When Did China's Economic Growth Start to Slow Down? A New Method of Tracking China's Per Capita GDP Trends and Cycles

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Abstract

This paper investigates whether China's recent economic slowdown was initiated by a declining long-term trend or a business cycle trough. Based on the Permanent Income Hypothesis, we introduce a consumption-based method to track trends and cycles of China's per capita GDP. First, using data from 1992Q1 to 2022Q4, we find that China's long-run trend growth decline started in 2019, six years later than the actual growth slowdown, which coincided with reduced external demand. Second, by identifying four business cycles from 1992 to 2022, we discover an interesting feature: a prolonged cycle from 2002 to 2019 driven by external demand. Third, the fiscal balance and M2 growth exhibit strong correlations with the cycle components in recent years. Finally, we validate our estimated cycles by linking them to historical events, comparing them with alternative decomposition methods, and assessing their accuracy as measures of output gaps.

Keywords: China's Trends and Cycles, Consumption, Permanent Income Hypothesis

JEL classification codes: C32, E21, E32

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1 Introduction

The slowdown in China's economic growth since 2013 raises the question of whether it stems from a decline in underlying trend growth or a business cycle recession (Bai and Zhang, 2017; Lin, 2012; Summers and Pritchett, 2014; Eichengreen et al., 2012, 2013). As emphasized by Orphanides (2003) and Auerbach (2011), misperceptions about long-run economic growth can lead to mistakes in monetary and fiscal policies. However, traditional decomposition methods that track trends and cycles, such as filtering methods, are primarily designed for advanced economies and may not directly apply to emerging economies with high growth such as China. For example, Aguiar and Gopinath (2007) demonstrate that the cycles measured by the HP filter in emerging economies are driven by permanent shocks and should instead be considered as trends.

In this paper, we introduce a consumption-based method to identify the trends and cycles of China's per capita GDP. This method is based on the unobservable component model (UCM), which assumes that only permanent shocks affect the long-run trend. We incorporate household consumption data in decomposition, inspired by the Permanent Income Hypothesis (PIH) that consumption is solely affected by the permanent shocks of income. In specific, we show that the function of household consumption can serve as a proxy for GDP trends, based on two corollaries derived from the PIH: first, that household consumption and income are cointegrated (King et al., 1991; Cochrane, 1994); and second, that household consumption follows a random walk (Hall, 1978). In other words, we identify the trends and cycles relying on the households' real-time perceptions of the permanent and transitory income shocks.

Our consumption-based method is inspired by Aguiar and Gopinath (2007), who develop a dynamic stochastic general equilibrium model and adopt PIH to identify the permanent and transitory shocks.[1] In a standard PIH framework, consumption can be expressed as the present value of lifetime income, suggesting that consumption and income should be cointegrated with a cointegrating vector of (1, -1) (Cochrane, 1994). This insight motivates the use of multivariate models to decompose trends and cycles, such as Cochrane (1994), Crucini and Shintani (2015), and Kim et al. (2007). They estimate the Beveridge-Nelson (BN) trends by constructing a vector error correction model (VECM) with log consumption/GNP ratio as the error correction term. Compared to these approaches, our consumption-based method functions more as a non-parametric model, directly measuring the GDP trends as a function of household consumption. [2]

We estimate the trends and cycles in China's per capita GDP from 1992Q1 to 2022Q4. Then, we link the estimated cycles to major historical events to confirm the business cycle positions and moving directions. Our findings indicate that the decline in China's long-term trend growth began in 2019Q2, roughly six years after the initial slowdown in actual per capita GDP growth since 2013Q4. This suggests that the slowdown in per capita GDP growth rate from 2013Q4 to 2019Q2 was primarily driven by cyclical recession, while the decline observed after 2019Q1 reflects a deceleration in long-term trend growth.

Meanwhile, our results reveal four business cycle periods, with one different feature compared to advanced economies: China experienced a prolonged cycle from 2002 to 2019, primarily driven by external demand. This cycle began with China's entry into the WTO, peaked just before the global financial crisis, and then declined alongside falling net exports and foreign direct investment (FDI).

[1]Aguiar and Gopinath (2007) are motivated by evidence that consumption is more volatile than GDP in emerging economies, a phenomenon also observed in China, as documented by Germaschewski et al. (2021).

[2]Beyond consumption, additional information has been incorporated into multivariate UCMs to identify trend and cycle components. For example, inflation is integrated through the Phillips curve, and the unemployment rate is included via Okun's Law (Gonzalez-Astudillo, 2019; Panovska and Ramamurthy, 2022; Sinclair, 2009).

Notably, the duration of this cycle exceeds the upper limit of the typical business cycle frequency band observed in advanced economies.[3] Additionally, we find that internal factors, such as fiscal balance and M2 growth rate become more correlated with the cycles in recent business cycle period.

To further validate the reliability of our methods and the accuracy of trends and cycles measurements, two approaches are employed. First, we compare the estimated cycles with the HP-filtered cycle and OECD composite leading indicators (CLI). By transforming the cycles into the frequency domain, we find that China's cycles are concentrated in the low-frequency domain, indicating the inapplicability of the filter methods. Lastly, we assess the performance of the estimated cycles as measures of the output gap using three criteria outlined by Furlanetto et al. (2023). Notably, the consumption-based method outperforms filtering methods in forecasting.

Our work is closely related to literature that focuses on estimating trends and cycles in China's economy. Earlier studies, such as Chong et al. (2009) and Chakraborty and Otsu (2013), assume linear time trends in China's GDP, conduct standard business accounting exercises, and show the importance of productivity and investment wedges on the cyclical behavior of China's macro time series. Relying on a structural vector autoregression model (SVAR), Zhang and Murasawa (2011, 2012) apply Beveridge-Nelson (BN) filter by incorporating additional inflation and money supply information. Then, they study the dynamics of inflation and suggest the existence of the Phillips curve. A recent study by Han et al. (2020) compares univariate and multivariate UCMs across various econometric specifications in separating China's GDP growth into trends and cycles from 1952 to 2017. Meanwhile, they suggest a deepening recession since 2015. Compared to these studies, we show that household consumption can serve as a proxy for the

[3] The business cycle frequency band is defined between 6 to 32 quarters, according to Stock and Watson (1999).

trends, which differs from previous literature that relies on econometric specifications and estimation methods. Another important paper is Chang et al. (2016), who adopt a six-variable VECM and utilize King et al.'s (1991) reduced-rank time-series method to decompose trend and cycle components. By analyzing the trend and cycle components of multiple macroeconomic variables, they conclude several key trend and cycle patterns that are different from the advanced economies. Relative to these papers, we rely on economic theory when identifying the trend and cycle components of China's per capita GDP.

The rest of the chapter is organized as follows: Section 2 describes the data. Section 3 introduces the methodology employed for identifying trends and cycles. In Section 4, we present our estimation of the trends, cycles, and their patterns. Then we link the cycles with major historical events. Section 5 uses two approaches to validate and evaluate the measured cycles. Section 6 provides robustness checks. Finally, Section 7 concludes.

2 Data and Patterns

Figure 1(a) shows the log value of China's real per capita GDP from 1992Q1 to 2022Q4. Notably, the per capita GDP has flattened in recent years, indicating a decline in the growth rate, which is reflected in the annualized growth rates shown in Figure 1(b). Splitting the period in two, we find that the average growth rate was 9.0% before 2013Q4, dropping to 5.6% afterward. Additionally, unlike advanced economies, China's log per capita GDP is smooth with minimal fluctuations, except during the COVID-19 period. This stability suggests that standard filtering methods may not capture meaningful cyclical fluctuations. Indeed, the HP-filtered cycles show a maximum fluctuation of only 2.5% (See Figure 3).

Figure 2(a) shows the real consumption-to-GDP (C/Y) ratio, with consumption and GDP deflated by the CPI and GDP deflator, respectively. The real C/Y ratio remains stable over time, mirroring the patterns observed in advanced economies as described in Kaldor's facts. Cochrane (1994) further highlights that a stable C/Y ratio is equivalent to cointegration between consumption and income, lending support to our consumption-based method.

While Chang et al. (2016) argue that the C/Y ratio has been declining in China, we attribute this difference to two main reasons. First, Chang et al. (2016) focus on the nominal C/Y ratio, as shown in Figure 2(b). Using 1992Q1 as the base year for both the CPI and GDP deflator, our results indicate that the GDP deflator has grown faster than the CPI, widening the gap between these measures over time. Specifically, by 2022Q4, the GDP deflator is 3.67 while the CPI is 3.07, suggesting that the inflation rate measured by the GDP deflator has, on average, been 2% higher than that measured by the CPI over the past 30 years. Second, Chang et al. (2016) use the data that ends in 2013. Our findings show that the C/Y ratio reached the bottom in 2012 and kept increasing since then. By including data post-2013 and transforming it into real terms, we observe a stable C/Y ratio, contrasting with the patterns observed by Chang et al. (2016). To further confirm this stability, we collect household survey data from the National Bureau of Statistics (NBS) and the China Household Income Projects (CHIP), confirming the stability of the C/Y ratio at both individual and household levels. Further details on the survey data and robustness checks are provided in the appendix.

The data on household consumption and GDP are collected from Chang et al. (2016), spanning from 1992Q1 to 2022Q4.[4] Two series are deflated using the CPI

[4]The dataset provides standardized macroeconomic time series for China, compiled from multiple sources, including the National Bureau of Statistics (NBS), People's Bank of China (PBC), WIND, and CEIC. It is cross-verified for accuracy and updated annually by the Federal Reserve Bank of Atlanta. The data can be accessed at: https://www.atlantafed.org/cqer/research/china-macroeconomy.

and GDP deflator, respectively. Then both are transformed into log per capita terms to align with the representative household settings in the PIH framework.[5] Using aggregate GDP and household consumption is also feasible. This replacement would only affect the long-run trend and leave cycles unchanged.[6] It is reasonable, as population changes primarily impact the long-run trend.

3 Consumption-based Trends and Cycles Decomposition Method

Trends and cycles decomposition takes the form of:

$$y_t = y_t^\tau + y_t^c \tag{1}$$

where y_t^τ and y_t^c represent trend and cycle components, respectively. Figure 3 presents the estimated cycles of China's per capita GDP using methods commonly applied in the existing literature. First, we include two filtering methods: the standard HP filter and the OECD CLI, which aggregates the common components of HP-filtered cycles across various macroeconomic time series. Second, we apply UCMs.[7] As shown in Figure 2, all methods yield cycles with minimal fluctuation, with the maximum deviation around 2.5%. This suggests that, based on these

[5]The measurement of consumption in PIH studies is widely debated, with significant contributions from Ziliak (1998) and Browning et al. (2014). Most studies emphasize non-durable goods, and we follow this approach by using household consumption per capita as our measure of individual consumption, excluding government expenditure.

[6]This replacement can be easily explained by adding the log value of population to both sides of Equation (2).

[7]We use both a univariate UCM and a bivariate UCM, where the latter augments the univariate model with a Phillips curve equation as introduced by Basistha and Startz (2008), and the estimated cycles are similar. The univariate UCM contains three equations: besides Equation (1), the trend component (y_t^τ) follows a random walk process with a drift term, while the cycle component (y_t^c) follows an AR(1) process. The bivariate UCM augments univariate UCM with a Phillips curve equation, expressed as $\pi_t = \alpha y_t^c + \beta_1 \pi_{t-1} + \beta_2 \pi_{t-2} + \epsilon_t$.

methods, China's economy appears to experience almost no business cycles.

Our consumption-based method builds based on a UCM, which assumes that trends follow a random walk process, while cycles follow a stationary process (Harvey, 1985; Clark, 1987). Instead of relying on additional assumptions for estimation (Stock and Watson, 1988; Morley et al., 2003), our method incorporates additional household consumption and shows that the function of consumption can measure the trends based on two corollaries derived from the PIH in China's context.

The first corollary is that household consumption and income are cointegrated (King et al., 1991, Cochrane, 1994). As Crucini and Shintani (2015) emphasize, consumption and income share the same stochastic trend in most macroeconomic models because of the long-run budget constraint identity. Hence, consumption provides additional information on the trend of income. Following Campbell and Mankiw (1989), we can apply this relationship to the log values of per capita consumption and per capita GDP.

$$y_t = \gamma + c_t + \mu_t \tag{2}$$

where y_t is log real per capita GDP, c_t is log real per capita consumption, γ is the constant term, and μ_t denotes the error term, which is I(0). Since the cointegration vector between consumption and GDP is (1, -1), this is equivalent to Kaldor's facts that the consumption-to-GDP (C/Y) ratio is stable over the long run.

Second, consumption follows a random walk (Hall, 1978). This is derived from the consumption Euler equation with uncertainty and a quadratic utility function based on the PIH.

$$c_t = \delta + c_{t-1} + \epsilon_t \tag{3}$$

where δ is the drift term, and ϵ_t is the i.i.d error term, denoting unexpected permanent income growth. By incorporating these conditions, per capita consumption serves as a proxy for per capita GDP trends within the UCM framework. [8]

$$\text{Trends:} \quad y_t^{\tau} = \gamma + c_t \tag{4}$$

$$\text{Cycles:} \quad y_t^{c} = \mu_t \tag{5}$$

With the empirical data, we confirm that household consumption follows a random walk process. However, the cointegration tests yield inconsistent results across different specifications: the Johansen test suggests a cointegration relationship, while the Engle-Granger test does not. Despite this, our primary objective is to obtain consistent estimates for trends and cycles. In the robustness checks, we explore two alternative approaches that pass the cointegration tests while yielding similar patterns as the trends and cycles in the baseline model. The first method constructs a VECM relying on the Johansen test. The second method incorporates additional variables to satisfy the criteria of the Engle-Granger test. Further details on the tests for random walk and cointegration can be found in the appendix.

An additional concern is whether standard PIH applies to China, given two key arguments: budget constraints and precautionary savings (Horioka and Wan, 2007; Chamon and Prasad, 2010; Wen, 2009; He et al., 2018). First, under budget constraints, rational households are unable to borrow sufficiently for consumption. Campbell and Mankiw (1989) describe such households as "hand-to-mouth" consumers, where the share of these consumers in the total population is denoted as λ. They propose the equation: $\Delta c_t = \lambda \Delta y_t + (1-\lambda)\epsilon_t$, indicating that consumption growth (Δc_t) is a weighted average of current income growth (Δy_t) and permanent

[8] Quah (1992) demonstrates that there is no unique solution in decomposing a time series into a unit-root process and a stationary process. Our consumption-based method imposes an implicit assumption that the shocks of trends and cycles are orthogonal. Although this represents a unique solution, it aligns with the theoretical expectations of the PIH and doesn't necessitate additional assumptions.

income growth (ϵ_t). Since the current income growth is serially correlated, this implies consumption growth is also serially correlated, which contradicts the random walk assumption. However, as we confirm that household consumption follows a random walk process, the budget constraints argument appears less applicable in this case.

Second, precautionary savings occur when households face income uncertainty. With the convex marginal utility of consumption, rational households will save to mitigate future risks, leading to current consumption being lower than its potential value under conditions of certainty. While we do not directly argue the validity of this mechanism, we estimate the potential consumption value without income risk by adjusting for the effects of potential income uncertainty, following Hahm and Steigerwald (1999). The detailed methodology and results are provided in the robustness checks.

4 China's Per Capita GDP Trends and Cycles

In this section, we start with the estimations of trends and cycles. Next, we link the estimated cycles to major historical events to confirm the positions and directions of the business cycles. Finally, we illustrate the observed patterns in these trends and cycles.

4.1 Trends and Cycles Estimations

Figure 4(a) shows the log value of actual real GDP per capita alongside the estimated trends. The difference between these two lines represents the estimated cycles, which are graphed in Figure 4(b). The value of the cycles quantifies the percentage deviation of actual per capita GDP from its potential level. A positive value indicates that actual per capita GDP exceeds the potential value, while a negative value indicates the opposite.

Besides the baseline estimated cycle, three alternative methods are shown in Figure 4(b). The first method applies Beveridge-Nelson decomposition with a bivariate VECM based on the Johansen tests (Cochrane, 1994; Garratt et al., 2006; Crucini and Shintani, 2015), achieving a correlation coefficient of 0.99 with the benchmark estimates. The second method includes net exports as an additional regressor in Equation (2) to meet the Engle-Granger test criteria, resulting in a correlation coefficient of 0.84 with the benchmark estimates. The third method estimates the cycles by adjusting the consumption data for the effects of potential income uncertainty, resulting a correlation coefficient of 0.95 with the benchmark estimates. Further details on these specifications are provided in the robustness checks.

4.2 Linking Cycles to Major Events

To verify that the estimated cycles accurately reflect China's economic history, we plot them alongside key historical milestones in Figure 5. Additionally, Table 1 provides a list of significant events with their corresponding cycle positions and directions.

The first cycle starts in 1992. Before this, China's economy faces a significant downturn in external demand, marked by declines in both exports and FDI, largely attributed to the Tiananmen Square Events. A pivotal moment occurs in 1992Q1 when national leader Deng Xiaoping embarks on his southern tour. Subsequently, China announces to establish a 'socialist market economy' during the 14th National Congress of the Communist Party of China. These reforms lead to relaxed bank credit controls, sparking an investment boom, inflation, and property bubbles. To address these challenges, the government implements a '16-point' plan and various indirect monetary policies, ending this cycle in 1995.

The next cycle begins with the 1997 Asian Financial Crisis, which significantly reduces external demand. In response, China's central government introduces expansionary fiscal and monetary policies, including a 100 billion yuan bond for infrastructure investment in 1998. From 1998 to 2000, the country undergoes major reforms in state-owned enterprises and the financial system, driving the economy from a peak to a trough.

In late 2001, China's entry into the World Trade Organization (WTO) marks a recovery from the trough. This entry leads to sharp increases in net exports and FDI until the 2008 Global Financial Crisis. As external demand shrinks, the Chinese government launches a 4-trillion yuan fiscal stimulus, driving the economy toward another peak. However, declining external demand in the years that follow pushes the economy from this peak back into a trough.

4.3 Trends and Cycles Patterns

Trends

Figures 6(a) and 6(b) plot the annualized growth rates of actual real per capita GDP and its trends using the benchmark method. Notably, the data shows that actual per capita GDP growth begins to slow in 2013Q4, while the trend growth remains relatively stable until 2019Q2 when it begins to decline. Based on these findings, we divide the data into three periods. Before 2013Q4, the actual growth rate is 9.0%, slightly above trend growth at 8.4%. Between 2013Q4 and 2019Q1, the actual growth rate falls to 6.1%, with trend growth declining by only 0.4% to 8.0%. After 2019Q2, both actual and trend growth rates drop significantly, indicating a combination of cyclical recession and trend slowdown. These results suggest that while the initial decline in actual per capita GDP growth was driven by cyclical recession, the post-2019 period reflects both long-term trend declines and cyclical recession. Meanwhile, Figure 7 plots the annualized growth rates of per capita GDP trends growth rate using alternative approaches.

Business Cycles

We use the Bry and Boschan (1971) algorithm to identify the turning points in China's business cycles.[9] According to the NBER definition, recessions are marked from a peak to the next trough, while expansions run from a trough to the next peak. From 1992Q1 to 2019Q4, we identify five peaks and five troughs, shown in Figure 8.[10] The cycle durations range from a minimum of two years to a maximum of nearly seventeen years, which is much longer than typical business cycles in the US based on filtering methods. As emphasized by Canova (1994), decomposition methods play an important role in determining the turning points of business phases.

The estimated cycles reveal a key feature that China experienced a prolonged cycle from 2002 to 2019, likely driven by external demand. As shown in Figure 9(a), real net exports surged after China entered the WTO in 2002, peaking before the global financial crisis. Following this peak, net exports fluctuated, with negative growth in 2016 and a significant drop in 2018. Foreign direct investment (FDI) followed a similar pattern, rising steadily after 2002, dipping during the global financial crisis, recovering, and plateauing by 2015 before declining again (Figure 9(b)). Meanwhile, we plot the estimated cycles using alternative approaches with

[9]The default algorithm uses a 2/2/5 rule, identifying cycles with a minimum of 2 quarters in upswings and downswings and a cycle lasting at least 5 quarters. However, to avoid capturing minor fluctuations, we adopt the 3/3/7 rule, as suggested by Kulish and Pagan (2021).

[10]We exclude the COVID-19 pandemic period, as consumption patterns were heavily constrained by lockdowns. The brief expansion in 2012Q1–2012Q4 is also excluded, as it appears to be a temporary reversal within a longer recession from 2008Q2 to 2019Q1.

the net exports and FDI in Figure 10.

To better understand the influence of internal and external factors on China's business cycles, we calculate the correlation between various macroeconomic time series and the estimated cycles during three business cycle periods, with the results shown in Table 2. This approach allows us to observe which variables exhibit strong correlation with the cyclical component of per capita GDP. For external factors, such as the log net exports and annual growth rate of FDI, their significance become evident after China's accession to the WTO.

Regarding the internal factors, fiscal balance and M2 growth exhibit particularly strong correlations with the business cycles. This highlights the importance of fiscal and monetary policy on China's business cycles (Chen and Zha, 2018; Chen et al., 2018). Meanwhile, two other monetary policy instruments—domestic credit and the required reserve ratio—show weaker correlations with the estimated cycles across all periods, underscoring the importance of M2 growth in understanding China's monetary policy. Figure 11 illustrates the estimated cycles alongside the M2 growth rate during the most recent cycle periods.

Additionally, gross fixed capital formation and fixed asset investment show increasing correlations with the cycles from the first to the third cycles. This shift aligns with Chang et al. (2016), who note that China's central government prioritizes investments to drive economic growth. All of these correlation values are robust when using other specifications, as shown in Table 3.

5 Evaluation

In this section, we present two approaches to demonstrate why the consumption-based method can effectively measure China's business cycles. First, we compare them with filtering methods. By transforming the cycles into the frequency domain, we find that China's cycles are concentrated in the low-frequency domain, indicating the inapplicability of filter methods. Then, we evaluate the estimated cycles as a measure of the output gap using the criteria established by Furlanetto et al. (2023) to assess their performance.

5.1 Comparison with Filtering Methods

Figure 12 compares the estimated cycles from our consumption-based method with those derived from the HP filter and the OECD CLI.[11] Both the HP-filtered cycles and the OECD CLI exhibit limited volatility, with their maximum amplitudes reaching around 2.5%. Notably, all three methods show trough-to-trough cycles exceeding eight years, which is longer than the typical cycle duration observed in the US (King et al., 1991; Stock and Watson, 1999). This suggests that filter methods commonly used for advanced economies may not be suitable for China.

To formally illustrate this inapplicability, we transform all estimated cycles into the frequency domain and plot the spectral density in Figure 13. The default settings for these filtering methods are tuned to capture US business cycle characteristics, which focus on fluctuations within a 6-32 quarters frequency band. As a result, they filter out variations at both lower and higher frequencies. However, the spectral density for China shows a different pattern, with most of the fluctuations concentrated in the low-frequency band, unlike the 'hump-shaped' pattern seen in the US. This highlights the limitations of applying standard filter methods to China's unique economic cycles.

[11] OECD CLI is measured by the common components of a list of HP-filtered macro time series.

5.2 Evaluate Cycles as Output Gap

The cycles measuring the deviation of actual real per capita GDP away from the potential align the definition of the output gap. Furlanetto et al. (2023) summarize three critical criteria for assessing output gap estimates. First, the output gap estimate should effectively predict future inflation. Second, ex-post revisions to the output gap with new data should not significantly alter the estimates. Finally, potential output growth should largely respond to shocks with permanent effects on output, while the output gap should primarily respond to transitory shocks.

Regarding the second criterion, we estimate our output gap as the difference between per capita GDP, per capita consumption, and an additional constant term. his approach ensures that when new data is incorporated, the constant term is the primary element affected, leaving the overall shape of the output gap unchanged. Thus, the estimated peaks, troughs, and economic phases remain stable. In the following section, we focus on the other two criteria. First, we compare the accuracy of our output gap in forecasting inflation against other common methods. Then, we use a structural vector autoregression (SVAR) model to assess how potential output growth and the output gap respond to monetary policy shocks.

Forecasting Future Inflation

Accurate inflation forecasting is crucial for central banks, particularly those following flexible inflation targeting regimes. To assess the predictive power of our consumption-based output gap estimate, we adopt a direct forecasting Phillips curve (Orphanides and Van Norden, 2005; Guérin et al., 2015; Furlanetto et al., 2023; Jarociński and Lenza, 2018).

We compare our output gap's ability to forecast inflation with those derived from the HP filter and OECD Composite Leading Indicator (CLI). The model we use is specified as follows:

$$\pi_{t+h}^{h} = \alpha + \sum_{i=1}^{n} \beta_i \pi_{t-i}^{1} + \sum_{j=1}^{m} \gamma_j y_{t-j}^{c} + \varepsilon_{t+h} \tag{6}$$

where $\pi_t^h = \log(P_t) - \log(P_{t-h})$ denotes inflation over h quarters end in quarter t, and y_{t-j}^c denotes output gap with j lags. We conduct separate regression estimates for each forecasting horizon, selecting the optimal number of lags based on the Akaike Information Criterion (AIC). Our pseudo-forecasting exercise is based on using 80% of the data (from 1992Q1 to 2015Q4) for estimation and the remaining 20% (from 2016Q1 to 2022Q4) for out-of-sample forecasts.

Table 4 presents the mean standard forecast errors for various forecast horizons, showing that our consumption-based output gap provides the most accurate inflation forecasts compared to other methods. We also conduct robustness checks by excluding the COVID-19 pandemic period, confirming the robustness of our results.

Sensitivity to Transitory Monetary Policy Shocks

Our decomposition method, rooted PIH, assumes that potential output responds primarily to permanent income shocks, while the output gap reflects the impact of transitory shocks. This distinction directly corresponds with the third criterion. To assess it, we implement a monetary SVAR model to quantify how potential GDP growth and the output gap respond to temporary monetary policy shocks.

The monetary VAR with Cholesky decomposition is as follows:

$$\begin{bmatrix} y_t \\ \pi_t \\ \Delta m2_t \end{bmatrix} = \alpha_0 + \beta_1 \begin{bmatrix} y_{t-1} \\ \pi_{t-1} \\ \Delta m_{t-1} \end{bmatrix} + \beta_2 \begin{bmatrix} y_{t-2} \\ \pi_{t-2} \\ \Delta m_{t-2} \end{bmatrix} + H\varepsilon_t \tag{7}$$

where y_t measures real activity, we estimate the regression using the output gap and the growth of potential output separately. The variables π_t denotes the inflation rate, and Δm_t denotes the growth rate of M2.[12] The transition matrix H is assumed to be a lower triangle with all diagonal entries equal to one based on the Cholesky decomposition (Sims, 1980). And the error term ε_t denotes the structural shocks.

The impulse response functions, shown in Figures 14(a) and 14(b), illustrate the effects of expansionary monetary policy shocks. In Figure 14(a), expansionary monetary policy leads to a short-term increase in both output and inflation, indicating the output gap's sensitivity to temporary shocks. Conversely, Figure 14(b) shows that potential output growth is largely unaffected, confirming that it responds more to permanent shocks. These results align with our hypothesis that monetary policy mainly affects the output gap, leaving potential output growth unchanged.

[12]Unlike the advanced economies where interest rates are the primary target of monetary policy, China utilizes the growth rate of M2 as its key policy target. Papers such as Fernald et al. (2014) and Chen et al. (2018) provide discussions on these differences.

6 Robustness Checks

6.1 Cointegration and Alternative Methods

A concern in our analysis is the cointegration between GDP and consumption. Our result shows that while the Johansen test confirms cointegration between log real GDP per capita and log real consumption per capita, the Engle-Granger test does not meet the criteria. To address this, we explore two additional methods for estimating trends and cycles that pass cointegration tests.

Vector Error Correction Model

First, we construct a VECM based on the Johansen tests. Cochrane (1994) pioneers the use of a VECM incorporating log consumption and log GNP to derive the Beveridge-Nelson (BN) trend. The identification strategy aligns with Blanchard and Quah (1989) decomposition of VAR structural shocks and development to VECM model by Pagan and Pesaran (2008). Applications of VECM by Crucini and Shintani (2015) focus on cross-country comparisons among G7 nations. We apply a similar VECM model, excluding time-deterministic terms.

$$\Delta c_t = \alpha_c + \beta_{c1}\Delta c_{t-1} + \beta_{y1}\Delta y_{t-1} + \varepsilon_t^c \tag{8}$$

$$\Delta y_t = \alpha_y + \gamma(c_{t-1} - y_{t-1}) + \beta_{c1}\Delta c_{t-1} + \beta_{y1}\Delta y_{t-1} + \varepsilon_t^y \tag{9}$$

Using the matrix algebra solution provided by Garratt et al. (2006) we can estimate the BN trend of both c_t and y_t. And the estimated cycles are then derived by subtracting the BN trend from the actual values of per capita consumption and per capita GDP. The correlation coefficient between these two cycles is 0.99, which suggests the consistence of our baseline estimates (See Figure 4(b)).

Adding Net Exports

An alternative approach is incorporating additional variables to satisfy the Engle-Granger test's criteria. Aguiar and Gopinath (2007) show that permanent shocks prompt households to increase their consumption, which, in turn, can lead to higher imports and a lower current account balance. Consequently, net exports are likely to correlate with long-term economic trends. By adding net export as an additional variable, our model successfully meets the Engle-Granger test's requirements for cointegration. Hence, we can rewrite Equation (4) and (5) and express the estimated trend and cycles as follows:

$$\text{Trends:} \quad y_t^\tau = \alpha + \beta c_t + \gamma n x_t \tag{10}$$

$$\text{Cycles:} \quad y_t^c = \mu_t \tag{11}$$

where nx_t denotes the log real net export. The coefficient α, β, γ, and μ_t can be estimated by regressing per capita GDP on household consumption and net exports. The correlation coefficient between these two cycles is 0.84. The plot can be found in Figure 4(b).

6.2 PIH with Precautionary Saving

When the marginal utility of consumption is convex, a rational household will save more for the future, resulting in current consumption being lower than its potential value under conditions of certainty. To account for this behavior, Hahm and Steigerwald (1999) introduces an additional regressor into the consumption growth equation as:

$$\Delta c_{t+1} = \beta_0 + \beta_1 E_t(v_t) + u_{t+1} \tag{12}$$

where $E_t(v_t)$ is the forecast error variance for the log per capita income, and u_{t+1} represents the forecast error of consumption growth. In this framework, $\beta_1 > 0$, and $\beta_1 E_t(v_t)$ captures the additional savings undertaken by consumers to guard against future uncertainty. Consequently, the potential consumption without uncertainty at time t is $c_t' = c_t + \beta_1 E_t(v_t)$. We use the GARCH(1,1) to estimate the forecast error variance for the log per capita income, and replace the observed consumption with the potential consumption value in applying the consumption-based method to decompose per capita GDP into trend and cycle components. The correlation coefficient between this cycle component and the benchmark value is 0.95. The figure is shown in Figure 4(b).

7 Conclusion

In conclusion, this study examines whether China's recent economic slowdown is driven by a decline in underlying trend growth or is part of a business cycle trough. Given the limitations of existing methods tailored for advanced economies, we developed a consumption-based method for trend and cycle decomposition relying on the PIH.

Our results show that the slowdown before 2009 was largely cyclical, reflecting a business cycle recession, while the post-2019 slowdown involved both a cyclical downturn and a significant decline in long-term trend growth. By applying the Bry and Boschan (1971) algorithm, we identify four distinct business cycle periods. Notably, China experiences a prolonged cycle from 2002 to 2019, driven by external demand.

We further validate our findings by linking the estimated cycles to key historical events, comparing them with alternative decomposition methods, and evaluating their effectiveness as measures of the output gap.

Our method provides a tool for policymakers and researchers to better understand emerging economies, particularly in terms of identifying long-term growth trends and business cycles. Future research could expand by applying the method to other developing economies and incorporating it into business cycle models.

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A Appendix: Tests

Random Walk

To estimate Equation (2), we incorporate the lagged value of per capita consumption and GDP growth as the information set at the time $t-1$ and estimate the equation with the heteroskedasticity and autocorrelation consistent (HAC) standard error as follows:

$$\Delta c_t = \alpha + \beta_1 \Delta c_{t-1} + \beta_2 \Delta c_{t-2} + \gamma_1 \Delta y_{t-1} + \gamma_2 \Delta y_{t-2} + \varepsilon_t \tag{13}$$

Table A.1 shows the estimated coefficients with 95% confidence interval. All coefficients are insignificant, which suggests the serial independence of consumption growth, hence the consumption follows a random walk.

Cointegration

Table A.2 Panel A presents the results of cointegration tests between per capita GDP and per capita consumption using three approaches. First, most of the Johansen test specifications, except for the quadratic trend model, suggest cointegration between per capita GDP and per capita consumption. Notably, the quadratic trend model, which assumes that the dependent variables follow an I(2) process, is unsuitable for our dataset. Second, the Engle-Granger test results do not support the presence of a cointegration relationship. The third approach tests the stationarity of the difference between log value of per capita GDP and consumption. Since we take the logarithm of these variables, we test the stationarity of the C/Y ratio. The equivalence between the stationarity of the C/Y ratio and the cointegration of consumption and GDP is detailed in Cochrane (1994). According to the ADF test, this ratio appears stationary when allowing for a drift but nonstationary when a trend is included.

Although the test results are inconsistent among specifications and approaches, our primary goal is to have consistent estimations of trends and cycles. In the robustness checks, we show that two alternative methods, satisfying the cointegration test, yield similar patterns in the estimated trends and cycles. The first method is to construct a VECM relying on the Johansen test. The second method entails incorporating additional variables to satisfy the criteria of the Engle-Granger test.

In Panel B, we present the estimated coefficients from regressing per capita GDP on per capita consumption, along with additional time-deterministic terms, using dynamic ordinary least squares (DOLS) with HAC standard errors. The insignificance of the consumption coefficient from "1" and the insignificance of the time deterministic terms lend support to Equation (3).

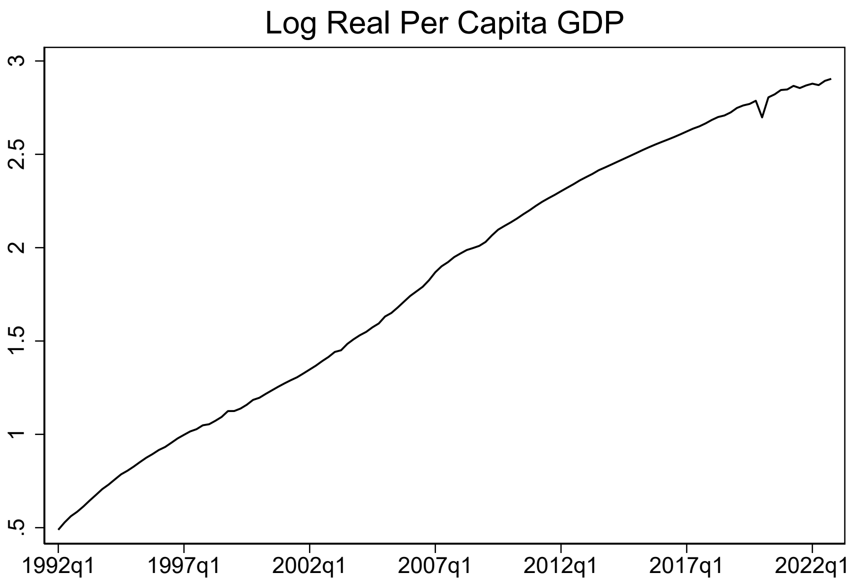
B Appendix: Household Survey Data and C/Y Ratio

The NBS provides data on per capita consumption expenditure at both aggregate and sectoral levels, with annual sectoral data available from 1998. Figure B.1 displays the ratios of real consumption to real GDP for disaggregate sectors from 1998 to 2019. Notably, the Food, Tobacco, and Liquor sector is the only one exhibiting a consistent decline, aligning with the Engel's law that suggests a decrease in the proportion of income spent on food as income rises. The Clothing sector shows an increase in its ratio during the 2000s, followed by a decline, yet its 2019 ratio remains higher than in 1998. Ratios for other sectors have risen over time. With the aggregate data, Figure B.2 presents a stable C/Y ratio. This indicates that although the disaggregate sectoral shares within the total consumption keep changing, the share of total consumption in terms of income is stable.

Meanwhile, we make use of CHIP household survey data. It conducts six waves of surveys in 1989, 1996, 2003, 2008, 2014, and 2019, reporting on the previous year's consumption expenditure and income at the household level. We exclude the 1989 survey due to the requirement for consumption certificates at that time. Figure B.3 illustrates the median, lower, and upper quantiles of the household consumption and income ratio for each surveyed year. In the years 1995 and 2002, we show the ratio of subcategories, including rural, urban, and migrations. The per household consumption and income ratio is stable over time.

Figure 1: **Log Real Per Capita GDP and Annualized Growth Rate**

(a) **Log Real Per Capita GDP**



(b) **Annulized Real Per Capita GDP Growth Rate**

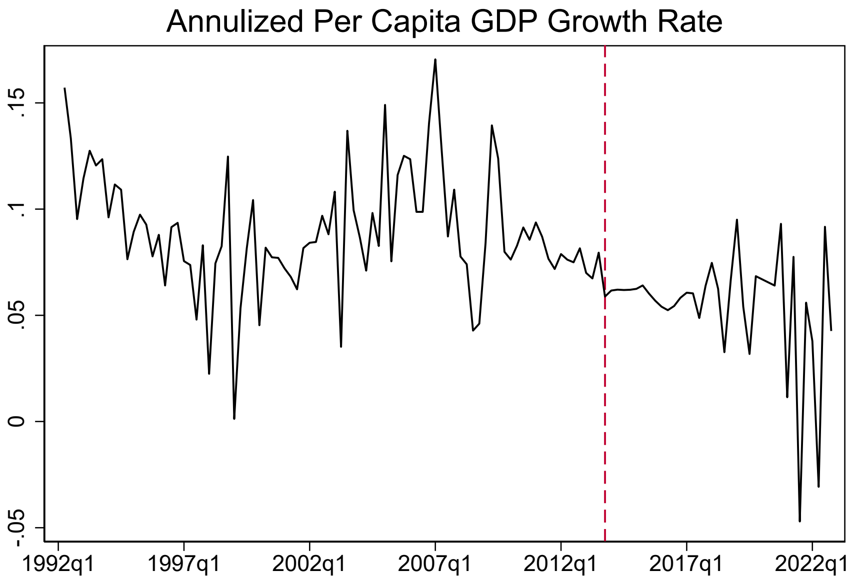
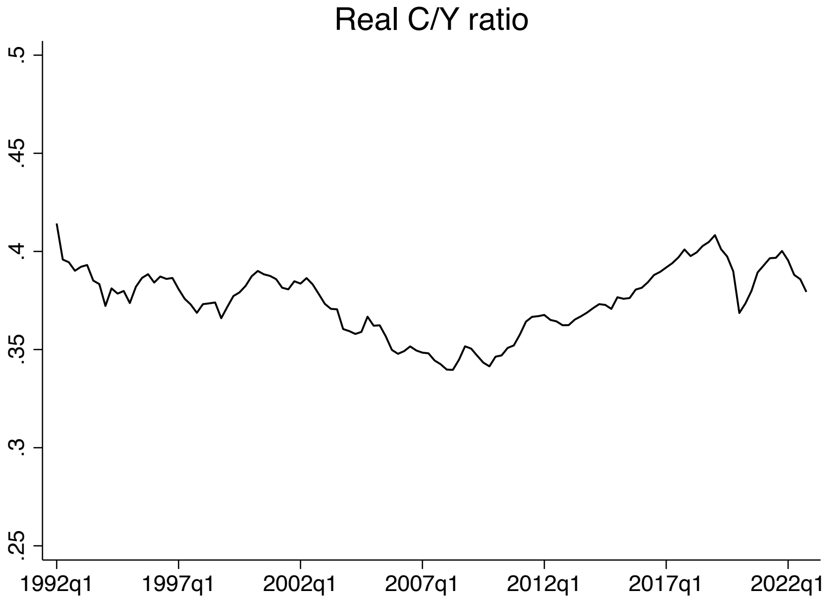


Figure 2: **Consumption to GDP Ratio in China**

(a) **Real C/Y Ratio**



(b) **Nominal C/Y Ratio**

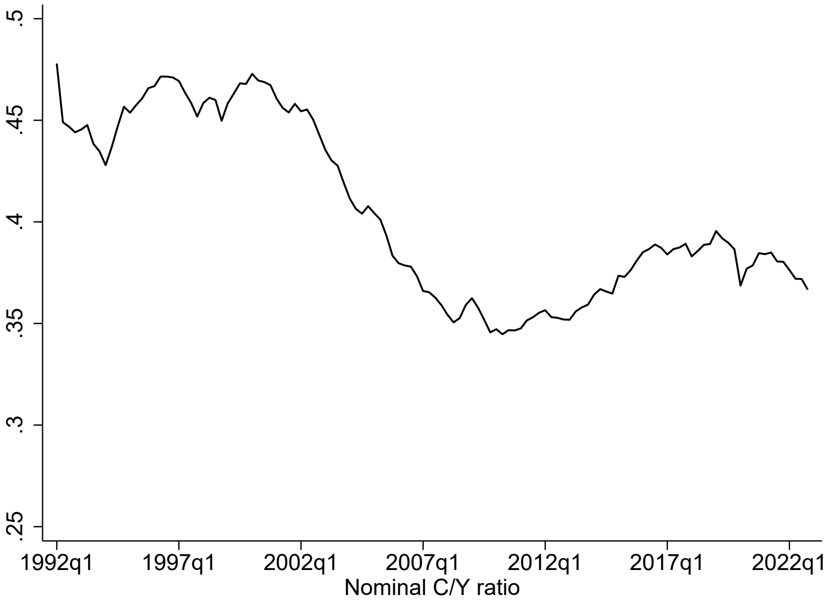
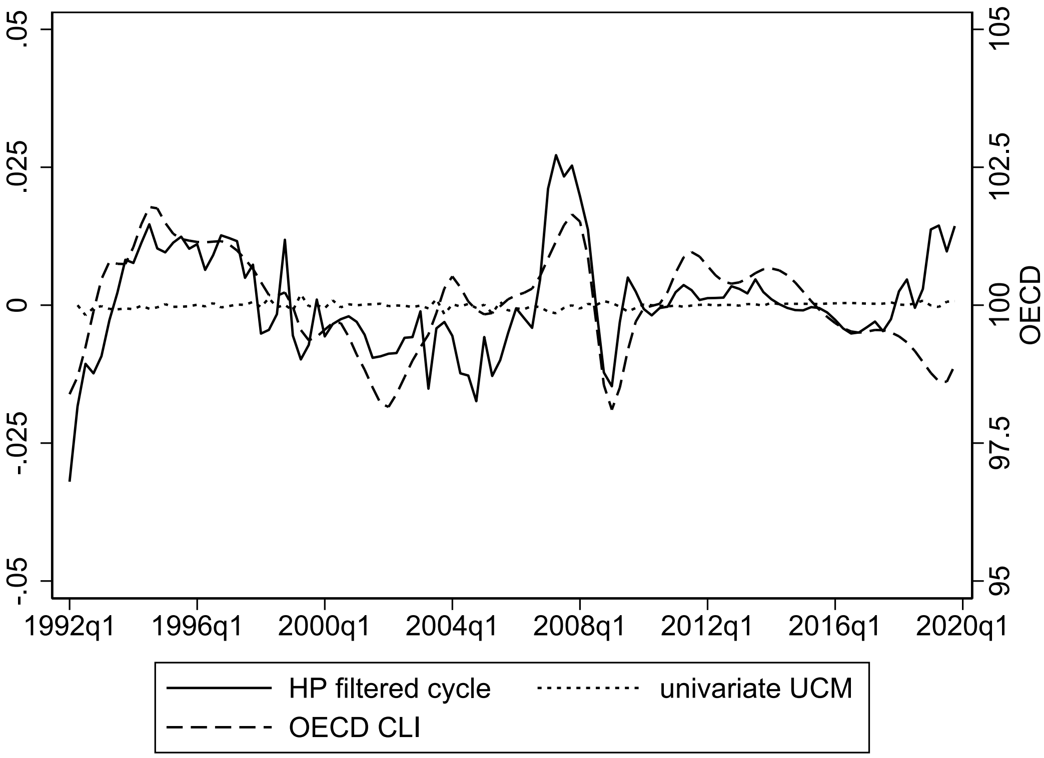


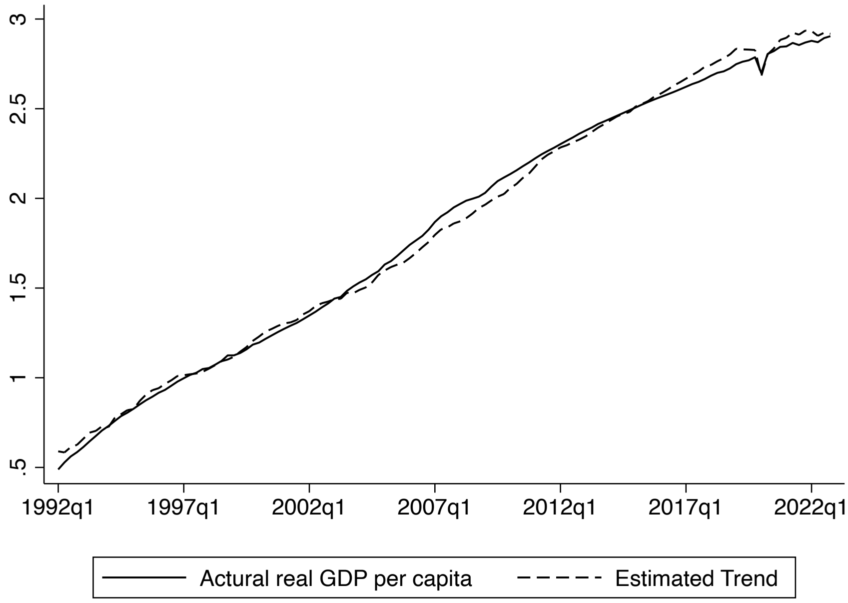
Figure 3: **Estimated Cycle with Existing Approaches**



Notes. The OECD Composite Leading Indicator (CLI), which measures the common component of HP-filtered cycles across multiple macroeconomic time series, is available at https://www.oecd.org/en/data/indicators/composite-leading-indicator-cli.html. The HP filter is estimated using the default smoothing parameter value of 1600. Estimates using alternative parameter values of 400 and 800 show strong correlations with the default, with correlation coefficients of 0.95 for 400 and 0.98 for 800. The UCM specifies that the trend follows a random walk with a drift, while cycles follow an AR(1) process. The OECD CLI is plotted using the right axis with a neutral value of 100, whereas the HP filter and UCM results are plotted using the left axis.

Figure 4: **Actual Log Real Per Capita GDP, Estimated Trend, and Cycles**

(a) **Actual Log Real Per Capita GDP and Estimated Trend**



(b) **Estimated Cycles**

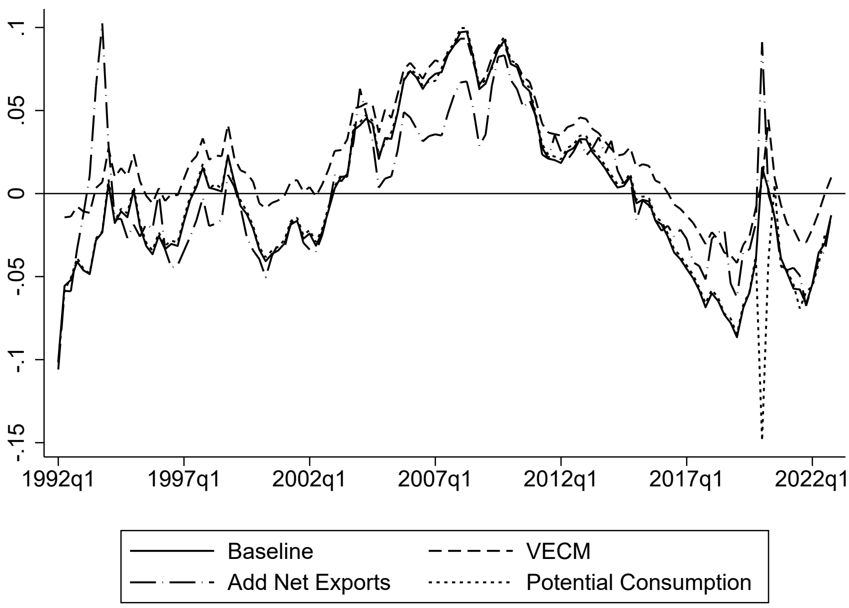


Figure 5: **Estimated Cycles and Major Events**

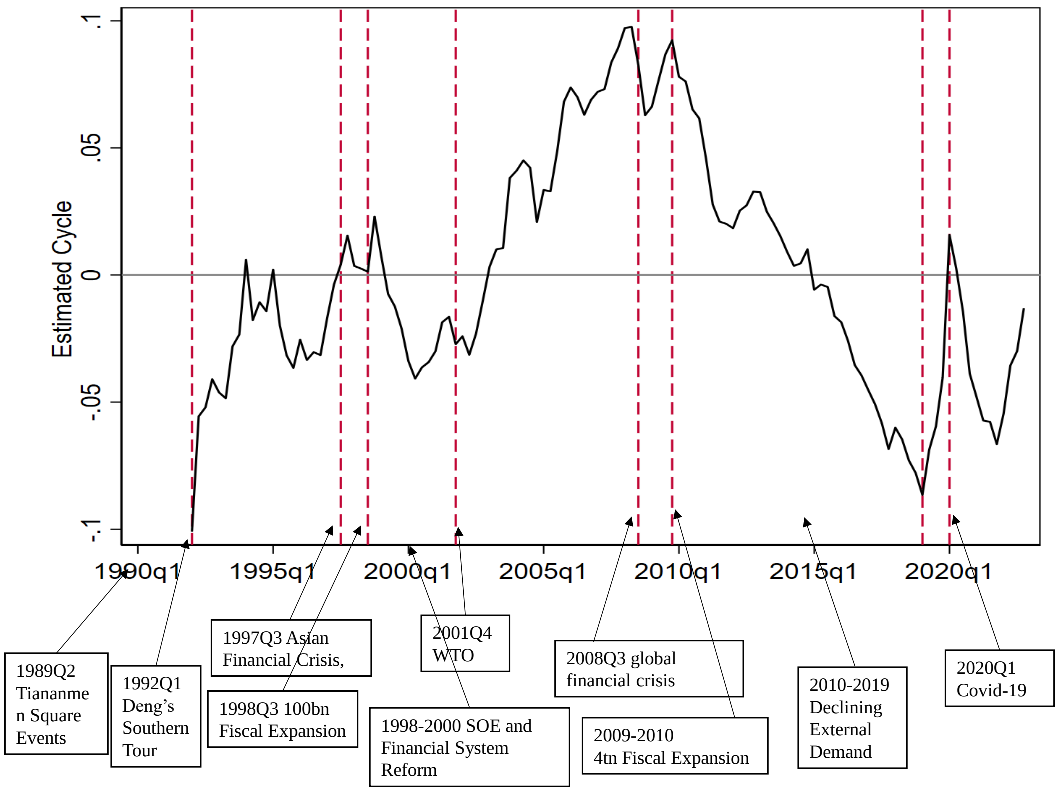
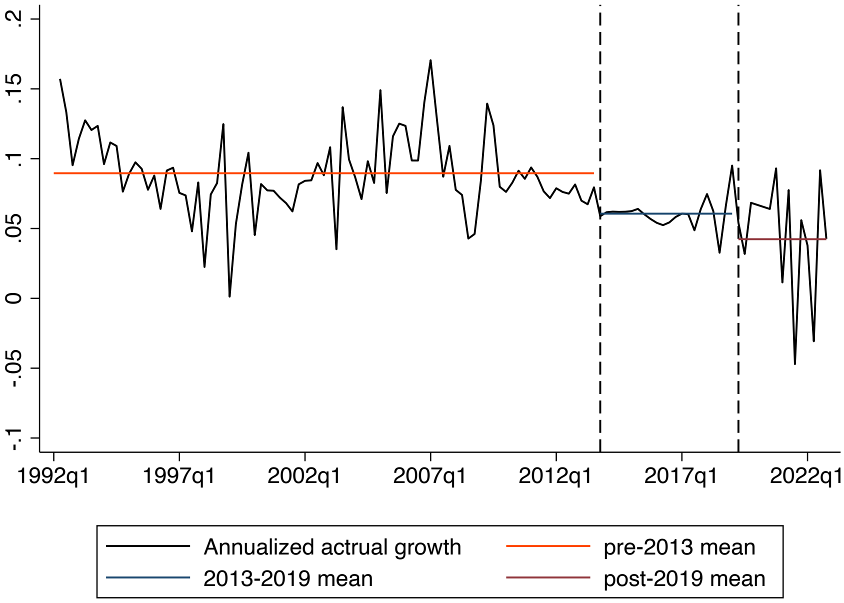


Figure 6: **Actual and Trend Per Capita GDP Growth over Subperiods**

(a) **Actual Per Capita GDP Growth**



(b) **Trend Growth**

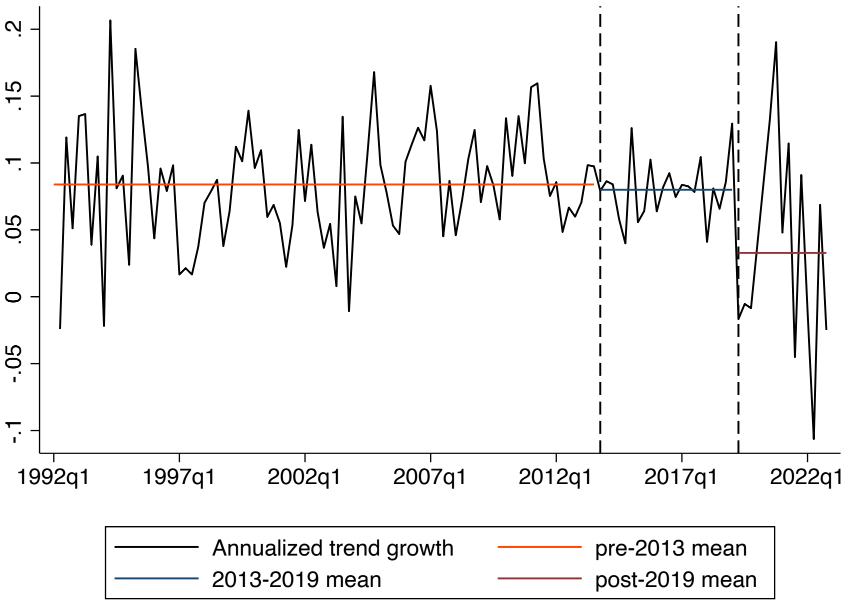
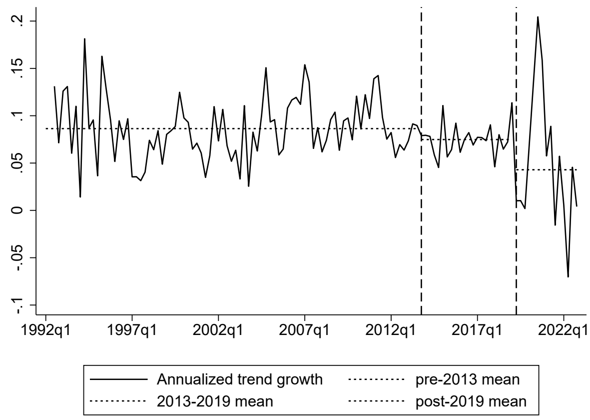
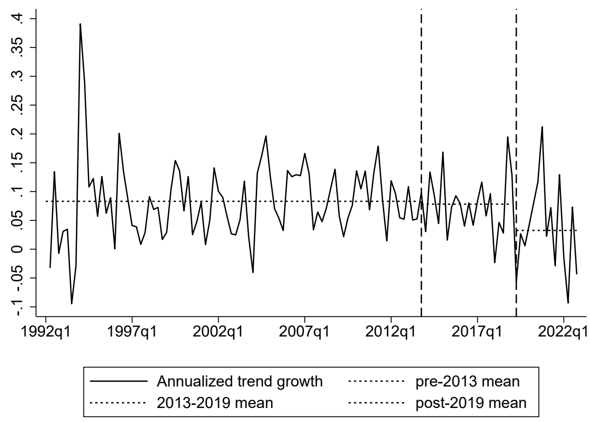


Figure 7: **Trend Per Capita GDP Growth over Subperiods Using Alternative Methods**

(a) **Methods: Applying VECM**



(b) **Methods: Adding Net Exports**



(c) **Methods: Using Potential Consumption**

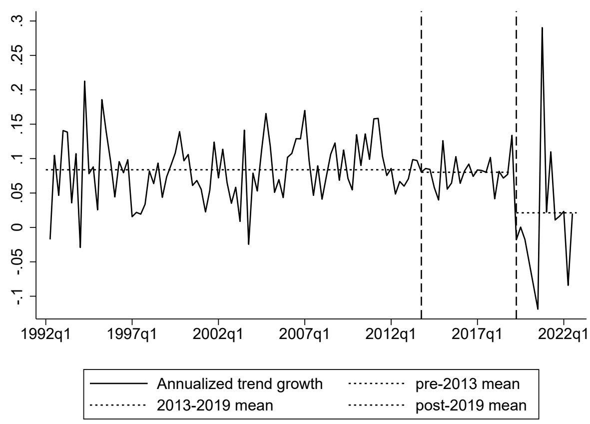
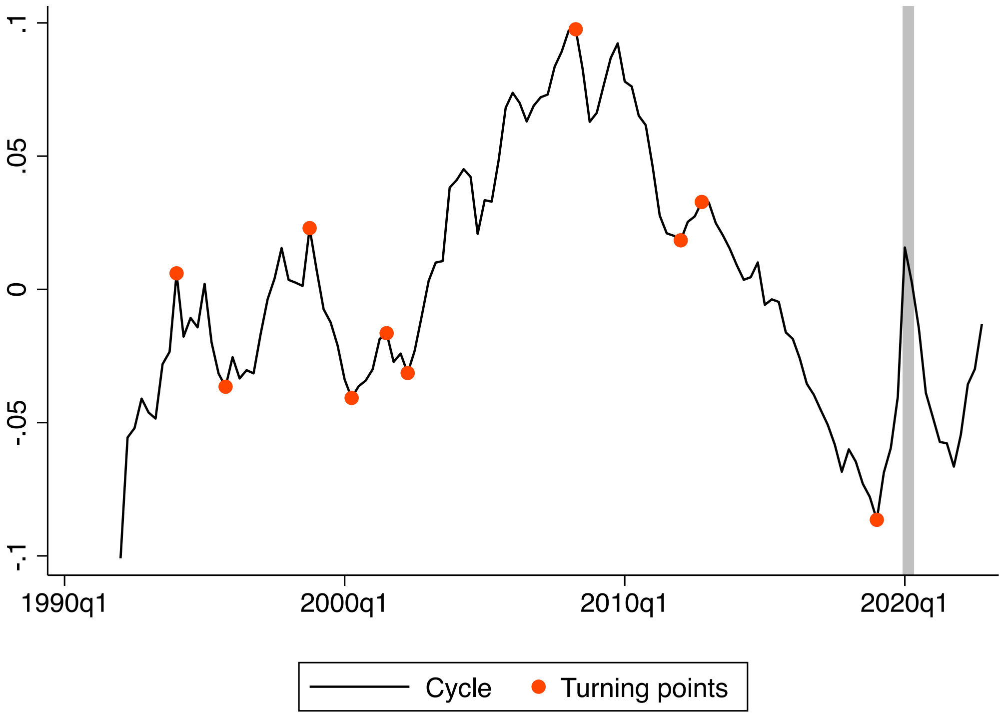


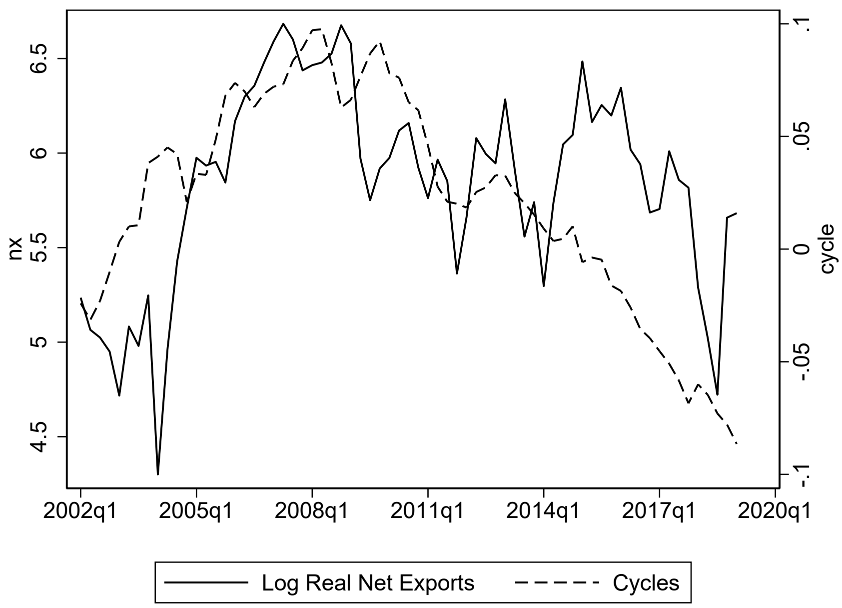
Figure 8: **Estimated Cycles and Turning Points**



Notes. The figure plots estimated cycles and turning points identified using Bry and Boschan's (1971) algorithm. The shaded area is the first two quarters of COVID-19

Figure 9: **Estimated Cycles with Net Exports and FDI**

(a) **Log Real Net Export and Cycles**



(b) **Log Foreign Direct Investment and Cycles**

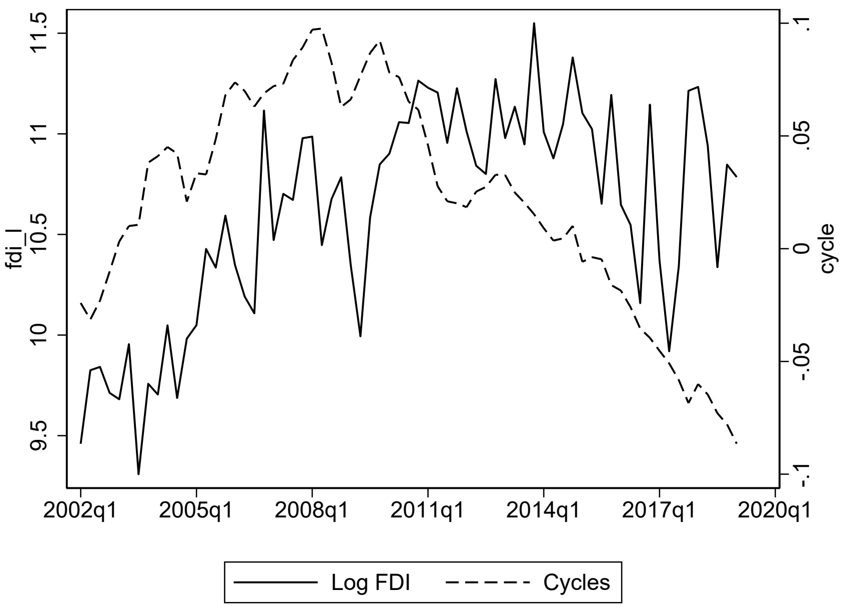
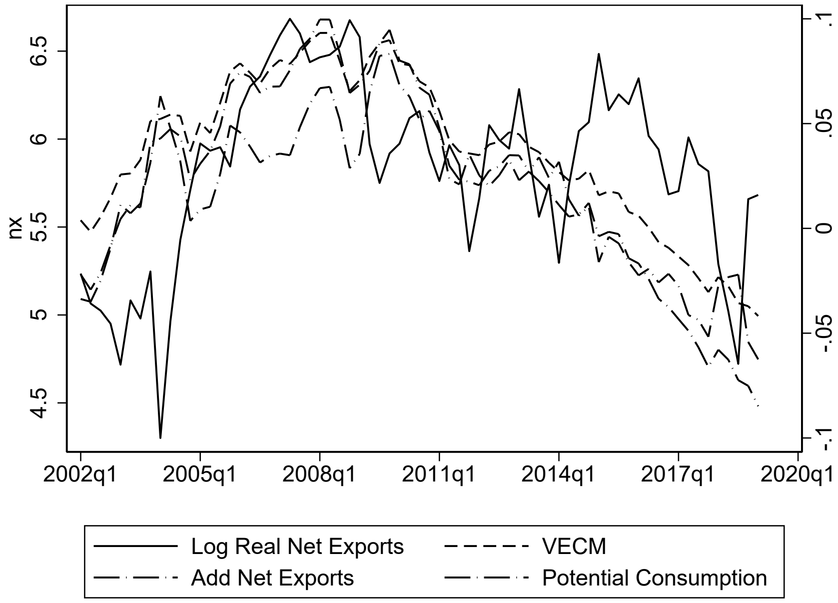


Figure 10: **Estimated Cycles using Alternative Methods with Net Exports and FDI**

(a) **Log Real Net Export and Cycles**



(b) **Log Foreign Direct Investment and Cycles**

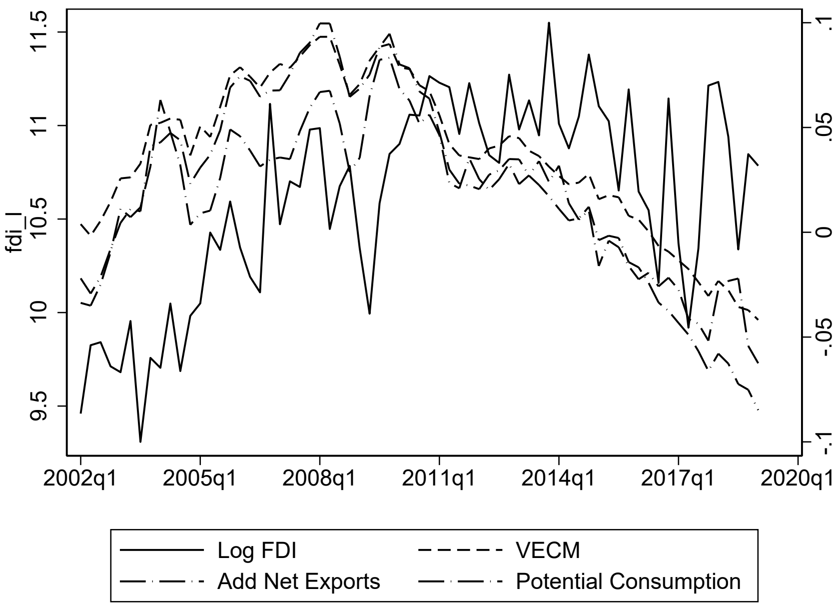
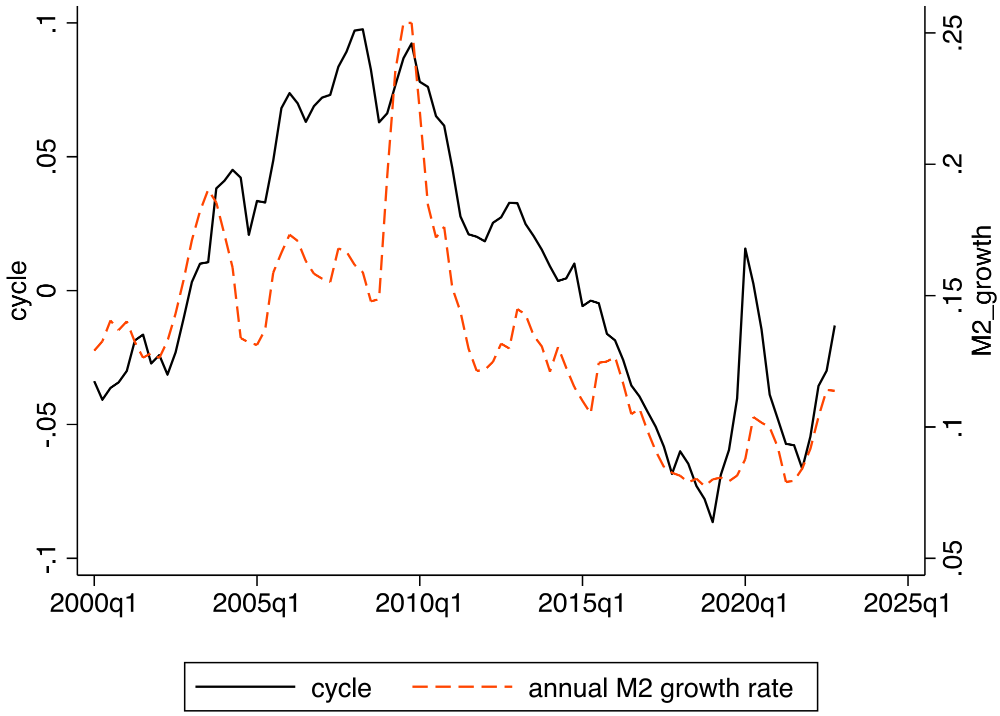


Figure 11: **Estimated Cycle and M2 Growth**



Notes. The correlation between the estimated cycle and annual M2 growth rate is 0.81 from 2000Q1 to 2022Q4

Figure 12: **Estimated Cycles and Filtering Methods**

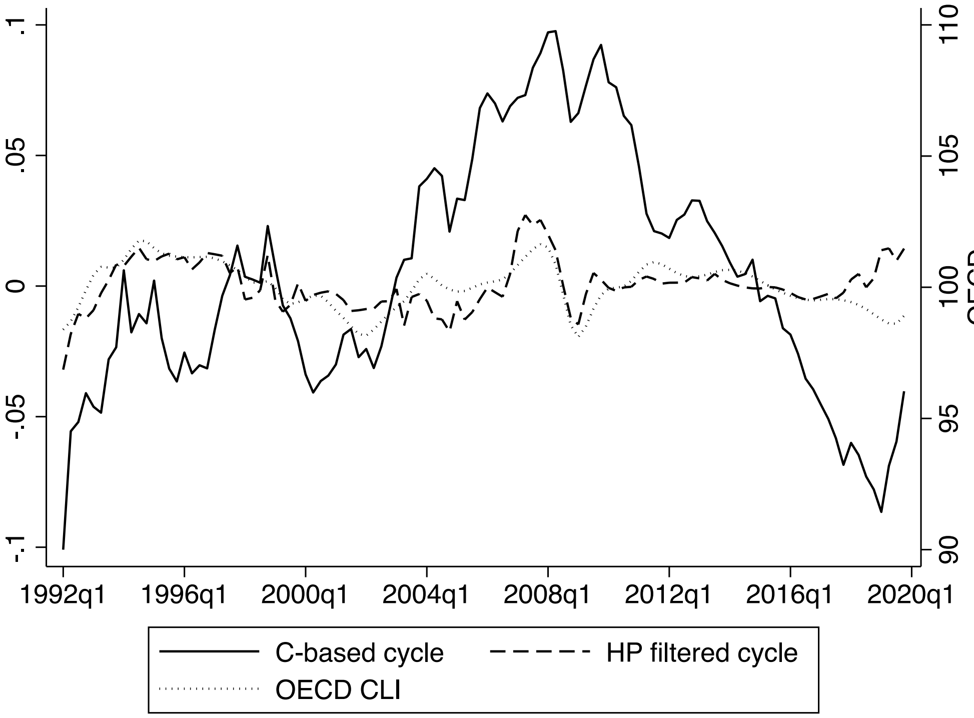
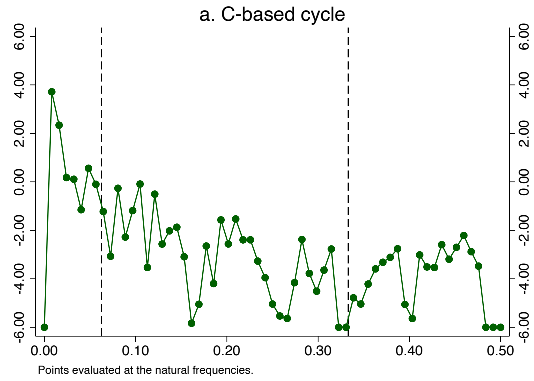
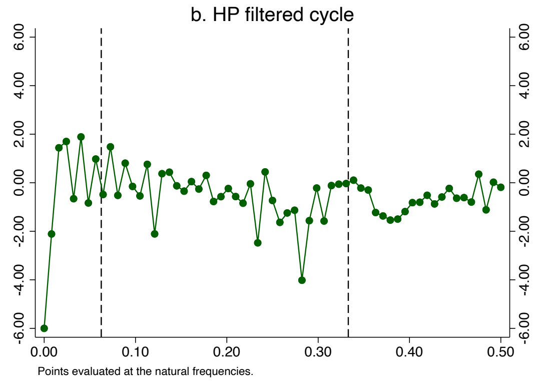


Figure 13: **Spectral Density of Estimated Cycles**

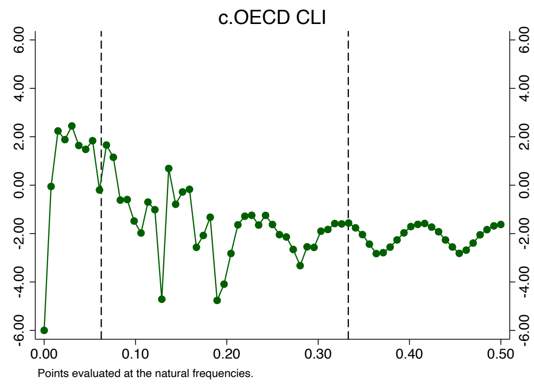
(a) **Consumption-based Methods**



(b) **HP filter**



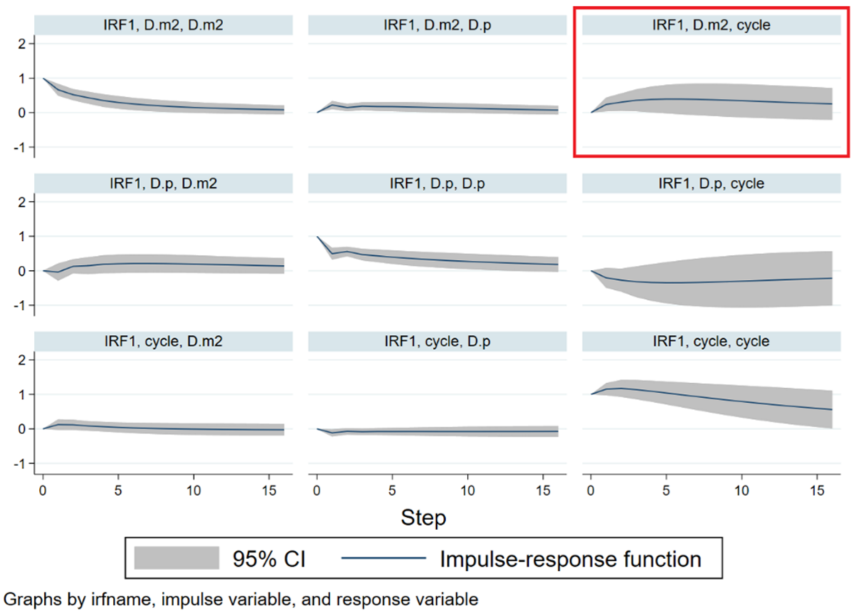
(c) **OECD CLI**



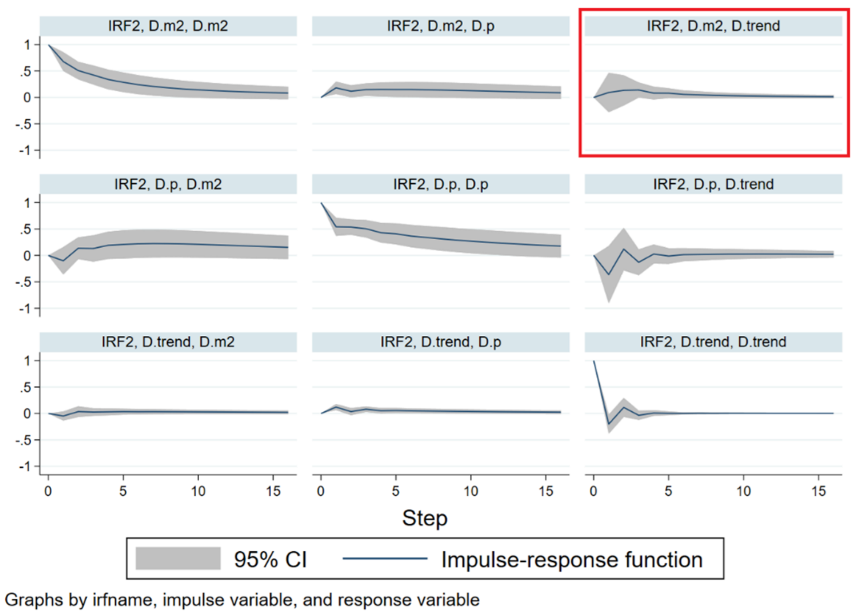
Notes. The dashed lines are the frequency at 6 and 32 quarters, and the area between the two lines is the business cycle frequency band. For all measurements, the fluctuation concentrates on the low-frequency band.

Figure 14: **IRF over the Whole Sample**

(a) **IRF with Output Gap**



(b) **IRF with Potential Output Growth**



Notes. Figure shows that an expansionary monetary policy increases short-term output, but has no impact on long-term potential output growth.

Table 1: **Major Events, Cycle Sign and Direction**

Date	**Event**	**Cycle Sign**	**Cycle Direction**
1989Q2	Tiananmen Square Event	-	$\downarrow$
1992Q1	Deng's Southern Tour	+	$\uparrow$
1997Q3	Asian Financial Crisis	+	$\downarrow$
1998Q3	100bn Fiscal Expansion	-	$\uparrow$
2001Q4	Join WTO	-	$\uparrow$
2008Q3	Global Financial Crisis	+	$\downarrow$
2009-2010	4th Fiscal Expansion	+	$\uparrow$
2010-2019	Declining FDI and Net Export	+/-	$\downarrow$

Notes:
1. Cycle Sign refers to the sign of the estimated economic cycle value, with a "-" indicating that the actual GDP per capita is below potential and a "+" suggesting the opposite.
2. Cycle Direction reflects the impact of events on these cycles: an "$\uparrow$" signifies an increase, while a "$\downarrow$" denotes a decrease.

Table 2: **Correlation between Estimated Cycles and Major Macro Time Series**

Series	Correlation with the estimated cycles		
	1992Q1-1995Q4	1996Q1-2000Q2	2002Q2-2019Q1
Internal			
Fiscal balance (% of nominal GDP)	No data	0.39	0.80
M2 (YoY growth)	0.29	-0.42	0.81
Fixed asset investment (YoY growth)	-0.05	-0.04	0.77
Gross fixed capital formation (YoY growth)	-0.55	0.11	0.54
Domestic Credit (YoY growth)	0.06	-0.06	0.05
Required reserve ratio (%)	No data	-0.04	-0.07
External			
Net export (log)	0.03	0.33	0.45
Nonreserve liability (log)	No data	-0.53	-0.05
Foreign direct investment (log)	No data	0.39	0.01
Net export (YoY growth)	0.54	-0.20	0.17
Nonreserve liability (YoY growth)	No data	-0.05	-0.04
Foreign direct investment (YoY growth)	No data	-0.04	0.76

Table 3: **Correlation between Estimated Cycles and Major Macro Time Series in 2002Q2-2019Q1**

Series	Different Specifications of Cycles		
	VECM	Add Net Exports	Potential Consumption
Fiscal balance (% of nominal GDP)	0.80	0.71	0.80
M2 (YoY growth)	0.81	0.81	0.80
Fixed asset investment (YoY growth)	0.77	0.76	0.76
Gross fixed capital formation (YoY growth)	0.56	0.57	0.54

Table 4: **Root Mean Squared Forecast Errors**

Pseudo-out-of-sample						
A. Full Sample						
h-period	1	2	3	4	6	8
Benchmark	0.006	0.011	0.015	0.018	0.025	0.031
HP filter	0.008	0.018	0.03	0.043	0.084	0.127
OECD CLI	0.008	0.017	0.029	0.042	0.075	0.109
B. Pre-Covid						
h-period	1	2	3	4	6	8
Benchmark	0.004	0.007	0.011	0.013	0.018	0.022
HP filter	0.004	0.009	0.013	0.016	0.022	0.03
OECD CLI	0.004	0.008	0.012	0.017	0.029	0.042

Table A.1: **Random Walk Test**

Dependent Variable	Δc_t					
	(1) OLS	**(2)** Newey-West	**(3)** OLS	**(4)** Newey-West	**(5)** OLS	**(6)** Newey-West
Δc_{t-1}	0.020	0.020	0.097	0.097	0.125	0.125
	[-0.283, 0.322]	[-0.282, 0.321]	[-0.238, 0.431]	[-0.244, 0.437]	[-0.215, 0.465]	[-0.201, 0.452]
Δc_{t-2}			-0.067	-0.067	-0.049	-0.049
			[-0.384, 0.250]	[-0.417, 0.283]	[-0.395, 0.296]	[-0.400, 0.302]
Δc_{t-3}					-0.191	-0.191
					[0.517, 0.134]	[-0.451, 0.068]
Δy_{t-1}	-0.344	-0.344	-0.424	-0.424	-0.481	-0.481
	[-0.772, 0.083]	[-0.840, 0.151]	[-0.905, 0.058]	[-1.021, 0.173]	[-0.975, 0.014]	[-1.051, 0.090]
Δy_{t-2}			0.211	0.211	0.175	0.175
			[-0.230, 0.651]	[-0.074, 0.495]	[-0.319, 0.669]	[-0.160, 0.510]
Δy_{t-3}					0.251	0.251
					[-0.203, 0.705]	[-0.056, 0.558]
No. of Obs	122	122	121	121	120	119

Notes:
1. 95% confidence intervals are reported in parentheses.
2. Columns 1, 3, and 5 report OLS results with one, two, and three lags, respectively.
3. Columns 2, 4, and 6 report results with Newey-West standard errors with one, two, and three lags, respectively.

Table A.2: **Cointegration Test & DOLS Regression**

Panel A. Cointegration								
	Johansen Test					Engle-Granger Test	ADF test for C/Y	
Specification	N	RC	C	RT	T	-	Drift	Trend
Cointegration	✓	✓	✓	✓	×	×	✓	×

Panel B. DOLS with HAC standard errors		Number of Observations: 121
Independent Variable	t	c_t
y_t	0.001	0.945
95% CI	[-0.005, 0.008]	[0.621, 1.268]

Notes:

1. "✓" means the test results suggest cointegration, and "×" means the test results suggest no cointegration relationship.

2. For the Johansen test, "N" stands for specification with no constant or trend, "RC" stands for specification with restricted constant, "C" stands for specification with unrestricted constant, "RT" stands for specification with restricted trend, and "T" stands for specification with unrestricted trend.

Figure B.1: **Sectoral C/Y Ratio from NBS Household Survey**

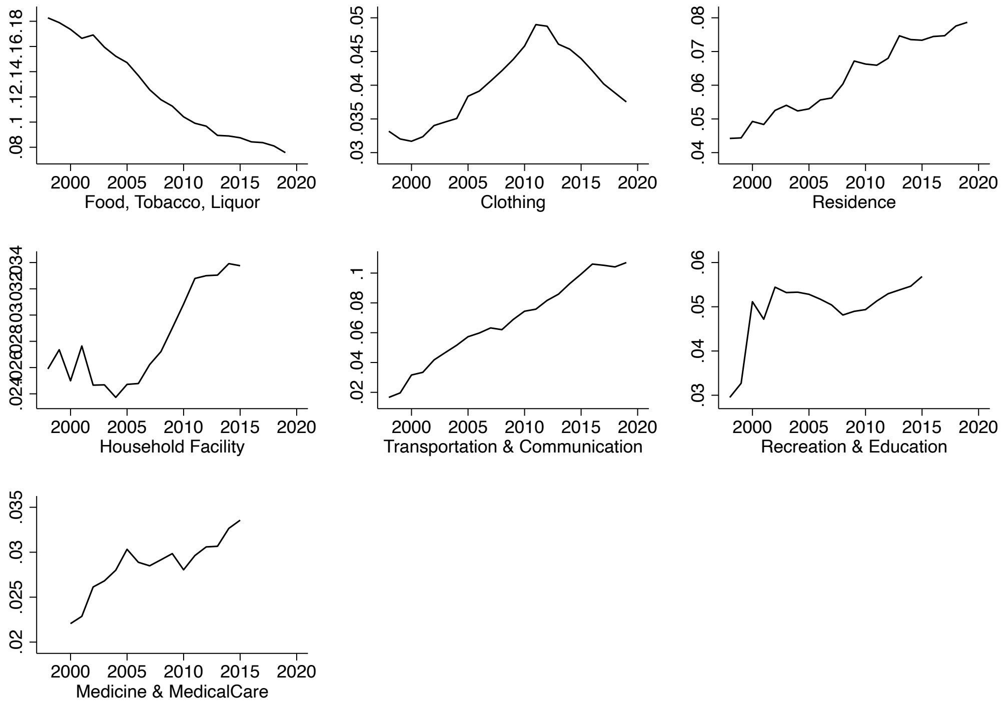


Figure B.2: **Per Capita C/Y Ratio from NBS Household Survey**

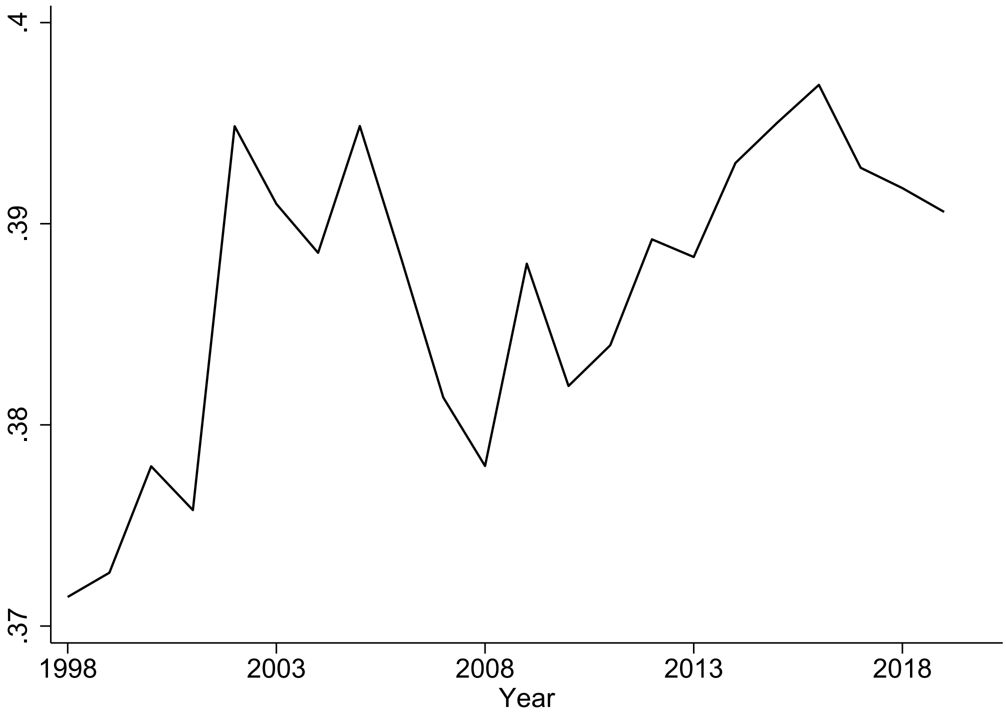
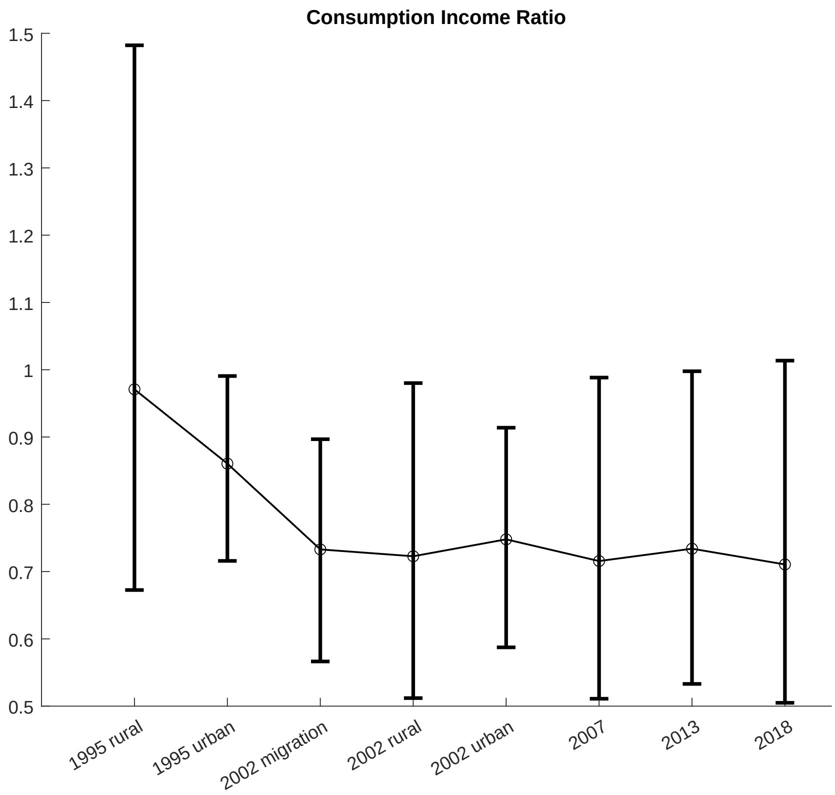


Figure B.3: **Per Household C/Y Ratio from CHIP Household Survey**



Notes. The figure shows the ratio between per household real consumption and real income collected from the Chinese Household Income Project (CHIP). The endpoints of vertical lines are the lower and upper quantiles, and the middle point is the median of each subsample. In years 1995 and 2002, we show the ratio of subcategories, including rural, urban, and migrations. The per household consumption and income ratio is stable over time.