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THE CHINESE OUTPUT GAP DURING THE REFORM PERIOD 1978-2002

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Abstract We estimate potential GDP for China comparing univariate and multivariate methods and derive a quarterly output gap series. For the multivariate, production function based estimates we employ aggregate data and data on five economic subsectors. We estimate production functions in levels as well as an EqCM specification, which we argue is better suited for identifying the long-run share of capital and labour in production. Our output gap estimates improve on earlier work which has so far been used in the emerging literature on macro-modelling of the Chinese economy. Drawing on the literature on Chinese economic growth, productivity measurement, and capital stock construction, we find that across a range of reasonable assumptions for capital and labour data specifications the output gap estimates remain correlated and robust. All our methods show that at the end of 2002 China is entering a period of economic upswing, but the current level of the output gap is much below the previous peaks in 1988/9 and 1994/5.

Keywords: output gap, growth regressions, EqCM specification of production function, Chinese capital stock data
JEL classification: E32, O47, O53

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Potential output

An important variable for the estimation of recent macro-econometric models is a measure for the deviation of actual economic activity from its potential. Every monetary authority responsible for maintaining some measure of inflation stability or 'optimal' production level must try to measure whether the economy produces above or below its sustainable long-run capacity. Equally, in economic modelling a measure for potential output features prominently in theories of inflation and monetary policy rules. Although potential output is synonymous with trend output and the quickest solution for obtaining potential output would be the identification of a statistical trend of one sort or another, calculating a solid measure of potential output is an exercise far from simple. The still emerging area of research on quarterly macro-econometric modelling of the Chinese economy so far contended itself with using simple statistical, univariate detrending methods.[1] Our estimates improve on this estimation method of the Chinese output gap by using a production function approach.

China is an economy in transition and is thus inherently less 'stable' than developed economies to which the methods of potential output determination are usually applied. We believe that the emerging nature of the economy, and its transition from a socialist to a market driven nation, does still warrant a search for the potential production capacity of the economy, the major difference compared to developed countries being the stronger growth of the variables which determine economic growth. Below we discuss the methods employed in the empirical output-gap literature and their applicability to a transition economy, outline the availability of appropriate data and summarise the voluminous literature on Chinese data quality more generally. We then proceed to present a number of alternative measures for potential output, testing for the sensitivity of input data related assumptions on the gap estimates. The analysis is related to and draws on a well established literature on growth accounting and growth regression analysis. What our analysis differs in is the emphasis of analysis – we focus on potential output rather than an identification of the factors behind the recent Chinese economic growth. In our production function estimations we explicitly address the problem of misspecification when estimating empirically standard production functions with the levels of capital and labour as the independent variables and offer a solution to the problem. We estimate an equilibrium-correction model and use the long-run results from the production function regressions as inputs into a subsequent growth accounting exercise. To the eager reader we recommend a quick glance at Figure 15 on page 37 – where ocular econometrics shows a close link between an overheating economy and inflation.

[1] Coe and McDermott (1996), Brandt and Zhu (2000)

Chasing potential output: an overview of methods

Our focus of the analysis in subsequent chapters of the thesis lies with the so called output gap y_t^{gap}, which is the difference of actual – observable – output as measured by reported GDP y_t and potential (trend) GDP y_t^*.[2] Equation (1) shows the relationship formally. e_t is a stochastic term.

$$y_t = const + y_t^{trend} + y_t^{cycle} + e_t = const + y_t^* + y_t^{gap} \tag{1}$$

Obtaining estimates of y_t^{gap} is important for central bankers and economic planners alike, still its nature as a latent variable renders estimates of it being far from definite. Other authors have produced good surveys of the existing literature and methods and have given detailed references for the estimation techniques.[3] Essentially, there are two techniques for obtaining the output gap. First, there are the univariate methods which try to fit a trend-line through a sample of GDP data. Second, there are multivariate methods which use production functions or a variant of growth accounting. There exist also a number of intermediate methods.[4]

Although some recent estimation techniques display a high level of data and econometric sophistication, the estimation of an output gap for China must remain at an intermediate level of complexity due to data constraints. In particular, data for the estimation of production functions is rarely available on a quarterly basis, and some variables such as indicators for capacity utilisation, working hours or educational attainment of workers are difficult to trace, if available at all.

The usual univariate statistical methods are a) to fit a linear trend through the observed GDP data, or use a time-varying trend such as b) a Hodrick-Prescott filter (Hodrick and Prescott 1997).[5] Although easy to use and less demanding in the data requirements, these trend based methods lack rigorous economic motivation, especially the time-varying trends. However, it is these latter,

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[2] We use the terms output and added value synonymously unless otherwise stated. The analysis always uses data for value added (GDP).

[3] See, for example, De Masi (1997) for a descriptive overview of methods including a discussion of the suitability of transition economies for such an exercise, McMorrow and Roeger (2001) for a comprehensive treatment for policy purposes, Castle (2003) for a more technical up-to-date overview with a UK focus and de Brouwer (1998) for further method discussion. To our knowledge there is no such work with an explicit focus on transition economies, and in particular the China focused literature has not moved beyond simple statistical approaches such as in Coe and McDermott (1996) and Brandt and Zhu (2000).

[4] For example, there are trending methods which condition on a set of non-GDP variables, see Conway and Hunt (1997) and de Brouwer (1998). The data requirements, among other a measure for capacity utilisation for which industrial survey data could serve as a proxy, are too demanding for an analysis on China covering the last 25 years.

[5] Similar methods are smoothing and filtering procedures such as i) the STAMP programme of Koopman, Harvey, Doornik and Shephard (1995), or ii) a band-pass filter (Baxter and King 1995). In effect, the time-varying trends come to rather similar conclusions, the main differences – if any – appear at the sample endings, and even these are negligible for the data used here. The end-period problem is aggravated by the imprecise data measurement which leads to data revisions.

arbitrarily flexible smoothing methods which can overcome the potential problem of overstated trend GDP growth in the 1990s as the smoothing or filtering horizon could be made flexible enough to pick up the trend change. Production functions on the other hand have a number of inherent short-comings as well: it is important to adjust for changes of economic structure and there are a number of assumptions to be made when it comes to determining input factors, e.g. deflators used in producing real variables and 'potential' input levels. [6]

Univariate methods

Linear trend

The estimation of the output gap as the difference of actual output and a linear line requires one major assumption only: that the economy grows at a stable rate over time. Such an assumption may be bold, particularly for an emerging nation where the growth rates have increased significantly after 1978, but have slowed down slightly in the late 1990s. During the 1990s, the actual growth rates in some years could have been smaller than those reported in the GDP statistics – which could lead to a large positive output gap in those years due to the artificially increased slope of the reported GDP series.[7] A linear trend can be a powerful tool if we try to account for breaks in the trend. Identifying a break at a time close to the break is difficult, and indeed dangerous for policy making if 'new' trend output is determined wrongly. We test for breaks in the annual GDP series using Chow-tests as provided in Doornik and Hendry's (1999) PcGive package.

Time-varying trends

A popular filter is the Hodrick-Prescott filter. This filter determines the trend subject to a loss function L, i.e. y_t^{trend} is determined such as to minimise a weighted sum of squared changes in the trend and deviations from the actual data.

$$L = \sum_{t}^{S} (y_t - y_t^{trend})^2 + l \sum_{t=2}^{S-1} (\Delta y_{t+1}^{trend} - \Delta y_t^{trend})^2 \qquad (2)$$

Using a Hodrick-Prescott (HP) filter has one major disadvantage: the ad-hoc procedure lacks fundamental economic justification, and the weighting factor l is set arbitrarily. Hodrick and Prescott (1997) suggest a smoothing factor of $l = 1{,}600$ for quarterly data and $l = 100$ for annual data.[8]

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[6] de Brouwer (1998)

[7] See the relevant data discussion on page 14.

[8] The appropriate size of the smoothing parameter l is a matter of dispute. Slevin (2001) for example considers l values in the range of 6.25 to 100 for annual GDP in Ireland. $l = \infty$ leads to a linear trend since the penalty on a change in trend is infinite.

A HP filter can help to overcome the problems of time changing equilibrium growth rates of an economy, and indeed McMorrow and Roeger (2001) favour the HP filter over a linear time trend for it allows for a partial correlation of cycle and trend. Also, it could help to overcome the potential measurement bias introduced by the possibly inflated GDP growth numbers. Generally, the HP filter has an endpoint problem, the identification of an output gap is difficult as potentially an ‘outlier’ can have big effects on the output gap estimate. Kaiser and Maravall (1999) point to the aggravating influence of the in itself often imprecisely measured most recent data – sizable data revisions are frequent phenomena. Also, Harvey and Jaeger (1993) and King and Rebelo (1993) argue that a HP filter applied to an integrated series can lead to spurious cyclicality. We will apply a HP filter with $l = 1{,}600$ to Chinese quarterly real GDP. An alternative to the HP-filter is the STAMP filter by Koopman et al. which avoids the end of sample problems – and gives virtually identical results to the HP filter in our analysis.

With the purely statistical methods, we have to suffice our analysis to univariate filtering, the data required for conditional filtering, see e.g. de Brouwer (1998), such as a NAIRU for China and capacity utilisation indices are not available. Another method we list for completeness only: McMorrow and Roeger (2001) and de Brouwer and Ericsson (1998) have used a structural vector autoregression method developed by Blanchard and Quah (1989), where long run restrictions are imposed on a bivariate VAR (first difference in quarterly real GDP and the inflation rate/unemployment rate) that allow for the identification of temporary and permanent shocks to the system. Aggregating the temporary shocks then leads to a stationary series which for (highly) developed and more stable countries can be interpreted as an output gap.[9] We have experimented with this methodology, however, we do not report the results here. The resulting output gap estimate bore some resemblance to other estimated gaps in magnitude and timing, but the estimated VAR(4) coefficients oftentimes lacked significance.

Production functions

A more rigorous approach founded in economic theory is the calculation of potential output by use of a production function, where we interpret the fitted value as potential output. As a first step, a standard Cobb-Douglas function is estimated, where *Y, A, L* and *K* are output, technical progress, labour and capital respectively.[10] Small letters denote logged data.

$$y_t = a_t + a\,l_t + bk_t + e_t \tag{3}$$

[9] Blanchard and Quah (1989) warn against interpreting this aggregated series of shocks as the output gap, still they show that their identified peaks and troughs for US data match perfectly the NBER series of peaks and troughs. McMorrow and Roeger (2001) find a rather low correlation of the B+Q gap estimates with alternative, related indicators and therefore do not recommend the method either.

[10] See Intriligator (1978) for example.

The residual e_t is interpreted as the output gap. a_t could be split up into a constant a_o and a_1*trend.* A standard hypothesis in a Cobb-Douglas production function is that the sum of the coefficients on the production factors is unity, $a + ß = 1$, i.e. the production process exhibits constant returns to scale. When we estimate the log-linearised version of equation (3), constant returns are tested for. In equation (4) constant returns to scale are imposed, and theoretically the ß coefficients from equation (3) and (4) are the same. The output elasticity of labour remains *(1-ß)*, and e^* indicates the difference to the residual in equation (3).

$$(y-l)_t = const + b\,(k-l)_t + d\,trend + e_t^* \tag{4}$$

The Cobb-Douglas production function assumes competitive markets in inputs and outputs, such that capital and labour earn their marginal product. Is this assumption compliant with a transition economy, where market forces are only gradually developing? The competitive market assumption is important if the elasticities of capital and labour are derived from firm level or national accounts. In our regressions we estimate the share of contribution from capital and labour, and no assumption about their prices is needed.[11] An alternative, and less rigid specification of a production function is the translog production function. The Cobb-Douglas production function is a restricted version of the translog function, which is a second order Taylor approximation to the general equation[12]

$$\ln Y = f(\ln X_1, \ldots, \ln X_n) \tag{5}$$

i.e. the second order approximation is

$$\ln Y_t = f(0) + \sum_{n=1}^{N} \left[\frac{d\,f(\bullet)}{d \ln X_n} \right]_{|\ln X = 0} \ln X_n + \tfrac{1}{2} \sum_{n=1}^{N} \sum_{m=1}^{N} \left[\frac{d^2 f(\bullet)}{d \ln X_n d \ln X_m} \right]_{|\ln X = 0} \ln X_n \ln X_m + e_t \tag{6}$$

and the econometric specification is shown in equation (7).

$$y_t = a + a\,l_t + b\,k_t + g_1 l_t^2 + g_2 k_t^2 + g_3 k_t l_t + e_t \tag{7}$$

The estimated coefficients a and b from equation (7) can be interpreted as Cobb-Douglas coefficients when evaluated at the geometric mean of the independent variables. Imposing constant returns to scale gives regression equation (8).

$$(y-l)_t = const + b\,(k-l)_t + g\,(k-l)_t^2 + d\,trend + e_t^{**} \tag{8}$$

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[11] Imbedded in the Cobb-Douglas production function, and the trans-log production function below, is also the assumption of efficient production, as inefficient firms could not survive in the competitive market. The efficiency hypothesis appears doubtful with regard to at least a part of the SOE sector. Kong, Marks and Wan (1999) try address the issue of inefficient production by means of a stochastic frontier estimation for four industrial sub-sectors in China. Their approach would allow for a new efficiency approach to the output gap. Unfortunately, the panel date required for nation wide estimates would be very difficult to collect. Using Cobb-Douglas, our potential output estimates are conditional on some given level of efficiency, where we would hope that changes in efficiency are absorbed into the TFP trend.

[12] See e.g Greene (2000, p. 217 and p. 640).

Dynamic production function

A likely shortcoming of the specifications of equations (3), (4), and (8) is the lack of lagged variables, which induces autocorrelated residuals of the regression. Introducing lags into the regression could improve the quality of the coefficient estimates, however this would render the remaining (autocorrelation adjusted) residual unsuitable for an interpretation as the output gap. The 'true' output gap would then have to be constructed from the improved (long-run) coefficient estimates. With a limited number of post-reform observations, possibly badly measured data, the absence of proxies for capacity utilisation or hours worked, and no reliable inventory data, the problem of measurement error can be addressed with a dynamic production function which identifies a more stable long-run relationship of factor inputs and value added in an equilibrium correction model (EqCM). Based on equation (4), the dynamic production function below assumes that the capital/labour ratio is weakly exogenous for the GDP/labour ratio.

$$\Delta(y-l)_t = const + \underbrace{z\Delta(y-l)_{t-1} + f\Delta(k-l)_t}_{ShortRunDynamics} + \underbrace{r_1(y-l)_{t-1} + r_2(k-l)_{t-1} + r_3(trend)_{t-1}}_{EquilibriumCorrection} + e_t^{**} \quad (9)$$

Estimation of equation (9) allows us to make a number of interesting observations. First, the long-run coefficient $b^{LR} = -{}^{r_2}\!/_{r_1}$ is free of cyclical short-term disturbances. Second, f displays cyclical forces of investment and output behaviour, the greater this number, the larger is the upward bias of *ß* in a static regression. Third, r_1 shows the time required for equilibrium adjustment. We estimate equation (9) such that all right-hand side variables enter independently in a one-step regression procedure. Longer lags of the differenced dependent and independent variables could be allowed for in the regression.

Growth accounting

This approach is closely related to the production function approach, but the calculation method is based on a simple, non-parametric addition of factor growth rates. What this method requires is a simple differencing exercise, based on equation (3) where an assumption for the share of labour and capital in production as well as trend TFP a^{trend} is necessary. We rearrange equation (3) to equal:

$$\begin{aligned} \dot{y}_t &= a\,\dot{l}_t + b\,\dot{k}_t + a^{trend} + e_t \\ \dot{y}_t^{gap} &= e_t = \dot{y}_t - a\,\dot{l}_t - b\,\dot{k}_t - a^{trend} \\ y_t^{gap} &= \sum_{i=0}^{t} \dot{y}_{t-i}^{gap} \end{aligned} \quad (10)$$

This technique allows us to experiment with the effects of different assumptions on the shares of capital and labour in production as well as different trends in TFP. Given our assumptions about potential factors of production, it is the cyclical effect that we are trying to measure with the growth accounting procedures. Growth accounting allows us – as many researchers have done before[13] – to form an opinion as to what factors have driven Chinese growth.

Potential input – potential output

Following the production function or the growth accounting approach, the estimation of potential output requires as inputs the *potential* factors of production.

$$
\begin{aligned}
Y_t &= A_t L_t^a K_t^{1-a} \\
Y_t^* &= A_t L_t^{*a} K_t^{*1-a} \\
Y_t^{gap} = Y_t - Y_t^* &= A_t K_t^{1-a} (L_t - L_t^*)^a
\end{aligned}
\qquad (11)
$$

It is a common assumption to set actual capital equal to potential capital, based on the argument that in competitive markets - and we assume that this holds true for a transition economy such as China as well – capital is the binding constraint, and that the use of capital is optimised. McKibbin and Vines (2000) for example argue for this approach. We acknowledge that a non-negligible portion of Chinese SOEs' assets is likely to be obsolete; nevertheless the 'book value' of these assets is a good indicator of what production capacity could be available potentially. Another caveat is the potential policy induced lending bias of state-controlled banks until recently to state owned companies (SOEs) in the industrial sector. This could qualify our assumed optimisation of capital holding. Not all authors of empirical work follow this simplifying assumption and therefore try to estimate potential capital inputs. Again, this more sophisticated analysis is not feasible for China due to a lack of suitable data.

The question is then: what is the potential level of labour input? Usually researchers attempt to estimate a natural level of unemployment, the NAIRU, and deduct that rate from the working population. Slevin (2001) and de Brouwer (1998) have done so for Ireland and Australia, respectively. For recent China, with unemployment rates being artificially suppressed by, initially, inefficient labour hoarding in state owned companies, and after 1997 when the SOEs started to lay off workers, by unrealistically low published unemployment rates, the estimation of a Chinese NAIRU is a difficult task. Nevertheless, up to the early 1990s, the socialist economy with inefficiently high employment levels provides for a good measure of potential labour input, i.e. actual labour is potential labour. This assumption requires us to construct a series for potential labour for the time after 1996 though. We discuss the necessary empirical adjustments below.[14] We

[13] Chow (1993), Hu and Khan (1996), Collins and Bosworth (1996), Bramall (2000), Fang (2000), Young (2000a), Wang and Meng (2001), Wang and Yao (2003)

[14] Solinger (2001) gives an overview on a wide range of reasons which complicate the estimation of a correct number for unemployment in China. Our assumption that reported employment is equal to the (potential)

aim to relate potential input factors of production to a measure of potential output, and by regressing potential variables on actual output we assume that actual GDP equals on average potential output – i.e. in the long-run the economy performs at its potential.[15]

Before we move on to discuss some wider data issues in China as well as issues specific to the calculation of (raw) labour and capital inputs, we have to focus attention on another measurement problem: how can we adjust for changing quality of the factors of production? For the capital variable, we try to split up the overall capital stock into groups of different quality.[16] The same quality considerations apply to labour inputs. China has invested heavily into educating younger generations, and the gains in education must be accounted for.[17] Wang and Yao (2003), or alternatively Barro and Lee (2001), construct refined country panels of education measures based on different levels of schooling completed by the working population. We prefer the former data set because it provides annual data points and is easy to update from recent CSYs; Barro and Lee have 5 year intervals.

Analysis by sector

Different sectors in the Chinese economy have experienced different growth paths in the past. In order to account for this we estimate production functions on aggregate data as well as five sub-sectors which account on average for 85% of the economy (see Figure 1): agriculture, industry, construction, transport (with post and telecommunications), and commerce (wholesale and retail trade, caterers).[18] This selection of sectors is driven by the available data in official Chinese statistics publications. Allowing for different sector dynamics could lead to improved estimates of the aggregate output gap, compared to a one-size-fits-all analysis based on aggregate data.

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working population is confirmed by comparing the CSY employment figures (the revised ones published after 1998) and the working population data of the 1990 census: for 1990 the respective numbers are 639m and 647m, close enough to give a good case for our estimate. See also Young (2000a, table VII).

[15] Roldos (1997) determines the 'potential' level of labour by using a HP filter. One could possibly extend that approach by smoothing the capital series and/or the output series in order to obtain 'potential' values. We try to avoid such an ad hoc procedure here and stick with non-smoothed data.

[16] We assume that (and test whether) foreign direct investment (FDI) and investment in research and development (R&D) facilities in China have a different impact as compared to 'ordinary' capital. Unfortunately, no better fit of the regressions could be achieved and we do not report the results here.

[17] Collins and Bosworth (1996), Barro and Lee (2001), and Wang and Yao (2003) deal with the issue in labour data is a general as well as China specific way, respectively. Roldos (1997) makes the point for both capital and labour – non-adjustent would lead to inflated Solow residuals of technical progress.

[18] Services are concentrated mainly in the latter two sectors. Analysis on a three sector basis (primary, secondary, tertiary) lack investment and employment data for the years 1978-1985.

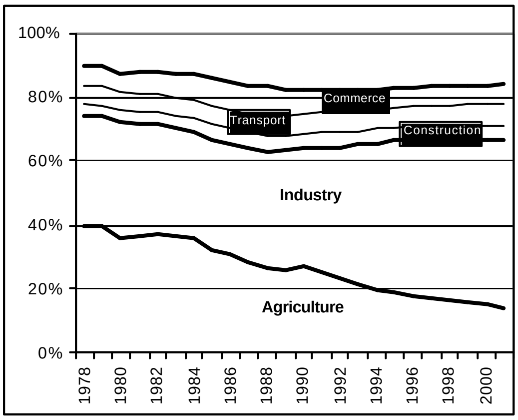

Figure 1: Cumulative sector shares in GDP

The factor inputs into the commerce sector – retail and wholesale trade – are most likely not well represented by fixed capital stock and labour alone. Working capital could play a bigger role for this sector than for others. The results of the production function estimation for the merchant sector must be considered with appropriate care. Young (2000a) has argued that agricultural production is subject to a number of special factors such as the weather, land, irrigated land and life-stock. The valuation of these factors in monetary terms is difficult, and again production functions will be difficult to estimate.

A general note on Chinese statistics reporting and data quality

A discussion of the aspects of data availability and reliability is in order with empirical work on emerging economies, and China in particular is no exception to this – as a large literature on Chinese data sources, data short-comings and alternative data construction methods documents. In what follows, we try to cover general data matters relating to the entire thesis, not only matters specific to the estimation of potential GDP.

Official Chinese data has been discussed by a number of researchers[19] and Rawski (2002) gives a critical overview of the current state of discussion. In general, authors point out three areas of potential difficulty with Chinese data. First, the measurement of data in China is a difficult task: the country is large, and the resources allocated to statisticians are small.[20] Second, data revisions and re-definitions are frequent and often not clearly advertised.[21] Third, with the marketisation of the economy there were growing incentives for local administrators to meet or over-achieve economic targets – hence introducing an upward bias to regional output variables. In particular, Rawski (2002) critiques the GDP data after 1998 but finds that GDP statistics before that year do not seem

[19], Wu (1995, 1997), Rawski (2001), and Perkins (2002)

[20] Zheng (2001) outlines the administrative system of Chinese data collection.

[21] Holz and Lin (2001)

to be affected by systematic bias.[22] Holz and Lin (2001, p. 58-59) in their table 7 list further detail on data revisions and breaks; Young (2000a, p.5-7) complements the lists of data revisions.[23]

For example, 1993 and 1998 saw breaks in the reporting structure. GDP reporting in 1993 changed from the pre-(1978) reform Material Product System (MPS) to the 'western' System of National Accounts (SNA); new industrial accounting procedures were adopted and a new tax system was introduced in January 1994.[24] Wu (1995) explains the conceptual framework of the MPS and SNA methods, where the major difference is the 'quasi-physical' measurement of output where many 'non-productive' services (passenger transport, health service, education) are treated as consumption but not production. First publications of SNA data date back to 1988 for GDP, where earlier data has been revised down to 1978. However, cost considerations and ideological concerns have led to what Wu calls a 'hybrid' system rather than a full adoption of the SNA principles.[25] Attempting to correct for all these issues seems a hopeless task, and we rely on the Chinese official data as the best proxy for reality. Emerging market data tend to be subject to data qualifications, and China is no exception to this. The large literature critiquing the data, however, reflects not only the importance of the issue, but equally the importance of the country.

Are Chinese data usable? Despite the actual and potential pitfalls with official Chinese data, leading China researchers have concluded that the data is usable, and they believe that the data are free of systematic bias.[26] Chow argues that many of the biases introduced at the regional level are neutralised for the country data as the national statisticians have no incentive to overstate the numbers. More recently, Holz (2003) has come to the defence of Chinese statistics, which in his opinion, despite a variety of measurement insufficiencies are most likely a truthful representation of the data available to the National Bureau of Statistics. Discussions and criticisms of specific

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[22] Rawski and Xiao (2001) report that in 1998 the number of staff of the Chinese National Bureau of Statistics (NBS) was reduced by 47% and staff are understood to resort to guessing numbers which regional offices failed to report. Also, in many enterprises which used to have dedicated members of staff working as statisticians to report data to the regional administration and Statistics Offices, these jobs become changed as managers become more concerned with profit creation. A peculiar example for data inconsistencies put forward by Rawski, is that while official GDP grew by 25% between 1997 and 2000, reported energy consumption fell by 13%. Indeed, the rather casual foundation of the Rawski criticisms has sparked a number of fierce replies from Chinese academics and statisticians who claim that there data has been collected to the best of knowledge and reject a 'case study' approach to judging overall data quality. Wong and Chan (2003) cite a list of researchers defending official Chinese statistics (p.3-4).

[23] Among other items, official Chinese data on industrial and service gross output was revised downwards by 9% in 1994, where data for earlier years was 'smoothed' accordingly. Young points out that no such revision was reflected in nominal aggregate GDP.

[24] The new accounting rules are now essentially 'western'. Holz and Lin (2001) discuss the details of the accounting and tax changes in the 1990s (p. 35-39).

[25] Wu (1997) points to the possibility of GDP underreporting until 1997 due to poor collection and reporting systems. Another reason for GDP underreporting could be due to the still not fully monetised economy, and it seems possible that value added by self-employed (*getihu*) continues to circumvent entry into the official statistics until today. In contrast, Wang and Meng (2001) draw a different picture. Using a large dataset on physical output (rather than potentially price distorted value series) of raw materials, energy production and freight transportation point to a 4% pa overstatement of growth in the 1990s.

[26] e.g. Chow (1993, 2002)

Chinese data series in the literature are picked up again below in the data sections of this chapter and the next. Some straightforward data criticisms are considered then and data such as the labour supply or the capital stock are constructed and corrected with the relevant contributions of researchers in mind. However, some data criticisms in the literature require a myriad of assumptions in the construction of an alternative data series, and indeed it seems doubtful whether these alternative data series are superior in precision and meaning. This thesis aims at evaluating the feasibility and prospects of western-style monetary policy in China – and official Chinese data should be the first port of call.

Data: GDP, capital, and labour

Growth type regressions and accounting procedures are the backbone for our estimation of potential output, and their major input variables are capital, labour, and value added.

GDP

Annual GDP and GDP deflator: We use the official GDP reported in the CSY 2002, where the implicit GDP deflator is recovered from the reported nominal and real growth rates. The resulting annual series of aggregate data matches closely the data used by Wang and Yao (2003). Annual value added data for the five sectors agriculture, industry, construction, transport and telecommunications, and commerce is collected from the CSYs as well.

Quarterly GDP deflator: Nominal GDP is also available since 1987 on a quarterly basis. Due to a lack of an official quarterly deflator we extrapolate a quarterly series from the annual GDP deflator. Calculating the quarterly GDP deflator from the annual, official implicit deflator by means of a log-linear extrapolation can be a hazardous exercise. In times of stable inflation a linear method of filling the gaps between the 4th quarter GDP deflator level data is without great side-effects, however in times of suddenly surging inflation the extrapolation method matters. Keeping in mind the methods suggested in the literature on estimating economic time series data from lower frequency data, we proxy the size of the quarterly steps with the relative quarterly movement of the price level. [27] [28]

Quarterly potential GDP: A similar issue arises when we extrapolate quarterly potential GDP from the annual estimators. The difference to the GDP deflator is that GDP is not a stock but a flow variable, where extrapolation with a constant geometric growth rate must ensure that the quarterly estimates must add up to the annual total. Hence, we must manipulate the level data, and not logged data.

[27] Boot, Feibes and Lisman (1967), Chow and Lin (1971, 1976), Harvey and Pierse (1984)

[28] The annual change in the CPI and the GDP deflator may be different, however the relative size of the quarterly steps for the GDP deflator is derived from the quarterly CPI.

Seasonal adjustment of quarterly GDP: An issue of particular concern are the possibly faulty quarterly GDP estimates during the period 1993-1996. The output gap estimate as the difference between observed, quarterly GDP and the latent potential GDP requires a smoothed, seasonally adjusted GDP series, otherwise the output gap – as the residual of difference of actual and potential GDP - is mainly driven by the seasonal fluctuations. The unprocessed – real or nominal - data series exhibits large quarterly fluctuations, the first quarter has a gross value added that is usually 25-35% below the GDP of the fourth quarter.[29] During 1993 and 1994, and to a lesser extent 1995, the quarterly fluctuations are more excessive than usual, and the seasonal pattern changes. After 1995, the data pattern assumes the pre 1993 seasonal pattern. The introduction of new reporting and tax rules in addition to the marketisation forces are likely factors to distort the reported numbers. There is little evidence for real events that could have lead to these severe interruptions during 1993/5. We therefore try to correct the GDP series for this time with the official year-on-year growth rates for real GDP. Using the real GDP of 1992 as a basis, we allow the data to follow the reported growth rates for 1993Q1 to 1995Q4. The left side of Figure 2 shows the adjustment. The augmented real GDP series allows for a meaningful seasonal adjustment for the entire period with the STAMP 5.0 filter of Koopman, Harvey, Doornik and Shephard (1995).

Real GDP adjustment for 1992-1995 | **Real GDP: series with 92-95 adjustment, and subsequent seasonal adjustment**

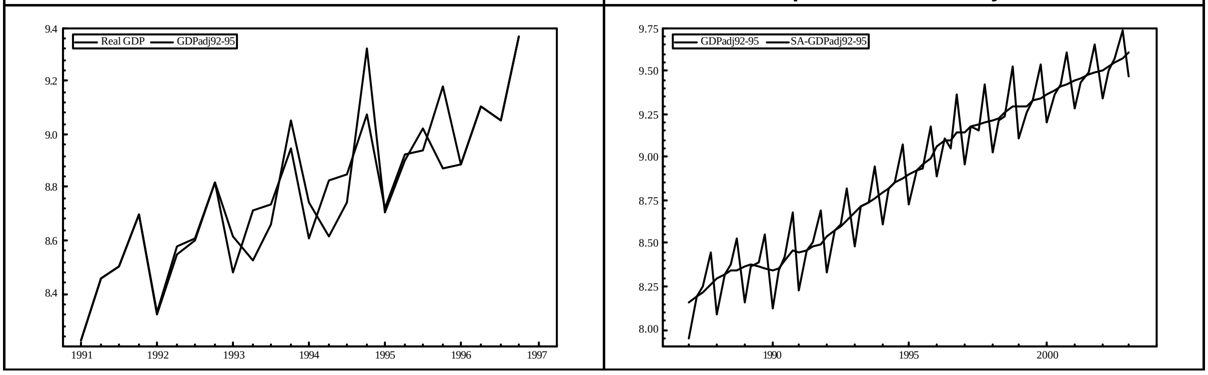

Figure 2: Logged quarterly real GDP: illustration of adjustments

Capital stock

No official data for capital stock of the Chinese economy exists for the entire period 1978-2002. However, reasonably detailed data for different kinds of investment of Chinese companies – even broken down to the level of different economic sectors such as agriculture and industry – exist and this data allows us to carry out an accounting exercise to obtain estimates of the real capital stock

[29] Rawski (1999) attributes the overly pronounced seasonal fluctuations to two factors. First, the Chinese New Year reduces output in many sectors during Q1. Second, Rawski relates the strong fourth quarter to investment behaviour in communist countries, where target spending and production are met by increased work in the final period in which factories try to meet their annual production target, followed by a slack period. Rawski takes this ‘communist’ pattern as a sign for the still restrained influence of market forces during the mid 1990s.

of the economy, and indeed five sub-sectors. We use the standard perpetual inventory method for calculating the capital stock:

$$K_t = I_t + (1-d)K_{t-1} \tag{12}$$

where K_t is the current real capital stock, I_t is the current period real investment and d is the depreciation rate. Our deflator is based on Wang and Yao (2003) for the period 1977-1990. From 1991-2002 we use the official Chinese fixed asset deflator. The resulting series matches the Wang and Yao data well for 1991-1997, however in 1998 and 1999 their deflator increases steeply to implausible levels – which lead to an underestimation of the influence of capital accumulation at the end of their period under analysis. The Chinese National Bureau of Statistics publishes a number of different investment series. We – as most other researchers – use their broadest series: investment in fixed assets. 'Total investment in fixed assets' is the most comprehensive investment series published. It includes investment in capital construction, real estate, 'innovation' and other fixed assets by all types of enterprises, but do it does not include working capital.[30] The use of the perpetual inventory method requires a crucial input variable: the initial capital stock. Much growth research on China has used the capital stock determined in Chow (1993, 2002) for the year 1952. It is interesting to note that based on the same 1952 figure, Chow and Wang and Yao (2003) come to different conclusions for the year 1977, where Chow's real capital stock is about 60% higher than the alternative series offered in Wang and Yao. Both series are compared against our own estimates in the appendix. Since it is the objective of this search for the Chinese output gap to obtain a robust result, we use both initial values in 1977 for alternative capital stock series. The last parameter relevant for the construction of the capital stock series is the deprecation rate d. The deprecation rates listed in various issues of the CSY are usually around 4 to 4.5%, and never outside the interval 3.5 and 5.5%. These deprecation rates are very low compared to internationally used rates, and we therefore consider four depreciation rates which follow from suggestions in the literature: 4%, i.e. the 'official' Chinese rate, 7% and 10% as more likely estimates of the depreciation rate, and 15% to satisfy a more extreme view in the literature.[31] Using the two initial values for the capital stock, Figure 3 displays the resulting alternative series for the (logged) capital stock. From the figure it becomes apparent that a depreciation rate of 15% is likely be too high, the resulting fall in capital in the early 1980s seems implausible for a rapidly emerging economy. We focus on the remaining three depreciation rates. Following the recent literature, we also consider capital stock series of 'higher quality' capital, i.e. arising out of foreign direct investment (FDI) and investment

[30] The CSY 2002 explains the series 243. Hu and Khan (1996) argue that it is preferable to focus on fixed asset investment instead of including 'working capital. The later variable – called 'circulating funds' in the CSYs – is usually a residual term in the national accounts and would likely distort the measurement of assets stock.

[31] Were more detailed data for sub-classes of assets available, we could experiment with time-varying depreciation rates for aggregate capital. Otherwise the introduction of time-varying depreciation rates is rather arbitrary.

in innovation.[32] The depreciation rates and deflators are the same as for ordinary capital. Initial capital stocks in 1977 are set to zero for both variables.

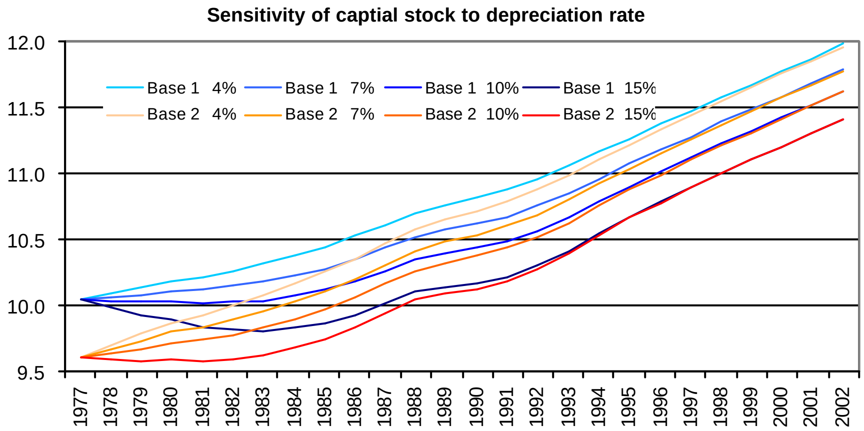

Figure 3: Alternative capital inputs – constructed from two initial capital values in 1977 with different rates of depreciation

There is less choice for sector data. We use Chow's (1993) estimates the capital series for 1978 to 1985. For the investment data we use 'total newly increased fixed assets' from various issues of the CSY. 'Total newly increased fixed assets' include asset addition through investment in capital construction, investment in innovation, investment in real estates developments and other fixed asset investments. This series is lower than the alternative investment in fixed assets, and is likely to reflect net additions.[33] The investment series are deflated by the aggregate economy fixed asset investment deflator. Table 1summarises the construction of the capital stock.

	Aggregate data	**Sector analysis**
Initial capital stock 1977	Based on 1977 capital stock from Chow (1993) and Wang and Yao (2003)	We use Chow's (1993) data for 1977-1985.
Investment series	Investment in fixed assets (CSY 2002, Table 6-2)	Newly increase fixed assets (CSY 2002, Table 6-13 plus 6-24)
Depreciation rate	4%, 7%, 10%, (15%)	4%
Deflator	Fixed asset investment deflator	See left.
Quality of capital stock	Using the same method as for the 'regular' capital stock, FDI and investment in innovation lead to a constructed capital stock of different quality.	N/A

Table 1: Construction of capital stock data

The perpetual inventory method for capital stock is the work horse of capital data construction, however it is subject to criticism which have to be kept in mind. Miller (1983), for example, lists caveats of the technique and emphasises that the method does not recognise the close link between retirement of obsolete capital and replacement by technologically more advanced machinery. In

[32] Investment in innovation is defined as something broader than just R&D investment. It includes, for example, the '…renewal of fixed assets and technological innovation of the original facilities…' CSY (2002, p. 243).

[33] The most recent definitions of the CSY are available at: http://www.stats.gov.cn/english/indicators/currentsurveysindicators/ . At four percent depreciated fixed asset investment often closely reflects the newly increased fixed assets series.

other words, the quality change embodied in new capital is neglected. Miller's criticism is alleviated if one assumes steadiness in the rising productivity of capital such that no discrete 'technology steps' are encountered. An alternative method to the perpetual inventory method is the one suggested by Ezaki and Sun (1999). Their capital estimate is the residual of an iterative growth accounting exercise where TFP and the capital stock are determined simultaneously. Their results on factor contributions to growth are very similar to our own results from the growth accounting procedures. The difference in resulting capital stock data must be small therefore. A third, naïve method of capital construction is to assume that the capital stock represents a constant ratio to GDP. Such an assumption seems particularly difficult for a transition economy. Figure 4 shows the ratio of our capital stock estimates as a ratio to GDP. The estimates based on the Wang and Yao's 1977 capital stock number seem more plausible, a halving of the capital/GDP ratio during the first ten years of the reform seems too drastic. Remarkable is the increase in the ratio since the last peak in the economic cycle in 1994 regardless of the initial value and deprecation assumption.[34]

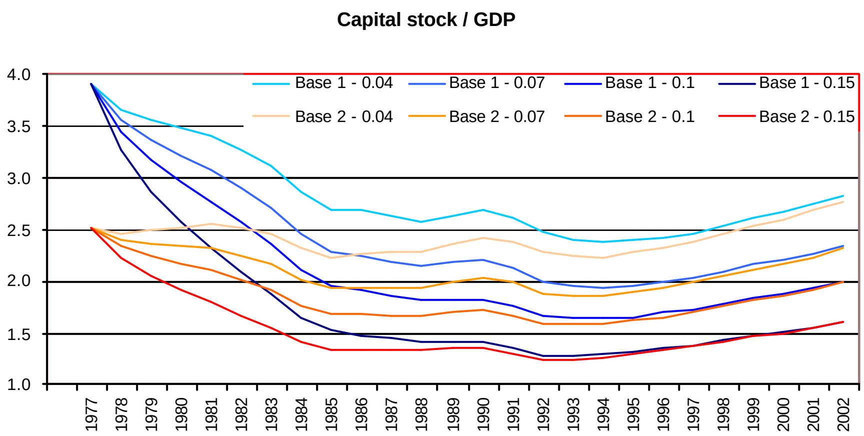

Figure 4: Alternative constructed capital stock data divided by GDP

Labour

The official employment data is used as a proxy for potential labour in the estimations of the production function.[35] While the sectoral data is well behaved in the sense that it does not display large jumps in the employment level, aggregate employment data – as published in the CSY 2002 – shows a big jump from 1989 to 1990, from 48% to 56% of the total population. Chow (2002) uses the data as reported in the Chinese National Bureau of Statistics (2002) Yearbook and does not adjust for the jump in employment. Young (2000b) explains that in 1997 the Statistics Bureau revised employment figures from 1990 to 1996 according to a new method that was applied in the census definitions. The 'old' system would not recognise temporary employed people earning less

[34] Typical values for the capital stock/GDP ratio during the mid 1990s are 2.0 and 2.75 for the US and the UK respectively.

[35] At the national aggregate level as well as the sectoral level, self-employed are included in the overall work-force total. Inclusion of data of self-employed is consistent for labour, capital and output statistics.

than the minimum wage of qualified permanent employees, the census definitions would recognise anybody earning a wage or management income as employed. The 1990 to 1997 data reflect these changes in definition, while the official data of 1989 and before were left unchanged. Sectoral employment data remained unaffected by the changes and is still compiled using the old method. Young uses sector data to construct a series of the 'old kind' after 1996.

In addition, 1996 saw a change in the government's approach to unemployment, as previously effectively unemployed people were made redundant in the state sector.[36] This led to a slower growth rate of employment overall. In other words, the employment level for years prior to 1997 is most likely inflated – and is thus a proxy for potential employment. Starting from 1998, official Chinese statistics exclude workers from their employment figures if they are registered with a firm but do not actively work (Holz and Lin, 2001). Indeed, this change is more serious for the purpose of estimating potential labour than the inflated data before 1997/8. For the production function estimation, the employment numbers as published in the CSY 2002 are used for the years 1990-1997, where for the years prior to 1990 the growth rate of the (aggregate) labour force as reported in pre-1998 CSYs is used to construct the labour series backwards. Divergence from the officially reported data leads to a reduction of the estimated output gap reversal from 1989 to 1990, however apart from these two years the effect of an adjustment in the pre 1990 labour data on the calculation of potential output is minor.

$$\begin{aligned} L_t &= Wpop_t * pr_t * (1 - ur_t) \\ L_t^* &= Wpop_t * pr_t \end{aligned} \qquad (13)$$

Actual labour L_t is determined by the working population $Wpop_t$ multiplied by the participation rate pr_t and the unemployment rate ur_t. There was no 'official' unemployment until around 1997 and we assume an unemployment rate of zero. Wang and Yao (2003) display estimates derived from various issues of the CSY for the population aged 15 to 64, a series which closely represents the (potential) working population.[37] The participation rate based on the age 15-64 group as $Wpop_t$ has risen steadily during the 1980s from 83% in 1978 to 87% in 1990 and has been steady since at close to 86%. Two observations on the available data are noteworthy. During the 1980s the ratio of workers over the total population was also steadily rising, while again the percentage of workers in the population has been entirely stable since 1990. In order to get an estimate for the potential labour force, we would like to construct potential labour for the years 1998 to 2002 by extrapolating from the then relevant 'participation rate' from the years prior to 1998. Unfortunately, using a rate of 56.5% of the overall population or 86% of those of working age gives a series of potential employment data which is slightly smaller than the actual published

[36] Jefferson, Rawski, Wang and Zheng (2000)

[37] This series includes men drafted to the military. The number of students in higher secondary and higher education have been growing but are not of a size that would majorly distort the use of the population of age 15-64 as the working population.

employment figures. We therefore stick with the official data for the last five observations and treat the reported labour figures from 1978 to 2002 as L^*_t.[38] We do this for aggregate as well as sector labour data.

Using raw (potential) employment figures as the labour input into production overlooks the importance of labour quality.[39] Wang and Yao (2003) improve on earlier estimates in this area[40] by constructing a labour quality index similar to Barro and Lee (2001). We use the Wang and Yao data since their data is at annual intervals and thus allows for a smoother development of the growth of human capital than the five year intervals of Barro and Lee's data set. Using Wang and Yao's method we update their series of education attainment with recent CSY data.[41] and then obtain a weighted average of human capital stock in years of education using the years of schooling displayed in Table 2. Equation (14) shows formally the construction of the education augmented labour series.

$$L_t^{H_i} = L_t * H_t^i = L_t * \sum_{j=1}^{6} P_t^j H_t^{j,i} \tag{14}$$

P_t^j is the share of working age population who hold a certain level of schooling as their highest educational attainment. We consider three specifications (*i = 3*) of the human capital index H_t^i.

First, we use a $H^{i=0}$ of unity throughout, i.e. we use the un-augmented labour series. Second, we obtain an index for the stock of human capital ($H_t^{i=1}$) where we try to weight years of schooling by the typical wage increase of an additional year of schooling. We chose the index of weights in Table 2 by taking guidance from work reported in Collins and Bosworth (1996), where we apply geometrically a rate of return per year of schooling of 10%. Collins and Bosworth (1996) use 7% and 12% and argue that the higher value is likely to be due to omitted variable bias in schooling regressions, their average return to schooling for their East Asia sample is of 10.7% (table 4, p. 152). There is a literature which focuses specifically on the returns to schooling in China. Johnson and Chow (1997) use 1988 cross-sectional data and find returns of about 3.5% per year of schooling, Knight (1996) mentions low returns to schooling, other more recent studies include Knight, Zhao and Li (2001), who mention similarly low returns, and Zhang and Zhao (2002) have

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38 Chinese data availability and quality takes it toll here. A NAIRU estimation could bring the required improvement of the data, however with unemployment data that cannot be reconciled with other published employment/unemployment numbers a NAIRU would be difficult to estimate.

39 For example, Chuang (1999) summarises this literature and gives compelling evidence from Taiwan.

40 Young (2000a), Collins and Bosworth (1996)

41 In fact their method requires data dated t+3, since they estimate the number of people how have successfully completed a given level of intermediate level schooling as the number of graduates from the lower level minus the graduates of higher level a number of years later. For the years 2000, 2001 and 2002 we extrapolate the number of graduates from a certain level of schooling by extrapolating with the average growth rate of an individual type of schooling over the previous three years. The data series are displayed in the appendix.

found an increase in returns to schooling from 4.7% in 1988 to 11.5% in 1999.[42] de Brauw and Rozelle (2002) look specifically at returns to education in rural areas and argue that by making adjustments to existing studies (e.g. for the number of hours worked) the returns to education are increased from the 3-4% range to 6-7%. Li and Luo (2002), who try to account for heterogeneity in ability, argue that the rate of return to education in younger Chinese workers is as high as 15%!

What rate of return would be a reasonable assumption for the human capital adjusted potential labour force? The impact of the different assumptions about the rates of return influences the estimated labour share in production, however the impact on the size of the output gap is small. We believe that the East Asian average return reflects best the potential impact education could have on production – and that the recent more market determined returns to education lend further support to this view. We hence use the 10% returns and apply the value of one for no schooling in calculating the index $H^{i=1}$.

Finally, we use average years of schooling for the population of age 15 and older as the labour capital index $H^{i=2}$. The average year of schooling has risen from about 2.5 years in 1977 to 5.5 in 2001.[43]

j	Type of schooling	Index value $H_t^{i=1}$	Years of schooling $H_t^{i=2}$
1	No schooling	1.00	0
2	Primary schooling	1.61	5
3	Junior secundary schooling	2.14	8
4	Senior secondary schooling	2.85	11
5	Special secondary schooling	3.14	12
6	Tertiary schooling	3.98	14.5

Table 2: Indexation of school level

The second of our methods is less arbitrary, however workers with no schooling enter with a zero weight. If one beliefs that workers with no schooling can add value to production, the third index might be preferred. Figure 5 displays the movement of the three labour series over time.

Any of the three methods can only serve as a proxy for labour quality and labour attainment; skill and learning-by-doing effects are not captured in any of these labour series. Young (2000a) tries to avoid the problems of not recognising uneducated workers as well as arbitrariness of an index such as in column three of Table 5 by indexing the different schooling levels by the returns derived from the groups' wages.[44] The human capital indices H^1 and H^2 are applied to the sector labour data as

[42] See their table 1, p. 36-7, for an overview of other studies' results.
[43] This is lower than the estimates of Wang and Yao (2003) and Barro and Lee (2001). However, using the weights obtained from the Wang and Yao data, we cannot reconcile the gap with their data.
[44] Although this is a sensible approach to avoid any arbitrariness in this issue, typical returns to schooling regressions do not capture a number of important factors impacting on the earned wage. Using a large,

well. However, it is uncertain whether all sectors benefit equally by better education. For example, the labour force in rural agriculture is likely to lag behind the national education averages. Last, we cannot control for changes in the working hours over the reform period.[45]

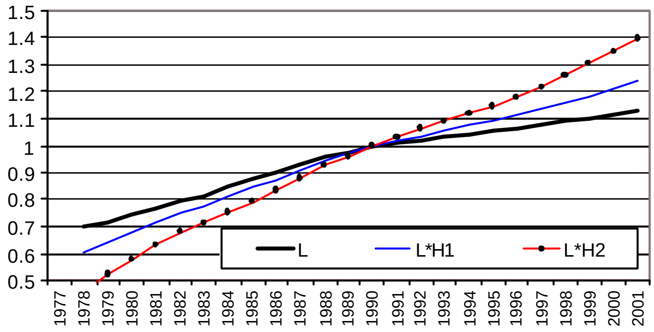


Figure 5: Comparison of the labour force and human capital augmented labour force

Integration properties of data

Empirically, the Cobb-Douglas production function assumes cointegration, as none of the input variables is stationary. Before we proceed to the estimation part, a brief discussion of the integration properties of the data is useful. Table 9 (page 47) shows the results from unit-root tests. GDP and the labour force are I(1) variables and the respective first differences are stationary. Capital is a border-line case. We conclude from the tests that the first differences of all capital variables are trend stationary, and that capital is therefore I(1).

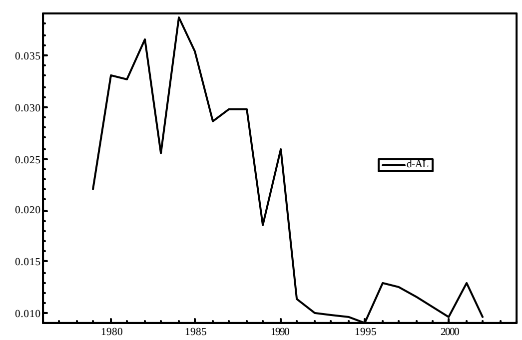
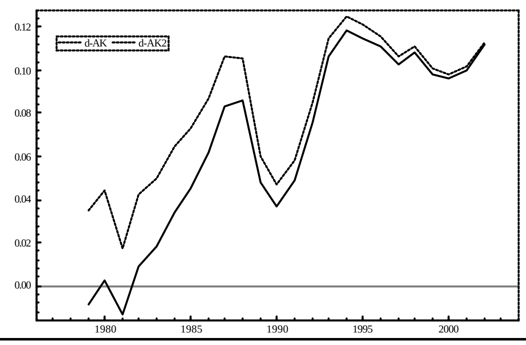
Growth rate of labour	Growth rate of real capital (10% depreciation)
	

Figure 6: Growth rates of labour and real capital

In the light of the quickly growing Chinese economy the assumption of trend stationary investment seems plausible. Indeed, is appears that since the mid 1990s the real investment rate has levelled

recently constructed data set on 7000+ urban Chinese workers, Knight and Yueh (2002) for example find that social capital is an important ingredient in then Chinese labour market.

[45] Hu and Khan (1996) in their detailed work on data come to the same conclusion. Official working hours in SOEs were reduced in 1995 from 48 hours per week to 44 and then 40 hours per week. Muellbauer (1984) for example finds that (the shifts in the tail of the distribution of) overtime hours are a good proxy for capacity utilisation.

off, after a rather steady rise from 1978 to 1995. With three I(1) variables the production functions assume cointegration (1,1) between the GDP/labour and the capital/labour ratio, such that the residuals of the regressions are stationary. We return to the issue of cointegration below.

Estimation

There is no ultimate output gap estimate, the results from estimating this latent variable are dependent on a number of assumptions, none of which a researcher can claim certainty about. de Brouwer (1998, p. 23) makes the point that therefore no output gap estimation method is likely to give an ultimate result; rather, all estimates form an information set. Our objective is to obtain an information set that allows us to refine a 'representative' output gap which can be used with confidence in macro-modelling of the Chinese economy. What emerges from our various estimation approaches is a pattern of output 'gaps' which in general are highly correlated with each other across different methods, specifications and data assumptions. We carry out our calculations on a range of possible assumptions about the input factors. Although one could argue for a preferred method on theoretical grounds, the search for a 'best' output gap measure is to an extent also an empirical question – and we must delay final judgement on the 'best' output gap estimate until we made use of the estimates in empirical macro-modelling. The appendix shows in detail the data inputs and regression results. Graphical illustration of all estimated gaps follows on page 33.

Univariate methods

Linear trend

Regressing a linear trend on real GDP (1987Q1 to 2002Q4) results in a 2.3% trend growth per quarter, equivalent to almost 10 percent real growth per annum. Figure 13 shows the estimated gap. A linear trend is arguably the least sophisticated method of estimating potential output, however if breaks in the trend, which can only be identified ex post, are recognised, this tool can be powerful. Li (2000) argues for trend stationarity of annual GDP and finds major structural breaks for aggregate GDP as well as all sector GDP series during the great leap forward in the early 1960s and during 1981-2 for aggregate GDP, agricultural and tertiary sector GDP, and in 1992 for industry.[46] Using recursive estimation of the trend slope in aggregate and sectoral GDP, we display our break tests in Figure 17 of the appendix. Compliant with Li's result, there is evidence for a break in 1981 for annual aggregate data, and in the mid 1990s for annual industrial output. The 1981 change in trend growth does not affect our aggregate economy quarterly estimation for the period 1987-2002. Since 1981 is so close to the start of the estimation period for our annual production function (1979/1980 – 2002) we do not allow for an extra trend from 1979-81.

[46] This is likely to be connected to Deng's southern visit in 1992 which lead to a speeding up of economic reforms.

HP-trend

The output gap derived from a HP-trend is similar in shape to that based on a linear trend, but by construction the gap is of smaller size overall. Figure 13 displays the output gaps derived from a linear and a HP ($l = 1{,}600$) trend on seasonally adjusted data.

On comparing the two series, one important assumption about growth potential becomes apparent. If one is to believe in a constant potential growth path, the Chinese economy has build up a sizable negative output gap since the late 1990s because real growth since 1997 has been lower than it used to be in the 'boom years' of the 1980s and early 1990s. However, an emerging market will not be able to maintain 10% real growth for ever, and a levelling-off effect should set in at some stage. The HP filter does not address the fundamental causes of this levelling-off effect, but it 'adjusts' the output gap estimates in the late 1990s to a smaller absolute value. The issue will resurface more clearly when we discuss trend TFP for growth accounting later.

Production function

We estimate static and dynamic Cobb-Douglas (CD) production functions and static translog functions.[47] The results of the static regressions give an annual output gap estimate as the residual, while the dynamic estimations provide a test for the size of the long-run capital share in output. All production functions we estimate for aggregate data and for the five sub-sectors identified on page 11. In order to measure the sensitivity of results to a range of reasonable assumptions about input factors, we consider as input data for the aggregate regressions combinations of

- three quality-augmented labour series $\left(L, L^{H_1}, L^{H_2}\right)$,
- two initial capital values in 1977,
- three different depreciation rates (4, 7, and 10 percent).

This gives 18 different aggregate data regressions. With the sector based regressions the construction of the data allows for a sensitivity analysis across the three labour series. All regressions include one linear trend only.[48]

[47] In dynamic translog functions the squared regressors are insignificant throughout and we do not report the results

[48] We disregard the potential 1981 break in the trend, and test for the 1992 break in trend for industry. The appendix on page 50 shows the effects of allowing for multiple trends in the regressions. Although trends for the periods 1978-85, 1978-88, 1992-2002, and 1995-2002 are often significant, they lead to sometimes large fluctuations in the coefficient on the capital share in production in the static regressions. To avoid arbitrariness in these results and in order to save degrees of freedom in our small data sample, we restrict the estimation to one trend. Reassuringly, in dynamic production functions the 1978-2002 trend is the only one that is ever significant.

Aggregate static Cobb-Douglas production function

Estimation of the CD production function in levels rejects the constant return to scale hypothesis for most of the possible data combinations and we do not report the level results. Since the production inputs are likely to follow a cyclical pattern, for which we cannot correct due to unavailable data on utilisation rates, the sum of coefficients for capital and labour is likely to be biased upwards. We therefore impose CRS and report the constrained Cobb-Douglas production function results as in equation (4) (see appendix on page 51 for estimation results). We experimented with the inclusion of different types of capital, namely capital stock arising from FDI and investment in innovation, in the regressions. However, we did not obtain robust estimates across our various input assumptions, and the signs of the coefficients on the additional capital inputs were frequently wrong.

The coefficient from a standard static CD production function for the capital share in production varies between 0.20 and 0.45, with a mean and median coefficient across the 18 regressions of close to 0.35, see Table 10 of the appendix. Naturally, the capital share coefficient is, ceteris paribus, higher for lower depreciation rates, a lower initial capital stock value, and the higher the growth rate of the labour quality index. The trend estimate, which proxies total factor productivity (TFP), varies between 4 and 6 percent, and is higher for slower growth rates of the labour quality index. In other words, more ‘aggressive’ adjustment for labour quality reduces the portion of growth allocated to TFP growth.

The coefficients on the capital/labour ratio and (TFP) trend are almost always highly significant, the output/labour and capital/labour ratio appear to cointegrate. The diagnostic tests reveal that the estimations suffer from two problems throughout: a strongly autocorrelated residual and the RESET test indicates misspecification. The diagnostics point us to the inclusion of lags of the dependent and independent variables. However, the residual from such a regression could not be interpreted as the output gap anymore. Together with the aforementioned potential data shortcomings there is a need for a richer dynamic specification in order to estimate unbiased long-run coefficients. This motivates a dynamic production function. The long-run coefficients derived from this estimation set-up will serve in the construction of potential output.

Figure 7 shows all estimated 18 output gaps are of similar shape and magnitude and only tend to differ at the minima and maxima of the cycle. Mean and median output gap from the 18 regressions are chosen as the representatives of this output gap estimation approach.

Sector based static Cobb-Douglas production function

Agriculture, industry and services are likely to follow different growth patterns and to have different factor shares. By allowing for these differences an output gap which is derived from the sum of the sector potential GDP estimates could be a superior estimate. We estimate Cobb-Douglas production functions for the five sectors agriculture, industry, construction, transport and telecommunications (T&T), commerce, plus a tertiary sector aggregate combining T&T and commerce data. Production in some sectors, most notably agriculture, is unlikely to be fully represented by a Cobb-Douglas function. Rather, land, irrigation, and areas affected by natural disasters are likely candidates to be included in agricultural production functions. We stick to pure CD production functions for reasons of parameter parsimony and because inclusion of land as a third factor of production did not give acceptable results.[49] The test for constant returns to scale is accepted for the construction and the T&T sectors only, but we impose CRS throughout. Table 13 in the appendix gives the estimation results. Most sector regressions suffer from autocorrelation, and the coefficients on the capital share appear to be unrealistically low (insignificantly different from zero for two out of three regressions) and high (almost unity) for the agricultural and industrial sector respectively. Agriculture and industry are the most important sectors in the economy and the implausible size of the capital share in production reduce our confidence in the estimates – although the labour share derived from wage payments confirms the regression estimates (see Figure 8)! For the same reasons as with the aggregate data we estimate dynamic production functions for the sector data and obtain more robust and plausible results which are then fed into a growth accounting spreadsheet.

Cobb-Douglas versus Translog production functions

We estimate translog production functions in order to obtain output gap estimates from an alternative production function specification. We impose constant returns to scale and estimate equation (8) for aggregate and sector data. The estimation results are displayed in Table 11 and Table 14. A number of interesting issues arise. First, likelihood ratio tests show that for aggregate data the translog function is a significant improvement over the restricted Cobb-Douglas specification (see Table 15). Second, aggregate data translog functions reveal a falling share of capital in production, the derivatives of the translog functions with respect to $^{K}/_{L}$ in Figure 19 show this clearly. Taking the average of our 18 identified capital/labour share time-series, we have evidence that the capital share has fallen from about 75% in 1978 to about 25% in 2002. Still, the dispersion in level of identified capital shares is large, some estimated coefficients start above one or fall below zero and are hence not plausible. Third, with the more flexible specification, the

[49] For some of the sectors, Hu and McAleer (2002) use more sector specific inputs into production. For example, for the agricultural sector they use land, machinery and fertiliser. We have experimented with regressions which incorporate some of these measures but decided to report none of the results here. In particular, land tends to enter with a negative coefficient (as in Hu and McAleer's work), an entirely implausible results, unless one can argue that too much land beyond a certain threshold is used. Second, for our potential output estimation is more difficult to argue for a potential level of fertiliser. Machinery is a variable which is close to fixed assets in agriculture. Chow (1993, table XII, p. 833) obtains sector estimates of similar magnitude for construction, transport and commerce. A significant and correctly signed variable is the ratio of land affected by natural disaster to sown land.

identified output gap for the mid 1990s is smaller than the one identified from the CD regressions. Figure 7 illustrates this. Fourth, the regressions suffer from similar diagnostic test failures as the static CD equations. All in all, the translog production function provides an acceptable alternative output gap estimate.

For sector based data the likelihood ratio tests indicate that the richer specification does not improve on the Cobb-Douglas estimates for most sectors. Also, the estimated coefficients are often insignificant, and the results for the time path of the factor share are often doubtful. Table 14, Table 16, and Figure 20 give the details. We report the results here only for completeness but do not use the estimated residuals in output gap calculations. Apparently, less than perfect data measurement and estimation seem to take their toll here.

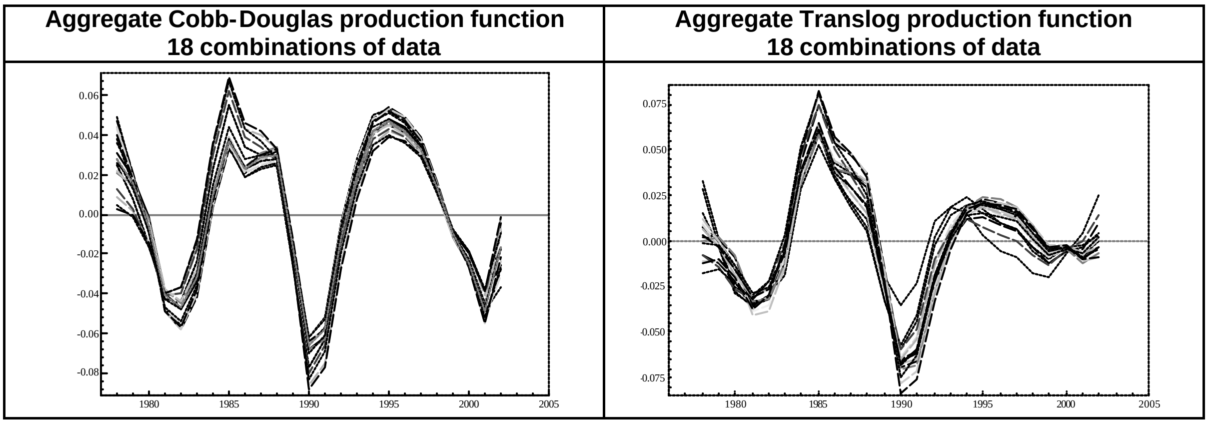


Figure 7: Aggregate output gaps: not much sensitivity to input data assumptions

Aggregate dynamic Cobb-Douglas production function

Chinese data could be subject to measurement error, and most static CD regressions fail at least one diagnostic test. The estimation of a dynamic production function allows for a better identification of the long run coefficient b^{LR}. We therefore estimate in a first step equation (9) including a lag of the independent variable. The results are shown in Table 12 of the appendix. The resulting b^{LR} is again the greater, ceteris paribus, the lower the depreciation rate, the lower the initial capital stock value, and the higher the growth rate of the labour quality index. The fit of the ECM specification is good overall with an R-sqr >0.8, the diagnostic tests are satisfactory, and the standard error is reduced to a third of the earlier, static regressions standard error. The numerical results are interesting. First, the long-run elasticity of capital appears to be rather robust between 0.3 and 0.35, much below the values suggested in earlier research.[50] Keeping in mind the results from Figure 3 and Figure 4, the capital variable K_2 based on (Wang and Yao 2003) appears to behave most reasonable and points at a long-run capital coefficient of 0.33-0.35. Second, the short-term

[50] Also, the research so far has used the usual static regression, which could have biased the results.

dynamics reveal a strongly pro-cyclical pattern of investment and growth: short term GDP per worker grows 1.5 fold to the capital/labour ratio. Third, about 50% of the output gap is closed after a year in China. We make use of the long-run capital share calculations in the growth accounting exercise below.

Previous studies found a capital share in production of 0.547 (Hu and Khan 1996, for the period 1979-1994), 0.59 (Wang and Meng 2001) or around 0.6 (Li 2003). The estimated 35% of capital share in our regressions is close to the usual 30/70 split between capital and labour in developed economies, and is lower than the conventional view on China suggests. China has been reliant on its industrial sector in the Mao era, and the sector was nurtured still after 1978. The results of earlier studies in the range of, roughly, 45-65% of capital share support this view. Our own results draw a slightly different picture, i.e. that of a more developed China. This is in part due to our shorter estimation period which focuses on the reform period, and possibly to regression misspecification in earlier papers.[51] [52]

Sector based dynamic Cobb-Douglas production function

The estimation results improve on the earlier estimates and are displayed in Table 16 (page 59). Diagnostic tests do not point to the problems encountered before, the R-sqr values in the range of 0.6 to 0.85 are satisfactory for differenced data, the standard error of the regressions is reduced by at least 30% compared to the standard regressions. The three estimated coefficients per sector show less variability than before, and the values seem more realistic for agriculture and industry with values of about 0.2 and 0.6 respectively. Still, the significance of the important EqCM coefficients is low for these two important sectors, and the regressions can at best point us to a range of reasonable results for agriculture. For the construction and the combined tertiary sector the capital coefficient is close to 0.3, where the latter improves on estimating the T&T and commerce sector separately. Again, we feed the β^{LR} coefficients into our growth accounting model.

Cointegration

All our regressions assume cointegration of between the GDP-labour and the capital-labour ratio. Does the data support this assumption? Ericsson and MacKinnon (2002) review different methods of testing for cointegration and provide the critical values for the relevant tests. We use two cointegration tests: First, following Engle and Granger (1987) we use the single equation Dickey-Fuller test on the residual derived from the static long-run relationship of the two variables in

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[51] Reporting of diagnostics is scarce in most related papers, and it is not apparent whether the authors have corrected for the specification problems we encounter here.

[52] Dynamic translog functions result in insignificant coefficients on the squared terms, but otherwise correctly signed and reasonably sized coefficients which are rather similar to the values obtained from the dynamic CD regressions.

question. Second, we use the trace test in a VAR setting developed by Johansen (1988). While the Dickey-Fuller tests for most of our 18 aggregate regressions give correctly signed test coefficients, the hypothesis of cointegration is rarely supported with statistical significance. The Johansen test does better in this respect and for aggregate data regressions the hypothesis of cointegration is accepted at the 90% or 95% confidence level for most data combinations. Sector data tends to perform worse than the aggregate data in either test. Keeping in mind the short period of available data, the evidence in favour of a cointegrating relationship between the $^{Y}/_{L}$ and various $^{K}/_{L}$ ratios is encouraging and validates our static and dynamic production estimations.

Side issue: a comment on the labour share

Obtaining a precise estimate for the labour share, which is a key input into any growth accounting calculations, is demanding on data. Traditionally, the labour share has been calculated from the national accounts as the share of wages (multiply the average wage per worker with the number of workers)[53] in added value. A more sophisticated and precise estimate of the labour share would look at production from a producers point of view, i.e. remove indirect taxes on the value of production and subsidies into production, but include taxes on factors of production, such as social security payments funded by the employer. Such data is not readily available for China, and we resort to the traditional method, where the average labour share according to the official data is around 72.5% on average, above 100% for the agricultural sector and below 25% for industry – see also Figure 8. Deriving the labour share from most likely poorly measured (official) average wages and employment numbers does not inspire greatest confidence in these labour share numbers and we therefore prefer the labour share estimates derived from the (Cobb-Douglas) production function estimations as coefficient inputs into the growth accounting. A drawback of the CD production function regression is the identification of a constant (average) share of capital and labour over the estimation period. From the aggregate translog production function it is clear that the share of capital has dropped over the last 25 years (Figure 19). However, apart from a falling share of capital in aggregate GDP, the translog derivatives show a great dispersion in the level of the share and we prefer to use the average coefficients from the dynamic CD production function regression.

The comparison of the accounting and the regression results are evidence for the large structural changes that China still has to master. It appears that labour is currently remunerated too generously in agriculture, and that either wages or the number of employment have to fall so that the accounting labour share resembles the regression result more closely in this sector.[54] For the

[53] See CSY 2002, tables 5-5, 5-20, 5-21, and 5-22.
[54] Possibly, GDP in agriculture is the most understated one of the five sectors, as produce used by farmers themselves is not recognised.

growth accounting exercise we use the estimated long-run capital share as obtained from the dynamic production function.

Labour share in aggregate economy	Labour share by sector[55]

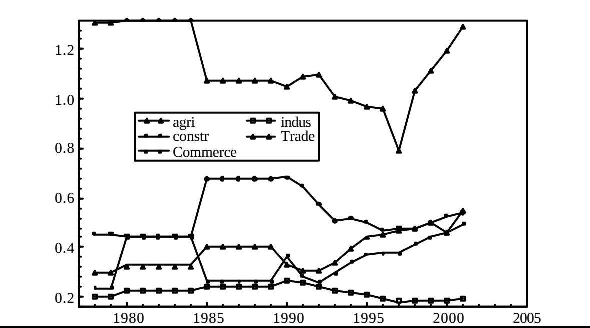


Figure 8: Labour share in economy, derived the ‘traditional way’ from national accounts data

Growth accounting

Aggregate data

Using the accounting procedures of equation (10), the analysis has the usual three parameters of interest, namely the labour share in output, the depreciation rate of capital, the specification of human capital, plus one new assumption: how do we treat trend TFP?[56] We use the individual, regression based labour/capital coefficients for each of the 18 different combinations of our input data assumptions, where as before we consider depreciation rates of 4%, 7% and 10%, the labour variable enters again as raw labour L, as well as quality adjusted labour series L^{H_1} and L^{H_2}.

Treatment of trend TFP, i.e. the trend in the residual of the growth accounting identity, warrants a discussion. Since the output gap increments are derived from the difference of a period’s total factor productivity and the productivity trend, the treatment of the trend is important. The two options available are either a static trend or a time-varying one. We apply a HP filter with a smoothing factor of l^{HP} equal to 1000. In Figure 9 on the left we display the TFP residuals for all our 18 possible combinations of data assumptions; the shape and indeed size are very similar. The right panel shows the TFP average residuals by depreciation rate. The smoothed line in either graph shows the HP filtered TFP trends with a l^{HP} equal to 1,000. We will use this smoothed trend for all 18 data combinations. The l^{HP} value is ad hoc, a value of 100 is usually applied to annual data, while 1,000 aims to provide an estimate of a less flexible trend. We used a number of different smoothing coefficients, but settled for $l^{HP} = 1{,}000$ as it allows for a long-term change in the level

[55] The horizontal lines in from 1980-84 and 1985-89 indicate missing data.
[56] The main reference for the empirical application is Organisation for Economic Co-operation and Development (2001).

of TFP without changing direction of the trend frequently. Alternatively, we also use a fixed TFP trend for calculating the output gaps.[57]

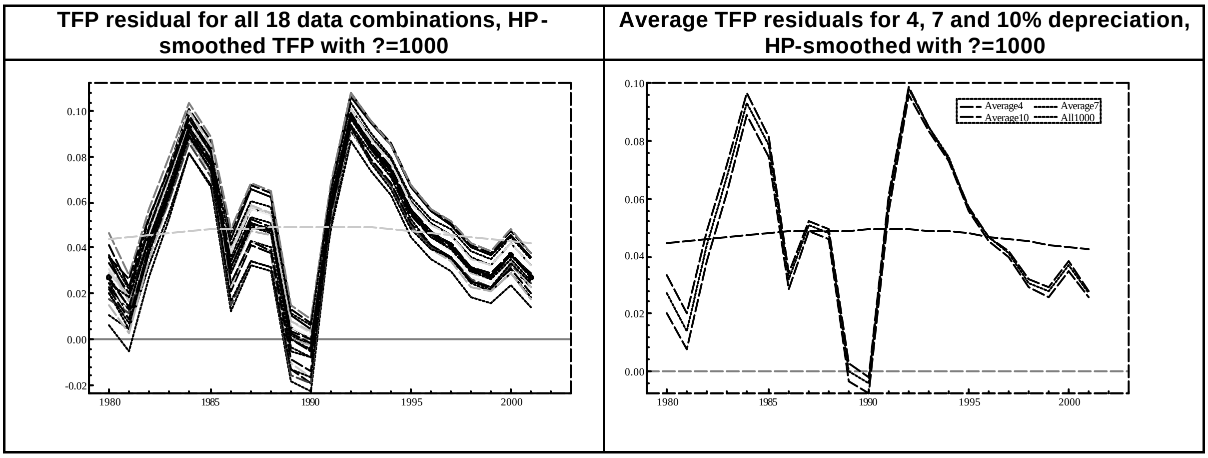


Figure 9: Estimates of aggregate economy TFP – the residual from growth accounting

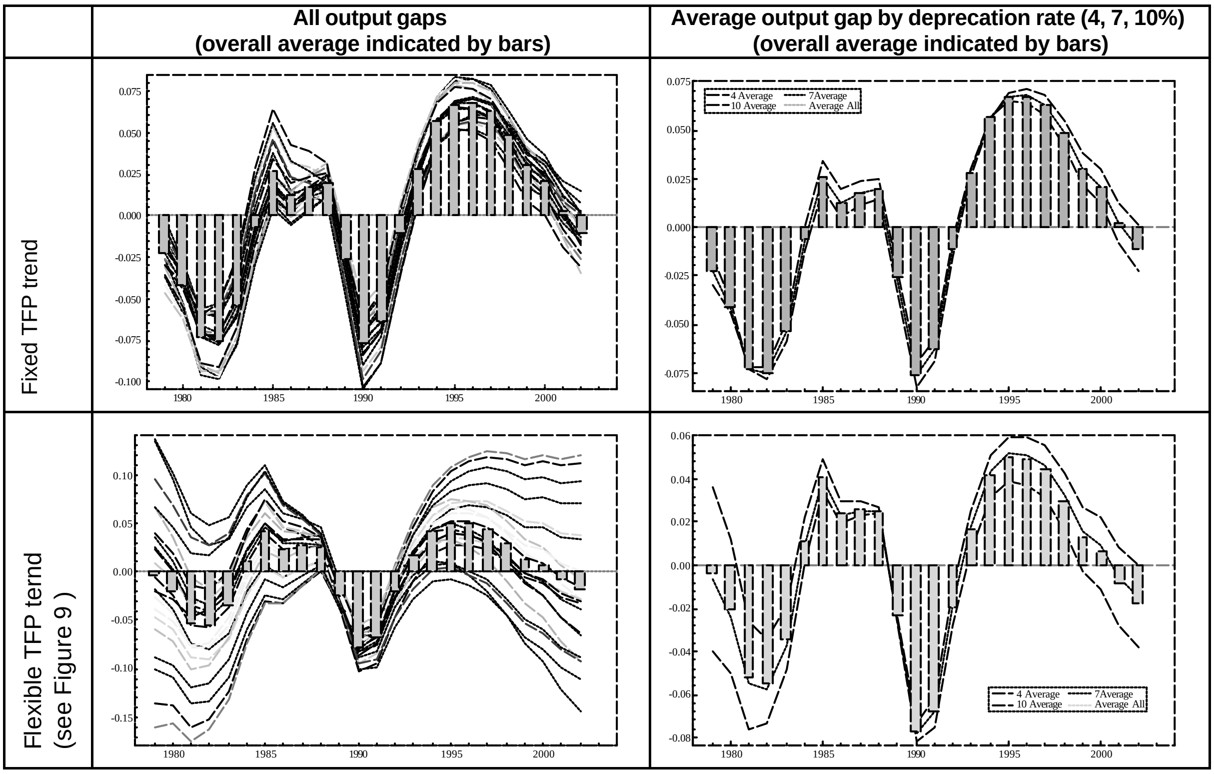


Figure 10: Aggregate economy output gaps from growth accounting

The choice of the TFP trend is rather important. A constant TFP trend leads to bigger output gap estimates. For aggregate data, the 1990s have seemingly seen a decline in TFP, and the HP-filtered trend accounts for that to an extent. As far as the average output gap is concerned, the assumption

[57] Another approach would allow for a stochastic trend. However, from preliminary estimations with a time varying trend, such a trend appears to mirror the shape of the TFP residual rather closely. This poses the question as to what time horizon of the fluctuations in then TFP trend we would consider as appropriate. Our inflexible treatment of trend TFP tries to focus on more long-term movements.

about a fixed or a flexible TFP trend does not matter much. However, while the individual gaps are almost identical if we apply the individual labour share estimates plus a constant TFP trend, the gaps diverge more if we use our ‘average’ flexible TFP trend. In Figure 10 we show the sensitivity of individual gaps to the input assumption, Figure 13 then compares the average annual and quarterly output gaps derived from aggregate data growth accounting with a fixed and flexible TFP trend to alternative output gap measures.

Sector based data

As for the aggregate data, we allow for a time-varying TFP trend within the sectors, where again we use a smoothing parameter of $l^{HP} = 1,000$. Figure 11 shows the estimated trends. The sector data seems to display a change in mean over time – something we interestingly do not see from the aggregate data. However the remaining 15% of the economy which are not captured in the five sectors we use here could account for this apparent discrepancy between sector and aggregate data. Because the increase in mean TFP over time in some sectors,[58] the assumption of a fixed TFP level would lead to more negative output gaps in the early periods, while 1990s output gap values could be inflated. We therefore use the flexible TFP trend in the sector growth accounting exercise.

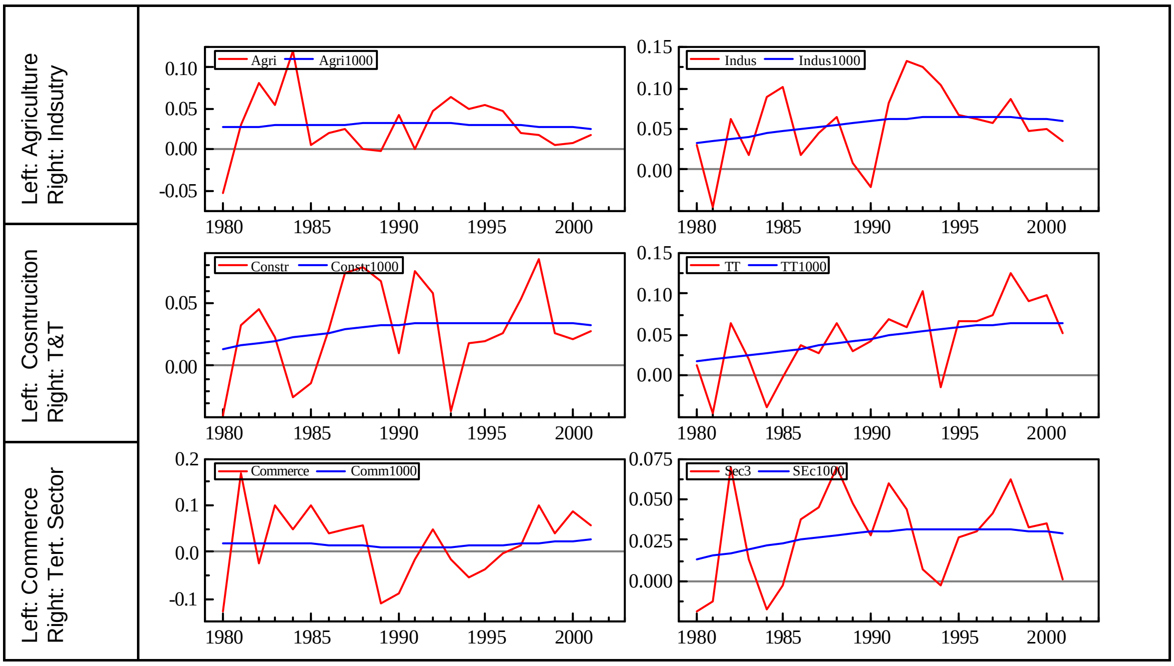


Figure 11: TFP residual by sector, HP TFP trend

Figure 12 shows the estimated output gaps by sector. The crucial gap (for the weighted average) is the one for industry, which accounts for the biggest portion in overall GDP. Indeed, the industrial output gap bears close resemblance to the overall output gap. Construction and services appear to react more abruptly to the stop-and-go macro policies introduced to reign in on the overheating

[58] Notice the very plausible increase in telecoms and transportation.

economy in 1985, 1989, and between 1993 and 1995. Construction also appears to lead the industrial cycle by two to three years. The aggregate output gap derived from the sum of potential sector GDP is displayed in Figure 14. We construct the aggregate GDP data from all five sectors and from agriculture, industry, construction plus the combined tertiary sector (indicated as (3+1)).

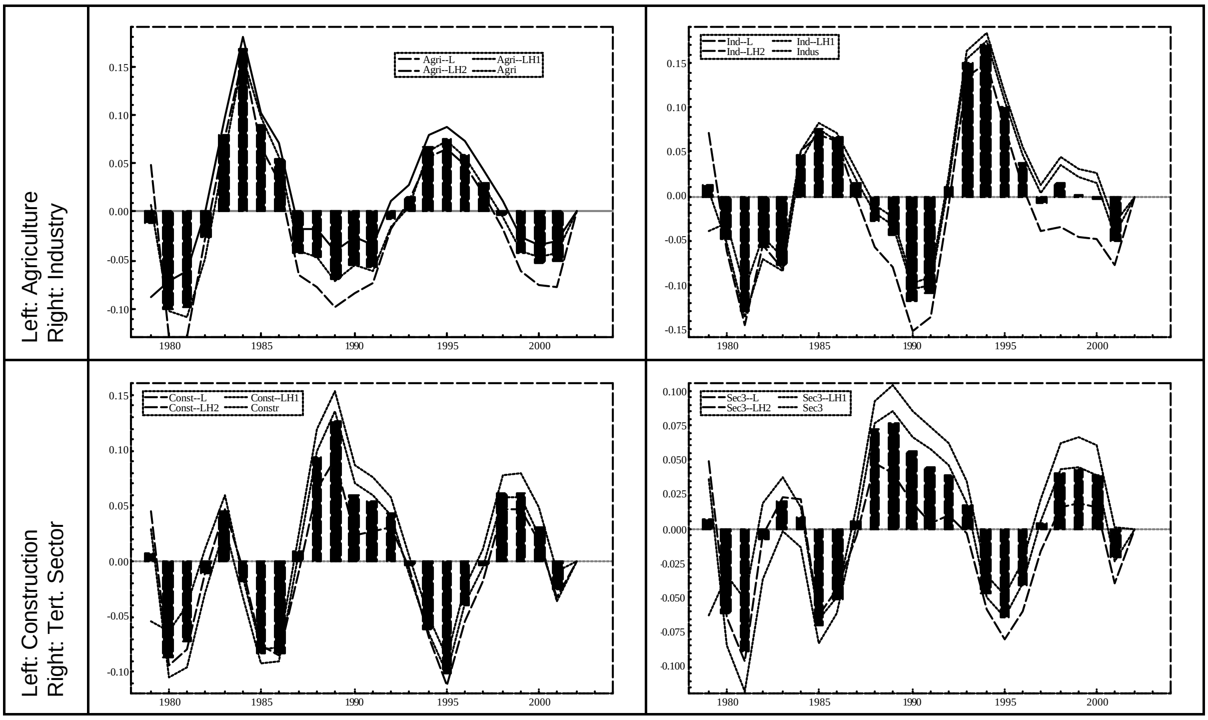


Figure 12: Output gap by sector: for labour data *L, LH_1, LH_2*, average displayed with bars

Comparison and discussion of output gaps

For the macro-model estimation we require a quarterly output gap series. Therefore the estimated annual potential GDP numbers are extrapolated to a quarterly series, where we apply a uniform geometric growth rate for quarterly numbers within a given year subject to the quarterly observations adding up to the annual total.[59] The resulting quarterly potential (real) GDP is deducted from the actual (real) GDP series.

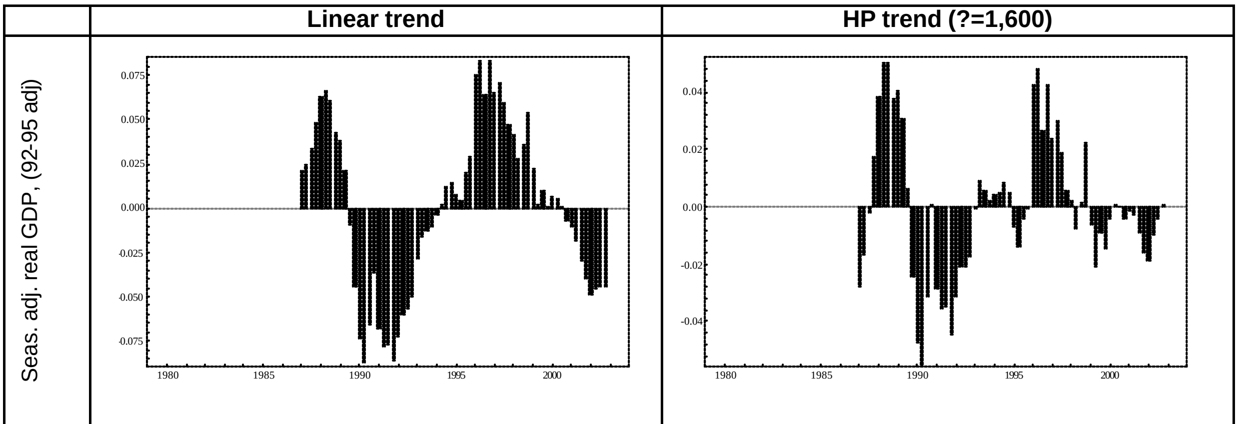


Figure 13: Quarterly output gap from linear and HP trend[60]

[59] As discussed on page 14f.
[60] Note the different scales on the residual graphs

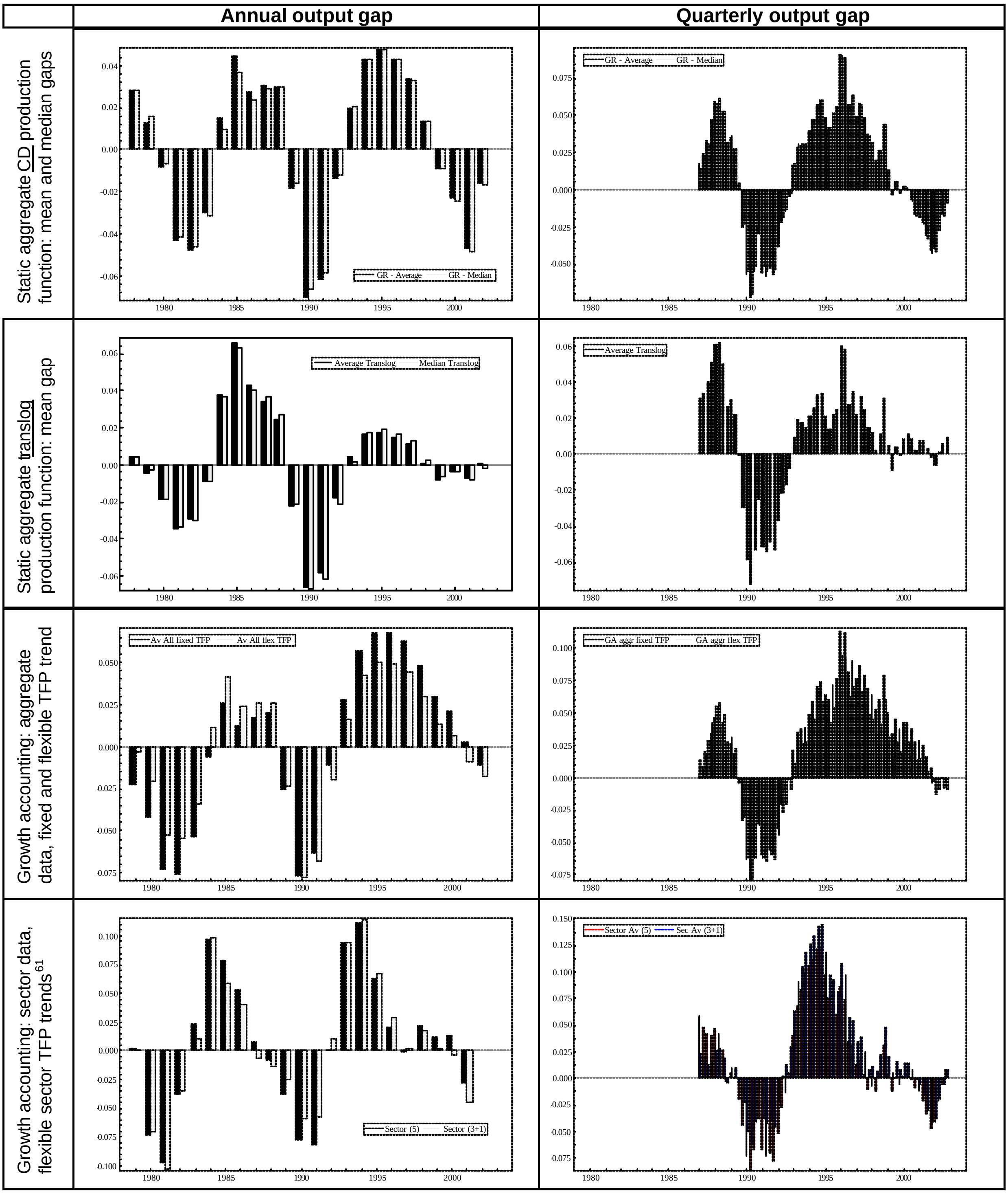


Figure 14: Annual and quarterly production function based output gaps

We estimate the output gaps such that over the 25 year horizon from 1978 to 2002 they sum to zero. This generally reasonable assumption is crucial when it comes to determining the size rather than the 'shape' of the current output gap development. The averaging assumption is imbedded in the idea that in the long-run the economy performs at potential. In Figure 13 we compare the quarterly output gaps derived from a linear and a HP-trend. The HP filter clearly leads to smaller

[61] The sum of the sectoral potential GDP is calculated

output gaps than the linear trend. Figure 14 shows the production function based output gaps. Noteworthy is the rather different shape of the aggregate output gap that emerges from the decomposition into sector gaps. Indeed, this sector based output gap appears to be more highly correlated with inflation that the other gaps.[62] Overall, the correlation of the annual and quarterly output gap estimates is high. Table 17 of the appendix displays the results. The correlation between the aggregate data estimates and the statistical method based gaps is rather high, indeed the correlation between the gap estimates from different input data assumptions are high. Lower is correlation between the sector based estimates and the other gaps. Table 3 provides some summary statistics of our out gap estimates. Clearly, the HP filter causes the smallest standard deviation in the gap estimate. Interestingly, the standard deviation of the sector based output gap estimates surpasses the linear trend variance, though by not much.

	Min	**Max**	**StDev**
Gap		**%**	
Linear trend	-8.8	8.3	4.7
HP trend	-5.6	5.0	2.4
CD mean	-7.3	9.1	4.0
CD median	-7.0	9.0	4.0
Translog mean	-7.2	6.1	3.1
GA aggr fixed TFP	-7.9	11.2	4.6
GA aggr flex TFP	-7.9	9.4	4.1
GA Sec (5)	-8.6	12.3	5.3
GA Sec (3+1)	-6.2	14.4	5.2

Table 3: Summary statistics of quarterly output gap estimates

The pattern of our Chinese output gap corresponds to anecdotal evidence and earlier descriptions in the literature.[63] The Chinese growth – and inflation – history is linked to a stop-and-go pattern of economic liberalisation, dynamic growth and quick overheating of the economy, followed by highly restricted credit allocation of banks and even partial reversal of reforms. The peaks of these cycles are in 1981, 1985, 1988, and 1994. Apart from the first one, the output gap graph clearly shows these peaks of an overheated economy. While the constraining measures after major price liberalisation reforms did not fully cool down the economy in 1986, the rather quickly following wave of banking and credit allocation reforms fuelled growth and inflation again. Determined to curtail inflation, the effective withdrawal of new credit facilities by the central authorities, together with the political and economic aftermaths of the Tiananmen incident forced the economy into a rapid and deep recession in 1989 and 1990. What is remarkable in the 1990s is the soft landing following the severe inflation and overheating in 1994 and the little effect of the Asian Financial Crisis in 1997 for the Chinese economy. Currently the economy appears to be on an economic upswing close to a long-run sustainable 'equilibrium', after the early years of the new century saw a somewhat depressed economy.

[62] See Figure 15 on page 37.
[63] Oppers (1997), Brandt and Zhu (2000)

Side issue: what factors have driven Chinese growth?

A large literature has analysed the causes of recent Chinese growth. Has it been due to mere factor accumulation, or 'smart' productivity growth? Our analysis does not target the issue explicitly, however is seems worthwhile noting our evidence on this in itself interesting issue before concluding the output gap scheme of the analysis. There is research championing both hypotheses, i.e. the factor accumulation and the productivity growth hypothesis. Hu and Khan (1996) find that during the 1979-94 period the contribution of capital growth and TFP growth to GDP growth has been 45 and 42 percent, respectively. Wang and Yao (2003) have similar results. Young (1995) more generally attributed growth in East Asia to pure factor accumulation, and other authors, including Krugman, have echoed this view. Our growth accounting results (Table 19) draw a rather balanced picture. Although the capital to GDP ratio is increasing again for most sectors, the rather low coefficients on the capital share of around 0.35 does not lend much weight to the capital contribution to output growth. Overall, we find evidence for smart growth during the entire reform period, where high TFP growth has contributed about 50% of growth.

Conclusions on potential output

Potential GDP and hence the output gap is a latent variable. By applying a number of alternative estimation approaches, a common pattern emerges which inspires confidence in our estimation results. Univariate methods tend to give extreme results, i.e. rather large or rather small output gap standard deviations, depending on the degree of flexibility one is prepared to allow for in the evolution of a trend. Production function based methods, including growth accounting techniques, have led us to intermediate, and most likely more realistic, magnitudes of the output gap. We find evidence that a decomposition into sector output gaps seems to improve the identification of an aggregate output gap. As preliminary evidence we refer to Figure 15.

As part of the estimation process we have dealt with and have offered solutions to a number of data issues, including the large quarterly fluctuations in official GDP, labour quality indices, potential labour data, and the transparent construction of a capital stock variable. Our dynamic, EqCM production functions deliver robust regression results and improve on the misspecification inherent in a level Cobb-Douglas production function regression. The resulting coefficients on the capital share is lower than suggested in the earlier literature. Comparing aggregate data and sector based data we find that an analysis at the sector level is rewarding and reveals interesting sector dynamics – plus an aggregated output gap that is more highly correlated with inflation. Our quantitative results match the qualitative evidence reported for China: a large negative economic effect surrounding the 1990 political situation, an overheating economy in the mid and late 1980s, and again in the early to mid 1990s. Most recently, China has entered a period of economic upswing after a soft landing during and after the Asian Crisis. Finally: it is difficult to argue for the ultimate output gap estimation. The ‘ultimate’ output gap is also a matter of empirical search – we will have to consider which output gap estimate would have a strong explanatory power in the subsequent estimation of a Chinese macro-model. As a secondary results, our growth accounting results show that China has benefited from ‘smart’, i.e. productivity driven growth. Possible future work could try to decompose the potential output estimates from the sectoral data into private and state owned sub-gaps. The private sector has been growing quickly in China, and private firms have been reported to perform better than SOEs.[64] Disentangling these would be illuminating for both the labour share estimates and the size and sign of the output gap. Obtaining the relevant data is a less than simple exercise for the era 1978-85/90 though.

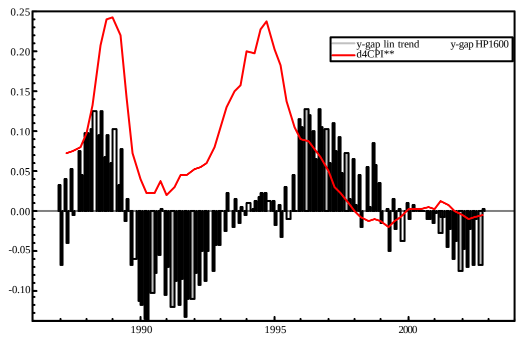
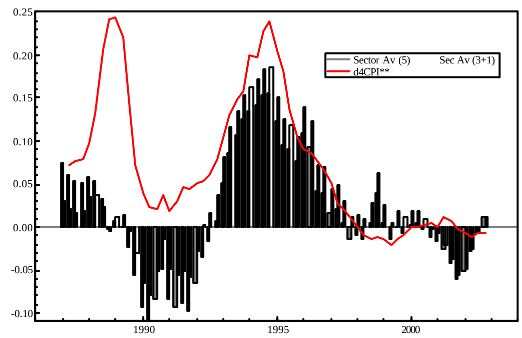
Output gap from linear and HP trend, annual inflation (‘old’ identification technology)	Output gap derived from sector output gaps (growth a/c) , annual inflation, (our new identification technology)
	

Figure 15: Does the output gap matter?

Does the output gap matter? Figure 15 compares the annual inflation rate with different (rescaled) output gap estimates. The left panel shows the output gap derived from univariate methods, namely a linear and a HP-filtered trend. The output gap derived from these methods, which resemble the output gaps used in the literature so far, matches the peak in inflation in 1988/9, but does rather badly for the inflationary peak in 1994. The contribution of this paper is demonstrated in the right figure. The output gap derived from sector based growth accounting cum EqCM identification of the capital and labour share does much better in explaining the strong inflationary pressure in 1994. Preliminary econometric Phillips curve estimations confirm this result.

[64] Jefferson, Rawski, Wang and Zheng (2000).

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Appendix

List of acronyms

CD	Cobb-Douglas
CPI	Consumer price index
CRS	Constant returns to scale
CSY	Chinese Statistics Yearbook
EqCM	Equilibrium correction model
FDI	Foreign direct investment
GDP	Gross domestic product
HP	Hodrick-Prescott
MPS	Material production system
NAIRU	Non-accelerating inflation rate of unemployment
PCB	People's Bank of China
SNA	System of national accounts
T&T	Transport and telecoms
TFP	Total factor productivity
VAR	Vector autoregression

Data

Value added data

	GDP data, in RMB 100 million, 1990 prices		Deflators	
	Own estimate	Hu and Khan (1996)	Own estimate (based on CSY)	Hu and Khan (1996)
1977	**5,901**	4,857	**0.5226**	0.5444
1978	**6,592**	5,455	**0.5498**	0.5518
1979	**7,093**	5,837	**0.5693**	0.5740
1980	**7,632**	6,212	**0.5920**	0.5936
1981	**8,029**	6,515	**0.6056**	0.6050
1982	**8,759**	7,046	**0.6045**	0.6042
1983	**9,714**	7,751	**0.6109**	0.6110
1984	**11,191**	8,804	**0.6408**	0.6420
1985	**12,702**	9,992	**0.7058**	0.7025
1986	**13,819**	10,763	**0.7383**	0.7302
1987	**15,422**	11,859	**0.7757**	0.7853
1988	**17,165**	13,200	**0.8697**	0.8892
1989	**17,869**	13,680	**0.9463**	0.9631
1990	**18,548**	14,383	**1.0000**	1.0000
1991	**20,254**	15,492	**1.0673**	1.0688
1992	**23,130**	17,876	**1.1516**	1.1313
1993	**26,253**	20,576	**1.3193**	1.2093
1994	**29,561**	24,303	**1.5818**	1.3705
1995	**32,665**		**1.7902**	
1996	**35,801**		**1.8962**	
1997	**38,951**		**1.9117**	
1998	**41,989**		**1.8658**	
1999	**44,970**		**1.8249**	
2000	**48,568**		**1.8416**	
2001	**52,114**		**1.8408**	
2002	**56,283**		**1.8193**	
2003	**-**			

Table 4: Data – value added and deflators

Labour

	Own estimates	Working population - Census 1982 and 1990	Human capital (Index H1)	Average years of schooling (Index H2)	Chow (2000)	Young (2000)	Hu and Khan (1996)	Population 15-64	CSY (pre 1998)	CSY (post 1998)
1977			**1.36**	**2.49**	393.8		393.8			
1978	**453.3**		**1.41**	**2.82**	401.5	401.5	401.5	543.1	401.5	401.5
1979	**463.4**		**1.46**	**3.14**	410.2	410.2	410.2	557.4	410.2	410.2
1980	**479.0**		**1.49**	**3.35**	423.6	423.6	423.6	571.9	423.6	423.6
1981	**495.0**		**1.52**	**3.56**	437.3	437.3	437.3	586.3	437.3	437.3
1982	**513.4**	522.0	**1.54**	**3.70**	453.0	453.0	453.0	603.3	453.0	453.0
1983	**526.7**		**1.55**	**3.77**	464.4	464.4	464.4	621.8	464.4	464.4
1984	**547.4**		**1.56**	**3.83**	482.0	482.0	482.0	640.6	482.0	482.0
1985	**567.1**		**1.56**	**3.89**	498.7	498.7	498.7	659.0	498.7	498.7
1986	**583.6**		**1.58**	**3.98**	512.8	512.8	512.8	678.0	512.8	512.8
1987	**601.2**		**1.59**	**4.08**	527.8	527.8	527.8	692.9	527.8	527.8
1988	**619.4**		**1.60**	**4.17**	543.3	543.3	543.3	708.9	543.3	543.3
1989	**631.0**		**1.62**	**4.25**	553.3	553.3	553.3	725.3	553.3	553.3
1990	**647.5**	647.0	**1.63**	**4.32**	639.1	565.3	567.4	741.5	567.4	647.5
1991	**654.9**		**1.64**	**4.40**	648.0	581.0	583.6	757.5	583.6	654.9
1992	**661.5**		**1.65**	**4.48**	655.5	591.3	594.3	769.9	594.3	661.5
1993	**668.1**		**1.66**	**4.56**	663.7	600.1	602.2	781.5	602.2	668.1
1994	**674.6**		**1.67**	**4.63**	672.0	611.9	614.7	792.6	614.7	674.6
1995	**680.7**		**1.68**	**4.70**	679.5	620.3		803.1		680.7
1996	**689.5**		**1.70**	**4.78**	688.5	624.0		813.6		689.5
1997	**698.2**		**1.71**	**4.88**	696.0	631.5		821.7		698.2
1998	**706.4**		**1.73**	**4.99**	699.6	618.0		829.6		706.4
1999	**713.9**		**1.75**	**5.10**		618.6		837.2		713.9
2000	**720.9**		**1.77**	**5.22**		623.5		844.0		720.9
2001	**730.3**		**1.79**	**5.35**		623.6		850.4		730.3
2002	**737.3**		**1.82**	**5.49**						-

Table 5: Data – labour quality indices

Capital stock

	Capital stock, in 1990 prices, RMB 100 million							
	Based on 1977 value of Chow (2002)				Based on 1977 value of Wang and Yao (2003)			
Depreciation rate:	4%	7%	10%	15%	4%	7%	10%	15
1977	23,022	23,022	23,022	23,022	14,838	14,838	14,838	14,838
1978	24,087	23,396	22,705	21,554	16,229	15,784	15,339	14,597
1979	25,205	23,840	22,517	20,403	17,662	16,762	15,887	14,490
1980	26,510	24,485	22,578	19,656	19,269	17,901	16,612	14,630
1981	27,402	24,723	22,273	18,660	20,451	18,601	16,903	14,387
1982	28,728	25,415	22,468	18,283	22,055	19,721	17,635	14,651
1983	30,243	26,300	22,885	18,205	23,837	21,004	18,535	15,118
1984	32,124	27,549	23,687	18,564	25,974	22,625	19,772	15,941
1985	34,313	29,095	24,792	19,254	28,409	24,515	21,269	17,024
1986	36,992	31,109	26,364	20,417	31,324	26,850	23,194	18,521
1987	40,435	33,854	28,651	22,277	34,993	29,893	25,797	20,666
1988	44,257	36,924	31,225	24,375	39,033	33,240	28,657	23,005
1989	47,138	38,991	32,754	25,370	42,123	35,565	30,443	24,206
1990	49,770	40,779	33,996	26,082	44,955	37,592	31,915	25,092
1991	52,888	43,033	35,705	27,279	48,266	40,070	33,833	26,438
1992	57,172	46,421	38,535	29,587	52,736	43,665	36,849	28,872
1993	63,064	51,350	42,860	33,327	58,805	48,787	41,343	32,720
1994	70,199	57,413	48,231	37,986	66,110	55,030	46,867	37,469
1995	78,104	64,107	54,121	43,001	74,179	61,891	52,893	42,562
1996	86,770	71,410	60,499	48,341	83,002	69,348	59,394	47,968
1997	95,918	79,030	67,068	53,709	92,300	77,113	66,073	53,391
1998	106,482	87,899	74,762	60,053	103,009	86,116	73,867	59,783
1999	117,419	96,942	82,482	66,241	114,085	95,283	81,676	66,012
2000	129,295	106,728	90,806	72,878	126,094	105,186	90,081	72,683
2001	142,784	117,918	100,386	80,607	139,711	116,484	99,734	80,441
2002	158,992	131,583	112,267	90,435	156,042	130,250	111,680	90,294

Table 6: Data – capital stock

Capital stock - comparisons

	Capital stock, in 1990 prices, RMB 100 million						Deflators	
	Own estimate: K1 (7% depr rate)	Own estimate: K2 (7% depr rate)	Chow (2000) (using own deflator)	Li (2003) (deflated?)	Wang and Yao (2003)	Hu and Khan 1996 (using own deflator)	Own estimate	Wang and Yao (2003)
1977	**23,022**	**14,838**	23,022		14,838	14,211	0.538	0.538
1978	**23,396**	**15,784**	26,090		16,081	15,319	0.541	0.541
1979	**23,840**	**16,762**	28,605		17,359	16,455	0.553	0.553
1980	**24,485**	**17,901**	31,047	15,735	18,805	17,643	0.570	0.570
1981	**24,723**	**18,601**	29,636	16,613	19,995	18,580	0.642	0.642
1982	**25,415**	**19,721**	32,636	17,781	21,478	19,893	0.616	0.616
1983	**26,300**	**21,004**	33,803	19,150	23,177	21,428	0.641	0.641
1984	**27,549**	**22,625**	35,466	20,788	25,331	23,481	0.688	0.688
1985	**29,095**	**24,515**	39,903	22,693	27,905	26,000	0.732	0.732
1986	**31,109**	**26,850**	43,273	25,003	30,742	28,486	0.770	0.770
1987	**33,854**	**29,893**	49,680	27,747	34,063	31,323	0.770	0.770
1988	**36,924**	**33,240**	54,457	30,860	37,651	34,401	0.874	0.874
1989	**38,991**	**35,565**	60,713	33,710	40,345	36,113	0.948	0.948
1990	**40,779**	**37,592**	66,509	36,454	43,060	38,013	1.000	1.000
1991	**43,033**	**40,070**	70,520	39,607	46,382	40,380	1.095	1.085
1992	**46,421**	**43,665**	72,321	43,696	50,846	43,342	1.263	1.226
1993	**51,350**	**48,787**	73,554	49,201	56,770	47,471	1.598	1.533
1994	**57,413**	**55,030**	89,687	55,757	63,896	52,612	1.765	1.692
1995	**64,107**	**61,891**	107,787	62,587	72,021		1.869	1.793
1996	**71,410**	**69,348**	122,992	70,159	80,705		1.943	1.865
1997	**79,030**	**77,113**	135,848	78,520	89,818		1.976	1.897
1998	**87,899**	**86,116**	147,900	88,171	98,450		1.973	2.165
1999	**96,942**	**95,283**			106,597		1.965	2.284
2000	**106,728**	**105,186**					1.986	
2001	**117,918**	**116,484**					1.994	
2002	**131,583**	**130,250**					1.971	

Table 7: Data – capital stock data and deflators of other authors

The two last entries from Wang and Yao show a very sharp increase in the deflator. However, for the years 1998 and 1999 no reason for this is apparent.

Sector data

Sector inputs: GDP and capital stock in RMB 100m, 1990 prices; labour in million workers;

	Agriculture				Industry				Construction				Transport and Telecommunications				Commerce			
	Y	deflator	K	L	Y	deflator	K	L	Y	deflator	K	L	Y	deflator	K	L	Y	deflator	K	L
1978	2,636	0.386	1,342	283.2	2,246	0.715	8,728	54.4	237	0.583	404	8.8	386	0.448	1,948	7.5	409	0.649	2,805	11.4
1979	2,797	0.450	1,552	286.9	2,442	0.725	9,484	56.2	255	0.563	438	9.4	416	0.443	2,131	7.8	445	0.494	3,092	12.3
1980	2,755	0.493	1,771	291.2	2,752	0.725	10,743	60.2	270	0.723	501	10.2	439	0.467	2,356	8.1	440	0.486	3,539	13.6
1981	2,948	0.524	1,733	298.4	2,799	0.732	10,595	62.3	299	0.694	522	10.6	448	0.472	2,306	8.5	571	0.447	3,619	14.8
1982	3,287	0.536	1,871	309.2	2,961	0.730	11,726	64.3	337	0.654	592	11.7	500	0.473	2,469	8.9	594	0.335	4,183	15.7
1983	3,559	0.551	2,033	312.1	3,248	0.731	12,803	66.0	389	0.696	658	13.1	550	0.482	2,679	9.5	724	0.320	4,718	17.2
1984	4,019	0.571	2,128	309.3	3,732	0.747	13,411	70.7	464	0.682	703	16.9	632	0.517	2,796	11.3	879	0.469	4,972	19.9
1985	4,091	0.621	2,340	311.3	4,412	0.782	15,313	75.6	549	0.761	848	20.7	718	0.567	3,192	12.8	1,133	0.775	5,312	23.1
1986	4,226	0.654	2,388	313.1	4,835	0.820	17,068	80.2	615	0.854	905	22.7	810	0.587	3,511	13.7	1,254	0.752	5,633	24.2
1987	4,424	0.724	2,444	317.2	5,473	0.838	19,135	83.5	704	0.946	953	24.2	891	0.612	3,832	14.5	1,423	0.815	6,030	25.8
1988	4,535	0.845	2,508	323.1	6,311	0.915	21,525	86.4	797	1.016	1,001	25.3	1,009	0.655	4,161	15.2	1,626	0.713	6,482	27.5
1989	4,676	0.904	2,562	332.8	6,632	0.978	23,712	85.6	840	0.945	1,041	24.4	1,057	0.744	4,429	15.2	1,491	1.131	6,838	27.7
1990	5,017	1.000	2,623	341.2	6,858	1.000	26,039	88.2	859	1.000	1,073	24.6	1,148	1.000	4,750	15.7	1,420	1.000	7,162	28.4
1991	5,137	1.029	2,704	349.6	7,846	1.031	28,692	90.4	935	1.086	1,108	24.8	1,276	1.105	5,219	16.2	1,484	1.407	7,623	30.0
1992	5,379	1.078	2,791	348.0	9,509	1.082	31,728	93.2	1,051	1.346	1,163	26.6	1,410	1.193	5,806	16.7	1,678	1.630	8,431	32.1
1993	5,632	1.222	2,865	339.7	11,420	1.239	34,947	95.4	1,163	1.964	1,327	30.5	1,585	1.340	6,670	16.9	1,789	1.728	9,324	34.6
1994	5,857	1.615	2,938	333.9	13,578	1.426	38,545	98.6	1,275	2.363	1,513	31.9	1,735	2.124	7,798	18.6	1,926	2.103	10,322	39.2
1995	6,150	1.950	3,019	330.2	15,479	1.597	42,171	100.6	1,382	2.763	1,669	33.2	1,944	1.572	8,938	19.4	2,040	2.418	11,167	42.9
1996	6,463	2.142	3,121	329.1	17,414	1.670	45,909	100.4	1,491	3.038	1,832	34.1	2,165	1.614	10,204	20.1	2,150	2.586	11,893	45.1
1997	6,690	2.124	3,265	331.0	19,382	1.672	49,997	99.0	1,627	2.956	1,984	34.5	2,399	1.583	11,741	20.6	2,333	2.640	12,642	48.0
1998	6,924	2.102	3,468	332.3	21,107	1.582	54,228	86.0	1,762	2.969	2,131	33.3	2,653	1.553	14,050	20.0	2,513	2.618	13,455	46.5
1999	7,118	2.033	3,737	334.9	22,901	1.532	58,419	83.9	1,898	2.882	2,344	34.1	2,953	1.510	16,457	20.2	2,694	2.565	14,239	47.5
2000	7,288	1.986	4,058	333.6	25,146	1.553	63,157	83.3	2,052	2.870	2,554	35.5	3,293	1.643	19,031	20.3	2,914	2.510	15,081	46.9
2001	7,493	1.952	4,429	329.7	27,384	1.556	68,282	83.7	2,203	2.933	2,737	36.7	3,507	1.489	22,420	20.4	3,145	2.488	16,024	47.4

Table 8: Data – sector GDP, capital stock, labour and deflator data

Integration properties of production function data

Unit-root test					
Variable, first differences of:	**Identifier (of level variable)**	**Depreciation rate**	**ADF-test with**	**Lag (0)**	**Lag (1)**
GDP	Y		Const	-2.683	-3.877**
Capital	K1	4%	Const	-1.944	-2.455
			Const and trend	-2.147	-3.881*
	K2		Const	-2.257	-3.207*
			Const and trend	-2.321	-3.647*
	K1	7%	Const	-2.071	-2.490
			Const and trend	-1.822	-4.076*
	K2		Const	-2.310	-3.130*
			Const and trend	-1.828	-4.180*
	K1	10%	Const	-2.252	-2.601
			Const and trend	-2.105	-3.877*
	K2		Const	-2.426	-3.162*
			Const and trend	-2.293	-3.999*
Labour (in levels)	L		Const	-8.676**	-3.454*
			Const and trend	-2.710	-2.351
	LH1		Const	-5.597**	-1.324
			Const and trend	-3.361	-2.145
	LH2		Const	-4.672**	-2.237
			Const and trend	-0.362	-1.344

Table 9: Unit-root tests of GDP, capital and labour

The critical values are -3.01 (*) and -3.79 (**) at the 95% and 99% confidence levels for regressions including a constant, and -3.69 (*) and -4.57 (**) for regressions with a constant and trend.

Potential output estimations

Test for breaks in linear trend in GDP

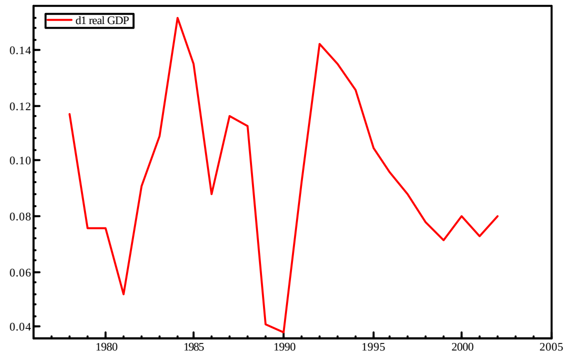

Figure 16: Annual real growth of GDP

Figure 16 shows annual real growth of GDP. The graph displays a large decrease in real growth in 1989/90, plus a rather linear decline in the growth rate after 1992. This graph raises the question of whether we want to allow for split trends, be it in the simple linear trend estimation or in the production function estimations. Figure 17 shows graphically the results from Chow Tests for breaks in the GDP series when regressed on a linear trend and a constant only. Each of the six figures below show in the top left corner the emerging trend coefficient with two standard error intervals from a recursive estimation. The remaining three graphs show clock-wise from the top right to the bottom left single and multiple Chow tests. The critical level is indicated for each Chow test with a vertical line. The one percent probability line is shown in each of the Chow test graphs. If it is surpassed, the test of a break has failed. Only aggregate GDP shows a significant break in the trend in 1981, while sector data does not seem to suffer from a break in trend during 1978-2002.

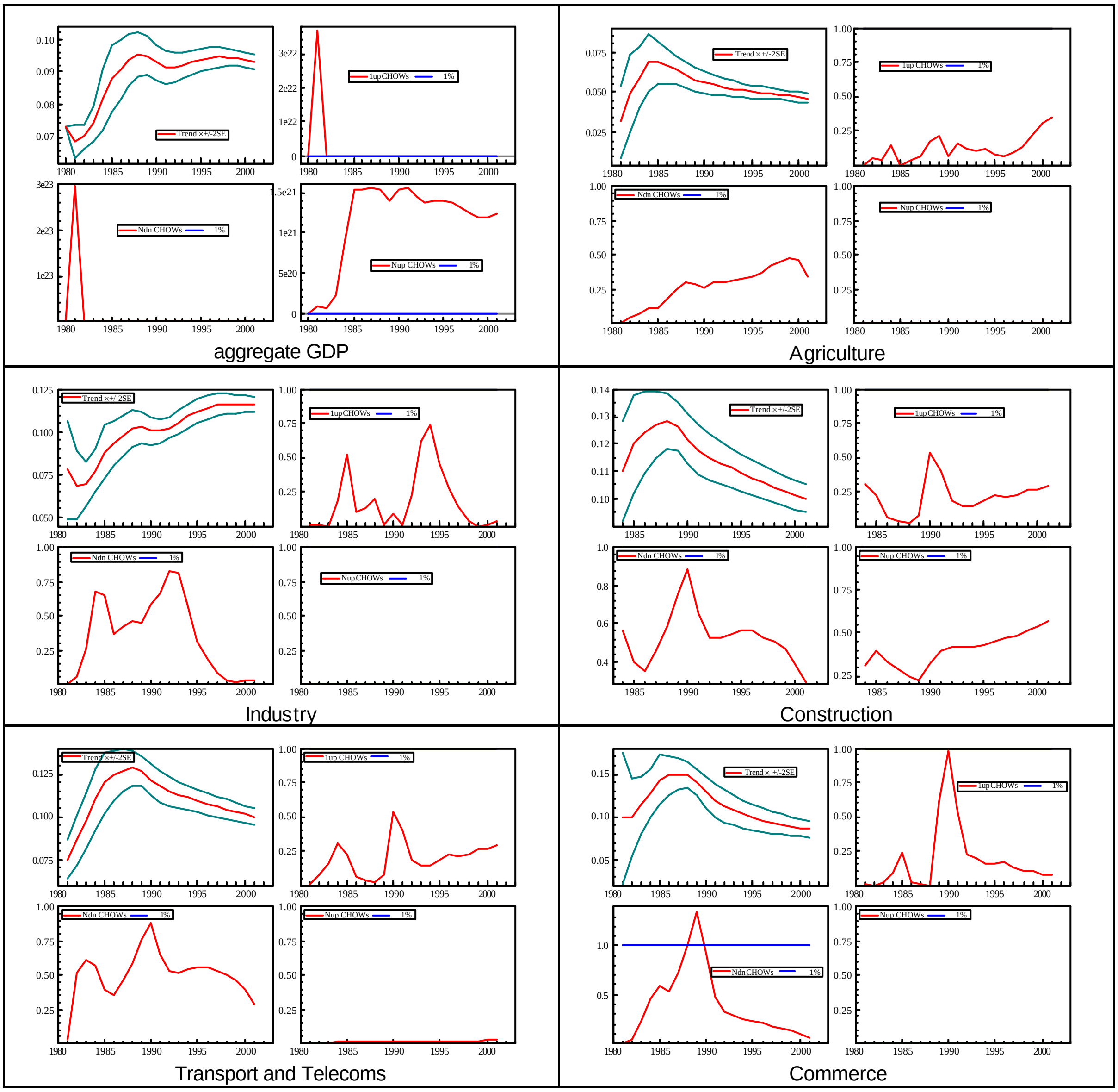

Figure 17: Chow test for breaks in GDP trend

Figure 18 displays the effect of including different trends into the growth regression. For the regressions, we use the Cobb-Douglas production functions with imposed constant returns to scale. The factors of production are thee variables $L*H_1$ and K_2, both of which are explained in the main text. We have experimented with four different trends, and their combinations: 1978-85, 1978-88, 1992-2001 and 1995-2001.

The selection of multiple trends in the production function estimation (equation (4)) can have a large impact on the coefficient of the capital/labour ratio. This is further evidence in favour of a dynamic production function specification where the coefficients are robust to the inclusion of trends. In order to avoid arbitrary output gap truncation we include a single trend only in the regression analysis. Figure 18 illustrates the point.

Selection of trends for growth regressions

Input variables:
Capital: K_1, 7% annual depreciation
Labour: Aggregate labour L

The regressions are constrained (constant returns to scale) Cobb-Douglas. The trends included in the respective regressions are stated above each figure.

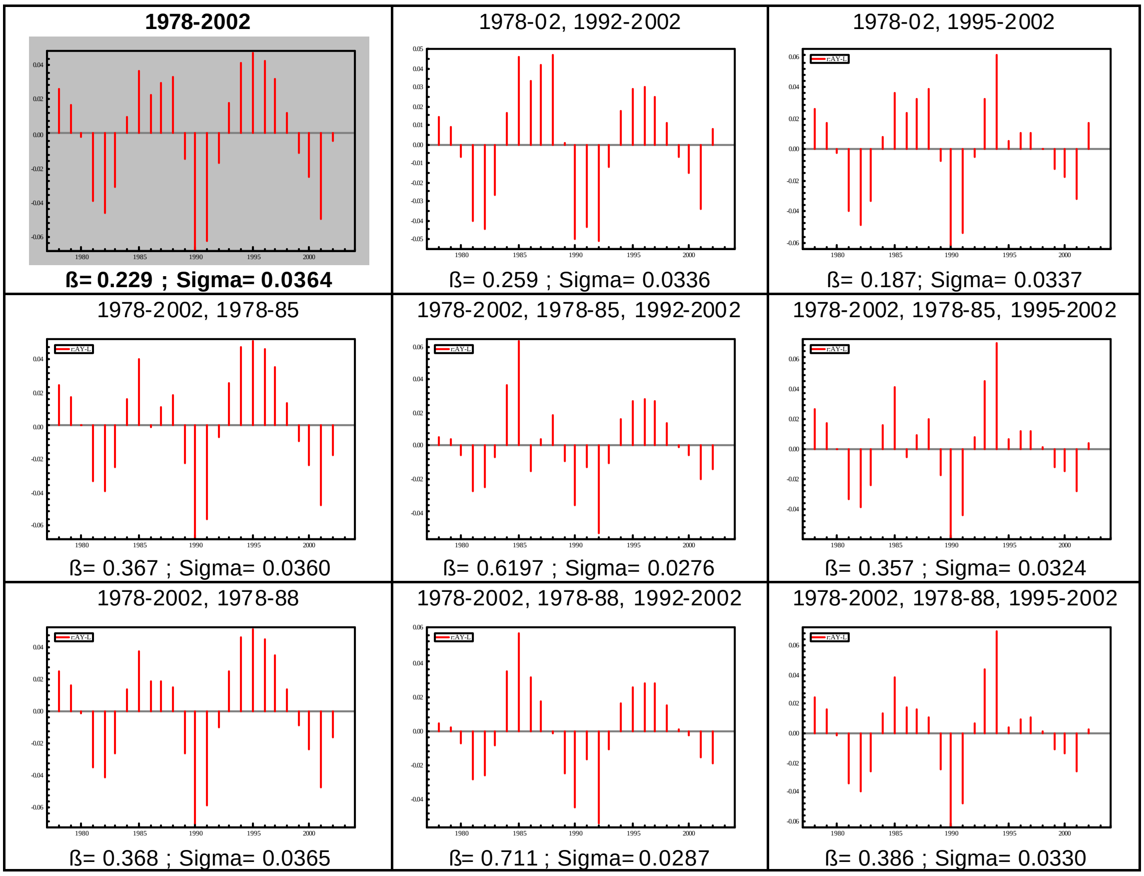

Figure 18: Selection of trends in growth regressions

Aggregate regressions results – static CD production function

Dependent variable: Y/L (t) , estimation period: 1978-2002 (25 observations)

Depreciation rate	Labour variable	Capital variable	K/L (t)		Trend 78-02		R-sqr	Sigma	log-L	Diagnostic tests
4%	L	K1	0.271	**	0.057	**	0.995	3.88%	47.34	AR**, RESET**
			0.071		*0.004*					
4%	L	K2	0.403	**	0.043	**	0.995	3.80%	47.89	AR**, RESET*
			0.100		*0.008*					
4%	LH1	K1	0.316	**	0.048	**	0.992	4.32%	44.67	AR**, RESET**
			0.076		*0.004*					
4%	LH1	K2	0.469	**	0.033	**	0.993	4.16%	45.64	AR**, RESET**
			0.104		*0.007*					
4%	LH2	K1	0.371	**	0.042	**	0.992	4.17%	45.54	AR**, RESET**
			0.067		*0.003*					
4%	LH2	K2	0.519	**	0.027	**	0.992	3.95%	45.91	AR**, RESET**
			0.086		*0.005*					
7%	L	K1	0.218	**	0.061	**	0.995	3.84%	47.62	AR**, RESET**
			0.056		*0.003*					
7%	L	K2	0.312	**	0.051	**	0.996	3.74%	48.27	AR**, RESET**
			0.075		*0.005*					
7%	LH1	K1	0.253	**	0.053	**	0.993	4.29%	44.83	AR**, RESET**
			0.060		*0.003*					
7%	LH1	K2	0.362	**	0.042	**	0.993	4.14%	45.76	AR**, RESET**
			0.079		*0.005*					
7%	LH2	K1	0.299	**	0.047	**	0.991	4.21%	45.29	AR**, RESET**
			0.055		*0.002*					
7%	LH2	K2	0.413	**	0.036	**	0.992	4.00%	46.63	AR**, RESET**
			0.070		*0.004*					
10%	L	K1	0.184	**	0.064	**	0.995	3.79%	47.96	AR**, RESET**
			0.045		*0.003*					
10%	L	K2	0.258	**	0.056	**	0.996	3.68%	48.67	AR**, RESET**
			0.060		*0.004*					
10%	LH1	K1	0.213	**	0.055	**	0.993	4.24%	45.14	AR**, RESET**
			0.049		*0.002*					
10%	LH1	K2	0.299	**	0.047	**	0.993	4.08%	46.07	AR**, RESET**
			0.064							
10%	LH2	K1	0.252	**	0.049	**	0.991	4.25%	45.12	AR**, RESET*
			0.047		*0.002*					
10%	LH2	K2	0.344	**	0.041	**	0.992	4.03%	46.39	AR**, RESET**
			0.059		*0.003*					

**), **) indicate significance at the 90% and 95% confidence level. Standard error in italics.*

****) The null hypothesis of the diagnostioc tests is that the regression residuals are well behaved.*
Rejection of null hypothesis is indicated.

All regressions include an economically uninteresting constant.

Table 10: Regression results – static production function, aggregate data

Aggregate regressions results - static Translog production function

Dependent variable: Y/L (t) , estimation period: 1978-2002 (25 observations)

Depreciation rate	Labour variable	Capital variable	K/L (t)		(K/L)^2 (t)		Trend 78-02		R-sqr	Sigma	log-L	Diagnostic tests
4%	L	K1	0.616	** -	0.243	**	0.039	**	0.997	3.19%	52.84	AR**, ARCH*
			0.117		*0.071*		*0.006*					
4%	L	K2	1.173	** -	0.265	** -	0.012		0.998	2.95%	54.83	AR**
			0.210		*0.061*		*0.015*					
4%	LH1	K1	0.619	** -	0.332	**	0.036	**	0.996	3.26%	52.33	AR**, ARCH*
			0.092		*0.079*		*0.004*					
4%	LH1	K2	1.127	** -	0.299	** -	0.007		0.997	2.86%	55.55	AR**
			0.149		*0.059*		*0.009*					
4%	LH2	K1	0.650	** -	0.349	**	0.033	**	0.994	3.54%	50.23	AR**, ARCH*, RESET**
			0.107		*0.113*		*0.004*					
4%	LH2	K2	1.310	** -	0.427	** -	0.016	*	0.996	2.56%	58.31	AR**, RESET*
			0.152		*0.076*		*0.008*					
7%	L	K1	0.392	** -	0.197	**	0.054	**	0.997	3.28%	52.17	AR**, ARCH*
			0.074		*0.065*		*0.004*					
7%	L	K2	0.727	** -	0.203	**	0.025	**	0.997	2.98%	54.53	AR**
			0.127		*0.055*		*0.008*					
7%	LH1	K1	0.415	** -	0.299	**	0.048	**	0.996	3.37%	51.45	AR**, ARCH*
			0.063		*0.078*		*0.003*					
7%	LH1	K2	0.722	** -	0.265	**	0.023	**	0.996	3.03%	54.11	AR**, ARCH*
			0.100		*0.059*		*0.006*					
7%	LH2	K1	0.420	** -	0.244	**	0.044	**	0.993	3.89%	57.89	AR**, ARCH*, RESET**
			0.075		*0.111*		*0.002*					
7%	LH2	K2	0.798	** -	0.317	**	0.018	**	0.995	3.20%	52.74	AR**, ARCH*, RESET**
			0.120		*0.087*		*0.006*					
10%	L	K1	0.280	** -	0.163	**	0.061	**	0.997	3.33%	51.75	AR**, ARCH*
			0.053		*0.060*		*0.002*					
10%	L	K2	0.483	** -	0.162	**	0.043	**	0.997	3.09%	53.63	AR**, ARCH*
			0.087		*0.051*		*0.005*					
10%	LH1	K1	0.307	** -	0.266	**	0.054	**	0.995	3.45%	50.90	AR**
			0.048		*0.076*		*0.002*					
10%	LH1	K2	0.505	** -	0.228	**	0.038	**	0.996	3.17%	53.03	AR**, ARCH*
			0.072		*0.057*		*0.004*					
10%	LH2	K1	0.312	** -	0.182	*	0.049	**	0.992	4.07%	46.75	AR**, ARCH*, Hetero**
			0.057		*0.100*		*0.020*					
10%	LH2	K2	0.518	** -	0.206	**	0.034	**	0.994	3.67%	49.35	AR**, ARCH*, RESET**
			0.091		*0.087*		*0.004*					

**), **) indicate significance at the 90% and 95% confidence level. Standard error in italics.*

****) The null hypothesis of the diagnostioc tests is that the regression residuals are well behaved. Rejection of null hypothesis is indicated.*

All regressions include an economically uninteresting constant.

Table 11: Regression results – static Translog production function, aggregate data

Time-varying share of capital from Translog production function

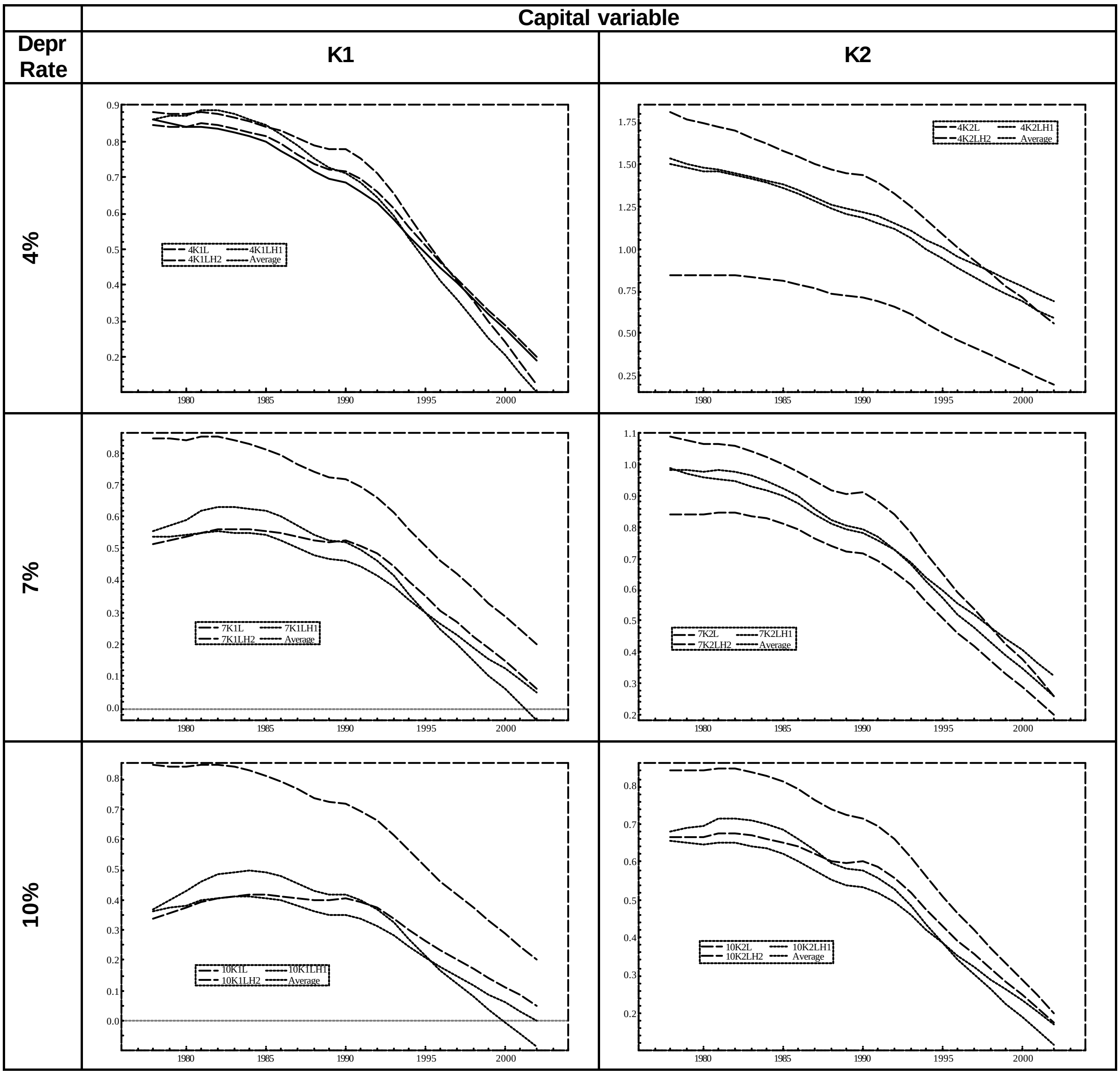

Figure 19: Capital share from Translog production function – aggregate data

Aggregate regressions results – dynamic CD production function

Dependent variable: d Y/L (t) , estimation period: 1980-2002 (23 observations)

Depreciation rate	Labour variable	Capital variable	LR-Beta	d Y/L (t-1)		d K/L (t)		Y/L (t-1)		K/L (t-1)		Trend		R-sqr	Sigma	Diagnostic tests***
4%	L	K1	**0.246**	0.452	**	1.295	**	- 0.569	**	0.140	**	0.029	**	0.828	1.39%	RESET*
				0.158		*0.335*		*0.099*		*0.049*		*0.006*				
4%	L	K2	**0.281**	0.441	**	1.241	**	- 0.582	**	0.163	**	0.028	**	0.838	1.37%	--
				0.157		*0.301*		*0.104*		*0.071*		*0.005*				
4%	LH1	K1	**0.347**	0.367	**	1.564	**	- 0.550	**	0.191	**	0.020	**	0.870	1.31%	--
				0.146		*0.331*		*0.088*		*0.191*		*0.004*				
4%	LH1	K2	**0.394**	0.372	**	1.449	**	- 0.565	**	0.222	**	0.019	**	0.872	1.30%	--
				0.147		*0.295*		*0.097*		*0.078*		*0.004*				
4%	LH2	K1	**0.284**	0.358	**	1.266	**	- 0.403	**	0.115	**	0.014	**	0.850	1.53%	RESET**
				0.158		*0.299*		*0.096*		*0.048*		*0.005*				
4%	LH2	K2	**0.340**	0.357	**	1.264	**	- 0.450	**	0.153	**	0.014	**	0.871	1.42%	RESET**
				0.147		*0.256*		*0.097*		*0.067*		*0.004*				
7%	L	K1	**0.230**	0.432	**	1.125	**	- 0.577	**	0.133	**	0.030	**	0.834	1.37%	RESET*
				0.158		*0.290*		*0.097*		*0.040*		*0.006*				
7%	L	K2	**0.283**	0.425	**	1.094	**	- 0.590	**	0.167	**	0.029	**	0.844	1.32%	--
				0.156		*0.259*		*0.101*		*0.055*		*0.005*				
7%	LH1	K1	**0.304**	0.363	**	1.321	**	- 0.558	**	0.169	**	0.022	**	0.870	1.31%	--
				0.147		*0.281*		*0.089*		*0.044*		*0.005*				
7%	LH1	K2	**0.342**	0.365	**	1.241	**	- 0.567	**	0.194	**	0.021	**	0.872	1.30%	--
				0.149		*0.256*		*0.096*		*0.061*		*0.004*				
7%	LH2	K1	**0.286**	0.337	**	1.163	**	- 0.422	**	0.121	**	0.015	**	0.849	1.53%	RESET**
				0.161		*0.275*		*0.093*		*0.038*		*0.005*				
7%	LH2	K2	**0.328**	0.321	**	1.191	**	- 0.460	**	0.151	**	0.015	**	0.872	1.41%	RESET**
				0.150		*0.239*		*0.093*		*0.052*		*0.004*				
10%	L	K1	**0.222**	0.421	**	0.971	**	- 0.581	**	0.129	**	0.031	**	0.836	1.36%	RESET*
				0.159		*0.247*		*0.097*		*0.036*		*0.006*				
10%	L	K2	**0.252**	0.408	**	0.961	**	- 0.590	**	0.149	**	0.030	**	0.847	1.31%	--
				0.157		*0.224*		*0.101*		*0.046*		*0.006*				
10%	LH1	K1	**0.280**	0.367	**	1.116	**	- 0.563	**	0.158	**	0.024	**	0.868	1.32%	--
				0.150		*0.242*		*0.090*		*0.039*		*0.005*				
10%	LH1	K2	**0.314**	0.366	**	1.066	**	- 0.570	**	0.179	**	0.023	**	0.870	1.31%	--
				0.152		*0.224*		*0.097*		*0.052*		*0.005*				
10%	LH2	K1	**0.290**	0.328	*	1.047	**	- 0.440	**	0.127	**	0.015	**	0.844	1.56%	RESET**
				0.165		*0.253*		*0.092*		*0.034*		*0.005*				
10%	LH2	K2	**0.329**	0.305	*	1.093	**	- 0.475	**	0.156	**	0.016	**	0.869	1.43%	RESET**
				0.153		*0.221*		*0.092*		*0.043*		*0.004*				

**), **) indicate significance at the 90% and 95% confidence level. Standard error in italics.*

****) The null hypothesis of the diagnostioc tests is that the regression residuals are well behaved. Rejection of null hypothesis is indicated.*

All regressions include an economically uninteresting constant.

Averages of LR-beta	**4% depr**	**7% depr**	**10% depr**
	0.315	0.296	0.281
	L	**LH1**	**LH2**
	0.252	0.330	0.309
	K1	**K2**	**Overall**
	0.276	0.318	**0.297**

Table 12: Regression results – dynamic CD production function, aggregate data

Sector regression results – static CD production function

Dependent variable: Y/L (t) , estimation period: 1978-2001 (24 observations)

Sector	Labour variable		K/L (t)		Trend 78-01		R-sqr	Sigma	log-L	Diagnostic tests
Agriculture	L		0.036		0.038	**	0.980	4.20%	43.63	AR**
			0.115		*0.004*					
Agriculture	LH1		0.000		0.031	**	0.965	4.34%	42.87	AR**
			0.125		*0.003*					
Agriculture	LH2		0.275	**	0.021	**	0.931	5.04%	39.28	AR**, Heterosk**
			0.111		*0.002*					
Industry	L		0.996	**	0.042	**	0.992	6.52%	33.06	AR**
			0.105		*0.006*					
Industry	LH1		1.022	**	0.041	**	0.990	6.52%	33.08	AR**
			0.103		*0.005*					
Industry	LH2		1.010	**	0.042	**	0.988	6.52%	33.06	AR**
			0.095		*0.004*					
Construction	L		0.344	**	0.038	**	0.967	5.21%	38.47	AR**, ARCH*, Heterosk*
			0.058		*0.002*					
Construction	LH1		0.356	**	0.032	**	0.938	5.64%	36.57	AR**, Heterosk**
			0.062		*0.002*					
Construction	LH2		0.381	**	0.029		0.942	4.48%	42.07	AR**, Heterosk*
			0.046		*0.002*					
TandT	L		0.358	**	0.038	**	0.991	3.65%	47.01	--
			0.281		*0.002*					
TandT	LH1		0.367	**	0.032	**	0.986	4.13%	44.04	Heterosk*
			0.032		*0.002*					
TandT	LH2		0.388	**	0.028	**	0.990	3.09%	51.03	Normality*
			0.023		*0.001*					
Commerce	L	-	0.328		0.016	**	0.666	11.04%	20.44	AR**, RESET**
			0.238		*0.004*					
Commerce	LH1	-	0.225		0.013	**	0.670	8.38%	27.64	AR*
			0.187		*0.005*					
Commerce	LH2	-	0.087		0.003	**	0.117	11.87%	18.69	AR**,RESET**
			0.221		*0.007*					
Tert. Sector	L		0.336	**	0.034	**	0.985	4.07%	44.36	AR**, ARCH*, Heterosk*
			0.030		*0.001*					
Tert. Sector	LH1		0.359	**	0.027	**	0.971	4.75%	40.67	AR**, Heterosk**
			0.035		*0.002*					
Tert. Sector	LH2		0.360	**	0.024	**	0.981	3.22%	49.99	AR*, Heterosk*
			0.023		*0.001*					

**), **) indicate significance at the 90% and 95% confidence level. Standard error in italics.*
****) The null hypothesis of the diagnostioc tests is that the regression residuals are well behaved.*
Rejection of null hypothesis is indicated.
All regressions include an economically uninteresting constant.

Table 13: Regression results – static production function, sector data

Sector regression results – static Translog production function

Dependent variable: Y/L (t) , estimation period: 1978-2001 (24 observations)

Sector	Labour variable	K/L (t)		(K/L)^2 (t)		Trend 78-01		R-sqr	Sigma	log-L	Diagnostic tests
Agriculture	L	0.100		- 0.307		0.039	**	0.981	4.14%	44.58	AR**
		0.087		*0.345*		*0.001*					
Agriculture	LH1	0.052		- 0.508		0.031	**	0.966	4.40%	43.11	AR**, Hetero*,
		0.100		*1.003*		*0.001*					
Agriculture	LH2	0.246	**	- 0.071		0.026	**	0.936	4.94%	40.32	AR**
		0.087		*0.961*		*0.002*					
Industry	L	1.033	**	- 0.034		0.041	**	0.992	6.68%	33.08	AR**, RESET**
		0.228		*0.186*		*0.010*					
Industry	LH1	1.185	**	- 0.219		0.036	**	0.990	6.50%	33.72	AR*, RESET**
		0.187		*0.210*		*0.007*					
Industry	LH2	1.236	**	- 0.360		0.037	**	0.989	6.40%	34.12	RESET**
		0.191		*0.265*		*0.005*					
Construction	L	0.331	**	0.619		0.038	**	0.969	5.12%	39.48	AR*, Hetero*
		0.058		*0.466*		*0.002*					
Construction	LH1	0.338	**	0.920	**	0.034	**	0.952	5.08%	39.67	Hetero*
		0.057		*0.379*		*0.002*					
Construction	LH2	0.374	**	0.435	*	0.030	**	0.952	4.18%	44.31	Hetero*, RESET*
		0.043		*0.214*		*0.002*					
TandT	L	0.381	**	- 0.045		0.038	**	0.992	3.68%	47.41	--
		0.039		*0.055*		*0.002*					
TandT	LH1	0.395	**	- 0.079		0.325	**	0.986	4.11%	44.73	--
		0.041		*0.073*		*0.002*					
TandT	LH2	0.392	**	- 0.012		0.028	**	0.990	3.16%	51.05	Norm*
		0.029		*0.060*		*0.001*					
Commerce	L	0.100		- 6.344	**	0.013	**	0.810	8.53%	27.22	--
		0.214		*1.627*		*0.004*					
Commerce	LH1	0.238		- 4.308	**	0.005		0.823	6.13%	35.13	RESET*
		0.165		*0.671*		*0.003*					
Commerce	LH2	0.459	**	- 3.416	**	0.006	*	0.824	5.44%	38.01	--
		0.118		*0.382*		*0.003*					
Tert. Sector	L	0.364	**	- 0.102		0.035	**	0.986	4.01%	45.34	AR**
		0.037		*0.077*		*0.002*					
Tert. Sector	LH1	0.383	**	- 0.132		0.028	**	0.972	4.71%	41.46	AR**, Hetero*
		0.040		*0.110*		*0.002*					
Tert. Sector	LH2	0.352	**	0.019		0.023	**	0.981	0.03%	50.02	AR*, Hetero*
		0.027		*0.090*		*0.001*					

**), **) indicate significance at the 90% and 95% confidence level. Standard error in italics.*
****) The null hypothesis of the diagnostioc tests is that the regression residuals are well behaved.*
Rejection of null hypothesis is indicated.
All regressions include an economically uninteresting constant.

Table 14: Regression results – static Translog production function, sector data

Time-varying share of capital from Translog production function

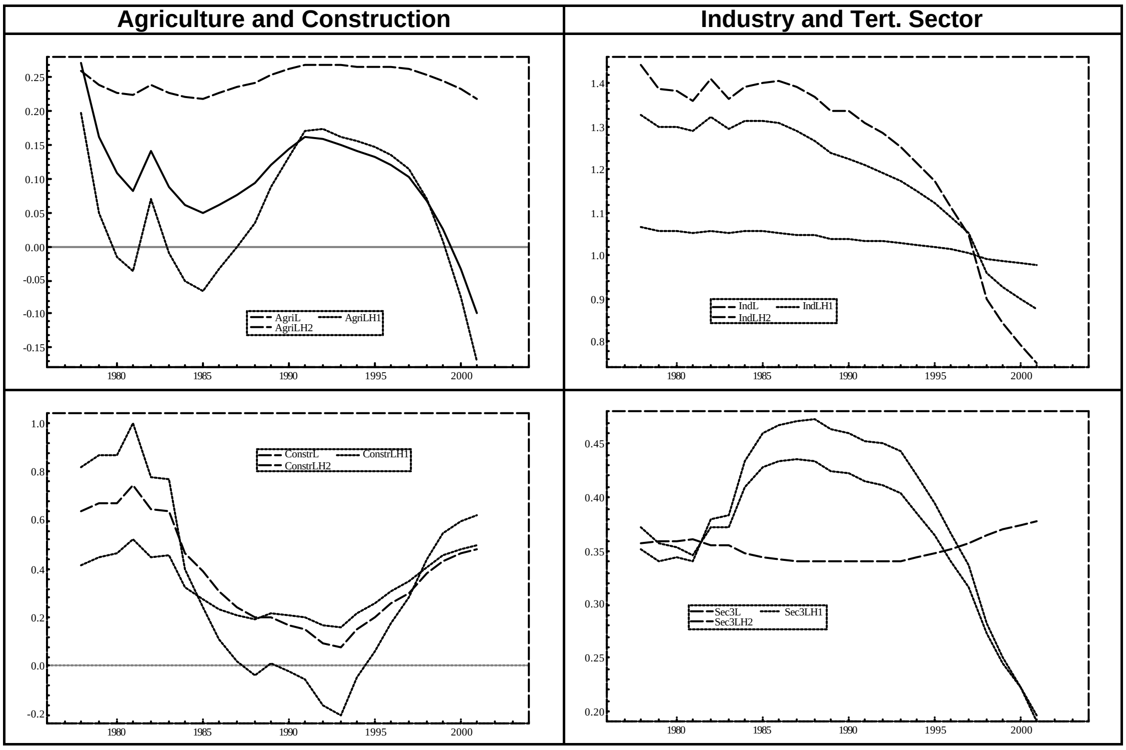

Figure 20: Capital share from Translog production function – sector data

CD vs Translog: likelihood ratio tests

Aggregate data							Sector data					
			LogLikelihood						LogLikelihood			
Depreciation rate	Labour variable	Capital variable	CD	Translog	Likelihood ratio test statistic		Sector	Labour variable	CD	Translog	Likelihood ratio test statistic	
4%	L	K1	47.34	52.84	**11.01**	**	Agriculture	L	43.63	44.58	**1.91**	
4%	L	K2	47.89	54.83	**13.88**	**	Agriculture	LH1	42.87	43.11	**0.48**	
4%	LH1	K1	44.67	52.33	**15.31**	**	Agriculture	LH2	39.28	40.32	**2.09**	
4%	LH1	K2	45.64	55.55	**19.82**	**	Industry	L	33.06	33.08	**0.04**	
4%	LH2	K1	45.54	50.23	**9.38**	**	Industry	LH1	33.08	33.72	**1.27**	
4%	LH2	K2	45.91	58.31	**24.80**	**	Industry	LH2	33.06	34.12	**2.12**	
7%	L	K1	47.62	52.17	**9.10**	**	Construction	L	38.47	39.48	**2.03**	
7%	L	K2	48.27	54.53	**12.52**	**	Construction	LH1	36.57	39.67	**6.19**	**
7%	LH1	K1	44.83	51.45	**13.24**	**	Construction	LH2	42.07	44.31	**4.49**	**
7%	LH1	K2	45.76	54.11	**16.69**	**	TandT	L	47.01	47.41	**0.79**	
7%	LH2	K1	45.29	57.89	**25.21**	**	TandT	LH1	44.04	44.73	**1.38**	
7%	LH2	K2	46.63	52.74	**12.23**	**	TandT	LH2	51.03	51.05	**0.04**	
10%	L	K1	47.96	51.75	**7.58**	**	Commerce	L	20.44	27.22	**13.57**	**
10%	L	K2	48.67	53.63	**9.91**	**	Commerce	LH1	27.64	35.13	**14.98**	**
10%	LH1	K1	45.14	50.90	**11.52**	**	Commerce	LH2	18.69	38.01	**38.65**	**
10%	LH1	K2	46.07	53.03	**13.92**	**	Tert. Sector	L	44.36	45.34	**1.97**	
10%	LH2	K1	45.12	46.75	**3.25**	*	Tert. Sector	LH1	40.67	41.46	**1.59**	
10%	LH2	K2	46.39	49.35	**5.92**	**	Tert. Sector	LH2	49.99	50.02	**0.05**	

Critical values: 3.81 (**) and 2.71 (*) for the 95% and 90% confidence level respectively, with one restriction

Table 15: Likelihood ratio test: Translog versus CD production function

Sector regression results – dynamic production function

Dependent variable: d Y/L (t) , estimation period: 1980-2002 (23 observations)

Sector	Labour variable	LR-Beta	d Y/L (t-1)	d K/L (t)	Y/L (t-1)	K/L (t-1)	Trend	land affected****	R-sqr	Sigma	Diagnostic tests***
Agriculture	L	**0.131**	0.350 *	-	- 0.365 **	0.048	0.016 **	- 0.717 **	0.526	2.70%	--
			0.190		*0.161*	*0.102*	*0.006*	*0.255*			
Agriculture	LH1	**0.055**	0.451 **	-	- 0.422 **	0.023	0.015 **	- 0.700 **	0.595	2.55%	--
			0.183		*0.154*	*0.098*	*0.005*	*0.241*			
Agriculture	LH2	**0.369**	0.548 **	-	- 0.420 **	0.155 *	0.011 **	- 0.729 **	0.626	2.66%	--
			0.167		*0.133*	*0.090*	*0.003*	*0.247*			
Industry	L	**0.571**	0.251	0.502 *	- 0.278	0.159	0.020 **		0.605	3.99%	RESET*
			0.241	*0.245*	*0.190*	*0.217*	*0.008*				
Industry	LH1	**0.564**	0.243	0.506 *	- 0.275	0.155	0.018 **		0.621	4.03%	RESET*
			0.240	*0.252*	*0.195*	*0.226*	*0.008*				
Industry	LH2	**0.753**	0.370	0.672 **	- 0.381 *	0.286	0.020 **		0.647	4.08%	--
			0.224	*0.246*	*0.198*	*0.212*	*0.008*				
Construction	L	**0.250**	0.463 **	0.432 **	- 0.521 **	0.130 **	0.019 **		0.729	2.71%	--
			0.153	*0.095*	*0.140*	*0.057*	*0.005*				
Construction	LH1	**0.250**	0.461 **	0.450 **	- 0.499 **	0.125 **	0.015 **		0.739	2.65%	--
			0.151	*0.098*	*0.131*	*0.554*	*0.004*				
Construction	LH2	**0.319**	0.400 **	0.427 **	- 0.645 **	0.206 **	0.018 **		0.734	2.66%	--
			0.161	*0.093*	*0.168*	*0.070*	*0.005*				
T&T	L	**0.299**	--	0.425 **	- 0.599 **	0.179 **	0.024 **		0.665	2.76%	--
				0.123	*0.199*	*0.073*	*0.007*				
T&T	LH1	**0.289**	--	0.421 **	- 0.550 **	0.159 **	0.019 **		0.683	2.78%	--
				0.137	*0.184*	*0.070*	*0.005*				
T&T	LH2	**0.356**	--	0.453 **	- 0.795 **	0.283 **	0.023 **		0.733	2.55%	--
				0.115	*0.220*	*0.085*	*0.006*				
								trend 78-88			
Commerce	L	**1.204**	--	0.318	- 0.215	0.259	0.015 **	0.021 **	0.649	5.14%	--
				0.268	*0.136*	*0.170*	*0.004*	*0.004*			
Commerce	LH1	**0.675**	--	--	- 0.265 *	0.179	0.015 **	0.020 **	0.631	5.27%	--
					0.145	*0.176*	*0.005*	*0.005*			
Commerce	LH2	**0.453**	--	0.399	- 0.342 **	0.155	0.012 **	0.019 **	0.620	5.28%	--
				0.267	*0.125*	*0.121*	*0.004*	*0.005*			
Tert. Sector	L	**0.257**	0.482 **	0.301 **	- 0.493 **	0.127 **	0.017 **		0.797	2.12%	--
			0.162	*0.084*	*0.143*	*0.051*	*0.004*				
Tert. Sector	LH1	**0.260**	0.452 **	0.325 **	- 0.441 **	0.115 **	0.012 **		0.817	2.11%	--
			0.161	*0.087*	*0.130*	*0.048*	*0.004*				
Tert. Sector	LH2	**0.324**	0.462 **	0.248 **	- 0.912 **	0.296 **	0.020 **		0.850	0.02%	--
			0.158	*0.072*	*0.196*	*0.070*	*0.004*				

**), **) indicate significance at the 90% and 95% confidence level. Standard error in italics.*
****) The null hypothesis of the diagnostioc tests is that the regression residuals are well behaved. Rejection of null hypothesis is indicated.*
*****) variable specific to agriculture: land affected by natural destaster/total agricultural land*
All regressions include an economically uninteresting constant.

Table 16: Regression results – dynamic production function, sector data

Correlation of output gap estimates

Quarterly output gaps:

	y-gap Lin	y-gap HP	*Average CD*	*Median CD*	*Average Translog*	*Sector Av (5)*	*Sec Av (3+1)*	*GA aggr fixed TFP*
y-gap Lin	1.00							
y-gap HP	0.83	1.00						
Average CD	0.90	0.82	1.00					
Median CD	0.89	0.82	1.00	1.00				
Average Translog	0.87	0.85	0.91	0.89	1.00			
Sector Av (5)	0.58	0.53	0.84	0.83	0.78	1.00		
Sec Av (3+1)	0.49	0.46	0.79	0.79	0.63	0.96	1.00	
GA aggr fixed TFP	0.87	0.74	0.90	0.89	0.84	0.74	0.72	1.00
GA aggr flex TFP	0.93	0.81	0.95	0.94	0.92	0.77	0.71	0.98

Table 17: Correlation of quarterly output gap estimates

Factor contribution to growth

Depreciation	4%						7%						10%					
Capital	K1			K2			K1			K2			K1			K2		
Labour	L	LH1	LH2	L	LH1	LH2	L	LH1	LH2	L	LH1	LH2	L	LH1	LH2	L	LH1	LH2
Capital																		
1980-88	16%	23%	18%	27%	38%	33%	11%	14%	13%	23%	27%	26%	6%	8%	8%	16%	20%	21%
1989-1992	30%	43%	35%	42%	58%	50%	24%	32%	30%	37%	44%	43%	20%	26%	27%	29%	36%	38%
1992-2002	27%	39%	32%	33%	47%	40%	26%	34%	32%	34%	41%	39%	26%	32%	34%	30%	38%	40%
Labour																		
1980-88	26%	34%	38%	25%	32%	35%	27%	36%	38%	25%	34%	36%	27%	37%	38%	26%	36%	36%
1989-1992	32%	38%	71%	31%	35%	66%	33%	40%	71%	31%	38%	67%	33%	41%	71%	32%	39%	67%
1992-2002	9%	15%	15%	9%	14%	14%	10%	16%	15%	9%	15%	14%	10%	16%	15%	9%	16%	14%
TFP																		
1980-88	58%	44%	43%	48%	31%	32%	62%	50%	49%	52%	39%	38%	66%	55%	54%	58%	44%	43%
1989-1992	37%	20%	-7%	28%	7%	-16%	43%	28%	-1%	33%	18%	-10%	46%	33%	3%	39%	25%	-5%
1992-2002	63%	46%	54%	58%	39%	46%	65%	50%	53%	57%	44%	47%	65%	51%	52%	60%	47%	47%

Table 18: Contribution to growth in post-reform China (own estimates): aggregate data

Sector	Agriculture			Industry			Construction			T&T			Commerce			Tert. Sector		
Labour	L	LH1	LH2	L	LH1	LH2	L	LH1	LH2	L	LH1	LH2	L	LH1	LH2	L	LH1	LH2
Capital																		
1980-88	-2%	-1%	-3%	58%	57%	76%	18%	18%	23%	28%	27%	33%	-23%	-26%	-17%	19%	19%	23%
1989-1992	-4%	-2%	-7%	71%	70%	94%	-1%	-1%	-2%	17%	17%	20%	4%	5%	3%	14%	14%	17%
1992-2002	17%	7%	32%	38%	38%	51%	25%	25%	32%	46%	44%	55%	53%	59%	40%	39%	40%	50%
Labour																		
1980-88	13%	22%	32%	25%	36%	19%	64%	75%	69%	62%	80%	70%	-7%	-8%	-10%	62%	77%	68%
1989-1992	68%	95%	104%	13%	19%	21%	-6%	7%	42%	17%	24%	40%	8%	6%	-4%	1%	10%	35%
1992-2002	-12%	12%	5%	-6%	-3%	-2%	32%	40%	35%	16%	23%	20%	26%	25%	42%	25%	32%	28%
TFP																		
1980-88	88%	79%	71%	17%	7%	4%	18%	7%	8%	10%	-7%	-4%	130%	133%	128%	19%	4%	9%
1989-1992	36%	7%	4%	16%	11%	-14%	107%	94%	60%	66%	59%	40%	87%	89%	100%	85%	76%	48%
1992-2002	95%	81%	62%	68%	65%	51%	43%	34%	32%	38%	32%	25%	21%	16%	19%	36%	28%	22%

Table 19: Contribution to growth in post-reform China (own estimates): sector data