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Constructing quarterly Chinese time series usable for macroeconomic analysis [☆]

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ABSTRACT

During episodes such as the global financial crisis and the Covid-19 pandemic, China experienced notable fluctuations in its GDP growth and key expenditure components. To explore the primary sources of these fluctuations, we construct a comprehensive dataset of GDP and its components in both nominal and real terms at a quarterly frequency. Applying two SVAR models to this dataset, we uncover the principal drivers of China's economic fluctuations across different episodes. In particular, our findings reveal the stark and enduring impacts of consumption-constrained shocks on GDP and all of its components, especially household consumption, both during and in the aftermath of the COVID-19 pandemic.

1. Introduction

Over the past four decades, China has experienced sustained growth. At the same time, its macroeconomy has also undergone significant fluctuations, particularly during the global financial crisis (GFC) and the Covid-19 pandemic periods. As China has become the second-largest economy in the world, the macroeconomic fluctuations in its GDP and various expenditure components have far-reaching impacts on the global economy. It is therefore crucial to understand the driving forces behind these fluctuations and to assess the magnitude and persistence of their impacts on the Chinese economy.

Research on China's macroeconomic fluctuations faces two primary data challenges. The first concerns the reliability of China's official quarterly GDP data. The National Bureau of Statistics of China (NBS) provides quarterly data on value-added measures of GDP (hereafter referred to as "GDP-va"). As Fernald et al. (2021) find, however, the quarterly data on GDP-va was excessively smooth between 2008 and 2016.[1]

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[1] In addition, the reliability of the reported *annual* GDP growth data from the NBS has been a topic of debate in the literature (Chen et al., 2019; Clark et al., 2020). This paper will not address this particular issue.

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A second, and arguably more critical, challenge pertains to the availability of data on various GDP components. China does not provide basic quarterly macroeconomic data, and much of the data it does provide is not necessarily internally consistent. For example, while the NBS offers quarterly data on contributions and contribution shares to 4-quarter growth rates of real GDP-va,[2] such data did not become available from the NBS until 2015. Data on quarterly year-to-date contributions are not available until 2009,[3] despite a pressing need for quarterly data dating back to 2000, a pivotal year marking the onset of rapid growth in China and serving as a baseline for much of the research. The absence of quarterly data on GDP components poses a significant challenge for researchers, market participants, and international institutions to timely assess economic conditions in China and to provide insights into the sources of China's macroeconomic fluctuations.

The goal of this paper is, therefore, twofold. First, we construct a comprehensive dataset of expenditure-based GDP (subsequently denoted as "GDP-exp") and its principal expenditure components, in both nominal and real terms, at a quarterly frequency suitable for analyzing macroeconomic fluctuations. Second, we use our constructed quarterly data to explore the sources of economic fluctuations since 2000.

Our method for constructing quarterly data follows a two-stage approach. In the first stage, we follow Fernald et al. (2021) to estimate the first principal component from their eight quarterly indicators without removing the trend. In the second stage, this principal component serves as the main interpolator for obtaining the quarterly series for GDP-exp and its various components. Throughout this data construction process, we seasonally adjust all the quarterly data. The constructed quarterly series for GDP-exp, its principal expenditure components, and its consumption subcomponents avoid the excessive smoothness evident in the NBS's official reports. Extending back to 2000Q1, our dataset offers researchers the opportunity to study macroeconomic fluctuations in China, an important yet understudied topic.

We utilize our quarterly time series to understand the driving forces behind China's economic fluctuations. We focus on the relative significance of various shocks during the GFC and Covid-19 periods. During both these periods, China's GDP growth experienced steep declines. We employ the structural vector autoregression (SVAR) approach by adopting the identification strategy of Brunnermeier et al. (2021). This strategy leverages the heteroskedasticity of structural shocks across notable episodes over our entire sample period from 2000Q1 to 2022Q4. This SVAR approach is particularly suited for studying the sources of China's economic fluctuations for two main reasons.

First, during China's macroeconomic development, there have been a number of notable government interventions, including the 2009 economic stimulus and the Covid lockdowns from 2020 to 2022. These policy actions were found to have significant effects on the Chinese macroeconomy during specific episodes.[4] The magnitude of the primary forces driving economic fluctuations, therefore, may have varied across these episodes.

Second, our goal is to identify multiple structural shocks simultaneously and compare their respective impacts across distinct episodes, rather than focusing on one single shock as in the traditional SVAR literature (Christiano et al., 1999; Cogley and Sargent, 2005; Sims and Zha, 2006). Given that the interrelationships among China's macroeconomic variables are not fully understood by scholars (mainly because of the lack of quarterly data), the identification through shock heteroskedasticity, based on the knowledge of distinct episodes without imposing other a priori restrictions, is especially appealing in the context of the Chinese economy.

We estimate an SVAR model of GDP-exp and its five expenditure components. Our estimated results indicate that the main sources of economic fluctuations across episodes are distinctively different. During the GFC period, for example, the external shock generated a substantial contraction in exports and imports, but not in investment and household consumption. Consequently, the response of GDP was modest. The economic stimulus shock, on the other hand, drove up investment during the economic stimulus period, but at the same time had a negative impact on exports of goods and services. This negative response of exports can be explained by an outcome of how fiscal stimulus crowded out investment of private manufacturing firms (as found by Chen et al. (2023)), which form a large portion of firms in the export sector. Economic fluctuations during the Covid-19 period tell a different story. The shock that constrained household consumption (the consumption-constrained shock) had immediate and large negative impacts on GDP and all of its components, especially household consumption expenditures. Accordingly, GDP fell significantly on impact. These negative effects persisted even after the Covid-19 period was over.

To understand how consumption-constrained shocks affect household consumption expenditure, we employ an SVAR model to analyze both the overall household consumption expenditures and its eight subcomponents. Our findings reveal that during the Covid-19 period, although consumption-constrained shocks reduced household consumption across all subcomponents, the "Education, Culture and Entertainment" and "Food, Tobacco, and Liquor" subcomponents were particularly hard hit. By contrast, the "Residence" subcomponent, primarily reflecting housing services, was least impacted. These findings are consistent with the observation that households, when confined to their homes during the periodic Covid lockdowns, increased their consumption of utilities like water and electricity. In the pre-Covid regime, on the other hand, housing demand shocks were pivotal in driving fluctuations across various household consumption subcomponents. Specifically, the housing demand shock emerged as the primary source of fluctuations in the "Residence" subcomponent among all eight structural shocks.

[2] The NBS indicates that the year-over-year growth rates of real total consumption, gross capital formation, and net exports for 2023Q2 are 5.32% (CEIC series CAASUQ), 2.07% (CEIC series CAASUR), and -1.09% (CEIC series CAASUS), respectively. Their cumulative total is 6.3%, which matches the year-over-year growth rate for GDP-va for 2023Q2 as reported by the NBS.

[3] In comparison, annual contribution data have been published since 1953.

[4] For instance, using detailed data from bank loans to Chinese firms, Chen et al. (2023) show how fiscal stimulus crowded out bank credit for the investment of private firms during the 2009 economic stimulus. Utilizing Baidu migration data, Fang et al. (2020) find that the January 2020 lockdown in Wuhan led to a reduction of population inflows to Wuhan by 76.98%, outflows from Wuhan by 56.31%, and intra-Wuhan movements by 55.91%.

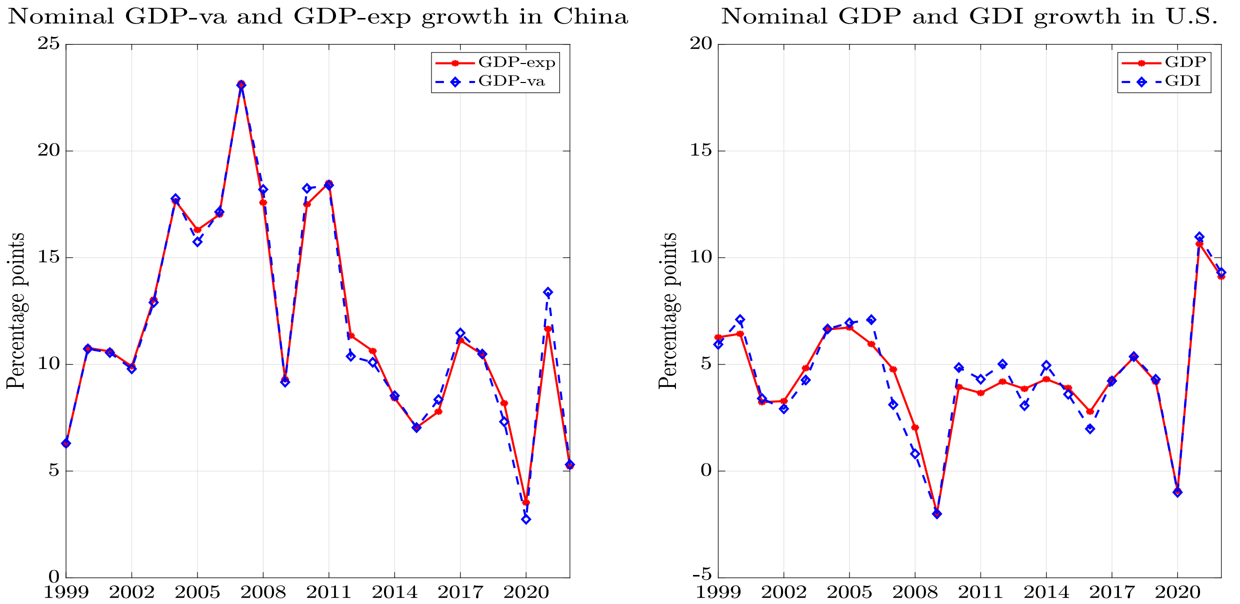

Fig. 1. Left panel shows annual nominal growth rates (%) of GDP-va and GDP-exp in China. Right panel shows annual nominal growth rates (%) of GDP and GDI in U.S.

Our empirical analysis builds upon and contributes to the growing literature on China's economic fluctuations. Fernald et al. (2014) utilize a factor-augmented vector autoregression model to estimate the efficacy of countercyclical monetary and fiscal policies on Chinese economic activity and inflation. Chang et al. (2016) establish stylized facts regarding a regime shift in the cyclical movements of the Chinese macroeconomy around 1998. This observation is confirmed by Fernald (2016), who calculates correlations of real investment, real consumption, and incomes across 40 countries from 1995-2010, identifying China as an outlier because of its very low or negative correlations. Chen et al. (2023) study the effects of the interaction between monetary and fiscal shocks on sectoral reallocation of resources during China's economic stimulus period.

In contrast to these studies, this paper is the first attempt to utilize an SVAR model with identification via shock heteroskedasticity to explore the roles of multiple structural shocks in Chinese macroeconomic fluctuations across various regimes, with a particular focus on the recent COVID-19 period. Our most important finding reveals the stark and enduring impacts of consumption-constrained shocks on household consumption and its subcomponents, both during and in the aftermath of the COVID-19 pandemic. This new finding suggests that COVID-19 may have permanently altered the nature of economic shocks on the Chinese economy.

The paper is structured as follows. Section 2 describes the procedures for constructing our quarterly time series of GDP. Section 3 discusses the procedures to construct components of expenditure-based GDP at both annual and quarterly frequencies. Section 4 presents the empirical framework with the identification strategy tailored to the Chinese economy, and provides the empirical results, including the history of identified shocks and the impulse responses to such shocks. Section 5 concludes.

2. Constructing quarterly expenditure-based GDP

The NBS reports two series of GDP: one series is measured by value added from the production side (GDP-va) and the other by how final goods and services are purchased from the expenditure side (GDP-exp). Similar to the U.S. measures of nominal GDP and nominal gross domestic income (GDI) that are not identical, the NBS measures of annual nominal GDP-va and annual nominal GDP-exp are not identical either. As Fig. 1 shows, however, the difference in the two series of China's GDP growth rates is generally small and similar in magnitude to the difference between U.S. GDP and GDI growth rates.

The primary GDP estimate cited by the NBS and the media is the growth rate of real GDP-va, which is nominal GDP-va divided by its implicit price deflator. We assume that price measures underlying NBS estimates of GDP correspond to the international standards used by the United States and other developed countries in their national accounts, as the NBS claims they do according to the following passage taken from a recent NBS GDP release[5]:

> China's System of National Accounts (2016) adopted the basic accounting principles, contents and methods of the United Nations' System of National Accounts (SNA) 2008, therefore the GDP data are internationally comparable. After the national economic censuses have been carried out, or the calculation methods and classification criteria have been changed, historical quarterly GDP data have been revised. Therefore, time series data of quarterly GDP are comparable since the first quarter of 1992.

[5] See the government's link http://www.stats.gov.cn/english/PressRelease/202304/t20230419_1938796.html.

We deflate annual GDP-exp by the price deflator for GDP-va, P_t^{GDPva}, to get annual real GDP-exp.

The quality of data sources provided by China's National Bureau of Statistics (NBS) has been questioned by many papers in the literature. One major criticism is that the NBS overestimates annual growth of real GDP since 2000. On the one hand, for example, recent work by Wu and Li (2021) assumes that the NBS measures nominal GDP correctly but mismeasures its price deflator.[6] Chen et al. (2019), on the other hand, use an alternative approach that presumes that deflators for GDP and its investment components are measured correctly while nominal GDP is mismeasured. While research efforts in Wu and Li (2021) and Chen et al. (2019) provide insights into the quality of the Chinese data, their assumptions cannot be both correct.

The purpose of our paper is not to assess which assumption is correct. Thus, we do not address mismeasurement issues related to the trend of annual real GDP growth and assume that over longer periods (two to five years) of time nominal and real GDP growth is measured correctly. We focus instead on addressing the smoothness problem of quarterly data as emphasized by a number of studies such as Fernald et al. (2021), Nakamura et al. (2016), Fernald et al. (2021), Wu and Li (2021), and Barcelona et al. (2022). This focus allows us to address the most pressing issue: the lack of a standard set of annual and quarterly macroeconomic time series comparable to those commonly used in macroeconomic literature on economic fluctuations. In particular, GDP components such as consumption, investment, and net exports do not even have quarterly data that can add up to the total value of GDP.

We begin with constructing the time series of quarterly expenditure-based GDP. As Fernald et al. (2021) emphasize, quarterly real GDP reported by the NBS is too smooth. Fernald et al. (2021) argue that Chinese imports, when measured with data from the International Monetary Fund (IMF) on exports to China from its trading partners, provide a robust measure of fluctuations in economic activity. These data are less likely to be subject to potential manipulation by Chinese authorities. To capture overall economic activity, their study identifies a set of eight non-GDP economic indicators that align well with this measure of inflation-adjusted imports. Fernald et al. (2021) detrend each of these series with a filter in Stock and Watson (2016) that is similar to an HP filter. The first principal component, which the authors call the "China Cyclical Activity Tracker" or C-CAT,[7] is extracted from these eight detrended and standardized series. Its movements are highly correlated with the detrended four-quarter growth rates of both their measure of externally validated real Chinese imports and, to a lesser extent, with NBS-reported GDP-va.

To construct real quarterly GDP-exp data that address the issue of excess smoothnes, we first construct C-CAT indicator as the interpolater. We use the same set of eight series as in Fernald et al. (2021) to estimate the C-CAT, but transform these series differently.[8] Of particular interest, we seasonally adjust the data and use the one-quarter difference of log data as an interpolator for obtaining quarterly GDP-exp. Unlike Fernald et al. (2021), we do not remove the trend in each series *prior to* estimating the first principal component of the eight series for the purpose of obtaining (log) level value of quarterly GDP-exp. Our principal reason for not detrending the indicators used to construct our C-CAT was to maintain consistency with the nondetrended GDP and subcomponents used in our SVAR estimation. A critique by Hamilton (2018) of using HP filtered data in a VAR is that data at the beginning and end of the sample will resemble a one-sided smoothed series, while data in the middle of the sample will be two-sided. This critique is especially pertinent given the heteroskedastic shock regime framework we use, as the HP filter assumes a fixed identical distribution data generating process. Nonetheless, we show in Appendix D that our constructed GDP and its subcomponents, as well as the outcomes of our SVAR estimation, are not materially affected by detrending the data for C-CAT estimation.

Fig. 2 displays the original C-CAT series of Fernald et al. (2021), downloaded from the Federal Reserve Bank of San Francisco website, alongside the two transformed series of our alternative C-CAT indicator. As one can see, although there are persistent differences between our alternative C-CAT and the published SF Fed C-CAT series at the low frequency horizon, the two series are highly correlated and resemble each other especially at the quarterly frequency that is the focus of our paper. Fig. 3 displays a comparison of (standardized) one-quarter growth rates of seasonally adjusted real GDP-va with our alternative C-CAT indicator. Between 2008Q1 and 2018Q4, quarterly growth rates of real GDP-va are much smoother than the alternative C-CAT, a finding consistent with Fernald et al. (2021). From 2019Q1 onward, however, these two series follow each other closely. As Fernald et al. (2021) concluded, "Chinese statistics, including GDP, became more reliable over time."

We use this alternative C-CAT series as an interpolator to derive quarterly real GDP-exp for 2000-2018, employing the method of Fernandez (1981).[9] We ensure that the average growth rate of our interpolated quarterly real GDP-exp series matches the average growth rate of the annual real GDP-exp series for the years when an Economic Census or an input-output table was published[10] as well as for 2018. This approach is consistent with the suggestions of Chen et al. (2019), allowing for average growth over multiple years to be consistent with NBS estimates.

Because the alternative C-CAT series is more volatile than the NBS's officially published growth rates of GDP-va, our interpolated quarterly growth rates of GDP-exp exhibit greater volatility as well. Indeed, interpolating the quarterly GDP-exp series with the

[6] Wu and Ito (2015) use a very similar approach to Wu and Li (2021), but do not explicitly state that nominal GDP is measured correctly by the NBS. Both works emphasize the mismeasurement of prices. Wu (2014) discusses measurement issues with nominal gross fixed capital formation (GFCF).

[7] The series C-CAT is regularly updated at https://www.frbsf.org/economic-research/indicators-data/china-cyclical-activity-tracker.

[8] These eight series are 1) the expectation subindex of the NBS' overall consumer confidence index, (2) industrial production of electricity in kilowatt hours, (3) China's General Administration of Customs (GAC) Free on Board (FOB) measure of Chinese exports, deflated by the export price index reported by the GAC, (4) fixed assets investment, deflated by its own price deflator, (5) total "floor space started" of commodity buildings in square feet, (6) industrial production (value added of industry) in real RMB, (7) railway freight carried in tons, and (8) retail sales of consumer goods, deflated by the consumer price index (CPI).

[9] Supplemental Appendices A-E detail our interpolation procedures, with a simple example to illustrate our interpolation method.

[10] Specifically, these years are 2002, 2004, 2005, 2007, 2008, 2010, 2012, 2013, 2015, and 2017.

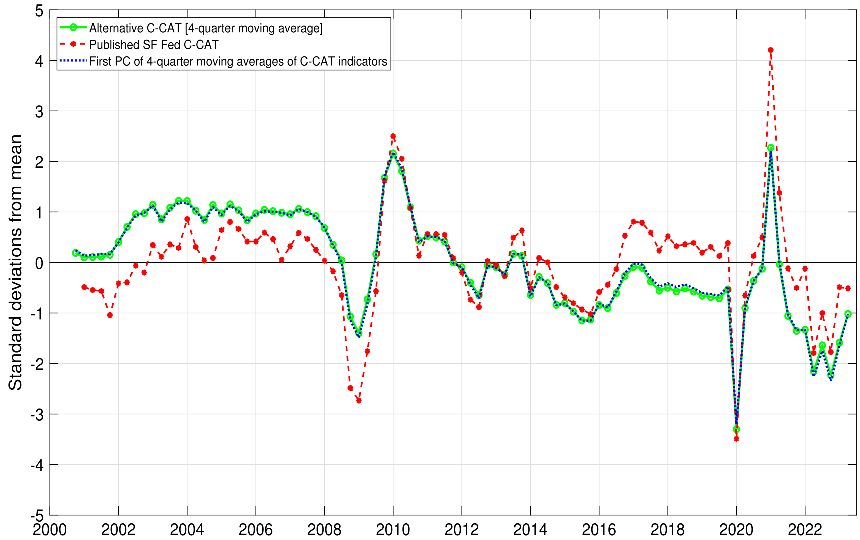

Fig. 2. Comparison of the SF Fed's published C-CAT indicator of Fernald et al. (2021) (red dashed line with stars) with our alternative C-CAT indicator. The green line with circles is the 4-quarter moving averages of standardized one-quarter growth rates of our alternative C-CAT indicator. The SF Fed's published C-CAT indicator is scaled to preserve one-standard deviation units over the 2000Q1-2023Q2 period. Thus, its standard deviation is less than one over the pre-Covid period from 2000 to 2019. (For interpretation of the colors in the figure(s), the reader is referred to the web version of this article.)

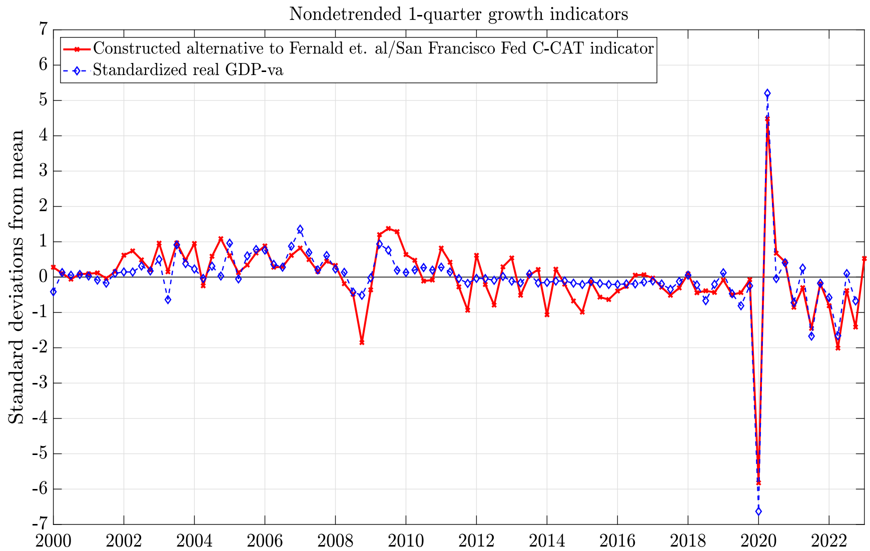

Fig. 3. Comparison of standardized one-quarter growth rates of seasonally adjusted real GDP-va (blue dashed line with diamonds) with standardized one-quarter growth rates of our alternative C-CAT indicator (red solid line with stars).

quarterly GDP-va series derived directly from NBS-published data results in an NBS-consistent quarterly GDP-exp series that is much smoother than our series, which is interpolated using the alternative C-CAT indicator (Fig. 4). For each year from 2019 to 2022, however, our interpolation method imposes a constraint that the annual growth rate derived from the interpolated quarterly GDP-exp series equals the annual growth rate of actual GDP-exp, so that the quarterly dynamics closely match those of real GDP-va.

3. Constructing components of expenditure-based GDP

In this section, we construct components of GDP-exp for analyzing the sources of economic fluctuations. The process involves two steps: first, constructing real annual GDP-exp components; second, creating quarterly data on GDP-exp components consistent with our previously constructed quarterly real GDP-exp. Supplemental Appendices A-E provide the technical details for each step.

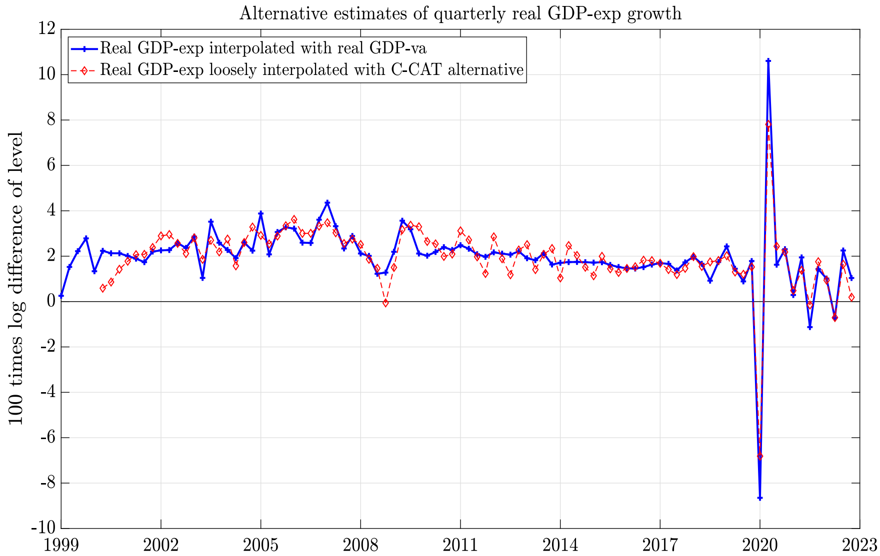

Fig. 4. Difference of log level values for the quarterly GDP-exp series interpolated by our alternative C-CAT indicator (red line with diamonds) and the quarterly GDP-exp series interpolated by the quarterly GDP-va series published by the NBS (blue line with pluses).

Table 1
Annual data: GDP-exp components and data sources.

GDP-exp and its components	Nominal	Real	Prices
GDP-exp	NBS	Implied	P^{GDPva}
HH+Gov Consumption	NBS	NBS Contrib	Implied
Household	NBS	Implied	NBS HH Survey, Holz (2014)
8 Components	NBS HH Survey	Implied	CPI, NBS HH Survey
Government	NBS	Implied	CPI, FAI price, Holz (2014)
GCF	NBS	NBS Contrib	Implied
Net Exports	NBS	NA	NA
Exports	NBS/SAFE	Implied	Customs/OECD
Imports	NBS/SAFE	Implied	Customs/OECD

Note: Entry labeled “HH” stands for household, “Gov” stands for government, “SAFE” stands for the State Administration of Foreign Exchange in China, “OECD” represents the Organisation for Economic Cooperation and Development, “NA” means “Not Applicable,” “Implied” means that the value is determined by the other two variables on the same row in the table, and “NBS Contrib” indicates that values are based on our calculation with published NBS contributions to annual real GDP-exp growth.

3.1. Annual components of GDP by expenditure

For annual data, the NBS publishes the contributions of three major GDP components (1) household and government consumption expenditures, (2) gross capital formation (GCF) as a measure of investment, and (3) net exports.[11] The sum of these contributions to real GDP growth is *exactly* identical to real *GDP-va*, not real *GDP-exp*, growth.

We use NBS published measures of the aforementioned three major components' shares of the contribution to annual real GDP-exp growth and Tornqvist index-based formulae to obtain components of real GDP-exp.[12] By construction, the sum of annual growth contributions from all components equals growth in real GDP-exp (measured as nominal GDP-exp deflated by P_t^{GDPva}). We then derive annual prices, quantities, and nominal expenditures for a set of GDP-exp variables listed in Table 1, alongside the sources for these series. We utilize different data sources to adjust several prices in the table to maintain consistency with growth of real GDP-exp and the NBS-published growth contributions from the three major components.

3.2. Interpolating quarterly GDP-Exp components: a non-technical description

This section presents a non-technical summary, for a general audience, of our method for constructing quarterly GDP-exp components. As shown in Fig. 4, the quarterly growth rates of our real GDP-exp series differ from those of the series interpolated with the

[11] Gross (fixed) capital formation is different from the series of fixed assets investment (FAI) reported by the NBS. Key differences are that land acquisitions and purchases of used capital are included in FAI but excluded from GCF. Another major difference is how capital depreciation is computed.

[12] Note that the growth contribution shares of all these components add up to 100%.

NBS-published GDP-va. We use this difference as an additive adjustment factor, which we refer to as "the C-CAT adjustment factor", for interpolating quarterly GDP-exp components.

For nominal household consumption, we use quarterly retail sales before 2002 and quarterly consumption expenditures from rural and urban household surveys[13] after 2001 as an interpolator, along with the C-CAT adjustment factor. This interpolated quarterly series is deflated by the quarterly price deflator for household consumption expenditures to obtain the real quarterly series.[14] The same interpolation methodology applies to quarterly nominal government consumption. The real variable is obtained by deflating quarterly nominal government consumption by the price deflator derived as follows. We first combine a weighted average of the CPI and the FAI price deflator following Appendix A to Holz (2014) and then adjust this price deflator to be consistent with growth contribution shares of nominal consumption. Quarterly nominal exports and imports are interpolated with quarterly series of nominal exports and imports reported by China's State Administration of Foreign Exchange (SAFE) in China,[15] as well as the C-CAT adjustment factor. The two interpolated nominal variables are deflated by the respective prices reported by the GAC.

Nominal GCF is the sum of nominal GFCF and nominal changes in inventories. We interpolate these two components separately. We obtain quarterly nominal GFCF by interpolating the series with the growth rate of nominal quarterly FAI (again excluding land value) adjusted by the alternative C-CAT. For quarterly real GFCF, we interpolate this series using the C-CAT adjustment factor and the real growth rate of quarterly FAI (excluding land value). For quarterly real changes in inventories, we use the interpolation method of Denton (1971).[16] Specifically, we interpolate quarterly real changes in inventories by the ratio of our constructed quarterly real GDP-exp and NBS-reported real quarterly GDP-exp as an interpolator.[17] The price deflator for inventories, based on Holz (2014), is then used to obtain quarterly nominal changes in inventories.[18] Nominal GCF is obtained by simply summing up nominal GFCF and nominal changes of inventories. Real GCF is estimated as the Fisher chain-weighted aggregate of real GFCF and real change in inventories. The quarterly price deflator of GCF is implied by nominal and real measures of quarterly GCF.

There exists a difference between the sum of these major quarterly nominal components and our constructed quarterly nominal GDP-exp. As detailed in Supplemental Appendices A-E, we treat this difference as a nominal residual to be distributed proportionally across quarterly nominal components. Similarly, there is a difference between the sum of growth contribution shares of the major quarterly real components and the growth rate of our constructed quarterly GDP-exp. We treat this difference as a real residual to be distributed proportionally across quarterly real components.

4. Empirical application

In this section, we first report some key properties of our newly constructed quarterly series of GDP and its components, comparing our data with those from emerging market economies and advanced countries. We then demonstrate how our data can be used in rigorous empirical analysis. Our analysis focuses on quantifying the significant differences in the economic impacts of various shocks between the GFC and Covid-19 periods. To this end, we analyze an SVAR model with our new quarterly dataset.

4.1. Unconditional moments

Table 2 compares several unconditional moments of our quarterly data with those of other countries, most of which are identical to those used in a study by Aguiar and Gopinath (2007). For additional context, we also include the corresponding moments for quarterly real GDP-exp interpolated with real GDP-va and its expenditure components, which we refer to as "NBS-consistent data." For our pre-pandemic sample period (2000Q1-2019Q4), the 4-quarter growth rates of CCAT-adjusted GDP and its components, including GCF, are as volatile as those from NBS-consistent data. The growth of CCAT-adjusted GDP-exp, however, is 13% more volatile than that of NBS-consistent GDP-exp (columns (1) and (2) of Table 2). This increased volatility is mainly due to a 33% rise in GDP volatility from the NBS-consistent data to the CCAT-adjusted data (columns (5) and (6)) during 2008Q1-2016Q4, a period characterized by excessively smooth NBS-reported 4-quarter GDP growth rates. The heightened volatility in CCAT-adjusted GDP can be attributed to a stronger correlation between net exports and other components in the CCAT-adjusted data compared to the NBS-consistent data, consistent with the dynamics of a rapidly growing China.

[13] Before 2013, we use the Household Survey on Income and Expenditure and Living Conditions; after 2013, we combine surveys on both rural and urban sectors. The rural and urban sectors were separately surveyed. Unlike retail sales, these surveys include expenditures on services.

[14] We interpolate the quarterly price deflator for household consumption expenditures by the CPI. This household-consumption price deflator is consistent with the NBS-published values of nominal household consumption expenditures and with the growth contribution of household and government consumption expenditures to the share of real GDP growth.

[15] These reports are based on the balance of payments (BOP).

[16] The method of Fernandez (1981) applies to log variables and is not applicable for interpolating changes in inventories because this variable can be negative.

[17] Annual real changes in inventories are reported by the NBS. We interpolate changes in inventories by using a sequence of various quarterly interpolators related to inventory data. These sets of interpolations are then spliced together to form a continuous series. We adopt this approach because some specific data, such as total industrial enterprise inventories, is only available on a quarterly basis starting from 2010. Additional interpolators used in our method include inventory measures surveyed by the Purchasing Managers' Index (PMI), industrial enterprise inventories of finished goods, commodity retail sales, and a proxy for inventories derived from other economic indicators. This proxy is calculated by subtracting retail sales and exported goods from the sum of imported goods and the value added in the primary and industrial sectors.

[18] Unlike other GDP components, the price deflator for inventories cannot be determined by the ratio of its nominal variable to its real variable because changes in inventories can be negative. In the United States, the inventory price deflator is determined by prices for industry-level inventory stocks (see Chapter 7 of https://www.bea.gov/resources/methodologies/nipa-handbook). Since this level of detail is unavailable for the NBS data, we do not adjust the price deflator for inventories by the alternative C-CAT.

Table 2
Unconditional moments of quarterly data.

Variable	China NBS (1)	China CCAT (2)	EMEs Median (3)	AEs Median (4)	2008Q1-2016Q4 NBS (5)	2008Q1-2016Q4 CCAT (6)
GDP	2.031	2.292	2.415	1.796	1.4106	1.8827
HHcsmp	2.375	2.449	2.515	1.347	2.2712	2.3317
Gcsmp	4.595	4.824	4.476	1.290	5.0457	5.3497
GCF	4.581	4.459	9.420	8.008	4.2964	4.2448
Exps	9.192	9.225	7.675	5.038	8.4404	8.4687
Imps	9.689	9.730	9.729	5.863	9.3101	9.3958

Note: The table reports the standard deviation (%) of 4-quarter growth rates for the period 2001Q1-2019Q4. "EMEs" stands for emerging-market economies, and "AEs" for advanced economies. The last two columns provide the standard deviation (%) of China data for the period 2008Q1-2016Q4. The label "NBS" represents NBS-consistent quarterly data, and "CCAT" denotes CCAT-adjusted quarterly data. The label "std." stands for standard deviation, "GDP" for real GDP, "HHcsmp" for household consumption, "Gcsmp" for government consumption, "GCF" for gross capital formation, "Exps" for exports, and "Imps" for imports. Emerging economies include Brazil (#), Ecuador, Israel, South Korea, Malaysia, Mexico, Peru, Philippines, Slovakia, South Africa, Thailand, Turkey (#), India (#), Indonesia, and Malaysia; advanced economies include Australia (#), Austria, Belgium (#), Canada (#), Denmark (#), Finland, France (#), Germany, Netherlands (#), New Zealand, Norway, Portugal, Spain, Sweden (#), Switzerland, the United Kingdom (#), and the United States. The symbol "#" indicates countries excluded from GCF calculations due to lack of data.

Table 2 also reveals that China's investment volatility is lower compared to other emerging and advanced economies. Chang et al. (2016) contribute this low volatility to China's investment-driven macroeconomic policies, which have moderated investment fluctuations. For instance, when private investment fell, the government frequently increased investment in state-owned enterprises (SOEs), thereby stabilizing total investment. By contrast, during the economic stimulus of 2009, increased bank loans to SOEs for investment inadvertently crowded out loans to non-SOEs for investment (Chen et al., 2023). Consequently, the volatility of China's GCF is significantly lower than that observed in both emerging and advanced economies (as shown in columns (2), (3), and (4) of Table 2).[19]

Government consumption is significantly more volatile than household consumption (columns (2) and (6)), mainly reflecting the government's active role in using its consumption to counterbalance fluctuations in other economic sectors. This high volatility of government consumption is common in emerging economies, but not in advanced ones (comparing columns (2), (3), and (4)). Similarly, the volatilities of exports and imports are much higher in both China and emerging economies than in advanced economies.

We also compute the moments of 1-quarter growth rates of our constructed series and the 1-quarter growth rates of detrended series; the results, when compared with other countries, are similar to those reported in Table 2. Taken together, these results demonstrate that our new quarterly dataset captures China's unique characteristics while being consistent with many features typical of emerging economies. Below, we outline an empirical model that utilizes this dataset for economic analysis.

4.2. The model

Let y_t be an $n \times 1$ vector of observed variables in time $t \in \mathcal{T} = \{1, ..., T\}$. We model y_t with the following system of equations.

$$y_t' A_0 = \sum_{j=1}^{p} y_{t-j}' A_j + c + \epsilon_t' D_t. \tag{1}$$

where A_0 is an $n \times n$ matrix of simultaneous relationships, $\left\{A_j\right\}_{j=1}^{p}$ are $n \times n$ matrices of coefficients at each lag j, c is an $n \times 1$ vector of constant terms, ϵ_t is an $n \times 1$ vector of independent structural shocks across time with each component of ϵ_t following the standard normal distribution, and D_t is an $n \times n$ diagonal matrix measuring the standard deviations of individual shocks.

The variance of shocks differs across time periods. Each time period corresponds to a distinct regime $m(t) \in \{1, \dots, M\}$. In each regime the variance of structural shocks is a different diagonal matrix is $\Lambda_{m(t)}$ such that $E\left[\epsilon_t \epsilon_t'\right] = \Lambda_{m(t)}$ and $D_t \equiv D_{m(t)} = \sqrt{\Lambda_{m(t)}}$. Structural errors $D_t \epsilon_t$ are thus distributed as mixture of normal distributions. Large disturbances can be captured by large magnitudes of D_t or $\Lambda_{m(t)}$.

The key question is whether model (1) is identified, i.e., whether A_j for $j = 0, 1, \dots, p$ is uniquely determined given the reduced-form residual $\Sigma_{m(t)}$. As Brunnermeier et al. (2021, footnote 4) argue, as long as shock variances differ *on average* across regimes, this SVAR model is well identified. To elaborate on their argument, note that

[19] In addition, unlike in other countries, China experienced a negative or negligible correlation between household consumption and investment after 2000 and before the Covid-19 pandemic, as reported by Chang et al. (2016).

Table 3
Quarterly data series used in the GDP model.

Variable	Description
GDP	Real gross domestic product
HHcsmp	Household consumption expenditure
Gcsmp	Government consumption expenditure
GCF	Gross capital formation
Exps	Exports
Imps	Imports

Note: The quarterly data are constructed by authors.

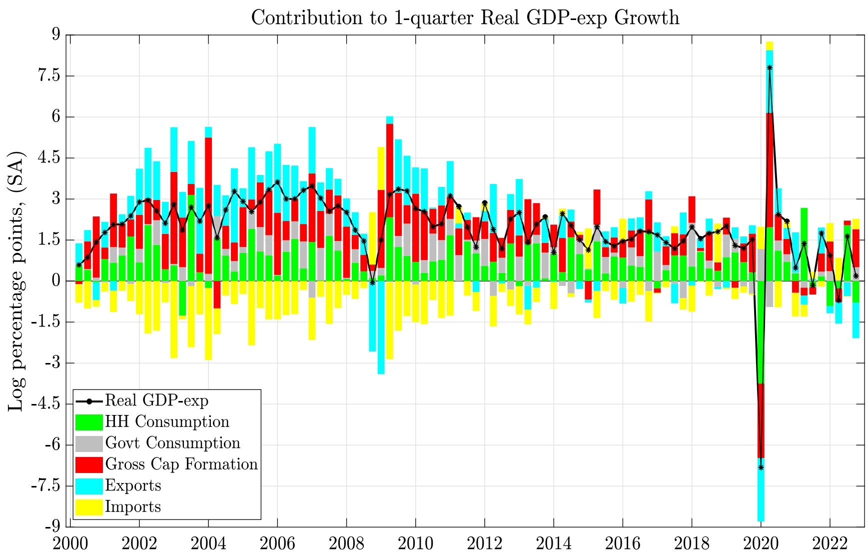

Fig. 5. Contributions of various GDP components to the quarterly growth rate of GDP-exp. The calculation is based on quarterly data constructed by authors.

$$\Sigma_{m(t)} = (A_0')^{-1} D^2_{m(t)} A_0^{-1} = (A_0')^{-1} \Lambda_{m(t)} A_0^{-1}. \tag{2}$$

For two different regimes i and j, we have

$$\Sigma_i^{-1}\Sigma_j = A_0 \left(\Lambda_i^{-1}\Lambda_j\right) A_0^{-1}. \tag{3}$$

The right-hand side of equation (3) is precisely the eigendecomposition of matrix $\Sigma_i^{-1}\Sigma_j$, where the columns of A_0 are the eigenvectors and the diagonal elements of the diagonal matrix $\Lambda_i^{-1}\Lambda_j$ are the corresponding eigenvalues. Since eigendecomposition is unique, A_0 is uniquely determined *up to scale* as long as these eigenvalues are distinctly different.[20]

While there are many ways to resolve this scaling issue, Brunnermeier et al. (2021) normalize the variance matrix by imposing restrictions

$$\frac{1}{M}\sum_{m=1}^{M} \log \lambda_{i,m(t)} = 1, \quad \forall i \in \{1,\dots,n\}, \tag{4}$$

where $\lambda_{i,m(t)}$ is the i-th diagonal element of $\Lambda_{m(t)}$. That is, the cross-regime (geometric) average variance of each variable is normalized to 1.

Because $A(L)$ is constant over time, the economy responds to shocks in the same way across different regimes, but the relative size of the shocks and the relative effects of shocks vary across regimes. Accordingly, plots of impulse responses always have the same shape, but different sizes across regimes.

Our first model, termed the "GDP model," includes GDP and its components as listed in Table 3: GDP, HHcsmp, Gcsmp, GCF, Exps, and Imps. All these six variables are in real terms and log level. The lag length is set to 4 quarters. The sample period spans from 2000Q1 to 2022Q4. Fig. 5 displays the contributions of various GDP components to quarterly growth of real GDP-exp. As can be seen from the figure, the sources of economic fluctuations are different across different periods. During the GFC regime (2008Q3-2008Q4), the slowdown in China's GDP growth was mainly attributable to negative growth of exports and investment, while imports

[20] Once A_0 is uniquely determined, A_j for $j = 1,\dots,p$ can be uniquely recovered from the corresponding reduced-form coefficient matrix.

Table 4
Quarterly data series used in the consumption model.

Variable	Description
HHcsmp	Household consumption expenditures
FTL	Food, tobacco, and liquor
Clth	Clothing
Res	Residence
HHFAS	Household facilities, articles, and services
Health	Health care and medical Services
Trans	Transportation and communication
ECE	Education, culture, and entertainment

Note: The quarterly data are constructed by authors.

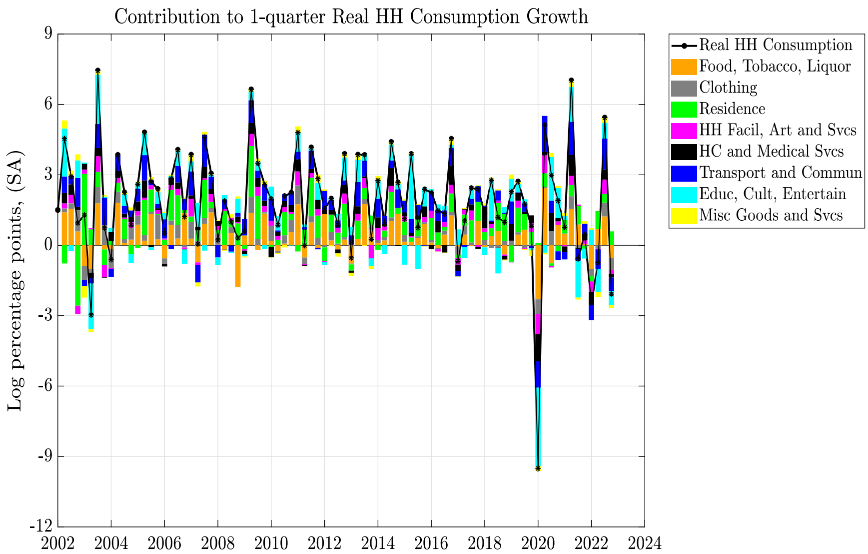

Fig. 6. Contributions of various consumption subcomponents to the quarterly growth rate of household consumption expenditure. The calculation is based on quarterly data constructed by authors.

experienced unprecedented negative growth.[21] Real GDP growth bounced back in 2009, a period of four-trillion RMB economic stimulus, when investment spiked. During the Covid-19 period, the sharp fall in 2020Q1 GDP growth can be largely attributed to the unprecedented negative growth in household consumption expenditure.

To maintain simplicity in our model and ensure easy interpretability of the results, we exclude financial and labor-market variables, as well as inflation, from the GDP model. Our model is not designed to identify or assess the effects of monetary policy shocks on inflation, financial markets, or labor markets. Instead, it focuses on the types of shocks that affected real GDP and its components across different episodes, providing insights into the potential outcomes derived from our newly constructed quarterly time series.

Following a similar strategy, we develop a second model, termed the “consumption model,” specifically to analyze the subcomponents of household consumption expenditures. This model is designed to understand the sources of substantial fluctuations in household consumption during the Covid-19 pandemic, focusing on its various subcomponents as detailed in Table 4. It aims to provide insights into how each subcomponent contributed to overall consumption changes during this period. All these eight variables are in real terms and log levels. Fig. 6 displays the contributions of various subcomponents to the quarterly growth of household consumption expenditure. Unlike the fluctuation of GDP growth, there were no time-varying fluctuations in household consumption until the Covid-19 lockdown. Fluctuations in household residence expenditures are an important contributor to fluctuations in household consumption prior to 2020Q1. During the Covid-19 period, expenditures on food, tobacco, and liquor (FTL) and education, culture, and entertainment (ECE) experienced the largest fluctuations. Negative growth in FTL and ECE contributed most to the negative growth of household consumption in 2020Q1 and 2022Q4.[22]

We identify distinct regimes based on the relative importance of sources driving economic fluctuations, as shown in Figs. 5 and 6, and our institutional knowledge. This narrative approach contrasts with Sims and Zha (2006), who model regimes for shock variances as a Markov-switching process. We identify the GDP model with five distinct regimes described in Table 5. The first regime covers the investment-driven period (2000Q1-2008Q2) when investment, especially in capital-intensive sectors, was a major driver

[21] Note that negative growth of imports contributes positively to GDP growth.

[22] The other two times China experienced significant negative growth in FTL were in 2007Q2 when CPI inflation was high and 2008Q4 during the GFC.

Table 5
Regimes dates for the GDP model.

Regime $m(t)$	Start	End	Description
1	2000Q1	2008Q2	Investment driven
2	2008Q3	2008Q4	GFC
3	2009Q1	2009Q3	Economic stimulus
4	2009Q4	2019Q4	Post-stimulus phase
5	2020Q1	2022Q4	Covid-19

of economic growth and fluctuations (Chen and Zha, 2020). The second regime covers the GFC outbreak (2008Q3-2008Q4), which significantly affected external demands for China's exports. The third regime covers the economic stimulus period (2009Q1-2009Q3), during which the Chinese government introduced monetary and fiscal stimulus to boost the economy. The fourth regime spans the post-stimulus period (2009Q4-2019Q4). The fifth regime corresponds to the Covid-19 period (2020Q1-2022Q4), during which all GDP components exhibited significantly greater volatility compared to earlier periods in the sample.

Unlike GDP, the growth in household consumption expenditures did not experience larger-than-normal fluctuations during the GFC period. By contrast, the largest fluctuation occurred during the Covid-19 period. In the consumption model, we identify only two regimes for the sample period: the first regime, from 2000Q1 to 2019Q4, captures the pre-Covid period; the second regime, from 2020Q1 to 2022Q4, covers the Covid-19 period.[23]

4.3. Economic interpretation of structural shocks

Our estimated variances of structural shocks change substantially across regimes for both models, implying strong identification. A structural shock *does not need to* be associated with any single variable because all the variables in the model system are endogenously and jointly determined. To determine the economic meaning of any particular shock, our labeling of structural shocks is consistent with the standard practice in the SVAR literature, where the meaning of a structural shock is inferred from the signs of impulse responses. For example, an aggregate demand shock is expected to increase both aggregate output and the price level, while an aggregate supply shock is expected to decrease aggregate output while increasing the price level. Unlike sign restrictions where signs of impulse responses are imposed to assess the impacts of a particular shock, our volatility approach uniquely determines impulse responses by distinct volatility regimes. We then assign an appropriate meaning to each shock by examining both the magnitudes of its variance relative to others and its effects across all variables in different regimes.

Another significant strand of SVAR literature focuses on direct restrictions imposed on A_0 or even on A_j for $j = 1, \ldots, p$. While many of these restrictions are motivated by economic theory or reasoning, the resulting signs of impulse responses to specific shocks do not always align with economic intuition. The well-known "price puzzle," where a monetary policy shock leads to an increase in both interest rates and inflation, exemplifies this problem. In such cases, the counterintuitive result—tighter monetary policy leading to higher inflation—goes against market expectations, hence the term "the price puzzle." Researchers have extensively explored other identifying restrictions or even alternative models to reconcile monetary policy shocks with expected outcomes.

All these discussions underscore one key point: the signs and magnitudes of impulse responses, directly or indirectly obtained, are crucial in assessing the sensibility of an estimated structural shock. In our volatility approach, we indirectly utilize the signs, magnitudes, and variances of impulse responses for shock identification. For shocks that are challenging to label or interpret, we name them after the variable with the largest immediate response. In summary, our and other approaches to interpreting shocks all rely on the signs and magnitudes of impulse responses, whether directly or indirectly. In Section 4.6, we offer further interpretations of our estimated structural shocks, drawing on external sources (i.e., other models).

4.4. Shock volatility

Table 6 presents the relative variances of the six structural shocks in the GDP model across different regimes.[24] All these shocks exhibit time-varying variances. For example, prior to the Covid-19 period, the economic stimulus shock has the largest variances (relative to one standard deviation) during the period of monetary and fiscal stimulus.[25] The external shock has the largest variances both in the GFC period and in the economic stimulus period. In particular, the estimated variance for the consumption-constrained shock is almost 4.5 times one standard deviation during the Covid period when household consumption suffered most. Fig. 7 displays the estimated time series of these three shocks over the sample. For the consumption-constrained shock, for example, one can see

[23] As a robustness check, we estimate the consumption model using the same five regimes as in the GDP model. The impulse responses during the Covid-19 period show little change.

[24] We will focus on dynamic impacts of a set of important shocks on the system in Section 4.5.

[25] During the Covid-19 period, the variance of the economic stimulus shock is also large as the government attempted to combat the economic slowdown. The most dominant shock in this period, however, is the consumption-constrained shock, which dwarfs the variances of all other shocks, including the economic stimulus shock.

Table 6
Relative shock variances for the GDP model.

Shock	2000Q1-2008Q2	2008Q3-2008Q4	2009Q1-2009Q3	2009Q4-2019Q4	2020Q1-2022Q4
Investment	1.26	1.17	1.25	0.52	1.05
Consumption-constrained	0.60	0.88	0.87	0.48	4.49
Government expenditure	0.97	0.82	0.84	1.63	0.91
Household consumption	0.89	0.82	0.85	0.64	2.52
Economic stimulus	0.77	0.90	1.13	0.91	1.39
External	0.64	1.45	1.68	0.81	0.79

Note: The values reported in the table are the estimates at the posterior mode of the GDP model.

Table 7
Relative shock variances for the consumption model.

Shock	2000Q1-20019Q4-	2020Q1 2022Q4
Non-ECE	0.73	1.37
FTL	0.67	1.48
Clth	1.40	0.71
Housing wealth	1.49	0.67
HHFAS	1.56	0.64
Health	1.14	0.88
Housing demand	0.99	1.01
Consumption-constrained	0.43	2.35

Note: The values reported in the table are the estimates at the posterior mode of the consumption model.

that the timings of consumption-constrained shocks are in line with those of Covid-19 lockdowns of Wuhan and the tier-1 cities in China.[26]

Table 7 presents the variances (relative to one standard deviation) of the eight structural shocks in the consumption model across the two regimes. We focus on two key economic shocks: the housing demand shock and the consumption-constrained shock. While the variance of housing demand shocks is similar across the two regimes, the consumption-constrained shock has the largest variance during the Covid-19 period. As shown in Fig. 8, housing demand shocks occurred randomly with similar magnitude throughout the sample, but consumption-constrained shocks hit the economy much harder during the Covid-19 period than in the pre-Covid period.

4.5. Dynamic impacts

Research on the sources of economic fluctuations in China has been limited in the existing literature. In this section, we explore the impact of various key economic shocks on the macroeconomy. Our analysis begins with the GDP model by focusing on three distinct regimes: the GFC period, the economic stimulus era, and the Covid-19 phase. We report estimated impulse responses with 68% posterior probability bands. Following the likelihood principle as argued by Sims and Zha (1999), we consider the responses significant if the 68% error bands do not include zero, effectively providing an 84% probability of the response either above or below zero.

During the GFC period, the model highlights the external shock as a principal catalyst for economic fluctuations. This shock exerts immediate and substantial negative effects on both imports and exports, as shown in the first column of Fig. 9.[27] These effects are more persistent than the impacts on other variables, partly due to the sluggish recovery of external demand for Chinese products by the U.S. and other developed countries. Investment (GCF) reacts negatively to the external shock, with this response statistically significant for 6 quarters. The response of household consumption, however, is both statistically and economically insignificant, consistent with the observation that quarterly growth in household consumption expenditures remained positive during the crisis, as shown in Fig. 5. While the external shock significantly impacts imports, exports, and investment, its effect on GDP is relatively minor, being statistically significant for only 5 quarters. As shown in Fig. 5, GDP growth, which began slowing from 2007Q2, was more influenced by a secular decline than by fluctuations around the trend.

The economic stimulus shock, manifested during the phase of the government's interventions to boost the economy, exerts prolonged and highly significant effects on investment (GCF) and government expenditures, as shown in the second column of Fig. 9. While GDP reacts positively and significantly to this stimulus shock, however, exports fall sharply during the first 5 quarters, a

[26] Specifically, Covid-19 lockdowns occurred in Wuhan during 2020Q1 and 2021Q3, in Beijing during 2020Q4, in Shanghai during 2022Q2, and in Shenzhen and Guangzhou during 2022Q4, during which the lockdown policy required an individual not to leave the house with only minimal exceptions (e.g., an individual was allowed to leave the house only once every few days to purchase necessary household items, and only one person can leave the house at a time).

[27] For all the impulse responses reported in this paper, the blue line indicates the estimate at the posterior mode, and the two red lines indicate the 68% probability bands.

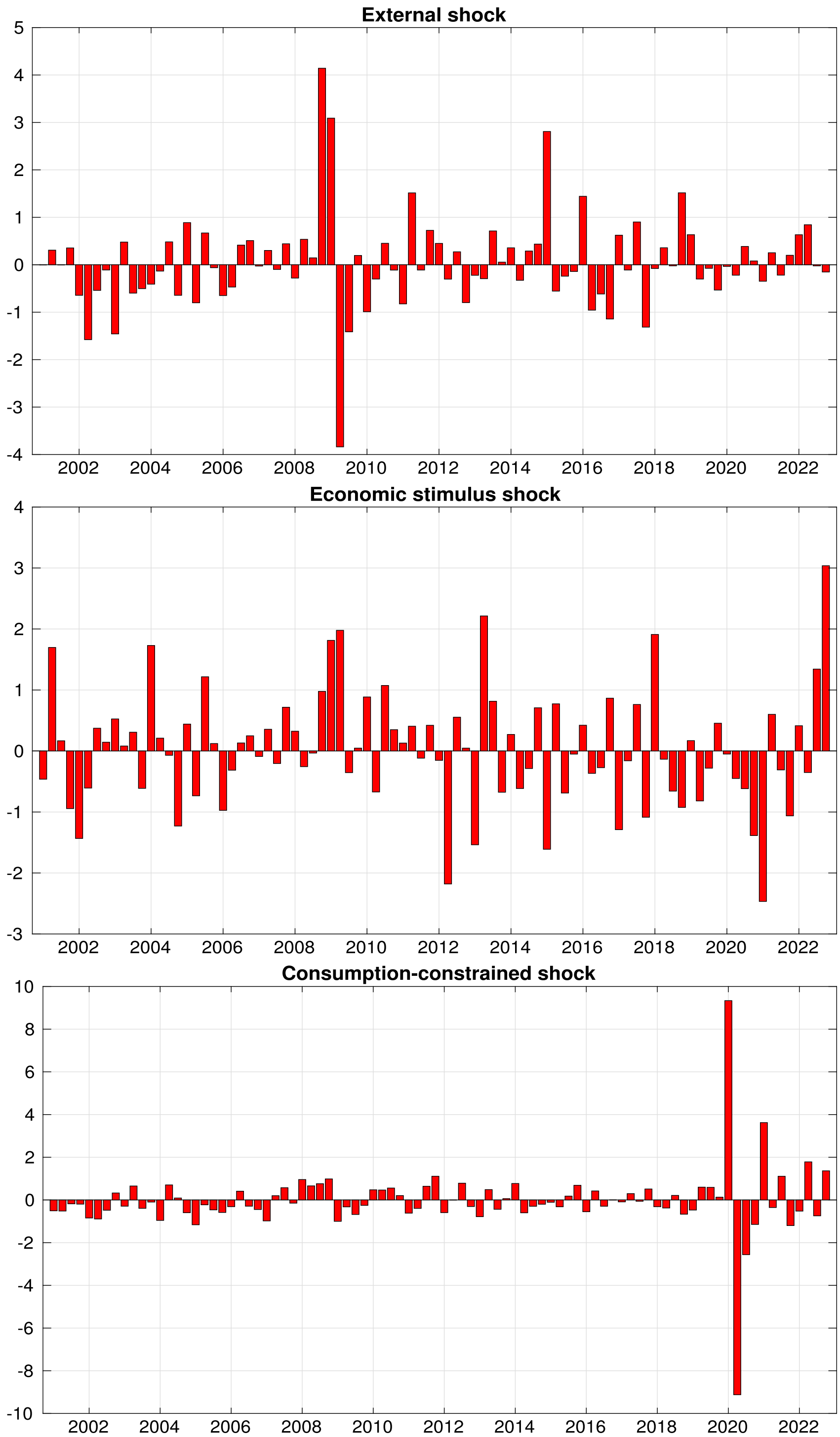

Fig. 7. The estimated series of three key structural shocks over the sample for the GDP model. These shock series, measured by standard deviations, are estimated at the posterior mode.

decline that is statistically significant. One plausible explanation is that bank credit for investment by private manufacturing firms—a significant portion of export businesses—is crowded out by fiscal stimulus (Chen et al., 2023).

By contrast, the consumption-constrained shock results in the most significant fluctuation, an order of magnitude greater than the effects of other shocks, as shown in the third column of Fig. 9. This shock produces large magnitudes in all the impulse responses, each statistically significant. During the Covid-19 period, various restrictions were imposed on both the supply and demand sides of

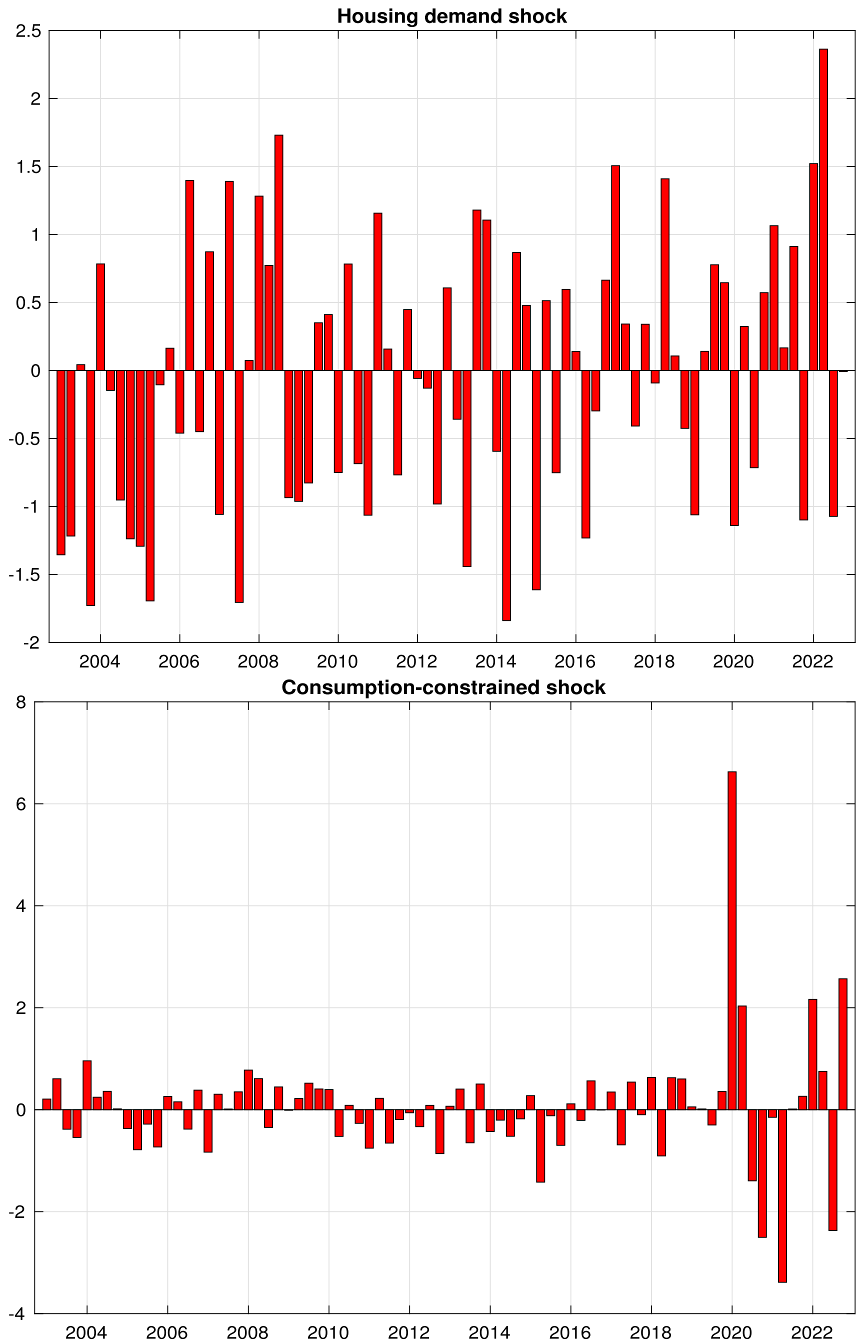

Fig. 8. The estimated series of two key structural shocks over the sample for the consumption model. These shock series, measured by standard deviations, are estimated at the posterior mode.

the economy. Our identified consumption-constrained shocks capture these unexpected measures. In particular, this shock induces significant and lasting negative impacts not only on household and government consumption expenditures but also on all other GDP components. Consequently, its impact on GDP is more pronounced than those of other structural shocks, leading to a sustained downturn in GDP and all its components. This shock compels households to curtail consumption, primarily due to social distancing measures and diminished income, and results in government shutdowns, business closures, declines in firm investment and imports of production intermediaries, transportation disruptions, and slumps in exports.

The consumption-constrained shock is the only shock that significantly drives down household consumption. We decompose the dynamic effects of this shock on household consumption from the GDP model into effects on its subcomponents in the consumption model, providing insights into the relative importance of each subcomponent. Fig. 10 presents the impulse responses from the

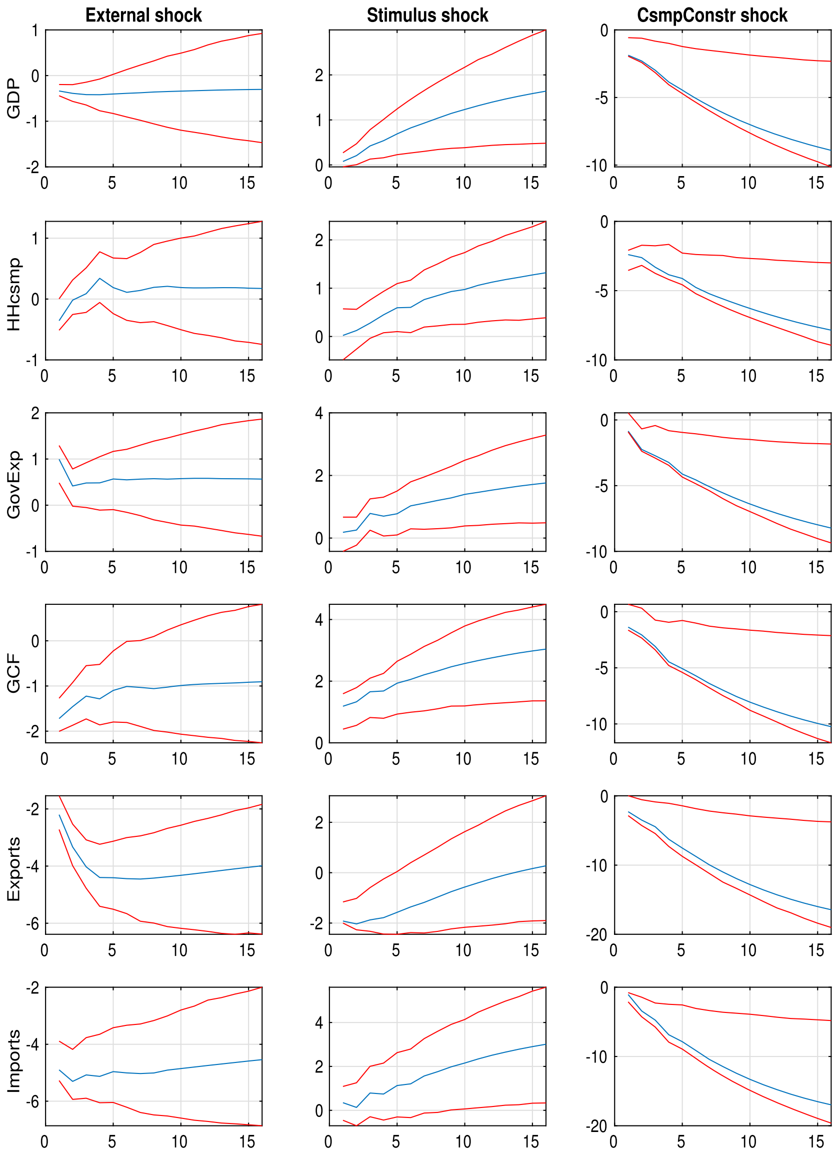

Fig. 9. Impulse responses to three key structural shocks with 68% error bands in the GDP model. The vertical scale shows deviations from the model-implied trend in percentage points, while the horizontal axis indicates quarters. The first column presents estimates from the GFC period; the second column from the economic stimulus period; and the third column from the Covid-19 period. “Stimulus shock” is shorthand for “Economic stimulus shock”, and “CsmpConstr” abbreviates “Consumption-constrained”.

consumption model. Among all eight shocks, the housing demand shock is most influential on residential consumption, labeled as “Residence” in the first column of Fig. 10. Fluctuations in residential consumption reflect changes in the demand for housing services, including property management, electricity, water, and fuel. These demands positively influence all consumption subcomponents. As illustrated in the first column of the figure, the responses of household consumption and its subcomponents are predominantly positive on impact (except for FTL) and show a persistent increase, with all responses statistically and economically significant. Our estimated housing demand shocks play a crucial role not only in the pre-Covid period but also during the Covid-19 period, as demonstrated in the top panel of Fig. 8.

During the Covid-19 period, the consumption-constrained shock we identify is predominant, both in its magnitude and in its significant effects on household consumption and its subcomponents. Unlike the housing demand shock, this shock exerts an immediate and substantial impact on household consumption and all its subcomponents (second column of Fig. 10). The pronounced negative effects on all subcomponents persist for years with high statistical significance, perhaps as a result of the shock’s adverse impact on households’ permanent income. A distinctive observation is the markedly pronounced effects of this shock on education, culture, and entertainment (ECE), food, tobacco, and liquor (FTL), clothing, and household facilities and services (HFAS). Periodic Covid lockdowns limited households from engaging in activities such as dining out, purchasing clothes and household items, and attending cultural or entertainment events. Among all subcomponents, the impact on residential consumption (Residence) is less severe

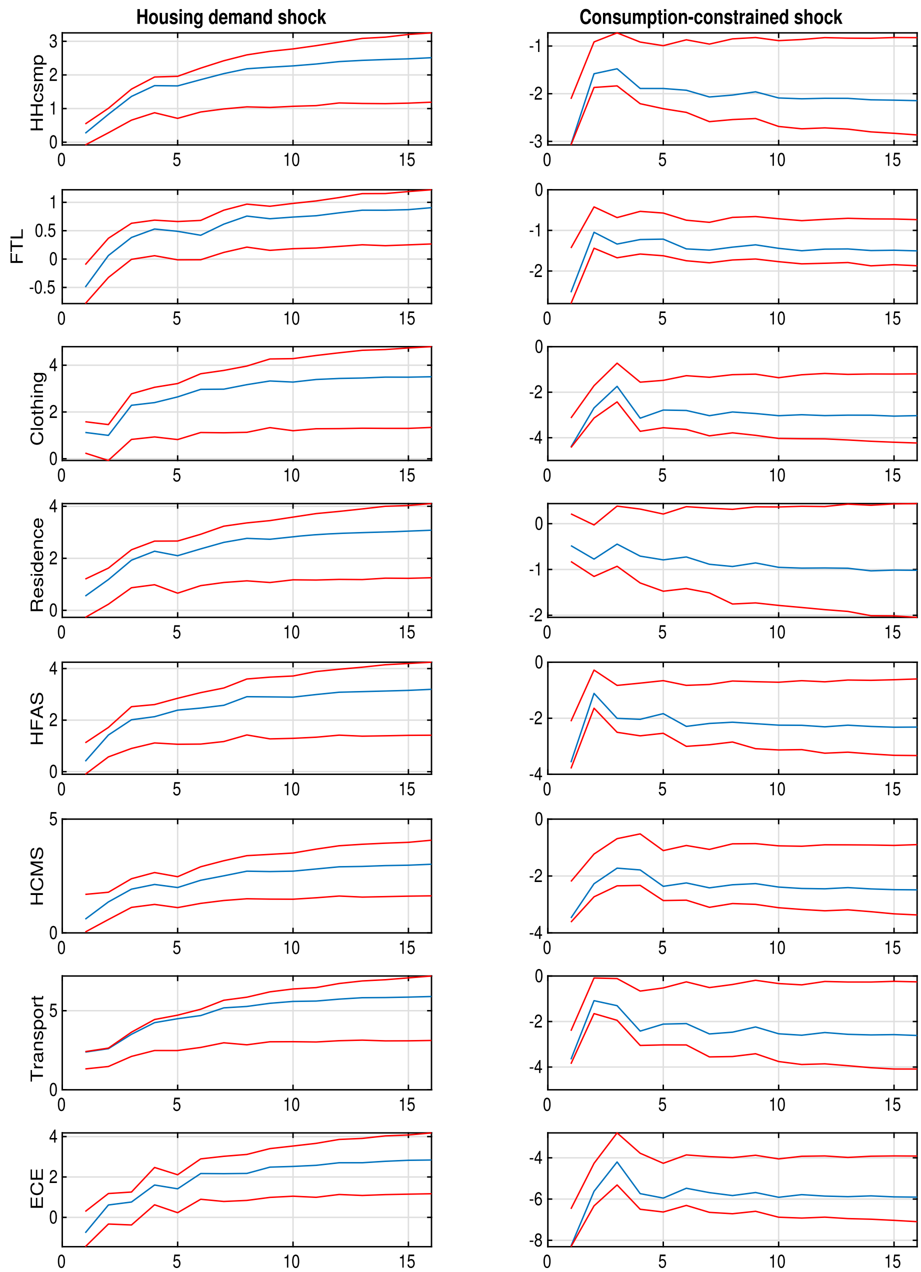

Fig. 10. Impulse responses to two key structural shocks with 68% error bands in the consumption model. The vertical scale shows deviations from the model-implied trend in percentage points, while the horizontal axis indicates quarters. The first column presents estimates from the pre-Covid period, and the second column from the Covid-19 period.

compared to the influence of the housing demand shock. This finding is plausible because households, confined to their homes, had increased demands for housing services—captured by housing demand shocks—relative to other types of expenditures.

4.6. Additional interpretations of structural shocks

As discussed in preceding sections, interpreting the identified shocks is always a challenge. The impulse responses presented in Section 4.5 are key to obtaining an economic interpretation of a particular shock. In addition to these within-model efforts, we also evaluate our estimated shocks against the disturbances obtained from other models. Table 8 reports the correlations of our three structural shocks with other sources. First, the external shock we identified correlates highly (0.48) with the U.S. corporate bond credit spread constructed by Gilchrist and Zakrajšek (2012), which rose sharply during the GFC period. This correlation suggests that the external shock captures shocks originated from the global financial crisis, distinct from other sources. Second, the

Table 8
Correlations of model shocks with shocks from other models.

	Model shocks			
Other models	External	Stimulus	CsmpConstr	CsmpConstr2
GZ premium	0.48***	0.07	0.13	0.09
Lockdown	0.02	0.17	0.47***	0.62***
China MP	0.01	0.48***	-0.18	0.03
BRW MP	0.17	-0.08	0.13	0.07
BS MP	0.17	0.05	0.16	0.15

Note: "GZ premium" refers to an innovation in the AR(1) process of the excess bond premium, as estimated by Gilchrist and Zakrajšek (2012). "Lockdown" denotes an innovation in the AR(1) process of the quarterly GDP-weighted average lockdown stringency index across provinces and municipality cities such as Beijing and Shanghai. "China MP" is a quarterly series of monetary policy shocks during the period 2003Q1-2011Q4, estimated by Chen et al. (2018), when China actively pursued M2-targeted monetary policy to promote economic growth. "BRW WP" represents the monetary policy shock series provided by Bu et al. (2021), with cumulated daily shocks converted to a quarterly average. "BS MP" is the monetary policy shock series provided by Bauer and Swanson (2023), with cumulated daily shocks converted to a quarterly average. The three asterisks "***" indicate statistical significance at the 1% level, and no asterisk indicates no statistical significance.

economic stimulus shock shows significant correlation (0.48) with China's monetary policy shocks, as estimated from the asymmetric policy reaction function by Chen et al. (2018). This finding implies that the economic stimulus shock partly reflects China's own expansionary monetary policy. On the other hand, its low correlation with the U.S. monetary policy shocks as shown in the last two rows of Table 8 suggests that the economic stimulus shock is distinct from monetary policies in other countries.

Third, the size of our consumption-constrained shock, as shown in Figs. 7 and 8, is enormous during the Covid-19 pandemic period, indicating that it likely reflects the stringent Covid-19 lockdown policies. The stringency index data for provinces and municipality cities, such as Beijing and Shanghai, are compiled by Oxford University.[28] We compute the quarterly GDP-weighted average stringency index across provinces and municipality cities, and estimate innovations to its AR(1) process. These innovations correlate significantly with the consumption-constrained shock from both our GDP and consumption models (0.47 and 0.62, respectively). All these statistically and economically significant correlations provide additional interpretations of our estimated structural shocks.

5. Conclusion

We have constructed a comprehensive dataset of major expenditure components of GDP, in both nominal and real terms, at quarterly frequency usable for macroeconomic analysis. We apply two SVAR models to our constructed quarterly data to study the sources of economic fluctuations across different episodes of the Chinese economy since 2000. Shocks that constrain household consumption have persistently negative effects on GDP and its components. The effects on household consumption were most pronounced during the Covid-19 period. This finding is in sharp contrast to the GFC period, in which shocks that negatively affect exports and imports were the main source of macroeconomic variations and household consumption did not suffer nearly as much as during the Covid-19 period. Our analysis about macroeconomic fluctuations during the economic stimulus period is also consistent with the findings in prior literature.

China has recently faced a number of headwinds, including its ailing real estate sector, its fragile financial system, and concerns over the solvency of its local governments. There is a pressing need to analyze the interactions between the real estate sector, the financial system, and the broader Chinese macroeconomy. It is our hope that our constructed data and empirical findings motivate further studies of the sources of economic fluctuations and their impacts in China.

CRediT authorship contribution statement

Kaiji Chen: Writing – review & editing, Writing – original draft, Investigation, Formal analysis. **Patrick Higgins:** Methodology, Investigation, Formal analysis, Data curation. **Tao Zha:** Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis.

Appendix A. Supplementary material

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.jimonfin.2024.103052.

[28] The data is available at https://ourworldindata.org/covid-stringency-index.

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