Business cycle measurement: A semantic identification approach using firm level data*

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Abstract

This paper uses a semantic approach for identifying business cycle movements. We infer positive and negative shocks to the economy directly from firms' responses in business tendency surveys. The new indicator can be shown to have excellent ex-ante forecasting properties for GDP growth.

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1 Introduction

Economic theory is very often based on concepts of equilibrium. Market solutions are derived from the idea of intersection of demand and supply, markets clear when the right price is quoted. Likewise, individual decisions such as the choice of optimal inputs in terms of quantity and prices can be modelled by equilibrium approaches where a solution obtains given market structure, profit maximisation objectives and certain state variables. A matter of interest thereby is, how this equilibrium looks in practice. What's this equilibrium like? When and how is it achieved? And how do deviations from this equilibrium which can be interpreted as business cycle fluctuations, look like? These questions are not easy to answer as they depend strongly on the definition of equilibrium.

The literature provides various methods to extract information about business cycle movements. For example, the Hodrick-Prescott-Filter (Hodrick and Prescott, n.d.) extracts the difference between trend and cyclical component, which is often interpreted as the business cycle, or the short-lived deviation of actual output from its trend path. There are several other filters available which we may characterise as technical filters. A second branch of business cycle measures use economic theory and econometrics to calculate deviations of actual output from potential output. For doing so, economic theory needs to provide a way for calculating potential GDP. A natural choice in this case is a hypothetical production function which is then put to the data. Due to its economic underpinning we may call these class of business cycle measures economic filters.

In our approach, we choose yet another way. We use statements of firms about their capacity utilisation on a quarterly frequency and compare these statements to an implicit desired level of capacities. The structure of the data allows us to derive a typical dynamic pattern of actual and desired capacity utilisation on a firm level. Based on this pattern and on the semantic content of the particular survey question we are able to define positive, negative shocks and the equilibrium. Owed to the fact that the basis for our identification is a semantic analysis we call this approach semantic filter.

After having extracted the business cycle measure we will compare it to actual GDP growth. We find that our indicator provides excellent ex-ante forecasts for GDP two quarters ahead.

The remainder of the paper is structured as follows. In section 2 the framework of the business cycle measurement is described, including details on the data and the empirical methodology used. Section 3 presents the results and performance of the constructed indicator and section 4 concludes.

2 Business Cycle measurement: framework

2.1 The data and its semantic content

Quite contrary to the usual aggregated analysis we use micro data on the firm level. The data source is the Swiss Economic Institute's (KOF) quarterly business tendency survey in the Swiss manufacturing industry. The data is available from 1999 first quarter to 2007 third quarter and consists of 25119 observations. There are two questions related to capacity utilisation. First, it is asked whether the technical capacities are currently too high, just right or too low (judgment). Secondly, firms are asked to quantify the capacity utilisation within the past three months in percentage points, where the firms can choose from a range of 50% to 110% in five percentage steps. From the latter we can calculate the percentage change in capacity utilisation from t to $t+1$ and compare this to the judgment about availability of capacities given by the firm in t.

The answer to the judgement question is interpreted as follows. A 'too low' is equivalent to a desire for expanding capacities, which should hence result in a reduction of capacity utilisation in the future. Likewise, a 'too high' statement implies the wish for increasing capacity utilisation by lowering capacities, for example.

The key to identify shocks in the economy is our ability to match the qualitative answer which tells whether or not firms are in need of more capacity and the change in their actual capacity utilisation. For example, if firms indicate that their technical capacities are too low and we observe that their use of capacity utilisation increases it is safe to say that this particular firm has been hit by a (positive) shock.

2.2 Semantic cross validation

The above interpretation requires some cross-checking with economics. Therefore, we next examine whether or not the data is consistent with basic considerations about plausible firm behaviour.[1] The first analysis will be based on contingency tables suggested by Ivaldi (1992). It is constructed as follows (see table 1).

Table 1: Principle structure of the contingency table

<table>
<tr><td colspan="2" rowspan="2"></td><td colspan="3">realisation</td></tr>
<tr><td>-</td><td>=</td><td>+</td></tr>
<tr><td rowspan="3">judgment</td><td>-</td><td>mm</td><td>me</td><td>mp</td></tr>
<tr><td>=</td><td>em</td><td>ee</td><td>ep</td></tr>
<tr><td>+</td><td>pm</td><td>pe</td><td>pp</td></tr>
</table>

[1] Borrowing from nonparametric econometrics we label this method semantic cross validation, where economics provides the benchmark for assessing the semantic interpretation.

The rows describe the judgment of the firms in t about their current technical capacity; '+' stands for 'too high', '=' for just right, '-' for too low. In the columns, the possible outcomes in capacity utilisation changes are listed. A '+' means that the level of capacity utilisation has been augmented between t and $t+1$, a '=' stands for an unchanged level and '-' means a lower level. On the basis of this classification of nine different states of the firms, we are able to identify states that can be associated with either positive or negative shocks. The remaining states will be considered equilibrium situations, or states during which adjustment takes place.

When looking at state *pm*, for example, firms positioned in this field consider their capacities in t as 'too high', but from t to $t+1$ their degree of capacity utilisation still declines. Using the previous arguments we can classify this state as a situation of a negative shock to the particular firm. The argumentation for state *mp* is similar. As capacities in t are stated as 'too low' and the capacity utilisation rises anyway in the next quarter, we can classify *mp* as a state of a positive shock. The equilibrium derived from this observations is the state *ee*, where capacity is 'just right' in t and hence there follows no change in capacity utilisation in $t+1$.

Following the same logic *mm* and *pp* characterise periods of adjustment towards the desired position, while the interpretation of *me*, *pe*, *em*, and *ep* is not that clear cut. Empirically (Müller and Köberl, 2007), it seems that *em* and *ep* are very close to the pure equilibrium situation while *me* and *pe* lean towards secondary positive and negative shock states.

For the sample in our study, the repartition of percentage shares to the different states are summarised in table 2.

The table shows a few interesting features. For example, the majority of firms find itself in a situation where capacities are sufficient (*ee*). When firms

Table 2: Empirical contingency table

sample 1999 – 2007		realisation -	realisation =	realisation +
judgment	-	2.7	3.0	2.4
judgment	=	25.4	30.1	25.7
judgment	+	2.8	3.5	4.4

The table entries report the shares of firms who judge their capacities according to the row labels and likewise experience a change in capacity utilisation as indicated by the column headers.

express a desire for more capacities (judgment '-') they increase (realisation '-') their capacities more often than they decrease it (2.7 vs. 2.4). Equivalently, when firms report 'too many' capacities a decrease of capacities follows in the next period with the highest probability. By contrast, shocks to this plausible pattern occur not very frequently (positive shock mp = 2.4, negative shock pm = 2.8). In a related work (Müller and Köberl, 2007) it has been shown that once being hit by positive shock the typical adjustment path of a firm is $mp \rightarrow mm \rightarrow ep \rightarrow em \rightarrow ep \ldots$. In other words, after a positive shock firm start to adjust capacities downward (mm) before they enter a period of sustained switching between the near equilibrium states.

All in all we may conclude that the semantic interpretation of the data provided in the previous subsection very well corresponds what is economically plausible. Therefore, we are confident in continuing regarding mp a measure of a positive and pm a measure of a negative shock respectively.

2.3 Construction of the indicator

In this section we describe the calculation of the business cycle measure. We use three approaches which differ only with respect to the way the benchmark is defined. Let x_t be either of the nine shares described in table 1. For example, in case of a negative shock, $x_t = pm_t$. Our business cycle measure is given by

$$bc_t^{(i)} = x_t - \mu_t^{(i)}, \;\; \mu_t^{(i)} = \begin{cases} \frac{1}{T}\sum_{j=1}^{T} x_t, & \text{for } i = 1 \\ x_t^*, & \text{for } i = 2 \\ \hat{x}_{t+1}|x_t, & \text{for } i = 3 \end{cases}$$

In case $i = 2$ the benchmark is the steady state share of x_t obtained from an approximation of the time series process of the nine states (see Müller and Köberl, 2007, for details). The approximation is an ergodic Markov-chain of order one assuming homogenous firms and stationarity. Similarly, for $i = 3$ we use the forecast of x_{t+1} based on its past and the estimated Markov-process. Since for $i = 1, 2$ the benchmark is a constant, the dynamic properties of the resulting business cycle measures are the same. Further, as we are able to distinguish between positive and negative shocks on a semantic basis, the interpretation of positive and negative values of the business cycle indicator changes. In fact, for $i = 1, 2$ we are going to use $bc_t = x_t$ directly since it will assume a value of zero in the absence of a shock and the value one if all firms are hit by this shock. In general, positive and negative shocks occur simultaneously, which provides us with a more differentiated picture of the economy as compared to a single measure net of positive and negative shocks.

The choice between $i = 3$ and the other two options will be left to the particular purpose of the analysis. In the empirical exercise to follow we focus on $i = 1, 2$ as it provides a slightly better model fit when estimating quarterly GDP.

3 Application

Before turning to the econometric exercise let us have a look at two of the business cycle indicators. Figure 1 displays $bc_t^{(1,2)} = pm_t^{(1,2)}$ and $bc_t^{(3)} = em_t^{(3)}$, that is a negative shock and a negative shock in the vicinity of the equilibrium state of the economy. The figure is scaled to make the time series comparable. The two business cycle indicators are range- and mean-adjusted to give them a standardisation. Furthermore, the figure is scaled to the year-on-year growth rate of quarterly real GDP. To make the picture even more accessible, the negative shocks have been inverted (multiplied by -1) and then plotted against quarterly real GDP. By simple visual analysis the correlation between the three series appears pretty large. In fact, the contemporaneous correlation between the GDP growth rate and $bc_t^{1,2}$ is $-.48$ while the correlation with GDP growth one quarter ahead amounts to $-.58$. The corresponding values for bc_t^3 are $-.60$ and $-.50$ respectively. These correlations are among the largest out within the set of nine potential business cycle series (nine for each i).

Notice that the business cycle indicators are not smoothed or filtered in any way. Therefore, they both appear rather spiky in comparison to the filtered GDP growth. Although the noisy appearance may seem inconvenient, it has the big advantage that the release of new data does not invalidate past observations. In other word, by construction, our indicator is free from revisions in the future. Next, we turn to estimation and forecasting GDP growth with the new indicators.

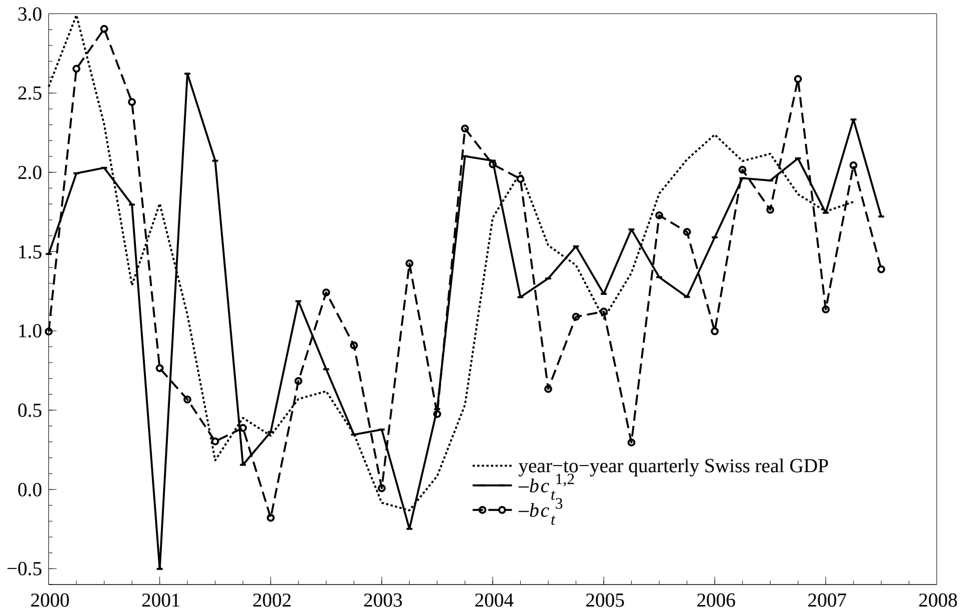

Figure 1: Business cycle measures: inverted negative shocks to the economy

3.1 Estimating and forecasting GDP growth

One important desirable property of a business cycle indicator is its ability to track and possibly forecast GDP growth. Our proposal has a publication lead of one quarter. It therefore has the potential of being a good nowcasting tool. We show next that this advantage extends to forecasting because $bc_t^{1,2}$ enters the corresponding forecasting equation with one lag.

For deriving the most appropriate model we use the following strategy. We first specify a general model for quarterly GDP growth as the dependent variable. The list of exogenous and predetermined variables comprises four lags of quarterly GDP, the contemporaneous business cycle measure and three of its lags, three seasonal dummies, and a constant. We then let *PcGets* (see e.g. Hendry and Krolzig, 2004) choose the best model subject to not deleting the constant at any step of the selection procedure. The sample for model selection is 2000 second quarter to 2006 first quarter which admits a valid ex-ante forecasting comparison. The resulting models read (absolute t-values in parentheses below the coefficient estimates):

$$\begin{aligned}
\triangle y_t &= \underset{(2.48)}{-0.92}\, em_t^{(3)} - \underset{(9.90)}{3.48}\, s_{2,t} - \underset{(6.39)}{1.68}\, s_{3,t} + \underset{(4.18)}{1.28} \\
\hat{\sigma} &= 0.521 \\
\bar{R}^2 &= 0.87 \qquad (3.1)
\end{aligned}$$

$$\begin{aligned}
\triangle y_t &= \underset{(2.08)}{-1.03}\, pm_{t-1}^{(1,2)} - \underset{(14.1)}{3.66}\, s_{1,t} - \underset{(6.12)}{1.87}\, s_{3,t} + \underset{(11.0)}{2.08} \\
\hat{\sigma} &= 0.541 \\
\bar{R}^2 &= 0.89 \qquad (3.2)
\end{aligned}$$

In both cases the null hypothesis of no autocorrelation up to order four and normality of the residuals cannot be rejected at any conventional level of significance. Hence, the properties of the estimations are very satisfactory and the business cycle indicator appears statistically significant and has the theoretically correct sign. When using t-values adjusted for potential heteroscedasticity we obtain even larger values (in absolut terms).

To complete the application we use equations (3.1) and (3.2) for forecasting. Notice that both model selection and estimation did not include observations after 2006 first quarter. Therefore, we may perform truly ex ante forecasts for the quarters up until 2007 third quarter for equation (3.1) and up until end of 2007 (equation (3.2)). The forecasts are depicted in figures 2 and 3.

Quite obviously, the forecasting performance of both equations is pretty impressive. Not only are the realised values within the 95% confidence bounds throughout the forecasting period, the absolute deviations are also very small.

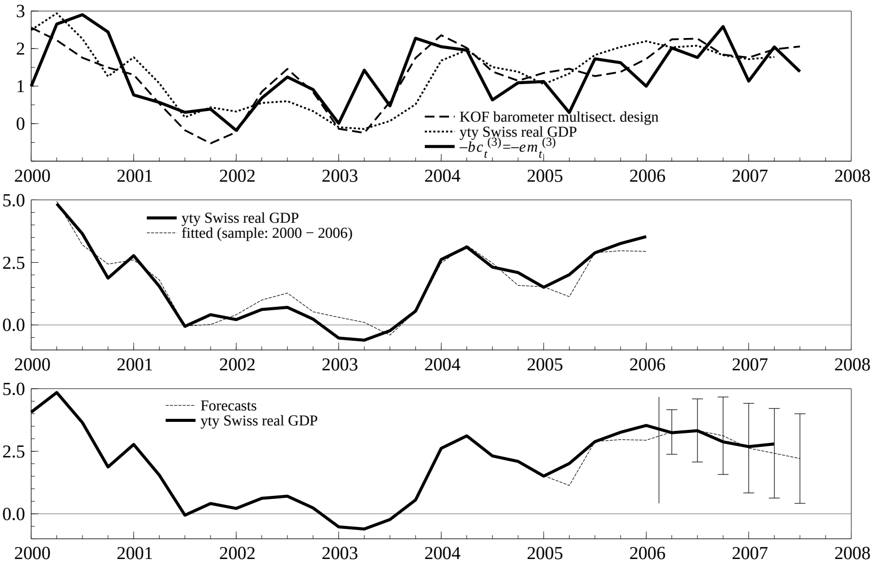

Figure 2: Business cycle measures and forecasting: $bc_t^{(3)}$

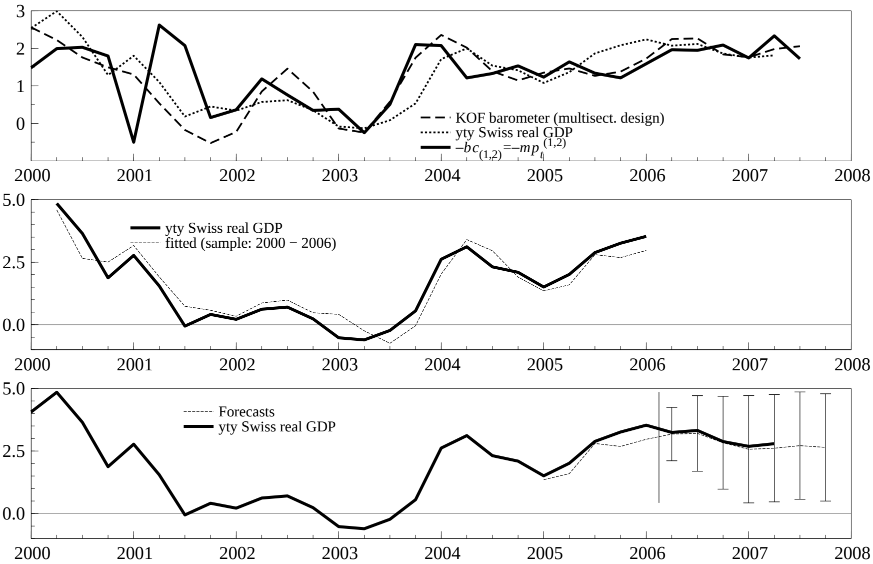

Figure 3: Business cycle measures and forecasting: $bc_t^{(1,2)}$

Another observation can be made in the top panels of figures 2 and 3 where in addition to quarterly year-to-year growth of real GDP the current official business cycle indicator of KOF is plotted. The correlation between all three series is rather high. The official series requires considerably more resources for calculation and is subject to revisions with every new release.

The middle panel of each figure displays the fitted values of the regression. Obviously, the fitted line is much smoother than the original business cycle measures. They therefore offer a possibility to report a more conventional business cycle measure. Doing so would, however, result in revisions in case the estimation is updated with new observations. As yet we have not decided whether or not to accept this disadvantage in exchange for a more traditional, smooth business cycle measure.[2]

To conclude this section, we could show that our business cycle indicator does indeed provide valuable information for gauging GDP growth. It is a useful tool for both nowcasting and short-horizon forecasting.

4 Summary and conclusion

In this paper we describe the derivation of business cycle indicators that is based on a semantic identification of shocks hitting the economy. We are able to identify positive and negative shocks. The new business cycle indicator has useful properties in that it is not subject to revision, has a publication lead of at least one quarter and can be used for two quarters ahead forecasting real GDP growth. On top of that, our indicator is very easy to compute.

Further research will – among others – be devoted to set the indicator in relation to simultaneous economic decisions by firms such as price setting.

[2] Notice also that our approach to business cycle measurement is based on identifying shocks. It is not clear that smoothness is a desirable property for shocks.

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