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What 31 provinces reveal about growth in China

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Abstract

It is important to understand the growth process under way in China. However, analyses of Chinese growth became increasingly more difficult after the real GDP doubling target was announced in 2012 and the official real GDP statistics lost their fluctuations. With a dataset covering 31 Chinese provinces from two decades, we have substantially more variation to work with. We find robust evidence that the richness of the provincial data provides information relevant to understand and project Chinese aggregates. Using this provincial data, we build an alternative indicator for Chinese growth that is able to reveal fluctuations not present in the official statistical series. Additionally, we concentrate on the determinants of Chinese growth and show how the drivers have gone through a substantial change over time both across economic variables and provinces. We introduce a method to understand the changing nature of Chinese growth that can be updated regularly using principal components derived from the provincial data.

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1. Introduction

The growth of the Chinese economy has been the main engine of the global economy over the last two decades. Pre-Covid, new Chinese GDP accounted every year was larger than the US and the euro area new GDP combined. China is now the second largest economy in the world, after the US and ahead of the euro area. Furthermore, a major reason why emerging markets had a relatively smooth activity following the Great Financial Crisis owes to a major infrastructure investment campaign in China which boosted the terms of trade for producers of commodities.

However, the time series of Chinese growth is also among the most frustrating time series to date. Until the end of 2019, it was desperately flat around 6%, mimicking the growth objective of the Chinese authorities. What is flat offers little hope of any attempt of econometric analysis. In addition, even considering alternatives, such as the famous Li Keqiang[1] index, offers only so much degrees of freedom to analyze the determinants of growth in China.

In this article, we explore the time series of economic variables at the level of 31 Chinese provinces to gain insight on the evolution and the determinants of economic activity in China. These data are published by the National Bureau of Statistics (NBS), People's Bank of China, China Ministry of Finance, Ministry of Human Resources and Social Security and by a Chinese real estate website company SouFun-CREIS. Data is originally available from 1999 at monthly, quarterly or annual frequency depending on the variable, but all series have been converted to quarterly frequency. While there is no a priori reason that province level data are of a better quality than national aggregate, we show that they do contain useful information to forecast Chinese economic activity. Their variance is informative in this statistical sense. Our analysis using panel and time series approaches shows five striking results.

First, province data help to project economic activity in China. Second, based on the province data we define a new indicator of Chinese growth (The 31 Provinces China Business Cycle Indicator, or 31P-CBCI) that can pick up fluctuations not present in the official data. It is updated quarterly as new provincial data becomes available and published at the Bank of Finland BOFIT webpage[2]. Third, the determinants of economic growth in China have changed around 2010. Before, growth was driven by urbanization and productivity. Since 2010, growth is driven by credit, house prices and public expenditure. In addition, urbanization has dragged on growth in this decade. Fourth, the group of provinces pulling Chinese growth up has changed. The determinants of growth after 2010 apply more homogeneously to a larger group of Chinese provinces and those with the strongest correlation to aggregate growth are now clustered across the coastal and central China. Five, we introduce a method to pinpoint changes in the underlying determinants of Chinese growth that can be easily updated.

This paper contributes to two strands of literature. First, it gives new insights to the literature focusing on the reliability of Chinese growth figures and measurement challenges of economic activity. The accuracy and authenticity of Chinese official figures has been questioned by many for decades already. Appendix 1.1 in Jia (2011) offers a thorough literature review on the studies of China's macro-data quality. For the late 1990s and early 2000s, Rawski (2001), Maddison and Wu (2006), Maddison (2006) and Young (2006) compare official GDP

[1] Li Keqiang index was created by The Economist as an alternative measure for Chinese growth using three indicators (the railway cargo volume, electricity consumption and bank loans) as reportedly preferred by the current Premier of China as better economic indicators than official GDP numbers. Other alternative GDP measures include for ex. The Conference Board's Total Economy Database (Wu, 2014), Barclay's index using PMIs, Bloomberg and Capital Economic indices using linear combination of various economic variables, The Lombard Street Index, as well as different estimated economic growth proxies as in Fernald et al. (2015) or Henderson et al. (2012).
[2] www.bofit.fi/en/monitoring/statistics/china-statistics/ Direct link to data

figures against various supply side indicators and find that the Chinese economy may have grown by a couple of percentage points less than the official growth would suggest. There are studies that contradict these results and find that the official data is roughly correct and may even understate the "true" economic growth (e.g. Holz, 2006a, 2006b, 2014; Clark et al., 2017a, 2017b; Perkins and Rawski, 2008). Further, it seems that information on different business sentiment indicators (Mehrotra and Rautava, 2008) and various other economic indicators (Mehrotra and Pääkkönen, 2011) convey useful information about developments in Chinese real economy.

Chinese official growth statistics started to raise more doubts again in the 2010s, after China explicitly announced its ambitious decade-long real GDP doubling target in 2012. Following the announcement, real GDP growth rate has been tracing its pre-announced annual targets to a frustrating degree losing practically all normal fluctuations. As a result, several alternative GDP measures have emerged to better capture fluctuations in Chinese economic growth.

Fernald et al. (2019) compose a China Cyclical Activity Tracker (China CAT) using a combination of eight non-GDP indicators revealing fluctuations not present in the official growth rates. The Conference Board's alternative estimate for Chinese GDP (Wu, 2014) is constructed on a sector-by-sector basis, relying on both official and constructed series. This GDP measure indicates larger volatility in the year-on-year estimates, sometimes showing higher growth rates than the official numbers (de Vries and Erumban, 2017). After a US State Department memo released by Wikileaks revealed that the current Chinese Premier, Li Keqiang, confided to the US ambassador in 2007 that to find out the true state of the economy, instead of the unreliable official GDP figures he himself turned to electricity consumption, bank loans and railway cargo volume. Li was at the time serving as a party committee secretary in the province of Liaoning. Also the Li Keqiang index reveals an economy much more volatile for the recent years than what the official figures suggest. Other alternative indices include Barclay's index, which uses purchasing manager indices, as well as the Bloomberg and Capital Economic indices, which use linear combinations of variables such as sectoral value added, freight, passenger traffic and retail sales. The Lombard Street Index takes the official nominal GDP and a range of price indices covering all expenditure components and calculates an alternative real GDP growth rate.

Chinese GDP growth has also been estimated using various techniques. Fernald et al. (2019) proxy China's economic activity with trade partner export data, whereas Henderson et al. (2012) turn to night-time light intensities from satellite data that is immune to falsification and misreporting. Clark et al. (2017a and 2017b) utilize this night-time light data to estimate an alternative weighted Li Keqiang-index. Kerola (2019) estimates Chinese real GDP growth rates with alternative deflators using official price index data.

Our contribution to this debate is to provide an alternative business cycle indicator using only official provincial macroeconomic data. Richness of the quarterly provincial data together with principal component analysis result in a new indicator that is able to capture fluctuations in Chinese growth also for the more recent years.

Second, our paper also contributes to the strand of literature concentrating on understanding and analyzing the determinants of Chinese growth. There are a number of structural factors in China that affect the growth process under way: e.g. ongoing shift towards a more service-based economy, decreasing workforce, limits to internal migration and ageing population. Greater awareness should be paid to the role played by structural transformations in China as business cycle fluctuations still play a much smaller role (Laurenceson, 2013 and Laurenceson and Rodgers, 2010).

As discussed with detail in Chen and Zha (2018), 1998 marked the beginning of the investment-driven phase in China, where government effectively controlled aggregate bank loans by explicit M2 supply growth targets to support investment especially in the heavy sector (e.g. infrastructure and real estate). The promotion of investment at the sacrifice of consumption also meant that the relationship between investment and consumption broke down, as the correlation between growth rates of investment and consumption changed from 0.80 to being statistically insignificant after 1998. Beginning of 2000s also marked the rise of China's role in global trade flows. However, as most of the investments were directed to the heavy, capital-intensive sector, they had little to do with increasing exports that were mostly produced in the labour-intensive sectors.

Laurenceson (2013) finds evidence that demand shocks are a much greater source of output growth variance in coastal provinces compared to inland provinces, which could be due to their greater exposure to international trade and investments and are thus more affected by demand shocks originating from overseas. Démurger et al. (2002) suggest that by the end of 1990s regions with similar geographical characteristics had converged, but inequality between coastal and landlocked provinces persisted. Major factors preventing national convergence seem to be inefficient capital allocation by the banking sector and low labour mobility. The eastern provinces grew faster also because of high amounts of foreign investment. Poncet and Barthélemy (2008) analyse correlation of the provincial data for 1991-2004 to see how synchronized business cycles are in China. Business cycles of the more remote provinces show low correlations with the rest of the country as business cycles between two provinces are more synchronized when production structures are more similar and labour can move more freely. Mehrotra et al. (2010) find important differences in the inflation process across provinces using New Keynesian Phillips Curve to model provincial inflation developments. What most explain these differences are the degree of development of the market system and the relative exposure to excess demand pressures (GDP growth, labour productivity, level of industrialization and migration). Gerlach-Kristen (2009) uses principal component analysis and finds evidence of both business and inflation cycle synchronization across most Chinese provinces, apart from mainly the northwestern provinces that have become less closely tied to developments in the rest of China.

Our contribution to this strand of literature is to use provincial data to show how the determinants of growth have changed in China during the past two decades both with respect to economic variables and across provinces. We show that during 1999-2010, aggregate growth was predominantly dependent on investments, internal migration and productivity of the urban workforce. After 2010, growth has been increasingly dependent on government expenditures, house prices and credit. We also show that after 2010, the new determinants of growth apply to a much larger share of provinces and those with the highest correlation to aggregate growth are mainly situated in coastal and central China. As an additional contribution, we introduce a simple method to pinpoint changes in the underlying determinants of Chinese growth that can be updated regularly.

This paper is organized as follows. Section 2 discusses issues about Chinese economic data compilation and the differences between national and provincial series. Section 3 introduces the provincial data used in more detail. Section 4 presents the empirical analysis, including an alternative indicator for Chinese growth and a method to reveal the changing nature of the growth determinants. Section 5 concludes.

2. National and provincial accounts

This section provides a short description of the Chinese economic data compilation and discusses the differences between national and aggregated provincial series.

2.1. Data compilation

Before 1985, China's national accounts were compiled according to the Material Production System developed in the Soviet Union and used by countries with centrally planned economies. Gradually China moved to the United Nations' System of National Accounts (SNA). A more conventional value added approach was introduced in 1992. China's national GDP was initially estimated only from the production side, and the expenditure approach was formally adopted by the National Bureau of Statistics (NBS) in 1993. Since 1992, both annual and quarterly national GDP estimates have been published by the NBS. Currently China compiles its national accounts according to the SNA 2008.

At the central level, the NBS is responsible for organizing, directing and coordinating the statistical work throughout the country. At the provincial level, the People's governments at all levels and all departments, enterprises and institutions may, according to the needs of their statistical work, set up statistics institutions (Vu, 2010). National GDP is compiled by NBS and (until very recently) gross provincial products (GPPs) were compiled by provincial bureaus of statistics (PBS).

In principle, the national GDP should equal aggregated gross provincial product. However, there has been a large discrepancy between the sum of Chinese GPPs and GDP, and the sum of GPP has been growing faster than the national GDP. The main reason for the discrepancy is the use of enterprises as statistical units (and not establishment) that can result in double counting. A local unit can be counted twice, first as part of the enterprise at the place where the enterprise is located but where the activity does not take place and second also as a local unit at the place where the activity takes place (Vu, 2010). Provinces also have incentives to exaggerate output due to growth targets and the use of statistics to measure local policy makers' achievements (Holz, 2014).

Data on enterprises whose output is above some cutting point are collected by surveys that are benchmarked on the economic census data covering industrial, construction and service activities. Data on smaller enterprises are estimated on the basis of administrative records like taxes. At the national level, administrative records on nonmarket services can be used directly. However, to identify services at the local level, different surveys are used. The same also occur to market services, surveys for the national level is carried out by the NBS and local bureaus of statistics take care of the surveys at local levels (Vu, 2010).

Overall, the NBS has little control over provincial statistics bureaus or over the statistics divisions of other central government departments and as a result most of the data compilation has occurred outside NBS control (Holz, 2014). Revelations during the last decade of some extensive data falsifications at the provincial level have caused the NBS to rely more on economic censuses, annual data from directly reporting units, and sample surveys to improve the accuracy of national figures. As a result, NBS took over the compilation of provincial gross product totals from 2019 onwards and begun to develop a new system to generate and analyze national and provincial balance sheets to improve the overall GDP compilation mechanism. Based on media reports, officials said the move was part of the central government's efforts to combat the discrepancies between provincial and national figures, but the shift could also mean better inclusion of businesses not counted in statistics so far.

Since the NBS took over the compilation of provincial gross product totals, the provincial data was revised extensively especially for 2018. Based on survey data the NBS revised downward the total provincial GDP of 2018 by 1 trillion yuan (140 billion euros). Largest cut was made in Tianjin province, where nearly 30% of the provincial GDP was reduced. For some, annual GDP was increased, largest correction was boosting Yunnan's GDP of about 17%. All provincial data used in this paper are updated in 2020 and are thus based on the revised series.

Overall, there is no reason to believe that provincial data would be of a better quality than the official national aggregates. But as these recent large NBS data revisions suggest, measurement errors in provincial data can easily occur in both directions. Moreover, while our data covers 11 economic variables for 31 provinces for 84 quarters (altogether some 28,000 observations), there is sufficient grounds for treating possible measurement errors as randomly distributed. Having substantially more variation to work with decreases the probability that the data would as a whole deviate from the underlying true economic activity in one direction of another.

2.2. Nominal and real growth rates

Figure 1 presents Chinese nominal GDP growth rates, both the official, national series and the aggregated provincial series. The series match to a high degree. For the provincial aggregate, growth peak before the great financial crisis dates a couple of quarters later than for the national growth and the economic recovery after the downturn is much stronger. After 2012 however, these two series paint a fairly similar picture of the Chinese economic development. This is not the case when looking at the real GDP series, as presented in Figure 2.

Apart from the obvious difference in the level of the real GDP growth rates, it is interesting that by aggregating provincial real GDP figures one reveals fluctuations not present in the national series for the more recent years. Especially after the China State Council explicitly announced the real GDP doubling target in 2012, the lack of fluctuations in the national real GDP series is hard to ignore. The ambitious official goal was to double China's real 2010 GDP by 2020. This explicit growth target seems to have forced officials pursue numbers to meet their mandated targets at many levels of the economy.

Figure 1: Nominal GDP growth rates in China: national and sum over provinces

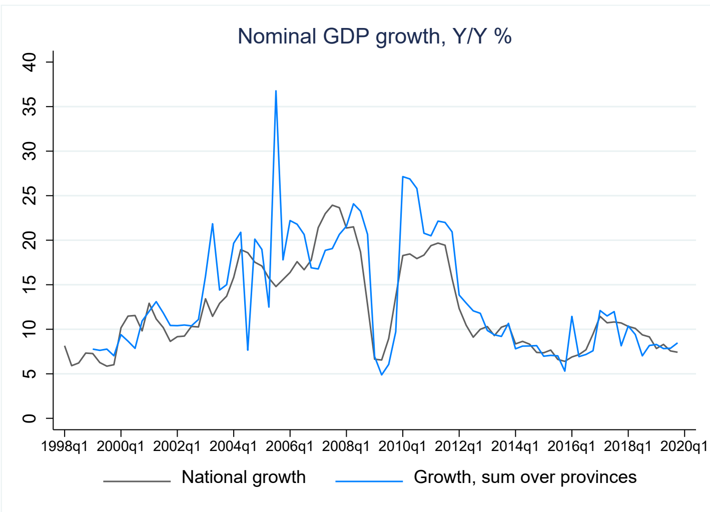
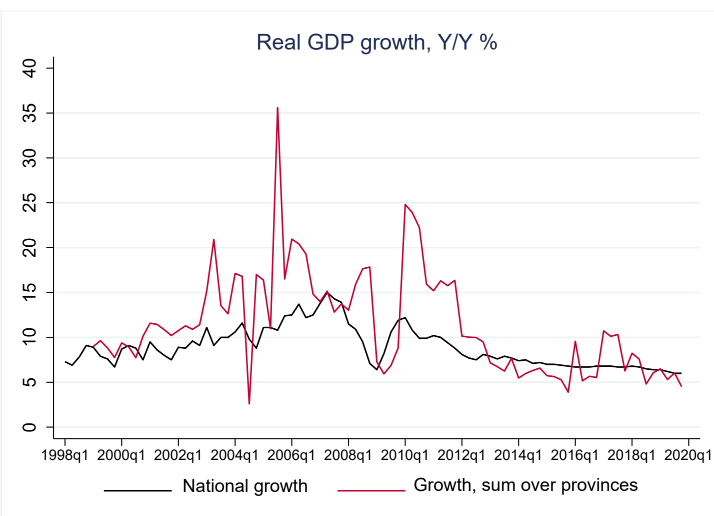


Figure 2: Real GDP growth rates in China: national and sum over provinces



All in all, it seems more doubt has been cast on China's real GDP figures than on nominal GDP numbers. Clark et al. (2017b) note that there is much less discrepancy on average with nominal growth rates than between official central government and provincial real GDP growth assessments. They infer that the NBS computes the national real GDP by taking the nominal growth rates reported by the provincial authorities and deflating them using a common deflator.

China's nominal GDP has also been subject to revisions as the NBS regularly conducts economic censuses that may induce revisions to economic data. Holz (2014) documents that for example in the 2006 benchmark revision following the 2004 economic census, the *nominal* value added for 1993-2004 were revised for all sectors, as the *real* growth rate was revised only for the tertiary sector. The retention of the original real growth rates for primary and secondary sectors is not plausible and the implication of not changing real growth rates is that the NBS adjusted the implicit deflator. But, the 2004 economic census collected no price data, and the NBS offered no explanation as to why and how it revised the sectoral deflators. This further points to the conclusion that nominal GDP series is overall a more reliable measure of the Chinese business cycle fluctuations than the real GDP. Hereafter, whenever we need to employ Chinese national GDP growth, we use the nominal series.

For the other economic variables used in this paper, discrepancies between national and aggregated provincial data are also rather prominent with consumption, urban employment and productivity. On the other hand, with bank loan growth, consumer price index, house price growth and investment growth the provincial and national series seem to match to a high degree. Time series of these economic variables are shown in Figure 9 in Appendix.

3. Data

We use a provincial macroeconomic dataset in quarterly frequency. Table 1 presents all variables and their summary statistics compared to the corresponding national figures. Series are primarily from the CEIC China Premium Database that compiles data from different sources. Nominal GDP series, CPI inflation, consumption expenditures, investments and population come from the National Bureau of Statistics. Bank loan series are compiled by the People's Bank of China, regional government expenditures by the Ministry of Finance and urban employment figures by the Ministry of Human Resources and Social Security. House price data comes from a Chinese private real estate website owner SouFun-CREIS. Real GDP series is computed by deflating nominal GDP by CPI inflation. Productivity is computed using real GDP growth and urban employment growth.

Population, urban employment, regional government expenditures and investments are available only at annual frequency. For population and urban employment, annual values are used for all respective quarters. For investments and government expenditures, quarterly observations are obtained by linear interpolation. For consumption and bank loans we have part of the time series in annual frequency (consumption until 2013 and bank loans until 2003). For 1999-2003 bank loan observations are linearly interpolated to quarterly frequency. Private consumption observations for 1999-2013 are modified to quarterly frequency using the Denton approach. Table 11 in Appendix gives a more thorough list of the different variables used.

Table 1: Summary statistics, provincial panel and respective national figures

	Provincial panel			National data		
	# of obs	Mean	Std.dev.	# of obs	Mean	Std.dev.
Nominal GDP	2,604	11.37	8.71	88	12.15	4.88
Real GDP	2,604	13.47	9.25	88	8.89	2.19
CPI inflation	2,604	2.10	2.28	82	2.03	2.09
Consumption	2,604	9.62	7.50	79	9.57	2.30
Bank loans	2,604	12.90	8.65	74	13.23	5.37
Investments	2,511	15.65	11.66	81	14.02	5.77
Gov't expenditures	2,511	13.95	9.36	82	16.88	16.22
House prices	2,490	4.61	6.00	71	5.11	4.29
Population	2,387	0.82	1.36	87	0.56	1.00
Urban employment	2,387	4.97	6.71	84	3.57	0.67
Productivity	2,542	9.03	11.38	84	5.45	1.72

Throughout this paper we utilize our provincial data in three different ways. First, we use it as a full panel, all 11 variables for 31 provinces. For the other two ways, we utilize the principal component analysis (PCA), originally invented by Karl Pearson already in 1901. The idea behind PCA is to ease the interpretation of large datasets by drastically reducing the number of variables while at the same time retaining as much statistical information as possible. PCA produces new variables (principal components) that are linear functions of the original dataset and that are uncorrelated with each other. The first principal component accounts for as much of the variance in the dataset as possible, and each succeeding component as much of the remaining variance[3]. For the second way of using our provincial data, we compress each of the economic variables across provinces into one component (the first principal component) at a time, calling these time series the *variable specific principal components*. For the third way, we compress the full provincial panel (all economic variables for all provinces) into principal components. We keep the eight first principal components[4] and call these time series the *full information principal components*. In the PCA analysis, all provincial variables are used in year-on-year growth rates and further standardized to have sample mean zero and unit sample variance.

[3] More e.g. in Jolliffe (2002)

[4] To determine the number of principal components we could have used e.g. information criteria-type methods (Bai and Ng, 2002). These methods can, however, produce surprisingly divergent conclusions (Hallin, 2007) and are thus far from conclusive. There also exist older, heuristic methods such as eigenvalue thresholding (Guttman, 1954) and scree plots (Cattell, 1996) that still are popular methods for factor retention. In our PCA analysis, we keep the eight first principal components as they all have an eigenvalue above 10 and each can explain at least 4 % of the total sample variance. These are also the principal components that are in the steep part of the scree plot curve before it flattens out.

Table 2: Proportion of variance explained by principal components

Proportion of variance explained by variable specific principal components for each variable in provincial panel		Proportion of variance explained by first eight full information principal components for the whole provincial panel		
	Proportion (%)		Proportion (%)	Cumulative (%)
Nominal GDP	56.6 %	Comp1	22.89 %	22.89 %
Real GDP	50.4 %	Comp2	13.16 %	36.05 %
CPI inflation	82.4 %	Comp3	9.74 %	45.80 %
Consumption	37.9 %	Comp4	6.57 %	52.37 %
Bank loans	57.3 %	Comp5	5.63 %	58.00 %
Investments	55.4 %	Comp6	5.29 %	63.29 %
Gov't expenditures	35.6 %	Comp7	4.21 %	67.50 %
House prices	56.5 %	Comp8	3.78 %	71.28 %
Population	39.7 %			
Urban employment	52.0 %			
Productivity	40.6 %			

Looking at the variable specific principal components (first panel, Table 2) for each of the economic variables, we see that the one for CPI inflation explains the largest amount of variation for the underlying provincial CPI data, over 82%. Lowest proportion of variance is explained by the variable specific principal components for government expenditures (35.6%), consumption (37.9%) and population growth (39.7%). The smaller the proportion that the variable specific principal component can explain, the more prevalent are idiosyncratic shocks across provinces. On the other hand, larger explanatory power means a stronger underlying common trend.

Turning into the first eight full information principal components obtained by compressing the whole provincial panel, we see that the first estimated principal component explains 22.9% of the total sample variance, while 13.2% is explained by the second component. The first eight components explain cumulatively 71% of the total sample variance. Next, we move on to the empirical estimations.

4. Empirical analysis

This section provides the empirical analysis. First, we show that provincial data is able to explain the majority of the variation in the national nominal growth rate and further that it is highly informative in projecting national growth. Using this provincial data, we build an alternative indicator for Chinese growth that is able to reveal fluctuations not present in the official real GDP growth. Second, we concentrate on the determinants of Chinese growth and show how the drivers have gone through a substantial change over time both across economic variables and provinces. We introduce a method to understand the changing nature of Chinese growth that can be updated regularly using principal components derived from the provincial data.

4.1. Projecting national growth with provincial data

We start by looking how well our provincial panel can project national GDP growth. To this end, we look first at the proportion of variance the provincial panel can explain of the contemporaneous national GDP, as presented by Table 3.

Table 3: Proportion of variance in contemporaneous national GDP explained by provincial time series

Variance explained by:	National nominal GDP	National real GDP
Provincial panel	0.606	0.350
Variable specific principal components	0.878	0.628
Full information principal components	0.893	0.681

When using the whole provincial panel data, we are able to explain 61% of the national nominal GDP's total variance. As we compress this panel data into variable specific principal components, the explanatory power increases to 87.8 %. With the first eight full information principal components, we can explain up to 89.3% of the variance. What is also imminent from Table 3, is that we are able to explain much less of the variance of the real GDP.

To find out how well we can project Chinese growth with provincial data, we begin by conducting granger causality tests. Our dependent variable is the national nominal GDP growth. As explanatory variables, we have the lagged value of the dependent variable and the lagged values of the provincial variables. We first use the full provincial panel and in turn replace the explanatory variables by the variable specific principal components and then by the eight full information principal components. We use the four-quarter lagged values for all explanatory variables. Table 4 presents the results.

Table 4: Granger causality test results: provincial panel, variable specific and full information principal components

Provincial panel	Overall R2 0.606, # obs: 2400				Variable specific principal components	Overall R2 0.814, # obs: 80				Full information principal components Largest factor loadings in parentheses	Overall R2 0.821, # obs: 80			
	Coeff	F-stat	Prob>F	Marginal R2		Coeff	F-stat	Prob>F	Marginal R2		Coeff	F-stat	Prob>F	Marginal R2
Inflation	-1.469	929.49	0.000	0.201	pc(inflation)	-0.961	51.65	0.000	0.154	Pc 3 (Credit + inv. - infl. - house prices)	0.486	57.64	0.000	0.249
Credit	0.128	164.53	0.000	0.030	pc(credit)	0.277	18.22	0.000	0.024	Pc 6 (House prices + inv. - consumption)	0.437	47.77	0.000	0.077
Investments	0.078	109.23	0.000	0.018	pc(investments)	0.368	8.89	0.004	0.014	Pc 2 (Productivity - urban empl.)	0.197	38.40	0.000	0.094
Productivity	0.040	23.99	0.000	0.003	pc(consumption)	-0.325	6.83	0.011	0.010	Pc 8 (Consumption - gov't expend.)	0.237	10.47	0.002	0.028
House prices	-0.051	12.21	0.001	0.013	pc(productivity)	0.438	6.61	0.012	0.011	Pc 4 (House prices - gov't expend.)	0.170	6.78	0.009	0.015
Consumption	-0.032	10.92	0.001	0.002	pc(gov't exp.)	-0.168	1.77	0.187	0.002	Pc 7 (Productivity + consumption)	-0.004	5.64	0.020	0.013
Gov't expend.	-0.011	1.35	0.245	0.000	pc(population)	-0.140	1.59	0.212	0.003	Pc 5 (House prices + credit)	-0.030	0.08	0.776	0.000
Population	-0.054	0.91	0.341	0.000	pc(urban empl.)	0.208	1.45	0.233	0.003	Pc 1 (GDP + investments)	-0.001	0.08	0.777	0.000
Urban empl.	0.008	0.35	0.553	0.000	pc(house prices)	-0.114	0.88	0.351	0.005					

Notes: Dependent variable nominal national GDP growth. All explanatory variables lagged by 4 quarters and sorted by their Prob>F-stat. Lagged dependent variable omitted from table.

The left most part of the table presents the granger causality results for the provincial panel variables. The first six provincial variables are statistically significant in explaining future national growth at the 1% level. These are inflation, credit, investments, productivity, house prices and consumption. The lagged provincial variables can explain a total of 61% of the total variance of future national growth.

Using the full provincial panel, we are forcing the coefficients for each variable to be the same across provinces. The rest of the table looks at whether the results hold in time series, i.e. after compressing the provincial panel into principal components. Using the variable specific principal components (middle section of the table) and full information principal components (right part of the table) we allow different factor loadings for each province and each variable.

We find that the result holds in time series, so that also the compressed components are highly significant in projecting Chinese aggregate growth[5]. The first three variable specific principal components are statistically significant in projecting future national growth at the 1 % level. These are inflation, credit and investments. With full information principal components, there are five components that are statistically significant in explaining future aggregate growth at the 1 % level and these are components number three, six, two, eight and four (sorted by their probabilities in explaining future national growth)[6]. With lagged variable specific and full information principal components we can explain 81 % and 82 % of the total variance of aggregate national growth, respectively.

In all, the provincial data seems to be highly relevant and provides information able to explain the majority of the variance of national growth. For that reason, the provincial data is an excellent candidate when thinking about alternative indicators for Chinese growth. As discussed in the introduction, there exists a long-standing debate over the reliability of China's GDP figures and especially after the real GDP growth series became flat since 2012, several alternative growth measures have emerged. We contribute to the search of missing fluctuations by computing three candidates as alternative growth indicators using the provincial data. For the first alternative growth indicator, we regress the national nominal GDP growth on its own lagged value and the lagged values of the full information principal components that were statistically significant in the granger causality tests presented in Table 4 (full information principal components 3, 6, 2, 8 and 4). For the second alternative growth indicator, we replace as explanatory variables the statistically significant variable specific principal components. These are the variable specific principal components of inflation, credit and investments. For the third alternative growth indicator, we use as explanatory variables the unaltered provincial variables that were statistically significant in Table 4: inflation, credit, investments, productivity, house prices and consumption. To assess the relative accuracy of these candidates, we compute cross-correlations between official growth rates and different alternative growth indicators.

Table 5 presents the cross-correlation of the official national growth rates (nominal and real), the Li Keqiang index, two publicly available Business Cycle Indicators (one by the NBS and one by the PBoC), as well as our three different growth indicator candidates constructed from the provincial panel.

[5] Instead of using static principal component analysis in economic forecasting à la Stock and Watson (2002) another option would be to use dynamic principal component analysis as in Forni et al. (2000). However, as it very likely would not increase the performance of our analysis (e.g. D'Agostino and Giannone, 2006; Boivin and Ng, 2005) but rather make the economic interpretation more difficult, we stick to the static principal component analysis.

[6] The first principal component is statistically insignificant and only able to explain less than 0.0 % of the total variance. Reason is that it was compressed initially from the full provincial panel where it explained 22.9 % of the total sample variance. Here we force the principal components to explain only one time series, namely the future national nominal GDP growth.

Table 5: Cross-correlation between official growth rates and alternative growth indicators, contemporaneous values

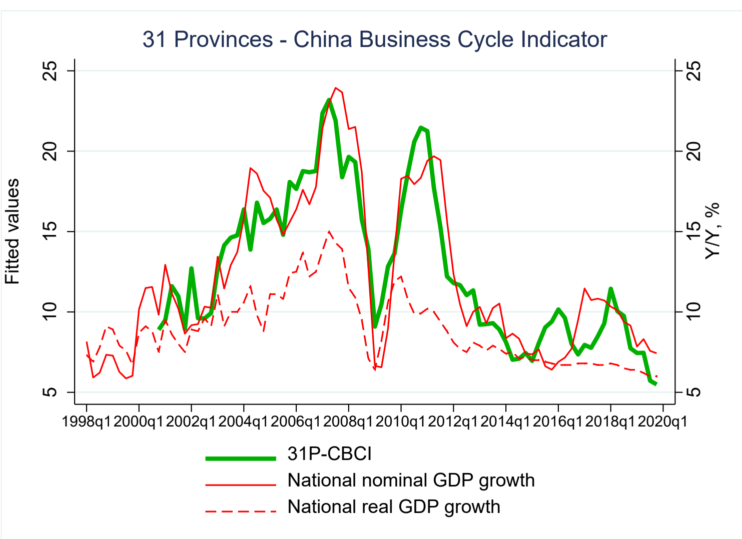
		National nominal GDP	National real GDP	Li Keqiang index	Business Climate Index, NBS	Business Climate Index, PBoC	Alternative growth indicators (1) Using stat.sign. full info PCs	(2) Using stat.sign. var spec. PCs	(3) Using stat.sign. provincial vars
National nominal GDP		1.00							
National real GDP		0.84	1.00						
Li Keqiang index		0.56	0.75	1.00					
Business Climate Index, NBS		0.84	0.68	0.49	1.00				
Business Climate Index, PBoC		0.87	0.82	0.65	0.83	1.00			
Alternative growth indicators	1) Using statistically significant full information principal components*	0.90	0.78	0.50	0.78	0.88	1.00		
	2) Using statistically significant variable specific principal components**	0.89	0.82	0.47	0.79	0.89	0.95	1.00	
	3) Using statistically significant provincial variables***	0.73	0.65	0.37	0.66	0.79	0.81	0.85	1.00

* Full information principal components PC2, PC3, PC4 PC6 and PC8. ** Variable specific principal components: pc(inflation), pc(credit) and pc(investments) *** Provincial variables: inflation, credit, investments, productivity, house prices and consumption

All alternative indicators computed by regressing nominal aggregate growth on its own (4 quarter) lagged value and the (4 quarter) lagged values of the statistically significant variables.

When using the unaltered provincial panel variables (the third alternative growth indicator), we have a correlation of 0.73 with the national nominal GDP and 0.65 with the real GDP. However, for the second and first alternative growth indicators, we have much higher correlation coefficients. Using variable specific principal components, the correlation is 0.89 with nominal and 0.82 with real GDP growth. With statistically significant full information principal components, the correlation is 0.90 with nominal and 0.78 with real GDP growth. The second and first alternative indicators are also highly correlated with the Business Climate Indices (correlation 0.78–0.89). We ultimately choose the first alternative as our main growth indicator, as it uses full information principal components and thus a larger amount of information from the panel than the second alternative. We name it 31 Provinces China Business Cycle Indicator (31P-CBCI). Figure 3 presents the 31P-CBCI alongside with official national GDP growth rates[7].

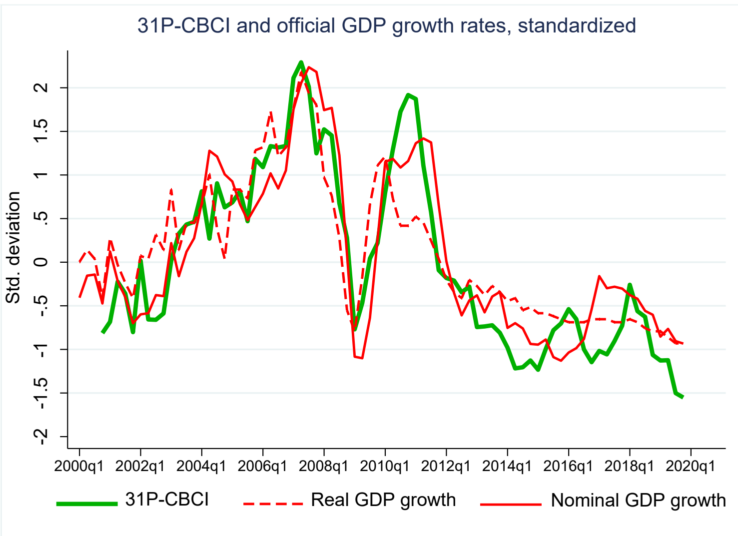
Figure 3: 31 Provinces China Business Cycle Indicator



[7] First and second alternative indicators are broadly similar in shape throughout the last two decades. Figure 10 in Appendix provides a similar presentation of the second alternative indicator.

As we use nominal GDP series when fitting the 31P-CBCI, its level is by construction closer to the level of the nominal than to the real growth rate. However, we are more interested to uncover business cycle fluctuations, which the official real GDP flattens out, than the actual level of the growth rate. Given our endeavor to extract these fluctuations and not growth rate levels, we standardize the three series to have zero mean and unit standard deviation (Figure 4)[8].

Figure 4: 31P-CBCI and official GDP growth rates, standardized series with zero mean and unit standard deviation

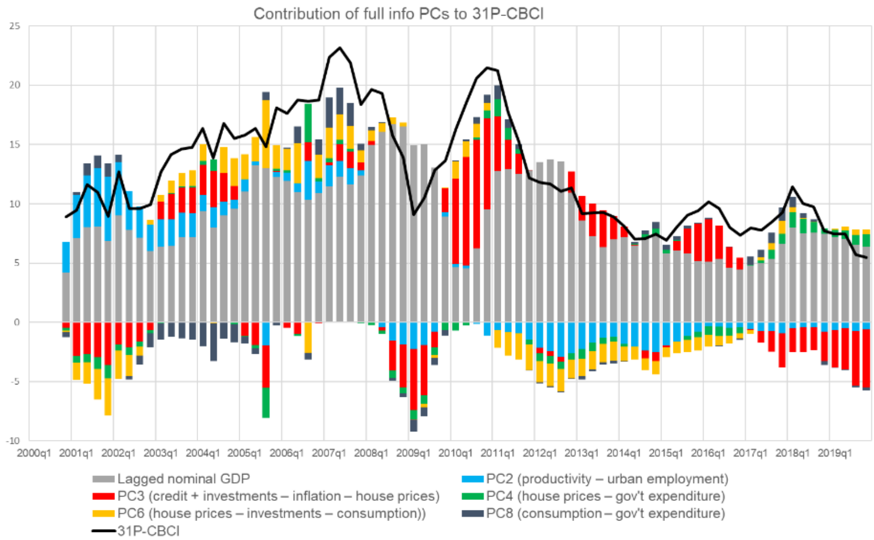


Based on the 31P-CBCI, there was an increase in growth rate in 2015, followed by a drop in 2016. We observe an abrupt acceleration of growth in 2017 and a loss of steam starting at the beginning of 2018 and further weakening during 2019. This contrasts with the steadiness of official growth series. In nominal terms, GDP growth decelerated between 2014 and 2015, then increased fast during the second half of 2016 and started to fall again after 2017. In real terms, growth rate is rather constant but what both official series indicate is that growth in 2019 Q4 was around one standard deviation below its trend. The 31P-CBCI points to a much lower growth rate relative to its trend at the end of the time span.

To further illustrate how each full information principal component contributes to the formation of the 31P-CBCI over time, we illustrate in Figure 5 the contributions of all the dependent variables (lagged nominal GDP growth and lagged full information principal components 2,3,4,6 and 8). In the figure, series' labels present the largest factor loadings for each principal component to better assess which macroeconomic variables are the main drivers. Factor loadings are more thoroughly discussed later in section 4.2.

[8] Data for standardized 31P-CBCI will be updated quarterly as new provincial data becomes available and published at the Bank of Finland BOFIT webpage. Data is downloadable. https://www.bofit.fi/en/monitoring/statistics/china-statistics/

Figure 5: Contribution of variables behind 31P-CBCI over time



Note: Constant term (value 3.388) omitted from the figure. Largest factor loadings of full principal components in parentheses.

Principal component 2 (reflecting developments in productivity and urban employment) contributes to Chinese growth mostly positively in the first half of the sample and mostly negatively in the second half of the sample, notably in the aftermath of the great financial crisis. Principal component 3 (strongest drivers being credit and investment relative to inflation and house prices) contributes to growth fluctuations with a strong cyclical pattern. It alternates periods where it pushes growth up and down for up to 3 years for each phase. Up-phases include 2003-2004, 2010-2012, 2015-2016 and down-phases 2001-2002, 2008-2009 and 2017-2019. In more recent years, it seems to be the main contributor to both the upturn of 2015 as well as the largest downward pulling factor for years 2018 and 2019. While the upturn of 2015 was mostly driven by principal component 3, the more recent acceleration of growth in 2017 had other drivers. There, we observe a combination of contributions from principal component 8 (consumption and government expenditure), principal component 6 (house prices, investments and consumption) and principal component 4 (house prices and government expenditure).

This figure also reveals that the contribution of the lagged dependent variable (nominal GDP growth) is quite large. However, we show in Appendix that excluding this lagged nominal GDP does not change our results. Figure 11 in Appendix presents an optional growth indicator computed using only our eight full information principal components, discarding the lagged nominal GDP growth. As can be seen, differences between this optional indicator and the 31P-CBCI are minimal and we thus stick to our more parsimonious model. Figure 12 in Appendix breaks this optional indicator into its driving principal components the same way as Figure 5 for the 31P-CBCI. What stands out in Figure 12 is that it sharpens our take on the most recent upturn in 2017 confirming it to be mostly demand driven, as principal component 7 (reflecting developments in productivity and consumption) seems to have the strongest positive contribution. Moreover, principal component 7 also appears as a negative contributor to growth in 2019. This points to the conclusion that the growth decline that started in 2018 broadened to the demand side during 2019.

Next, we look more closely to the determinants of the Chinese growth and how they have changed during the past two decades.

4.2. Determinants of Chinese growth

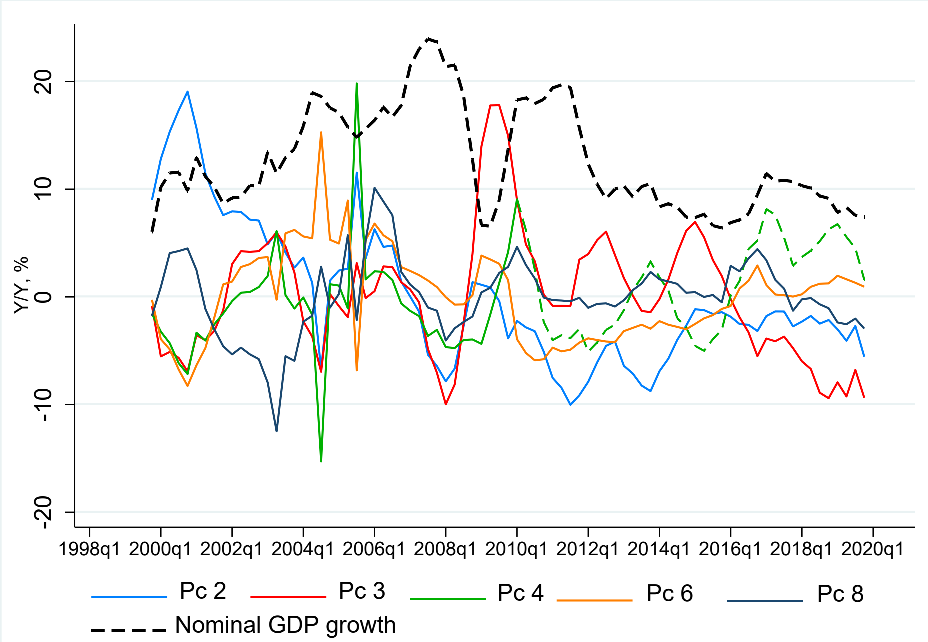
We begin by taking a closer look at the five full information principal components that were found to be statistically significant in explaining future aggregate growth (Table 4, section 3.1.) and were used in building the 31P-CBCI. The principal components are estimated using the whole provincial panel, so they compress information from all the economic variables for 31 provinces. Figure 6 presents the time series of these five principal components and Table 6 their factor loadings.

Table 6: Factor loadings of the full information principal components

Principal component 2	Factor loading	Principal component 3	Factor loading	Principal component 4	Factor loading	Principal component 6	Factor loading	Principal component 8	Factor loading
Productivity	1.318	Credit	3.197	house prices	2.093	house prices	1.578	consumption	1.036
Population	0.756	Investments	1.488	consumption	1.408	Investments	1.256	Real GDP	0.408
Gov't expenditures	0.646	consumption	1.045	Real GDP	1.187	Credit	0.729	Urban employment	0.288
Real GDP	0.465	Real GDP	0.820	Nominal GDP	0.764	Gov't expenditures	-0.121	Nominal GDP	0.281
consumption	0.383	Urban employment	0.562	Productivity	0.490	Productivity	-0.252	Population	0.195
house prices	-0.173	Nominal GDP	0.159	Urban employment	0.439	Population	-0.317	Productivity	0.169
Nominal GDP	-0.194	Gov't expenditures	0.013	Credit	0.257	Real GDP	-0.327	Credit	0.063
Investments	-0.257	Population	-0.141	Population	-0.694	Nominal GDP	-0.506	house prices	-0.016
Credit	-0.985	Productivity	-0.341	Investments	-1.305	Urban employment	-0.625	Inflation	-0.326
Inflation	-2.455	house prices	-1.812	Inflation	-1.339	Inflation	-0.660	Investments	-0.349
Urban employment	-2.567	Inflation	-2.164	Gov't expenditures	-1.694	consumption	-1.372	Gov't expenditures	-0.761

Principal component 2 has highest factor loadings in productivity and urban employment, the latter with a minus sign. Hence, we consider this principal component to give an indication on the fluctuation of "productivity in urban areas". Principal component 3 has highest positive factor loadings in credit and investments and highest negative factor loadings in inflation and house prices, it is therefore an indicator of "credit in real terms". Principal component 4 has highest factor loadings in house prices and government expenditures, the latter with a minus sign, a combination of variables that is more difficult an interpretation. Principal component 6 has highest positive factor loadings in house prices and investments and highest negative with consumption. It can be seen as indicating the deviations of investment from consumption. Finally, principal component 8 has highest positive factor loading in consumption and highest negative in government expenditures, it captures the difference between private consumption and government expenditures.

Figure 6: Five full information principal components statistically significant in explaining future aggregate growth



Note: dashed line for Pc 4 denotes correlation turning negative after 2010 in Table 7

To further assess the combination of macroeconomic variables pulling aggregate growth, we regress the national GDP growth on these five full information principal components. All explanatory variables, including the lagged dependent variable, are lagged by four quarters. Results are presented in Table 7 (left panel) where principal components used as explanatory variables are sorted by their marginal R-squared values for the entire sample.

Table 7: Regression results, dependent variable national nominal GDP growth

Principal components *with largest factor loadings*	Whole time span				Before 2010				After 2010			
	Coeff.	t	P >|t|	Marginal R2	Coeff.	t	P >|t|	Marginal R2	Coeff.	t	P >|t|	Marginal R2
National GDP growth (lagged)	0.561	9.19	0.000	0.275	0.799	3.8	0.001	0.086	0.568	6.73	0.000	0.234
Pc3: *Credit + investments - inflation - house prices*	0.485	10.90	0.000	0.322	0.699	4.87	0.000	0.122	0.319	5.70	0.000	0.107
Pc6: *House prices + investments - consumption*	0.438	9.43	0.000	0.142	0.557	4.31	0.000	0.076	0.513	4.19	0.000	0.077
Pc2: *Urban employment - productivity*	0.196	6.20	0.000	0.072	0.366	2.08	0.047	0.024	0.262	2.07	0.046	0.015
Pc8: *Consumption - gov't expenditures*	0.238	7.17	0.000	0.030	0.222	1.70	0.100	0.015	0.348	3.04	0.005	0.026
Pc4: *House prices - gov't expenditures*	0.169	4.34	0.000	0.026	0.124	1.14	0.263	0.005	-0.119	-1.20	0.237	0.004
Number of observations	77				37				40			
R-squared	0.834				0.810				0.879			

Note: Dependent variable: nominal aggregate GDP growth. All four quarter lagged values.

Looking first at the full sample, we find that Chinese aggregate growth is driven predominantly by credit and investments (over inflation and house prices), i.e. credit and investment in real terms. Principal component 3 clearly has the highest marginal R-squared explaining for around 32 % of the total variance of future aggregate growth. Principal component 6, which captures the difference between house prices and investments with respect to consumption, explains around 14 % of the total variance of Chinese nominal growth rate. Principal component

2 explains around 7 % of the total variance and reflects developments in the productivity of urban employment. Thus, what our statistical model of Chinese growth suggests is that national growth for the last two decades has been mainly grounded on credit, investments and house prices as well productivity of its urban areas.

Next, we want to assess whether these drivers of Chinese growth have evolved over time. Throughout the first decade of the 21st century, China grew at an accelerating pace reaching 15 % year-on-year just before the financial crisis. Growth was primarily based on resource-intensive manufacturing, exports and low-paid labor. Since then, growth has moderated. Several structural constraints, such as decreasing workforce, slowing productivity, limits to internal migration and ongoing shift towards a more service-based economy are likely causal factors of this deceleration. Furthermore, the financial crisis outlined the vulnerabilities of an export-led growth strategy. As a result, China started to put more emphasis on domestic demand, self-sufficiency and economic independence.

We divide our sample period in two equally sized sub-periods, before and after 2010. This way we can consider the decade before the great financial crisis separately from the years of more moderate growth. The second sub-period is also the one during which China officially aimed to double its real GDP and became more or less fixated with numerical growth targets.

To examine how the growth drivers have changed, we explore our provincial data further in three different ways. As a simple first experiment, we redo the previous regression separately for these two sub-periods, before and after 2010. Results are presented in Table 7 center and right panels. Principal components used as explanatory variables are the same for both sub-samples and for the full time span. When looking at the reported regression coefficients, it is immediately evident that most of the growth determinants have a higher marginal R-square for the entire sample than for each of the sub-samples. This means that the full information principal components that we estimate over the full sample capture persistent phenomena and changes in fluctuations that are relevant across the two sub-samples.

We also find that several of the principal components are relevant in either samples. Their marginal R-square, although smaller than for the full sample for some, have been remarkably stable. The main exception is PC4 that reflects differences between government and private sector expenditures, which changes sign. Strikingly, we observe that this faster public expenditure pull growth down before 2010 and up thereafter. We also see a decline in the estimated coefficients for principal components 2 that reflects urban productivity and 3 that reflects real credit and investment. These changes would suggest that real credit and investment and urban employment and productivity matter somewhat less to aggregate growth after 2010.

4.3. Determinants of Chinese growth: further insights from the 31 Chinese provinces

We dive one step further into the province level data to gain further insights on Chinese growth. We assess whether what is true for the aggregate also applies to individual Chinese provinces. As discussed in the introduction, there exists significant heterogeneity across provinces in terms of growth, cycles and structural changes. Exploiting the dataset for 31 provinces, we can study how each province fits into the empirical model of Chinese growth presented in Table 7.

Our approach is to construct for each province its representation in our full information factor model shown in table 7. This representation is obtained by building full information principal components 2, 3, 4, 6 and 8 for each province using the factor loadings for each economic variable as in Table 6 and the respective economic variable time series for each province. We then multiply the obtained regional principal components 2, 3, 4, 6 and 8 by model coefficients presented in Table 7 (left most panel). As a result, we have 31 time series representing our full information factor model for each province. In order to see how well these provincial models are correlated with future aggregate growth, we compute the correlation coefficients between provincial models and aggregate national growth. Correlation coefficients for each province are presented in Table 12 in the Appendix.

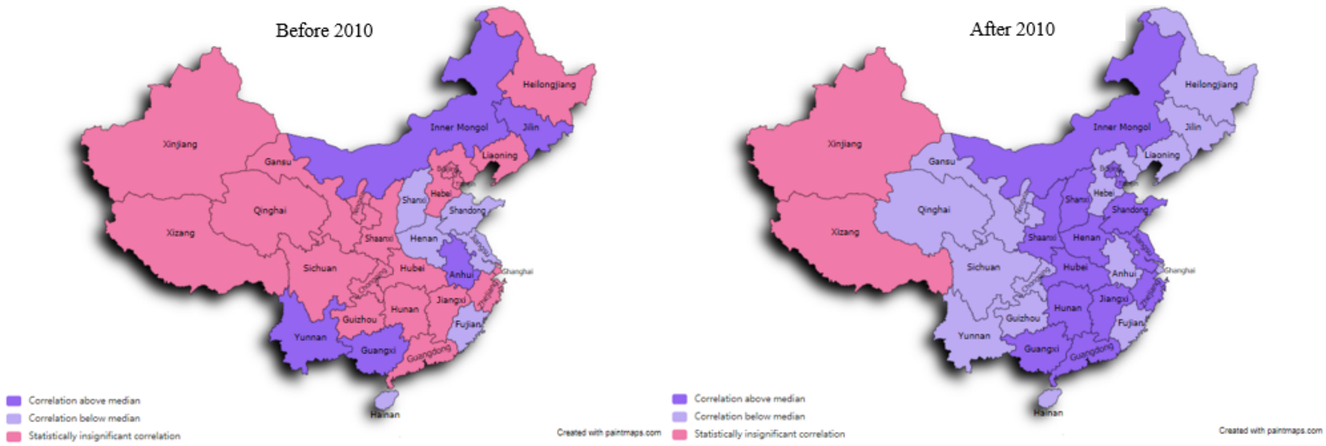
Figure 7 helps to visualize these results. For a majority of provinces, our statistical model of Chinese growth applied to economic developments in the province is positively correlated with national growth in China, This is the case of all (light and dark) blue provinces. This is not the case however for pink provinces (four provinces in the far west, Xinjiang, Tibet, Qinghai and Gansu, Heilongjiang in the far north-east as well as two provinces – Hubei and Guizhou – in central China). For these, our statistical model of Chinese growth does not apply, i.e. growth in these provinces has had other determinants than the ones that prevail at the national level and for a majority of provinces.

Provinces with statistically significant correlation with future national aggregate growth are further divided in two depending on whether the correlation is above or below the median of the statistically significant correlation coefficients. If correlation is above (below) median, province is colored in dark (light) blue. Provinces with the strongest statistically significant correlation (dark blues) are scattered mostly in the coastal region.

Figure 7: Correlation between provincial growth model and future aggregate growth, full time span

We now turn to the evolution of the determinants of growth before and after 2010 by computing the correlation of the province level model prediction with national nominal growth for each sub-sample. The shift across provinces is presented by the two maps in Figure 8. Again, blue represents provinces that are correlated with future aggregate growth and pink represents statistically insignificant correlation. The model applies to a much larger number of provinces since 2010, as growth has become more homogeneous across provinces. Only Xinjiang and Tibet (Xizang) remain uncorrelated with national growth for both subsamples.

Figure 8: Correlation between provincial growth model and future aggregate growth, two different time spans



As a second way to study changes in the determinants of growth, we continue to dig a bit deeper into the analysis of provincial data. We use the grouping of provinces presented in Figure 7 to compare the determinants of growth with panel regressions across blue and pink provinces[9], both for the full sample and for each sub samples. Importantly, we include the national growth rate as a control variable to capture province specific developments. Table 8 presents these panel regression results[10].

[9] Doing the groupings based on correlations with the province level GDP growth obtains very similar groupings and hence regression results.

[10] We note that both the lagged provincial inflation and lagged national GDP are highly significant in all specifications. Further, the coefficient of provincial inflation is negative, which may seem somewhat puzzling at first. However, as inflation is by default included in the nominal GDP series, this negative coefficient is likely to be some form of mean reversion correcting for the coefficient of the lagged nominal GDP. Indeed, if excluding the lagged dependent variable, the coefficients of provincial inflation lose some or all their statistical significance and even become positive in some of the specifications.

Table 8: Panel regression results, dependent variable national nominal GDP growth

	Full time span 1999-2019				Before 2010				After 2010			
	Provincial model correlated with national growth		Insignificant correlation between provincial model and national growth		Provincial model correlated with national growth		Insignificant correlation between provincial model and national growth		Provincial model correlated with national growth		Insignificant correlation between provincial model and national growth	
		Marginal R2		Marginal R2		Marginal R2		Marginal R2		Marginal R2		Marginal R2
L4. National GDP	0.811***	0.253	0.985***	0.358	0.811***	0.211	0.852***	0.238	0.658***	0.136	0.785***	0.172
	(0.026)		(0.048)		(0.048)		(0.070)		(0.034)		(0.091)	
L4. credit	0.126***	0.034	0.145***	0.039	0.071***	0.012	0.085**	0.010	0.212***	0.058	0.237***	0.076
	(0.010)		(0.021)		(0.016)		(0.033)		(0.017)		(0.037)	
L4. consumption	-0.035***	0.001	-0.018	0.000	-0.057***	0.006	-0.019	0.000	0.007	0.000	-0.050	0.003
	(0.011)		(0.024)		(0.017)		(0.028)		(0.015)		(0.046)	
L4. investments	0.085***	0.025	0.033**	0.003	0.089***	0.023	0.047	0.002	0.037***	0.005	0.023	0.002
	(0.008)		(0.014)		(0.014)		(0.044)		(0.010)		(0.022)	
L4. gov't expenditures	-0.045***	0.004	0.067***	0.009	-0.090***	0.016	-0.045	0.002	0.041***	0.004	0.090***	0.029
	(0.010)		(0.018)		(0.016)		(0.037)		(0.010)		(0.023)	
L4. inflation	-1.401***	0.198	-1.418***	0.272	-1.383***	0.236	-1.283***	0.240	-1.265***	0.064	-1.427***	0.115
	(0.058)		(0.084)		(0.092)		(0.114)		(0.090)		(0.196)	
L4. productivity	0.043***	0.004	-0.002	0.000	0.069***	0.009	0.031	0.002	0.014	0.000	-0.031	0.003
	(0.009)		(0.017)		(0.017)		(0.026)		(0.010)		(0.025)	
L4. population	-0.052	0.000	0.074	0.000	-0.069	0.000	-0.148	0.001	0.086	0.000	0.083	0.000
	(0.060)		(0.174)		(0.073)		(0.176)		(0.076)		(0.319)	
L4. urban employment	0.018	0.000	-0.051**	0.002	0.155***	0.017	0.488***	0.070	-0.051***	0.004	-0.109***	0.022
	(0.014)		(0.024)		(0.029)		(0.076)		(0.015)		(0.032)	
L4. house prices	0.012	0.000	-0.055*	0.056	-0.097***	0.006	-0.109**	0.095	0.056***	0.009	0.083*	0.103
	(0.010)		(0.033)		(0.032)		(0.047)		(0.010)		(0.046)	
Constant	2.849***		0.807		4.201***		4.540***		2.426***		1.363*	
	(0.253)		(0.581)		(0.650)		(1.339)		(0.292)		(0.762)	
Observations	1,848		462		888		222		960		240	
R-squared	0.625		0.587		0.485		0.612		0.743		0.603	

Robust standard errors in parentheses. Variables all in growth rates. Lag 4 quarters. Dependent variable national nominal GDP
*** p<0.01, ** p<0.05, * p<0.1

Looking first at the full time span results, we find that credit growth in the two groups of provinces has a rather similar positive effect on future aggregate growth. Investments have a higher weight in the blue provinces and there we also note the negative coefficient for consumption growth on future aggregate growth as this could reflect the crowding out effect of investments in heavy, capital-intensive sectors. Productivity in blue provinces is correlated with future aggregate growth, whereas this is not true for the pink provinces. And growth in government expenditures has a negative coefficient for the blue provinces whereas the coefficient is positive and has a larger marginal R-squared value among the pink provinces. Overall, these results indicate that during the past two decades, pink provinces have been more dependent on government expenditures and credit growth, whereas blue provinces are relying relatively more on productivity and investments.

When looking at the two time spans separately, two main results emerge. First, we find that over time business activities are replaced by public expenditure, credit and house prices. Before 2010, provinces that are correlated with future aggregate growth were more strongly depending on investments and productivity than those provinces with no statistically significant correlation to aggregate growth. After 2010, growth is being supported extensively more by public expenditures, credit and house prices for both groups of provinces. Before 2010, increasing house prices were in fact crowding out future aggregate growth, but after 2010 the sign of the coefficient changes and the marginal R-squared is larger. For the blue provinces, the coefficients for investments and productivity are smaller, less significant statistically and have smaller marginal R-squared values after 2010.

Second, we find that the reallocation of labor towards cities that used to drive growth becomes less prominent over time. Before 2010, aggregate growth seems to have been supported by internal migration and urbanization. Urban employment and its productivity was driving growth in both groups of provinces. After 2010 however, this source of growth seems to have run its course as more urban employment in both groups of provinces is reducing aggregate growth.

Altogether, this panel based analysis of growth in the 31 provinces confirm the main trends identified with our principal components based statistical model of Chinese growth: growth in China has become more dependent on government expenditure and credit while it was driven more by productivity and investment before 2010. These new determinants of growth also apply more homogeneously to a larger group of Chinese provinces since 2010.

4.4. Monitoring the determinants of Chinese growth

We complete the empirical analysis by estimating principal components across subsamples before and after 2010. This is also our third way of studying the changing drivers of Chinese aggregate growth. We compare the granger causality tests between estimated principal components and national nominal growth, for the sub-periods in Table 9 and Table 10.

Table 9: Granger causality between national nominal GDP growth and principal components, before 2010

Before 2010: Granger causality

	Coeff	F-stat	Prob>F	Marginal R2
Pc 2: *Urban employment - productivity*	0.713	26.13	0.000	0.178
Pc 3: *Consumption - gov't expenditures - house prices*	0.443	31.64	0.000	0.117
Pc 5: *Investments - productivity*	0.387	13.80	0.001	0.088
Pc 1: *Population - inflation*	0.327	6.38	0.018	0.031

# of obs: 37
R-squared: 0.843

Note: lagged value of the dependent variable omitted from results. Explanatory variables lagged by 4 quarters.

Table 10: Granger causality between national nominal GDP growth and principal components, after 2010

After 2010: Granger causality

	Coeff	F-stat	Prob>F	Marginal R2
Pc 2: *House prices - inflation*	0.245	111.77	0.000	0.100
Pc 3: *Credit + consumption*	0.204	116.10	0.000	0.092
Pc 8: *Credit + investments*	0.232	43.02	0.000	0.035
Pc 1: *Inflation + investments + gov't expenditures*	0.282	26.87	0.000	0.032
Pc 5: *Inflation + credit - consumption*	0.079	10.53	0.003	0.006

# of obs: 40
R-squared: 0.971

Note: lagged value of the dependent variable omitted from results. Explanatory variables lagged by 4 quarters.

This new approach to structure the statistical information of the province data confirms our main results. Before 2010, national growth was driven predominantly by urban employment and productivity, as well as consumption, investments and population growth. Principal component 2 (urban employment over productivity) explains around 18 % of the total variance of national Chinese growth while principal component 3 (consumption over government expenditures and house prices) explains around 12 % of the total variance.

The determinants of growth change after 2010, with national growth becoming driven predominantly by house prices and credit. Principal components 2 (house prices over inflation) and 3 (credit and consumption) have the highest explanatory powers, around 10 % of total variance.

All in all, these results confirm our previous analyses. However, as this third method only requires principal component analysis followed by a simple regression, it can be updated regularly with little effort. Hence, this method can be used in a regular manner to pinpoint changes in the underlying determinants of Chinese growth.

5. Conclusion

In this article, we find robust evidence that provincial data provides information relevant to understand and project Chinese aggregate economic growth. Consequently, we use it to build an alternative indicator for Chinese economic growth (the 31 Provinces China Business Cycle Indicator, or 31P-CBCI) and reveal fluctuations that have been missing from the official growth series for the more recent years. We find two separate short upturns during 2015 and 2017. As the upturn of 2015 seems to have been mostly credit-driven, the second growth ascent in 2017 was due more to public sector expenditure. Since 2018, growth has been declining mainly due to reduced real credit.

Looking at the determinants of Chinese aggregate growth, we find that the drivers have changed both with respect to economic variables and across provinces. Before 2010, growth was driven predominantly by rural population moving to cities, as well as by investments and productivity. After 2010, growth through reallocation of labor has run its course to a large extent and growth has become more dependent on government expenditures, credit growth and house prices. Moreover, these new growth determinants seem to apply more homogeneously to the majority of Chinese provinces. A natural question is whether such determinants can sustain growth persistently?

For years now in China, indebtedness has continued to rise. Trying to reach the impressive goal of doubling real 2010 GDP by 2020 has required constant stimulus to the economy, with the result that debt has ballooned. Gross aggregate debt of the Chinese government, non-financial corporations and households is already close to 300 % of GDP. In most historical cases where countries have accumulated debt as rapidly, GDP growth has eventually come to a halt and precipitated a major financial sector crisis. In China, the bulk of the debt is issued by the corporate sector while the debt of Chinese households and the public sector remains relatively low. Many real estate developers are deeply indebted, apartments are very expensive related to income and they are also purchased by many for investment purposes. Understandably, there has been reluctance to let housing prices decrease in the fear of social unrest. However, Chen and Wen (2017) show how a growing housing bubble can crowd out productive capital investment, prolong the economic transition and reduce social welfare.

In 2020, as the covid-19 pandemic is depressing global GDP growth into negative territory, Chinese economy has recovered better than expected and it seems likely that China will be the only G20 country to see positive full year growth. However, further research should assess whether Chinese fiscal policy will facilitate the transition away from heavy industry to a service based economic model while coping with the challenge of an ageing population.

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APPENDIX

Figure 9: National time series and their provincial aggregated counterparts

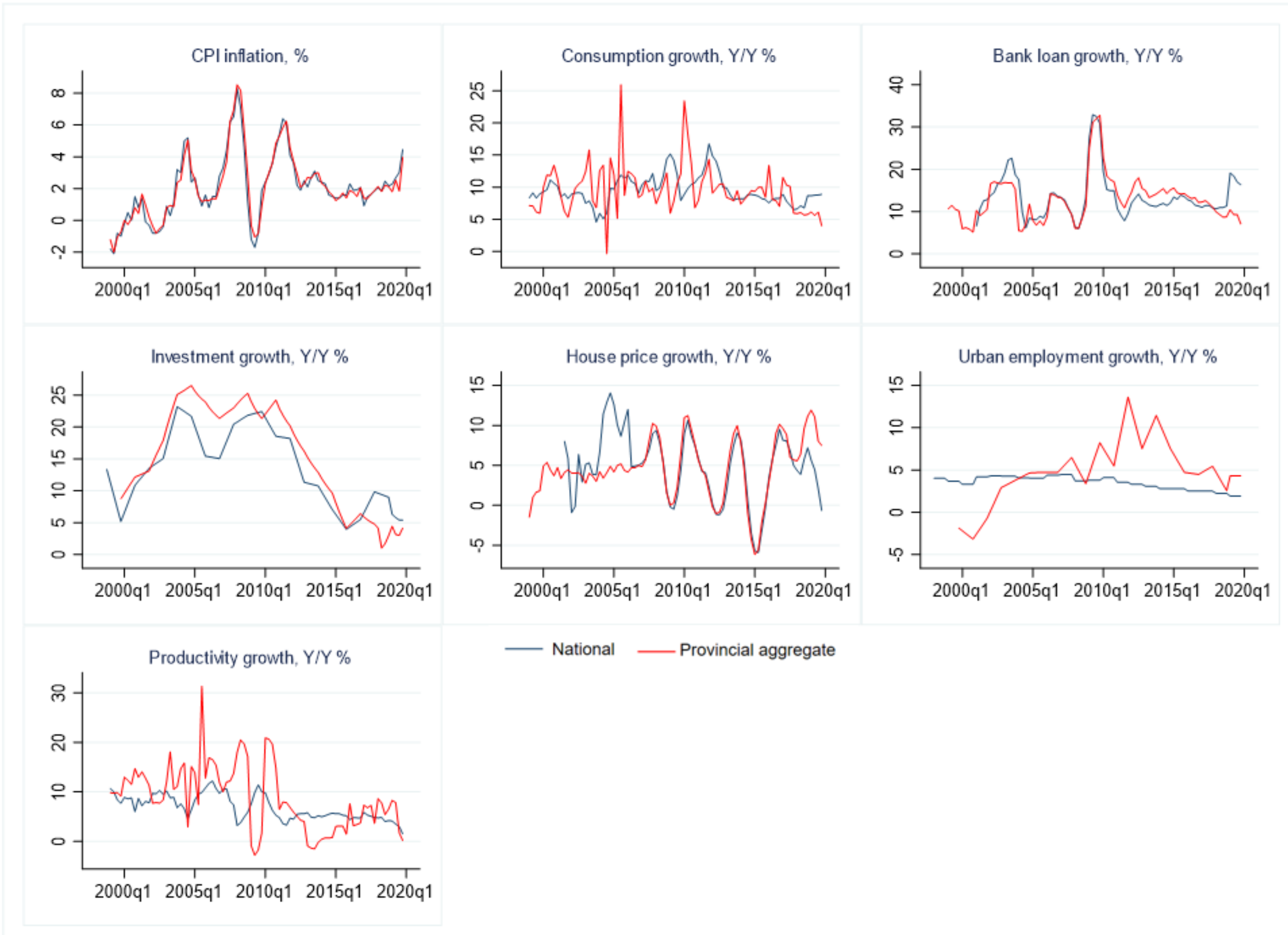


Figure 10: Alternative indicator 2: using statistically significant variable specific principal components

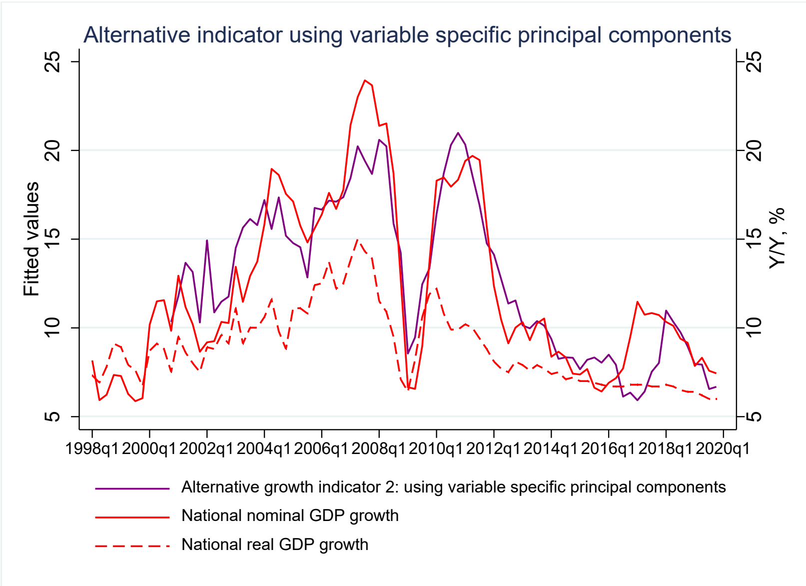


Figure 11: Alternative indicator vs. optional indicator if using only full information principal components 1-8 (without lagged national GDP)

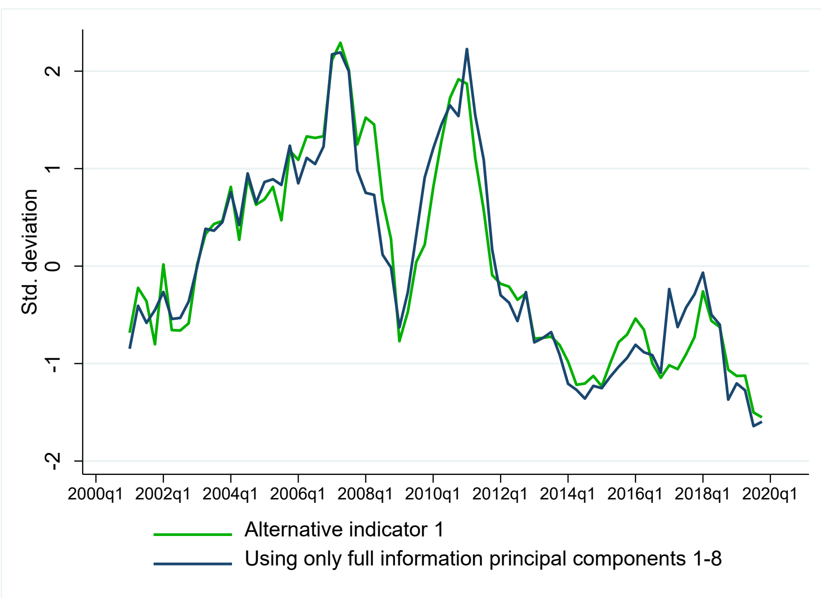
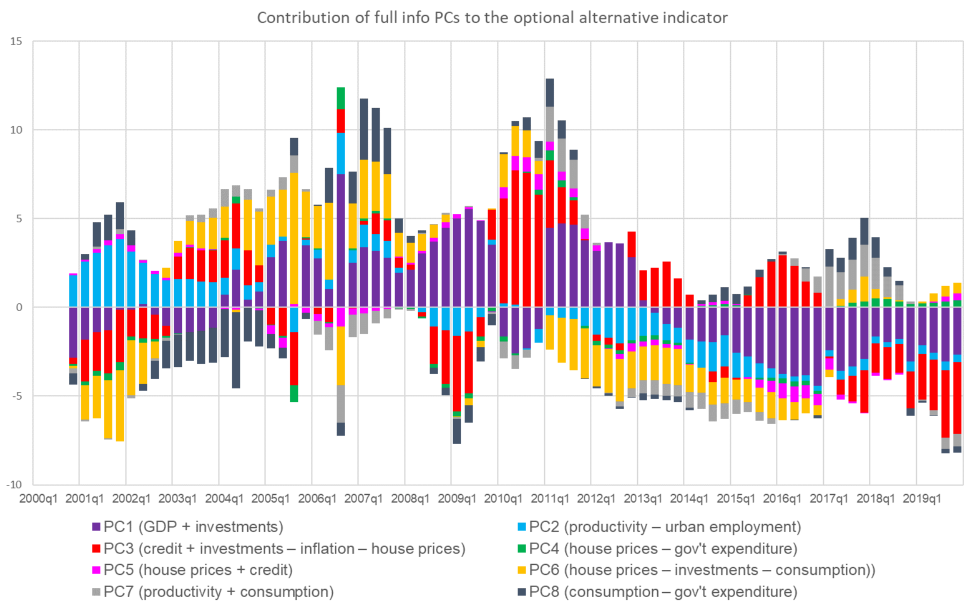


Figure 12: Contribution of full information principal components behind the optional indicator



Note: Constant term (value 12.214) omitted from the figure. Largest factor loadings of full principal components in parentheses.

Table 11: List of provincial variables used

Variable	Details	Source	Original frequency	Conversion method for higher frequency
Nominal GDP		NBS	Quarterly	
Real GDP	Computed by deflating nominal GDP by CPI inflation	Computed	Quarterly	
Consumption	Private consumption expenditure per capita	NBS	Annual until 2013, quarterly since 2014	Denton approach 2)
Credit	Bank loans, CNY	PBoC	Annual until 2003, monthly since 2004	Linear interpolation
Inflation	Consumer price index	NBS	Monthly	
Investments	Gross fixed capital formation	NBS	Annual	Linear interpolation 1)
Gov't expenditure	Local government expenditures	China Ministry of Finance	Annual	Linear interpolation 1)
House prices	Index, city house prices matched to provinces	SouFun-CREIS	Monthly	
Population	Thousands of people Last observation 12/2018	NBS	Annual	Original value used for all periods
Urban employment	Millions of people Last observation 12/2018	China Ministry of Human Resources and Social Security	Annual	Original value used for all periods
Productivity	Computed using real GDP and urban employment growth rates	Computed	Quarterly	

Note: all non-computed variables retrieved from CEIC China Premium Database.

1) Linear interpolation carried out directly in CEIC Data Manager (User guide, p.78).

2) Denton approach interpolates observations using information obtained from related indicators observed at desired frequency (here real GDP growth).

Table 12: Correlation coefficients between provincial full information factor model and aggregate national growth

Correlation between provincial model and aggregate national growth			
	Full time span	Before 2010	After 2010
Anhui	0.6151***	0.6176***	0.7058***
Beijing	0.473***	0.0666	0.7917***
Chongqing	0.5225***	0.0409	0.7552***
Fujian	0.6768***	0.5307***	0.6849***
Gansu	0.2009	0.2948	0.4909***
Guangdong	0.6326***	0.3571	0.789***
Guangxi	0.6481***	0.5675***	0.8482***
Guizhou	0.1654	0.3031	0.6791***
Hainan	0.362***	0.4589***	0.7232***
Hebei	0.4674***	0.2682	0.7522***
Heilongjiang	0.1815	0.1133	0.5451***
Henan	0.6438***	0.5405***	0.7712***
Hubei	0.3026	0.2665	0.838***
Hunan	0.4783***	0.0509	0.8043***
Inner Mongolia	0.7766***	0.688***	0.8025***
Jiangsu	0.6806***	0.4251***	0.7982***
Jiangxi	0.5016***	0.2885	0.7966***
Jilin	0.6937***	0.6184***	0.6408***
Liaoning	0.5714***	0.401	0.6327***
Ningxia	0.5626***	0.2249	0.6181***
Qinghai	0.1092	0.0428	0.4814***
Shaanxi	0.5517***	0.2001	0.8481***
Shandong	0.7351***	0.5557***	0.7861***
Shanghai	0.436***	0.102	0.5774***
Shanxi	0.6602***	0.4371***	0.7909***
Sichuan	0.4232***	0.1374	0.6773***
Tianjin	0.6428***	0.3988	0.809***
Tibet	0.2557	0.1723	0.309
Xinjiang	0.1263	0.1801	0.3247
Yunnan	0.5993***	0.6641***	0.7399***
Zhejiang	0.6446***	0.3235	0.7748***
# of obs	77	37	40
Median (of stat.sign.coefficients)	0.607	0.556	0.755

Note: *** denotes statistical significance at 1 % level

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