	European Union
INSEE	National Institute of Statistics & Economic Studies, in France
NBER	National Bureau of Economic Research
OECD	Organization for Economic Co-operation & Development
ESI	Economic Sentiment Indicator
BBQ	Bry-Boschan Quarterly Algorithm
TP	Turning points
PCA	Principal Component Analysis
RMSE	Root Mean Squared Error
AIC	Akaike Information-Criterion
AR	Auto-regressive
ARIMA	Auto-regressive Integrated Moving Average

CHAPTER 1

INTRODUCTION

In the world of economics, making good decisions usually depends upon relevant information about the non-corporate real sector (Dresse, 2009). Early and accurate signals of the state of the economy is crucial for all economic agents and particularly decision makers to adjust and act accordingly to try to avoid any negative repercussions on the economy and society when possible.

In this matter, Business survey data present timely information on the overall state of the economy as well as on key macroeconomic variables and are widely used in short-term policy analysis. The Business Tendency Surveys (BTS) represent a set of simplified questions directed to business manager about their sentiment regarding current and future activity of several economic variables related to their firm . Their availability in a timely manner with respect to national account publication, allows detecting possible changes in the business cycle phases and to prevent any slowdown at an early stage. Further, they are used as “early warning indicators“ of economic crises since they are founded on firms’ sentiment. Many international organizations (OECD, European Central Bank) and national policymakers (Ministries, Central Banks and national statistics office) around the world conduct BTS under different taxonomy and rely heavily on it for business cycle analysis and short-term forecasting. According to the European commission, these surveys are an indispensable tool for monitoring the evolution of the EU and the euro area economies (European Commission, 2020). The survey results are generally presented in form of balance indicators, yet many select several individual indicators and combine them into a single composite indicator which could be coincident, leading or lagging.

Many researchers have studied the ability of business survey indicators to monitor and forecast economic activity. Cesaroni and al.(2015), analyze the Italian growth cycle using business survey data. On the basis of the Harding Pagan algorithm , they confirm that the survey variables are able to early detect all the turning points in the GDP growth's cycle. In his study, Andersson (2007)finds that including business survey indicators, as explanatory variables in different VAR models to forecast Swedish GDP, improves forecast accuracy for different forecast horizon (Andersson, 2007).

Few studies have been done on this subject in Lebanon. Nevertheless, in her paper, (Jad, 2010) extracts several composite indicators from the BDL business survey and assess their reliability in monitoring the Lebanese business cycle. Two composites successfully lead the reference series turning points by an average of one quarter. Another coincident indicator reflecting business climate as a whole proved successful in explaining the different phases of expansions and contractions (Jad, 2010).

The work presented in this thesis is a direct elaboration of the approach used by (Jad, 2010). However, it is extended by constructing coincident composite indicators to detect the business cycle's turning points, and estimate short-term fluctuations using different econometrics models. Even though leading indicators are of interest yet combining the coincident survey variables into a composite coincident indicator can supplement quantitative statistics in shaping a clearer picture of the direction of the economy, particularly for countries with weak statistical reporting systems. Indeed, in Lebanon, where statistical sources of business cycle analysis are very limited, Business tendency surveys are of great importance and are extensively used by monetary authorities to monitor economic activity across different sectors. The central bank of Lebanon started conducting quarterly BTS since 1996[1]. The results are analyzed in conjunction with a quantitative Coincident Indicator(CI)[2] adopted in 1994 as monthly estimate of the GDP.

The aim of this thesis is to assess the ability of Business surveys to monitor and forecast economic activity in Lebanon on a quarterly basis. For this purpose, a composite indicator is constructed as a tool to gauge the direction of the economy in parallel to the Coincident Indicator. Particularly, a Confidence Indicator coincident with economic activity is compiled for each surveyed sector and then aggregated into a single Economic Sentiment Indicator (ESI) to better capture overall economic activity. The motive behind constructing a single composite indicator is to reduce the number of false alarms and missed turning points relative to its individual components. Further the composites have the capability to react to various sources of economic fluctuations and at the same time can be resilient to perturbations affecting only one of the components. The use of composite indexes is consistent with the traditional view of the business cycle developed by Burns and Mitchell. In particular, composite indexes can reveal common turning point patterns in a set of economic data in a clearer and more convincing manner than the behavior of any individual component (Handbook on CCI, 2017).

The first step is to assess the performance of the ESI in monitoring economic activity in Lebanon relative to the CI. To do so, we measure and analyze the business cycle in Lebanon, by detecting relevant turning points as proposed in Burns and Mitchel

[1]BTS started with the industrial and trade sector in 1996 and followed with the construction and tourism sector in 1998 and 2000, respectively.

[2] Composite coincident indicator on the real sector composed of 8 components.

(1946); however, we consider a growth cycle approach as the indicators retrieved from BTS measured as balance of opinions contain no trend. Accordingly, the CI Q.o.Q growth series is used comply with this approach. The Bry-Boschan non-parametric algorithm is used to detect relevant turning points and measure different phases of the growth cycle i.e. expansion and contraction. According to the BBQ algorithm, the ESI was able to successfully match most of the CI's turning points with high degree of concordance reaching 84% between phases. The phases derived from the ESI were able to match the main economic developments across the period as well.

Our findings are elaborated by examining whether augmented AR and ARIMA models that include ESI as explanatory variable perform better their corresponding benchmark in forecasting Lebanon's economic growth proxied by CI. The forecast comparison is conducted using CI Q.o.Q quarterly growth rates from 2000Q1 to 2019Q4. A pseudo out of sampling forecasting approach is adopted to evaluate forecast accuracy of the different models relative to the benchmark model. The forecasts are evaluated using standard forecast evaluation criteria-Root Mean Square Errors (RMSE). The empirical analysis finds that the augmented models are superior to benchmark for all forecast horizons, with more than 30% improvement for the augmented AR model compared to its benchmark across all forecast horizons. Thus, confirming the predictive power of business surveys indicators in forecasting short-term growth by giving insight on part of the dynamics of the economy, particularly business "sentiment" not captured otherwise by purely quantitative data.

The confidence indicators compiled in this thesis, shed light on cyclical movements in sectors of the economy not covered by quantitate statistics. More importantly, the ESI can be used as a complementary tool for policymakers and the private sector for short-term signal of business activity to adjust accordingly when possible. In Lebanon where statistical capacity is limited, these composite indicators present an indispensable tool for closely monitor and predicting short-term economic fluctuations on a micro(by sectors) as well as a macro(national) level.

The thesis is organized as follows. The second section discusses the literature. Section three presents the data together with the construction of the composite indicators followed by the adopted methodology. The empirical results are outlined with some brief description in section four. In section five the results are discussed in detail with some interpretation. Finally, the main limitations of the study are presented in the conclusion .

CHAPTER 2

LITERATURE REVIEW

In their classical work "Measuring Business Cycles", Burns and Mitchel (1946) define and measure cycles by detecting a set of turning points in a series that measures period of expansions and contraction. When a broad range of economic cycles took place during roughly the same time, the behavior was described as a business cycle or "reference cycle" (Burns & Mitchell, 1946). This definition of business cycles referred to the aggregate level of economic activity i.e. time series in levels.

However, researchers started to investigate alternative ways of defining cycles by excluding the trend component in the series. The growth cycle instead (the deviation from trend and sometimes called deviation cycle) can be identified as cycles in deviations from a long-term trend. This approach was first introduced by Mintz (1969) by studying the reference cycle on time series by removing the trend component. Several forms of detrending methods are offered to perform this task (Phase average, cumulative average, HP-Filter, Baxter and King, refer to (Mazzi, Ataman, & Mitchell, 2017). Nonetheless, the two approaches of business cycles have different characteristics and stylized facts. Classical cycles are longer in duration with significantly asymmetric phases i.e. recessions are rarely recorded while growth cycles are shorter with expansions and recessions registering similar durations. Researchers, such as Pagan (1997) and Harding and Pagan (1999), have gained interest in the growth cycle at the expense of the business cycle, which was reasoned as more relevant for policymakers and the private sector. Also, growth cycle has also strong relationship with economic theory, particularly on potential output and output gap, based on Okun's law (Okun, 1962).

Cyclical analysis is often performed using composite indicators to emphasize cyclical patterns in the data and reduce the volatility of individual indicators. They can be qualitative or quantitative and are classified into lagging leading and coincident with respect to the reference series (Eurostat, United Nations 2017). They are established to track or anticipate economic conditions. In this matter, Business Tendency Survey (BTS) Indicators present well-established tools for the assessment and analysis of economic development and fluctuations in the business/growth cycle. The relevance of such indicators is strengthened by their very high timeliness. Likewise, the use of balance is practical and entirely adequate for cyclical analysis as the series frequently contain no trend (OECD, 2003). The survey data retrieved in from of balance series are frequently used to construct composite indicators to reflect business conditions on a sectoral level as well as on an aggregate level. Their use is widely common among international institutions, central banks and statistical agencies; The Directorate General for Economic and Financial Affairs of the European Commission (DG ECFIN) at the European Commission selects a set of questions from its BTS to compile confidence indicators in several European countries to monitor economic developments in regard to the reference variable they are supposed to track i.e. Industrial Production for industrial confidence indicator (European Commisson, 2016). Still, other composite indicators use BTS data in combination with quantitative statistics to obtain a more systematic cyclical indicator system such as the OECD "Composite Leading Indicators" system (OECD, 2012).

To detect and assess the specific features of a cycle, a set of turning points must be identified to define periods of expansion (upturn) and recession (slowdowns). Irrespective of the type of cycle, business cycle or growth cycle, researchers have used two major methods to determine cyclical turning points: non-parametric and parametric approach.

The Bry-Boschan (1976) algorithm is the best known non-parametric approach developed to replicate Burns and Mitchel 's definition of determining turning points; later approximated by Harding and Pagan (2002) for quarterly data. The algorithm consists of simple decision rules : In a first stage, candidates turning points are selected, then some censoring rule is applied to eliminate the TP which do not satisfy some criteria (e.g. minimum phase/cycle duration). Accordingly, business survey data has proven effective and reliable in matching the dating chronology of the reference cycles. In a growth cycle approach, Kitrar et al.(2020) used the Bry-Boschan algorithm and found that the ESI was successful in matching GDP growth's turning points in Russia (Kitrar et al., 2020). Cesaroni et al.(2010) asserts that current production indicator from the BTS data are closely related to industrial production levels in three European countries, hence able to match turning points in the industrial sector for each country. Further, the business cycle stylized facts retrieved from the survey are in line with that of the GDP (Cesaroni et al, 2010). In a more recent paper, Cesaroni et al.(2015) analyze the Italian growth cycle using data from the Italian Survey on Inflation and Growth Expectations (SIGE). On the basis of the Harding Pagan algorithm, they confirm that survey variables are able to early detect all the turning points in GDP growth's cycle (Cesaroni et al., 2015).

As for parametric method, the Markov-switching model popularized by Hamilton (1989) is very common. He suggests time series modeling characterized by discrete changes in regimes for analyzing business cycles. This approach is used for real time detection of turning points (vs the ad-hoc dating of BBQ algorithm) and particularly recessions. Hamilton suggests modeling sudden changes in the behavior of a time series as the outcome of a Markov switching process, which is governed by an endogenous probability rule. In particular, Hamilton fits a Markov switching univariate model to monthly changes in GNP and obtains dates for the US business cycle using the estimated recession probabilities. His econometric model was able to reproduce the US business cycle chronology estimated by the NBER Dating Committee (Hamilton, 1989).

Finally, results of the BTS are often used as a tool for forecasting economic development expressed by the main macroeconomic indicators represented by GDP or its proxy. Generally, two approaches have been adopted for economic forecasting: time-series methods and structural economic models. In time series modeling, economic theory is mainly used as a guide to variable selection, and past behavior of data is used to forecast the future. In contrast, structural economic models are founded on formal economic theory and attempt to translate this theory into empirical relations (Stock, 2001). Economic forecasting with BTS variables is mostly done using time series methods. The balance series (individually or aggregated) are used as explanatory variables in simple short-term nowcasting and forecasting models (United Nations, 2015). There is evidence that models that incorporates BTS data, are superior to benchmark quantitative models in forecasting short-term economic activity. Using simple time series models, Sdrakas and Viguie (2003) found including the first principal component from business survey data in a VAR model significantly improved forecasting accuracy in estimating Euro area GDP, relative to a pure AR model (Sdrakas and Viguie, 2003). In his study, Anderson (2007) uses an out-of-sample forecasting technique to assess the predictive ability of consumer and business survey indicators in forecasting Swedish GDP growth. He finds VAR models that include survey data, improves forecast accuracy for different forecast horizon relative to Random-walk and pure AR models (Andersson, 2007). Moreover, Cesaroni et al.(2015) used Binary autoregressive and univariate dynamic models to forecast Italian GDP growth. They conclude that employment and investment indicators significantly improve forecasting accuracy with respect to benchmarks (Cesaroni et al, 2015).

CHAPTER 3

DATA AND METHODOLOGY

This chapter present the data used to construct composite indicators as well the adopted methodology for identifying turning points and performing short-term forecast.

3.1 Data

The data used in this research is described in detail in this section together with the compilation of composite indicators from the BDL Business Tendency Survey.

3.1.1 Reference series

The BDL Coincident Indicator (CI) is used as reference series since the GDP series is only available on annual basis up to 2018 and incur significant revisions. The CI is a composite indicator adopted by the Central Bank of Lebanon in 1994 as a monthly estimate of the Gross Domestic Product (GDP). It is composed of eight quantitative indicators (Electricity Production, Petroleum Derivatives, Cement, Cleared Checks, Imports, Exports, Money Supply M3,Flow of Passengers) chosen accurately to reflect economic activity in Lebanon. All the components are expressed in real terms and weighted according to their contribution to GDP (Jad, 2013). First, the seasonally adjusted monthly CI data is converted to quarterly data though averaging and then transformed into Quarter-on-Quarter (Q.o.Q) growth rates correspondingly. By taking the simple growth rate, the trend is removed which allows us to work in a growth cycle approach while ensuring stationarity of the series. The series is available from 1993Q1 to 2019Q4[3].

[3]Seasonally adjusted monthly data for the BDL coincident is taken from the BDL's website : http://www.bdl.gov.lb/app/webroot/statistics/

3.1.2 BDL Business Survey

The BDL Business Tendency survey is a simple qualitative survey gathering informed opinions and expectations of enterprise managers on the evolution of their businesses on a quarterly basis in Lebanon, since 1996. The survey is conducted in January, April, July and September on a nationally representative sample of 1200 firms in four sectors[4], stratified by governorates and firm size[5]. Respondents are asked to report their opinion on the evolution of their past, current and future business activity regarding several key economic variables such as production, sales, prices, number of employees, stock of goods, etc... .The questionnaire[6] consists of several close-ended questions with predefined answers: increase, remain unchanged, decrease or below normal, above normal. The BTS methodology is in line with the best practices[7],particularly BDL has implemented similar methods to those employed by INSEE and Banque de France. Besides, the questionnaire is in line with international standard, specifically the harmonized business tendency surveys implemented by the OECD (Jad, 2010)

The indicators extracted from the survey are represented in form of balances computed as the weighted[8] difference between the percentage of positive and negative answers reported by the firms. The results in form of Balance of Opinion (BO) can range from -100 to +100 and are analyzed with respect to the same quarter in previous

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4 Industrial, Commerce, Construction and Tourism sector.

5 Firm size is measured in terms of number of employees.

6 A sample Questionnaire can be found in table 10 of the Annex.

7 Refer to Jad (2010) for a more detailed examination on the methodology, sampling, and output generation process of the BDL business survey.

8 Balances are weighted according to firm size measured in real turnover volumes.

year i.e. on annual basis. A BO that is positive present an improvement in business conditions while a negative one indicates a decline in activity , and any BO close or equal to 0 is considered normal business condition or “business as usual”. The surveys’ results complement real, monetary and financial quantitative data, to help monetary authorities in assessing Lebanon’s economic situation and therefore implementing adequate timely policies (Jad, 2010).

The BDL business survey data (unadjusted) in form of balance of opinions are taken from the Statistics and Economics Research Department at the Central Bank of Lebanon. The balance of opinions from the BTS are first seasonally adjusted using X13-Arima, then smoothed by centering the series around the mean (remove the average). Data is available from 1996 for the Industrial and Commerce sector, and from 1998 and 2000 for the Construction and Tourism sector respectively.

3.1.2.1 BTS Variables

A total of 65 indicators are derived from the five Business tendency surveys. Indicators are grouped on the basis of the question’s horizon: From one hand we have (Ex-post) coincident indicators illustrating business conditions in the current quarter i.e. either as the level registered at the end of the quarter or evolution compared to same quarter in previous year. From another hand, we have (Ex-ante) forward-looking indicators illustrating prediction of the same set of economic variables for the following quarter[9]. Since our goal is to construct coincident indicators from the BTS, we only consider Ex-post variables (27 variables). Besides, the forward-looking indicators are highly volatile, and did not record any relevant relationship with the reference series on the level of correlation and cross correlation. The sample considered for this study starts

[9] The full list of BTS indicator is found in table 9 of the Appendix.

from the first quarter of 2000 to take into account the availability of data for the tourism sector and ends in the fourth quarter of 2019.

3.1.2.2 Composite Indicator by sector: Confidence Indicators

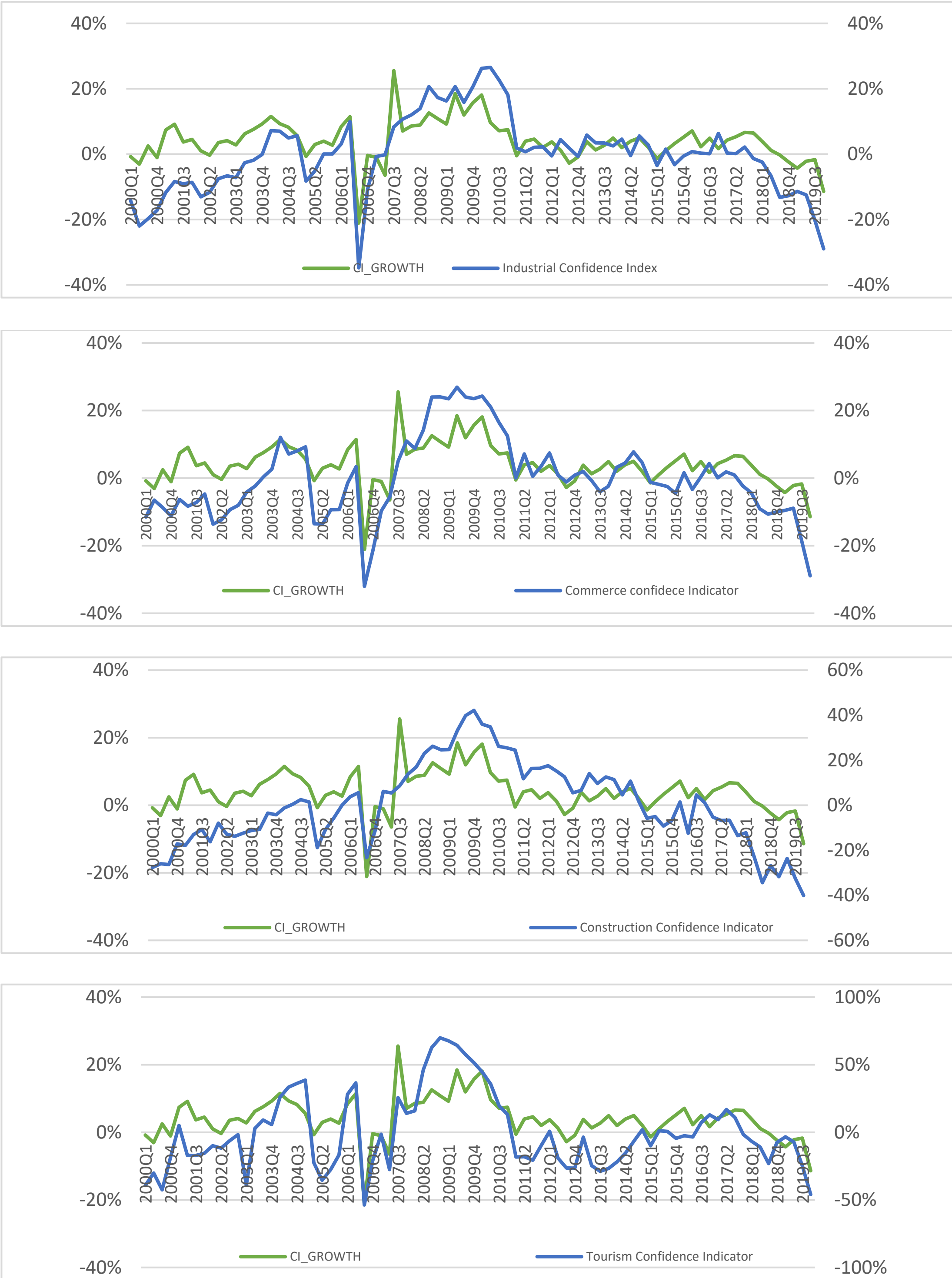
Most institutes that conduct BTS select a set of survey indicators and combine them into composite cyclical indicators to better summarize overall activity and reduce the risk of false signals. These composite indicators are produced to track different economic phenomena, most commonly economic activity/growth related either to the entire economy or to a particular sector. The latter could be coincident, lagging or leading with the economic activity. Nevertheless, additional indices can be produced to track the evolution of other economic variables such as the fluctuation in price levels, employment levels and investment levels.

As a first step to our analysis, four composite indicators are compiled to summarize economic fluctuations on a sectoral level. The hotel and restaurant sector are combined to represent the tourism sector as they are closely related. Accordingly, for each sector, the most relevant variables coincident with economic activity are grouped into a composite indicator named “Confidence”. A simple procedure is followed to select the indicators. First all the variables are graphed against the reference series to visualize the behavior against time, detect any outliers and assess if the series exhibits considerable noise. In the second step, all variables that exhibit a correlation below 50% with the CI are excluded. The variables are mainly selected to maximize the correlation with the reference series. Then, to ensure that the considered variables move together and belong to the same cycle, selected indicator must be strongly correlated with the main BTS variables in the remaining surveyed sectors. Following these simple steps and while always taking into account economic relevance, 12 indicators are finally selected to construct the four confidence indicators. They are illustrated in the table 1 below and the correlation between them can be found in Table 10 of the Appendix.

Sector	Economic indicator	Horizon	Correlation with CI
Industrial Sector	Production	Compared to same quarter in the previous year	79%
	Number of employees	Compared to same quarter in the previous year	66%
	Investment	Compared to same quarter in the previous year	66%
	Registered orders	Current level at the end of the quarter	62%
	Industrial Confidence Indicator		**78%**
Commerce Sector	Sales	Compared to same quarter in the previous year	75%
	Number of employees	Compared to same quarter in the previous year	57%
	Stocks	Current level at the end of the quarter	54%
	Commerce Confidence Indicator		**79%**
Construction Sector	Construction and public works	Compared to same quarter in the previous year	63%
	Number of employees	Compared to same quarter in the previous year	54%
	Portfolio of projects	Current level at the end of the quarter	54%
	Construction Confidence Indicator		**64%**
Tourism Sector	Restaurant-Turnover	Compared to same quarter in the previous year	79%
	Hotel- Turnover	Compared to same quarter in the previous year	66%
	Tourism Confidence Indicator		**77%**

Table 1 Selected BTS indicators

The four Confidence indicators are computed by taking the arithmetic average of the selected balances in each sector. The choice for equal weights is inspired by the European Commission's practices in compiling "confidence indicators" for economies in the European Union and in applicant countries since the 1980s (European Commisson, 2016).The goal behind the construction of such indicators is to summarize the results and reflect economic perception in each surveyed sector by closely choosing variables matching economic activity. When studied, the average indicator (Confidence) would provide the overall result of a surveyed sectors in one figure. The ability to analyze economic development in different sectors in Lebanon on a regular basis otherwise not covered by conventional quantitative statistic presents a major advantage of compiling these indicators. Each Confidence Indicator is graphed against the reference series in Figure 1 below



Note: Left-hand axis corresponds to the CI Q.o.Q growth and the right-hand axis to the confidence indicators balance of opinion.

Figure 1 Confidence Indicators against reference series

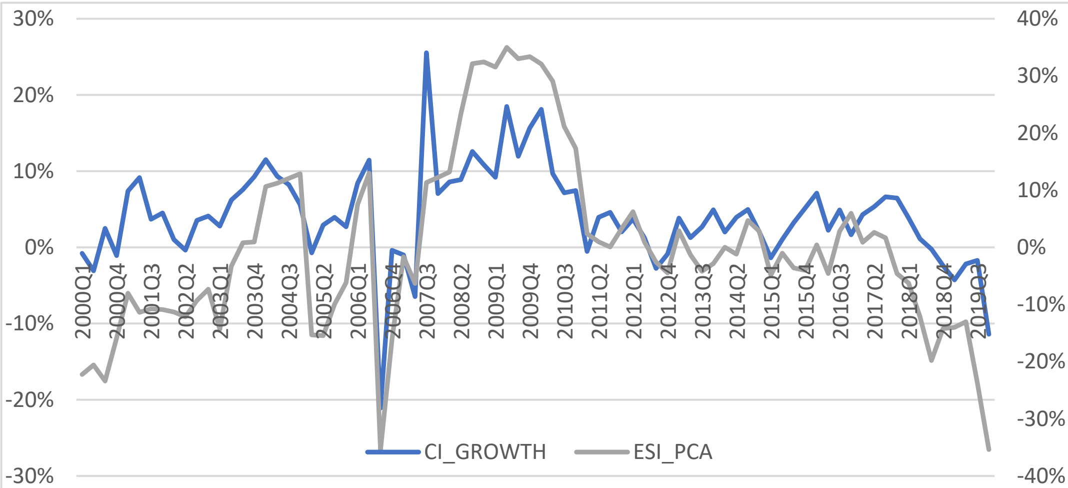
3.1.2.3 Economic Sentiment Indicator

To have an overall picture of economic activity in Lebanon and to be able to work efficiently in detecting turning points as well as to perform a better forecast, the four confidence indicators are aggregated into a single composite indicator named Economic Sentiment Indicator (ESI). The aim of aggregating the different sectors is to better summarize the economic fluctuations in Lebanon rather than movements particular to one sector, therefore capturing economic activity on an aggregate level. However, not all sectors are assumed to have the same importance in regard to the business cycle; therefore, several weighing schemes are applied on the basis of the first principal component (i.e. PCA), sector's contribution to GDP and finally equal weight. The table below illustrates the different ESI considered together with their components' weights and correlation with the reference series.

Components	ESI-Equal Weights	**ESI-PCA Weights**	ESI-GDP Weights
Industrial Confidence index	20%	**27%**	18%
Commerce Confidence Index	20%	**27%**	35%
Construction Confidence Index	20%	**24%**	31%
Tourism Confidence Index	20%	**22%**	16%
Correlation with CI	69.9%	**80.1%**	78.7%

Table 2 Different weighting method and their correlation with reference series

After careful examination and different trials, the PCA is selected as most appropriate weighting methods for our cycle analysis. It coincides strongly the CI and exhibits the highest correlation which is highly significant. Furthermore, it exhibits strong correlation with all the confidence indicators.



Note: Left-hand axis corresponds to the CI Q.o.Q growth and the right-hand axis to the ESI balance

Figure 2 ESI and CI Growth

Figure 2 displays the ESI against the reference series. First, we notice how the dating chronology in the ESI is consistent with the economic sense. They are able to detect all the major phases of the Lebanese business cycle: the 2004-2005 political tensions, 2006 war with Israel, the period of economic boom from 2007 till 2010, the Syrian war in 2011, presidential vacancy 2014-16 and the recession that began in at the beginning of 2017. Secondly, both ESI and the CI move closely together and appear to be synchronized, most turning points are in line with one another. However, some exceptions occur in the period 2016-2107: the through/peak in the ESI lead that of the CI resulting in opposite trend. From another side, by combining the confidence indicators from each sector into a single aggregate indicator, the correlation with the CI increases to 80% higher than any confidence indicator.

3.2 Methodology

The methodology adopted to assess the ability of the ESI to monitor and forecast the reference series is presented in this section. First, the method of detecting turning points is illustrated , followed by the estimation and forecast technique adopted.

3.2.1 Detecting turning points

In this section , the methodology developed to estimate Lebanon's turning points chronologies of the business cycle is developed. The definition of the business cycle is formulated in term of turning points in a series, as proposed in Burns and Mitchel (1946); However, classical business cycle fails to identifies fluctuations of small magnitude as the series are in level, resulting in asymmetric duration of phases with expansion episodes occurring more frequently than recession. Additionally, Lebanon differs considerably in nature and characteristics of short-run macroeconomic fluctuations from industrialized economies; Cycles are shorter and irregular. Therfore, a growth cycle approach is adopted in this study for two main reasons. First, the studied sample consists of only 80 quarterly observations (2000Q1,2019Q4), thus "classical" cyclical analysis may not be appropriate for our analysis as the long duration of classical cycles results in detecting few turning points. Secondly, business sruvey times series do not contain a trend when formed in "balance". Therefore they are best analyzed in a context of deviation from trend. Accordingly the reference series is detrended by simple differencing by taking the annual quarterly growth rate of the reference series.

To identify and measure the specific feature of the cycle, a set of turning points should be detected first to measure periods of expansion and contractions. Detection of the growth cycle is based on a non-parametric algorithm capable of identifying relevant turning points. Particularly, Harding and Pagan (1999) algorithm is considered which is a quarterly approximation of the algorithm proposed by Bry and Boschan (1976). It is a simple and generally accurate tool to analyze the business and growth cycle and it has been heavily applied in the literature. It is quite reliable and is used by the NBER.

3.2.1.1 Bry-Boschan Quarterly Algorithm (BBQ)

The non-parametric procedure, considered to obtain a dating chronology on a univariate aggregated time series, i.e. the reference series and the ESI, is considered in the following algorithm:

- Candidate turning points are detected following the below rule which is the base of the Bry and Boschan (1971) algorithm:

  peak occurring at time t, if $Y_{t-k}<Y_t > Y_{t+k}$, $k=1...K$

  trough occurring at time t, if $Y_{t-k}> Y_t < Y_{t+k}$, $k=1...K$

  K is set to 2 for quarterly data, as this ensures yt a local maximum/minimum relative to the two quarters on either side of Y_t. K is referred to as symmetric window parameter (turn phase).

- In order to ensure that peaks and troughs alternate, a procedure is developed using the following rule: in the presence of a double through, the lowest value is chosen; in the presence of a double peak, the highest value is chosen.

- Additional “censoring “ rules are set in order to combine the turning points determined to comply with predetermined criteria for cycles : A minimum phase duration of 2 quarters for expansions/contractions and complete cycle length (expansion +contraction) is set to a minimum of 5 quarters.

- Additional step adopted : turning points occurring within six months of the beginning or end of the series are disregarded.

The BBQ add-in in Eviews is used to implement the steps described above.

3.2.1.2 Cycle characteristics

Once turning points are identified, the characteristics about the cycle /phases i.e., duration, amplitude and cumulative movement are analyzed to identify stylized fact about the duration and dynamics of the phases of the growth cycle. IN particular, the chronologies and cyclical properties derived from the ESI are compared to that of the reference series.

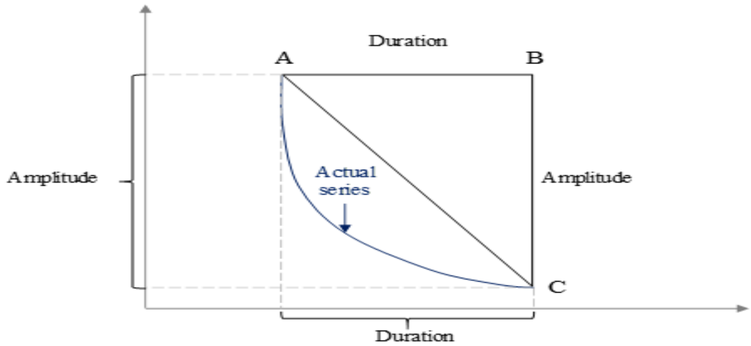


Figure 3 ABC triangle

The characteristics of the cycles are demonstrated above through an illustration of the contraction phase by the triangle ABC. Point A is the peak, i.e. the turning point when the expansion transitions into the contraction phase and point C depicts the trough i.e. the turning point when the contraction transitions into the expansion phase. The first characteristic is presented by the base of the triangle ABC which measures the phase duration, denoted as D_i (AB length), by the number of quarters between peak and trough. Then, the amplitude (BC length) denoted as A_i, is presented by the height of differences between peak and trough. It describes the severity of the recessions and the strengths of the expansions. Finally, the area of the triangle ABC given by Ct= 0.5*(Di *Ai) is referred to by Harding and Pagan as the “triangle approximation” to cumulative movements. It estimates the total gain (loss) in the considered index over the phase (Harding & Pagan, 1999).

3.2.1.3 Concordance

The extent to which the ESI comove with the reference series is assessed by computing a concordance index, originally proposed by Harding & Pagan(1999). The degree of concordance between the specific cycle (ESI) and the reference cycle(CI growth) is measured by the fraction of time they are both in the same state i.e. expansion or contraction. Particularly let "state" $S_{i,t}$ be a series taking the value of 1 when the CI growth series is in expansion and 0 when it is in contraction .We define the states of the ESI series, $S_{j,t}$, in the same way.

Mathematically then, the degree of concordance is computed as :

$$C_{i,j} = T^{-1}\left\{\sum_{t=1}^{T}\left(S_{i,j}\cdot S_{j,t}\right)+\left(1 - S_{i,j}\right)\cdot(1 - S_{i,j})\right\}$$

Where T is the sample size .

This index captures whether the ESI is pro or counter-cyclical. If it is exactly pro-cyclical then the index would be equal to one, while a value of 0 illustrates an exact counter-cyclical relationship. The concordance index also represents a way to summarize information on the clustering of turning points. If the turning points of a specific and reference cycle are coincident then the index would equal one (Pagan, 1999). Hence in our analysis have high values for this index are desired to confirm that the ESI's dating chronology parallels that of the CI.

3.2.1.4 Smoothing

Nonetheless, the CI and ESI series are particularly noisy and appear to register a break during the 2006 war. Particularly, the reference series has been heavily impacted by this shock, disrupting the trend of the CI in the following years, possibly resulting in false signals. The fluctuations in the post-war period are particularly volatile and of short duration, thus disturbing the series' behavior and its analysis; the pattern is not clear and cannot be associated with any relevant economic or political event. Therefore, to have a clearer picture, the two series are smoothed to eliminate the irregular components and focus on the cyclical phases and neglect small noises that might complicate our analysis in the next section. The method that yields the most suitable results is a simple moving average method[10]. It was able to relatively remove the outlier in 2006/7 and smooth the series without significant changes to the dating chronology.

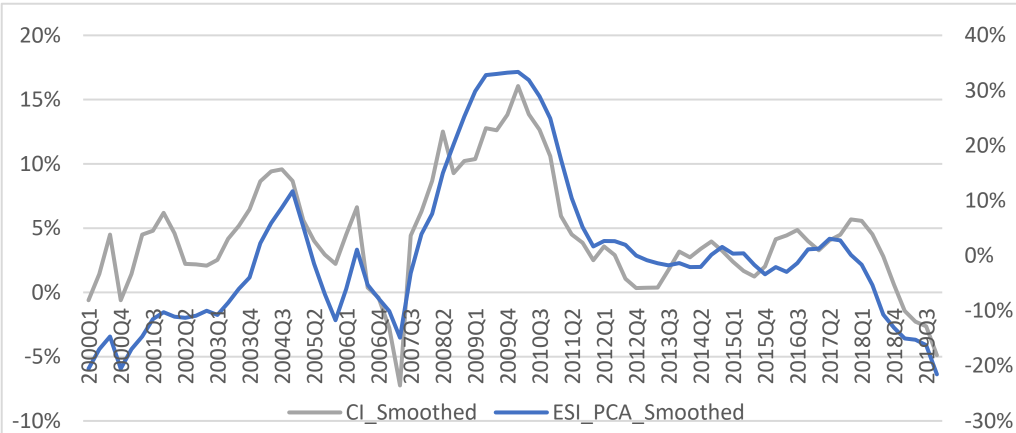


Figure 4 Comparative chart – Smoothed

The smoothed reference and ESI series give a sharper picture of the direction of the economy. The relationship between both series significantly improves as noticed by Figure 4 and is further confirmed by increase in the correlation coefficient to 84%. The next section develops the methodology adopted to construct different time-series models to forecast the CI.

[10] Four quarters moving average

3.2.2 Modeling and Forecast

3.2.2.1 Modeling

After detecting the turning points, different econometric models are constructed to evaluate short-term forecast of the CI using the ESI as explanatory variable. In this study, a time series method is used to construct simple univariate and bivariate econometric models to forecast the CI growth. The objective is to assess the ability of BTS survey variables/information represented by the ESI to forecast quarterly economic growth (CI growth) across different horizons. Accordingly, one AR and another ARIMA model incorporating the ESI as explanatory variable are evaluated against their benchmark. The econometric models are estimated using Ordinary Least squares (OLS) method as it is the most common and efficient estimation method for linear models when the main assumptions for linear regression are satisfied.

Experience has taught that good in-sample fit of a forecasting model does not certainly lead to good out-of-sample performance. Therefore, the approach used in this thesis to forecast the CI is based on the pseudo out of sample forecasting technique proposed by Stock and Watson (2003). According to Stock and Watson (2008)"pseudo out- of-sample forecasting mimics the practice of a real-time forecaster by performing all model specification and estimation using data through date t, making a h-step ahead forecast for date t+h, then moving forward to date t+1 and repeating this through the sample"(p.3-4). Forecast comparison using this method allows capturing model specification uncertainty, model instability, and estimation uncertainty, as well as to the uncertainty of future events (Stock & Watson, 2008).

3.2.2.2 Unit Root Testing

Prior to constructing the models, stationarity in both series must be ensured thus Augmented Dickey-Fuller (ADF) and Philips-Perron (PP) test are conducted to test for the presence of unit roots in both the CI and ESI. Both ADF and PP tests reject the null hypothesis of a unit root in the CI Q.o.Q growth series. As for the ESI, it is expected to be stationary in nature since it is represented in form of balances-deviation from trend. However, according to the ADF and PP test, we fail to reject the null of a unit root in constant at around 16%. Still, as the series is quite short and a subset of a larger sample, business survey data in form of balances might display a local stochastic trend in specific sub-samples. Besides, the test results suggest a break structural break might be distorting the results. Therefore, a Break Unit Root point test is performed, and a break was detected in the third quarter of 2006 as a result of the war with Israel. To mitigate this issue, a dummy variable is considered in the models to account for the July 2006 war. Consequently, the ESI balance series is not differenced as it would mislead our results.

3.2.2.3 Models

Benchmark Models

1-The benchmark model denoted as Model 1, is a pure autoregressive (AR) model considered to estimate the CI growth using its own past values as predictors only. The model states that a variable yt is generated by its past together with a residual term. The residual represents the effects of all exogenous variables and is assumed to be random such that et has zero mean [E(e)= 0] , constant variance [E(e2)= σ2]and no autocorrelation [E($e_i e_{t.}$)=0] The number of lags is selected according to AIC and adjusted R^2.We start with 8 lags as independent variables reducing the number of lags step by step to finally select an AR(4)model. Formally :

$$Y_t = c + B_1Y_{t-1} + B_2Y_{t-2} + B3Y_{t-3} + B_4Y_{t-4} + e_t$$

Where c is a constant ,Yt is annual quarterly growth rate of the CI , and et the error term.

2-An alternative ARIMA(2,3) model, denoted as mode 2 is considered for benchmark purpose. The number of lags is automatically selected according to AIC .

$$Y_t = c + B_1Y_{t-1} + B_2Y_{t-2} + B3e_{t-1} + B_4e_{t-2} + B_5e_{t-3} + B_6e_t$$

where c is a constant , Yt the annual quarterly growth rate of the CI , et the error term.

Augmented models

3-An augmented AR(4) model denoted as model 1' is constructed by adding the ESI and its lags as explanatory variable to the benchmark model. The first, fourth and fifth lags of ESI are included as they are highly significant and improve adjusted R^2 and AIC significantly.

$$Y_t = c + B_1Y_{t-1} + B_2Y_{t-2} + B3Y_{t-3} + B_4Y_{t-4} + B_5ESI_t + B_6ESI_{t-1} + B_7ESI_{t-4} + B_8ESI_{t-5} + e_t$$

Where Y_t is annual quarterly growth rate of the CI, c is a constant, ESI the quarterly constructed indicator and e_t the error term.

4-An augmented ARIMA mode denoted as model 2' is developed by adding the ESI and its first and fourth lags to the benchmark ARIMA model.

$$Y_t = c + B_1Y_{t-1} + B_2Y_{t-2} + B3e_{t-1} + B_4e_{t-2} + B_5e_{t-3} + B_6ESI_t + B_7ESI_{t-1} + B_8ESI_{t-4} + B_9e_t$$

where c is a constant, Y_t the annual quarterly growth rate of the CI, ESI the constructed indicator and e_t the error term.

3.2.2.4 Residual diagnostic

To ensure that our estimators are BLUE, serial correlation and homoscedasticity, i.e. equal variance of the residuals , assumptions are examined. First, "No autocorrelation" assumption requires the error terms to be stochastically independent through time. Formally, E(ei,ej) =0 for $i \neq j$. If not satisfied, we end up with biased estimated variance of regression coefficient leading to unreliable statistical testing. The homoscedasticity requires each error term e_i to have the same finite variance denoted σ^2. Formally, $Var(e_i)= \sigma^2$ for all i=1,2…,n. If violated, then heteroskedasticity is present and the OLS estimators become inefficient. While estimator remains unbiased, the estimated standard error is wrong. Because of this, confidence intervals and hypotheses tests cannot be relied on.

The DW test together with the LM test confirm that the residuals of all the models are not serially correlated. Nevertheless, according to both White test and Breusch Pagan test, we reject the null of homoscedasticity in all the 4 models. Therefore, to mitigate the heteroskedasticity problem, the standard errors and covariance are measured using the Newey West fixed band-width parameter. Consequently, according to the white test, heteroskedasticity is no longer present. We should note that the dummy variable was excluded from the equations since once added, heteroskedasticity problem rose again.

3.2.2.5 Forecasting exercise

In the following section, the steps followed to perform the pseudo-out-sample forecast of the CI using the four models is described.

First, the sample is divided into estimating sample(in-sample) consisting of the first 60 observations and forecasting sample (out-of-sample) of the last 20 observations.

When performing pseudo out-of-sample forecast, model estimation can either be rolling (using a moving data window of fixed size) or recursive (using an increasing data window, always starting with the same observation) (Stock & Watson, 2008). In this thesis, recursive estimation is used starting 2014Q4 to perform multiperiod h-step ahead recursive forecasts across all four models for forecast horizons t+1,t+2 and t+4.

Therefore, for the first one-step ahead forecast, the data used for initial parameter estimations of the models starts from 2000q1(or the first available observation) till 2014q4 and forecasts are produced for t+1, 2015Q1. The sample is extended one period using an expanding window while anchoring the start date and the models are re-estimated to generate new forecasts, this time for 2015Q2. The last forecast uses data on CI growth until 2019Q3 and the forecast is made for 2019Q4. This yields a total of 20 out-of-sample forecasts to evaluate for each of the four models. Accordingly, to perform the two and four-step ahead forecast, the same recursive estimation procedure is followed. For the first two-step ahead forecast, estimation sample starts in 2000q1 and ends in 20141q4, yet the first forecast is produced for 2015Q2.The sample is then extended one periods to estimate the models and perform forecast for 2015q3 this time. This results in 19 forecasts for each of the four models. Further, the four-step ahead forecast is performed similarly resulting in a total of 17 forecasts.

Forecast errors are recorded and used to calculate the root mean square errors (RMSEs). The RMSE is used when ranking the performance of the forecasting models and is defined as:

$$\mathrm{RMSE} = \sqrt{\sum_{i=1}^{n} \frac{(\hat{y}_i - y_i)^2}{n}}$$

Where $\hat{y}_i$ is the pseudo out of sample forecast of CI growth and y_i its actual value. In addition, relative RMSE is used to measure for any improvement/deterioration compared to benchmark models; It is simply calculated as :

$$\text{Relative RMSE} = \frac{\text{RMSE}}{\text{RMSE}_b}$$

where RMSE_b is the RMSE from a benchmark model, either model 1(AR) or model 2(ARIMA).

It should be noted that for forecasting purposes, both CI and ESI are not smoothed as our aim is to forecast the actual CI growth without transformation. Econometric models are analyzed using EViews 10 software. The roll user object is used to perform recursive estimation and n-period ahead forecast for the models.

CHAPTER 4

EMPIRICAL RESULTS

The results of this thesis are presented in this chapter. The dating chronology and growth cycle characteristics obtained from the ESI are depicted and compared to the reference series, in section 4.1. Estimation and forecast results from the econometric models developed in section 3.2.2, are depicted in section 4.2.

4.1 Growth cycle measurement

4.1.1 Turning Points

The turning points identified using the BBQ algorithms in the CI Q.o.Q growth series and the ESI, are presented together with phases' duration, in table 3.

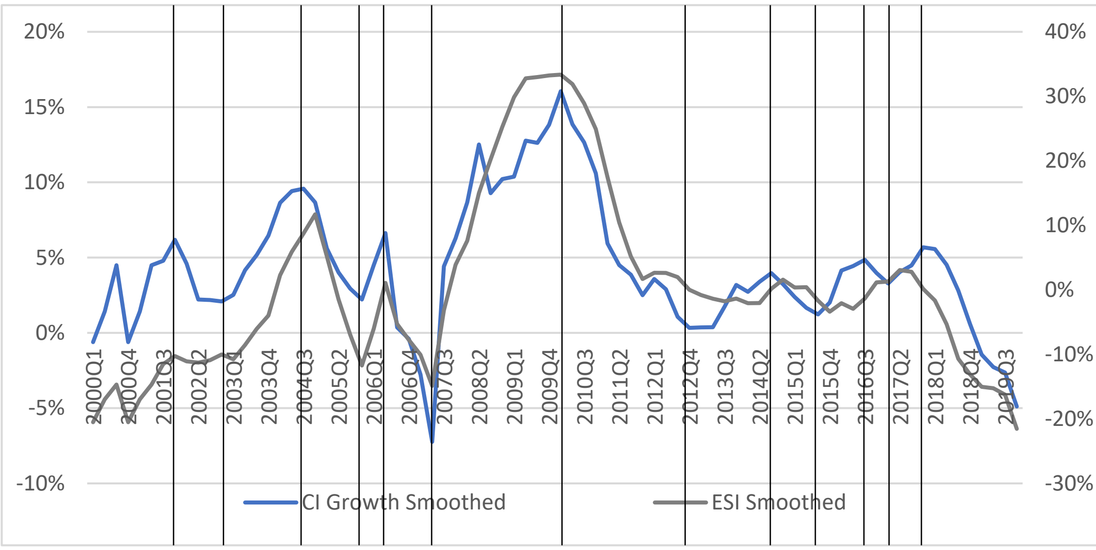
Turning points for CI Smoothed				Turning points for ESI Smoothed			
Peaks	Recession duration	Troughs	Expansion Duration	Peaks	Recession duration	Troughs	Expansion Duration
2001Q4	4 Quarters	**2002Q4**	7 quarters	**2001Q4**	2quarters	**2002Q2**	10quarters
2004Q3	5 quarters	**2005Q4**	2 quarters	**2004Q4**	4 quarters	**2005Q4**	2 quarters
2006Q2	4 quarters	**2007Q2**	12 quarters	**2006Q2**	4 quarters	**2007Q2**	10 quarters
2010Q1	11 quarters	2012Q4	7 quarters	**2010Q1**	16 quarters	2014Q1	3 quarters
2014Q3	4 quarters	**2015Q3**	4 quarters	**2014Q4**	4 quarters	**2015Q4**	6 quarters
2016Q3	2 quarters	2017Q1	2 quarters				
2017Q4		-		**2017Q2**		-	

Table 3 Turning points

According to the BBQ Algorithm, 13 points turning points (TP) are detected for the CI Q.o.Q smoothed series forming six complete cycles. The last peak (2017Q4) is not matched with its corresponding trough therefore the duration of last recession is not defined. Moreover, this results in seven peaks and six troughs with phases' duration ranging between two to twelve quarters.

As for the ESI smoothed series, 11 turning point are detected forming five complete cycles, one cycle less than the CI. This results in three missed and one extra TP with respect to the reference dating chronology: the ESI fails to detect two troughs (2012Q4 and 2017Q1) as well as one peak (2016Q3 peak) registered in the reference series while registering an additional trough in 2014Q1. A total of six peaks and five troughs are detected with phases duration ranging between two and sixteen quarters.

Nonetheless, the ESI matched most of the TP detected by the CI. Out of the 13 TP detected in the CI, 10 were matched by the ESI yet some were lagging/leading by one to two quarters. Namely, six peaks and four throughs are matched and highlighted in bold in table 3 .The ESI dating chronology up until 2010Q1 is exactly the same as that of the reference TP with the exception of 2004Q4 trough which is lagging the reference trough by one quarter. The difference in dating chronology occurs after 2012.



Note: Left-hand axis corresponds to the CI Q.o.Q growth and the right-hand axis to the ESI balance
Note: Vertical lines represents the turning points detected in the CI growth series.

Figure 5 Comparative chart ESI against the reference

According to figure 5, both ESI and the CI move closely together and appear to be synchronized, most turning points are in line with one another. However, in some sub-sample the relationship is not well-defined. In particular deviations in dating chronology occurs during the 2010-2014 period resulting in different phases' duration and contradicting trend. Namely, the significant downturn that started as of 2010Q1 is detected by both series, yet it ends eleven quarters later in 2012Q4 for the CI while it lasts considerably longer for the ESI ending 16 quarters later in 2014Q1. This leads the ESI to record the longest phase duration throughout this period lasting around four years. This results in a more pronounced upturn in the CI lasting 8 quarters ending in 2014Q3 compared to a three-quarter expansion for the ESI ending in 2014Q4 .Thus the two series moved in opposite trend in 2013, an expansion in the CI against a continued downturn in the ESI.

Additionally, the ESI does not record the short-lived contraction of 2016-2017 nor the expansion that follows and ends in 2017Q4, contrarily to the reference series. This results in contradicting trend in the 2015-2018 period with two peaks registered by the reference series, 2016Q3 and 2017Q4 compared to only one peak registered by the ESI, 2017Q2. The last peak registered by the ESI is detected two quarter ahead of the CI's 2017Q4 peak. Furthermore, the ESI appears to mimic or slightly lead the reference series for the remaining period of the sample.

The contractions phases registered in the ESI are illustrated by the shaded areas in Figure 6 while unshaded area refer to periods of expansion.

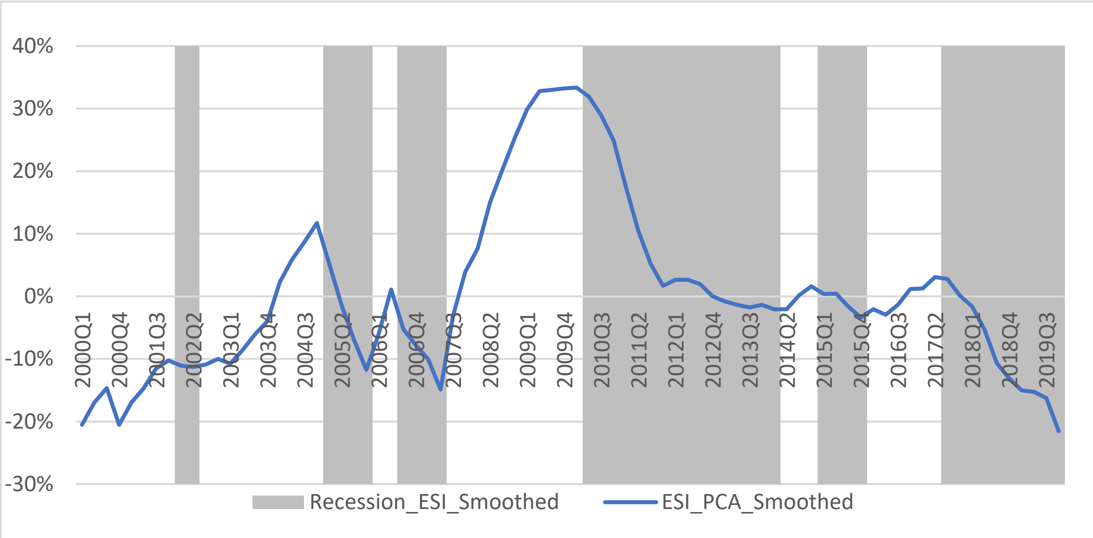


Figure 6 ESI Recession Shading

4.1.2 Cyclical analysis

Here that the turning points are detect , the cyclical attributes of the ESI and the reference series are presented, in terms of average duration, amplitude, cumulative movement of each phase of the cycle.

	Cycles CI Smoothed	Cycles ESI Smoothed
Duration expansion contraction	 5.67 5	 6.4 6
Amplitudes: expansion contraction	 7.48% -7.56%	 18.83% -16.16%
Cumulation: expansion contraction	 43.80% -33.20%	 105.94% -105.99%

Table 4 Cycle Characteristics

According to the results from the algorithm in table 4, the duration of a complete cycle averages around 10.7 quarter in the reference series. The average phase duration is quasi-symmetric ranging between 5.67 quarters for expansions and 5 quarters for recession , typical for growth cycle. As for the ESI, the average duration of a full cycle is 12.4 quarters marginally longer compared to the reference cycle. Further, phases are quasi-symmetric in duration as well with the expansion phase averaging 6.4 quarters against 6 quarters for contractions.

Moreover, the amplitude for expansion and recessions is balanced on average for both series. However ,one important difference is that the ESI display a higher amplitude level reaching 19% and -16% for expansions and contraction respectively against 7.5% and -7.6% for the CI.

The cumulative movement represents the sum of the amplitudes calculated for each period based on the turning point previously determined and depends on the duration, the form and the amplitude of the phase. The cumulative movement differ relatively among the CI phases with expansion phases registering 44% against -32% for contractions, on average. However, the ESI displays considerably higher but more symmetric movement between phases recording 106% and -106% for both expansions and contraction on average, respectively . While the CI point to more pronounced cumulative movement for expansion phases compared to contractions , the ESI point to more balanced behavior .

Finally, according to the formula, the degree of concordance between the CI growth series and the ESI registered 0.83 which is remarkably high. It shows the close relationship between the cyclical properties of both series and demonstrates that most of the phases, upturn or downturn registered in each series, occur mostly at the same time.

4.2 Estimation and forecasting

This section exposes the results from the OLS estimation and more notably the forecast performance from each of the considered models.

4.2.1 Parameter estimation

The estimation results of the augmented AR and ARIMA and their corresponding benchmark models are presented for comparison using data available until 2014Q4. Table 5 below presents the parameter estimates together with their standard errors in parenthesis. In addition, statistical significance is highlighted with the asterix symbol[11].Regression model accuracy metrics are presented as well (AIC,R^2…).

According to the results, the benchmark models fail to fully explain the variation in the CI, with adjusted R^2 ranging between 0.2 and 0.27. The constant and first three autoregressive coefficient in the AR(4) model are positive while the fourth is negative. All coefficients are significant with an adjusted R^2 of 0.2. By contrast, in the ARIMA model, the coefficient estimate of the first lag is negative while that of the second lag is positive together with the three MA terms. The coefficients are all insignificant, yet the model has a higher adjusted R^2 and lower AIC compared to the AR(4) benchmark.

The results show improvement of the augmented models over their corresponding benchmark in explaining the dependent variable. The independent variables are able to explain 77% and 88% of the variation in CI growth for the augmented AR(4) and ARIMA model respectively. The additional coefficients corresponding to the ESI variable are all significant at the 1% level in both models. The coefficients' sign of the ESI variable is the same across the augmented models.

[11] * significant at 10% , ** significant at 5% , *** significant at 1%.

Specifically, the contemporaneous and fifth lag of the ESI's coefficient are both negative while the first and fourth lag coefficient are positive .However, coefficient value vary slightly between models. The coefficient for ESI_t is around 0.467 in the augmented AR against 0.385 in the augmented ARIMA while that of the fourth and fifth lag are-0.239 and 0.129 respectively in the former compared to -0.208 and 0.130 in the latter.

From another hand, we notice how the second autoregressive coefficient and third lag of the error become significant when combined with the ESI explanatory variable in the augmented ARIMA .This model possesses the lowest AIC among the four models at -4.012. Moreover, the p-value corresponding to the F-test rejects the null that all slope coefficients are equal to zero in all the models

Eq Name: Method: Dep. Var:	AR_4 Least squares CI Growth	ARIMA Least Squares CI Growth	AR_4_ESI Least Squares CI Growth	ARIMA_ESI Least Squares CI Growth
C	0.054 (0.0138)**	0.049 (1.1664)	0.041 (0.0078)***	0.037 (0.0094)***
Y_{t-1}	0.250 (0.0958)***	-0.189 (6.4248)	0.207 (0.1234)	-0.232 (0.3301)
Y_{t-2}	0.200 (0.0724)**	0.126 (5.9533)	0.326 (0.1129)***	0.235 (0.1098)**
Y_{t-3}	0.287 (0.1078)**		0.122 (0.1454)	
Y_{t-4}	-0.345 (0.2306)*		-0.348 (0.1762)*	
e_{t-1}		0.630 (0.7947)		0.702 (0.4814)
e_{t-2}		0.110 (10.4771)		-0.123 (0.1544)
e_{t-3}		0.481 (5.6333)		0.512 (0.2247)**
ESI_t			0.467 (0.0685)***	0.385 (0.0585)***
ESI_{t-1}			-0.142 (0.0360)***	
ESI_{t-4}			-0.239 (0.0733)***	-0.208 (0.0838)***
ESI_{t-5}			0.129 (0.0471)***	0.130 (0.0538)***
Observations:	56	58	51	53
R-squared:	0.259	0.338	0.819	0.835
Adjusted R-squared	0.201	0.274	0.785	0.805
F-statistic	4.451	5.309	23.820	27.798
Prob(F-stat)	0.004	0.001	0.000	0.000
AIC	-2.718	-2.818	-3.879	-4.012

Table 5 Estimation results

4.2.2 Forecast results

The results from the pseudo out-of-sample forecast of the CI growth produced by each model for horizons t+1,t+2 and t+4 are presented in terms of RMSE and relative RMSE to benchmark 1(AR) and to benchmark 2(ARIMA), in this section.

4.2.2.1 One step ahead

According to the one step ahead forecast results reported in table 6, the AR benchmark model has an RMSE of 0.421. The alternative ARIMA benchmark has a lower RMSE of 0.436 constituting 3.8% deterioration in accuracy compared to AR benchmark model. Among the two models employing survey data, the forecasting performance varies slightly, yet they both present a considerable improvement with respect to benchmark. The lowest RMSE is found for the augmented AR model (model 1') at 0.0279, constituting a 34% improvement compared to benchmark , while the ARIMA augmented model (model 2') presented a 27% improvement compared to its corresponding benchmark .

#	Models	RMSE	RRMSFE to 1	RRMSFE to 2
1	AR_4	0.0421	1.00	0.96
2	ARIMA	0.0436	1.04	1.00
1'	**AR_4_ESI**	**0.0279**	**0.66**	**0.64**
2'	ARIMA_ESI	0.0321	0.76	0.73

Table 6 RMSE from one-step ahead forecast (t+1)

The produced forecasts for model 1'are illustrated against the actual reference series, in figure 6. The last one-step ahead forecast produced by this equation for the fourth quarter of 2019 point to negative growth of 8.1% in the CI against an actual value of negative 11.4%.

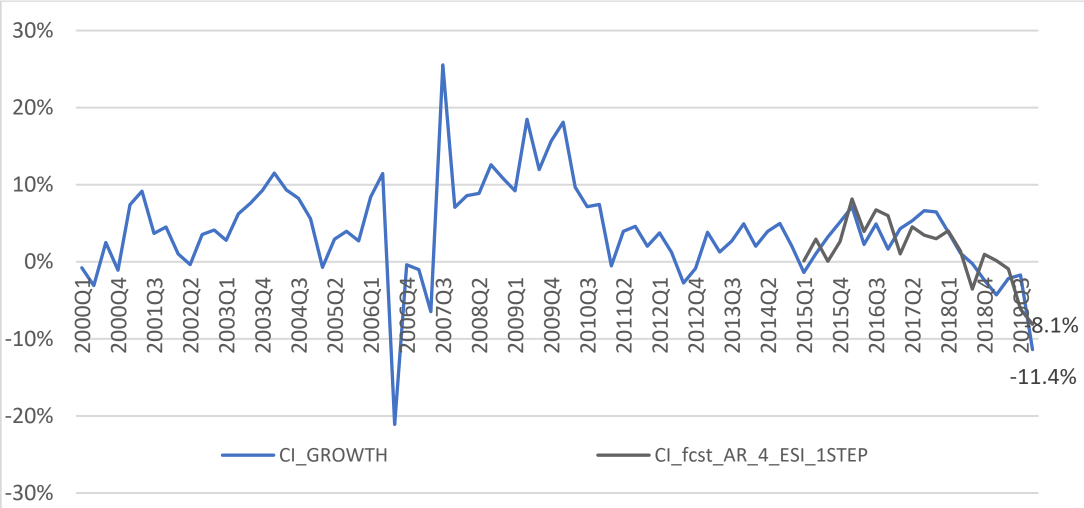


Figure 7 One Step Ahead Forecast of model 1’

4.2.2.2 Two-step ahead

As for the two-step ahead forecast, according to the results in table 7, model 1 has a RMSE of 0.041. The alternative ARIMA benchmark (model 2) has a RMSE of 0.039 presenting a shy improvement of 5 % compared to model 1.Furthermore, similarly to one step ahead ,all models incorporating the ESI variable demonstrates considerable progress over their corresponding benchmark. Nonetheless, the augmented AR(4) model (model 1’) presents again the largest improvement with a RMSE of 0.028 representing a 31% reduction with respect to its benchmark (model 1), while the ARIMA augmented model (model 2’) indicates a 22% reduction in RMSE relative to its corresponding benchmark.

#	Models	RMSE	RRMSE to 1	RRMSE. To 2
1	AR_4	0.0410	1.00	1.05
2	ARIMA	0.0391	0.95	1.00
1'	**AR_4_ESI**	**0.0281**	0.69	0.72
2'	ARIMA_ESI	0.0343	0.84	0.88

Table 7 RMSE from two step-ahead forecast (t+2)

The two step-ahead forecast produced by model 1’ model is illustrated in figure 7. The forecast point to a negative 8.4% Q.o.Q growth in the CI against an actual reduction of 11.4% .This compares to a positive 1.3 % and 0.4 % forecast produced by benchmark model 1 and 2 respectively.

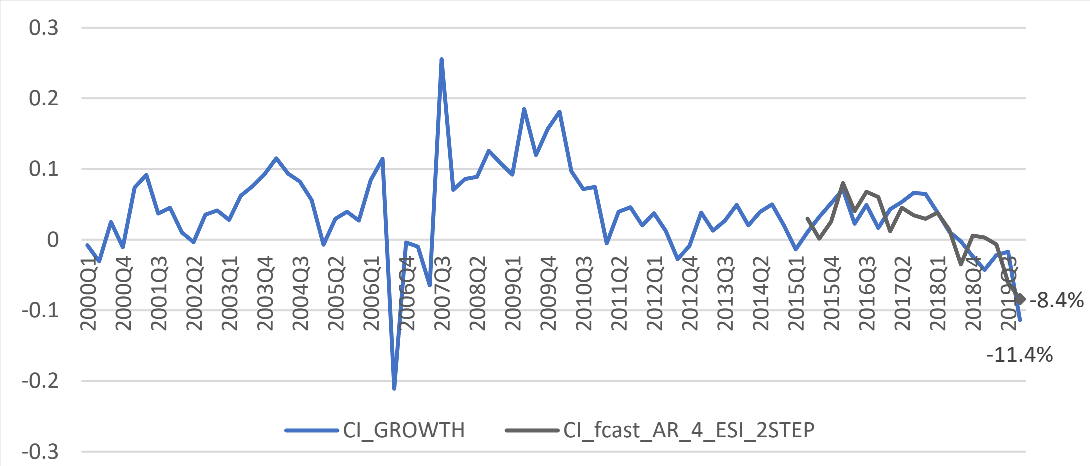


Figure 8 Two step-ahead forecast of model 1'

<u>4.2.2.3</u> <u>Four step- ahead</u>

According to table 8, the RMSE from the four-step ahead forecast produced by the ARIMA benchmark is relatively lower compared to the AR(4) benchmark. Yet, both benchmark models have a higher RMSE when compared to RMSE from t+1 and t+2 forecast. As for the augmented models, the 4th order augmented AR model (model 1’) has the lowest forecast error among all models with a 36% improvement over the its benchmark compared to 4% improvement of the augmented ARIMA model relative to its corresponding benchmark.

#	Models	RMSE	RRMSE to 1	RRMSE to 2
1	AR_4	0.0438	1.00	1.07
2	ARIMA	0.0408	0.93	1.00
1’	**AR_4_ESI**	**0.0279**	**0.64**	**0.68**
2’	ARIMA_ESI	0.0393	0.90	0.96

Table 8 RMSE from four step-ahead forecast (t+4)

The forecasted values of the reference series produced by model 1' are illustrated in figure 8, registering -8.3% for 2019Q4.

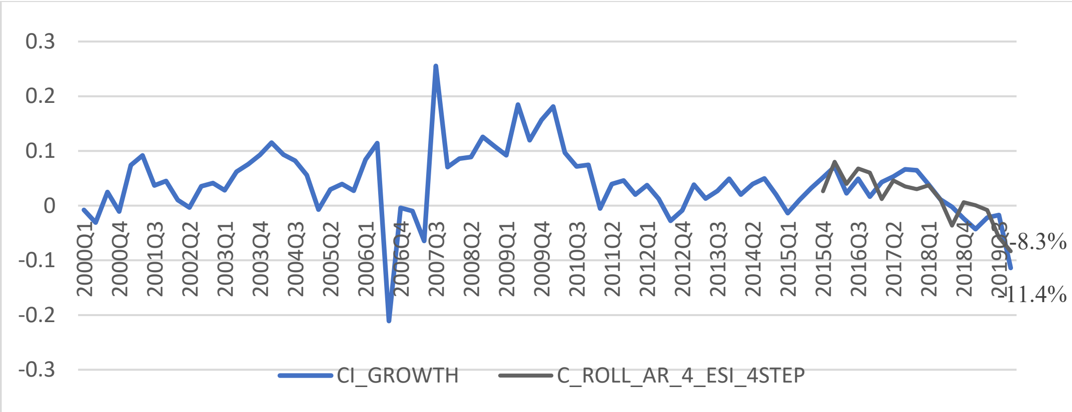


Figure 9 Four step-ahead forecast of model 1'

What is apparent is that model 1', the augmented AR(4) model performs best for all forecast horizons with respect to all other models considered. Furthermore, the forecasted values of the CI Q.o.Q from this model, do not differ much between different forecast horizons. The first, second and fourth step forecasted values for the fourth quarter of 2019 are -8.1% , -8.4% and -8.3% respectively compared to values of -8.9 , -9.1 and -10.2% in the ARIMA augmented model.

CHAPTER 5

DISCUSSION

In this chapter, the results presented in chapter 4 are discussed and interpreted in detail to establish the validity of the ESI to monitor and forecast the CI and thus Lebanese economic activity.

5.1. Turning point analysis and inference

According to the results, we infer that the ESI is a reliable coincident indicator able to monitor economic growth in Lebanon on a quarterly basis. First, the graphical illustration and high correlation coefficient of 84% with the reference series demonstrate a close relationship between them. Furthermore, the BBQ algorithm reveal a nearly identical dating chronology to that of the CI Q.o.Q growth. The ESI captures nearly the same cyclical movement as the reference series. It successfully matched most of the reference series' turning points , particularly 10 out of the 13 reference TP were matched, yet some were leading or lagging by one or two quarter. Further, the cycle/phases characteristics in terms of duration and amplitude correspond well to the reference series and to major economic and political developments witnessed during the period. The average duration of the compete growth cycle for both ESI and CI is approximately similar at around 3 years, consistent with previous findings done by Jad (2016). However, the CI cycles derived by the Bry-Boschan method averaged around 4 years in her study; we can attribute this discrepancy due to different sample covered in each study as Jad(2016) starts her sample in 1996 and ends in 2016 and does not include the consecutive internal and external shocks witnessed as of the end of 2017. Therefore, it may not be appropriate to compare cyclical attributes between two unidentical phases , particularly for Lebanon where phases are especially shaped by unexpected local and regional political developments

Furthermore, the average duration of the phases is quite similar and symmetric for both series, even though ESI's phases are one quarter lengthier. Phases symmetry confirm the growth cycle characteristics of the identified cycles. However, difference occur in the amplitude and cumulative movement within phases of the ESI compared to the CI. We argue that this results mostly from the volatile nature the balance indicators (ESI) and its sensitivity to reach extreme value more easily compared to the CI growth series. Even though balances are expressed in percentage they cannot be interpreted as growth rates as they are bounded by ± 100 and are based on business sentiment.

Nevertheless, most cyclical characteristics and turning points are compatible between the CI and ESI. Further, the high degree of concordance with the reference series confirms the strong relationship with reference series thus its reliability to monitor growth cycles in Lebanon. These conclusions are in line with previous findings stressing on the usefulness of business survey indicators to monitor cyclical developments in Lebanon, presented by Jad(2010) through a graphical and correlation analysis. The additional turning point chronology presented in this thesis, provides a more concrete manner to formalize the reliability of the BDL BTS indicators in detecting and monitoring growth cycles in Lebanon.

The constructed composite indicator(ESI) successfully explain economic development in Lebanon in a timely manner. The detection of the last peak ahead of the reference series , highlights the importance of the business survey indicator in monitoring the growth cycle .Given the usual delay in national account publication and conflicting trend of the CI, the business survey indicators were the only indicators during 2018 to signal this significant downturn, which deepened later and turned into financial and economic crisis. The simplicity and timelines of these indicators present the major advantage against other cyclical indicators, specifically CI in this study. Consequently, the use of the BDL business surveys is reasoned as equally important to the CI in monitoring economic activity in Lebanon, and even more accurate in some periods.

However, we should point that the ESI fails to mimic the reference series' trend in two sub-sample resulting in three missed turning points. In the first sub-sample from 2010 to 2014, the ESI record a long-sustained contraction resulting in the missed trough of 2012Q4 thus challenging the upward trend of the CI in 2013. Although difficult political and economic conditions governed during this conflicting period~~,~~ especially the negative repercussions from Syrian conflict after 2011, however GDP figures point to a 3% growth in 2013 compared to 2% in 2012, in line with CI growth trend. Therefore, we argue that the contradicting trend with the reference series might have resulted from the qualitative nature of the ESI. In the case of sample survey-based estimates, major sources of error can arise from coverage , sampling, non-response, response, processing, and problems in dissemination indicator leading to inaccuracy of the survey-based indicator to reflect the true population value.

Nonetheless, plausible explanation appears to support the ESI's trend over the reference, during the second conflicting period i.e. 2017-2018. We argue that two of the missed turning points are the results of an overestimation of the CI in 2017 -2018 period, rather than any error related to survey-based indicators. This could be supported by the trend of GDP growth which recorded 0.5% and -1.9% in 2017 and 2018 respectively, against a positive 5.7% and 0.5% recorded in the CI during that period. The ESI however, captures the last peak of 2017Q2 two quarters earlier than the CI and clearly shows this negative trend in 2018 with a significant drop of balances averaging around 1.8% and -7.7% in 2017 and 2018 respectively, similar to the trend in GDP growth.

The use of composites such as the CI has some flaws due to its quantitative nature and its compilation method. For example, import statistics, a component of the CI, are revised regularly by the customs office which if applied may alter the index‘s value. In addition, the index’s base year is still fixed at 1993, thus it has not been revised to reflect the recent economy as population , disposable incomes , employment and mainly the structure of the economy significantly evolved during the last 27 years.

5.2 Forecast

Regarding short-term forecast, results show that including business survey indicators in simple time series models as explanatory variables improves forecast accuracy of economic activity proxied by CI growth in this thesis. First from the estimation results we showed how the additional ESI coefficients are all significant in the augmented models thus have a higher goodness of fit and lower AIC compared to benchmark. More importantly, results from the out-of-sample forecast proved adding the ESI composite indicator to the simple AR and ARIMA benchmarks considerably improves short-term forecast of the CI growth. The forecast results demonstrate a significant reduction in RMSE in both augmented models relative to their corresponding benchmark .However we infer that the Augmented AR(4) model is most appropriate as it provides consistently the highest forecast accuracy with more than 30% improvement across all forecast horizons.

On the other hand, benchmark models are reasoned not relevant for forecasting the CI growth. These simple time series models(AR and ARIMA) are unable replicate the unique cyclical behavior of the CI given the recurrent shocks that Lebanon encounters, particularly post 2017. In particular, the benchmark models fail to forecast the CI's negative growth trend in 2019 and instead points to a positive growth ranging between 0.4% and 1.2.% on average during that year, across the different forecast horizons. Therefore, adding business survey data to simple short-term models is deemed essential to produce a more reliable and accurate forecast of economic activity in Lebanon compared to classical time series forecasting methods (AR,ARIMA) .This is justified by survey's timeliness and sensitivity to shocks which could help produce more realistic forecast based on businesses' informed opinion. These conclusions are in line with previous work done by Cesaroni et al (2015) and, Sdrakas and Viguie (2003) which underlined the predictive power of business tendency survey in short-term forecast of different GDP growth compared to benchmark .

The CI growth forecast produced by model 1'(Augmented AR(4)) are the closest to actual values of CI growth during the out-of-sample forecast period from 2015 till 2019. Nonetheless, both augmented models were able to forecast the large drop in growth in 2019Q4 for all the forecast horizons which is remarkable given the difficulty to forecast such a negative shock. Forecast produced by both models were below -8% for 2019Q4 close to the actual -11.4%, in contrast to a positive CI growth forecast produced by both benchmarks.

We can notice that the forecast from the different horizon from each augmented models do not differ significantly across horizons, which can be argued to be due to the inclusion of several lags of both the CI and the ESI .Furthermore, One observation can be done on the similarity of the RMSE for t+1 and t+4 forecast for model 1' which produce the most accurate forecast compared to the t+2 forecast horizon. We assert that this could be due to the fact that the ESI's second lag is not included as explanatory variable while the first and fourth are included in the model. Still, the RMSE is not much different for the t+2 forecast at 0.281 compare to 0.279 for t+1 and t+4.

Although the augmented models are superior to benchmark in terms of forecast accuracy ,yet they were unable to always produce close forecast values of the CI with important discrepancies from actual values for some periods, even for the best performing model (model1'). This occurrence is normal as our model are very simple and exclude essential variables. Particularly, the dummy variable to control for the effects of the 2006 war which was supposed to be included in each equation would have improved estimation and forecast accuracy if the heteroskedasticity problem did not arise .Additionally, developments arising in essential sectors affecting economic activity are not captured such as the external , fiscal and monetary sector. We argue using only information from the real sector cannot always produce very accurate forecast of fluctuations in economic activity .

CHAPTER 6

CONCLUSION

In this thesis we have constructed confidence indicators for each surveyed sector of the BDL Business tendency survey and later combined them into a single aggregate ESI to monitor and forecast growth cycles in Lebanon.

Using a non-parametric approach of detecting turning points(TP), the ESI was concluded reliable in mirroring the cyclical movement of the reference series. According to the BBQ algorithm its dating chronology correspond well to that of the CI and to major economic and political developments. Accordingly, the constructed ESI in this thesis presents an accurate tool to reliably monitor economic activity in Lebanon on a quarterly basis and reduce the probability of detecting false turning points when focusing only on quantitative indicators such as the CI. Moreover, an interesting effort can be directed towards detect turning points in real time using a modern parametric approach such as a Markov-switching regime and evaluate the results again the classical BBQ method.

On the other hand , we can firmly conclude from the pseudo out of sample forecast, that the models incorporating the ESI and its lags as explanatory variable are superior to benchmark in forecasting the CI for the 2015 2019 period. The best forecast corresponding to the AR augmented model which improved short-term forecast by more than 30% compared to simple AR and ARIMA models for horizon t+1, t+2 and t+4. However, the forecast values are not always exact , thus one must examine the capability of developing more accurate and complex models to replicate a closer behavior of the CI growth in terms of exact magnitude by including additional variables from the fiscal, monetary and external sector i.e. fiscal deficit, BDL reserves level, NFA.

Definitively, the work from this thesis might be used in a number way to have a better understanding of the Lebanese economy. First the constructed confidence indicators will allow for quarterly economic analyses on a sectorial and micro level, otherwise only available on an annual basis from the national accounts' publications, which are significantly delayed.

Further the ESI can complement the Coincident indicator in understanding the dynamics in each cycle and analyze the sources of fluctuation each quarter. It is a powerful tool that can complement the CI in areas that are not covered by standard quantitative data ,particularly economic agents' sentiment. By complementing the CI with the ESI , the probability of detecting false turning points can be reduced .Also, the ESI summarize overall economic activity and permits to detect turning points and perform short-term forecast for the following quarter when CI is still not published.

We should mention the CAS published its first Quarterly GDP figures in 2019. The series goes back to 2016, and when updated the same exercise done in this study can be performed to examine which indicator CI or ESI has stronger relationship with quarterly GDP growth by comparing turning points and short-term forecasts.

Nevertheless, the limitations of this study are presented here. The main limitation comes from the type of data used. The data from these surveys are qualitative which can give rise to the problem of subjectivity in respondents' answers. Besides, sampling and non-response error are always in place and might be a factor to misrepresent the sample results. From another hand our small dataset consists of only

80 quarterly observations which may not be enough for a deep analysis and inference of the findings.

Regarding the cyclical methodology , the selected smoothing method could be criticized as the four-quarter moving average technique gives more weights to previous quarters rather than current ant t+1 values / quarter leading to a lagging series . However, in the trial phase , each technique (HP filter, exponential smoothing) was giving substantially different results regarding cycle characteristics and TP chronology. We found that it was the most efficient smoothing methods as it did not alter turning point chronology and was relevant to all the major economic and political events occurring during that period.

APPENDIX

Economic indicator	Start date	Horizon	Type
Industrial Sector			
A01 - Production	**1996**	**Compared to same quarter in the previous year**	**Coincident**
A02 - Demand	**1996**	**Compared to same quarter in the previous year**	**Coincident**
A03 - Foreign demand	**1996**	**Compared to same quarter in the previous year**	**Coincident**
A04 - Prices of goods	**1996**	**Compared to same quarter in the previous year**	**Coincident**
A05 - Prices of raw materials	**1996**	**Compared to same quarter in the previous year**	**Coincident**
A06 - Number of employees	**1996**	**Compared to same quarter in the previous year**	**Coincident**
A07 - Monthly Wage Rate	**1996**	**Compared to same quarter in the previous year**	**Coincident**
A08 - Percentage change in wages	**1996**	**Compared to same quarter in the previous year**	**Coincident**
D01 - Investment	**1996**	**Compared to same quarter in the previous year**	**Coincident**
B01 - Stock of goods	**1996**	**Current level at the end of the quarter**	**Leading**
B02 - Stock of raw materials	**1996**	**Current level at the end of the quarter**	**Leading**
B03 - Registered orders	**1996**	**Current level at the end of the quarter**	**Leading**
C01 - Production expectations	1996	Expectations for the following quarter	Leading
C02 - Demand expectations	1996	Expectations for the following quarter	Leading
C03 - Foreign demand expectations	1996	Expectations for the following quarter	Leading
C04 - Prices of goods expectations	1996	Expectations for the following quarter	Leading
C05 - Prices of raw materials expectations	1996	Expectations for the following quarter	Leading
C06 - Number of employees expectations	1996	Expectations for the following quarter	Leading
C07 - Stock of goods expectations	1996	Expectations for the following quarter	Leading
C08 - Stock of raw materials expectations	1996	Expectations for the following quarter	Leading
D02 - Investment expectations	1996	Expectations for the following quarter	Leading
E01 - Overview	1996	Expectations for the following quarter	Leading
Commerce Sector			
A01 - Sales	**1996**	**Compared to same quarter in the previous year**	**Coincident**
A02 - Prices	**1996**	**Compared to same quarter in the previous year**	**Coincident**
A03 - Number of employees	**1996**	**Compared to same quarter in the previous year**	**Coincident**
A04 - Monthly wage rate	**1996**	**Compared to same quarter in the previous year**	**Coincident**
A05 - Percentage change in wages	**1996**	**Compared to same quarter in the previous year**	**Coincident**
B01 - Stocks	**1996**	**Current level at the end of the quarter**	**Leading**
C01 - Sales expectations	1996	Expectations for the following quarter	Leading
C02 - Prices expectations	1996	Expectations for the following quarter	Leading
C03 - Number of employees expectations	1996	Expectations for the following quarter	Leading
C04 - Stocks expectations	1996	Expectations for the following quarter	Leading
D01 - Overview	1996	Expectations for the following quarter	Leading
Construction Sector			
A11 - Construction and public works	1998	**Compared to same quarter in the previous year**	**Coincident**
A12 - Construction	1998	**Compared to same quarter in the previous year**	**Coincident**
A13 - Public works	1998	**Compared to same quarter in the previous year**	**Coincident**
C01 - Costs	1998	**Compared to same quarter in the previous year**	**Coincident**
E01 - Number of employees	1998	**Compared to same quarter in the previous year**	**Coincident**
B01 - Portfolio of projects	1998	**Current level at the end of the quarter**	**Leading**
D01 - Investment	1998	**Current level at the end of the quarter**	**Leading**
A21 - Construction and public works expectations	1998	Expectations for the following quarter	Leading
A22 - Construction expectations	1998	Expectations for the following quarter	Leading
A23 - Public works expectations	1998	Expectations for the following quarter	Leading
D02 - Investment expectations	1998	Expectations for the following quarter	Leading
F01 - Overview	1998	Expectations for the following quarter	Leading
Café and Restaurant Sector			
A01-Real Turnover Volume	2000	**Compared to same quarter in the previous year**	**Coincident**
Prices	2000	**Compared to same quarter in the previous year**	**Coincident**
Employees	2000	**Compared to same quarter in the previous year**	**Coincident**
Volume of Investment (real)	2000	**Compared to same quarter in the previous year**	**Coincident**
A01-Real Turnover Volume Expectations	2000	Expectations for the following quarter	Leading
Prices Expectation	2000	Expectations for the following quarter	Leading
Employees expectations	2000	Expectations for the following quarter	Leading
Volume of Investment (real) expectation	2000	Expectations for the following quarter	Leading
Overview	2000	Expectations for the following quarter	Leading
Hotel Sector			
A01-Real Turnover Volume	**2000**	**Compared to same quarter in the previous year**	**Coincident**
Room Occupancy	**2000**	**Compared to same quarter in the previous year**	**Coincident**
Prices	**2000**	**Compared to same quarter in the previous year**	**Coincident**
Employees	**2000**	**Compared to same quarter in the previous year**	**Coincident**
Volume of Investment (real)	**2000**	**Compared to same quarter in the previous year**	**Coincident**
Real Turnover Volume Expectation	2000	Expectations for the following quarter	Leading
Room Occupancy Expectation	2000	Expectations for the following quarter	Leading
Prices Expectation	2000	Expectations for the following quarter	Leading
Employees Expectation	2000	Expectations for the following quarter	Leading
Volume of Investment (real) Expectation	2000	Expectations for the following quarter	Leading
Overview Expectation	2000	Expectations for the following quarter	Leading

Source : Statistics and Economic Research Department , Banque Du Liban

Table 9 List of BDL Business Tendency Survey Indicators

COMMERCIAL ENTERPRISES (Q4-2019)			
DECREASE = ↘	STABILITY = →	INCREASE = ↗	
A - EVOLUTION			
Indicate the evolution of the following indicators during the first quarter 2020 compared to the same quarter of the previous year.	*PLEASE PUT AN "X" IN THE CORRESPONDING BOXES.* ↘	→	↗
Sales Volume			
Prices			
Number Of Employees			
Average Monthly Wage Rate			
If The Average Monthly Wage Rate Has Increased, Please State The Percentage Change?		%	
B - ACTUAL SITUATION			
What is the present situation of the following indicators at end of the first quarter 2020?	Lower than normal	Normal	Higher than normal
Stock Of Finished Goods			
C - EXPECTATIONS			
How do you expect the following indicators to evolve during the second quarter 2020 compared to the previous quarter?	↘	→	↗
Sales Volume			
Prices			
Number Of Employees			
Stocks Of Goods			
D - OVERVIEW	↘	→	↗
How do you expect the activity in your commercial sub-sector to evolve during the next three months ?			

Source Banque Du Liban , Statistics and economics Research Department

Table 10 Sample Questionnaire of the BDL Business Tendency Survey

	CI Growth	Ind - Producti	Ind - Employe	Ind- Investm	Ind - Orders	Com- Employe	Com- Sales	Com - Stocks	Const- Const	Const- Employe	Const - Portfolio	Restaur ant	Hotel Turnover
CI Growth	100%												
Ind - Production	79%	100%											
Ind - Employement	66%	87%	100%										
Ind- Investment	66%	79%	75%	100%									
Ind - Orders	62%	91%	84%	65%	100%								
Com-Employement	57%	82%	85%	67%	87%	100%							
Com-Sales	75%	93%	82%	73%	85%	83%	100%						
Com - Stocks	54%	44%	30%	52%	30%	40%	45%	100%					
Const- Const and PW	63%	86%	76%	78%	81%	78%	83%	47%	100%				
Const- Employement	54%	84%	78%	74%	88%	83%	79%	36%	91%	100%			
Const - Portfolio of porjects	54%	83%	76%	74%	86%	81%	78%	41%	94%	96%	100%		
Restaurant Turnover	79%	84%	75%	74%	70%	71%	88%	48%	73%	66%	66%	100%	
Hotel Turnover	66%	70%	61%	59%	54%	59%	76%	42%	55%	46%	47%	87%	100%

Table 11 Correlation between selected survey variables

Unit root test	**Exogenous**	**Null Hypothesis: CI Growth has a unit root**	**Null Hypothesis: ESI has a unit root**
Augmented Dickey Fuller (ADF)	Constant	p=0.017	p=0.168
	Constant, Linear Trend	p=0.035	p=0.460
Philp Perron (PP)	Constant	p=0.000	p=0.201
	Constant, Linear Trend	p=0.000	p=0.557
Breakpoint Unit Root Test	Constant, Linear Trend, Break specified for 2006Q3	N.A.	p< 0.10 *

Note: MacKinnon (1996) one-sided p-values reported for the ADF and PP test.

(*) Perron (1989, 1993) asymptotic one-sided p-values (lambda=0.3375).

Table 12 Unit Root Tests

Model 1 (AR)			
Heteroskedasticity Test: White			
Null Hypothesis : homoscedasticity			
F-statistic	1.555	Prob. F(14,41)	0.135
Obs*R-squared	19.425	Prob. Chi-Square(14)	0.149
Scaled explained SS	98.023	Prob. Chi-Square(14)	0.000
Model 2 (ARIMA)			
Heteroskedasticity Test: White			
Null Hypothesis : homoscedasticity			
F-statistic	0.631	Prob. F(22,35)	0.871
Obs*R-squared	16.471	Prob. Chi-Square(22)	0.792
Scaled explained SS	89.410	Prob. Chi-Square(22)	0.000
Model 1' (AR_4_ESI)			
Heteroskedasticity Test: White			
Null Hypothesis : homoscedasticity			
F-statistic	1.312	Prob. F(8,42)	0.264
Obs*R-squared	10.195	Prob. Chi-Square(8)	0.252
Scaled explained SS	8.426	Prob. Chi-Square(8)	0.393
Model 2' (ARIMA_ESI)			
Heteroskedasticity Test: White			
Null Hypothesis : homoscedasticity			
F-statistic	0.261	Prob. F(9,43)	0.982
Obs*R-squared	2.747	Prob. Chi-Square(9)	0.974
Scaled explained SS	2.011	Prob. Chi-Square(9)	0.991

Table 13 White Heteroskedasticity Test

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