Is ‘Normal’ Capacity Utilisation Constant over Time?

Analyses with Macro and Micro Data from Business Tendency Surveys

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Abstract
The rate of capacity utilisation is an important business cycle indicator, as it relates directly to the stress on the current capacity to produce goods and services. From a policy perspective, technical bottlenecks indicate inflationary pressure, whereas idle capacity above normal points to a deflationary situation. Unfortunately, it is not clear which rate of capacity utilisation should be regarded as normal. In addition, the level of normal capacity utilisation can change over time. When the substitutability of physical capital declines, firms will tend to keep more idle reserves to make sure they can cope with unexpected orders. On the other hand, with technical and organisational progress making production more flexible, the level of normal rate of capacity utilisation could increase. In a similar fashion, a move on to just-in-time production could lift the normal rate of capacity utilisation. These reflections imply that the rate of capacity utilisation is not, or not always, a stationary variable. However, due to the ambiguity of the theoretical predictions, it is not clear whether we should expect an increase or a decline in the level that is considered normal. In this paper we refer to business tendency surveys from 34 countries to address this question empirically. Apart from this ‘global’ perspective, we undertake a more detailed examination of a large set of micro data referring to Switzerland. Our main findings are that the level of capacity utilisation to be considered normal is indeed not constant. During the last few decades, it appears to have decreased rather than increased.

Keywords
Capacity utilisation, normal utilisation, non-stationarity

JEL Classification
D24, E32, L60

1. Introduction

The rate of capacity utilisation is an important business cycle indicator, as it relates directly to the stress on the current capacity to produce goods and services. From a policy perspective, technical bottlenecks indicate inflationary pressure, whereas idle capacity above normal points to a deflationary situation.

Yet, it is far from obvious which rate of capacity utilisation should be regarded as normal. Moreover, the level of normal capacity utilisation can change over time. When the substitutability of physical capital declines, firms will tend to keep more idle reserves to make sure they can cope with unexpected orders. On the other hand, with technical and organisational progress making production more flexible, the level of normal rate of capacity utilisation could increase. In a similar fashion, a move on to just-in-time production could lift the normal rate of capacity utilisation. These reflections imply that the rate of capacity utilisation is not, or not always, a stationary variable. However, due to the ambiguity of the theoretical predictions, it is not clear whether we should expect an increase or a decline in the level that is considered normal.[1]

In this paper we refer to business tendency surveys from 34 countries to address this question empirically. Apart from this ‘global’ perspective, we undertake a more detailed examination of a large set of micro data referring to Switzerland. Our main findings are that the level of capacity utilisation to be considered normal is indeed not constant. During the last few decades, it appears to have decreased rather than increased.

Business tendency surveys (BTS) are conducted in a considerable and increasing number of countries. For our purposes, they are invaluable, as they reflect some unique information on technical capacity. In particular, in some surveys, firms are asked to make a judgement on their capacity utilisation in qualitative terms (normal, above or below normal). Moreover many surveys at the same time ask to give a quantitative estimate of the firm’s rate of capacity utilisation in per cent. In this paper, we shall refer to this type of BTS-data in three ways.

First, we refer to a set of quarterly BTS data comprising 34 countries from 1970 to 2008. This allows us to start with a calculation and comparison of averages of the quantitative indicator across countries. Moreover, we shall use a fixed effect model to identify whether there is a component of average capacity utilisation that reflects trends rather than cycles.

In a second step, we refer to the micro data from the manufacturing survey conducted by the Swiss Economic Institute (KOF). In particular, we identify those firms that assess their capacity utilisation as normal along with the corresponding statements on the rate of capacity utilisation in per cent. This information is aggregated across firms and the resulting variable is examined in various ways. These analyses cover years from 1984 to 2007.

Finally, stationarity of normal capacity utilisation will be analysed on the firm level (firm by firm and pooled). For this analysis, we shall restrict the sample to firms that participated in the survey for at least nine years. Again, we identify those observations where a firm assessed capacity utilisation as normal and revert to the corresponding quantitative information. Linear and non-linear regression will be used to characterise the firms’ profiles of normal capacity utilisation through time, and the information will be aggregated and summarised.

The remainder of the paper is organised as follows: After the short review of the evidence so far in this introductory section, we shall discuss and describe the data that we refer to (section 2). Then, we present our empirical analyses referring to international data (section 3) and to our data from Switzerland (section 4). Section 5 summarises and concludes.

[1] See e.g. Shapiro et. al. (1989) and Bansak et al. (2007).

The data

1.1. International data

For the first part of our analyses, the international evidence, we refer to BTS data from the manufacturing industry of those countries that conduct surveys including questions on capacity utilisation. To such questions (quantitative: capacity utilisation in per cent; qualitative: assessment of present rate of capacity utilisation) are now core items of the EU's harmonised BTS, but most other OECD countries as well as a few others conduct surveys with have similar questions.

The focus of this step of our analysis in on the national seasonally adjusted quarterly time series on capacity utilisation survey data on in per cent, which we denote as $CapU_{ij}$, where i denotes the country that the data refer to and j the quarter. We refer to other series than this only, if our target series is not available and other data, such as not seasonally filtered quantitative data or qualitative data, can be used to estimate the missing values of interest.

Our BTS data on capacity utilisation have been obtained from various sources. For EU-members, the Economics and Financial Affairs division of the European Commission publishes quarterly BTS data on capacity utilisation in per cent as well as the balance indicator for the assessment of the present level on capacity utilisation, both as original values and seasonally adjusted.[2] The time series generally start in 1985q1 or with the beginning of EU membership. Data for non EU-members countries as well as for some member countries going back beyond 1985q1 were taken from the OECD Main Economic Indicators online data base.[3] Finally, for New Zealand, a quarterly series on capacity utilisation was obtained directly from the New Zealand Institute of Economic Research (NZIER) in Wellington.[4]

The data were carefully screened for consistency, and the following adjustment was made: The time series for India (2000q2 to 2007q2, not seasonally adjusted) from the OECD is labelled 'balance indicator'. The range (79.7 to 97.5) makes it obvious, that this in fact has to be the percentage series, and we refer to it accordingly.

Whenever we could refer to BTS data on capacity utilisation that did not have our target format, i.e. a seasonally adjusted quarterly series on the rate of capacity utilisation in per cent, we devoted some effort to derive reasonable estimates of the target series. In particular, we performed the following steps:

1. For Australia, Brazil, Canada, China, India, Russia and South Africa, the OECD Main Economic Indicators provide our target series only without seasonal adjustment. We filtered these series, relying on the standard additive equal seasonal components model.
2. For Indonesia, the OECD Main Economic Indicators provide 14 data points of the not seasonally adjusted rate of capacity utilisation. As these data are too short for the standard seasonal filter, requiring at least four repeated periods affected by seasonality, but upon inspection appeared highly seasonal, we calculated seasonal factors by regression of the series through the origin on four quarterly dummies, and then the deviation of those from the average, which we then used to seasonally adjust the raw data.

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[2] They were obtained online from http://ec.europa.eu/economy_finance/db_indicators/surveys9185_en.htm. For this draft of the paper, these data are as of 28 July 2008.

[3] See 'Leading Indicators and Tendency Surveys' on http://www.oecd.org. For this draft of the paper, these data are also as of 28 July 2008.

[4] We herewith thankfully acknowledge.

3. For Japan and South Korea, the OECD Main Economic Indicators provide quantitative data on the rate of capacity utilisation as an index series only (1999=100). We adjusted this series by shifting it down so that the maximum would match the average of the maximum of our target series across all other countries.
4. For Norway, we have data on our series of interest from 1987q1. However, another series, firms operating at full capacity in per cent starts in 1973q4, and those two series are highly correlated. We hence estimated the earlier part of our target series by linear regression.
5. For New Zealand, the OECD Main Economic Indicators provides a series that is labelled 'manufacturing: firms operating at full capacity, %'. It covers 1970q1 to 2008q1, and during this long period, it is consistently moving above zero, though not considerably. For 1990q1 to 2007q1, the correlation with the NZIER data on capacity utilisation is as high as 0.81. We hence refer to the OECD series to estimate capacity utilisation in per cent for data points from 1970q1 to 1989q4 and 2007q2 to 2008q1.

These steps result in an unbalanced panel comprising 3206 observations of tabulated or estimated data on the seasonally adjusted rate of capacity utilisation.

Furthermore, to control for the business cycle, we need appropriate series that are measured independently of the survey data on capacity utilisation. Now, business cycle theory offers different definitions of a cycle.[5] Particularly; three types of cycles are distinguished: the classical cycle, the trend cycle and the growth rate cycle. For our purpose, the classical cycle, which is usually non-stationary, is not useful. We hence compute two alternative measures only, reflecting the trend cycle and the growth cycle, respectively.

Most studies are concerned with economy-wide capacity utilisation refer to the output gap, i.e. the difference between actual and the potential output or to closely related concepts and related concepts. We can broadly distinguish three of methods of quantification:[6] survey based estimates, statistical estimates (peak-to-peak, filtering (Hodrick Prescott, SVAR model) and the production function approach. These approaches have in common that they are based on some statistical procedure rather than referring strictly to economic theory.[7]

Our first measure for the cycle is the output gap, computed from GDP time series, where trend ('potential') GDP is extracted by low-pass filtering the natural logarithm of GDP with the Hodrick-Prescott-filter ($\lambda = 1600$). The output gap, i.e. the difference between actual GDP and the HP-filtered and de-logged series is expressed as a percentage of the latter. Our other series for the cycle is the year on year (YoY)[8] growth rate of quarterly GDP.

The GDP data that we use to compute these two measures are the quarterly volume indices from the OECD Main Indicators. For most countries, the GDP volume index is covering more data points than the survey data, but occasionally, the GDP series are shorter, and for the calculation of the YoY growth rate of GDP, four additional data points are lost for each country. For the unbalanced output gap panel, $n = 2682$: The joint unbalanced panels comprise less observations than either of three univariate panels: $n = 2223$ for the survey data and the output gap and $n = 2135$ for the survey data and the quarterly YoY GDP growth rate.

[5] For an overview; see Harding and Pagan, (2005).

[6] See e.g. Chagny and Döpke (2001) and Dergiades and Tsoulfidis (2007).

[7] See Cogley (1997).

[8] Theoretically, the QoQ growth rate would be more adequate to the growth rate concept which is based on acceleration/deceleration. But QoQ time series of growth rates reflect much more noise than YoY time series. This is true for the GDP, too. Therefore, we refer to YoY growth rate only.

The cross-correlation of the capacity utilisation series with the two indicators for the cycle shows that capacity utilisation is moving synchronically with the output gap, whereas the GDP growth rate leads by two quarters, which is in line with the prior expectation of a lead of the growth series before the output gap.

1.1.1. Data from Switzerland

1.1.2. Survey data

For Switzerland, the KOF Swiss Economic Institute has a long tradition in performing BTS in several economic sectors, including the manufacturing industry. On average, the manufacturing survey gets 1261 responses per quarter. One of the few quantitative items in the questionnaire is the rate of capacity utilisation. In addition, there is a qualitative item, the assessment of the 'technical capacity', where respondents have to state whether they feel that given the current business situation, the firm's technical capacity is 'too high', 'normal' or 'too low'. Based on these answers we can calculate the 'normal' rate of *CapU*.

We aggregate the normal capacity utilisation micro data to total manufacturing referring to different weighting methods. Alternatively, we restrict our sample to those firms that participated in the survey on a continuous basis for at least nine years between their first and their last observation, as we need a full cycle of durable equipment investment to identify a trend of normal capacity utilisation (*NormCapU*).[9] Thus, we obtain an unbalanced panel data set of observations where capacity utilisation is rated as normal, comprising 1,619 firms over a time period of 96 quarters, which makes a total of 61,135 observations.

1.1.3. Business cycle indicators

For Switzerland, we shall rely on the same two business cycle indicators as for the international analyses, reflecting the trend cycle and the growth cycle, respectively.

Again, the output gap is estimated with the Hodrick-Prescott-filter ($\lambda = 1600$). To eliminate the seasonal disturbances in our actual Swiss GDP series, it is deseasonalised by Census X11. As the YoY growth rate of quarterly GDP is already a working like a seasonal filter, no prior filtering of the Swiss GDP series is performed. According to the cross-correlation with *NormCapU*, the YoY GDP leads *NormCapU* by two quarters, which is in line with the prior expectation of a lead of the latter before the former.

1.1.4. Trend indicators

There are various approaches to define trends within these two cycle concepts. We refer to the following:

Time

With a time trend, we expect a long-run effect on the judgement of the normal rate of *CapU*. As discussed above, there are arguments to expect a positive sign (e.g. technical progress, optimisation of logistic, better organisation) or a negative sign (e.g. high intensity of technical capacity, high individual investment for one machine).

[9] Cycles with this duration are commonly called 'Juglar cycles', see Kacapyr (1996).

Boom

Our boom variable is binary and distinguishes between boom and slack economic development. If the output gap is positive or the GDP YoY growth rate is above mean, its value is 1, else its value is 0 (see figures 1.1 and 1.2). The hypothesis is that the availability of information changes over time. Being in a boom phase, the adaptive behaviour diminishes over time and therefore the judgement on normal *CapU* does today not follow the total *CapU* as strong as on earlier times.

Peak and through

The following concepts hence look for non-linear relationships. We identify full cycles and expect that within a full cycle there is a homogenous judgement of the normal *CapU*. But we expect to see between the full cycles a trend.

Unfortunately, the definition of a cycle along these four concepts is not that easy. We start with the cycle definition of Bry and Boschan (1971). To get homogenous cycles, we enlarge the full cycle to at least three years. The cycles are than defined from peak to peak and from trough to trough (see figures 1.3 and 1.4).

Meandown and meanup

For the cycles measured from intercept to intercept, we construct the 95-percent confidence interval for the mean of the relevant cycle and ignore peaks and troughs that fall within this interval.

Figure 1.3 shows the four cycles based upon YoY growth rate, whereas Figure 1.4 shows the different cycles obtained using the output gap series.

Figure 1.1: Definition of boom dummy I based on the output gap time series.

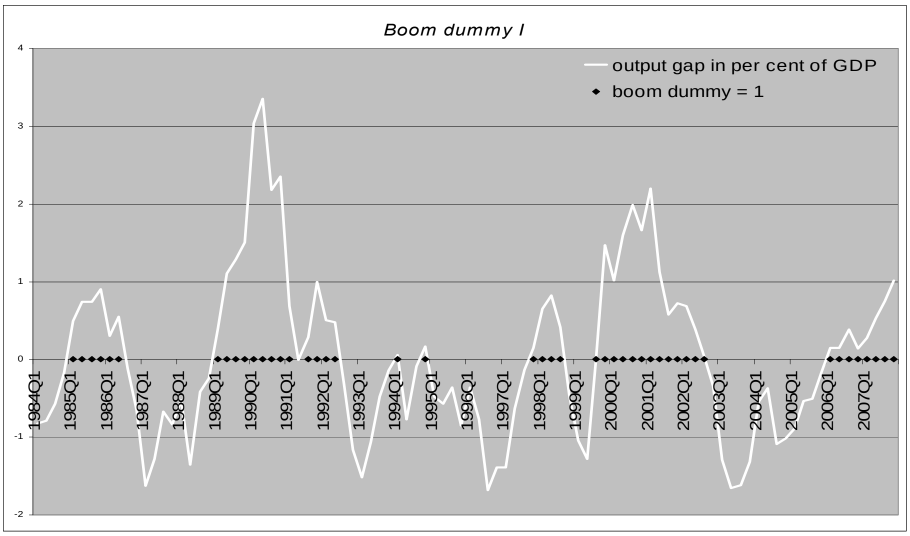


Figure 1.2: Definition of boom dummy II based on the GDP growth rate time series.

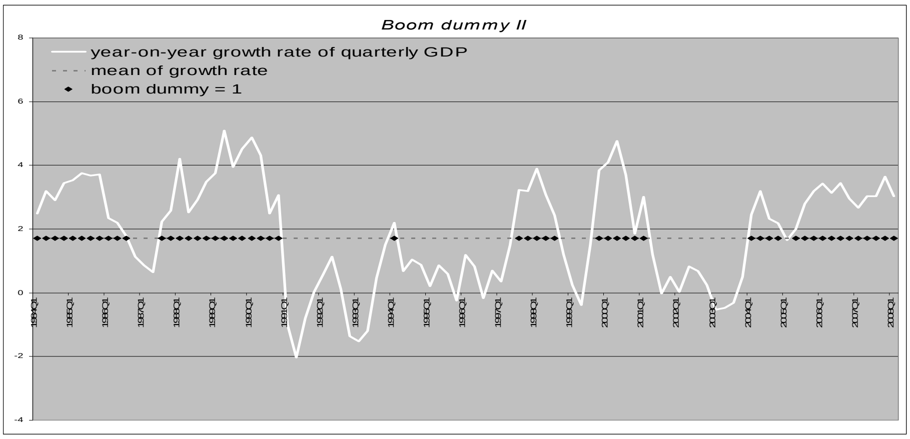


Figure 1.3: Definition of the cycle dummies based on output gap series.

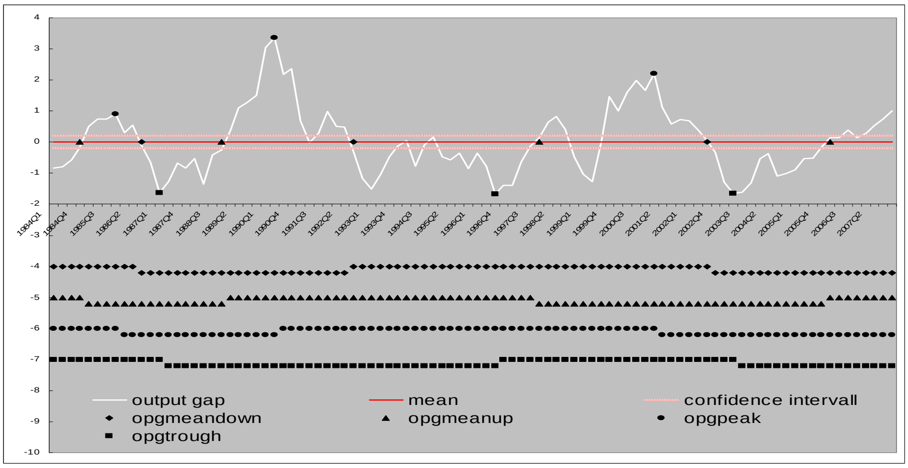
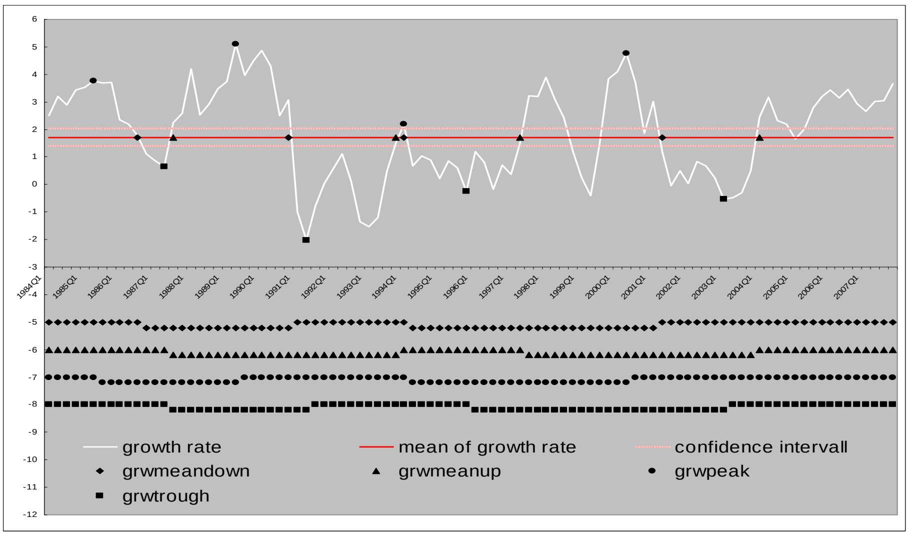


Figure 1.4: Definition cycle dummies based on the YoY GDP growth rate



2. Evidence from a cross-country panel data set

This section reports the results of our analyses referring to the international panel data.

The first hypothesis that we confront the data with can be stated as follows:

H1: The average rate of capacity utilisation is constant.

More specifically, the recent decades witnessed rapid technological progress (e.g. ICT and the Internet) that in principle allowed for dramatic change in logistics (e.g. just-in-time production). The introduction of so-called ERP (enterprise resource planning) systems might imply that resources are used more efficiently and idle time is reduced to a minimum. Accordingly, average capacity utilisation could be higher today than in 1984. Consequently, we can infer that the perception of 'normal' capacity utilisation could have changed in the same direction and state our second hypothesis:

H2: The rate of capacity utilisation considered as 'normal' is not increasing.

In the international analysis, we cannot match micro data on qualitative and quantitative assessments of capacity utilisation, so that we shall analyse the evolution of the rate of capacity utilisation without anchoring it to situations that are explicitly judged as 'normal'. However, implicitly, if there was a pronounced trend in the average level of capacity utilisation that cannot be attributed to the business cycle, it would be reasonable to conclude that what is considered normal would be adjusted accordingly.

Recall that our unbalanced panel for the rate of capacity utilisation comprises 3206 observations. The mean of $CapU_{ij}$ is 80.2, and its standard deviation amounts to 6.94. The data go back to 1970q1, where we start with 28 series from 7 countries, and they stretch to 2008q2, where we can draw on information from 20 countries. Figure 2.1 shows the mean values of $CapU_{ij}$ by year for the unbalanced sample. Obviously, there is a lot of variation, but for this period, no pronounced trend emerges.

Figure 2.1: Mean value of $CapU_{ij}$ by year, country coverage 7 to 34

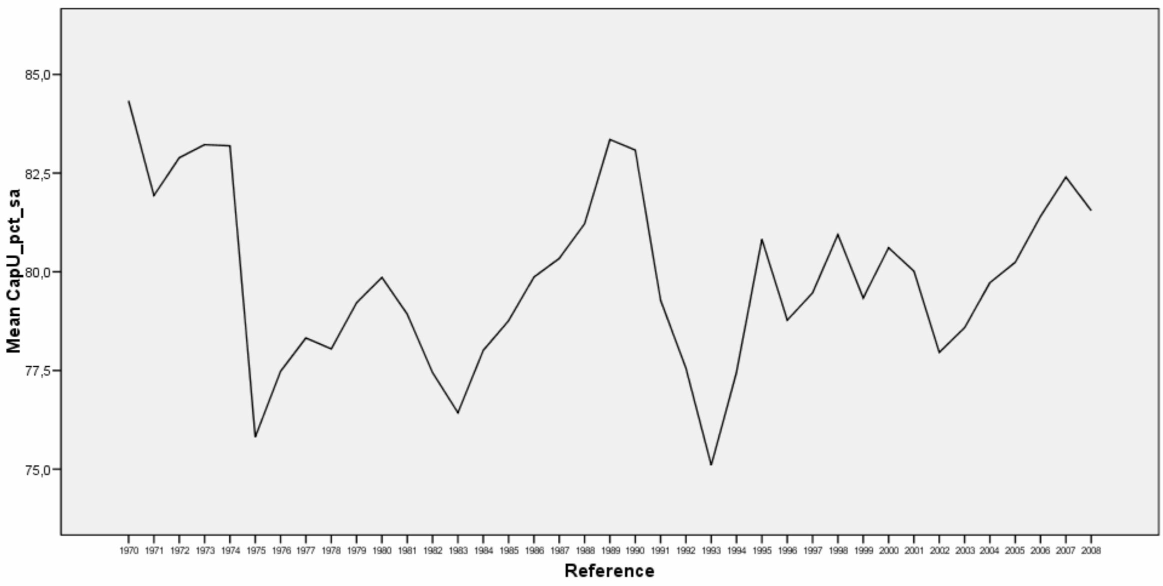


Table 2.1 shows the descriptive statistics of $CapU_{ij}$ by country. Most countries' mean values do not differ substantially from the overall sample mean of 80.2 %. A few countries stand out, though. In particular, Indonesia and Russia are more than 15 percentage points below the sample mean. Yet, as Indonesia's mean is based on a very limited number of recent observations, covering only 3.5 post-crisis years (2002q1–2005q2), and Russia's data refer to the time following the collapse of the Soviet economy, there are economic reasons to expect a somewhat below average capacity utilisation. On the other hand, we need to be aware of substantial differences in levels across countries, so that this has to be taken care of when the data are pooled.

Table 2.1: descriptive statistics of $CapU_{ij}$ by country, in per cent

Country	mean	n	Std. deviation	Country	mean	n	Std. deviation
Australia	82.1	49	1.72	India	88.8	29	7.35
Austria	82.3	50	1.82	Ireland	75.2	94	3.61
Belgium	79.0	121	2.89	Italy	75.7	154	2.70
Brazil	82.1	46	1.77	Japan	79.0	153	8.11
Canada	81.3	152	4.11	Korea (South)	72.3	73	4.12
Switzerland	83.8	154	3.33	Luxemburg	83.7	94	3.03
China	84.6	24	1.90	Netherlands	82.5	147	2.58
Czech Republic	82.8	67	4.37	Norway	82.4	138	2.70
Germany	83.6	154	3.51	New Zealand	89.2	153	2.13
Denmark	82.3	86	2.36	Poland	73.1	65	5.67
Spain	79.8	154	3.03	Portugal	78.9	126	2.49
Finland	85.4	62	2.31	Russia	50.9	60	7.59
France	84.4	130	2.02	Slovakia	77.9	59	4.55
UK	81.9	94	2.42	Sweden	85.6	50	1.85
Greece	76.1	94	1.80	Turkey	76.7	76	3.07
Hungary	81.0	50	2.70	USA	80.4	145	3.91
Indonesia	66.5	14	2.49	South Africa	73.4	89	10.08

The maximum number of countries for which we have data is 34, and this relates to the years 2002–2005, where the panel is balanced, but very short. If we want to construct a balanced panel covering all 154 quarters, we arrive at a subset of 4 countries only (Germany, Italy, Spain and Switzerland).

Clearly, if we want to infer some general conclusions about the mean level of capacity utilisation across time, we cannot restrict the analyses to any of the two balanced panel outlined above, as either four years over the whole country sample or four countries across the whole sample period would be too specific to the particular years or sample involved.

Another way to look at the panel is how the country coverage increases if we start with subsequently later years. For 1970 and 1971 we have data on *CapU* for 7 countries. The number initially increases gradually, to nine for 1972 and 1973, to 10 for 1974 and 1975, to 11 for 1976 to 12 for 1977 and 1978, and to 13 for 1979–1984. For 1985, it jumps to 17, from where it again increases gradually to its maximum of 34, and it then decreases to 20 for 2008q2. As we need to cover a considerable span of time to be able to make any inferences about trends in our data, we decided to take 1985 as a starting year for analyses of sensitivity to sample selection bias. This ensures that we are dealing with at least 17 countries for all quarters.

Going back to the data plotted in Figure 2.1, if we regress these on a yearly linear time trend, we get a significantly negative slope coefficient, but its magnitude is only 0.065, so that taking this at face value, we would conclude that *CapU* tends to decline by 0.00065 percentage points per year, which is practically meaningless. For the shorter sample period from 1985 to 2008, the time trend is essentially zero (t = –0.06). The negative slope for the entire period is hence artificial. Given the volatility of the series, the slope of the time trend depends on which starting and end point we choose, so that no interesting insights can be gained from such regression exercises.

Now, Figure 2.1 also suggests that, as can be expected, the average of the rate of capacity utilisation is highly cyclical. Hence, if we could purge *CapU* from its cyclical component, the remaining variance might be more informative for our purpose. To this end, we regress *CapU* on our business cycle indicators. To control for the difference in country averages of *CapU*, we include country fixed effects. However, no period fixed effects are included, as they would compete with the business cycle indicators and at the same time pick up any trend, which would make it hard to interpret such a regression. Instead, we shall analyse the residuals of the regression without time regressors (trend or period dummies), which will, apart from the noise, reflect any movement of *CapU* trough time that is not already accounted for by the business cycle indicators. The equation to be estimated is hence

$$CapU_{it} = \beta_0 + \beta_i + \beta_1\, BC_{it} + u_{it}\,, \qquad (2\text{-}1)$$

where β_i denotes country fixed effects and *BC* the business cycle indicators. The cross correlation with the capacity utilisation series with the two indicators for the cycle shows that capacity utilisation is moving synchronically with the output gap, whereas the GDP growth rate leads by two quarters, which is in line with the prior expectation of a lead of the growth series before the output gap. Moreover, both partial correlations are significantly positive. We hence consider them one at a time as well as both together (with regard to their respective lead/lag-structure vis-à-vis *CapU*), as they might convey different information on the cyclical position of the economy. The results are given in Table 2.2.

Table 2.2 shows that in the fixed model both business cycle indicators indeed have significant and substantial explanatory power for *CapU*. However, when we look at the residuals from the regressions, we see that there still is pronounced autocorrelation, but no perceivable time trend.

The residuals from the regression specified in Equation 2-1 are shown in Figures 2.2 and 2.3, where the former covers the entire sample from 1970 onwards, and the latter the control period starting in 1985.

Recall that the residuals, apart from the noise, reflect any movement of *CapU* trough time that is not already accounted for by the business cycle indicators. Obviously, despite coefficients of determination in the regressions amounting to close to 90 %, there still is considerable autocorrelation in the residual series. Non-stationarity, however, is visible only with respect to the variance of the residual series; as before, the levels do not reveal any obvious trend. Accordingly, this analysis tends to reject H1 (capacity utilisation is constant), but we cannot reject H2 (capacity utilisation is not increasing).

Table 2.2: Fixed effects regressions of $CapU_{it}$ on statistical business cycle indicators

	Model 1	Model 2	Model 3
β_0	73.6*	72.0*	72.3*
β_1	F = 236.3*	F = 230.7*	F = 232.3*
Output gap$_{t-1}$	0.56*		0.37*
YoY growth rate of GDP$_t$		0.61*	0.51*
R^2	0.88	0.88	0.88
N	2135	2031	2009

Figure 2.2: *CapU* not explained by country fixed effects and business cycle, 1970–2008

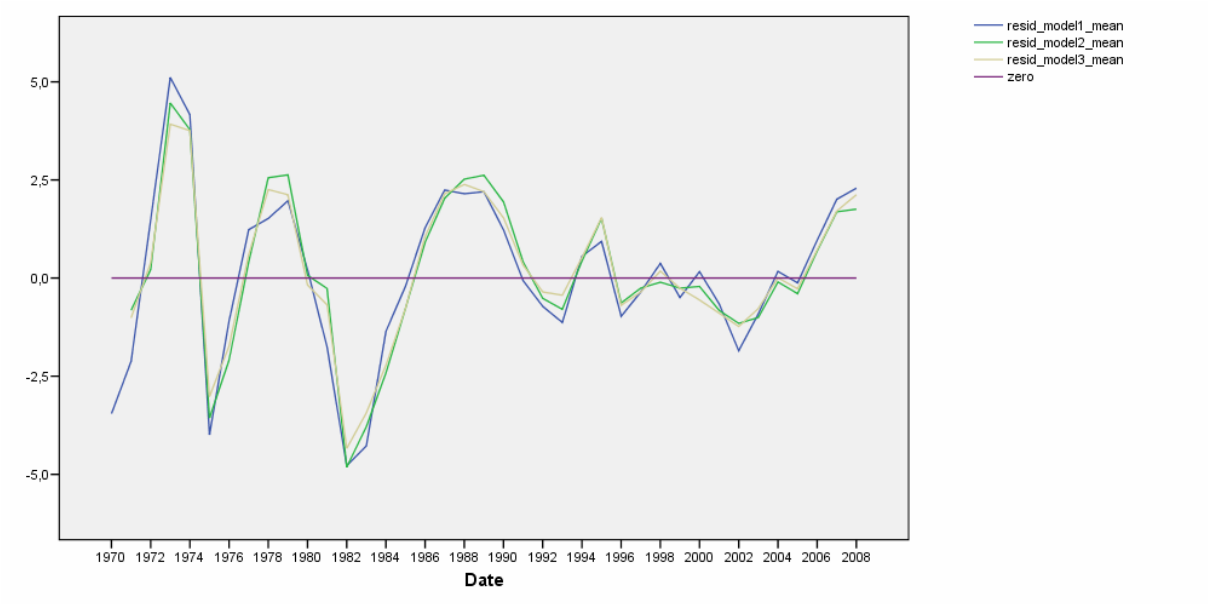
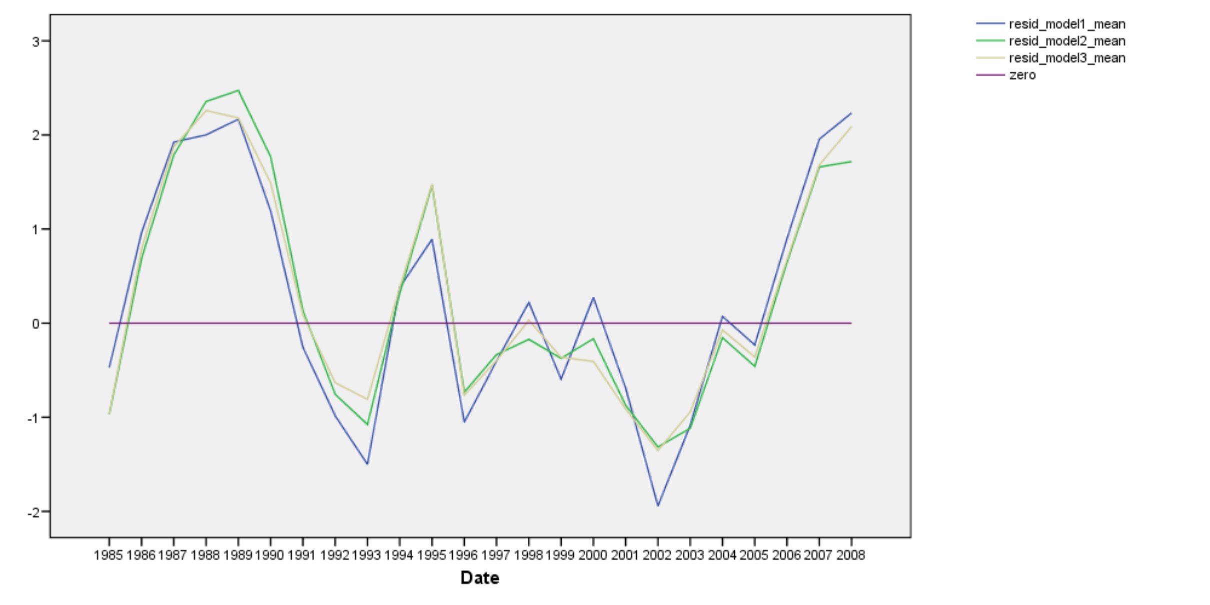


Figure 2.3: ***CapU*** **not explained by country fixed effects and business cycle, 1985–2008**



3. Evidence from Switzerland

The empirical evidence for Switzerland is the same as for the OECD as a total. But the findings are in a first reaction counter-intuitive. Therefore, we want to get a confirmation of this result using micro data. The micro data is used in two ways: judgement of the normal rate of capacity utilisation by calculating of a new index and by panel analysis.

3.1. Aggregated data

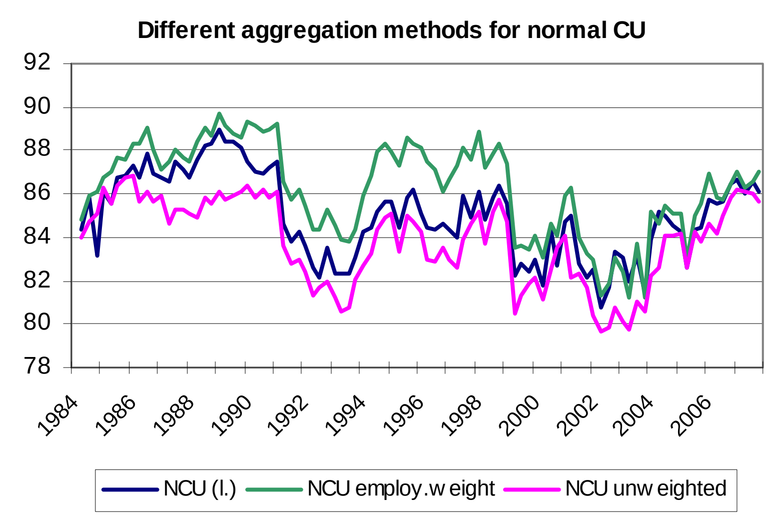
3.1.1. Index of normal capacity utilisation

The OECD data on the rate of capacity utilisation is calculated from all firms, e.g. from firms judging the technical capacities as too high, normal or too small. Isolating the level of normal capacity is only possible if you dispose of the corresponding micro data. KOF asks in its BTS in manufacturing not only the rate of capacity utilisation but additionally a judgement of the size of the technical capacity too. We therefore dispose not only on the qualitative information to this question but also the response of each firm to the quantitative question on the degree of *CapU*.

For our purpose we selected only firms judging its technical capacity as 'normal'. The way of aggregation to a new index of normal capacity utilisation (*NormCapU*) for total manufacturing can have a considerable impact on the results.[10] Therefore, we aggregated these firms in three different ways (see figure 3.1): no weighting (which means equal weight for every observation), firm-specific weighting (to give an impression of the importance of the weights based on the size of the firms), and the international standard of double weighting (firm-specific weighting and weighting according to the census of enterprises).

[10] See Vanhaelen and Dresse (2000).

Figure 3.1



The effect of weighting influences particularly the level of the indicator. Equal weighting produces an indicator which is quite lower (mean=83.7%) than the other two ones. The firm specific size weighting pushes the indicator up to a mean of 86.2%. The indicator with double weighting has a mean of 84.9% and will be called New Index of *NormCapU*. These results indicate that the big firms note in average a higher rate of capacity utilisation as 'normal'.

The level-effect is not surprising. But surprising is the strong movement over time. Obviously, the firms include different elements in its appreciation of the normal *CapU*.

3.1.2. Decomposition of *normal CapU*

Obviously, the Index with only 'normal' responses is neither only a constant value nor a linear trend. It seems to include, apart from other things, a business cycle component. This would mean that firms adapt its judgement of the *CapU* to the actual business situation. In a phase of long lasting high (low) activities und high (low) rate of capacity utilisation, firms increase (decrease) in their perception the level of 'normal' capacities.

Non-synchronically seasonal factors can disturb the coherence between two or more variables. The explanatory and the response variables are therefore based on deseasonalised time series wherever a seasonal component is detected in the data.

After controlling for the business cycle and seasonality any time trend in the data should still be possible to isolate if there is any time trend at all. The sign of the trend-coefficient would indicate if the technical progress and the increase of the capital intensity produce positive or negative trends in the normal utilisation degree of the technical capacities. We use the following equation:

$$NormCapU = a + b\,BC_t + c\,T + u \qquad \text{3-1}$$

BC Business cycle indicators
T Time trend, linear and nonlinear
t Shift by t periods
u Noise

3.1.3. Results

3.1.3.1. Output gap and other trend indicators

In Equation 3-1 we define in a first step as BC-variable the output gap and combine it with different linear and non-linear trends discussed above.

Taking just the output gap and a linear time trend as right-hand variables, the output gap is significant and has the expected sign (see Table 3.1). There is indeed an adaptive behaviour of the firms according to the business cycle. In boom (weak) phases they interpret as a normal *CapU* at a higher (lower) level of the rate of capacity utilisation. The time variable has a negative sign which implies that the judgement of a normal *CapU* by the firms goes along with a lowering degree of *CapU* over time. But the explanatory power of *NormCapU* is with an adjusted R^2 of 0.22, which is quite small.

Replacing the time variable by the boom variable, the result does not improve. The output gap is still significant and with the correct sign. The boom variable is negative but turns out to be insignificant. Figure 3.2 shows the *NormCapU*, the output gap and the corresponding boomphase dummies.

The four nonlinear trend variables explain much more of the development of *NormCapU*. In interpreting the results, it has to be considered that the last coefficient in an equation (e.g. in Eq 3 in Table 3.1. the coefficient of Peak4) covers a period which is shorter than a full business cycle and therefore cannot be interpreted.

Introducing a nonlinear trend defined as constant within a full cycle, all equations show diminishing coefficients over time (see Figure 3.3). In all four cases, looking over the time period, every coefficient is lower than the one before. Not all periods are statistically significant but increase the adjusted R^2 in parts considerably.

The results are quite conclusive; rejecting a positive trend over time of the rate of capacity utilisation judged as 'normal'. This supports the findings from the international data and the first results for Switzerland.

Figure 3.2

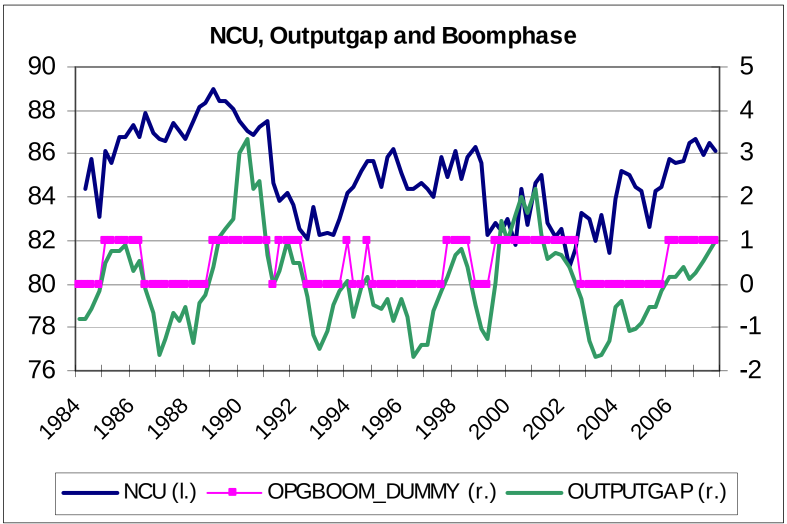
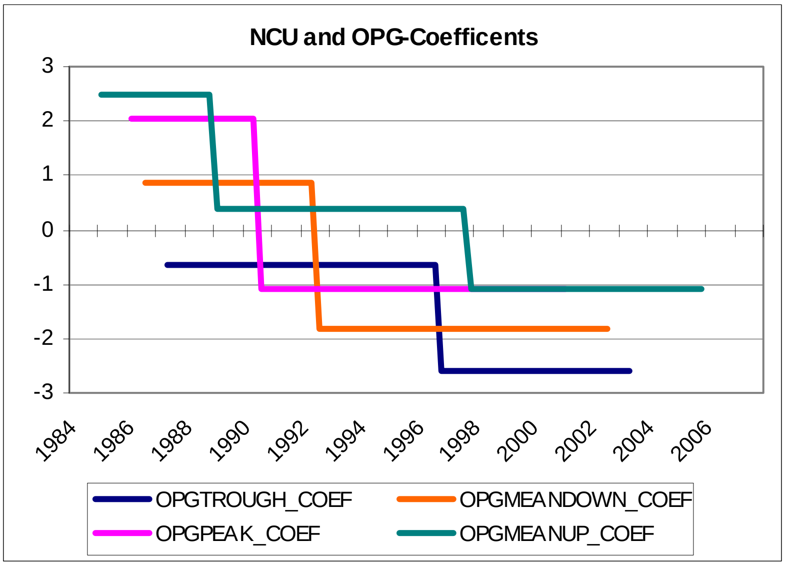


Figure 3.3



3.1.3.2. GDP YoY Growth Rate and Trend Indicators

In Equation 3-1 we now define the GDP-YoY growth rate as our BC-variable and combine it with the different linear and non-linear trends, constructed on the same principle as in the last section.

Taking just the GDP-YoY growth rate and a time trend as right-hand variable, both are significant and the output gap has the expected positive sign (see Table 3.2). There is indeed an adaptive behaviour of the firms according to the business cycle. The coefficient of the trend-variable defined by time is again small, but significantly negative. The size is similar as in the growth cycle concept which underlines this effect. The explanatory power of these two variables is better then in the equation with the output gap.

Replacing the time variable by the boom variable, the result gets worse. The growth rate is still significant and with the correct sign. The boom variable is positive but insignificant.

The four nonlinear trend variables explain much more of the development of *NormCapU* than did the variables trend and boom. In interpreting these results, it has to be considered that the last coefficient in an equation (e.g. in Eq 3 of Table 3.2 the coefficient of Peak5) covers a period which is shorter than a full business cycle and therefore cannot be interpreted.

The nonlinear trend variables defined as constant within a full cycle, show in most equations diminishing values of the coefficients over time (see Figure 3.5). The only exception is the variable ‘meandown’ where the coefficient of meandown4 is higher the the one of meandown3. Not all periods are statistically significant but increase the the GDP-YoY growth rate adjusted R^2.

In general, the equations with the GDP-YoY growth rate and a trend variable as right hand variables explain a higher part of the variance than the equations with the output gap. The results reject again a positive trend of the rate of capacity utilisation judged as ‘normal’.

Figure 3.4

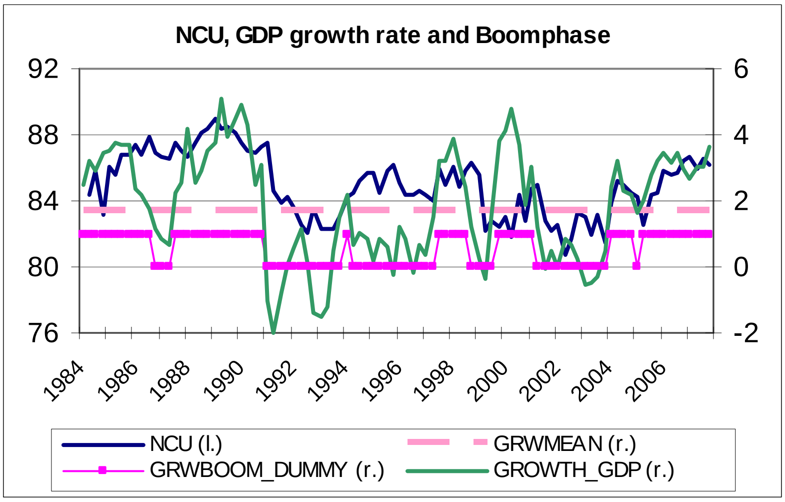


Figure 3.5

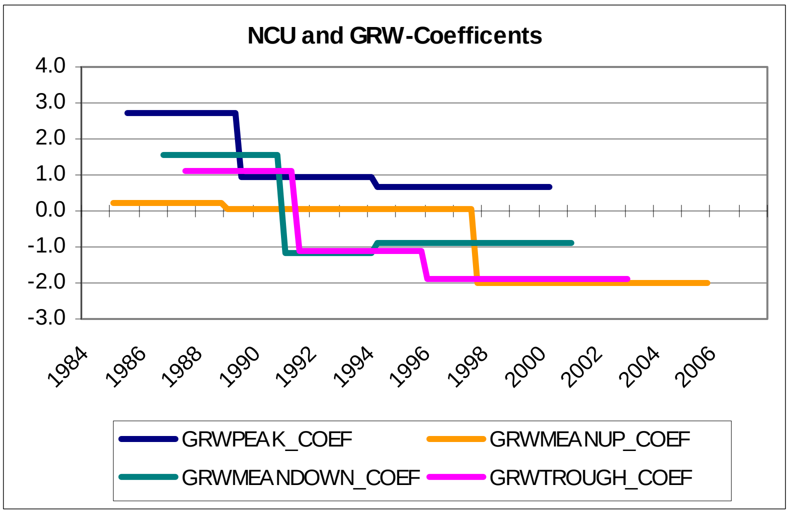


Table 3.1 **NCU and Outputgap**

	Eq 1 Coef.	t-Stat.	Eq 2 Coef.	t-Stat.	Eq 3 Coef.	t-Stat.	Eq 4 Coef.	t-Stat.	Eq 5 Coef.	t-Stat.	Eq 6 Coef.	t-Stat.
Constant	86.434	240.383	85.232	238.983	85.447	158.201	86.186	179.141	85.805	165.170	84.686	100.964
Outputgap	0.374	2.229	0.631	2.079	0.302	2.137	0.487	2.943	0.193	1.214	0.483	3.342
Time	-0.030	-4.671										
Boom			-0.561	-0.883								
Peak2					2.042	3.212						
Peak3					-1.091	-1.874						
Peak4					-1.294	-2.131						
Trough2							-0.638	-1.155				
Trough3							-2.603	-4.492				
Trough4							-1.193	-1.916				
Meandown2									0.876	1.440		
Meandown3									-1.836	-3.200		
Meandown4									-1.165	-1.858		
Meanup2											2.476	2.717
Meanup3											0.372	0.424
Meanup4											-1.083	-1.236
Meanup5											1.210	1.223
R2 adj.	0.217		0.040		0.453		0.254		0.352		0.438	
N	95		95		95		95		95		95	

Table 3.2 **NCU and GDP growth rate**

	Eq 1 Coef.	t-Stat.	Eq 2 Coef.	t-Stat.	Eq 3 Coef.	t-Stat.	Eq 4 Coef.	t-Stat.	Eq 5 Coef.	t-Stat.	Eq 6 Coef.	t-Stat.
Constant	85.123	243.691	83.694	334.874	83.072	134.097	85.018	196.865	84.562	179.751	84.341	195.300
Growth rate	0.634	7.237	0.611	3.931	0.617	7.442	0.442	4.619	0.476	5.229	0.693	7.907
Time	-0.027	-5.097										
Boom			0.295	0.576								
Peak2					2.717	4.202						
Peak3					0.954	1.466						
Peak4					0.658	1.041						
Peak5					-0.168	-0.272						
Trough2							1.110	2.372				
Trough3							-1.124	-2.186				
Trough4							-1.892	-4.406				
Trough5							-1.250	-2.760				
Meandown2									1.534	3.250		
Meandown3									-0.985	-1.749		
Meandown4									-0.031	-0.062		
Meandown5									-1.502	-3.442		
Meanup2											0.222	0.492
Meanup3											0.032	0.061
Meanup4											-1.987	-4.398
Meanup5											-0.969	-1.991
R2 adj.	0.474		0.328		0.574		0.581		0.624		0.544	
N	95		95		95		95		95		95	

3.2. Micro Data

3.2.1. Individual approach

Having analysed both international and Swiss capacity utilisation on an aggregate level, we now turn to Swiss micro data. We think there are two appropriate ways to deal with the available data. In the first part, we analyse the rate of capacity utilisations that are considered as ‘normal’ for each firm individually. We restrict our sample to these firms that feature a time span of at least nine years between their first and their last observation. In the second part, the data used in the first part is integrated in a panel structure and analysed accordingly.

Considering the firm by firm approach first, we run a regression of capacity utilisation considered as normal on a time trend for each firm separately. Afterwards, we summarise the coefficients of the time trend variable from the different regressions and compute descriptive statistics. These statistics are used to get a general idea of the changes in the perception of normal capacity utilisation.

First, we run a regression of capacity utilisation on a linear time trend only (3-2).

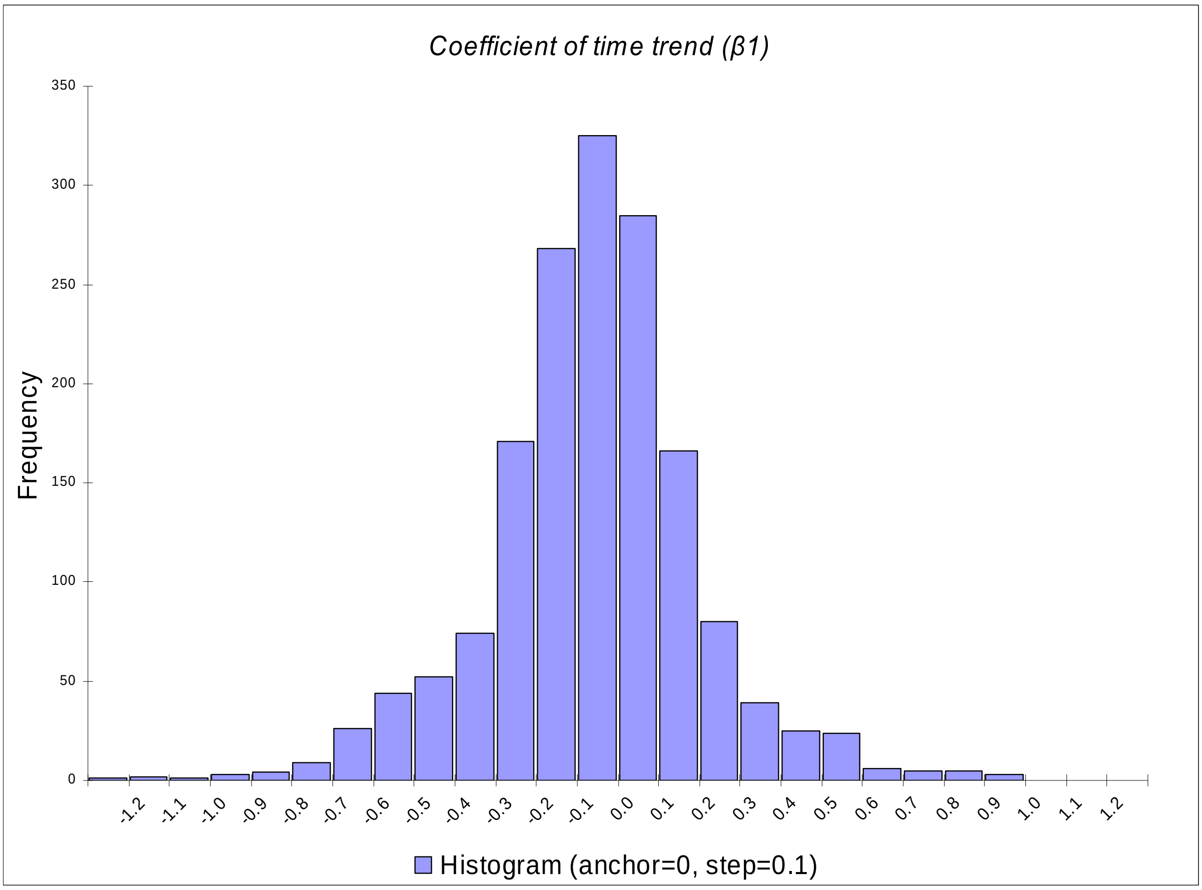
$$CapU = \beta_0 + \beta_1\, T + u \tag{3-2}$$

Due to the limited number of observations for each firm, we are restricted to use such a simple model. The first basic regressions indicate that we are dealing with a slightly negative trend (Table 3.3 and Figure 3.7).

Table 3.3: Summary of the firm by firm regressions on a linear time trend

Sample information		*Coefficients of the linear time trend (β1)*			
Industry	Manufacturing	Mean	-0.059	Std. Dev.	0.26
Time period	1984q1-2007q4	Median	-0.051	Skewness	-0.072
Number of firms	1619	Maximum	0.95	Kurtosis	4.90
Average *CapU*	83.97	Minimum	-1.24	Jarque-Bera	245.16

Figure 3.7: Histogram of the coefficients of the time trend variable, firm-level.



When we estimate the same equation but with some sample restrictions (e.g. different time periods, business sizes or industry branches), the results are rather similar to the one above.

After having run simple linear regressions for every firm, we now introduce a boom dummy based on different measures of the Swiss business cycle as a new independent variable. The reasoning behind the introduction of a variable that features a business cycle pattern is that during prosperous times, managers might consider their rate of capacity utilisation normal at higher levels.

Now we are able to run a regression of capacity utilisation on a linear time trend and one of the boom dummies for every firm in the sample and over the whole time period (3-3).

$$CU = \beta_0 + \beta_1 Trend + \beta_2 Boom + u \qquad (3\text{-}3)$$

The results of these regressions with two independent variables differ hardly from those obtained before; the slope parameter of the trend variable is still slightly negative (see Table 3.4, Figure 3.8, Table 3.5 and Figure 3.9).

Table 3.4: Firm by firm regressions on time trend and boom dummy (output gap)

Sample information		*Coefficients of the linear time trend (β1)*			
Industry	Manufacturing	Mean	-0.060	Std. Dev.	0.27
Time period	1984q1-2007q4	Median	-0.050	Skewness	-0.150
Number of firms	1616	Maximum	0.94	Kurtosis	5.22
Additional Variable	Boom I	Minimum	-1.42	Jarque-Bera	336.53

Figure 3.8: Histogram of coefficients of time trend variable obtained from different regressions on the firm-level including the boom dummy I as an independent variable.

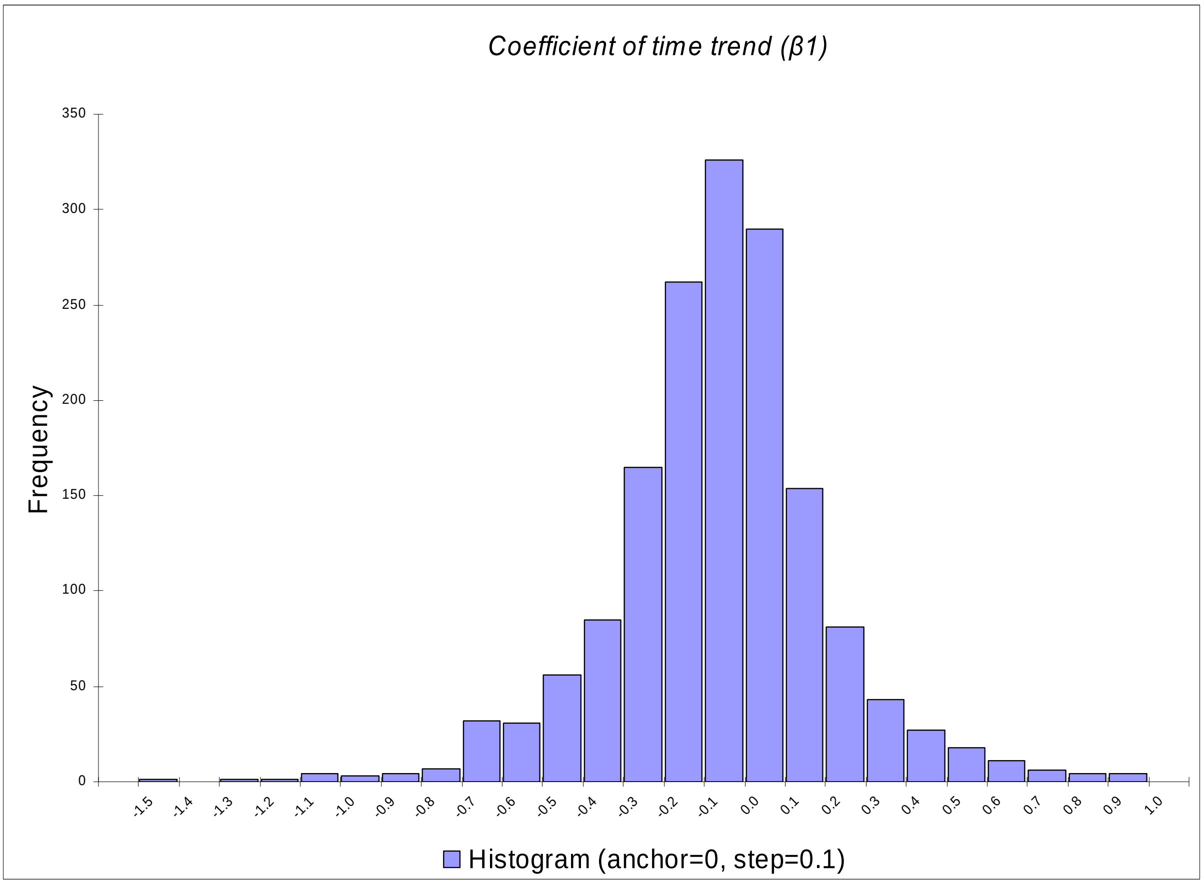
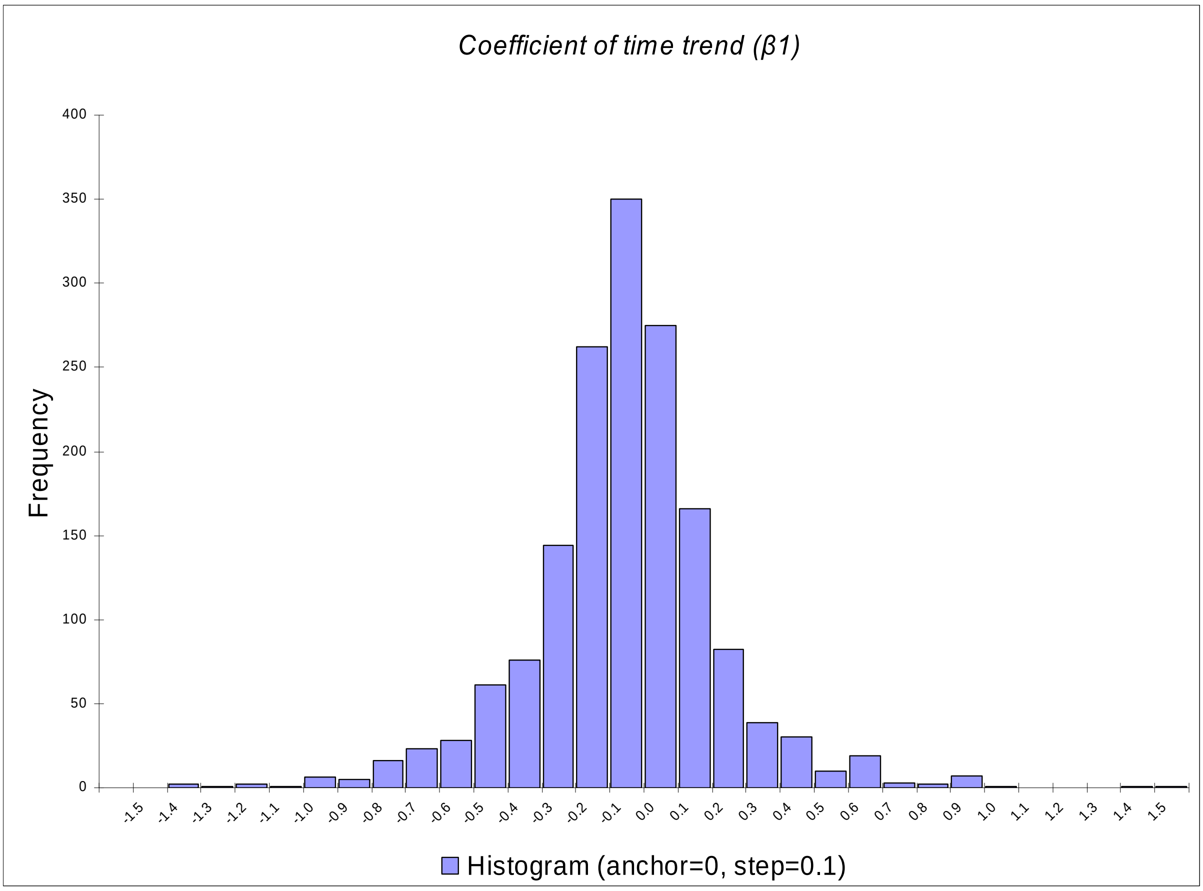


Table 3.5: Firm by firm regressions on time trend and boom dummy (growth rates)

Sample information		*Coefficients of the linear time trend (β1)*			
Industry	Manufacturing	Mean	-0.054	Std. Dev.	0.28
Time period	1984q1-2007q4	Median	-0.049	Skewness	0.031
Number of firms	1613	Maximum	1.52	Kurtosis	6.37
Additional Variable	Boom II	Minimum	-1.36	Jarque-Bera	765.0498

Figure 3.9: Histogram of the coefficients of time trend variable obtained from regressions on the firm-level including boom dummy II as independent variable.



The firm-level analysis of the quarterly Swiss BTS data gives rise to the somewhat counterintuitive conclusion (bearing in mind technological progress and process innovation) that the rate of capacity utilisation had to be higher 24 years ago than today in order to be considered as normal. For the moment, we can reject H2 but fail to reject H1. However, the slope parameter is only small in absolute value and close to zero. Last but not least, a negative mean of the trend coefficient across firm-individual regressions does not necessarily imply statistical significance. Therefore, we now turn to panel data analysis.

3.2.2. Panel data analysis

The panel preserves the same time dimension as above (quarterly data from 1984q1 to 2007q4), but we introduce a cross-sectional firm dimension as well. As it is often the case with micro data, we are concerned with an unbalanced panel data set. However, since we think that the perception of capacity utilisation is unrelated to the probability of a firm remaining in the sample, the statistical properties of our panel should be preserved (Wooldridge 2003, pp. 468f). With panel data, we are able to use more independent variables than in our firm-level regressions. Therefore, we can abandon the simplification of a linear time trend and introduce time period dummies instead. This allows a better modelling of the changes in the perception of normal capacity utilisation. In the panel regression we can also control for seasonal effects by including seasonal dummies and instead of using a binary boom variable we include the original GDP series. We experiment with different lags of both time series, output gap and GDP growth rate. Those lagged series are chosen for which the 'fit' of the model (measured by adjusted R squared) is best. Furthermore, we included within cross-section fixed effects because the 1619 firms included are of different business size and operate in various industries. Post-estimation tests strongly support the significance of these fixed effects. At this point, only the problem of serially correlated errors remains. We address this by estimating the White coefficient covariance and therefore get robust standard errors. Table 3.6 summarises the result of the first panel regression with output gap as reference series; Table 3.7 for the regression using growth rates.

Table 3.6: Panel Regression Output with output gap as GDP reference series

Time Dimension:		1984Q1 to	2007Q4	Total observations:			61135
Periods included:			95	R-squared			0.50
Cross-sections included:			1619	Adjusted R-squared			0.49

Variable	*Coefficient*	*t-Statistic*	*Probability*	*Variable*	*Coefficient*	*t-Statistic*	*Probability*
C	85.53	244.82	0.00	PER11	-1.21	-2.89	0.00
OUTPUTGAP	0.53	8.60	0.00	PER12	-1.01	-2.36	0.02
@SEAS(2)	0.52	5.86	0.00	PER13	-2.49	-5.66	0.00
@SEAS(3)	0.78	7.47	0.00	PER14	-1.73	-3.86	0.00
@SEAS(4)	0.67	6.97	0.00	PER15	-1.31	-2.88	0.00
PER2	0.61	2.13	0.03	PER16	-5.18	-11.63	0.00
PER3	0.51	1.54	0.12	PER17	-4.47	-9.38	0.00
PER4	0.38	1.06	0.29	PER18	-5.30	-10.43	0.00
PER5	0.62	1.70	0.09	PER19	-6.57	-12.93	0.00
PER6	0.39	1.00	0.32	PER20	-5.45	-10.20	0.00
PER7	-0.91	-2.12	0.03	PER21	-2.52	-4.87	0.00
PER8	-3.06	-7.44	0.00	PER22	-2.40	-4.62	0.00
PER9	-4.22	-9.84	0.00	PER23	-1.29	-2.31	0.02
PER10	-3.98	-9.00	0.00	PER24	-0.65	-1.16	0.25

White period standard errors & covariance (d.f. corrected)
Cross-section fixed (dummy variables)

Table 3.7: Panel Regression Output with YoY growth rate GDP reference series

Time Dimension:		1984Q1 to	2007Q4	Total observations:			61135
Periods included:			95	R-squared			0.50
Cross-sections included:			1619	Adjusted R-squared			0.49

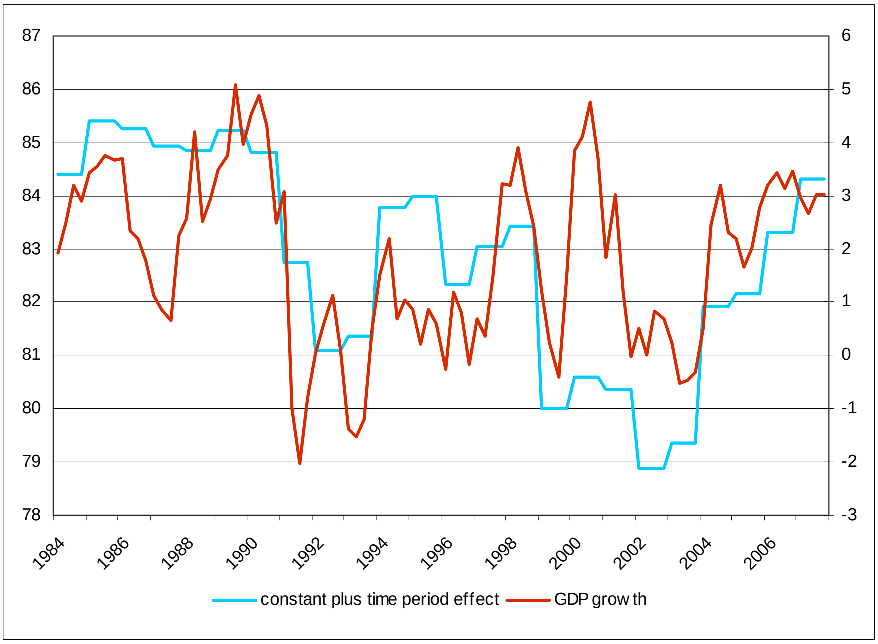
Variable	*Coefficient*	*t-Statistic*	*Probability*	*Variable*	*Coefficient*	*t-Statistic*	*Probability*
C	84.39	232.08	0.00	PER11	-0.60	-1.43	0.15
Growth_lag1	0.30	7.87	0.00	PER12	-0.39	-0.90	0.37
@SEAS(2)	0.51	5.80	0.00	PER13	-2.05	-4.56	0.00
@SEAS(3)	0.83	7.88	0.00	PER14	-1.33	-2.95	0.00
@SEAS(4)	0.75	7.80	0.00	PER15	-0.97	-2.15	0.03
PER2	1.00	3.62	0.00	PER16	-4.38	-9.71	0.00

PER3	0.86	2.62	0.01	PER17	-3.79	-8.12	0.00
PER4	0.53	1.49	0.14	PER18	-4.04	-8.11	0.00
PER5	0.46	1.26	0.21	PER19	-5.51	-10.85	0.00
PER6	0.83	2.17	0.03	PER20	-5.05	-9.34	0.00
PER7	0.41	1.08	0.28	PER21	-2.48	-4.78	0.00
PER8	-1.63	-3.93	0.00	PER22	-2.22	-4.27	0.00
PER9	-3.30	-7.72	0.00	PER23	-1.07	-1.94	0.05
PER10	-3.01	-6.55	0.00	PER24	-0.09	-0.16	0.88

White period standard errors & covariance (d.f. corrected)
Cross-section fixed (dummy variables)

Not all period dummies are significant, but most are. The results indicate that the GDP variables are statistically significant but their coefficient is relatively low considering the similar pattern of the aggregate capacity utilisation series (see above) and the output gap or growth series. If we plot the constant plus the relevant period effect against time we can see that the yearly time dummies ‘soak up’ some business cycle movement (Figure 3.10).

Figure 3.10*: CapU* explained by constant plus the yearly time period effect



Not only explain the yearly time dummies the specific time effect but also they incorporate a large fraction of business cycle induced movement in capacity utilisation. To avoid this problem, we define longer time periods that last exactly one cycle.

After having defined eight dummy sets for different cycle concepts, we repeat the panel regressions from the beginning but substitute our yearly time dummies with our cycle dummies. We use the GDP variables from the regression before (contemporaneous output gap and one quarter lagged growth rate) and, again, try to maximise the ‘fit’ of the model (measured by adjusted R squared) by using different cycle dummies.

It turns out that for both underlying GDP reference series, the cycle dummy concept ‘meanup’ is best suited for our purpose. Table 3.8 summarises the regression results with the output gap series as a control for business cycle movements; Table 3.9 gives the results with growth rates.

Table 3.8: Panel Regression Output with ‘opgmeanup’ as cycle concept

Time Dimension:	1984Q1 to	2007Q4	Total observations:	61135
Periods included:		95	R-squared	0.49
Cross-sections included:		1619	Adjusted R-squared	0.47

Variable	*Coefficient*	*t-Statistic*	*Probability*
C	85.61	241.79	0.00
OUTPUTGAP	0.78	13.82	0.00
@SEAS(2)	0.54	6.04	0.00
@SEAS(3)	0.81	7.68	0.00
@SEAS(4)	0.82	8.45	0.00
OPGMEANUP2	0.44	1.53	0.13
OPGMEANUP3	-2.23	-5.96	0.00
OPGMEANUP4	-4.11	-9.47	0.00
OPGMEANUP5	-1.19	-2.20	0.03

White period standard errors & covariance (d.f. corrected)

Cross-section fixed (dummy variables)

Table 3.9: Panel Regression Output with ‘grwmeanup’ as cycle concept

Time Dimension:	1984Q1 to	2007Q4	Total observations:	61135
Periods included:		95	R-squared	0.49
Cross-sections included:		1619	Adjusted R-squared	0.48

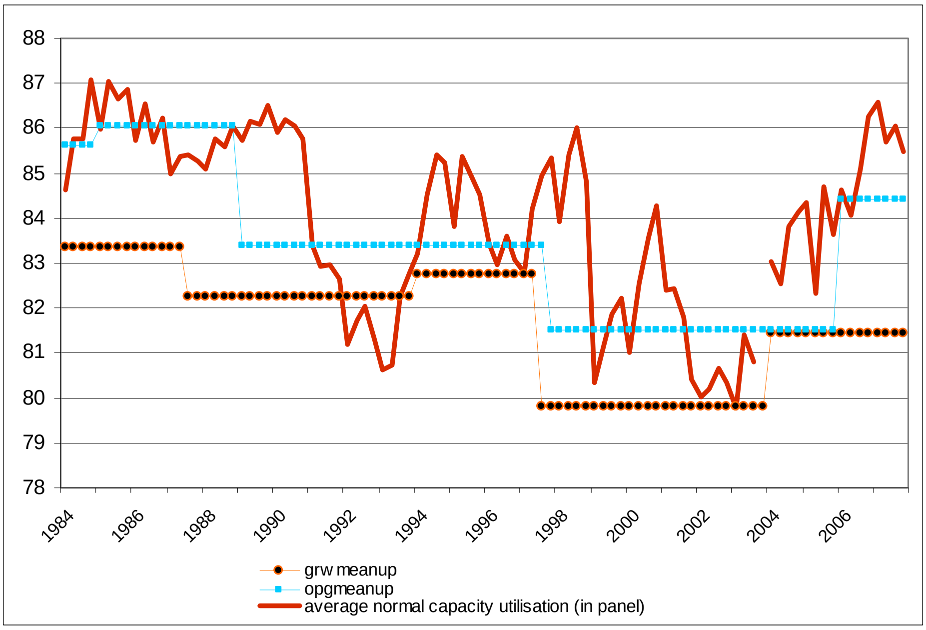
Variable	*Coefficient*	*t-Statistic*	*Probability*
C	83.37	345.83	0.00
BIP_VJ00LAG1	0.86	23.55	0.00
@SEAS(2)	0.53	5.95	0.00
@SEAS(3)	1.10	10.48	0.00
@SEAS(4)	1.03	10.76	0.00
GRWMEANUP2	-1.12	-4.68	0.00
GRWMEANUP3	-0.61	-1.98	0.05
GRWMEANUP4	-3.58	-10.33	0.00
GRWMEANUP5	-1.95	-4.49	0.00

White period standard errors & covariance (d.f. corrected)

Cross-section fixed (dummy variables)

These regressions indicate that there are significant cycle specific movements in normal capacity utilisation. Only one cycle dummy (‘opgmeanup2’) is not significant on the 5 per cent level. However, we have to bear in mind, that the first and the last dummies do not cover full cycles (see Figure 1.3 and 1.4 respectively). The first cycle dummy (‘opgmeanup1’) might cover only a fraction of the full cycle. Therefore it is possible, that this fraction is not significantly different from the second cycle dummy (‘opgmeanup2’), the relevant t-value becomes small. The plot of the coefficients of the cycle dummies supports this assumption (Figure 3.11).

Figure 3.11: Value of the cycle coefficient (‘meanup’ concept) plus the constant from panel regression and averaged normal capacity utilisation time series



As already suggested, we have to treat the first and the last cycle dummies with suspicion. If we ignore these cycle dummies, we can infer from Figure 3.11 a negative trend over the last cycles. There is also another possibility to ease the problem of partial cycle. We can use the cycle concept that most likely does not contain an incomplete cycle at the end of the observed time period. At this time (July 2008), almost every economic forecast predicts a contraction of the economy. In light of this, the ‘peak’ cycle concept seems particularly expedient. The next two tables sum up the results from the corresponding regressions (Table 3.10 and 3.11).

Table 3.10: Panel Regression Output with opgpeak as cycle concept

Time Dimension:	1984Q1 to	2007Q4	Total observations:	61135
Periods included:		95	R-squared	0.49
Cross-sections included:		1619	Adjusted R-squared	0.47

Variable	*Coefficient*	*t-Statistic*	*Probability*
C	85.69	300.01	0.00
OUTPUTGAP	0.43	8.72	0.00
@SEAS(2)	0.56	6.32	0.00
@SEAS(3)	1.00	9.50	0.00
@SEAS(4)	0.97	10.11	0.00
OPGPEAK2	0.06	0.24	0.81
OPGPEAK3	-3.06	-9.42	0.00
OPGPEAK4	-3.81	-9.30	0.00

White period standard errors & covariance (d.f. corrected)
Cross-section fixed (dummy variables)

Table 3.11: Panel Regression Output with 'grwpeak' as cycle concept

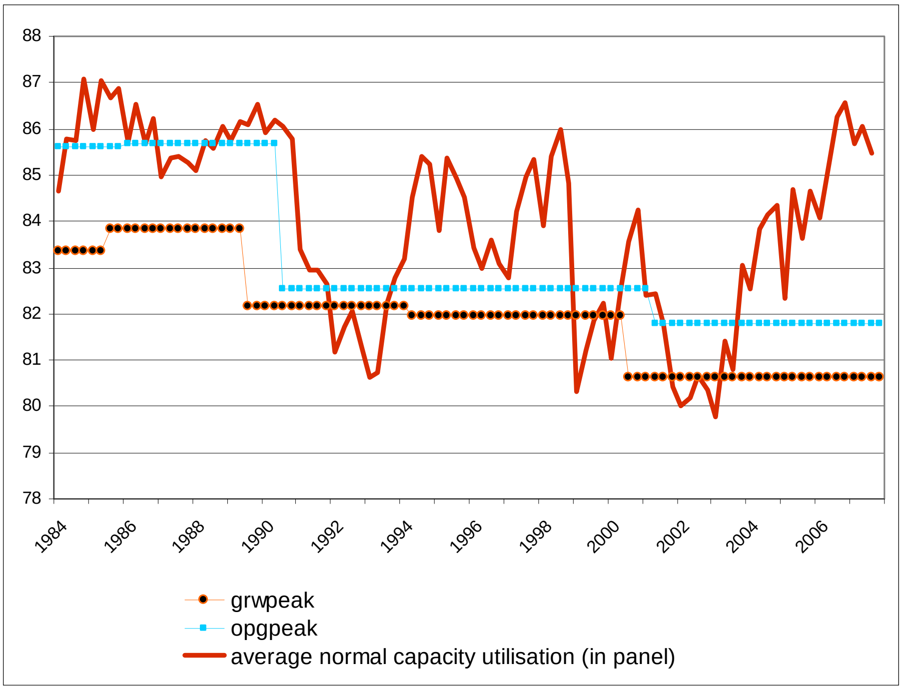
Time Dimension:	1984Q1 to	2007Q4	Total observations:	61135
Periods included:		95	R-squared	0.49
Cross-sections included:		1619	Adjusted R-squared	0.48

Variable	*Coefficient*	*t-Statistic*	*Probability*
C	83.28	264.56	0.00
BIP_VJ00LAG1	0.73	21.08	0.00
@SEAS(2)	0.55	6.16	0.00
@SEAS(3)	1.03	9.88	0.00
@SEAS(4)	0.99	10.46	0.00
GRWPEAK2	0.48	1.81	0.07
GRWPEAK3	-1.21	-3.62	0.00
GRWPEAK4	-1.40	-3.79	0.00
GRWPEAK5	-2.74	-6.42	0.00

White period standard errors & covariance (d.f. corrected)
Cross-section fixed (dummy variables)

Again, except the first cycle dummy, all variables are highly significant. By using the 'peak' concept, we only solved the problem of partial cycles for the last one. Obviously, the first cycle variable in our models still lacks significance. A look at the plot of the time dummies coefficient plus constant supports the same conclusion already drawn before (Figure 3.12). The fraction of the first cycle is too short to have a significantly different effect from the second full cycle. However, our previous finding, that there is a slightly negative movement in capacity utilisation, is further supported by using the peak cycle concept.

Figure 3.12: Value of the cycle coefficient ('peak' concept) plus the constant from panel regression and averaged normal capacity utilisation time series



4. Summary and Conclusions

The rate of capacity utilisation is an important business cycle indicator, as it relates directly to the stress on the current capacity to produce goods and services. From a policy perspective, technical bottlenecks indicate inflationary pressure, whereas idle capacity above normal points to a deflationary situation.

Unfortunately, it is not clear which rate of capacity utilisation should be regarded as normal. In addition, the level of normal capacity utilisation can change over time. When the substitutability of physical capital declines, firms will tend to keep more idle reserves to make sure they can cope with unexpected orders. On the other hand, with technical and organisational progress making production more flexible, the level of normal rate of capacity utilisation could increase. In a similar fashion, a move on to just-in-time production could lift the normal rate of capacity utilisation. These reflections imply that the rate of capacity utilisation is not, or not always, a stationary variable. However, due to the ambiguity of the theoretical predictions, it is not clear whether we should expect an increase or a decline in the level that is considered normal.

In this paper we refer to business tendency surveys from 34 countries to address this question empirically. Apart from this ‘global’ perspective, we undertake a more detailed examination of a large set of micro data referring to Switzerland. Our main findings are that the level of capacity utilisation to be considered normal is indeed not constant. During the last few decades, it appears to have decreased rather than increased.

This result holds with international panel data as well as when we perform more detailed analyses based on micro data from Switzerland.

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