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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 underscore the distinct impacts of consumption-constrained shocks on household consumption and its various subcomponents throughout the Covid-19 pandemic.

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I. 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]

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

[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.

[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.

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 Chinas 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

[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 2019 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%.

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.

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. Chen and Zha (2020) 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 represents the first attempt to use an SVAR model with identification via shock heteroskedasticity to explore the roles of multiple structural shocks in Chinese macroeconomic fluctuations across various regimes, with special attention to the recent Covid-19 period.

This paper is structured as follows. Section II describes the procedures for constructing our quarterly time series of GDP. Section III discusses the procedures to construct components of expenditure-based GDP at both annual and quarterly frequencies. Section IV 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 V concludes.

II. Constructing quarterly expenditure-based GDP

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.[5] 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.

[5]Wu and Ito (2015) use a very similar apporach 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).

The purpose of our paper is not to assess which assumption is correct, nor does it address the potentially mismeasured trend of real GDP. Rather, our paper addresses one pressing issue: the lack of a standard set of annual and quarterly macroeconomic time series comparable to those commonly used in macroeconomic literature. 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. Moreover, as Fernald et al. (2021) emphasize, quarterly real GDP reported by the NBS is too smooth. Following Fernald et al. (2021), we do not address mismeasurement issues related to annual real GDP growth, but rather focus on addressing the smoothness problem of quarterly data. We assume that over longer periods (two to five years) of time nominal and real GDP growth is measured correctly. Similar to much of marcroeconomic research in the literature, seasonally-adjusted quarterly data are essential for an analysis of economic impacts of different shocks in different periods. In this section, therefore, we construct real quarterly GDP-exp data that address the issue of excess smoothness. Based on our constructed quarterly GDP-exp, Section III then constructs components of GDP-exp at both annual and quarterly frequencies.

II.1. **Constructing C-CAT indicator as the interpolater.** 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 Figure 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:[6]

> China's System of National Accounts (2016) adopted the basic accounting principles, contents and methods of the United Nation's System of National

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

> 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.

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

A number of studies have argued that real GDP growth in China has been overly smooth in recent decades, particularly in the 2010s.[7] To address this smoothess issue, 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,[8] 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.

We use the same set of eight series as in Fernald et al. (2021) to estimate the C-CAT, but transform these series differently.[9] 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)

[7] See, for example, Nakamura et al. (2016), Fernald et al. (2021), Wu and Li (2021), and Barcelona et al. (2022).

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

[9] These eight series are 1) the expectation subindex of the NBS' overall consumer confidence index, (2) industrial production of electricity in killowat 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 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).

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.

Figure 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. Figure 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."

II.2. **Interpolating quarterly real GDP-exp.** 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). While Supplemental Appendices A-E detail our interpolation procedures, we offer a simple example to illustrate our interpolation method.

In national income and product accounting, interpolation often involves distributing an annual aggregate "flow" variable Y_t among the four quarters of the year as $y_{t,1}, y_{t,2}, y_{t,3}$, and $y_{t,4}$, with the help of a related higher frequency (quarterly), but lower quality, indicator series $x_{t,q}$.[10] For instance, in the U.S. National Income and Product Accounts, the Bureau of Economic Analysis applies the proportional Denton method, based on Denton (1971), as

[10]For notational consistency, we denote the annual year-t value of variable X by X_t. and the quarter q value of X in that year by $X_{t,q}$. To simplify notation in appendix, we use the convention that $X_{t+1,q} = X_{t,q+4}$.

their primary interpolation approach. This method aims to minimize the sum of squared deviations $(\frac{y_{t,q}}{x_{t,q}} - \frac{y_{t,q-1}}{x_{t,q-1}})^2$ while ensuring that the sum of the quarters equals the annual total, i.e., $Y_t = \sum_{q=1}^{4} y_{t,q}$. We refer to this constraint as the "adding up" constraint. Denton's method is a specific implementation of a broader econometric model $y_{t,q} = \boldsymbol{X_{t,q}\beta} + u_{t,q}$, where $\boldsymbol{X_{t,q}}$ may be a row vector[11], $\boldsymbol{\beta}$ is a column vector, and $u_{t,q}$ is a residual that makes the "adding up" constraint satisfied.

The Chow and Lin (1971) method considers the error term $u_{t,q}$ to follow an AR(1) process $u_{t,q} = \rho u_{t,q-1} + \epsilon_{t,q}$. Fernandez (1981) assumes $\rho = 1$, and under this assumption, his algorithm yields the best linear unbiased estimates of $\boldsymbol{\beta}$ and $y_{t,q}$, minimizing the sum of squares $(\Delta y_{t,q} - \Delta \boldsymbol{X_{t,q}\beta})^2$ where Δ is the first difference operator. Entering annual GDP as Y_t, rather than its log, would increase the variance of $u_{t,q}$ over time, potentially leading to overfitting near the sample's end. Using the log of GDP, however, mitigates this problem by minimizing the sum of squared differences between quarterly GDP growth $\Delta\log(y_{t,q}^{GDP})$ and fitted values, typically a linear function of one or more related quarterly growth rates.[12] The "adding up" constraint is then reformulated as the average of four-quarter growth rates – a weighted average of quarterly growth rates – equalling ΔY_t^{GDP}.

The Fernandez (1981) approach we employ results in interpolated values that satisfy the equation:

$$\Delta\log(Y_t) = \frac{1}{4}\sum_{q=1}^{4}\log\left(\frac{y_{t,q}}{y_{t-1,q}}\right) \approx \log\left(\frac{\sum_{q=1}^{4} y_{t,q}}{\sum_{q=1}^{4} y_{t-1,q}}\right).$$

To ensure that the first and last terms of this expression are exactly equal, we perform a subsequent proportional Denton interpolation of Y_t with the first stage estimates $y_{t,q}$ to guarantee the "adding up" constraint is met.

In addition to the optimization criterion that relates the growth rates of the interpolators to the growth rate of the series being interpolated, the estimate of β offers valuable insights into into the performance of a chosen interpolater. For illustrative purposes, we assume that in the U.S., quarterly real GDI is not as accurately measured as quarterly real GDP. We consider a scenario where our goal is to interpolate annual real GDI from 1952 to 2022 using U.S. quarterly real GDP data, applying the Fernandez-Denton method outlined in

[11]In practice, if a vector $\boldsymbol{X_{t,q}}$ proves more effective than a scalar $x_{t,q}$ for a particular application, one can often use a version of the proportional Denton approach by fitting a regression to the annual data, forming quarterly fitted values using the regression coefficients, and then using these fitted values as the related quarterly indicator.

[12]The interpolation always includes a constant as one of the regressors to account for any mean differences.

this section.[13] This interpolation method gives the estimate of the constant term less than 1E-7, while the estimated slope coefficient on real GDP growth is 0.953. Consequently, the interpolated quarterly GDI growth rates exhibit a strong correlation with both the quarterly GDP growth rates (0.987) and the published quarterly GDI growth rates (0.910), exceeding the official correlation (0.895) between reported quarterly GDP and GDI growth rates.

Turning our focus back to China, in our interpolation regression, the left-hand side variable is the logarithmic difference of annual real GDP-exp, while the right-hand side variables include a constant term and the logarithmic difference of the quarterly alternative C-CAT indicator. The interpolated quarterly growth rates are then transformed into the log-level series. 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[14] 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 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 (Figure 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.

III. 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.

[13]We use the U.S. as an example for clarity, because quarterly GDI data is available, allowing us to evaluate the accuracy of our interpolation method. By contrast, quarterly GDP-exp data is not available in China.

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

III.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.[15] 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.[16] 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.

III.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 Figure 4, the quarterly growth rates of our real GDP-exp series differ from those of the series interpolated with the 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[17] 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.[18] The same interpolation methodology applies to quarterly nominal

[15]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.

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

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

[18]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

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,[19] as well as the C-CAT adjustment factor. The two interpolated nominal variabes 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).[20] 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.[21] The price deflator for inventories, based on Holz (2014), is then used to obtain quarterly nominal changes in inventories.[22] Nominal GCF is obtained by simply

consumption expenditures and with the growth contribution of household and government consumption expenditures to the share of real GDP growth.

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

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

[21]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.

[22]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.

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.

IV. 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.

IV.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-inconsistent data to the CCAT-adjusted data (columns (9) and (10)) 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.

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)-(4), and (6)-(7) of Table 2), even when taking into account the standard deviation across countries (columns (5) and (8)).[23]

Government consumption is significantly more volatile than household consumption (columns (2) and (10)), 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)-(4), and (6)-(7)), and there is a wide dispersion of this volatility among emerging economies (column (5)). 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.

IV.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, $\{A_j\}_{j=1}^{p}$ 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

[23] 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).

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 $m(t) \in \{1, \ldots, M\}$. In each regime the variance of structural shocks is a different diagonal matrix $\Lambda_{m(t)}$:

$$E\left[\epsilon_t \epsilon_t'\right] = \Lambda_{m(t)}$$

such that $D_t \equiv D_{m(t)} = \sqrt{\Lambda_{m(t)}}$. 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 $j = 0, 1, \ldots, p$ 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

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

For two different regimes i and j, we have

$$\Sigma_i^{-1} \Sigma_j = A_0 \left(\Lambda_i^{-1} \Lambda_j\right) A_0^{-1}. \tag{2}$$

The right-hand side of equation (2) 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.[24]

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

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

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

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

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. Figure 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 experienced unprecedented negative growth.[25] Real GDP growth bounced back in 2009, a period of four-trillion RMB economic stimulus, when investment spiked. During the Covid-19 lockdown 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. Figure 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

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

the largest fluctuations. Negative growth in FTL and ECE contributed most to the negative growth of household consumption in 2020Q1 and 2022Q4.[26]

We identify distinct regimes based on the relative importance of sources driving economic fluctuations, as shown in Figures 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 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.[27]

IV.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 need not 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

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

[27]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.

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 IV.6, we offer further interpretations of our estimated structural shocks, drawing on external sources (i.e., other models).

IV.4. **Shock volatility.** Table 6 presents the relative variances of the six structural shocks in the GDP model across different regimes.[28] 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.[29] The external shock has the largest variances both in the GFC period and

[28]We will focus on dynmaic impacts of a set of important shocks on the system in Section IV.5.

[29]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.

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 sufferred most. Figure 7 displays the estimated time series of these three shocks over the sample. For the consumption-constrained shock, for example, one can see 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.[30]

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 Figure 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.

IV.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 Figure 9.[31] 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

[30]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.)

[31]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.

(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 Figure 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 Figure 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 Figure 9. While GDP reacts positively and significantly to this stimulus shock, however, exports fall sharply during the first 5 quarters, a 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 Figure 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 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. Figure 10 presents the impulse responses from the consumption model. Among all eight shocks, the housing demand shock is most influential on residential consumption, labeled as "Residence" in the first column of Figure 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 Figure 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 Figure 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 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.

IV.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 IV.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 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, distinct from monetary policies in other countries.

Third, the size of our consumption-constrained shock, as shown in Figures 7 and 8, is enormous during the Covid-19 pandemic period, indicating that it likely reflects the stringent Covid-19 policies. The stringency index data for provinces and municipality cities, such as Beijing and Shanghai, are compiled by Oxford University.[32] 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.

V. 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 duirng 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.

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

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 labelled "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.

TABLE 2. Unconditional moments of quarterly data

	China		Emerging economies			Advanced economies			2008Q1-2016Q4	
Variable	NBS	CCAT	Median	Mean	Std.	Median	Mean	Std.	NBS	CCAT
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
GDP	2.031	2.292	2.415	2.549	0.917	1.796	1.848	0.494	1.4106	1.8827
HHcsmp	2.375	2.449	2.515	2.693	1.110	1.347	1.546	0.575	2.2712	2.3317
Gcsmp	4.595	4.824	4.476	4.582	2.257	1.290	1.516	0.582	5.0457	5.3497
GCF	4.581	4.459	9.420	10.356	3.481	8.008	8.413	1.636	4.2964	4.2448
Exps	9.192	9.225	7.675	7.860	1.522	5.038	5.135	1.453	8.4404	8.4687
Imps	9.689	9.730	9.729	10.095	2.318	5.863	5.885	0.881	9.3101	9.3958

Note: The table reports the standard deviation (%) of 4-quarter growth rates for the period 2001Q1-2019Q4. 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 3. Quarterly data series used in the GDP model

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

Note: The quarterly data are constructed by authors.

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.

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

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.

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.

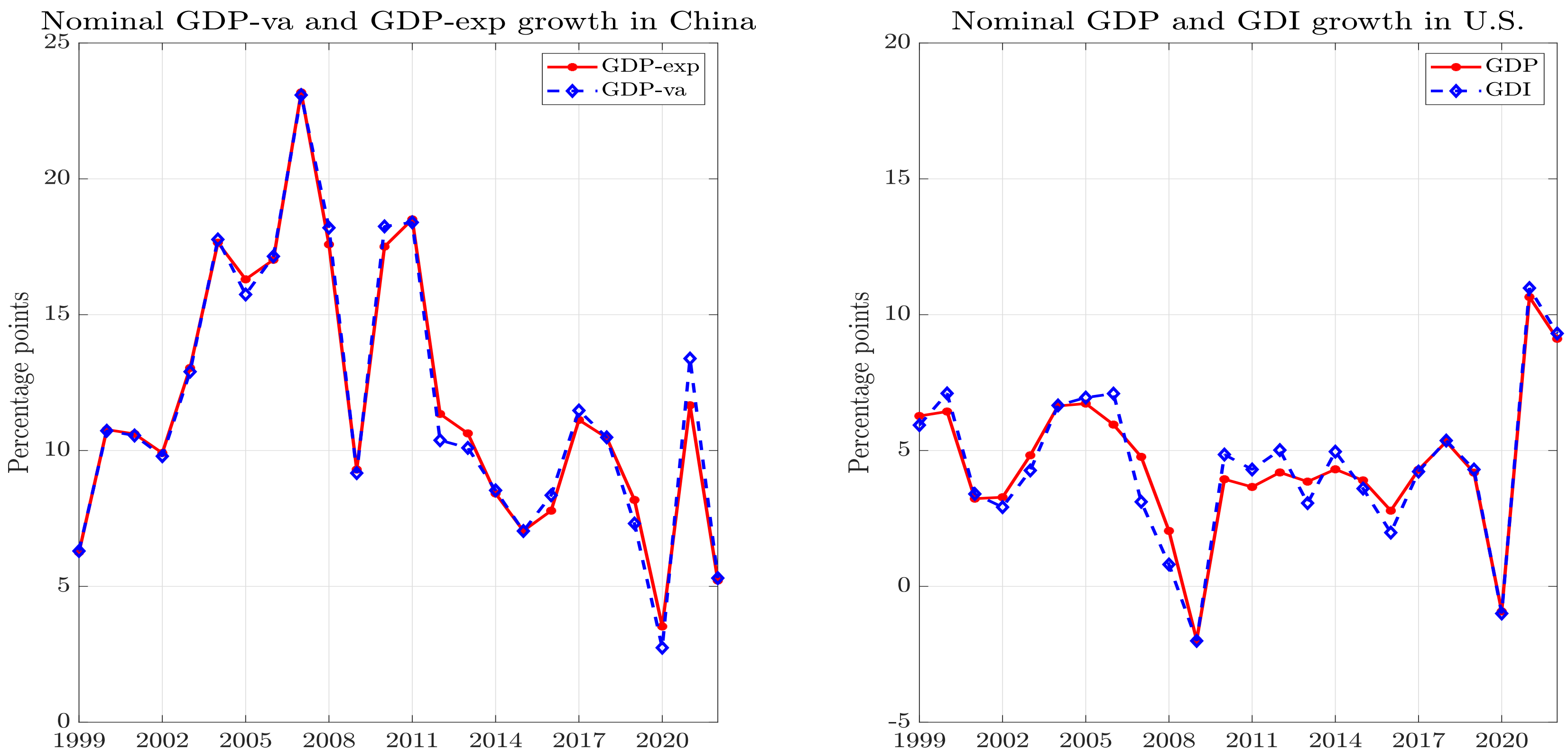


FIGURE 1. Left panel shows annual nominal growth rates (%) of GDP-va and GDP-exp in China. Right panel shows annual nominal growth rates (%) of GDP and GDI in U.S.

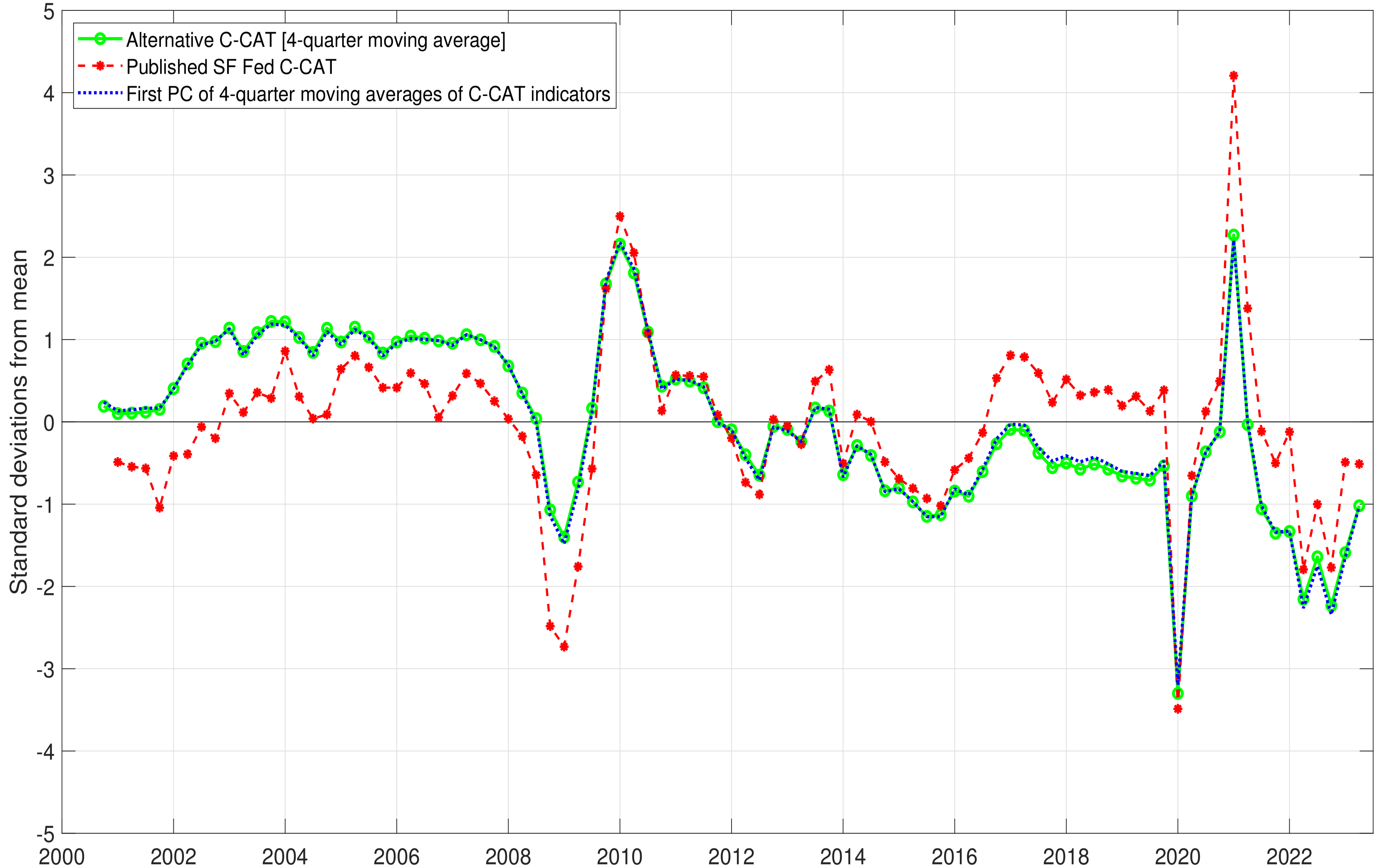


FIGURE 2. Comparison of the SF Fed's published C-CAT indicator of Fernald et al. (2021) (red dashed line with stars) with our alternative C-CAT indicator. The green line with circles is the 4-quarter moving averages of standardized one-quarter growth rates of our alternative C-CAT indicator. The SF Fed's 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.

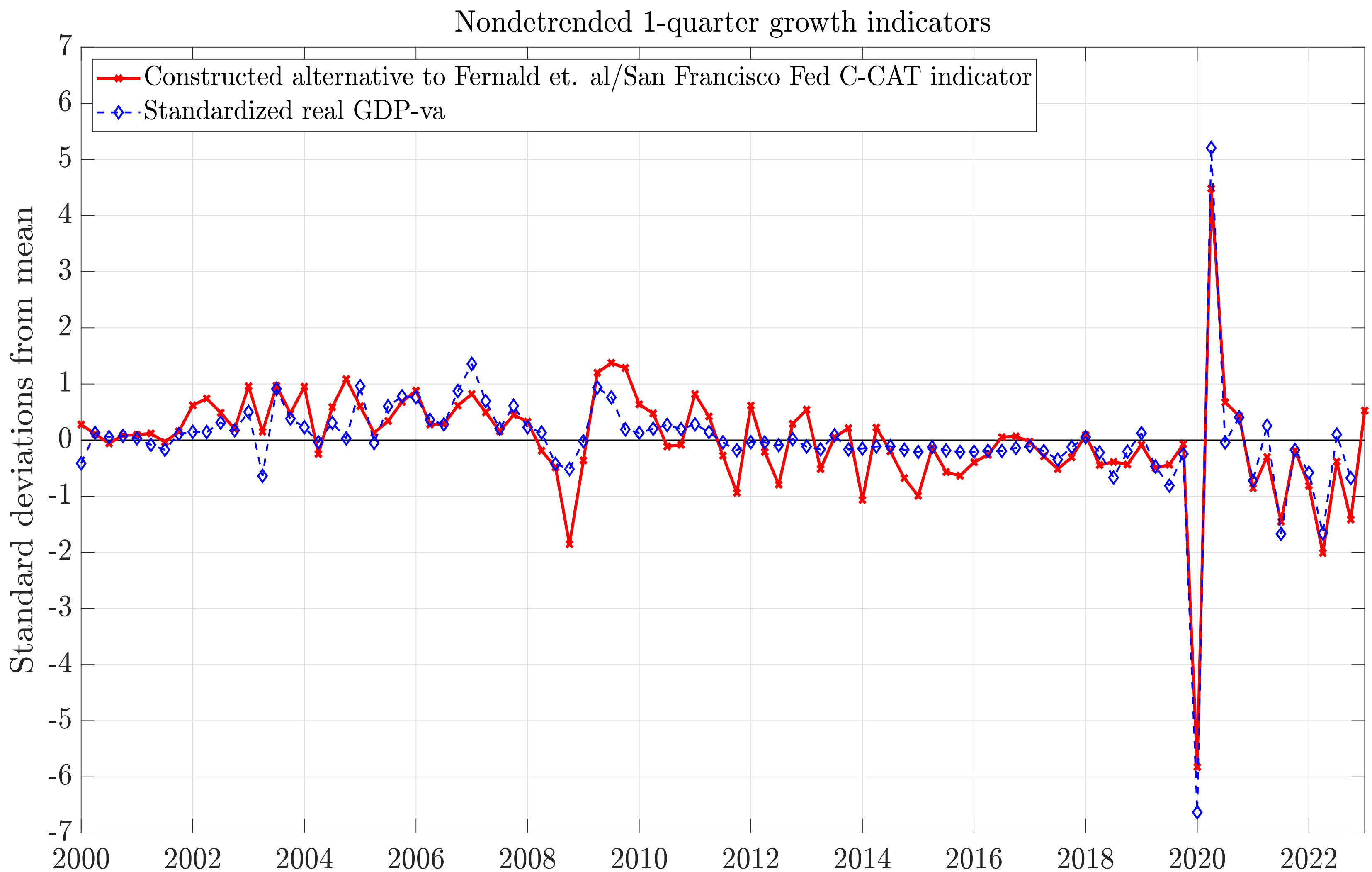


FIGURE 3. Comparison of standardized one-quarter growth rates of seasonally adjusted real GDP-va (blue dashed line with diamonds) with standardized one-quarter growth rates of our alternative C-CAT indicator (red solid line with stars).

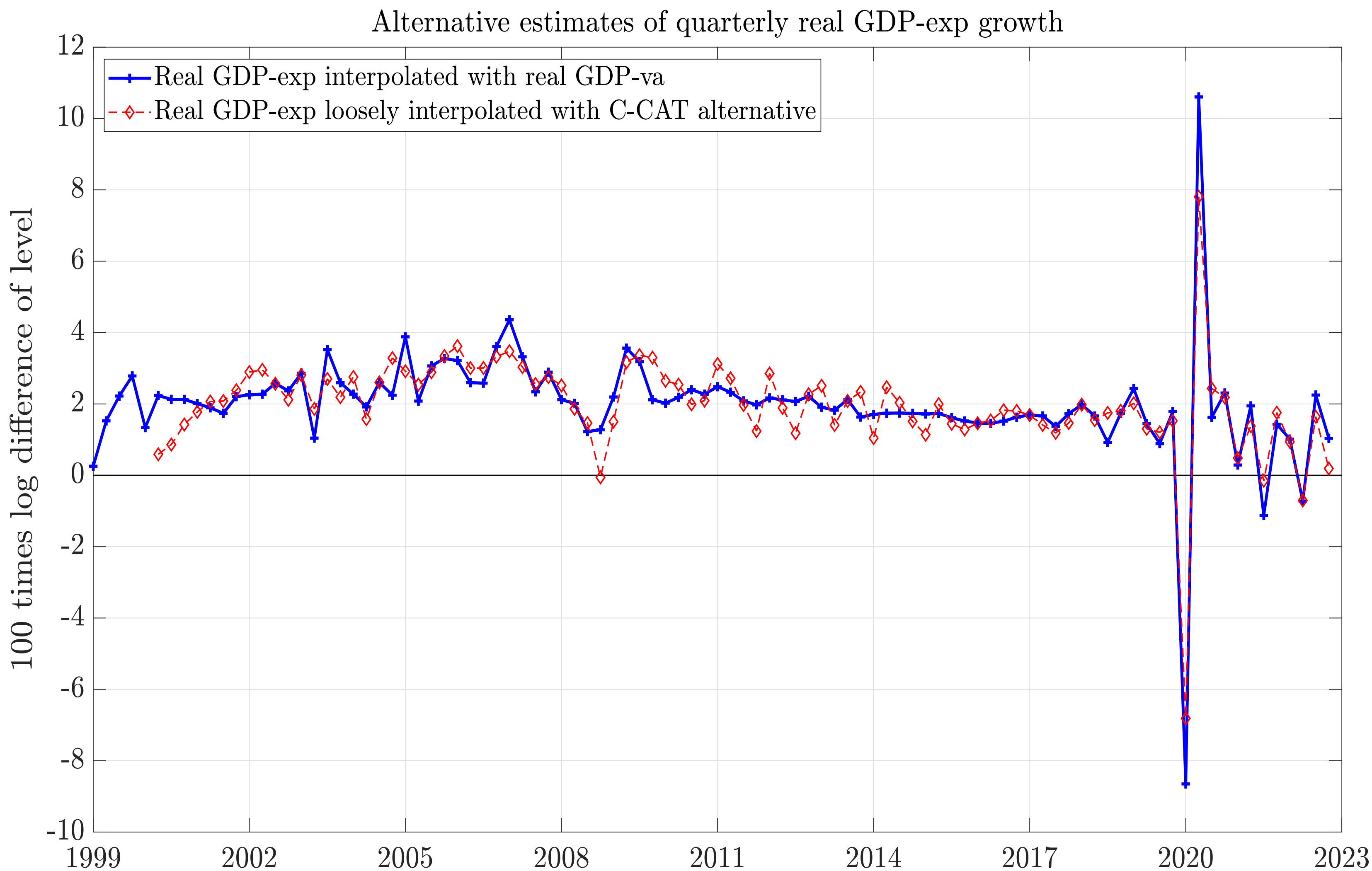
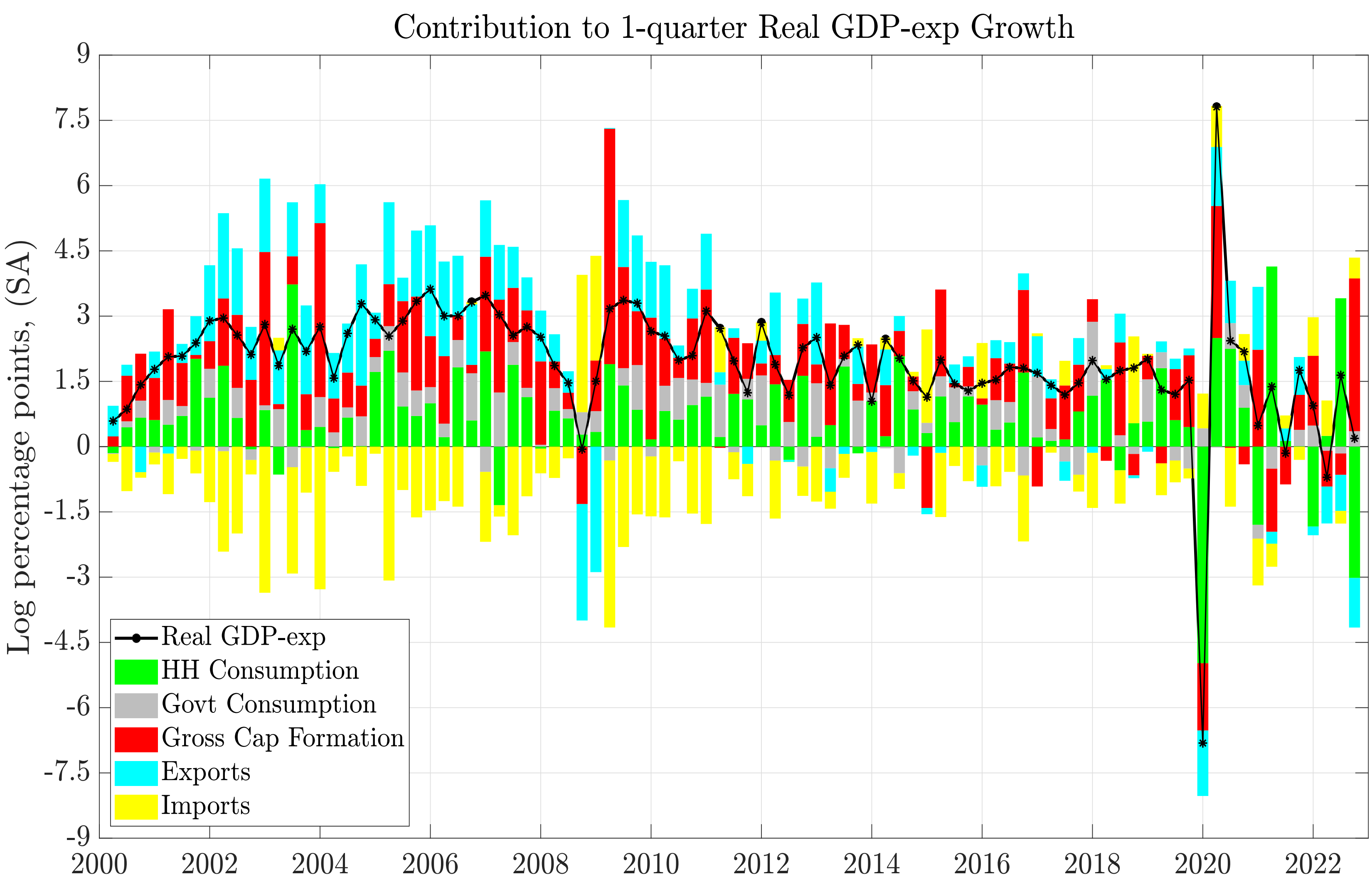
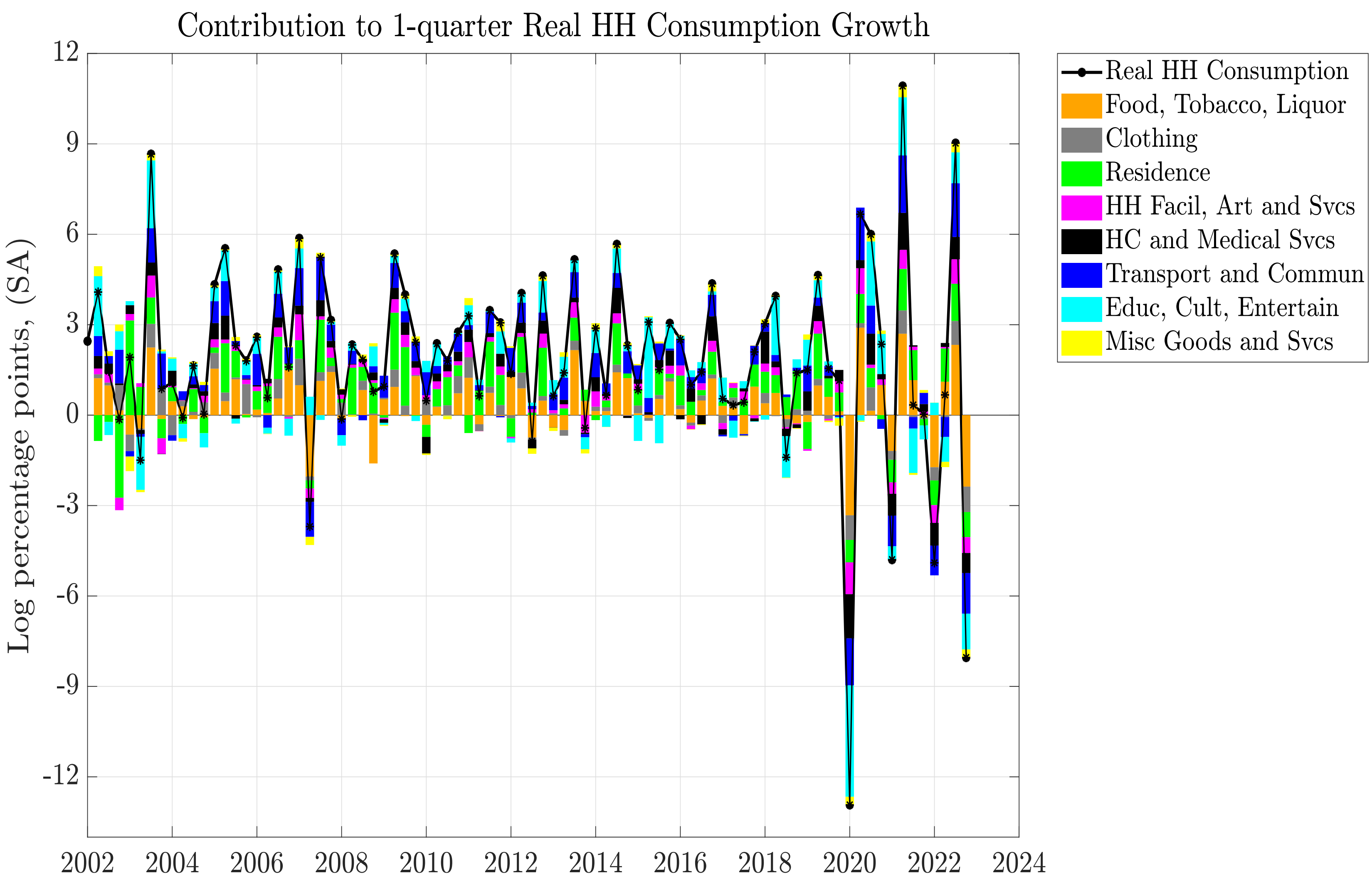


FIGURE 4. Difference of log level values for the quarterly GDP-exp series interpolated by our alternative C-CAT indicator (red line with diamonds) and the quarterly GDP-exp series interpolated by the quarterly GDP-va series published by the NBS (blue line with pluses).



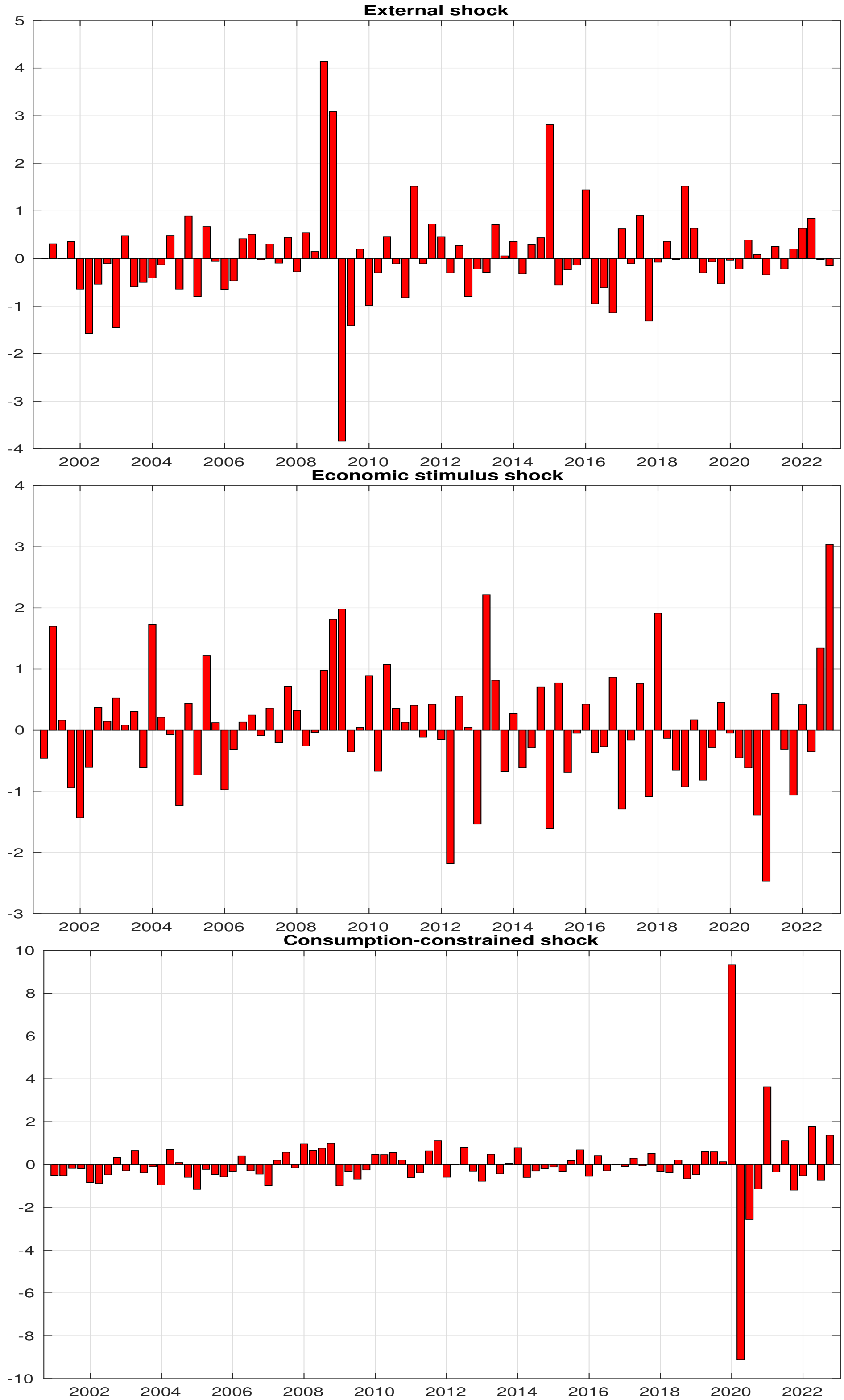
Note: The calculation is based on quarterly data constructed by authors.

FIGURE 5. Contributions of various GDP components to the quarterly growth rate of GDP-exp



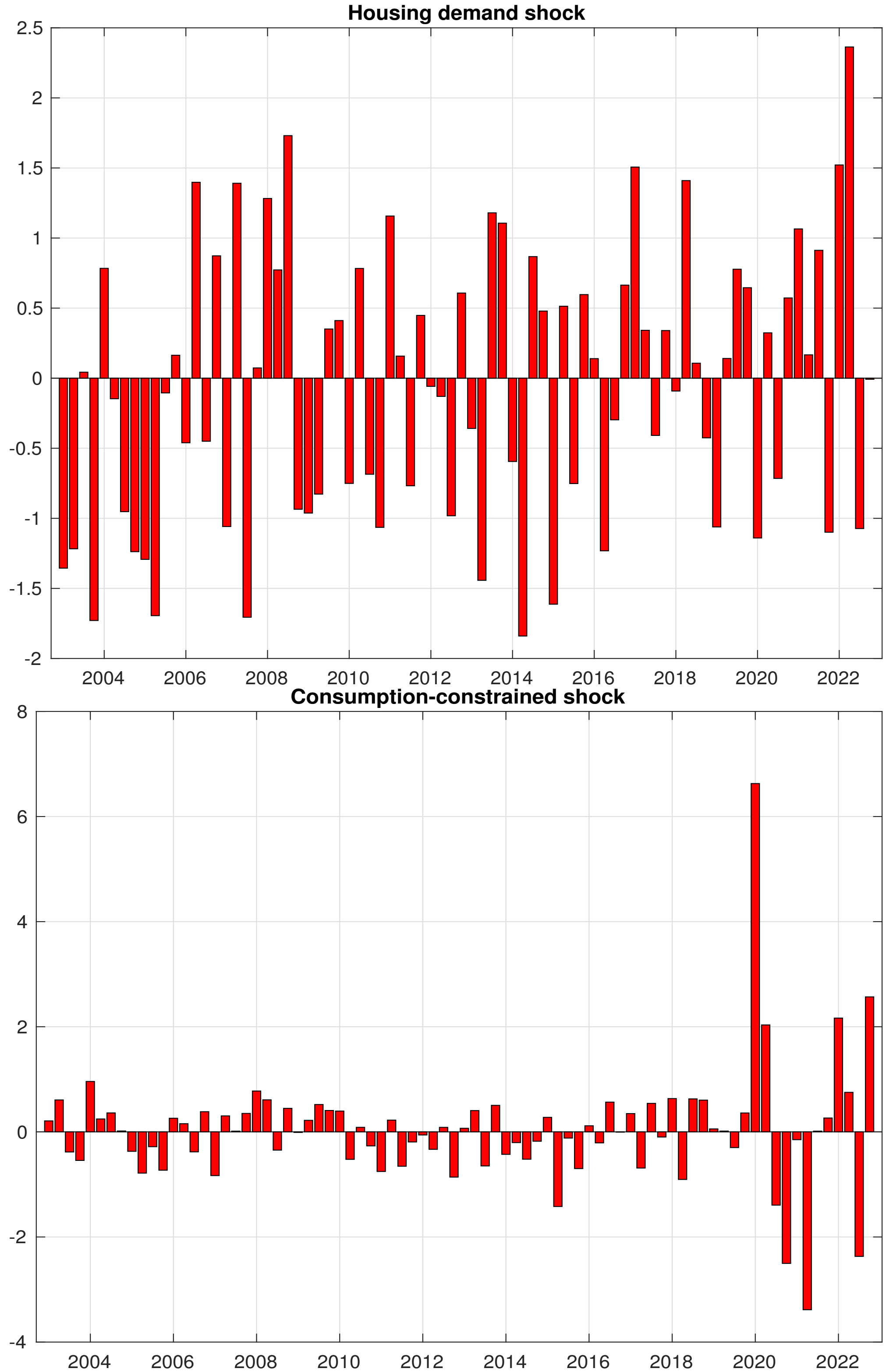
Note: The calculation is based on quarterly data constructed by authors.

FIGURE 6. Contributions of various consumption subcomponents to the quarterly growth rate of household consumption expenditure



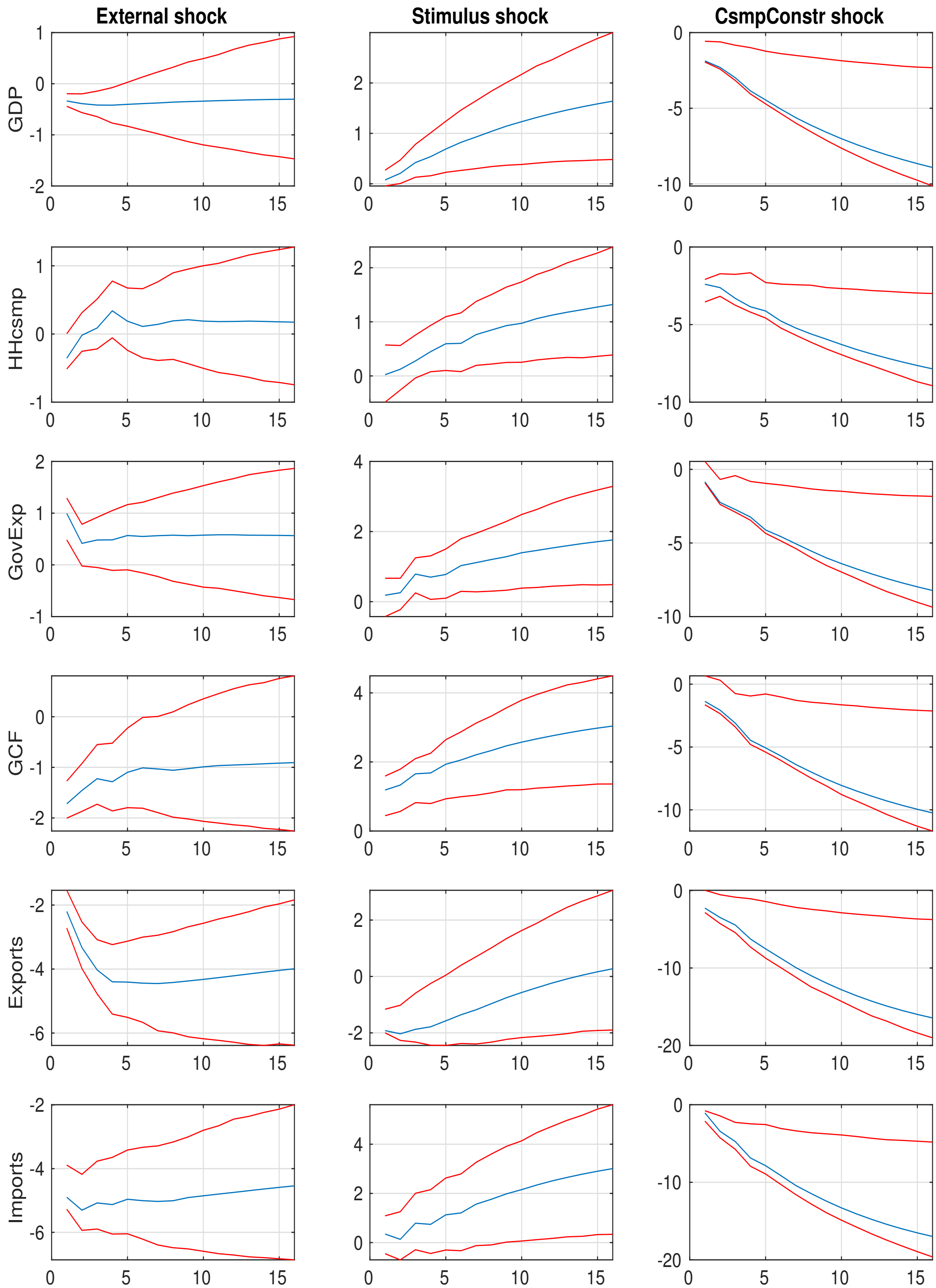
Note: These shock series, measured by standard deviations, are estimated at the posterior mode.

FIGURE 7. The estimated series of three key structural shocks over the sample for the GDP model



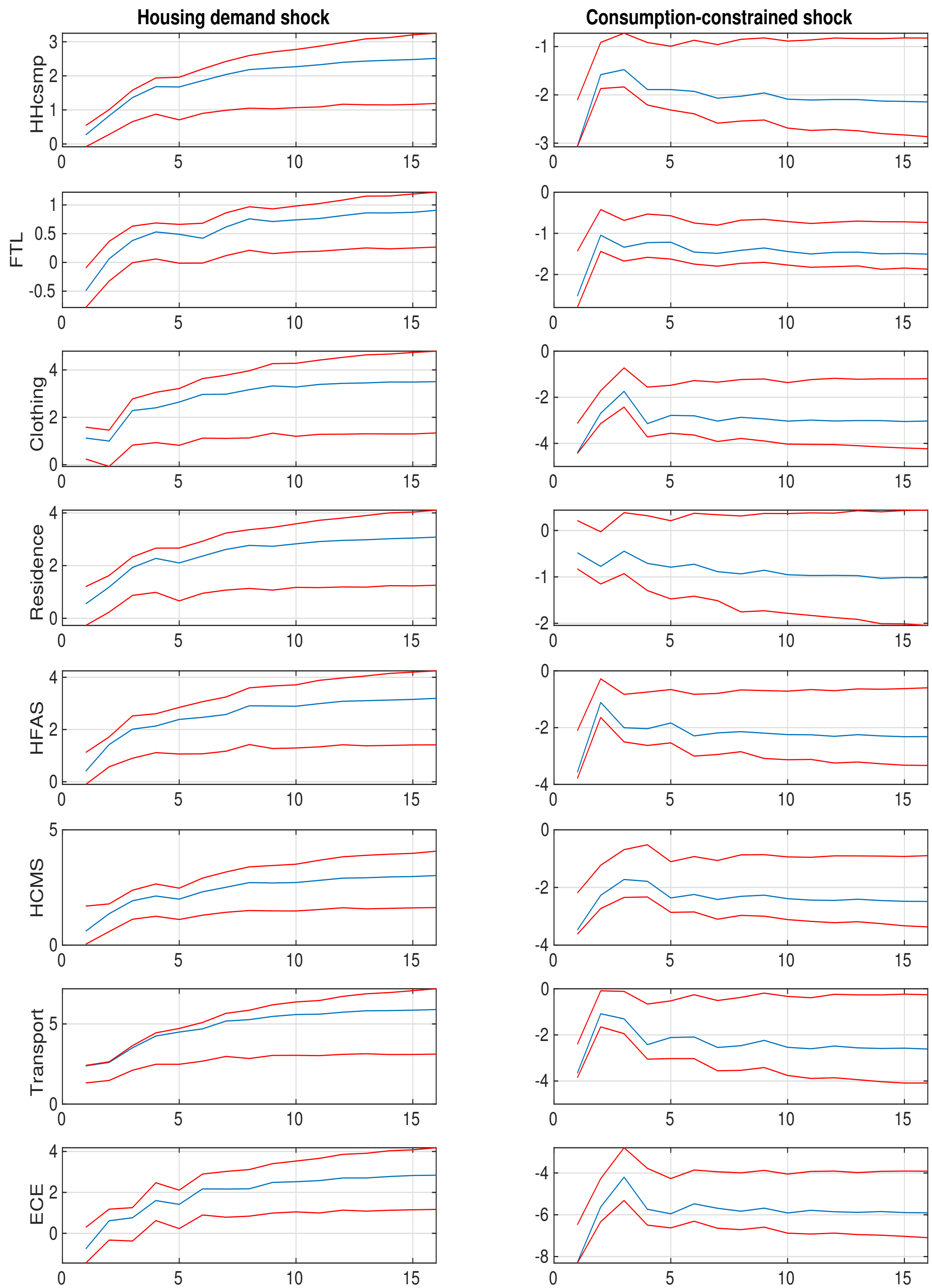
Note: These shock series, measured by standard deviations, are estimated at the posterior mode.

FIGURE 8. The estimated series of two key structural shocks over the sample for the consumption model



Note: 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".

FIGURE 9. Impulse responses to three key structural shocks with 68% error bands in the GDP model



Note: 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.

FIGURE 10. Impulse responses to two key structural shocks with 68% error bands in the consumption model

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Supplemental Appendices

Not Intended for Publication

Appendices A and B provide a fairly non-technical general overview of how we interpolate the expenditure side measure of GDP and its subcomponents to the quarterly frequency with some accompanying results. The methods, results, and figures cited in these two appendices, as well as in Appendix E, do not include the C-CAT related adjustments used to make real GDP-exp growth less smooth. The C-CAT adjustments we describe in the main text, however, build off of a number of the series mentioned in these three sections. Appendix C provides technical details describing the C-CAT related adjustments to aggregate GDP-exp and the related subcomponent data both to reduce the smoothness of GDP-exp and to maintain internal quarterly consistency with GDP-exp and its subcomponents. Appendix D provides more granular technical details on the methods and data used for interpolating GDP-exp subcomponents, prior to any of our C-CAT adjustments, while maintaining aggregation consistency within and between GDP subcomponents. It also presents some visual and numerical evidence that the annual series are highly correlated with the quarterly series they are being interpolated by. Appendix D presents a comparison between using detrended data and nondetrended (raw) data for estimating the C-CAT series used to construct our quarterly GDP and its subcomponents. Appendix E concludes with the technical details of the interpolation algorithm we use and how we modify the algorithm so that aggregated real GDP-exp only has to equal the NBS average in multi-year windows rather than in every single year.

Appendix A. Overview of data construction prior to adjustments made to reduce smoothness of real GDP growth

For the BEA's estimates of quarterly real U.S. GDP, both the seasonally adjusted and the non-seasonally adjusted series aggregate up to the published annual total up to the level of decimal precision of the data[33]. The NBS has published seasonally adjusted data on growth in real GDP-va relative to the prior quarter's level since 2010:Q4. But, unlike for U.S. real GDP-exp estimates, the implied annual total is not exactly consistent with published annual real GDP-va even after accounting for decimal precision. Moreover, the implied 4-quarter growth rate of China's real GDP-va derived from the published seasonally adjusted 1-quarter growth rate is not exactly consistent with the published NBS 4-quarter growth rate of real

[33]Currently, the maximum level of precision is annualized millions of 2017 dollars, rounded to the nearest integer value.

GDP-va. This implies that it is not possible to derive a quarterly measure of real GDP-va that will simultaneously be consistent with the NBS published measures of 1-quarter growth, 4-quarter growth, and full-year over full-year growth. With this in mind, we follow Higgins and Zha (2015) in our construction of quarterly real GDP-va. This approach insures that, unlike the NBS measure of quarterly real GDP-va [see Figure S3], our series is exactly consistent with the NBS annual measure of real GDP-va. Our general approach is to use NBS data on year-to-date and four-quarter real GDP-va growth and quarterly nominal GDP-va to derive the non-seasonally adjusted level of real GDP-va. We then seasonally adjust this series and use it to interpolate annual real GDP-va ensuring quarterly consistency with the annual aggregate.

As explained above, the 4-quarter log difference of our series is not exactly consistent with the published NBS measure, but Figure S2 is consistent with the fact that it is closer on average [0.1388/100 log points in average absolute difference for our measure compared to 0.1567/100 log points difference for the published NBS measure of quarterly seasonally adjusted real GDP-va] to that measure over the common sample 2011-2022 sample period.

Prior to our adjustments following Fernald et. al (2021) to make real GDP less smooth, our measure of annual expenditure side real GDP is derived by deflating China's National Bureau Statistics (NBS) published annual measure of nominal expenditure side GDP[34] by the annual implicit price deflator for the value-added (va) measure of GDP, the primary GDP estimate cited by the NBS and the financial press.[35]. The NBS publishes the contributions of three GDP subcomponents (1) household and government consumption expenditures (C), (2) gross capital formation (GCF) and (3) net exports to annual full year over full year real GDP growth[36]. The sum of these contributions to real GDP growth is *exactly* identical to the published NBS measure of real *GDP-va*, not real *GDP-exp*, growth. Though generally close to each other, the NBS measures of annual nominal *GDP-va* and annual nominal *GDP-exp* are not identical much like the U.S. measures of nominal GDP and nominal gross domestic income (GDI) are not in spite of their theoretically equivalence. But, as figure **??** shows, the difference in the two China GDP growth rates is generally small and similar in magnitude to the differences between U.S. GDP and GDI growth.

[34]As a notational shorthand, we use GDP-exp to denote GDP measured by the expenditure side and GDP-va to GDP measured by the value added or production side approach.

[35]Also for notational convenience, for a variable X, we denote the annual year-t value of X by $X_{t\cdot}$ and the quarter q value of X in that year by $X_{t,q}$. To simplify notation below, we also specify that $X_{t+1,q} = X_{t,q+4}$.

[36]They also publish these contributions to four-quarter real GDP growth, but we do not utilize these.

More importantly, it is also the case that the real GDP-exp subcomponent contributions to real GDP-va growth are not identical, even up to rounding, to the corresponding calculated nominal GDP-exp subcomponent contributions to nominal GDP-exp growth. So it can't be the case that the NBS is simply deflating the subcomponents by an overall GDP deflator, suggesting there may be some merit to our approach. This is illustrated in figure S3; in each of the figure's subplots, the red solid lines are contributions to real GDP-va growth calculated using published NBS contributions data. The dashed blue lines are contributions to real GDP-exp growth constructed by multiplying each subcomponent's contribution share to nominal GDP-exp growth with real GDP-exp growth. For each subcomponent, the alternative contributions are highly correlated, but the difference can be as large as one percentage point.

We deflate annual GDP-exp by the price deflator for GDP-va, P_t^{GDPva}, to get annual real GDP-exp. Since nominal GDP-exp does not equal nominal GDP-va, we use NBS published measures of the three major subcomponents' share of the contribution to annual real GDP growth and the Tornqvist index based relationship

$$\Delta log(X_t^{real}) = \frac{X_t^{ShGDP} \Delta log(\frac{NomGDP_t^{exp}}{P_t^{GDPva}})}{.5(\frac{X_{t-1}^{nom}}{NomGDP_{t-1}^{exp}} + \frac{X_t^{nom}}{NomGDP_t^{exp}})} \tag{S1}$$

where X is either the C or GCF subcomponent of nominal GDP-exp $NomGDP_t^{exp}$ and X_t^{ShGDP} is the NBS's published measure of the share of X's contribution to real GDP growth, to get annual real growth rates of these subcomponents. Annual full year inflation rates for C and GCF are consequentially

$$\pi_t^X = \Delta log(\frac{X_t^{Nom}}{X_t^{Real}}) \tag{S2}$$

This decomposition has to be modified for net exports, as well as exports and imports, as we elaborate further in Appendix D.

We derive annual prices, quantities and nominal expenditures for the richer set of GDP-exp listed in Table S1 alongside the sources for these series. We 'discuss further in Appendix D, but note a few of the most pertinent details. The first is that the fact that having time series data for 2 series out of nominal, real quantities, and own-price values for a particular GDP subcomponent uniquely determines the third via equation (S2). Entries labelled "Implicit" in the table means that values are implicitly determined by data for the other 2 of these terms.

The isolated label "NBS" in the table means GDP-exp subcomponent data are directly taken from the National Bureau of Statistics while "NBS contrib." means that values are determined using equation (S3) above.

Related Tornqvist index equations which we often utilize to relate prices and quantities for GDP subcomponents to prices and quantities of a higher level aggregate, or more formally, when $X_1, ..., X_N$ are subcomponents of Y with prices P^Y and $P^{X_1}, ..., P^{X_N}$ and real quantities Q^Y and $Q^{X_1}, ..., Q^{X_N}$[37] are

$$\Delta log(P_t^Y) \simeq \sum_{i=1}^{N} [.5(\frac{X_{t-1}^{i,nom}}{Y_{t-1}^{nom}} + \frac{X_t^{i,nom}}{Y_t^{nom}})\Delta\{log(P_t^{X_i})\}] \tag{S3}$$

and

$$\Delta log(Q_t^Y) \simeq \sum_{i=1}^{N} [.5(\frac{X_{t-1}^{i,nom}}{Y_{t-1}^{nom}} + \frac{X_t^{i,nom}}{Y_t^{nom}})\Delta\{log(Q_t^{X_i})\}]. \tag{S4}$$

Equation (S3) and (S4) will hold approximately if we have independent measures for the terms on both the right side and the left side of equation (S3) or (S4). For example, when we separately derive inflation rates for total final consumption expenditures and both its household consumption and government consumption subcomponents. Since equation (S3) will only hold approximately initially in this case, we force it to hold exactly by adding the constant adjustment factor $\pi_t^{Y,Adj} = \Delta log(P_t^Y) - \sum_{i=1}^{N}[.5(\frac{X_{t-1}^{i,nom}}{Y_{t-1}^{nom}} + \frac{X_t^{i,nom}}{Y_t^{nom}})\Delta\{log(P_t^{X_i})\}]$ to each term inside the curly braces of equation (S3).

After deriving annual measures for the GDP subcomponents in Table S1 we derive quarterly measures using the data sources in Table S2. Again we provide most of the technical details in Appendix D, but provide the highlights here. The original data in the second through fourth columns of Table S2 are usually quarterly or monthly, typically not seasonally adjusted, and sometimes "year-to-date" (ytd). When ytd, January values are often missing but quarterly series can still be derived. Even when January values are available, we generally convert monthly data to quarterly prior to our own seasonal adjustments so that we don't have to worry about accounting for the timing of the Chinese New Year. After all of these transformations, the related quarterly series of prices, quantities or nominal spending will generally not aggregate up to the related annual GDP subcomponent, so interpolation is

[37]In the dataset, we normalize real quantities to 2008 RMB. When determined implicitly, annual price deflators will equal 1 in 2008 and quarterly price deflators will approximately average to 1 in that year.

used to insure consistency. When interpolating annual GDP subcomponents to the quarterly frequency, the U.S. Bureau of Economic Analysis generally uses the so-called proportional Denton method, which minimizes the sum of the squared differences of the ratios of the interpolated values to the indicator/interpolater[38]. However, we have found that this method sometimes produces overly volatile interpolated values at the beginning of a series which can be problematic given the short time series length of much China's macroeconomic data. So prior to a second step proportional Denton interpolation, we use a first-stage interpolation that is an adaptation of the Fernandez (1981) interpolation approach[39]. As we describe in more detail in Appendix D, the adaptation minimizes the sum of squared differences between $\Delta log(Y_{t,q})$, the quarterly log differences of the interpolated series, and $[1, \Delta log(\mathbf{X}'_{t,q})]\boldsymbol{\beta}$, a linear function of the log differences of the generally scalar, but possibly vector, $\mathbf{X}'_{t,q}$ subject to the constraints

$$\begin{aligned}\Delta \log Y_t = \frac{1}{16}[&\Delta \log Y_{t-1,2} + 2\Delta \log Y_{t-1,3} + 3\Delta \log Y_{t-1,4} + 4\Delta \log Y_{t,1} \\ &+ 3\Delta \log Y_{t,2} + 2\Delta \log Y_{t,3} + \Delta \log Y_{t,4}]\end{aligned} \tag{S5}$$

for $t \geq 2$. Because of the equation (S5) constraint, the interpolated quarterly growth rates are $[1, \Delta log(\mathbf{X}'_{t,q})]\boldsymbol{\beta} + \epsilon_{t,q}$, where the residual term is from an iid Gaussian distribution. The right hand side of equation (S5) is only approximately equal to $log(\frac{Y_t}{Y_{t-1}})$, so the second stage proportional Denton interpolation of Y_t with the interpolated series $Y_{t,q}$ from the first stage interpolation is used to ensure exact aggregation. An advantage of the first stage interpolation is the interpretability of $\boldsymbol{\beta}$. If $X_{t,q}$ aggregated to an annual frequency closely follows and grows at the same rate as Y_t, then we should observe $\boldsymbol{\beta} \approx [0, 1]'$.

As an example, figure S4 shows the annual log growth rates of the GDP-exp measure of household consumption expenditures, retail sales, and the quarterly Household Survey[40] measure of consumption expenditures which we have aggregated. The three measures of consumption growth are highly correlated, but the GDP-exp has a somewhat tighter fit with

[38]See Chapter 4 of *NIPA Handbook: Concepts and Methods of the U.S. National Income and Product Accounts* at `https://www.bea.gov/resources/methodologies/nipa-handbook`.

[39]Fernandez (1981), A Methodological Note on the Estimation of Time Series. The Review of Economics and Statistics , Aug., 1981, Vol. 63, No. 3 (Aug., 1981), pp. 471-476.

[40]More precisely, data since 2013 are collected in the Household Survey on Income and Expenditure and Living Conditions. Prior to 2012, data were collected in separately in the Urban Household Surveys and Rural Household Surveys. We combine and splice these data together.

the Household Survey measure of consumption than with retail sales[41]. Moreover, when we interpolate the GDP-exp consumption subcomponent jointly with retail sales, Household Survey consumption, and our first stage adapted Fernandez interpolation approach, the coefficient on Household Survey consumption is 0.803 while the coefficient on retail sales is only 0.052. Hence we do not use the retail sales data to interpolate when the Household Survey consumption data is available. Since the retail sales data is available before the quarterly Household Survey consumption measure is, we multiplicatively splice the former series through 2002:Q1 with the latter series beginning in that same quarter[42], and use the spliced series to interpolate the GDP-exp subcomponent.

Finally, as shown in figure S5, when we separately interpolate the real GDP-exp subcomponents and aggregate them up, the aggregated real quarterly subcomponents can have a much different growth rate than real GDP-exp directly interpolated by quarterly real GDP-va[43]. Although we prefer the alternative estimates of GDP-exp where excess smoothness has been removed by utilizing our alternative C-CAT measure, when restricting ourselves to NBS-consistent estimates of GDP, we prefer the directly interpolated GDP-exp measure, as described in Appendix D as we essentially subsume the aggregation residual with the change in private inventories. We do this because the NBS does not release comprehensive enough quarterly inventory related data beyond the industrial sector to serve as a reliable interpolater. We relegate more details regarding some of the other interpolations to Appendix D.

Appendix B. Real GDP and subcomponent contributions to growth when working with NBS-based GDP estimates

Figure S6 shows the subcomponent contributions to annual real growth. It is evident that much of the 2020 and 2022 dips are due to household consumption and, to a lesser extent, non real estate related gross fixed capital formation. It is also evident that the contribution of exports to real GDP growth fell sharply from the 2000s to the 2010s. These were offset,

[41]Over the common 2003-2022 sample, the average absolute difference between the log growth rates of the GDP-exp subcomponent and retail sales is 2.04 percentage points. For the GDP-exp subcomponent and the Household Survey measure, the average absolute difference is 1.33 (log) percentage points.

[42]I.e. the spliced series has the same growth rate as retail sales through 2002:Q1 and the same growth rate as Household Survey consumption after that quarter.

[43]Though if we then aggregate these series back up to the annual frequency, their growth rates are quite close.

to some extent, by a smaller subtraction of imports from growth. Exports also were a large subtraction from growth in 2009. China insulated itself from this outcome to a sharp one-time surge in non real estate related gross fixed capital formation. The contribution to growth from residential and non residential structures investment began slowing in the first half of the 2010s before stabilizing to some extent in the second half of that decade. This structures investment was not much of a factor in the 2020 decline in GDP growth, but played a moderate to modest role direct role in the 2022 fall in growth. These bars do not include the role residence related household consumption spending played in that decline, which we show in figures S17 and S7 and discuss in Appendix D.

Figure S8 show S10 similar decompositions for one-quarter and four-quarter real GDP growth not adjusted for excess smoothness. Because change in inventories is estimated as a residual for the NBS-based estimates of quarterly GDP, we combine this subcomponent with GFCF in the plots. In figure S8, we see household consumption and gross capital formation are responsible for most of the one-quarter decline in 2020:Q1 GDP. Figure S10 shows that on a four-quarter basis, the decline is concentrated in household consumption expenditures. That plot also shows that all of the subcomponents are strongly procyclical with the exception of government consumption expenditures.

Appendix C. Modification of real GDP-exp to remove excess smoothness

To interpolate real GDP-exp growth, we use a further adaptation of the Fernandez (1981) approach. Both are described in Appendix D. Rather than imposing the restriction that the full-year over full-year growth rate of the interpolated real GDP-exp series equals the published NBS annual measure in every year of the sample, we impose the looser restriction that the average growth rate of the interpolated series equals the published NBS average growth rate only between years of either an Economic Census or where a year where an input-output table is published. As described in the China Statistical Yearbook and Wu 2007[44], following incorporation of results from an Economic Census Year – 2004, 2008, 2013, and 2018 – the NBS revises historical GDP growth between census years[45] using what the NBS calls the

[44]Wu (2007), The Chinese GDP Growth Rate Puzzle: How Fast Has the Chinese Economy Grown?. Asian Economic Papers, Vol. 6, No. 1, 2007.

[45]The data can be further revised back in time when, for example, methodological improvements to GDP measurement are introduced such as the treatment of research and development as investment rather than an intermediate expense as described in the 2019 China Statistical Yearbook: http://www.stats.gov.cn/sj/ndsj/2019/indexeh.htm.

"trend deviation approach". Years where input-output (IO) tables are published[46]. include NBS collection and publication of data showing industrial sector interdependencies and their respective contributions to the final demand categories for GDP-exp subcomponents. This approach, which we call loose Fernandez interpolation, allows GDP growth to be less smooth than NBS or NBS based-measures but does not allow for growth over longer 5-to-10 year periods of time to systematically differ from NBS estimates as Chen et. al (2019) and Wu et. al (2014, 2015, 2020) argue and estimate they do.

To best capture the joint dynamics of real GDP growth and our alternative C-CAT we use a multi-step approach. After first estimating the 1-quarter C-CAT alternative $C_t^{AltCCAT}$ over the entire 2000-2023 sample, we "loosely" interpolate real GDP-exp with this alternative over the 2000-2018 period, imposing the multi-growth restriction over years between Economic Census or IO table years[47] and the 2018 year concluding the sub-sample. We then construct a variable that is the fitted interpolated quarterly GDP-exp growth rates $\hat{g}_t^{Pre19}$ through 2018:Q4 and 0 thereafter, and include this variable as an interpolator in a second stage "loose" Fernandez interpolation along with a constant and a dummy variable that is zero before 2019 and 1 thereafter and is interacted both a constant and $C_t^{AltCCAT}$. [48]. We split the subsample at 2018, rather than 2019 because, arithmetically, $\frac{3}{8}$ths of the full-year 2020/2019 growth rate is accounted for by the 2019:Q2-2019:Q4 quarterly growth rates. Splitting in 2018, rather than 2019, gives the interpolation more flexibility in accounting for 2020 growth.

The multi-year periods where the growth average restrictions are imposed are the same years from the first stage regression and each year between 2018 and 2022. We impose the year-by-year growth restrictions starting in 2018 both to insure the dynamics closely match the dynamics of real GDP-va and the close correspondence with of real GDP-va growth and $C_t^{AltCCAT}$ over the last five years of the sample.

To construct subcomponents consistent with our estimate of quarterly real GDP-exp that is adjusted to be less smooth than real GDP-va, we build off our initial "NBS-based" estimates of quarterly GDP-exp that presumed NBS estimates of GDP and related subcomponent data were measured correctly. In particular, to get quarterly nominal GDP-exp, we simply multiply our "NBS-based" estimate by the ratio of the second stage estimate

[46]These are 1990, 1992, 1995, 1997, 2000, 2002, 2005, 2007, 2010, 2012, 2015, 2017, and 2020

[47]I.e. 2002, 2004, 2005, 2007, 2008, 2010, 2012, 2013, 2015, and 2017.

[48]I.e., the 4 column interpolation matrix in the second-stage interpolation has entries $[1,(1-Dum19_t)\hat{g}_t^{Pre19}, Dum19_t, Dum19_t * C_t^{AltCCAT}]$. The use of the dummy interacted fitted values $\hat{g}_t^{Pre19}$ in the second stage regression insures it has a coeffiecient close to 1.00 [0.9924].

alternative C-CAT interpolation of quarterly real GDP-exp to our "NBS-based" estimate of quarterly real GDP-exp interpolated with real GDP-va. Similar to Chen et. al (2019), but unlike the studies by Wu and coauthors, this presumes that the implied "NBS based" GDP-exp quarterly price deflator is correctly measured. For both household and government nominal consumption expenditures, nominal gross fixed capital formation, and nominal exports and imports, we "loosely" interpolate[49] the "NBS-based" annual estimate with the same interpolater quarterly nominal (log) growth rates used in the "NBS-based" interpolations but then adjust the interpolater growth rates by adding the difference in the (log) quarterly growth rates between the C-CAT alternative based real GDP-exp estimate and the "NBS-based" real GDP-exp estimate.

For all but gross fixed capital formation[50], we deflate our alternative C-CAT interpolated nominal subcomponent by the "NBS based" price deflator estimated as described in the appendix. Finally, we multiply our "NBS based" quarterly real change in inventories by the ratio of alternative C-CAT real GDP-exp and "NBS based" real GDP-exp and maintain the same price deflator based on Holz (2014)[51].

All of these adjustments give us nominal and real estimates for a 6 subcomponent partition of GDP-exp: both household and government consumption expenditures, change in inventories, GFCF, exports, and imports. But these estimates will not be exactly consistent with directly estimated/interpolated alternative C-CAT estimate of real GDP-exp and the associated nominal GDP-exp measure. To resolve these differences, in each quarter we multiply the nominal and real estimates of the two consumption measures and GFCF by the ratio

[49]For the post-2000 periods, the years are the same as those used in the second stage C-CAT interpolation of GDP-exp. We also use include the pre-2000 period in the interpolation but do not augment the pre-2000 growth rates of the interpolater with an additive adjustment factor. The pre-2000 period is included to reduce end-point distortions at the beginning of the sample. The pre-2000 constraint years for the average growth restrictions are, as applicable, 1990, 1992, 1995 and 1997 since these are IO table years.

[50]We interpolate real GFCF directly with growth in interpolated nominal GFCF deflated by a fixed assets investment price adjusted to be consistent with GCF in the first stage after adding the difference between alternative C-CAT real GDP-exp growth and "NBS based" real GDP-exp growth.

[51]Unlike the other GDP subcomponents, the price deflator for inventories cannot be determined by the nominal to real ratio, as change 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 not available with NBS data, we treat the inventories price deflator as fixed and do not modify it in our adjustments/derivations below.

of C-CAT based GDP-exp to the current stage sum of the 6 subcomponents. When nominal/real changes in inventories are positive, we also multiply these by this ratio and when they are not we leave as is. After these adjustments, in each quarter, whatever discrepancy is left between C-CAT based nominal GDP and the sum of the six subcomponents is eliminated by solving for the unique positive adjustment factor a that eliminates the discrepancy when exports are multiplied by a and imports are multiplied by $\frac{1}{a}$[52].

These adjustments generate a set of 6 nominal GDP subcomponents consistent with the nominal C-CAT aggregate, but the real subcomponents need to be adjusted further. Quarter by quarter, we numerically solve for a multiplicative adjustment factor that will ensure real GDP subcomponent consistency as well[53].

Due to the measurement issues with inventories we mentioned above, we combine this category with GFCF and work with GCF in our SVAR estimation.

Appendix D. Detrended versus Nondetrended Data

Given that the indicators used to construct the C-CAT in Fernald et al. (2021) have been detrended, it is imperative to investigate whether our decision not to detrend the data materially impacts our alternative C-CAT and our measure of C-CAT adjusted real GDP growth. Figure S11 presents a comparison between the C-CAT used to interpolate real GDP-exp (green solid line) and an alternative C-CAT (blue dashed line marked with diamonds), which is constructed by taking the first principal component of the eight indicators after applying the same biweight filter and 24-quarter filtering parameter as do Fernald et al. (2021). The C-CAT measures exhibit a high correlation (0.943), though it is somewhat lower in the shorter pre-pandemic era (0.868). The more pronounced downward trend in our C-CAT is evident in Figure S12, which shows standardized 4-quarter averages of both C-CATs we have constructed, as well as the standardized C-CAT from the San Francisco Fed (black solid line). Not surprisingly, the San Francisco Fed's C-CAT correlates more strongly with

[52]Straightforward algebra shows that if NX^* is the estimate of net exports that resolves the discrepancy and X and M are the current estimates of nominal exports and imports, then $a = \frac{NX^* \pm \sqrt{NX^{*2}+4XM}}{2X}$, and only one of these roots is positive.

[53]In particular, starting from 2000, after solving for or initializing quarter $t-1$ quantities and prices, and time t nominal spending amounts implies time t quantities uniquely determine time t prices. Using the prior stage time t quantities solved above, we numerically determine the unique multiplicative scale factor a_t that when used to multiply the positive time t quantities and divide the negative time t quantities [imports and, occasionally, change in inventories] implies a Fisher chain weighted growth rate coinciding with our alternative C-CAT measure.

the 4-quarter moving average of the detrended alternative C-CAT we constructed (0.973) than with the moving average of our benchmark C-CAT (0.776).

For comparison, we now create an alternative measure of real GDP by detrending the data, interpolating it with the detrended C-CAT, reintegrating the trend growth of GDP into this series, and then using the series to perform a Denton interpolation of real GDP-exp[54]. Figure S13 illustrates the growth rate of 1-quarter real GDP-exp interpolated with both the detrended C-CAT (blue line of alternating dots and dashes marked with filled circles) and the nondetrended C-CAT (red dashed line marked with open diamonds). The series are highly correlated (ρ=0.983), albeit slightly less in the pre-pandemic sample (ρ=0.944). Notably, the most significant discrepancy occurs at the beginning of the sample. When considering the period from 2003 to 2019, the correlation between the series rises to 0.990. Such a high correlation suggests that not detrending the data for C-CAT estimation does not significantly affect our constructed GDP and its subcomponents, nor the outcomes of our SVAR estimation[55]

Appendix E. Further technical details for constructing NBS-consistent subcomponents without adjustments for excessive smoothness

E.1. **Consumption.** We start with the NBS published annual measures of nominal total consumption expenditures $C_t^{nom,Total}$, the NBS measure of the contribution share of total consumption expenditures to real GDP-exp growth, and equation (S1) to derive $C_t^{real,Total}$ and the implicit price deflator $P_t^{C^{Total}} = \frac{C_t^{nom,Total}}{C_t^{real,Total}}$. The NBS does not appear to publish separate price deflators for household $[C_t^{nom,HH}]$, and government $[C_t^{nom,Gov}]$ consumption expenditures. However, the NBS does publish annual nominal and real growth rate measures of resident consumption levels that imply a price measure $P_t^{C^{Resid}}$ that is very highly correlated with $P_t^{C^{Total}}$ when both series are log differenced[56]. Following the appendix of

[54]To simplify, the detrended C-CAT is interacted with a dummy variable that shifts from one to zero starting in 2019:Q1 and with one minus that dummy. This makes it more comparable with the similar dummy interactions used with the standard nondetrended C-CAT.

[55]This is perhaps unsurprising, given that after normalizing the two sets of factor loadings to sum to 1, the largest absolute difference between any loading estimated with detrended data and its counterpart estimated with nondetrended data is under 0.005. The correlation between the two sets of eight factor loading coefficients is as high as 0.997.

[56]From 1978-2021, corr($\Delta log(P^{C^{Total}})$,$\Delta log(P^{C^{Resid}})$)=0.99, which is higher than corr($\Delta log(P^{C^{Total}})$,$\Delta log(P^{CPI})$)=0.95 over the same period.

Holz (2014)[57], we set $\Delta log(P_t^{C^{Gov,Proxy}}) = 0.87\Delta log(P_t^{CPI}) + 0.13\Delta log(P_t^{FAI})$, where P_t^{FAI} is the fixed assets investment (FAI) price deflator.

Based on equation (S3), via non-linear least squares we estimate the following equation

$$\begin{aligned} \Delta log(P_t^{C^{Total}}) = \alpha_t^{HH}(a^{HH} + b^{HH}\Delta log(P_t^{C^{Resid}})) \\ +(1-\alpha_t^{HH})(a^{Gov} + b^{Gov}\Delta log(P_t^{C^{Gov,Proxy}})) + e_t^{PC}, \end{aligned} \tag{S6}$$

where $\alpha_t^{HH} = .5(\frac{C_t^{nom,HH}}{C_t^{nom,HH}+C_t^{nom,Gov}} + \frac{C_{t-1}^{nom,HH}}{C_{t-1}^{nom,HH}+C_{t-1}^{nom,Gov}})$, with $C_t^{nom,HH}$ denoting nominal household consumption expenditures and $C_t^{nom,Gov}$ denoting nominal government consumption expenditures. After estimating this non-linear regression, we set $\Delta log(P_t^{C^{HH}}) = \hat{a}^{HH} + \hat{b}^{HH}\Delta log(P_t^{C^{Resid}}) + \hat{e}_t^{PC}$ and $\Delta log(P^{C_t^{Gov}}) = \hat{a}^{Gov} + \hat{b}^{Gov}\Delta log(P^{C_t^{Gov,Proxy}}) + \hat{e}_t^{PC}$, and set $C_t^{real,HH} = \frac{C_t^{nom,HH}}{P_t^{C^{HH}}}$ and $C_t^{real,Gov} = \frac{C_t^{nom,Gov}}{P_t^{C^{Gov}}}$.

We use quarterly CEIC data on rural and urban per-capita consumption expenditures as well as the size of the rural and urban populations to Fernandez-Denton interpolate $C_t^{nom,HH}$ into $C_{t,q}^{nom,HH}$ after combining and seasonally adjusting the rural and urban consumption series[58]. Figure S14 shows the annual log growth rates of $C_t^{nom,HH}$ and its interpolater which have a 0.95 cross correlation with each other. Figure S15 shows the quarterly log growth rates of the interpolater and the resulting interpolated series $C_{t,q}^{nom,HH}$, where the correlation of the two log growth rates is 0.97. We Fernandez-Denton interpolate $P_t^{C^{HH}}$ defined above with $P_{t,q}^{CPIsa}$ resulting in $P_{t,q}^{C^{HH}}$, and define real quarterly household consumption expenditures as $C_{t,q}^{real,HH} = \frac{C_{t,q}^{nom,HH}}{P_{t,q}^{C^{HH}}}$. $C_t^{nom,Gov}$ is interpolated with seasonally adjusted quarterly government general public budget expenditures, resulting in $C_{t,q}^{nom,Gov}$, while, again following Holz (2014), $P_t^{C^{Gov}}$ is Fernandez-Denton interpolated by a weighted average of the quarterly log differences of the seasonally adjusted CPI [with weight 0.87] and the seasonally adjusted FAI price [with weight 0.13]. This resulting series, $P_{t,q}^{C^{Gov}}$, is used to deflate $C_{t,q}^{nom,Gov}$ and then to Fernandez-Denton interpolate $C_t^{real,Gov}$ into $C_{t,q}^{real,Gov}$. We then use equation (S4) to construct a Tornqvist index of $C_{t,q}^{real,HH}$ and $C_{t,q}^{real,Gov}$ which we use to interpolate $C_t^{real,Total}$ into $C_{t,q}^{real,Total}$. Finally, to better maintain internal consistency, in each quarter, we add the

[57]The quality of China's GDP statistics. China Economic Review 30 (2014) 309338.

[58]The original NBS data are from the Household Survey on Income and Expenditure and Living Conditions starting in 2013 and the Urban Household Survey and Rural Household Survey prior to this date. The CEIC data start in 2002, so after combining and seasonally adjusting the rural and urban series, we splice it together with SA data on retail sales before interpolating $C_t^{nom,HH}$.

generally very small difference between $\Delta C_{t,q}^{real,Total}$ and the log-difference in the Tornqvist index of $C_{t,q}^{real,HH}$ and $C_{t,q}^{real,Gov}$ to the log differences of both $C_{t,q}^{real,HH}$ and $C_{t,q}^{real,Gov}$.

The rural and urban per-capita consumption expenditures data are disaggregated into eight categories that are also consistent with the disaggregation for China's Consumer Price Index[59]. This allows us to decompose real household consumption expenditures growth and inflation − both for household consumption consistent with GDP-exp and the CPI − into contributions from these eight sources. Figure S16 shows the annualized 1-quarter inflation rates for $P_{t,q}^{C^{HH}}$ defined above, the seasonally adjusted CPI, and a Tornqvist index constructed using the eight CPI subindexes. The inflation rate for the Tornqvist index of CPI subcomponents, which we see tightly fits aggregate CPI inflation, is decomposed into contributions from those same subcomponents. The inflation rate for $P_{t,q}^{C^{HH}}$ has some nontrivial differences with the two CPI measures of inflation. To eliminate this discrepancy, we define the one-quarter inflation rate for each of the eight household consumption subcomponents as the CPI inflation rate for the corresponding subcomponent and the difference between the inflation rate $\Delta log(P_{t,q}^{C^{HH}})$ and the inflation rate for the Tornqvist index of CPI subcomponents. Figure S17 decomposes one-quarter log growth in real household consumption expenditures into contributions from its eight subcomponents. Spending on food, tobacco and liquor as well as residence related spending account for much of the fluctuations in consumption growth in both the pre-pandemic and post-pandemic eras. Emerging as more important contributors to fluctuations in pandemic-era consumption growth are education, culture and entertainment[60] as well as transportation and communication. Nevertheless, the pandemic-era swings in consumption growth generally show broadly distributed contributions in both positive and negative directions. A similar chart decomposing four quarter real household consumption growth is provided in figure S7.

E.2. **Net exports.** The NBS publishes an annual measure of net exports consistent with annual nominal GDP-exp measurement, but only publishes the constituent measures of exports and imports back to 2016. For $t \geq 2016$, we set $EXP_t^{nom,Adj} = EXP_t^{nom,NBS}$ and

[59]Those categories, along with our estimates of their 2022 nominal household spending shares, are Food, Tobacco and Liquor (30.5%), Clothing (5.6%), Residence [which, consistent with SNA standards, includes imputed homeowners' equivalent rent] (24.0%), Household Facilities, Articles and Services (5.8%), Health Care and Medical Services (8.6%), Transport and Communication (13%), Education, Culture and Entertainment (10.1%), and Miscellaneous Goods and Services (2.4%).

[60]There are some isolated prepandemic quarters where this component has an outsize contribution to growth, but we suspect these may partly due to measurement error.

$IMP_t^{nom,Adj} = IMP_t^{nom,NBS}$ and recursively define $EXP_t^{nom,Adj}$ and $IMP_t^{nom,Adj}$ for $t < 2016$ via the sequence of equations

$$\begin{aligned} EXP_{t-1}^{nom,Adj} &= aEXP_t^{nom,Adj}\frac{EXP_{t-1}^{nom,BOP}}{EXP_t^{nom,BOP}} \\ IMP_{t-1}^{nom,Adj} &= \frac{1}{a}IMP_t^{nom,Adj}\frac{IMP_{t-1}^{nom,BOP}}{IMP_t^{nom,BOP}} \\ EXP_{t-1}^{nom,Adj} - IMP_{t-1}^{nom,Adj} &= NX_{t-1}^{nom,NBS}, \end{aligned} \tag{S7}$$

$EXP_t^{nom,BOP}$ and $IMP_t^{nom,BOP}$ are balance of payments (BOP) based imports and exports, and $a > 0$ is the unique positive adjustment factor that satisfies equations (S7) at each step[61]. These BOP based measures of foreign trade begin in 1998, so from 1993 to 1997 we utilize the recursive set of equations (S7) and use measures of free on board (fob) goods exports and cost, insurance, and freight (cif) goods imports from China's General Administration of Customs[62].

To get real measures of exports and imports, we use OECD annual measures of goods exports and imports prices $P_t^{EXP,OECD}$ and $P_t^{IMP,OECD}$ to proxy for total exports/import prices[63]. To adjust these prices to be consistent with annual NBS estimates of net exports share of the contribution to annual real GDP-exp growth NX_t^{ShCont}, we add an adjustment factor

$$\pi_t^{NXadj} = -\frac{NX_t^{ShCont} - NX_t^{ShContProxy}}{.5(\frac{EXP_t^{nom,Adj}+IMP_t^{nom,Adj}}{GDP_t^{nom}} + \frac{EXP_{t-1}^{nom,Adj}+IMP_{t-1}^{nom,Adj}}{GDP_{t-1}^{nom}})}, \tag{S8}$$

determined by equation (S1), to the log difference in export prices $\pi_t^{EXPadj} = \Delta log(\frac{P_t^{EXP,OECD}}{P_{t-1}^{EXP,OECD}}) + \pi_t^{NXadj}$ and subtract it from $\pi_t^{IMPadj} = \Delta log(\frac{P_t^{IMP,OECD}}{P_{t-1}^{IMP,OECD}}) - \pi_t^{NXadj}$, where

[61]One can see this by subtracting the second of equations (S7) from the first, substituting $NX_{t-1}^{nom,NBS}$, multiplying both sides of the resulting equation by a, and using the unique positive root of the resulting quadratic equation

[62]The adjustment factors are generally a bit further than 1.00 in this case as we are using growth in goods exports/imports to proxy growth in total exports/imports

[63]The OECD prices begin in 2008. Prior to this, we use commodity and non-commodity goods exports and imports prices – also from the OECD – and regression equations relating them to total OECD goods exports and imports prices, to get goods exports/imports prices back to the late 1980s.

$$NX_t^{ShContProxy} = .5(\frac{EXP_{t-1}^{nom,Adj}}{GDP_{t-1}^{nom}} + \frac{EXP_t^{nom,Adj}}{GDP_t^{nom}})(log(\frac{\frac{EXP_t^{nom,Adj}}{P_t^{EXP,OECD}}}{\frac{EXP_{t-1}^{nom,Adj}}{P_{t-1}^{EXP,OECD}}})- \\ .5(\frac{IMP_{t-1}^{nom,Adj}}{GDP_{t-1}^{nom}} + \frac{IMP_t^{nom,Adj}}{GDP_t^{nom}})(log(\frac{\frac{IMP_t^{nom,Adj}}{P_t^{IMP,OECD}}}{\frac{IMP_{t-1}^{nom,Adj}}{P_{t-1}^{IMP,OECD}}}). \tag{S9}$$

These adjustments imply the adjusted real exports measure $EXP_t^{real,Adj} = \frac{EXP_t^{nom,Adj}}{P_t^{EXP,Adj}}$ and adjusted real imports measure $IMP_t^{real,Adj} = \frac{IMP_t^{nom,Adj}}{P_t^{IMP,Adj}}$. Figure S19 shows how export and import price inflation have been adjusted. Of particular note, mid-2000s export price inflation has been adjusted up and import price inflation has been adjusted down to maintain consistency with the NBS data.

Logarithmic growth in quarterly SA BOP measures of exports/imports, spliced together with SA log growth measures of fob goods exports and cif goods imports are used to Fernandez-Denton interpolate these adjusted measures of exports/imports into $EXP_{t,q}^{nom,Adj}$ and $IMP_{t,q}^{nom,Adj}$. Figures S20 and S21 show that these adjusted GDP-exp measures of nominal exports and imports closely match the BOP based measures. Adjusted export and import prices $P_t^{EXP,Adj}$ and $P_t^{IMP,Adj}$ are interpolated with a seasonally adjusted measure of export and import prices from the Customs administration and Haver Analytics[64]. Finally, $EXP_t^{real,Adj}$ and $IMP_t^{real,Adj}$ are Fernandez-Denton interpolated with $\frac{EXP_{t,q}^{nom,Adj}}{P_{t,q}^{EXP,Adj}}$ and $\frac{IMP_{t,q}^{nom,Adj}}{P_{t,q}^{IMP,Adj}}$, resulting in slightly different quarterly price deflators.

E.3. **Gross capital formation.** We use equation (S1) to determine growth in real GCF $\Delta(log(IGross_t^{real})) = \frac{IGross_t^{ShGDP}\Delta(log(GDP_t^{real}))}{.5(\frac{IGross_{t-1}^{nom}}{GDP_{t-1}^{nom}} + \frac{IGross_{t-1}^{nom}}{GDP_{t-1}^{nom}})}$. The resulting associated implicit price deflator is $P_t^{IGross} = \frac{IGross_t^{nom}}{IGross_t^{real}}$. Nominal gross fixed capital formation (GFCF), $IFixed_t^{nom}$, is Fernandez-Denton interpolated into $IFixed_{t,q}^{nom}$ by $FAI_{t,q}^{Total}$ – fixed assets investment excluding land (FAIexL). Figure S22 shows the annual growth rates of the interpoland and interpolater. The correlation is 0.885, but we can see the relationship becomes somewhat less strong beginning around 2016. Figure S23 shows an analogous picture for the quarterly

[64]The customs administration export/import prices begin in 2005, so the annual prices are also Fernandez-Denton interpolated in sequence by log differences of the Consumer Price Index, GDP Deflator, effective exchange rate, and purchasers price index and sequentially spliced together before doing a final Fernandez-Denton interpolation with the spliced series.

growth rates in which the high correlation between the two growth rates [0.97] is evident. The quarterly change in private inventories is determined as a residual after rearranging the GDP accounting identity to $V_{t,q}^{nom} = GDP_{t,q}^{nom} - FS_{t,q}^{nom}$, where $FS_{t,q}^{nom}$ denotes final sales of domestic product whose consumption and net exports subcomponents are derived above.

Following Holz (2014), we set the annual price deflator P_t^{VProxy} and the seasonally adjusted quarterly price deflator $P_{t,q}^{VProxy}$ for the change in private inventories to Tornqvist indexes of the price deflators for primary industry and secondary industry va GDP since these primarily account for goods producers. A quarterly deflator $P_{t,q}^{GCFProxy}$ that is a Tornqvist index of the quarterly inventory deflator $P_{t,q}^{VProxy}$ and $P_{t,q}^{FAI}$, the seasonally adjusted FAI price deflator[65], is used to deflate the sum $IGross_{t,q}^{nom} = IFixed_{t,q}^{nom} + V_{t,q}^{nom}$. The log difference of this deflated sum is used to Fernandez-Denton interpolate $IGross_t^{real}$ into $IGross_{t,q}^{real}$, resulting in the the implicit GCF deflator $P_{t,q}^{IGross} = \frac{IGross_{t,q}^{nom}}{IGross_{t,q}^{real}}$. The difference between $\Delta log(P_{t,q}^{IGross})$ and $\Delta log(P_{t,q}^{GCFProxy})$ is used to additively adjust the log differences of the quarterly inventory proxy and FAI deflators described above, resulting in the price deflators $P_{t,q}^{IFixed}$ and $P_{t,q}^{V}$. A similar additive adjustment between the log differences of P_t^{IGross} and a Tornqvist index of P_t^{FAI} and P_t^{VProxy} produces the deflators P_t^{IFixed} and P_t^{V} , which in turn determine $IFixed_t^{real} = \frac{IFixed_t^{nom}}{P_t^{IFixed}}$ and $V_t^{real} = \frac{V_t^{nom}}{P_t^{V}}$[66]. Fernandez-Denton interpolation is used to interpolate $IFixed_t^{real}$ by $IFixed_{t,q}^{nom}/P_{t,q}^{IFixed}$[67], while Denton interpolation without any differencing is used to interpolate V_t^{real} by $\frac{V_{t,q}^{real}}{P_{t,q}^{V}}$[68].

Though not used for our SVAR estimation, we further disaggregated GFCF into portions representing residential real estate, non-residential real estate, and a remaining portion. Our approach is primarily based on Xianchun et al. (2021)[69]. In particular, we determine the annual totals of FAIexL – FAI_t^{Total} – that is attributable to residential real estate

[65]As of this writing in 2023, the FAI deflator ends in 2019. We splice it together with the seasonally adjusted corporate goods investment price, which is available into 2023.

[66]We have also, alternatively, used Fisher subtraction to derive these terms: See Liu, Yanjun, Hamalainen, Nell and Bing-Sun Wong (2003) Economic Analysis and Modelling Using Fisher Chain Data Canada Department of Finance Working Paper, No. 2003-13.

[67]By construction the growth rate of the interpolated series is very close to the growth rate of the interpolater

[68]This approach, rather than Denton interpolation, is used because the interpolater occasionally is negatively valued, ruling out Fernandez-Denton interpolation.

[69]Xu Xianchun, Jia Hai, Li Jiao, and Li Junbo (2021). Chapter 1: Research on the Role of Real Estate Economy in Chinas National Economic Growth. pp. 1-28 in Statistical Analysis on Key Economic Areas of China.

(FAI_t^{ResRE}) and nonresidential real estate ($FAI_t^{NonResRE}$), and set their gross fixed capital formation analogs to $IFixed_t^{nom,ResRE} = \frac{FAI_t^{ResRE}}{FAI_t^{Total}} IFixed_t^{nom}$ and $IFixed_t^{nom,NonResRE} = \frac{FAI_t^{NonResRE}}{FAI_t^{Total}} IFixed_t^{nom}$. We Fernandez-Denton interpolate each nominal GFCF measure by their corresponding seasonally adjusted measure of FAIexL.

To determine annual price deflators and real measures of residential and nonresidential real estate GFCF, we assume that for both residential and nonresidential structures, growth in floor space under construction differs from growth in real GFCF by a fixed constant [70], and determine the associated implicit price deflators as $P_t^{I,Res^A} = \frac{IFixed_t^{nom,ResRE}}{IFixed_t^{real,ResRE^A}}$ and $P_t^{I,NonRes^A} = \frac{IFixed_t^{nom,NonResRE}}{IFixed_t^{real,NonResRE^A}}$. The constant is calibrated so that the average value of $\Delta log(P_t^{I,NonRes})$ over the 2004-2010 period is equal to the average value of $\Delta log(P_t^{I,NonRes})$ over the same 2004-2010 period in the 2015 China Industrial Productivity (CIP) Database 3.0[71] described in a collection of 3 papers by Harry Wu and coauthors [72].

At both the annual and quarterly frequency, simple subtraction determines nominal GFCF outside of the real estate sector which we label $IFixed_t^{nom,Oth} = IFixed_t^{nom} - IFixed_t^{nom,ResRE} - IFixed_t^{nom,NonResRE}$ and $IFixed_{t,q}^{nom,Oth} = IFixed_{t,q}^{nom} - IFixed_{t,q}^{nom,ResRE} - IFixed_{t,q}^{nom,NonResRE}$. After determining $IFixed_t^{real,ResRE}$ and $IFixed_t^{real,NonResRE}$, we use "Tornqvist subtraction" after rearranging equation (S4) to determine real GFCF outside of the real estate sector which we label $IFixed_t^{real,Oth}$. Fernandez-Denton interpolation with quarterly SA growth in residential (nonresidential) floor space in progress is used to determine $IFixed_{t,q}^{real,ResRE}$ and $IFixed_{t,q}^{real,NonResRE}$. A related quarterly Tornqvist subtraction produces an interpolater for $IFixed_t^{real,Oth}$ which we use with Fernandez-Denton interpolation to construct $IFixed_{t,q}^{real,Oth}$.

E.4. **Adapted Fernandez (1981) interpolation.** Suppose we have an annual time series Y_t, where $1 \leq t \leq T$, and a related quarterly time series $X_{t,q}$, whose log difference, we believe, is a strong candidate interpolater series for $\Delta \log Y_t$. I.e., we believe the following model:

[70] One can show that growth in U.S. residential investment in single-family structures closely follows growth in floor space under construction. For both residential and nonresidential structures in China, floor space in progress on a monthly basis is determined by that CEIC variable in combination both with floor space started and floor space completed. Further details available upon request.

[71] See `https://www.rieti.go.jp/en/database/CIP2015/index.html`.

[72] In particular, the CIP data imply 2004-2010 average annual log growth rate for real nonresidential structures investment a little over 27 percent. Floor space under construction for nonresidential real estate grew a little over 31 log percent points per year over the same year. Hence, we increase 4 log percentage points to the implied inflation rates for both residential and nonresidential structures investment.

$$\Delta \log Y_{t,q} = [1, \Delta \log X_{t,q}]\beta + \varepsilon_{t,q} \tag{S10}$$

where $Y_{t,q}$ is unobserved and, crucially, we assume $\varepsilon_{t,q}$ is iid $N(0, \sigma_\varepsilon^2)$. This distinguishes it from the weaker assumption for the Chow-Lin (1971) model that $\varepsilon_{t,q}$ is an AR(1) process. With the Fernandez (1981) problem, the interpolated series $\Delta \log \hat{Y}_{t,q}$ and the regression coefficients are the solution to the following problem:

$$\{\{\{\Delta \log \hat{Y}_{t,q}\}_{q=1}^4\}_{t=1}^T, \hat{\beta}\} = \arg \min_{\{\{\Delta \log \hat{Y}_{t,q}\}_{q=1}^4\}_{t=1}^T, \beta} \sum_{t=1}^{T} \sum_{q=1}^{4} \{\Delta \log Y_{t,q} - [1, \Delta \log X_{t,q}]\beta\}^2 \tag{S11}$$

subject to the constraints

$$\begin{aligned} \Delta \log Y_t &= \frac{1}{16}[\Delta \log Y_{t-1,2} + 2\Delta \log Y_{t-1,3} + 3\Delta \log Y_{t-1,4} + 4\Delta \log Y_{t,1} \\ &\quad +3\Delta \log Y_{t,2} + 2\Delta \log Y_{t,3} + \Delta \log Y_{t,4}] \end{aligned} \tag{S12}$$

for $2 \leq t \leq T$. Constraint (S12) is motivated by the approximation:

$$\begin{aligned} &\Delta \log \frac{Z_{t,1} + Z_{t,2} + Z_{t,3} + Z_{t,4}}{Z_{t-1,1} + Z_{t-1,2} + Z_{t-1,3} + Z_{t-1,4}} \\ \approx\ &\frac{1}{16}[\Delta \log Z_{t-1,2} + 2\Delta \log Z_{t-1,3} + 3\Delta \log Z_{t-1,4} + \\ &4\Delta \log Z_{t,1} + 3\Delta \log Z_{t,2} + 2\Delta \log Z_{t,3} + \Delta \log Z_{t,4}] \end{aligned} \tag{S13}$$

The solution to (S11) is derived by the following sequence of equations:

$$\mathbf{p}_1 = \frac{1}{16}[0, 1, 2, 3] \tag{S14}$$

$$\mathbf{p}_2 = \frac{1}{16}[4, 3, 2, 1] \tag{S15}$$

$$\mathbf{B} = (\begin{bmatrix} \mathbf{I}_{T-1} & \mathbf{0}_{(T-1)x1} \end{bmatrix} \otimes \mathbf{p}_1) + (\begin{bmatrix} \mathbf{0}_{(T-1)x1} & \mathbf{I}_{T-1} \end{bmatrix} \otimes \mathbf{p}_2), \tag{S16}$$

$$\mathbf{D} = \mathbf{I}_{4T-1} + \begin{bmatrix} \mathbf{0}_{1x(4T-2)} & 0 \\ -\mathbf{I}_{4T-2} & \mathbf{0}_{(4T-2)x1} \end{bmatrix} \tag{S17}$$

$$\mathbf{Z} = \begin{bmatrix} 1 & \Delta\log X_{1,2} \\ 2 & \Delta\log X_{1,3} \\ . & . \\ . & . \\ 4T-2 & \Delta\log X_{T,3} \\ 4T-1 & \Delta\log X_{T,4} \end{bmatrix} \tag{S18}$$

$$\hat{\beta} = [(\mathbf{Z}'\mathbf{B})(\mathbf{B}'(\mathbf{D}'\mathbf{D})^{-1}\mathbf{B})^{-1}\mathbf{B}'\mathbf{Z}]^{-1}\mathbf{Z}'\mathbf{B}(\mathbf{B}'(\mathbf{D}'\mathbf{D})^{-1}\mathbf{B})^{-1} \begin{bmatrix} \Delta\log Y_2 \\ \Delta\log Y_3 \\ . \\ . \\ \Delta\log Y_{T-1} \\ \Delta\log Y_T \end{bmatrix} \tag{S19}$$

$$\begin{bmatrix} \Delta\log \hat{Y}_{1,2} \\ \Delta\log \hat{Y}_{1,3} \\ . \\ . \\ \Delta\log \hat{Y}_{T,3} \\ \Delta\log \hat{Y}_{T,4} \end{bmatrix} = \mathbf{Z}\hat{\beta} + (\mathbf{D}'\mathbf{D})^{-1}\mathbf{B}(\mathbf{B}'(\mathbf{D}'\mathbf{D})^{-1}\mathbf{B})^{-1}\{ \begin{bmatrix} \Delta\log Y_2 \\ \Delta\log Y_3 \\ . \\ . \\ \Delta\log Y_{T-1} \\ \Delta\log Y_T \end{bmatrix} - \mathbf{B}'\mathbf{Z}\hat{\beta}\} \tag{S20}$$

The matrix $\mathbf{B}$ imposes the constraints (S12), while $\mathbf{D}$ is a differencing matrix. If we want to impose a multi-year average growth constraints, say by requiring that average growth between years j and $j+h$ equals the observed average, we sum rows j through $j+h$ of the identity matrix $\mathbf{I_T}$ and multiply the sum by $\frac{1}{h+1}$. We then replace rows of j through $j+h$ of $\mathbf{I_T}$ with this combined weighted sum of rows. Further average growth restrictions can be imposed similarly, thereby generating $\tilde{\mathbf{I_T}}$. We then replace $\mathbf{B}$ with $\tilde{\mathbf{I_T}}\mathbf{B}$ and replace $[\Delta\log Y_2, ..., \Delta\log Y_T]'$ with $\tilde{\mathbf{I_T}}[\Delta\log Y_2, ..., \Delta\log Y_T]'$ in equation (S19) above. Once we have the estimated values $\{\Delta\log \hat{Y}_{1,q}\}_{q=2}^4$ and $\{\{\Delta\log \hat{Y}_{t,q}\}_{q=1}^4\}_{t=2}^T$, we solve for the level by setting $\hat{Y}_{1,1} = \exp(\frac{11}{8}\log(Y_1) - \frac{3}{8}\log(Y_2))$and using the recursion

$$\hat{Y}_{t,q} = \hat{Y}_{t,q-1}\exp(\frac{\Delta\log \hat{Y}_{t,q}}{4}) \tag{S21}$$

Since equation (S13) is only an approximation, $\frac{1}{4}\sum_{q=1}^{4}\hat{Y}_{t,q}=Y_t$, will only hold approximately. To make sure it holds exactly, we use proportional Denton interpolation to interpolate Y_t with $\hat{Y}_{t,q}$. The MatLab programs are available at

http://www.mathworks.com/matlabcentral/fileexchange/24438-temporal-disaggregation-library

and the function call is denton_uni_prop(Ylf,Xhf,2,1,4) where Ylf is the low frequency variable Y_t and Xhf is the high frequency variable $\hat{Y}_{t,q}$. The interpolated value $\hat{Y}^*_{t,q}$ is multiplied by $\frac{1}{4}$ so that the sum of the quarterly values equals the annual total.[73] $\frac{1}{4}\hat{Y}^*_{t,q}$ is the time series returned in the program[74]

An obvious question is, why don't we simply use standard Chow-Lin (1971) interpolation. The Chow-Lin set-up would assume

$$Y_{t,q}=[1,X_{t,q}]\beta_q+u_{t,q}$$

$$u_{t,q}=\rho_q u_{t,q-1}+e_{t,q}$$

with $e_{t,q}$ iid $N(0,\sigma_e^2)$. However, the level of GDP grows exponentially, so it is not plausible that $e_{t,q}$ has a constant variance. The variance should be larger at the end of the sample then the beginning. One could of course adapt Chow-Lin (1971) to handle data in log differences imposing constraints like (**??**) and (S12).

[73]Unlike the Chinese NIPAs, in the U.S. NIPAs, the average of the quarterly values equals the annual total.

[74]For some series, the first non-missing quarter of the quarterly interpolater is the first quarter of a year T_0 where the growth rate of the annual series to be interpolated is available. When we want to interpolate the quarterly values for that year, we replace the missing value $\Delta\log X_{T_0,1}$with $\frac{1}{4}(\sum_{q=2}^{4}\Delta\log X_{T_0,1}+\Delta\log X_{T_0+1,1})$.

GDP-exp subcomponent	**Nominal**	**Real**	**Prices**
GDP-exp	NBS	Implicit	P^{GDPva}
HH+Govt. Consum. Expend	NBS	NBS contrib	Implicit
Household	NBS	Implicit	NBS HH Survey, Holz (2014)
8 subcomponents	NBS HH Survey	Implicit	CPIs, NBS HH Survey
Government	NBS	Implicit	CPI, FAI price, Holz (2014)
Gross Cap Form. (GCF)	NBS	NBS contrib	Implicit
Fixed (GFCF)	NBS	Implicit	FAI price
Resid. Real Estate	Res RE FAI excl land	Res floor space, RIETI CIP Data	Implicit
Nonres. Real Estate	Nonres RE FAI excl land	Nonres floor space, RIETI CIP Data	Implicit
GFCF ex real estate	FAI excl land and RE	Implicit	Various FAI prices
Change in inventories	NBS	Fisher subtraction GCF - GFCF	Implicit
Net exports	NBS	X	X
Exports	NBS/SAFE	Implicit	Customs/OECD
Imports	NBS/SAFE	Implicit	Customs/OECD

Table S1. GDP-exp granular subcomponents and sources for annual data

GDP-exp subcomponent	**Nominal**	**Real**	**Prices**
GDP-exp	Nominal GDP-va	Real GDP-va	Implicit
HH+Govt. Consum. Expend	Sum	Tornqvist	Implicit
Household	HH Survey, Retail sales	Implicit	CPI
8 subcomponents	NBS HH Survey	Implicit	CPIs
Government	MOF Govt. Exp.	Implicit	CPI, FAI price, Holz (2014)
Gross Cap Form. (GCF)	Sum	Fisher subtr. GDP - C,Exp,Imp	Implicit
Fixed (GFCF)	FAI ex land	Nom GFCF/Adj FAI price	Implicit
Resid. Real Estate	Res RE FAI excl land	Res floor space in progress	Implicit
Nonres. Real Estate	Nonres RE FAI excl land	Nonres floor space in progress	Implicit
GFCF ex real estate	FAI excl land and RE	Torn subtr.: RGFCF less RE	Implicit
Change in inventories	GDP - other subcomp.	Special	P^{GDPva} for prim./sec. Ind, Holz
Net exports	NBS	X	X
Exports	SAFE BOP Exports	Nominal/Customs Exp Price	Implicit
Imports	SAFE BOP Imports	Nominal/Customs Imp Price	Implicit

Table S2. GDP-exp Sources of data and interpolaters for quarterly GDP-exp granular subcomponents

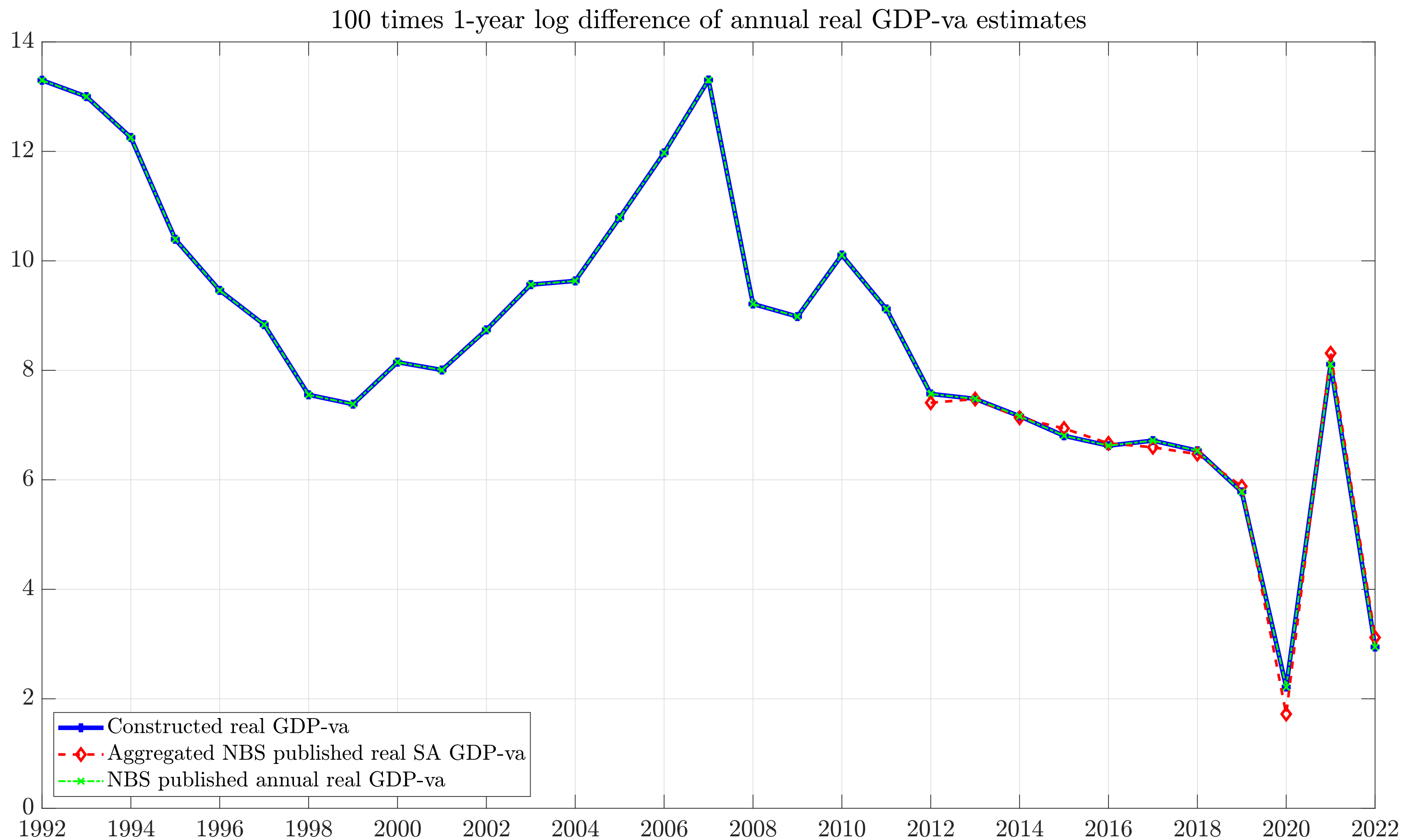

FIGURE S1. The red line with diamonds denotes the NBS quarterly measure of seasonally adjusted real GDP-va aggregated to the annual frequency. The blue solid line is our NBS-consistent measure of seasonally adjusted quarterly real GDP-va. The green dashed line with crossmarks is the published NBS measure of annual real GDP-va. All three series have been multiplied by 100 after log-differencing.

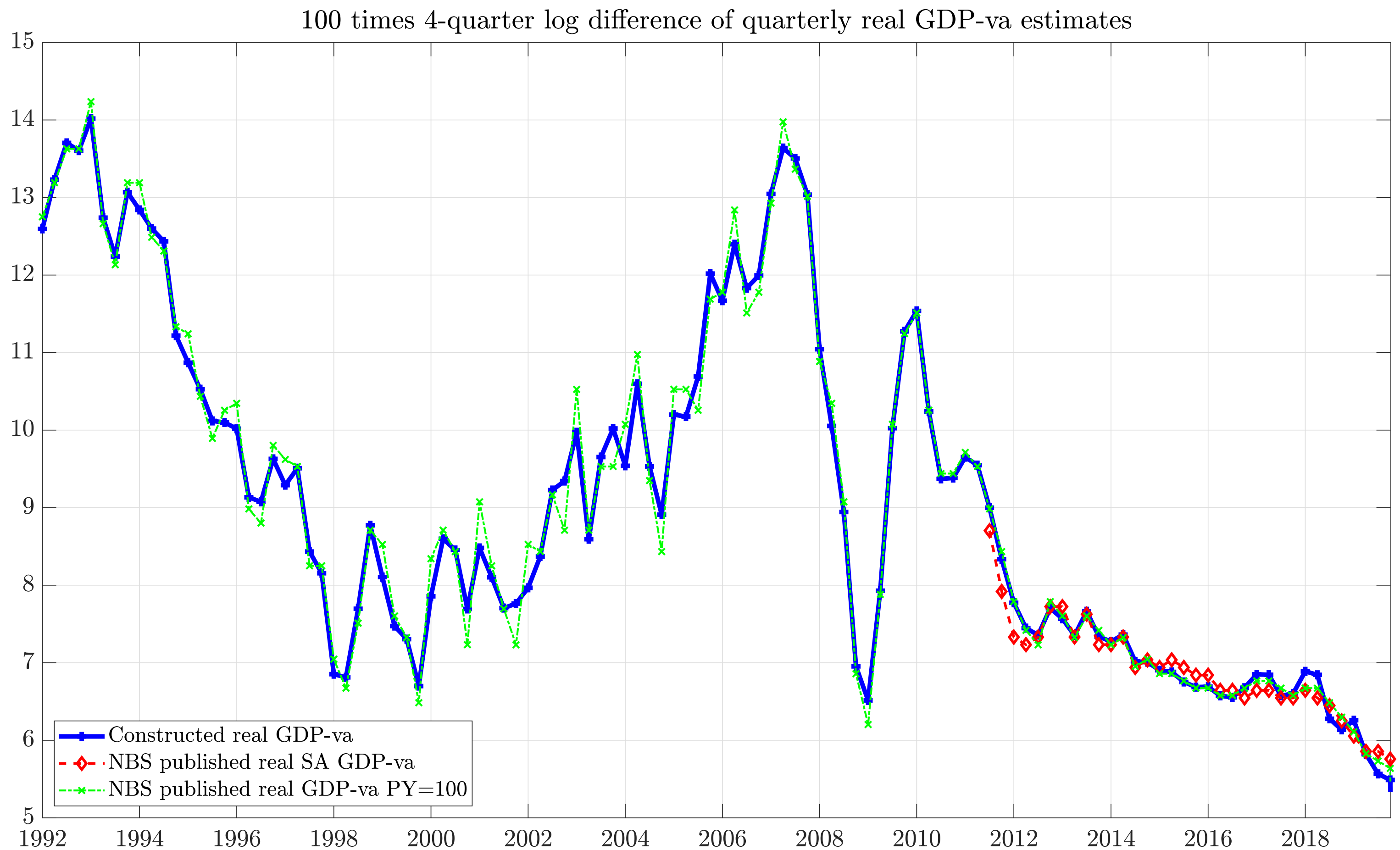

FIGURE S2. The red line with diamonds denotes the NBS quarterly measure of seasonally adjusted real GDP-va. The blue solid line is our NBS-consistent measure of seasonally adjusted quarterly real GDP-va. The green dashed line with crossmarks is the published NBS measure of the 4-quarter gross growth rate of real GDP-va multiplied by 100. All three series have been converted converted to 4-quarter log differences, and multiplied by 100.

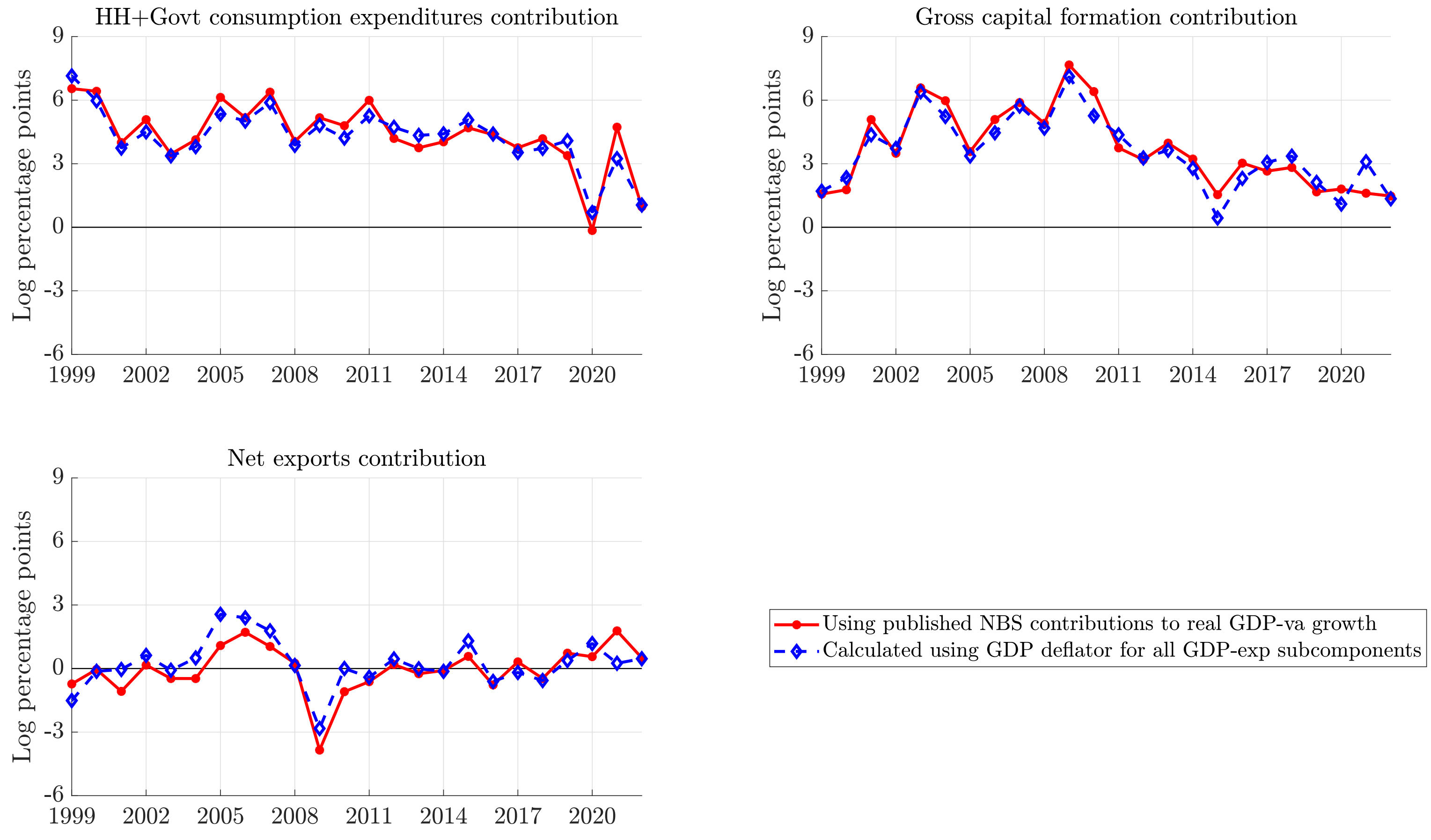

FIGURE S3. For each subplot, the red solid lines are contributions to real GDP-va growth constructed with published NBS GDP contributions data. The dashed blue lines are contributions to real GDP-exp growth constructed by multiplying each subcomponent's contribution share to nominal GDP-exp growth by real GDP-exp growth.

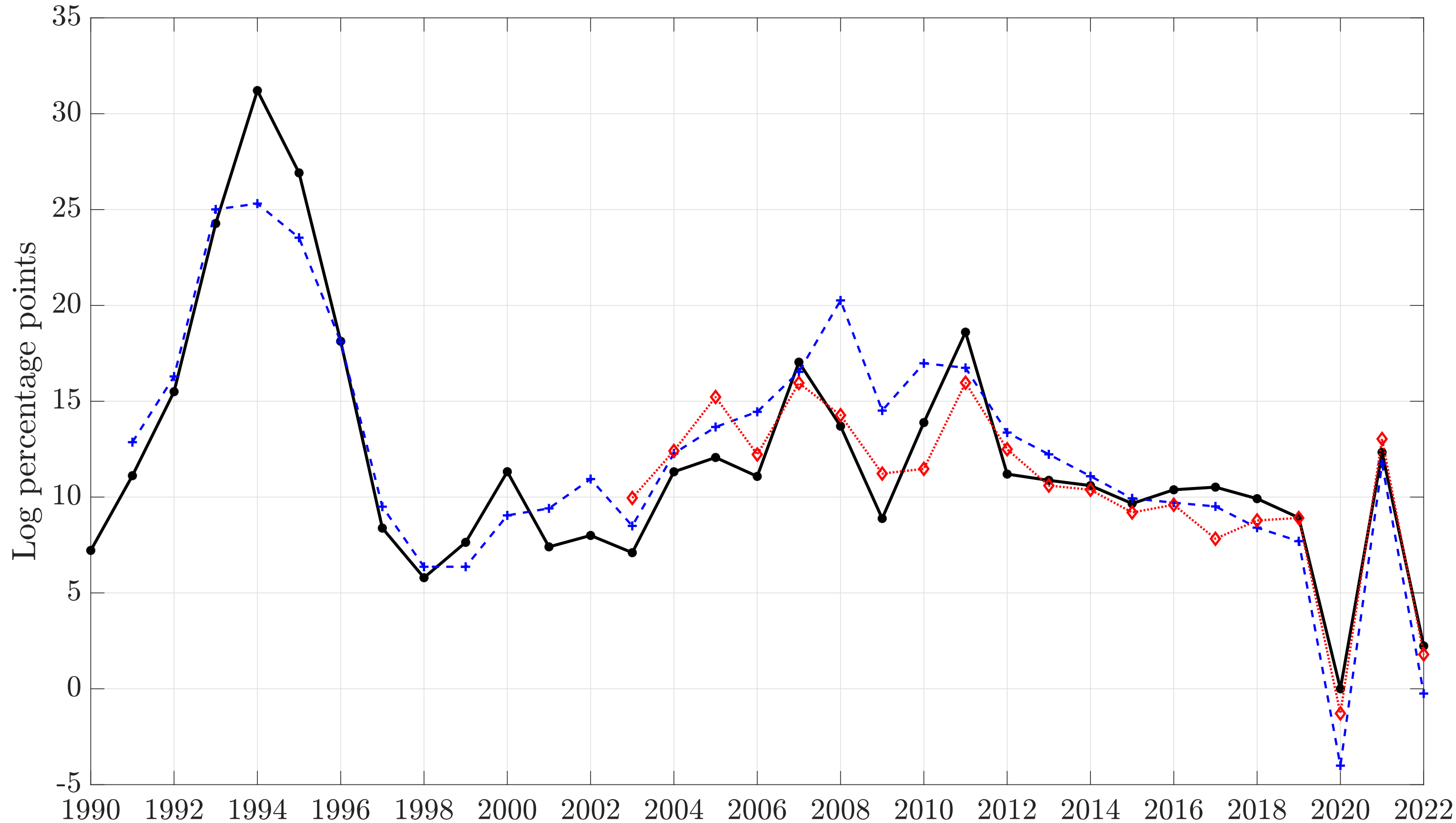

FIGURE S4. The black solid line marked with asterisks is the NBS measure of nominal household consumption. The blue dashed line with plus sign marks is nominal retail sales. The red dotted line is the Household survey measure of household consumption expenditures converted from per-capita to total. All series have been log differenced and multiplied by 100.

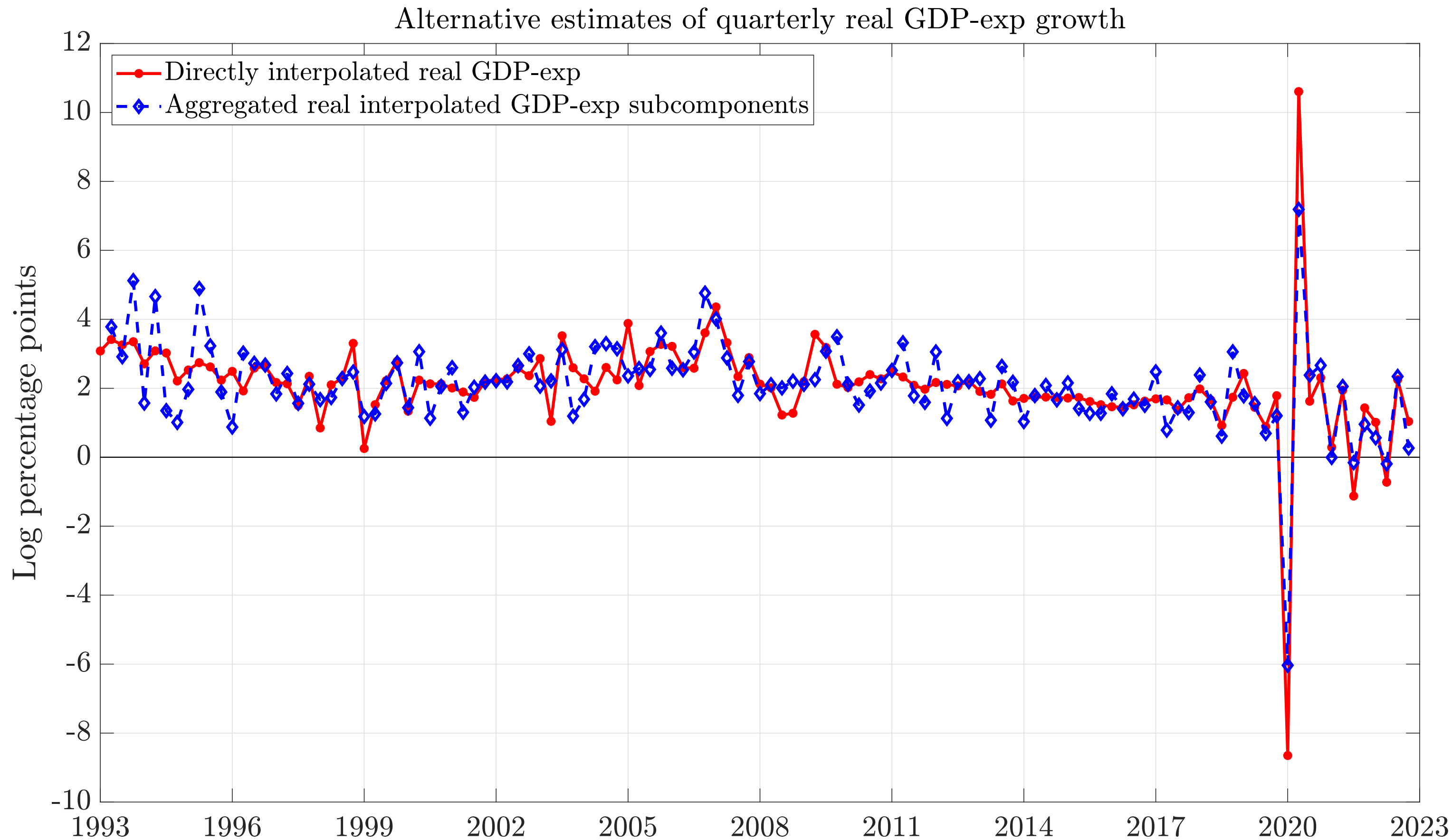

FIGURE S5. The red solid line marked with filled circles is the NBS consistent measure of quarterly seasonally adjusted real GDP-va. The blue dashed line marked with open diamonds is an aggregated version of the separately interpolated subcomponents. Both series have been log differenced and multiplied by 100.

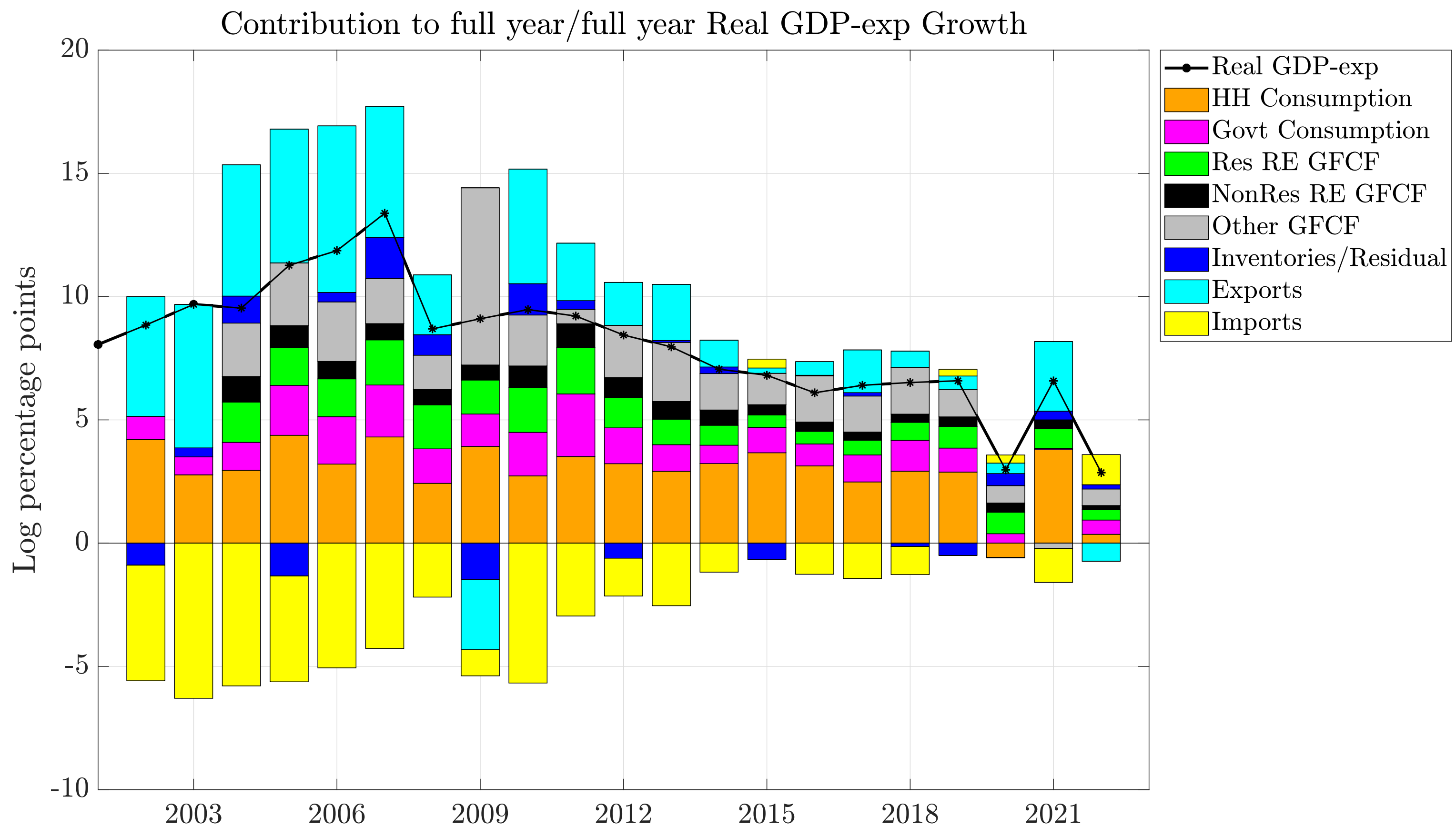

FIGURE S6. The chart shows the subcomponent contributions to the measure of real GDP-exp growth that has not been modified to remove excess smoothness.

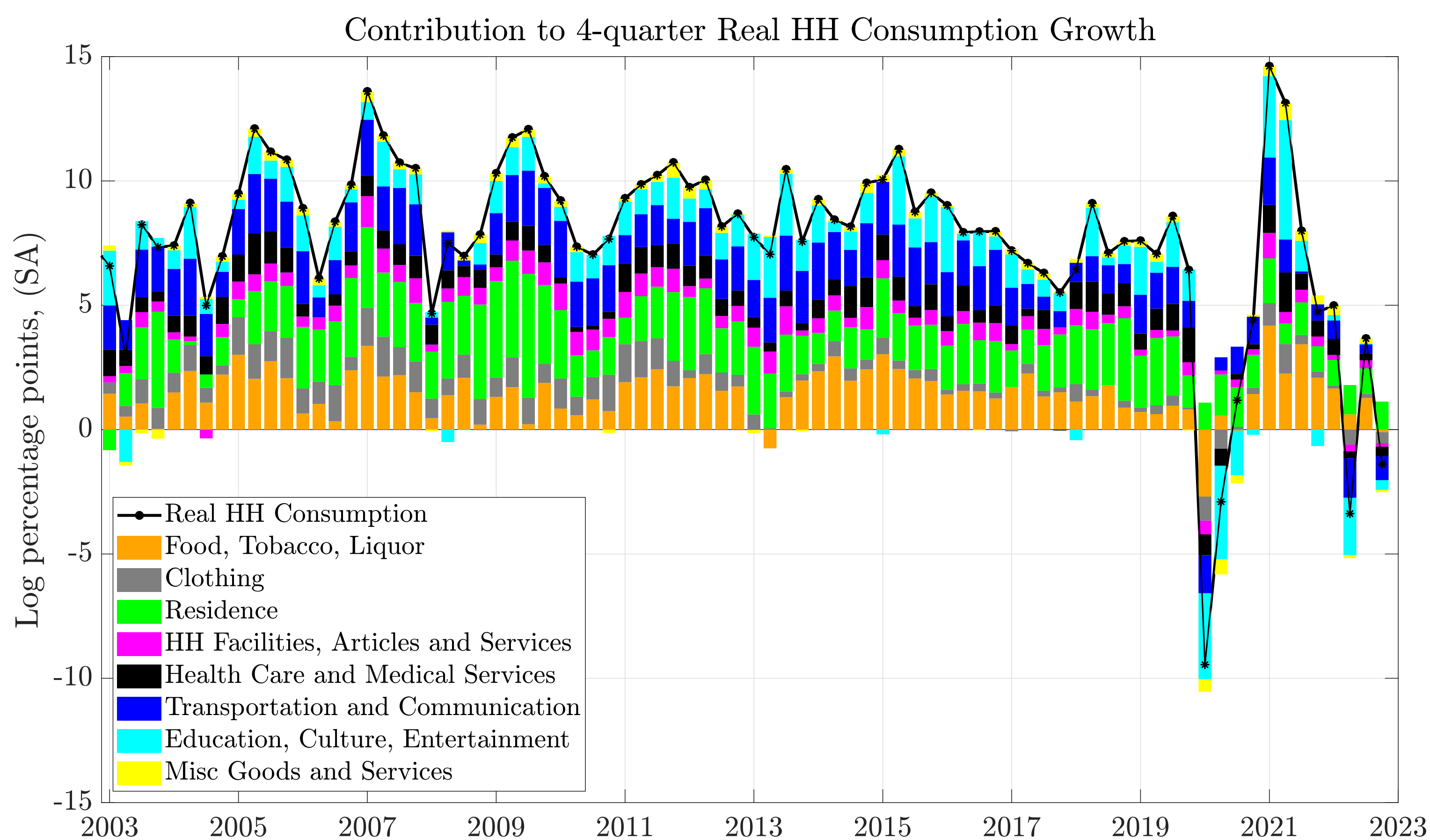

FIGURE S7. The chart shows the subcomponent contributions to 4-quarter growth in real household consumption expenditures. Four quarter log difference of aggregate consumption series has been multiplied by 100.

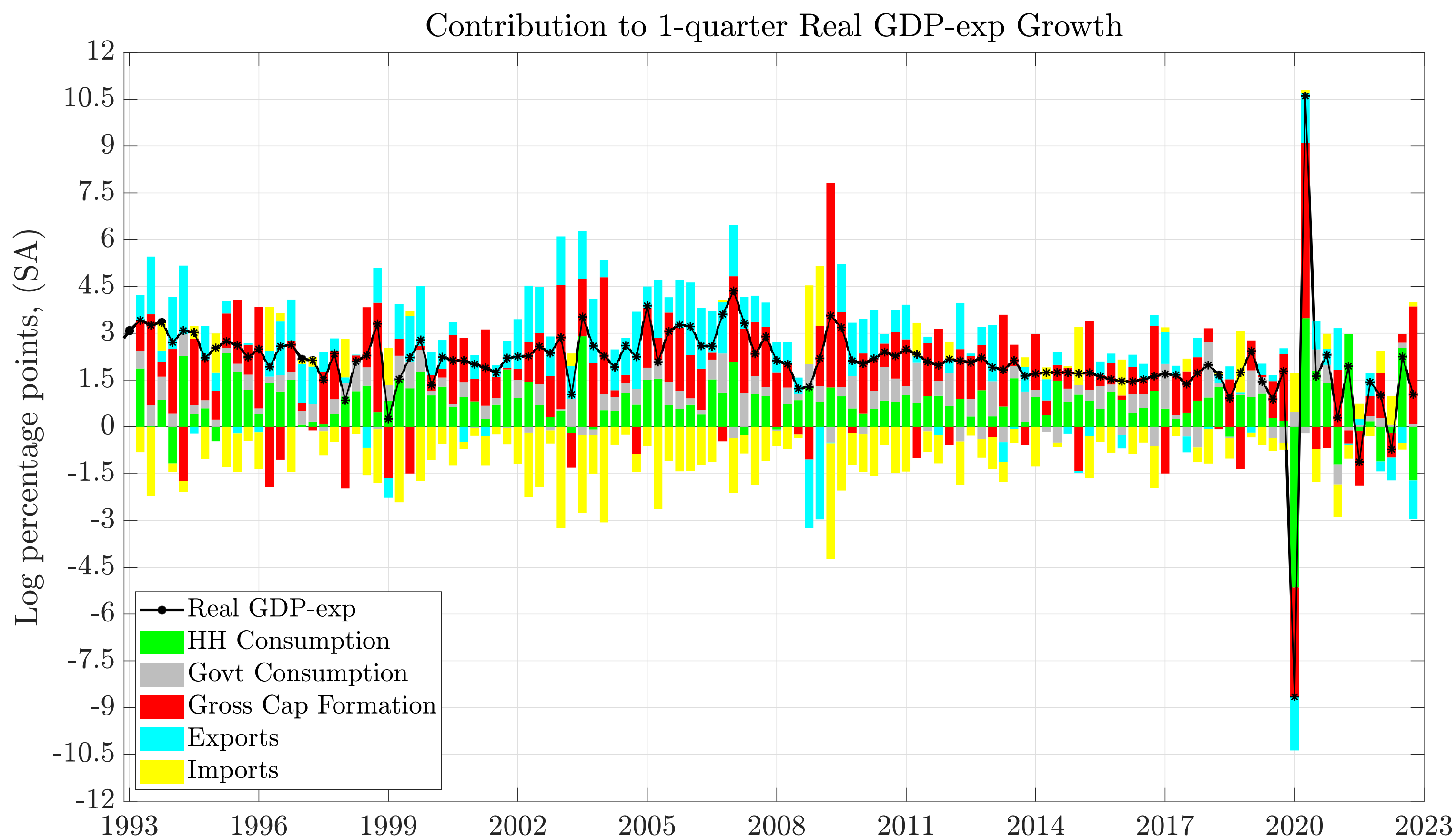

FIGURE S8. The chart shows the subcomponent contributions to 1-quarter growth in the real GDP-exp not adjusted for excess smoothness using the alternative C-CAT. Real GDP-exp has been log differenced and multiplied by 100.

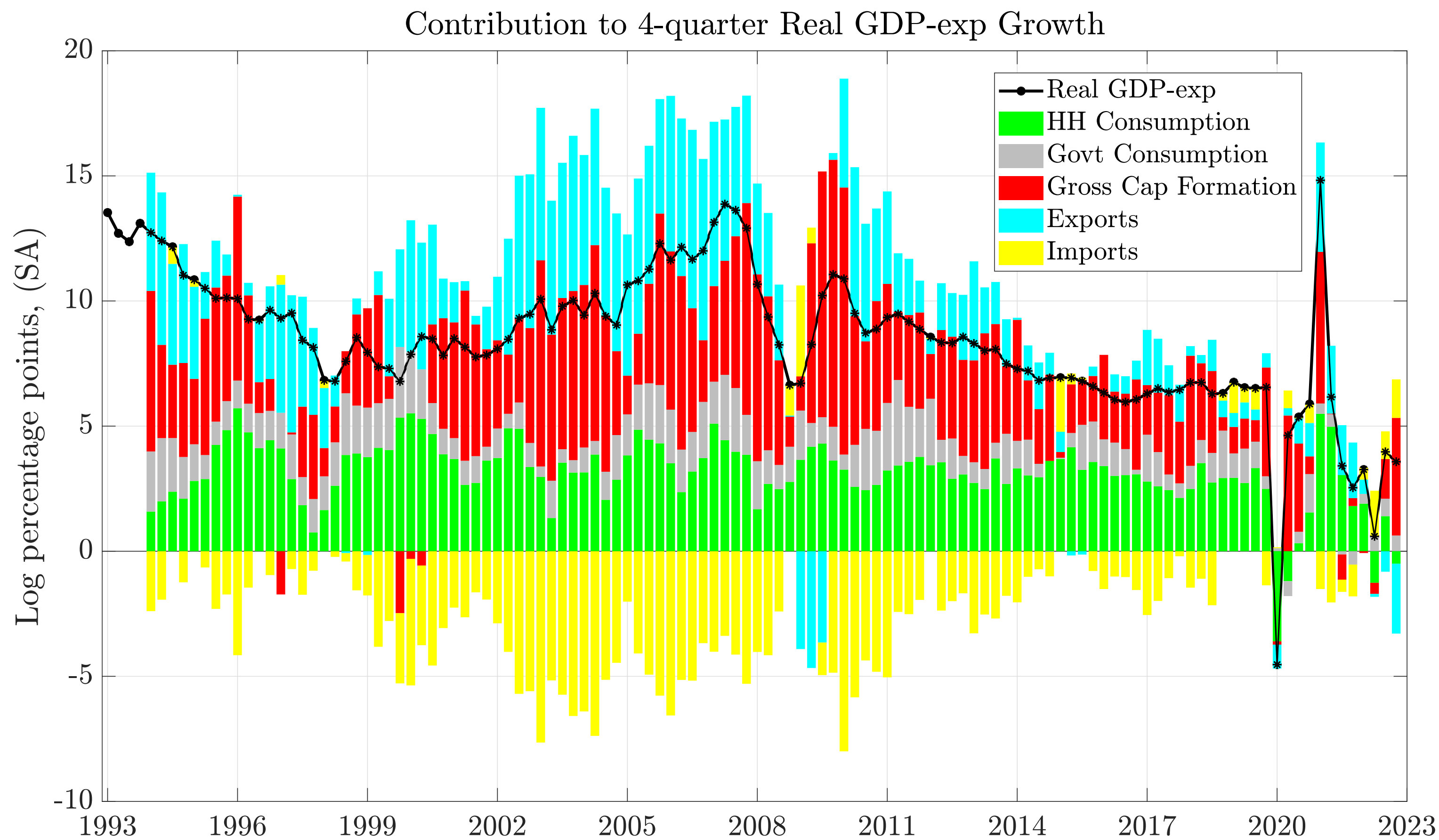

FIGURE S9. The chart shows the subcomponent contributions to 4-quarter growth in the real GDP-exp not adjusted for excess smoothness using the alternative C-CAT. The 4-quarter log difference of real GDP-exp has been multiplied by 100.

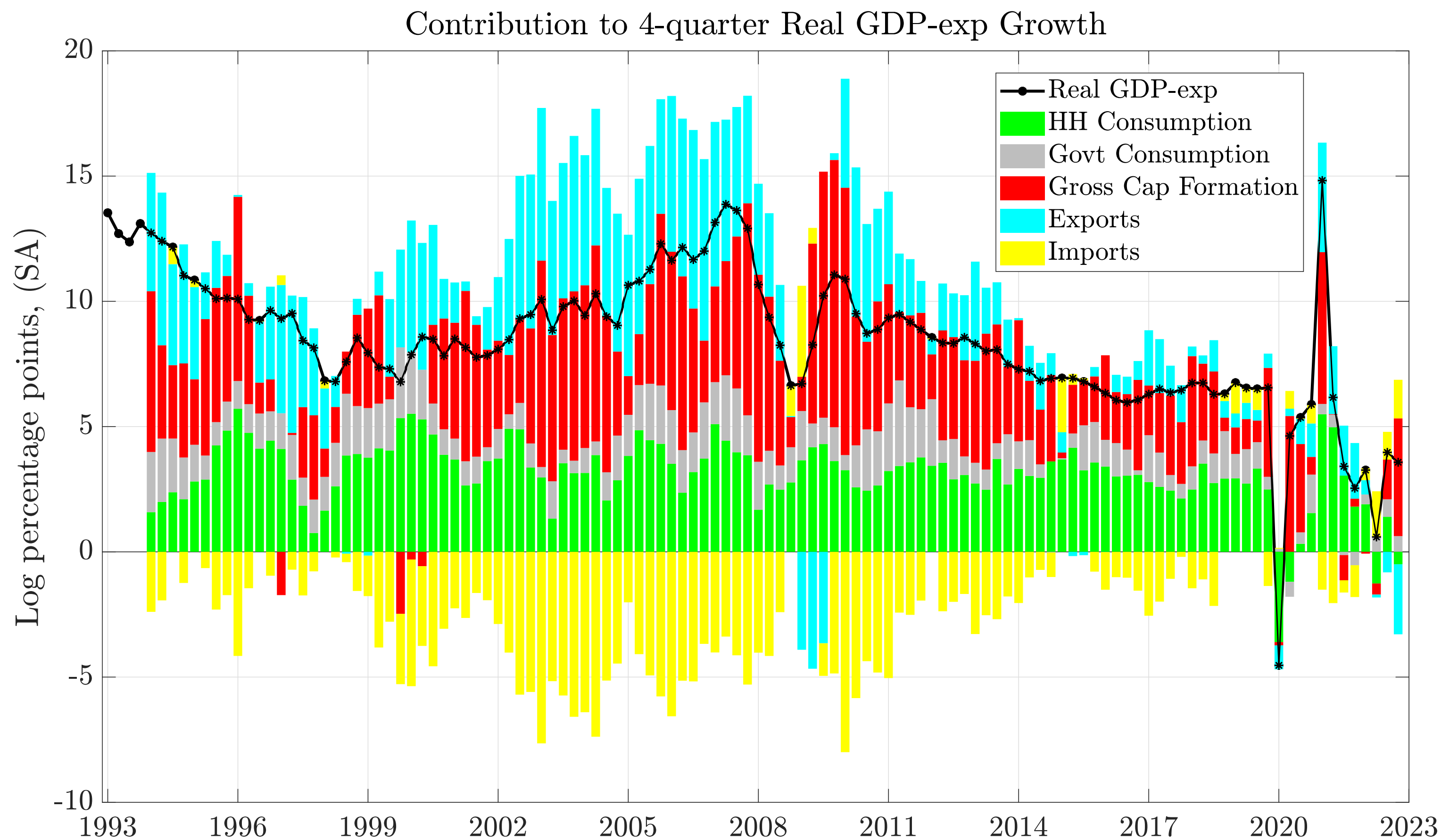

FIGURE S10. The chart shows the subcomponent contributions to 4-quarter growth in the real GDP-exp not adjusted for excess smoothness using the alternative C-CAT. The 4-quarter log difference of real GDP-exp has been multiplied by 100.

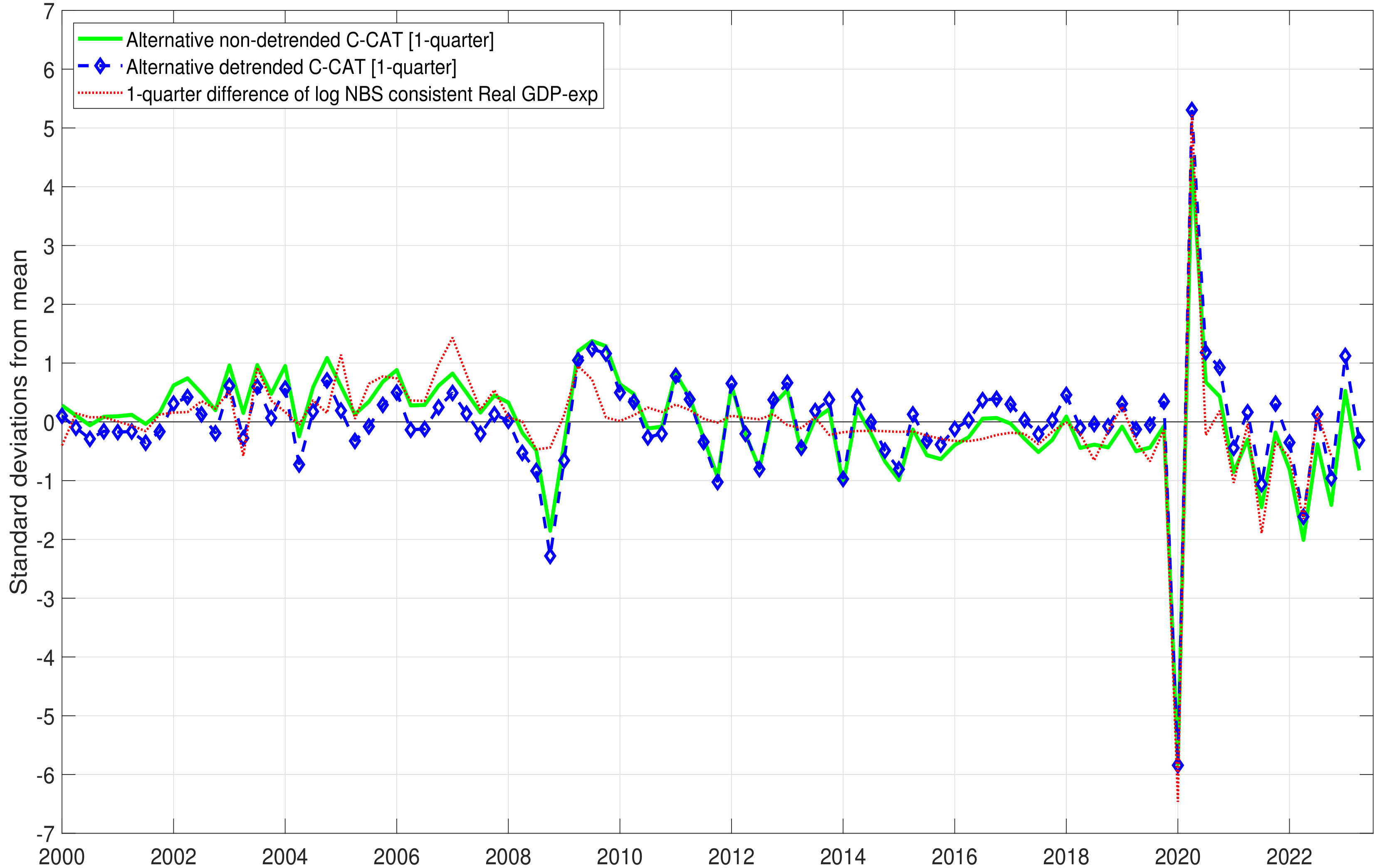

FIGURE S11. Standardized measures of alternative C-CATs and 1-quarter real GDP-exp growth. Our standard C-CAT constructed with non detrended data used to interpolate real GDP-exp for use in our SVAR is represented by the green line. The dashed blue line marked with diamonds shows an alternative C-CAT constructed with detrended data. The red dotted line shows the NBS consistent measure of standardized real GDP-exp growth constructed by interpolating real GDP-exp with an NBS consistent measure of real GDP-va.

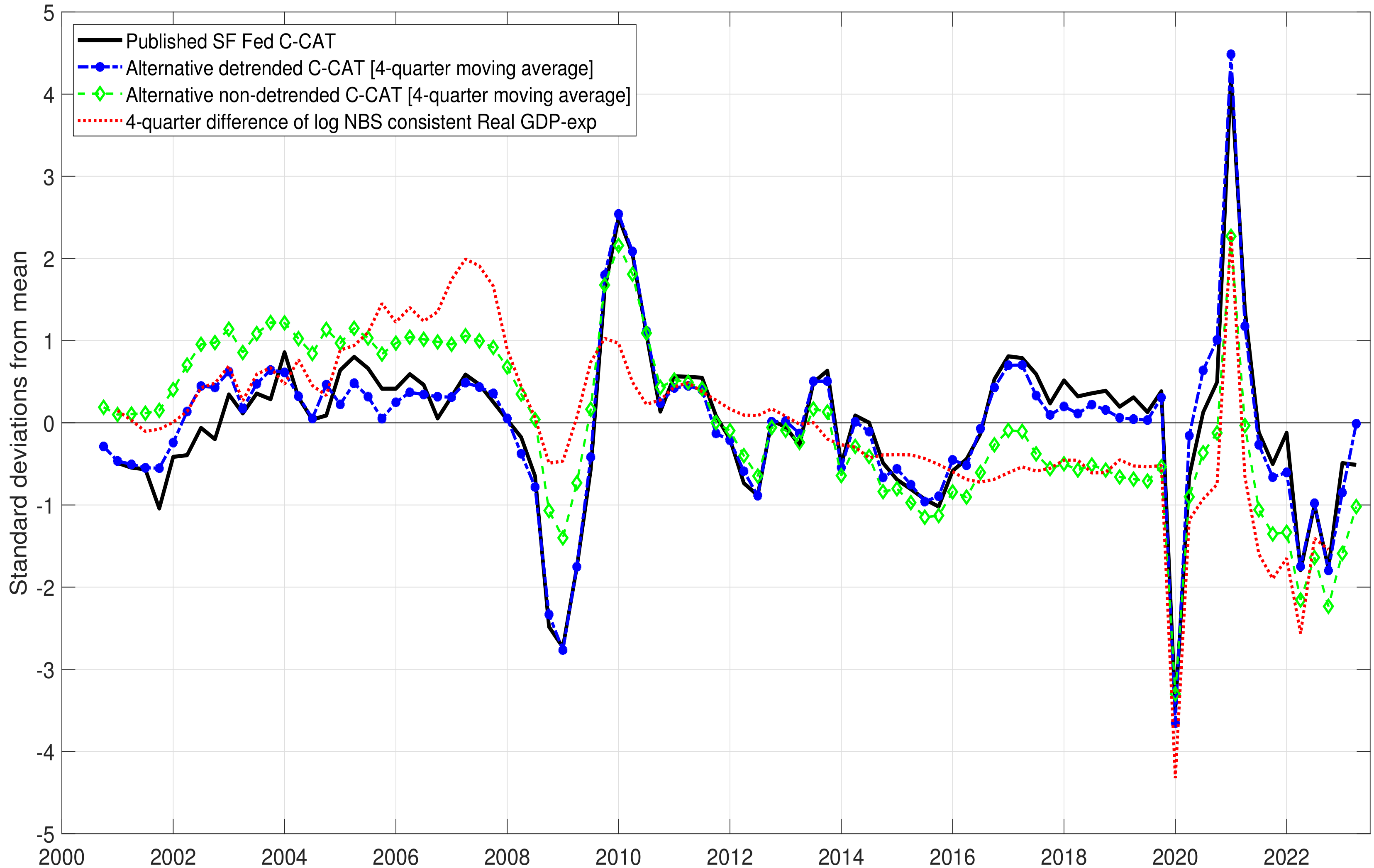

FIGURE S12. Standardized 4-quarter measures of alternative C-CATs and real GDP-exp growth. The standarized moving 4-quarter average of our standard C-CAT constructed with non detrended data used to interpolate real GDP-exp for use in our SVAR is represented by the dashed green line with diamonds. The standardized moving average of an alternative C-CAT constructed with detrended data is represented by the alternating dash-dotted blue line marked with filled circles shows . The red dotted line shows the NBS consistent measure of standardized 4-quarter real GDP-exp growth constructed by interpolating real GDP-exp with an NBS consistent measure of real GDP-va. The black solid line shows the standardized San Francisco Fed C-CAT originally constructed for Fernald et al. (2021).

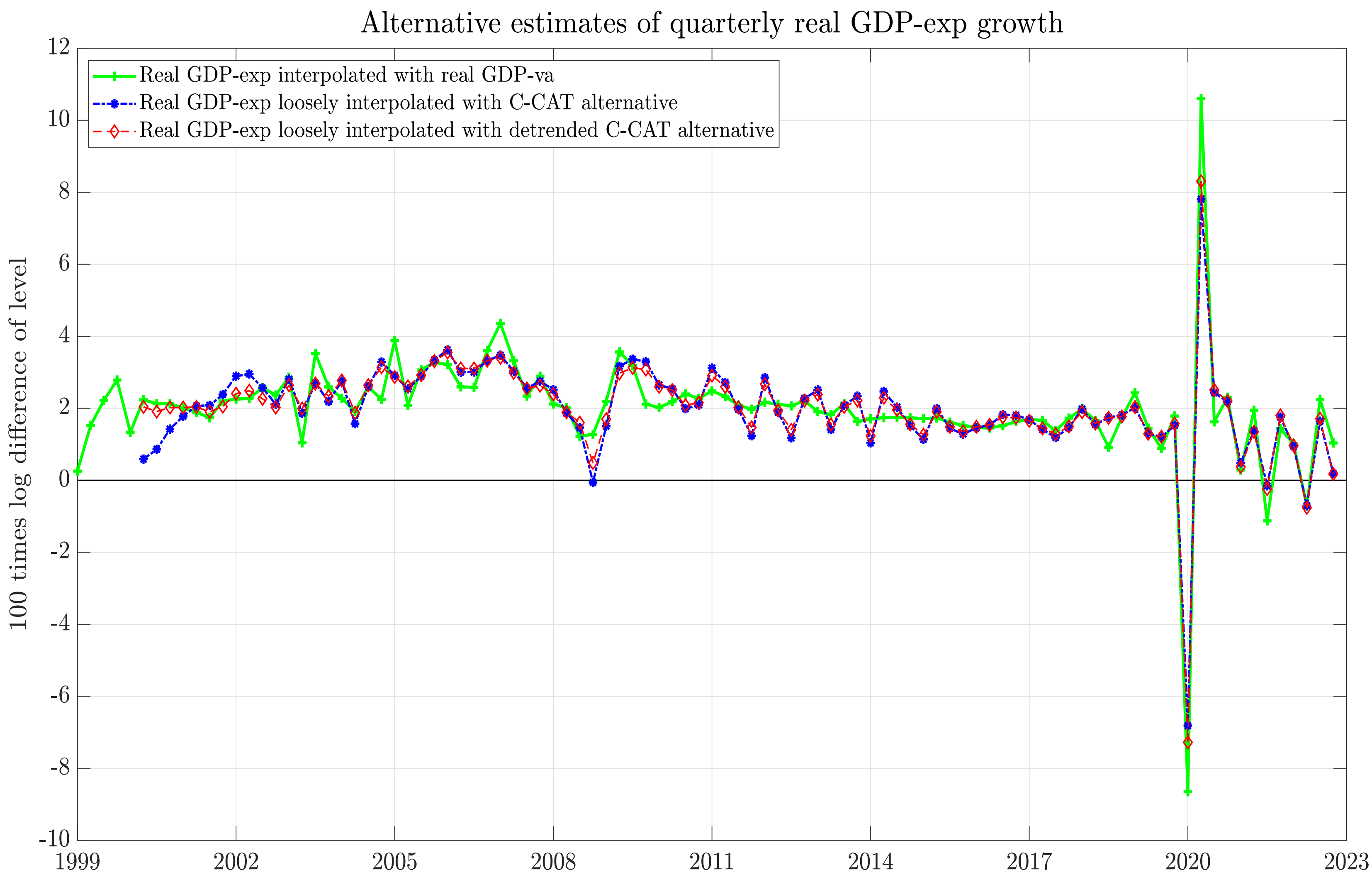

FIGURE S13. Measures of 1-quarter real GDP-exp growth. The solid green line marked with plus signs denotes NBS consistent real GDP-exp interpolated with real GDP-va. The blue line with alternating dashes and dots marked with filled circles denotes the real GDP-exp measure loosely interpolated with our non-detrending C-CAT that is used in the SVAR. The dashed red line with unfilled diamonds corresponds to real GDP-exp loosely interpolated with an alternative detrended C-CAT.

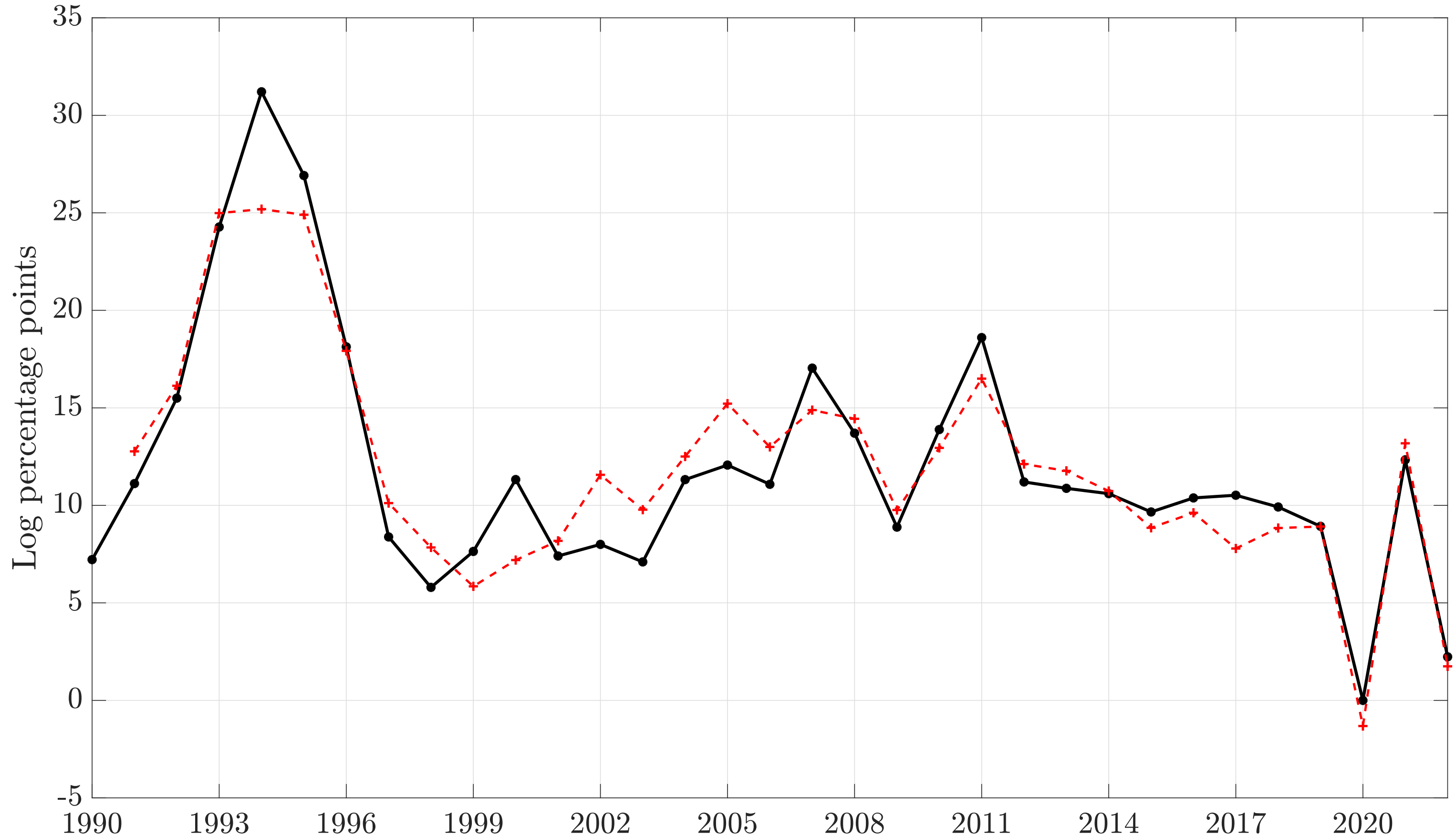

FIGURE S14. The black solid line denotes the annual NBS measure of nominal household consumption. The red line is our spliced interpolater of household survey consumption expenditures and retail sales converted to an annual frequency. Both series have been log differenced and multiplied by 100.

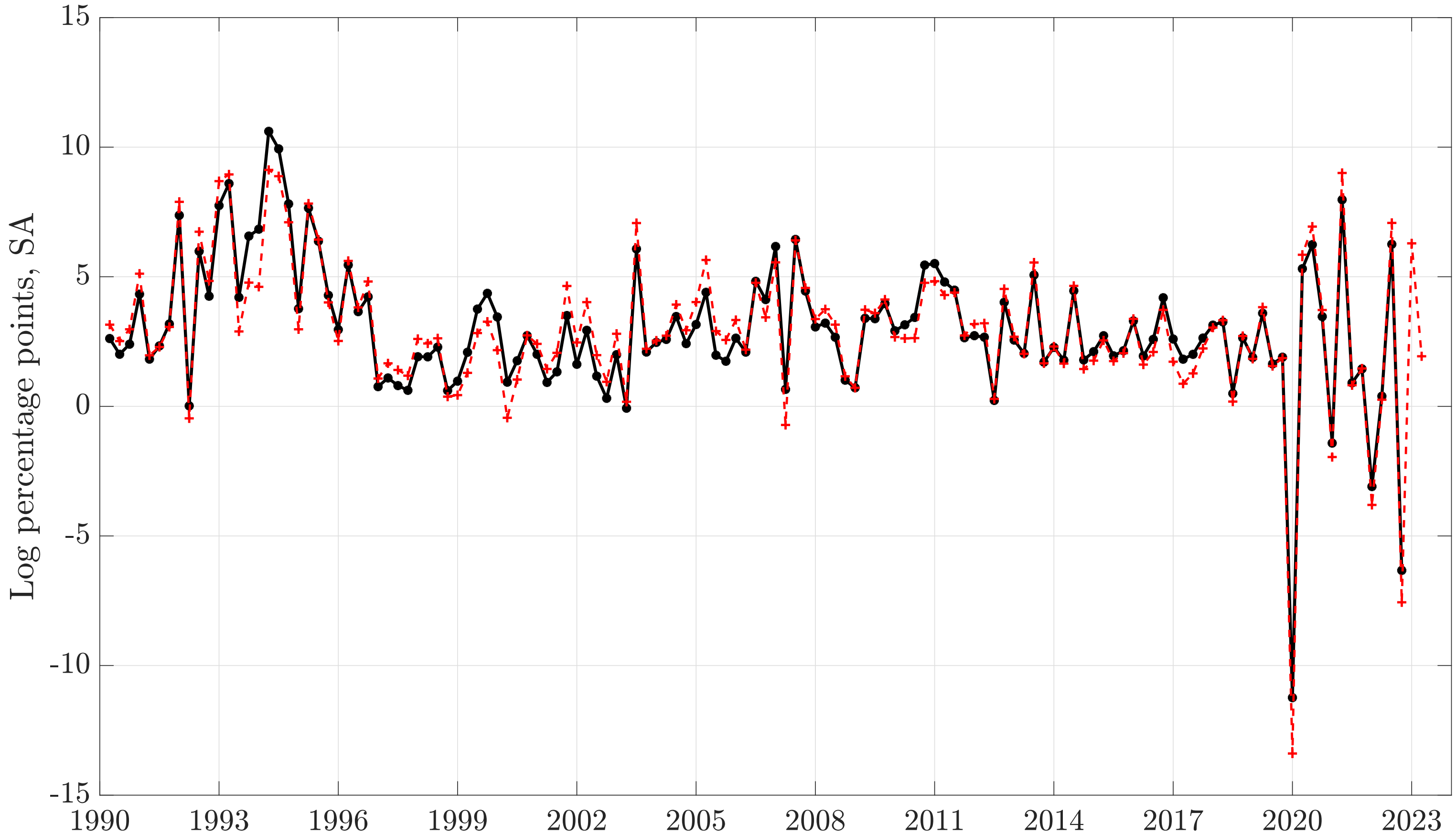

FIGURE S15. The black solid line denotes the NBS measure of nominal household consumption expenditures interpolated to the quarterly frequency but not adjusted for excess smoothness in real GDP-exp. The red line is our spliced interpolater of household survey consumption expenditures and retail sales converted. Both series have been log differenced and multiplied by 100.

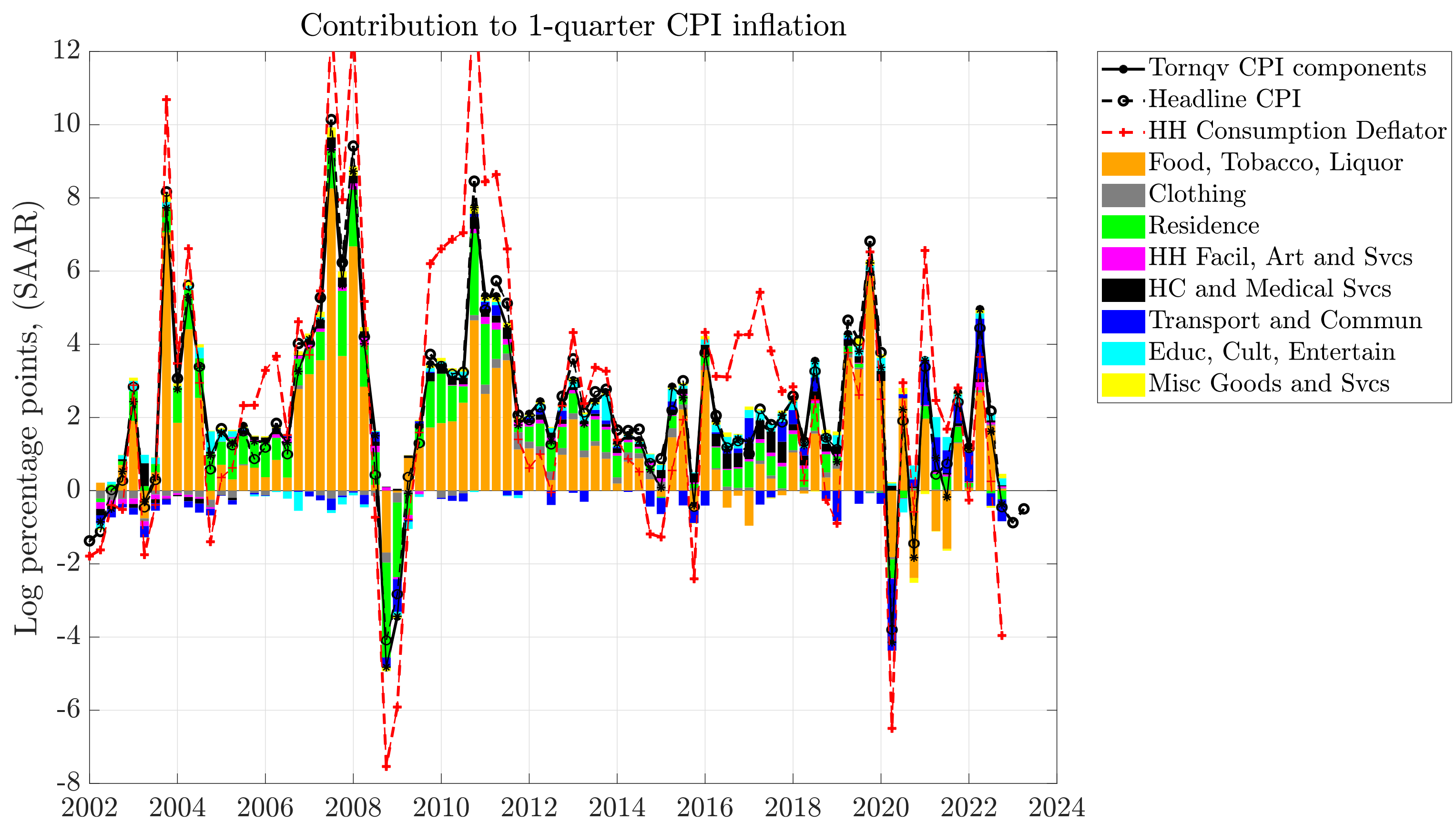

FIGURE S16. One quarter consumption related annualized log inflation rates. The dashed red line shows inflation for our constructed quarterly GDP-exp household consumption price deflator $P_{t,q}^{C^{HH}}$. The dashed black line marked with open circles is seasonally adjusted CPI inflation. The solid black line with filled black circles is a Tornqvist index of a partition of CPI into eight CPI subindices. The stacked bars are subcomponent contributions to the Tornqvist index of CPI subcomponents.

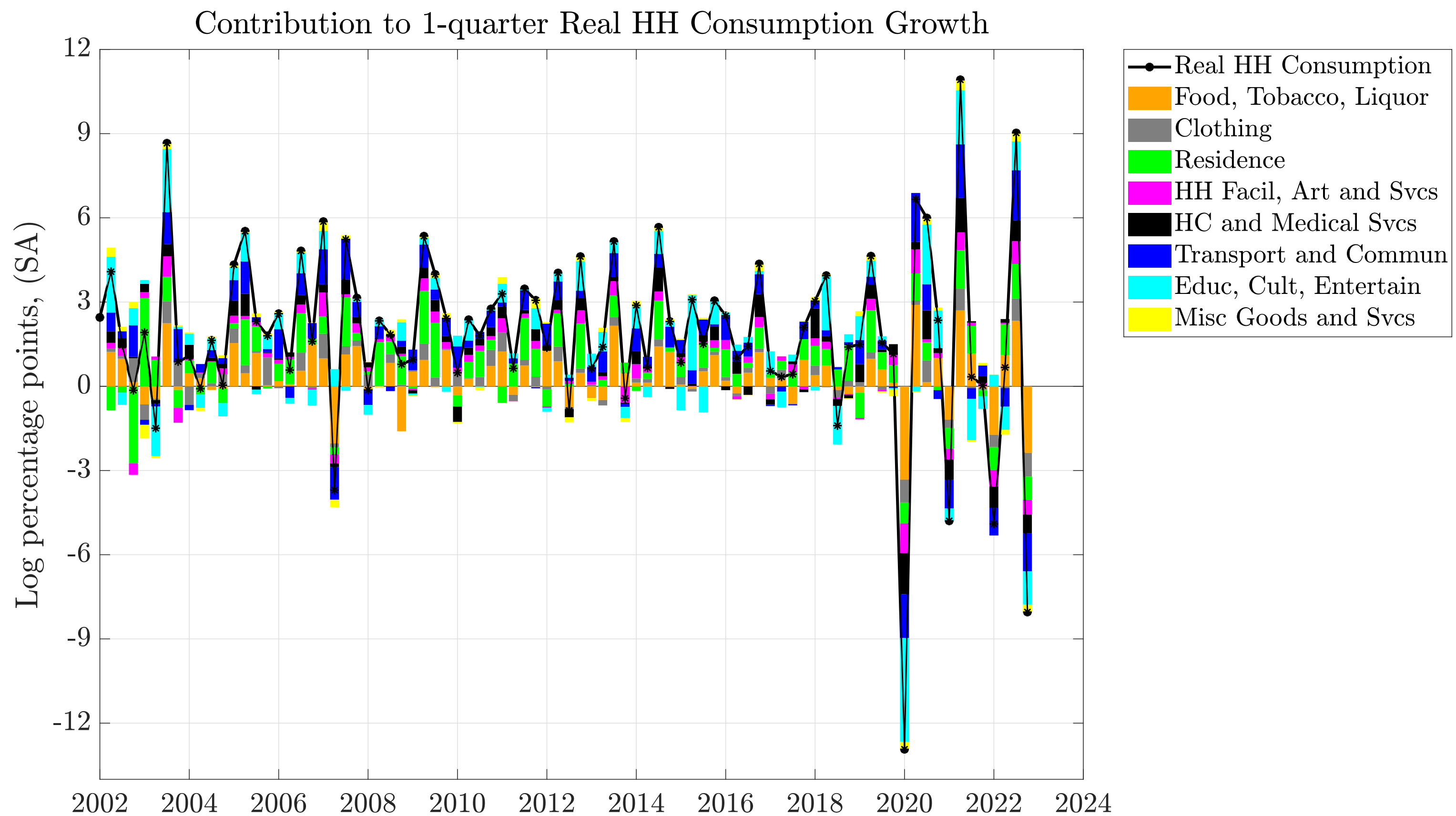

FIGURE S17. One quarter log growth rate of real household consumption expenditures decomposed into contributions from eight subcomponents.

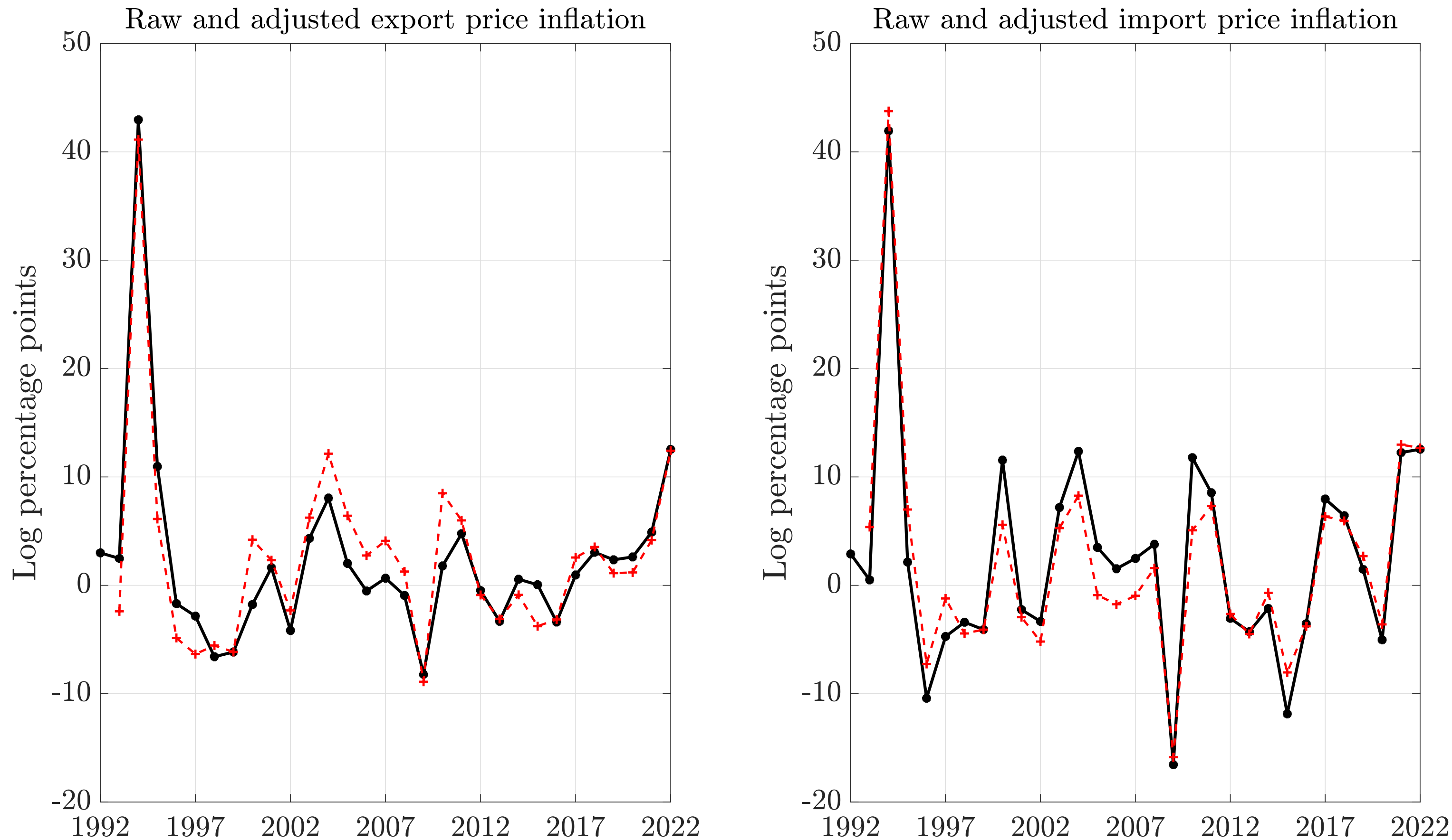

FIGURE S18. The left panel shows annual full year over full year for raw export prices constructed data from OECD data [black line] and a measure adjusted to be consistent with the NBS measure of real net exports [red dashed line]. The right panel shows the same measures for import prices.

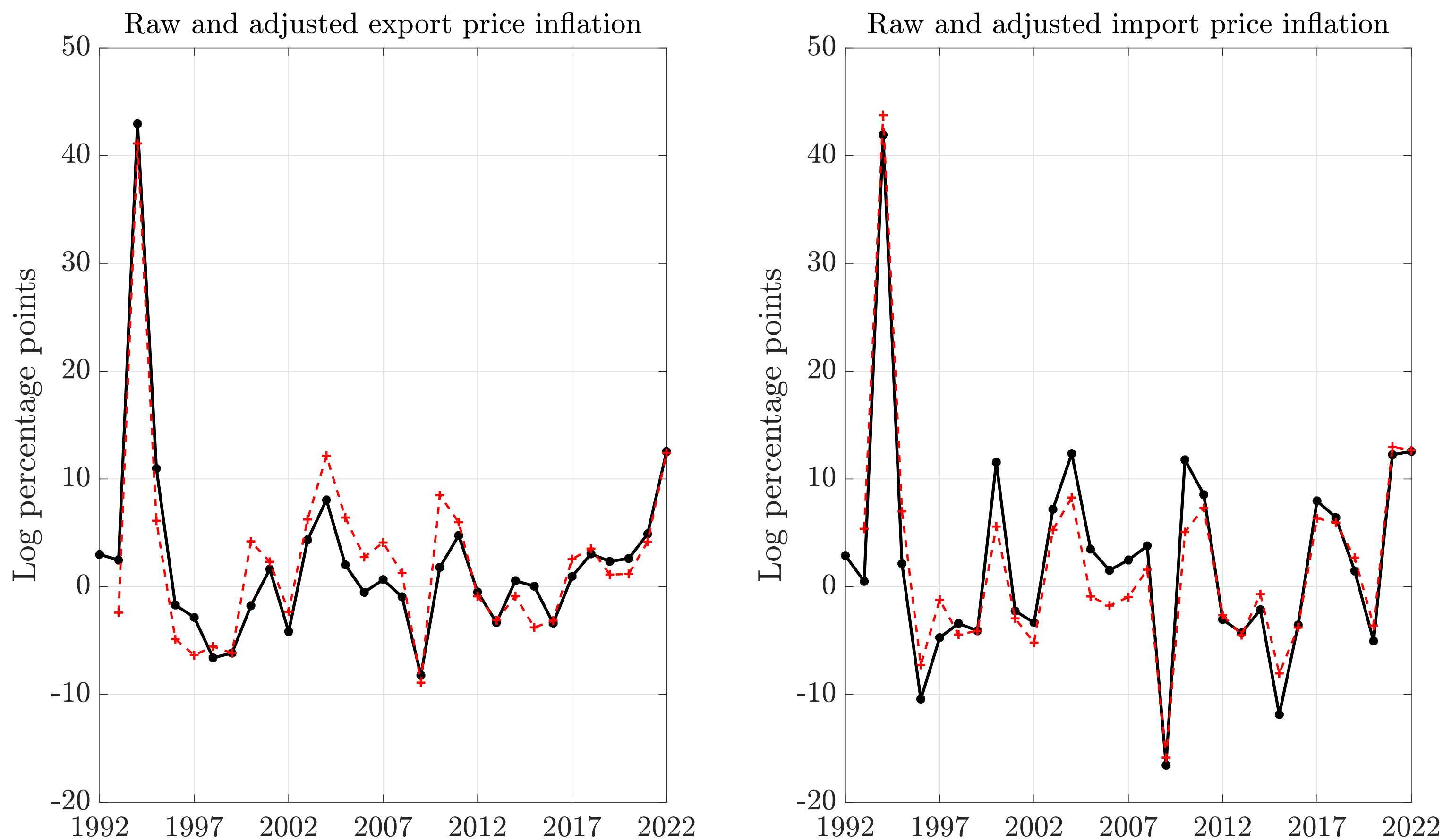

FIGURE S19. The left panel shows annual full year over full year for raw export prices constructed data from OECD data [black line] and a measure adjusted to be consistent with the NBS measure of real net exports [red dashed line]. The right panel shows the same measures for import prices.

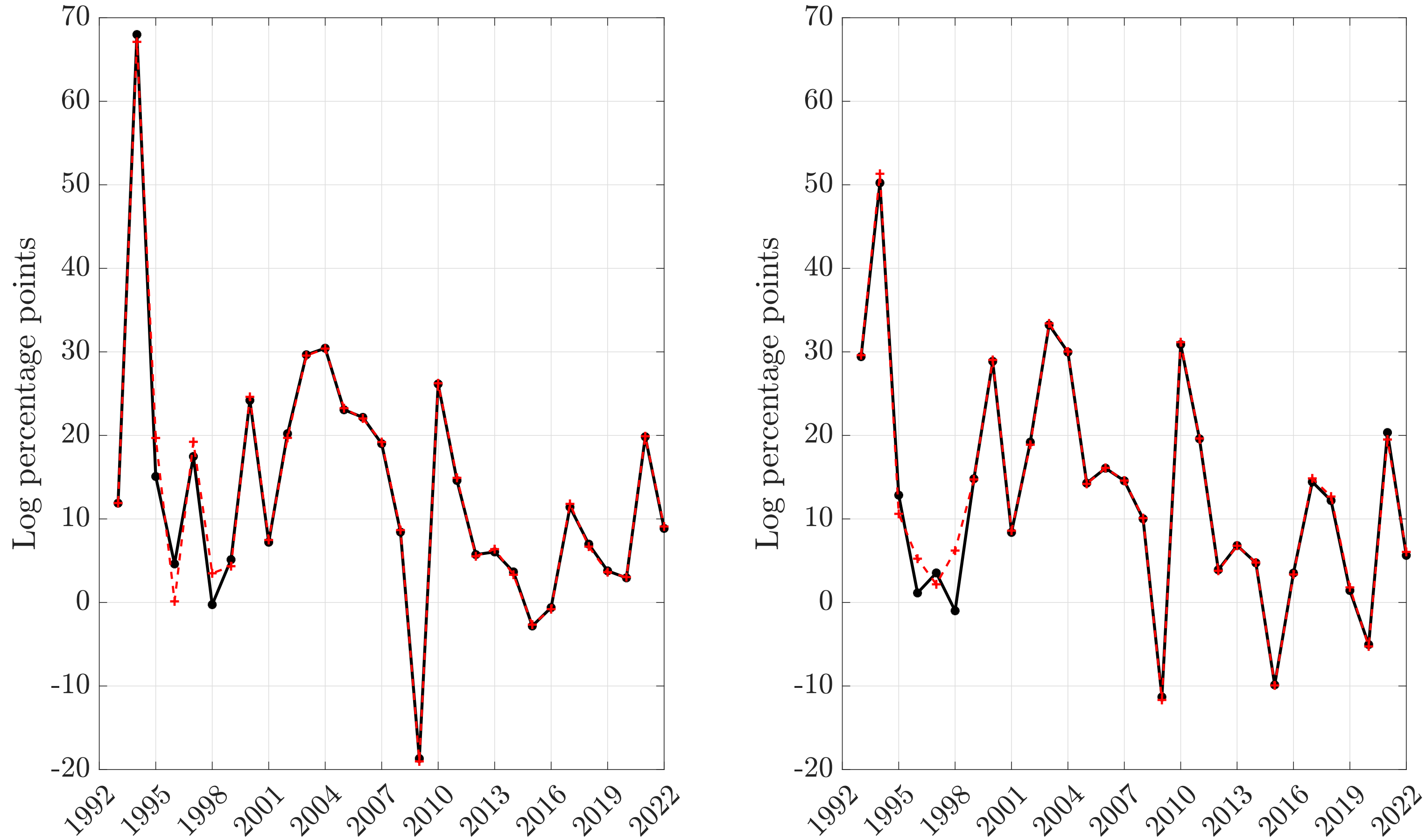

FIGURE S20. The left chart shows the annual log growth rates of $EXP_t^{nom,Adj}$ [solid black line] and the primarily BOP/fob measure of nominal exports [dashed red line]. The right chart shows the annual log growth rates of $IMP_t^{nom,Adj}$ [solid black line] and the primarily BOP/cif measure of nominal imports [dashed red line]. Data consistent with NBS measure of GDP-exp, not the version corrected for excess smoothness.

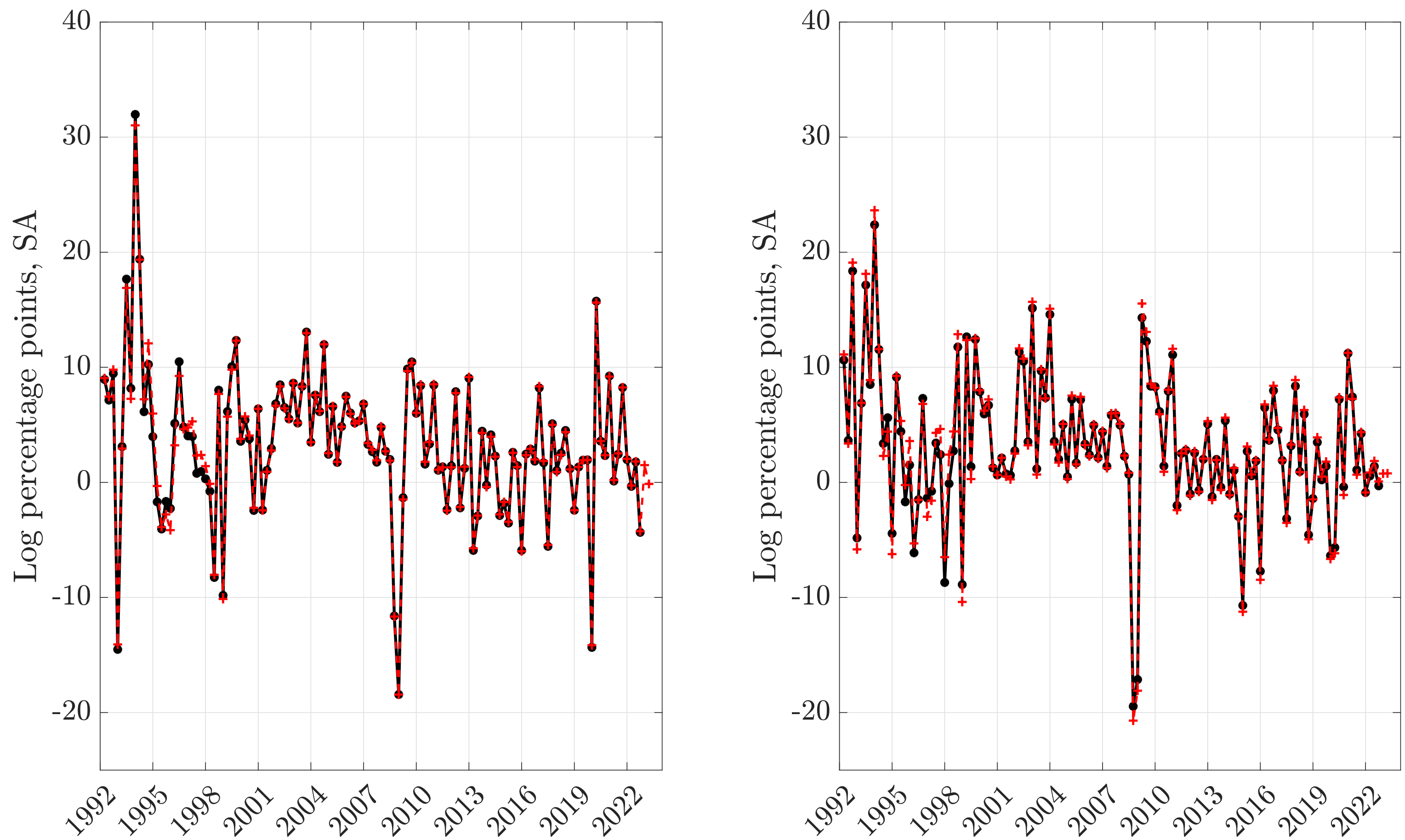

FIGURE S21. The left chart shows the quarterly log growth rates of $EXP_{t,q}^{nom,Adj}$ [solid black line] and the primarily BOP/cif measure of nominal imports [dashed red line]. The right chart shows the quarterly log growth rates of $IMP_{t,q}^{nom,Adj}$ [solid black line] and the primarily BOP/cif measure of nominal imports [dashed red line]. Data consistent with NBS measure of GDP-exp, not the version corrected for excess smoothness.

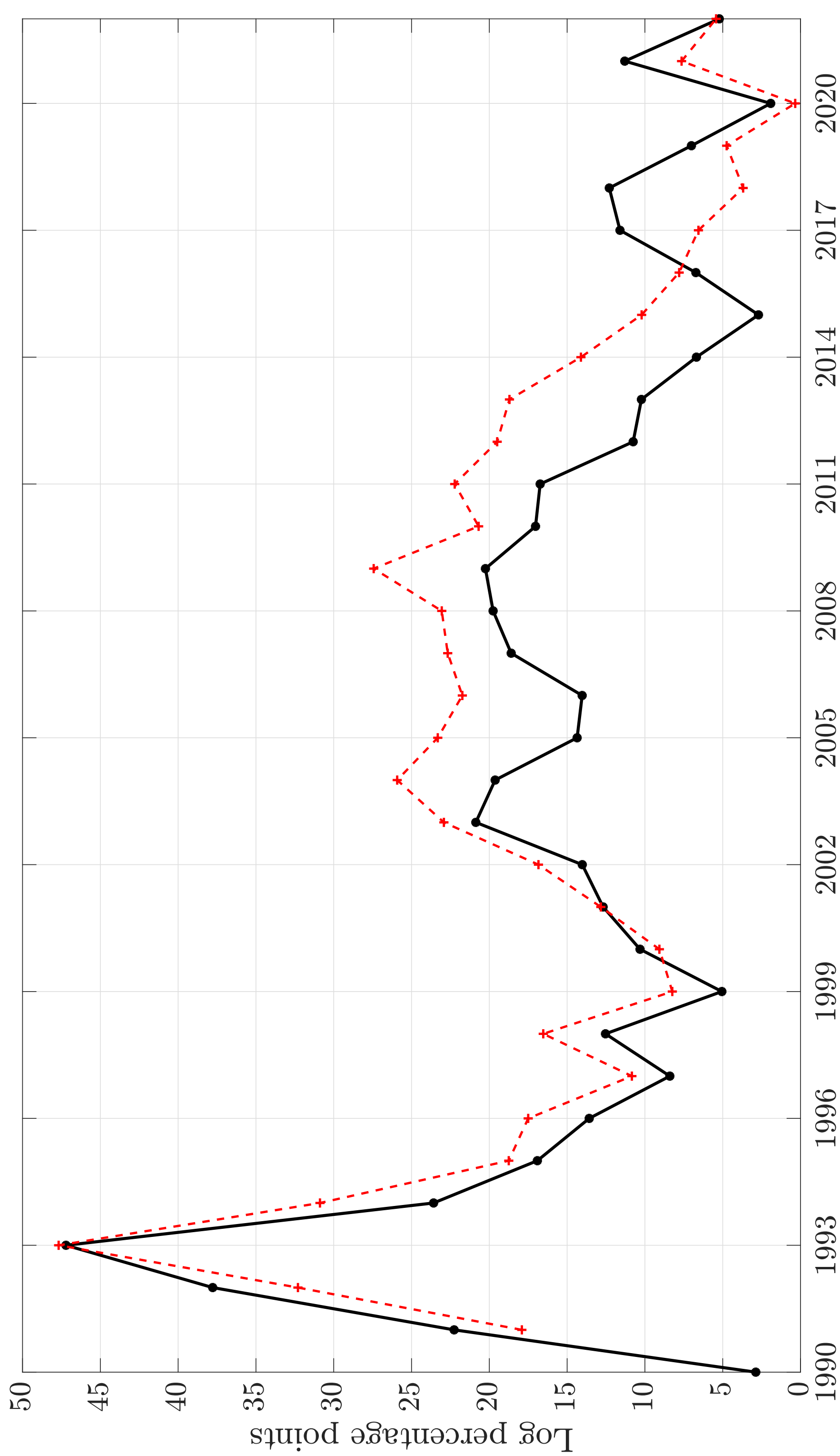

FIGURE S22. Full year over full year logarithmic growth rates of NBS GDP-exp subcomponent final nominal gross capital formation [black solid line] and constructed annual fixed assets investment excluding land [red dashed line]. Data consistent with NBS measure of GDP-exp, not the version corrected for excess smoothness.

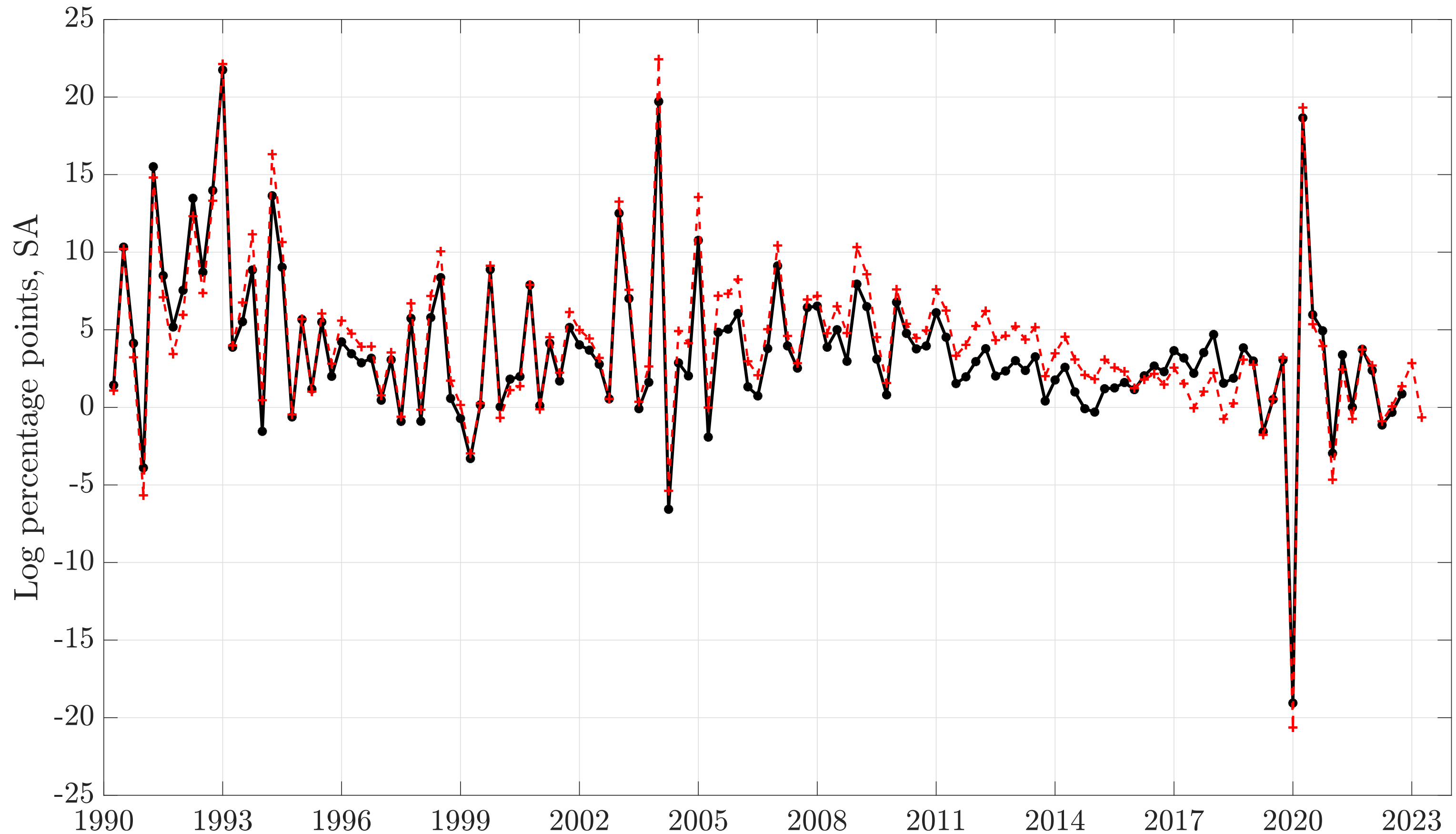

FIGURE S23. Quarterly logarithmic growth rates of interpolated NBS GDP-exp subcomponent gross capital formation [black solid line] and constructed quarterly fixed assets investment excluding land [red dashed line].. Data consistent with NBS measure of GDP-exp, not the version corrected for excess smoothness.