Leading Properties of the Business Tendency Survey

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Master thesis for the Master of Economic Theory and Econometrics degree

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August 2009

Preface

This thesis was written during my student employment at Statistics Norway's Research Department.

I want to thank my fellow students and colleagues who have been very helpful in providing me with an inspiring work environment. A special thanks to my supervisor Roger Bjørnstad who has always been available to answer my questions and give me comments and new ideas for my analysis. Thanks to Joseph Brooks for proofreading the text. Thanks finally to my family and friends for your support and patience, always.

Summary

An important goal of macroeconomic policy is the stabilization of business cycles. For the conduct of policy, good predictions and identification of the business cycle are necessary. The industrial confidence indicator (ICI), obtained from the Business Tendency Survey (BTS) conducted by Statistics Norway among business leaders in the manufacturing sector, may be useful in this respect. This thesis aims to investigate the leading properties of the ICI with regard to economic activity in the manufacturing sector and the economy as a whole (the mainland economy). Specifically, I will seek to formulate a dynamic empirical model of the business cycle, with lags of the indicator as explanatory variables.

In Norway, the BTS has been the object of several studies, but the question of the leading properties of the ICI has yet to be explicitly addressed. There is, however, an international literature on the topic; several studies suggest that the ICI is useful for forecasting purposes. Some of these results vary across countries. Different studies also reach different conclusions as to the nature of this relationship, e.g. whether the ICI is a leading or a contemporaneous indicator. The variety of methodologies employed may explain some of these discrepancies (Mourougane and Roma 2002).

The BTS contains information which may be analyzed in a variety of ways. When attempting to use data from this survey for the purpose of modeling and forecasting quantitative economic phenomena such as GDP growth, several things should be taken into consideration. First, when answering the survey, respondents choose between a few alternative responses such as “better”, “worse” or “no change” without indicating the magnitude of the change. That is, results obtained from the survey are mainly qualitative in nature, while the phenomena we wish to explain are mainly quantitative. Second, indicators extracted from this survey, like the ICI, represent an aggregation of answers across firms which may not be optimal: information relevant to modeling may be lost.

After a presentation of these issues, the matter of model specification is discussed. As economic theory fails to give an unambiguous answer as to the preferred model, a general-to-specific modeling approach is used to arrive at the final model specifications. This technique is not unproblematic: the successive removal of insignificant variables could lead to cumulative errors (leaving out relevant variables while keeping irrelevant ones), and the

resulting model could possibly be over-fitted or misspecified. One can argue that these problems are primarily finite-sample issues (Campos et al. 2005). Initially, and after each variable elimination, the intermediate model's validity is checked through various tests; if eliminating a variable leads to misspecified models, the variable is kept even though it is not significant. Models are estimated using ordinary least squares regression (OLS), and model validity is checked through a battery of diagnostic tests. All estimations are performed using the econometric software package OxMetrics (version 5). The general-to-specific procedure is carried out using an automated model selection feature of the module PCGive in OxMetrics, Autometrics.

This approach leads to four final model specifications for the output gap and quarter-on-quarter growth in the manufacturing sector and the mainland economy. The ICI appears to be leading movements in output by two quarters. As the results are fairly similar regardless of how we measure economic activity, the analysis will focus on the models of the output gap. The long-run properties of the models are considered, and no obvious inconsistencies are found. Using these models and the latest available figures of GDP, one can make short-term forecasts of the output gap. Such predictions are of particular interest in the context of the financial crisis which has also impacted the Norwegian economy. The model predicts that the output gap is largest in absolute value (that is, farthest below trend) at 2009:2. For the manufacturing sector, output is predicted to return at trend level by 2009:4, while recovery is expected to be somewhat slower in the mainland economy.

The paper is organized as follows: Section 2 is a review of literature: Section 2.1 presents the phenomenon of business cycles, and discusses their costs and the effectiveness of stabilization policy. Next, in section 2.2, some theoretical justifications for the predictive role of confidence indicators and empirical studies on the predictive power of industrial confidence indicator are presented. Data and methods are presented in section 3. Section 3.1 offers a brief presentation of the survey and defines the ICI. The quantification of survey data and problems relating to the aggregation of micro data are discussed here. Next, summary statistics and a graphical presentation of the data are presented in section 3.2. Section 4 describes the general to specific-approach used to arrive at the final econometric specifications. The model selection procedure results in four terminal models. Section 5 gives the results of the analysis and an evaluation of the models. The ICI appears to be leading GDP fluctuations by two quarters. Section 6 presents the models predictions for the short run (until 2009:4). Section 7 concludes.

Contents

1. Introduction

An important goal of macroeconomic policy is the stabilization of business cycles. For the conduct of policy, good predictions and identification of the business cycle are necessary. The industrial confidence indicator (ICI) obtained from the Business Tendency Survey conducted by Statistics Norway, may be useful in this respect. This thesis aims to investigate the leading properties of the ICI with respect to economic activity in the manufacturing sector and the economy as a whole (the mainland economy). Specifically, I will seek to formulate a dynamic empirical model of the business cycle, with lags of the indicator as explanatory variables.

The BTS is a survey conducted among business leaders in manufacturing and mining, where respondents are asked to indicate the direction of the expected or realized change in several firm-specific economic variables (volume of incoming orders, production etc.). In Norway, the BTS has been the object of several studies, but the question of the leading properties of the ICI has so far not been explicitly addressed. There is, however, an international literature on the topic; with several studies suggesting that the ICI is useful for forecasting purposes. Results sometimes vary across countries, and different studies reach somewhat different conclusions as to the nature of this relationship, e.g. whether the ICI is a leading or a contemporaneous indicator. The variety of methodologies employed may explain some of these discrepancies (Mourougane and Roma 2002).

In this thesis, a general-to-specific modeling approach is used to obtain the final model specifications. Models are estimated using ordinary least squares regression (OLS), and model validity is checked through a battery of diagnostic tests. The ICI lagged two periods is significant in explaining movements in output in both the manufacturing sector and the mainland economy as a whole, suggesting the ICI is indeed a leading indicator of output. The final models appear to follow moderate movements in output reasonably well, but fail to describe the more dramatic peaks and troughs. Once the final models are specified, they can be used to make predictions for the short term. Such predictions are of particular interest in the context of the financial crisis which has also impacted the Norwegian economy. The model predicts that the output gap is largest in absolute value (that is, farthest below trend) at 2009:2. For the manufacturing sector, output is predicted to return to trend level by 2009:4, while recovery is expected to be somewhat slower in the mainland economy.

The paper is organized as follows: Section 2 is a review of literature: In section 2.1 I present the phenomenon of business cycles, and discuss their costs and the effectiveness of stabilization policy. Next, in section 2.2, some theoretical justifications for the predictive role of confidence indicators and empirical studies on the predictive power of industrial confidence indicator are presented. Data and methods are presented in section 3. Section 3.1 offers a brief presentation of the survey and defines the ICI. Next, summary statistics and a graphical presentation of the data are presented in section 3.2. Section 4 describes the general to specific-approach used to arrive at the final econometric specifications. Section 5 gives the results of the analysis. The final models are subjected to diagnostic tests for validity in section 5.1. Sections 5.2 and 5.3 discuss the manufacturing sector and the mainland economy separately. The long-run properties of the models are discussed in section 5.4. Section 6 presents the models predictions for the short run (until 2009:4). Section 7 concludes.

2. Literature review

Business cycles are usually considered undesirable, so governments conduct stabilization policy aiming to improve welfare by dampening these deviations of output, consumption and other economic variables from their trend levels. If the industrial confidence indicator is useful in predicting business cycles, this may improve the possibility of conducting effective stabilization policy. To motivate this thesis, I will first present some literature on the welfare cost of business cycles and the possibility for welfare improving stabilization policies. Then I will discuss theory and empirical evidence regarding the predictive capabilities of industrial confidence indicators.

2.1 Business Cycles

We can think of time series of GDP and other economic variables consisting of on the one hand long term growth, and on the other hand short run fluctuations, or business cycles. Expansionary periods (booms) are followed by periods of contraction (recessions). The cycle is recurring, though not strictly periodic. Business cycles are also persistent, lasting at least one year, distinguishing them from the seasonal fluctuations within the year. Stabilization policy can be both countercyclical monetary and fiscal policy. Fiscal policy takes automatic stabilizers into recognition, for instance in a recession, reduced economic activity reduces the tax base and government revenue, while increased payments of unemployment benefits add to government expenditures, leading to a countercyclical deficit. Stabilization policy can also include discretionary policy, deliberately increasing expenditure or cutting taxes to combat a recession.

To simplify the debate on the costs of business cycles and the appropriate policy, we can distinguish between two views on business cycles: the neo-classical and the Keynesian perspectives (Gali 2005:588). In Real Business Cycle (RBC) theory, aggregate productivity shocks create fluctuations in the economy; business cycles are the economy's optimal response to supply side shocks. A positive shock to productivity leads to higher real wages, and so workers will want to work more. Symmetrically, negative shocks lead to households reducing their supply of labor as they want more leisure when the real wage they could obtain in the labor market drops. In other words there is no involuntary unemployment in this model.

From a Keynesian perspective, business cycles are inefficient: Business cycles reflect market failures; during periods of contraction in the economy, the degree of resource utilization is inefficiently low. In the short run, demand may be too low to maintain full employment. The result could be a short term equilibrium with low demand, low investments and involuntary unemployment. From this perspective, there is room for demand management/stabilization policy in the form of discretionary fiscal and monetary policy.

Even in RBC-models, business cycles may still be costly compared to the steady state without shocks to productivity, if households are risk averse. Risk averse agents care about the variability of output, consumption and employment over time, as well as their mean values. Aggregate consumption fluctuates with the business cycle (though it is usually less volatile than GDP), and risk averse agents find such fluctuations in consumption costly. Lucas (2003) estimates the value to a representative agent of removing all consumption fluctuations, and finds the gain to be small: around 0,0005% of annual consumption. Furthermore, Lucas estimates that no more than 30% of consumption fluctuations could be removed through better policy. Lucas concludes that stabilization policies (beyond what was conducted the last 50 years) have little chance of improving welfare. There is controversy surrounding the degree of risk aversion Lucas uses in his calculations. With more risk aversion, the estimated costs of consumption fluctuations will be higher. Returns on stocks are much higher than return on bonds; this “equity premium puzzle” suggests risk aversion is higher.

Gali, Gertler and Lopez-Salido (2007) consider the costs of inefficient fluctuations. Markups in wage and price settings imply a distorted steady state: product and labor market structures create an efficiency loss through a suboptimal labor supply in equilibrium (the marginal product of labor exceeds the marginal rate of labor-leisure substitution, i.e. employment is too low). When output is at the efficient level, we would expect negligible costs of fluctuations (a first order loss); however a distorted steady state would increase the costs of fluctuations. The efficiency loss when unemployment is above trend exceeds the efficiency gain when the gap decreases following a symmetric increase in employment.

They find that even though the average cost of business cycles are small (estimates in the same range as Lucas), there are large welfare losses during major recessions.

Another concern is that business cycles may be asymmetric: This will be the case if there are mechanisms at work causing unemployment to go more easily up than down. In general, loss of human capital, social costs of unemployment etc may lead to persistence of high unemployment rates (hysteresis). A recession, then, will not be followed by an economic boom of the same magnitude. HP-filtering data to identify business cycles would also impose symmetry. In some sense, this might underestimate the damage of recession to the economy. When estimating the small overall welfare loss of business cycles Gali et al make an implicit symmetry assumption. If our concern about asymmetry are justified, Gali et al's findings of large welfare costs of recessions could indicate large potential gains from stabilization policies.

Business cycles also have distributional effects not captured by the representative-agent framework of the above authors. There is no unemployment in these models, rather adjustment is made in a reduction of hours worked or in a reduction of real wages. Although the loss to the average household may be negligible, those who become unemployed will experience large income losses. Social insurance schemes mean some risk is diversifiable, however full insurance will usually not be feasible. Clark et al (1994) demonstrate that unskilled labor, particularly young and inexperienced workers, experience large losses in consumption compared to other people.

We should also consider other costs of unemployment, such as loss of human capital and social costs. Economists have typically been reluctant to consider these other costs as they are typically difficult to observe in the data. However, there is evidence that these costs are important, and may help explain the persistence of unemployment. Winkelmann and Winkelmann (1998) use panel data analysis to estimate the effect of unemployment on the well-being of German men. They find that unemployment causes a large decline in life satisfaction. Furthermore, this reduced well-being is only in a small part explained by the loss of income: the non-pecuniary costs of unemployment by far exceed the loss of income associated with unemployment. Such findings may indicate that the representative-agent framework used by Lucas and others underestimates the costs of business cycles, and that policy with an aim to stabilize the cycle can be preferable.

In the last 50 years, there has been a reduction in GDP volatility in the industrialized countries (disregarding for now the current financial crisis). Evidence suggests better macroeconomic policy, with countercyclical (structural/discretionary) fiscal policy can help explain this (Gali 2005:594). Gali and Perotti estimate a fiscal policy rule for groups of industrialized countries before and after 1992. They find that policy has become more countercyclical for all groups of countries (2003:18). Though evidence supports the claim that fiscal policy is effective, problems of information and time inconsistency may complicate policy implementation: it may be difficult to identify shocks to the economy, and understand correctly how the economy functions. Also, fiscal policy should be temporary; however the reversal of expansionist policies may be politically difficult (Andersen 2005).

2.2 On confidence indicators

There exists a considerable literature on confidence indicators and their role in forecasting. The ICI is a standardized indicator, allowing for meaningful comparison across countries. Many studies on the forecasting abilities of the ICI from other countries will therefore be of interest for this thesis. Section 2.2.1 will consider some theoretical arguments as to why an indicator of industrial confidence may be leading of actual economic developments. Section 2.2.2 then summarizes results from several studies which have aimed to test this leading relation.

2.2.1 Theoretical justification

When we investigate the leading properties of the ICI, we are interested in whether the indicator contains information beyond simply extrapolating a trend in economic activity. One reason to expect this would be if business leaders have private information and observe shocks before they are propagated through the economy. For example, a drop in foreign demand for our exports (while domestic demand, in the short run, remains unchanged), would lead to an immediate drop in incoming orders and buildups of stock for some exporting firms. Transmission mechanisms then propagate this shock through the economy. This results in a drop in the ICI preceding the fall in GDP.

Taylor and McNabb (2007:187) suggest two reasons why confidence can cause business cycles. First, there is the problem of self-fulfilling prophecies. With the presence of strategic complementarity, the optimal investment of one investor depends positively on the investments of the competitors. If all producers expect demand to be low, they will reduce their output accordingly, and so the low demand they expected will be realized. Second, confidence can be related to policy. Differences in economic policy may cause rational fluctuations in confidence.

2.2.2 Empirical evidence

Many economic indicators useful for forecasting, such as GDP or industrial GDP, are available only with a lag and may be subject to later revisions. As the ICI is obtained from surveys, it is generally available before other economic indicators. For this reason, it may be helpful in forecasting, provided it does in fact have leading properties.

There is little literature on the relationship between the ICI and economic activity in Norway. Biørn (1982) uses net figures from the BTS – but not the ICI – to construct an indicator for the optimal stocks and desired incoming orders in the manufacturing sector. Stensrud (1981) estimates a series of linear contemporaneous relationships between economic growth and net figures for each of the three questions that make up the basis for the ICI. Models are estimated by industry; only a minority of the models establish a significant relationship at the 10%-level, and results appear to vary between industries. Data from the BTS are used in Svendsen (1996) to test hypotheses of expectations formation. The data lends some support to extrapolative expectations formation in a general form, while the rational expectations hypothesis is rejected in most forms. However, these essays do not explicitly address the question of the leading properties of an aggregate such as the ICI for economic activity.

There is, however, literature on this for Euro area and OECD countries. As the ICI is an indicator obtained from a standardized survey, the findings from these studies are of interest to this thesis. There is a wide range of methods used in the literature to investigate the link between confidence indicators and economic activity. This might explain the lack of consensus about whether the ICI and other such indicators are leading and procyclical (Mourougane and Roma 2002:14).

Mourougane and Roma (2002) investigate whether including confidence indicators – the ICI and the composite indicator ESI – improve economic forecasting. They estimate a linear relationship between real GDP growth and first difference of the ICI. In four of the six European countries examined, the contemporaneous ICI is significant in explaining real GDP growth; for the last two countries, the indicator becomes significant when it is lagged one quarter. The authors estimate various specifications including the level of the indicator, lags of GDP growth and other indicators, suggesting robustness of these results. Comparing the forecasting errors of confidence-based models and an autoregressive (ARIMA)-model, the ICI-model appears to make better forecasts in four countries.

Santero and Westerlund (1996) use graphical analysis and correlation analysis for 11 OECD countries and find that business sentiment indicators are useful for prediction in most countries. They note that the degree of usefulness varies between countries. For this reason, they warn against generalizing results from one country's experience.

Karl Taylor and Robert McNabb (2007) examine data on GDP, business and consumer confidence indicators and several other potentially leading indicators for four European countries. Using cross correlation-coefficients and variance decomposition, they find that the business confidence indicator is a procyclical leading indicator of output. The authors also investigate the usefulness of the indicator in predicting recessions; they use a probit model to evaluate the ability of the business confidence indicator and other leading indicators to predict turning points four quarters ahead. Here, results vary between countries: in the UK and France business confidence plays a significant role in predicting recessions.

3. Data

As the aim of this thesis is to establish a dynamic empirical model of the business cycle, results will crucially depend on the data used to arrive at this model. This section will seek to give a presentation of the data. First, the Business Tendency Survey is introduced, and issues related to the use of survey data are discussed. Section 3.2 then presents summary statistics.

3.1 The Business Tendency Survey

I use data from the Business Tendency Survey (BTS) from the years 1988 – 2008. The survey is a qualitative survey of business leaders' perception of the current economic climate. Such business surveys were first conducted in Germany in 1949, with the aim to collect information about the business cycle early in the cycle. The BTS is now a standardized survey administered by the Directorate General Economic and Financial Affairs (DG ECFIN), which allows for meaningful comparison between countries. In Norway, the BTS was developed in 1973 and implemented in 1974 (Statistics Norway 2003).

In 2002, the gross sample of firms contained 720 units, covering 54% of employment and 62% of aggregate sales in the sector. The variables of interest in the questionnaire are often taken from the national accounts, such as employment and output. Typical questions ask about the actual development from the last to the current quarter, as well as expectations for the following quarter. For most questions, respondents choose to answer "larger/better", "same" or "smaller/worse". In other words, the survey is mainly qualitative. The question of how much better/worse is not answered.

To use the responses in a qualitative survey in order to make quantitative economic predictions, several approaches are possible. Numbers published by Statistics Norway in connection with the survey are typically either diffusion indexes or net figures. For a given question, the diffusion index is equal to the percentage of respondents who answered "better" plus half the percentage that answered "same". The net figure, occasionally referred to in the literature as a "balance", is computed as the percentage of respondents who answered "better" minus the percentage that answered "worse". From the survey, we could extract several potentially leading indicators. Respondents are asked to identify bottlenecks in production: a shortage of labor could indicate an ongoing or coming boom, while insufficient demand could be indicative of a recession. In this paper, we will focus on the industrial confidence indicator (ICI) as a potential procyclical leading indicator. The numbers we use in the analysis are seasonally adjusted.

The ICI, then, represents an aggregation of answers both across responses and across industries. Svendsen (1996) suggests that aggregation entails loss of information, and uses micro (firm-level) data in her analysis. Both diffusion indices and net figures represent methods of aggregating individual firms' responses. That is, the shares that answered "better", "same" or "worse" are transformed into a single figure. Underlying the validity of such aggregation is the notion of a certain symmetry in the answers. The diffusion index, for instance, is based on the assumption that half of the respondents who report "no change" from the previous quarter has actually experienced an improvement, while the other half has experienced worsening conditions. There is a risk that some information may be lost in this aggregation. Entorf (1993) finds that the share of respondents who answer "worse" is a better leading indicator than the balance or net figures. The shares of "same" and "better" exhibit a positive correlation. Considering that there may be certain thresholds for how much better or worse the situation must be before they respond accordingly, these thresholds then appear to be asymmetric, and so the net figure would be misleading.

The second aggregation occurs across industries. In this thesis, I have used the aggregate ICI for the manufacturing sector. Alternatively, one could consider the indicator separately by industry or sector (consumer goods, investment goods or intermediate goods). The indicators may have better forecasting abilities on the disaggregate level, if there are lags in production. Entorf (1993) finds that consumer goods lead investment goods. When demand increases following a period of recession, firms will typically first increase their production of consumer goods to meet the new, higher demand, and only seek to increase investment later as they approach full capacity. A disaggregate indicator then, may be leading more periods.

There are, however, advantages to using the ICI as our leading indicator. First, survey responses are likely to exhibit some degree of randomness. Aggregation across sectors or industries means each figure is based on a larger number of observations, so an aggregate measure such as the ICI will be less exposed to such adverse effects. Moreover, the ICI is a standardized figure and its leading properties have been the object of several studies. Hence the ICI, though it may not be the optimal indicator obtainable from the BTS, does allow comparison with such other findings.

3.2 Summary statistics.

To give an overview of the data, we present summary statistics of the relevant variables. Data on GDP and the ICI is quarterly from 1988:1 to 2008:4, that is 84 observations. As the analysis uses lagged variables, regressions will be based on fewer observations.

Table 1 Summary statistics

Variable of interest	*Mean*	*Standard deviation*
ICI (seasonally adjusted)	3.155	7.147
Output deviation from trend (in logs), manufacturing sector	-0.000293	0.0196
Output deviation from trend (in logs), mainland economy	-0.000128	0.0110
Quarter-on-quarter growth rate, manufacturing sector	0.00279	0.0199
Quarter-on-quarter growth rate, mainland economy	0.00611	0.010

Table 1. Summary statistics. Means and standard deviations of the variables used in the analysis.

Data on GDP in the manufacturing sector and the mainland economy are obtained from the quarterly national accounts. Figures are seasonally adjusted. Deviations from trend are obtained by HP-filtering data in OxMetrics (setting $\lambda = 1600$). Where nothing else is indicated, this trend is based on observations from 1988:1 to 2008:4. The ICI has a positive mean value, not significantly different from zero. Output in the manufacturing sector is more volatile than in the mainland economy.

Table 2 presents correlation coefficients of both measures of economic activity and the indicator. Correlation coefficients for 1-period lagged variables are also included. "t-values" for the corresponding simple linear regression are reported in parentheses.

Both measures of economic activity appear to be positively correlated with the ICI. For the output gap, this correlation seems to be stronger for lagged values of the ICI. If, on the other hand, the quarter-on-quarter growth rate is the chosen measure of economic activity, the correlation seems stronger for contemporaneous values of the indicator. There is a positive correlation between economic activity in the manufacturing sector and in the (mainland) economy as a whole.

Table 2 Correlation coefficients

Correlation coefficients			
$\rho(\hat{y}^m, ICI)$	0.221**	$\rho(\hat{y}^m, ICI_{-1})$	0.289***
	(2.06)		(2.72)
$\rho(\hat{y}, ICI)$	0.192*	$\rho(\hat{y}, ICI_{-1})$	0.294***
	(1.78)		(2.77)
$\rho(\hat{y}^m, \hat{y})$	0.547***	$\rho(\hat{y}^m_{-1}, \hat{y})$	0.385***
	(5.92)		(3.76)
		$\rho(\hat{y}^m, \hat{y}_{-1})$	0.239**
			(2.21)
$\rho(\Delta y^m, ICI)$	0.235**	$\rho(\Delta y^m, ICI_{-1})$	0.191*
	(2.17)		(1.76)
$\rho(\Delta y, ICI)$	0.380***	$\rho(\Delta y, ICI_{-1})$	0.304***
	(3.70)		(2.87)
$\rho(\Delta y^m, \Delta y)$	0.533***	$\rho(\Delta y^m_{-1}, \Delta y)$	0.070
	(5.67)		(0.631)
		$\rho(\Delta y^m, \Delta y_{-1})$	-0.119
			(-1.07)

*Table 2. Correlation coefficients of the ICI and output deviations in the manufacturing sector ($\hat{y}^m$) and the mainland economy ($\hat{y}$). Estimation sample is 1988:2 – 2008:4. t-values from the associated simple linear regression in parentheses. *,**,*** significant at the 10, 5, 1-% level respectively.*

To present a first impression of the relationship between the indicator and the business cycle, we plot time series of the output gap against the ICI (figure 1). From the figure, we observe that the ICI series at times reaches its peak and trough values some time before output. At other times however, the indicator appears to be contemporaneous rather than leading. Output volatility is high in the manufacturing sector, which may complicate drawing unambiguous conclusions from visual inspection alone.

Figure 2 plots time series of deviations from trend of mainland GDP, together with the ICI. Here too, it is not clear whether the ICI is a contemporaneous or a leading indicator of output deviations. For the later part of the time series, the ICI appears to be systematically leading, while for the earlier years the series appear to move together. For now, we can conclude that visual inspection of the series does not refute the possibility of a leading relationship. We should also consider the possibility that the relationship is not stable over time, which would reduce the ICI's relevance for forecasting purposes. In any case, when the final econometric model specifications are evaluated, parameter stability should be considered.

Figure 1 The ICI and the output gap, manufacturing sector

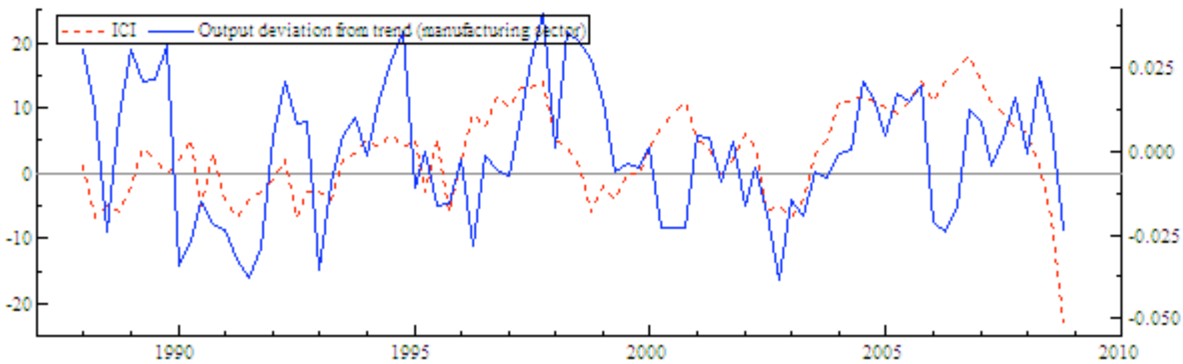

Figure 1. The ICI (left axis) and output deviations from trend in the manufacturing sector (right axis), 1988 – 2008.

Figure 2 The ICI and the output gap, mainland economy

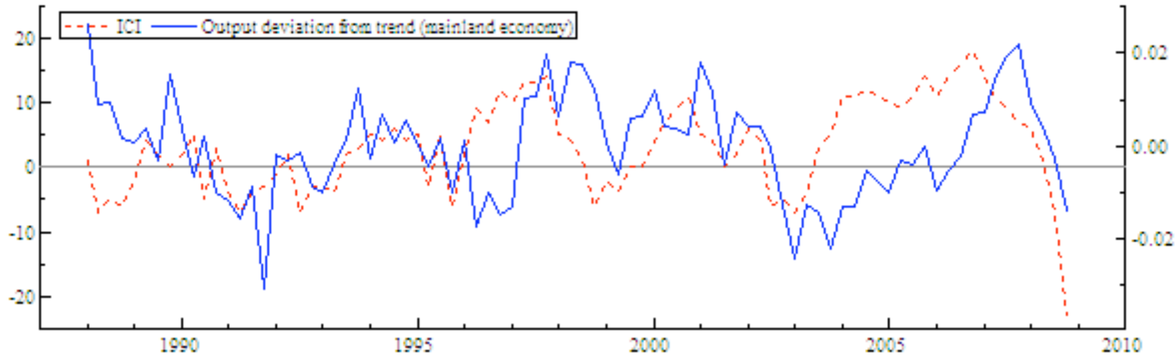

Figure 2. The ICI (left axis) and output deviations from trend in the mainland economy (right axis), 1988 – 2008.

4. Specification

The purpose of this thesis is to investigate whether the ICI is a leading indicator for economic activity. Specifically, I wish to investigate a relation $y_t = f(x_{t-i})$ where *y* is some measure of economic activity and x_{t-i} is the indicator lagged *i* periods. To test this relationship empirically, we need to specify this relationship more precisely. I will assume this relation to be log-linear.

4.1 Dependent and explanatory variables

We need a measure of economic activity, and the alternatives are deviation from trend or quarter-on-quarter growth. It is not clear that one is more suitable than the other. The two measures are also related: We can write (log) deviation from trend as $\hat{y}_t = \log Y_t - \log Y_t^*$, where Y_t^* is HP-filtered trend GDP. Quarter on quarter growth is found by $\Delta y_t = \log Y_t - \log Y_{t-1}$. From these definitions, we can write:

$$\hat{y}_t - \hat{y}_{t-1} = \log Y_t - \log Y_t^* - (\log Y_{t-1} - \log Y_{t-1}^*)$$
$$\Delta y_t = \Delta \hat{y}_t + \Delta y_t^*$$

Hence, the quarter-on-quarter growth rate can be written as the sum of the growth of trend GDP and the growth of deviation from trend GDP from one quarter to the next. In other words, there is only a minor difference between the two measures of activity. For this reason, we expect to find fairly similar results independent of which explanatory variable we choose, though the interpretation of the results will be somewhat different.

We include lags of the endogenous variable. One reason is technical; we want to avoid autocorrelation in the disturbances. Time series data will often exhibit autocorrelation; failing to consider this will lead to a dynamic misspecification. We would risk $\text{cov}(\varepsilon_t, \varepsilon_s) \neq 0, \quad t \neq s$, which would lead to misleading inference. By including lagged values of *y*, we can achieve spherical disturbances: $\text{cov}(\varepsilon_t, \varepsilon_s) = 0, \quad t \neq s$. Furthermore, the ICI may have predictive power even if it does not explain all the autocorrelation in the data. Including lagged values of *y* also helps interpreting the results. The time series of economic activity (be that deviation from trend or quarter-on-quarter growth), will typically exhibit autocorrelation. We could imagine that the BTS respondents observe last period's development and extrapolate. We wish to find out if the ICI contains information beyond a simple autoregressive process. Including lags of the endogenous variable would control for this, so that if the indicator does turn out to be significant, we can assume it is relevant beyond simply extrapolating a trend.

Next, there is the problem of how to include the indicator: whether we should include the first difference of the ICI or its level as the explanatory variable. The ICI is based on net figures from three questions where the respondents are asked to compare this quarter to the previous (or expectations of the coming quarter). The resulting level of the indicator then reflects changes in outlook, and the ICI in levels should be used to predict movements of output. On the other hand, we can think of reasons why the first difference might have better leading properties than the level of the indicator: Growth in the indicator reflects that more respondents experience improving economic prospects. A high and falling level on the ICI would reflect that many firms, but fewer compared to the previous period, are experiencing and expecting an improvement of conditions. This might be indicative of a reversal of an economic boom; the high level of the indicator would be misguiding. There is also the matter of choosing the appropriate lag for the indicator; that is, by how many quarters the ICI is leading with respect to output fluctuations. Again, it is difficult to decide a priori which lag length is appropriate.

4.2 A General-To-Specific Approach

As theory fails to give unambiguous answer to which model specification we should prefer, we will follow a general-to-specific approach. This way, we will seek to establish an empirical model of the ICI and the business cycle. General-to-specific modeling starts with the formulation of a general unrestricted model (GUM), which includes a large number of explanatory variables. Usually, some of these are relevant, that is, they are part of the true underlying data-generating process, while others are irrelevant. Ideally, the sequential removal of statistically insignificant variables leads to an empirical model with only the relevant variables left on the right hand side.

Campos et al (2005: 16) point out four potential dangers of this approach: first of all, the general unrestricted model may be misspecified. The general-to-specific approach works through a series of hypothesis tests (t-tests): A misspecified model, with for instance heteroskedastic or autocorrelated errors, will lead to misleading values for the t-statistics, and the sequential removal of insignificant variables from the model will be compromised. Second, there is the risk of excluding relevant variables. Third, one risks retaining irrelevant variables. The process of sizing down the GUM to the final model is through a sequence of model estimations and tests for statistical significance. In each of these iterations we risk both type 1 and type 2 errors; some have feared that the cumulative impact of these errors could lead to the final model being too unreliable, that is, likely to be either over-fitted or misspecified. However, Campos et al. (2005:17) argue that these issues are "primarily finite sample issues". Finally, there is the risk of selecting a misspecified final model, in which case conclusions are compromised. To avoid this, the model resulting after each deletion is subjected to a set of diagnostic tests. If the tests fail, that is if the deleting the variable lead to a misspecification, the variable is kept even though it lacks statistical significance.

Our first step is to establish the initial models. This is complicated by issues of multicollinearity. The general-to-specific approach should decide not only the appropriate lag lengths of the ICI, but also whether lags of the indicator should be included as levels or as first differences. However, including both first differences and the level of the ICI for all periods is not feasible; to avoid issues of multicollinearity, we can only include one lag of the level. For this reason, preliminary regressions are performed in order to choose which lag of the first difference to include in the model. Four equations with 0-3 quarters lagged values of the ICI in levels as the explanatory variable, including lags of the endogenous variable are estimated. (Results in Annex). While lagged values of the ICI in levels did not prove significant in explaining GDP in the manufacturing sector, the ICI lagged two periods is significant in explaining GDP in the mainland economy. We note these results are independent of how we measure GDP fluctuations. As a result, the indicator in levels lagged two quarters is chosen to be included in the initial model.

Our initial models then, are:

For the manufacturing sector:

$$(1)\ \hat{y}_t^m = \alpha + \sum_{i=0}^{3} \beta_i \Delta x_{t-i} + \delta x_{t-2} + \sum_{i=1}^{3} \gamma_i \hat{y}_{t-i}^m + \varepsilon_t$$

$$(2)\ \Delta y_t^m = \alpha + \sum_{i=0}^{3} \beta_i \Delta x_{t-i} + \delta x_{t-2} + \sum_{i=1}^{3} \gamma_i \Delta y_{t-i} + \varepsilon_t$$

For the mainland economy as a whole:

$$(3)\ \hat{y}_t = \alpha + \sum_{i=0}^{3} \beta_i \Delta x_{t-i} + \delta x_{t-2} + \sum_{i=1}^{3} \gamma_i \hat{y}_{t-i} + \varepsilon_t$$

$$(4)\ \Delta y_t = \alpha + \sum_{i=0}^{3} \beta_i \Delta x_{t-i} + \delta x_{t-2} + \sum_{i=1}^{3} \gamma_i \Delta y_{t-i} + \varepsilon_t$$

Tables 3 and 4 show the four initial models, estimated, as well as results from selected diagnostic tests. The test for normally distributed disturbances is a Jarque-Bera test modified for small samples and a multivariate model. Under the null hypothesis of normality, the test statistic is χ^2-distributed with two degrees of freedom. The test for heteroskedasticity is based on a regression of the residuals on the regressors and their squares. The Durbin-Watson statistic is included for each model, however, this statistic should be interpreted with caution, as the models include lags of the endogenous variable as a regressor. When this is the case, the Durbin-Watson test may fail to detect autocorrelation. Hence, we include an additional test for fifth-order autocorrelated errors. The test is the Lagrange multiplier test for autocorrelated errors; the test statistic is based on the R^2 from an auxiliary regression of the residuals on their lagged values. Under the null of no r^{th}-order correlation, the test statistic is $\chi^2(r)$-distributed. The Chow-test is a test of parameter constancy testing whether there is a break in 2003:1.

Table 3 General unrestricted models (GUM)

Variable of interest	*Manufacturing sector*		*The mainland economy*	
	(1) Deviations from trend (^y)	(2) Quarter on quarter growth	(3) Deviations from trend (^y)	(4) Quarter on quarter growth
y_{t-1}	0.558***	-0.220*	0.445***	-0.388***
	(0.114)	(0.114)	(0.119)	(0.120)
y_{t-2}	-0.0195	-0.141	0.280**	-0.0753
	(0.125)	(0.113)	(0.128)	(0.127)
y_{t-3}	-0.0223	-0.094	-0.00382	-0.107
	(0.112)	(0.112)	(0.118)	(0.114)
Δx_t	0.000304	0.000539	0.000281	0.000467**
	(0.000425)	(0.000476)	(0.000211)	(0.000225)
Δx_{t-1}	0.000757	0.00115**	0.000239	0.000519*
	(0.000468)	(0.000523)	(0.000245)	(0.000262)
Δx_{t-2}	0.000566	0.000615	0.000441*	0.000367
	(0.000504)	(0.000556)	(0.000256)	(0.000266)
Δx_{t-3}	-0.000912*	-0.00108**	0.0000228	-0.000129
	(0.000478)	(0.000533)	(0.000242)	(0.000256)
x_{t-2}	0.000704**	0.000962**	0.000442**	0.000879***
	(0.000351)	(0.000403)	(0.000178)	(0.000248)
Constant term	-0.00312	0.00145	-0.00202*	0.00708***
	(0.00221)	(0.00247)	(0.00110)	(0.00155)
R^2	0.391	0.211	0.527	0.333

*Table 3. General (unrestricted) models. Estimates reported with standard errors in parentheses. *,**,*** significant at the 10%, 5% and 1%-level respectively. The estimation sample is 1989:1 – 2008:4.*

Table 4 Diagnostic tests for the general unrestricted models (GUM)

Test	(1)	(2)	(3)	(4)
Normality: $\chi^2(2)$	1.467	9.639***	1.098	0.498
	(0.480)	(0.0081)	(0.578)	(0.780)
Heteroskesdasticity: F-statistic	1.169	0.386	0.579	0.868
	(0.321)	(0.981)	(0.886)	(0.607)
5th order autocorrelation: $\chi^2(5)$	0.618	0.403	1.164	1.920
	(0.687)	(0.845)	(0.337)	(0.103)
Chow-test: break at 70% (2003:1)	0.614	0.612	0.556	0.373
	(0.897)	(0.899)	(0.936)	(0.994)

Table 4. Diagnostic tests for the general (unrestricted) models, rejection probabilities in parenthesis.
,,*** significant at the 10%, 5% and 1%-level respectively.*

Overall, the models appear well specified. The exception is model (2) – quarter-on-quarter growth in the manufacturing sector – which appears to exhibit non-normal residuals. Non-normal residuals makes inference difficult, so the general-to-specific approach of sequentially removing insignificant variables is problematic (there will be a higher risk of dropping relevant variables and/or keeping irrelevant ones). Keeping this in mind, we will try to obtain a final model specification for model 2 as well, however results should be interpreted with caution.

Once the initial model is formulated and issues of misspecification are considered, variables that are insignificant at the 5%-level are removed sequentially. The process of model selection can be automated using econometric software. I have used OxMetrics 5, with the module PCGive and its Autometrics feature. The algorithm implemented in the Autometrics software is the third version of automated general-to-specific modelling. This algorithm, like the earlier version tested by Hoover and Perez (1999) performed well in monte carlo studies (Hoover and Perez 1999, Doornik 2009).

This procedure allows for misspecification tests to be carried out automatically after each variable deletion, ensuring a congruent final model. In some cases, the method will lead to several final model candidates, depending on the path in which variables are deleted from the specification.

To choose between terminal models, we can use economic theory or some standard criterion for selection. In the context of this thesis, there are no strong theoretical arguments to choose one final specification over another, so some other way of model selection is needed. A good model should have few explanatory variables, *K* (parsimony) and a low sum of squared errors, *SSE* (goodness of fit); normally there will be a tradeoff between these two qualities. Several criteria are possible, based on different loss functions each weighting parsimony versus goodness of fit. To choose one final model, the Schwarz criterion (SC), minimizing $\ln\left(\frac{SSE}{T}\right)+\frac{2K}{T}$ is used, which is the default suggested by the Autometrics model selection algorithm.

5. Results

For the manufacturing sector, we end up with the following two models: The output gap (1') is a function of itself lagged one period and the first difference of the ICI lagged two periods. Growth (2') is a function of the lagged first difference of the ICI:

$$(1')\ \hat{y}_t^m = \alpha + \beta_2 \Delta x_{t-2} + \gamma_1 \hat{y}_{t-1}^m + \varepsilon_t$$

$$(2')\ \Delta y_t^m = \alpha + \beta_2 \Delta x_{t-2} + \varepsilon_t$$

For the mainland economy, the output gap (3') is a function of itself lagged one and two periods, and the first difference and level of the ICI lagged two periods. Growth (4') is a function of its own lagged value, the contemporaneous first difference of the ICI and the level of the ICI, lagged two periods:

$$(3')\ \hat{y}_t = \alpha + \beta_2 \Delta x_{t-2} + \delta x_{t-2} + \sum_{i=1}^{2} \gamma_i \hat{y}_{t-i} + \varepsilon_t$$

$$(4')\ \Delta y_t = \alpha + \beta_0 \Delta x_t + \delta x_{t-2} + \gamma_1 \Delta y_{t-1}^m + \varepsilon_t$$

Table 3 sums up the results from the general-to-specific modeling approach; these are the estimated terminal models. In all four specifications, our results support that the ICI is a leading and procyclical indicator for economic activity: We get positive and significant estimates for either the first difference or the level of the indicator lagged two periods. The leading quality of the indicator then, seems robust to our choice of endogenous variable; whether we measure economic activity by growth or by deviation seems to matter little. This is in line with our discussion in part 3 regarding the close relation between these two variables. Results are also fairly similar when we compare results for the manufacturing sector.

Table 5 Final models obtained by Autometrics

Variable of interest	*Manufacturing sector*		*The mainland economy*	
	(1')	(2')	(3')	(4')
	Deviations from trend	Quarter on quarter growth	Deviations from trend	Quarter on quarter growth
y_{t-1}	0.546***	-	0.458***	-0.379***
y_{t-2}	-	-	0.218**	-
Δx_t	-	-	-	0.00654**
Δx_{t-2}	0.00105**	0.00113**	0.000484**	-
x_{t-2}	-	-	0.000358**	0.000706***
Constant term	-0.00063	0.00316	-0.00179*	0.00653***
Schwartz criterion	-5.288	-5.028	-6.679	-6.491
R^2	0.335	0.0635	0.511	0.260

*Table 5. Principal results. With the exception of the constant term, estimates are only reported if they are significant at the 5%-level or above. See above discussion of the general-to-specific approach. *,**,*** significant at the 10%, 5% and 1%-level respectively. The estimation sample is 1989:1 – 2008:4.*

5.1 Model evaluation. Diagnostic tests.

R^2 measures how much of the variation in y is explained by our model relative to the total variation in y. Care should be taken in interpreting R^2, especially as a tool to compare models, as the unadjusted R^2 is (weakly) increasing in the number of regressors, while our models contain different numbers of explanatory variables. Nonetheless, it is a useful starting point in evaluating our models. R^2 ranges from 0,0635 (model 2') to 0,511 (model 3'). Model (2'), which includes only the ICI as an explanatory variable, has a very low value of R^2. Only a share of 0,0635 of the total variation in y is explained by the model. This may indicate that although the lagged ICI is statistically significant, quantitatively its predictive power may be limited. Models 1', 3' and 4' also feature fairly low values of R^2, especially considering that we are dealing with time series data. These low values of R^2 could also indicate that we have omitted relevant explanatory variables from our model.

Figures 3a – 3d show the plotted residuals from our four models. Though it is difficult to draw unambiguous conclusions about model specification from visual inspection of the residual plots alone, they may prove useful in suggesting which problems we have to be aware of in the analysis. We notice that positive values of the residuals at time t tend to follow positive residuals at time t-1; this impression is stronger from figures 3c and 3d (residuals from models 3 and 4). Overall, the residual plots suggest a possible problem of autocorrelated errors, which should be tested for formally.

Figures 3a – 3d Residuals plotted against time

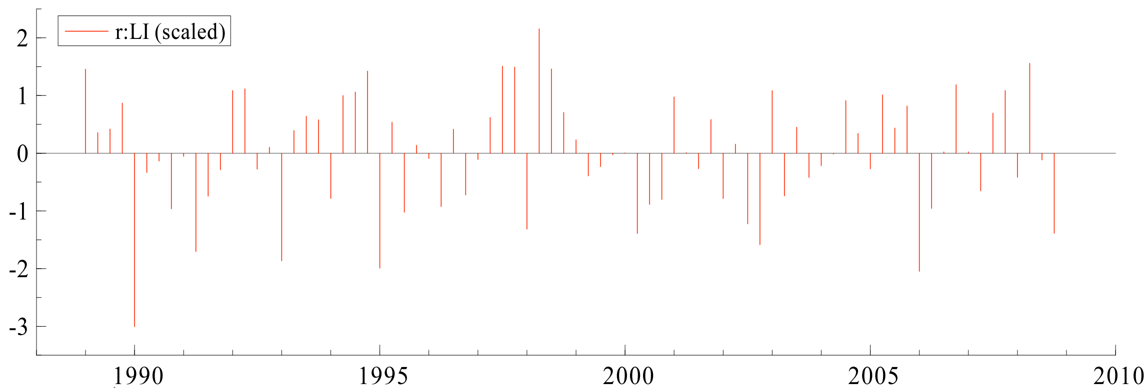

Figure 3a. Residuals plotted against time, model (1').

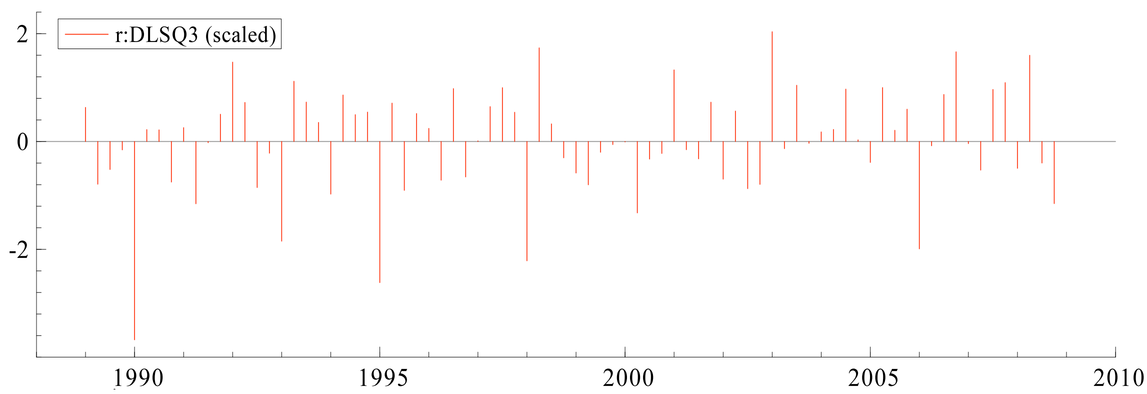

Figure 3b. Residuals plotted against time, model (2').

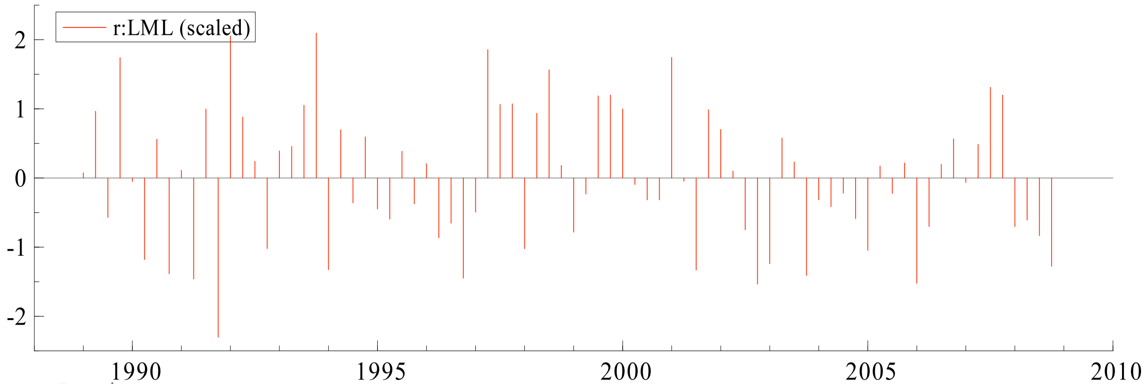

Figure 3c. Residuals plotted against time, model (3').

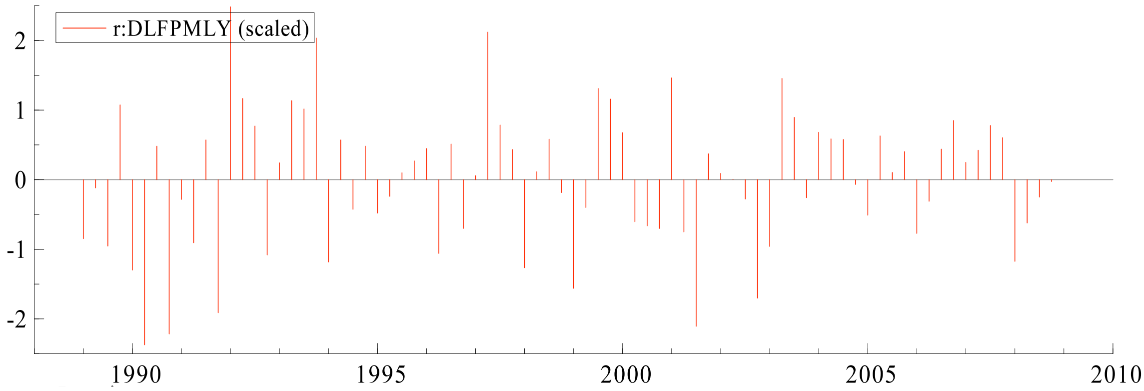

Figure 3d. Residuals plotted against time, model (4').

Figure 1 and 2 indicated possible parameter instability; for mainland GDP, the ICI appeared to be more leading during the later part of the time series. Diagnostic tests for the unrestricted models in section 4 included a Chow-test for parameter inconstancy, testing for a break at 2003:1. This test indicated no such structural break for any model.

Because of the importance of parameter stability for forecasting, recursive estimation is performed, in order to investigate further whether the final models exhibit parameter instability. Parameters are estimated recursively starting with an estimation sample of only the first $M = 10$ observations. Figures 4a – 4f plot sequences of estimates and their approximate 95% confidence intervals. If the parameter is constant, the sequence should converge smoothly on the final estimate. Panels 4d and 4f suggest a jump in the estimates of δ in models 3' and 4' around 1997. However, the graph could also indicate an outlier value of a variable. From these graphs of successive estimates, I cannot conclude that parameter instability is present.

To clarify the issue further, recursive estimation allows for break-point Chow-tests to be calculated at all points $t=M, \ldots, T$. The test statistic Figures 5a – 5d graph the results of these successive Chow-tests scaled by their critical values (significance level set at $\alpha = 5\%$). These figures indicate no significant break at any point for any model, further supporting the results from section 4 of no significant parameter instability.

Figures 4a – 4f Recursive estimates

Figure 4a recursive estimates of β_2, model (1')

Figure 4b recursive estimates of β_2, model (2')

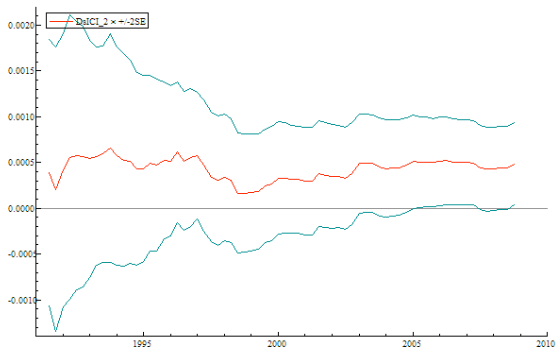

Figure 4c recursive estimates of β_2, model (3')

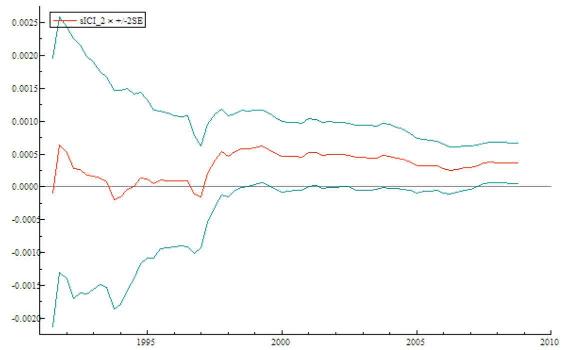

Figure 4d recursive estimates of δ, model (3')

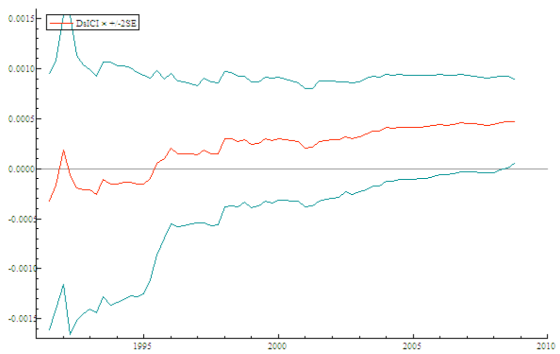

Figure 4e recursive estimates of β_0, model (4')

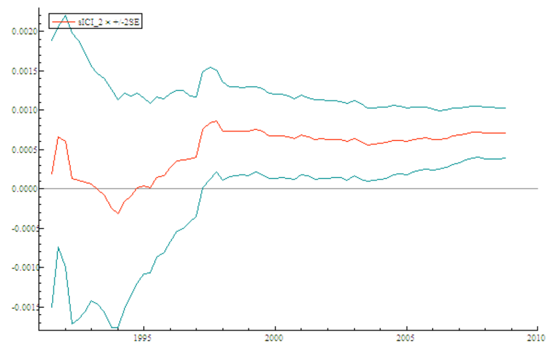

Figure 4f recursive estimates of δ, model (4')

Figures 5a – 5d Chow tests

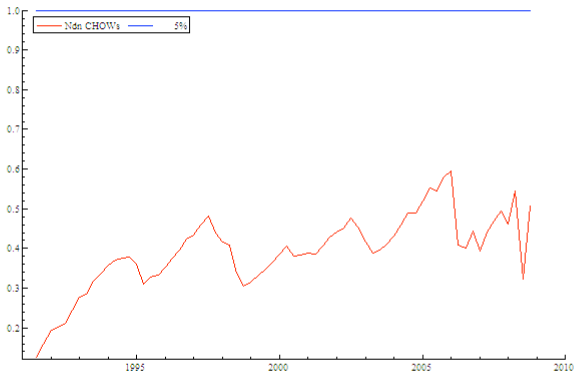

Figure 5a. Sequence of break-point Chow-tests; results scaled against a critical value, model (1')

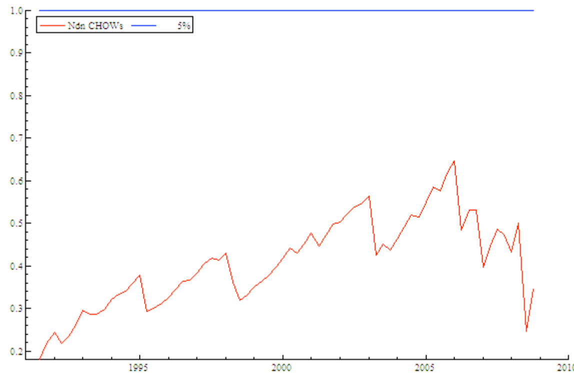

Figure 5b. Sequence of break-point Chow-tests; results scaled against a critical value, model (2')

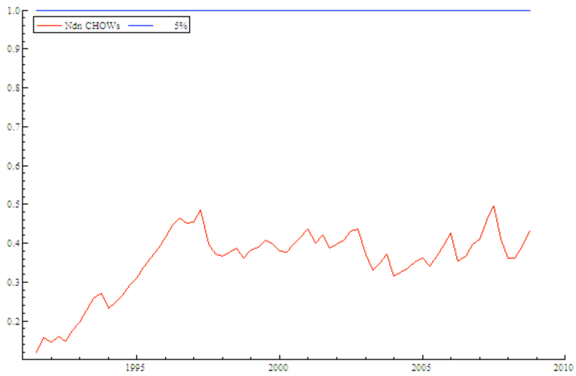

Figure 5c. Sequence of break-point Chow-tests; results scaled against a critical value, model (3')

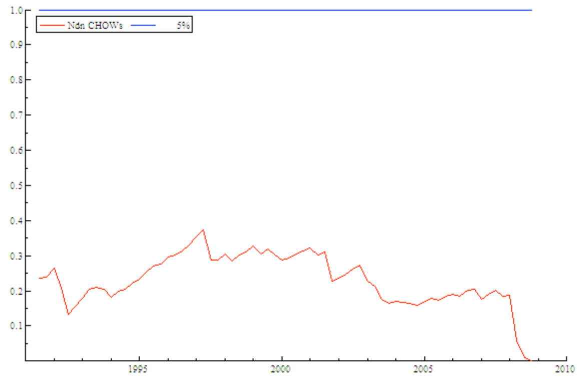

Figure 5d. Sequence of break-point Chow-tests; results scaled against a critical value, model (4')

Table 5 presents a set of diagnostic tests: We have included tests for heteroskedastic, autocorrelated and normal disturbances, and a RESET-test for misspecification. Rejection probabilities are reported for the normality test, the heteroskedasticity test and the RESET-test. The tests for normality, heteroskedasticity and autocorrelation are the same as described in section 3.3.2. With the exception of model (2'), we do not reject normality, for model (2'), normality of the residuals is rejected at the 1% level. For model 1, we reject the null of no heteroskedasticity at the 10%-level (but not at the 5%-level). To test for regression misspecification, the RESET-test uses products and squares of the regressors as proxies for omitted variables, and tests the null of no joint significance. For model (4'), the null is rejected at the 10%-level, indicating omitted variables. The DW-statistic and tests for 1st and 5th order autocorrelation are included in the table. Both tests indicate no autocorrelation of the errors. In summary, using the five percent level of significance, models appear reasonably well specified, with the possible exception of model (2'), which features non-normal residuals.

Table 6 Diagnostic tests for the final models

Test	(1')	(2')	(3')	(4')
Normality: $\chi^2(2)$	2.4916	9.0321**	1.1247	0.63746
	(0.2877)	(0.0109)	(0.5699)	(0.7271)
Heteroskesdasticity: F-statistic	1.9648*	0.40195	0.61094	1.1286
	(0.0944)	(0.6704)	(0.8455)	(0.3557)
RESET: F-statistic	0.24059	0.0048143	0.41923	2.8141*
	(0.6252)	(0.9449)	(0.5193)	(0.0976)
Durbin-Watson	1.95	2.29	1.97	1.96
1^{st} order autocorrelation: $\chi^2(1)$	0.0017205	2.0408	0.017884	0.094433
	(0.9669)	(0.1531)	(0.8936)	(0.7586)
5^{th} order autocorrelation: $\chi^2(5)$	1.8383	6.3543	5.3278	4.6076
	(0.8710)	(0.2733)	(0.3772)	(0.4656)

*Table 6: Diagnostic tests. P-values reported in parenthesis. *,**,*** significant at the 10%, 5% and 1%-level respectively. The estimation sample is 1989:1 – 2008:4.*

As mentioned earlier, all four models yield qualitatively similar results. Models (1') and (3') have the highest values for R^2. They appear to be reasonably well specified; using the five percent level of significance, our set of diagnostic tests fail to show omitted variables or nonspherical disturbances. In the following interpretation, I will focus on these two models.

5.2 The manufacturing sector: within sample fit

As we use log-linear specifications, the coefficients β_i have the interpretation of semi-elasticities of output with respect to the indicator. The estimated short-run semi-elasticity for output in the manufacturing sector is 0,00105. That is, a one point increase in the ICI at time t-2 corresponds to a 0,105 percent increase in GDP of the manufacturing sector in period t.

Figure 6 shows actual and fitted values of output deviation from trend in the manufacturing sector. The fitted values seem to follow the movements of the actual values, though possibly with a lag: the actual series appears to peak before our model. In addition, the model yields output fluctuations of smaller magnitude than we observe in the data. The model follows small fluctuations of the output gap fairly well, but fails to predict the larger deviations of output from trend.

Figure 6 Actual and fitted values, manufacturing sector

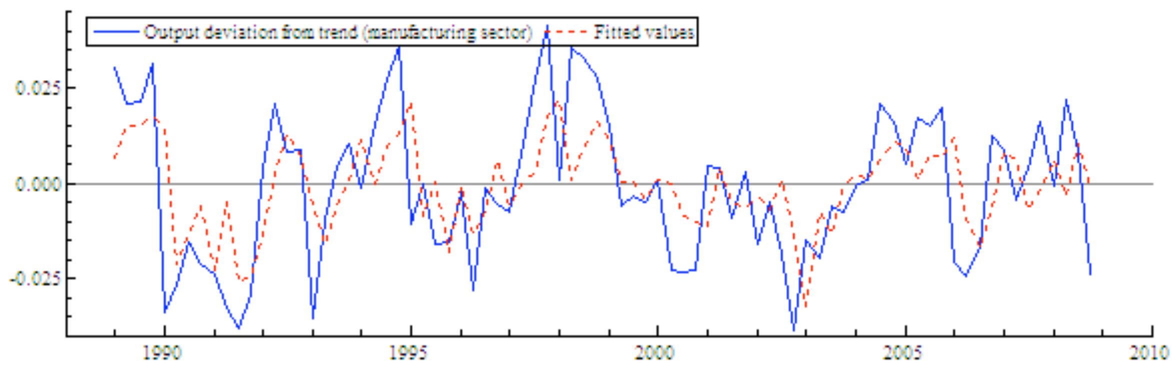

Figure 6: Actual vs. fitted values. Model (1').

5.3 Mainland economy: within sample fit

Figure 7 shows actual and fitted values of log deviations from trend in the mainland economy. The impression from figure 7 is not all that different from figure 6. The deviations of output from trend predicted by model (3') roughly follow the movements of the actual time series. There appears to be a lag; the model predicts peak values some time after they occur in the actual time series.

Figure 7 Actual and fitted values, mainland economy

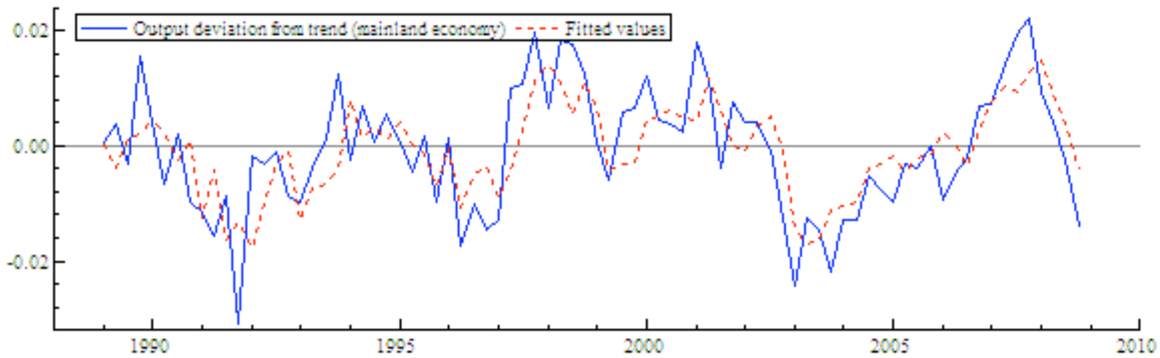

Figure 7: Actual vs. fitted values. Model (3').

We can find the short run effect on log deviation from output directly from the equation:

$$\frac{\partial \hat{y}_t}{\partial x_{t-2}} = (\beta_2 + \delta) = 0,000484 + 0,000358 = 0,000842$$

That is, a one point increase in the ICI at time t-2 corresponds to a 0,0842 percent increase in GDP in period t.

5.4 Long run effects

Our primary interest is the leading properties of the ICI and its usefulness in forecasting business cycles. Thus the main focus of this thesis will be the short run. However, one should also consider the long-run effects implied by the final models. A discussion of the long-term effect of a permanent shock to the ICI may help suggest the way the model adjusts to equilibrium. In addition, considering the long run effects can provide a test of consistency of our model. With the usual assumptions about the steady state of the economy, the model implies a steady-state value of the ICI. Inserting for the coefficients from table 5, this value can be calculated. If the model implies an "unreasonable" steady-state value of the steady state ICI, the consistency of the model could be questioned.

To analyze the long run effects, certain assumptions regarding the steady state of the economy should be made explicit. In the long run, we should have output at trend and a constant level of the ICI. It is difficult to say a priori what this steady state level of the ICI, x^{ss}, must be, i.e. if x^{ss} should be nonzero in steady state. For instance, if there is steady state growth in the manufacturing sector and this growth translates into increased demand for each existing firm, this steady state level x^{ss} could be positive as a representative firm should experience more incoming orders each quarter in steady state. However, it seems unlikely that the ICI should be very large in absolute value in steady state.

The analysis of long-run effects is limited to the mainland economy (model 3'). For the manufacturing sector, the model does not predict any long-term effects on output of a permanent change in the ICI, nor does the specification imply a steady state ICI level. ICI enters the final model (model 1') as a first difference only, and not in levels. The dynamic multipliers of y^m with respect to a permanent increase in x^{ss} converge to zero; the speed of convergence is determined by the autoregressive parameter γ_1.

We consider the effects of a permanent increase in x^{ss}. To consider the long term effects, we rewrite model (3') as an error correction model (ECM):

$$\hat{y}_t = \alpha + \beta_2 \Delta x_{t-2} + \delta x_{t-2} + \gamma_1 \hat{y}_{t-1} + \gamma_2 \hat{y}_{t-2} + \varepsilon_t$$

$$\Delta\hat{y}_t = \alpha + \beta_2 \Delta x_{t-2} + \delta x_{t-2} - (1-\gamma_1)\Delta\hat{y}_{t-1} - (1-\gamma_2-\gamma_1)\hat{y}_{t-2} + \varepsilon_t$$

$$\Delta\hat{y}_t = \beta_2 \Delta x_{t-2} - (1-\gamma_1)\Delta\hat{y}_{t-1} - (1-\gamma_2-\gamma_1)\left(\hat{y}_{t-2} - \frac{1}{(1-\gamma_2-\gamma_1)}(\alpha + \delta x_{t-2})\right) + \varepsilon_t$$

In the long run, we would have growth at trend level in all periods: $\Delta y_t = \Delta y_t^*$, so $\Delta\hat{y}_t = \Delta\hat{y}_{t-1} = 0$. We assume the ICI to be at some constant steady state level, so $\Delta x_{t-2} = 0$. Setting all shocks to zero in steady state yields the following equation:

$$\hat{y}^{ss} = \frac{\alpha}{(1-\gamma_2-\gamma_1)} + \frac{\delta x^{ss}}{(1-\gamma_2-\gamma_1)}.$$

The long run multiplier associated with x^{ss} is

$$\frac{\partial \hat{y}^{ss}}{\partial x^{ss}} = \frac{\delta}{(1-\gamma_2-\gamma_1)}.$$

We can use our estimates from table 1 to evaluate this expression:

$$\widehat{\frac{\partial \hat{y}^{ss}}{\partial x^{ss}}} = \frac{\hat{\delta}}{(1-\widehat{\gamma_2}-\widehat{\gamma_1})} = \frac{0{,}00036}{(1-0{,}218-0{,}458)} = 0{,}001105.$$

This long run semi-elasticity of output with respect to the ICI is only slightly larger than the short run semi-elasticity (0,000842). Our model suggests that most of the adjustment of output to a permanent shift in the ICI happens immediately after the initial two-period lag.

As the output gap should be zero in the long run, the idea of a steady state deviation from trend is problematic. Setting $\hat{y}^{ss} = 0$, the model yields the following expression for x^{ss}:

$$x^{ss} = \frac{\alpha}{\delta}$$

In the long run, we could imagine a link between the steady state ICI and the trend level of output. Assuming output at trend in steady state, and inserting our estimates from table 1, we find:

$$x_t^{ss} = \frac{0,00179}{0,00036} = 5\,.$$

This steady-state value of the ICI is not unreasonably high, it is also consistent with the average values of the ICI in our sample ($\bar{x} = 3.1807$, $\sigma_x = 7.19$). This analysis of the long-run properties of the model does not detect inconsistencies in the model.

6. Predictions

Once the empirical models linking the business cycle to the ICI are established, we are interested in what predictions the model implies for the future. This is of particular interest now, in the current climate of global financial crisis and economic slowdown. The world economy is experiencing the most severe economic downturn since World War 2. The crisis is less severe in Norway compared to most other countries. One reason is that the currency has depreciated, improving the competitiveness of the exporting sector. Economic policies imply that the automatic stabilizers have a stabilizing effect. Fiscal policy in response to the crisis has been more expansive than in other countries, and the petroleum sector is relatively insensitive to the business cycle in the short term.

This is not to say that the Norwegian economy is unaffected by the global economic slowdown. Unemployment has increased, albeit from a very low level, and is expected to increase further: in may 2009, Statistics Norway predicted unemployment (as defined in the Labor Force Survey) would peak at 5% in 2011. (Statistics Norway, 2009)

In this context then, we considered our models' predictions for the short term. Using available data from the BTS (available up until 2009:2) and from the quarterly national accounts (until 2009:1), the models can be used to predict log deviation from trend output from 2009:2 to 2009:4 in the manufacturing sector and in the mainland economy. The inclusion of one additional observation of GDP will lead to the trend GDP being re-estimated, so the time series of GDP deviation from trend will be changed compared to the series used to obtain the final models in section 4. As a result, the model will have slightly different estimated coefficients for relevant parameters, even keeping the estimation sample the same.

Figures 8 and 9 illustrate these predictions. Error bars show an approximate 95%-confidence interval for the predicted outcomes, taking parameter uncertainty into account.

Our model predicts that the economic downturn has reached the bottom now, at the end of the second quarter of 2009. Recovery is expected to happen faster in the manufacturing sector, where the output gap is expected to reach positive values by 2009:4. For the mainland economy, the model predicts a somewhat smaller initial drop in output, as well as a slower recovery, with output staying below trend longer.

The actual value of GDP of the first quarter of 2009 lies below the lower bound of the 95%-confidence interval of the forecasts. Recalling figures 6 and 7, the model's predicted values have historically been less volatile than the actual time series of the output gap. It is not unlikely that the actual drop in output, for the manufacturing sector and the economy as a whole, is substantially larger than predicted by the models. These findings may indicate that the model is less useful for predicting the severity of larger economic downturns such as the financial crisis.

Figure 8 Predictions for the manufacturing sector

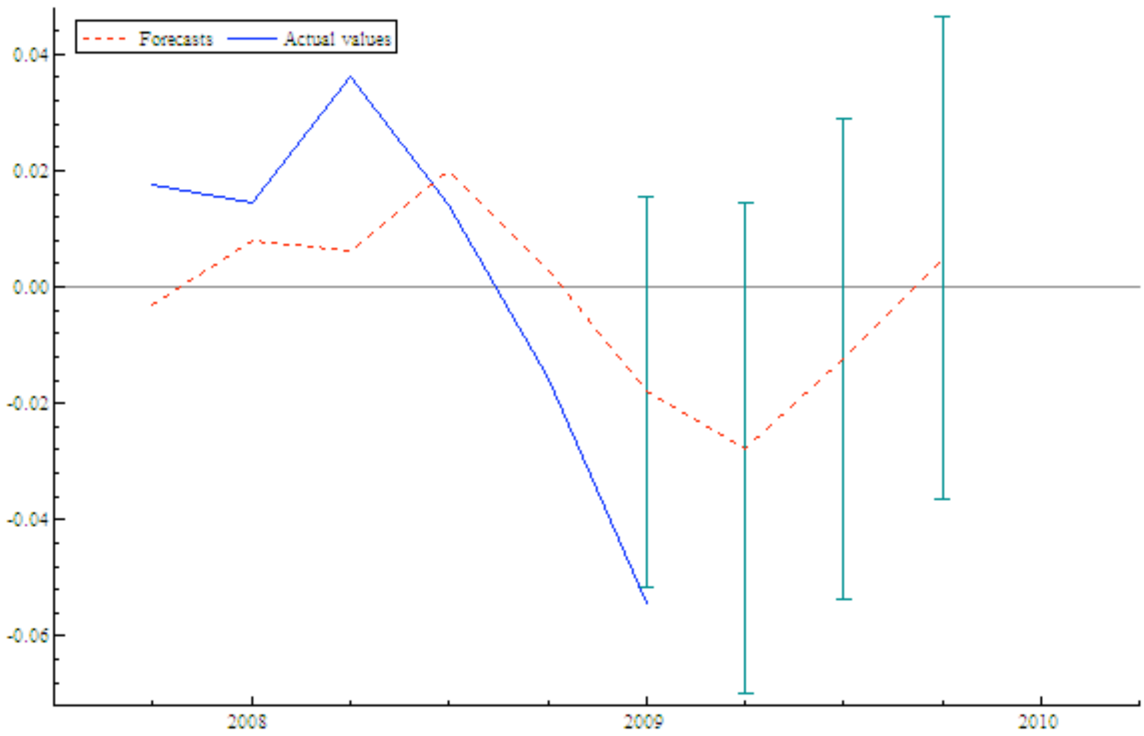

Figure 8: Actual and predicted values for the output gap in the manufacturing sector. Error bars show an approximate 95%-confidence interval for the forecasts, including parameter uncertainty.

Figure 9 Predictions for the mainland economy

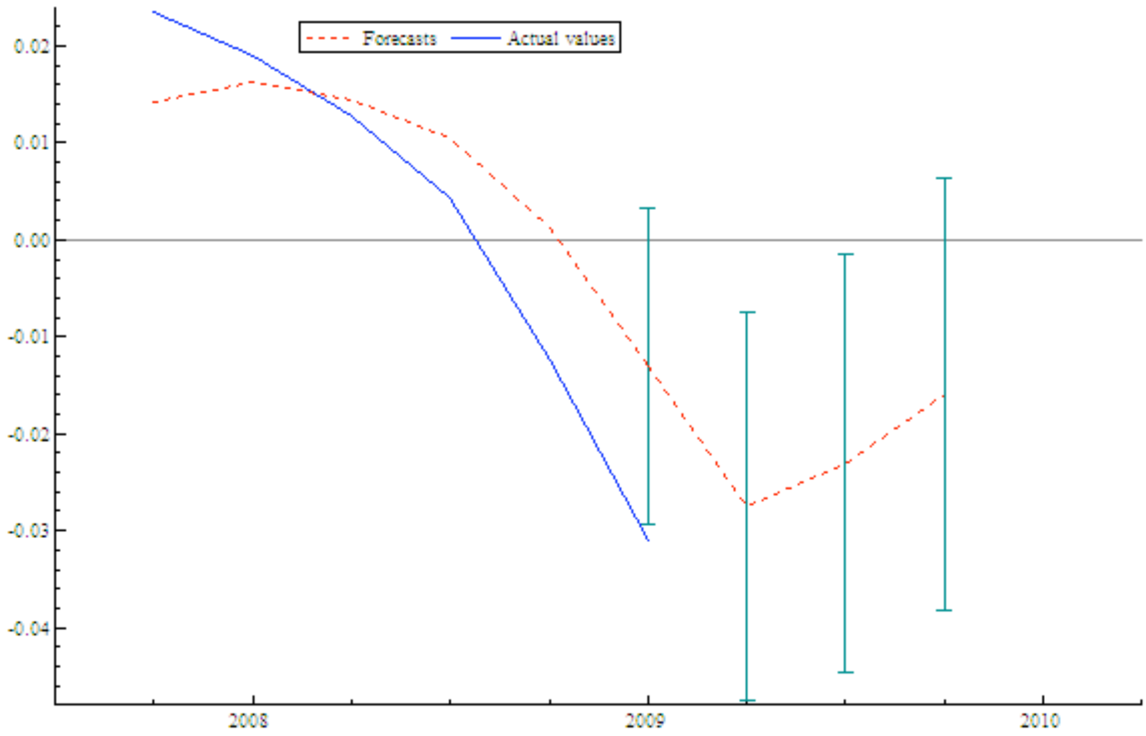

Figure 9: Actual and predicted values for the output gap in the mainland economy. Error bars show an approximate 95%-confidence interval for the forecasts, including parameter uncertainty.

7. Conclusions

Fluctuations in output, investment and employment lead to both economic and non-economic costs. Though there is some academic disagreement concerning the magnitude of these costs, in practice policymakers view the stabilization of business cycles as one of the principal aims of economic policy. Problems of information may pose a hindrance to the conduct of efficient stabilization policy to counter undesirable business cycles. Economic indicators, especially those available early and with little need of later revisions, can improve forecasts; these more accurate forecasts can in turn make possible a more efficient implementation of countercyclical policy.

In this context, this thesis wished to examine whether the ICI is in fact leading actual economic activity. Specifically, using a general-to-specific modeling approach, a dynamic empirical model of the business cycle is formulated. Lags of the indicator prove significant in explaining GDP, supporting the hypothesis that the indicator is indeed leading. The ICI is leading and might therefore be useful in timing economic policy.

The model is not without its weaknesses. First of all, the explained variation as measured by the R^2 is low; a significant portion of GDP variation is left unexplained by the model. Second, the model appears to be unable to predict the major fluctuations in output. This is made clear in the predictions in the context of the current financial crisis, where the predicted values of the output gap are much smaller (in absolute value) than the observed deviations from trend.

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Annex: Preliminary regressions

Output gap in the manufacturing sector

	Coefficient	Std.Error	t-value	t-prob	Part.R^2
$\hat{y}^m_{t-1}$	0.519198	0.1139	4.56	0.0000	0.2239
$\hat{y}^m_{t-2}$	-0.000489229	0.1269	-0.00386	0.9969	0.0000
$\hat{y}^m_{t-3}$	0.00284591	0.1131	0.0252	0.9800	0.0000
Constant	-0.00237394	0.002214	-1.07	0.2871	0.0157
x_t	0.000147052	0.0004245	0.346	0.7300	0.0017
x_{t-1}	0.000412234	0.0005759	0.716	0.4764	0.0071
x_{t-2}	0.000833235	0.0005603	1.49	0.1413	0.0298
x_{t-3}	-0.000916561	0.0004779	-1.92	0.0591	0.0486

Quarter-on-quarter growth rate in the manufacturing sector

	Coefficient	Std.Error	t-value	t-prob	Part.R^2
Δy^m_{t-1}	-0.260196	0.1142	-2.28	0.0257	0.0672
Δy^m_{t-1}	-0.161128	0.1153	-1.40	0.1667	0.0264
Δy^m_{t-1}	-0.111666	0.1136	-0.983	0.3287	0.0133
Constant	0.00245974	0.002474	0.994	0.3235	0.0135
x_t	0.000347965	0.0004764	0.730	0.4675	0.0074
x_{t-1}	0.000558464	0.0006502	0.859	0.3932	0.0101
x_{t-2}	0.000837544	0.0006409	1.31	0.1954	0.0232
x_{t-3}	-0.00101761	0.0005301	-1.92	0.0589	0.0487

Output gap in the mainland economy

	Coefficient	Std.Error	t-value	t-prob	Part.R^2
$\hat{y}_{t-1}$	0.442627	0.1158	3.82	0.0003	0.1686
$\hat{y}_{t-2}$	0.283681	0.1207	2.35	0.0215	0.0712
$\hat{y}_{t-3}$	-0.00309204	0.1168	-0.0265	0.9790	0.0000
Constant	-0.00200420	0.001073	-1.87	0.0659	0.0462
x_t	0.000279173	0.0002083	1.34	0.1843	0.0244
x_{t-1}	-4.34198e-005	0.0002798	-0.155	0.8771	0.0003
x_{t-2}	0.000651359	0.0002674	2.44	0.0173	0.0761
x_{t-3}	-0.000450068	0.0002371	-1.90	0.0616	0.0477

Quarter-on-quarter growth rate in the mainland economy					
	Coefficient	Std.Error	t-value	t-prob	Part.R^2
Δy_{t-1}	-0.398597	0.1173	-3.40	0.0011	0.1382
Δy_{t-2}	-0.0685502	0.1258	-0.545	0.5875	0.0041
Δy_{t-3}	-0.105642	0.1136	-0.930	0.3554	0.0119
Constant	0.00720406	0.001522	4.73	0.0000	0.2373
x_t	0.000451118	0.0002216	2.04	0.0454	0.0544
x_{t-1}	3.86973e-005	0.0003053	0.127	0.8995	0.0002
x_{t-2}	0.000766923	0.0003023	2.54	0.0133	0.0821
x_{t-3}	-0.000408919	0.0002507	-1.63	0.1073	0.0356