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Declan Curran and Michael Funke

Taking the temperature

– forecasting GDP growth for mainland China

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Abstract

We present a new composite leading indicator of economic activity in mainland China, estimated using a dynamic factor model. Our leading indicator is constructed from three series: exports, a real estate climate index, and the Shanghai Stock Exchange index. These series are found to share a common, unobservable element from which our indicator can be identified. This indicator is then incorporated into out-of-sample one-step-ahead forecasts of Chinese GDP growth. Recursive out-of-sample accuracy tests indicate that the small-scale factor model approach leads to a successful representation of the sample data and provides an appropriate tool for forecasting Chinese business conditions.

Keywords: Forecasting, China, Leading Indicator, Factor Model, Growth Cycles
JEL-Classification: C32, C52, E32, E37

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The usual disclaimer applies.

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Tiivistelmä

Tässä tutkimuksessa esitellään uusi Manner-Kiinan taloutta kuvaava ennakoiva suhdanneindikaattori. Indikaattori estimoidaan dynaamisen faktorimallin avulla, ja se koostuu viennistä, kiinteistömarkkinoiden luottamusindeksistä ja Shanghain pörssin hintaindeksistä. Näillä aikasarjoilla on yhteinen, havaitsematon elementti, jonka avulla indikaattori voidaan identifioida. Tämän indikaattorin avulla voidaan muodostaa Kiinan BKT:n kasvua koskevia yhden neljänneksen ennusteita. Rekursiivisten testien perusteella indikaattori edustaa hyvin sen estimointiin käytettyä dataa, ja sitä voidaan käyttää Kiinan suhdannevaihteluiden ennakoimisessa.

Asiasanat: ennustaminen, Kiina, ennakoiva indikaattori, faktorimalli, kasvusyklit

1 Introduction

Over the past decades, China's economic performance has been nothing short of sensational, and, as a consequence, its role in the world economy has increased dramatically. This is reflected in the phenomenal growth of China's GDP, which has risen at an average annual growth rate of 8.4 percent over the last decade. In 2004, its share in PPP-valued world GDP reached 13.2 percent.[1] This remarkable growth is not confined solely to the domestic economy: China overtook Japan in 2005 as the world's third largest exporter after a surge in demand for its electronic goods led to a 35 percent jump in the country's overseas sales.[2] The Chinese economy also managed to steer clear of the severe macroeconomic instability that afflicted many of its Asian neighbors in the late 1990s. Given these developments, the need for timely estimates of Chinese economic activity has become all the more acute. Yet, despite China's importance for the world economy, the number of studies developing and investigating leading indicators of economic activity in China is surprisingly scant.[3]

Despite the dearth of reliable forecasting methods emanating from the forecasting fraternity, Marcellino (2005) suggest reliable and accurate forecasting may be possible by constructing coincident and leading indicators through estimation of a common factor model. One has to wonder, however, if this approach, based on the methodology developed by Stock and Watson (1989, 1991, 1993), is sufficiently broad to assess an economy as dynamic as China's or sufficiently nuanced to capture economic conditions particular to China. As we illustrate in Section 2, recent Chinese economic development must be characterized as a growth cycle rather than as a traditional business cycle. The difficulty and the uncertainties arising from the transition process in China make growth cycle analysis a less-than-ideal tool for monitoring and forecasting the Chinese economy. We therefore concentrate on developing a composite leading indicator for the Chinese GDP growth rate itself to analyze *growth rate cycles*. It is our belief that, properly tailored to the attributes of

[1] See IMF (2005). The IMF (2004) examines the issue of whether the Chinese growth experience differs fundamentally from the growth experiences of Japan or the newly industrialized countries (NICs), which include Hong Kong, Singapore and Taiwan and the ASEAN-4 (Indonesia, Malaysia, the Philippines, and Thailand). The key insight is that mainland China's current growth performance is not unprecedented.
[2] "China's exports overtake those of Japan", Financial Times, April 14, 2005.
[3] Very recently, Nilsson and Brunet (2006) noted the exceptional difficulty in finding suitable composite leading indicators for China (see http://www.olis.oecd.org/olis/2006doc.nsf/LinkTo/std-doc(2006)1). The Deutsche Bank Research publishes a "China Overheating Indicator," which can be used as a leading indicator for inflation (see http://www.dbresearch.de/servlet/reweb2.ReWEB?rwkey=u1076388).

the Chinese economic climate, the calculation of a leading indicator for mainland China's growth cycles represents a potentially fruitful avenue for research.

The remainder of this paper is structured as follows. Section 2 briefly describes the nature of the available Chinese GDP data and considers GDP data revision issues, as well as presenting a chronology of Chinese growth cycles. Section 3 deals with specification and econometric issues inherent in the common factor model developed from Stock and Watson's work, and presents the empirical results. In section 4, recursive out-of-sample forecast accuracy tests are presented. In the final section, we discuss conclusions and policy issues based on our findings.

2 Chinese GDP data and the chronology of China's growth rate cycles

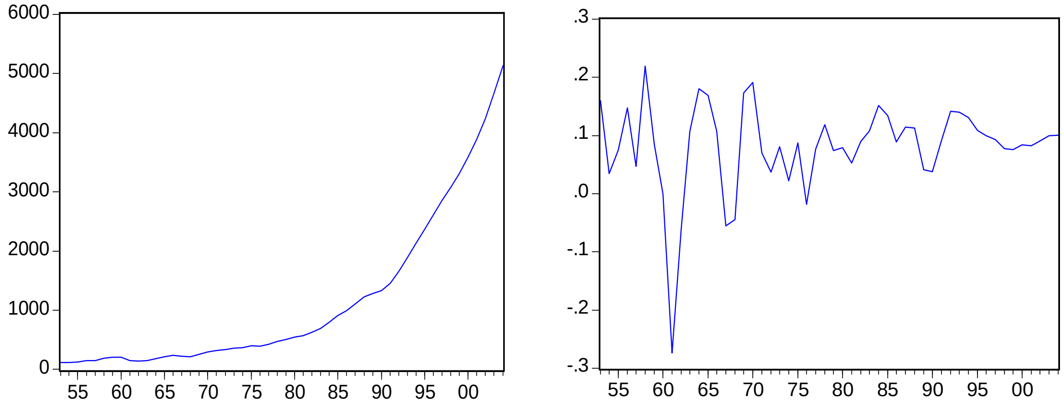
In this section, we review the main characteristics of China's GDP data to better understand the reference series, i.e. the variable the leading indicator is supposed to lead. China has only recently made the transition of its system of national accounts to universally accepted national accounting practices. Li (1997) identifies three phases in the development of China's national accounts: 1952-1984, 1985-1992, and 1992 to the present day. The first stage saw the implementation by the then State Statistical Bureau (SSB) of a Materials Production System (MPS) of accounts suited to the centrally planned economy. Instead of such terms as Gross Domestic Product, the MPS featured such aggregate indicators of economic activity as National Income and Uses of National Income. The second stage involved the co-existence of the MPS and the Standardized National Accounts (SNA) system advocated by the OECD. In 1985, the SSB began officially estimating GDP and the value added of the tertiary sector, which, prior to 1978, had been considered a "non-productive" sector. The third stage, which brings us up to the present day, has seen the SSB (now the NBS) abandon aggregate indicators such as National Income and Uses of National Income and concentrate on establishing a national accounts system compatible with the SNA. GDP estimation is beginning to internalize the principles espoused in the 1993 SNA.[4]

[4] For a detailed account of differences between existing Chinese GDP measurement techniques and 1993 SNA guidelines, see Xu (2003), who concludes that China's ongoing transition to the 1993 SNA does not detract from the international comparability of Chinese GDP estimates.

As one would expect, China's transition from a socialist production accounting method, with its neglect of items such as depreciation and "non material" services, toward an internationally recognized system of national accounts has not been without blemish. A number of idiosyncrasies have surfaced in the measurement of Chinese GDP growth, e.g. China's use of unusual methods of constructing price indices and deflating GDP that may overestimate GDP growth.[5] Wu (1997) notes vestiges of the previous national accounts system may still exist within the Chinese system, creating the possibility that unreformed fragments of the statistical data collection system at the grassroots level could contribute to GDP underreporting. Moreover, while random sampling surveys are the main component of Chinese national accounting system, elements of administrative reporting remain.[6] That said, statutory measures have been taken to address such issues. The revised Statistics Laws of 1996 safeguard this central role of random sample surveys and censuses, with administrative reports relegated to a supplementary role. Two unpublished government decrees in 1998, however, made it clear that local government interference in statistical reporting would not be tolerated. Holz (2003, pp. 157-162) notes that the NBS has also taken large strides toward improved data quality. Since the late 1990s, a restructuring of the statistical reporting system has seen the NBS improve data accuracy both by collecting higher quality data from a smaller number of enterprises and by increasing the number of enterprises that report their economic data directly to the NBS via the internet. The NBS has thus endeavored to create a core of reliable reporting from which high quality data on economic activity can be compiled.

[5] For a discussion of Chinese price indices, see Gu and Xu (1997). The NBS reports real GDP growth indices in comparable prices, as discussed by Wu (1997, p. 8).
[6] The veracity of Chinese GDP figure came under scrutiny in 1997/98 when provincial estimates exceeded the national figures compiled by the NBS; see Rawski (2002) and Holz (2003).

Figure 1. Long-run trends in annual Chinese real GDP and year-on-year real GDP growth



Real GDP index, 1953-2004 (1952=100)

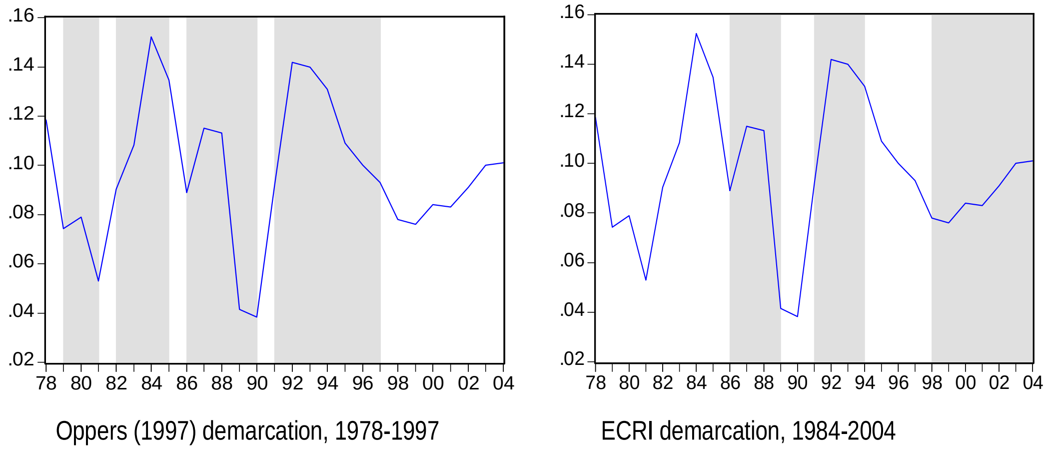
Real GDP growth, 1953-2004, in percent

Figure 1 illustrates long-run trends in both Chinese GDP and year-on-year GDP growth over the period 1953-2004. Two interesting features emerge from Figure 1: estimates of Chinese real economic activity over the 1953-2004 period display a positive trend throughout, while year-on-year growth displays a distinct cyclical pattern. This clearly indicates that the common rule of thumb that a downturn consists of at least two consecutive quarters of negative GDP growth does not apply – post-reform China has not experienced negative GDP growth. Rather than speaking of a Chinese business cycle, therefore, it is more appropriate to talk in terms of a Chinese growth cycle. Oppers (1997) has proposed a division of cycles based on the rates of GDP growth, suggesting the following demarcation: 1979 to 1981, 1982 to early 1986, mid-1986 to 1990, and 1991 onward. The cycle is assumed to start in the first year of increasing growth and end in the last year of decreasing growth.[7] Similarly, the Economic Cycle and Research Institute (ECRI) have identified a pattern of peaks and troughs over the 1983-2004 period (see Figure 2). Both appear to provide reasonable approximations of the Chinese growth cycle.[8]

[7] See Oppers (1997), p. 5.

[8] European Cycle Research Institute (2005), "Growth Rate Cycle Peak and Trough Dates, 20 countries, 1949-2004," (see www.businesscycle.com). Please note that Oppers' (1997) demarcation of the Chinese growth cycle covers the period 1979–1997, while the ECRI demarcation covers the period 1983–2004.

Figure 2. Demarcations of the Chinese growth cycle



China began calculating quarterly GDP estimates in 1992. It now publishes quarterly data approximately fifteen days after the relevant quarter.[9] However, the NBS only began benchmarking quarterly GDP to verified annual GDP in 2003. Prior to 2003, no adjustments (benchmarking, revising, or seasonal adjustments) were carried out on the quarterly data, and the data was left in its initial state [see Liu (1997) and Jin (2004)]. China's quarterly data is compiled in cumulative form and estimated using eight economic sectors: agriculture, industry, construction, transport, storage, post and telecommunication services, wholesale & retail trade and catering services, finance and insurance, real estate, and other services. The last five sectors comprise tertiary industry. While annual GDP is compiled from sources such as annual statistics reports, annual sample surveys, business accounting information, budget and financing statistics, most of the basic data for quarterly GDP is collected through monthly and quarterly surveys [see Liu (1997) and OECD (2002)]. This divergence in data sources leads to inconsistencies between annual GDP estimates and quarterly totals, resulting in the need for benchmarking of the quarterly totals against annual data. As outlined by Jin (2004), the NBS uses a simple pro rata technique for benchmarking the quarterly data.[10]

The NBS releases two quarterly GDP series: a real GDP index and nominal Gross Domestic Product. Both are in *cumulative* form.[11] These data series, as well as a wide

[9] See Dong (2003) and Jin (2004).
[10] Maitland-Smith (2003) provides a comprehensive overview of techniques for benchmarking quarterly national accounts data to annual data. For a broader discussion of techniques for estimating quarterly GDP at constant prices, see Maitland-Smith (2001) and Davies (1997).
[11] To construct quarterly data in cumulative form, take, for example, the nominal GDP series. The quarter one figure for each year gives the actual nominal GDP estimate for that quarter. The quarter two figure is the sum of the GDP estimates of quarters one and two. The quarter three estimate is the summation of GDP esti-

range of other Chinese data, are available from the CEIC database.[12] For the purposes of this paper, we wish to construct a real GDP series in constant prices (in levels rather than cumulative form) from which we can assess for the presence of a conventional business cycle, as well as a series of year-on-year real GDP growth to detect the presence of a growth cycle similar to that seen in the annual real GDP data. This series of year-on-year real GDP growth will serve as a reference series for the construction of our composite leading indicator in section three. As it is compiled in cumulative form, the real GDP index for each quarter of a given year is calculated as if that same quarter in the previous year was set to 100. It is this feature of the real GDP index that facilitates the construction of the two series we require – real GDP in constant prices and year-on-year real GDP growth. Raw data limitations are the reason Chinese quarterly GDP estimates are compiled in cumulative [see Liu (1997) and Jin (2004)]. Yet this cumulative form cannot be used to establish the quarter-to-quarter change in the real GDP index; we merely observe the changes between a quarter in any given year and the same quarter in the previous year, and therefore cannot simply transform cumulative real GDP index into levels. Thus, we take an indirect route to solve this problem, constructing cumulative real GDP in constant prices using the working assumption that in order to use the real GDP index as a deflator for the nominal GDP series, a suitable base year for constant prices must be identified.

We assume that in a year where the four cumulative quarterly real GDP index figures are relatively stable, the quarter-to-quarter real GDP growth is also relatively stable. The minimum coefficient of variation can be used to determine this stability. Once we identify and appropriate base year (2000 in our case), it is as if we have pinned down each of the four quarters of that year to their actual, as opposed to cumulative, growth rates. This allows us to establish the quarter-to-quarter changes throughout the series – and in the process allows us to use the real GDP index as a deflator as if it were in levels. Starting from the base year values, a cumulative constant price real GDP can be constructed quite easily using the GDP series as the deflator. It is also relatively straightforward to convert this newly constructed series from cumulative form to levels through a residual process.[13] With the help of a little numerical dexterity, we have constructed our quarterly real GDP

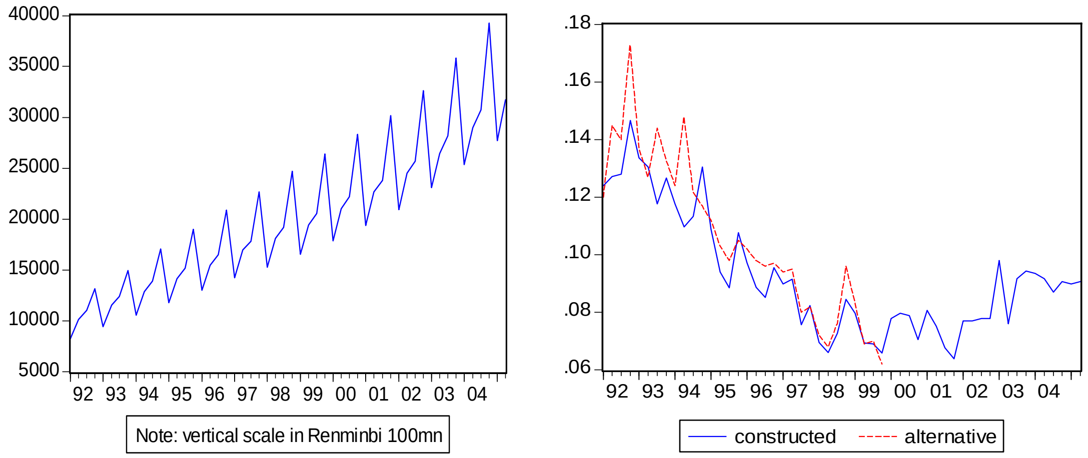
mates for the first three quarters, and the fourth quarter GDP figure comprises of the GDP estimates for the four preceding quarters. The fourth quarter figure should equal the annual GDP figure for that year.

[12] See www.ceicdata.com.

[13] Once the quarter one GDP figure is subtracted from the cumulative quarter two figure, the residual gives us the actual quarter two GDP figure. In the same way, the actual GDP figures for quarters three and four can be obtained from the cumulative data.

series in levels, from which the corresponding growth rate series has been constructed using a log-difference transformation. Both are illustrated in Figure 3.

Figure 3. Quarterly real GDP and real GDP growth rates



Real GDP (constant 2000 prices), 1992Q1–2005Q2

Real GDP y-o-y growth (in percent), 1992Q1–2005Q2

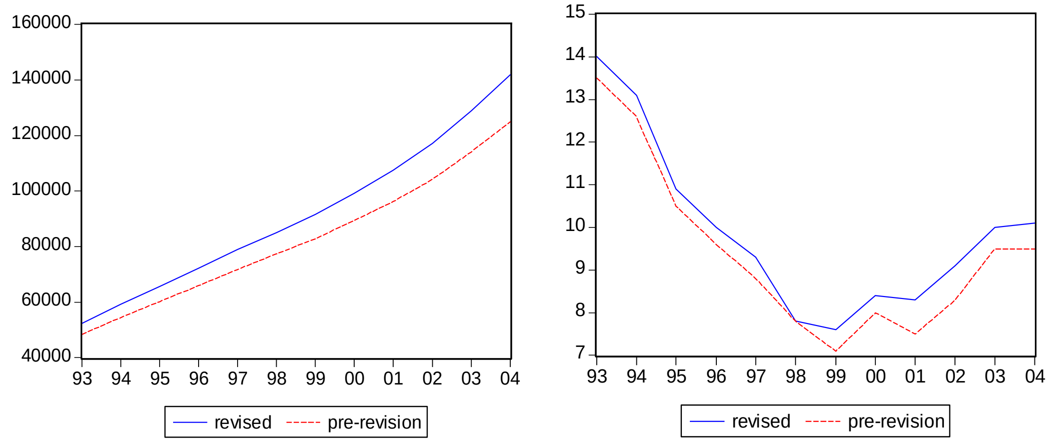
A number of salient features can be discerned from Figure 3. Considering Chinese quarterly real GDP first (left-hand panel), the absence of a traditional business cycle is once again evident, with the series exhibiting a sustained positive trend over time. Furthermore, Chinese quarterly real GDP exhibits very strong seasonal effects. If one considers the year-on-year growth rate of real GDP, however, these strong seasonal effects are not present (right-hand panel). As it is this GDP growth series that will be utilized for the remainder of this paper, this feature is of particular importance.

Of even greater significance is the question of just how accurate our newly constructed GDP growth series actually is. To gauge the accuracy of our newly constructed series, we compare it to quarterly real GDP growth as estimated by Abeysinghe and Gulasekaran (2004), who apply Chow-Lin related techniques to annual real GDP data ranging from 1979-1999 and obtain the associated quarterly growth rates. The two real GDP growth series are denoted as “constructed” and “alternative” in Figure 3, respectively. On the whole, our newly constructed GDP growth series exhibits a strong correlation with the alternative series, particularly from the first quarter of 1995 to the last quarter of 1999 (i.e. they share a noticeable overlap for much of that period). Before 1995, despite a tendency of the Abeysinghe and Gulasekaran (2004) estimates to exceed our series by 1-2.5% in certain quarters, a number of corresponding data points as well as a common trend are discernable. In all, one would have to say that the clear similarities between our constructed GDP growth series, which has the benefit of benchmarked quarterly real GDP, and the Abeysinghe and Gulasekaran (2004) estimates, based on disaggregated annual GDP data, over the entire 1992-1999 period appear to provide a strong endorsement of our newly constructed series.

While our newly constructed GDP growth series appears to perform very well, one further issue must be addressed – the recent substantial revision to Chinese annual GDP data. In December 2005, official revisions of China's annual GDP revealed an economy worth 16 trillion yuan in 2004, 17 percent more than previously thought. Some 93 percent of the increase was ascribed to the services sector. As a result, the share of services in the economy jumped to 41 percent.[14] Most of the unearthed GDP comes from four categories. The first is real estate, which has boomed in the coastal provinces, and boosted demand for architects, developers and other building services. The second is retail and catering; the third is transport and telecommunication services. The final component is the surge in media and technology services. Most of these activities were not captured by a statistical system geared to measure factory production. The revision period of the GDP data runs from 1993, as the 1992 First National Tertiary Industry Census had already enabled the NBS to revise annual GDP data for the period 1978-1992. This dominant role of the services sector in the revised GDP data is captured neatly in Figures 4 and 5, where it is evident that only the tertiary industry exhibits a pronounced difference in its pre- and post-revision trends, both in levels and year-on-year growth. The figures for primary and secondary industries remain virtually unchanged after the revision.

[14] Under the revised figures, it appears China's services sector is rather well developed and roughly as large as the services sectors of Japan, South Korea and Taiwan at a similar stage of development (although the 41 percent of GDP claimed by services is still substantially below the 60-75 percent typical of advanced economies). Crucially, the rising share of services cast serious doubt on the usefulness of industrial production indices as a reference series.

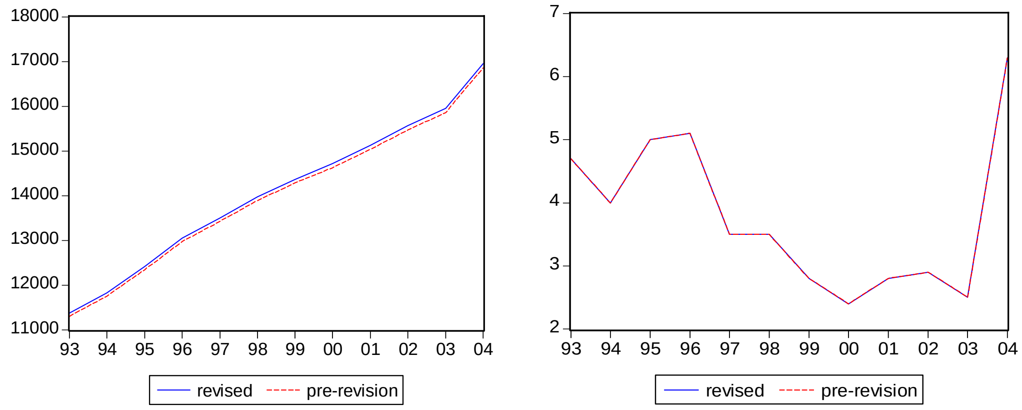
Figure 4. Chinese pre- and post- revision annual GDP, 1993-2005



Real GDP (2000 prices) in renminbi 100 million

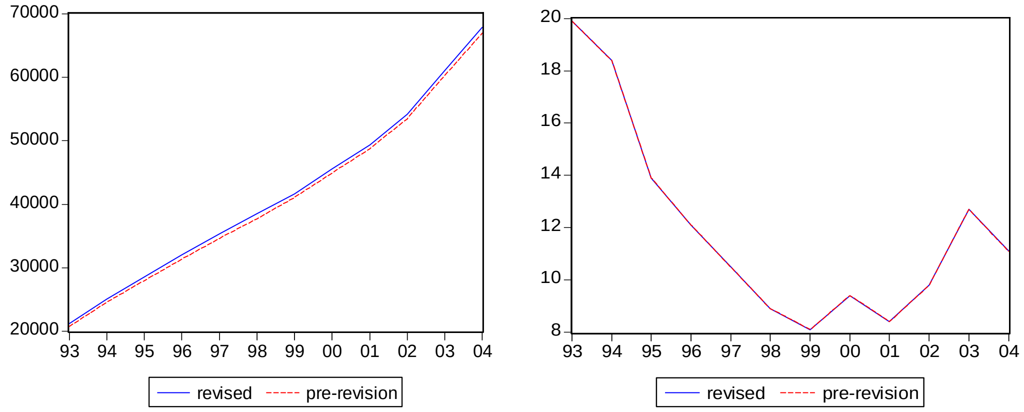
Real GDP y-o-y growth (in percent)

Figure 5. Annual Chinese pre- and post-revision value added, by industry (1993-2005)



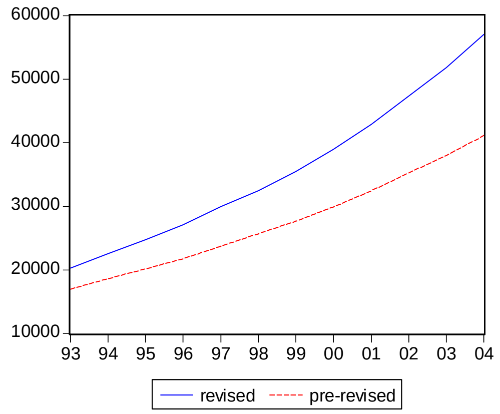
Primary industry value added, RMB 100 million

Growth (y-o-y, percent) in primary value added

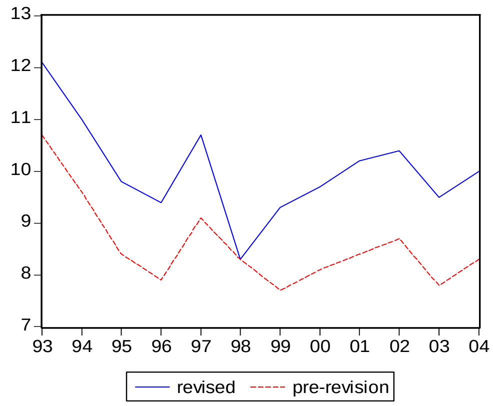


Secondary industry value added, RMB 100 million

Growth (y-o-y, percent) in secondary value added



Tertiary industry value added, RMB 100 million



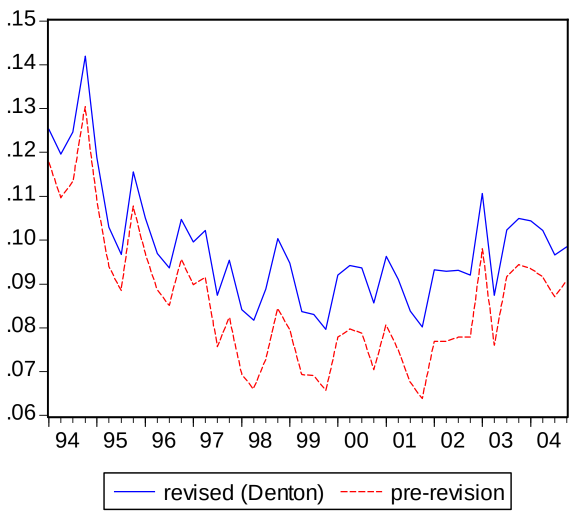
Growth (y-o-y, percent) in tertiary value added

The visual impressions created by Figures 4 and 5 confirm that the pre- and post-revision real GDP data share a large common component and that the divergences between the two are predominantly driven by the services sector. This presents us with an opportunity to use the quarterly real GDP data that existed prior to the 2005 revision to disaggregate the post-revision annual GDP data into quarterly frequency.

The issue of temporal aggregation has been considered extensively in the econometric literature and numerous solutions have been proposed so far. Broadly speaking, two alternative approaches have been followed: (i) methods that make use of the information obtained from related indicators observed at the desired higher frequency, and (ii) methods that rely upon time series models to derive a smooth path for the unobserved series. The first approach includes the Denton (1971) procedure and the method suggested by Chow and Lin (1971) and further developed by Fernández (1981) and Litterman (1983). The latter approach comprises of model-based methods relying on the ARIMA representation of the series to be disaggregated [Wei and Stram (1990)].

Here, we use the proportional Denton procedure for temporal disaggregation of the recently revised Chinese GDP data. The proportional Denton method of distribution of the revised annual GDP series by use of an associated "indicator series" imposes the constraint that the interpolated series obeys the annual totals. The missing intra-period data are obtained through quadratic minimization of the differences between the realigned and original series. Unlike the simple pro rata distribution approach, the proportional Denton procedure avoids the problem of discontinuities between fourth quarter and the first quarter of the following year.[15] As discussed above, the pre-revision and revised annual real GDP data share a large common component; namely, the primary and secondary sectors, which, as illustrated in Figures 4 and 5, have remained virtually unchanged despite the revision process. This fact is utilized in our expansion of the revised annual GDP data into a newly constructed quarterly GDP rate series; we take the pre-revised quarterly GDP data as the indicator series for our temporal disaggregation and then construct the corresponding quarterly real GDP y-o-y growth rate series. Figure 6 compares our newly constructed revised real GDP growth rate with its pre-revision counterpart. Figure 6 reveals a revised quarterly real GDP growth rate series that exhibits all the characteristics discussed thus far. The revised series exceeds the pre-revision series throughout the period in question, and this divergence appears to increase over time, a feature consistent with burgeoning services sector growth that was not fully captured in the pre-revision data, Finally, as one would expect, our revised series mirrors the growth cycles observed in the pre-revision data.

Figure 6. Pre- and post-revision quarterly real GDP growth



In the following section, as we develop a composite leading indicator of Chinese quarterly economic growth, our constructed pre-revision quarterly real GDP growth rate series will initially serve as reference series against which the performance of our leading indicator

[15] The method is recommended by the IMF as "relatively simple, robust, and well-suited for large-scale applications" [see Bloem et al. (2001)]. EUROSTAT provides the software ECOTRIM for temporal disaggregation of time series using the Chow-Lin (1971) and the Denton (1981) procedure (see http://www.oecd.org/dataoecd/60/5/21781488.ppt).

can be assessed. We will then proceed to use our revised quarterly real GDP growth rate series as reference series.

The use of this revised reference series offers two important benefits: it enables us to address the issue of Chinese National Bureau of Statistics' sizable December 2005 data revision and serves as a robustness check against which to assess the suitability of our composite leading indicator.

3 A leading indicator for Chinese growth rates

Traditionally, leading indicators have been developed to identify *growth cycles*, i.e. deviations in economic activity from the trend. While growth cycles are not hard to identify in long time series, they are difficult to measure accurately in short samples. This stems from the fact that the unobserved trend estimates tend to be very unstable near the end. This difficulty and the uncertainties arising from the transition process in China make growth cycle analysis a less-than-ideal tool for monitoring and forecasting the Chinese economy. We therefore develop a composite leading indicator for the quarterly growth rate itself, i.e. we are analyzing *growth rate cycles*.[16] Furthermore, we do not consider deviation cycles; China's recent institutional shake-ups and transformation process make removal of a stochastic trend from the data a fairly daunting task. The rich body of research on leading indicators can be traced back to the seminal work of Burns and Mitchell (1946). The leading indicator is itself an unobserved variable, a ghost. As there are numerous ways to calculate leading indicators, the issue becomes one of which ghost to pursue. The first stage of this pursuit involves the identification of a set of potential leading variables. The second stage involves estimating a small-scale factor model using the methodology developed by Stock and Watson (1989, 1991, 1993).[17] The factor model approach represents a massive step forward in leading indicator research as it captures the cyclical co-movement of various economic activities. It is this cyclical co-movement that is the hallmark of each economic

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[16] What has emerged in recent years is the recognition that growth cycles and growth rate cycles can be monitored in a complementary fashion. Growth cycles, however, are better suited to historical analysis, while growth rate cycles are more appropriate for real-time monitoring and forecasting. Another reason for using year-on-year growth rates of GDP rather than a measure of the output gap is that output gap measurement is particularly likely to be imprecise for China.

[17] For a comprehensive discussion of a whole host of relevant econometric issues not discussed here, see Kim and Nelson (1999) and the references cited therein.

cycle. While this framework has been fully developed for most advanced economies, the framework is still being extended to transition economies.

The initial stage of identifying potential leading variables is hampered by the fact that the set of Chinese component series from which a selection can be made is somewhat limited. Moreover, some of the series that do exist are only available for a limited historical period. In spite of these restrictions, we have succeeded in collecting a comprehensive dataset, initially containing 134 variables, from which our potential leading variables can be selected.[18] The data source used is the *CEIC* database. The size and scope of the dataset allows us to describe the Chinese economy on a broad basis as sectoral data can be taken into consideration. Attaining this all-encompassing view of Chinese economic activity is of particular importance given the nature of the Chinese economic transformation. As the Chinese economy matures and integrates with the global economy, China will inevitably become more exposed to macroeconomic shocks, both internal and external.

Given the fundamental importance of variable selection in the construction of leading indicators, it is not surprising that establishing a set of criteria for identifying suitable variables has long been the source of considerable discussion in the leading indicator literature [see Moore and Shiskin (1967), Boehm (2001), and Marcellino (2005)]. The selection criteria utilized here are broadly in line with those supported in the literature (some lend themselves more easily to formal evaluation than others, of course). A bit of fine-tuning is needed in any case to capture the unique attributes of the Chinese economic transformation. Thus, our selection of potential indicators uses the following criteria: (1) economic significance – there has to be an economic reason for the observed leading relationship before the series can be accepted as an indicator; (2) breadth of coverage – series with a wide coverage in terms of representing the economic activity of interest are preferred to narrowly-defined series; (3) frequency of publication – monthly series are preferred to quarterly series; (4) absence of excessive revisions; and (5) timeliness of publication and easy accessibility for data collection and updating. Once we have assembled a group of potential indicators that meet the criteria, it remains to examine the relationship between these candidate variables and the reference series with an eye to identifying leading indicator properties. Naturally, a visual inspection of the trends exhibited by the potential indica-

[18] The variables in the dataset are categorized as follows: real estate, fiscal, household income and expenditure, retail sales, employment, prices, retail sales, consumer confidence, prices, foreign trade, monetary, interest rates, exchange rates, fixed asset investment, foreign direct investment, transportation, and financial markets.

tors and the reference series over time is the obvious starting point. As a more rigorous next step, cross-correlation analysis is performed on the de-trended individual series and the reference series to scrutinize variables that have given signals in the past. The number of lags at which the correlation has the highest value is a guide to the average lag of the indicator over the reference series, while the value of the correlation coefficient is a measure of the general fit of individual indicator series in relation to the reference series.[19]

Our final selection of indicator series consists of three variables: exports, real estate climate index (RECI), and the Shanghai Stock Exchange (SSE) composite index. Graphs of these three indicator series spanning the maximum sample period available are provided in Appendix 1. A brief discussion of these variables' characteristics illustrates their adherence to our selection criteria, as well as their broad economic scope.

Export data is intuitively appealing as a potential indicator of Chinese economic activity because it captures China's burgeoning role in international trade.[20] Export data, denominated in US dollars, is available in monthly frequency from January 1992 and the data is released in current prices. As Chinese export price indices are not available to us, we must find another means of deflating this data. We have worked with two deflators: the US export (all commodities) price index and the Chinese producer price index. The two resulting constant price export series are virtually identical, so our factor model results are not affected by our choice of deflator.

The real estate climate index (RECI), developed by the National Bureau of Statistics in 1997, describes the present situation and future trend of the real estate market in China. Based on the monthly statistics of Chinese real estate development, the RECI is calculated based on eight indices related to land, financial capital, and sales prices in the real estate market and thus functions as a composite index of the Chinese real estate market.[21]

[19] One strand of the literature has recently suggested the use of large-scale factor models [see Stock and Watson (2002) and Forni et al. (2000, 2001)]. The idea is to include a broad dataset to use all available information efficiently. This nonparametric estimation procedure is based on principal components. It does not address the problem that a growing cross-section dimension leads to an increased number of parameters and therefore higher uncertainty of coefficient estimates than in state-space models, however. We do not pursue the large-scale factor model approach due to the limited number of time series leading GDP in mainland China. It is also worth mentioning that we have not treated expansions and recessions as distinct processes in a switching model as suggested by Diebold and Rudebusch (1996), since China did not experience a recession during the sample period. An excellent up-to-date assessment of the vast literature is provided by Marcellino (2005).

[20] As noted in Section 1, China overtook Japan in 2005 as the world's third largest exporter, after a surge in demand for its electronic goods led to a 35 percent jump in the country's overseas sales.

[21] The eight indices are: investment in real estate development, financial appropriation (access to credit); revenue from transfers of land, area of land development, area of newly-started buildings, area of completed buildings, area of unsold buildings, sales price of commercial buildings.

Data is collected through the Overall Statistics Reporting System on Fixed Assets from 31 provincial statistical offices, providing us with a countrywide barometer of the investment climate. Since China's macroeconomic growth is driven more by fixed investment than by household consumption, it is especially vulnerable to any slowing of corporate investment spending. In investment cycles, the leading indicators are profit margins, product prices and property prices, which forecast corporate cash flow or ability to borrow.

As with exports and RECI, the inclusion of the SSE composite index, from an economic standpoint, is intuitively appealing. Equity prices should play an important role for GDP, whether one takes a conventional asset market view, or the credit market view. Stock and Watson (2003) recently examined the role of asset prices, including equity prices, in forecasting both output and inflation in seven OECD countries, obtaining plausible findings for output forecasts. The availability of a monthly SSE composite index since 1990 and its broad scope across Chinese industries also strengthen the series' credentials for inclusion in the common factor model. The composite index encompasses a number of indices of listed shares, categorized by industry and constructed from a sample of the A and B shares listed on the SSE.[22] The conventional channel through which share prices influence GDP growth is a wealth effect, whereby increasing share prices lead the holders of these assets to consume and invest this newfound wealth. However, the relatively low holding of shares among the Chinese public suggests that, in the Chinese case, it is a valuation effect that is at play. Thus, given the investment cycle underpinning Chinese GDP growth, share prices reflect investors' expectations of the future profitability of the listed firms.[23]

Having identified three suitable variables for inclusion in our composite leading indicator model, we now proceed to develop a model for the Chinese economy. The empirical methodology involves constructing a common unobserved factor from our selected indicators, following the tradition of dynamic factor analysis. This common factor is assumed to represent the shared influence of the state of the economy on the leading indicator.[24] To the best of our knowledge, this is the first attempt to construct such a composite

[22] SSE shares range from A, B, and C to signify types of shares traded. A-shares are held only by residents of China and are traded in renminbi. B-shares are denominated in renminbi, but payable in foreign currency and are designated for foreign investors. C-shares are wholly owned by state-owned enterprises and not publicly traded. See http://www.china-fund.com/.

[23] For example, the People's Bank of China notes in its survey of urban household saving (Feb. 2006) that 4.1 percent of the households surveyed chose "stocks" as their major financial asset.
See http://www.pbc.gov.cn/english//detail.asp?col=6400&ID=656 .

[24] This modeling philosophy, certainly not new in the econometric literature, has recently been rigorously laid out and applied using U.S. data by Chauvet (1998), Kim and Nelson (1999), and Kaufmann (2000).

leading indicator for China using a dynamic common factor model. One fundamental problem arises from the fact that structural change is endemic in China, implying that conventional econometric modeling techniques, which proceed under the assumption that there is a structurally stable "true" economy to be discovered, are inappropriate. The factor model approach, however, allows us to overcome this difficulty as it incorporates the Kalman Filter and thus enables the econometric model itself to adjust its parameters in the light of economic change.

For the purposes of our factor model, we denote our three series are follows:

Let Y_{1t} be the fourth difference of exports, Y_{2t} the fourth difference of RECI, and Y_{3t} the fourth difference of the SSE composite index.[25] Unit root tests for the three series suggest that one cannot reject the hypothesis of the three differenced series being I(0). Borrowing from Stock and Watson (1989), we consider the following dynamic factor model:

(1) $$Y_{1t} = D_1 + \gamma_{11} I_{t-1} + e_{1t}$$

(2) $$Y_{2t} = D_2 + \gamma_{21} I_t + e_{2t}$$

(3) $$Y_{3t} = D_3 + \gamma_{31} I_t + e_{3t}$$

(4) $$(I_t - \delta) = \phi(I_{t-1} - \delta) + \varpi_t \qquad \varpi_t \sim iid\ N(0,\ 1)$$

(5) $$e_{it} = \psi_{i,1} e_{i,t-1} + \psi_{i,4} e_{i,t-4} + \varepsilon_{it} \qquad \varepsilon_{it} \sim iid\ N(0,\ \sigma_i^2) \qquad i = 1,\ 2,\ 3$$

where I_t is the common component (leading indicator) that enters equation (1), (2), and (3) with different weights.[26] These weights γ_i indicate the extent to which each series is affected by the common component, I_t, which arises from a single source. In (4), it is as-

[25] We have constructed a quarterly index because, as discussed in Section 2, monthly GDP data for China are not available. Another reason is that month-to-month movements in leading indicators tend to be characterized by a high noise-to-signal ratio. Stock and Watson (1989) have therefore elected to smooth the resulting monthly series to improve the indicator's forecasting performance. Here, we have aggregated each of the three monthly series into quarterly averages.

[26] We have lagged I_t in equation (1) to take into account the phase shift between Y_{1t}, Y_{2t}, and Y_{3t}.

sumed that the unobserved component follows a stationary first-order autoregressive process. The autoregressive structure of the idiosyncratic component is given in (5). The main identifying assumption in the model is that (e_{1t}, e_{2t}, e_{3t}) are mutually uncorrelated at all leads and lags. Stock and Watson (1991) have shown that the parameters D_i and δ are not separately identified. Therefore, they suggest writing the model in deviations from means and thus concentrating the likelihood function.

(6) $$y_{1t} = \gamma_{11} i_{t-1} + e_{1t}$$

(7) $$y_{2t} = \gamma_{21} i_t + e_{2t}$$

(8) $$y_{3t} = \gamma_{31} i_t + e_{3t}$$

(9) $$i_t = \phi \, i_{t-1} + \varpi_t \qquad \varpi \sim iid \;\; N(0,\ 1)$$

(10) $$e_{it} = \psi_{i,t} e_{i,t-1} + e_{i,t-4} + \varepsilon_{it} \qquad \varepsilon \sim iid \;\; N(0,\ \sigma_i^2) \qquad i = 1,\ 2,\ 3$$

where $y_{it} = Y_{it} - \overline{Y}_i$ and $i_t = I_t - \delta$. In general, for Kalman filter estimation, the model is expressed in its state-space form. The latter is composed of two parts: the measurement and the transition system. The following two equations describe our model in deviations from mean in a particular state-space representation.

(11)
$$\begin{pmatrix} y_{1t} \\ y_{2t} \\ y_{3t} \end{pmatrix} = \begin{pmatrix} 0 & \gamma_{11} & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ \gamma_{21} & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ \gamma_{31} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \end{pmatrix} \begin{pmatrix} i_t \\ i_{t-1} \\ e_{1t} \\ e_{1,t-1} \\ e_{1,t-2} \\ e_{1,t-3} \\ e_{2t} \\ e_{2,t-1} \\ e_{2,t-2} \\ e_{2,t-3} \\ e_{3t} \\ e_{3,t-1} \\ e_{3,t-2} \\ e_{3,t-3} \end{pmatrix}$$

$$j_t = H\beta_t$$

[Measurement equation]

(12)
$$\begin{pmatrix} i_t \\ i_{t-1} \\ e_{1t} \\ e_{1,t-1} \\ e_{1,t-2} \\ e_{1,t-3} \\ e_{2t} \\ e_{2,t-1} \\ e_{2,t-2} \\ e_{2,t-3} \\ e_{3t} \\ e_{3,t-1} \\ e_{3,t-2} \\ e_{3,t-3} \end{pmatrix} = \begin{pmatrix} \phi & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & \psi_{11} & 0 & 0 & \psi_{14} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & \psi_{21} & 0 & 0 & \psi_{24} & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \psi_{31} & 0 & 0 & \psi_{34} \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \end{pmatrix} \begin{pmatrix} i_{t-1} \\ i_{t-2} \\ e_{1,t-1} \\ e_{1,t-2} \\ e_{1,t-3} \\ e_{1,t-4} \\ e_{2,t-1} \\ e_{2,t-2} \\ e_{2,t-3} \\ e_{2,t-4} \\ e_{3,t-1} \\ e_{3,t-2} \\ e_{3,t-3} \\ e_{3,t-4} \end{pmatrix} + \begin{pmatrix} \omega_t \\ 0 \\ \varepsilon_{1t} \\ 0 \\ 0 \\ 0 \\ \varepsilon_{2t} \\ 0 \\ 0 \\ 0 \\ \varepsilon_{3t} \\ 0 \\ 0 \\ 0 \end{pmatrix}$$

$$\beta_t = F\beta_{t-1} + \nu_t$$

[Transition equation]

In the above state-space representation, the fourteen rows of the transition equation describe identities. Estimation of the model will allow the unobserved components ("states") to be uncovered. The parameters are estimated by the recursive Kalman filter algorithm. Using numeric derivatives, the BHHH algorithm is employed to maximize the likelihood with respect to the unknown parameter vector.[27] The recursive procedure calculates the optimal estimator of the state vector based on all information available at time t. Once filtering is performed, we can use smoothing techniques for information made available after time t. The smoothed estimator is based on more information than the filtered estimator and therefore will generally have a smaller mean square error than the filtered estimator without smoothing. Here, we use the fixed interval-smoothing algorithm as introduced in Harvey (1993).[28] This procedure involves a backward pass of the data through the Kalman filter from $t = T$ to $t = 1$.[29]

Table 1. Parameter estimates of the Dynamic Factor Model, 1998Q2-2005Q2

Parameters	Estimates	*t*-values
γ_{11}	0.206	2.90
γ_{21}	-0.074	2.08
γ_{31}	-0.206	2.47
ϕ	0.956	17.23
ψ_{11}	0.728	7.24
ψ_{14}	0.457	5.56
ψ_{21}	0.483	5.52
ψ_{24}	0.615	8.46
ψ_{31}	0.800	6.97
ψ_{34}	0.337	3.33
σ_1^2	0.108	2.67
σ_2^2	0.170	3.68
σ_3^2	0.229	3.30
Log-likelihood	23.06	
Diagnostics	Test statistics	*p*-values
LB(ε_1)	2.57	0.63
LB(ε_2)	2.22	0.70
LB(ε_3)	1.54	0.67

Note: LB(ε_i): Ljung-Box Q-test measuring general AR(4) residual autocorrelation.

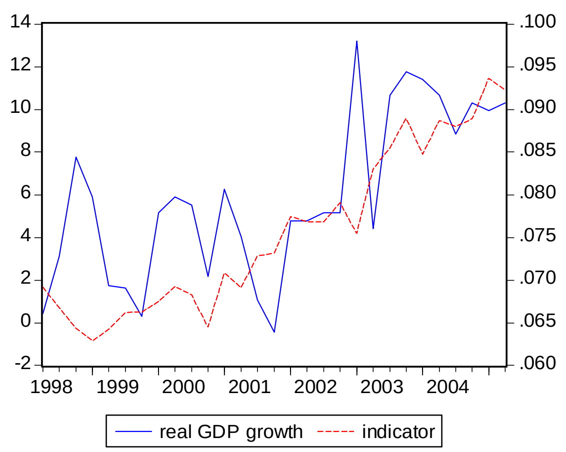
[27] Since the simplex algorithm is more robust to initial parameter starting values than the BHHH algorithm, we use the simplex algorithm to provide initial parameter estimates for the BHHH algorithm, which in turn provides the final parameter estimates along with their corresponding variance-covariance matrix.

[28] Harvey (1993) introduces three smoothing algorithms: fixed point smoothing, fixed lag smoothing, and fixed interval smoothing. The filtered estimator assumes that agents have the latest information set at hand, while the smoothed estimator takes future information into account.

[29] The GAUSS code developed to perform the Kalman filtering and the maximum likelihood estimation largely draws on programs kindly made available by Chang-Jin Kim.

At this point, it is useful to consider our estimates in greater detail. All parameters are consistent with those predicted by theory and statistically significant at the 5-percent level. According to the results, at least, the model seems to fit the data quite well. With regard to the estimated autoregressive coefficient ϕ, the coefficient is positive and significant. This suggests a great deal of persistence in growth rate cycle fluctuations. To check the adequacy of the model specification, we analyze the disturbances ε_i. If the model is correctly specified, then the residuals are serially uncorrelated and normally distributed. The Ljung-Box tests for residual autocorrelation are satisfactory, their results providing evidence that does not allow one to reject the null hypothesis of uncorrelated distributed residuals. The overall impression conveyed by these results is that the model works quite well. Given these parameter estimates, we get $i_{t|t}$ and $I_{t|t}$, t = 1, 2, ..., T, by running the Kalman filter.

Figure 7. Leading indicator It and real GDP growth



Note: Real GDP growth is measured in percent (right scale) and the leading indicator has been normalized to 1 in 2000Q1 (left scale).

The first step in our evaluation of the leading indicator constructed by the dynamic common factor model is to look at how well the measure performs in tracking real GDP growth over the 1998Q2-2005Q2 sample period.[30] As illustrated in Figure 7, turning points of the leading indicator, I_t, appear to lead real GDP growth turning points throughout 1998/99.

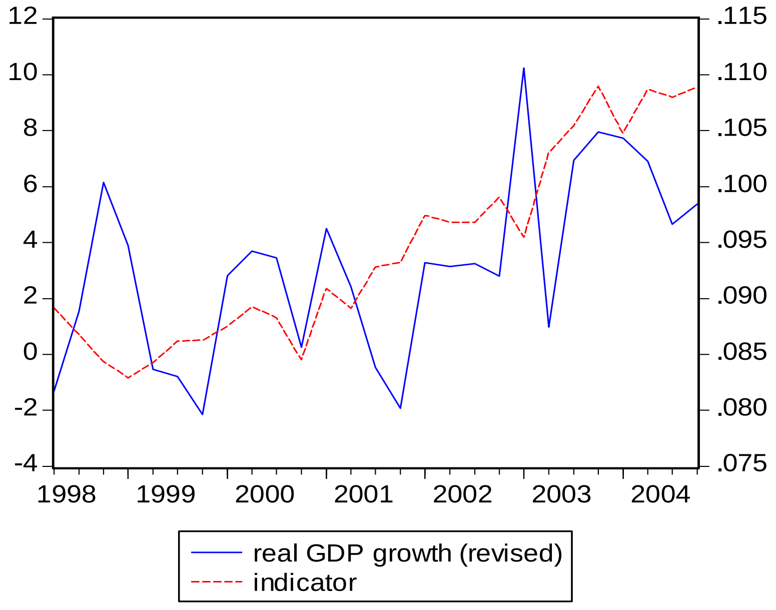
[30] This sample period is determined by the fact that the real estate climate index is only available from 1997Q1 onward.

From 2001 to the end of the sample period, the leading indicator performs quite well indeed, displaying a healthy lead over the reference series turning points for virtually every quarter. Only in 2000 does the indicator move contemporaneously with the reference series for sustained period of time. This result indicates it is possible to find smooth underlying leading indicator components for the Chinese growth rate cycle. Recalling that the leading indicator is intended for prediction, it is not important whether the index represents causal factors or merely symptoms coming in advance of changes in GDP – its success or failure must be judged on predictive power alone.

We now consider the components of our common factor model in light of the substantial upward revision of Chinese GDP figures in December 2005. The data revision was aimed almost exclusively at tackling under-valuation of the services sector and the sources of the newly found GDP were real estate services, retail and catering, transport and communication services, and media and technology services. Primary and secondary industries were virtually untouched by the revision. As these services appear to be largely of the non-traded variety, one would not expect export data to be unduly affected by the revision. It is also likely that our real estate climate index is capable of factoring in high demand for real estate services that may have gone unmeasured in GDP figures, so we should expect our leading indicator to perform better when the revised GDP series (as opposed to the pre-revision data) is used as the reference series due to the increased proportion of services captured in the revised figures. The revised quarterly real GDP growth series constructed in Section 2 using the Denton procedure provides us with a method of testing the performance of our indicator I_t against a revised quarterly real GDP growth series.[31]

[31] The revised quarterly real GDP growth series constructed using the Denton procedure ends in 2004Q4. Thus, the sample period for Figure 8 is 1998Q2-2004Q4.

Figure 8. Leading indicator I_t and revised real GDP growth



Note: Revised real GDP growth is measured in percent (right scale) and the leading indicator has been normalized to 1 in 2000Q1 (left scale).

In Figure 8, the revised quarterly real GDP growth series bears a striking resemblance to its pre-revision counterpart in Figure 7 due to the use of pre-revision nominal GDP as the benchmark series in the Denton temporal aggregation. As discussed previously, this choice of benchmark is particularly suited to the December 2005 revision, given the revision's almost exclusive focus on the services sector. As a result, our common factor indicator remains robust despite the GDP revision and continues to display strong leading properties with respect to the reference series. Having established the leading indicator properties of the unobserved common factor embodied in the factor model, Section 4 further explores the usefulness of this indicator in generating out-of-sample one-step-ahead forecasts of Chinese quarterly real GDP growth. Once such forecasts are constructed, a range of forecasting performance tests may be used to assess the predictive power inherent in our leading indicator.

4 Analysis of out-of-sample forecasting accuracy

In Section 3, we relied on a bare-bones small-scale factor model to reveal an unobserved common component reflecting China's investment-led growth cycle of recent years. Obviously, a number of valid questions concerning the robustness and forecast accuracy of this leading indicator now need to be addressed. It is therefore pertinent to undertake a more rigorous examination of the forecasting potential inherent in our leading indicator. The most meaningful and sound tests of forecast accuracy of any leading indicator are out-of-sample tests.[32] To achieve this, we perform a predictive ability exercise in which one-step-ahead forecasts of quarterly y-o-y real GDP growth are generated and the usefulness our indicator as a predictor can be assessed.[33] To calculate the incremental predictive power of the leading indicator, we estimate the following nested models:

(13) $$GDP_t = \alpha + \beta\ GDP_{t-1} + e_{1t}$$

(14) $$GDP_t = \alpha + \beta\ GDP_{t-1} + \delta\ I_t + \eta\ I_{t-1} + e_{2t}$$

where GDP_t and GDP_{t-1} denote the quarterly real GDP y-o-y growth rate at times *t* and *t-1*, respectively; I_t and I_{t-1} denote the leading indicator at time *t* and time *t-1*, respectively; and the error terms, e_{1t} and e_{2t}, are *iid* in the nested models.

In the following out-of-sample forecasting exercise, the univariate autoregressive (*AR*) model serves as a benchmark model, against which the merits of including our indicator as a predictor can be evaluated. Although sometimes labeled a "naive" model, it is often difficult for other models to produce forecasts better than those of the *AR* model. The lag orders of the different models have been specified using the Akaike information criterion (AIC) and the Schwarz information criterion (SIC).[34] Figure 9 provides a visual impression of the forecasting performance of the nested models, with "*R*" denoting the incremental one-step-ahead out-of-sample forecasts generated by the restricted model, equa-

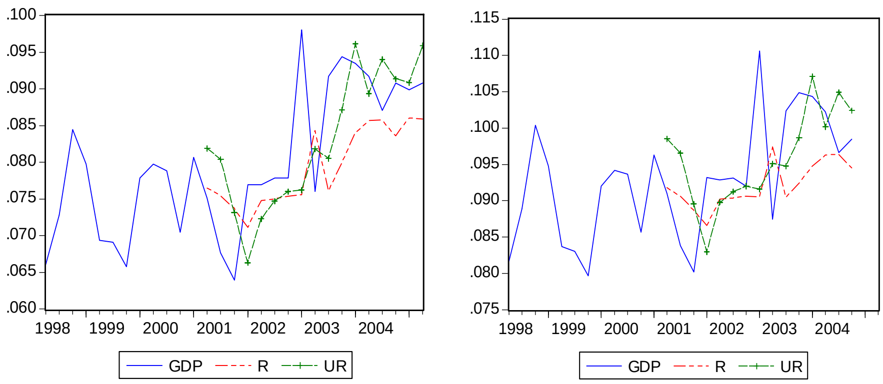
[32] In-sample tests can be biased by the use of the same data for estimation and forecast evaluation.

[33] Clements and Hendry (2005) are emphatic that considerable care is needed in interpreting forecast comparisons. One reason multi-step forecasts may be poor guides on the credence of a model is that multi-step forecasts require strong exogeneity of the variables, while for one-step-ahead forecasts need only weak exogeneity.

[34] The empirical literature has shown that the inclusion of lags of the unobserved factors may improve the forecasting ability of the models. See, for example, Artis et al. (2005), Camba-Mendez et al. (2001), and Stock and Watson (2002).

tion (13), and "*UR*" denoting those generated from the unrestricted model, equation (14), over the period 2001Q2-2005Q2. These incremental forecasts have be constructed both for pre-revision and revised quarterly Chinese real GDP growth series. The parameters of the models in (13) and (14) are estimated using a recursive scheme, with 1998Q2-2001Q1 serving as the initial estimation period for the first one-step-ahead forecast. From that point on, each model's parameter estimates utilize additional data as the one-step-head forecasting moves forward through time. A number of insights can be gleaned from Figure 9. First, while there may be little to choose between the two sets' forecasts in the early stages of the 2001Q2-2005Q2 sample period, the unrestricted one-step-ahead forecasts appear to perform relatively better than their restricted counterparts later in the sample period. Second, both the relatively better performance of the unrestricted forecasts and the importance of the forecasting horizon hold for pre-revision and revised real GDP growth. In light of this observation, as well as the fact our revised quarterly real GDP growth series ends in 2004Q4, we continue our evaluation of forecasting accuracy using the pre-revision real GDP growth data and corresponding forecasts. The results for the revised forecasts are reported in Appendix 2.

Figure 9. Real GDP growth and one-step-ahead forecasts, 2002Q2- 2005Q2



Pre-revision quarterly y-o-y real GDP growth Revised GDP quarterly y-o-y real GDP growth

Having motivated an appreciation of the forecasting quality of models which include our leading indicator, we now statistically test the predictive performance of the indicator. To assess out-of-sample predictive performance the Diebold and Mariano (1995, 2002) test and the encompassing test statistics for a pair of nested models developed by Clark and McCracken (2001) and McCracken (2004) have been employed.

When one has several reasonable forecasting models, superior forecasting performance can be identified by putting the alternative models to a head-to-head test. As discussed by Enders (2003), this can be achieved by holding back a portion of the observations from the estimation period, estimating the alternative models over the shortened span of data, and using these estimates to forecast the observations of the forecast period. One can then compare the properties of the forecast errors from the two models. To create an impression of the forecasting accuracy of the factor model, we first apply the Diebold and Mariano (1995, 2002) test of equal forecasting accuracy. This test is based on the difference of squared forecast errors of two competing forecast models.[35] Under the "equal accuracy" null hypothesis, the forecast accuracy of the two models is not statistically different. In Table 2, each cell in the second column contains the asymptotic *p*-values for the Diebold and Mariano (1995, 2002) statistic. A significance level below 0.10 or 0.05 indicates a rejection of the null hypothesis. The various out-of-sample tests are carried out as follows:

(i) The forecasting equations (13) and (14) are estimated using data for the period 1998Q2-2002Q1.

(ii) An out-of-sample forecast is carried out for the subsequent period 2001Q2-2005Q2, using the recursive scheme mentioned above. The forecasts are evaluated by calculating the mean squared error (MSE) for a one-step forecast horizon.

(iii) Steps (i) and (ii) are repeated, except that the forecasting equations are now estimated for the periods 1998Q1-2002Q1 and 1998Q1-2003Q1 and the out-of-sample forecasts are calculated for the periods 2002Q2-2005Q2 and 2003Q2-2005Q2, respectively. The out-of-sample predictive performance of the leading indicator is presented in Tables 2 and 3.

Table 2. Diebold and Mariano (1995, 2002) test for equal forecasting accuracy

Forecast sample	*p*-value	Durbin-Watson statistic
1. 2001Q2-2005Q2	0.18	0.90
2. 2002Q2-2005Q2	0.01	0.91
3. 2003Q2-2005Q2	0.01	1.08

Note: The weighting scheme of the autocovariances follows Newey and West (1987).

[35] Regarding the loss function specification, we report the results for the quadratic loss. We do not show the results for the absolute loss case as the results were qualitatively identical with both loss function specifications.

Table 3. Encompassing tests of Clark and McCracken (2001) and McCracken (2004)

	Encompassing tests			
Forecast sample	*MSE-f*	*MSE-t*	*ENC-f*	*ENC-t*
1. 2001Q2-2005Q2	3.31**	0.88**	5.68***	2.33***
2. 2002Q2-2005Q2	7.25***	2.23***	7.62***	3.34***
3. 2003Q2-2005Q2	13.27***	2.36***	14.04***	4.06***

The encompassing tests of Clark and McCracken (2001) and McCracken (2004) incorporate and further develop the forecast accuracy tests of Granger and Newbold (1976) and Diebold and Mariano (1995, 2002).[36] In Table 3, the statistics denoted "*MSE-f*" and "*MSE-t*" test for equal mean squared error of the restricted and unrestricted forecast series. The latter is in the spirit of the regression-based test for equal mean squared error (MSE) proposed by Granger and Newbold (1976). The inclusion of these test statistics in Table 3 allows us to consider the results of Table 2 in light of the bootstrapped test statistics constructed by Clark and McCracken (2001) and McCracken (2004). The statistics denoted "*ENC-f*" and "*ENC-t*" address the question of whether forecasts generated by the univariate *AR* model of equation (13) encompasses those of equation (14), thereby indicating that the inclusion of the indicator in equation (14) adds no additional predictive information. The *ENC-t* test, developed by Harvey et al (1998), draws on Diebold and Mariano (1995), while the *ENC-f* test owes its origins to Clark and McCracken (2001). As noted above, the null hypothesis is that of "equal accuracy" for the two MSE tests and "forecast encompassing" for the ENC tests, and, as discussed in Clark and McCracken (2001), these tests are all one-sided, with the only rejection regions of interest under the alternative hypothesis residing in the right-hand tail.

The results of the tests in Tables 3 and 4 strongly reject both the null hypotheses of equal forecast accuracy and forecast encompassing. Thus, we can conclude that our indicator possesses significant forecasting potential, with findings for more recent forecasting samples actually gaining in significance. The fact that the forecasting performance of the

[36] Using Monte Carlo simulations, Clark and McCracken (2001) find that, in commonly used sample sizes, the *ENC-f* test is more powerful than both the *ENC-t* test and the out-of-sample forecasting test proposed by Diebold and Mariano (1995). Following McCracken (2004), the critical values for each of the *ENC-T* and *ENC-F* test statistics are obtained using a bootstrap procedure since the test statistics are non-standard in the case of nested models and contain nuisance parameters.

augmented model displays a marked improvement for forecast sample 3 implies that the advantages of including our leading indicator are not systematic. It should also be noted that the Durbin-Watson statistic provided in Table 2 rules out the possibility that these significant results are driven by correlation between the MSPEs of the two sets of forecasts. These findings confirm that the quarterly y-o-y real GDP growth forecasts of the augmented model are generally better than the forecasts of the rival benchmark model. Overall, the results indicate that the leading indicator can serve as a valuable aid for short-term forecasting of the Chinese economy.

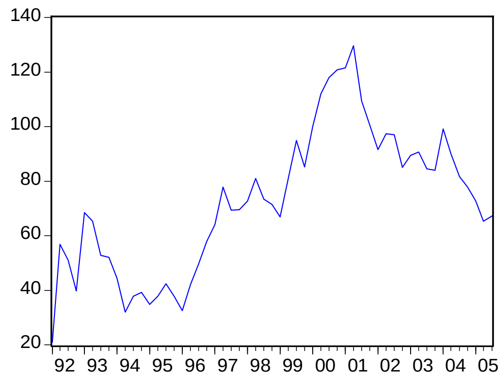
5 Conclusions

Economic developments in economies in transition undoubtedly involve a high degree of uncertainty, which complicates the construction of suitable leading indicators of economic activity. Against this background, our paper provided insights into the usefulness of small-scale factor models proposed by Stock and Watson (1989, 1991, 1993) in the forecasting of mainland China’s quarterly y-o-y real GDP growth. Measures of Chinese economic activity, however, possess a number of idiosyncrasies, stemming both from China’s own economic transition and its relatively recent adoption of an OECD-approved national accounting system. First and foremost is the realization that recent Chinese economic development must be characterized as a growth cycle, rather than as a traditional business cycle. Further, the difficulty and the uncertainties arising from the transition process in China make growth cycle analysis a less-than-ideal tool for monitoring and forecasting the Chinese economy. We therefore developed a composite leading indicator for the quarterly y-o-y real GDP growth rate itself, i.e. we sought to analyze *growth rate cycles*. With respect to Chinese national accounts data, we discussed how difficulties due to the publication of quarterly data in cumulative form can be successfully overcome. Recent revisions in Chinese GDP data, most notably those in December 2005, are also captured in our model. We applied the Denton procedure to disaggregate the revised annual Chinese GDP data, which allowed us to consider our leading indicator with respect to both pre- and post-revision quarterly real GDP growth.

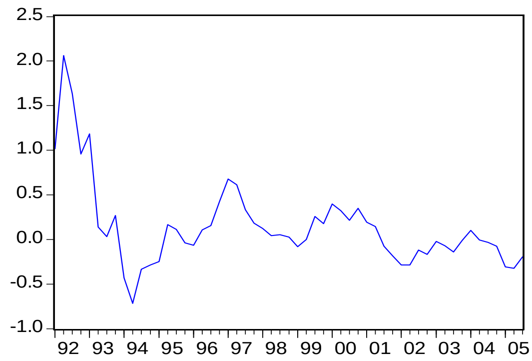
A further challenge arose in compiling a comprehensive economic dataset sufficiently broad in scope to span the full spectrum of Chinese economic activity over a lengthy time period. Having accomplished this, a set of criteria for identifying indicator series with suitable leading properties was adopted. The three indicator series from which our leading indicator is constructed (exports, the real estate climate index, and the Shanghai Stock Exchange composite index) are intuitively appealing from an economic perspective. They incorporate the investment-led nature of Chinese growth, the burgeoning role of international trade, as well as the rapid growth of the Chinese services sector. These three series have been found to share an underlying, unobservable element, which, by virtue of the factor model and its Kalman filter estimation of parameters and state vectors, yield our leading indicator of economic activity. Upon establishing the leading indicator properties of the unobserved common factor embodied in the factor model, we explored the usefulness of this indicator in generating out-of-sample one-step-ahead forecasts of Chinese quarterly real GDP growth. Once these forecasts were constructed and their forecasting quality considered, a range of forecasting performance tests were utilized to assess the predictive power inherent in our leading indicator. All strongly rejected both the null hypotheses of equal forecast accuracy and "forecast encompassing," leading us to conclude our indicator possesses significant forecasting potential.

Taken together, the out-of-sample forecast accuracy tests suggest such a leading indicator model is a promising, relatively low-cost forecasting tool that can be usefully applied to Chinese economic conditions. Of course, it should be stressed that the use of larger samples and/or prediction periods in the future may yield additional evidence that could be useful for understanding the Chinese growth cycles. Until such a time as China's economic transition enters a more tranquil forecasting climate, our leading indicator model may represent the most feasible thermometer available for gauging Chinese economic activity.

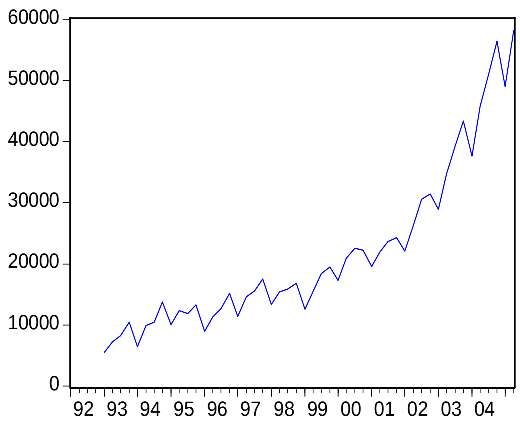
Appendix 1. Indicator series in levels and growth rates (y-o-y)



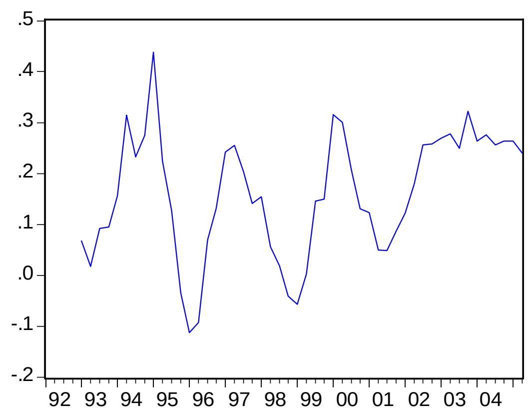
SSE index (2000Q1=100), 1992Q1-2005Q2



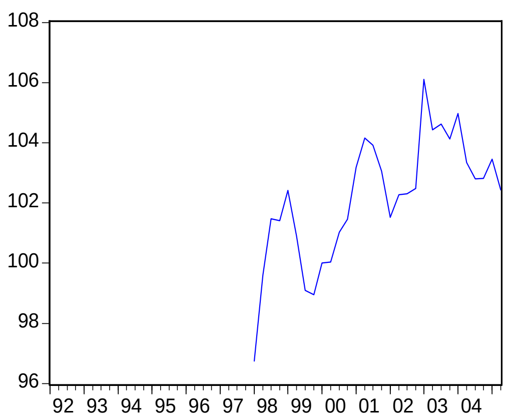
SSE index y-o-y growth (in percent), 1992Q1-2005Q2



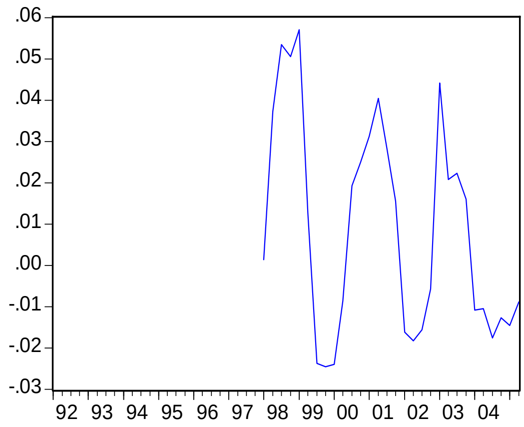
Exports (2000 prices, US$ m), 1992Q2-2005Q2



Exports y-o-y growth (in percent), 1992Q2-2005Q2



RECI (2000Q1=100), 1998Q1-2005Q2



RECI y-o-y growth (in percent), 1998Q1-2005Q2

Appendix 2. Tests of forecast accuracy and forecast encompassing for revised Chinese quarterly real GDP growth, y-o-y

Diebold and Mariano (1995, 2002) test for equal forecasting accuracy

Forecast sample	*p*-value	Durbin-Watson statistic
1. 2001Q2-2005Q2	0.36	0.75
2. 2002Q2-2005Q2	0.02	0.86
3. 2003Q2 -2005Q2	0.03	0.92

Note: The weighting scheme of the autocovariances follows Newey and West (1987).

Encompassing tests of Clark and McCracken (2001) and McCracken (2004)

	Encompassing tests			
Forecast sample	*MSE-f*	*MSE-t*	*ENC-f*	*ENC-t*
1. 2001Q2-2005Q2	1.23*	0.34*	3.97**	1.78**
2. 2002Q2-2005Q2	5.85***	1.94***	6.17***	2.85***
3. 2003Q2-2005Q2	8.03***	1.75***	9.10***	3.13***

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