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Recovering from COVID

ABSTRACT The COVID business cycle was unique. The recession was by far the deepest and shortest in the US postwar record and the recovery was remarkably rapid. The cycle saw an unprecedented reallocation of employment and consumption away from in-person services toward goods that can be consumed at home and outdoors. This paper provides a simple empirical model that attributes these and other anomalies in real economic activity to a single unobserved shock. That shock is closely connected to COVID deaths and diminishes in importance over the expansion, consistent with self-protective measures like masking, pandemic fatigue, and eventually the availability of the vaccine. The COVID shock and anomalous COVID dynamics largely disappeared by late 2022. It appears that macrodynamics have returned to normal and that the structural shifts wrought by the COVID-19 pandemic have had limited effects on the underlying economic trends of key indicators, despite notable changes like the prevalence of remote work. The greatest macroeconomic legacy of the COVID business cycle has been on the national debt.

Five years ago from the date of the Spring 2025 *Brookings Papers on Economic Activity (BPEA)* Conference, the economy was collapsing at a breathtaking pace. In New York City, deaths from COVID-19 were growing exponentially, and the virus, about which much was still being

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learned, was spreading across the United States. Much of the country was in lockdown. Millions of workers had been laid off: Initial weekly claims for unemployment insurance, which normally range between 200,000 and 300,000 and which peaked around 650,000 during the financial crisis recession, were nearly 6 million in the week ending March 28, 2020. As uncertainty mounted and consumers stayed home, real consumption fell by 6.6 percent in March and another 11 percent in April.[1] Closer to home, the *BPEA* conference was, for the first time, held virtually using a technology new to most participants, a harbinger of broad social and technological changes to come.

Compared to other business cycles, the COVID recession was highly unusual. The National Bureau of Economic Research–dated recession lasted only two months, by far the shortest on record (NBER 2023). The initial recovery was nearly as rapid as the collapse: In two months following the April trough, real Personal Consumption Expenditures (PCE) grew by 14 percent and the unemployment rate fell 3.8 percentage points.[2] The recession and recovery were associated with an unprecedented sharp shift in consumption away from in-person services like restaurants and toward goods, especially goods that can be consumed at home and outdoors.

Economists responded in real time, producing a high-quality body of work documenting the collapse and assessing the economic and public health programs launched in response; see, for example, the two issues of the *BPEA* papers in the summer and fall of 2020 devoted to the COVID-19 pandemic. Much less, however, has been written about the equally unusual recovery.

The purpose of this paper is to provide a comprehensive assessment of macroeconomic dynamics over the course of the COVID business cycle. To do so, we examine the joint behavior of 128 monthly and 23 additional quarterly economic time series, focusing on measures of real economic activity. It has long been recognized that, prior to the COVID-19 pandemic, the comovements of macroeconomic time series are well described by a small number of common macroeconomic factors in a dynamic factor model (DFM) (Sargent and Sims 1977; Forni and Reichlin 1998; surveyed in Stock and Watson 2016). A DFM therefore provides a tractable starting point for studying the behavior of the economy over this period.

1. Bureau of Economic Analysis (BEA), "Real Personal Consumption Expenditures," retrieved from FRED series PCEC96.

2. Bureau of Labor Statistics (BLS), "Unemployment Rate," retrieved from FRED series UNRATE.

We reach four main conclusions.

First, the COVID business cycle was unprecedented in the postwar record in the depth and speed of the collapse, its sectoral shifts in consumption, production, and employment, the speed of the recovery, and—unlike all other expansions since 1960—the return of GDP to its pre-recession trend. A pre-COVID DFM utterly fails to describe this episode, even getting the sign of the changes in many variables wrong. This stands in contrast to the well-established finding that DFMs provide a reliable description of postwar US business cycle dynamics, which, with the additional assumption of invertibility, implies that the shocks driving business cycles are captured by (spanned by) the factors. For example, a DFM with large conventional shocks, but no new factors, quantitatively explains the financial crisis recession (Stock and Watson 2012). This time *was* different.

Second, this anomalous behavior can be traced to a single novel aggregate shock, the COVID shock. Although we estimate it using only economic data, the COVID shock traces out the waves of COVID deaths. It diminishes as self-protective measures such as masking are adopted and pandemic fatigue sets in during the summer and fall of 2020, and the shock largely disappears once individuals either are vaccinated or have decided against vaccination. Remarkably, the diminishing link from deaths to the COVID shock and its timing matches the diminishing behavioral effect from deaths to reduced contacts estimated by Atkeson, Kopecky, and Zha (2024) solely from epidemiological data. From March 2020 through December 2021, the single COVID shock explained 95 percent of the variation in the unemployment rate, 97 percent of the variation in establishment employment growth, 75 percent of the variation in personal consumption, 73 percent of the variation in consumption of services, 37 percent of the variation in consumption of durables, and 56 percent of the variation in housing starts. It is sometimes said that the COVID recession was comprised of many shocks—uncertainty, aggregate demand, labor supply, reallocation, and perhaps others. In our empirical model, there is just one shock—the COVID shock—to which all these macroeconomic channels responded.

Third, although the post-COVID period is too short and too recent to draw firm empirical conclusions, preliminary evidence suggests that the pre-COVID macroeconomic dynamics have returned or, more precisely, conventional macrodynamics never disappeared or changed, they were just masked by the massive COVID shock. As the COVID shock dissipated, conventional dynamics resurfaced, and by 2023 the expansion largely looked like a normal expansion.

Although there do not seem to be lingering COVID effects on business cycle dynamics, an open question is whether the COVID-19 pandemic and the changes it induced have had long-term effects on core macroeconomic measures such as consumption, investment, labor force participation, and productivity. The COVID recession accelerated remote work, drove a persistent increase in the number of new businesses, increased attention to supply chains, and changed the labor force through COVID deaths, long COVID, and accelerated retirements. It also led to a persistent increase in the debt-to-GDP ratio. At the moment, however, growth rates of macroeconomic aggregates are largely what they were pre-COVID.

Fourth, the root problem was the COVID shock, and the most effective macroeconomic policy was to diminish, then extinguish that shock directly, which was ultimately accomplished by Operation Warp Speed and the development and free distribution of the vaccine. Within a year of the vaccine's introduction, the economy was in most regards back to normal. The Coronavirus Aid, Relief, and Economic Security (CARES) Act of March 2020 provided social insurance, especially in the extensions and innovations in unemployment insurance benefits and preserving job matches. The stimuli later in the pandemic, however, largely addressed the aggregate demand symptoms of the COVID shock. By the time the American Rescue Plan (ARP) and its fiscal year 2021 stimulus of $1.2 trillion (5.0 percent of GDP) were enacted in March 2021,[3] vaccine distribution was in full force, the COVID shock was waning, and the unemployment rate stood at 6.1 percent. This stimulus supercharged the remaining recovery but added significantly to the national debt and contributed to the post-COVID inflation.

I. Review of the COVID Recession and Recovery

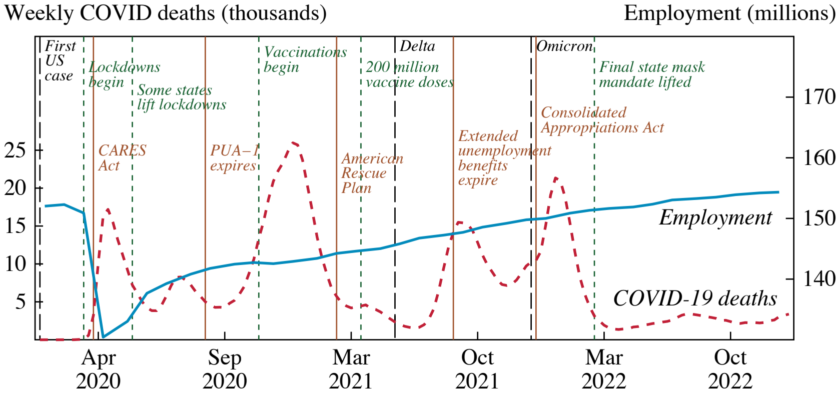
I.A. The COVID Timeline

The 2019 novel coronavirus (COVID-19) originated in Wuhan, China, with initial cases reported in early December 2019.[4] As shown in the COVID timeline in figure 1, the first confirmed US case of COVID-19 was detected on January 20, 2020. The SARS-CoV-2 virus spread rapidly, with

3. International Monetary Fund, "Nominal Gross Domestic Product for United States," retrieved from FRED series NGDPSAXDCUSQ; and Congressional Budget Office (2021).

4. Unless otherwise noted, dates and information in this section are taken from the David J. Sencer Centers for Disease Control and Prevention (CDC) Museum, "CDC Museum COVID-19 Timeline," https://www.cdc.gov/museum/timeline/covid19.html#; CDC, "Surveillance and Data Analytics," https://www.cdc.gov/covid/php/surveillance/index.html; CEA (2022); and Tax Policy Center (2024). See also The COVID Crisis Group (2023) and Macedo and Lee (2025) for more fulsome narratives.

Figure 1. The COVID-19 Pandemic Timeline



Source: CDC; BLS; and authors' illustration.
Note: Vertical lines indicate macroeconomic policies (solid), virus variants (long-dashed), and major events during the pandemic (dashed).

lockdowns ordered in Wuhan on January 23 and in Italy on February 23. On March 11, the World Health Organization declared COVID-19 a pandemic, and on March 13 the US administration declared a national emergency. Tests for COVID-19 were scarce in the first few months of the pandemic; rapid testing was not authorized until late August 2020 and even then tests were rationed. The virus spread unevenly. With some exceptions, such as air travel and transportation hubs, policies on nonpharmaceutical interventions (NPIs) were left to the states with the Centers for Disease Control and Prevention (CDC) issuing guidance but not regulations or orders. Accordingly, state NPIs, such as masking mandates, remote schooling, and so forth, varied substantially. Some states started lifting restrictions in late April 2020 while others kept them in place much longer; the last state to lift its universal indoor masking mandate, Hawaii, did so in March 2022.

On December 11, 2020, the Food and Drug Administration issued an emergency use authorization for the Pfizer-BioNTech COVID-19 vaccine, the first such authorization, less than one year after the SARS-CoV-2 virus was initially sequenced and eight months after the start of Operation Warp Speed, the initiative to develop the vaccine. Vaccine administration commenced on December 14, 2020, and expanded with supply; by the end of May 2021, half of the US population had received at least one dose. Vaccine hesitancy was widespread, however, so uptake slowed: By June 2022, only 67 percent of the population was fully vaccinated. Throughout the pandemic, the virus mutated, typically with increasingly transmissive variants superseding the prior dominant strain; these include the Gamma variant (January 2021), the Delta variant (June 2021), and the Omicron variant (November 2021). Infections and deaths occurred in waves, due in part to new variants, changes in mandated NPIs, and changes in self-protective behavior. Because of incomplete vaccination, deaths from the Delta and Omicron variants were high, with 475,000 COVID deaths occurring between August 2021 and December 2022. By mid-February 2024, an estimated 1.19 million Americans had died from COVID. Atkeson and Kissler (2024) estimate that through that date, the vaccine saved approximately 800,000 US lives, the sum of which is remarkably close to the March 16, 2020 estimate of 2.2 million US deaths from an uncontrolled COVID-19 pandemic made by Ferguson and others (2020).

The combination of lockdowns, other mandatory NPIs, self-protective behavior, and widespread uncertainty resulted in a collapse of economic activity starting in the second week of March 2020 and accelerating in the third week of March as schools closed and businesses laid off workers. From its peak on February 19 to its trough on March 23, the S&P 500 fell by 32 percent. From February 18 through March 16, economic uncertainty, as measured by the Chicago Board of Options Exchange's Volatility Index (VIX), more than quintupled, reflecting deep unknowns about the virus and its economic consequences. Initial claims for unemployment insurance rose from 273,000 for the week ending March 14 to 2,914,000 for the week ending March 21, then to 6,137,000 for the week ending April 4, an order of magnitude greater than its peak weekly rate during any previous postwar recession.[5]

Confronted with this collapse, fiscal and monetary authorities took extraordinary measures. In March 2020, the Federal Reserve reduced the federal funds rate by 150 basis points to 0–0.25 percent and took additional emergency measures to ensure liquidity; see Kashyap and others (2025) and Gagliardone and Gertler (2024) for a quantification of monetary policy accommodation. Congress authorized three rounds of direct payments or tax rebates to individuals: up to $1,200 for adults in the CARES Act, signed on March 27, 2020; $600 in the December 27, 2020 Consolidated Appropriations Act; and up to $1,400 per person (including dependents) in the March 11, 2021 ARP. Between executive and legislative actions, federal

5. Employment and Training Administration, "Initial Claims," retrieved from FRED series ICSA.

expenditures and tax expenditures through COVID-related programs totaled \$6.8 trillion through February 2025.[6]

I.B. The COVID Recession and Recovery Compared to Prior Business Cycles

The COVID business cycle was unusual in many ways. We collect these key features into five stylized facts:

1. The recession was unusually steep and short. It was the deepest postwar recession, as measured by the peak-to-trough rise in the unemployment rate, and it was by far the shortest contraction in the 170-year NBER record, lasting only two months (the next shortest is the seven-month contraction starting in March 1919).
2. Sectoral dispersion during the cycle was unprecedented in the postwar record. Normally, services consumption and employment are less cyclical than goods, especially durable goods. In the COVID recession, however, services collapsed and took years to recover fully, whereas, after the initial contraction in March and April 2020, real consumption of durables soared and by June 2020 exceeded its February value by 9.4 percent.[7]
3. The COVID cycle was accompanied by strongly expansionary fiscal policy: From the first to the third quarter of 2020, the debt-to-GDP ratio increased by 17.4 percentage points to 124 percent, a cyclical increase exceeded only during the financial crisis recession and early recovery.[8]
4. The dynamics of the recovery were highly unusual. During the first six months after the April 2020 trough, the recovery was extraordinarily rapid. Establishment employment grew by 19 percent at an annual rate, compared to a 1 percent mean for this window in prior recoveries after 1960.[9] This was followed by a slower phase through February 2021, in which growth rates were comparable to historical

6. Committee for a Responsible Federal Budget, "COVID Money Tracker," https://www.COVIDmoneytracker.org/, updated on February 12, 2025.

7. BEA, "Real Personal Consumption Expenditures: Durable Goods," retrieved from FRED series PCEDGC96.

8. Office of Management and Budget and Federal Reserve Bank of St. Louis, "Federal Debt: Total Public Debt as Percent of Gross Domestic Product," retrieved from FRED series GFDEGDQ188S.

9. BLS, "All Employees, Total Nonfarm," retrieved from FRED series PAYEMS; and authors' calculations detailed in replication files.

norms, then by a faster phase starting in March or April 2021 through the end of 2021. By the end of 2021, the economy was near or at full employment.

5. The COVID business cycle was the first trend-stationary business cycle since 1960, that is, it was the first in which the level of GDP reattained its pre-recession trend.

The first four stylized facts are evident in figure 2, which plots the logarithms of selected activity variables for the COVID cycle and for the previous seven business cycles, relative to their value at the NBER business cycle peak. All series exhibit a precipitous but very short collapse in March and April, which turns around in May (the first stylized fact).

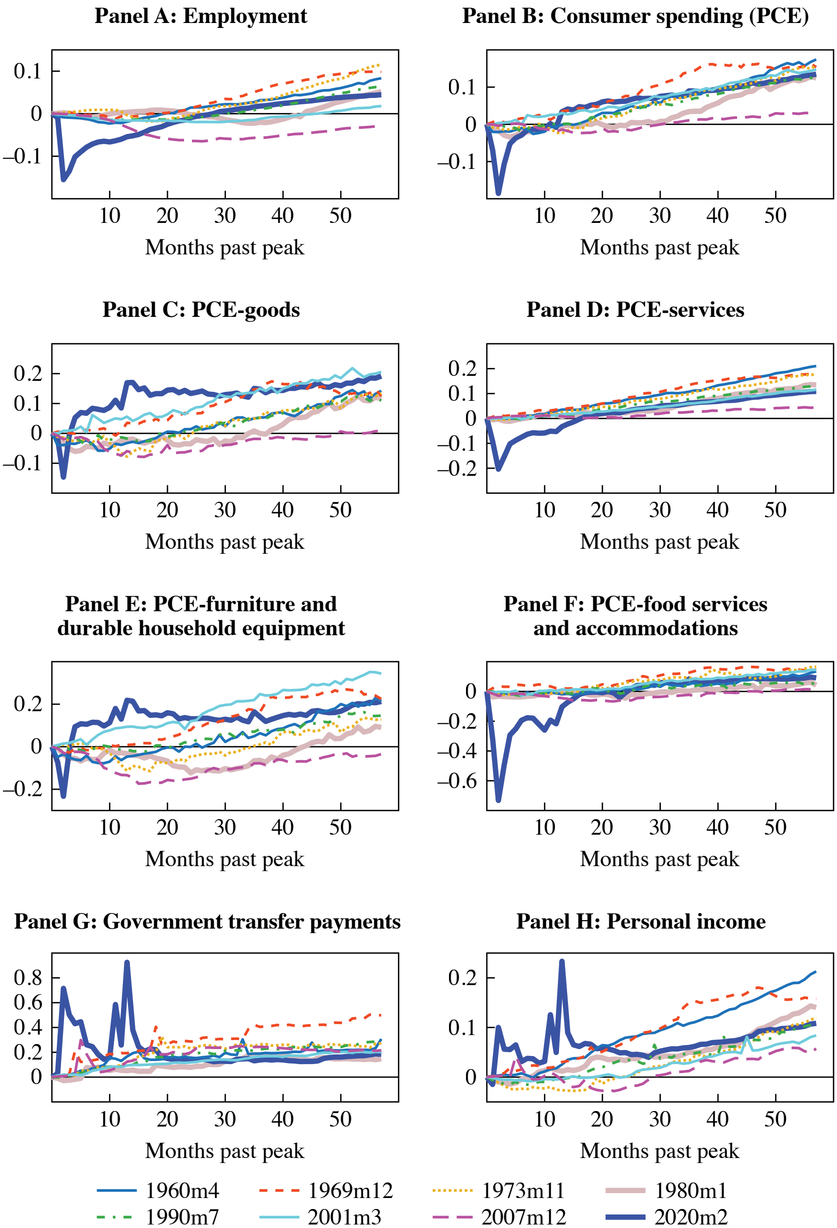
The second stylized fact—the unprecedented sectoral shift—is evident in figure 2, panels C–F, and in the full set of figures in the online appendix (also see CEA 2022). Because of voluntary and mandated self-protection measures, consumption shifted sharply from high-contact services such as dining out, air travel, nonurgent health care, and concerts to goods that can be used at home or outdoors. High-contact services, such as food services and accommodations (panel F) and health care, fell sharply and recovered slowly, both because of a fall in demand and a decline in supply (e.g., low-density restaurant seating).[10] In contrast, demand for goods surged after an initial contraction, both durable goods, such as recreational equipment and furniture, and nondurable goods, such as food at home. Services that were complementary to home consumption of goods—in particular, transportation and warehousing—surged as consumption shifted from in-person to at-home. The run on nondurable home goods and off-premises alcoholic beverages in March 2020 is also clearly visible.

Figure 3 provides another visualization of the unprecedented dispersion of cyclical responses during the COVID recession and early expansion. The figure plots the 5 percent, 25 percent, 50 percent, 75 percent, and 95 percent percentiles of the cross-section distribution of 128 monthly time series from 1960 to 2024, where the data series are generally monthly growth rates, standardized using pre-COVID sample means and standard deviations and, if the series is countercyclical, multiplied by −1 (for more on the data, see section III.A).

Figure 3, panel A, shows the pre-COVID period. Recessions are easily recognized as a negative shift in the cross-section distribution leading to a downward shift in the quantiles plotted in the figure. Also evident is an

10. BEA, "Real Personal Consumption Expenditures: Services: Health Care," retrieved from FRED series DHLCRX1Q020SBEA.

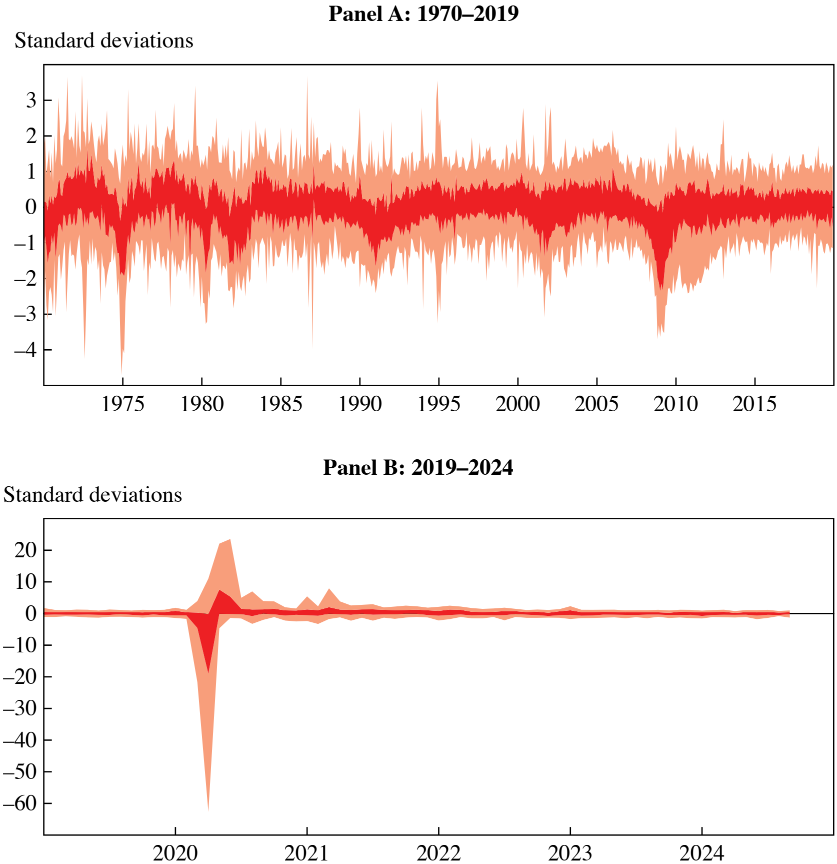
Figure 2. Aggregate Time Series over the COVID and Prior Business Cycles



Source: Authors' calculations.

Note: Lines are logarithms of the indicated series, relative to its value on the NBER-dated peak, over all US business cycles since 1960. The COVID business cycle data are bolded. The business cycles starting in January 1980 and July 1981 are combined.

Figure 3. Time Series of Cross-Section 25–75 Percent (Dark) and 5–95 Percent (Light) Quantiles of 128 Monthly Activity Variables



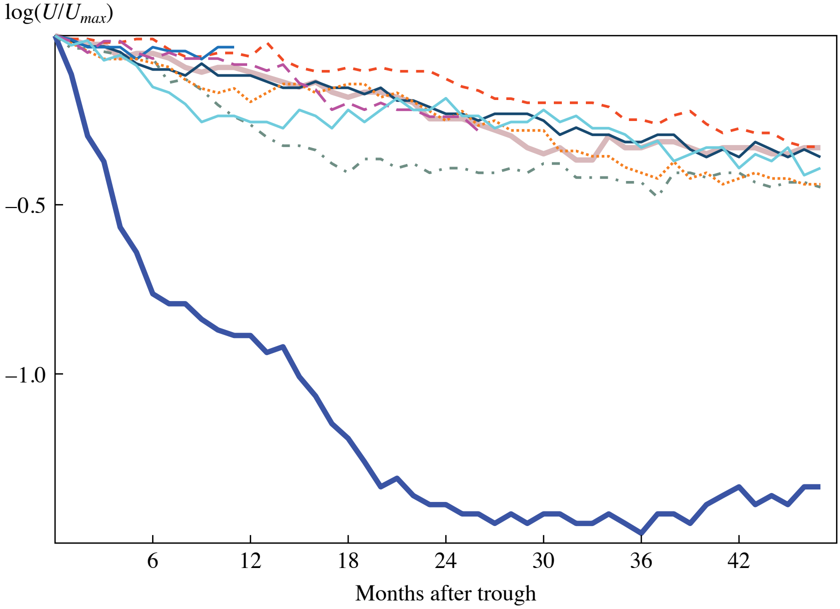
Source: Authors' calculations.
Note: Units are pre-COVID standard deviations. Countercyclical series such as the unemployment rate are multiplied by –1.

increased negative skew in the distributions during recessions that leads the lower quantiles to shift down more than the upper quantiles.[11]

Figure 3, panel B, shows the monthly quantiles over the COVID period. The COVID recession also exhibits a negative shift and skew, but the scale of the shift is an order magnitude larger than in the pre-COVID period.

11. Adrian, Boyarchenko, and Giannone (2019) find the predictive distribution for US GDP growth exhibits a similar pattern with a negative shift and negative skew during recessions.

Figure 4. Log Unemployment Rate During Expansions



Source: Authors' calculations.

Note: The unemployment rate is relative to its value at its series-specific peak, taken to be the month of its maximal value on or following each NBER-dated cyclical trough. See legend from figure 2.

During the financial crisis recession of 2007–2009, the lowest values of the median, 25th, and 5th percentile of the cross-section distribution were –1.2, –2.4, and –3.6 standard deviations, whereas in the COVID recession they were –3.9, –19.0, and –62.7.

The third stylized fact—the extraordinary fiscal response—is evident in figure 2, panel G. Clearly, the amount of government transfer payments during the COVID recession into 2021 was unprecedented compared to prior postwar recoveries.

The fourth stylized fact—the rapid recovery—is especially striking in the labor market. Figure 4 plots the natural logarithm of the unemployment rate over expansions relative to its series-specific cyclical peak (here, the month of the maximal unemployment rate following the NBER-dated cyclical trough). This figure is a variation on figure 1 in Hall and Kudlyak (2022a), who document that, during pre-COVID postwar expansions, the unemployment rate consistently fell by 0.10 log points per year (SE = 0.02). The Hall and Kudlyak (2022a) regularity is evident in figure 4 in the tightly clustered paths during the pre-COVID expansions.

The COVID path is dramatically different. During the COVID expansion, the fall in the log unemployment rate had three distinct phases. The first, lasting six months through October 2020, saw a remarkable drop of 0.76 log points from a rate of 14.8 percent in April to 6.9 percent in October. The second phase, lasting approximately another six months to April 2021, was much slower—but still faster than the rate in Hall and Kudlyak (2022a)—with the unemployment rate declining 0.12 log points. In the third phase, roughly May–December 2021, it fell another 0.45 log points, a rate of decline nearly three times its October 2020–April 2021 rate and six times the benchmark in Hall and Kudlyak (2022a). By the end of 2021, the unemployment rate stood at 3.9 percent, arguably full employment.

As can be seen in figure 2 and in the full set of charts in the online appendix, many other indicators follow this three-phase expansion, although the dates of these phases can differ by a month or two from the unemployment rate (consumption tends to lead employment).

This unusual pattern of an extremely rapid, moderate, then rapid phase is quantified for selected series in table 1. The first two columns compare the log point changes in the first six months after the April 2020 trough (month zero) to the first six months following the eight previous post-1960 NBER cyclical troughs; the other pairs of columns examine the post-trough months corresponding to November 2020–February 2021 and March–December 2021.[12] Growth rates are typically in a normal range during the second phase, then unusually strong in the third phase.

The fifth stylized fact—the unique trend stationarity of the COVID recovery—is evident in figure 5. The failure of post-1960 expansions to reattain the prior trend reflects multiple factors, including the underlying unit root behavior of GDP and a long-term slowing of the underlying trend growth rate in GDP in the United States and indeed among developed economies globally. Notably, the trend stationarity of the COVID recession was unique to the United States and did not obtain in the euro area (Giannone and Primiceri 2024).

12. Although most series exhibit this three-phase structure, the precise dating varies slightly from series to series, with the unemployment rate and labor market variables lagging consumption by a month or two. The dates used in table 1 represent a compromise between the phase dates for the labor market and consumption variables.

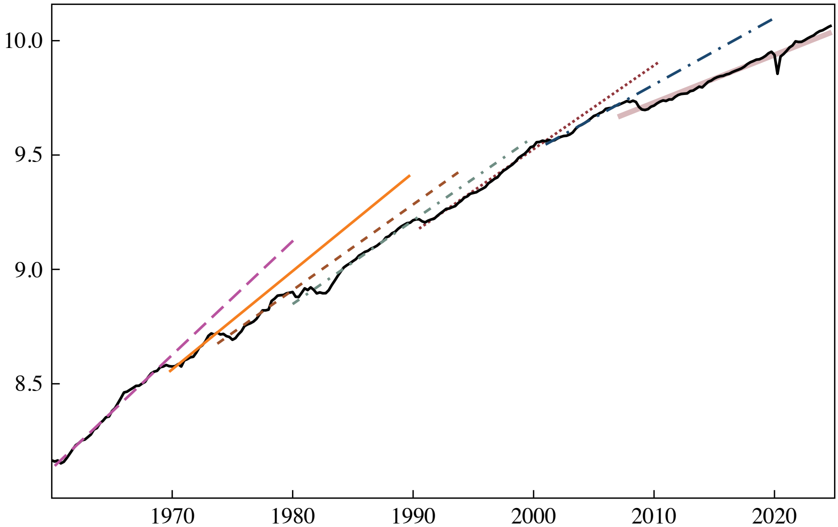
Table 1. Log Point Change (Annual Rate) of Major Economic Indicators in the Early, Middle, and Late Stages of Cyclical Expansions, 1960–2010 and 2020

	Months 1–6		*Months 7–10*		*Months 11–20*	
Indicator	*1960–2010*	*2020*	*1960–2010*	*2020*	*1960–2010*	*2020*
Unemployment rate	–0.016	–1.526**	–0.073	–0.321*	–0.031	–0.556**
	(0.037)		(0.051)		(0.035)	
Personal income less transfers	0.030	0.181**	0.033	–0.011	0.041	0.038
	(0.006)		(0.008)		(0.005)	
Industrial production	0.082	0.262*	0.058	–0.032	0.040	0.069*
	(0.012)		(0.015)		(0.01)	
Employment	0.010	0.177**	0.020	0.02	0.017	0.052*
	(0.004)		(0.006)		(0.003)	
Employment-goods	–0.005	0.148**	0.014	0.01	0.006	0.041**
	(0.008)		(0.009)		(0.006)	
Employment-services	0.014	0.225**	0.024	0.028	0.024	0.062*
	(0.003)		(0.008)		(0.002)	
Employment-accommodations and food services	–0.009	0.86**	0.013	–0.053	0.020	0.167**
	(0.007)		(0.006)		(0.004)	
PCE	0.037	0.346**	0.047	0.013	0.035	0.082*
	(0.009)		(0.01)		(0.006)	
PCE-goods	0.041	0.454**	0.056	0.013	0.039	0.061*
	(0.02)		(0.02)		(0.011)	
PCE-nondurable goods	0.023	0.284**	0.033	–0.004	0.029	0.075*
	(0.013)		(0.014)		(0.009)	
PCE-durable goods	0.090	0.803**	0.109	0.043	0.058	0.036
	(0.051)		(0.05)		(0.025)	

Source: Authors’ calculations.

Note: Entries are log point changes of the indicator, at an annual rate, over the indicated window following an NBER-dated cyclical trough, with standard errors of the mean decline for the pre-COVID recessions in parentheses. Month zero is the cyclical trough. Personal income and consumption are real. Post-April 2020 trough absolute growth exceeds **5 or *1.5 times the mean pre-COVID growth for the comparable pre-COVID expansion window.

Figure 5. Log Real GDP and Peak-to-Peak Trends



Source: Authors' calculations.
Note: Straight lines are linear time trends estimated over a given business cycle using NBER dates. The business cycles starting in January 1980 and July 1981 are combined.

I.C. Measurement Issues

The abruptness of the shutdown raises a date alignment issue. The reference week for the Current Population Survey, the week containing the 12th, was in the second week of March as shutdowns were just starting, so the March unemployment rate increased only 0.9 percentage points from February to 4.4 percent in March, before jumping to 14.8 percent in April. Similarly, the reference period for the establishment survey is the pay period including the 12th. In contrast, National Income and Product Accounts (NIPA) flow data are obtained from surveys that typically cover the entire month, so NIPA series measure any collapse during the second half of March. For example, real PCE fell 6.6 percent in March and another 11 percent in April. In reality, weekly employer data (Cajner and others 2020), initial claims for unemployment insurance (which skyrocketed in the third and fourth weeks of March), and daily spending data (Cox and others 2020) indicated that the collapse in employment and spending were temporally closely aligned and began in earnest in the second half of March. Thus, the apparent lag of employment relative to consumption in official monthly data (see figure 2, panels A and B) is an artifact of the survey dates.

The COVID lockdowns introduced other measurement problems. Surveys that are normally done in person or on site needed to shift to remote surveys, the enormous spikes caused problems for multiplicative seasonal adjustment, the volume of unemployment insurance claims overwhelmed state offices leading to backlogs and reporting problems, and there were potential misclassifications of Current Population Survey respondents; see Cohen (2020) and Davis and others (2023).

I.D. Related Literature

There is a large body of literature on the COVID recession. One strand augments SIR (Susceptible-Infected-Removed) epidemiological models of infection with endogenous self-protective behavior, both voluntary (staying home) and policy responses such as lockdowns and mask mandates. In those models, the self-protective behavior reduces the frequency of social contacts and/or the probability of transmission given contact with an infected individual, so the transmission probability (β in the SIR model) is a function of some observable disease outcome such as the death rate. These models can be used to develop optimal policy given the infection externality (e.g., Eichenbaum, Rebelo, and Trabandt 2021), to evaluate public health interventions (e.g., Baqaee and others 2020), and to quantify COVID fatigue through time variation in the feedback (e.g., Droste and Stock 2021; Atkeson, Kopecky, and Zha 2021, 2024). Atkeson and Kissler (2024) show that a surprisingly simple version of a behavior-augmented SIR model, modified to allow for the evolution of different viral strains and seasonality, is able to match the complex evolution of deaths remarkably well.

Another strand of the literature focuses on tracking the high-frequency events of the recession (e.g., Chetty and others 2024; Diebold 2020; Lewis and others 2021). A number of papers document the sectoral shift toward goods during the recession (e.g., Barrero, Bloom, and Davis 2020; Greenwood, Laarits, and Wurgler 2023), how targeted fiscal policy can be effective if such a shift is driven by sectoral supply shocks (Guerrieri and others 2022), and the increase in uncertainty (e.g., Altig and others 2020). Other papers focus on empirical estimation of the causal effects of various interventions, including NPIs (e.g., Tian and others 2020; Chernozhukov, Kasahara, and Schrimpf 2020; Gupta, Simon, and Wing 2020; Baek and others 2021), the Paycheck Protection Program (Hubbard and Strain 2020; Granja and others 2022), the individual payment and unemployment insurance programs (e.g., Auerbach and others 2022; Chetty and others 2024), and the Federal Reserve's liquidity facilities (e.g., Goldberg 2022). The early literature on the COVID recession is reviewed by Brodeur and others (2021) and covered broadly in the papers in the summer and fall 2020 issues of the *BPEA*.

Given the intense study of the COVID recession, there are surprisingly few papers on the subsequent recovery. Some papers examine longer-term consequences of COVID-induced changes, such as working from home, on productivity (e.g., Bloom and others 2025), inequality (e.g., Stantcheva 2022), real estate values (e.g., Van Nieuwerburgh 2023), labor force participation (Abraham and Rendell 2023), and retirement (Davis and others 2023).

A few papers address the practical difficulties arising in estimating macroeconomic models using data that include the COVID business cycle; these include Carriero and others (2024), Lenza and Primiceri (2022), and Diebold (2020). At a technical level, this paper is closely related to Ng (2021), which modifies a pre-COVID DFM to better fit the COVID recession.

II. Analytical Framework

Given the unprecedented macrodynamics of the COVID business cycle, it is tempting to declare that everything about the COVID-19 pandemic was different so that one should adopt a modeling strategy with, say, structural breaks and widespread nonstationarity. But while the COVID-19 pandemic *was* unique, the virus did not change the fundamental features of economic behavior that underpin macrodynamics: Consumers partially smooth income, investment decisions and price setting rely on expectations of future conditions, it takes time to design, make, and ship products, to find a job, to adjust to a change in interest rates, and so forth. We therefore adopt a parsimonious approach to modeling the COVID cycle, in which conventional business cycle dynamics do not change; there is but one thing new, the virus. The virus can affect economic activity in new ways, such as shifting consumption patterns. It can also manifest through conventional channels, for example, by increasing uncertainty and restraining both aggregate demand and aggregate supply.

The analytical framework we use is a DFM. For our purposes, DFMs have three virtues. First, the pre-COVID comovements of real economic indicators are well described by a DFM with a small number of common factors (Sargent and Sims 1977; Forni and Reichlin 1998; for a survey, see Stock and Watson 2016). Second, a DFM provides a highly parsimonious way to introduce a single new feature—the COVID shock—which introduces new dynamics and responses but does not change conventional macrodynamics. Instead of everything about the economy changing, COVID is simply layered on top. Third, this highly parsimonious approach introduces relatively few new parameters to estimate from the time series data, a useful feature given that the entire COVID episode lasted perhaps two years.

Specifically, we consider a DFM that consists of conventional, or pre-existing, factors, F_t, and potentially one or more new COVID factors, C_t. It will turn out (section III) that a scalar factor C_t suffices to explain the COVID period, and our discussion in this section incorporates this assumption. Let Y_t denote a vector of many time series variables and let u_t denote a vector of error terms ("idiosyncratic disturbances") with limited dynamic and cross-correlation. The augmented DFM is:

$$Y_t = \Lambda F_t + \Gamma C_t + u_t \tag{1}$$

$$\begin{pmatrix} C_t \\ F_t \end{pmatrix} = \begin{pmatrix} \Theta_{CC}(L) & \Theta_{CF}(L) \\ \Theta_{FC}(L) & \Theta_{FF}(L) \end{pmatrix} \begin{pmatrix} \varepsilon_t^C \\ \varepsilon_t^F \end{pmatrix}, \tag{2}$$

where Λ and Γ are factor loading matrices, ε_t^C is the structural COVID shock, ε_t^F are conventional structural shocks, the structural shocks are serially and mutually uncorrelated, $\Theta_{CC}(L)$ is the structural moving average relating the COVID shock to the COVID factor, that is, the impulse response function (IRF) of the COVID factor to the COVID shock and so forth for the other elements of the structural moving average matrix $\Theta(L)$, and intercepts are suppressed. Equation (1) relates the factors to observable variables, and equation (2) describes the dynamics of the factors in response to their structural shocks.

Pre-COVID, only the F elements of equations (1) and (2) are present, that is, $Y_t = \Lambda F_t + u_t$ where $F_t = \Theta_{FF}(L)\varepsilon_t^F$. We impose that Λ and $\Theta_{FF}(L)$ do not change from the pre-COVID to COVID periods; however, this assumption is testable (we test it in section V.A).

This augmented DFM introduces multiple channels in which the COVID shock can affect the macroeconomy. It induces changes in the COVID factor C_t, which can induce new comovements in observables (through different column spaces of Λ and Γ). The COVID shock can induce changes in F, through $\Theta_{FC}(L)$, that manifest in the same way as conventional shocks, for example, by reducing aggregate demand. Conventional shocks can in turn affect the COVID shock, through $\Theta_{CF}(L)$; for example, a positive shock to aggregate demand can increase economic activity thereby increasing infections. This feedback from conventional shocks to the COVID factor can be seen as the counterpart of the behavioral feedback equation in a behavioral SIR model, in which ε_t^C captures COVID deaths and the behavioral response to deaths and ε_t^F reflects the effect of economic activity on contacts, augmented for lagged effects.[13]

Combined, equations (1) and (2) provide a decomposition of Y_t into movements from conventional shocks, COVID shocks, and idiosyncratic movements:

$$Y_t = \Theta_{YF}\left(L\right)\varepsilon_t^F + \Theta_{YC}\left(L\right)\varepsilon_t^C + u_t, \tag{3}$$

where $\Theta_{YF}(L) = \Lambda\Theta_{FF}(L) + \Gamma\Theta_{CF}(L)$ and $\Theta_{YC}(L) = \Lambda\Theta_{FC}(L) + \Gamma\Theta_{CC}(L)$. Because the factors and the shocks are unobserved, they are not identified without additional assumptions.

II.A. Identification and Estimation of F and C

We identify the spaces spanned by$\{F_t\}$ and $\{F_t,\ C_t\}$ by assuming (i) $C_t = 0$ in the pre-COVID period, and (ii) Λ does not change between the pre-COVID and COVID periods. With these assumptions, we estimate the factors and factor loadings by first estimating F and Λ by principal components in the pre-COVID period, which yields estimates of the factor loadings $\hat{\Lambda}$ and estimates of the pre-COVID factors $\hat{F}_t = \left(\hat{\Lambda}'\hat{\Lambda}\right)^{-1}\hat{\Lambda}'Y_t$ for pre-COVID values of t. During the COVID period, the C factor(s) and Γ are then estimated by principal components applied to $Y_t - \hat{\Lambda}\hat{F}_t$, where $\hat{F}_t = \left(\hat{\Lambda}'\hat{\Lambda}\right)^{-1}\hat{\Lambda}'Y_t$ is now computed over the COVID period. The predicted value of Y given the factors is then $\hat{Y}_t = \hat{\Lambda}\hat{F}_t + \hat{\Gamma}\hat{C}_t$.[14]

These assumptions identify the space spanned by F_t. As discussed in the next section, we use three pre-COVID factors. We normalize the F factors

13. For example, the behavioral component of the SIR model in Atkeson and Kissler (2024) is $\ln\beta(t) = \ln\bar{\beta} - \kappa(t)\dot{D}(t) + \psi(t)$, where $\beta(t)$ is the SIR transmissivity parameter, $\kappa(t)$ is the semi-elasticity of transmission with respect to the current death rate, and $\psi(t)$ is a shifter of transmissibility. Given the infection fatality rate, over which an individual has little control, $\beta(t)$ is a direct measure of an individual's risk, so it aligns with our interpretation of C_t. The parameter $\beta(t)$ subsumes the biological transmissibility of the virus given a contact ($\bar{\beta}$), any protective measures to reduce that transmissibility (e.g., masking), and any measures to reduce the frequency of contacts (e.g., working at home, closing schools). In terms of equation (2), the innovation in $\kappa(t)\dot{D}(t)$ corresponds to the COVID shock ε_t^C, lags of ε_t^C enter as linear predictors of $\kappa(t)\dot{D}(t)$, and economic activity enters by increasing contacts through $\psi(t) = \Theta_{CF}\varepsilon_t^F$.

14. To avoid identities (e.g., sectoral components of employment that sum to total employment), the factors from the DFM model are estimated using only subaggregates. Principal components estimation was modified for missing observations; see Stock and Watson (2016).

by making the first F factor be the best factor predictor of employment growth pre-COVID (the "employment factor") and making the second F factor be the best factor predictor of PCE growth pre-COVID (the "PCE factor"). The third factor is the residual orthogonal to the first two and with a unit factor loading on industrial production. These normalizations are only used for a stability test in section V.A and a counterfactual calculation in section VI.A.

II.B. Identification of Factor Shocks

As with structural vector autoregressions (VARs) with observable variables, the structural IRFs $\Theta(L)$ are not identified without further assumptions. In the context of equation (2), the vast literature on structural macrodynamics focuses on identification of $\Theta_{FF}(L)$; see the survey in Ramey (2016). In contrast, our interest is in the elements of $\Theta(L)$ that involve the novel COVID shock ε_t^C.

First, we discuss what is meant by a COVID economic shock. Our interest is in the effect of the COVID-19 pandemic on macroeconomic variables. It is not just the evolution of the virus itself that matters here—viruses, including serious ones, circulate all the time—it is also the perceptions of economic agents about the virus, which in turn induce changes in economic behavior. Like the seasonal flu, COVID-19 has a direct effect on labor supply because the sick don't work; unlike the seasonal flu, the fear of contagion leading to severe illness and death induced changes in policy (lockdowns) and behavior (shopping less, shifting to at-home consumption) that had macroeconomic consequences. Once the vaccine became available, the vaccinated were far less susceptible to severe illness and death, so the continuing spread of the virus had reduced behavioral effects. In addition, COVID fatigue potentially reduced the effect of the virus on economic activity, which in the context of equation (2) (in which $\Theta(L)$ is not time-varying) would manifest as smaller COVID shocks. Thus, the COVID shock comprises both direct effects (e.g., labor supply) and a shock to those perceptions of COVID that induce behavioral change: news about deaths, transmissivity (new strains), treatment (antivirals), severity (availability of vaccines), and so forth. To the extent that the COVID shock induces sectoral reallocation, it also captures the costs of those reallocations, which would weigh on overall performance; see Fujita, Ramey, and Roded (2024). Because COVID shocks have both direct and perception elements, in principle there could be multiple COVID shocks and factors; however, we find that a single COVID factor suffices empirically, so our exposition focuses on the case of scalar C_t and ε_t^C.

Our identification of the COVID shock relies on the biology of the virus. Specifically, we assume that (iii.a) the conventional factor shocks ε_t^F do not affect the COVID factor C within the month, although (iii.b) the COVID shock can affect the F factors within the month. These assumptions impose a single restriction on $\Theta_{CF}(L)$, that $\Theta_{CF,0} = 0$, where $\Theta_{CF,0}$ is the contemporaneous effect of F_t on C_t.

Assumption (iii.a) stems from our interpretation of the COVID factor as virus-induced, behavior-altering perceptions of risk and COVID biology. Economic activity, both consumption of services and production, exposes people to the virus, but there are lags from the date of an economic shock (say, receiving a stimulus check) to exposure (going out to dinner and becoming infected) to becoming symptomatic to hospitalization to death. For the initial strain, the latency period from exposure to symptomatic was estimated to be approximately five days (see the review in Baqaee and others 2020). There were additional delays between showing symptoms and hospitalization, and Atkeson and Kissler (2024) take the mean time from hospitalization to death to be thirty days, although this varied as treatments changed. There were additional administrative delays of up to a week before a death was reported. In principle, self-protective behavior could be triggered by observing an increase in infections, in deaths, or both. Infection rates, however, had significant reporting problems: The time from infection to public reporting could be more than a week, early in the pandemic tests were rationed so infections were underreported, and later in the pandemic home testing resulted in an unknown amount of underreported infections. Atkeson (2021) finds a better fit in a behavioral epidemiological model if the feedback from observed COVID risks to self-protective behavior relies on reported deaths rather than infections, which makes sense both because of problems with reporting of infections and because the relevant shock to perceptions is the threat of severe harm. Atkeson and Kissler (2024) model self-protective behavior as depending on observed COVID deaths. In short, a (daily) shock to economic activity affected COVID perceptions only with a delay, which, if deaths is the measure used, is on the order of four to eight weeks after the interaction that eventually leads to death. This motivates assumption (iii.a).

Assumption (iii.b) aligns with the actual course of events during the COVID cycle. The arrival of the virus in the United States, and in particular the exponentially increasing deaths in New York City—that is, the COVID shock of early to mid-March 2020—induced uncertainty, abrupt lockdowns, and voluntary self-protective behavior, which reduced aggregate demand

and labor supply. The COVID shock also induced a large and immediate fiscal response in the signing of the CARES Act on March 27, 2020, with disbursements beginning immediately. Thus, within the month of March alone, the COVID shock induced shifts in aggregate demand, aggregate supply, and fiscal policy that were contemporaneous at the monthly level. These are all conventional macroeconomic channels—that is, F's—through which the unforeseen and novel COVID shock immediately affected economic activity.

Finally, we assume that (iv) the moving average $\Theta(L)$ is invertible, so that equation (2) can be written as a structural VAR, where under assumption (iii.a), ε_t^C is the innovation in the C_t equation (up to scale), and ε_t^F can be recovered (up to a nonsingular transformation) from the vector of innovations in F_t after conditioning on ε_t^C.

Estimation of the decomposition (3) and counterfactuals for the F shocks (done in section VI) requires estimation of the shocks and parameters in the DFM equations (1) and (2). This would be straightforward if the COVID period were long, but the COVID period is short while the pre-COVID period is long. Moreover, the dimension of the DFM switches over the COVID boundary. We therefore use a hybrid structural VAR-local projection estimation method that uses the pre-COVID data where possible and the COVID sample where necessary. For the counterfactuals, $\Theta_{FF}(L)$ is estimated using a pre-COVID VAR(6). The COVID shock ε_t^C is estimated as the residual from the regression of $\hat{C}_t$ onto a single lag of $\left(\hat{C}_t, \hat{F}_t\right)$; to remove the influence of the extreme March and April 2020 observations, this regression is estimated over July 2020–February 2023, and ε_t^C for spring 2020 is computed using those coefficients and is set to zero outside March 2020–February 2023. Then, $\Theta_{FC}(L)$ is estimated by the coefficients of the regression of F_t onto the current through fourth lags of $\hat{\varepsilon}_t^C$; denote the residuals from this regression $\hat{F}_t^F$. The stability of $\Theta_{FF}(L)$ across the COVID boundary is examined in section V.A using a VAR separately in the pre-COVID (using $\hat{F}_t$) and COVID (using $\hat{F}_t^F$) samples, where a VAR(2) is used in both samples for comparability. For details, see the online appendix.

III. Evidence of a Single COVID Factor

This section further quantifies how the COVID cycle differed from previous cycles and shows that a standard DFM, augmented with a single COVID factor, provides a concise numerical summary of those differences and of the COVID business cycle dynamics.

III.A. Data Set and Number of Pre-COVID Factors

The data set consists of 128 monthly real economic indicators comprised of aggregate consumption and its components (22 series), employment (43 series), industrial production (33), personal income (13), housing starts and permits (10), orders and inventories (5), and other series (2). Some calculations additionally use twenty-three quarterly real indicators of economic activity. Some outliers were removed from the pre-COVID sample but not from the COVID sample. With a few exceptions, the variables are transformed to be first differences of logarithms. All series are demeaned and standardized using pre-COVID means and standard deviations, so they are mainly monthly growth rates in pre-COVID standard deviation units. See the online appendix for the complete list of series and data preprocessing details.

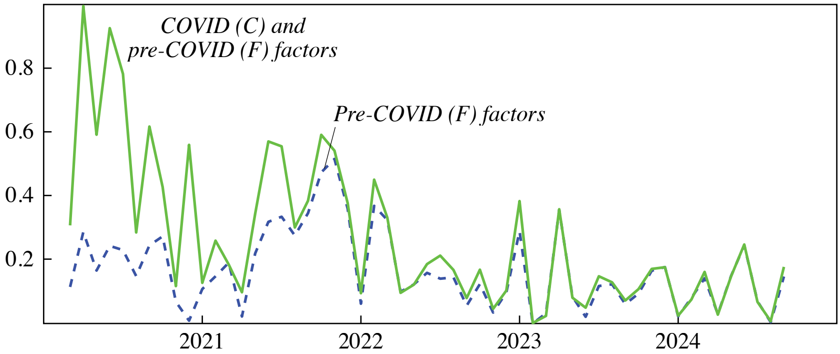
The NBER dates the 2020 recession peak as February 2020 (quarterly, 2019:Q4). Not all of our monthly series are consistently available before 1970, so we use January 1970–February 2020 (1970:Q1–2019:Q4) as the pre-COVID monthly (quarterly) sample and March 2020–September 2024 (2020:Q1–2024:Q3) as the COVID sample. The results are generally robust to starting the pre-COVID sample instead in 1960 (using missing data methods) or in 1984.

The factors are estimated using the seventy-seven monthly series (of the 128 total) that are not linked by identities and are observed from January 1970 through September 2024. In the monthly data set, a single factor explains 13 percent of variability in the series over the pre-COVID sample (that is, the average R^2 across the series is 0.13 for the one-factor model), which increases to 25 percent using three factors. The Bai-Ng (2002) information criterion is indifferent between two and three factors, so we use three pre-COVID factors.

III.B. Results: A Single COVID Factor

We focus here on results for the factors and the C-augmented DFM in equation (1). The factor estimation results show that: 1) While the pre-COVID factors F have some explanatory role during the COVID recession, they fail to explain the movements of many sectoral variables; 2) adding a single COVID factor C captures a great deal—for many series, nearly all—of the anomalous COVID dynamics that are unexplained by the pre-COVID factors; 3) the COVID factor explains the unusual sectoral movements during the COVID cycle; and 4) the COVID factor is well approximated as a factor measuring reallocation between goods and services.

Figure 6. Cross-Sectional R^2 by Month, *F* and *F* & *C* Factors



Source: Authors' calculations.

Figure 6 summarizes the cross-sectional R^2 of the F factors, and also of the combined F and C factors for each month from March 2020.[15] The pre-COVID factors explain only a fraction of this cross-sectional variation early in the COVID cycle, whereas from March to July 2020 the marginal R^2 of the C factor exceeds 60 percent. This importance of the C factor subsides quickly: Its marginal R^2 is less than 10 percent from 2022 on and is essentially zero in 2023.

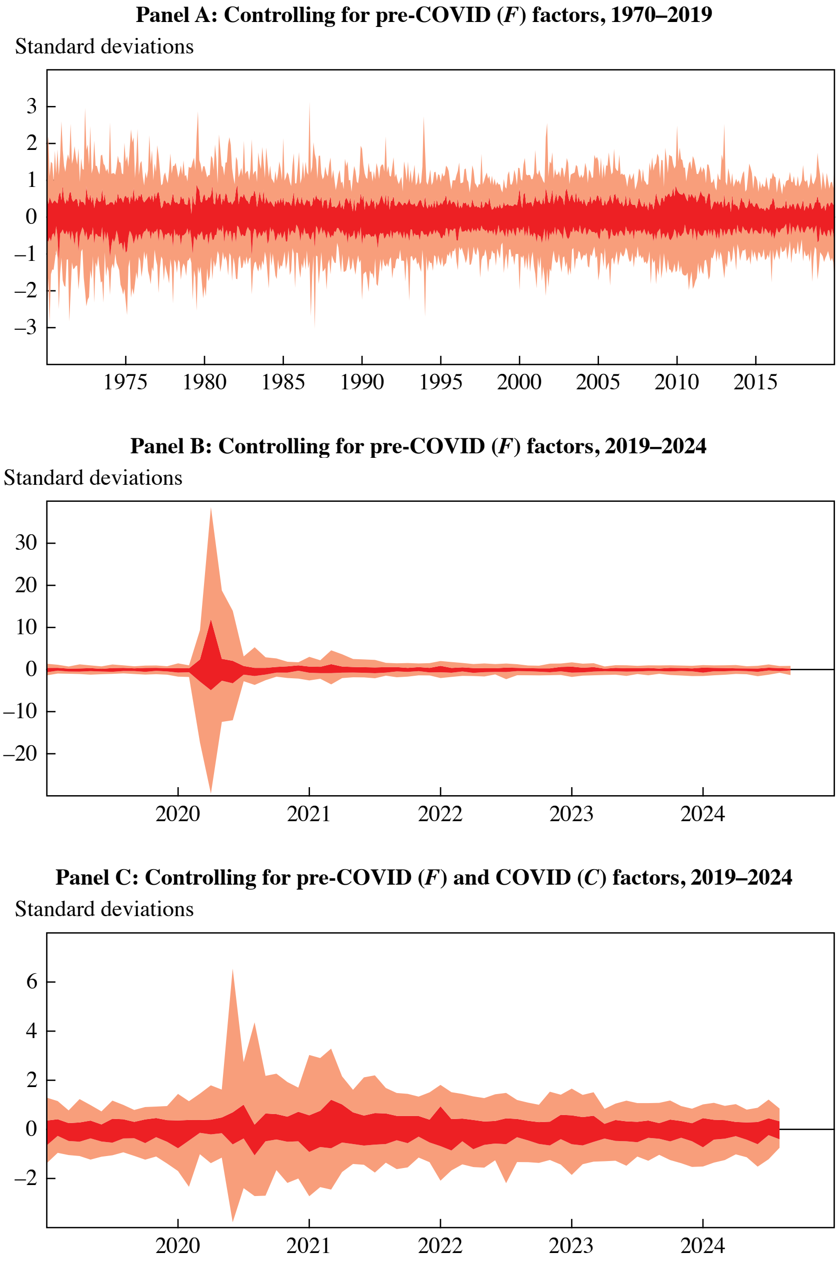
Figure 7 provides an alternative visualization of the cross-sectional explanatory power of the C factor. It displays cross-sectional quantiles of the standardized residuals $\hat{u}_t$ from equation (1) using only the F factors (panels A and B) and using the F and C factors (panel C).[16] As can be seen in figure 7, panel A, the F factors remove the pre-COVID cyclic pattern evident in figure 3, panel A, but as can be seen in figure 7, panel B, only partially reduce the cross-sectional dispersion early in the COVID cycle. In contrast, when the single COVID factor is added in figure 7, panel C, there is much less excess cross-sectional dispersion.

The quantitative importance of the C factor varies by series. Figure 8 plots actual and predicted values of percentage growth rates of the series in figure 2, where the predicted values are computed using only the F factors,

15. At date t, the cross-sectional R^2 of the F factors is the R^2 of $\hat{\Lambda}\hat{F}_t$ as a predictor of vector Y_t. For the combined factors, it is the cross-sectional R^2 of $\hat{\Lambda}\hat{F}_t + \hat{\Gamma}\hat{C}_t$ for Y_t. The marginal cross-sectional R^2 of the C factor is the difference between these two R^2's.

16. Because of the timing misalignment between the survey period for the Current Employment Situation, the mid-March 2020 COVID shock, and flow series such as consumption and investment, the monthly residuals plotted in figure 7, panel C, are from a regression of the series Y_{it} onto F_t, C_t, and one lead and one lag of C_t.

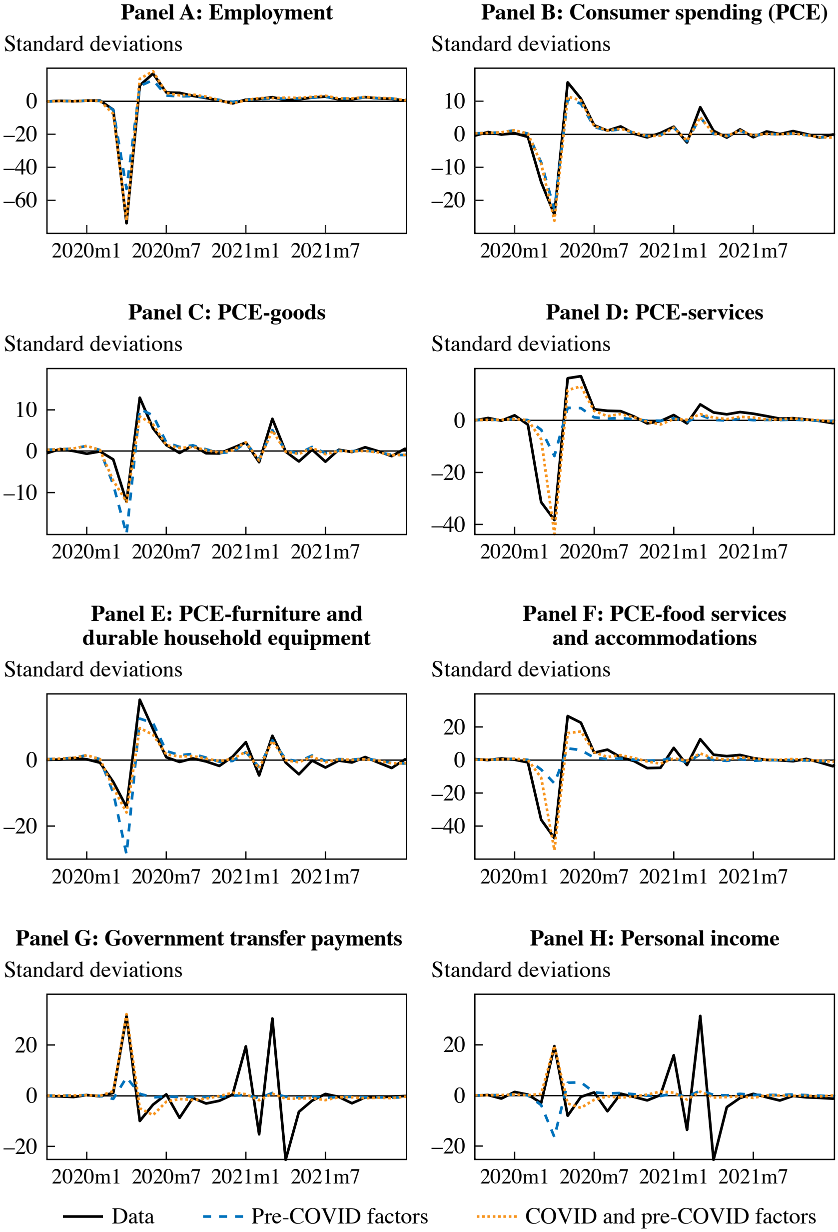
Figure 7. Time Series of Cross-Section Quantiles of Residuals of 128 Monthly Activity Variables, Controlling for Three Pre-COVID (*F*) Factors and Additionally Controlling for Both *F* and *C* Factors



Source: Authors' calculations.

Note: See the notes to Figure 3. The dark-shaded region shows 25–75 percent quantiles and the light region shows 5–95 percent quantiles.

Figure 8. Factor Model Fits During COVID



Source: Authors' calculations.

Note: Series are monthly growth rates (quarterly for GDP), demeaned and standardized using pre-COVID means and standard deviations. Actuals (solid) are predicted using F (dashed) and using both F and C (dotted).

Table 2. Estimates of Γ for Selected Series

	Γ
Panel A: Monthly model: PCE components	
Total	–3.4
Goods	7.9
Durable goods	10.0
Motor vehicles and parts	6.6
Furnishings and durable household equipment	12.6
Recreational goods and vehicles	16.2
Other durable goods	–4.9
Nondurable goods	0.1
Food and beverages (home consumption)	–4.2
Clothing and footwear	–10.7
Gasoline and other energy goods	–13.9
Other nondurable goods	15.1
Services	–30.1
Health care	–60.4
Transportation services	–14.8
Recreation services	–34.6
Food services and accommodations	–40.3
Financial services and insurance	0.3
Housing and utilities (excl. energy)	21.6
Housing and utilities (energy)	–5.9
Other services	–3.9
Final consumption expenditures of nonprofits (NPISHs)	11.5
Panel B: Quarterly model: output, employment, and productivity	
GDP	3.5
Employment	–3.9
Labor productivity	6.1
Unemployment rate	8.4
Labor force participation rate	–7.9

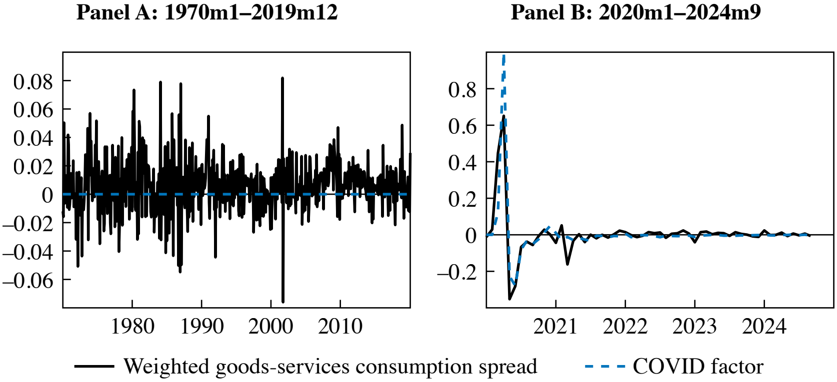
Source: Authors' calculations.

Note: The table shows the value of Γ, the factor loading on the COVID factor (C), where C is normalized to +1 in April 2020 (or 2020:Q1 for quarterly variables), and each observable variable is in pre-COVID standard deviation units.

and then using both the F and C factors (see the online appendix for these predicted-actual plots for all series). The growth of aggregate employment and consumption is well explained by the F factors over this period, with a negligible role for the C factor. In contrast, for consumption (figure 8, panel C) and employment in goods-producing sectors and in construction, the F factors overpredicted the decline, while for services consumption and employment (including services components), the F factors substantially underpredict the decline. These prediction errors are nearly all resolved by including the COVID factor.

The marginal R^2 of the C factor for a given series depends on the value of Γ for that series. Table 2 presents estimates of Γ for selected variables, using the normalization that $C_t = 1$ in April 2020 for the monthly model

Figure 9. COVID Factor and the Weighted Goods-Services Consumption Spread



Source: BEA and authors' calculations.

or the first quarter of 2020 for the quarterly model, where the series are in pre-COVID standard deviation units; negative values of Γ indicate that the COVID shock depresses the series. Panel A shows results from the monthly model for consumption. Evidently, the *C* factor captures the shift in consumption toward goods (positive Γ), especially goods that can be consumed at home and outside, away from goods used for work or social occasions (clothing and footwear), and away from services, especially services involving contact with the general public (eating out, hotels, entertainment). Similar patterns are evident for sectoral employment (not shown). Panel B shows results for the quarterly model and focuses on output, employment, and productivity. GDP fell less than it would have during a typical recession, given the large declines in *F* (positive Γ), while employment fell more (negative Γ), yielding a COVID-attributed increase in labor productivity. The COVID factor exacerbated the rise in the unemployment rate and, given the less than normal fall in GDP, resulted in a flattening of the typical GDP/unemployment relationship (Okun's law); see Fujita, Ramey, and Roded (2024) for a discussion of parallels with the aftermath of World War II.

The estimated COVID factor, normalized to +1 in April 2020, is plotted in figure 9. Consistent with figure 6, the COVID factor is small after June 2021 and essentially zero after January 2023. It turns out that the COVID factor has a simple empirical counterpart, the weighted spread Δ ln(PCE-goods) – 13.5 Δ ln(PCE-services), where 13.5 is the ratio of the Γ coefficients for PCE-services to PCE-goods in table 2, rescaled from pre-COVID standard deviation units to growth rates. This spread, which exhibits only moderate cyclical behavior in the pre-COVID period, is potentially useful for future time series applications as an observable version of the COVID factor (Ng 2021; Lenza and Primiceri 2022).

IV. The COVID Timeline Through the Lens of the DFM

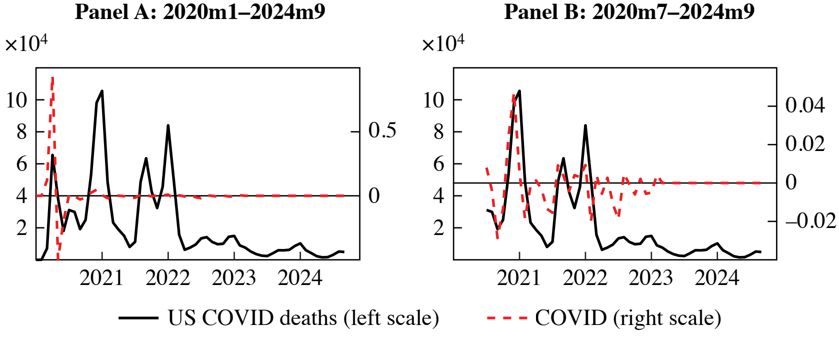
We now turn to a discussion of the COVID shock, identified as described in section II.B, and its ability to explain the anomalous macrodynamics over the COVID cycle.

IV.A. The COVID Shock

Figure 10 plots the COVID shock and monthly COVID deaths. It is striking how closely the COVID shock tracks deaths, given that the COVID shock is estimated solely from economic data. The magnitude of the movements in the shocks, relative to the deaths, falls over time: The coefficients in a regression of the COVID shock on COVID deaths over the four eight-month windows starting in March 2020 are 0.083, 0.027, 0.025, and 0.013. This decline in sensitivity of the economic shock to COVID deaths is consistent with pre-vaccine adaptations and methods of self-protection, such as masking, with pandemic fatigue, and with the increasing availability of the vaccine over the winter and spring of 2021. This decline in the sensitivity of activity to deaths is qualitatively consistent with the estimates in Droste and Stock (2021) and the calibration in Atkeson and Kissler (2024). The decline in sensitivity estimated here is larger than in those papers; however, the sample here is longer (extending into when the vaccine was available) and all the estimates are noisy because of the limited data (we refrain reporting standard errors for these eight-observation time series regressions).

The F factors spiked in the spring of 2020—that is, it appeared that there were large conventional shocks—but those spikes were in fact almost entirely driven by the COVID shock. This is shown in figure 11, which decomposes the four factors into their variation arising from the COVID shock and the conventional shocks; for example, the COVID shock contribution to the COVID factor is $\Theta_{CC}(L)\,\varepsilon_t^C$ in equation (2). The effect of the COVID shock on F dies out, however, and by mid-2021 the conventional factors are largely driven by the conventional shocks. Notably, the two largest values of F_{2t} (the PCE F-factor) after the summer of 2020 occur in January and March 2021, coinciding with the personal payments under the Consolidated Appropriations Act and the ARP, with the March 2021 shock being roughly 2.5 times the January 2021 shock, aligning quite closely with the relative size of the two stimulus checks ($600 and $1,400).

Figure 10. The COVID Shock and Monthly COVID Deaths over the COVID Period starting January 2020 and July 2020



Source: CDC and authors' calculations.

Interestingly, feedback from the conventional shocks to the COVID factor has a small net effect.

Taken together, these results strongly suggest that the COVID economic shock is a response to perceived changes in risk of serious illness or death from COVID-19. This perceived risk, and the impact of that risk on economic behavior, decreased over time as more was learned about the virus, as self-protective measures came into use, as COVID fatigue set in, and as the vaccine became available. The large spikes in the conventional factors in figure 11 are nearly entirely a consequence of the COVID shock, not the contemporaneous conventional shocks. The only large conventional shocks during the COVID period were those from the second and third pandemic stimulus payments.

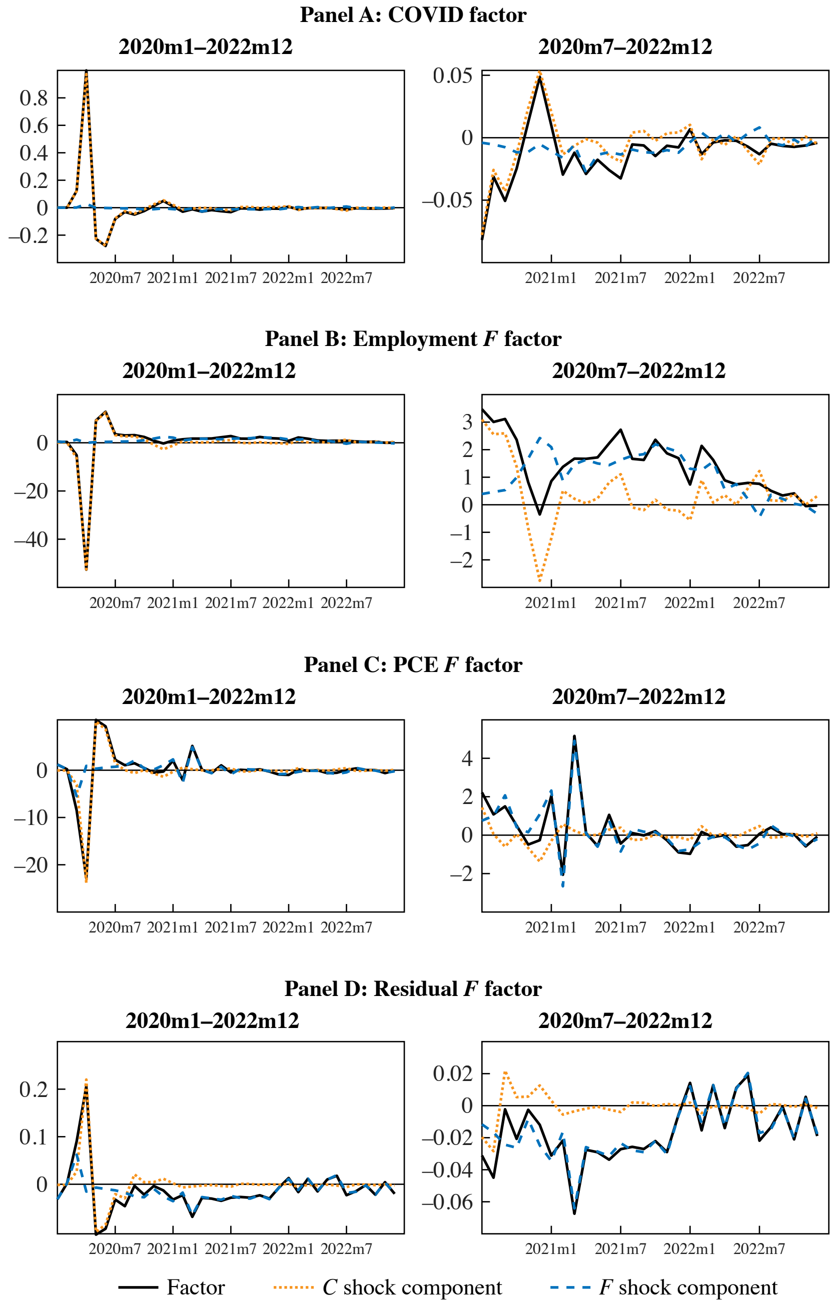
IV.B. Historical Decompositions

Figure 12 presents historical decompositions of the monthly growth rate of PCE and some of its components into the contribution of the conventional factor shocks and the COVID shock, that is, the first and second terms on the right-hand side of equation (3). Figure 13 presents these decompositions for the levels of payroll employment and the unemployment rate. Monthly growth rates are in pre-COVID standard deviation units; levels are in native units.

Looking across these series and the rest of the decompositions, which are in the online appendix, leads to several high-level conclusions.

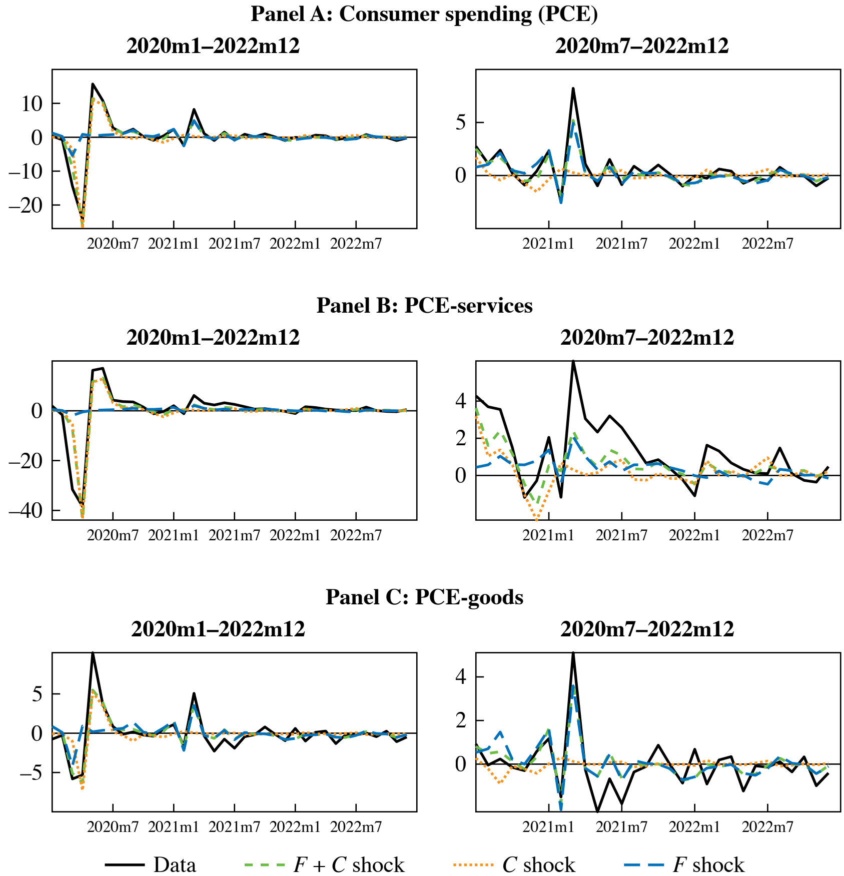
First, the COVID shock explains the anomalous sectoral reallocation, notably the extraordinary decline in PCE-services, the smaller decline and

Figure 11. Decomposition of the COVID and Conventional Factors into COVID and Conventional Shock Components



Source: Authors' calculations.

Figure 12. Decomposition of Monthly Growth of Consumption and Selected Components into COVID and Conventional Shock Components

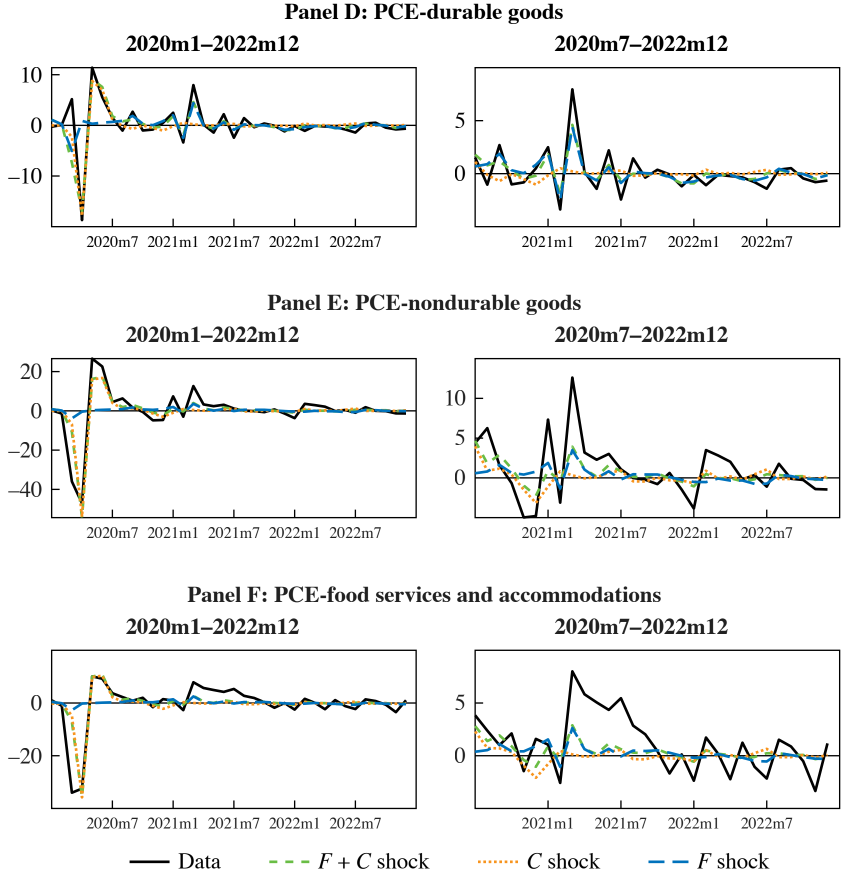


(*continued on next page*)

large rebound of PCE-nondurables, and the small decline and (to a lesser degree) the rebound of PCE-durables. This is also true for most PCE components, such as food services and accommodations and transportation services.[17] The COVID shock also explains the anomalous behavior of sectoral employment through 2020, both at the primary disaggregated

17. For some consumption series, the COVID factor lags the initial March drop; however, this is a consequence of the COVID factor putting considerable weight on employment series, which had only modest declines in March for the survey week for reasons discussed in section I.C.

Figure 12. Decomposition of Monthly Growth of Consumption and Selected Components into COVID and Conventional Shock Components (*Continued*)

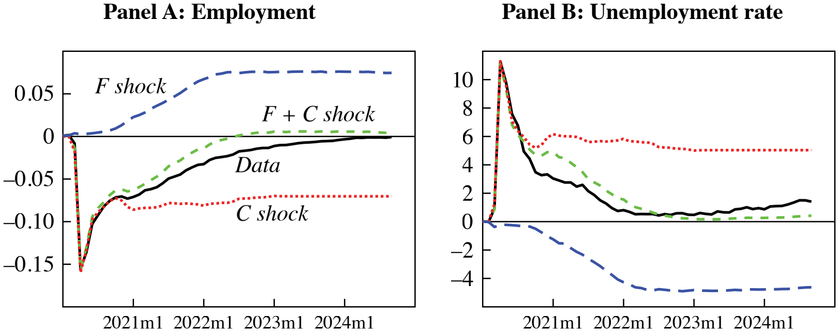


Source: Authors' calculations.

level of goods and private services and at the next level of disaggregation. For example, the COVID shock explains the collapse and slow recovery of employment in accommodations and food services and the smaller sharp contraction in health care employment.

Second, the COVID shock explains, in a quantitative sense, the fast dynamics of the recession and the early stages of the recovery: the sharp jump of the unemployment rate (figure 13) and its rapid decline through the fall of 2020, the sharp decline and rapid recovery of the labor force

Figure 13. Decompositions of Payroll Employment and the Unemployment Rate (Levels) into COVID and Conventional Shock Components



Source: Authors' calculations.
Note: Values are differences from their values in 2020:M1. The logarithm of employment is shown in panel A and the level of unemployment rate in panel B.

participation rate, and the sharp decline and rebound of total employment and total PCE.

Third, there are a few series that are not well explained by the shocks, either because they have a large one-month error, plausible lagged effects, or because of a systematic trend mismatch. One example of a large one-month error is the spike in consumption of food and beverages off-premises (not shown) in March 2020. This is partly attributable to the consumption-employment data timing misalignment, but is also attributable to the anticipatory shifting forward of purchases for April into March, which occurred for alcohol and household staples (toilet paper, disinfectant, etc.) but not for other goods, and which is not captured by the COVID shock timing that peaked in April. The demand for transportation services, a major component of which is air travel, also is not well fit in 2021, arguably because of unmodeled lags. Air revenue passenger miles (not shown) plummeted during the pandemic and did not see strong growth until the vaccine was widely available. With the availability of the vaccine and the ARP stimulus checks, transportation services grew strongly through the spring and summer of 2021 in a way that appears in the DFM as a residual. Plausibly, this residual reflects a limitation of our using only four lags, because air travel has built-in delays from vacation planning to ticketing to travel. A similar but smaller underprediction is present for food services and accommodation and for total services consumption, driven by these components. An example of a systematic shift in the trend is housing starts, especially in the West and South, in which the DFM does not capture the growth in demand for new homes in 2022–2023.

V. Did the Economy Catch Long COVID?

An open question is the extent to which the COVID recession and recovery wrought lasting structural changes in the economy. Clearly the pandemic introduced or speeded up some microeconomic structural changes, such as working remotely, and also induced some macroeconomic changes, notably the high debt-to-GDP ratio that is a legacy of the three COVID stimulus plans. Other structural shifts include deaths of a substantial number of workers, early retirements of older workers (Davis and others 2023), a portion of the labor force having long COVID (Blanchflower and Bryson 2023), and many American children missing a year of in-person school. There are also less tangible effects, such as the loss of trust in government.

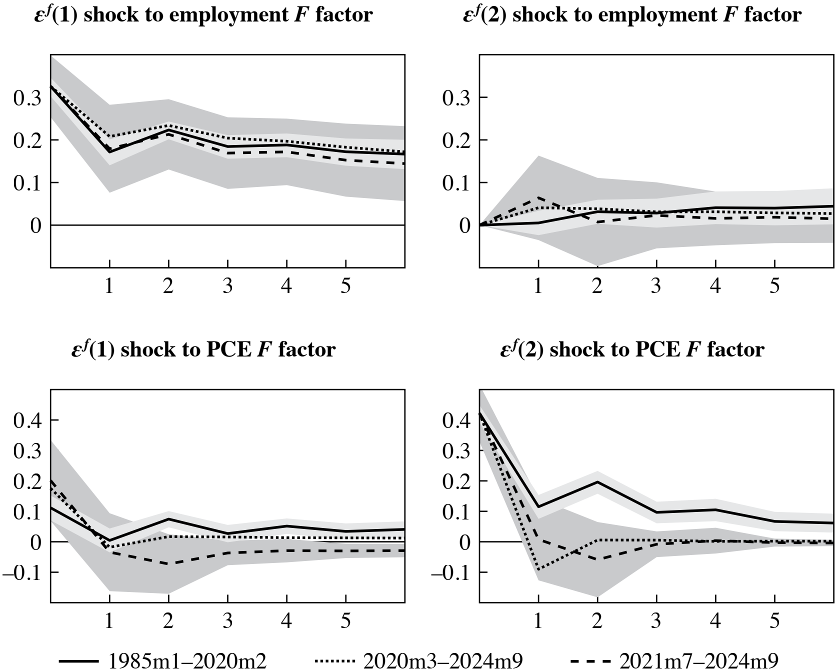
Only five years after the pandemic—and at most three years after the end of the COVID shock—it is too soon to know for sure whether there are lasting changes in economic variables. With this caveat, we take an initial look, first at potential changes in business cycle dynamics, then at potential changes in long-term aggregate growth rates. In short, we find scant evidence of any long COVID effects at the level of macrodynamics or aggregate, and even sectoral, growth.

V.A. Macrodynamics

We assess the stability of conventional business cycle dynamics pre- versus post-COVID by examining the stability first of Λ and $\Theta_{FF}(L)$.

To assess the stability of Λ, we apply Andrews's (2003) end-of-sample stability test, which allows for non-Gaussian errors, to each of the 128 monthly series. We compare estimates of Λ from the pre-COVID period to those from the post-COVID period (March 2023–September 2024). Of the 128 series, five reject at the 5 percent level, and eleven reject at the 10 percent level (see the online appendix for details). Among those that reject stability of Λ, there are no clear patterns. Although the short post-COVID period means that the power of the test will be low, these results are consistent with Λ not changing after the COVID episode.

Figure 14. *F*-to-*F* **Impulse Response Functions $\Theta_{FF}(L)$ for the First and Second *F* Factors: Pre-COVID and COVID Sample Estimates**



Source: Authors' calculations.

Note: Impulses use Cholesky factorization with the employment factor ordered first and the PCE factor ordered second, estimated using a VAR(2) in $(\hat{F}_{1t},\hat{F}_{2t})$ for the pre-COVID samples and a VAR(2) in $(\hat{F}^F_{1t},\hat{F}^F_{2t})$ for the COVID samples, where $\hat{F}^F_t$ is the residual from the regression of $\hat{F}_t$ onto zero to four lags of $\hat{e}^C_t$ (see the online appendix). Shading denotes 95 percent error bands for the pre-COVID (light) samples and 2021:M7–2024:M9 (dark) samples. Shock standard deviations over the periods 1985:M1–2020:M2, 2020:M3–2024:M9, and 2021:M7–2024:M9 are respectively 0.33, 0.43, and 0.34 for the first shock and 0.42, 1.24, and 0.42 for the second shock.

To assess the stability of $\Theta_{FF}(L)$, we estimated $\Theta_{FF}(L)$ for the first two factors over three periods: January 1985–February 2020, March 2020–September 2024, and July 2021–September 2024.[18] The results, displayed in figure 14, show considerable stability for three of the four IRFs, except that the IRF for shock 2 to factor 2 shows reduced persistence in the COVID

18. Estimation is described in section II.B. Only the first two factors are used because the third factor is quantitatively unimportant during the COVID sample.

and post-COVID period. The standard deviation of the innovation to factor 2, the PCE factor, was much larger during 2020 through the middle of 2021 than before or after, consistent with this factor capturing the three large fiscal stimuli of March 2020 and January and March 2021. The standard deviations of the innovation to factor 1 increased modestly during March 2020–June 2021, then returned to pre-COVID levels.

These results are consistent with the macroeconomy returning to normal rather quickly: Business cycle dynamics pre-COVID and post-vaccine are quite similar.

V.B. Trend Growth Rates and Sectoral Shares

We now turn to the question of whether there have been long-term shifts in aggregate and sectoral growth rates as a result of the COVID-19 pandemic, using quarterly data so we can examine NIPA aggregates. The first two columns of table 3 provide mean growth rates over the two thirty-year periods prior to the pandemic. The final two columns are estimates of the instantaneous trend growth rate for 2019:Q4 and 2024:Q3, quarters during which the unemployment rate was 3.6 percent and 4.2 percent, respectively, at or near full employment. The trend growth rate is estimated by one-sided exponential smoothing with a smoothing parameter of 0.95.

The most striking feature of table 3 is how similar are the smoothed growth rates at the 2019:Q4 peak and nearly five years later, at least for the main aggregates. GDP growth is the same to one decimal point. There are sectoral differences, however; for example, services consumption growth is substantially stronger in 2024:Q3 than in 2019:Q4 (2.5 percent versus 2.0 percent) while durable goods consumption is weaker. Industrial production growth has slowed, consistent with a continuing decline in domestic goods production. Figure 15 provides the comparison of the final two columns of table 3 for multiple sectors of consumption, employment, and industrial production. For consumption and employment, the smoothed values in 2024:Q3 versus 2019:Q4 are highly correlated and fall along the 45° line, consistent with there being no substantial lingering changes. For industrial production, the correlation is also high but with a slope less than one, reflecting the long-term slowdown of industrial production growth seen in table 3.

VI. Assessment and Lessons

VI.A. How Well Does the DFM Explain the Five Anomalies?

The addition of a single COVID factor and its COVID shock to a conventional DFM provides a parsimonious explanation of the five stylized

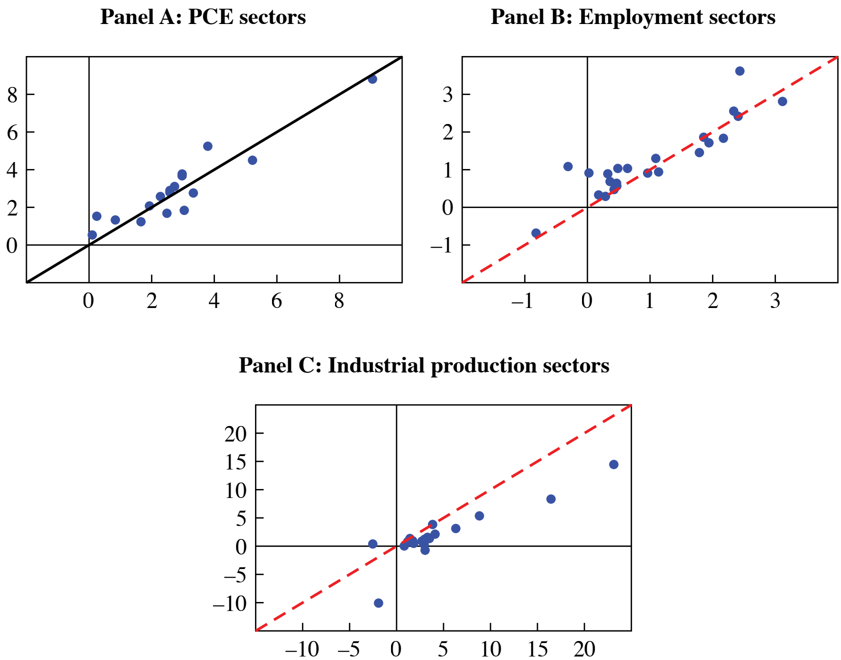
Table 3. Trend Growth Rates of Selected Series

	Average growth rate		*Smoothed growth rate*	
	1960–1989	*1990–2019*	*2019:Q4*	*2023:Q3*
GDP	3.49	2.49	2.42	2.51
Nonfarm business sector: labor productivity (output per hour) for all workers	1.96	2.02	1.68	1.67
Employment (CES)				
CES: total nonfarm	2.33	1.11	1.32	1.43
CES: goods producing	0.70	−0.44	0.95	1.09
CES: GD manufacturing	0.84	−0.92	0.42	0.47
CES: private service producing	3.10	1.68	1.64	1.63
CES: SE wholesale trade	2.28	0.39	0.49	1.03
CES: SE retail trade	2.88	0.56	0.18	0.33
CES: SE professional and business services	3.58	2.31	1.94	1.71
CES: government	2.54	0.78	0.51	0.92
PCE				
Total	3.67	2.69	2.42	2.73
PCE: Q goods	3.40	3.26	3.35	3.30
PCE: Q durable goods	5.21	5.20	5.27	4.89
PCE: Q nondurable goods	2.62	2.21	2.40	2.49
PCE: Q services	3.93	2.40	1.97	2.47
Industrial production				
Total index	3.18	1.67	0.56	0.49
Consumer goods	4.75	2.27	2.79	1.53
Materials	5.22	2.74	5.05	2.68
Manufacturing	5.17	3.14	4.94	2.55
Gross private domestic investment	3.89	3.57	3.50	3.41
Government consumption expenditures and gross investment	2.64	1.27	1.54	1.87
Personal income	3.71	2.62	2.62	2.30
Personal income excluding transfers	3.49	2.41	2.59	2.31

Source: Authors' calculations.

Note: Smoothed growth at indicated dates is the one-sided exponential average with discount factor 0.95.

Figure 15. Smoothed Growth Rates of Sectoral Real Activity for 2024:Q3 Versus 2019:Q4, with 45° Line



Source: Authors' calculations.
Note: Smoothed growth rate at indicated dates is the one-sided exponential average with discount factor 0.95. Values for 2019:Q4 are shown on the *x*-axis and values for 2024:Q3 are on the *y*-axis.

facts about the COVID cycle in section I.B across the 128 monthly and additional quarterly real economic time series we consider.

The COVID shock explains the first stylized fact, the sharp and deep initial contraction in March and April. As shown in figure 7, panel C, the COVID shock also explains nearly all of the unprecedented sectoral shifts, with a few exceptions such as the anticipatory run on alcohol and home sanitary products in March 2020 and the pent-up demand for air travel in the late spring and summer of 2021. With the benefit of the new literature on epidemiological-economic models, the economics of these anomalies are well understood as manifestations of self-protective behavior and mandated NPIs prior to the vaccine. What is noteworthy is not why they occurred, but that there is a parsimonious statistical explanation—the single COVID shock—that captures this behavior empirically.

In a statistical sense, the DFM explains the final two anomalies, the rapid recovery and trend reversion of GDP. These explanations raise a number of questions about mechanisms, so we discuss them in some detail, including how they relate to the unprecedented fiscal expansion (the third anomaly).

The rapid recovery (the fourth anomaly) occurred in three phases: very fast (roughly the first five months, or May through September 2020), moderate (months 6–10, or October 2020–February 2021), and fast (roughly months 11–20, or March through December 2021). The DFM attributes the fast first phase to a large negative COVID shock. Over the late spring of 2020, employers and consumers adapted to the new environment by adopting self-protection measures such as social distancing, masking, and Plexiglas protections at retail establishments. These adaptations, combined with the end of the spring wave of deaths, appear in the DFM as a negative COVID shock, that is, good news about the ability to continue economic activity despite the virus. In addition, the summer wave of COVID deaths was substantially smaller than the spring wave which, in conjunction with adaptation to COVID-19, led to small COVID shocks in the summer and early fall of 2020.

These adaptations and outcomes—the negative, then small COVID shocks—facilitated reopening of businesses from May 2020 through the early fall. Arguably, other developments also contributed to the rapidity of the reopening. First, as Hall and Kudlyak (2021, 2022b) stress, the preponderance of workers were on temporary layoff, so they could return to their prior job and avoid time-consuming searching by workers and employers. Second, Autor and others (2022a, 2022b) and Granja and others (2022) estimate that the Paycheck Protection Program (PPP), part of the CARES Act of March 2020, also made a modest contribution to the rehiring during this period because it paid for workers to return to the firm's payroll (from layoff and unemployment insurance) even if they were not actually working. Using the estimates in Autor and others (2022a, 2022b), this contributed perhaps 1–2 percentage points to the decline in the unemployment rate over this period, although the literature on the PPP, including Hubbard and Strain (2020), suggests that these gains were at considerable fiscal cost. Third, as documented and discussed by Decker and Haltiwanger (2023) and Kwan and others (2025), there was a surge in new business formations, facilitated in part by tools (such as Zoom) that make working from home more productive and facilitate labor market entry, for example, for the disabled (Bloom, Dahl, and Rooth 2024) and home caregivers. Fourth, and running counter to these labor market tailwinds, Hornstein and others (2024) estimate that generous pandemic unemployment insurance programs under the CARES Act, such as the Pandemic Unemployment Assistance program, held back the recovery of aggregate employment by 3.4 percentage points from April through December 2020.

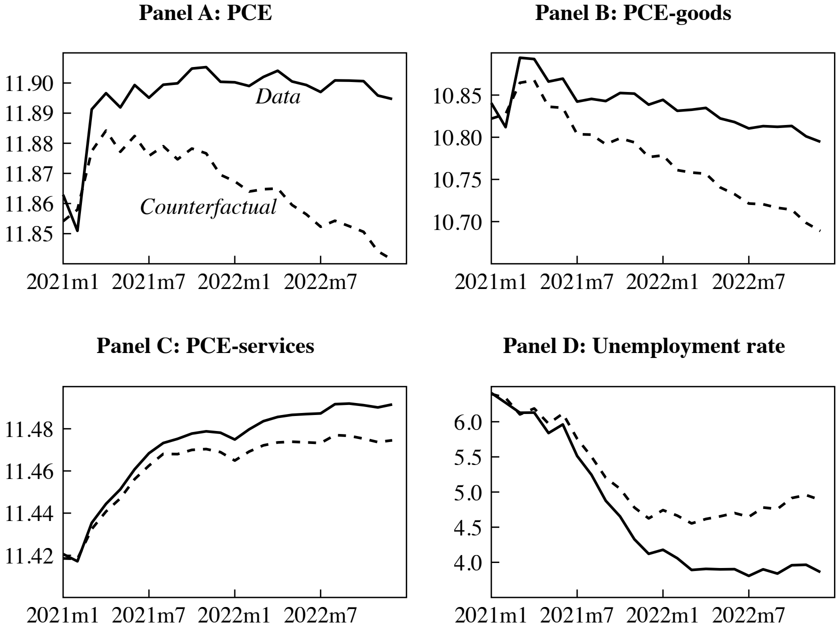
The DFM attributes the second, slower phase of the expansion (months 6–10 of the expansion), with its growth rates comparable to prior expansions, to the positive COVID shocks in December 2020 and January 2021 (figure 10), which correspond to the winter deaths peak from the Beta variant; in fact, the December 2020 COVID shock was second in size only to the much larger March 2020 shock. Leaning against this COVID shock were the transfers, disbursed in January 2021, under the Consolidated Appropriations Act; that act also extended many of the expiring CARES Act pandemic unemployment benefits, further stimulating demand but, as shown by Hornstein and others (2024), tempering an expansion of labor supply. According to the decompositions, for many series including aggregate employment and PCE, these factors largely offset over this phase, resulting in much slower economic growth than in April–September 2020.

The third phase of the expansion, from March 2021 to December 2021, saw a return to above-normal growth, although less strong than during the first phase. By then, the vaccine was widely available. Despite the surge in COVID deaths in September 2021 (Delta variant) and January–February 2022 (Omicron) among the unvaccinated, by mid-spring the COVID shock was essentially zero (figure 10), consistent with the widespread availability of the vaccine for those who wanted it or a lack of economic dampening from COVID-19 by those who did not. With the COVID shock essentially gone, the conventional factors drove growth during this phase.

The most prominent shocks during this third expansion phase were the second and third rounds of stimulus checks under the Consolidated Appropriations Act of 2021 and especially the ARP, which were disbursed in January and March 2021, along with other provisions that affected tax year 2021 (including expansions of the Child Tax Credit and the Earned Income Tax Credit). The shock decompositions (figure 12) provide some circumstantial evidence linking the strong recovery to the ARP. The conventional shocks explain the jumps in consumption in January and March 2021. In addition, the decline in the unemployment rate largely tracks its predicted value, and starting in the spring of 2021 the decline is attributed to the conventional shocks (figure 13).

We refine these observations by conducting a counterfactual that removes this fiscal stimulus. In the context of the DFM, the space of the F shocks includes the fiscal shock. Inspection of figures 11 and 12 suggests that the

Figure 16. Counterfactual Prediction for GDP and the Unemployment Rate Absent the Fiscal Stimulus of January–March 2021



Source: Authors' calculations.
Note: Logarithms of PCE are shown in panels A–C.

fiscal shocks of January–March 2021 appear in the PCE factor. We therefore treat the shock to PCE as including these fiscal shocks, where the PCE shock is identified as the first shock in a Cholesky factorization of the F factors. As a counterfactual, we set the PCE shock to zero in January–March 2021. One justification for this approximate method for identifying the fiscal shock is that there were no other notable non-COVID economic surprises during this period (CEA 2022, chap. 2).

Figure 16 presents the actual and counterfactual values of the unemployment rate and overall PCE, PCE-goods, and PCE-services under the counterfactual of no additional stimulus. According to these estimates, the second and third round of stimulus pulled forward the decline of the unemployment rate from its March 2021 value of 6.1 percent to 5 percent by approximately two months. Absent these two stimulus programs, we estimate that the unemployment rate would have fallen at an annual rate of 0.37 log points per year over this third phase, from March 2021 to December 2021, still faster than the Hall and Kudlyak (2022a) rate but slower than the actual rate of 0.53 log points per year. Given our approximate way of identifying the fiscal shock, these estimates are best viewed as suggestive, and the results are somewhat sensitive to alternative identifying schemes. Still, they do suggest that the two stimulus plans contributed substantially to the speed of the expansion in the third phase.

The final anomaly is the COVID trend reversion of GDP. The estimates of the decomposition of the levels of PCE in figure 12 provide an estimate of the cumulative effect of the COVID and conventional shocks on the levels of these series. For all these series, the return to zero of the COVID shock by mid-2021 accounts for most but not all of the series regaining their prior trend value; that is, the COVID shock alone would have produced unit root behavior (base drift) in the series. The counterfactual estimates for PCE in figure 16 suggest that the two final stimulus plans raised the level of PCE by roughly 5.3 percent by the end of 2022. This is a plausible contribution, given that the two stimulus plans combined amounted to 8.5 percent of GDP in fiscal year 2021 and 2.5 percent in fiscal year 2022 (CEA 2022, table 2-1).

Although this explanation of the third, fast phase of the expansion and of the trend reversion has focused on the expansionary effect of the two stimulus plans, especially the ARP, there are other complementary explanations. Because temporary layoffs had returned to normal levels by the end of 2020, the work by Hall and Kudlyak (2021, 2022b) and PPP do not explain the fast third phase. Instead, one possible explanation is the improvement in technology for working at home, along with the increased access it provides to pull some potential workers into the labor force, which could have led to a persistent increase in entrepreneurial activity (Decker and Haltiwanger 2023). If so, this would have important implications for a long-lasting shift to faster labor market dynamics. In any event, more work remains to sort out the economics of the fast third phase and trend reversion of GDP.

VI.B. Lessons

The COVID business cycle was triggered by just one thing: the novel coronavirus and COVID-19. The threat of severe illness and death triggered a macroeconomic shock that was the macroeconomic manifestation of the epidemiological shock. In our identified DFM, the macroeconomic shock, which is estimated solely from aggregate and sectoral economic data, turns out to be tightly linked to COVID deaths, with a coefficient that declines over time as individuals and governments deploy self-protective measures, as COVID fatigue sets in, and ultimately as the vaccine becomes widely available. The macroeconomic COVID shock affected the economy both directly through new channels and indirectly through conventional channels, including reducing both aggregate demand and aggregate supply and sowing uncertainty.

Because the source of the disturbance was the COVID shock, from a macroeconomic perspective the most important policy measures were those that reversed, then eliminated the shock. Early in the pandemic this was done through self-protection, mandatory NPIs, and by initiating Operation Warp Speed.

Public health policy, especially around NPIs, was divisive and broadly distrusted. The economic costs of NPIs were often ignored by public health officials, public health information and communication were chaotic, nonexperts suddenly became experts and injected noise, and citizens were left alienated and confused (e.g., Macedo and Lee 2025). There have been several retrospectives, and while all agree that the pre-vaccine public health measures were rife with failures, they disagree on the lessons. The COVID Crisis Group (2023) draw on interviews with experts and their own experience to conclude that the top-down, expert-driven approach was the right one but failed because of incomplete information, rigidity of the public health system, insufficient central authority, and inconsistent communication. In contrast, Macedo and Lee (2025) draw on empirical evidence to conclude that the command-and-control approach to public health was bound to fail based on pre-COVID evidence. They point to the small effects of mandated NPIs during the crisis (e.g., Goolsbee and Syverson 2021a, 2021b) and prolonging of certain NPIs with high costs but low public health benefits, like school closures, to conclude that the pre-vaccine public health policy significantly diminished trust in government and science. The *Lancet* COVID-19 Commission (Sachs and others 2022) also criticizes the simplistic views of social behavior that underlaid divisive public health measures. In any event, the decline in trust in scientists (Algan and others 2021) contributed to misinformation and vaccine hesitancy: From August 2021 through December 2022, a period during which the vaccine was widely and freely available, there were more than 475,000 COVID deaths.

From a macroeconomic perspective, the novel COVID macroeconomic shock effectively disappeared when the perceived threat of COVID-19 subsided with the widespread availability of the vaccine. A key lesson is: When faced with a novel shock, take effective policy actions to address that shock directly. Operation Warp Speed and the free availability of the vaccine did so.

Most of federal spending during the pandemic was not, however, on measures that directly addressed the COVID shock; rather, it was on measures designed to dampen the macroeconomic impact of the COVID shock. Given the magnitude of the spending, we believe that additional research on the effects and cost of these policies is needed; however, that research must recognize interactions with the pandemic. As usual, labor market policies such as Pandemic Unemployment Assistance and PPP provided social insurance; uniquely, during the COVID-19 pandemic, by keeping workers out of the labor market, they reduced exposure and deaths, thereby diminishing the COVID shock.

From a fiscal perspective, the largest pandemic-era program was the ARP. The ARP was signed on March 11, 2021, by which time more than 50 million doses of the vaccine had been administered and one month before all Americans adults became eligible for vaccination. The Congressional Budget Office (2021) scored the ARP as adding $1,164 billion to the deficit through September 2021, and another $528 billion in fiscal year 2022, of which $93 billion was for public health (Kates 2021). Because the macroeconomic COVID shock was nearly vanquished by the date of its enactment, in hindsight the ARP is best viewed as conventional deficit-financed fiscal stimulus applied to an economy with an unemployment rate of 6.1 percent. Because of the vaccine rollout, the ARP also coincided with pent-up demand for consumption that had been postponed during the pandemic, such as air travel to visit now-vaccinated family, vacations, and entertainment services.

With no COVID shock to retard growth, we estimate that the ARP expedited the final phase of the recovery, contributed to a decline of the unemployment rate from 6.1 percent in March 2021 to 3.9 percent in December 2021—a decline of 0.45 log points that would have taken four years at the rate estimated by Hall and Kudlyak (2022a)—and raised employment and output to their prior trend levels. These benefits, however, came at significant costs, adding 7.5 percentage points to the debt-to-GDP ratio over fiscal years 2021 and 2022, thereby reducing future fiscal headroom. Although the jury remains out, recent studies point to the ARP stimulus as being a source of excess demand pressures that contributed to the pandemic-era inflation.[19] With these observations, one could reasonably conclude that the ARP was too much, too late. Given the magnitude

19. Dynan and Elmendorf (2024) make the case for the ARP stimulus being the key driver of this inflation. There are, however, other factors and views: the energy price increases in late 2020 through early 2022 (Bernanke and Blanchard 2025), supply chain disruptions and the inability of sectoral supply to keep up with sectoral demand shifts (di Giovanni and others 2025), and the role of energy prices in driving short-run inflationary expectations (Beaudry, Hou, and Portier 2025).

of this policy experiment, more work is needed to better understand labor market dynamics during the third, fast phase of the COVID recovery, the role of the ARP, and the ARP's subsequent consequences.

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Comments and Discussion

COMMENT BY

MARK GERTLER[1] This paper provides a lively retelling of the COVID recession and recovery, viewed through the lens of some interesting formal econometrics. Despite bringing back some unpleasant memories, I found the paper highly enjoyable to read.

Any story of the COVID recession begins with the rapid decline in spending in the virus-exposed service sector and, after a brief decline, the rapid rise in spending in the less exposed goods sector. By contrast, in conventional recessions, the goods/services spread is procyclical, not countercyclical. It also displays much less volatility. These facts ultimately provide the essence of the authors' argument that the dynamics of the COVID recession differed in two basic ways: first, the sharpness and brevity of the initial contraction in real activity, and second, the reallocation away from services in favor of goods. Using their formal econometric framework, the authors further argue that the period of unusual COVID dynamics was relatively brief, roughly from the onset in March 2020 to mid-2021. After this point, conventional business cycle dynamics resumed.

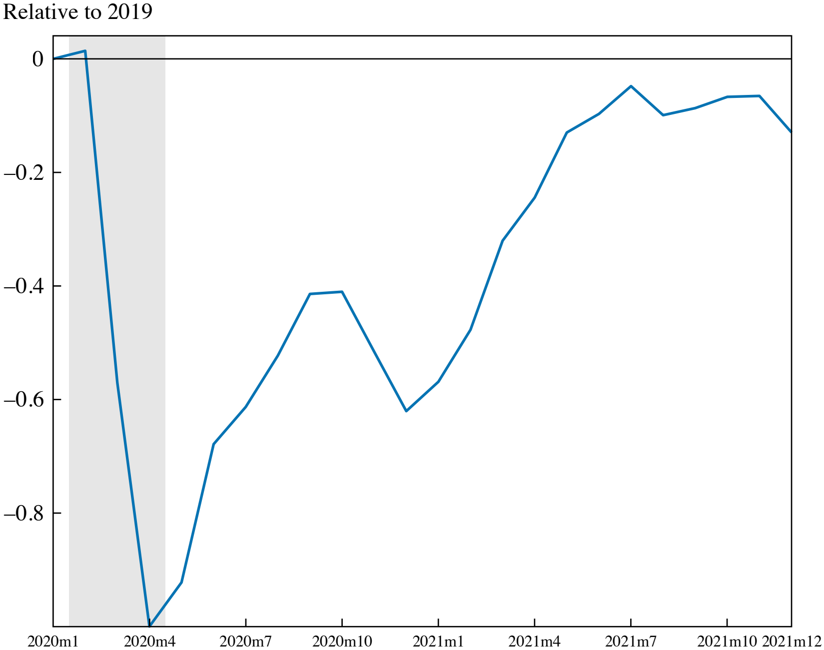
Let me first provide some descriptive evidence that sheds light on the authors' hypotheses. I then review their formal statistical model. Finally, I finish with several comments.

DESCRIPTIVE EVIDENCE A good way to see the special nature of the COVID recession is to track the behavior of restaurant dining. Using data from OpenTable, figure 1 plots dinner reservations over the course of the pandemic, relative to reservations at the end of 2019.[2] Keep in mind that

1. I thank Hyein Han for outstanding research assistance.

2. OpenTable, "State of the Industry: The Restaurant Industry, by the Numbers," https://www.opentable.com/c/state-of-industry/.

Figure 1. OpenTable Dinner Reservations

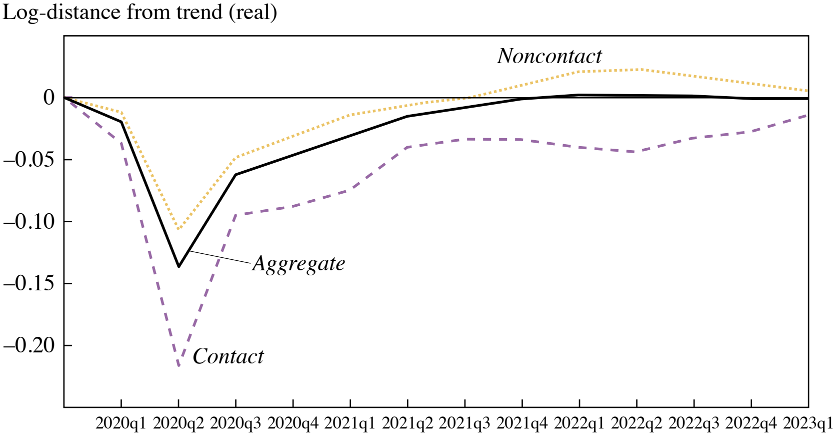


Source: OpenTable.
Note: OpenTable's state of the restaurant industry for the United States, measured as the share of 2019 reservations.

restaurant dining normally does not display much cyclical behavior. In this instance, however, restaurant reservations basically collapse to zero between the onset of the pandemic in March 2020 and the trough of the recession in April 2020. In contrast to the response to standard business cycle shocks, which are typically delayed and hump-shaped, the response to COVID shock was immediate and seismic. The fear of serious illness undoubtedly motivated people to stop dining out. For similar reasons, on the supply side, restaurant employees wanted to avoid work. Facilitating the rapid decline in restaurant dining was the rapid growth in online grocery shopping.

Over the next six months nearly half the ground was made up, consistent with the authors' evidence of a rapid recovery over this period for broader indicators of economic activity. By the middle of 2021, restaurant dining was effectively back to normal. As the authors note, at this time, due to a variety of factors, the virus was under control. The return of restaurant dining

Figure 2. Contact Versus Noncontact Sectors



Source: Reproduced from Cirelli and Gertler (2025) with permission, copyright American Economic Association.

Note: Figure shows the log-distance from trend of real revenue of the aggregate economy and the contact and the noncontact sectors as classified in Cirelli and Gertler (2025). Nominal output data come from the BEA and are transformed to real using the chain-type price indexes for gross output for private industries. Trends assumed are 4 percent for nominal output and 2 percent for prices.

to pre-COVID levels in mid-2021 is consistent with the authors' evidence of the return to conventional business cycle dynamics at this time.

For a broader perspective, figure 2, taken from Cirelli and Gertler (2025), tracks the quarterly revenue behavior of industries directly exposed to virus (contact) versus those not directly exposed (noncontact). Following Kaplan, Moll, and Violante (2020), Cirelli and Gertler start with the Bureau of Economic Analysis (BEA) North American Industry Classification System (NAICS)'s two-digit classification of twenty-one private sector industries. They then use the Kaplan, Moll, and Violante (2020) classification of each industry into contact or noncontact based on the degree of personal interaction involved either in the buying or supplying of the relevant product. The contact sector, which contains mostly services, constitutes roughly a quarter of total revenues. The noncontact sector is dominated by industries that are traditionally more cyclical, including construction, manufacturing, and wholesale trade.

Each of the series in figure 2 is a log deviation from trend from 2019:Q4 through 2023:Q1. Overall, the figure clearly illustrates the distinctive nature of the COVID recession. The economy collapses in 2020:Q2, with a sharp, 13 percent drop in aggregate private sector revenues relative to trend, followed by a quick reversal. Further, the contact sector dominates the drop, with a roughly 22 percent drop relative to trend. Indeed, this is true even though the noncontact sector contains the normally procyclical industries. Indeed, allowing for the fact that the contact sector revenue data are quarterly while the restaurant data are monthly, the two series behave similarly over the recession and recovery period. After dominating the contraction in the early part of the recession and recovery, the contact sector returns mostly to normal by late 2021 and practically back to trend by the end of 2022.

COVID-AUGMENTED DYNAMIC FACTOR MODEL In light of the descriptive evidence, I turn to the authors' formal econometric framework. The authors develop a simple dynamic factor model (DFM) that allows for a set of conventional factors F_t that help explain postwar business cycles prior to the pandemic and a COVID-era-specific factor C_t designed to capture the unusual features of this recession described above. Let Y_t be a vector of roughly one hundred macro-relevant time series and u_t a vector of idiosyncratic shocks associated with each of these series, that is, one per series. The DFM is then:

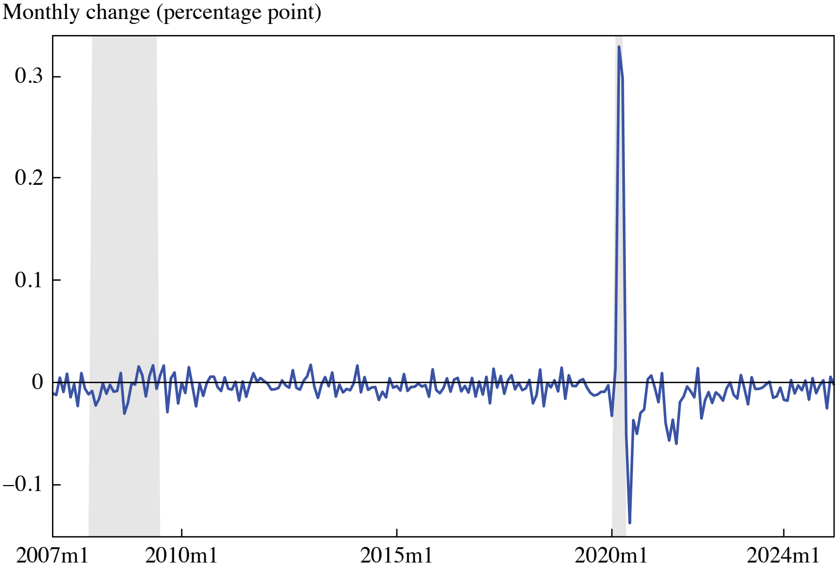
$$Y_t = \Lambda F_t + \Gamma C_t + u_t,$$

where Λ is the loading of the conventional factors F_t on Y_t while Γ is the loading of the COVID factor. The authors assume that for pre-pandemic data, Γ equals zero. As a result, they identify Λ by estimating the conventional factor model on pre-pandemic data.

To analyze the dynamics, the framework also requires equations of motion for F_t and C_t. In general, the evolution of each factor will depend on their own lags along with the lags of the other factors and a set of associated structural shocks, ε_t^F and ε_t^C. Here ε_t^F is a vector of structural shocks associated with the conventional factors, while ε_t^C is the COVID shock. As the authors emphasize, the COVID shock captures both a direct effect, where the illness reduces both demand and supply, as well as a perhaps quantitatively important indirect effect, where fear of catching the virus does the same. In any event, the goal is to trace the impact of the COVID shock in order to formally characterize the unusual dynamics over this period.

To identify ε_t^C, the authors use timing restrictions. In particular, they assume the COVID shock affects the conventional factors immediately with the month and, by contrast, the conventional factors affect the spread of COVID-19 only with a lag. That a COVID shock could have a large immediate impact on economic activity should not be controversial in light of the descriptive evidence in figures 1 and 2. It is true that the epidemiological literature suggests a feedback effect wherein economic activity affects the

Figure 3. Weighted Spread $\Delta\ln(PCE_{goods}) - 3.8\Delta\ln(PCE_{services})$



Source: BEA (retrieved from FRED series DGDSRV1Q225SBEA and DSERRG3M086SBEA).
Note: In the spread, the weight 3.8 equals the ratio of estimated COVID-shock factor loadings on services and goods consumption. Both PCE series are deflated by their own chain-type price indexes to obtain real consumption.

spread of the virus. However, the authors make the case that any feedback only happens with a lag greater than a month. Thus, it should not be controversial to suggest that the authors' COVID shock is plausibly exogenous.

FINDINGS Given their econometric framework, the authors reach three sets of conclusions: First, COVID-induced dynamics may be captured by single factor and the shock to this factor ε_t^C covaries with COVID deaths and with a weighted spread between goods and services output. Second, the COVID shock accounts for most of the variation in economic activity through mid-2021, including both aggregate and cross-sectional variation. Third, there were no persistent COVID-induced business cycle dynamics. After mid-2021, pre-COVID dynamics resumed. There were a few changes (e.g., remote work), but the economy was, in their view, mostly resilient.

Figure 3 sheds some light on how the model may be capturing COVID dynamics. The authors show that the COVID shock is highly correlated with the following weighted spread between the growth rates of goods and services: $\Delta(PCE_{goods}) - 3.8\Delta(PCE_{services})$; PCE denotes Personal Consumption Expenditures. The figure plots this spread from 2007:M1 through 2024:M12.

There is almost no variation pre-pandemic. Note, however, the huge positive jump in the spread during the COVID recession. While both goods and services exhibited negative growth over this period, the percentage drop in services was actually large. This outcome, combined with a rather large weight of 3.8 on services' growth, accounts for the huge positive jump in the weighted spread. It is the startling jump in this factor that accounts for the unusual sharp contraction in economic activity. After the business cycle trough, the growth in both goods and services turns positive. Given the large weight on services though, the weighted spread turns negative, which contributes to the immediate (partial) bounce back in growth. By late 2021 the shocks dissipate. Thus, on the whole the COVID factor is central in the early part of the recession and recovery. But it plays no significant role after 2021. Over this later period, conventional business cycle dynamics resumes.

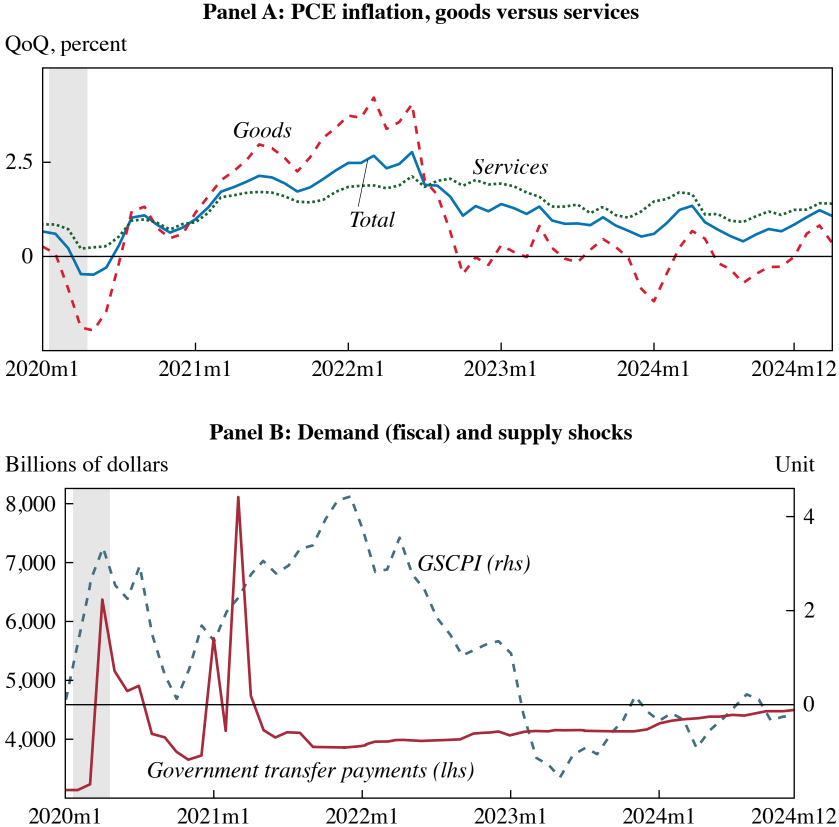
THREE ISSUES I next provide some comments on three sets of issues that I think would be useful to address in follow-up work (either by the authors or others): first, the inflation surge, which was, in my opinion, as distinctive a feature of the COVID recession and recovery as was the services-to-goods reallocation; second, the COVID-era increase in costs, including food and housing costs, issues that reflect the persistent impact of the COVID-19 pandemic; finally, another issue reflecting the pandemic's persistent effect, namely, the impact of the recession and recovery on fiscal sustainability.

The inflation surge. Underlying the high and persistent inflation of the 1970s was the unmooring of long-term inflation expectations. By contrast, during the recent inflation, long-term inflation expectations remained reasonably well anchored. In this sense, the recent surge was a unique feature of the COVID period. It also fits the broad theme of the authors' characterization of the period in the respect that it is associated with a reallocation between services and goods. In particular, as figure 4, panel A, shows, it was goods inflation that led the overall rise in inflation. Goods inflation, further, was strongly correlated with the share of goods in overall consumption spending.[3]

Importantly, however, the inflation surge did not take hold until late spring, when the authors' COVID shock was beginning to dissipate. This begs the question of how we are to think of where inflation fits in the authors' analysis. I think we would all agree that COVID-era dynamics triggered the surge. Indeed, figure 4, panel B, shows two factors generally thought to be important drivers of the inflation increase: first, fiscal stimulus, measured by total government transfers; and second, the Federal Reserve Bank of

3. See Guerrieri and others (2023) for an overview of the inflation surge.

Figure 4. The Inflation Surge

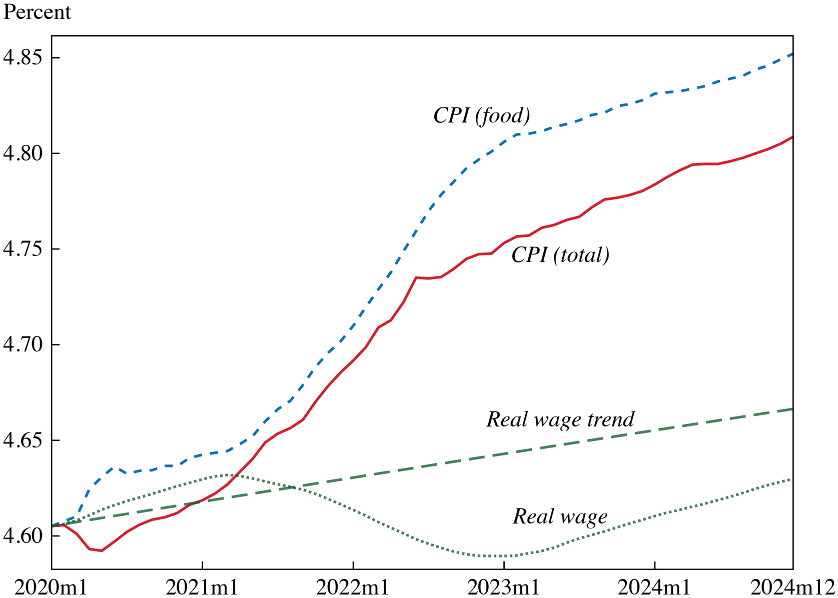


Source: BEA and the Federal Reserve Bank of New York.

Note: Panel A plots the quarter-over-quarter percentage change in the chain-type PCE price index. Panel B shows government Social Security transfer payments (retrieved from FRED series W823RC1) and the GSCPI.

New York's Global Supply Chain Pressure Index (GSCPI). The first factor, along with highly expansionary monetary policy, contributed to increasing demand and hence inflation. However, as the authors make clear, it is the second conventional factor (the one tied to consumption spending) and not the COVID factor that accounts for the round of fiscal stimulus that most directly contributed to the surge. Similarly, the behavior of the GSCPI, which captures a role for supply factors in the surge, is likely also not explained by the COVID factor, given the timing. All this is to suggest is that there is room for tightening the description of how the real sector dynamics during the pandemic led to the inflation surge.

Figure 5. Prices, Real Wages, and Food Prices

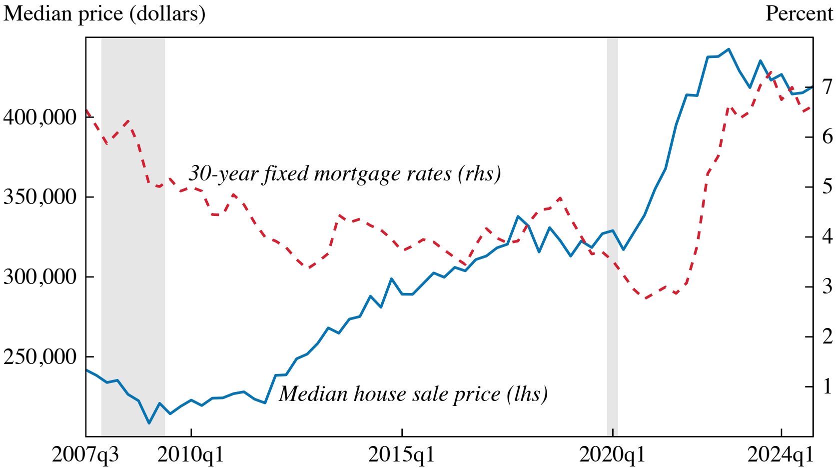


Source: Bureau of Labor Statistics; Federal Reserve Bank of Atlanta; and Afrouzi and others (2024).

Note: Figure compares CPI for all items and for food (retrieved from FRED series CPIAUCSL and CPIUFDSL) with real wage index for the median worker, constructed by the Federal Reserve Bank of Atlanta's Wage Growth Tracker using the Current Population Survey (CPS) micro data. The wage index is normalized to one in December 2015, and the fitted values of a linear time trend over January 2016–December 2019 are plotted by fitting a linear time trend on the pre-period data (January 2016–December 2019). Specifically, Afrouzi and others (2024) estimate real wage = $\beta_0 + \beta_1 \times$ (months since December 2015) + measurement error. They take estimates of β_0 and β_1 and construct a predicted real wage index.

Costs. Next, I turn to several issues regarding the persistent effects of the COVID-19 pandemic. The first set of issues involves costs, an issue that brought down incumbent parties across the globe. As figure 5 shows, the Consumer Price Index (CPI) rose more than 20 percent over the COVID era. Perhaps naively, I am going to assume that individuals do not have money illusion and instead care about relative prices. The bottom line plots the behavior of real wages, measured as the median nominal wage normalized by the CPI. The figure suggests that by the end of 2024, real wages returned to where they were at the beginning of the pandemic. However, as Afrouzi and others (2024) note, prior to the pandemic, real wages were growing on average at an annual rate of roughly 1.3 percent. The implication is that over the COVID recession and recovery real wages fell roughly 5 percent relative to trend, as shown by the figure. Of course, food prices

Figure 6. Housing Prices and Mortgage Rates



Source: US Census Bureau; Department of Housing and Urban Development; and Freddie Mac.
Note: Figure plots the median sales price of houses sold in the United States (retrieved from FRED series MSPUS) and the thirty-year fixed-rate mortgage average (retrieved from FRED series MORTGAGE30US). Both series are monthly.

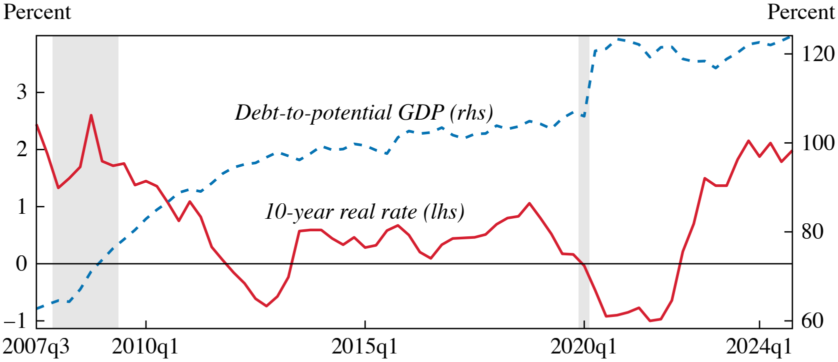
were a particular source of concern. As the figure shows, the CPI with food grew more than an additional 5 percent relative to the CPI. Overall, this stagnation of real wages and general persistent drop in purchasing power for key items was a significant source of dissatisfaction that deserves further investigation.

Housing costs. Figure 6 presents two basic indicators of housing costs: the mortgage rate and housing prices. Since 2022, both variables have been unusually high. How is this related to COVID-19? Note first that unusually expansionary monetary policy involving both the federal funds rate and asset purchases pushed the thirty-year mortgage rate to record lows. Extraordinarily low mortgage rates, possibly in conjunction with other COVID-related factors, helped boost housing prices. The reversal of monetary policy, again featuring both conventional and unconventional tools, pushed mortgage rates up. But housing prices have been relatively slow to respond, leaving households in a world where both prices and mortgage rates are high.

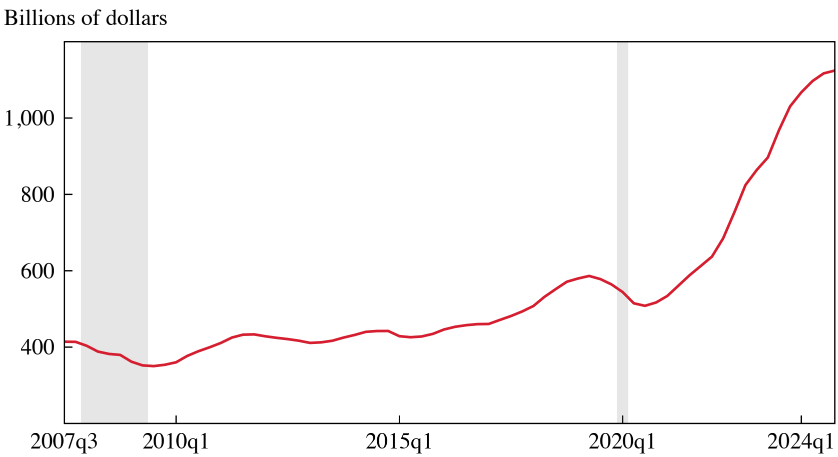
Fiscal unsustainability. The last issue I discuss that has been affected by the COVID-19 pandemic is fiscal sustainability. As the authors note, over the pandemic era there has been a persistent and significant increase in the ratio of debt to GDP. Panel A of figure 7 illustrates this by plotting the ratio

Figure 7. Fiscal (Un)sustainability

Panel A: Government debt-to-GDP ratio and ten-year real government rate



Panel B: Federal interest expenses



Source: Federal Reserve Board; Federal Reserve Bank of St. Louis; US Treasury; Congressional Budget Office; and BEA.

Note: Panel A plots the ten-year real interest rate (nominal ten-year Treasury yield, retrieved from FRED series DGS10, minus ten-year breakeven inflation rate, retrieved from FRED series T10YIE) and the federal debt-to-potential GDP ratio (retrieved from FRED series, GFDEBTN / NGDPPOT × 100). Panel B shows federal interest outlays (retrieved from FRED series A091RC1Q027SBEA).

of government debt to potential output. A second important consideration is that interest rates have risen significantly over this period. The figure plots the real long-term rates, measured as the ten-year government bond rate minus the ten-year breakeven inflation rate. The real rate increases from under 100 basis points pre-COVID to more than 200 basis points post. The tightening of monetary policy described above is certainly one causal factor. The piling up of government debt is likely another. In any event, the increase in both short and long real rates has had dramatic effects on the federal fiscal situation. Not only is the debt-to-GDP ratio way up, but interest expenses are also now the largest component of government expenditures. As panel B shows, interest expenses have more than doubled over the pandemic period. While, as the authors have shown, the US economy in many ways showed incredible resilience to the COVID-19 pandemic, climbing out of this fiscal mess will prove challenging.

CONCLUSION No doubt, as typically happens with papers by Stock and Watson, this one will become a standard reference for the historical analyses of the COVID cycle. I would only suggest a part 2, either by the authors or by someone else, that connects the detailed analysis of real sector in this paper to the behavior of inflation and costs over the pandemic era.

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COMMENT BY

LUCREZIA REICHLIN The COVID-induced recession was distinct in its speed, depth, and sectoral characteristics. Consumption patterns shifted dramatically from services to goods, and the labor market experienced an unprecedented disruption followed by a rapid recovery.

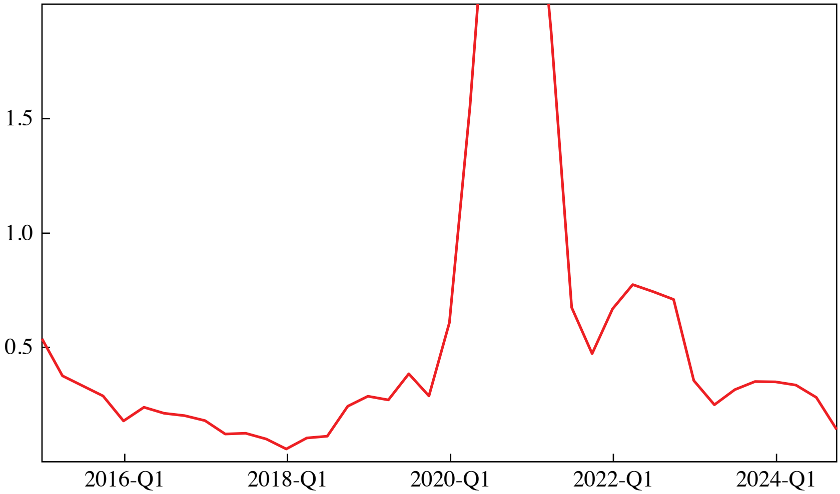
It is sometimes said that everything changed with the COVID-19 pandemic. This paper argues the contrary: The COVID recession—unlike previous ones in the postwar United States—can be considered as a temporary event that did not leave any scar on the economy. By the end of 2020, the exceptional features characterizing the COVID episode were over. This is argued by showing that, post-2021, the resilience of employment and consumption was mostly explained by regular business cycle shocks, which are also those characterizing the pre-COVID historical experience, and that most macroeconomic variables returned to their pre-pandemic levels by late 2021. The structural analysis suggests that the resilience of consumption and the labor market in the second part of the recovery are to be attributed to the large second and third fiscal stimuli of early 2021. The paper, however, remains agnostic on costs and benefits of those measures as it does not analyze inflation or public debt evolution, although it acknowledges that this is a key question for further research.

The analysis is evidence of the effectiveness of the timely and robust response to the COVID shock (i.e., the lockdown and related measures to minimize social interaction), which caused the economy to close down as the death toll increased; but also, more controversially, the analysis is evidence of the effectiveness of the second and third fiscal stimuli.

In my comments I will focus on the essential aspects of the analysis and offer some complementary observations to evaluate the interpretation of the results. I conclude that the statistical analysis of the COVID recession and first phase of the recovery, describing it as an exceptional and temporary event, is persuasive and supported by other statistical evidence. I will also agree with the authors that there is evidence that the second and third fiscal stimuli had a role in explaining the resilience of the US economy in 2021 and 2022, but I will argue that more work is needed to establish this more firmly. Other changes in the economy associated with the pandemic, leading to an increase in productivity, may also have had a role. The weaker recovery of the European economies suggests that demand policy and productivity developments may not be independent. Finally, I will provide some evidence on the dynamics of the sectoral distribution of inflation and economic activity to shed some light on the role that demand versus reallocation and relative price changes had in explaining the inflation surge associated with the second and third phases of the recovery. I will argue that, post-COVID, the exceptional dispersion of sectoral inflation points to sizable relative price changes as a driver of aggregate inflation. Although this does not rule out the contribution of demand policy, and in particular the late fiscal expansions, to explaining the inflation surge of 2022, it suggests that this is not the whole story.

INTUITION OF THE METHODOLOGY The authors' analysis relies on a factor model estimated on a large number of time series capturing aggregate and sectoral real economic activity. The authors distinguish between three F factors, capturing normal business cycle comovements based on historical

Figure 1. US GDP Nowcast: Rolling Four-Quarter Root Mean Square Forecast Error (RMSFE)



Source: Now-Casting Economics Ltd.

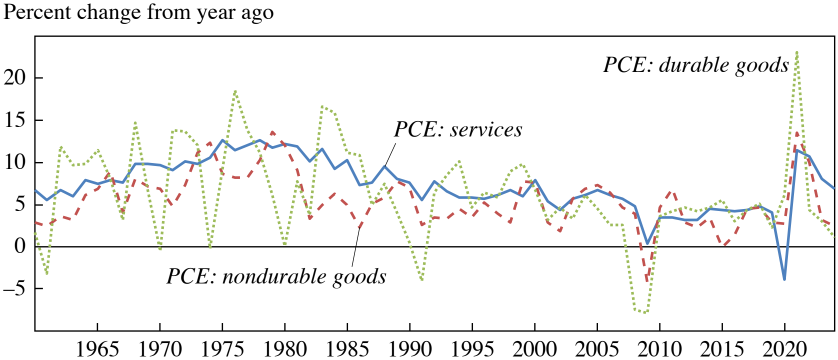
patterns of fiscal and monetary policy, and a *C* factor (COVID factor), constructed as a temporary factor introduced to account for comovements specific to the COVID period, including sectoral reallocation and the initial fiscal stimulus. Structural shocks, impulse response functions, and variance decompositions are then computed from the estimated factor model. The effort of the paper is to identify robust stylized facts, an exercise that is essential for identifying any structural explanations of the events.

An intuitive way to describe the model developed by the authors is to think of the COVID recession and first phase of the recovery as an extra dimension of business cycle dynamics, capturing an exceptional but temporary event. Essentially, the COVID factor can be thought of as a dummy variable that does not contaminate the regular business cycle dynamics and whose effect is reabsorbed entirely by early 2021.

As complementary evidence, I report, in figure 1, the rolling root mean square forecast error from a nowcasting model of GDP growth estimated on pre-COVID parameters but whose forecasts are updated in real time on an expanding information set by running a Kalman filter as new data become available.

The chart shows that the forecast error shoots up at the beginning of the recession as the model does not anticipate it, but declines rapidly by the end

Figure 2. Consumption in Goods and Services



Source: Bureau of Economic Analysis (retrieved from FRED series PCEND, PCEDG, and PCES).

of 2021 and returns to pre-COVID level by the end of 2023. This evidence supports the view that the COVID episode is captured by a *dummy* variable that is uninfluential on the performance of a model estimated on pre-COVID data. This dummy variable is essentially what Stock and Watson capture by the orthogonal COVID factor.

This way of characterizing the COVID-19 pandemic is also consistent with findings by Lenza and Primiceri (2022), who estimate a monthly vector autoregression (VAR) over the sample 1988:M1–2020:M5, omitting April to May 2020, and find that impulse response functions are the same as those estimated pre-COVID. Lenza and Primiceri conclude that dropping the extreme observations from the pandemic era is acceptable for the purpose of parameter estimation. Stock and Watson go a step further and show that the COVID factor captures the exceptional reallocation from services to goods in both activity and consumption during that period.

As additional evidence to that provided in the paper, figure 2 plots the Personal Consumption Expenditures (PCE) of services and goods over time. The chart shows the exceptional characteristics of the COVID recession. While normally consumption of services is smoother than consumption in goods and the service-good consumption ratio goes up in recessions, with COVID-19 the opposite happened. This is particularly striking when comparing the COVID recession with the global financial crisis.

THE ROLE OF THE FISCAL MEASURES IN EARLY 2021 Having estimated the model, the authors show that, starting in 2021, consumption and employment have been mostly explained by the regular factors while the COVID factor had no role to play. The evidence provided shows that, since 2021, there has been nothing exceptional in business cycle dynamics. The economy, after having experienced an exceptionally deep recession and an equally exceptionally fast recovery, resumes its normal pattern of growth and cross-sectional comovement.

Figure 8 in the paper shows the key result but also raises some questions of interpretation. Since 2021, consumption and employment are almost perfectly explained by the regular factors but government transfers and personal income are not, since they feature two large shocks associated with the fiscal stimuli of January and March 2021.

How can we interpret these shocks? Figure 3 reports the ratio between savings and personal disposable income (panel A) and personal consumption plotted against real disposable income (panel B). The two peaks in the savings rate and in personal disposable income correspond to what Stock and Watson identify as shocks to the factors loading government transfers and personal income in their figure 8. It appears that the shock in government transfers was equivalent to a shock in personal income that went into savings rather than consumption.

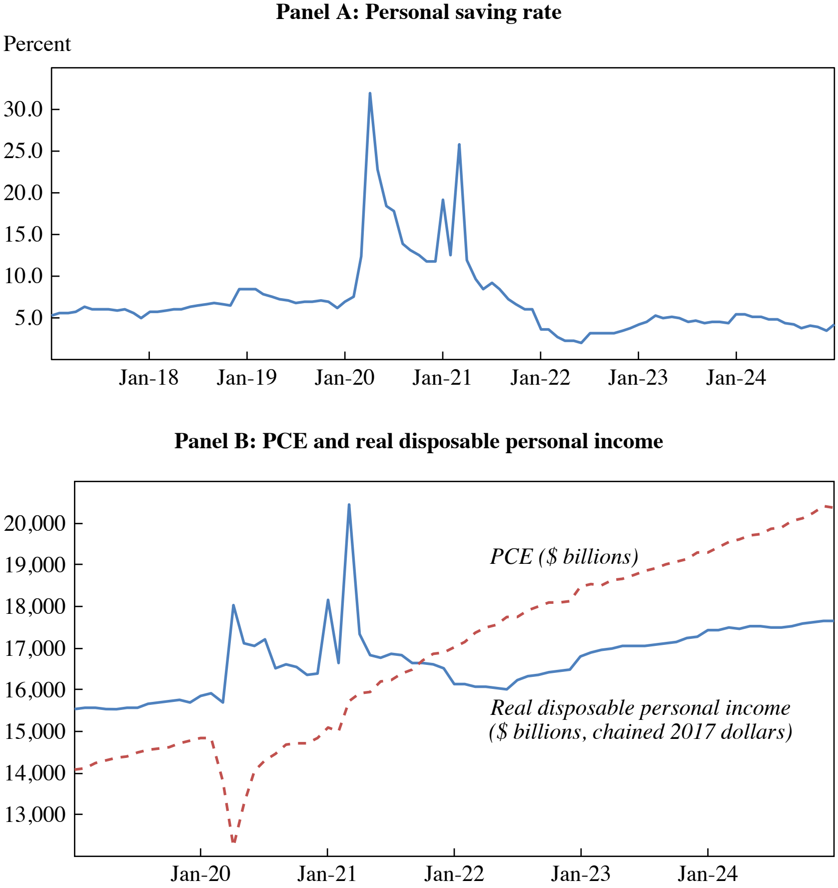
The model interprets these as regular business cycle shocks (shocks to the conventional factors), but they are exceptional in size and in their transmission across variables.

The authors go a step further and identify the two spikes as a fiscal shock affecting the consumption factor by defining it as the first shock in a Cholesky factorization of the factors. On the basis of a counterfactual exercise (see figure 16 in the paper), consisting of shutting down this fiscal shock between January and March 2021, they then conclude that the strength of consumption and employment in the second and third phase of the recovery is due to the fiscal stimuli of 2021. The counterfactual, however, cannot be clearly interpreted in a causal way. Moreover, as the authors themselves acknowledge, this is a very rough identification strategy, which relies on the hypothesis that no other shocks were relevant in that window. But many other things were going on in 2021, including changes in the labor market and in productivity as the authors themselves discuss in the paper.

The role of fiscal policy in explaining the resilience of consumption and employment is, however, supported by research that identifies demand shocks as the main drivers of economic activity since late 2021. This is, for example, the finding by Giannone and Primiceri (2024) on the basis of a structural VAR and the identification of demand and supply shocks (their result is reported in figure 4).

Another piece of evidence, consistent with the fiscal story, comes from a comparison of the post-COVID recovery in the United States with that

Figure 3. Savings, Consumption, and Personal Income

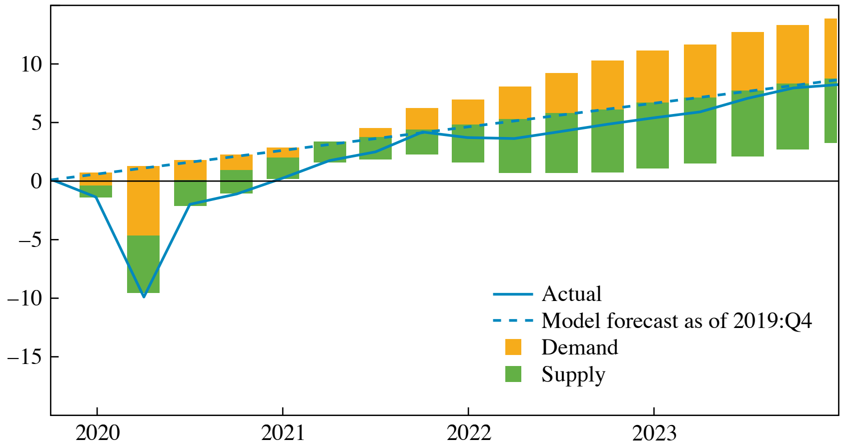


Source: Bureau of Economic Analysis (retrieved from FRED series PSAVERT, PCE, and DSPIC96).

of the euro area and with the recovery following the global financial crisis in both jurisdictions. Figure 5 reports GDP and components for the United States and the euro area, indexed so that the first quarter of each of the two recessions is set to zero. The charts plot observed data against pre-recession trends calculated over the previous ten years. They show that where fiscal support was weak—the euro area in both episodes and the United States after the global financial crisis—the economy did not return to pre-recession trend. This time in the United States was different, and this may be linked to the exceptional fiscal expansion of 2021.

Figure 4. Contribution of Demand and Supply Shocks to US GDP

100 × log deviation from 2019:Q4



Source: Reproduced from Giannone and Primiceri (2024) with authors' permission.

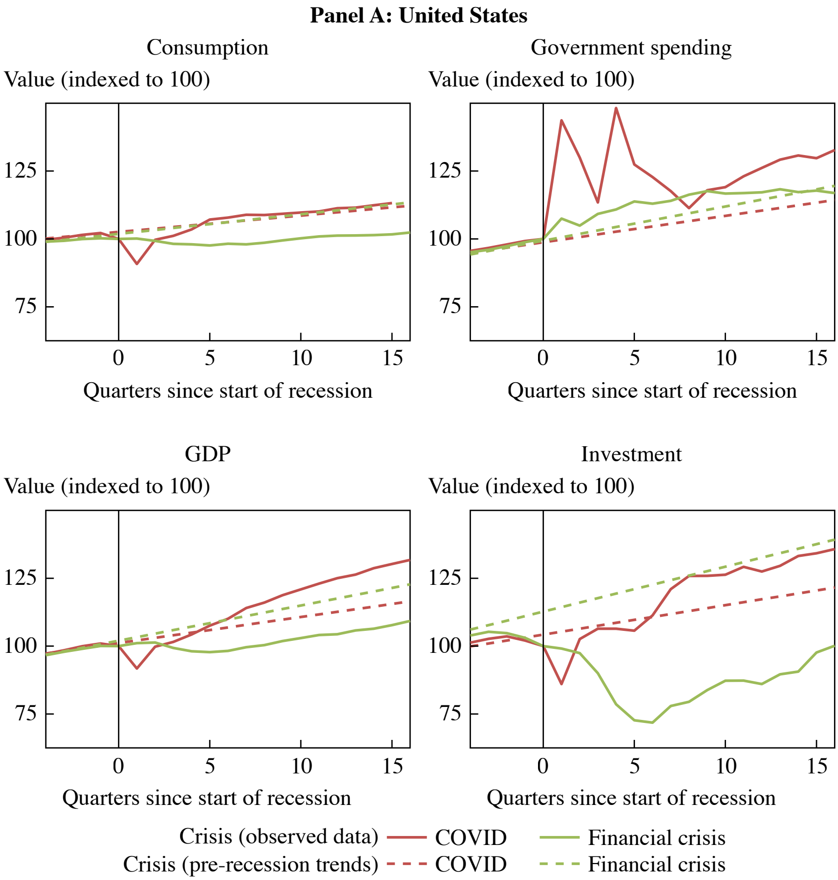
If we add to these considerations the result of figure 5 in the paper, which reports the log of GDP and its peak-to-peak trend from the National Bureau of Economic Research (NBER) recessions dating since 1960, showing that the COVID recovery is unique in having brought the economy back to its pre-recession trend, we may conclude that the long-term scars left by other recessions in the United States or elsewhere might be explained by insufficient fiscal support. This is certainly the most controversial message of the paper.

LONG-TERM SCARS An alternative explanation of why this time the US economy did not experience long-term scars coming out of the recession, briefly discussed in the paper, is the increase in labor productivity that has followed the COVID recession.

Indeed, the COVID factor is associated with a large part of the drop in labor force participation and with an acceleration of digitalization and working from home. As an example of the acceleration of digitalization, figure 6 reports the time series of e-commerce retail sales over total retail sales (seasonally and nonseasonally adjusted). The chart shows that e-commerce jumped up at the beginning of 2020 and converged persistently to a higher ratio.

Increase in digitalization is also evident in Europe. The crisis acted as a powerful accelerator for digital transformation across multiple sectors. According to Eurostat, for example, the share of European Union internet

Figure 5. GDP and Components Around the Global Financial Crisis and the COVID-19 Pandemic

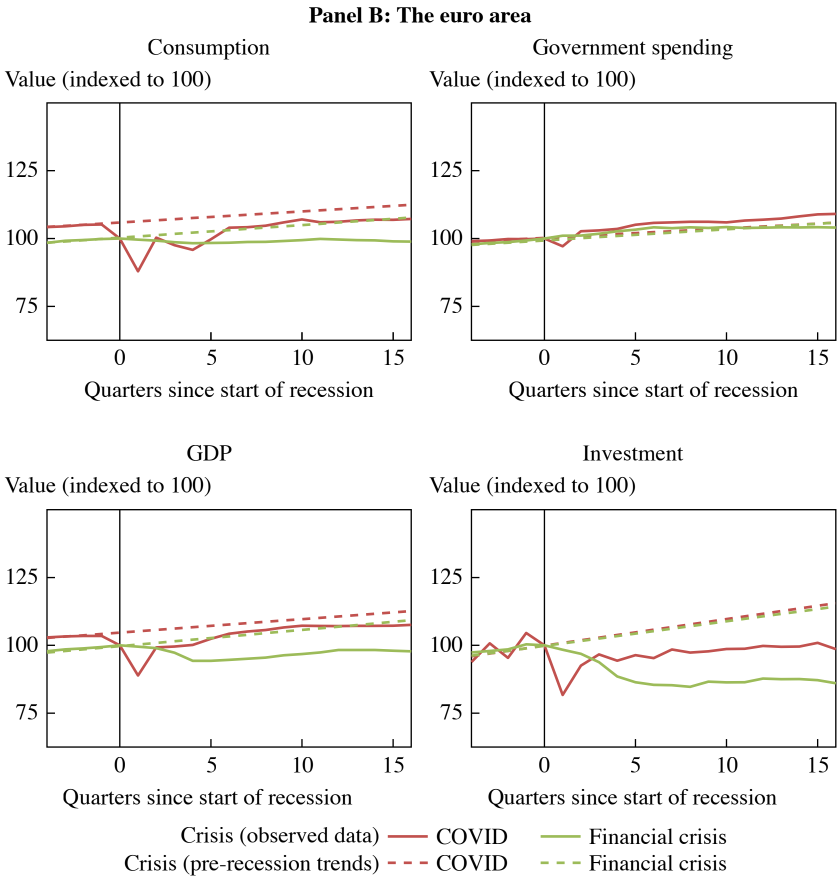


users who bought goods or services online rose from 60 percent in 2019 to 72 percent in 2021. However, this failed to lead to a persistent increase in productivity.

Figure 7 compares labor productivity dynamics in the United States with those of the euro area. It shows that labor productivity jumped up both in the United States and the euro area in relation to the COVID-19 pandemic, but while in the United States it converged to a higher level on a persistence basis, in the euro area it declined after the initial increase.

Can this difference be explained by the fact that in Europe the fiscal stimulus was not as strong? A conjecture is that the fiscal stimulus may have had a role not only in supporting aggregate demand in the short run

Figure 5. GDP and Components Around the Global Financial Crisis and the COVID-19 Pandemic (*Continued*)

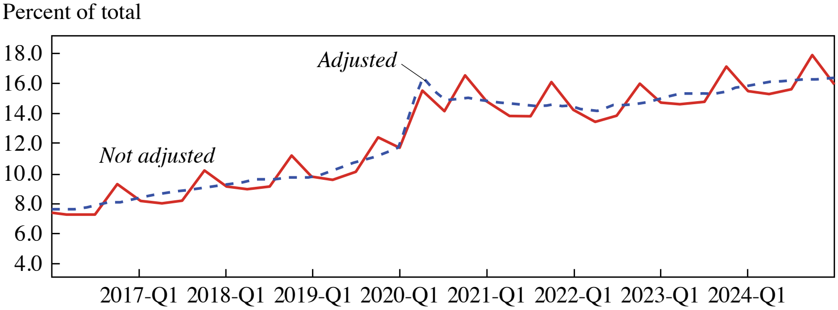


Source: Author's calculations based on data from Eurostat (online data code namq_10_gdp) for the euro area, and from Bureau of Economic Analysis (retrieved from FRED series GDP, GPDI, and W068RCQ027SBEA) and International Monetary Fund (retrieved from FRED series NCPHIRSAXDCUSQ) for the United States.

but also in affecting the economy in the medium run. This is just a conjecture, and there are other factors that affected productivity negatively in the euro area, especially after the energy crisis following the outbreak of the Russia-Ukraine war. Nonetheless, the difference is striking, and perhaps we can learn something from cross-country comparison.

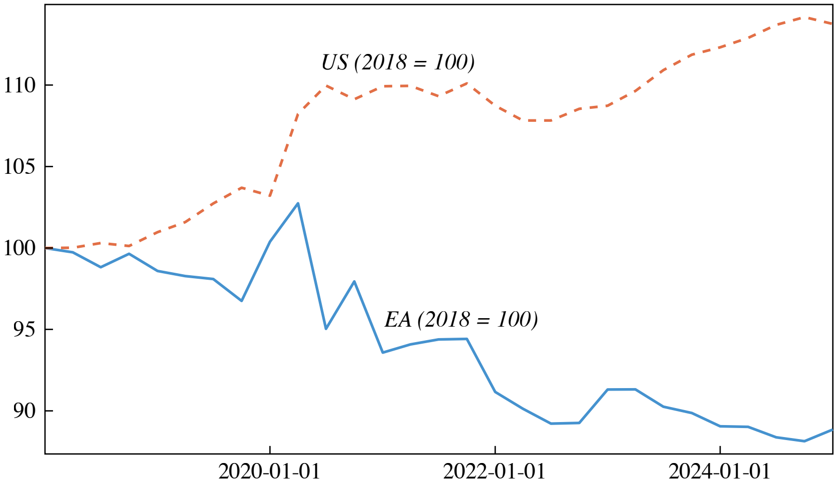
WHAT CAN WE LEARN FROM PRICE DYNAMICS? The COVID recession and recovery were associated with sectoral reallocation of economic activity

Figure 6. Estimated Quarterly US Retail E-Commerce Sales as a Percentage of Total Quarterly Retail Sales: 2016:Q1–2025:Q1



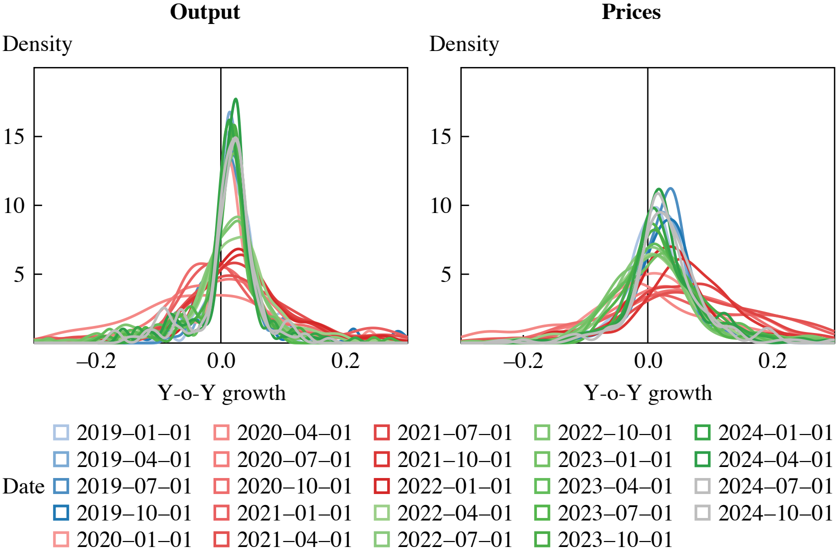
Source: Reproduced from US Census Bureau (2025).

Figure 7. Labor Productivity in the United States and the Euro Area



Source: Author's calculations based on data from Bureau of Labor Statistics (retrieved from FRED series OPHNFB) for the United States, and from the European Central Bank (data set series key MNA.Q.Y.I9.W0.S1.S1._Z.LPR_HW._Z.F._Z.IX.LR.N) for the euro area.

Figure 8. Empirical Density of Cross-Sectional Data over Time—COVID Crisis

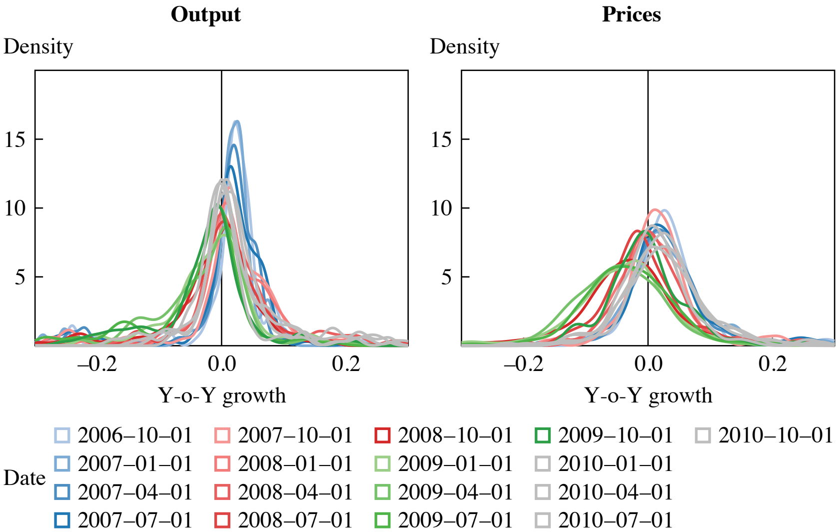


Source: Author's calculations.
Note: For output data, see the main paper. Price data are from Bureau of Economic Analysis, aggregated as in Ahn and Luciani (2024).

and supply chain disruptions. This, in turn, led to relative price changes (see, e.g., Guerrieri and others 2023). The inflation surge experienced since late 2021 is likely to be the result of both relative price changes following supply disruption and the aggregate demand developments discussed in the last section. On the other hand, the increase in productivity since early 2020 must have exercised a negative effect on inflation. We typically think of demand as having a more even effect on sectoral inflation than supply and reallocation shocks (for evidence, see Guerrieri and others 2023). It is therefore interesting to look at the evolution of sectoral distributions of prices and quantities over time.

Figure 8 plots the evolution of the empirical densities of cross-sectoral data over time. Groups of lines indicate pre-COVID years, the period from January 2020 to January 2022 (the recession and the first and second phases of the recovery), and the following years until the end of 2024. The pre-COVID period corresponds to a narrow distribution for both quantities and prices, with quantities suggesting most sectors had moderate and uniform output growth and prices indicating low and stable inflation across sectors.

Figure 9. Empirical Density of Cross-Sectional Data over Time—Financial Crisis



Source: Author's calculations.
Note: For output data, see the main paper. Price data are from Bureau of Economic Analysis, aggregated as in Ahn and Luciani (2024).

With the COVID recession and first phase of the recovery, both the output and price distributions become wider and flatter, showing wide sectoral dispersion in line with the reallocation story. While the quantity distribution first shifted to the left and then moved back to the right, the price distribution shifted to the right in a more persistent way, which is to be expected given downward price rigidity. Interestingly, the dispersion of inflation is also more persistent than that of sectoral economic activity, indicating the association between persistent relative price adjustments and increase in average inflation. The later period sees a return of the pre-COVID shape in real activity sectoral densities and a decrease in the dispersion and mean of sectoral inflation. The decline in mean inflation, which is likely the consequence of contractionary monetary policy, was not associated with a slowdown of mean economic activity, possibly a symptom of positive productivity developments.

Figure 9 reports the densities for the global financial crisis for comparison. It shows a less pronounced dispersion of sectoral prices and quantities, supporting the view that reallocation effects were much stronger and persistent during and post-pandemic.

CONCLUSIONS This paper firmly establishes the fact that recovery from the COVID-19 pandemic was unique in postwar experience and in having left no scars on the economy. It was a tribute to the power of economic policy. Many questions, of course, remain open for further research.

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GENERAL DISCUSSION Şebnem Kalemli-Özcan highlighted the importance of matching the inflation and real wage dynamics with the cross-sectional pattern in the data, as well as in the aggregate, referencing her own work with coauthors on the topic.[1] She explained that the fiscal stimulus played a bigger role in the United States compared to Europe. In addition, Kalemli-Özcan and coauthors have demonstrated that fiscal stimulus in a supply-constrained economy will be inflationary.

David Romer observed that there is a disconnect between how one intuitively tells the story of what happened and what the dynamic factor model seems to be telling us. Intuitively, all three fiscal packages were responses to the COVID-19 pandemic, not independent shocks, since they almost certainly wouldn't have happened without the pandemic. With that way of thinking, it's natural to ask: What parts of the recovery and the inflation were because of the fiscal packages? The dynamic factor model,

1. Julian Di Giovanni, Şebnem Kalemli-Özcan, Alvaro Silva, and Muhammed A. Yildirim, "Quantifying the Inflationary Impact of Fiscal Stimulus Under Supply Constraints," *AEA Papers and Proceedings* 113 (2023): 76–80.

instead, Romer explained, sees the COVID shock as one shock that, among other things, caused a permanent fall in output, and sees the fiscal packages—at least the later ones—as additional shocks that happened to follow the COVID shock and conveniently offset that fall. He leaned toward the view that this disconnect points to the dynamic factor model missing something important, but perhaps it's telling us that the story that seems intuitively right is too convoluted, and that the multiple-shocks view is more informative.

James Stock offered a different view, arguing that, especially early in the pandemic, rather than considering a range of different, sequential shocks, we ought to think of it as one big shock: the COVID shock. This one shock led to uncertainty, a drop in consumption, reallocation, fiscal stimulus, and so on. The pandemic-related economic behavior tapered off in the later parts of the recovery, and therefore, the same explanation does not hold for the later shocks.

Michael Kiley highlighted three phenomena during the COVID episode: high-pressure labor market, inflation, and scarring, asking how much of the trend reversion was due to a high-pressure labor market, and how much of the cost was inflation?

Douglas Elmendorf pointed to related research with his coauthor Karen Dynan on the causes of the COVID-era inflation, focusing on fiscal policy.[2] First, he addressed what he called a conflation in the inflation discussion of shifts in the supply curve—a supply shock—and movements along the curve because of shifts in demand. Thus, Elmendorf argued, the supply chain index used by the authors is not a measure of a supply shock. Rather, it measures the mismatch between the quantity demanded and the quantity supplied, which increased during the pandemic. Second, in early 2021 before the American Rescue Plan was enacted, multiple forecasts expected a nearly full recovery in the labor market by the end of the year. Following the enactment, Elmendorf continued, forecasters even expected an overshooting of the potential output but surprisingly did not expect a surge in inflation, presumably owing to their forecast simply being an extrapolation of the nearly flat Phillips curve seen in earlier data.

Ben Bernanke observed that the actual output gap has not exceeded 2 percent of GDP at any time since 2020 while it was nearly 6 percent in

2. Karen Dynan and Douglas Elmendorf, "Fiscal Policy and the Pandemic-Era Surge in US Inflation: Lessons for the Future," working paper 24–22 (Washington: Peterson Institute for International Economics, 2024).

1966, which made him question the suggested link to inflation.[3] Bernanke commented that the conclusion that the pandemic-era recovery was marked by excess demand and constrained supply chains runs into the issue of reconciling this with the fact that domestic industries were not producing at capacity, specifically mentioning the domestic auto industry where production in fact fell.

Highlighting the significant change in the real interest rate and inflation following the pandemic, Fabrizio Perri asked the authors if their framework would be able to support an inquiry into these metrics. For example, was there a level change in the real interest rate, and how much of this was driven by fiscal policy?

Mark Mazur commented that the fiscal stimulus extended beyond the Economic Impact Payments, not least considering the child tax credit payments that were paid out during the second half of 2021. Mazur then made the point that the scale of the fiscal stimulus was also likely greater than policymakers had expected, pointing specifically to the Paycheck Protection Plan and Employee Retention Credit as possibly having been vulnerable to fraud.

Elmendorf pondered the lessons learned from this episode, focusing on one in particular: Typically, most of the concern about countercyclical fiscal policy has been whether it can act fast enough and at a sufficient scale, not least in light of the arguably insufficient stimulus following the global financial crisis given the size of the output gap. Following the COVID-19 pandemic, the opposite concern is warranted—excessive stimulus comes with its own issues. This highlights the potential value of more responsive automatic stabilizers, and the uncertainty around the outcomes during this episode underscores the value of automatic stabilizers in avoiding overspending, relative to preconceived packages.

Louise Sheiner said that if fiscal policy was indeed the main driver that ushered the economy back to trend growth, then we should conclude that the fiscal stimulus was not excessive but instead well calibrated to get us back on track. However, she worried that the lesson many would instead be left with in the wake of the COVID recession was that fiscal policy

3. Bureau of Economic Analysis and Congressional Budget Office, "100*(Real Gross Domestic Product-Real Potential Gross Domestic Product)/Real Potential Gross Domestic Product," retrieved from FRED series GDPC1 and GDPPOT, https://fred.stlouisfed.org/graph/?g=f1cZ.

was inflationary, which could have a negative impact on the willingness to use this type of intervention in the future. Sheiner suggested a worthwhile research question would be what the right size stimulus would look like in order to not discourage the use of fiscal policy altogether moving forward.

Janice Eberly brought up authors' 2012 *BPEA* paper on the global financial crisis, recalling that in their previous paper, the authors concluded a lack of fiscal stimulus was not a driver of the slowness of the recovery.[4] Eberly suggested the possibility that the COVID recession may have been more amenable to fiscal stimulus than the global financial crisis and asked the authors to expand on the use of fiscal policy as a tool.

On the topic of productivity, referencing his own research with coauthor Hassan Sayed, Robert Gordon commented that the trend in business productivity growth between 2010 and 2019 was a mere 1.1 percent before reaching 5.6 percent in 2020.[5] Productivity then turned negative in 2021 as the economy recovered. Gordon argued that this pattern was not unique to the COVID-19 pandemic, pointing to the global financial crisis as a similar example: In 2009, productivity grew 6.6 percent and then slowed significantly. Gordon described how excess layoffs during the global financial crisis, notably in construction, manufacturing, and finance, and the subsequent gradual rehiring of these workers were the driving forces behind slow productivity in the 2010s. Their research further shows that the same explanation holds for the COVID recession, instead using the following industry breakdown: contact services, work-from-home services, and goods production.

Steven Davis commented that the paper overlooked a distinct feature of the COVID recession relative to earlier recessions, which may help explain the trend reversion. Davis pointed out that, in addition to the temporary layoffs, there was also an extraordinary withdrawal from the labor force, which took longer to unwind. Referencing his own work with Jose Maria Barrero and Nicholas Bloom, Davis highlighted that workers who voluntarily withdrew from the labor force during the pandemic because of health concerns for either themselves or someone close to them, were mostly less educated, older, and/or living with someone whose health was

4. James H. Stock and Mark W. Watson, "Disentangling the Channels of the 2007–2009 Recession," *Brookings Papers on Economic Activity*, Spring (2012): 81–135.

5. Robert J. Gordon and Hassan Sayed, "A New Interpretation of U.S. Productivity Growth Dynamics, 1950–2023," discussion paper 19569 (London: Centre for Economic Policy Research, 2024).

compromised.[6] By early 2023, the impact of these health concerns on labor force participation had mostly dissipated, expanding labor supply and employment. Hence, Davis suggested that part of the recovery the authors attribute to fiscal stimulus could instead be due to the reversal of an extraordinary labor supply shock.

John Haltiwanger highlighted that one metric that has not reverted to the trend is business formation: Typically, business formation falls during a recession and takes a long time to recover; however, during the COVID-19 pandemic, after an initial brief decline, business formation increased sharply in the summer of 2020 and has remained remarkably strong through early 2025. Key sectors have played an outsized role including e-commerce, as well as the information and professional, scientific, and technical services sectors. Davis agreed that remote work technologies were likely to have contributed to a rise in business formation even as uncertainty remains around the magnitude of this effect. He pointed out that these technologies also expanded employment opportunities for a range of different populations, including those with physical impairments, certain psychological conditions, and those who live in remote places. Davis proposed that increased labor force participation of these groups may also have contributed to the trend reversion.

Katharine Abraham drew attention to a variety of lasting effects on the labor market following the pandemic beyond what can be seen in the macroeconomic aggregates emphasized in the paper. Abraham pointed to the surge in business formation as an outcome worth investigating, as opposed to simply a contributor to the recovery. Similarly, the decline in work hours as well as the increase in work from home have likely left a permanent mark on the labor market, and studying these as outcomes in their own right would be useful.

Steven Braun expressed concern regarding the loss of human capital for a generation of students, the long-term effects of which we have yet to see. This is arguably an important aspect of the recovery as well. Mark Watson agreed that the most interesting question may be how things are going to unfold over the long term. He emphasized that the authors' results are preliminary, and long-term questions should be addressed down the line when these outcomes are available to study.

6. Jose Maria Barrero, Nicholas Bloom, and Steven J. Davis, "Long Social Distancing," *Journal of Labor Economics* 41, no. S1 (2023): 129–72.

Braun also asked why the effects in 2021 of the more aggressive Omicron variant did not seem to show up in the authors' results. Stock responded that the Omicron wave occurred quite late in the recovery when vaccinations were widely available and the COVID fatigue had set in, resulting in people changing their protective behavior. As a result, the effect was limited to a small subsample of the population who had not been vaccinated. The effects in the data are small, yet visible.

Jón Steinsson thought that the second phase of the recovery as shown by the authors was particularly interesting. He noted that the authors argued that the F dynamics did not change after the pandemic and asked them if the explanation for the observed pattern here was unusual F shocks. Watson responded that the interpretation of the early F shocks should be that they did indeed come from the pandemic, but he admitted that their model did not capture this explicitly due to the lag structure the authors use.

Watson further stressed that while each business cycle discussed in their paper was different, a small number of channels could generally help explain the recession. However, the same channels that helped explain all other recessions could not explain the COVID recession—a different, transitory shock was needed.

------------- Appendix -----------

Recovering from COVID

May 7, 2025

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Appendix 1: Data Series

- Data Sources: Unless otherwise noted, the data are from FRED at the Federal Reserve Bank of St. Louis. Exceptions to this are:
  - The PCE data are from NIPA tables 2.8.4 and 2.8.5.
  - The quarterly TFP series dtfp and dtfp_util are from John Fernald's webpage at https://www.johnfernald.net/TFP
- The data series are summarized in the tables on the following pages. The columns of the table are
  - Name: The FRED series names (as appropriate).
  - Series Description
  - Sample period available for analysis
  - Trans: Transformation Code with 2 denoting first difference, 4 denoting logarithm and 5 denoting the first difference of the logarithm.
  - Factor: "Y" means that the series was used to estimate the factors.
  - Outlier: 1 means that the series was adjusted for outliers in the pre-COVID sample period, and 0 otherwise.

Monthly Series

Name	Description	Smpl	Trans	Factor	Outlier
PCE Real Quantities					
Qpceall	PCE: Q Personal consumption expenditures (PCE)	1959:M1-2024:M11	5		0
Qpcegoods	PCE: Q Goods	1959:M1-2024:M11	5		0
Qpcegdsdur	PCE: Q Durable goods	1959:M1-2024:M11	5		0
Qpcegdsdurmotorveh	PCE: Q Motor vehicles and parts	1959:M1-2024:M11	5	Y	0
Qpcegdsdurfurn	PCE: Q Furnishings and durable household equipment	1959:M1-2024:M11	5	Y	0
Qpcegdsdurrecgoods	PCE: Q Recreational goods and vehicles	1959:M1-2024:M11	5	Y	0
Qpcegdsdurother	PCE: Q Other durable goods	1959:M1-2024:M11	5	Y	0
Qpcegdsnd	PCE: Q Nondurable goods	1959:M1-2024:M11	5		0
Qpcegdsndfood	PCE: Q Food and beverages purchased for offpremises consumption	1959:M1-2024:M11	5	Y	0
Qpcegdsndclothes	PCE: Q Clothing and footwear	1959:M1-2024:M11	5	Y	0
Qpcegdsndenergy	PCE: Q Gasoline and other energy goods	1959:M1-2024:M11	5	Y	0
Qpcegdsndother	PCE: Q Other nondurable goods	1959:M1-2024:M11	5	Y	0
Qpceservices	PCE: Q Services	1959:M1-2024:M11	5		0
Qpceserhealth	PCE: Q Health care	1959:M1-2024:M11	5	Y	0
Qpcesertrans	PCE: Q Transportation services	1959:M1-2024:M11	5	Y	0
Qpceserrec	PCE: Q Recreation services	1959:M1-2024:M11	5	Y	0
Qpceserfoodacc	PCE: Q Food services and accommodations	1959:M1-2024:M11	5	Y	0
Qpceserfin	PCE: Q Financial services and insurance	1959:M1-2024:M11	5	Y	0
Qpceserother	PCE: Q Other services	1959:M1-2024:M11	5	Y	0
Qpcenpish	PCE: Q Final cons exp of nonprofits (NPISHs)	1959:M1-2024:M11	5	Y	0
Qpceserhousxenergy	PCE: Q Housing and utilites (excl. energy)	1959:M1-2024:M11	5	Y	0
Qpceserhousenergy	PCE: Q Housing and utilites (energy)	1959:M1-2024:M11	5	Y	0
Employment CES					
PAYEMS	CES: Total Nonfarm	1959:M1-2024:M11	5		0
USPRIV	CES: Total Private	1959:M1-2024:M11	5		0
USGOOD	CES: Goods Producing	1959:M1-2024:M11	5		0
USMINE	CES: GD: Mining and Logging	1959:M1-2024:M11	5	Y	1
USCONS	CES: GD: Construction	1959:M1-2024:M11	5	Y	0
MANEMP	CES: GD: Manufacturing	1959:M1-2024:M11	5	Y	1
DMANEMP	CES: GD:Man:Durable goods	1959:M1-2024:M11	5	Y	1
NDMANEMP	CES: GD:Man:Nondurable goods	1959:M1-2024:M11	5	Y	0
CES0800000001	CES: Private Service Producing	1959:M1-2024:M11	5		1
USWTRADE	CES: SE:Wholesale Trade	1959:M1-2024:M11	5	Y	0
USTRADE	CES: SE: Retail Trade	1959:M1-2024:M11	5	Y	0
CES4300000001	CES: SE: Transportation and wharehousing	1972:M1-2024:M11	5	Y	1
CES4422000001	CES: SE: Utilities	1964:M1-2024:M11	5	Y	1
USINFO	CES: SE: Information	1959:M1-2024:M11	5	Y	1
CES5552000001	CES: SE: Finance and Insurance	1990:M1-2024:M11	5	Y	0
CES5553000001	CES: SE: Real Estate	1990:M1-2024:M11	5	Y	0

USPBS	CES: SE: Prof and Bus Services	1959:M1-2024:M11	5	Y	0
CES6561000001	CES: SE: Education services	1990:M1-2024:M11	5	Y	0
CES6562000001	CES: SE: Health care and social assistance	1990:M1-2024:M11	5	Y	0
CES7071000001	CES: SE: Arts entertainment recreats	1990:M1-2024:M11	5	Y	0
CES7072000001	CES: SE: Accomodation and food services	1990:M1-2024:M11	5	Y	0
USSERV	CES: SE: Other Services	1959:M1-2024:M11	5	Y	0
USGOVT	CES: Government	1959:M1-2024:M11	5		1
CES9091000001	CES: GO: Federal	1959:M1-2024:M11	5	Y	1
CES9092000001	CES: GO: State	1959:M1-2024:M11	5		0
CES9092161101	CES: GO: ST: Education	1959:M1-2024:M11	5	Y	0
CES9092200001	CES: GO: ST: nonEducation	1959:M1-2024:M11	5	Y	0
CES9093000001	CES: GO: Local	1959:M1-2024:M11	5		0
CES9093161101	CES: GO: LO: Education	1959:M1-2024:M11	5	Y	0
CES9093200001	CES: GO: LO: nonEducation	1959:M1-2024:M11	5	Y	1
Employment CPS					
CLF16OV	CPS: Labor Force	1959:M1-2024:M11	5		0
CE16OV	CPS: Employed	1959:M1-2024:M11	5		0
UNEMPLOY	CPS: Unemployed	1959:M1-2024:M11	5		0
UNRATE	CPS: Unemployment Rate	1959:M1-2024:M11	2	Y	0
CIVPART	CPS: LFPR	1959:M1-2024:M11	2	Y	0
Jolts					
JTSJOL	Job Openings Total Nonfarm	2000:M12-2024:M10	5		0
JTS1000JOL	Job Openings Total Private	2000:M12-2024:M10	5		0
JTSHIL	Hires Total Nonfarm	2000:M12-2024:M10	5		0
JTS1000HIL	Hires Total Private	2000:M12-2024:M10	5		0
JTSQUL	Quits Total Nonfarm	2000:M12-2024:M10	5		0
JTS1000QUL	Quits Total Private	2000:M12-2024:M10	5		0
JTSTSL	Total Separations Total Nonfarm	2000:M12-2024:M10	5		0
JTS1000TSL	Total Separations Total Private	2000:M12-2024:M10	5		0
Industrial Production					
INDPRO	IP: Total index	1959:M1-2024:M11	5		0
IPFPNSS	IP:Mk: Final products and nonindustrial supplies	1959:M1-2024:M11	5		0
IPCONGD	IP:Mk: Consumer goods	1959:M1-2024:M11	5		0
IPDCONGD	IP:Mk: CG: Durable	1967:M1-2024:M11	5		1
IPB51110S	IP:Mk: CG:D:Automotive products	1967:M1-2024:M11	5	Y	1
IPB51121S	IP:Mk: CG:D: Home electronics	1987:M1-2024:M11	5	Y	0
IPB51122S	IP:Mk: CG:D: Appliances furniture carpeting	1987:M1-2024:M11	5	Y	0
IPB51123S	IP:Mk: CG:D: Miscellaneous goods	1967:M1-2024:M11	5	Y	0
IPNCONGD	IP:Mk: CG: Nondurable	1967:M1-2024:M11	5		0
IPB51210S	IP:Mk: CG:ND:Non-energy	1987:M1-2024:M11	5	Y	0
IPB51211S	IP:Mk: CG:ND:NE:Foods and tobacco	1967:M1-2024:M11	5	Y	0
IPB51212S	IP:Mk: CG:ND:NE:Clothing	1967:M1-2024:M11	5	Y	0
IPB51213S	IP:Mk: CG:ND:NE:Chemical Products	1974:M1-2024:M11	5	Y	0

IPB51214S	IP:Mk: CG:ND:NE:Paper products	1974:M1-2024:M11	5	Y	1
IPB51220S	IP:Mk: CG:ND:Energy	1974:M1-2024:M11	5	Y	0
IPBUSEQ	IP:Mk: Business equipment	1967:M1-2024:M11	5		0
IPB52110S	IP:Mk: BE: Transit	1974:M1-2024:M11	5	Y	1
IPB52120S	IP:Mk: BE:Information processing	1987:M1-2024:M11	5	Y	1
IPB52130S	IP:Mk: BE:Industrial and other	1987:M1-2024:M11	5	Y	0
IPB52300S	IP:Mk: Defense and space equipment	1967:M1-2024:M11	5	Y	1
IPB54100S	IP:Mk: Construction supplies	1967:M1-2024:M11	5	Y	0
IPB54200S	IP:Mk: Business supplies	1967:M1-2024:M11	5	Y	0
IPMAT	IP:Mk: Materials	1959:M1-2024:M11	5		0
IPZ53010S	IP:Mk: MAT:Non-energy	1987:M1-2024:M11	5		0
IPDMAT	IP:Mk: MAT:NE:Durable	1967:M1-2024:M11	5	Y	0
IPNMAT	IP:Mk: MAT:NE:Nondurable	1974:M1-2024:M11	5	Y	1
IPB53300S	IP:Mk: MAT:Energy	1974:M1-2024:M11	5	Y	1
IPMANSICS	IP:Ind: Manufacturing SIC	1959:M1-2024:M11	5		0
IPMAN	IP:Ind: Manufacturing NAICS	1992:M1-2024:M11	5		0
IPDMAN	IP:Ind: MAN: Durable manufacturing	1992:M1-2024:M11	5		0
IPNMAN	IP:Ind: MAN: Nondurable manufacturing	1992:M1-2024:M11	5		0
IPMINE	IP:Ind: Mining	1959:M1-2024:M11	5		0
IPUTIL	IP:Ind: Utilities	1959:M1-2024:M11	5		0
Sales					
CMRMTSPLx	Real Manu. and Trade Industries Sales	1959:M1-2024:M9	5		0
Personal Income Real					
PI	Personal Income real	1959:M1-2024:M11	5		0
A576RC1	Wages and Salaries real	1959:M1-2024:M11	5		0
A132RC1	WS: Private real	1959:M1-2024:M11	5	Y	0
B202RC1	WS: Government real	1959:M1-2024:M11	5	Y	0
A038RC1	WS: Supplements real	1959:M1-2024:M11	5	Y	0
A041RC1	Proprietors Income real	1959:M1-2024:M11	5		0
A048RC1	Rental Income real	1959:M1-2024:M11	5	Y	0
PIROA	Personal Income Receipts on Assets real	1959:M1-2024:M11	5	Y	0
PCTR	Personal Current Transfer Receipts real	1959:M1-2024:M11	5		0
A063RC1	Gov Transfers to Persons real	1959:M1-2024:M11	5	Y	0
DSPI	Disposal Personal Income real	1959:M1-2024:M11	5		0
PSAVERT	Personal Savings Rate	1959:M1-2024:M11	5		0
W875RX1	Real Personal Income Excluding Transfers	1959:M1-2024:M11	5		0
Orders and Inventories					
ACOGNO	New Orders for Consumer Goods	1992:M2-2024:M9	5	Y	0
AMDMNOx	New Orders for Durable Goods	1959:M1-2024:M10	5	Y	0
AMDMUOx	New Orders for Nondefense Capital Goods	1959:M1-2024:M10	5	Y	0
BUSINVx	Total Business Inventories	1959:M1-2024:M9	5	Y	0
ISRATIOx	Total Business: Inventories to Sales Ratio	1959:M1-2024:M9	4	Y	0
Housing Permits and Starts					

PERMIT	HO: Permits Total	1960:M1-2024:M11	4		0
PERMITMW	HO: PE: Midwest	1960:M1-2024:M11	4		0
PERMITNE	HO: PE: Northeast	1960:M1-2024:M11	4		0
PERMITS	HO: PE: South	1960:M1-2024:M11	4		0
PERMITW	HO: PE: West	1960:M1-2024:M11	4		0
HOUST	HO: Starts Total	1959:M1-2024:M11	4		0
HOUSTMW	HO: ST: Midwest	1959:M1-2024:M11	4	Y	0
HOUSTNE	HO: ST: Northeast	1959:M1-2024:M11	4	Y	0
HOUSTS	HO: ST: South	1959:M1-2024:M11	4	Y	0
HOUSTW	HO: ST: West	1959:M1-2024:M11	4	Y	0
Misc					
UMCSENTx	Consumer Sentiment Index	1959:M5-2024:M10	1	Y	0

Additional Quarterly Series

Name	Description	Smpl	Trans	Factor	Outlier
NIPA Real					
A191RA3Q086SBEA	Gross domestic product	1959:Q1-2024:Q3	5		0
A006RA3Q086SBEA	Gross private domestic investment	1959:Q1-2024:Q3	5		0
A007RA3Q086SBEA	GPDI Fixed investment	1959:Q1-2024:Q3	5		0
A008RA3Q086SBEA	GPDI Nonresidential	1959:Q1-2024:Q3	5		0
B009RA3Q086SBEA	GPDI Nonresidential Structures	1959:Q1-2024:Q3	5	Y	0
Y033RA3Q086SBEA	GPDI Nonresidential Equipment	1959:Q1-2024:Q3	5	Y	0
Y001RA3Q086SBEA	GPDI Nonresidential Intellectual property products	1959:Q1-2024:Q3	5	Y	0
A011RA3Q086SBEA	GPDI Residential	1959:Q1-2024:Q3	5	Y	0
B020RA3Q086SBEA	Exports	1959:Q1-2024:Q3	5		0
B253RA3Q086SBEA	Exports Goods	1959:Q1-2024:Q3	5	Y	0
B646RA3Q086SBEA	Exports Services	1959:Q1-2024:Q3	5	Y	0
B021RA3Q086SBEA	Imports	1959:Q1-2024:Q3	5		0
B255RA3Q086SBEA	Imports Goods	1959:Q1-2024:Q3	5	Y	0
B656RA3Q086SBEA	Imports Services	1959:Q1-2024:Q3	5	Y	0
B822RA3Q086SBEA	Government consumption expenditures and gross investment	1959:Q1-2024:Q3	5		0
B823RA3Q086SBEA	Gov Federal	1959:Q1-2024:Q3	5		0
B824RA3Q086SBEA	Gov Federal National defense	1959:Q1-2024:Q3	5	Y	0
B825RA3Q086SBEA	Gov Federal Nondefense	1959:Q1-2024:Q3	5	Y	0
B829RA3Q086SBEA	Gov State and local	1959:Q1-2024:Q3	5	Y	0
Productivity					
OPHNFB	Nonfarm Business Sector: Labor Productivity (Output per Hour) for All Workers	1959:Q1-2024:Q3	5	Y	0
OPHPBS	Business Sector: Labor Productivity (Output per Hour) for All Workers	1959:Q1-2024:Q3	5		0
dtfp	TFP growth rate (Fernald)	1959:Q1-2024:Q3	1	Y	0
dtfp_util	Utilization-Adjusted TFP growth rate (Fernald)	1959:Q1-2024:Q3	1		0

Appendix 3: Estimation Details

The estimation approach aims to keep the number of parameters estimated over the short COVID period to a minimum. We procede as follows:

- $\Lambda, \Gamma, C_t, F_t$ are estimated as described in Section III.A.
- The decomposition in equation (3) uses

$$Y_t = \Lambda F_t^F + \Lambda F_t^C + \Gamma C_t^F + \Gamma C_t^C + u_t \tag{1}$$

  where

$$F_t^F = \Theta_{FF}(L)\varepsilon_t^F$$
$$F_t^C = \Theta_{FC}(L)\varepsilon_t^C$$
$$C_t^F = \Theta_{CF}(L)\varepsilon_t^F$$

  and

$$C_t^C = \Theta_{CC}(L)\varepsilon_t^C$$

- With the normalization $\Theta_{CC}(0) = 1$, assumptions (iiia) and (iv) imply that ε_t^C can be obtained as the residual from the regression of C_t onto lags of (C_t, F_t). We use one lag in this regression, so that

$$\varepsilon_t^C = C_t - (\rho_{CC}C_{t-1} + \rho_{CF}F_{t-1}) \tag{2}$$

  where ρ_{CC} and ρ_{CF} are estimated by OLS over the sample period 2020m7-2023m2, and ε_t^C is then constructed from (2) over 2020m3-2023:m2 and $\varepsilon_t^C = 0$ for other dates.

- The coefficients of the lag polynomial $\Theta_{FC}(L)$ are estimated by regressing F_t onto current and four lags of ε_t^C. This allows calculation of

$$F_t^C = \Theta_{FC}(L)\varepsilon_t^C$$

  and

$$F_t^F = F_t - F_t^C.$$

- The decomposition of C_t into $C_t^C + C_t^F$ then follows from

$$(1 - \rho_{CC}L)C_t = \varepsilon_t^C + \rho_{CF}F_{t-1} = \varepsilon_t^C + \rho_{CF}(F_{t-1}^C + F_{t-1}^F).$$

  Which yields

$$C_t^C = (1 - \rho_{CC}L)^{-1}(\varepsilon_t^C + \rho_{CF}F_{t-1}^C)$$

  and

$$C_t^F = (1 - \rho_{CC}L)^{-1}\rho_{CF}F_{t-1}^F. \tag{3}$$

- Equation (1) can then be used to decompose Y_t into components associated with ε_t^C (that is $\Lambda F_t^C + \Gamma C_t^C$) and with ε_t^F (that is $\Lambda F_t^F + \Gamma C_t^F$). These decompositions are used in Figures 11-13 in the text.

The counterfactuals were computed by changing the values of ε_t^F, leading the changes in $\{F_t^F,\, C_t^F\}$. This is done as follows:

- The lag polynomial $\Theta_{FF}(L)$ is estimated using the pre-COVID (1985-2020m2) observations on F_t^F (where $F_t^F = F_t$ during the pre-COVID period). Specifically, we estimate a VAR(6) model $\Phi(L)F_t^F = \varepsilon_t^F$ and set $\Theta_{FF}(L) = \Phi(L)^{-1}$.
  - The value of ε_t^F is then computed as $\varepsilon_t^F = \Phi(L)F_t^F$ over the entire sample period.
  - Counterfactuals of ε_t^F, say $\varepsilon_t^{F,Counterfactual}$ are then computed as described in Section VI.A.
- $F_t^{F,Counterfactual}$ was computed as $F_t^{F,Counterfactual} = \Phi(L)^{-1}\varepsilon_t^{F,Counterfactual}$.
- The value of $C_t^{F,Counterfactual}$ is computed from (3) using $F_t^{F,Counterfactual}$.
- The counterfactual values of Y_t are then computed from (1) replacing (F_t^F, C_t^F) with $(F_t^{F,Counterfactual}, C_t^{F,Counterfactual})$. These are the values plotted in Figure 16.

Appendix 4: Andrews End-Of-Sample Stability Tests for Λ

As described in Section V, we carried out Andrews (1993) end-of-sample stability tests for Λ, using an in-sample period of 1985m1-2020m2 (pre-COVID) and an out-of-sample period of 2023m3-2024m9 (post-COVID), and where the post-COVID period was suggested by the R^2 plot in Figure 6.

There was little evidence of instability. Of the 128 series, five series had p-values less than 0.05. These were

Series	p-value
CES: SE: Information	0.04
CES: GO: ST: nonEducation	<0.01
CPS: Unemployed	0.05
HO: PE: Northeast	0.01
PCE: Q Health care	0.04

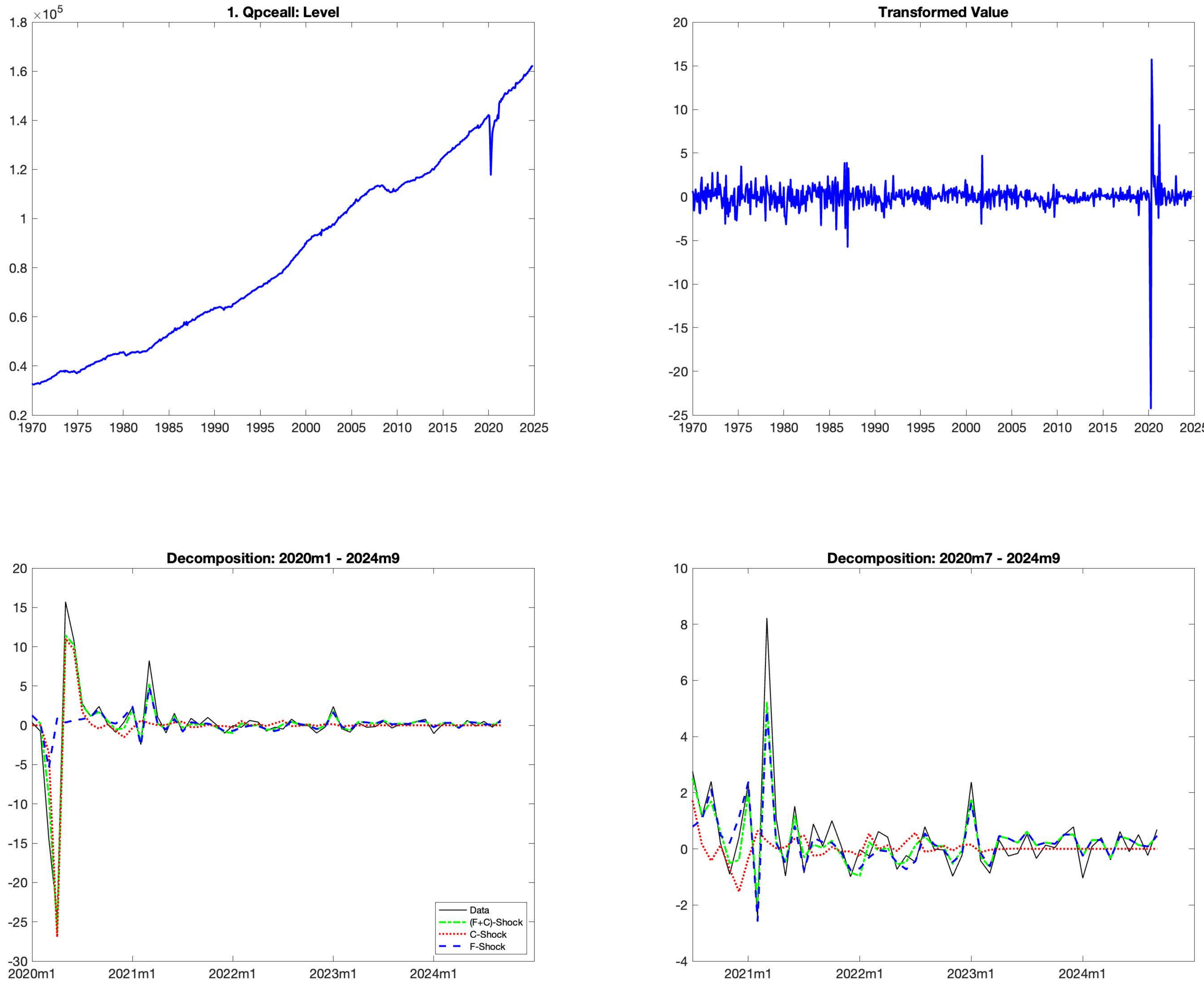
Across the 128 series, the selected percentiles of the p-values are shown in the following table

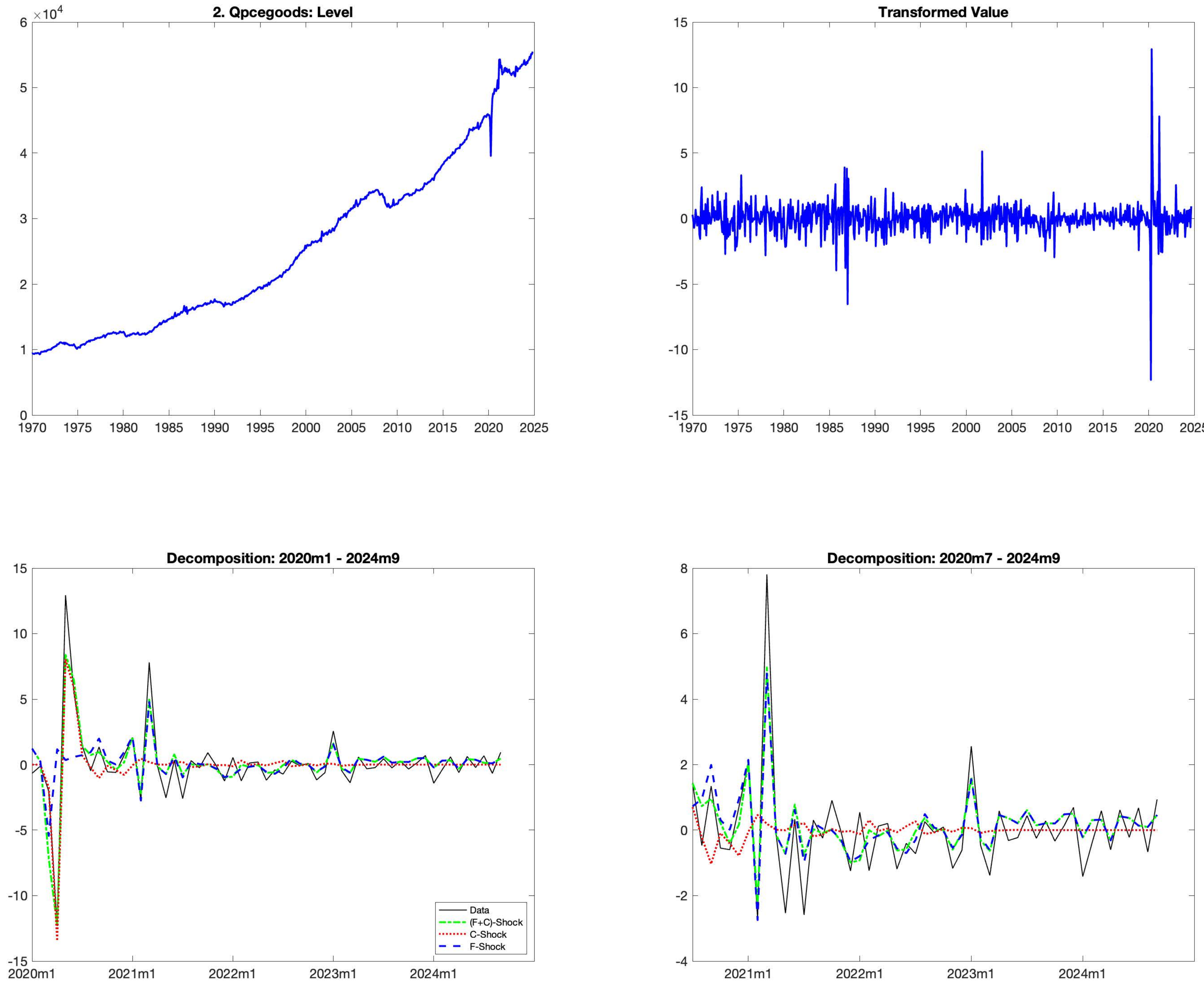
Percentile	Value
0.05	0.07
0.25	0.33
0.50	0.62
0.75	0.79
0.95	0.96

Appendix 2: Data Plots and Factor Shock Decomposition

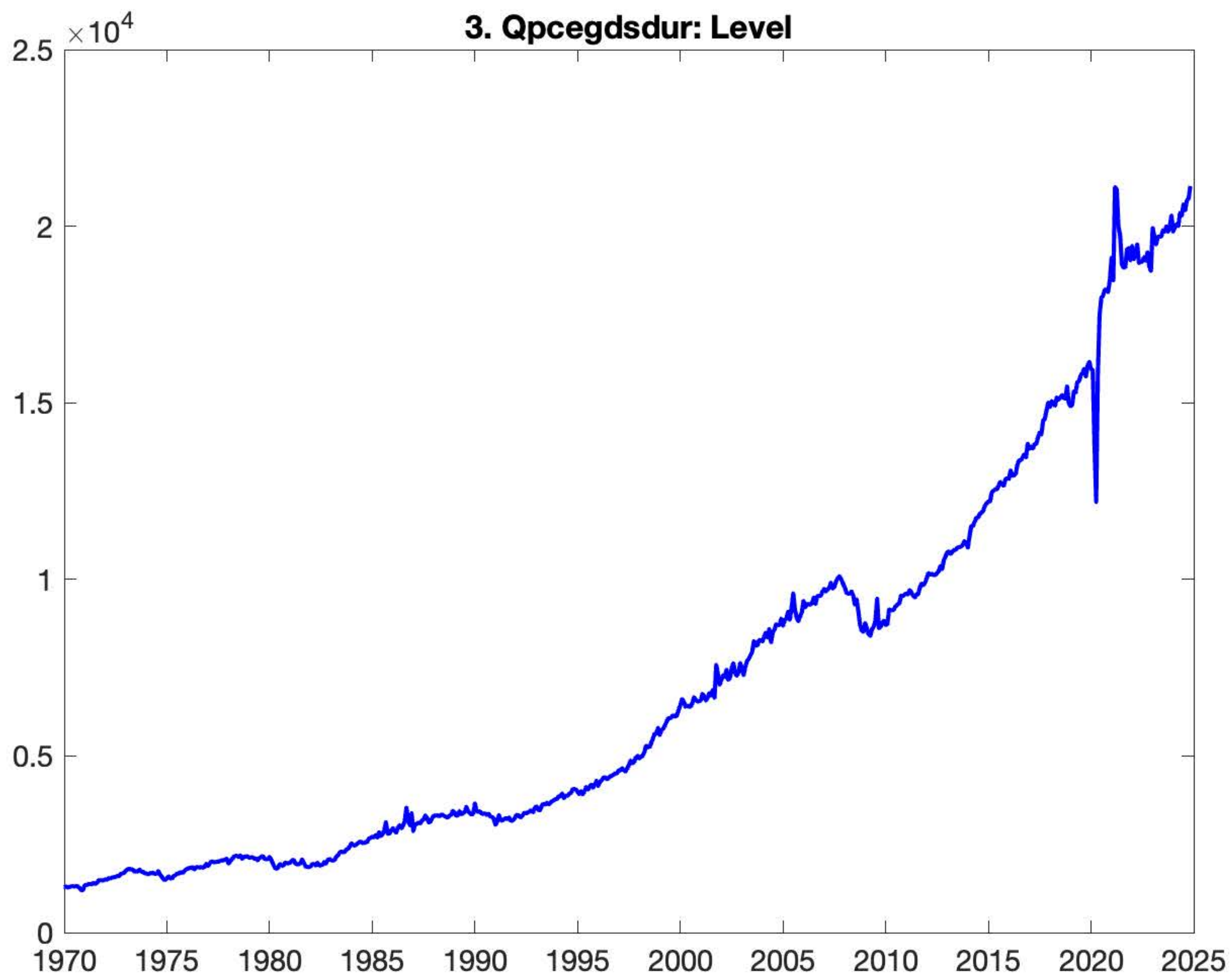
Each page shows a four panel figure for each series. The panels are

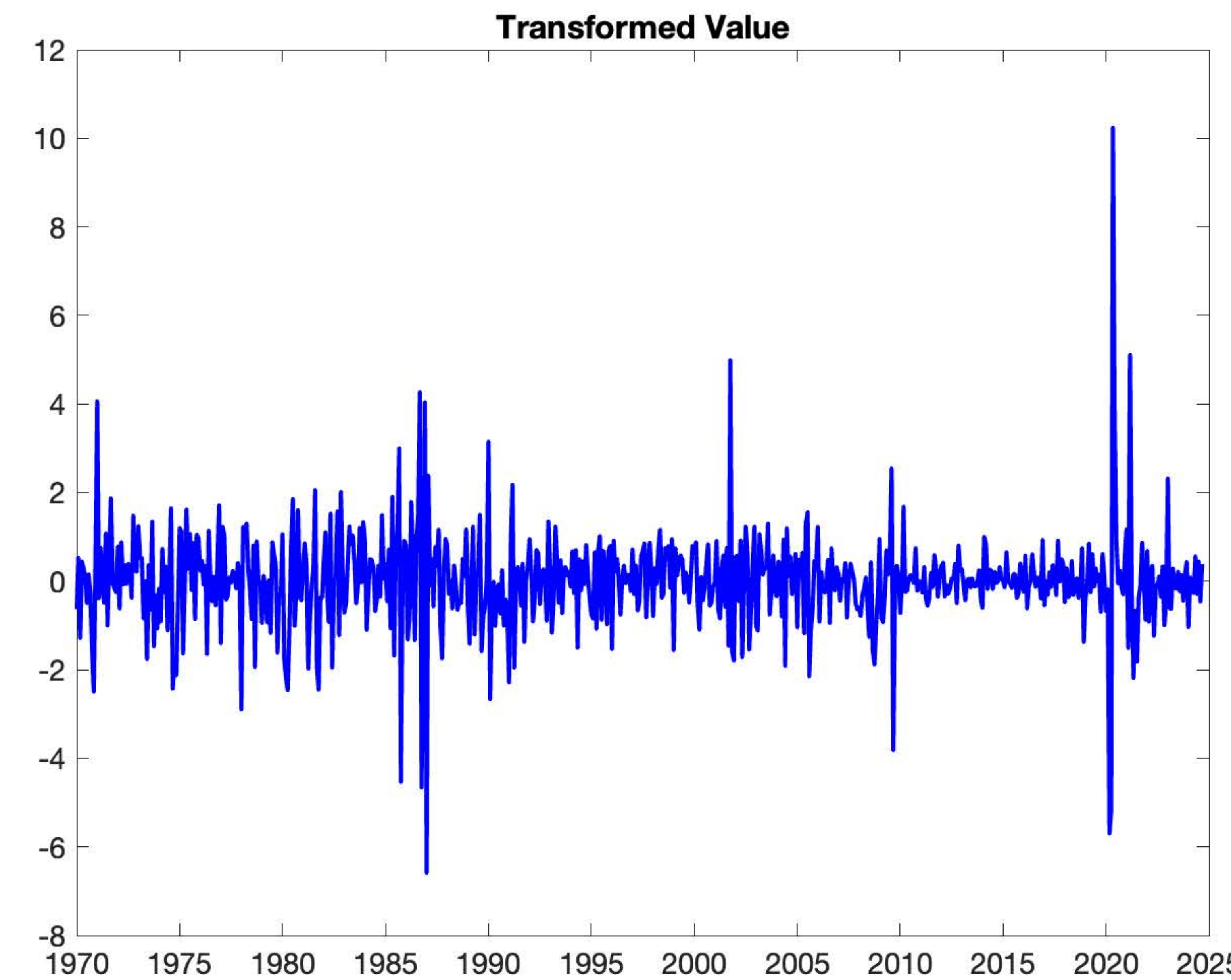
- Panel (1,1): The raw data series
- Panel (1,2): The transformation data series (in Pre-COVID standard deviation units)
- Panels (2,1) and (2,2): The factor-shock decomposition of the series over the COVID period as shown in Figure 12 in the text.

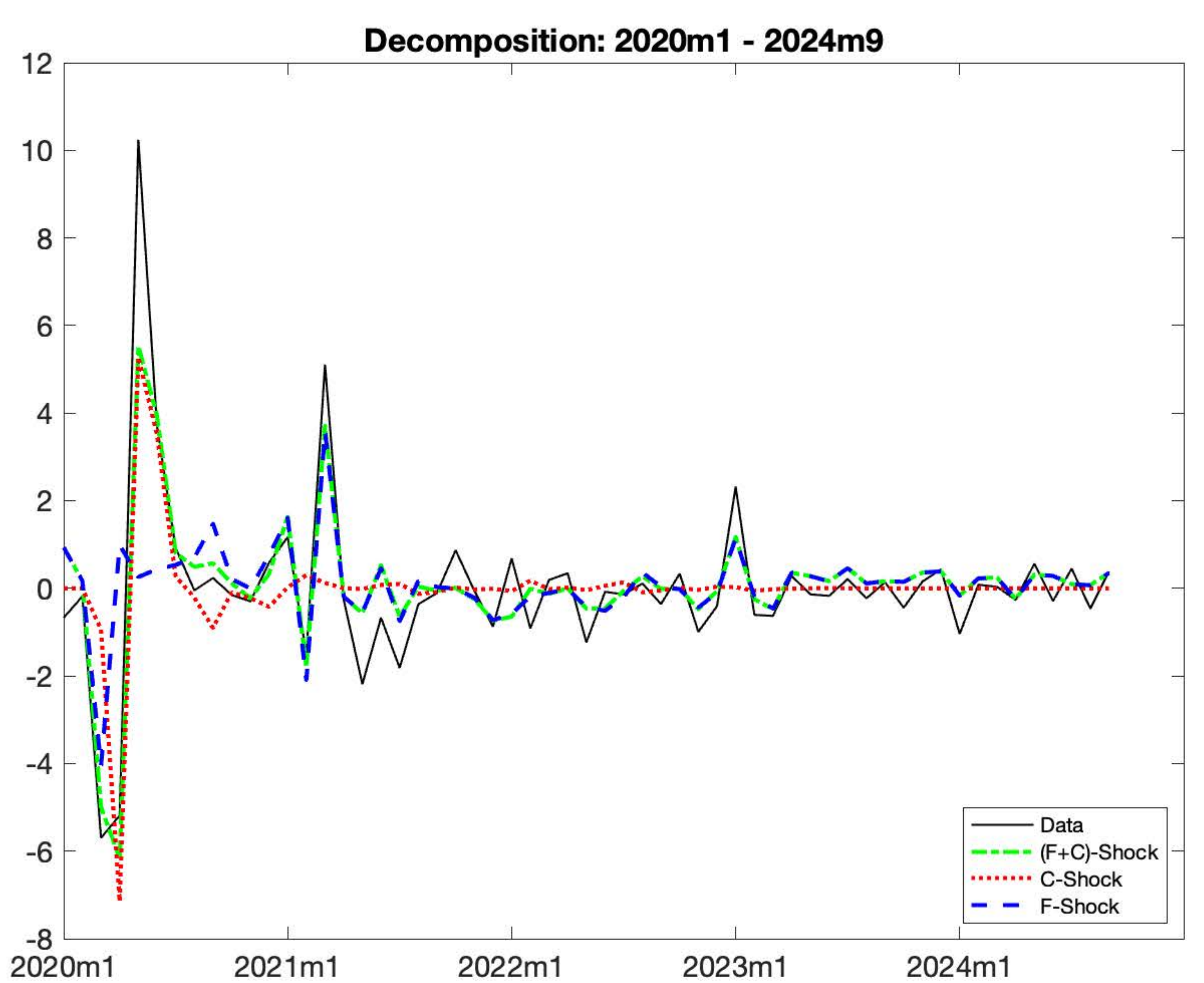

1. Qpceall: Level
Transformed Value
Decomposition: 2020m1 - 2024m9
Decomposition: 2020m7 - 2024m9
Data
(F+C)-Shock
C-Shock
F-Shock
2020m1
2021m1
2022m1
2023m1
2024m1

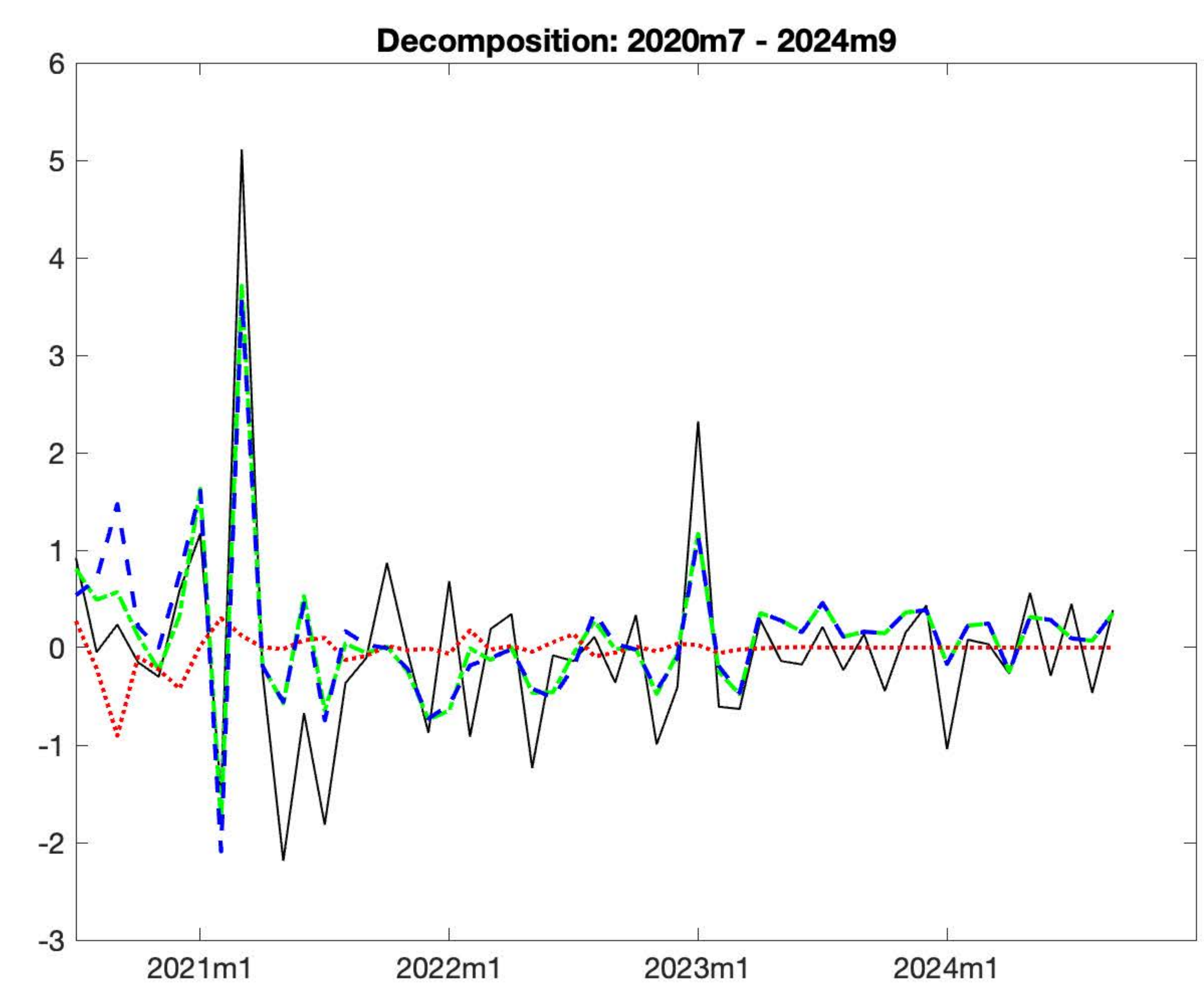


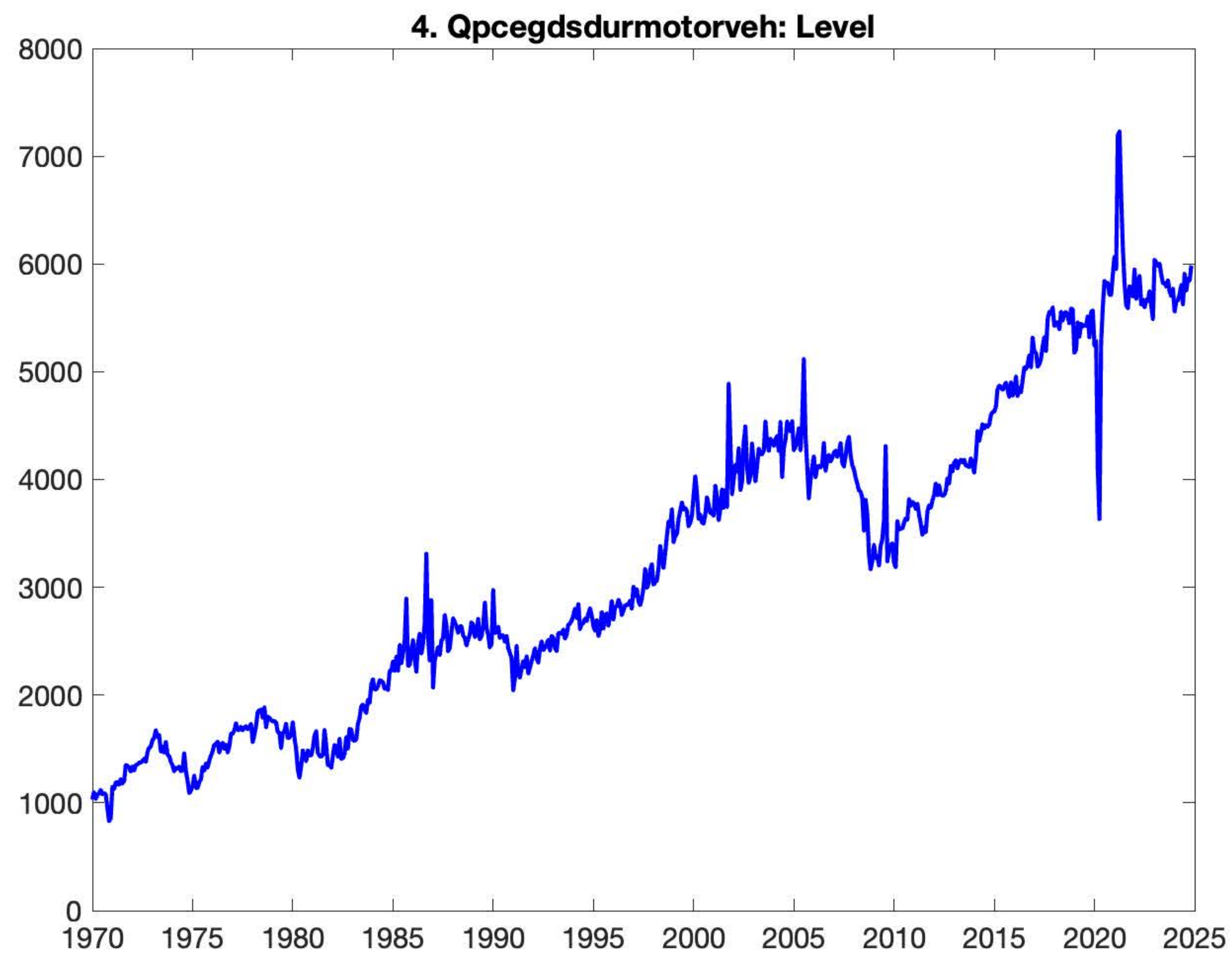
2. Qpcegoods: Level
Transformed Value
Decomposition: 2020m1 - 2024m9
Decomposition: 2020m7 - 2024m9
Data
(F+C)-Shock
C-Shock
F-Shock

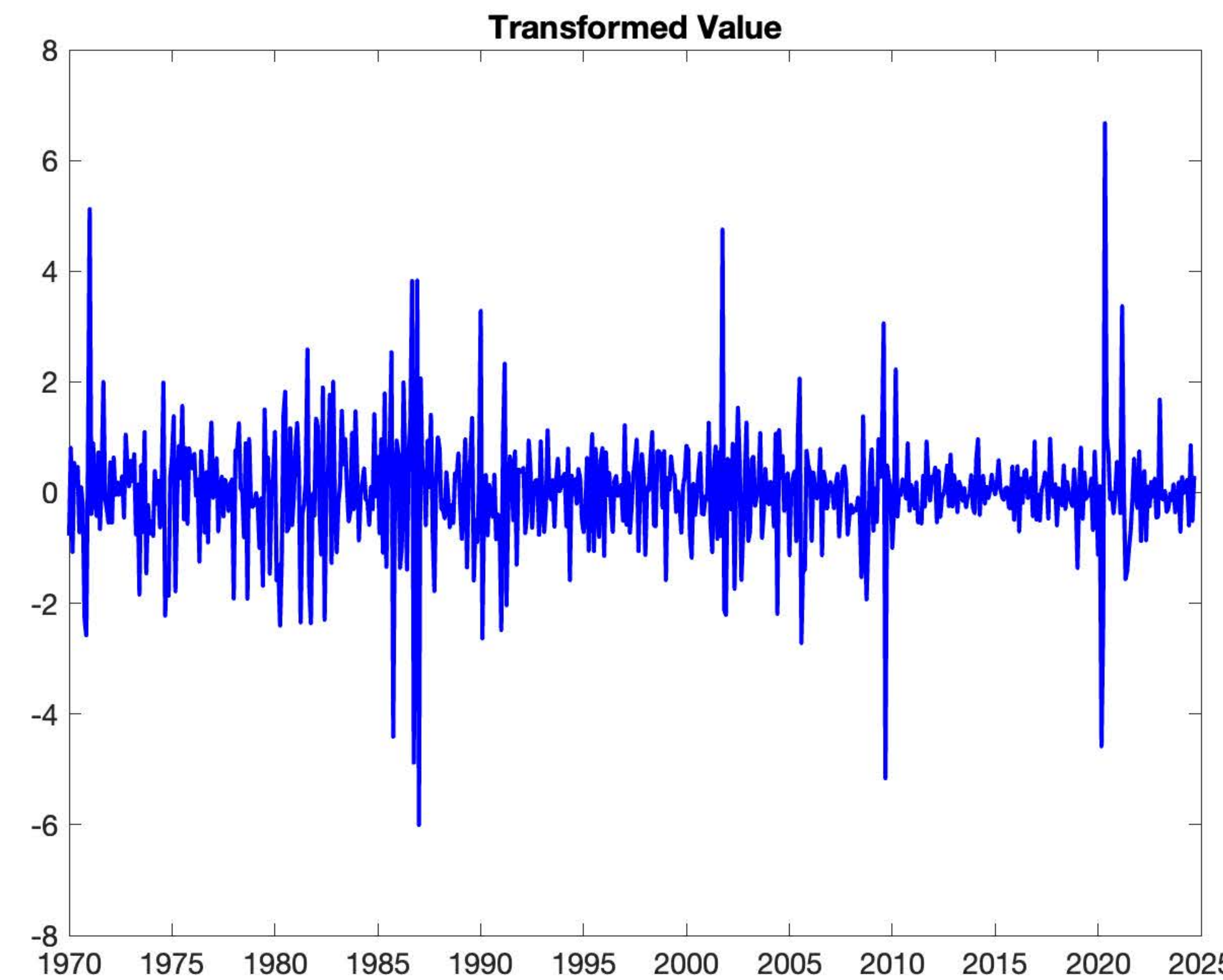

3. Qpcegdsdur: Level
×10^4

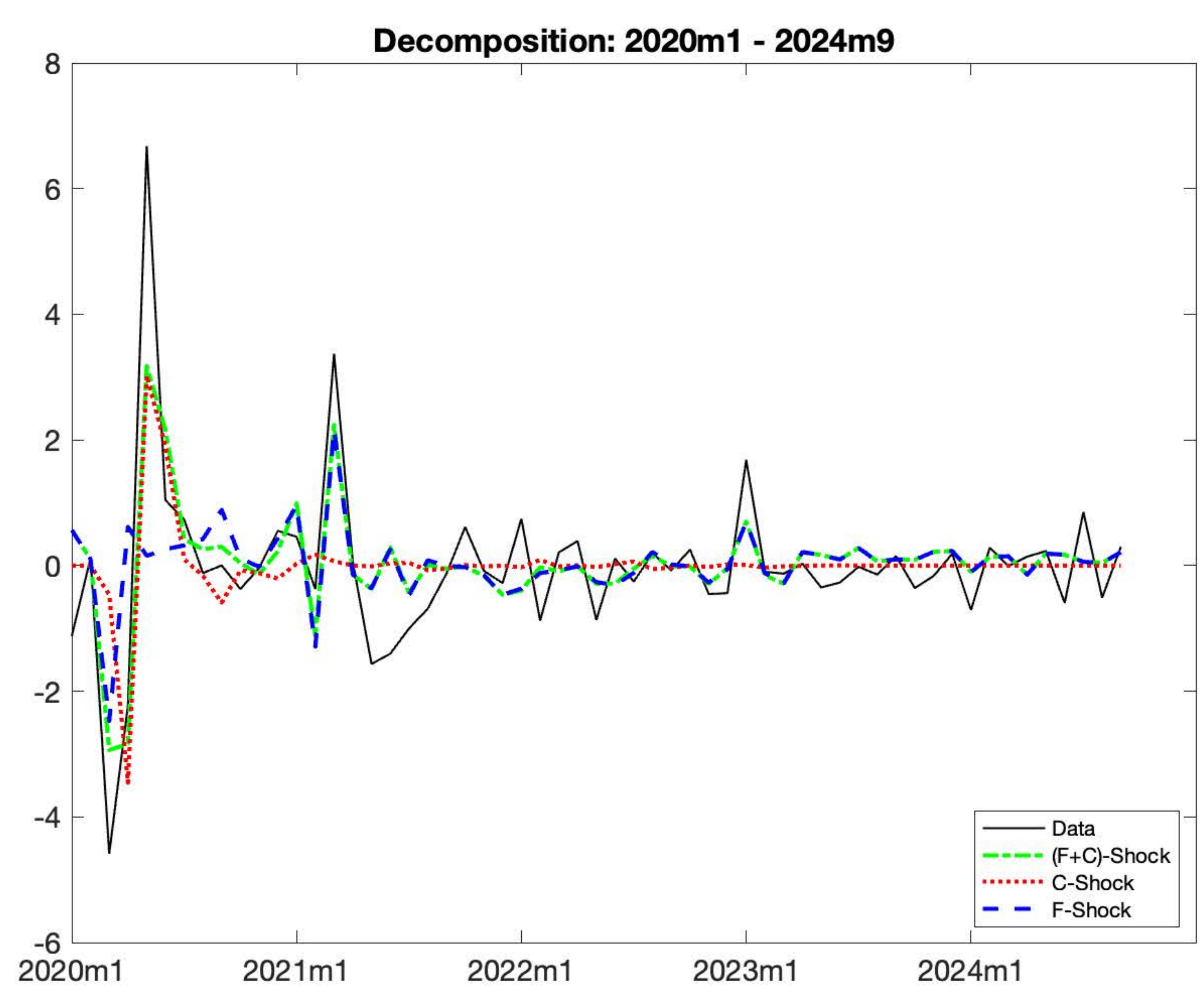

Transformed Value

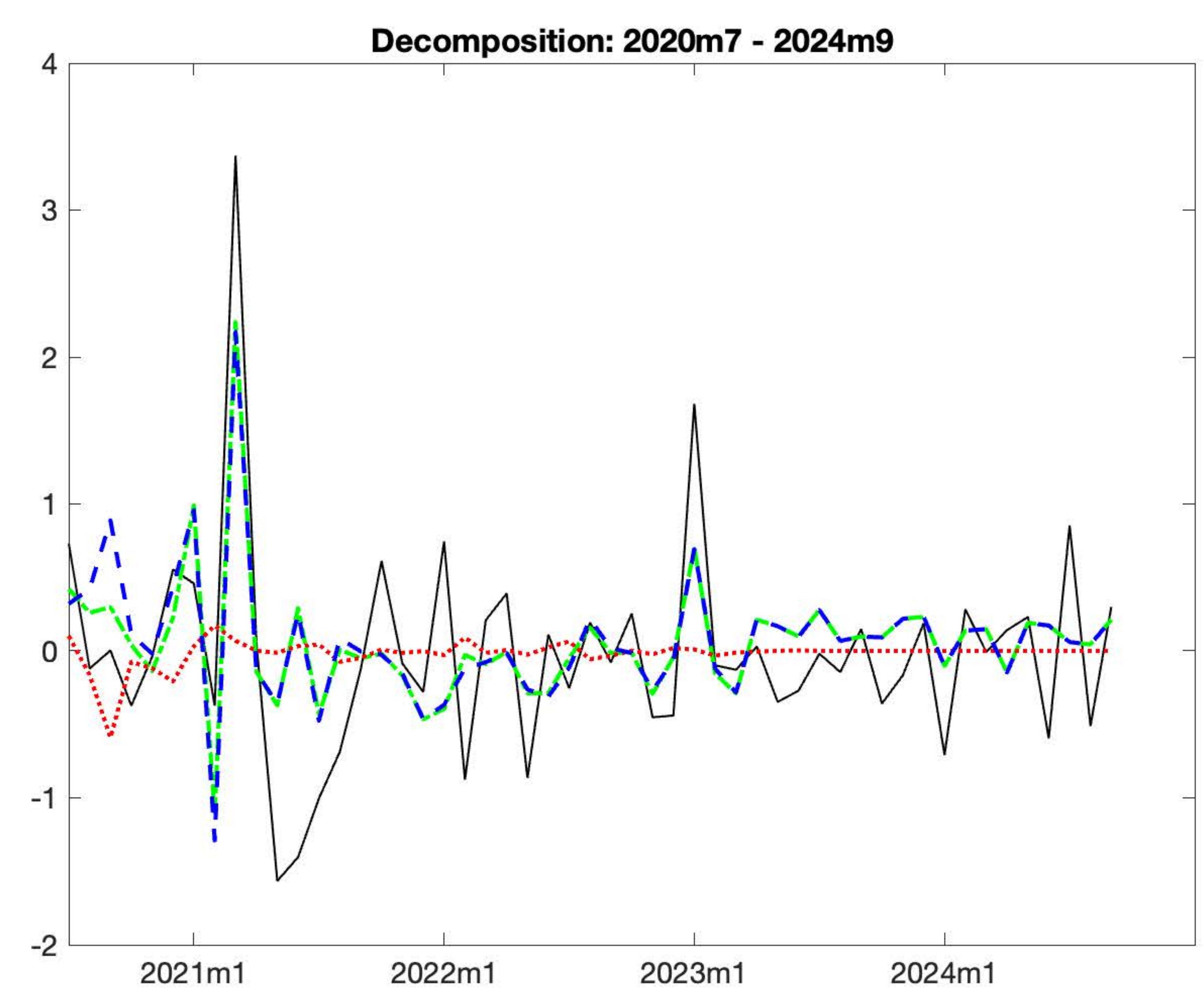

Decomposition: 2020m1 - 2024m9
Data
(F+C)-Shock
C-Shock
F-Shock

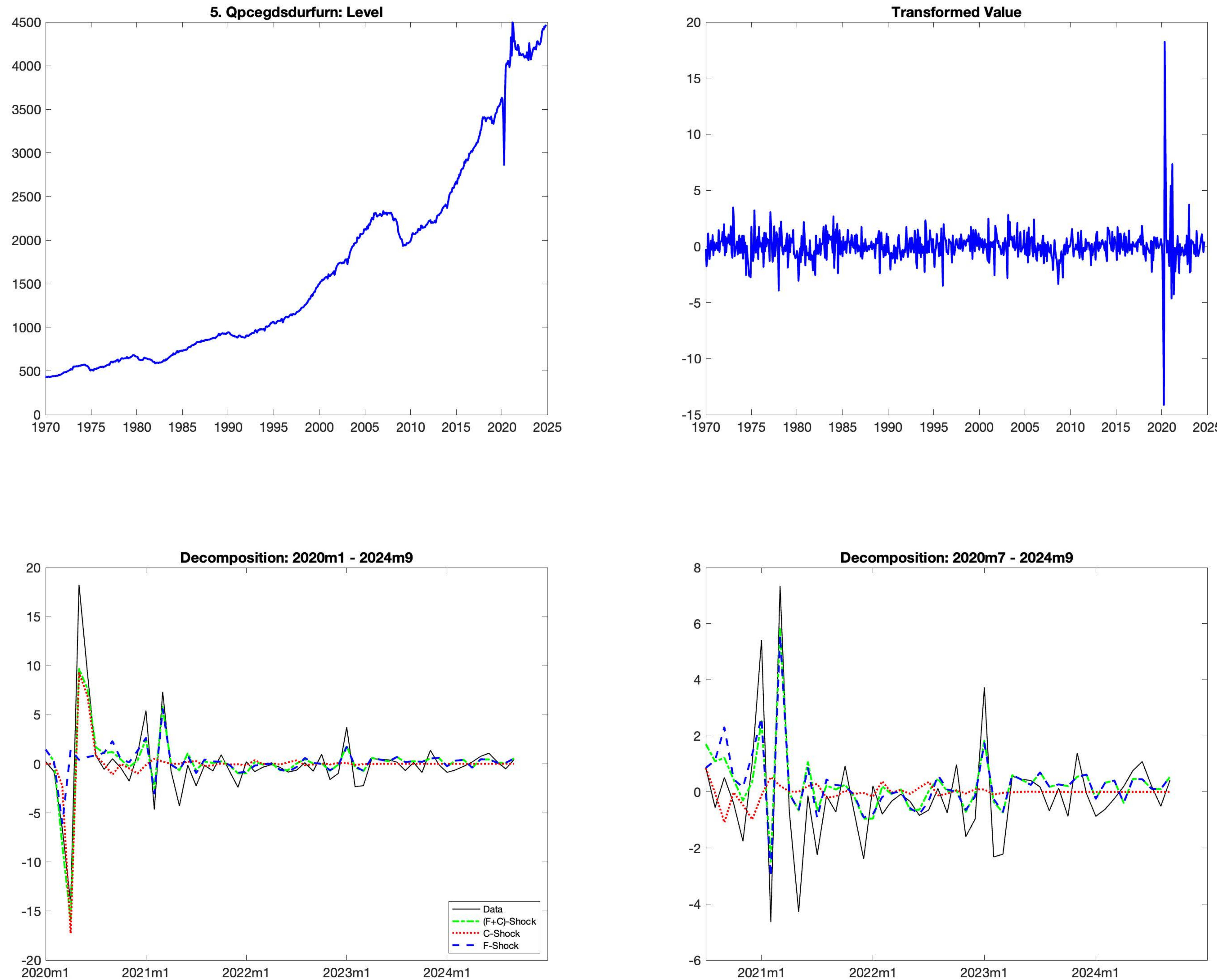

Decomposition: 2020m7 - 2024m9

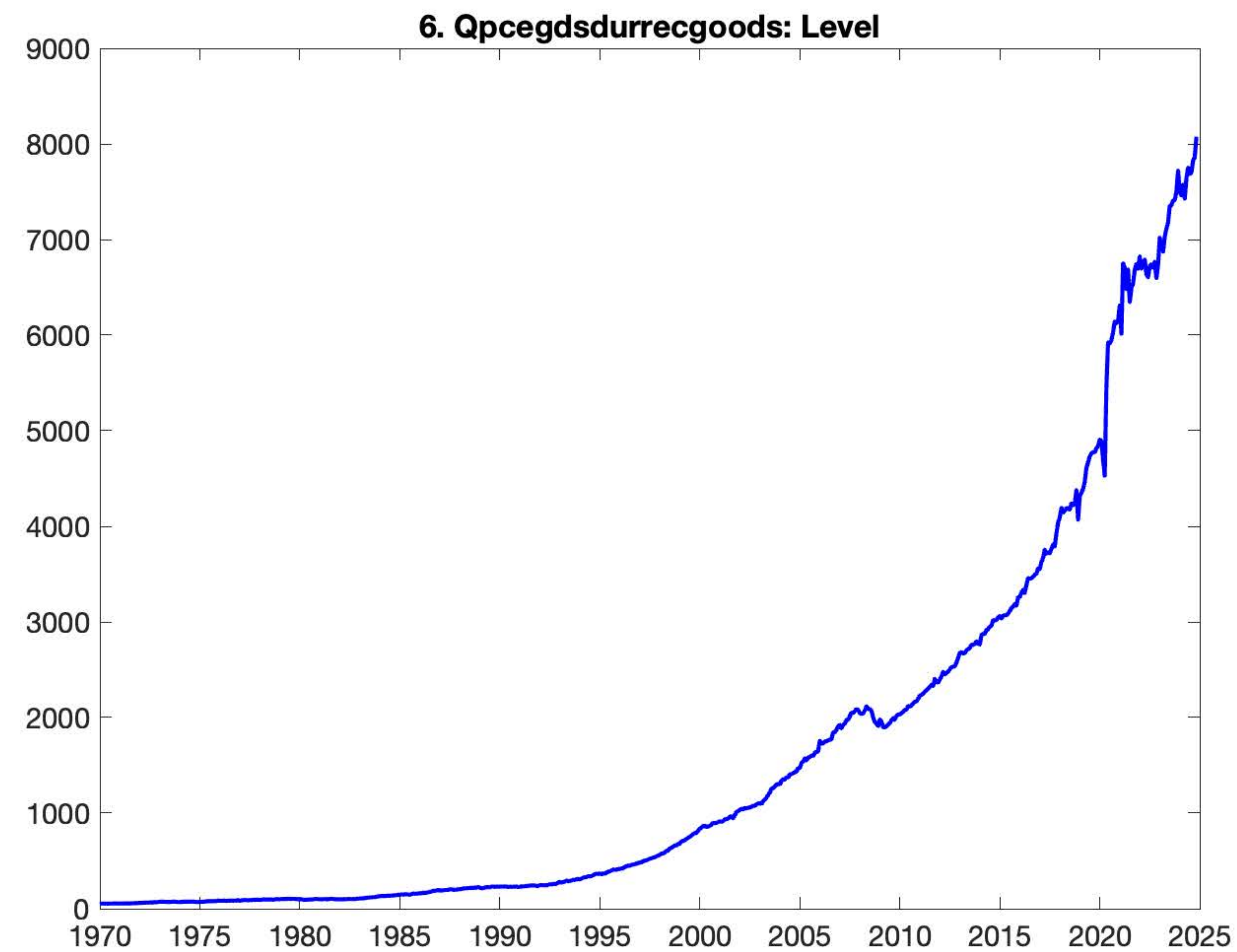

4. Qpcegdsdurmotorveh: Level

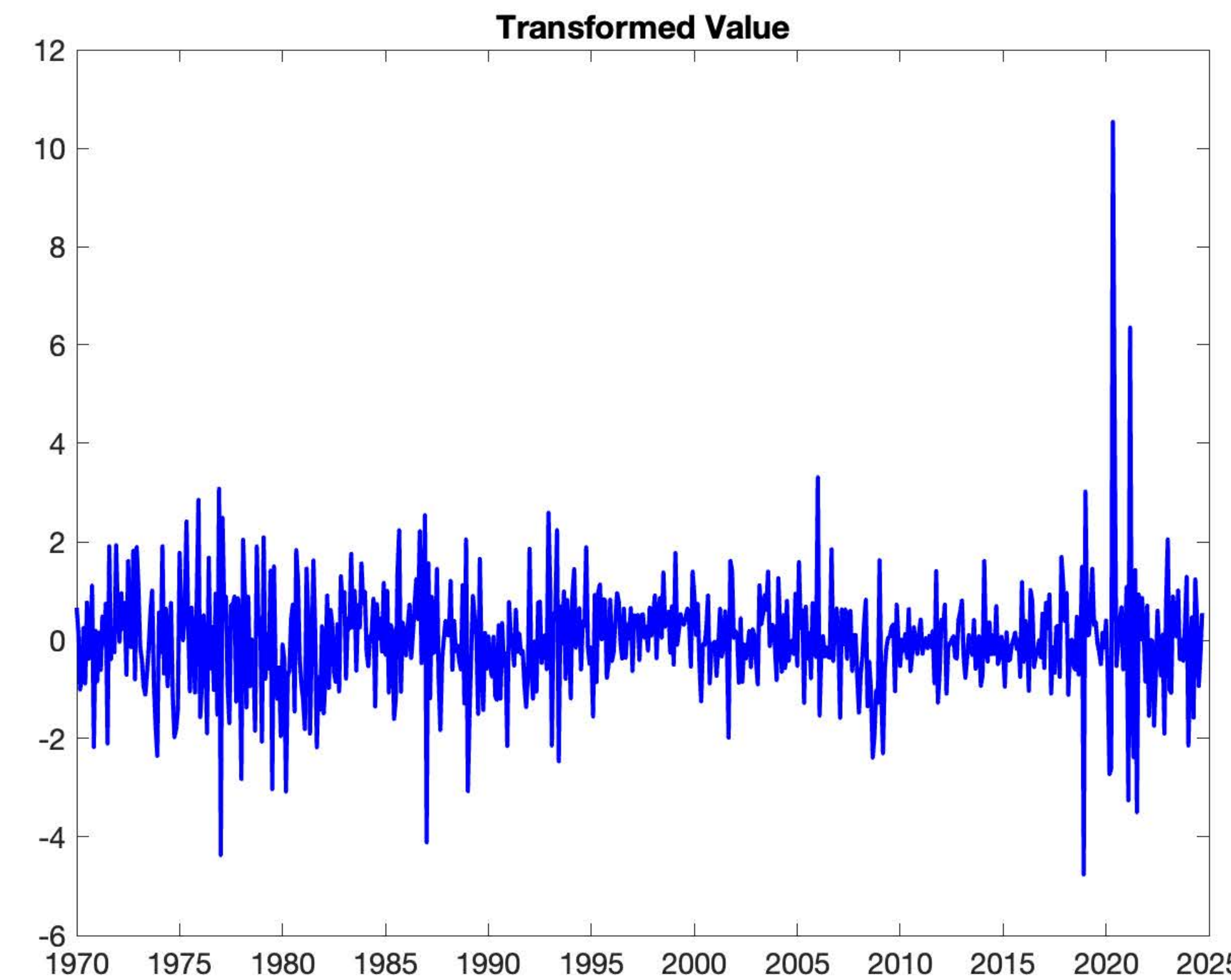

Transformed Value

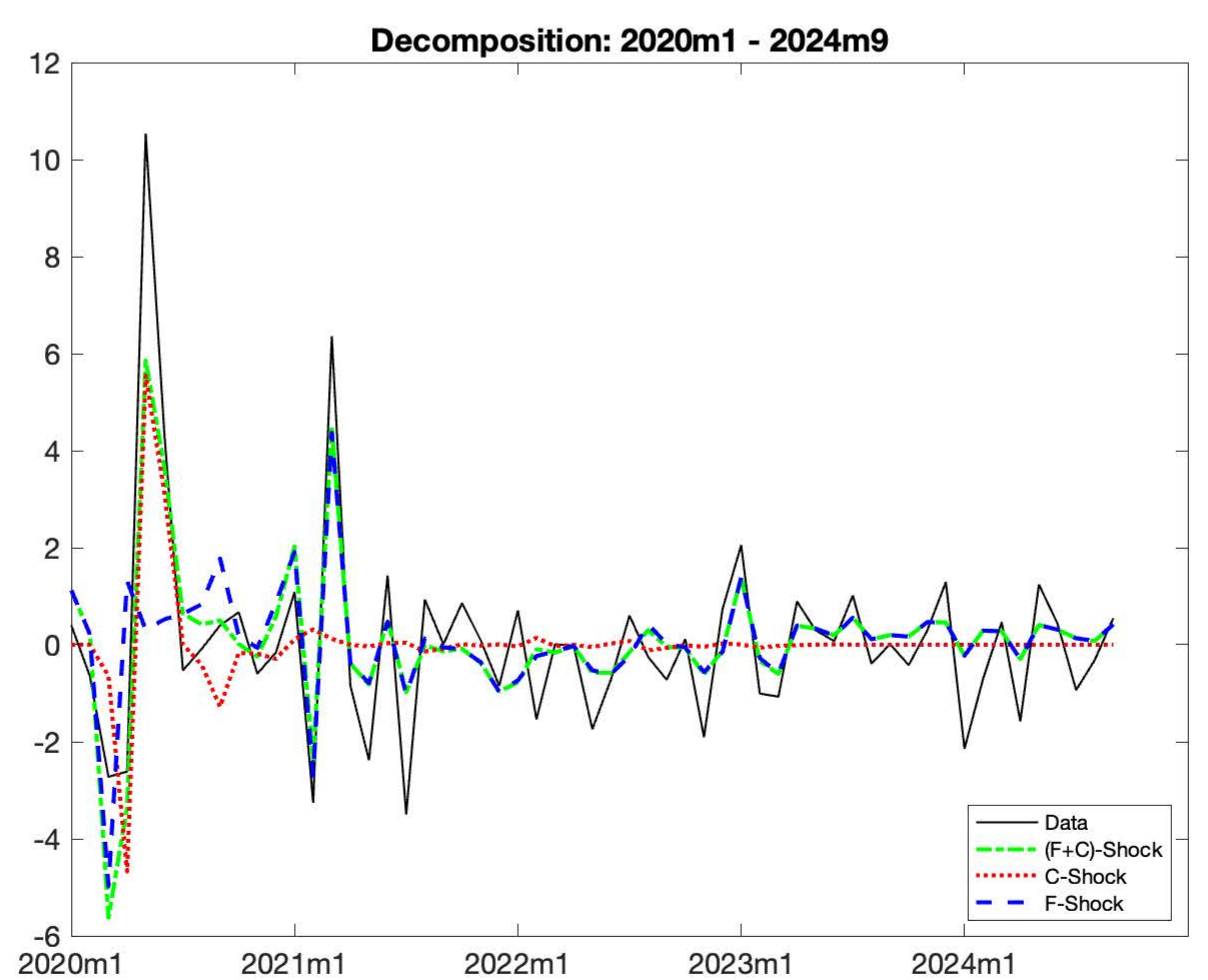

Decomposition: 2020m1 - 2024m9
Data
(F+C)-Shock
C-Shock
F-Shock

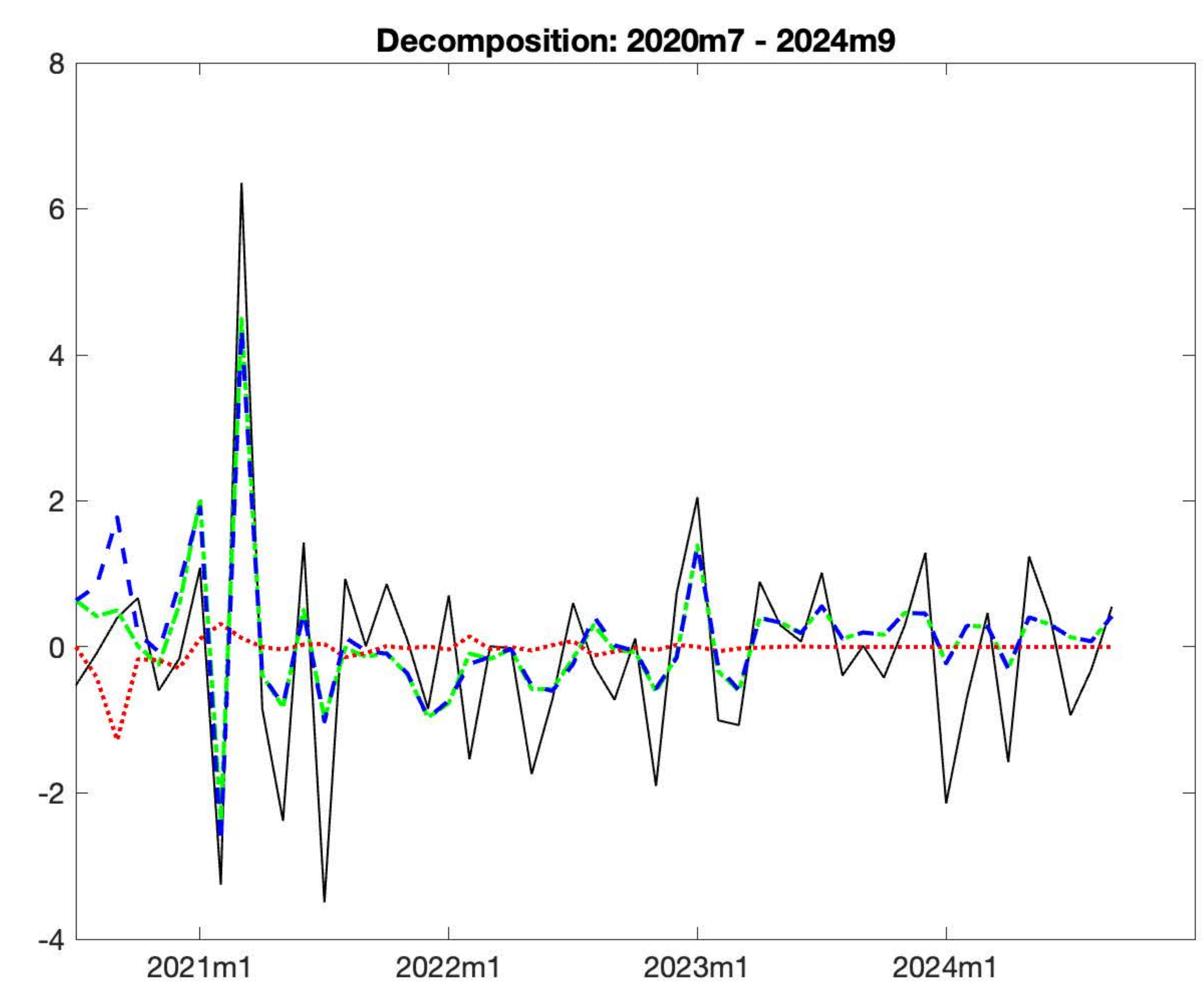

Decomposition: 2020m7 - 2024m9

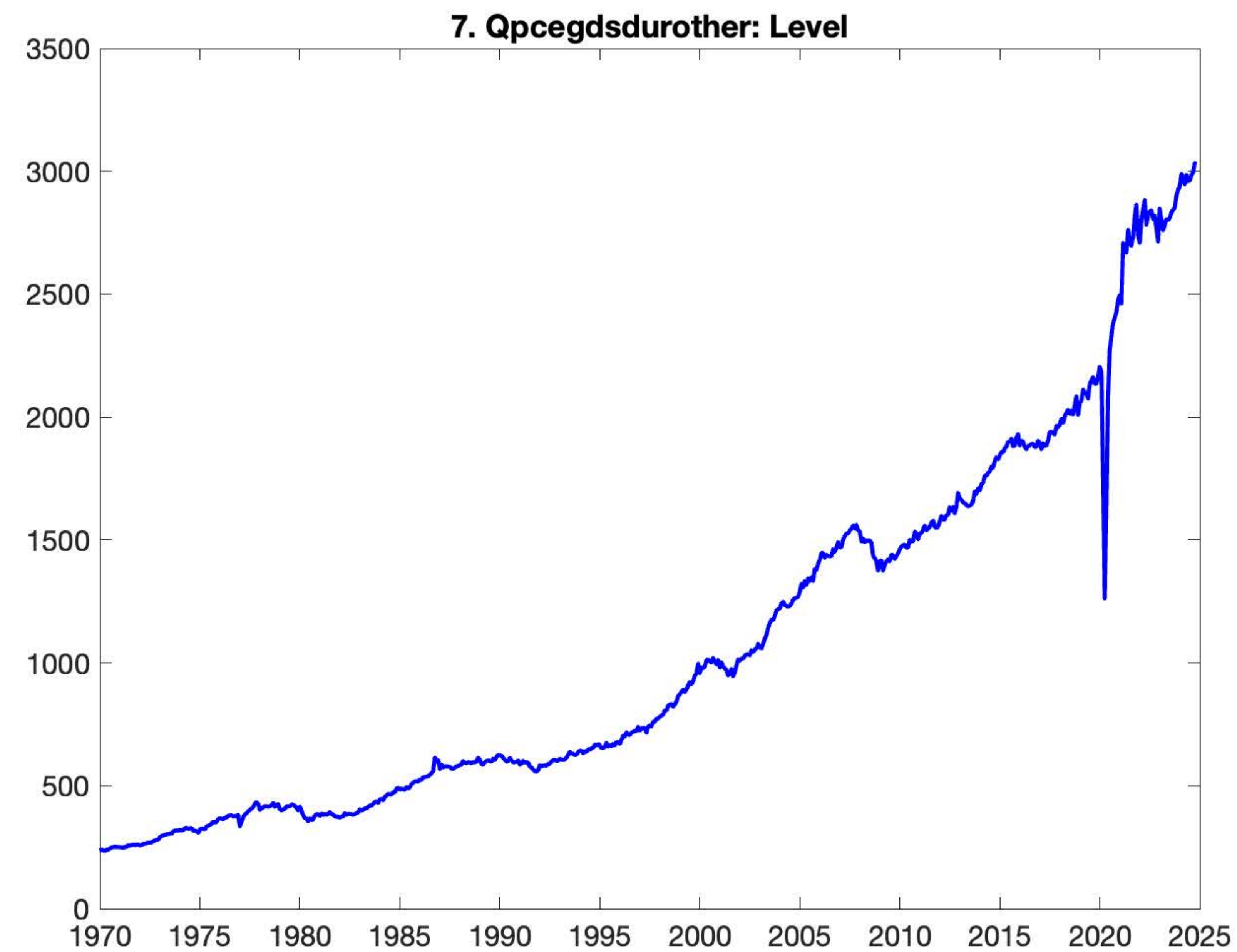

5. Qpcegdsdurfurn: Level
4500
4000
3500
3000
2500
2000
1500
1000
500
0
1970
1975
1980
1985
1990
1995
2000
2005
2010
2015
2020
2025
Transformed Value
20
15
10
5
0
-5
-10
-15
1970
1975
1980
1985
1990
1995
2000
2005
2010
2015
2020
2025
Decomposition: 2020m1 - 2024m9
20
15
10
5
0
-5
-10
-15
-20
2020m1
2021m1
2022m1
2023m1
2024m1
Data
(F+C)-Shock
C-Shock
F-Shock
Decomposition: 2020m7 - 2024m9
8
6
4
2
0
-2
-4
-6
2021m1
2022m1
2023m1
2024m1

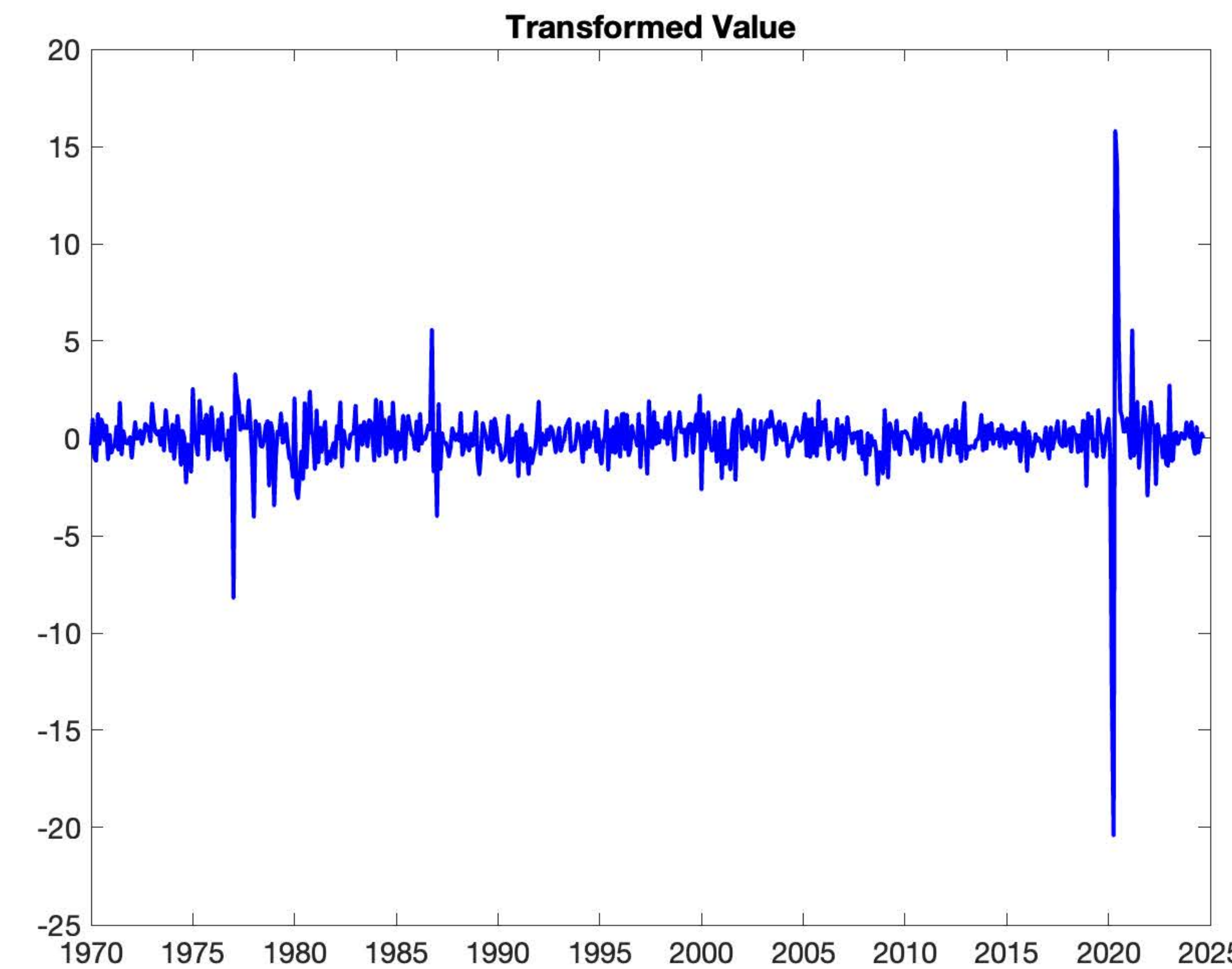

6. Qpcegdsdurrecgoods: Level

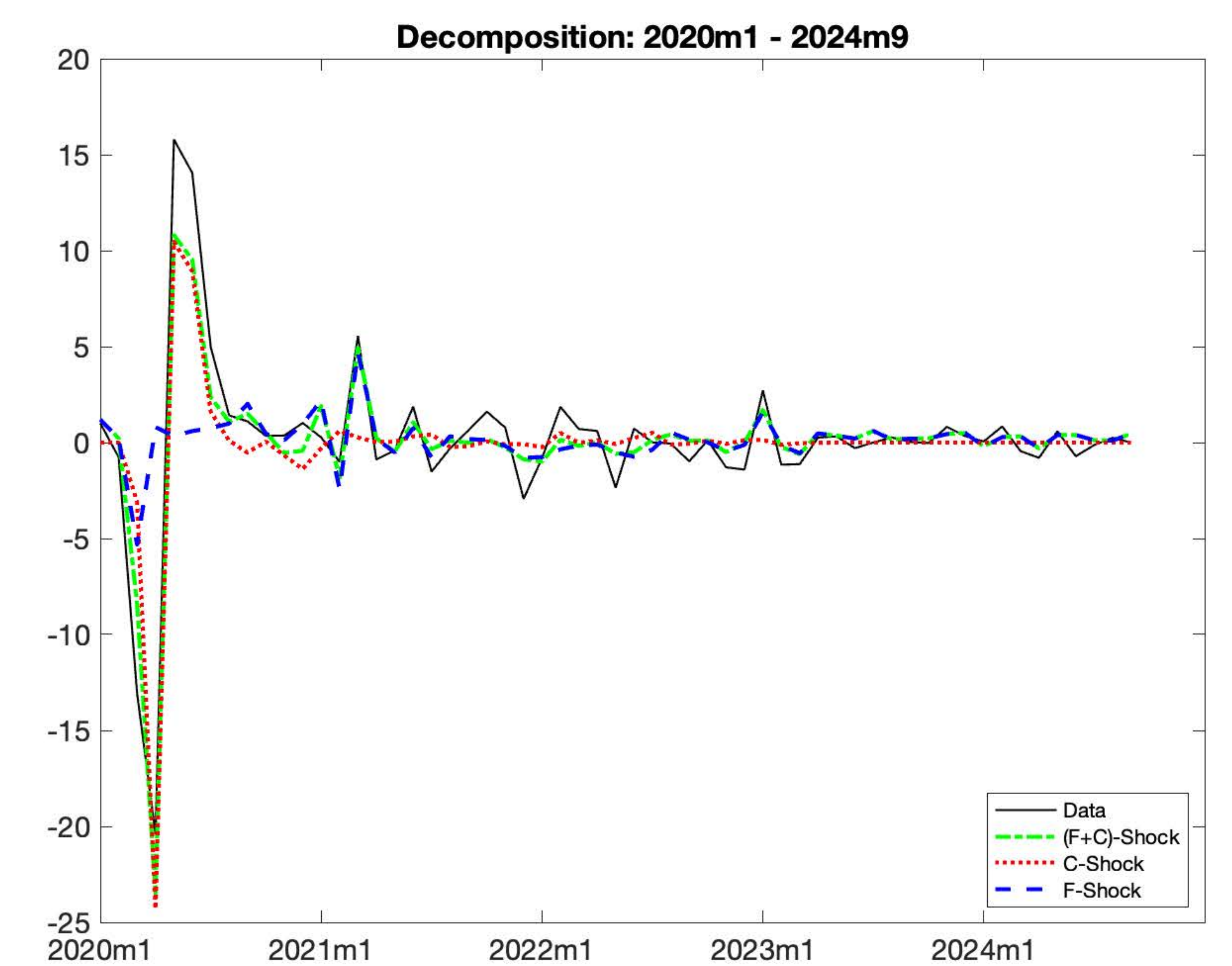

Transformed Value

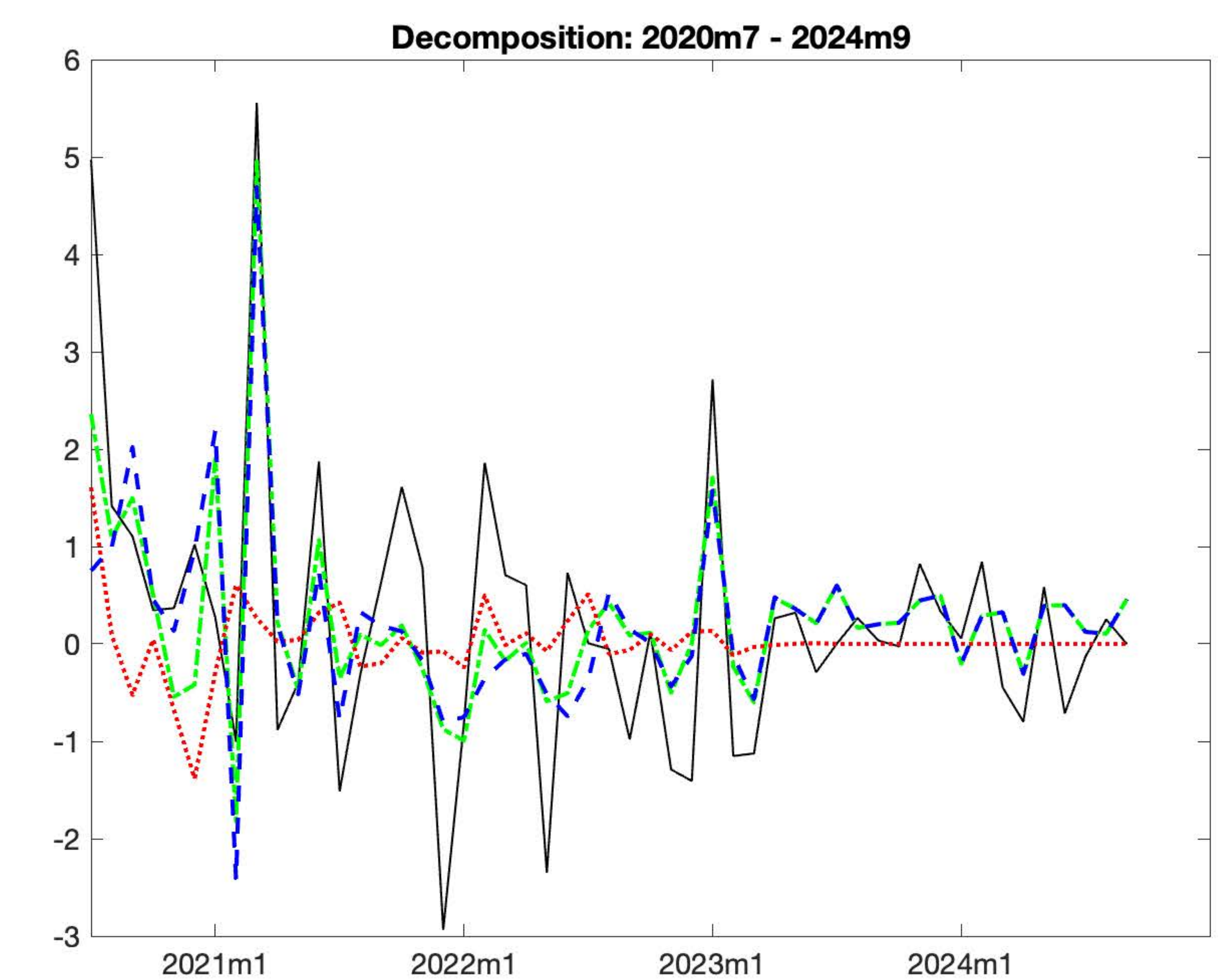

Decomposition: 2020m1 - 2024m9
Data
(F+C)-Shock
C-Shock
F-Shock

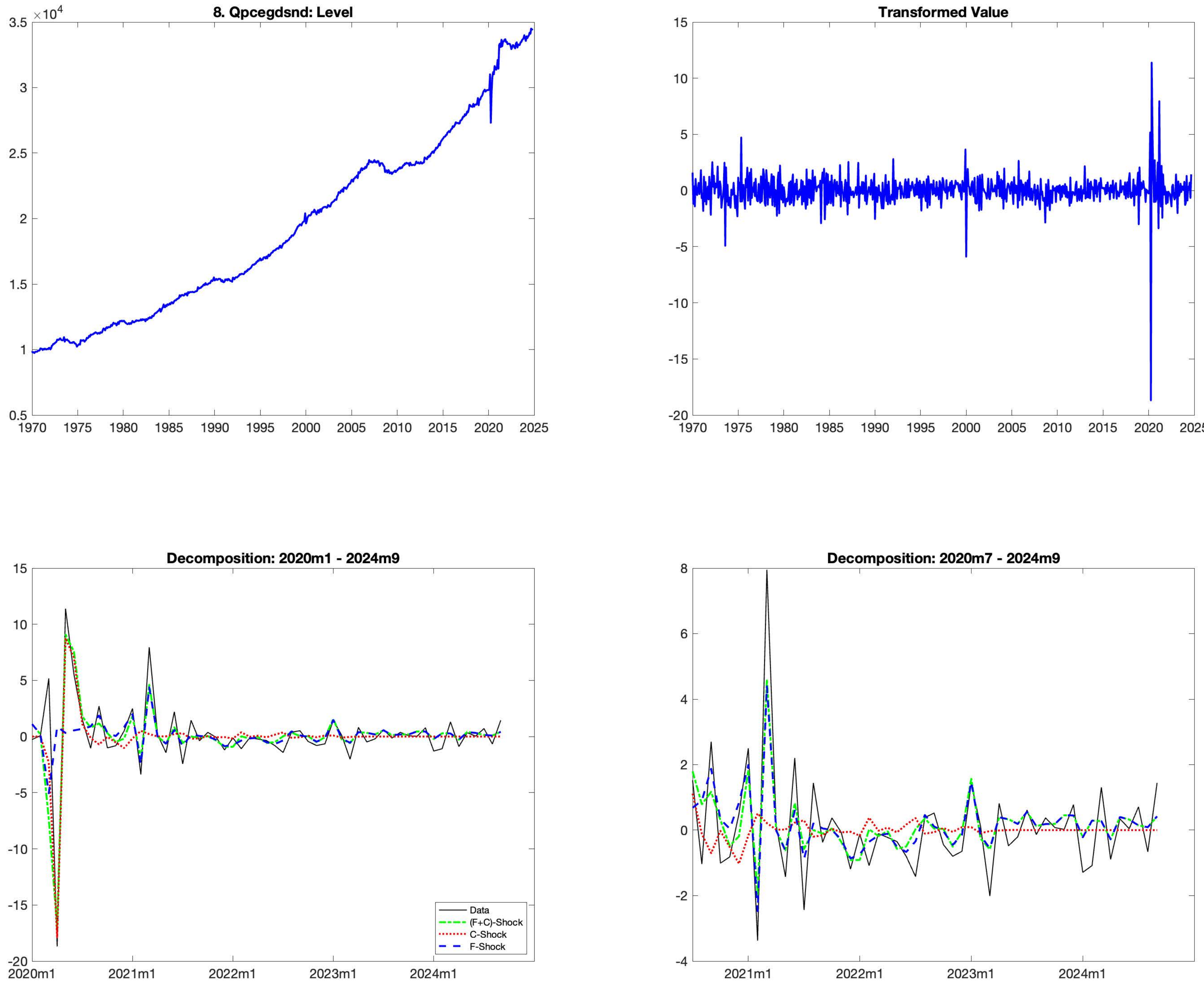

Decomposition: 2020m7 - 2024m9

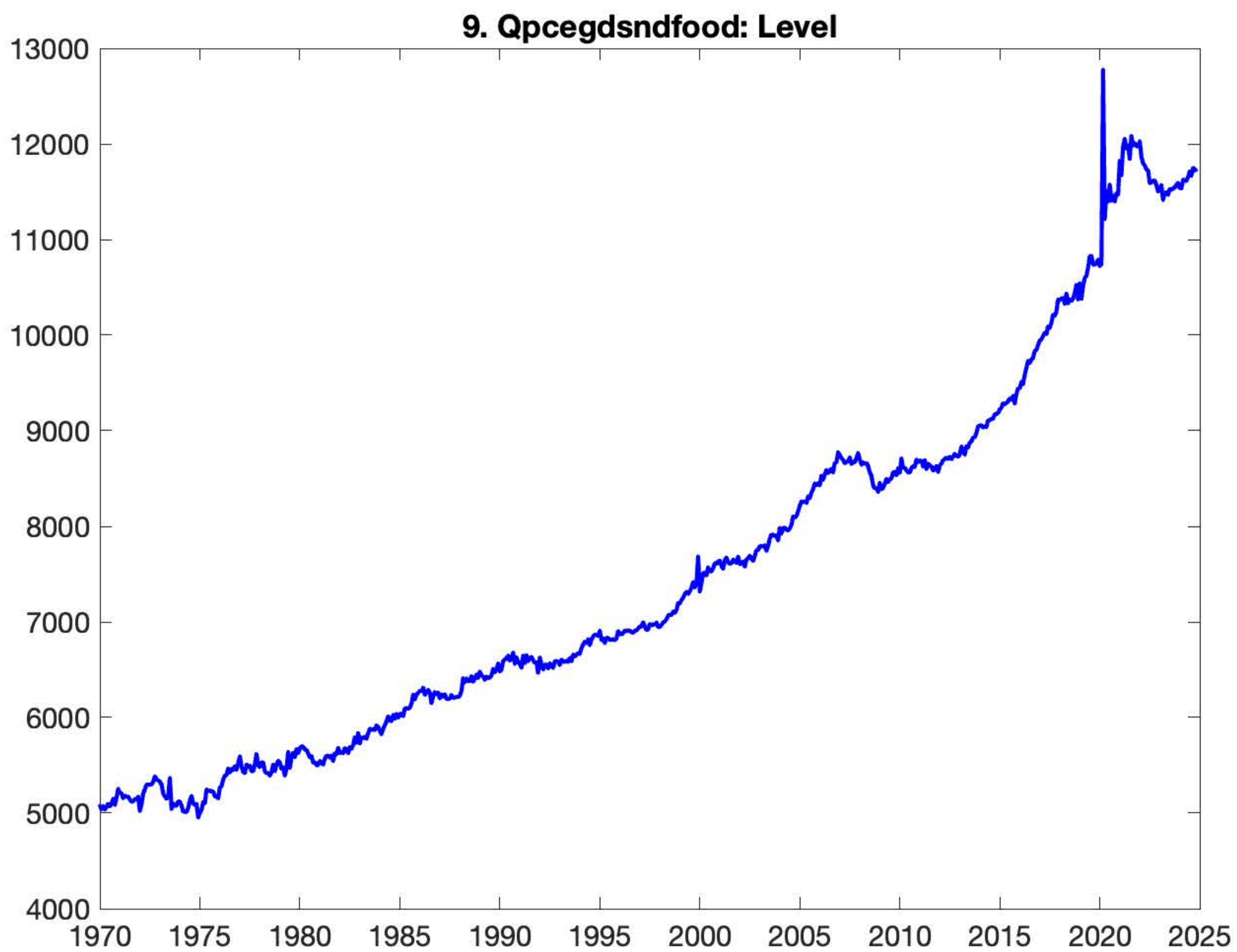

7. Qpcegdsdurother: Level

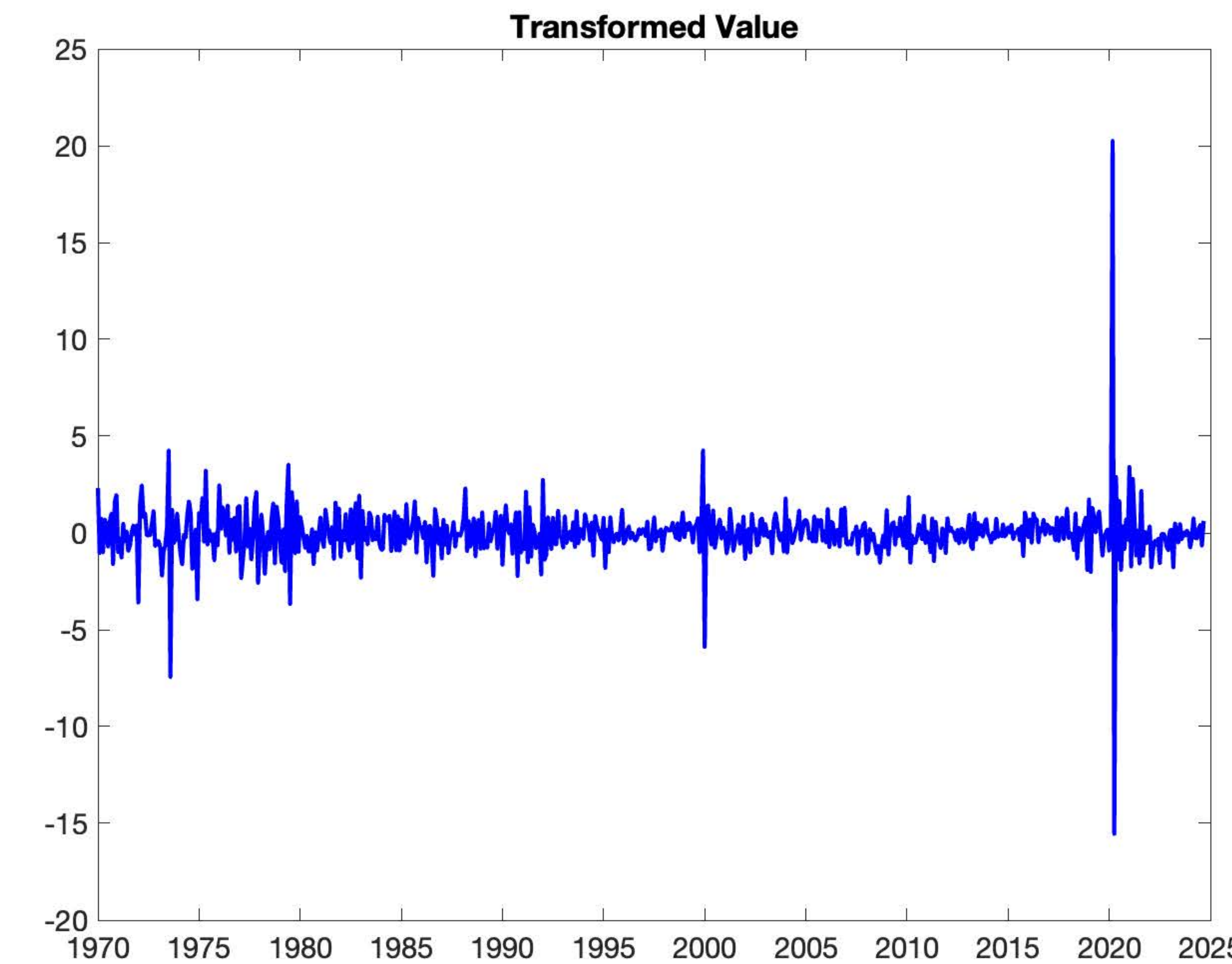

Transformed Value

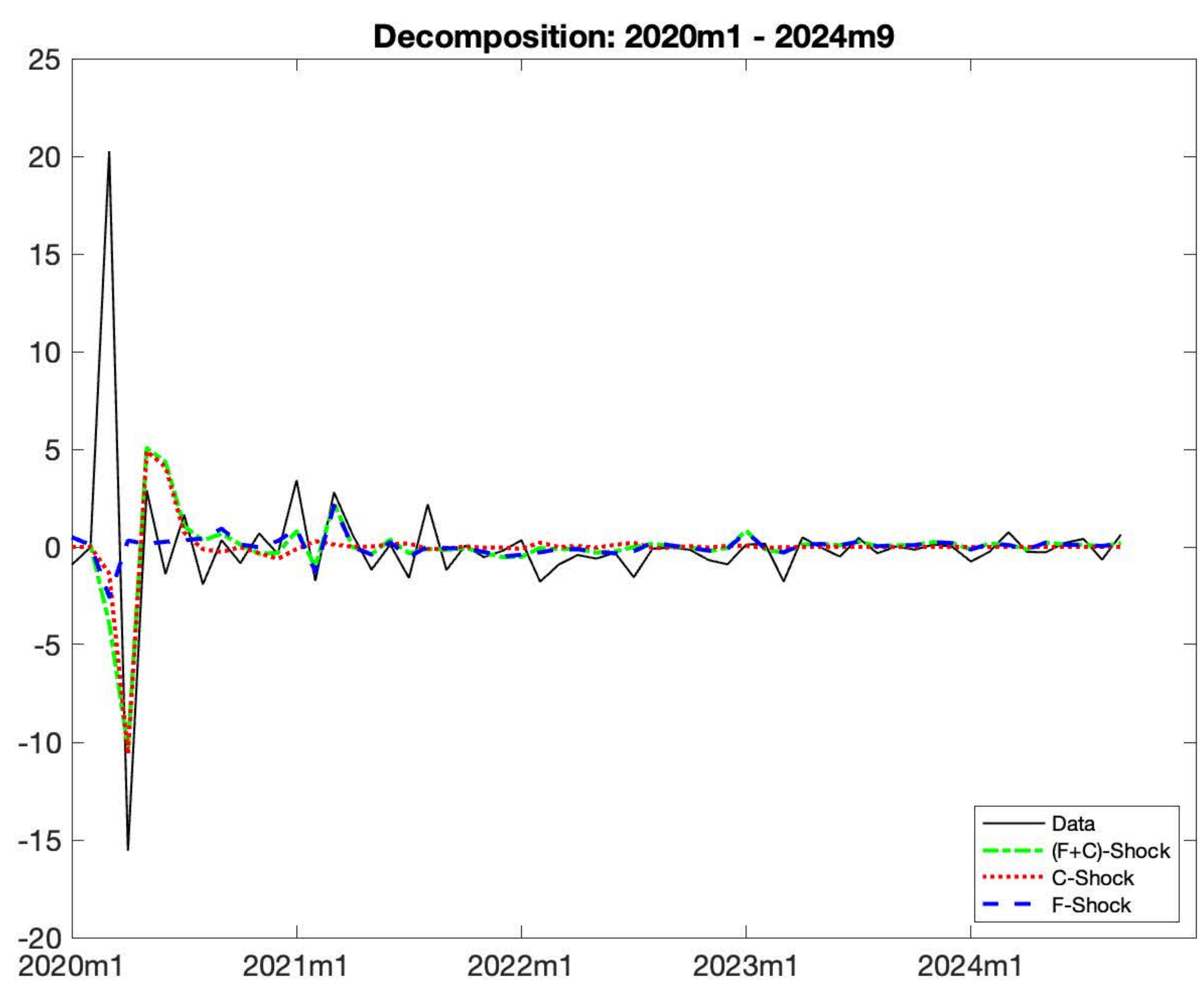

Decomposition: 2020m1 - 2024m9
Data
(F+C)-Shock
C-Shock
F-Shock

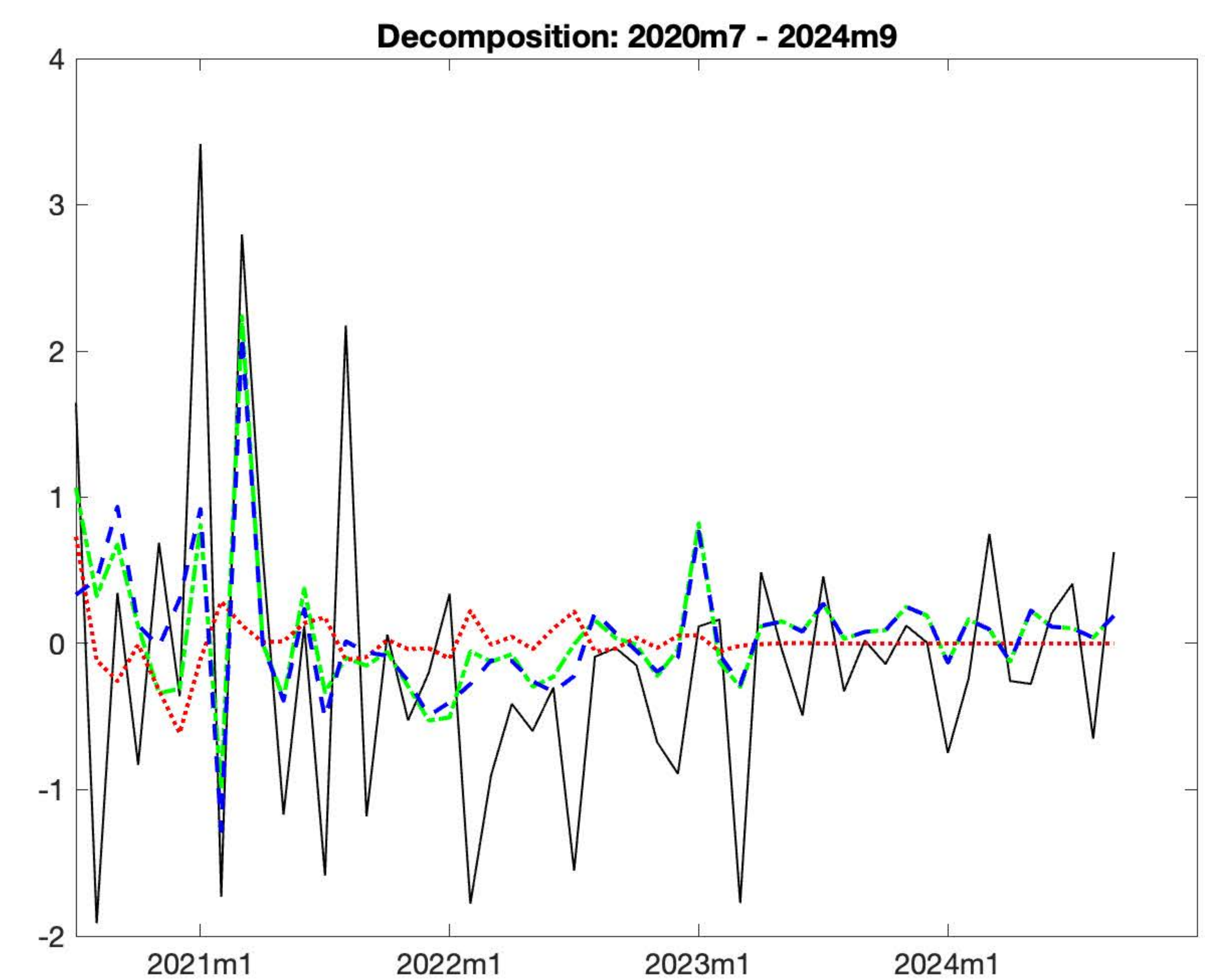

Decomposition: 2020m7 - 2024m9

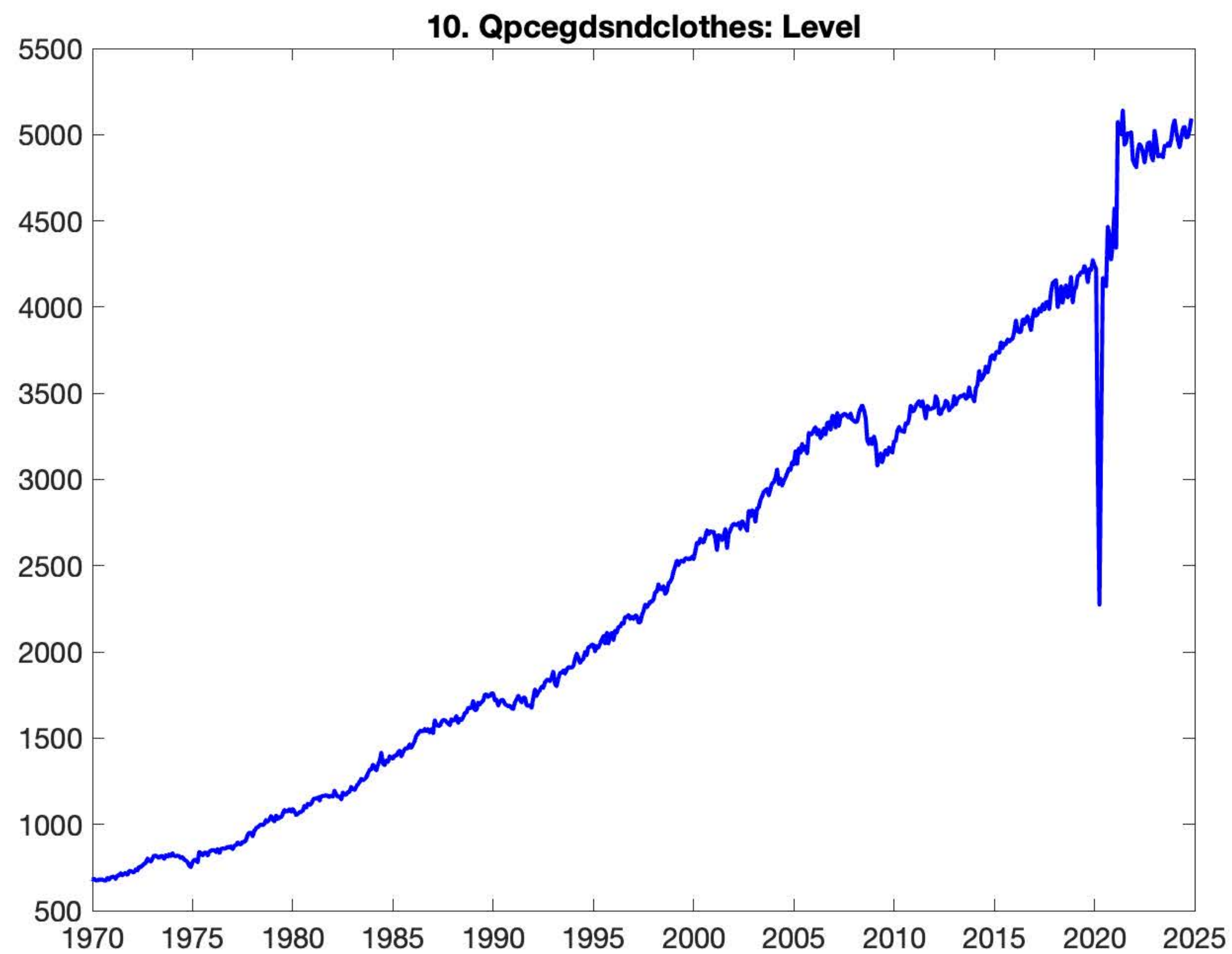

8. Qpcegdsnd: Level
×10^4
3.5
3
2.5
2
1.5
1
0.5
1970
1975
1980
1985
1990
1995
2000
2005
2010
2015
2020
2025
Transformed Value
15
10
5
0
-5
-10
-15
-20
Decomposition: 2020m1 - 2024m9
2020m1
2021m1
2022m1
2023m1
2024m1
Data
(F+C)-Shock
C-Shock
F-Shock
Decomposition: 2020m7 - 2024m9
8
6
4
2
0
-2
-4

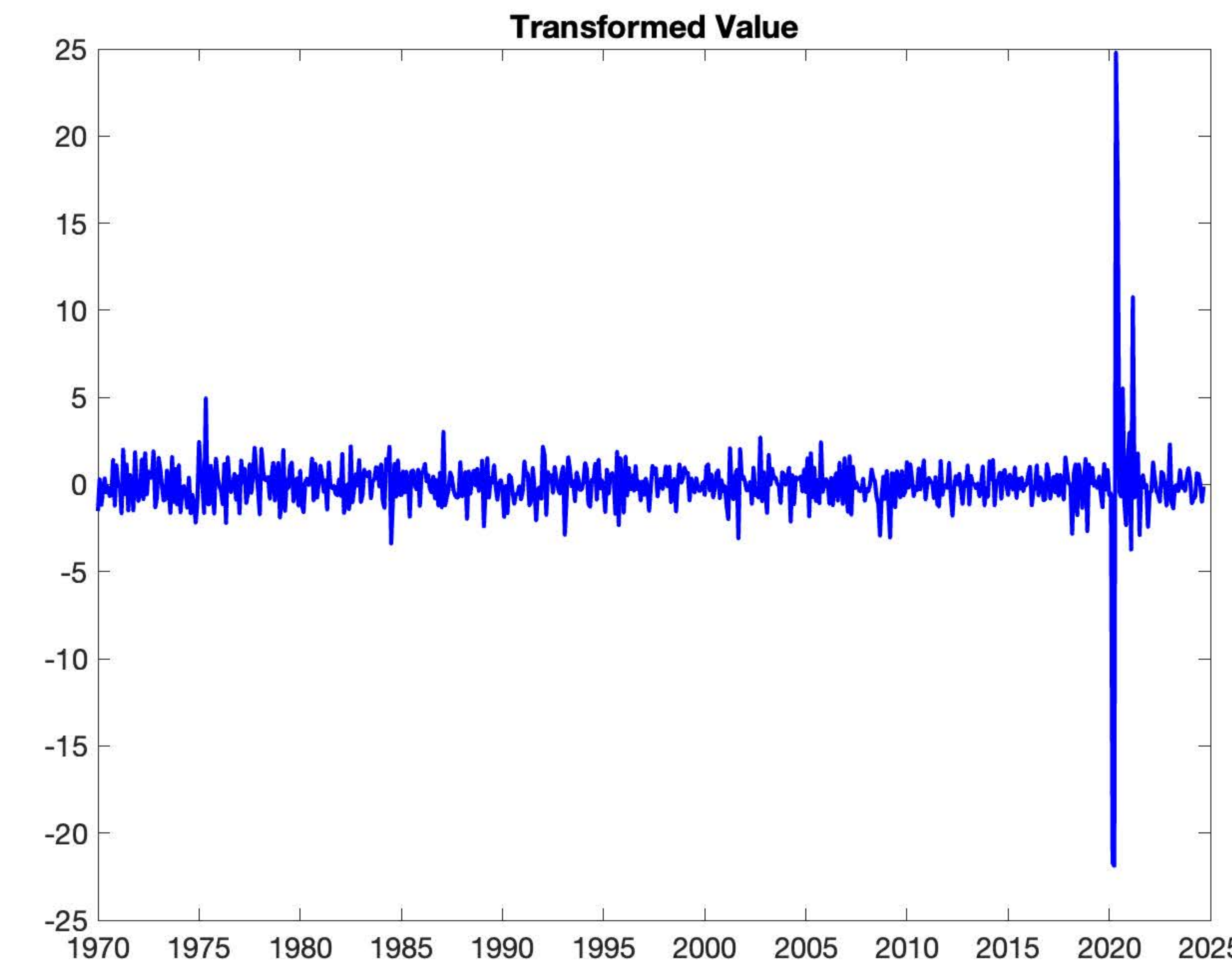

9. Qpcegdsndfood: Level
13000
12000
11000
10000
9000
8000
7000
6000
5000
4000
1970
1975
1980
1985
1990
1995
2000
2005
2010
2015
2020
2025

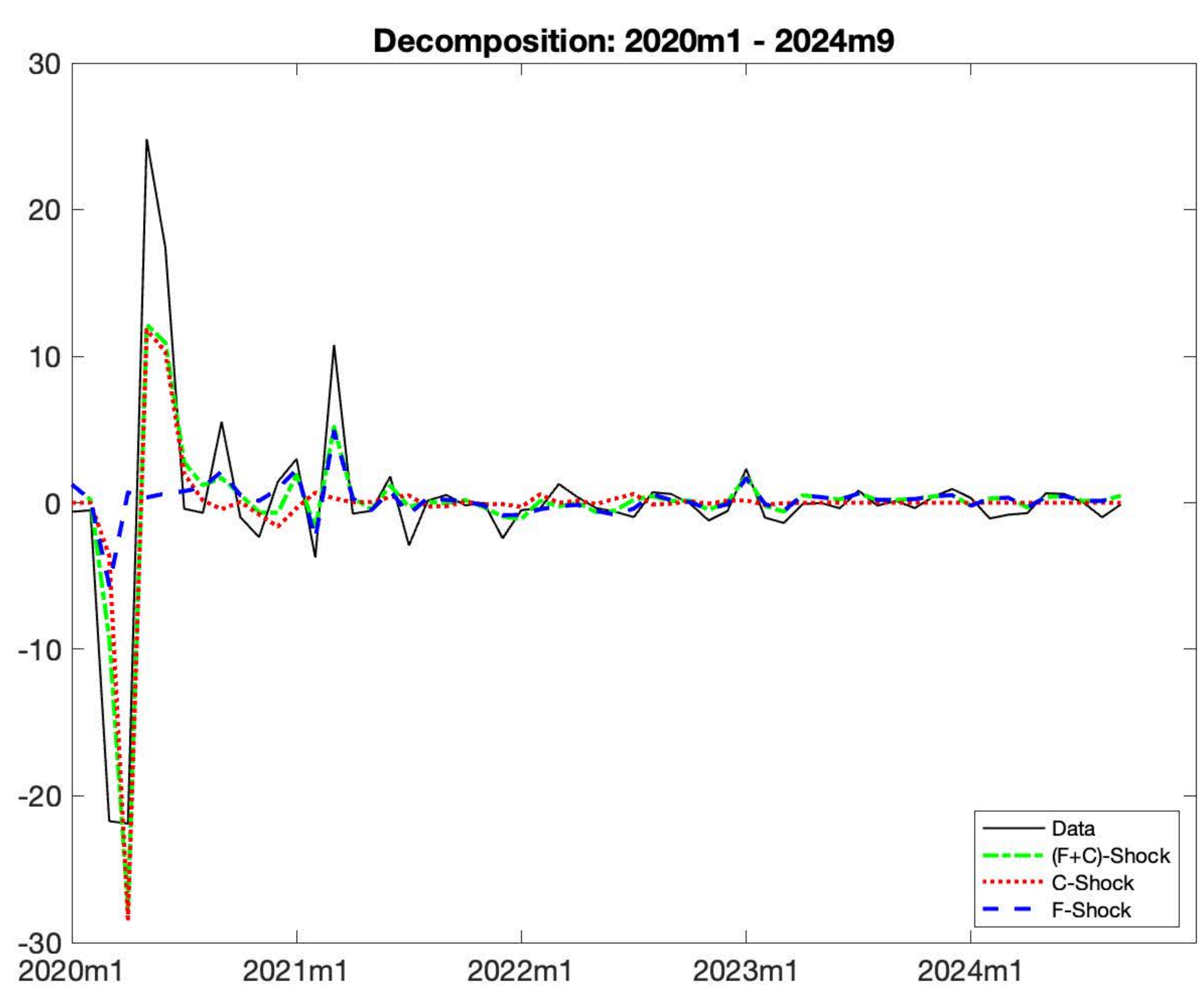

Transformed Value
25
20
15
10
5
0
-5
-10
-15
-20
1970
1975
1980
1985
1990
1995
2000
2005
2010
2015
2020
2025

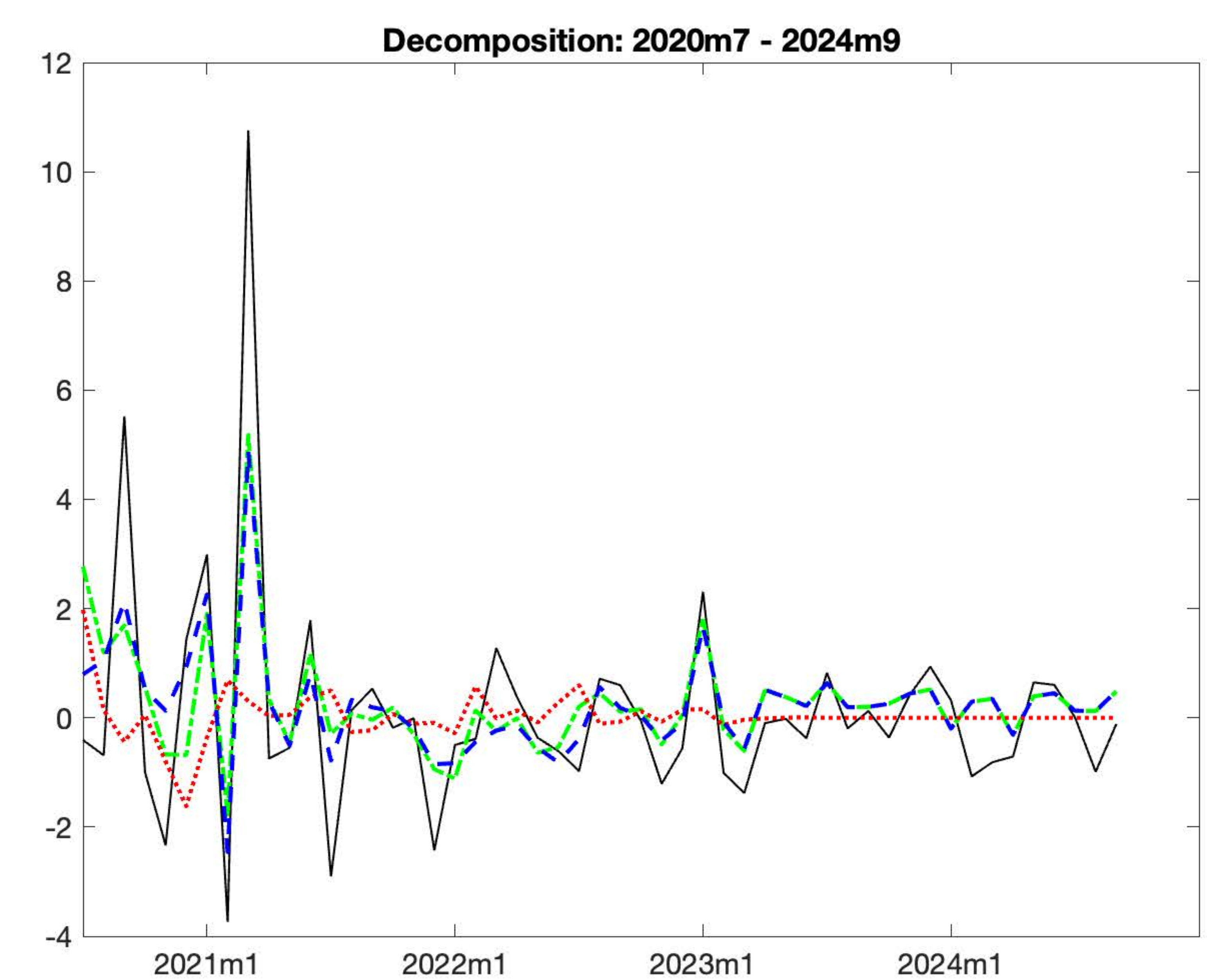

Decomposition: 2020m1 - 2024m9
25
20
15
10
5
0
-5
-10
-15
-20
2020m1
2021m1
2022m1
2023m1
2024m1
Data
(F+C)-Shock
C-Shock
F-Shock

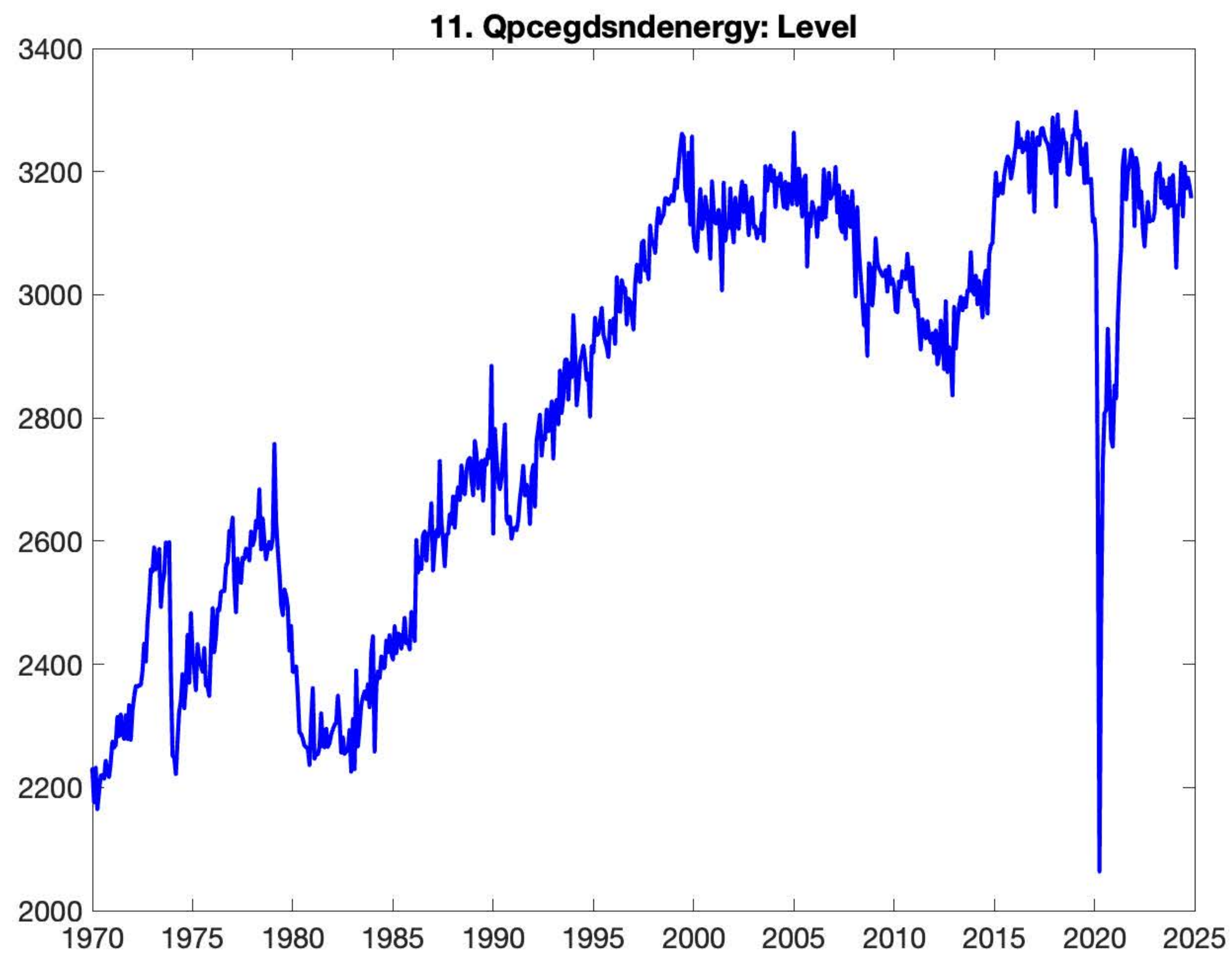

Decomposition: 2020m7 - 2024m9
4
3
2
1
0
-1
-2
2021m1
2022m1
2023m1
2024m1

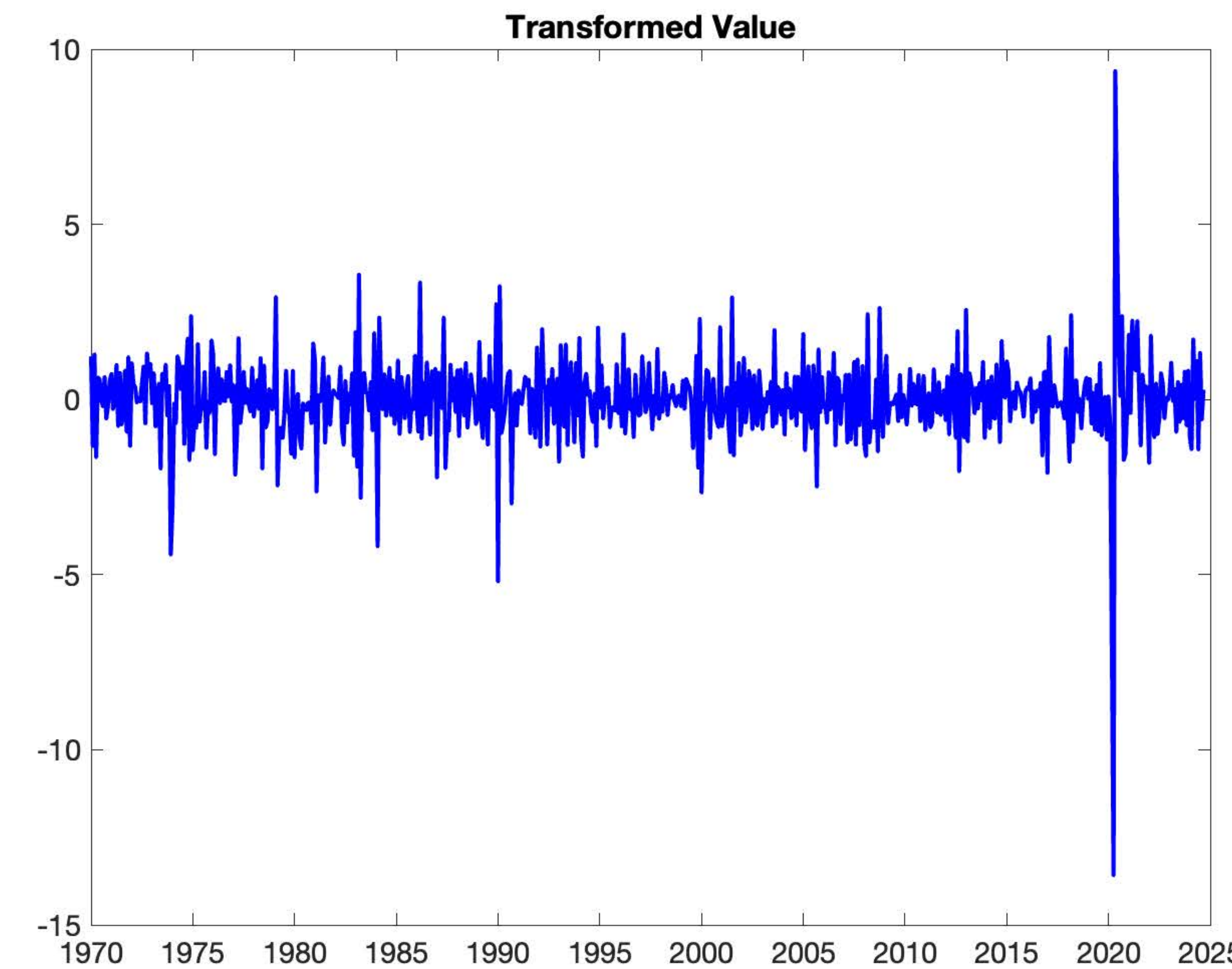

10. Qpcegdsndclothes: Level

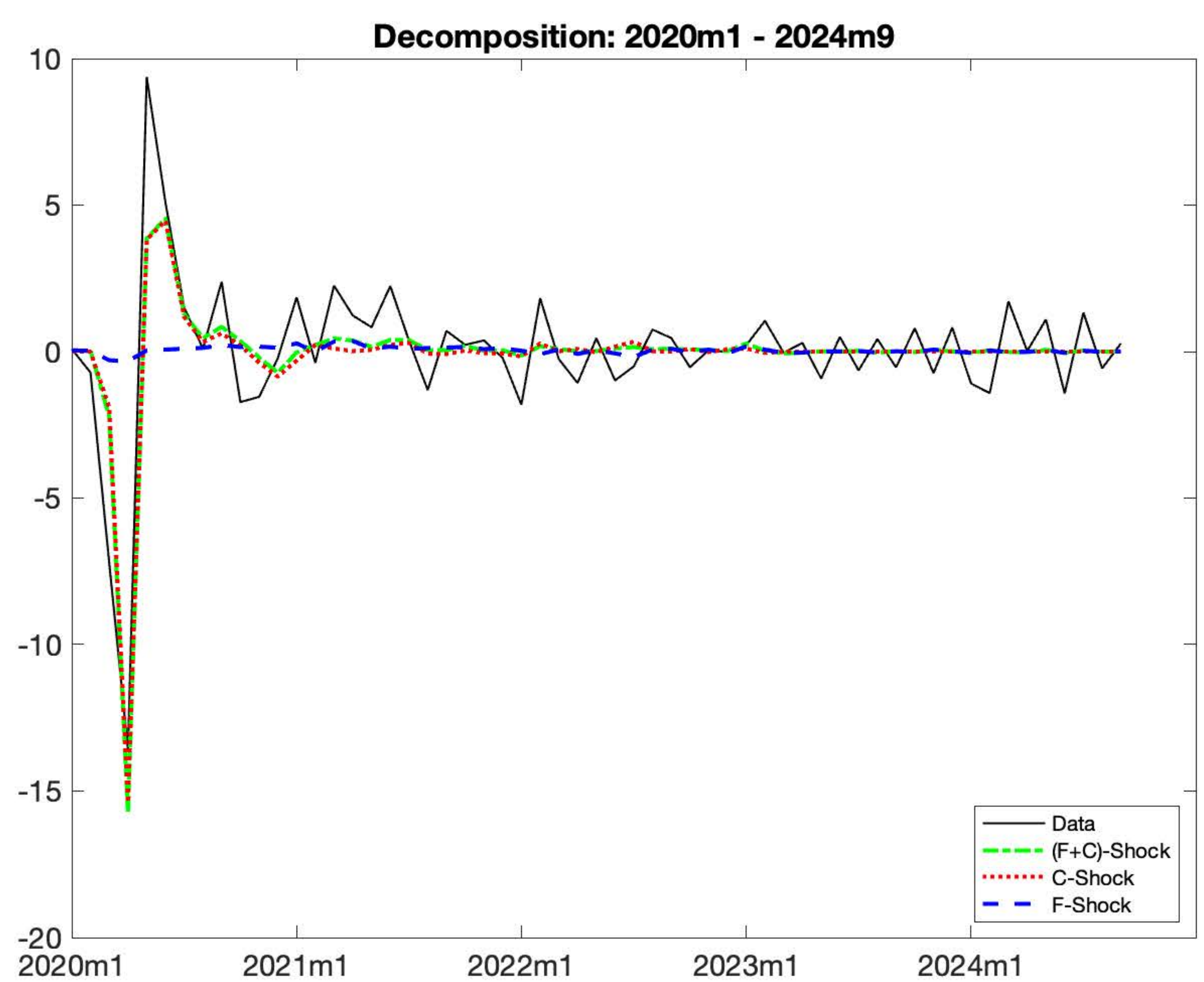

Transformed Value

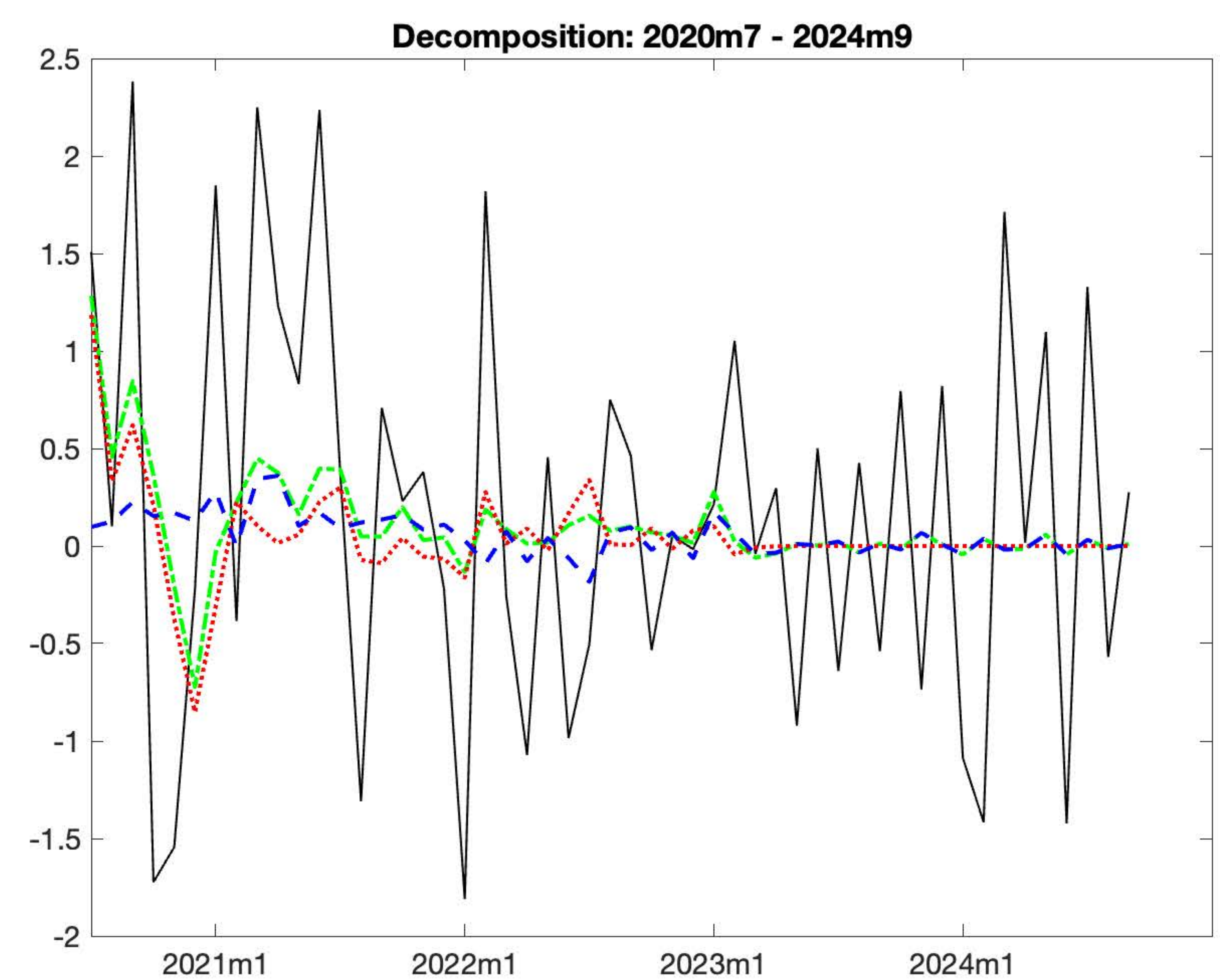

Decomposition: 2020m1 - 2024m9
Data
(F+C)-Shock
C-Shock
F-Shock

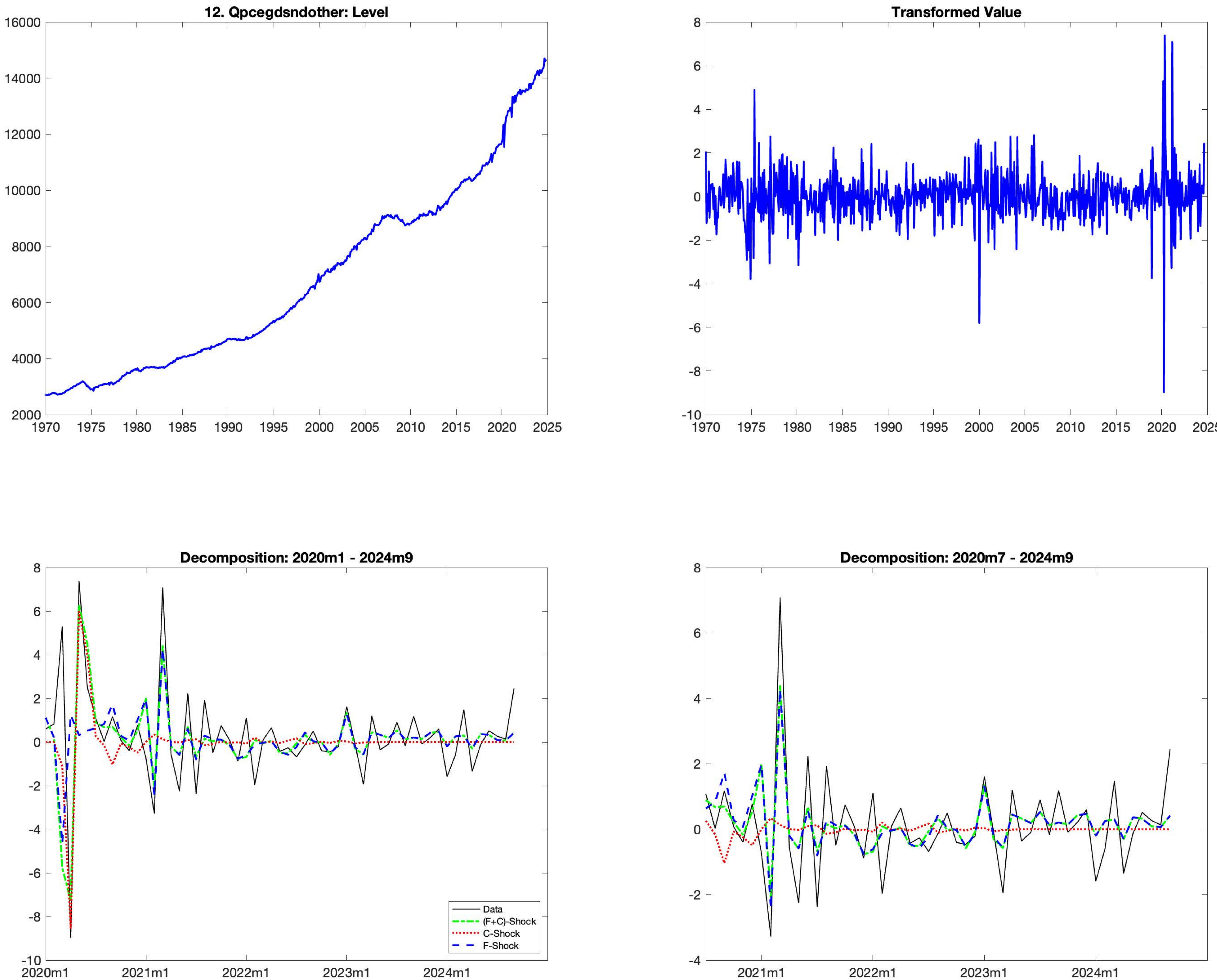

Decomposition: 2020m7 - 2024m9

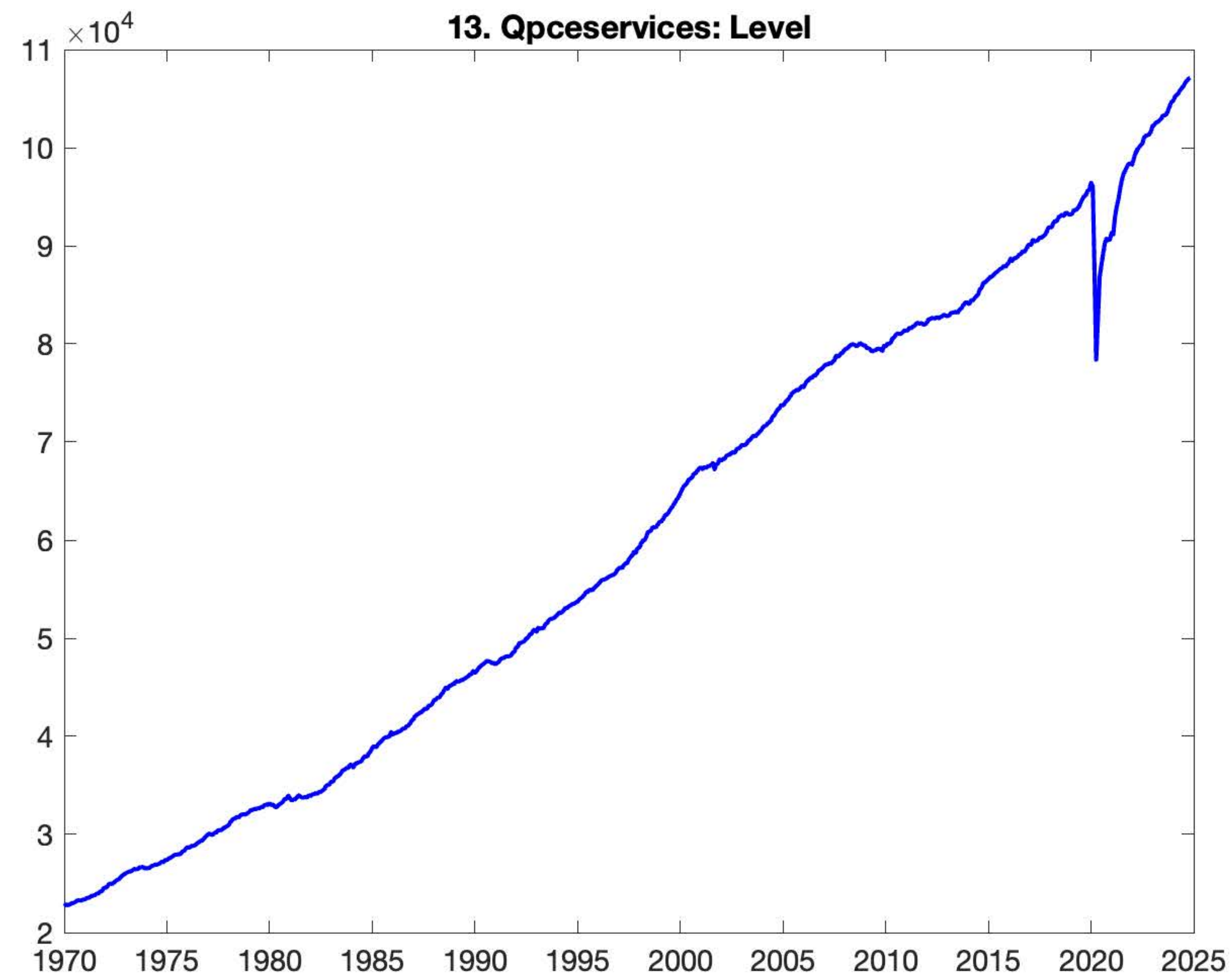

11. Qpcegdsndenergy: Level
3400
3200
3000
2800
2600
2400
2200
2000
1970
1975
1980
1985
1990
1995
2000
2005
2010
2015
2020
2025

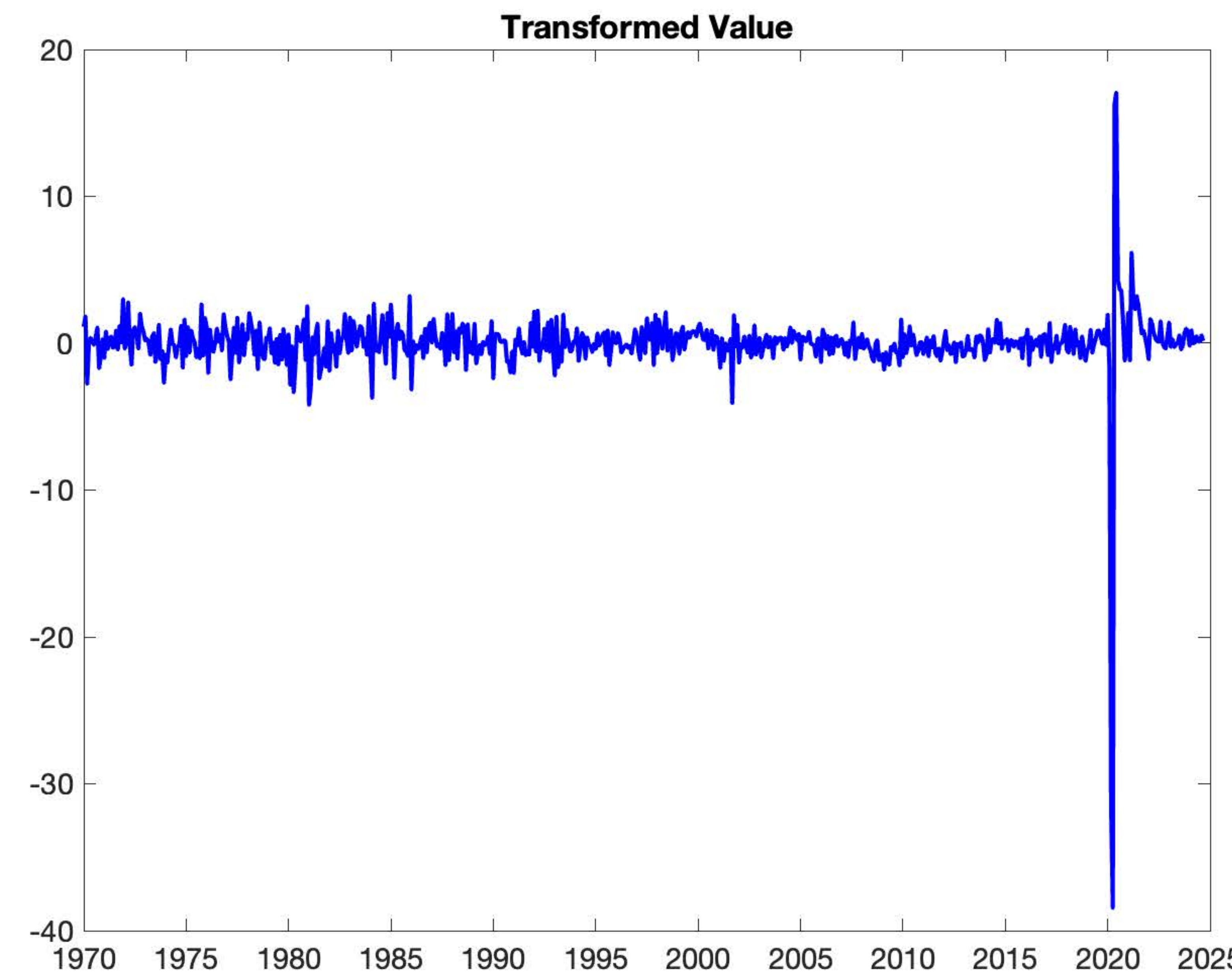

Transformed Value
10
5
0
-5
-10
-15
1970
1975
1980
1985
1990
1995
2000
2005
2010
2015
2020
2025

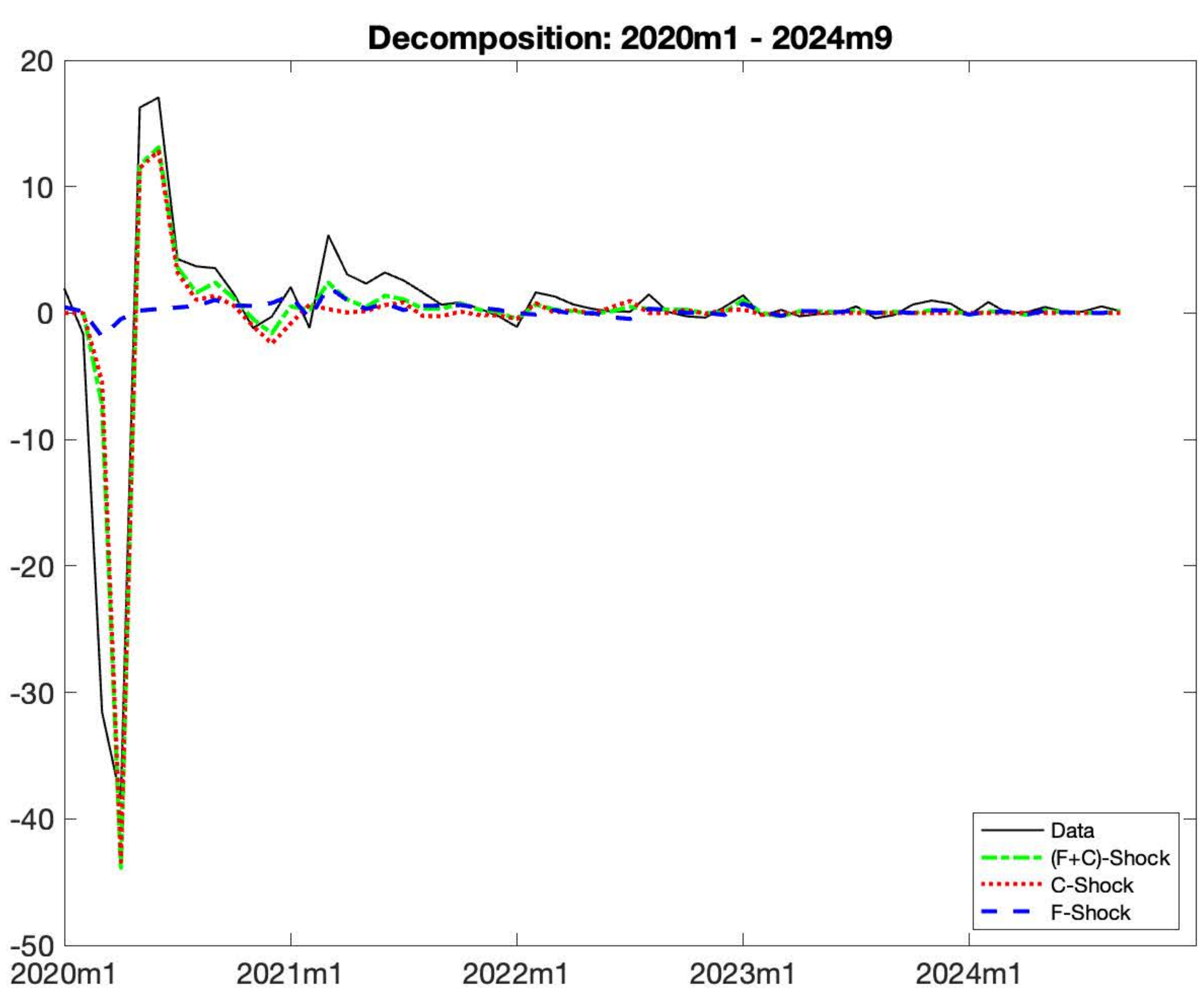

Decomposition: 2020m1 - 2024m9
10
5
0
-5
-10
-15
-20
2020m1
2021m1
2022m1
2023m1
2024m1
Data
(F+C)-Shock
C-Shock
F-Shock

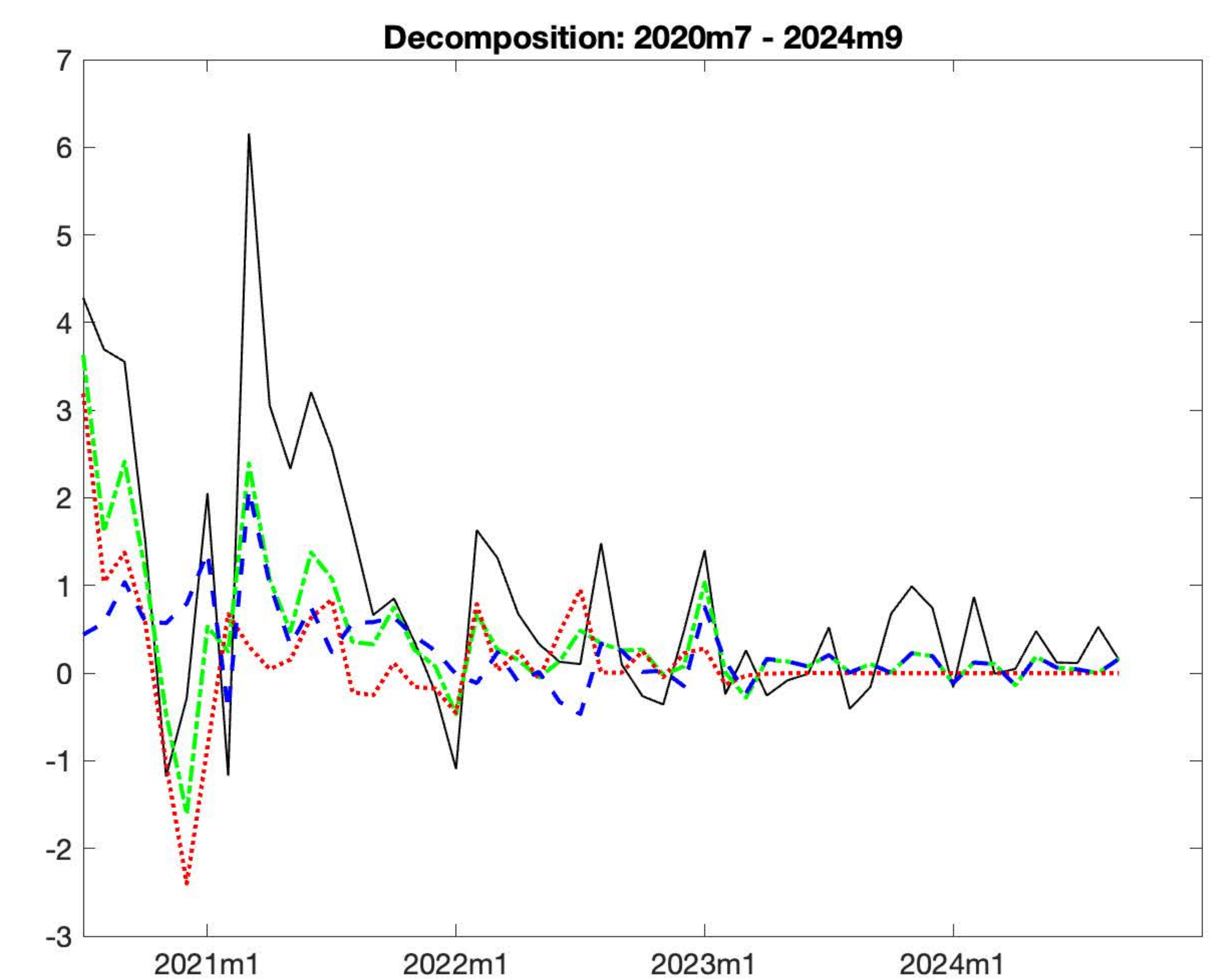

Decomposition: 2020m7 - 2024m9
2.5
2
1.5
1
0.5
0
-0.5
-1
-1.5
-2
2021m1
2022m1
2023m1
2024m1

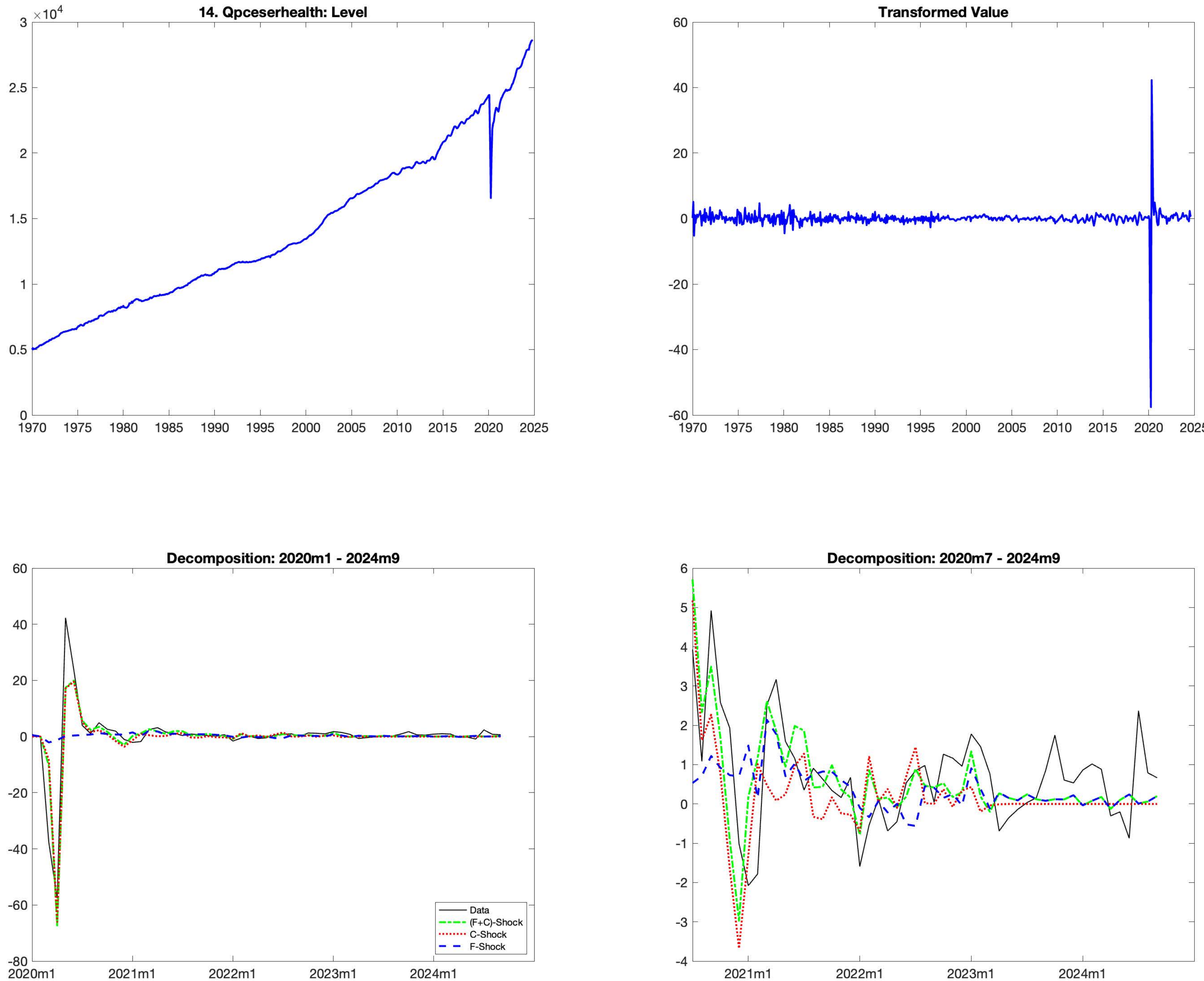

12. Qpcegdsndother: Level
Transformed Value
Decomposition: 2020m1 - 2024m9
Decomposition: 2020m7 - 2024m9
Data
(F+C)-Shock
C-Shock
F-Shock


13. Qpceservices: Level
×10^4

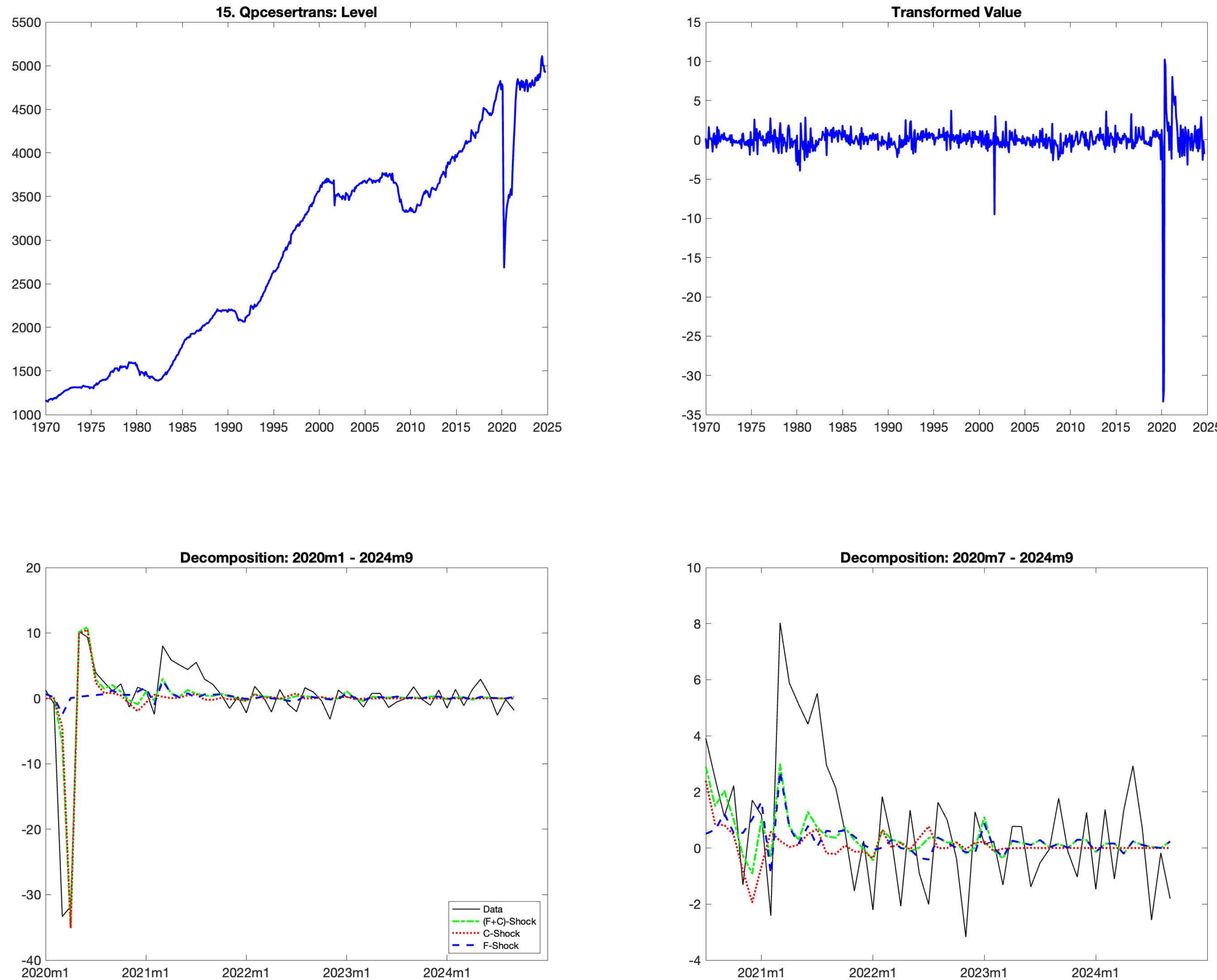

Transformed Value

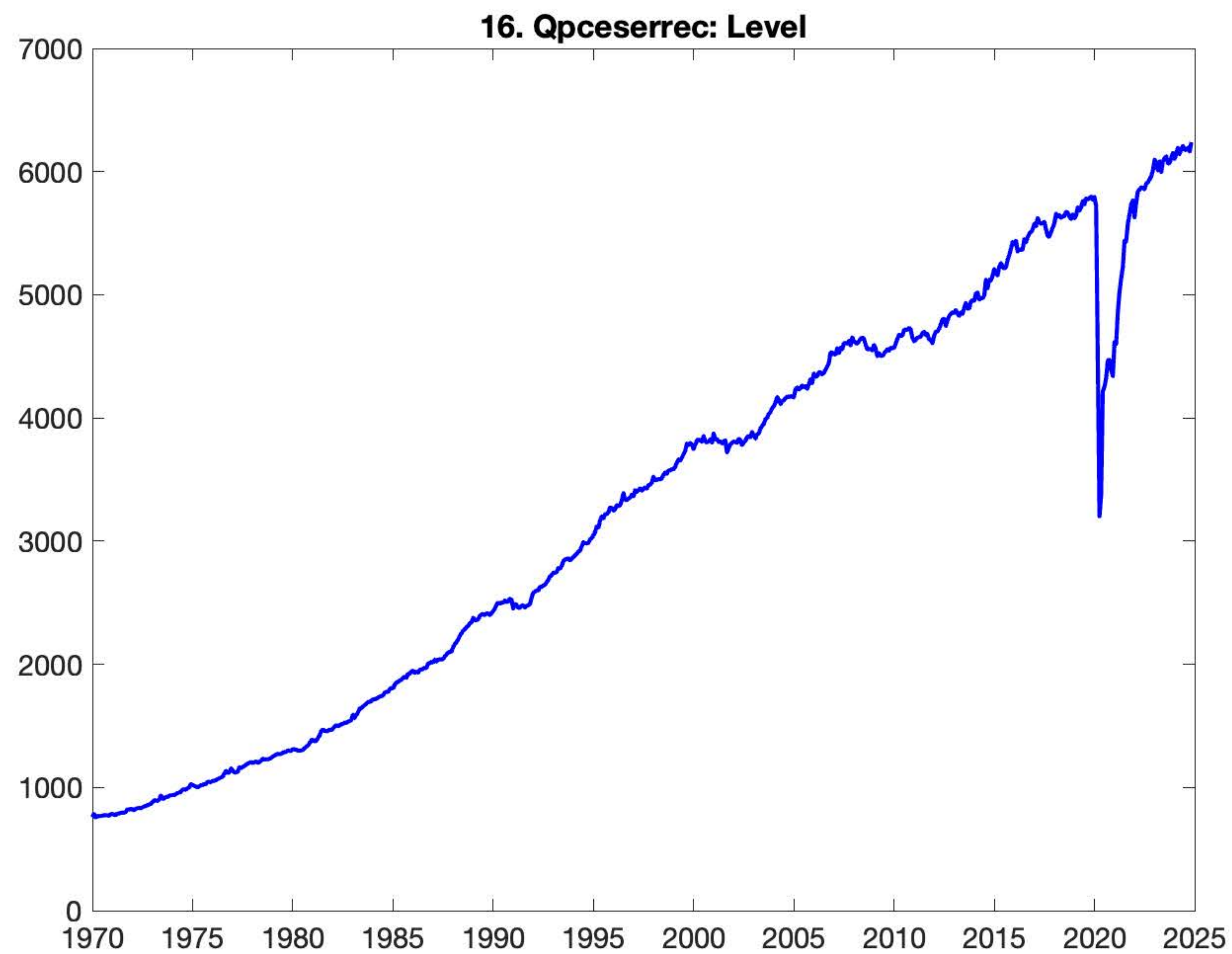

Decomposition: 2020m1 - 2024m9
Data
(F+C)-Shock
C-Shock
F-Shock

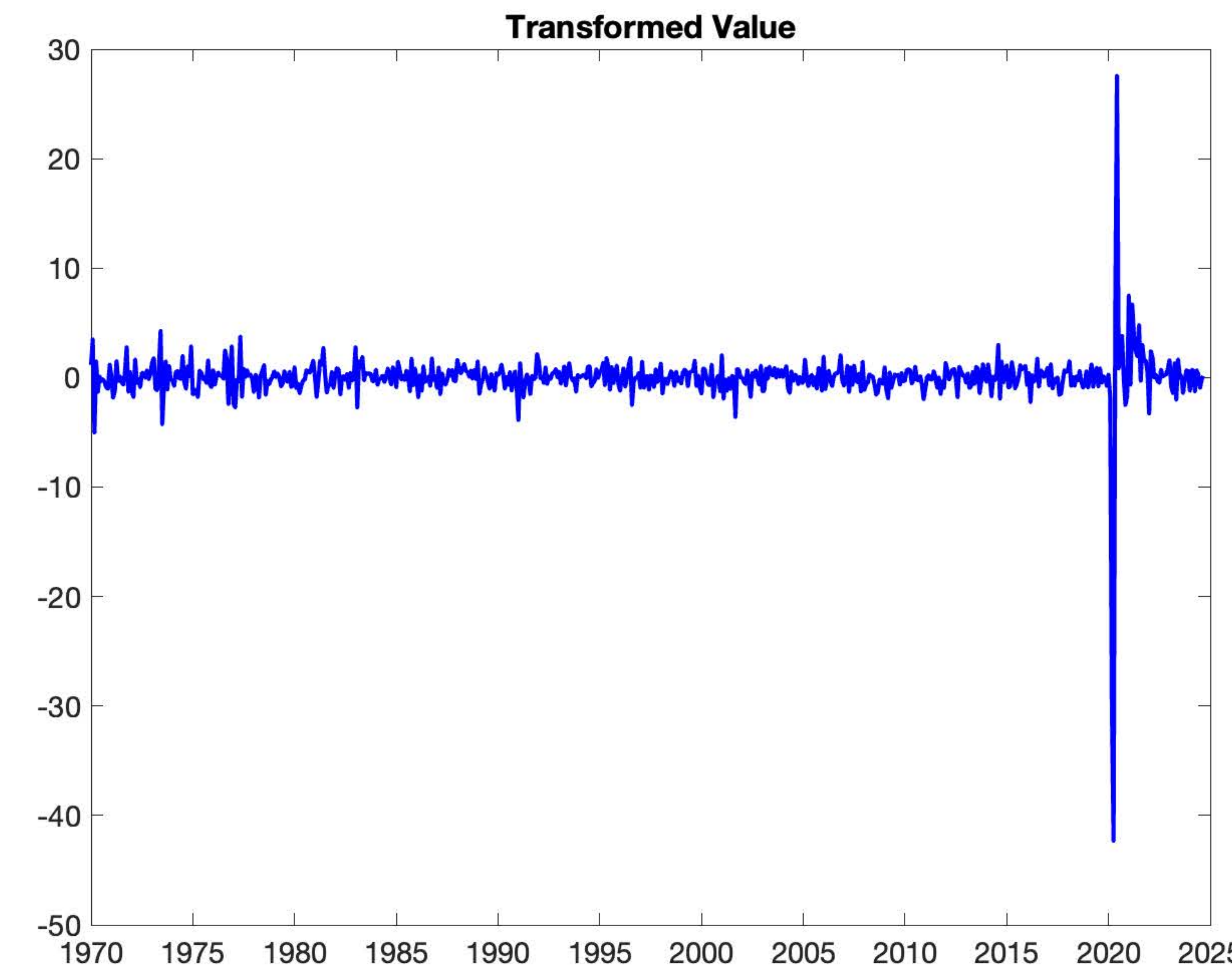

Decomposition: 2020m7 - 2024m9

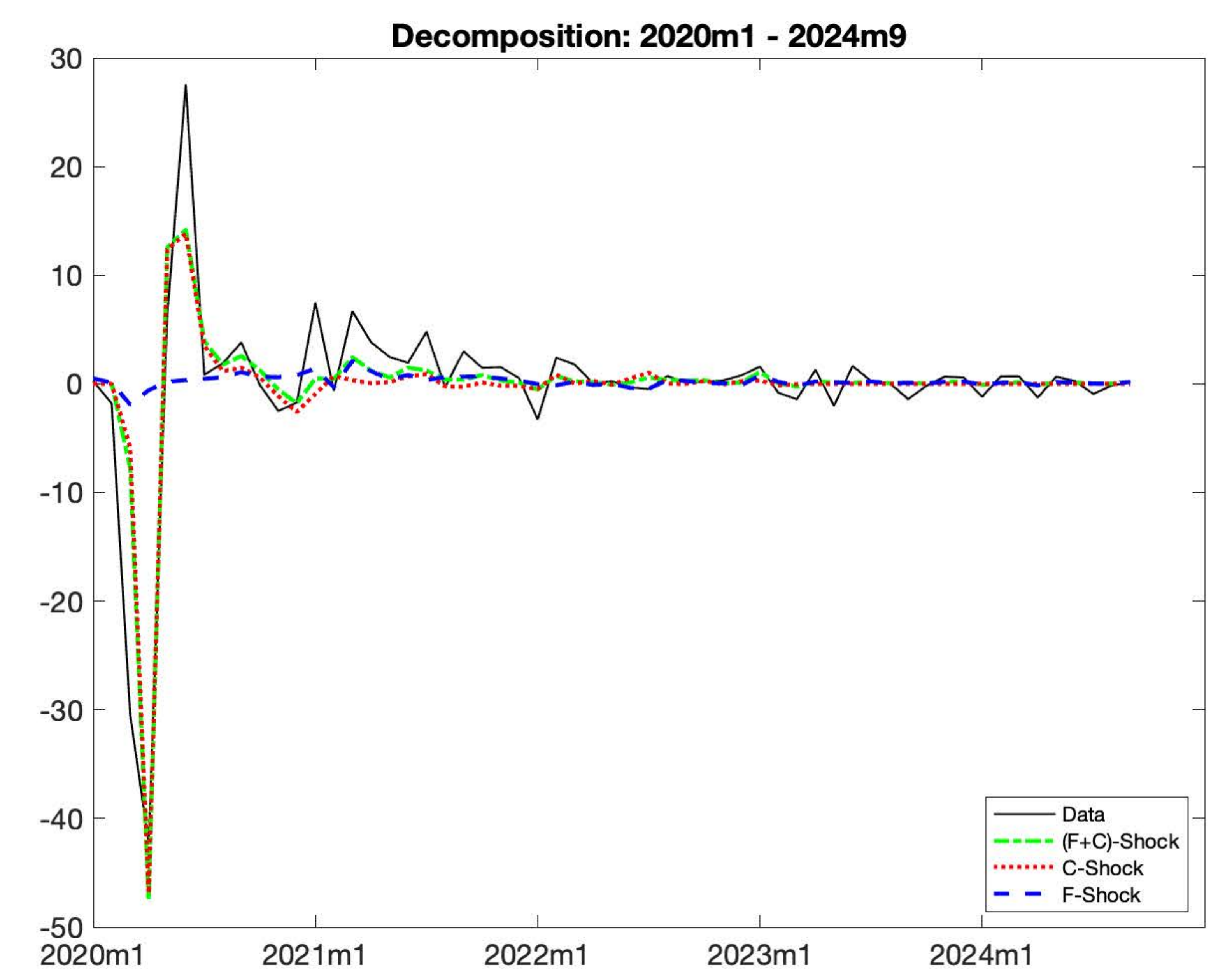


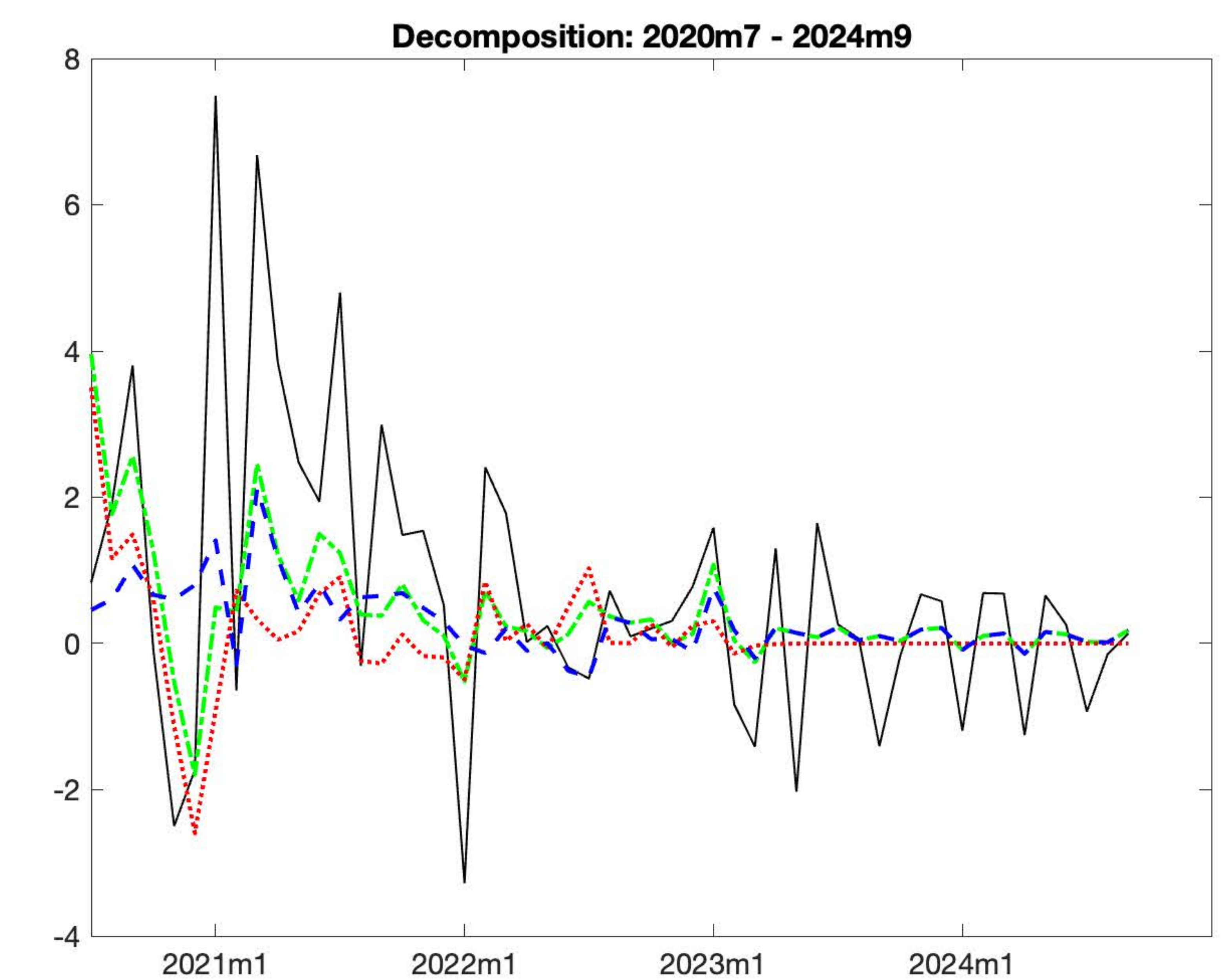
14. Qpceserhealth: Level
Transformed Value
Decomposition: 2020m1 - 2024m9
Decomposition: 2020m7 - 2024m9
Data
(F+C)-Shock
C-Shock
F-Shock

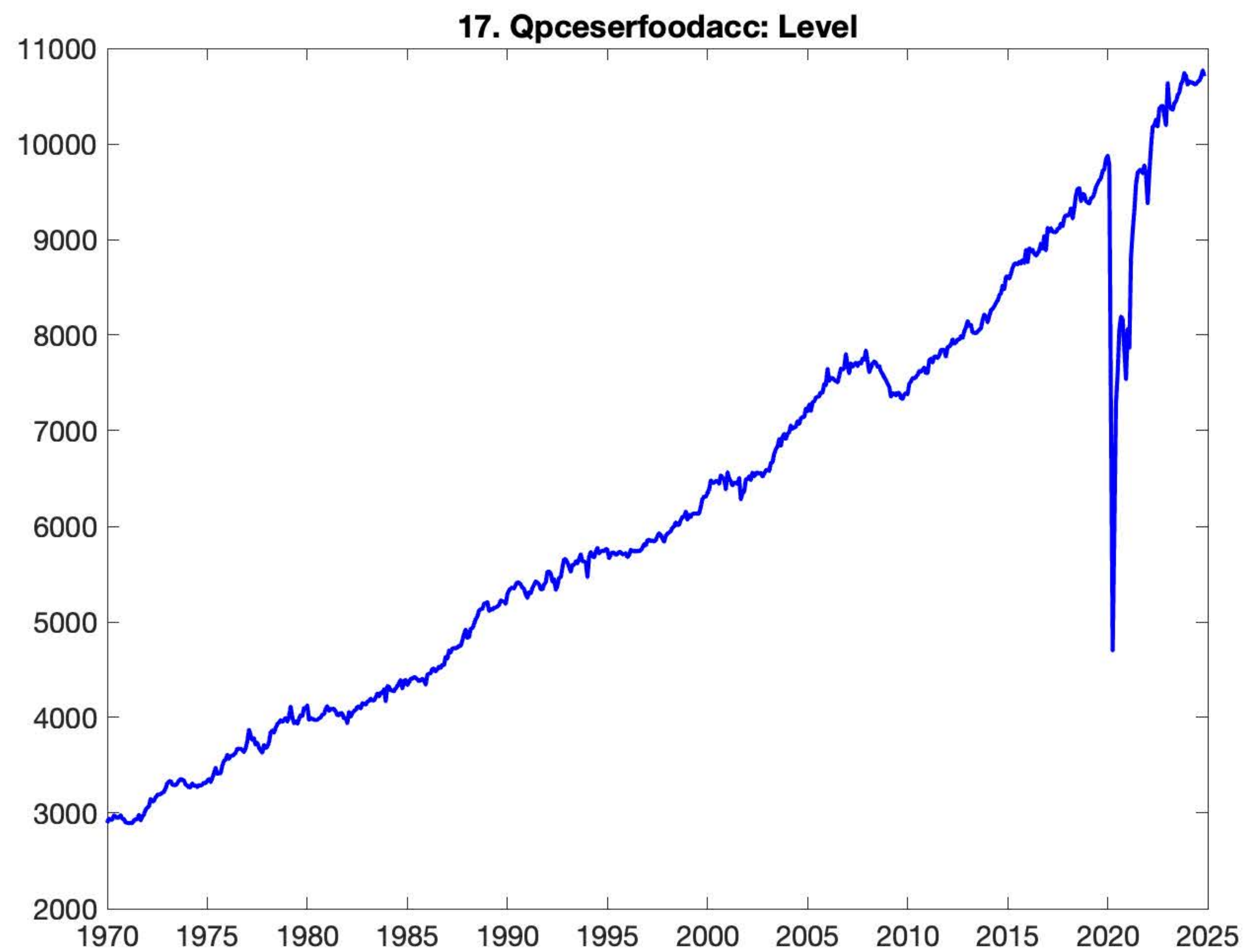

15. Qpcesertrans: Level
Transformed Value
Decomposition: 2020m1 - 2024m9
Data
(F+C)-Shock
C-Shock
F-Shock
Decomposition: 2020m7 - 2024m9

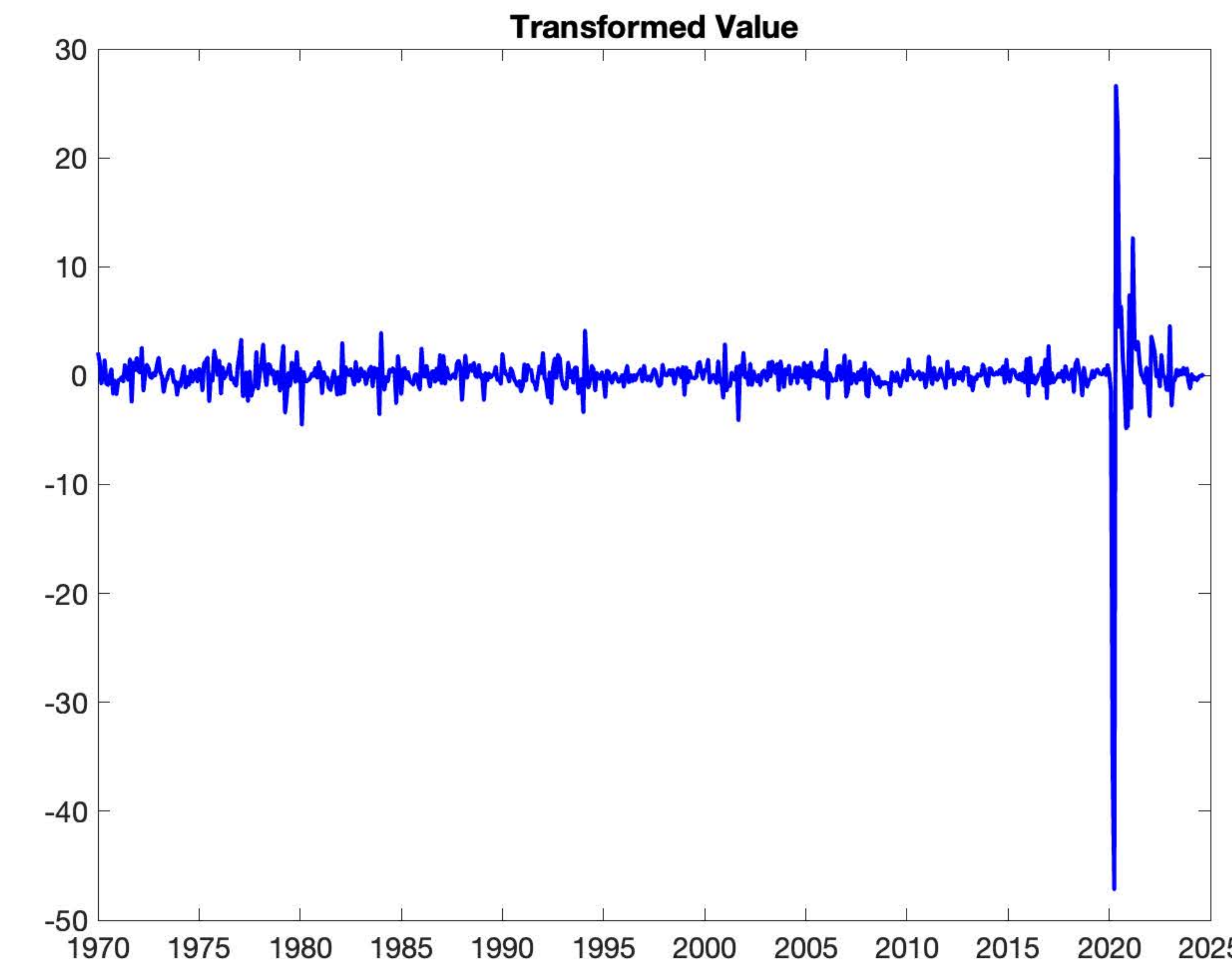

16. Qpceserrec: Level

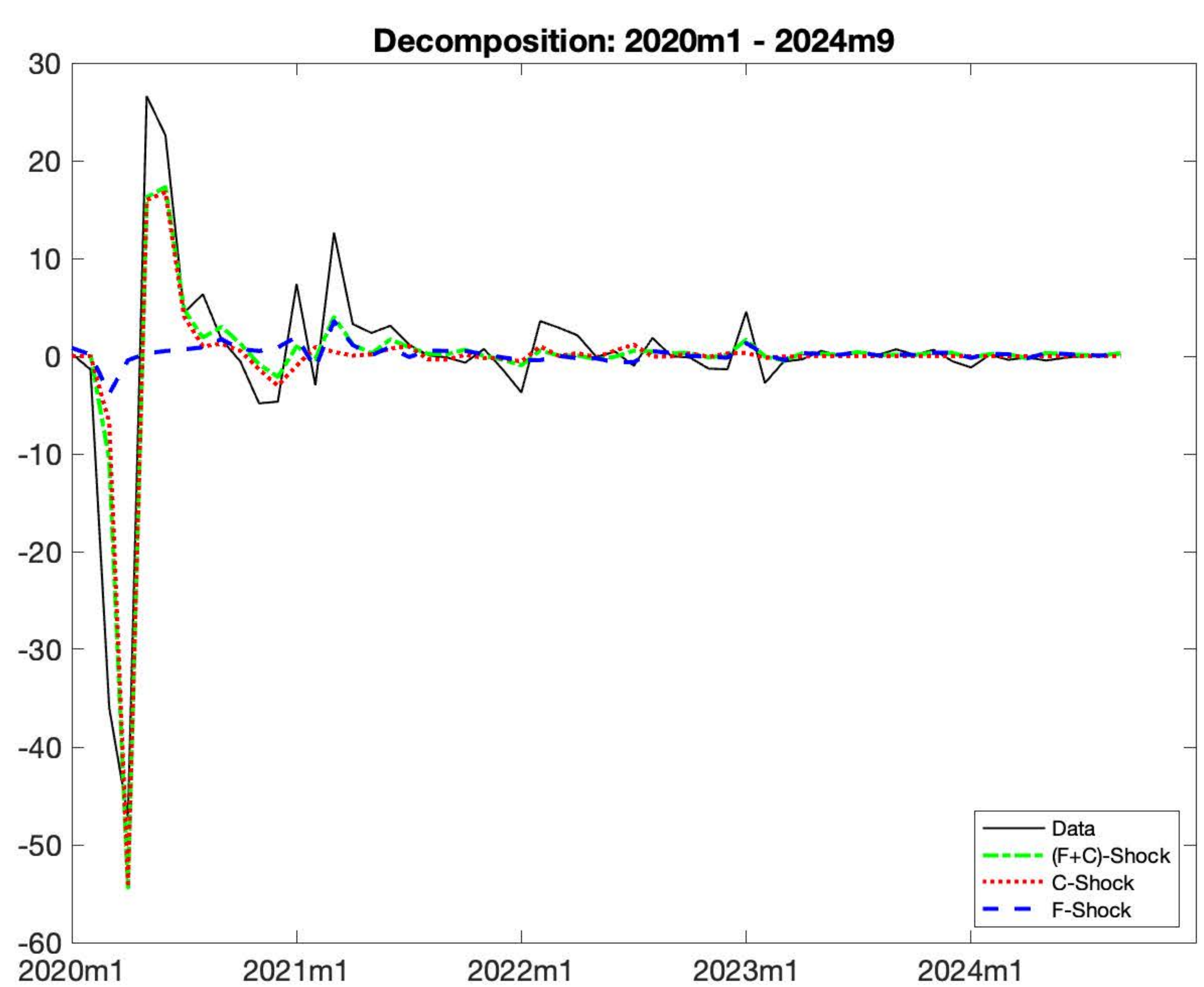

Transformed Value

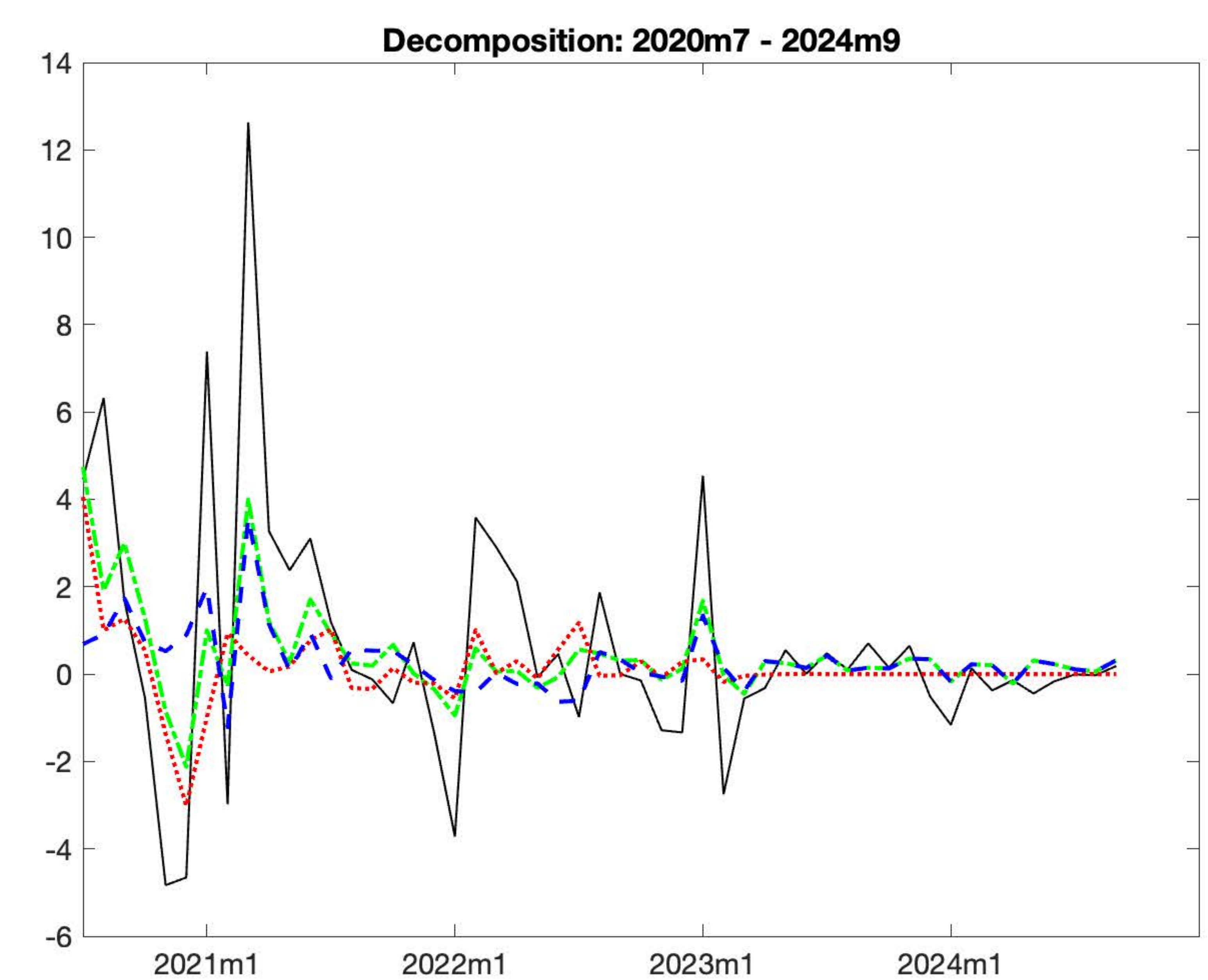

Decomposition: 2020m1 - 2024m9
Data
(F+C)-Shock
C-Shock
F-Shock


Decomposition: 2020m7 - 2024m9

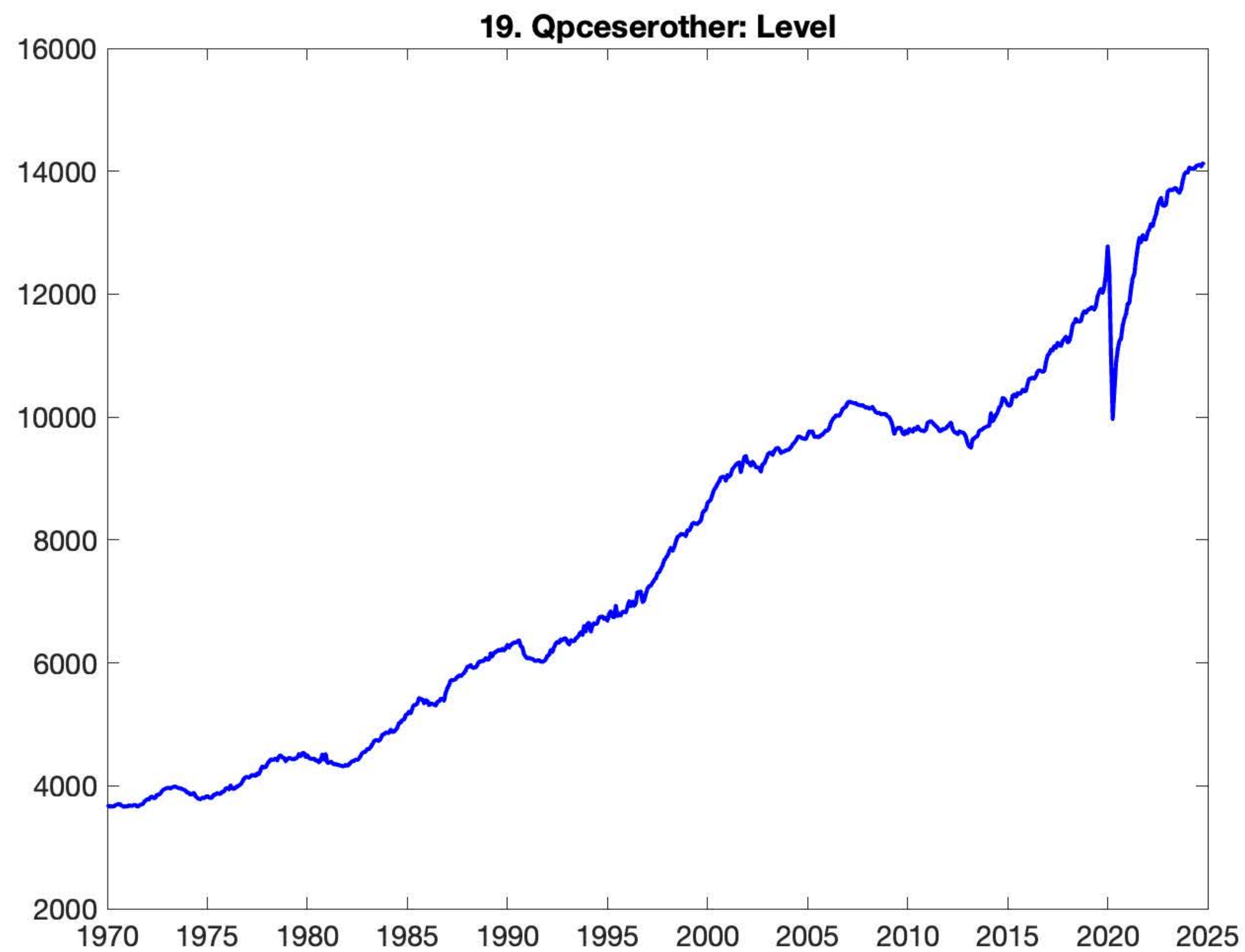

17. Qpceserfoodacc: Level

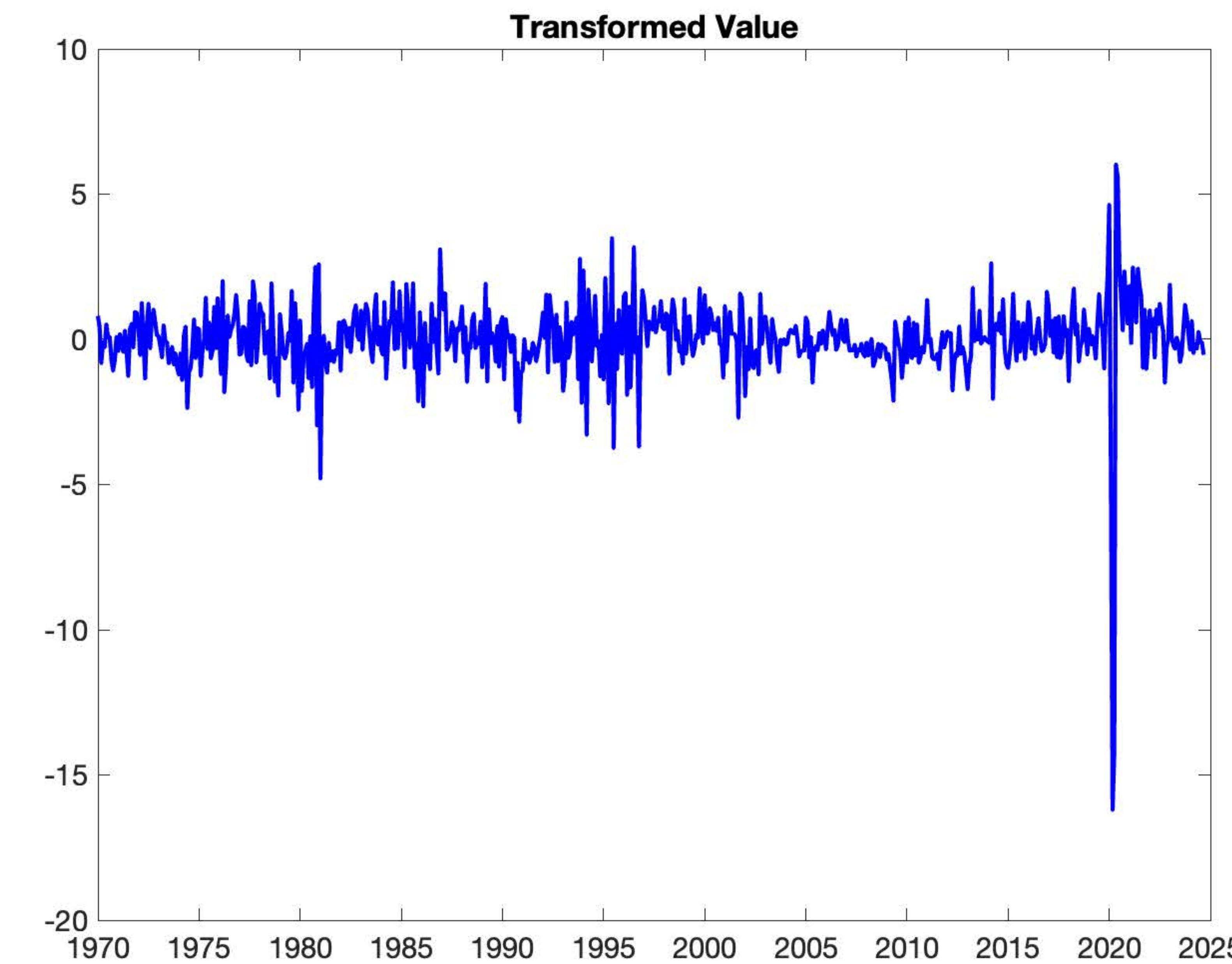

Transformed Value

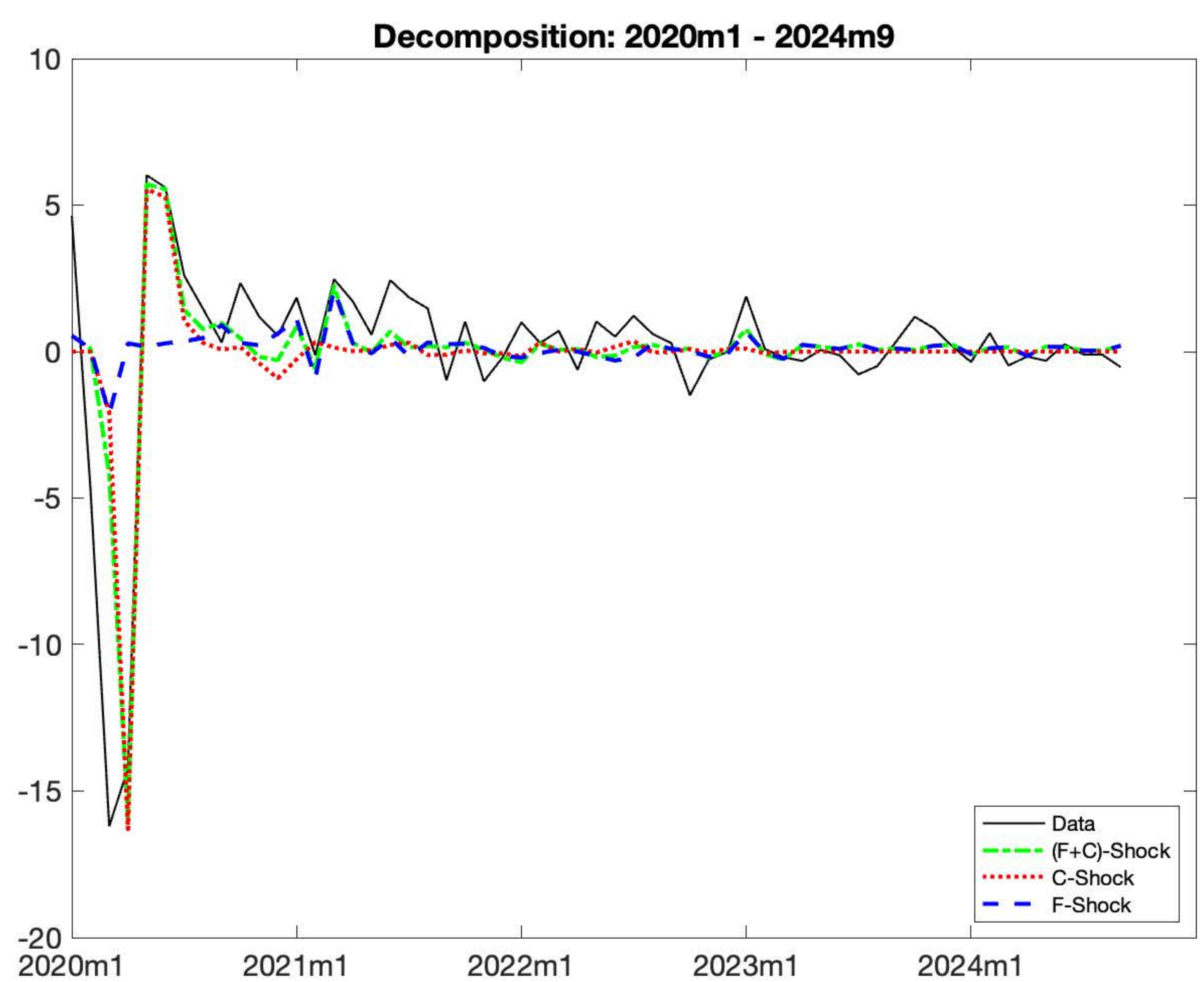

Decomposition: 2020m1 - 2024m9
Data
(F+C)-Shock
C-Shock
F-Shock

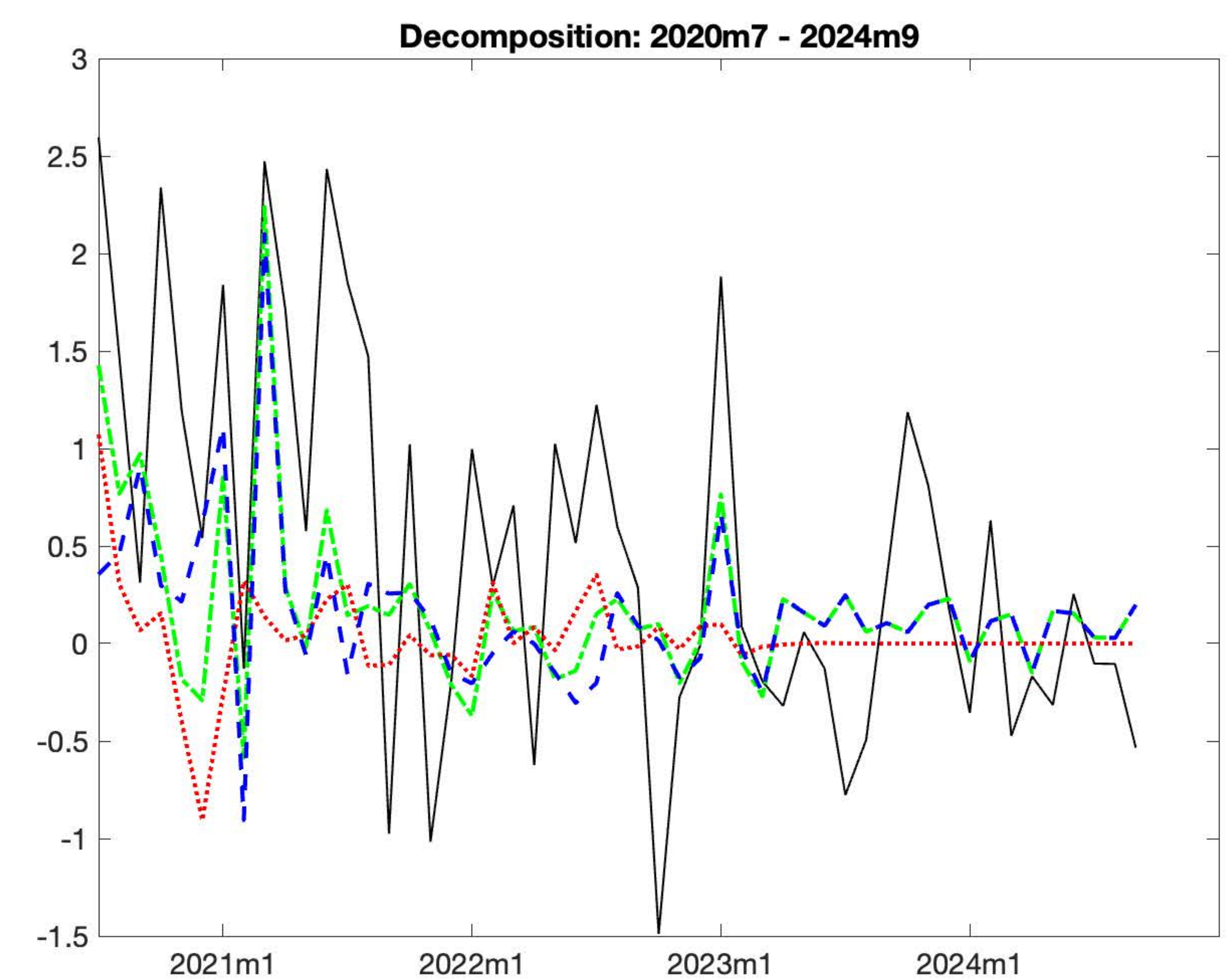

Decomposition: 2020m7 - 2024m9

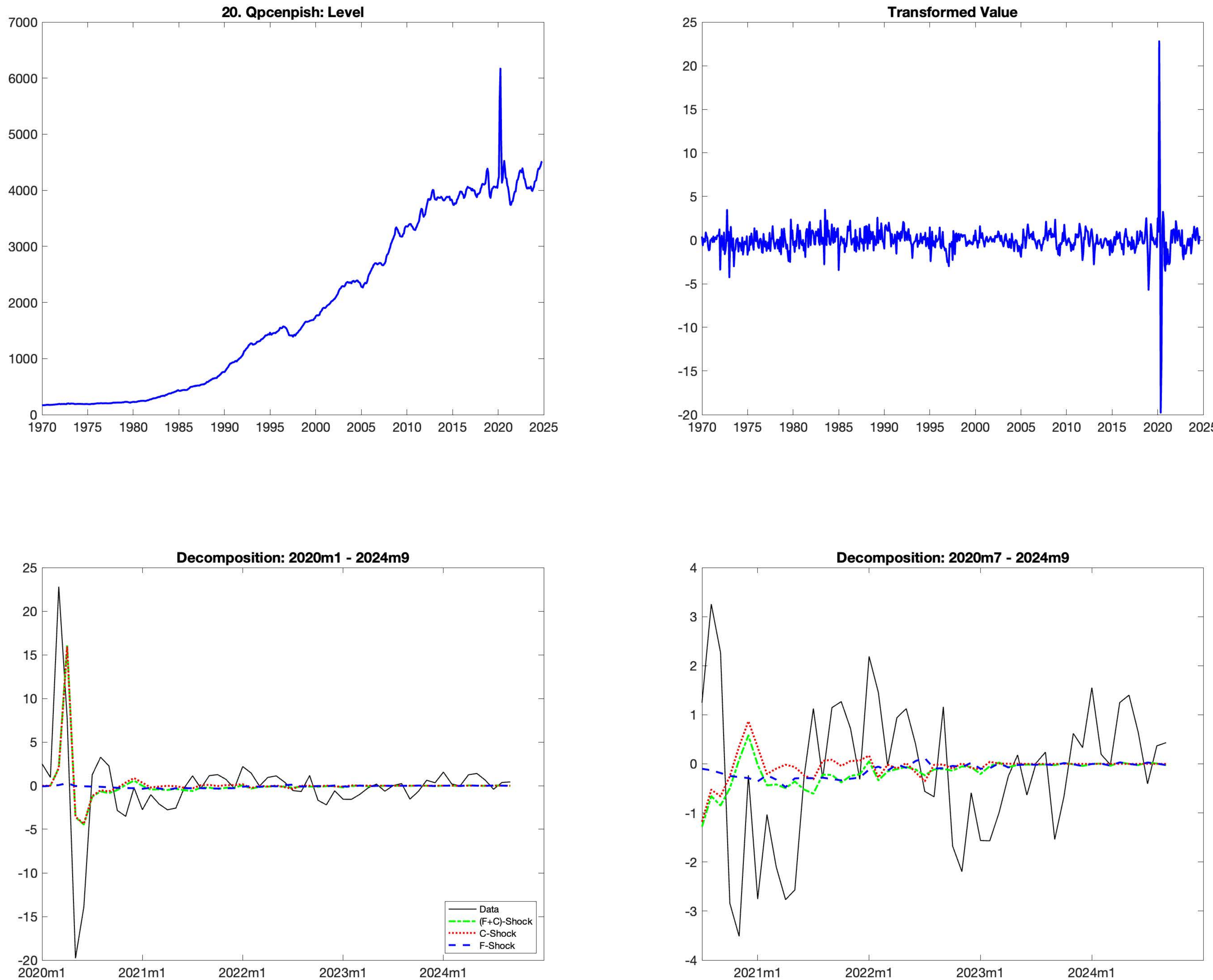

18. Qpceserfin: Level
Transformed Value
Decomposition: 2020m1 - 2024m9
Decomposition: 2020m7 - 2024m9
Data
(F+C)-Shock
C-Shock
F-Shock

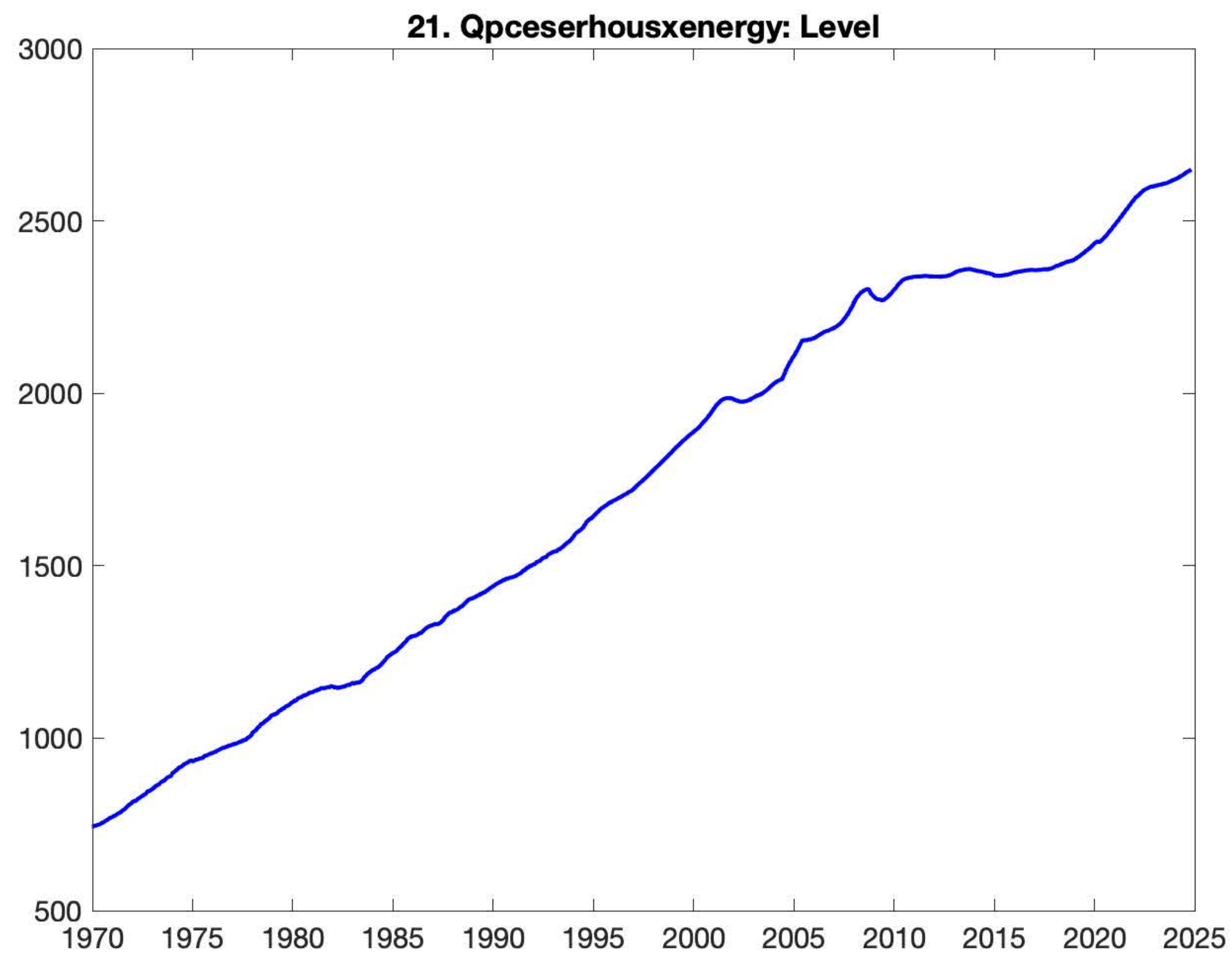

19. Qpceserother: Level


Transformed Value

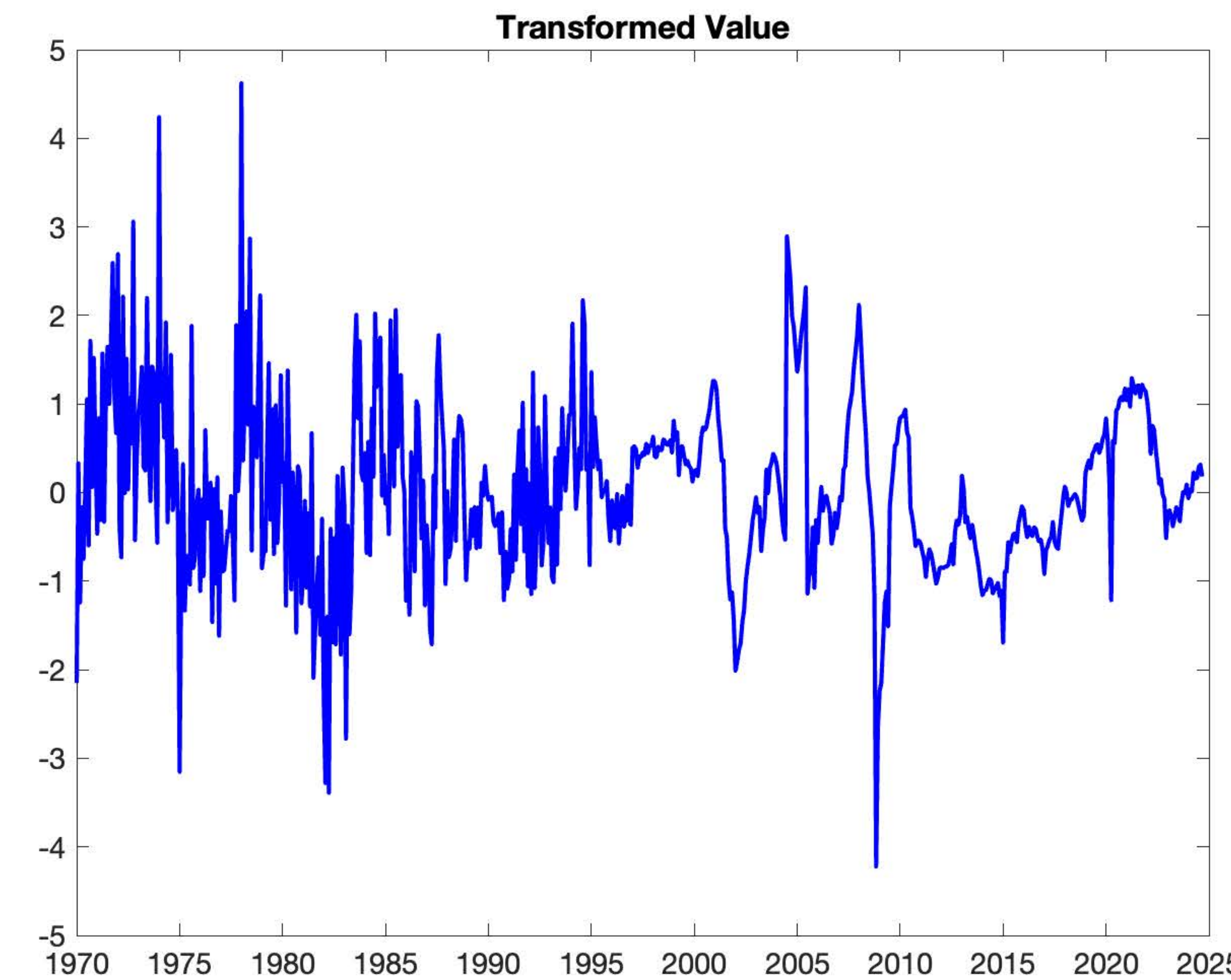

Decomposition: 2020m1 - 2024m9
Data
(F+C)-Shock
C-Shock
F-Shock


Decomposition: 2020m7 - 2024m9

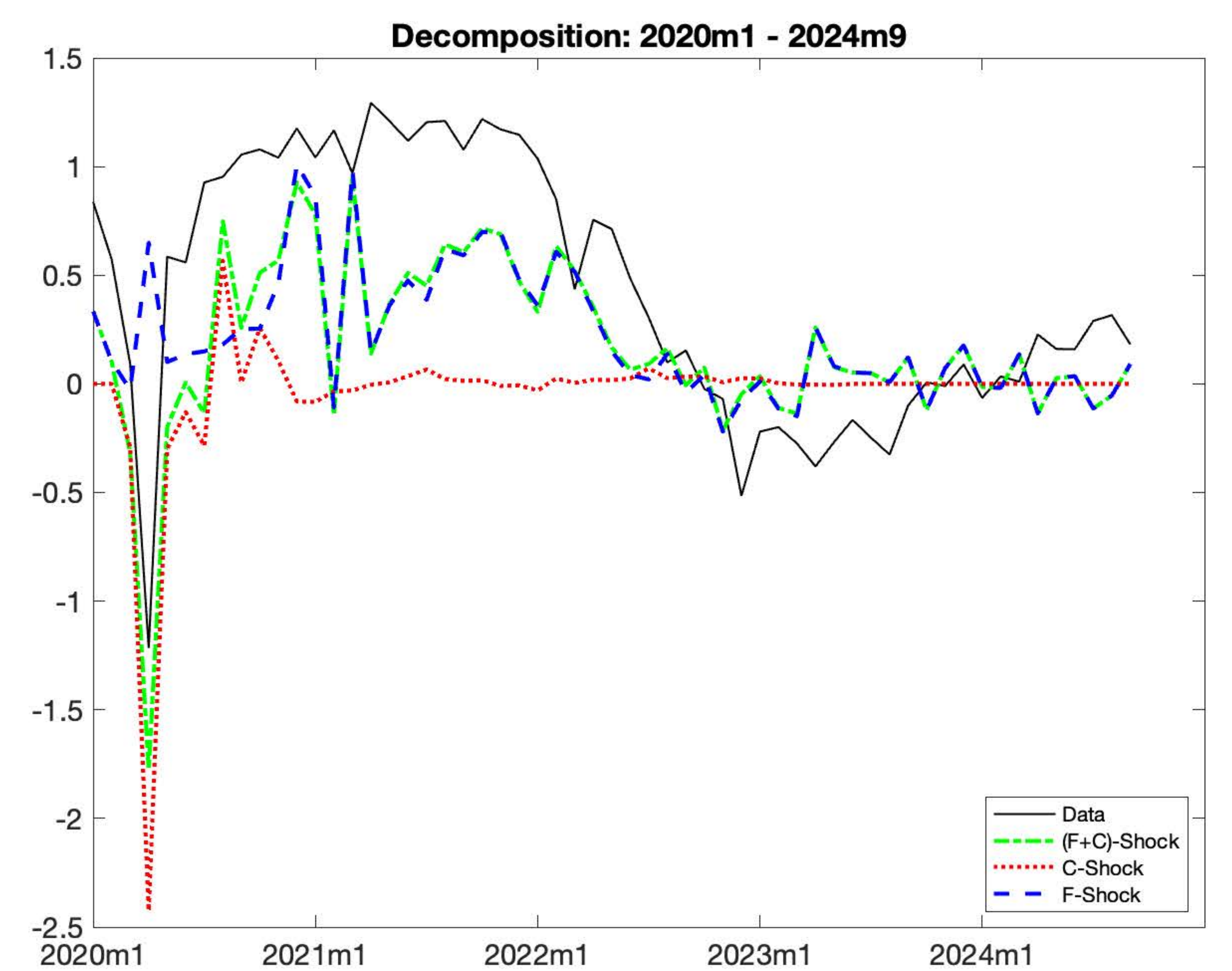

20. Qpcenpish: Level
Transformed Value
Decomposition: 2020m1 - 2024m9
Decomposition: 2020m7 - 2024m9
Data
(F+C)-Shock
C-Shock
F-Shock



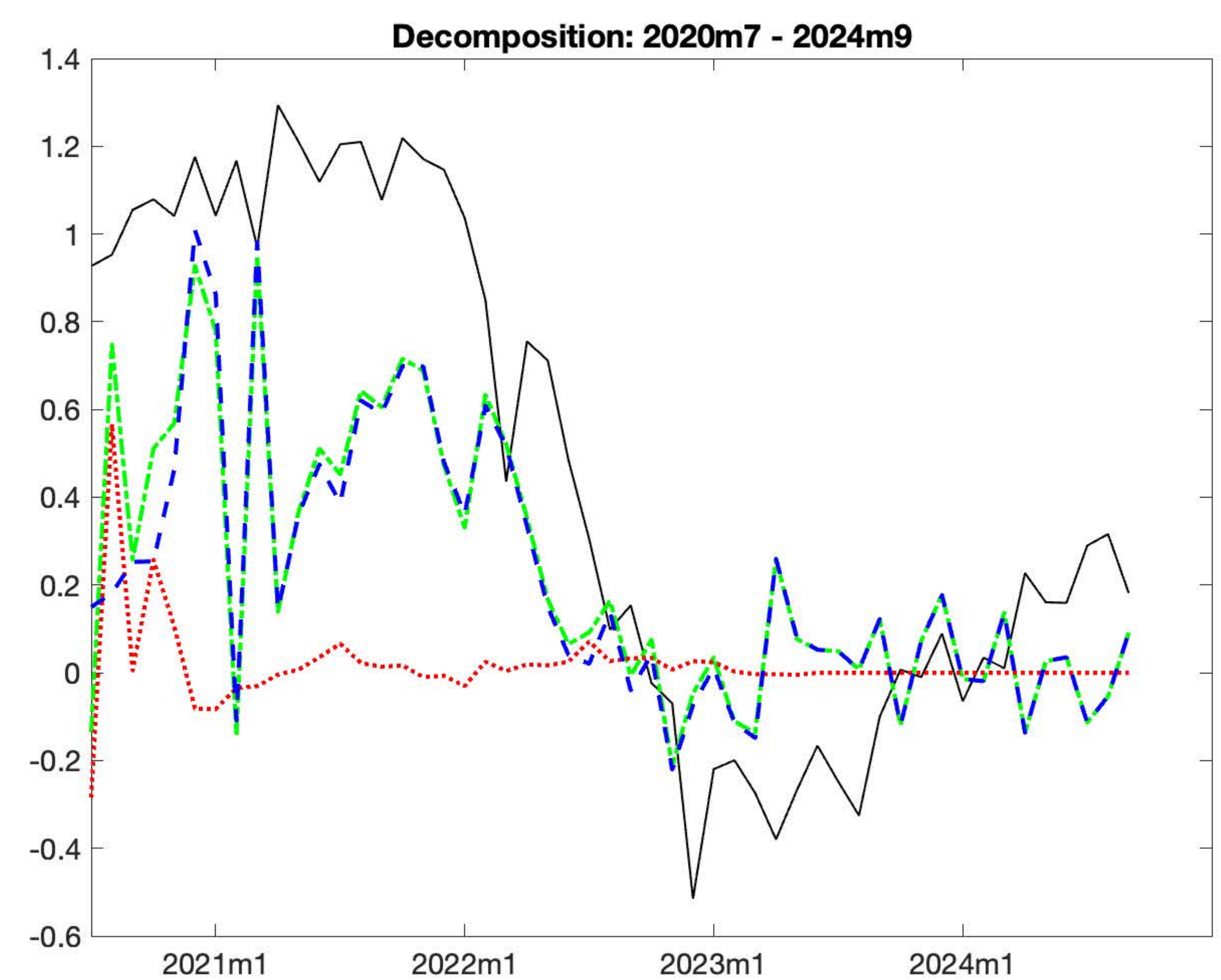
21. Qpceserhousxenergy: Level



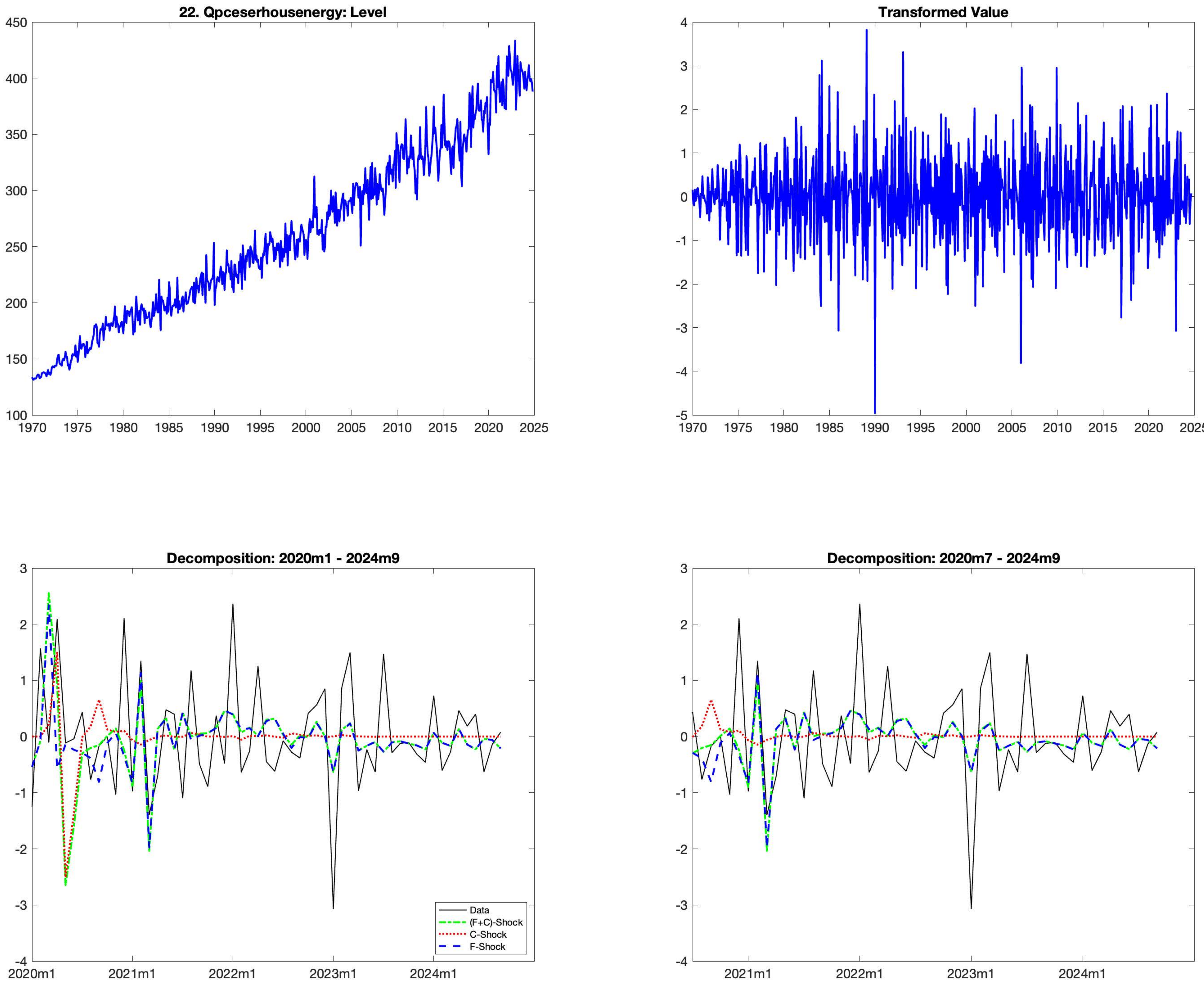
Transformed Value

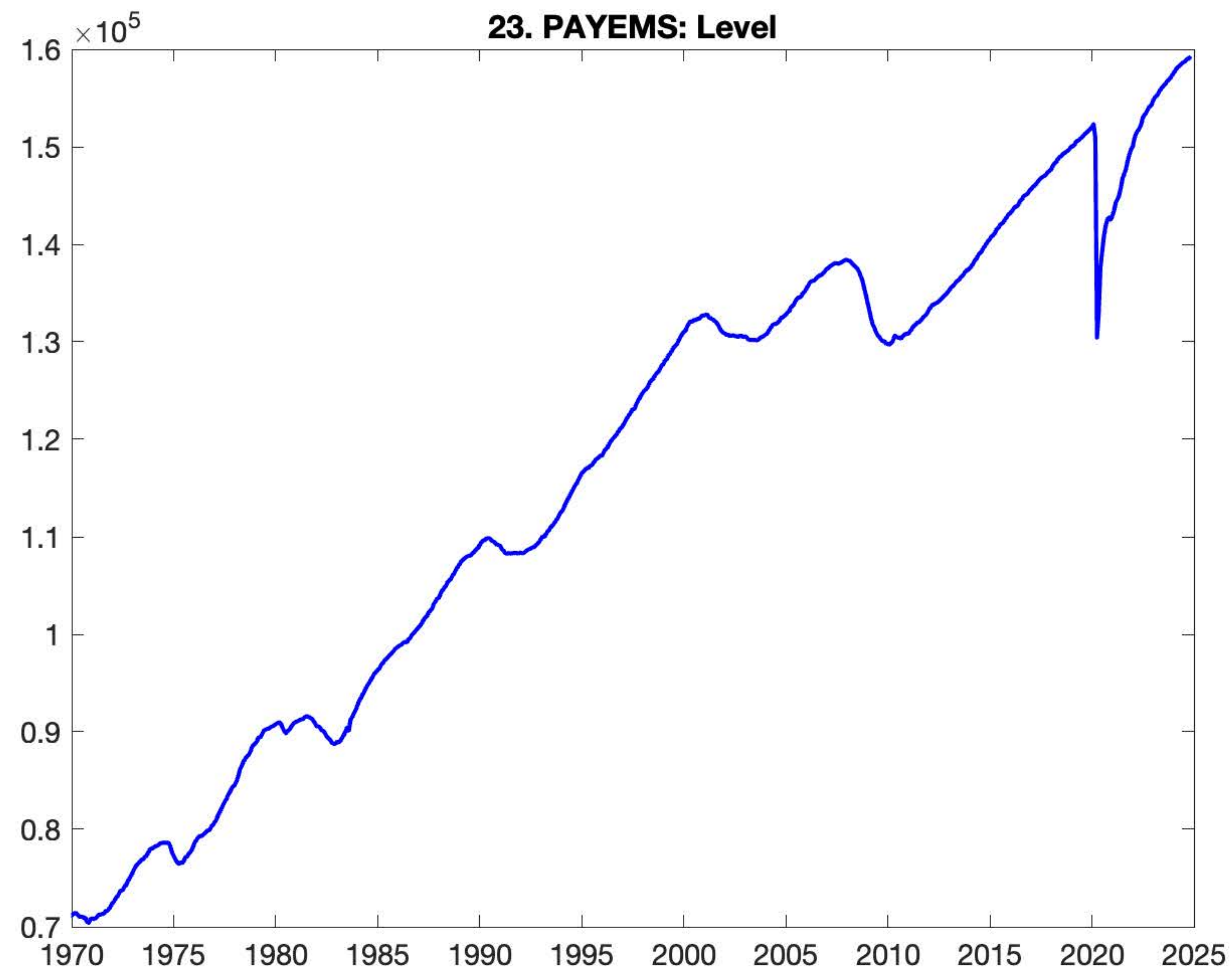


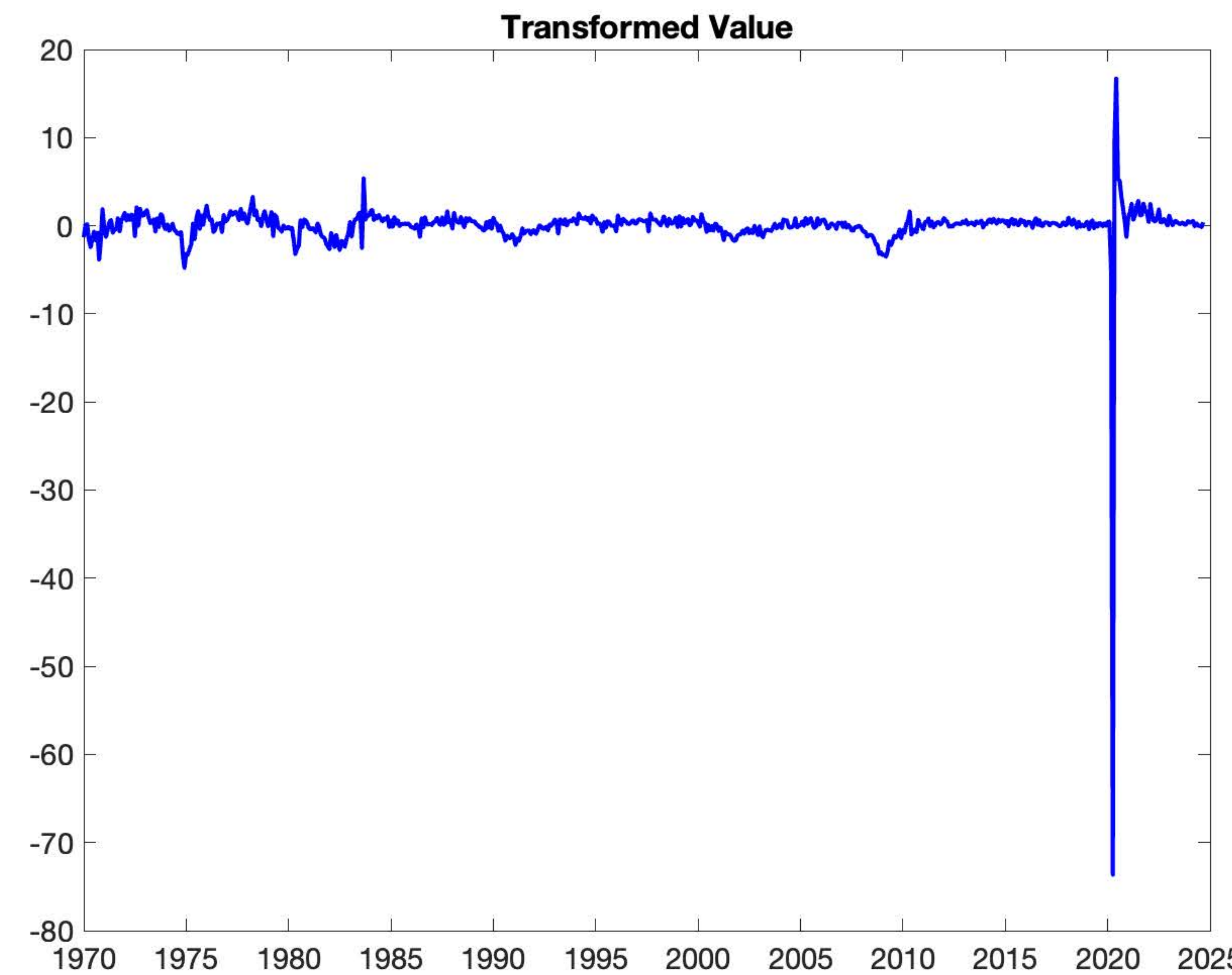
Decomposition: 2020m1 - 2024m9
Data
(F+C)-Shock
C-Shock
F-Shock

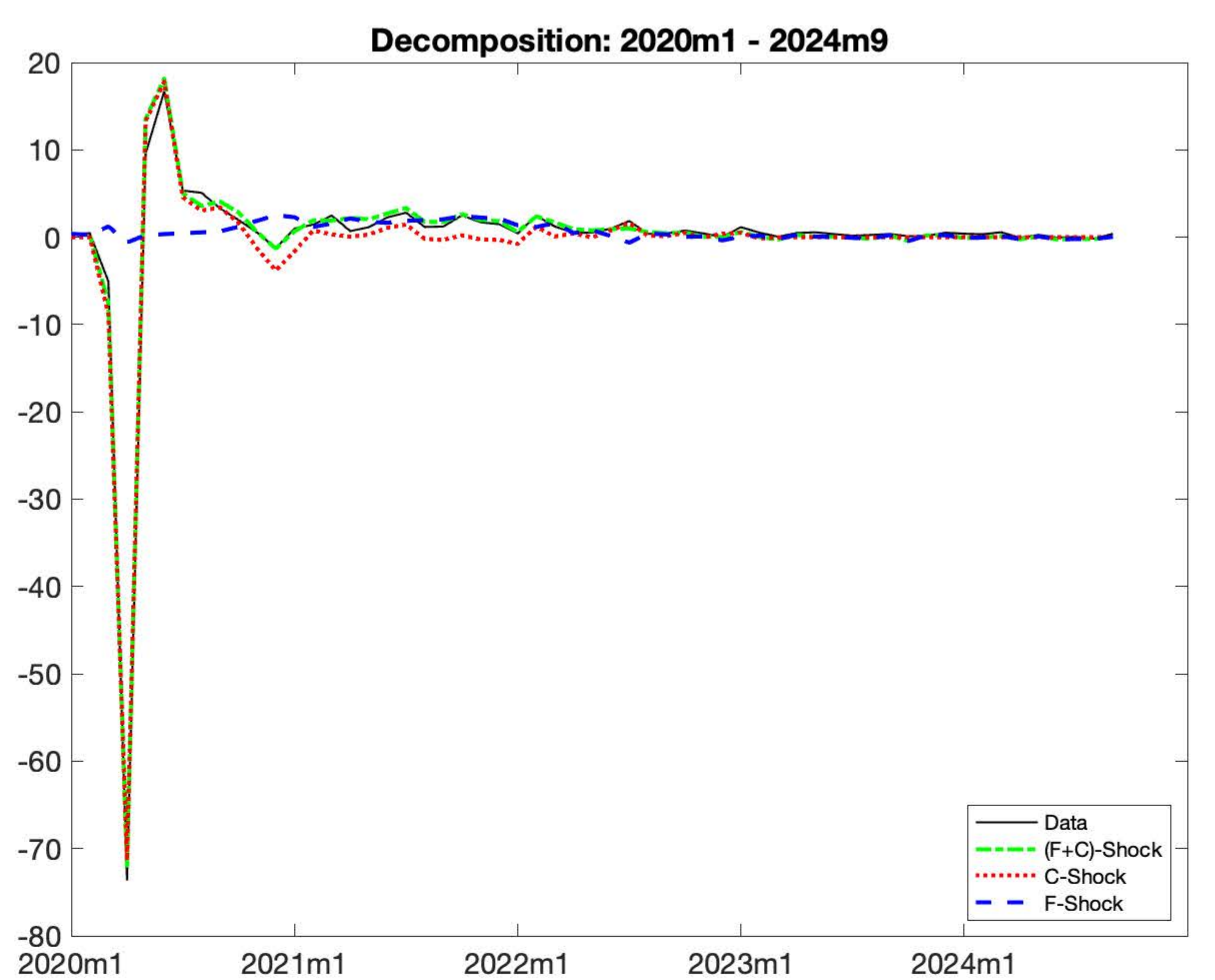


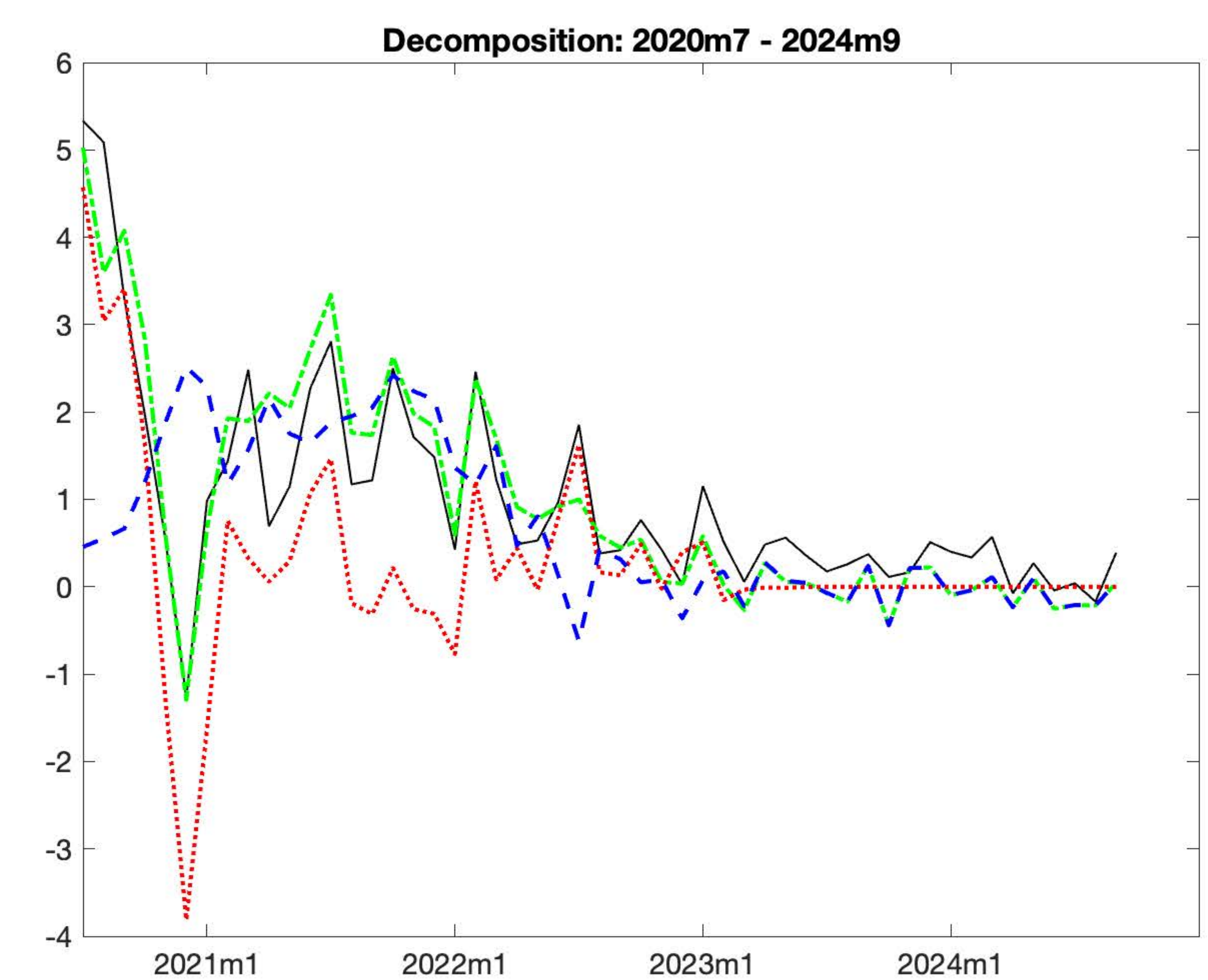
Decomposition: 2020m7 - 2024m9

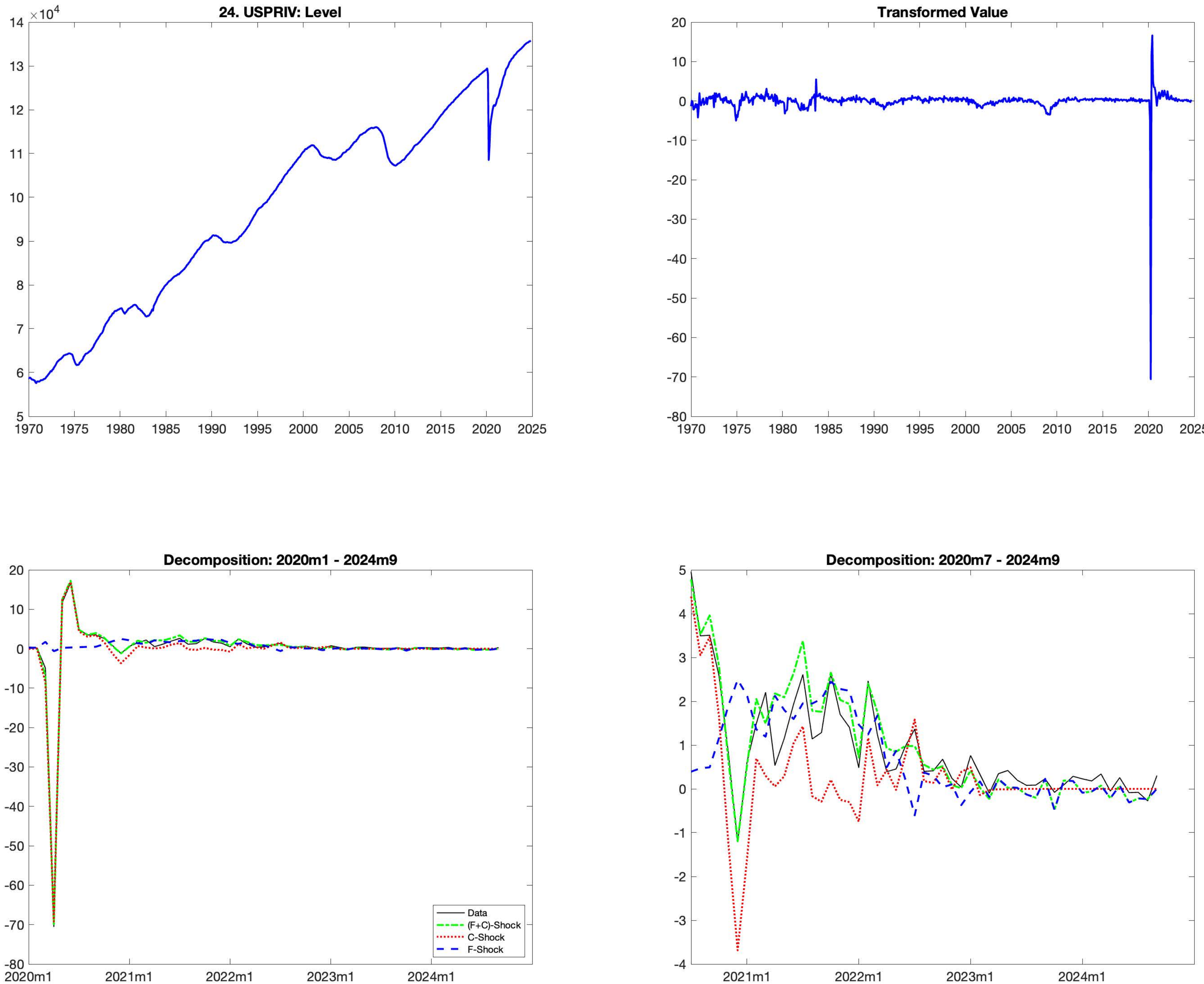

22. Qpceserhousenergy: Level
Transformed Value
Decomposition: 2020m1 - 2024m9
Data
(F+C)-Shock
C-Shock
F-Shock
Decomposition: 2020m7 - 2024m9

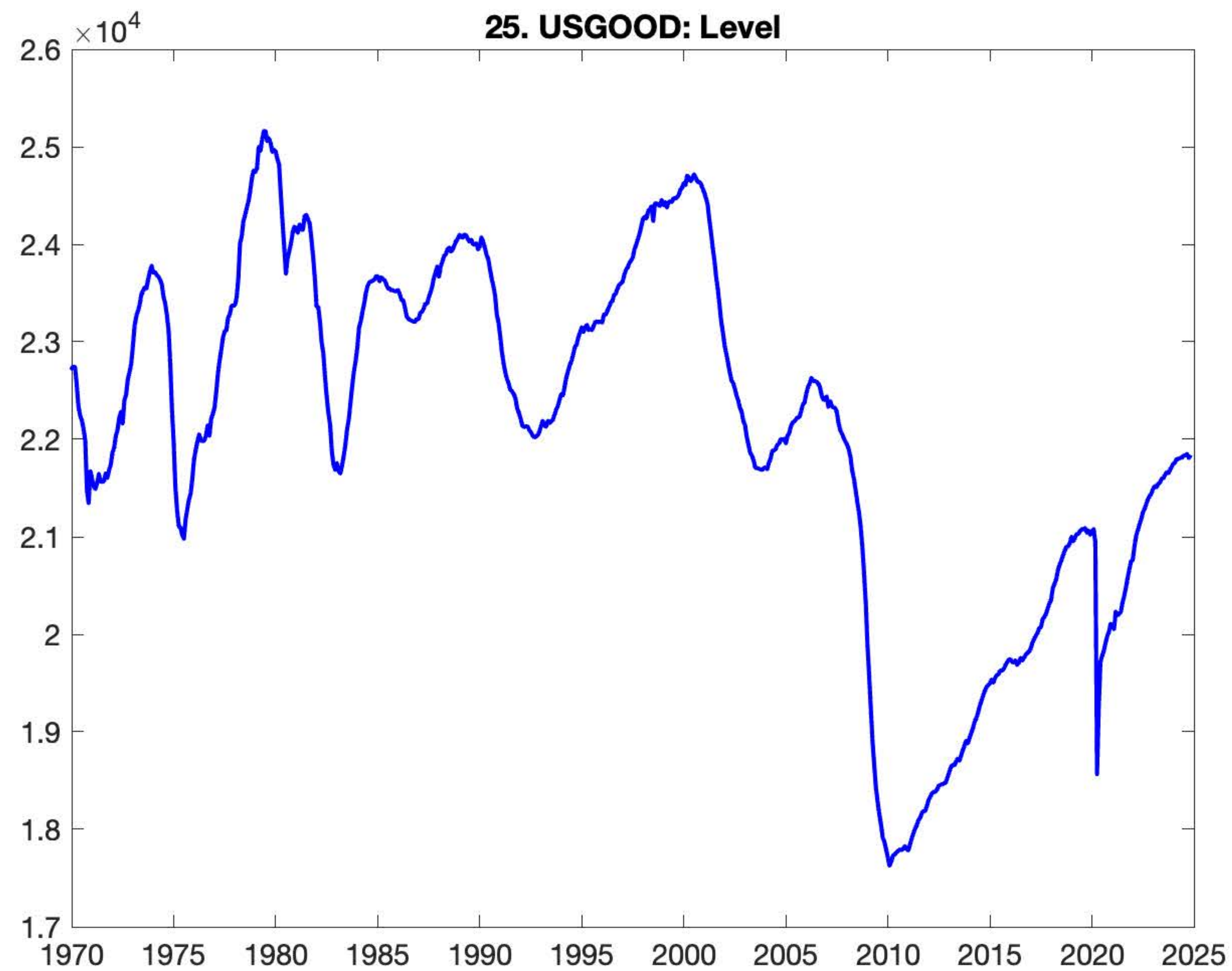

23. PAYEMS: Level
×10^5
1.6
1.5
1.4
1.3
1.2
1.1
1
0.9
0.8
0.7
1970 1975 1980 1985 1990 1995 2000 2005 2010 2015 2020 2025

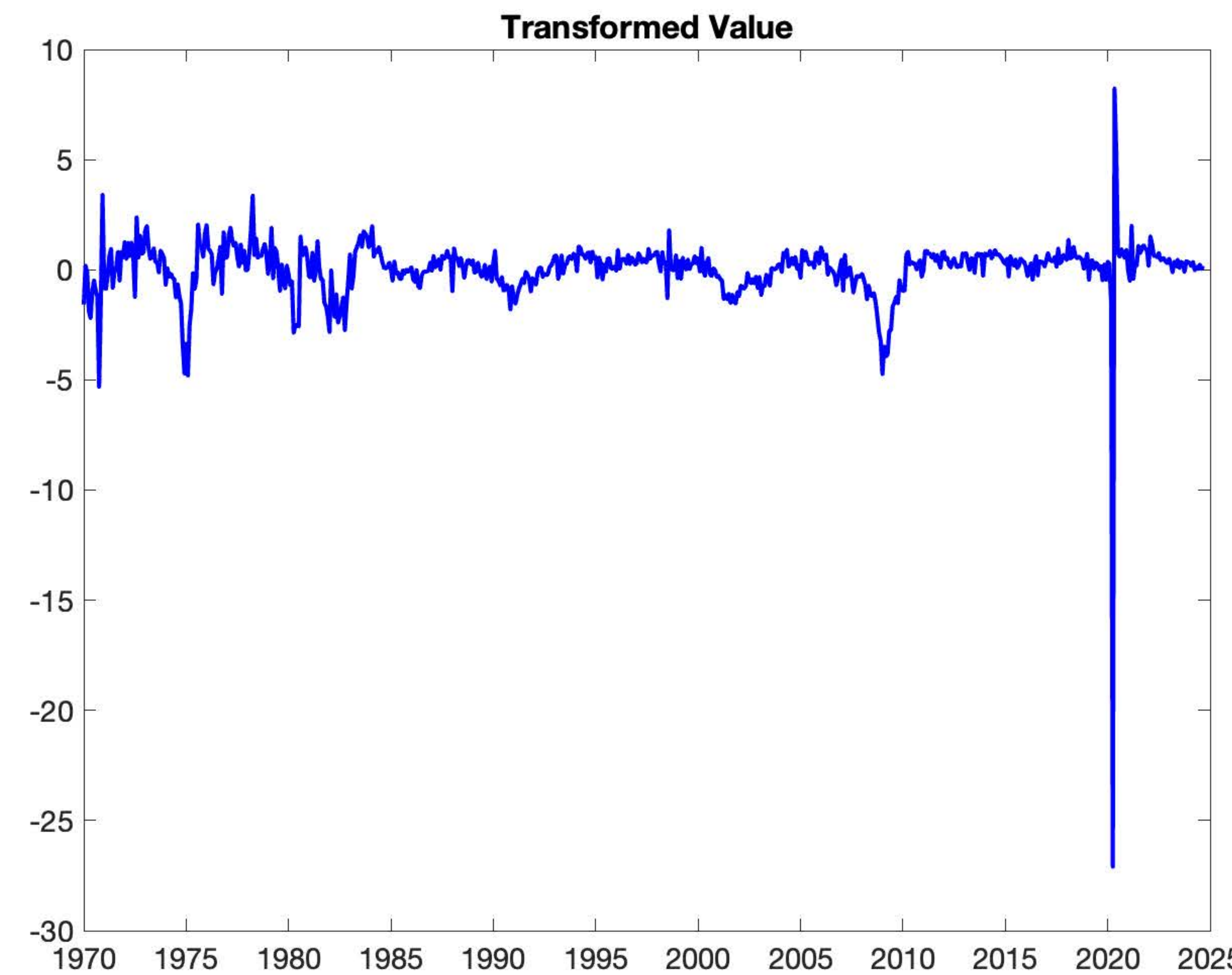

Transformed Value
20
10
0
-10
-20
-30
-40
-50
-60
-70
-80
1970 1975 1980 1985 1990 1995 2000 2005 2010 2015 2020 2025

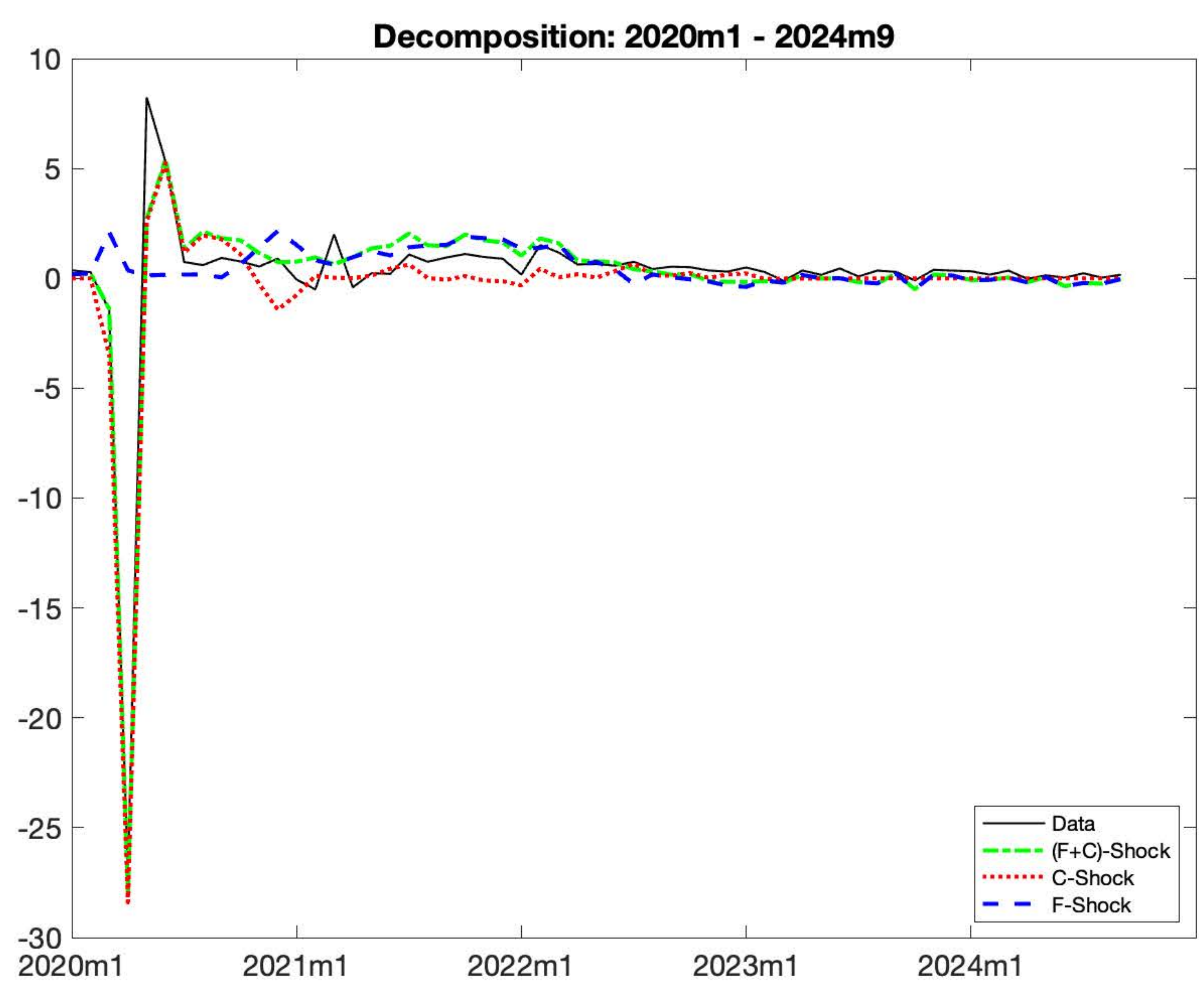

Decomposition: 2020m1 - 2024m9
20
10
0
-10
-20
-30
-40
-50
-60
-70
-80
2020m1 2021m1 2022m1 2023m1 2024m1
Data
(F+C)-Shock
C-Shock
F-Shock

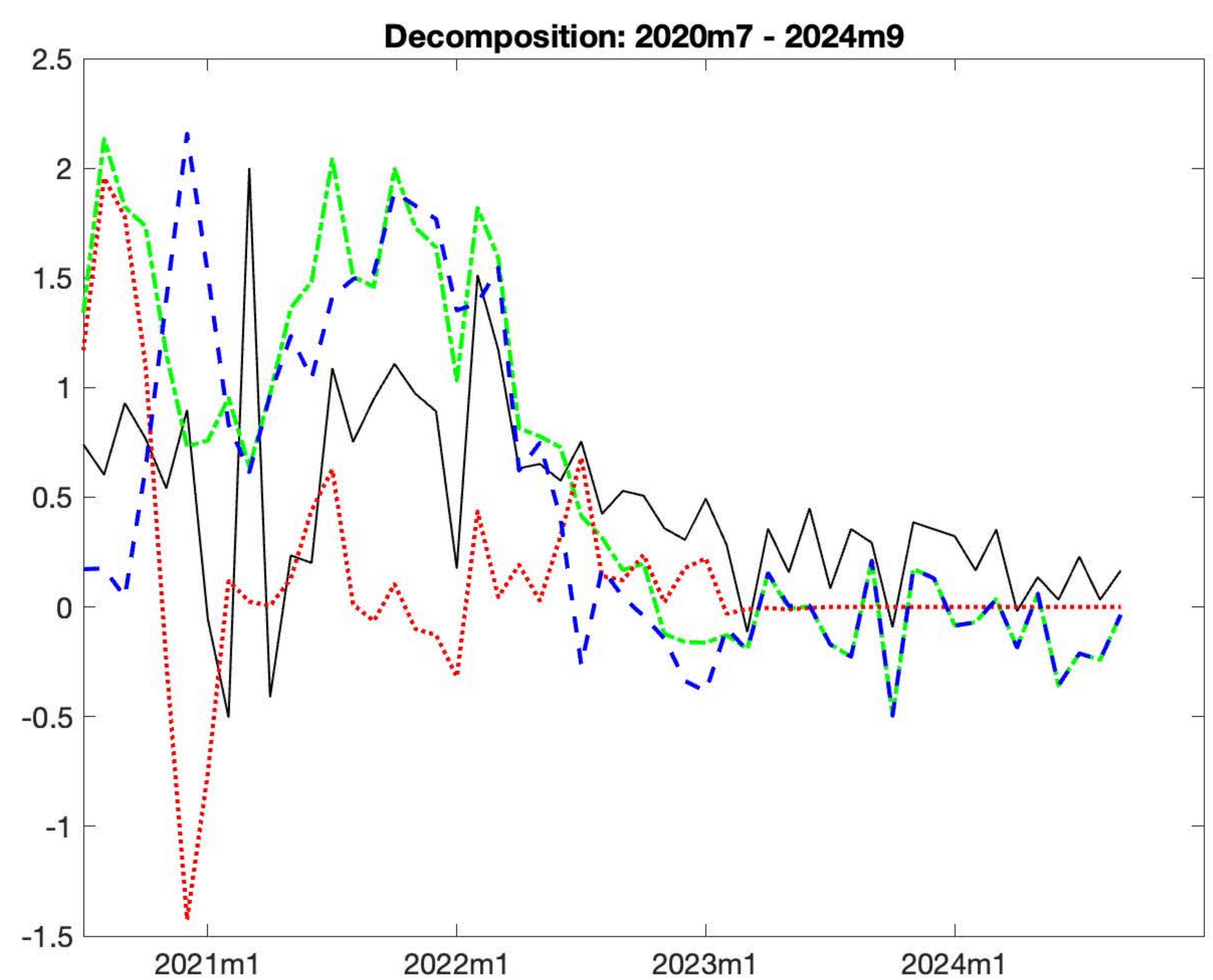

Decomposition: 2020m7 - 2024m9
6
5
4
3
2
1
0
-1
-2
-3
-4
2021m1 2022m1 2023m1 2024m1

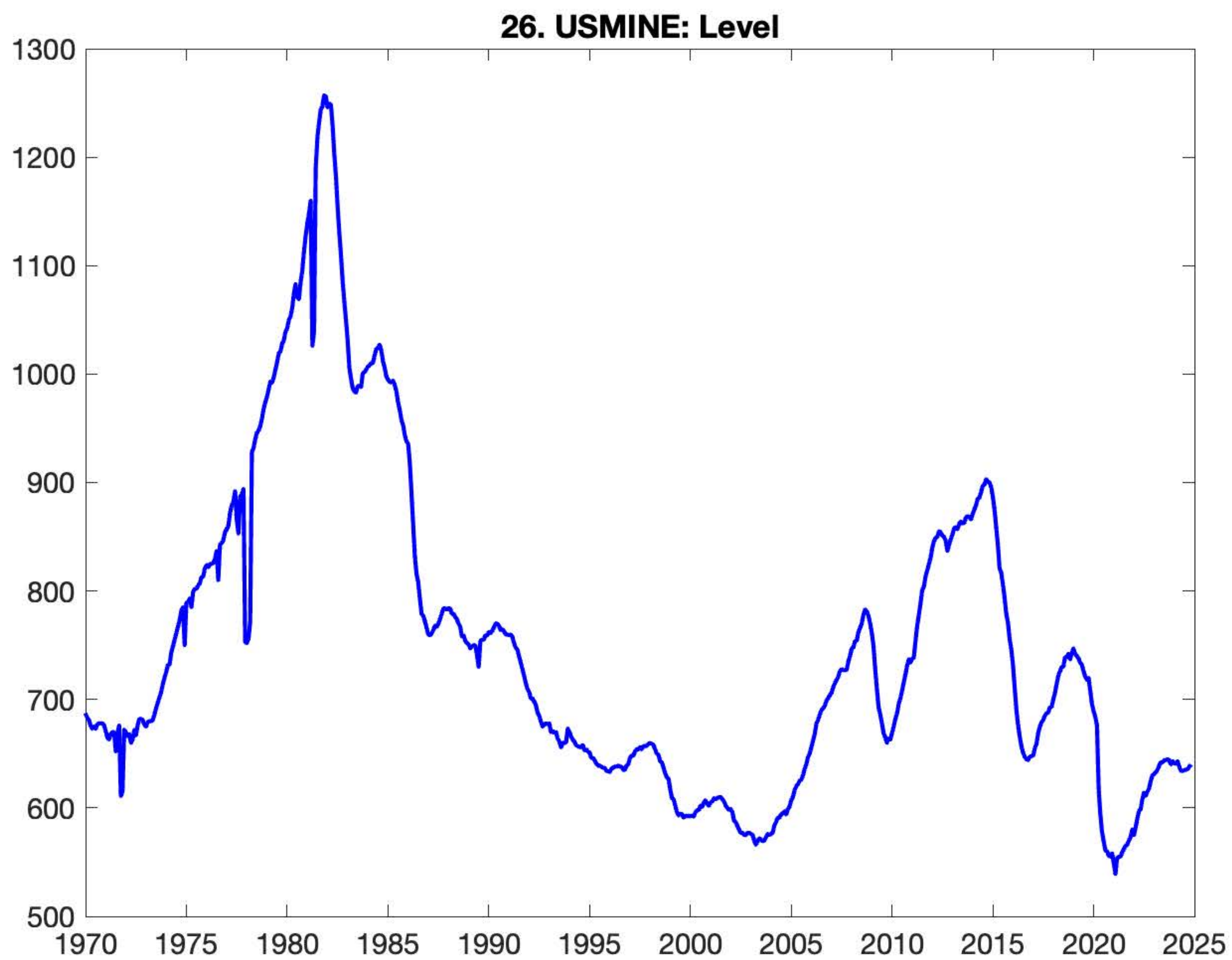

24. USPRIV: Level
×10^4
14
13
12
11
10
9
8
7
6
5
1970 1975 1980 1985 1990 1995 2000 2005 2010 2015 2020 2025
Transformed Value
20
10
0
-10
-20
-30
-40
-50
-60
-70
-80
1970 1975 1980 1985 1990 1995 2000 2005 2010 2015 2020 2025
Decomposition: 2020m1 - 2024m9
20
10
0
-10
-20
-30
-40
-50
-60
-70
-80
2020m1 2021m1 2022m1 2023m1 2024m1
Data
(F+C)-Shock
C-Shock
F-Shock
Decomposition: 2020m7 - 2024m9
5
4
3
2
1
0
-1
-2
-3
-4
2021m1 2022m1 2023m1 2024m1

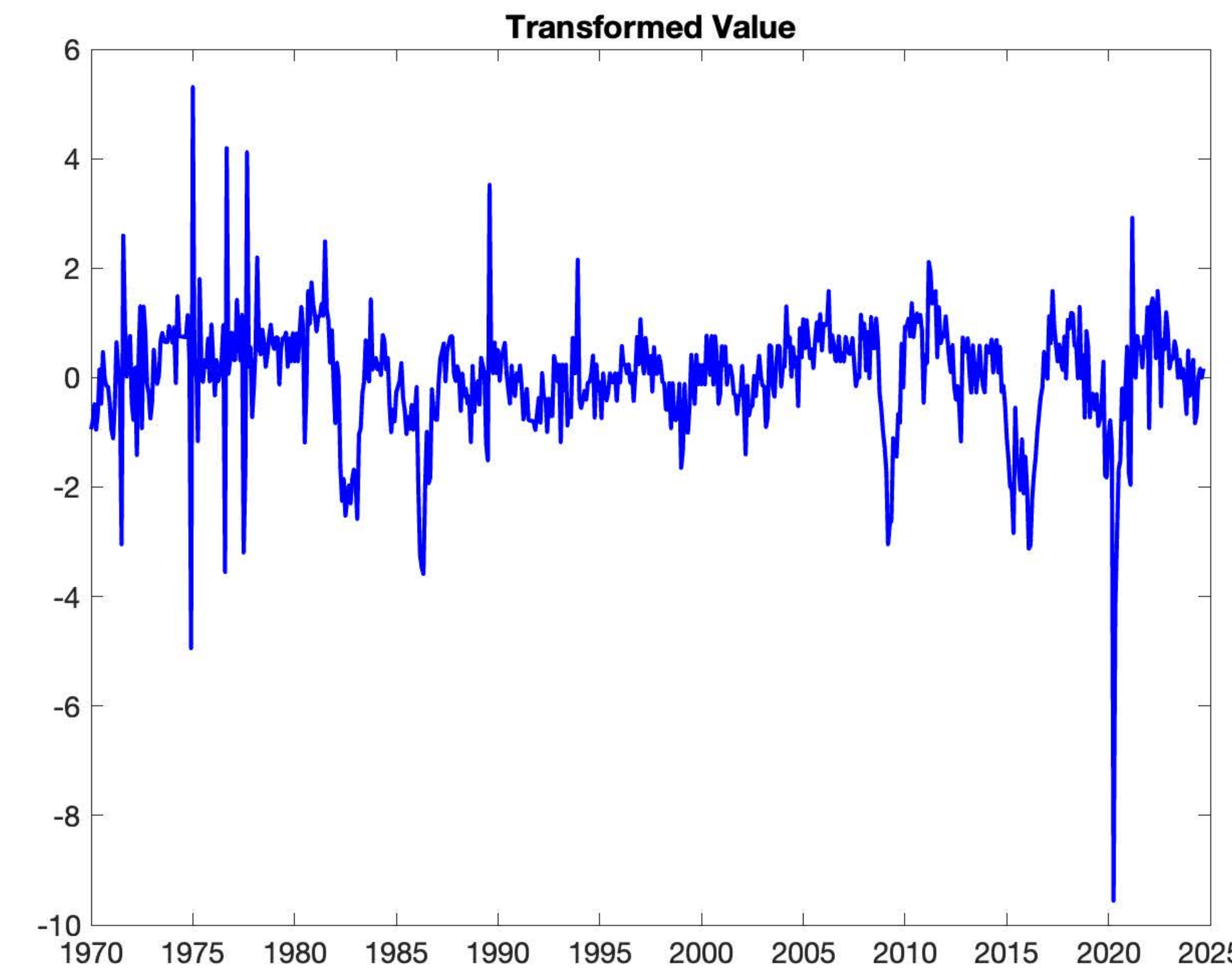

25. USGOOD: Level
×10^4
1970 1975 1980 1985 1990 1995 2000 2005 2010 2015 2020 2025

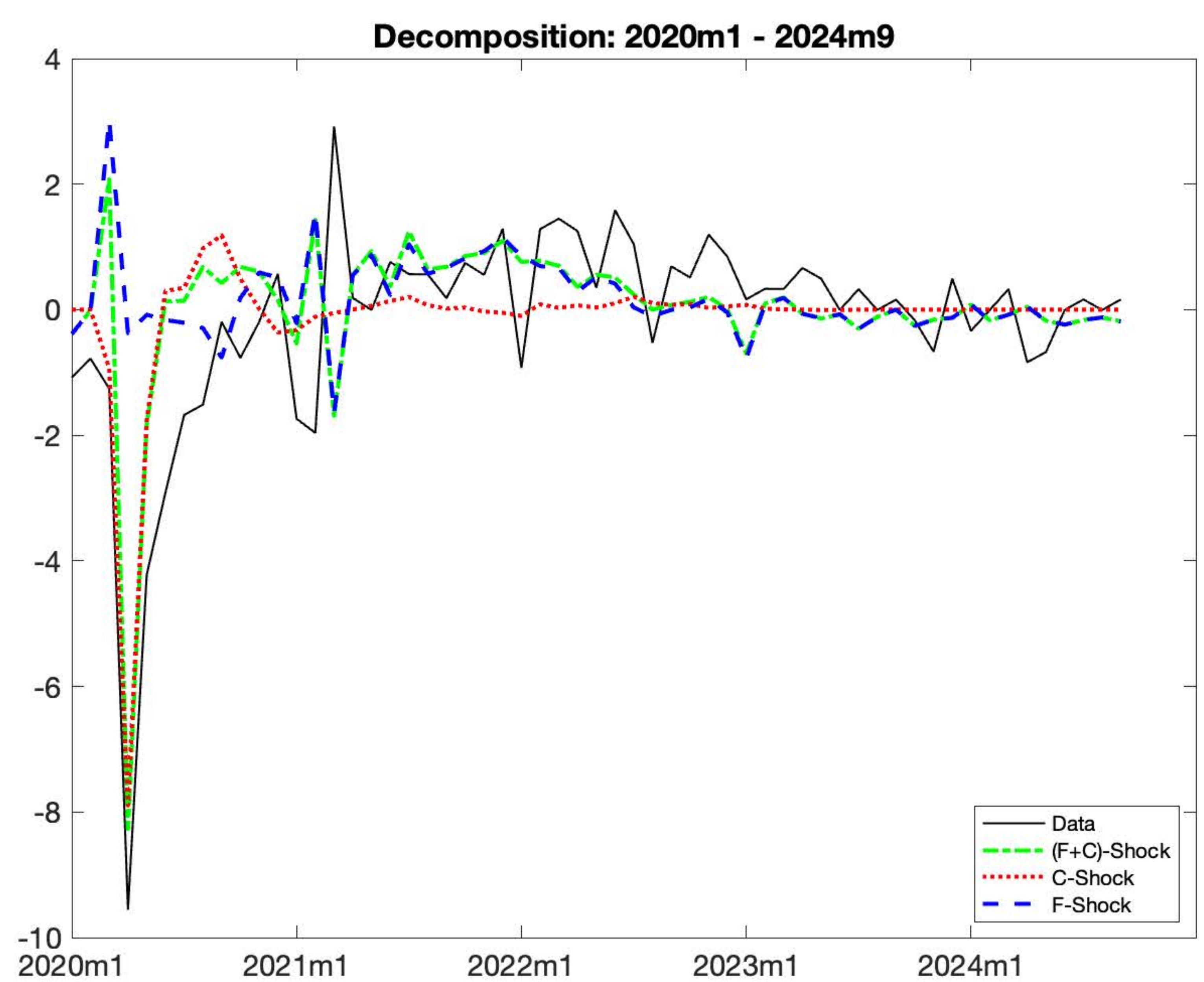

Transformed Value
1970 1975 1980 1985 1990 1995 2000 2005 2010 2015 2020 2025

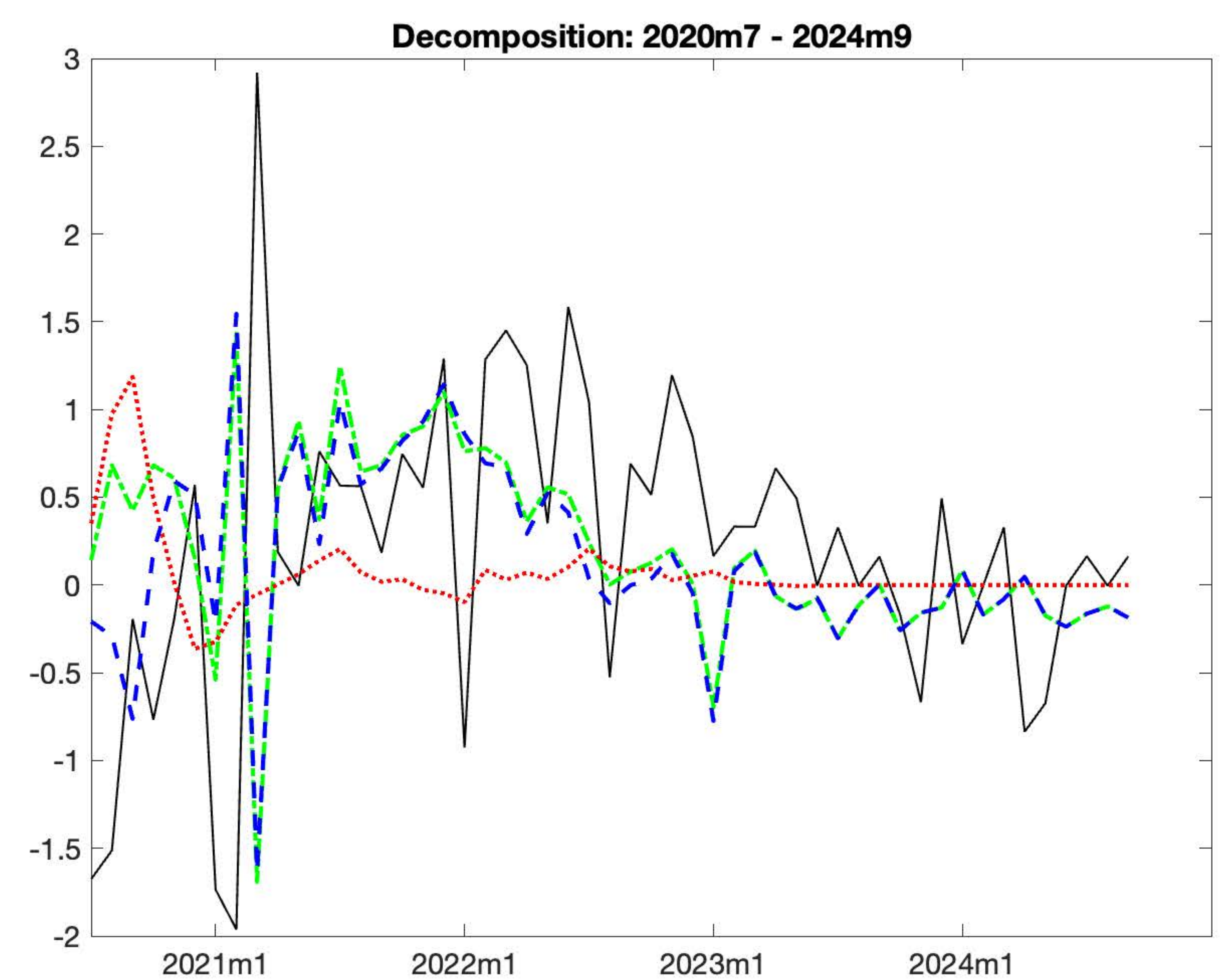

Decomposition: 2020m1 - 2024m9
Data
(F+C)-Shock
C-Shock
F-Shock
2020m1 2021m1 2022m1 2023m1 2024m1

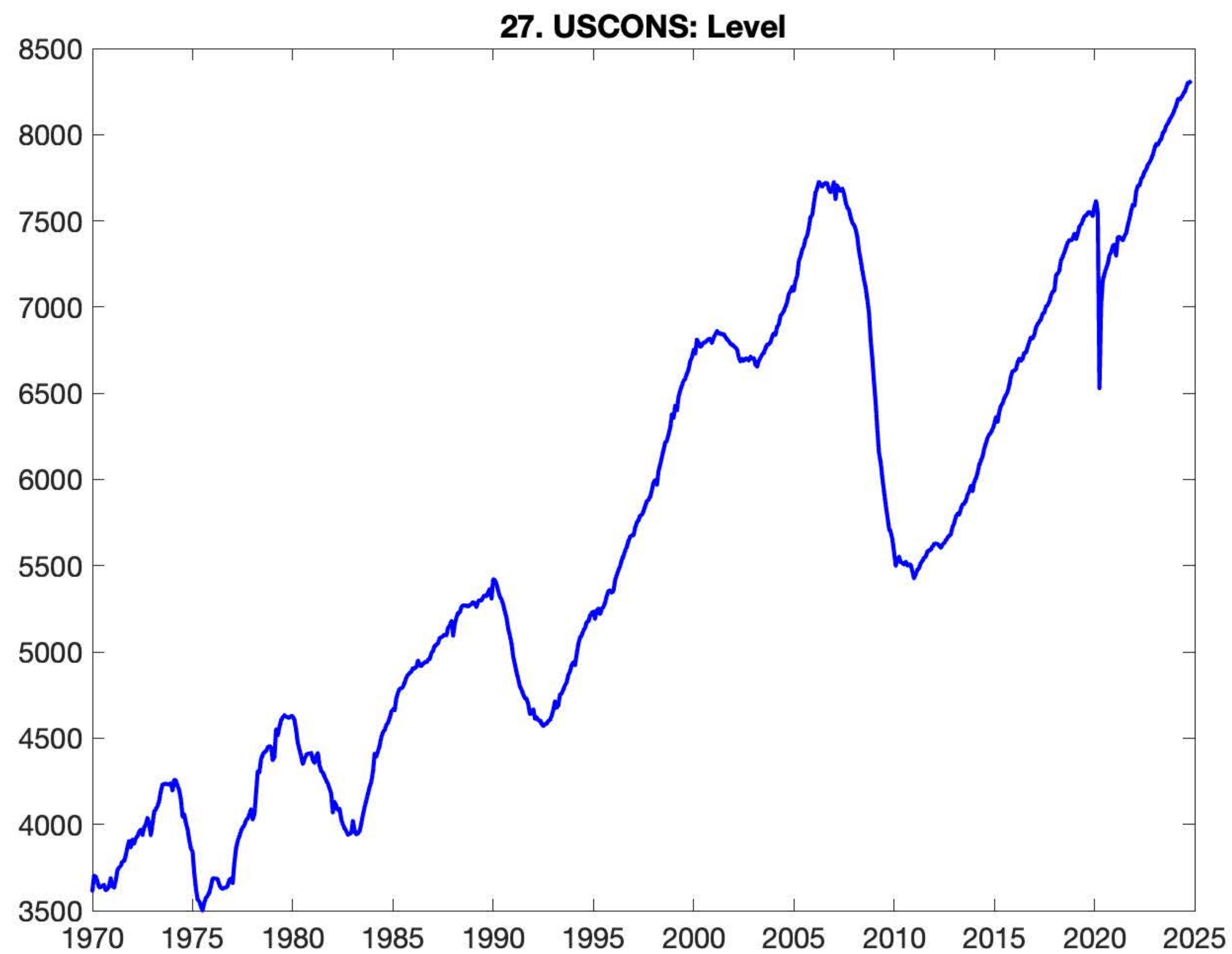

Decomposition: 2020m7 - 2024m9
2021m1 2022m1 2023m1 2024m1

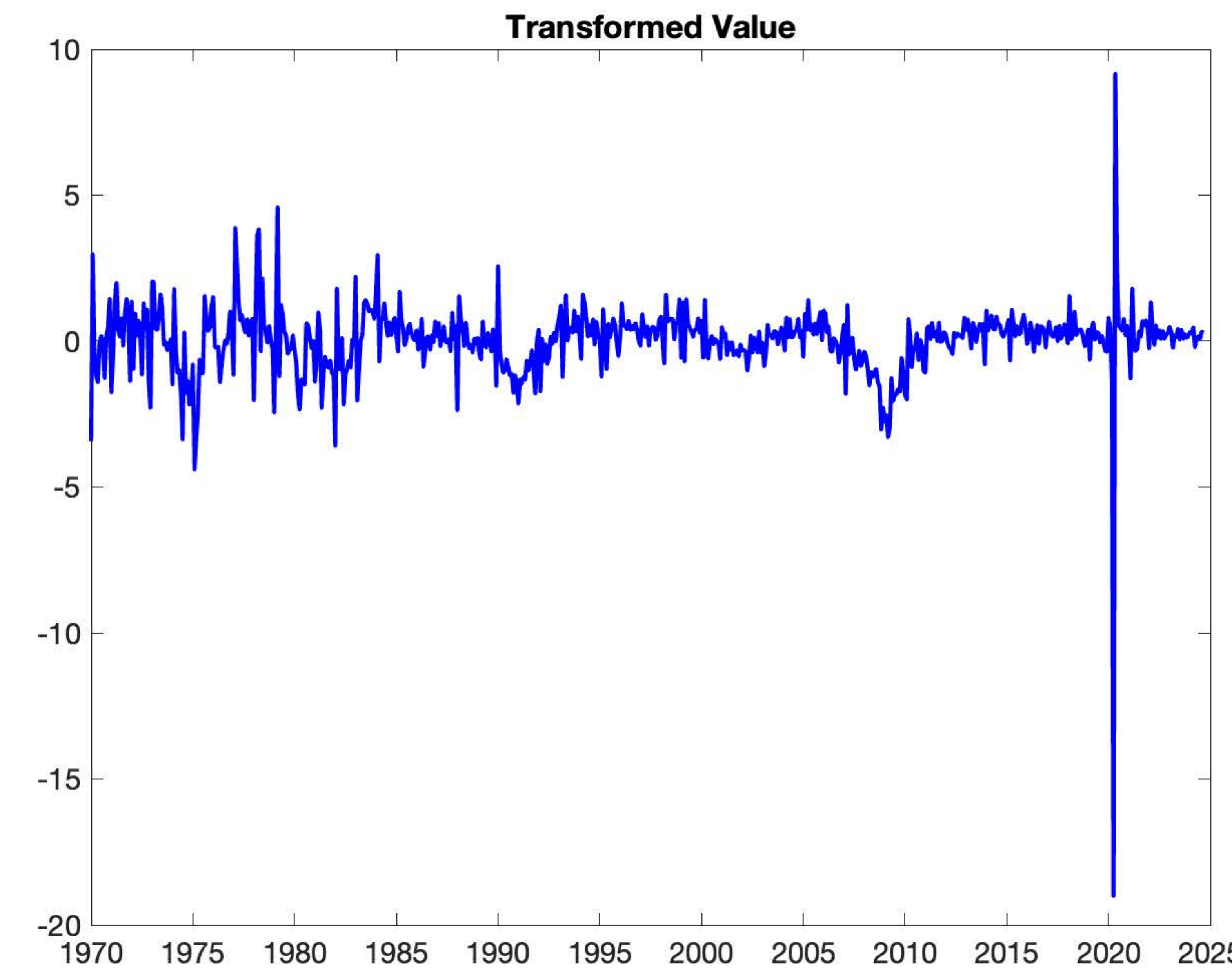

26. USMINE: Level

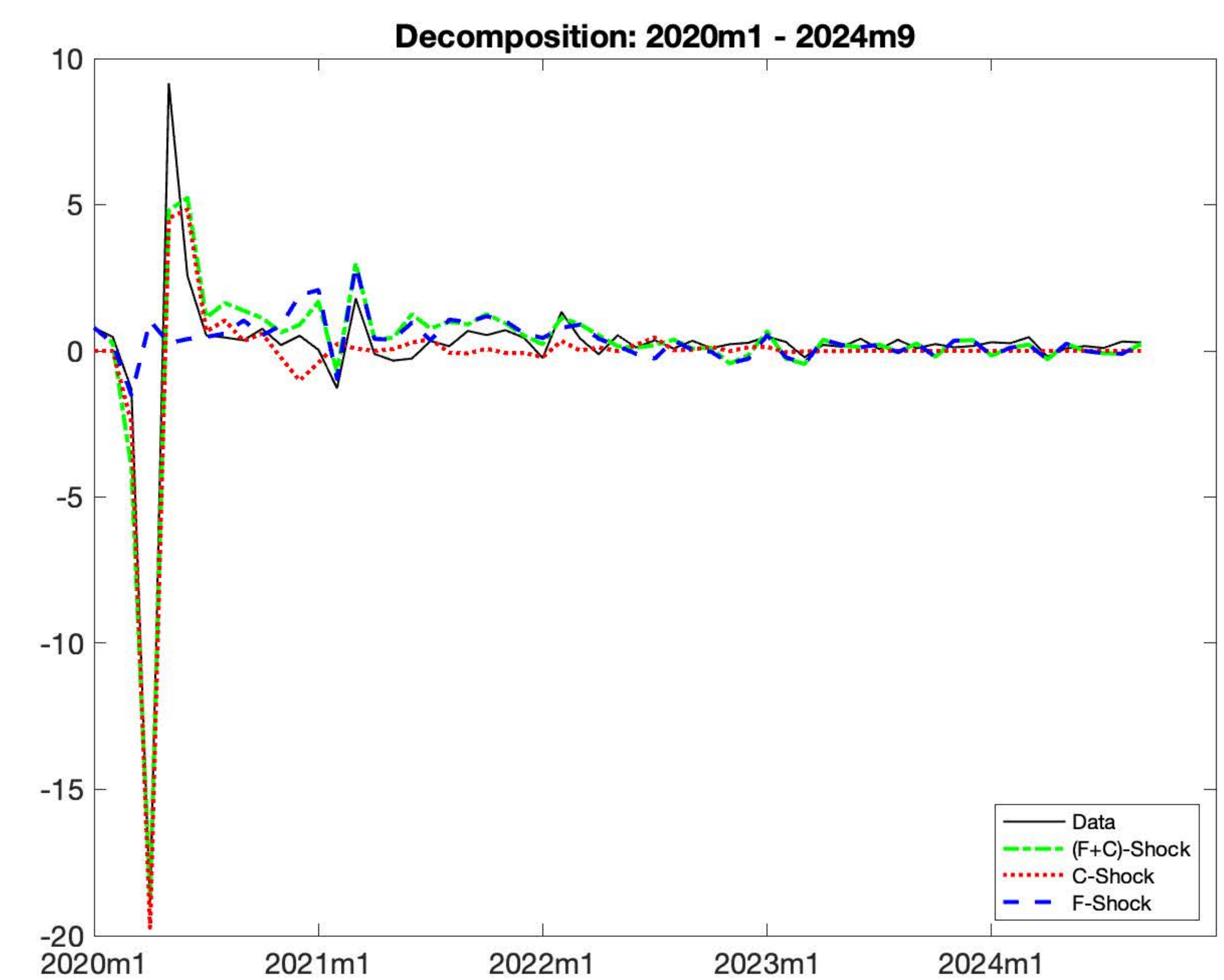

Transformed Value

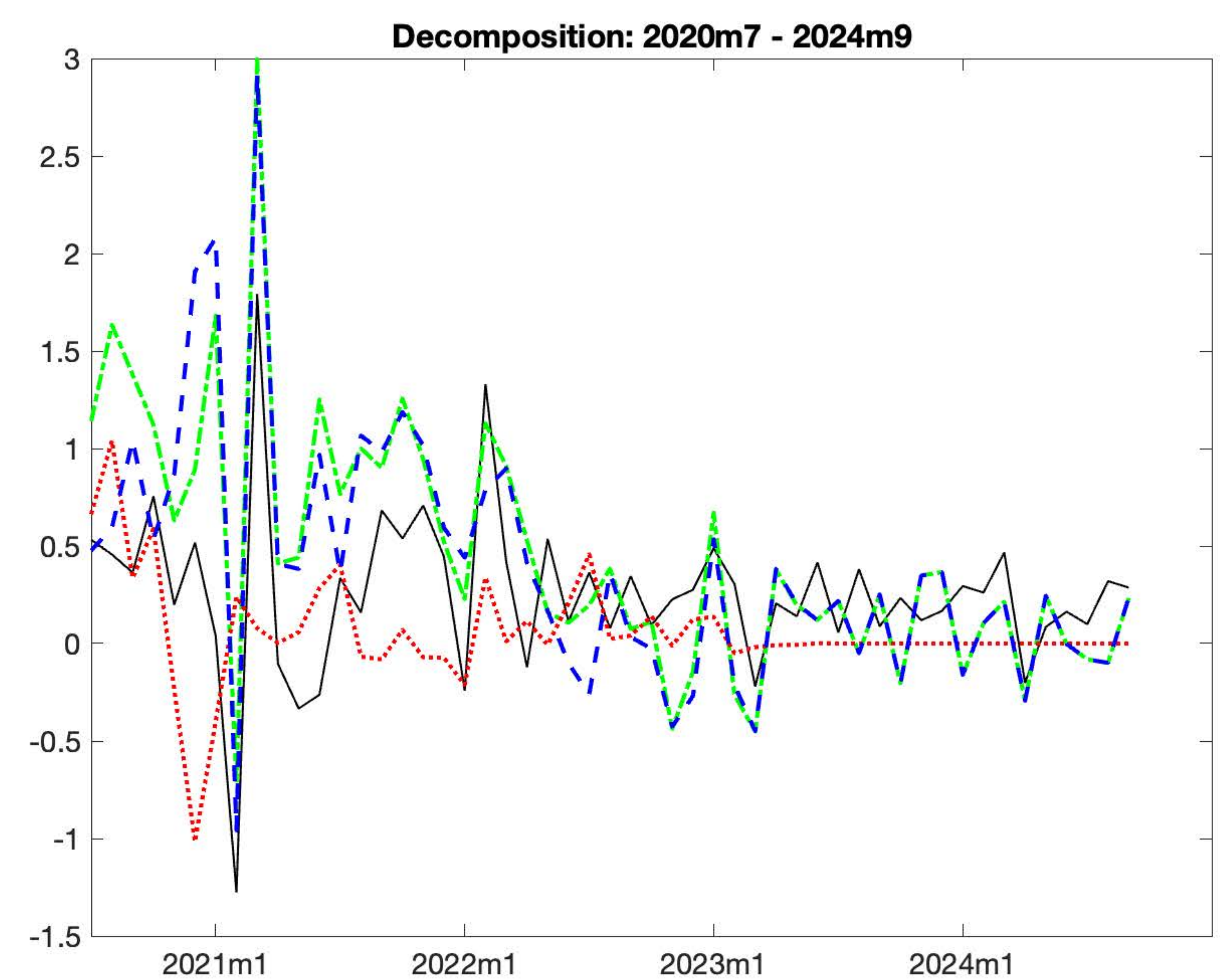

Decomposition: 2020m1 - 2024m9
Data
(F+C)-Shock
C-Shock
F-Shock

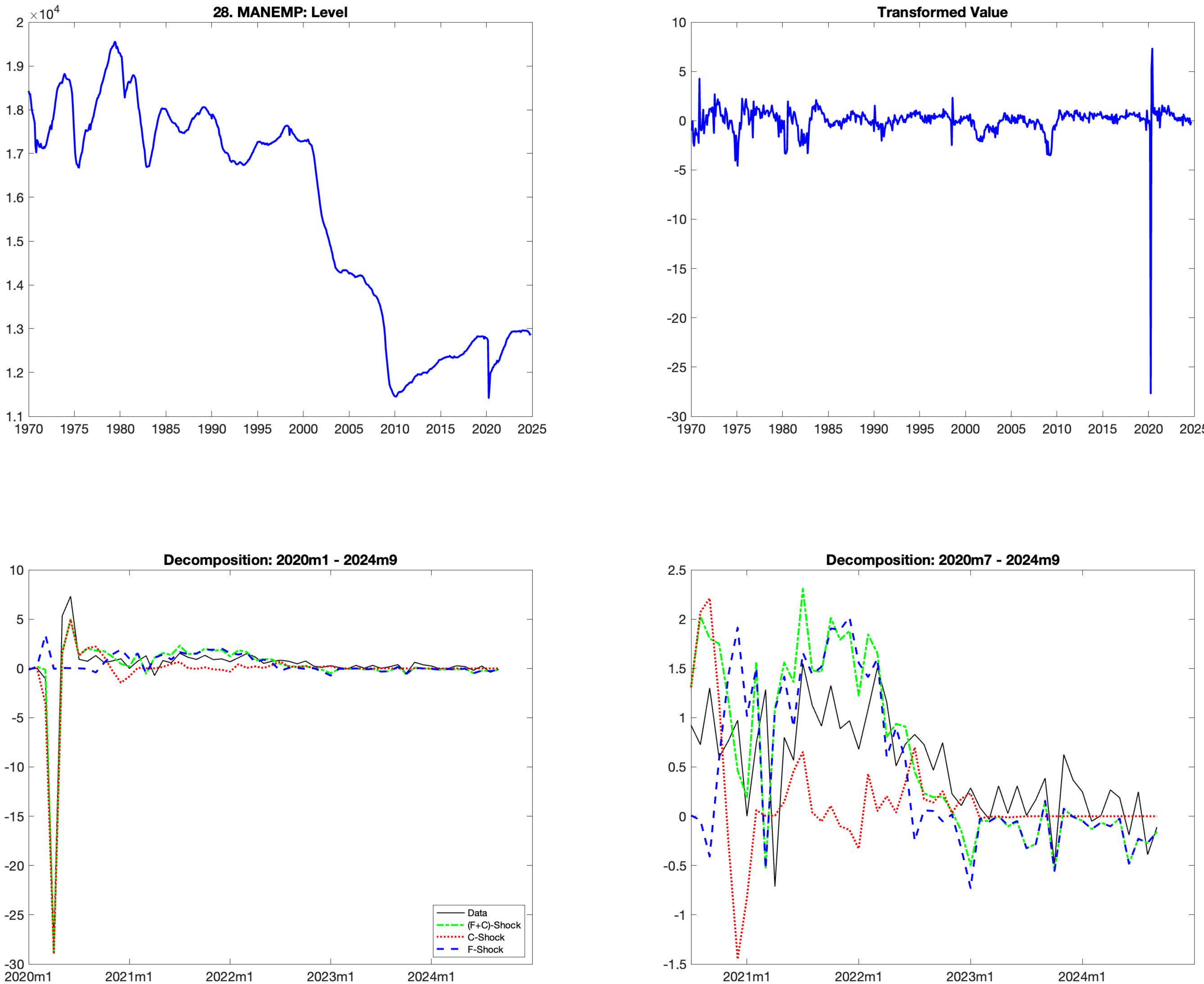

Decomposition: 2020m7 - 2024m9


27. USCONS: Level

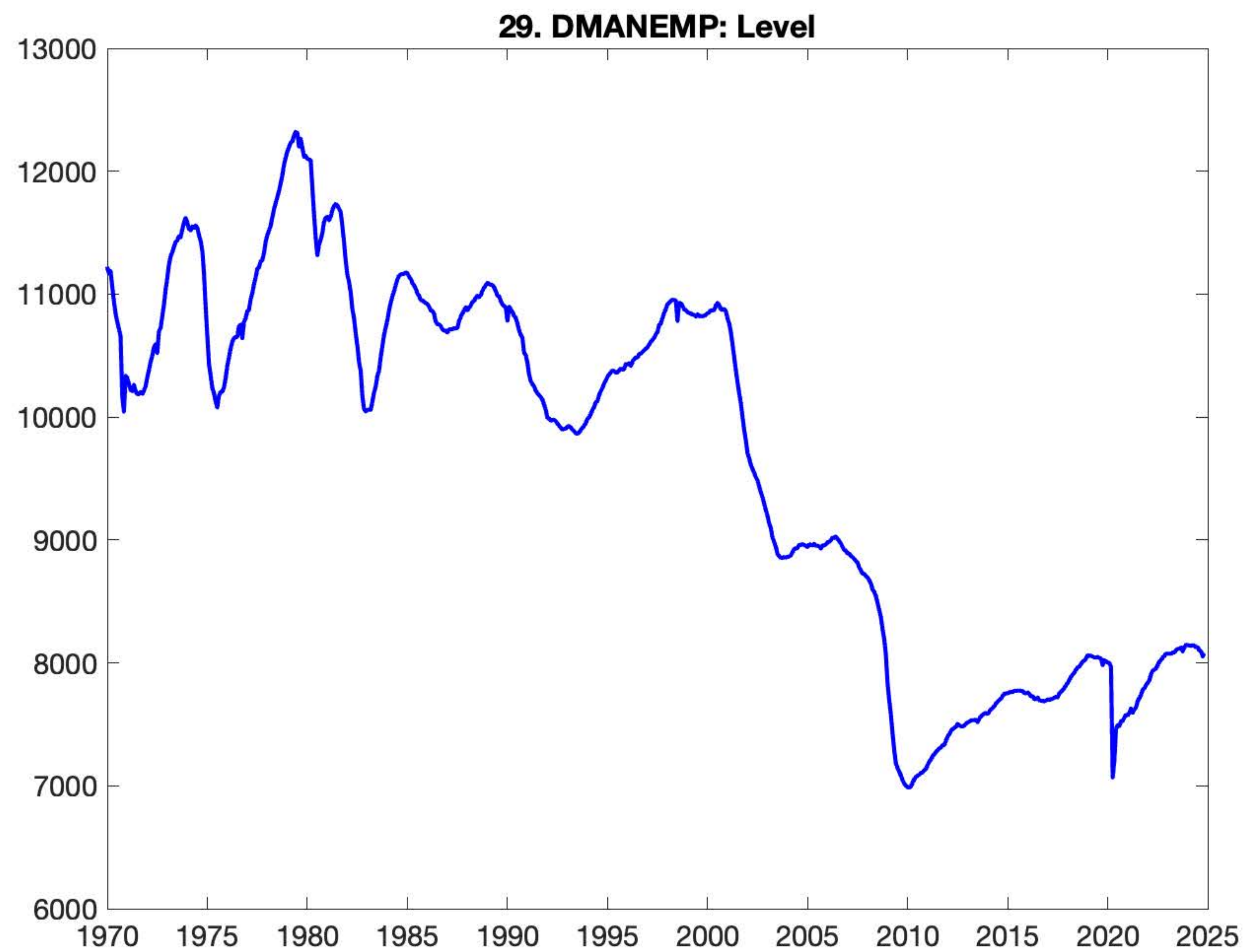

Transformed Value

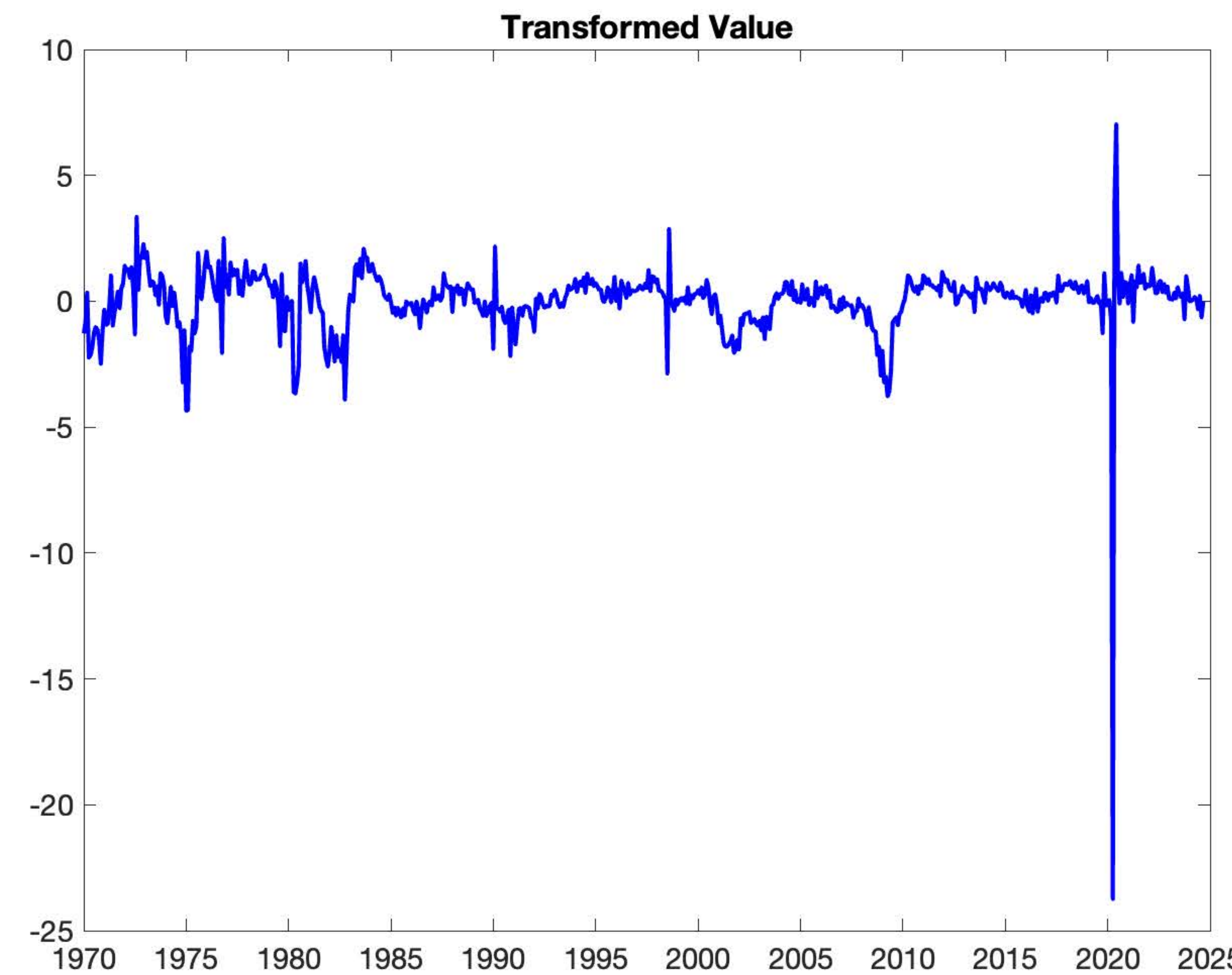

Decomposition: 2020m1 - 2024m9
Data
(F+C)-Shock
C-Shock
F-Shock

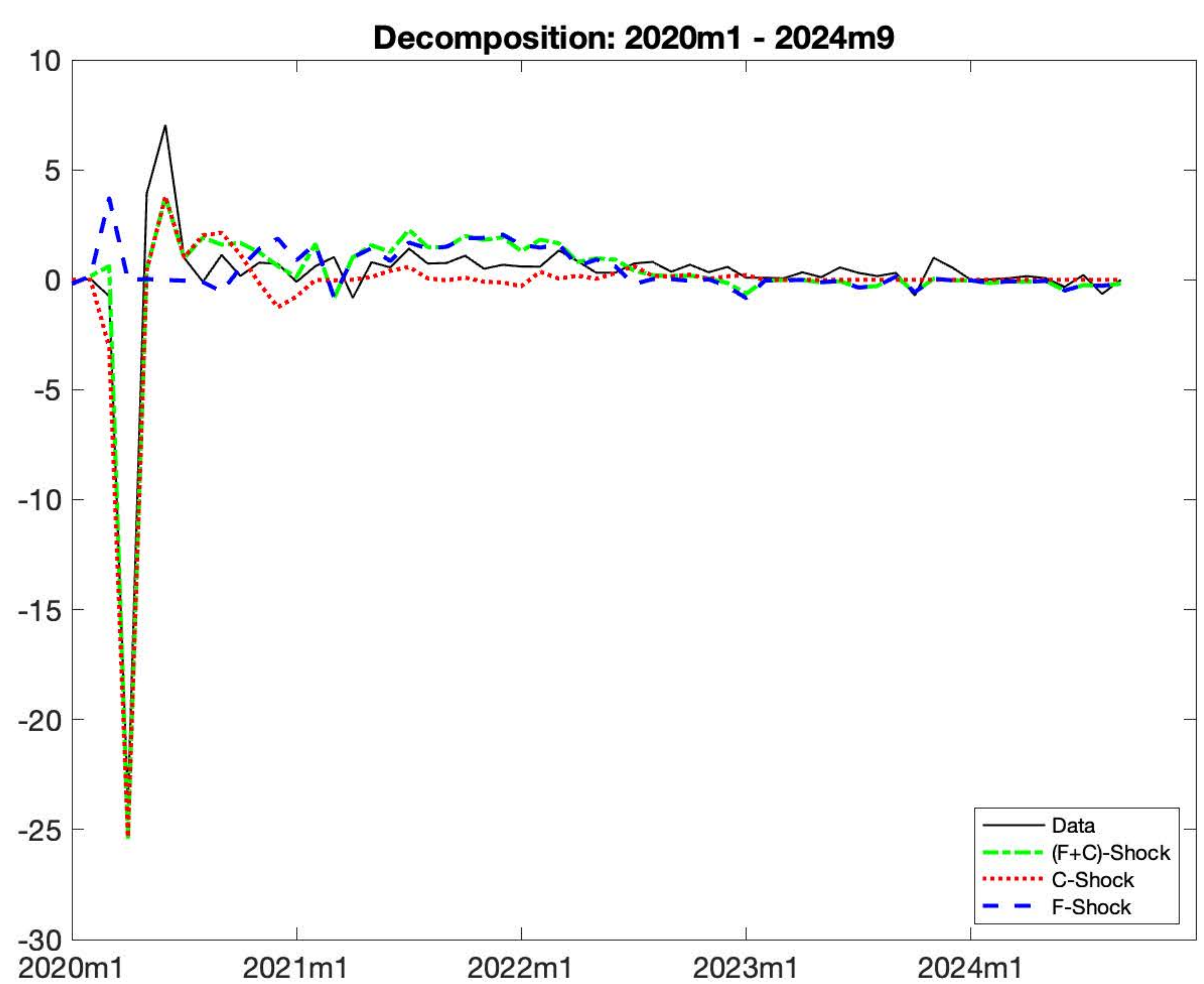

Decomposition: 2020m7 - 2024m9

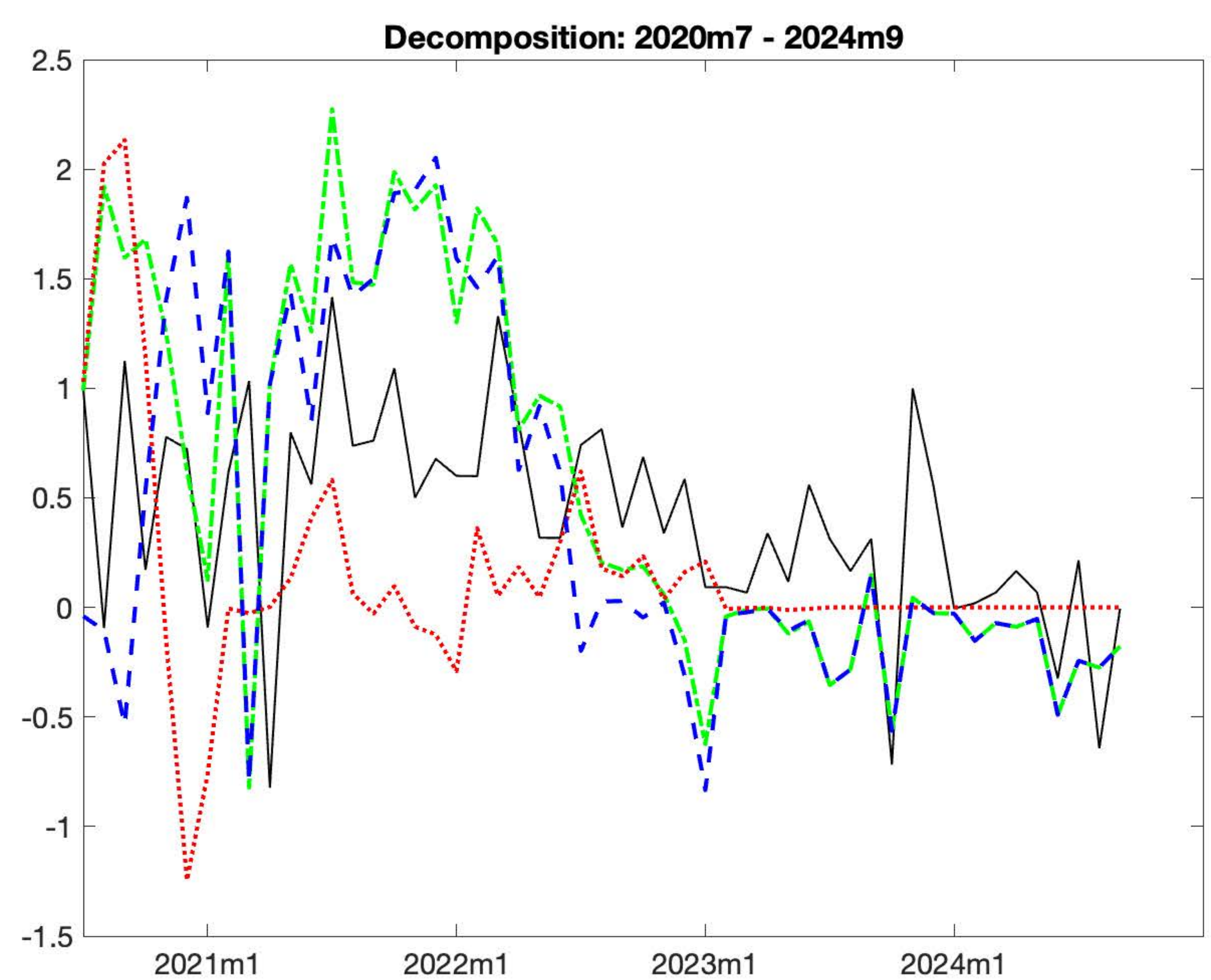


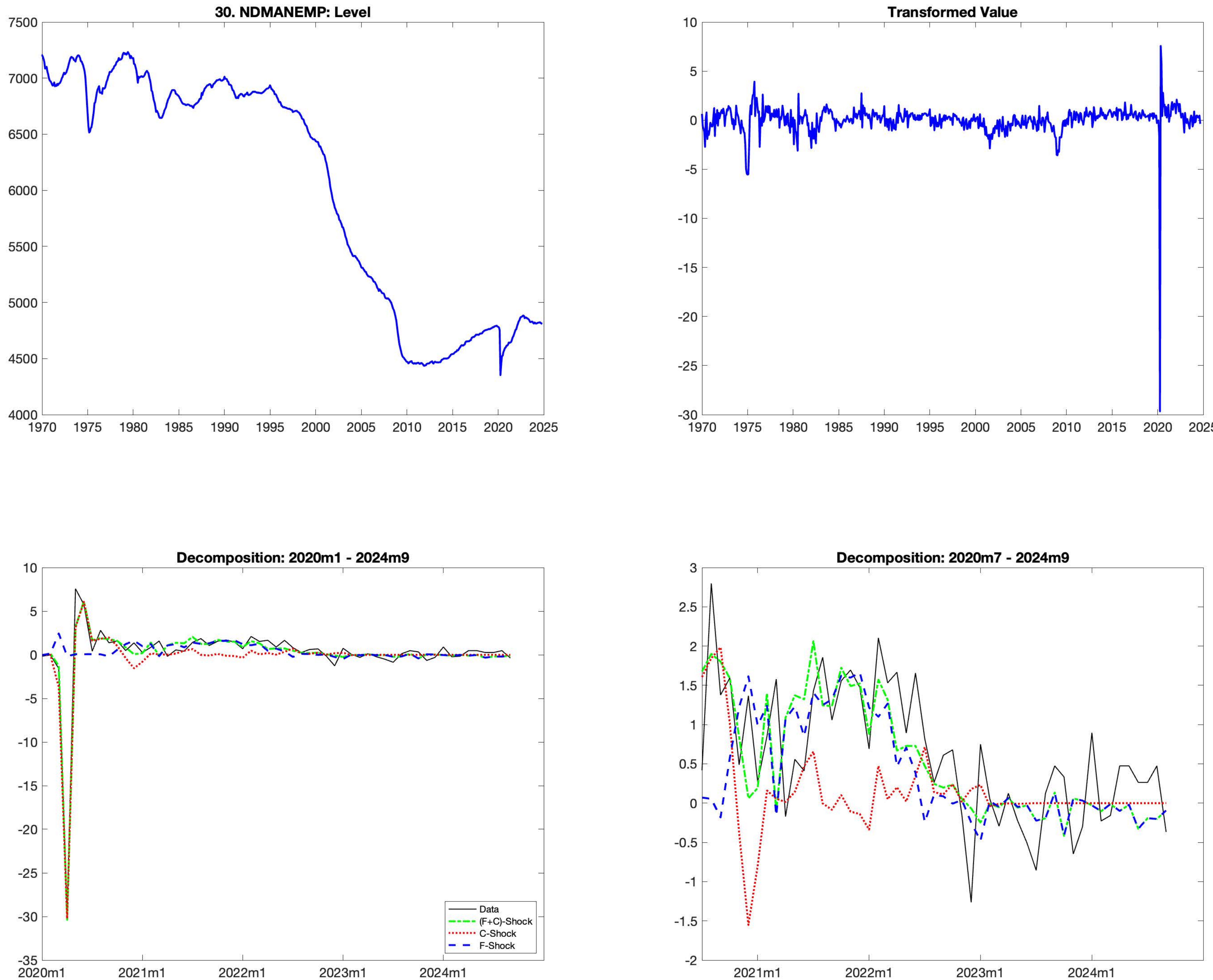
28. MANEMP: Level
Transformed Value
Decomposition: 2020m1 - 2024m9
Decomposition: 2020m7 - 2024m9
Data
(F+C)-Shock
C-Shock
F-Shock

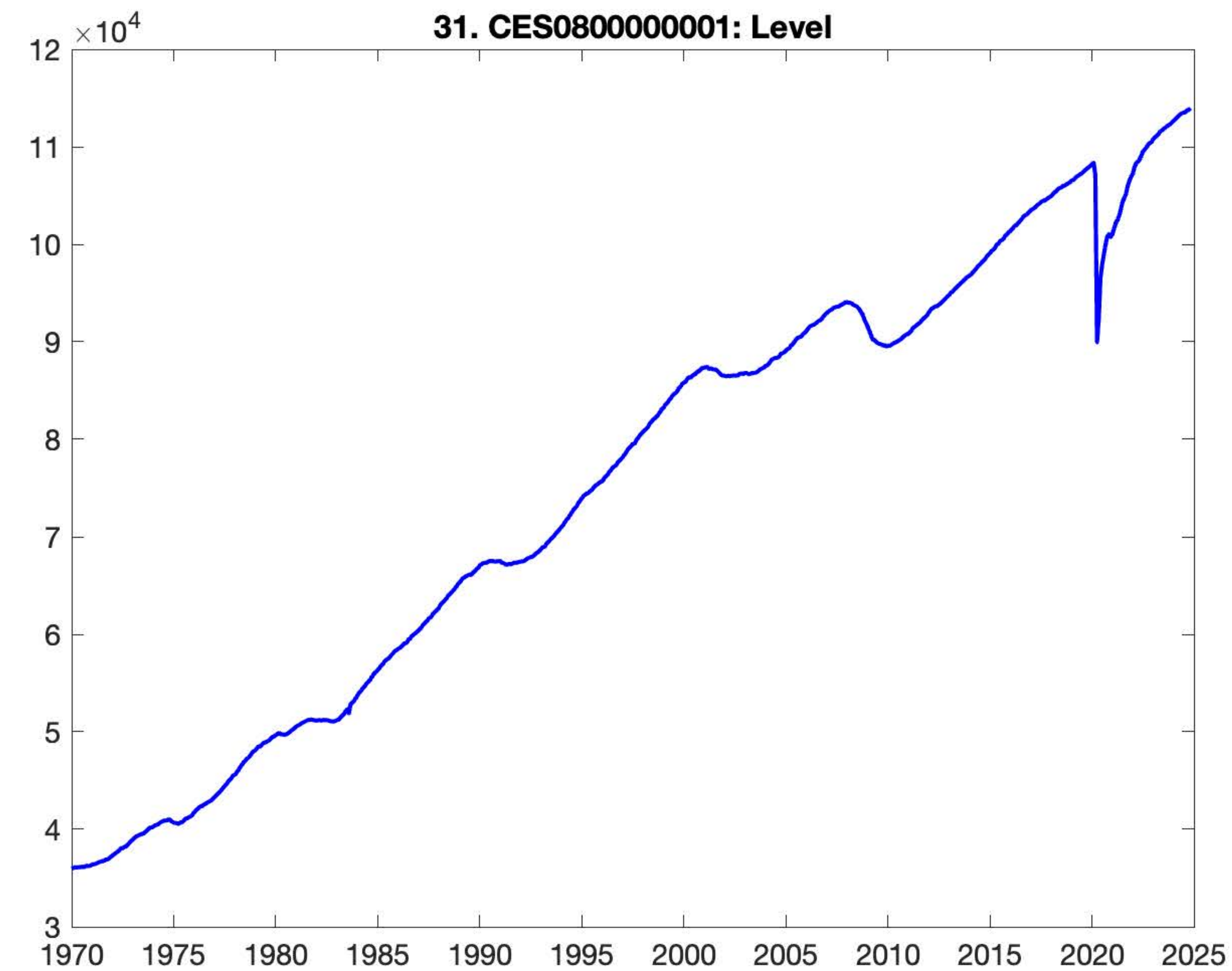

29. DMANEMP: Level
13000
12000
11000
10000
9000
8000
7000
6000
1970
1975
1980
1985
1990
1995
2000
2005
2010
2015
2020
2025


Transformed Value
10
5
0
-5
-10
-15
-20
-25
1970
1975
1980
1985
1990
1995
2000
2005
2010
2015
2020
2025

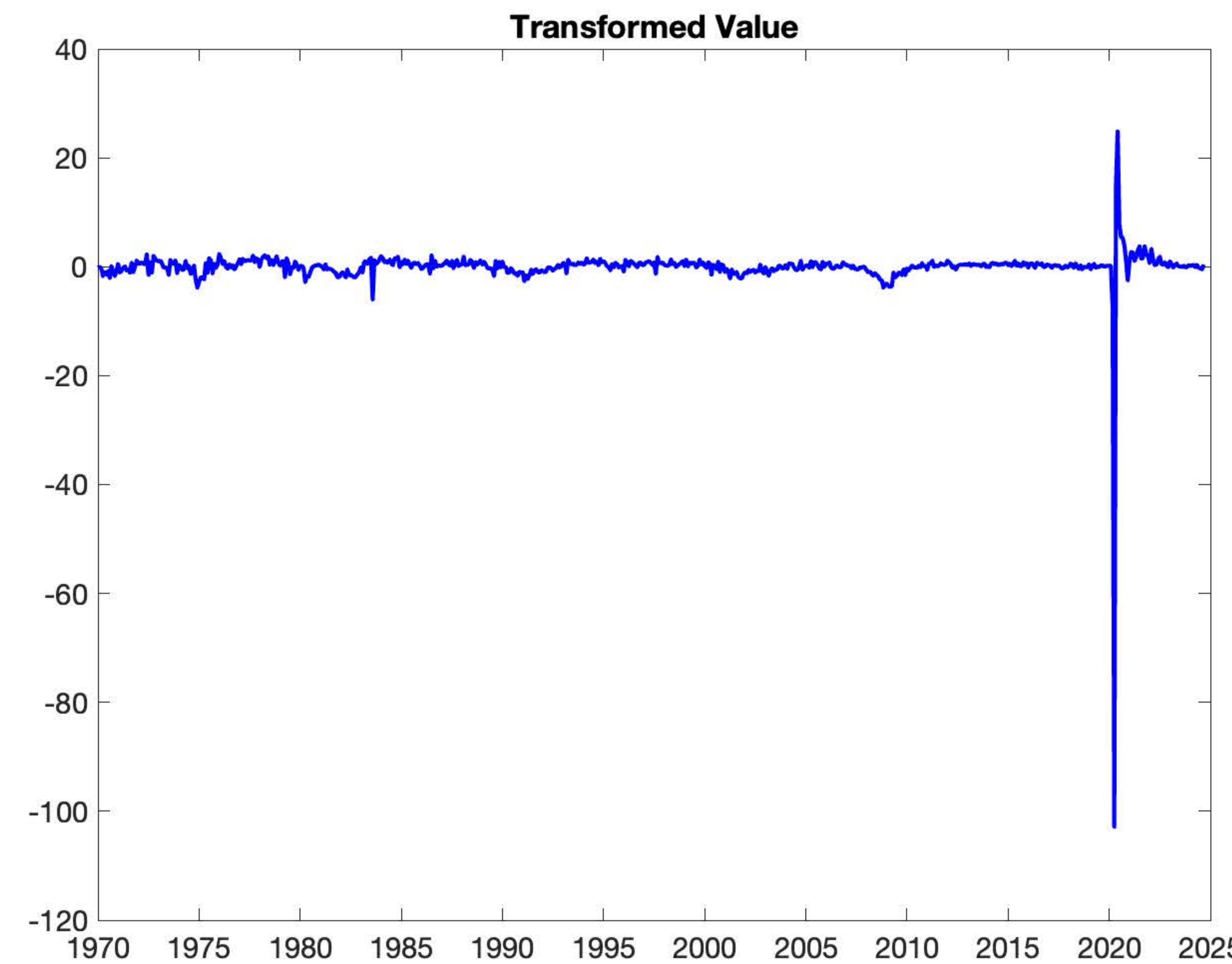

Decomposition: 2020m1 - 2024m9
10
5
0
-5
-10
-15
-20
-25
-30
2020m1
2021m1
2022m1
2023m1
2024m1
Data
(F+C)-Shock
C-Shock
F-Shock


Decomposition: 2020m7 - 2024m9
2.5
2
1.5
1
0.5
0
-0.5
-1
-1.5
2021m1
2022m1
2023m1
2024m1

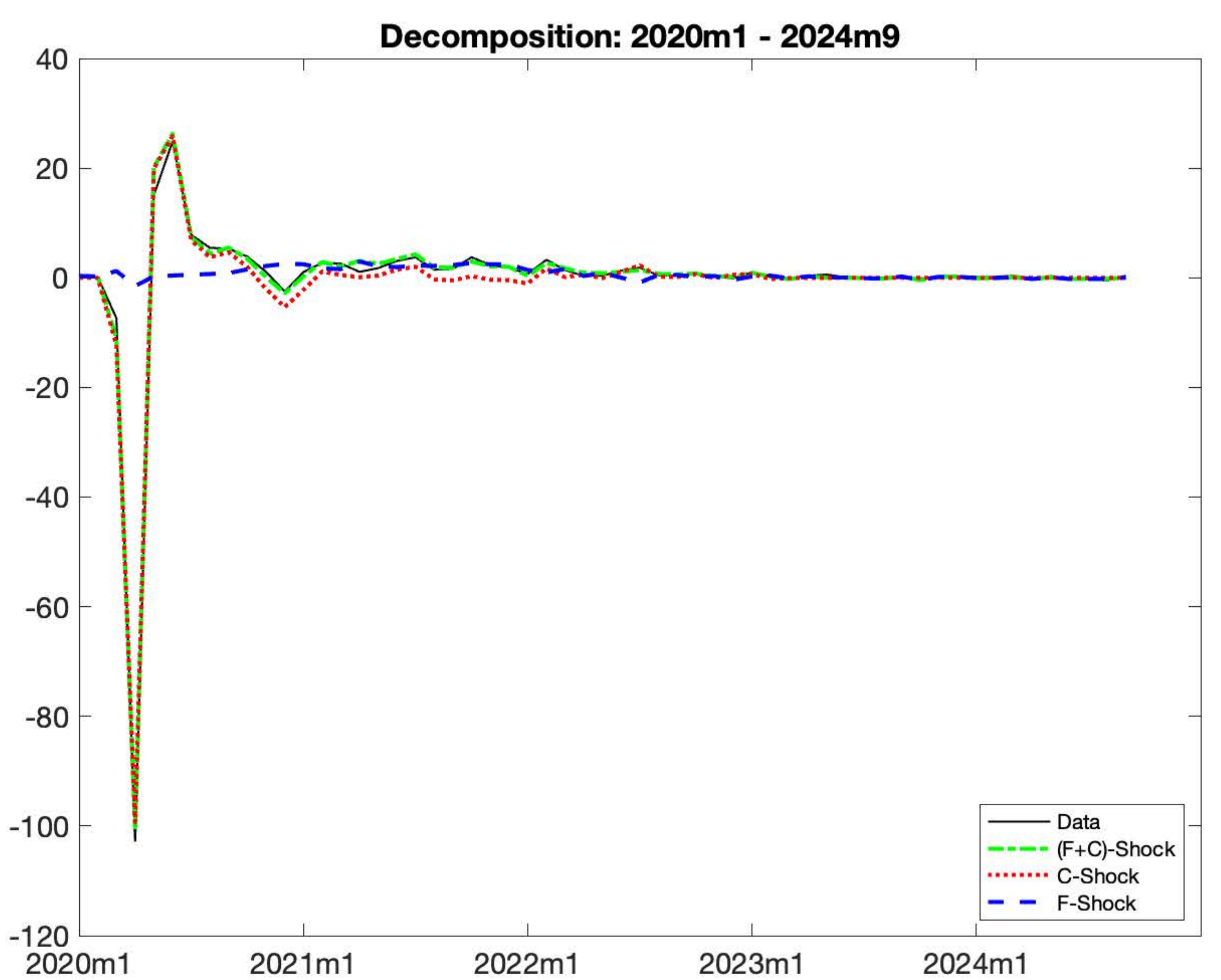

30. NDMANEMP: Level
Transformed Value
Decomposition: 2020m1 - 2024m9
Decomposition: 2020m7 - 2024m9
Data
(F+C)-Shock
C-Shock
F-Shock



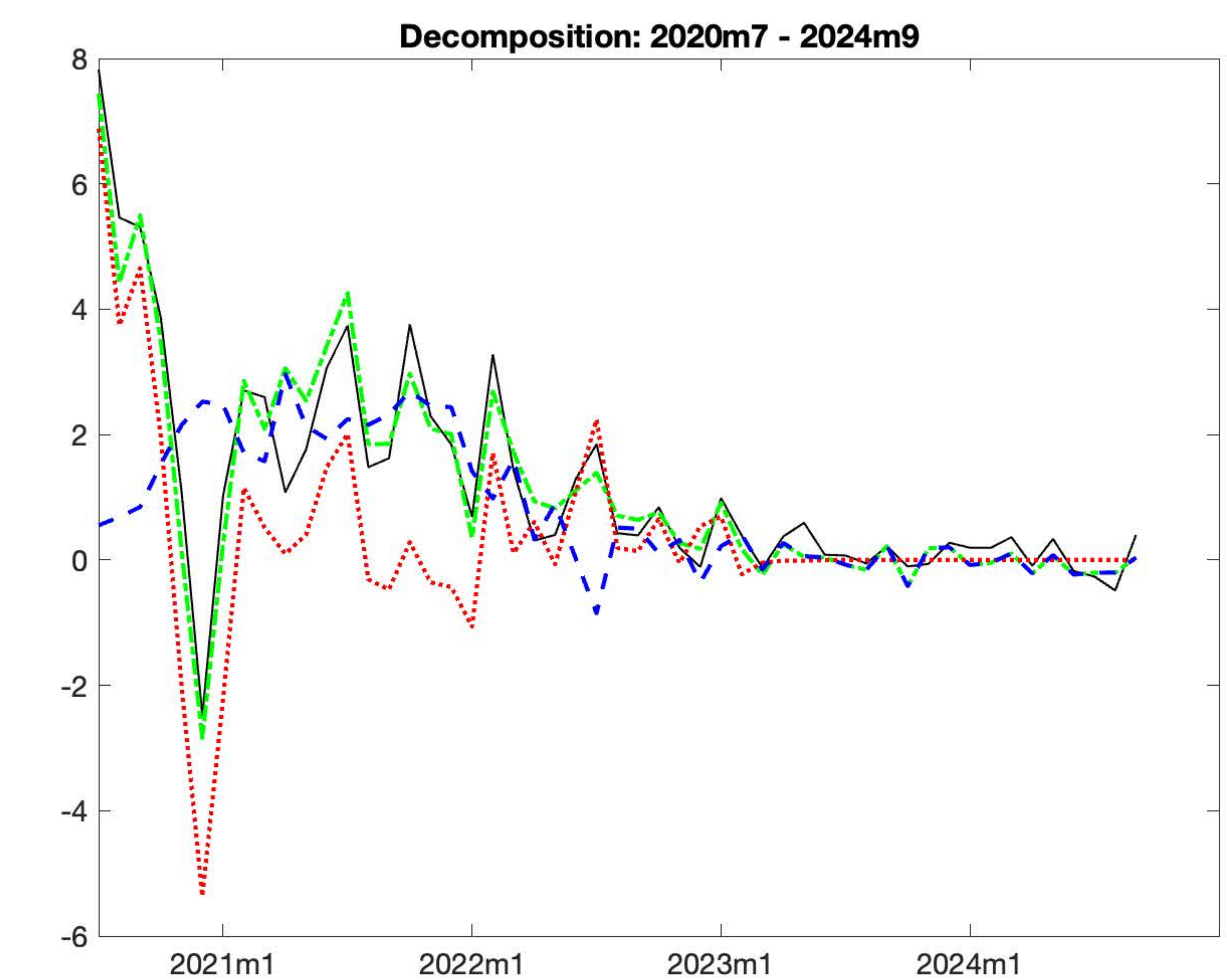
31. CES0800000001: Level
×10^4
12
11
10
9
8
7
6
5
4
3
1970
1975
1980
1985
1990
1995
2000
2005
2010
2015
2020
2025



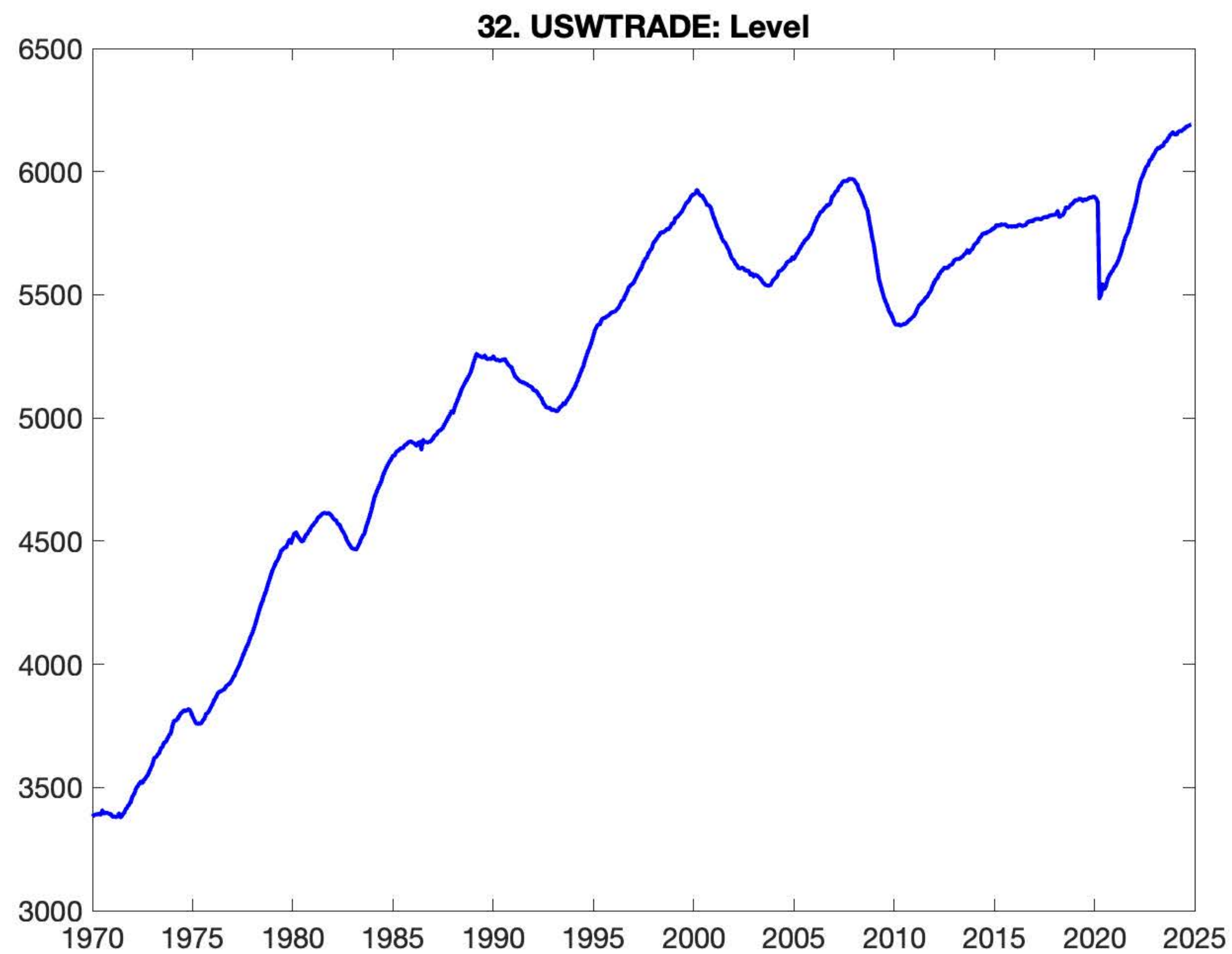
Transformed Value
40
20
0
-20
-40
-60
-80
-100
-120
1970
1975
1980
1985
1990
1995
2000
2005
2010
2015
2020
2025

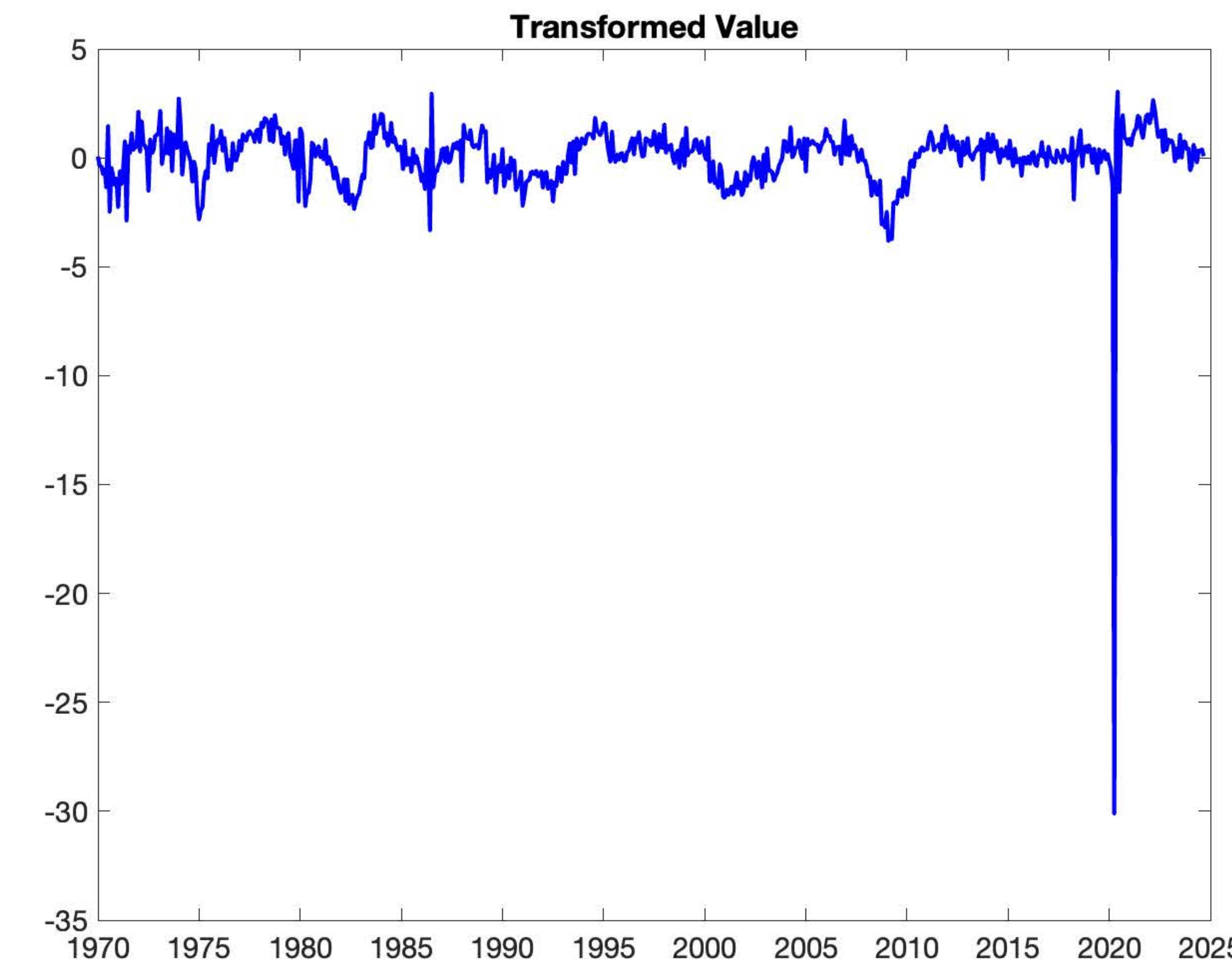


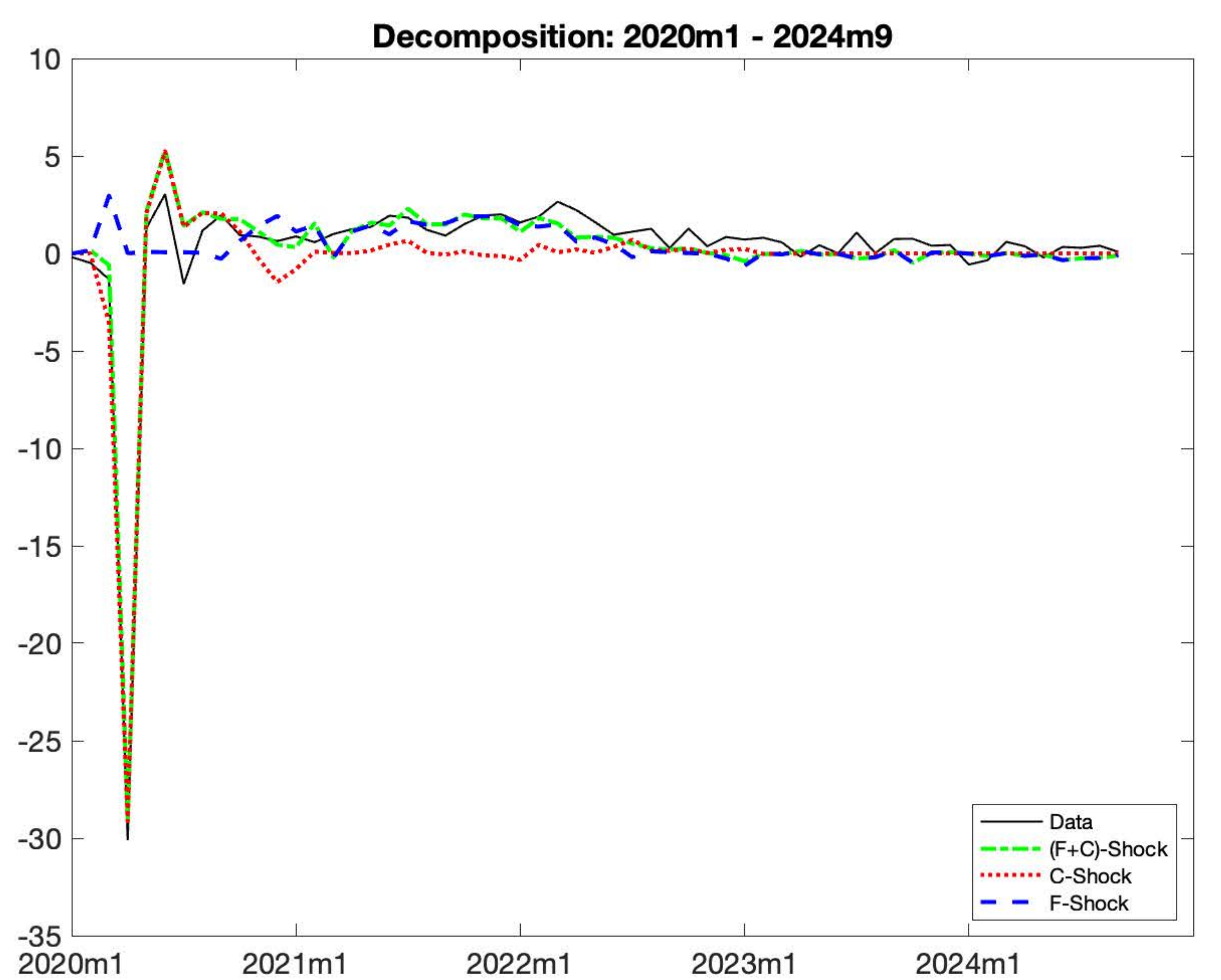
Decomposition: 2020m1 - 2024m9
40
20
0
-20
-40
-60
-80
-100
-120
2020m1
2021m1
2022m1
2023m1
2024m1
Data
(F+C)-Shock
C-Shock
F-Shock

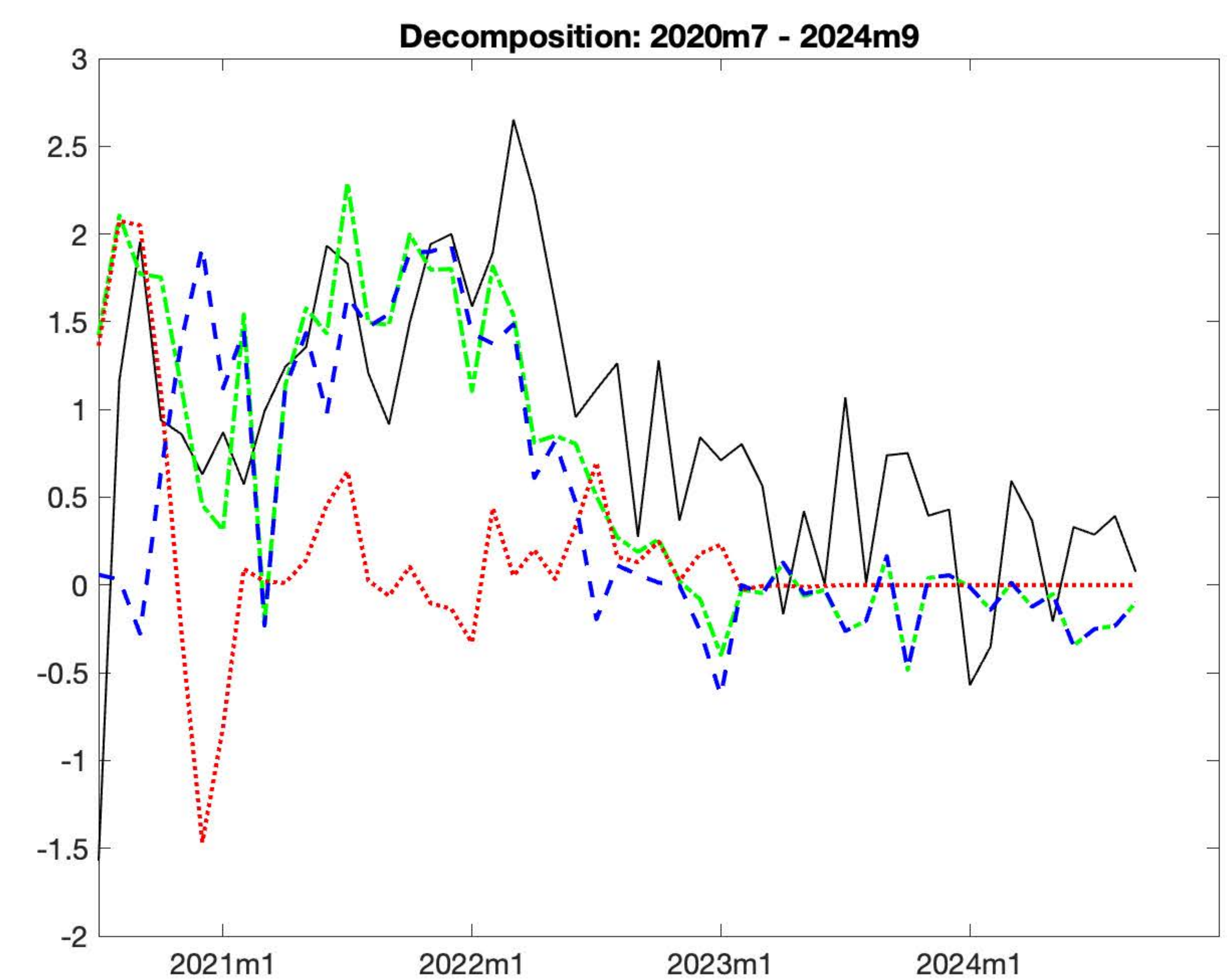


Decomposition: 2020m7 - 2024m9
8
6
4
2
0
-2
-4
-6
2021m1
2022m1
2023m1
2024m1

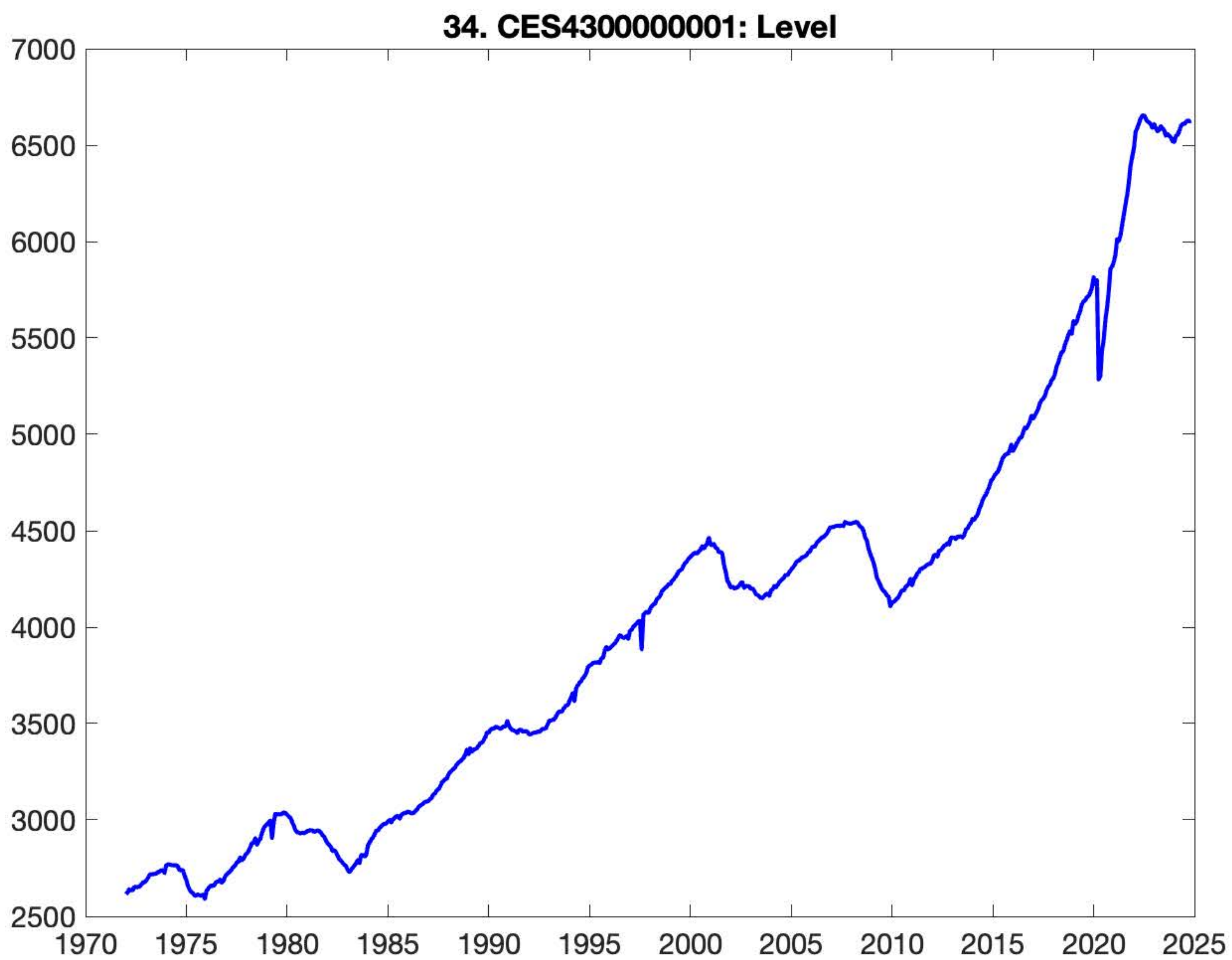

32. USWTRADE: Level
6500
6000
5500
5000
4500
4000
3500
3000
1970 1975 1980 1985 1990 1995 2000 2005 2010 2015 2020 2025

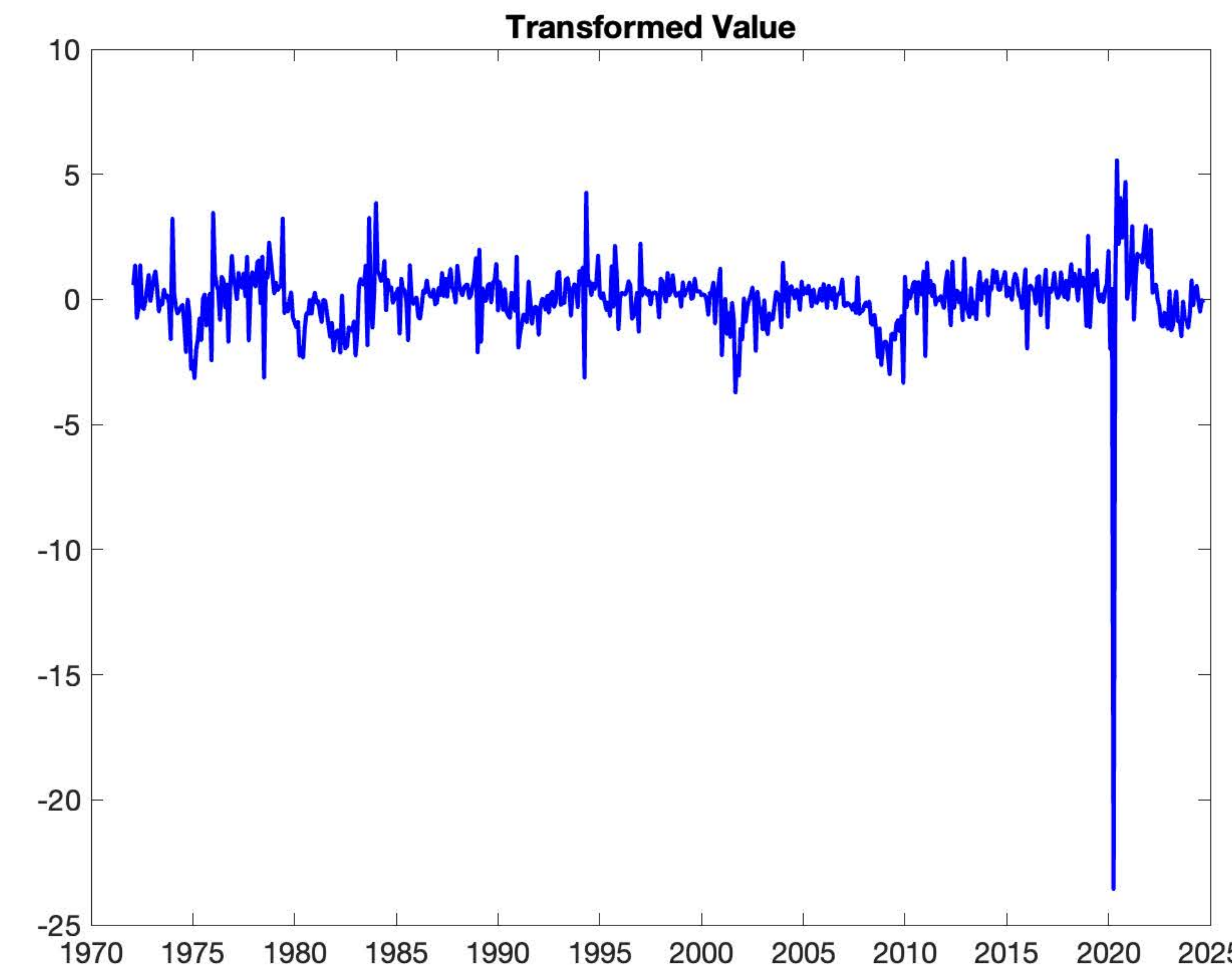

Transformed Value
5
0
-5
-10
-15
-20
-25
-30
-35
1970 1975 1980 1985 1990 1995 2000 2005 2010 2015 2020 2025

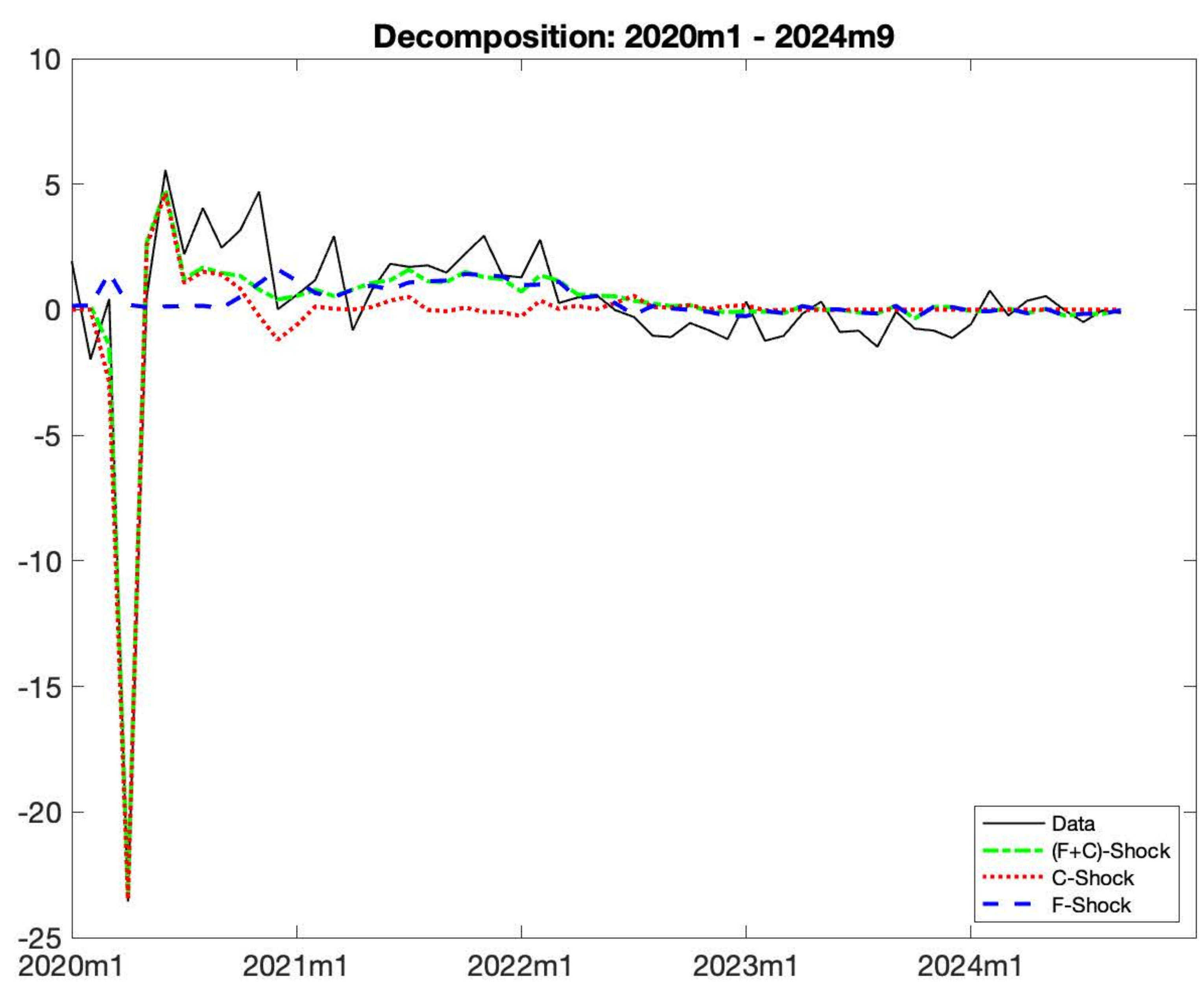

Decomposition: 2020m1 - 2024m9
10
5
0
-5
-10
-15
-20
-25
-30
-35
2020m1 2021m1 2022m1 2023m1 2024m1
Data
(F+C)-Shock
C-Shock
F-Shock

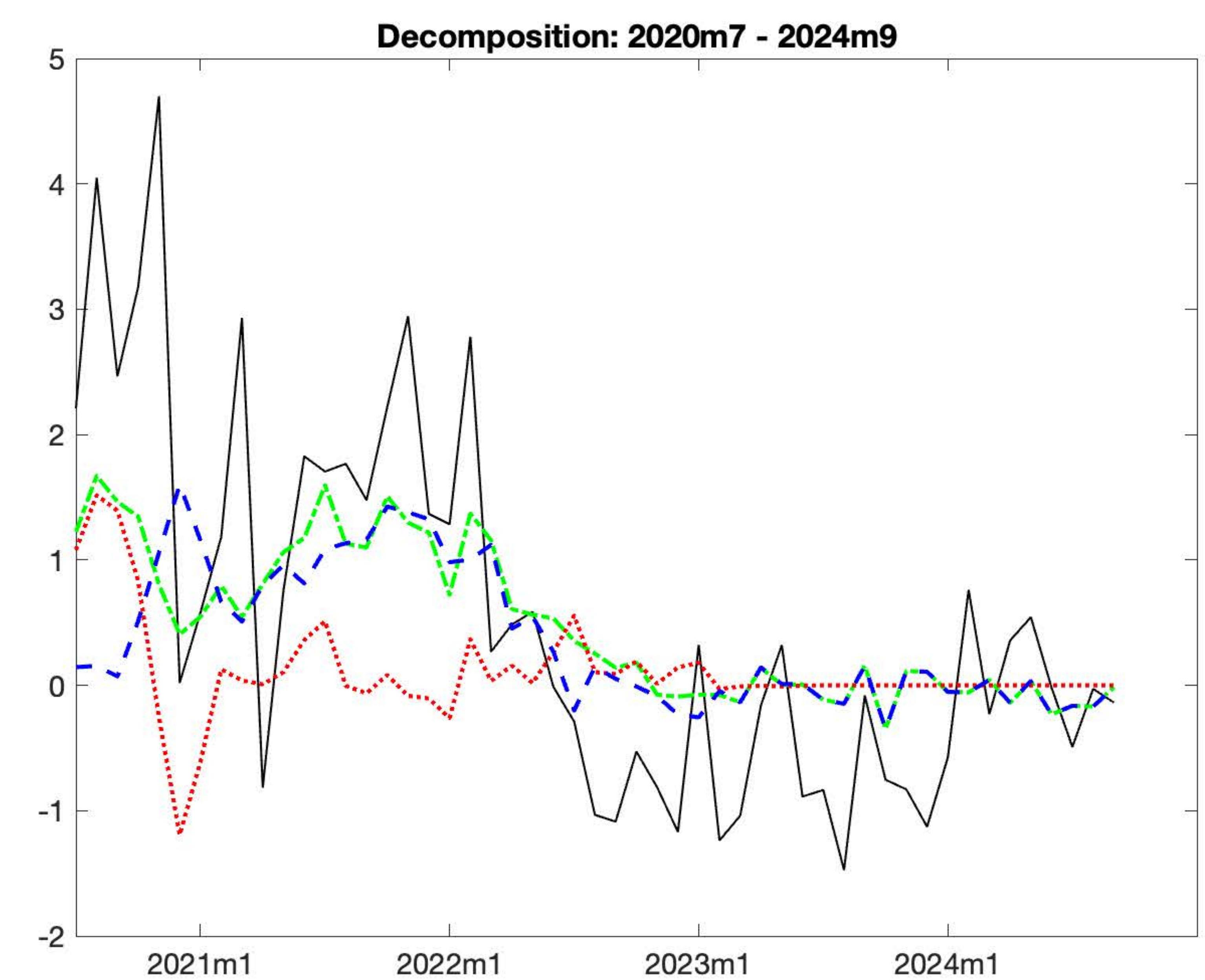

Decomposition: 2020m7 - 2024m9
3
2.5
2
1.5
1
0.5
0
-0.5
-1
-1.5
-2
2021m1 2022m1 2023m1 2024m1

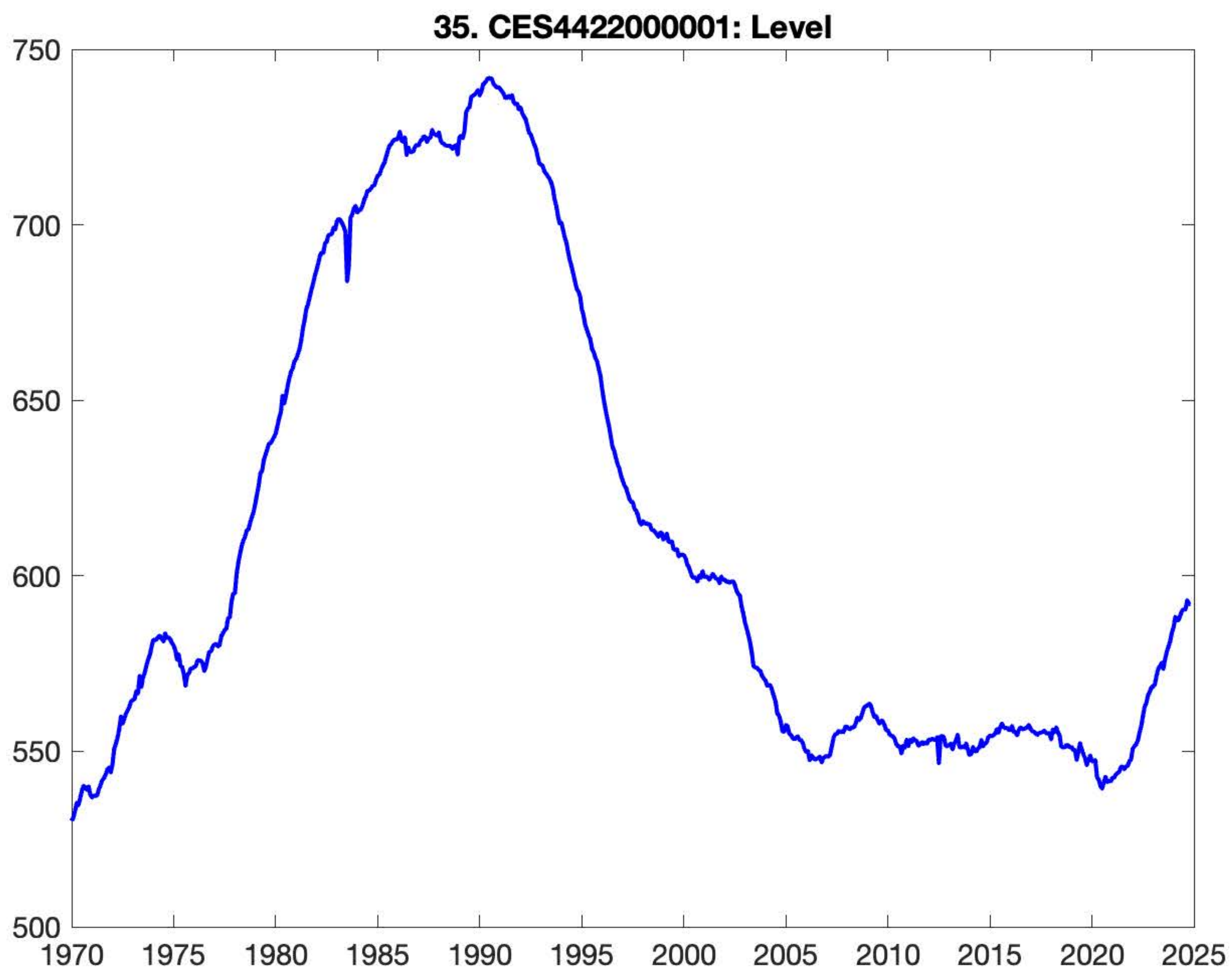

33. USTRADE: Level
×10^4
Transformed Value
Decomposition: 2020m1 - 2024m9
Decomposition: 2020m7 - 2024m9
Data
(F+C)-Shock
C-Shock
F-Shock
2020m1
2021m1
2022m1
2023m1
2024m1

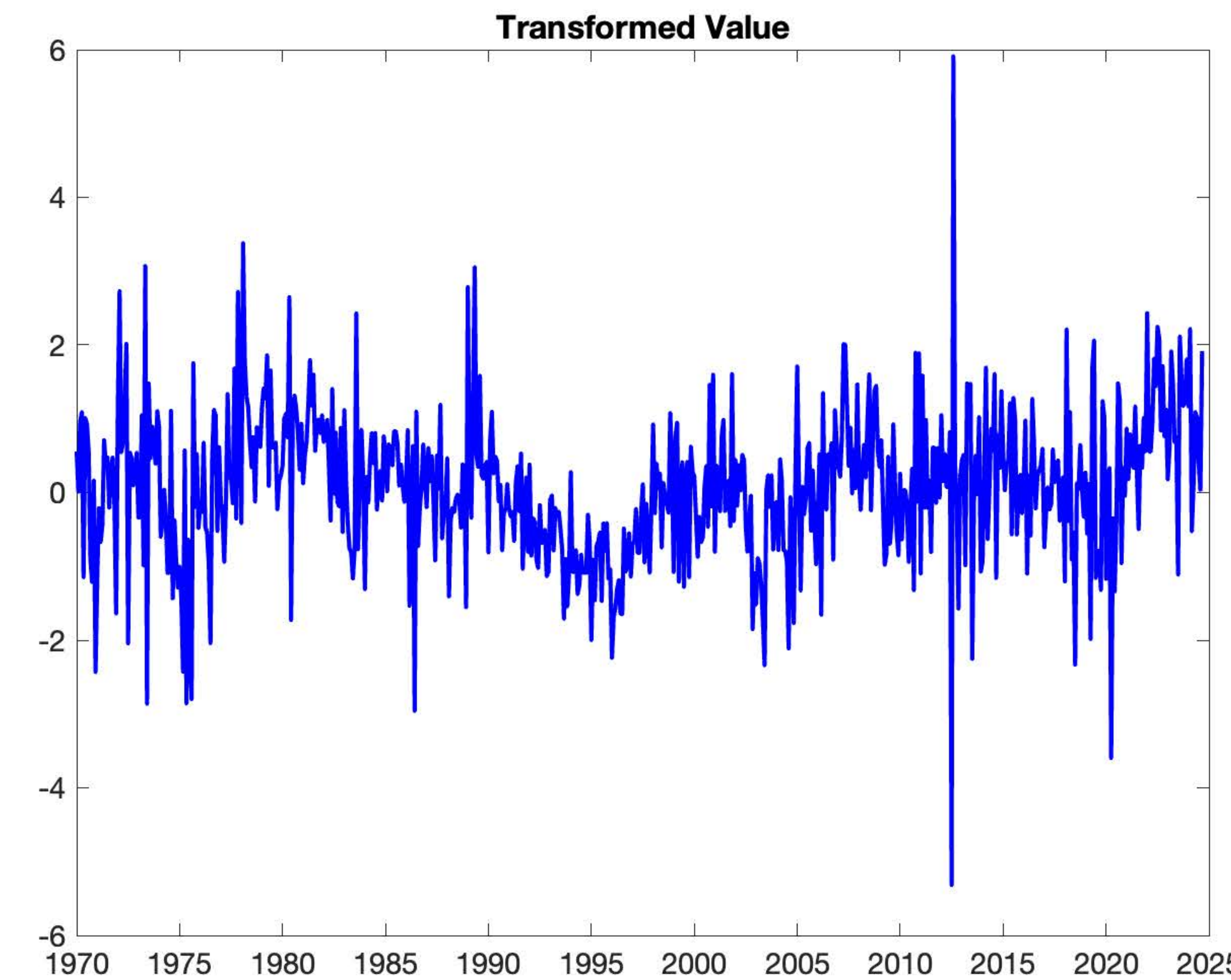

34. CES4300000001: Level

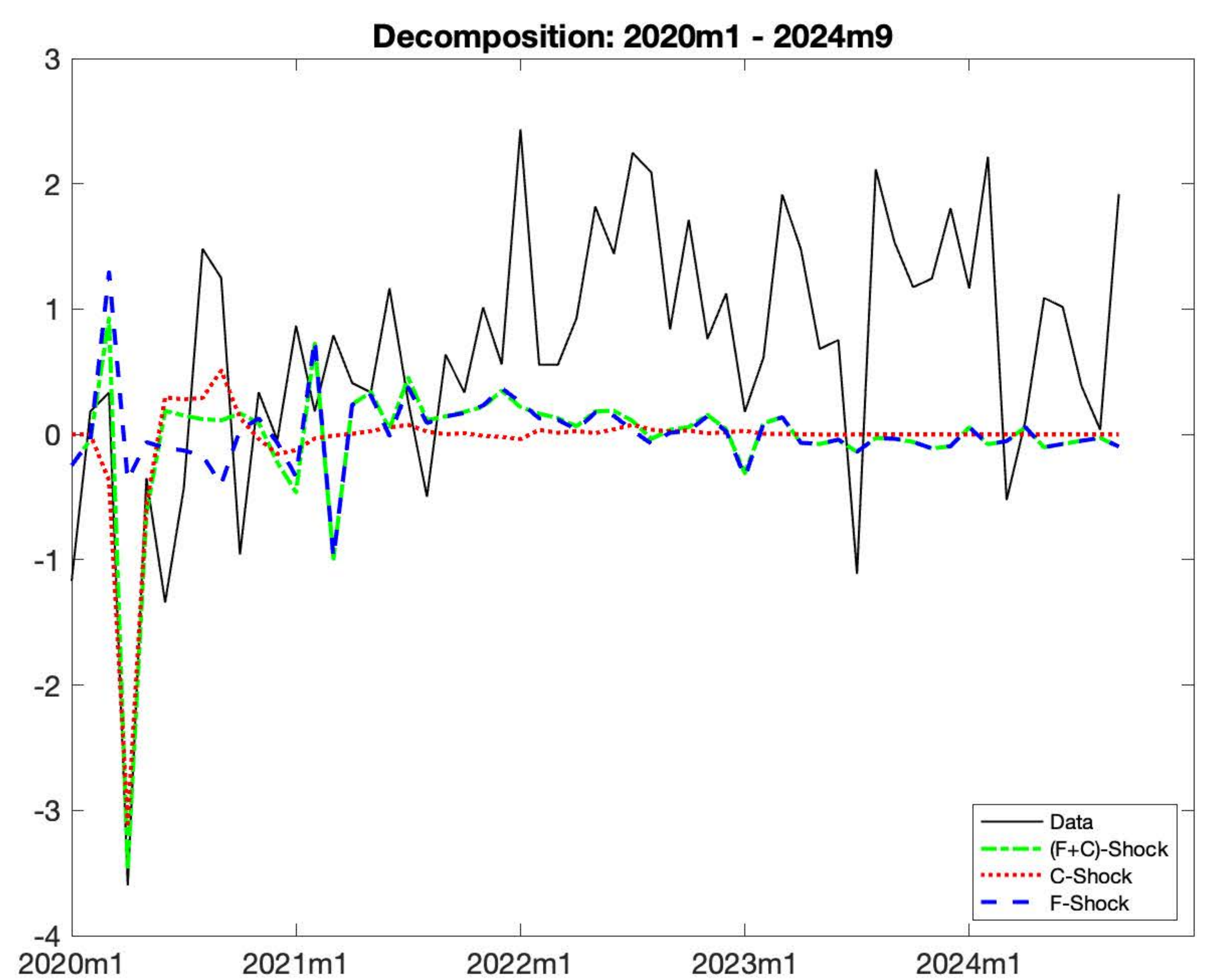

Transformed Value

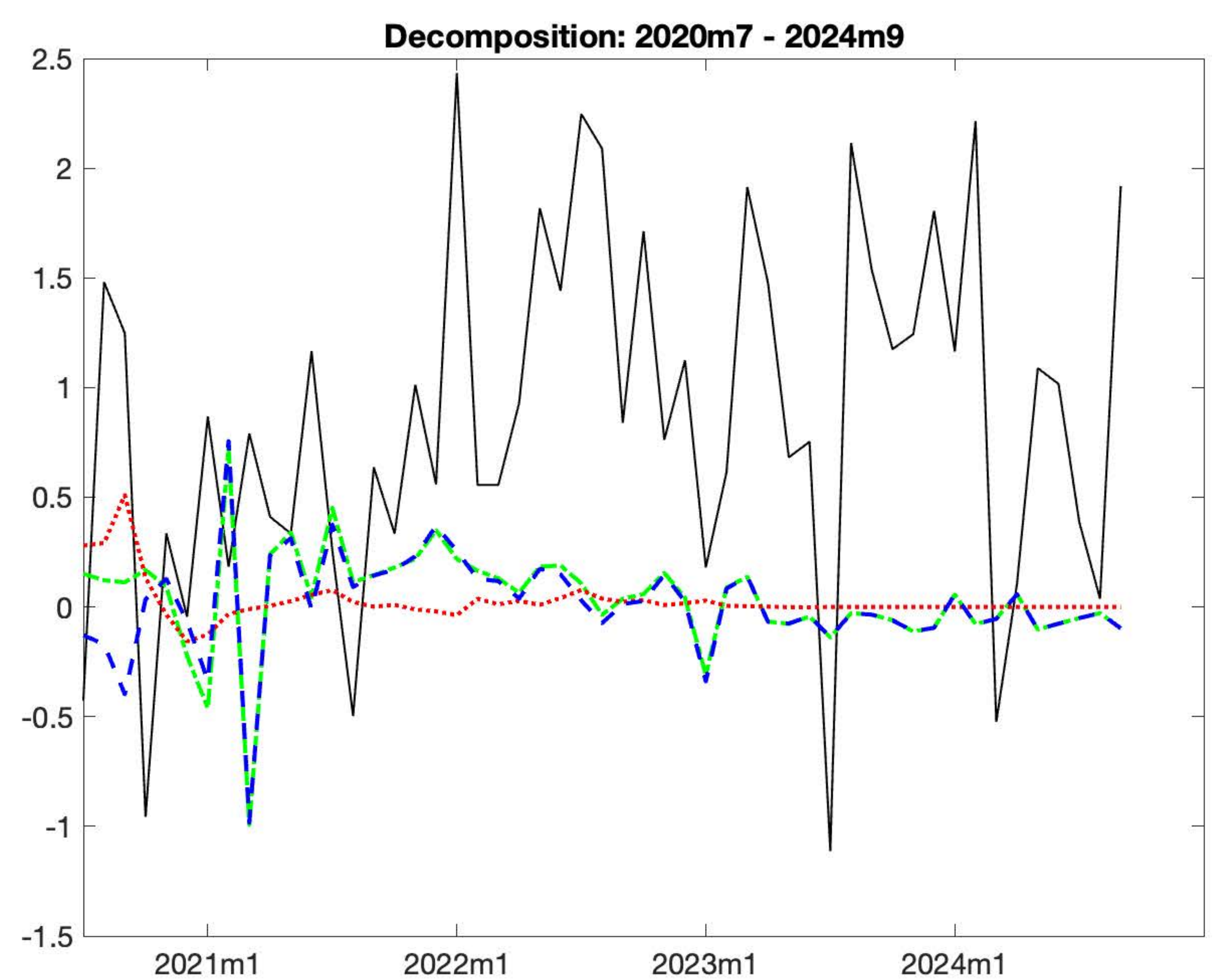

Decomposition: 2020m1 - 2024m9
Data
(F+C)-Shock
C-Shock
F-Shock

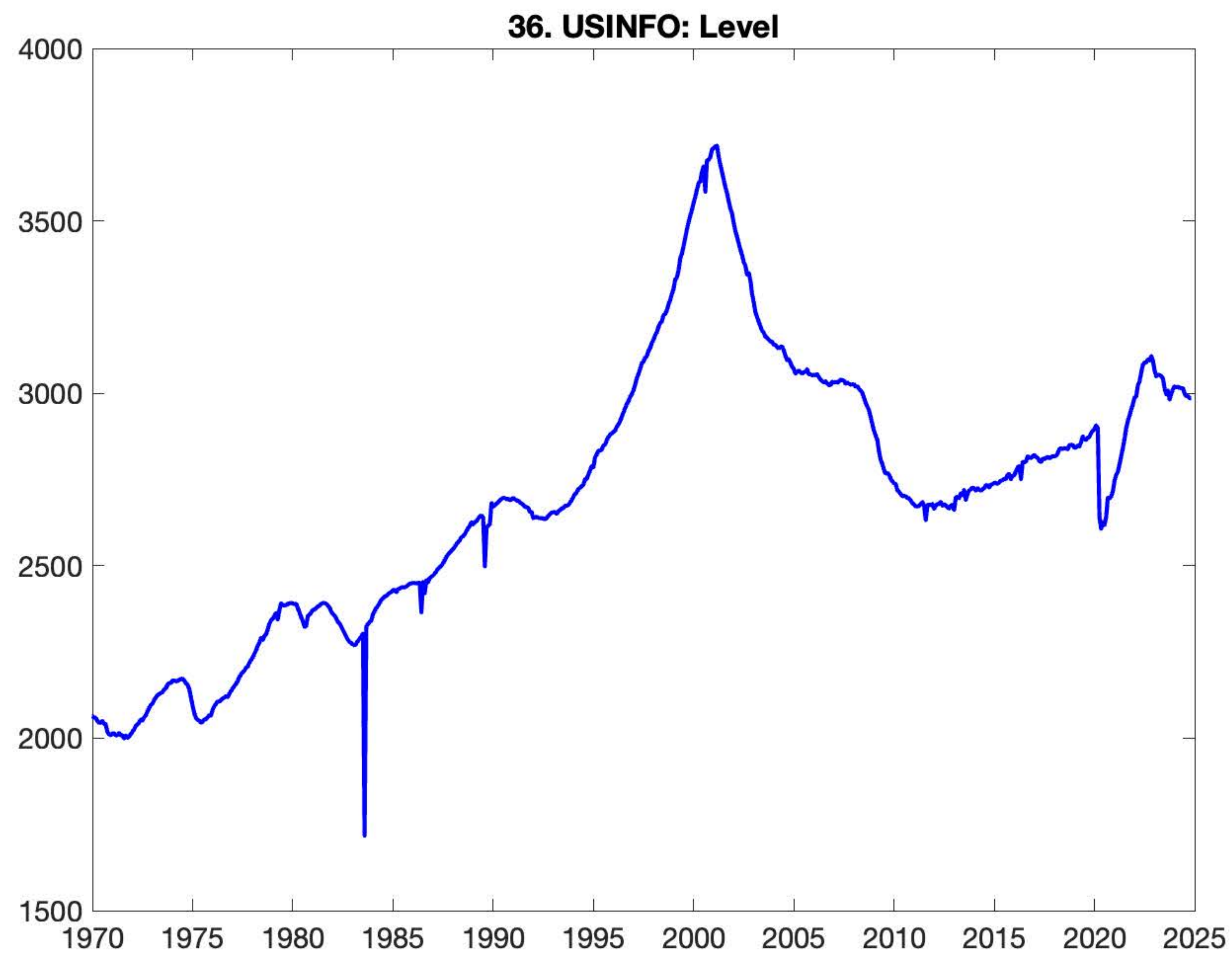

Decomposition: 2020m7 - 2024m9

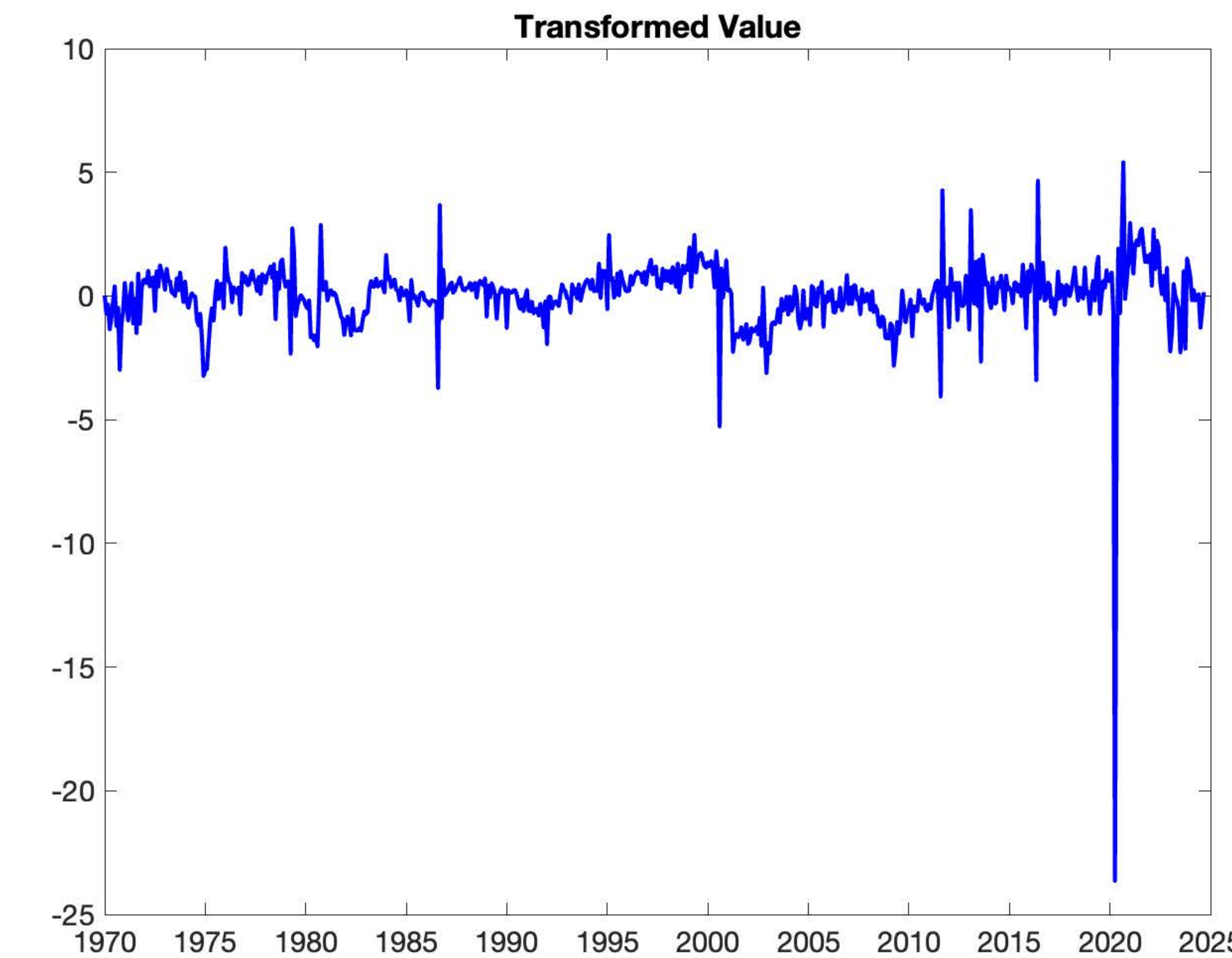

35. CES4422000001: Level

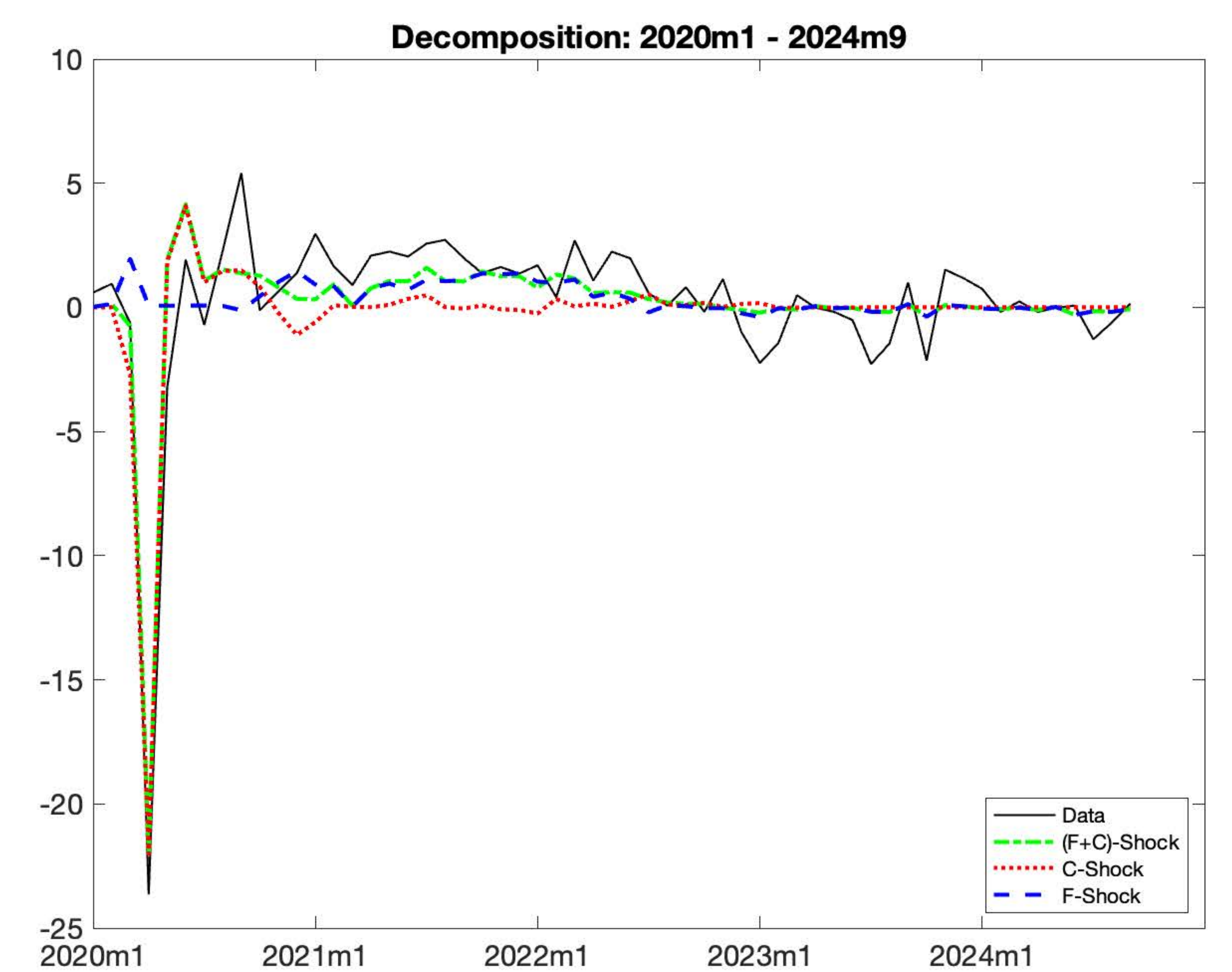

Transformed Value

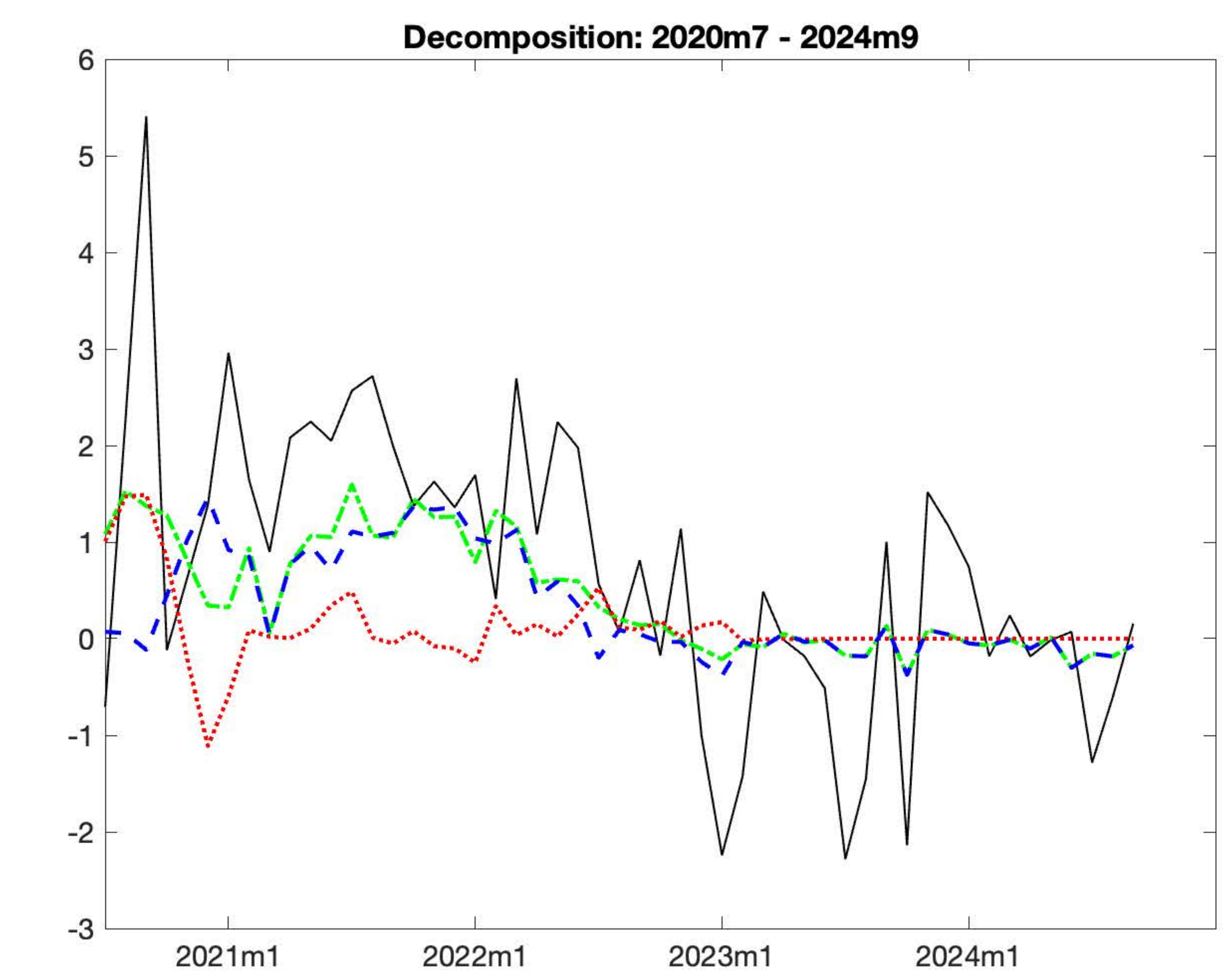

Decomposition: 2020m1 - 2024m9
Data
(F+C)-Shock
C-Shock
F-Shock

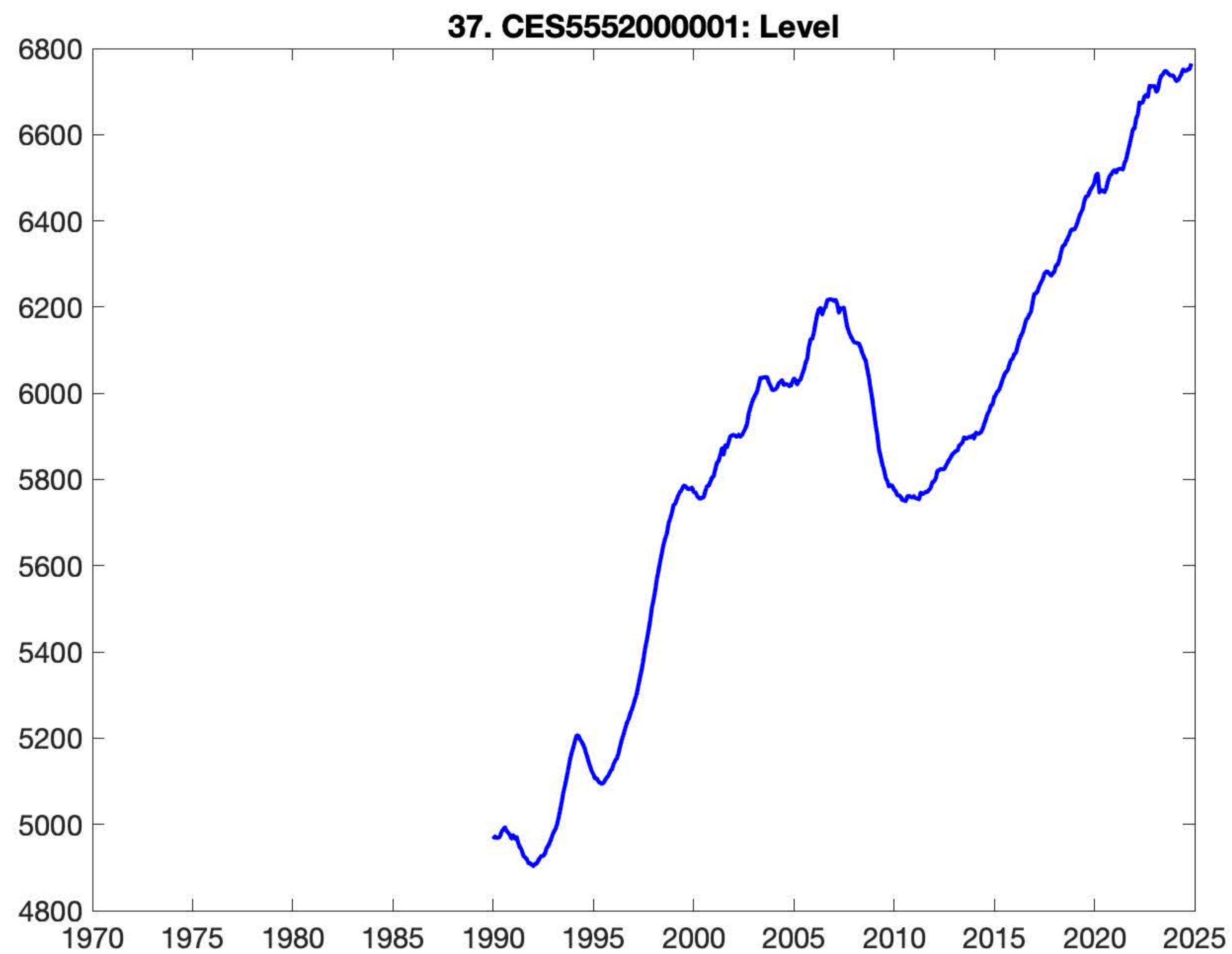

Decomposition: 2020m7 - 2024m9

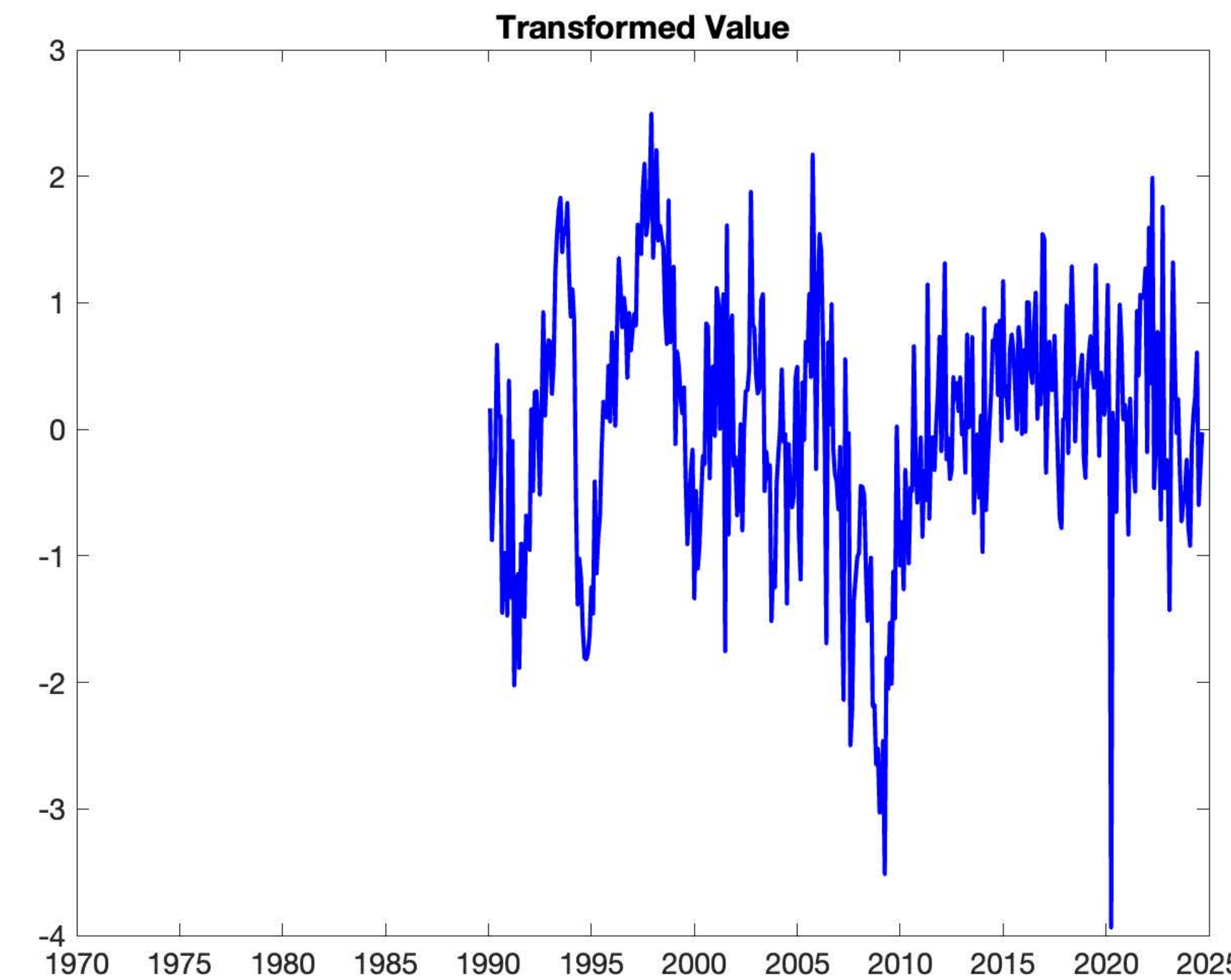

36. USINFO: Level

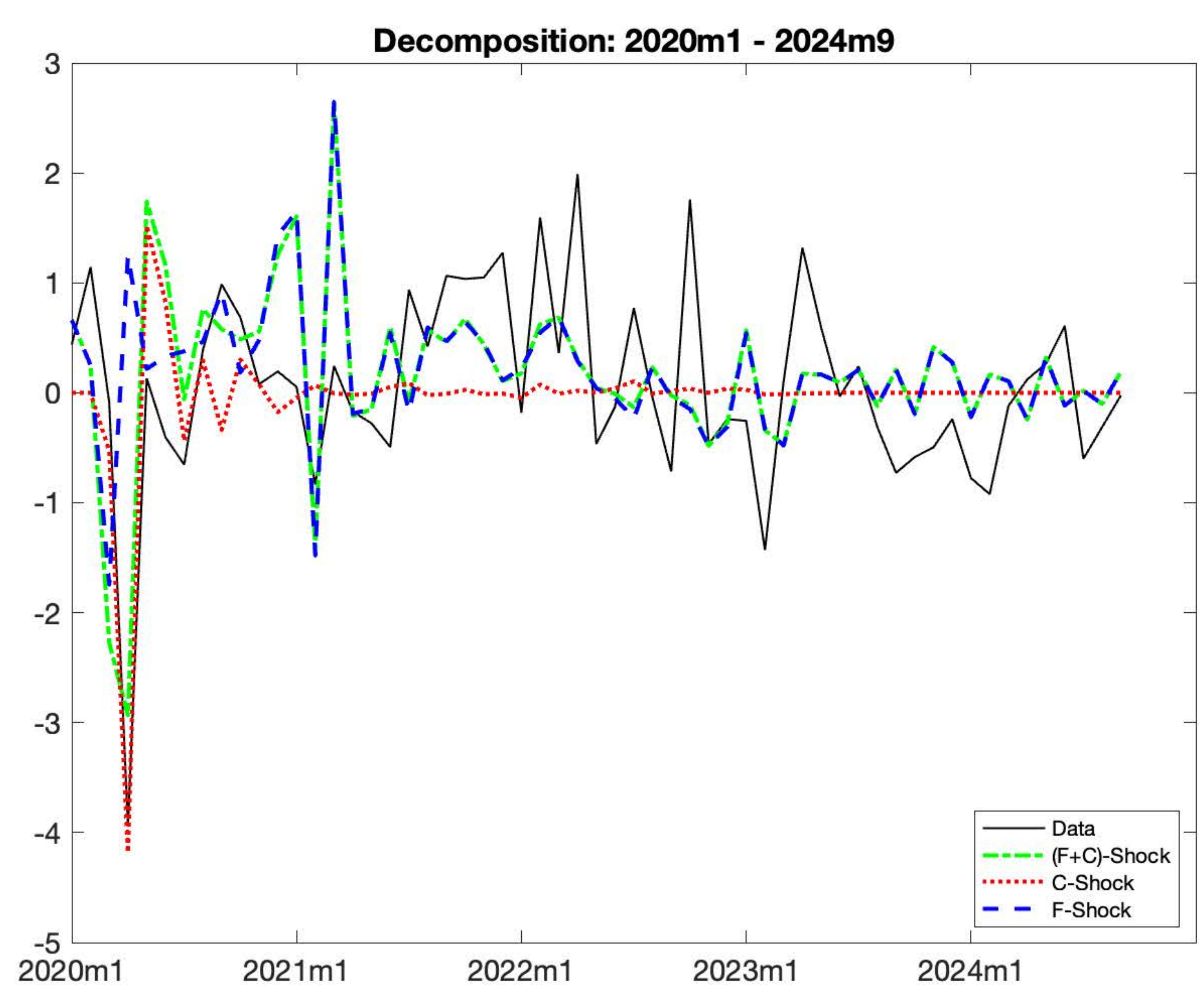

Transformed Value

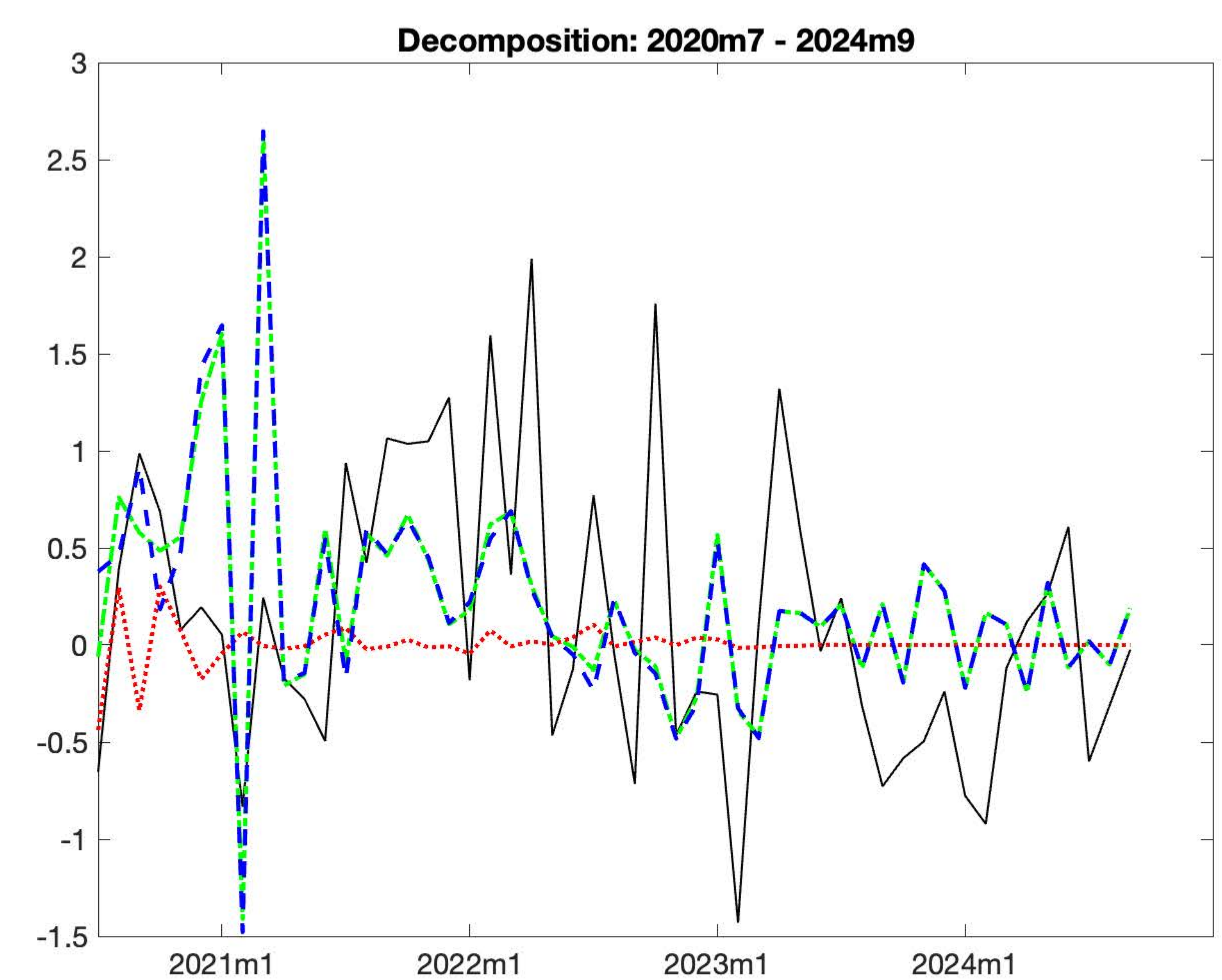

Decomposition: 2020m1 - 2024m9
Data
(F+C)-Shock
C-Shock
F-Shock

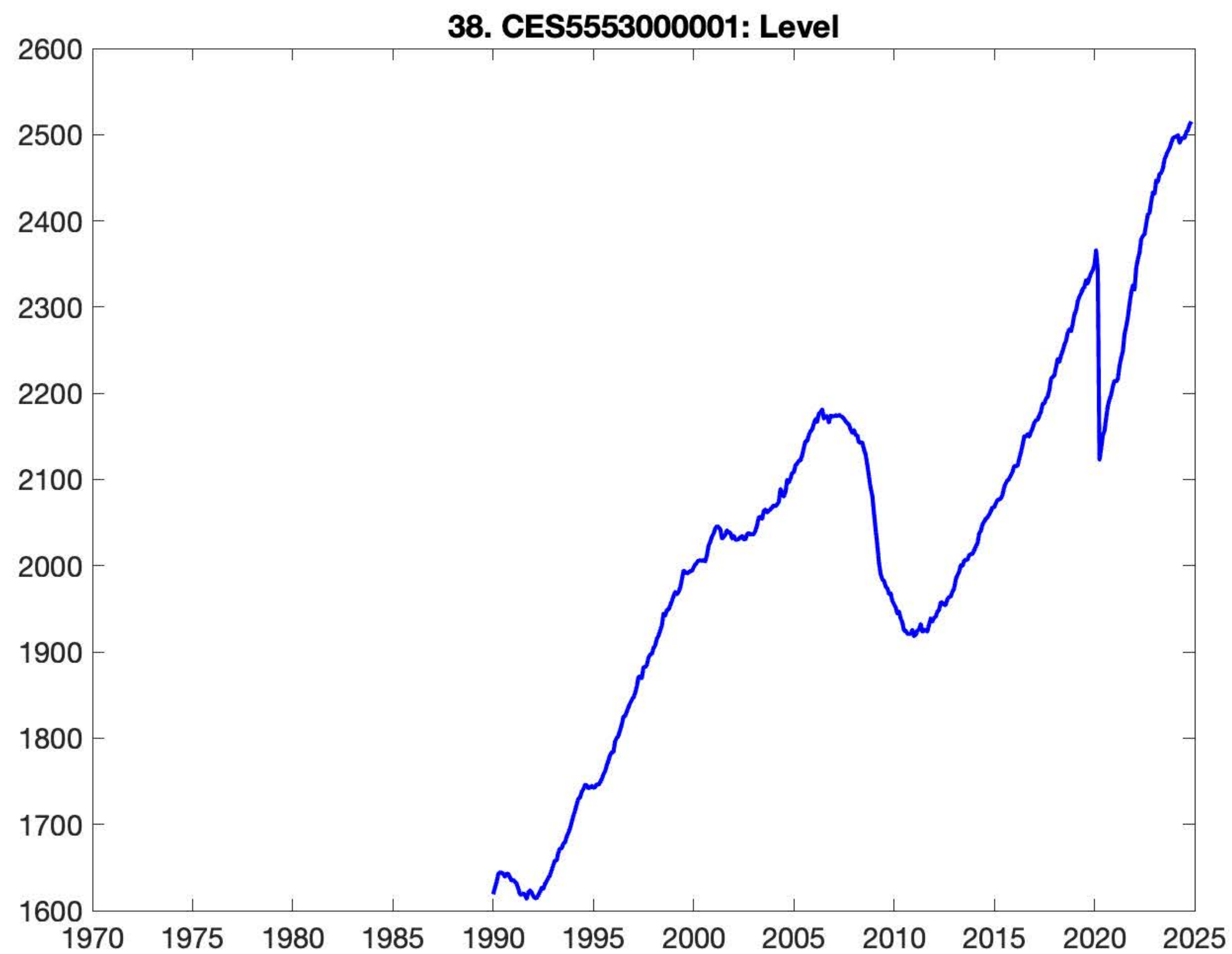

Decomposition: 2020m7 - 2024m9

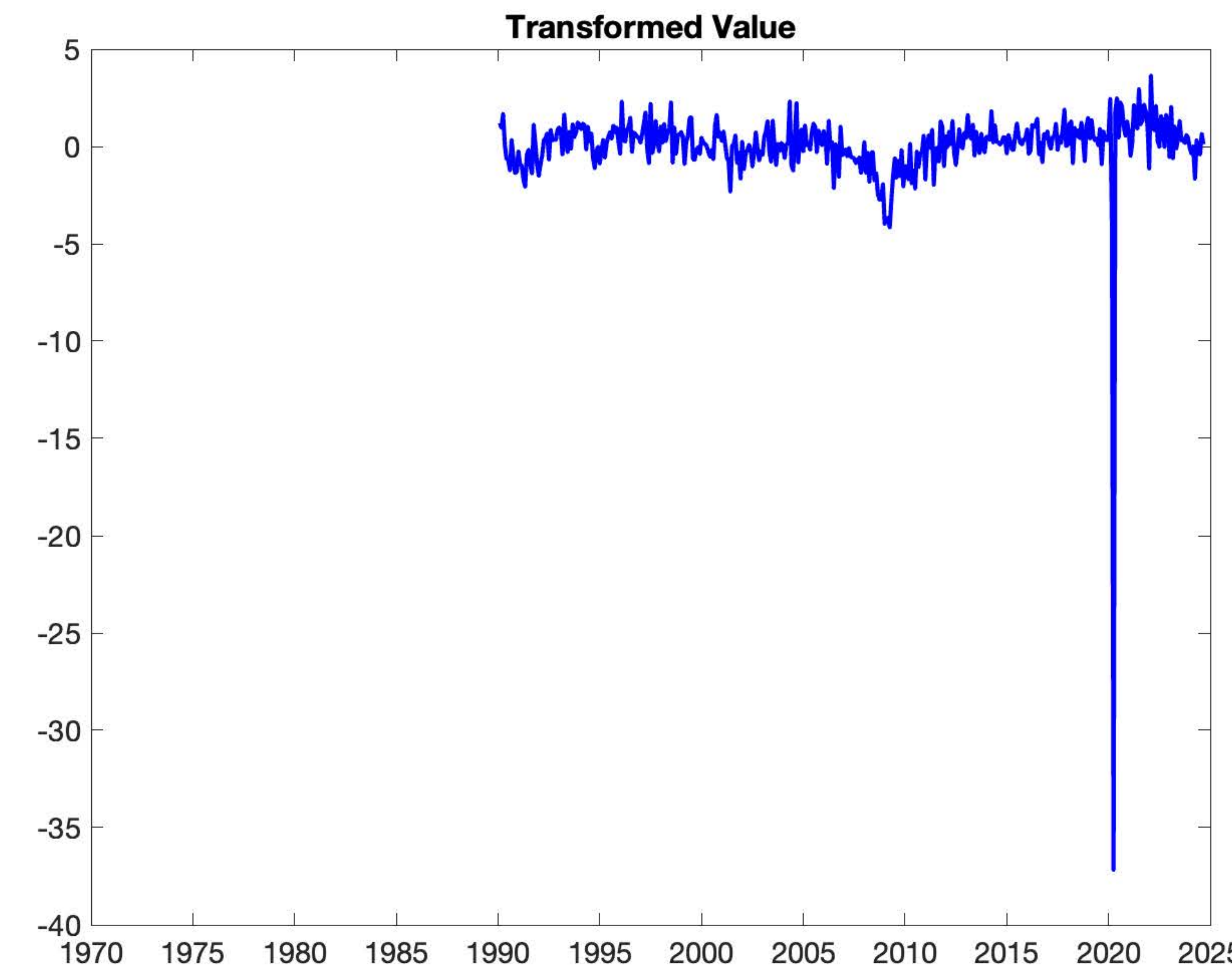

37. CES5552000001: Level
6800
6600
6400
6200
6000
5800
5600
5400
5200
5000
4800
1970 1975 1980 1985 1990 1995 2000 2005 2010 2015 2020 2025

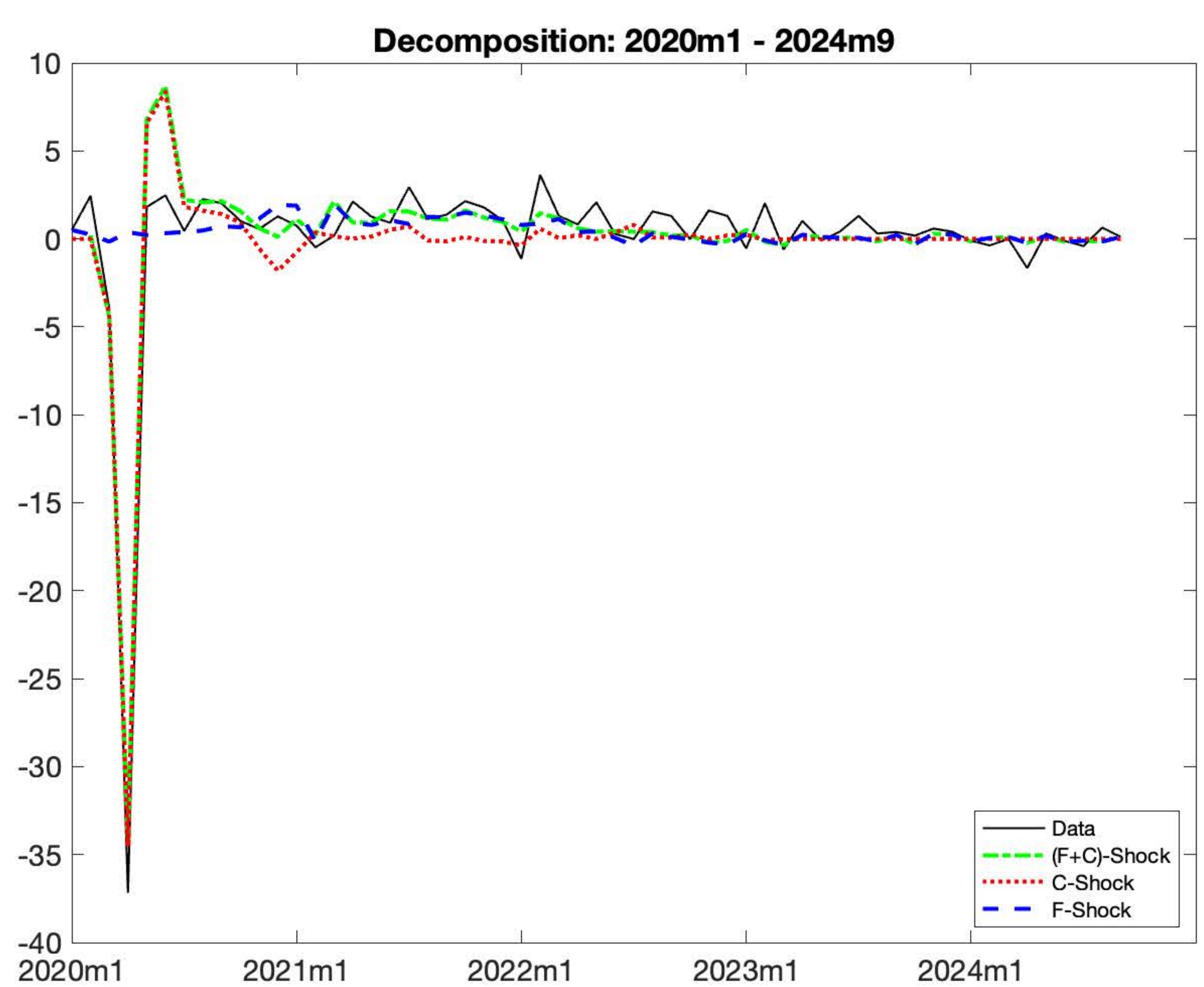

Transformed Value
3
2
1
0
-1
-2
-3
-4
1970 1975 1980 1985 1990 1995 2000 2005 2010 2015 2020 2025

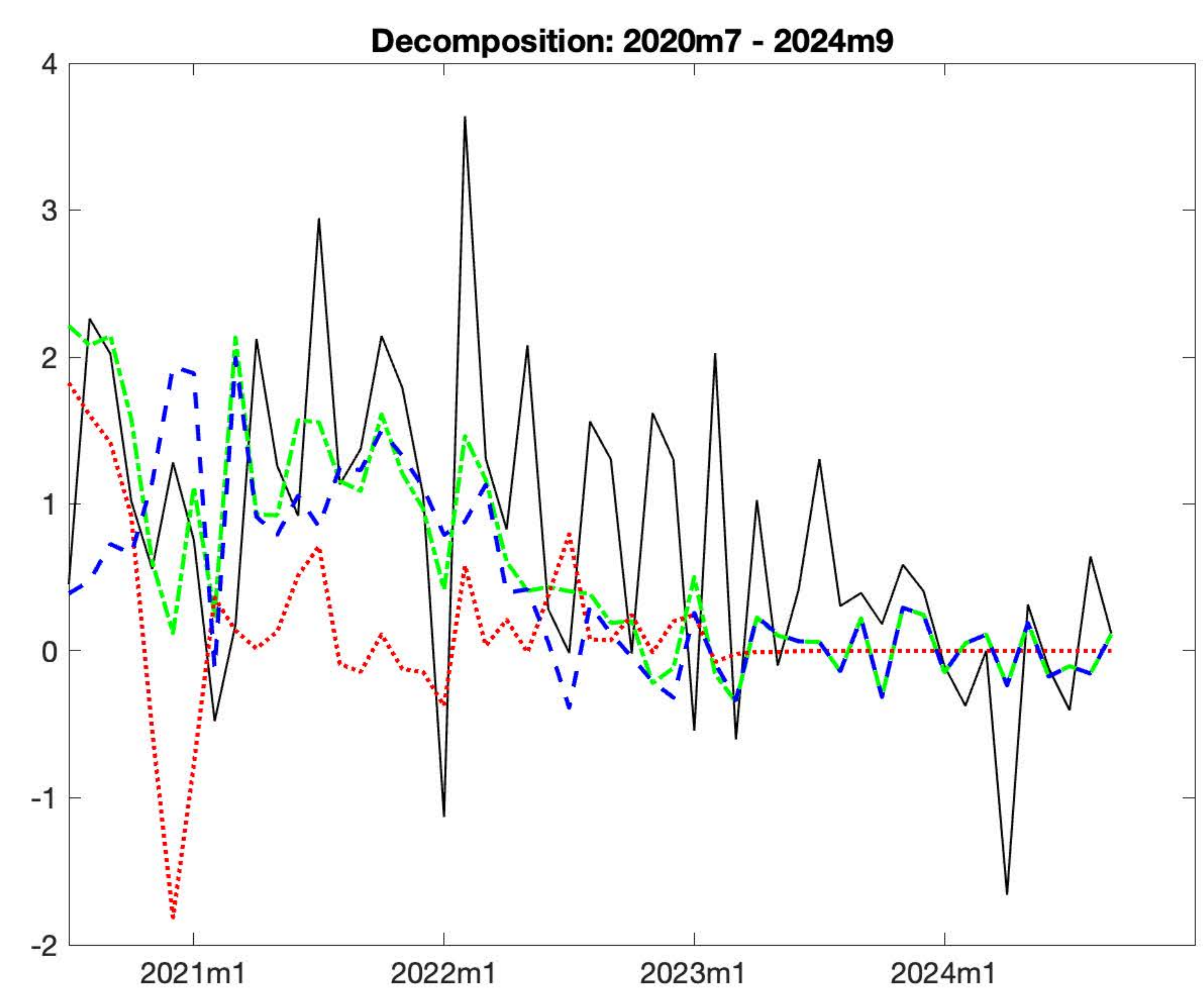

Decomposition: 2020m1 - 2024m9
3
2
1
0
-1
-2
-3
-4
-5
2020m1 2021m1 2022m1 2023m1 2024m1
Data
(F+C)-Shock
C-Shock
F-Shock

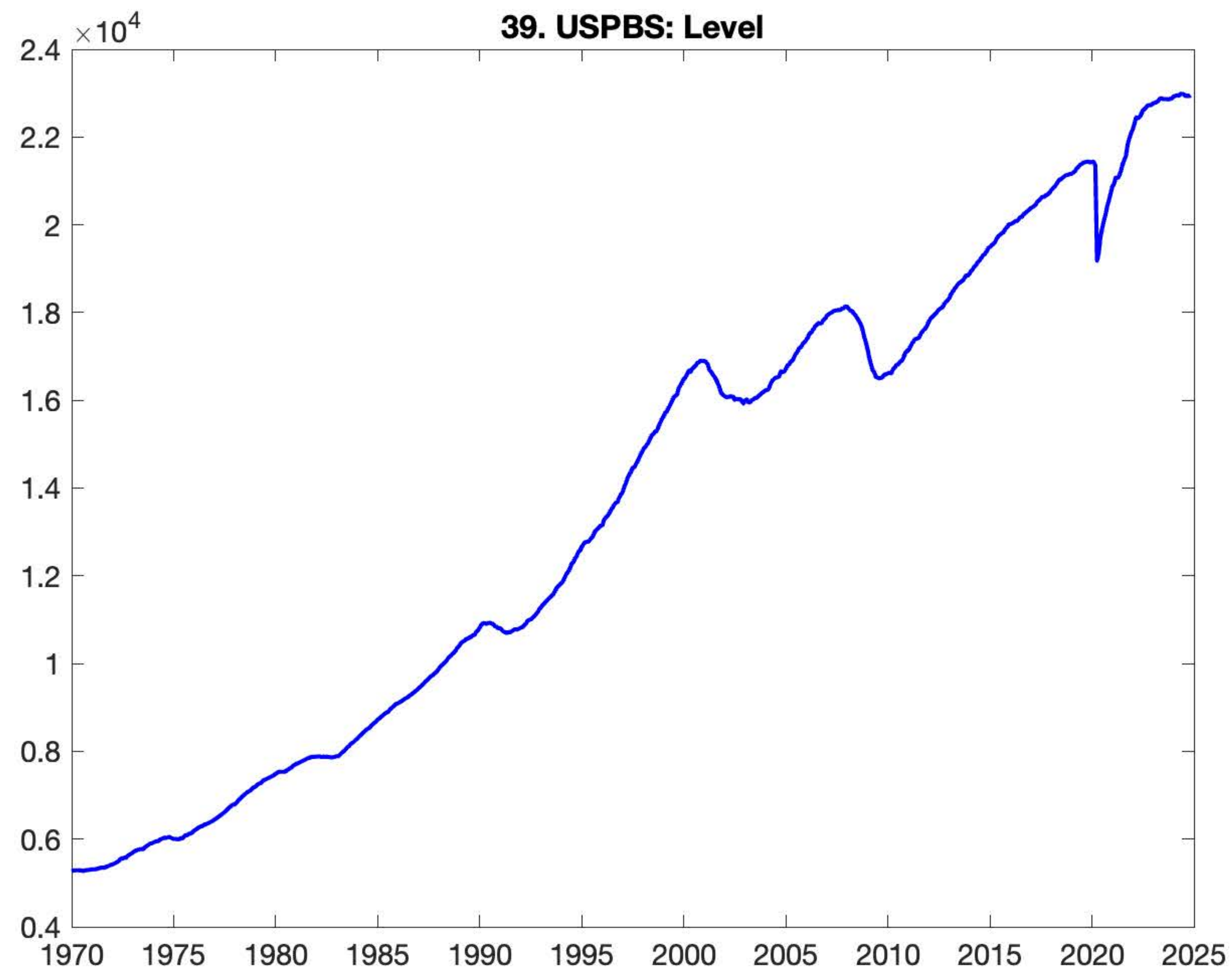

Decomposition: 2020m7 - 2024m9
3
2.5
2
1.5
1
0.5
0
-0.5
-1
-1.5
2021m1 2022m1 2023m1 2024m1

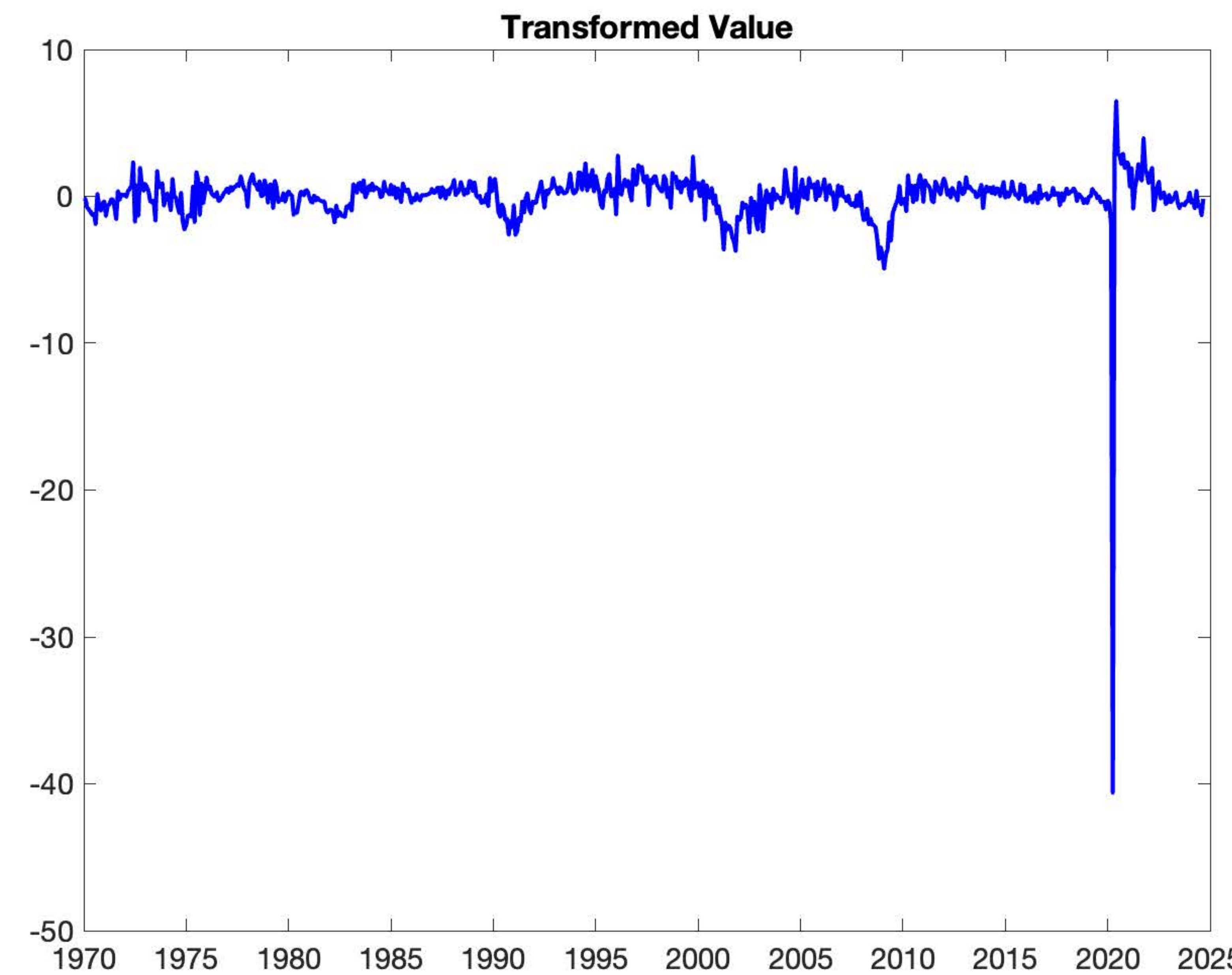

38. CES5553000001: Level
2600
2500
2400
2300
2200
2100
2000
1900
1800
1700
1600
1970 1975 1980 1985 1990 1995 2000 2005 2010 2015 2020 2025

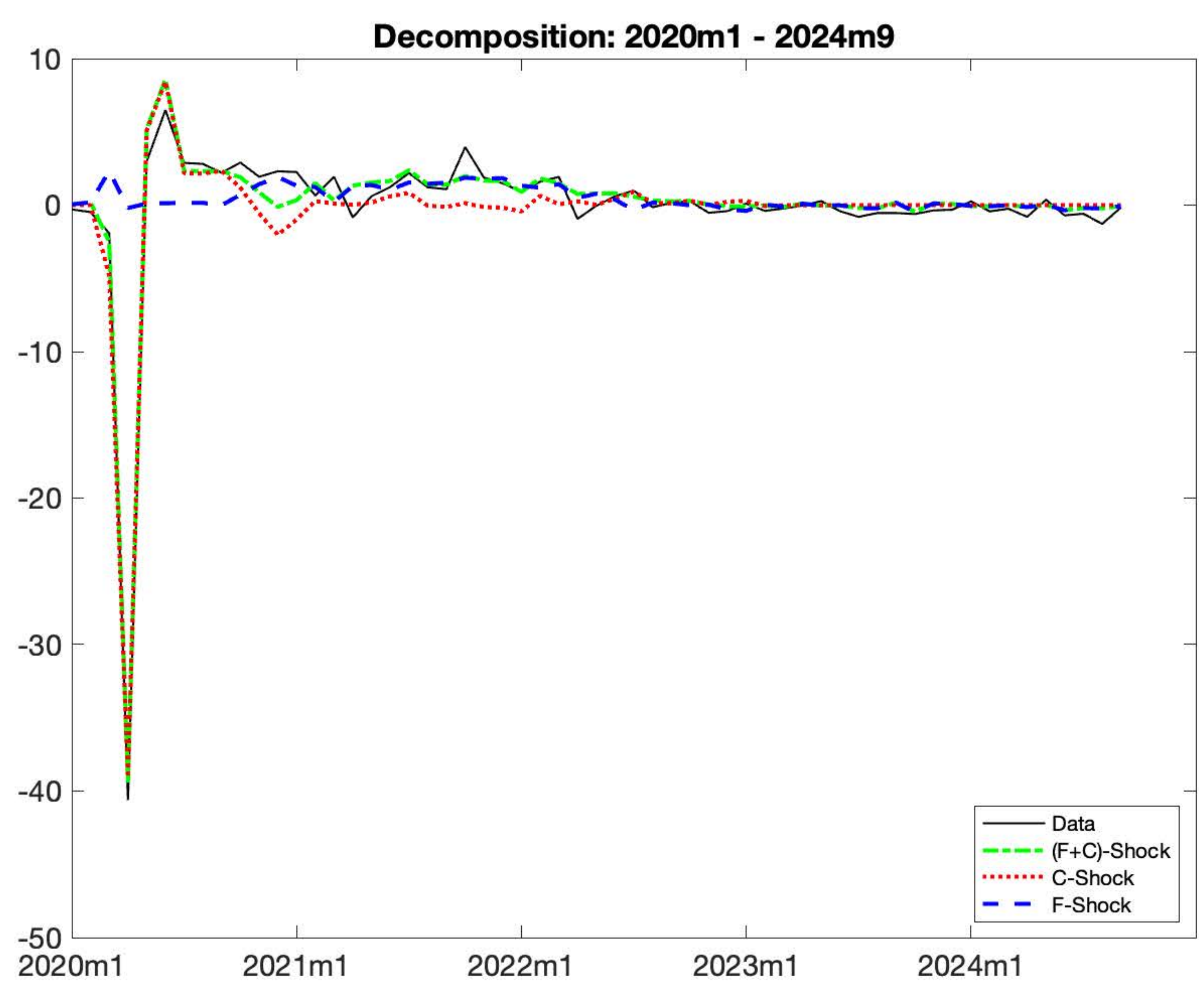

Transformed Value
5
0
-5
-10
-15
-20
-25
-30
-35
-40
1970 1975 1980 1985 1990 1995 2000 2005 2010 2015 2020 2025

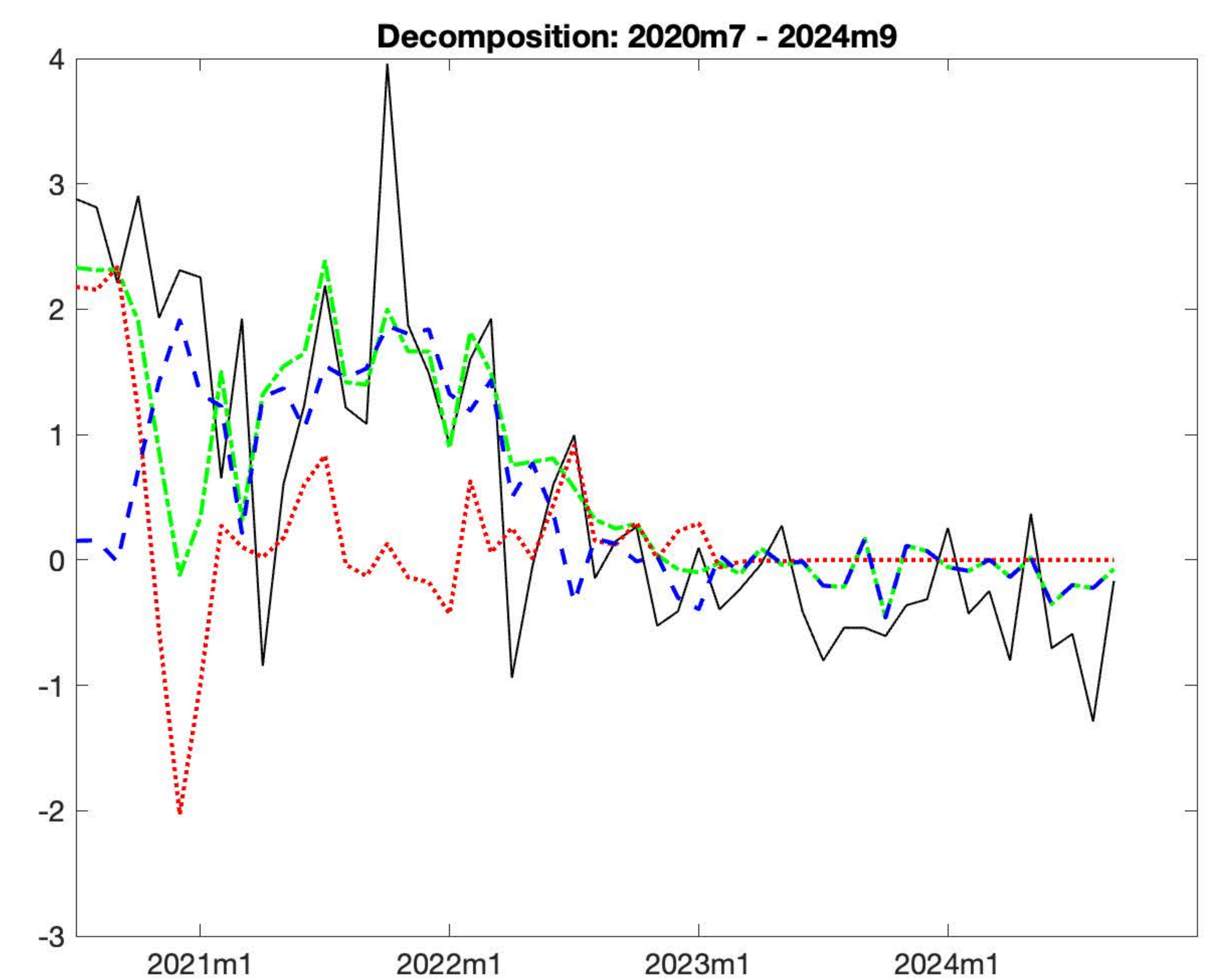

Decomposition: 2020m1 - 2024m9
10
5
0
-5
-10
-15
-20
-25
-30
-35
-40
2020m1 2021m1 2022m1 2023m1 2024m1
Data
(F+C)-Shock
C-Shock
F-Shock

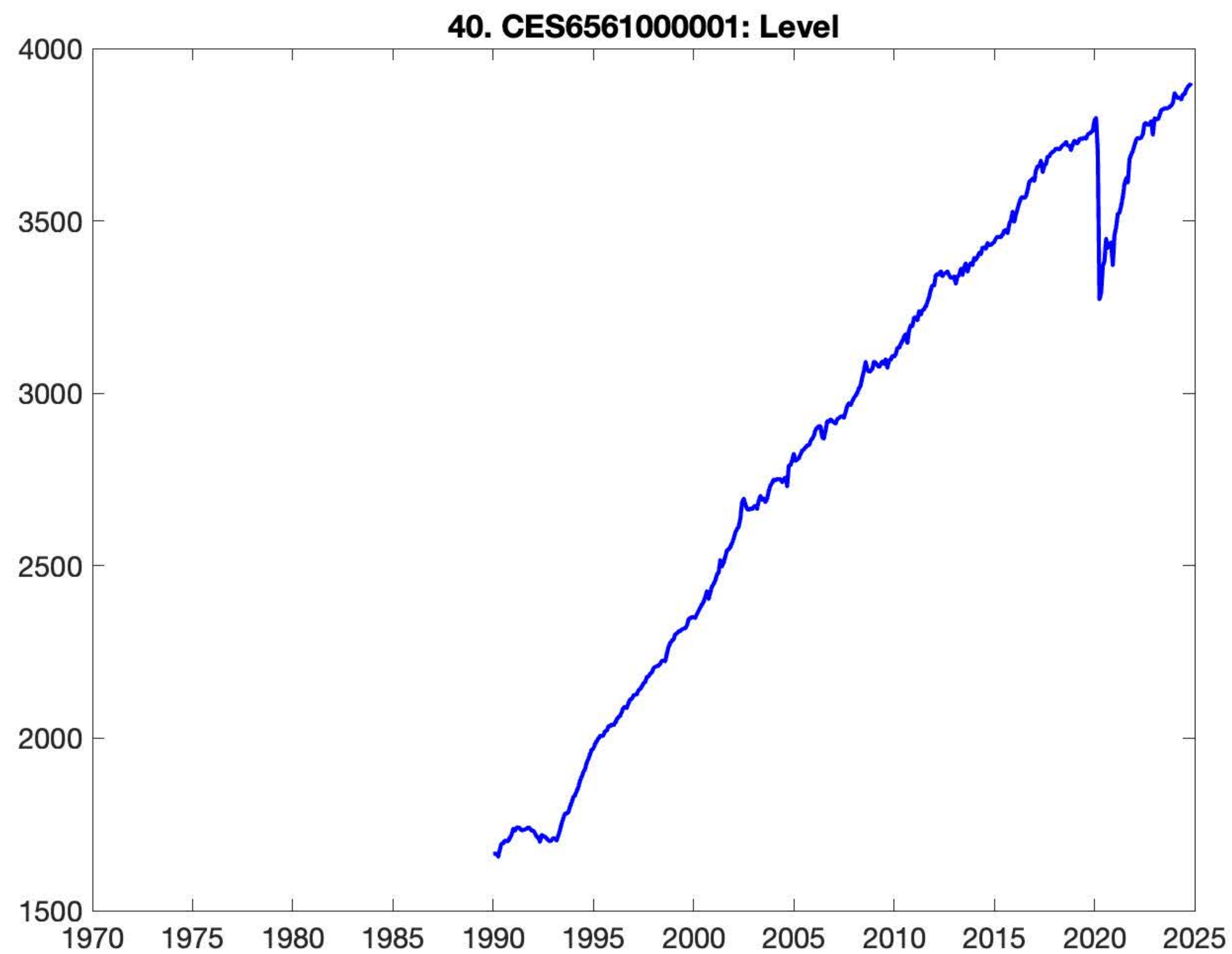

Decomposition: 2020m7 - 2024m9
4
3
2
1
0
-1
-2
2021m1 2022m1 2023m1 2024m1

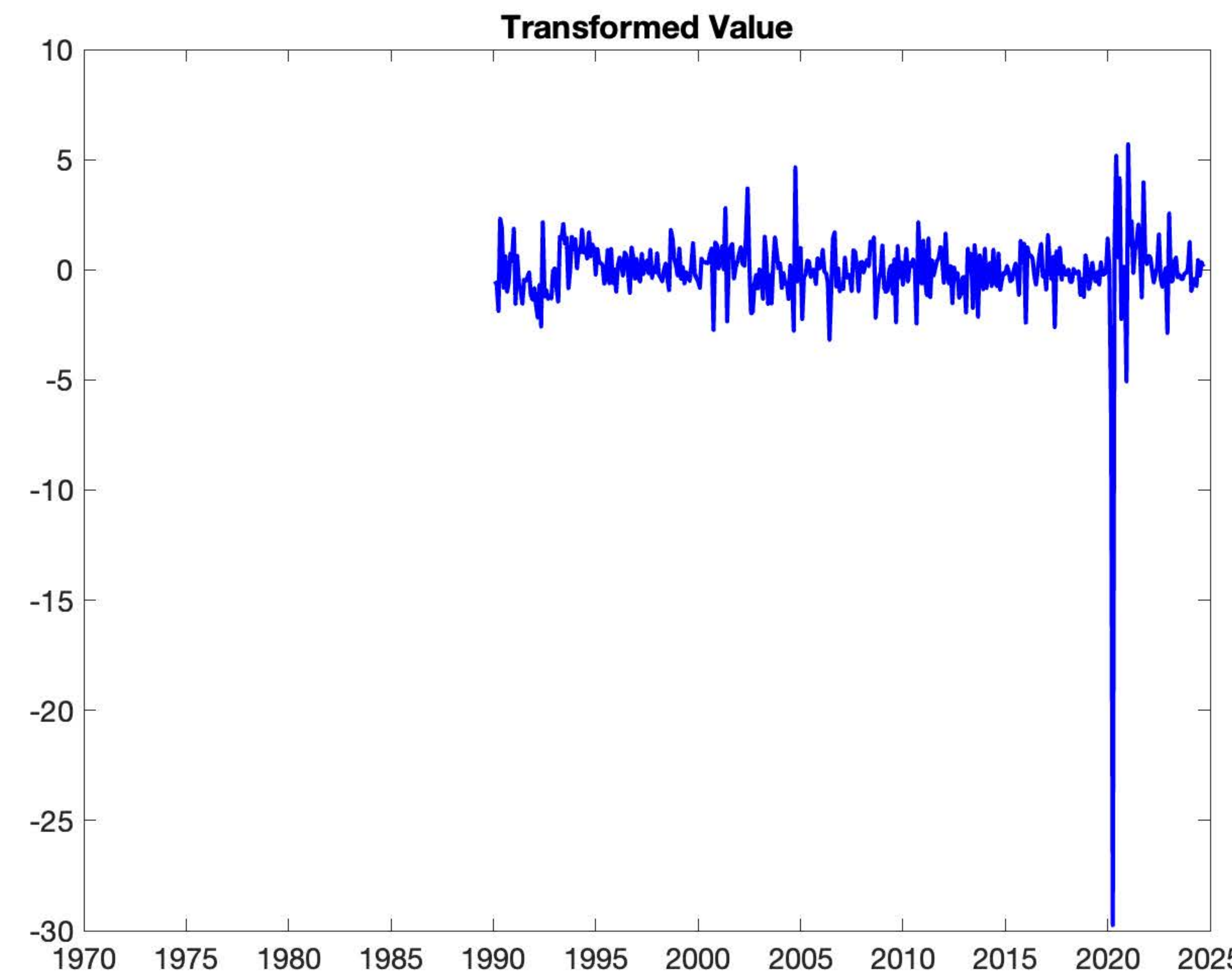

39. USPBS: Level
×10^4
2.4
2.2
2
1.8
1.6
1.4
1.2
1
0.8
0.6
0.4
1970 1975 1980 1985 1990 1995 2000 2005 2010 2015 2020 2025

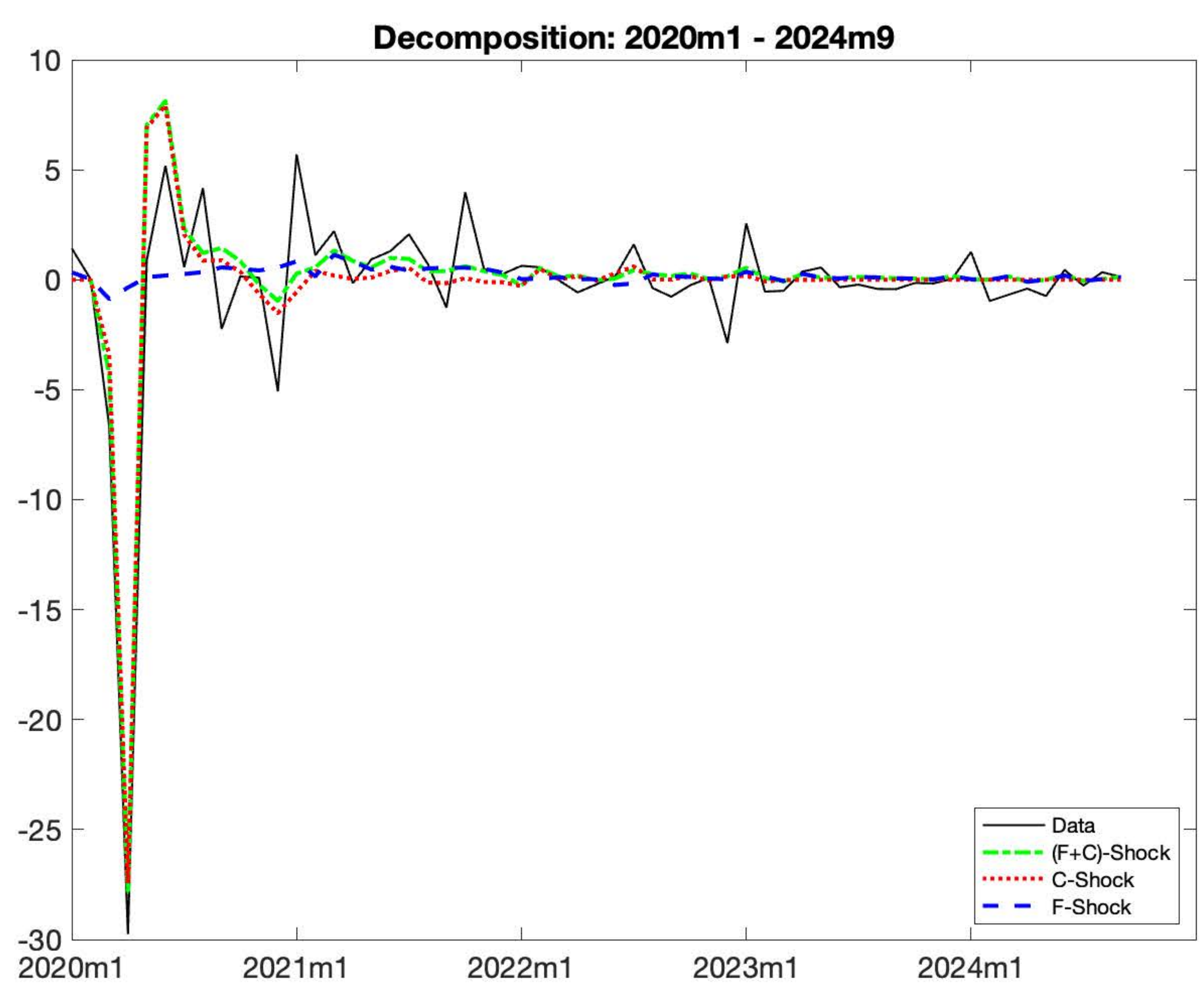

Transformed Value
10
0
-10
-20
-30
-40
-50
1970 1975 1980 1985 1990 1995 2000 2005 2010 2015 2020 2025

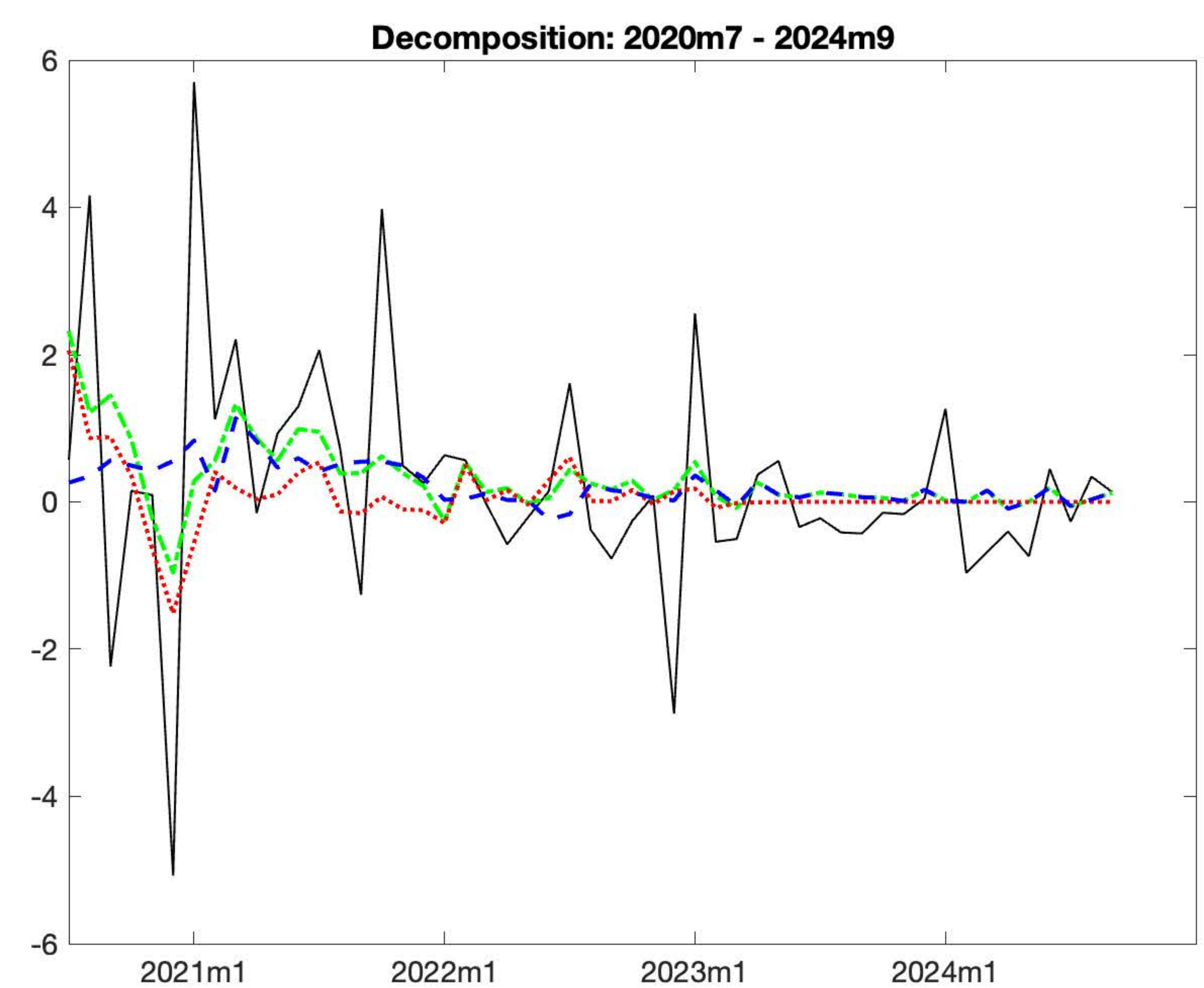

Decomposition: 2020m1 - 2024m9
10
0
-10
-20
-30
-40
-50
2020m1 2021m1 2022m1 2023m1 2024m1
Data
(F+C)-Shock
C-Shock
F-Shock

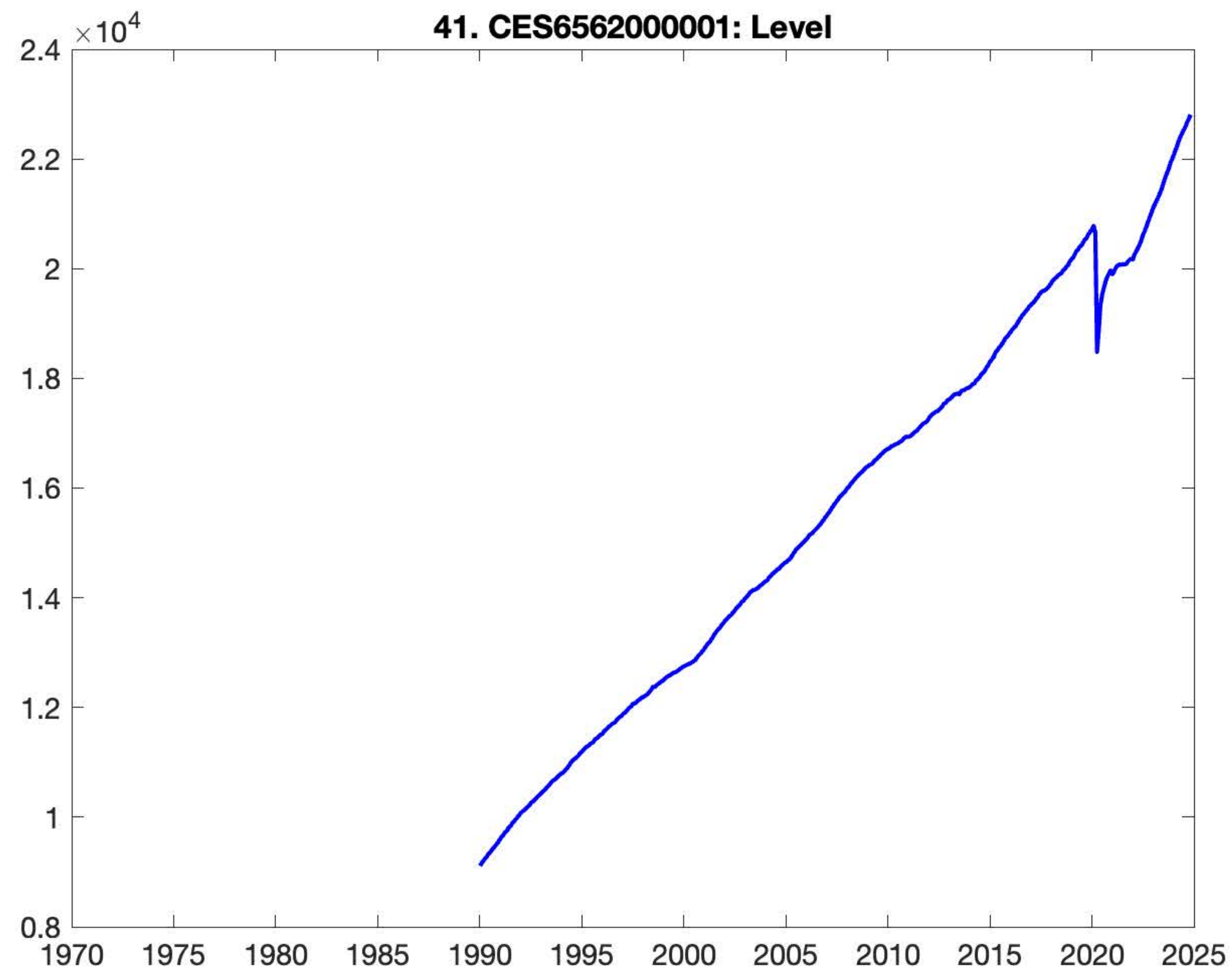

Decomposition: 2020m7 - 2024m9
4
3
2
1
0
-1
-2
-3
2021m1 2022m1 2023m1 2024m1

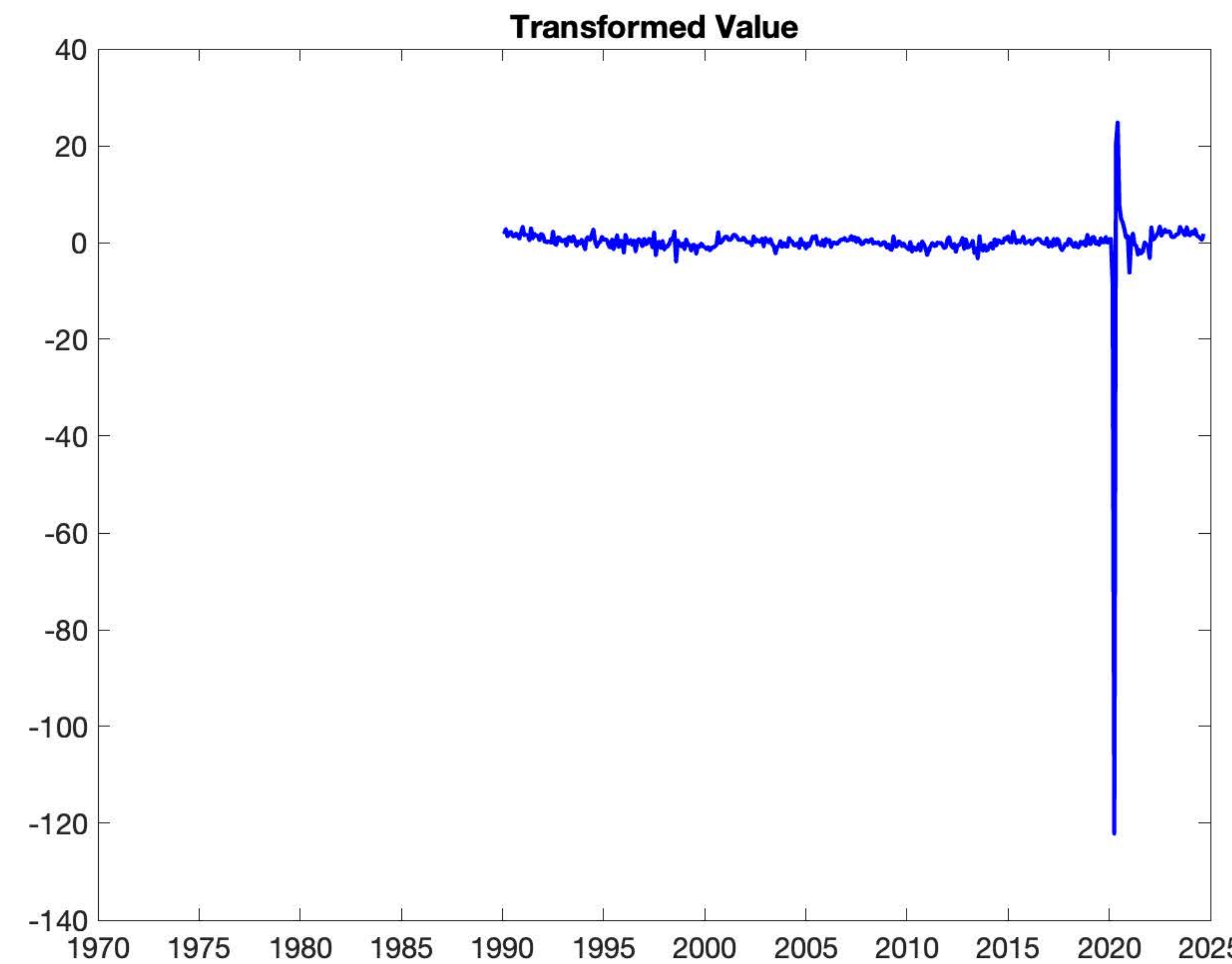

40. CES6561000001: Level
4000
3500
3000
2500
2000
1500
1970
1975
1980
1985
1990
1995
2000
2005
2010
2015
2020
2025

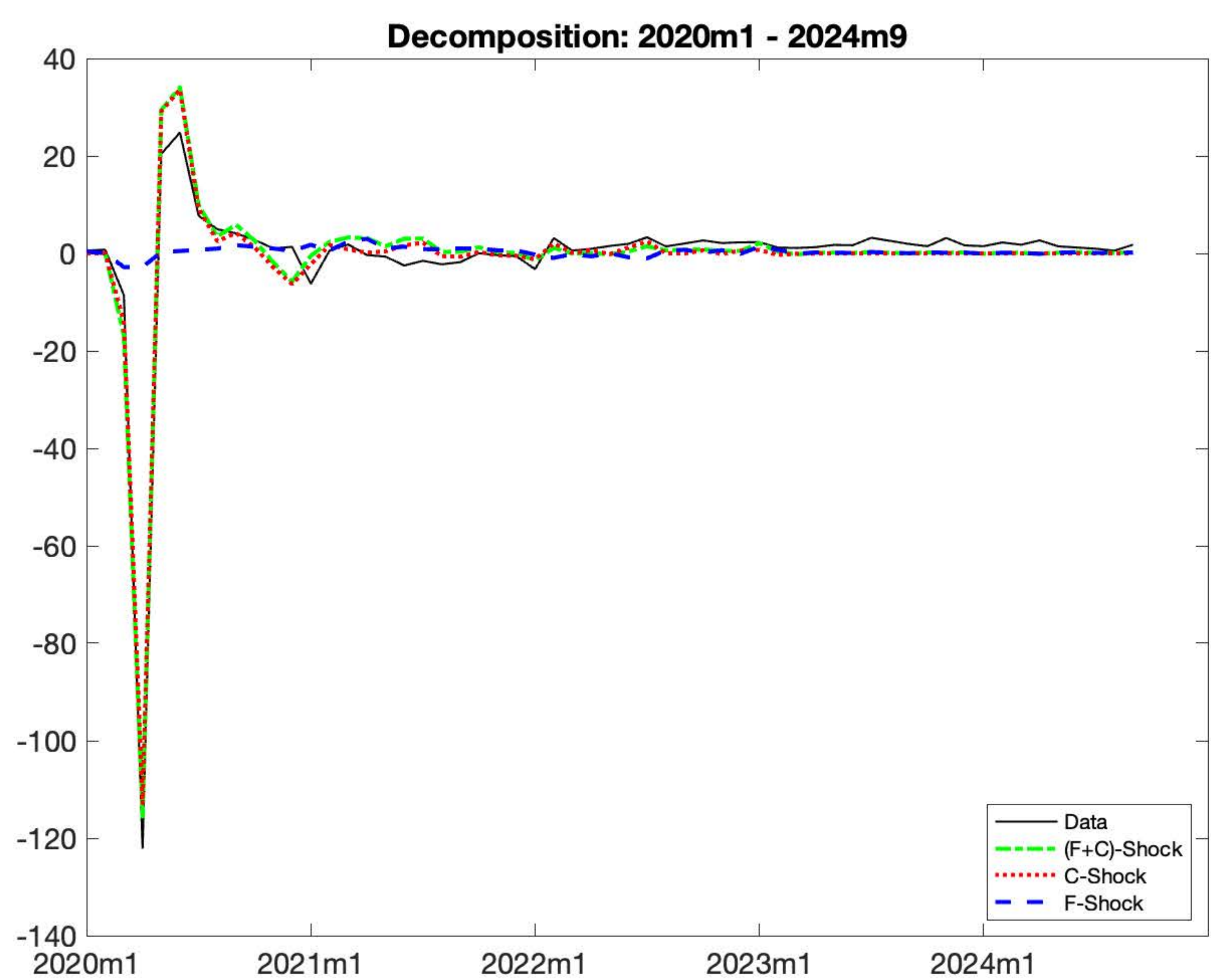

Transformed Value
10
5
0
-5
-10
-15
-20
-25
-30
1970
1975
1980
1985
1990
1995
2000
2005
2010
2015
2020
2025

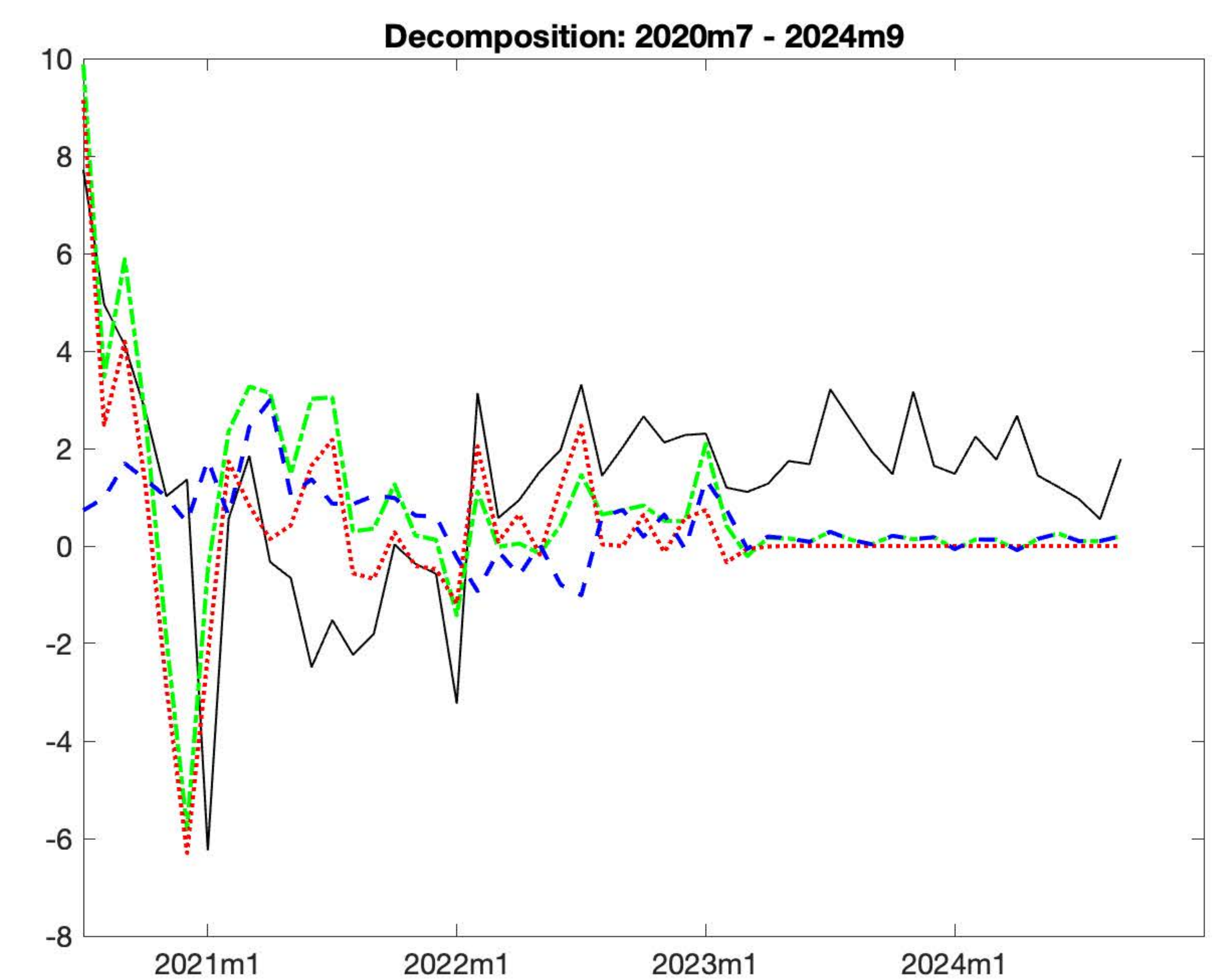

Decomposition: 2020m1 - 2024m9
10
5
0
-5
-10
-15
-20
-25
-30
2020m1
2021m1
2022m1
2023m1
2024m1
Data
(F+C)-Shock
C-Shock
F-Shock

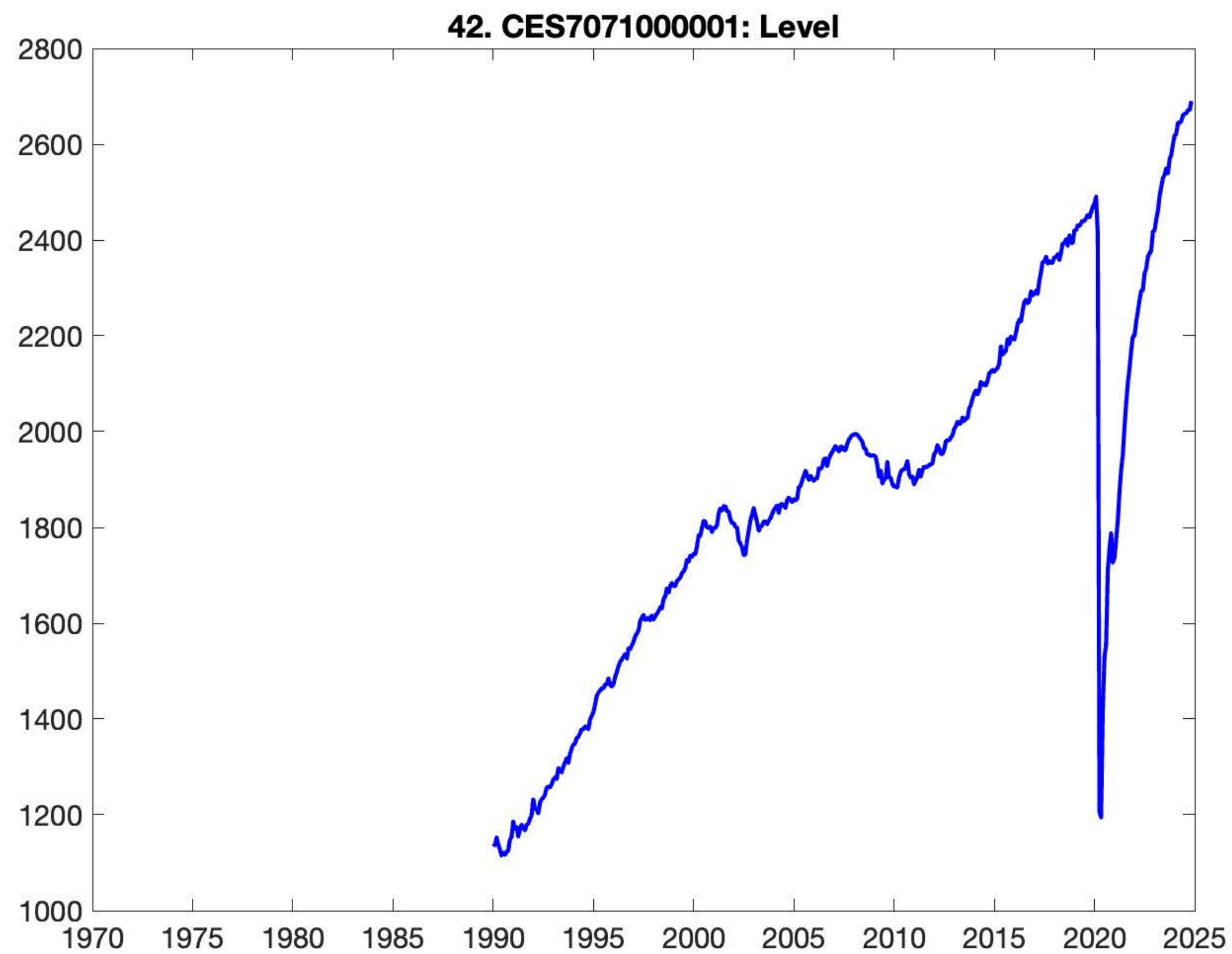

Decomposition: 2020m7 - 2024m9
6
4
2
0
-2
-4
-6
2021m1
2022m1
2023m1
2024m1

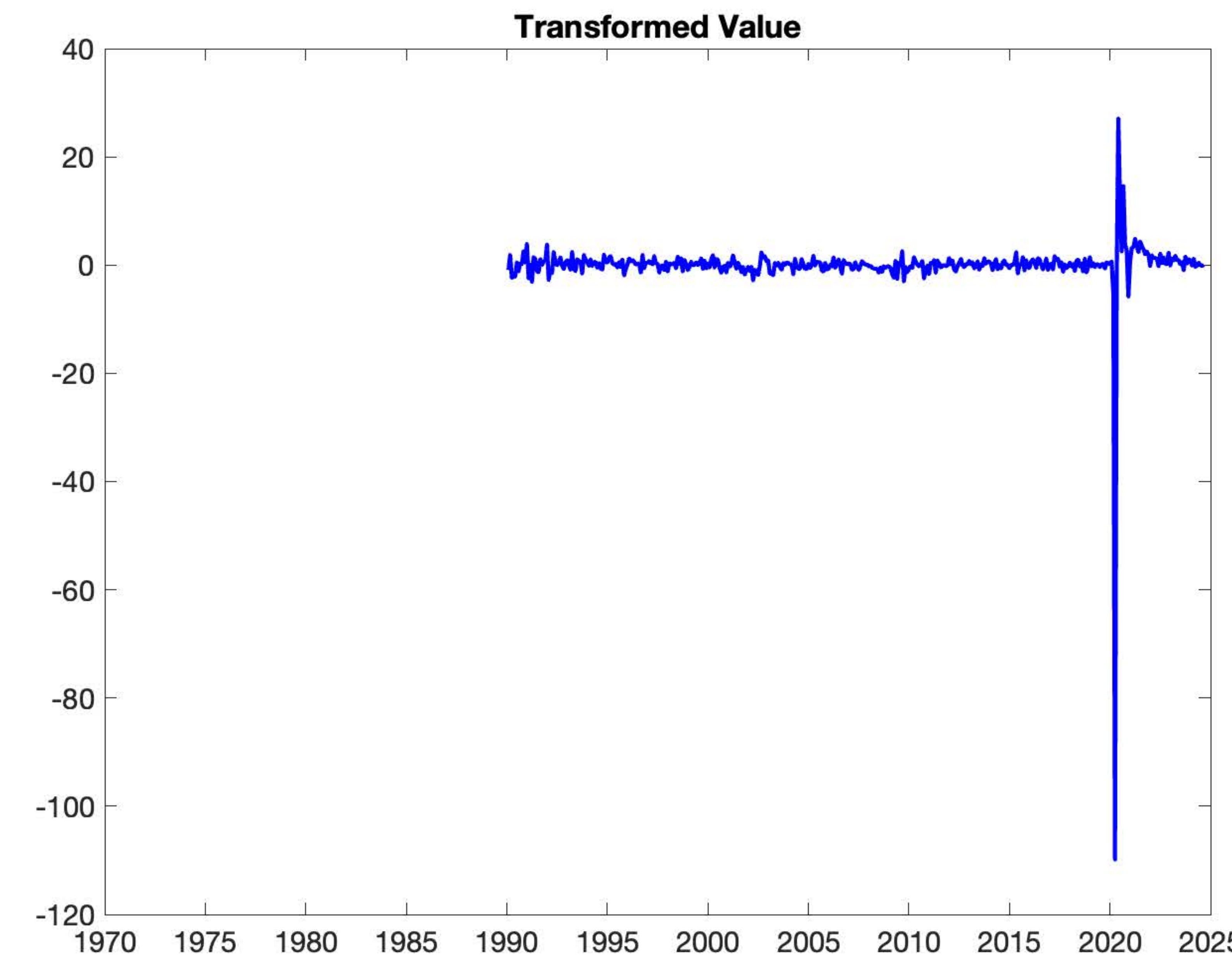

41. CES6562000001: Level
×10^4
2.4
2.2
2
1.8
1.6
1.4
1.2
1
0.8
1970 1975 1980 1985 1990 1995 2000 2005 2010 2015 2020 2025

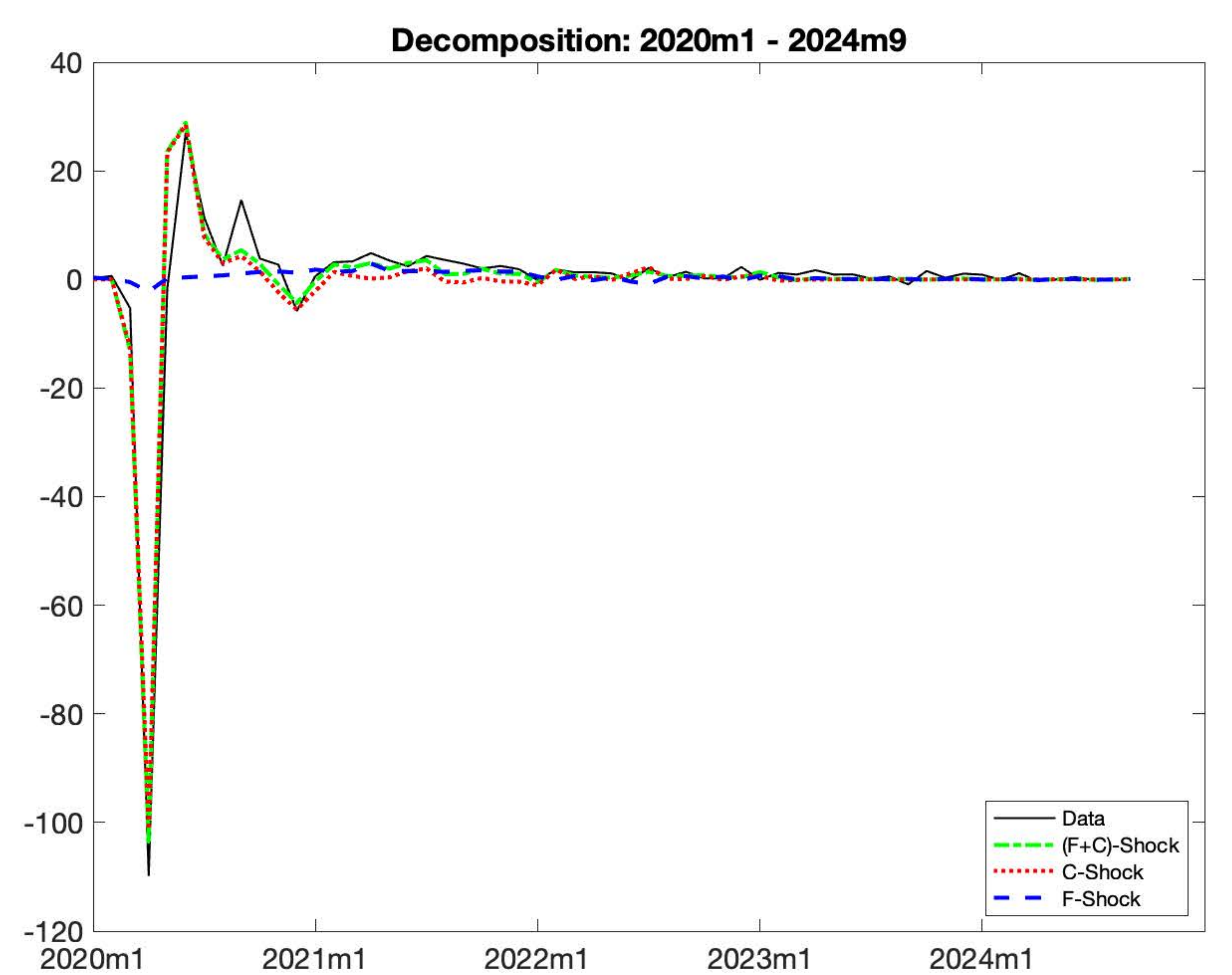

Transformed Value
40
20
0
-20
-40
-60
-80
-100
-120
-140
1970 1975 1980 1985 1990 1995 2000 2005 2010 2015 2020 2025

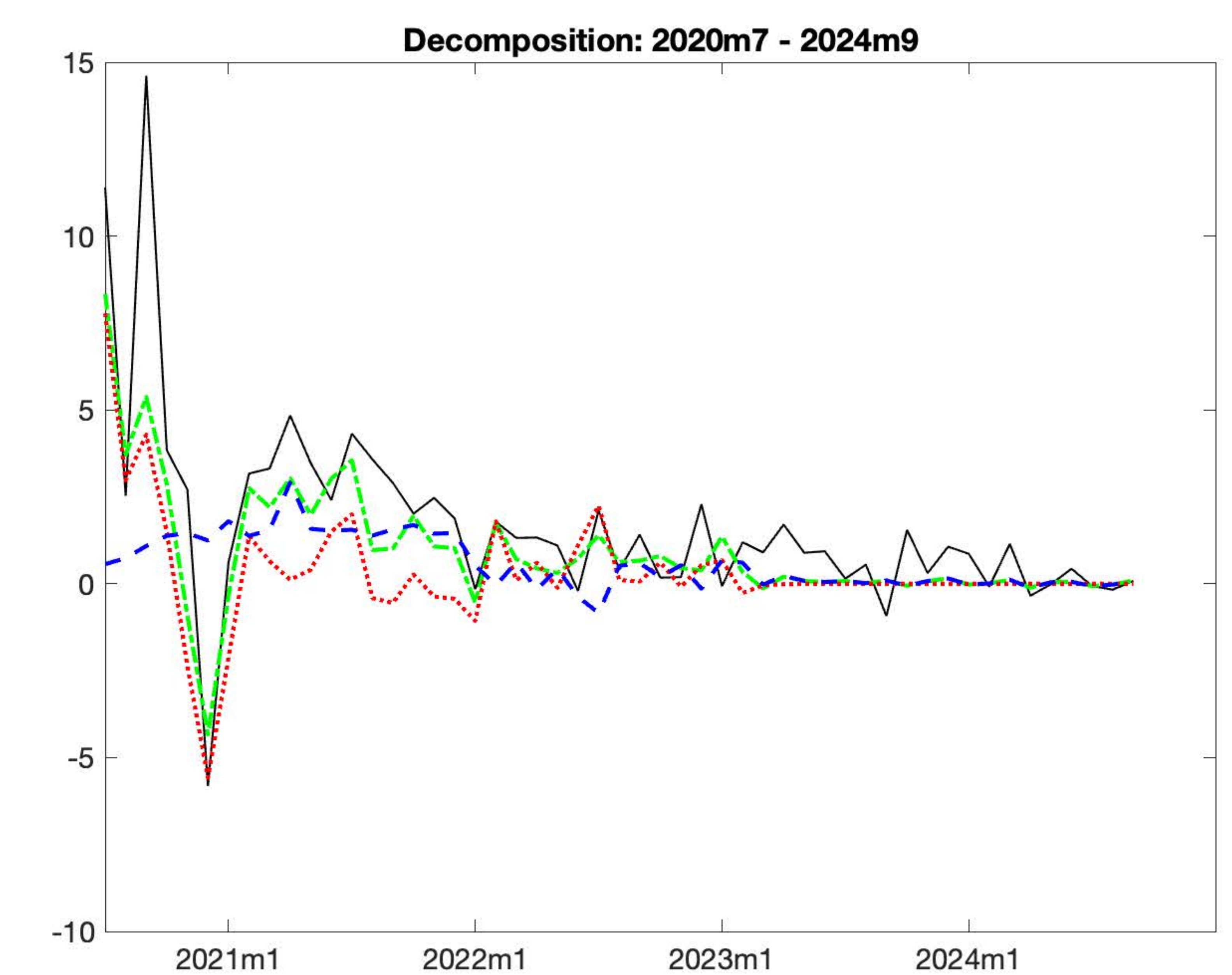

Decomposition: 2020m1 - 2024m9
40
20
0
-20
-40
-60
-80
-100
-120
-140
2020m1 2021m1 2022m1 2023m1 2024m1
Data
(F+C)-Shock
C-Shock
F-Shock

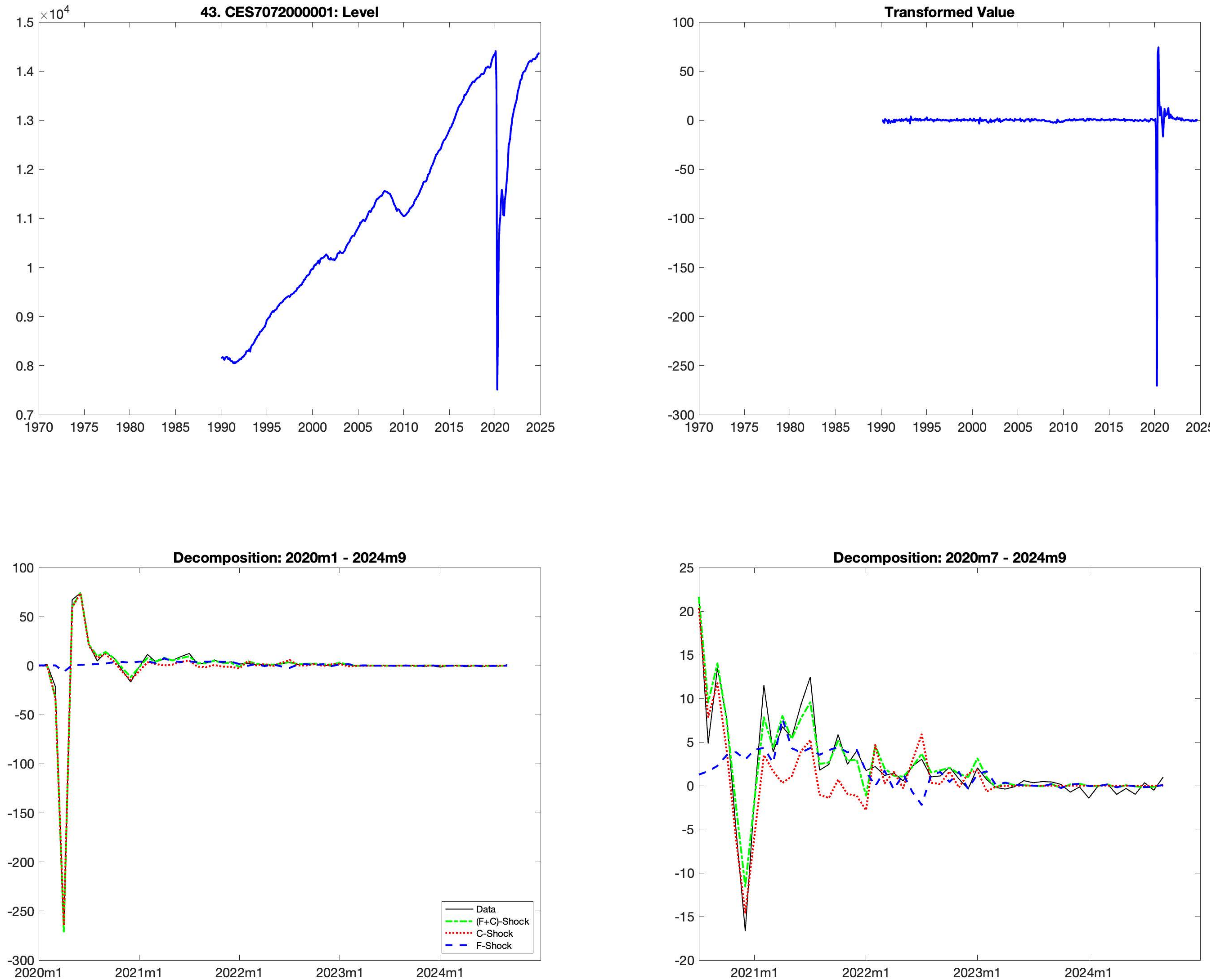

Decomposition: 2020m7 - 2024m9
10
8
6
4
2
0
-2
-4
-6
-8
2021m1 2022m1 2023m1 2024m1

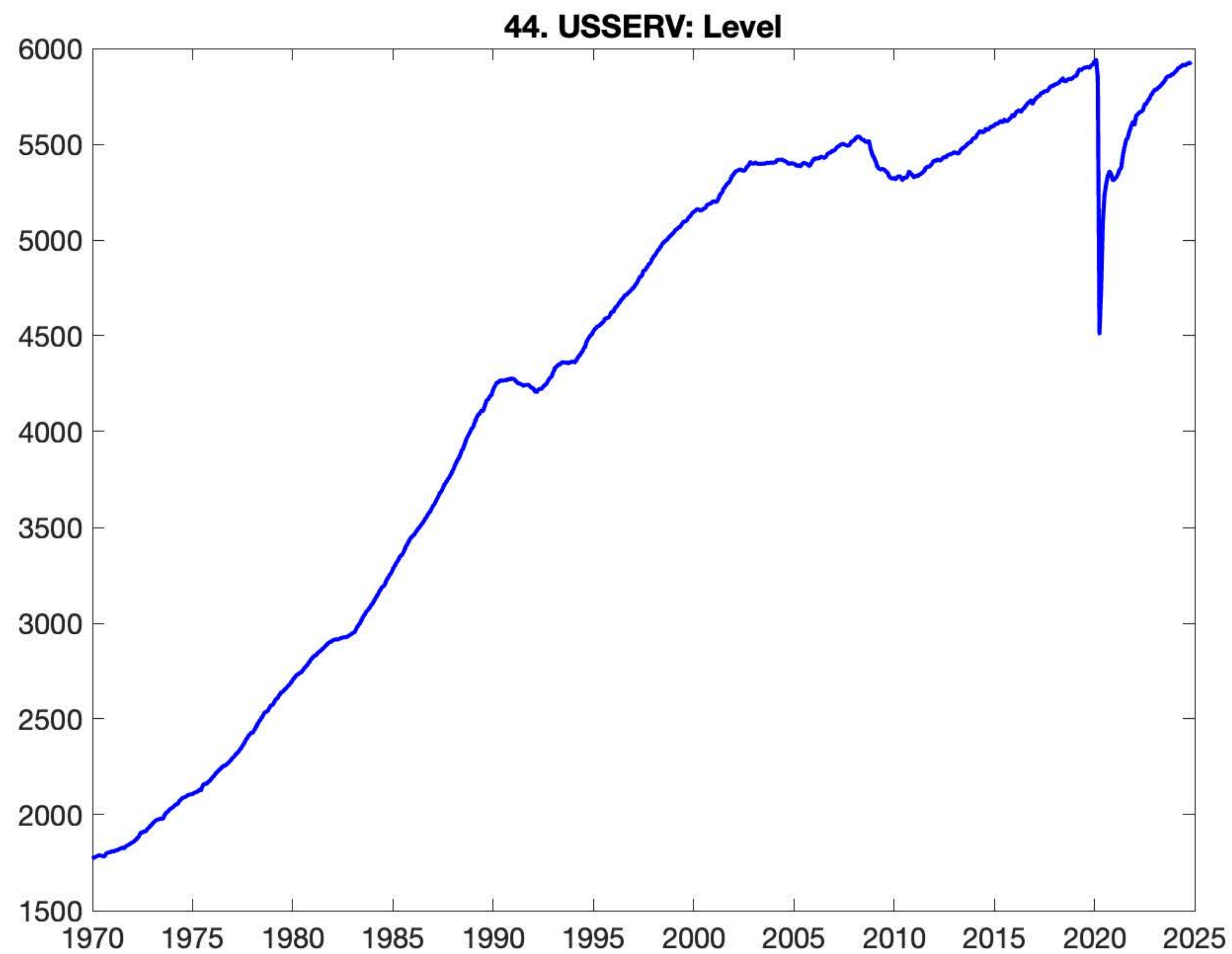

42. CES7071000001: Level
2800
2600
2400
2200
2000
1800
1600
1400
1200
1000
1970 1975 1980 1985 1990 1995 2000 2005 2010 2015 2020 2025

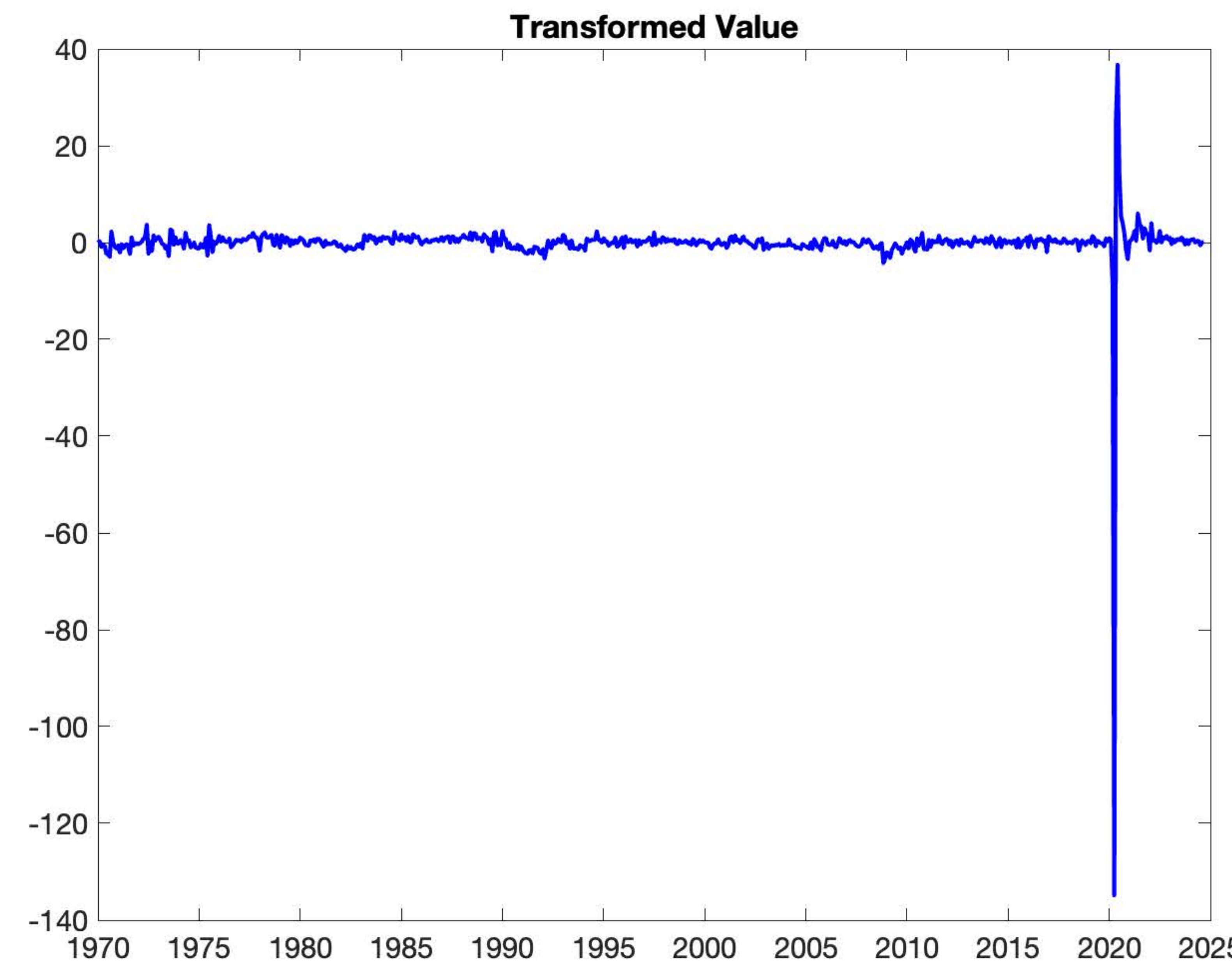

Transformed Value
40
20
0
-20
-40
-60
-80
-100
-120
1970 1975 1980 1985 1990 1995 2000 2005 2010 2015 2020 2025

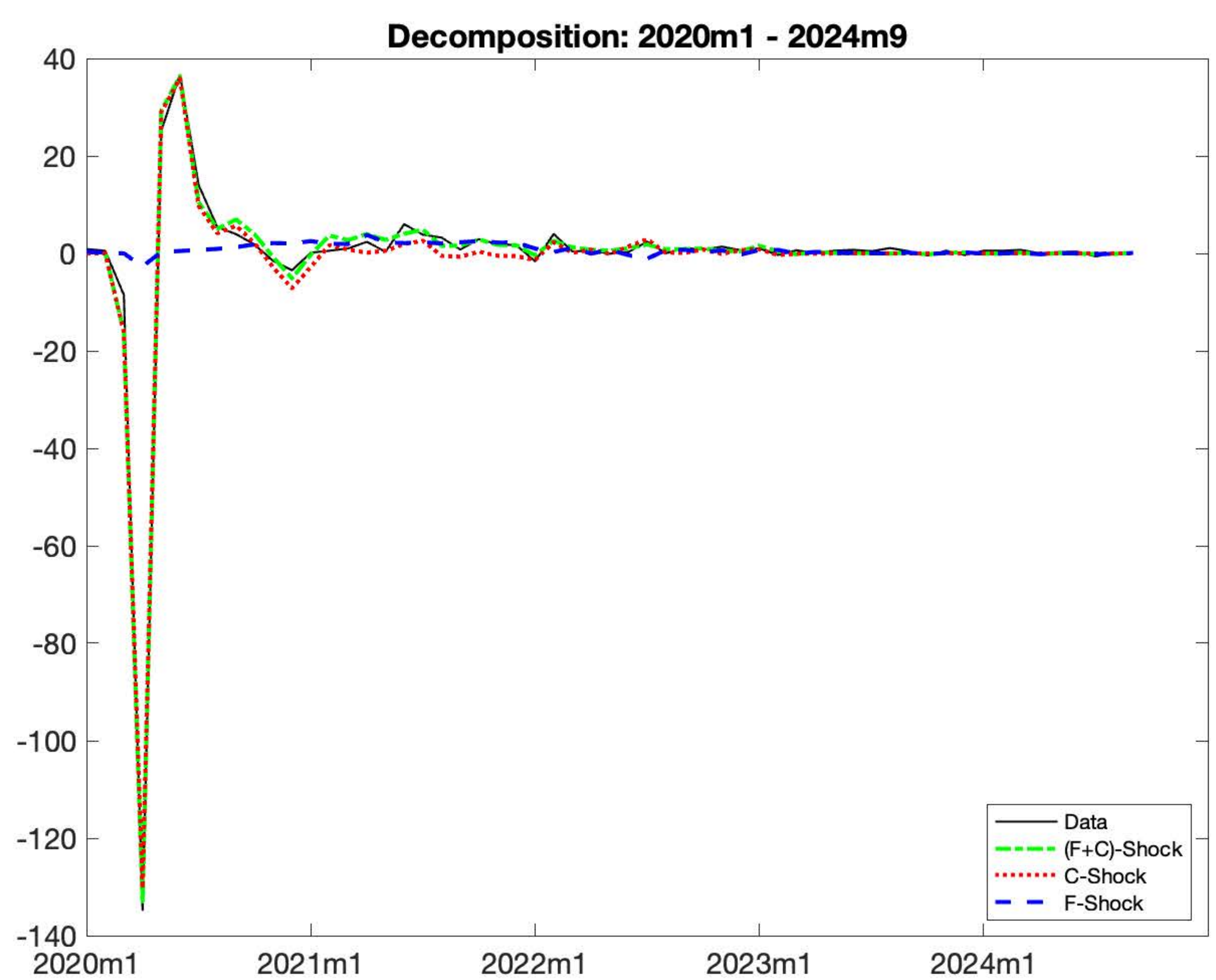

Decomposition: 2020m1 - 2024m9
40
20
0
-20
-40
-60
-80
-100
-120
2020m1 2021m1 2022m1 2023m1 2024m1
Data
(F+C)-Shock
C-Shock
F-Shock

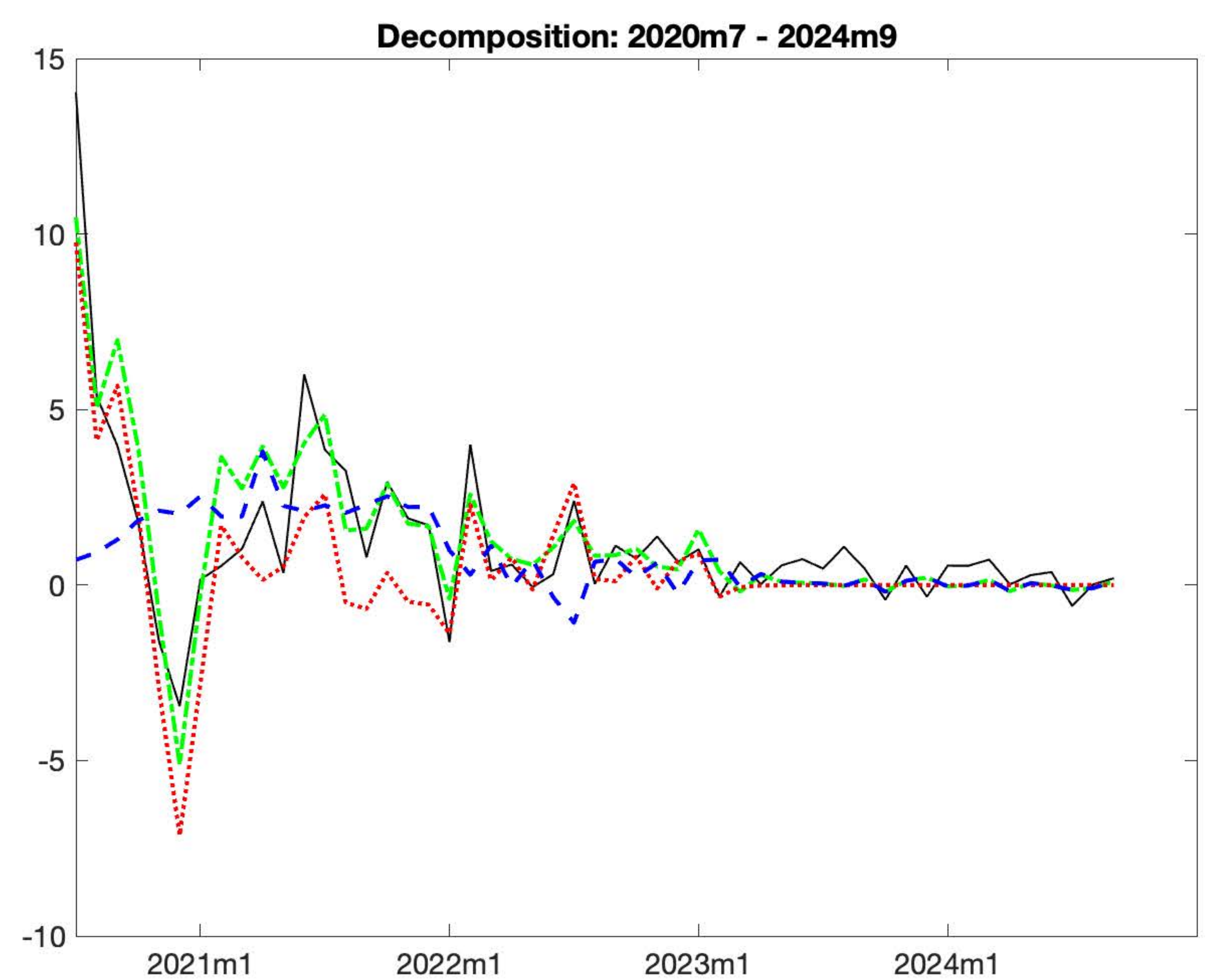

Decomposition: 2020m7 - 2024m9
15
10
5
0
-5
-10
2021m1 2022m1 2023m1 2024m1

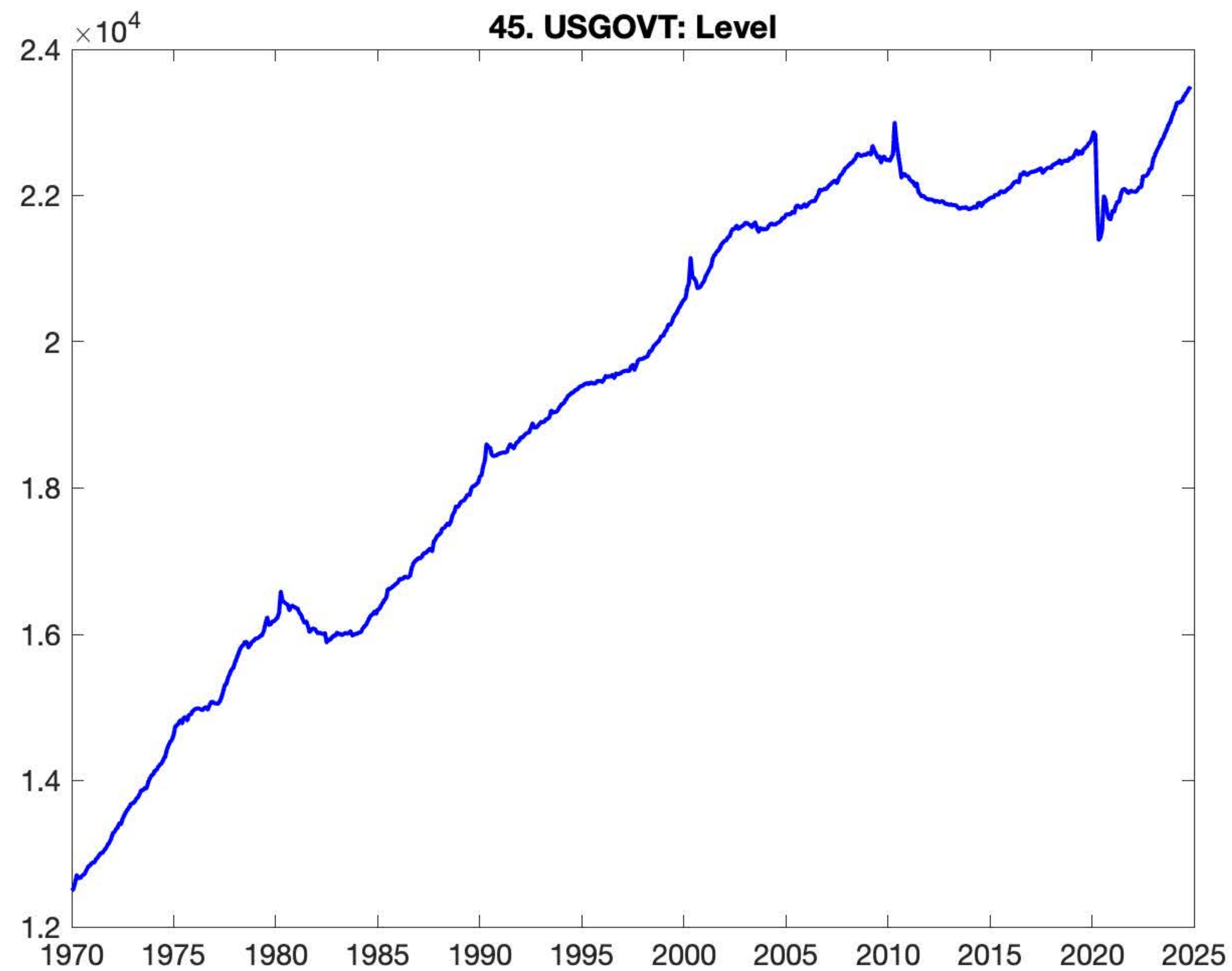

43. CES7072000001: Level
×10^4
Transformed Value
Decomposition: 2020m1 - 2024m9
Decomposition: 2020m7 - 2024m9
Data
(F+C)-Shock
C-Shock
F-Shock
1970
1975
1980
1985
1990
1995
2000
2005
2010
2015
2020
2025
2020m1
2021m1
2022m1
2023m1
2024m1


44. USSERV: Level

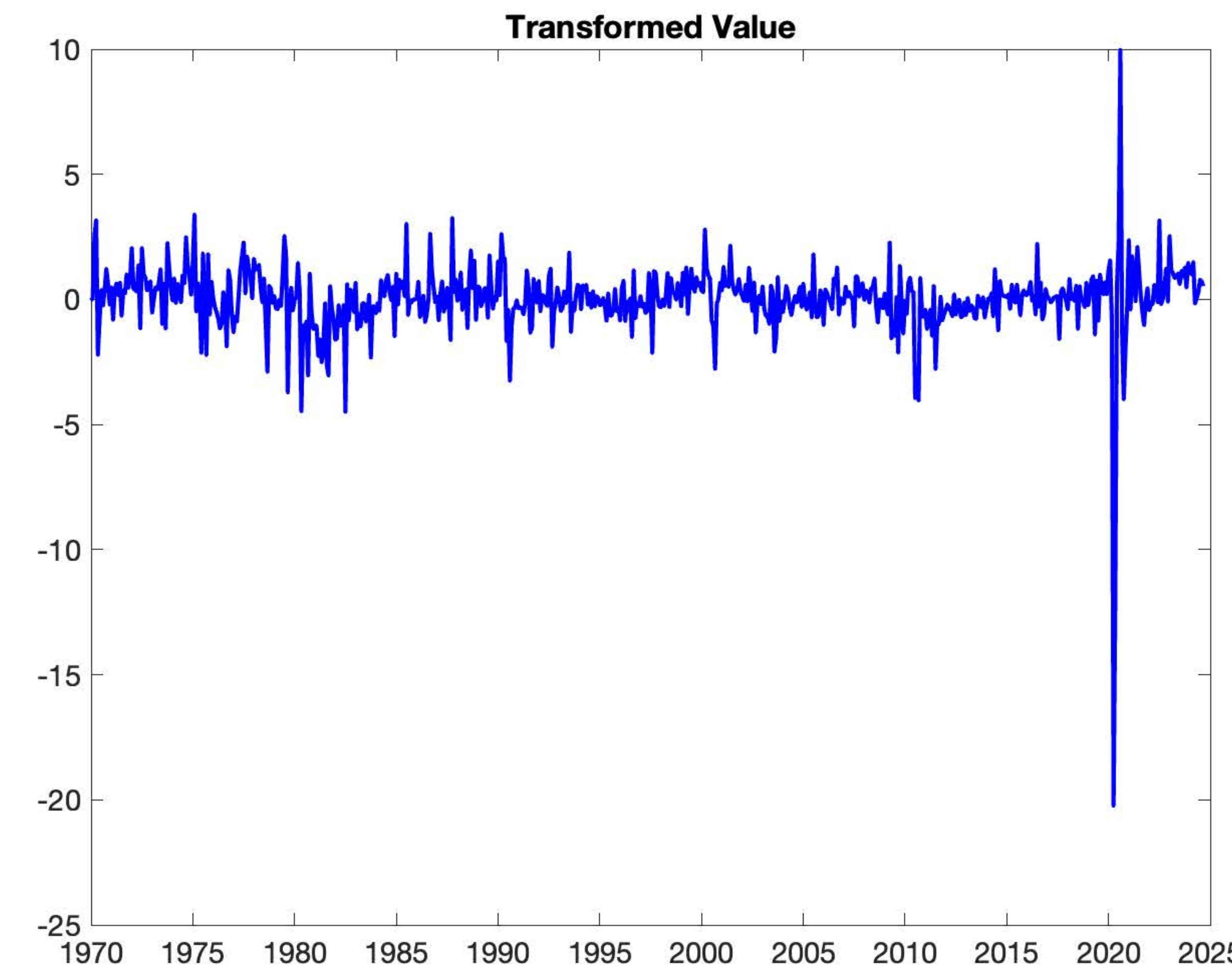

Transformed Value


Decomposition: 2020m1 - 2024m9
Data
(F+C)-Shock
C-Shock
F-Shock

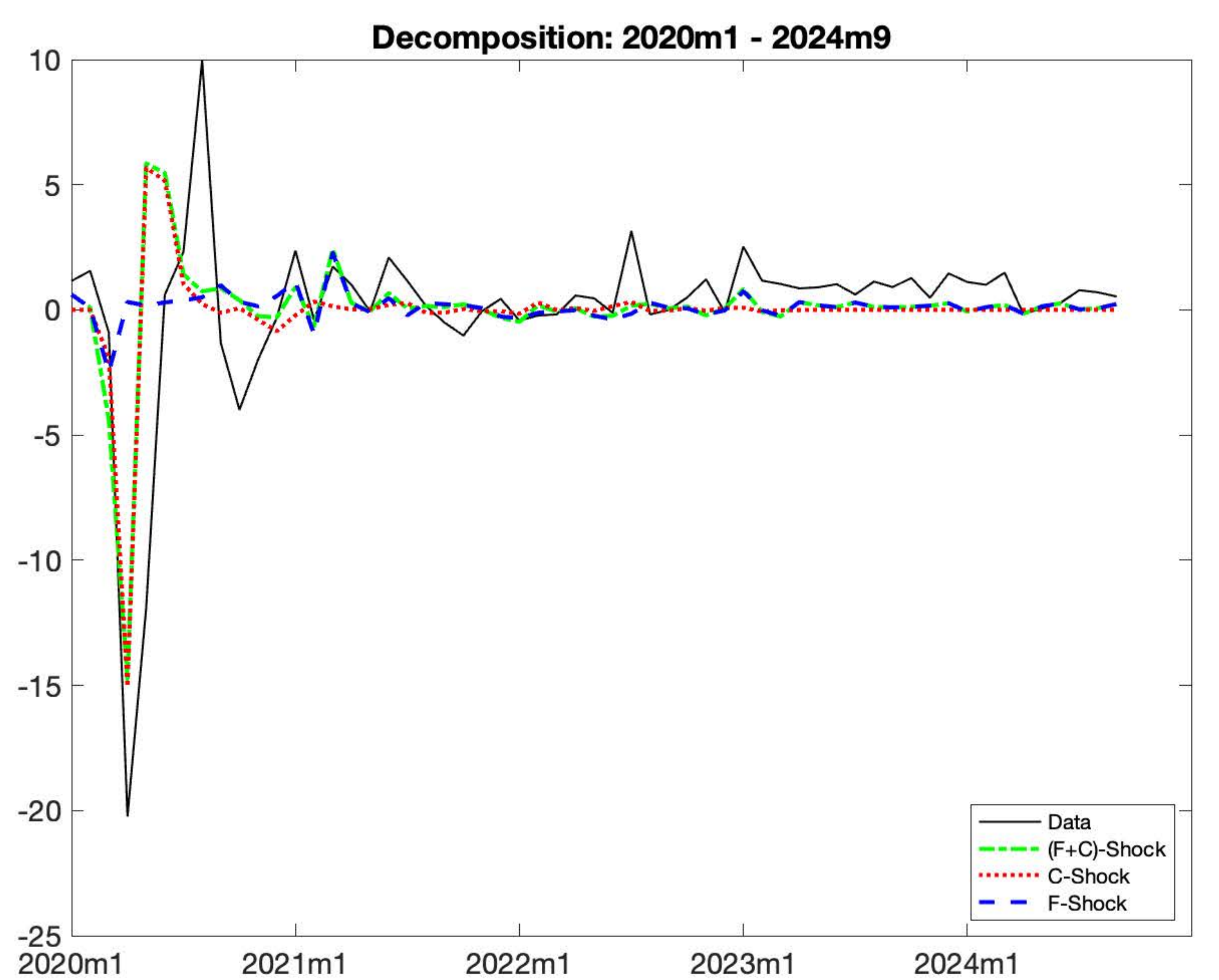

Decomposition: 2020m7 - 2024m9



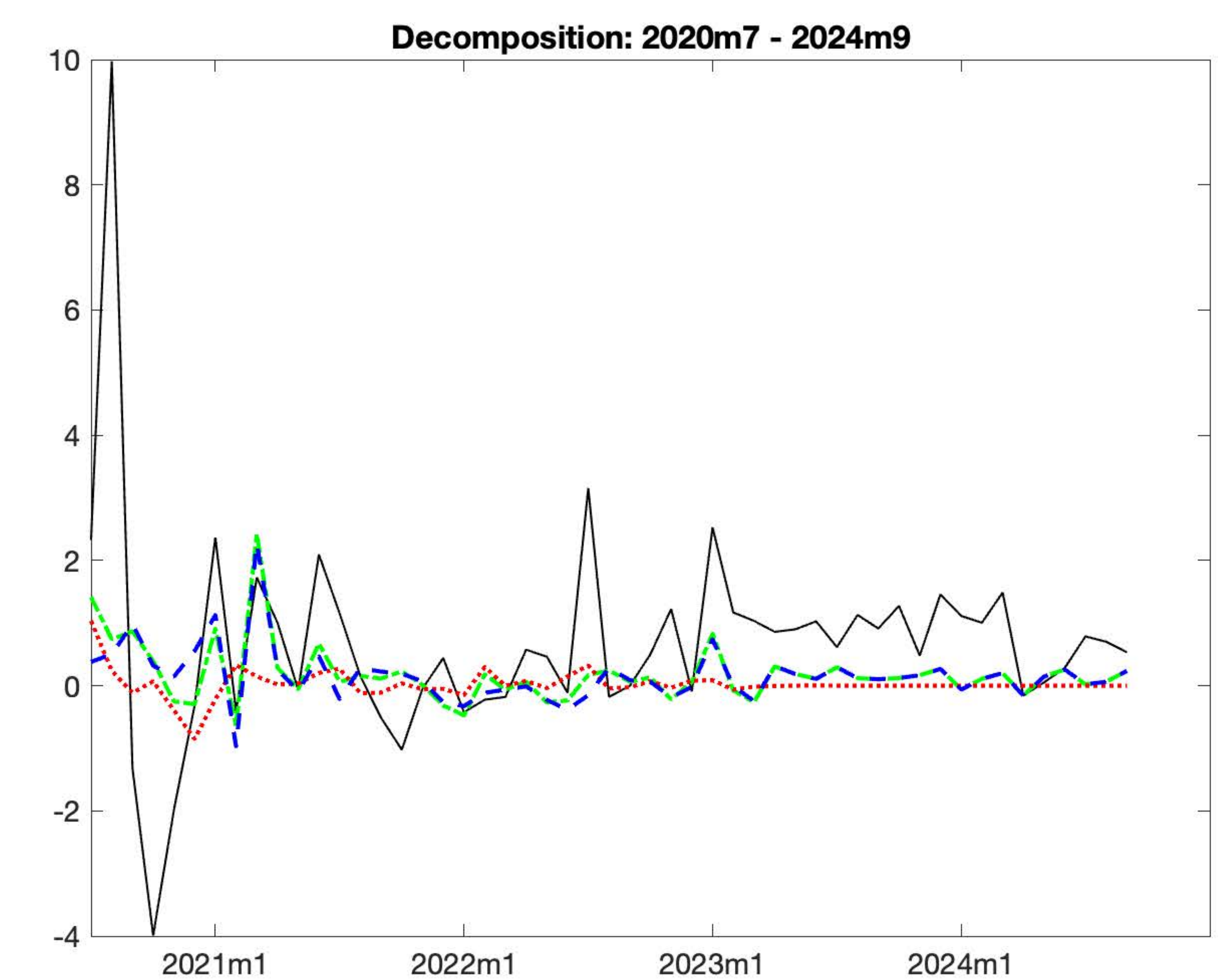
45. USGOVT: Level
×10^4
2.4
2.2
2
1.8
1.6
1.4
1.2
1970
1975
1980
1985
1990
1995
2000
2005
2010
2015
2020
2025



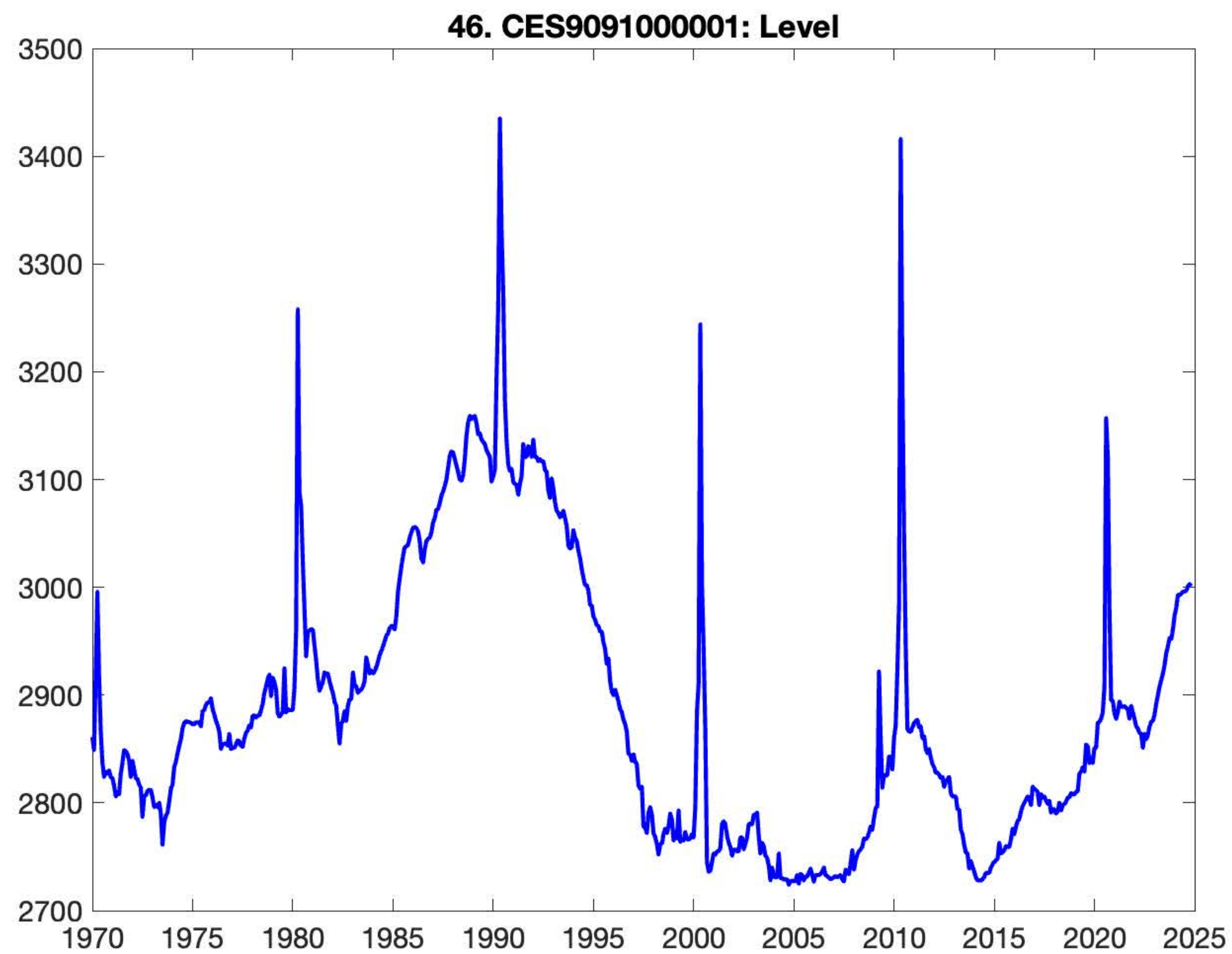
Transformed Value
10
5
0
-5
-10
-15
-20
-25
1970
1975
1980
1985
1990
1995
2000
2005
2010
2015
2020
2025

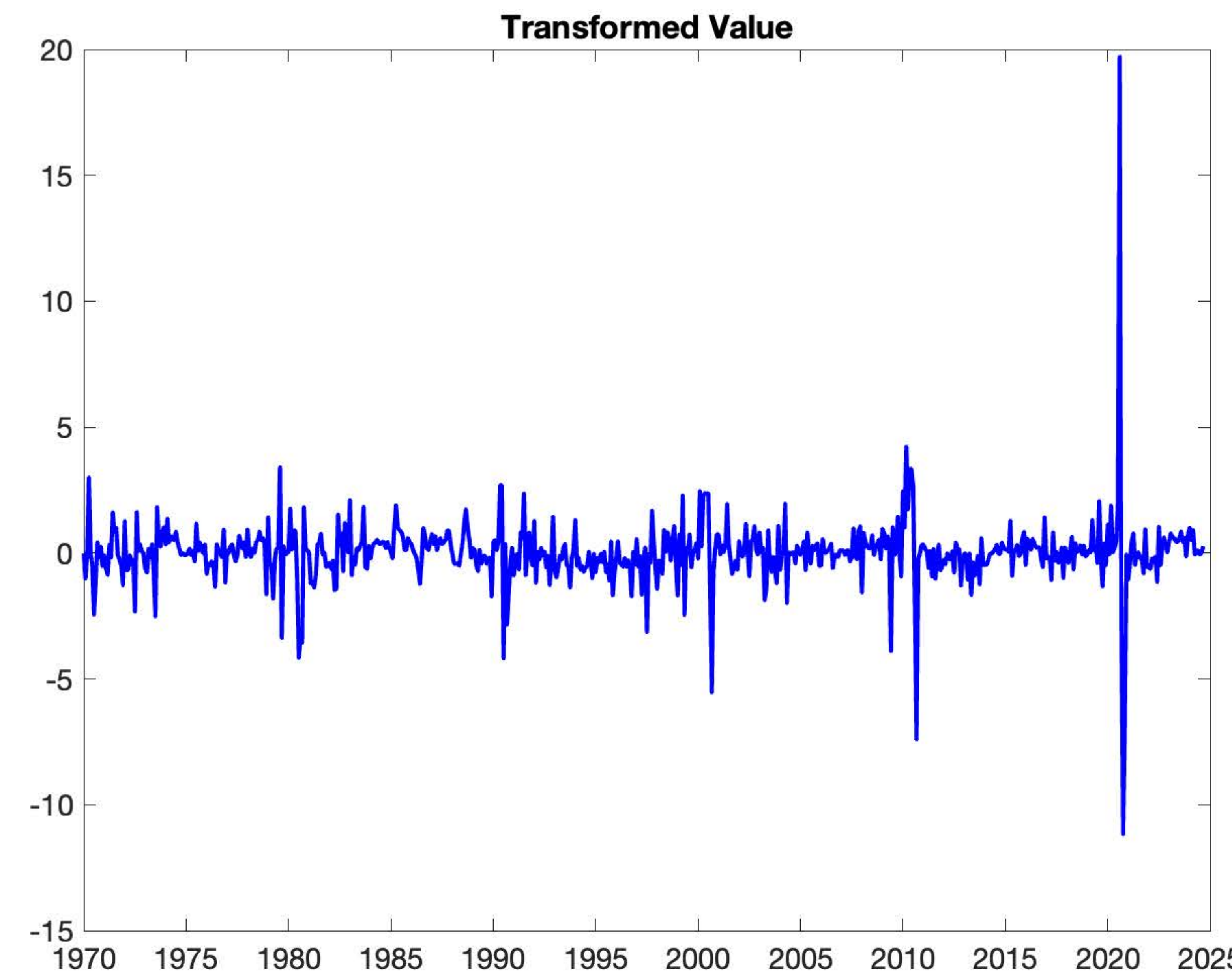


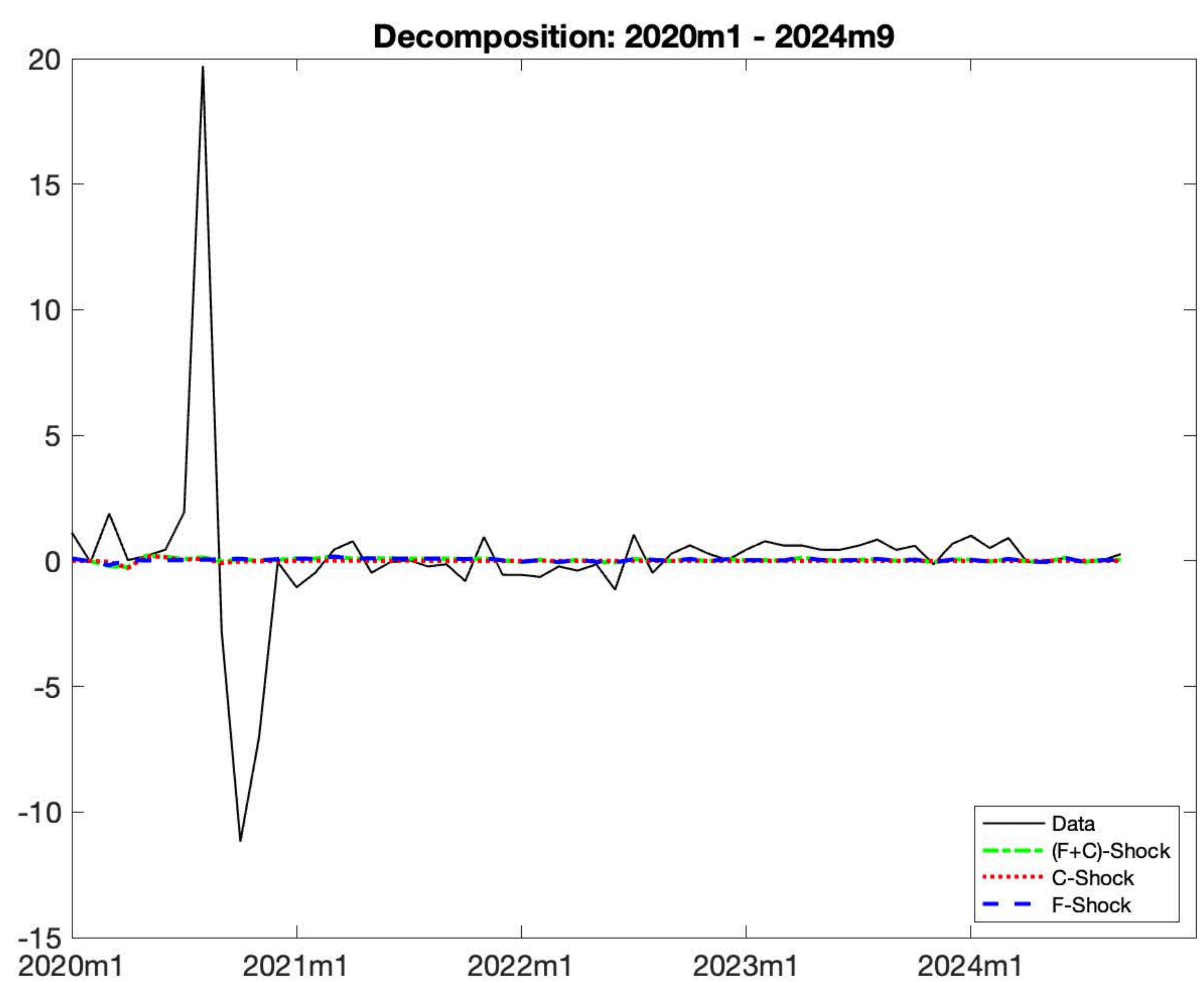
Decomposition: 2020m1 - 2024m9
10
5
0
-5
-10
-15
-20
-25
2020m1
2021m1
2022m1
2023m1
2024m1
Data
(F+C)-Shock
C-Shock
F-Shock

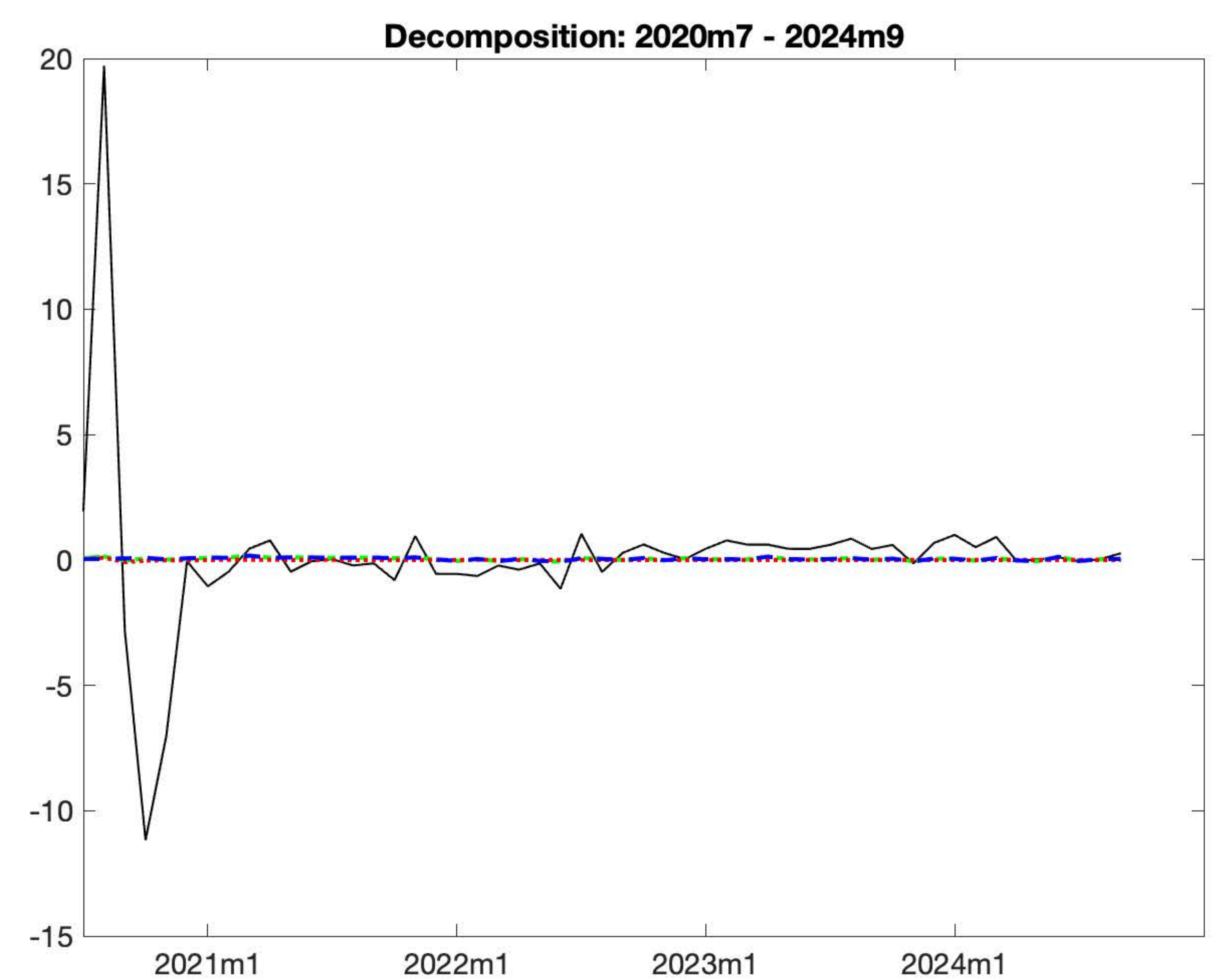


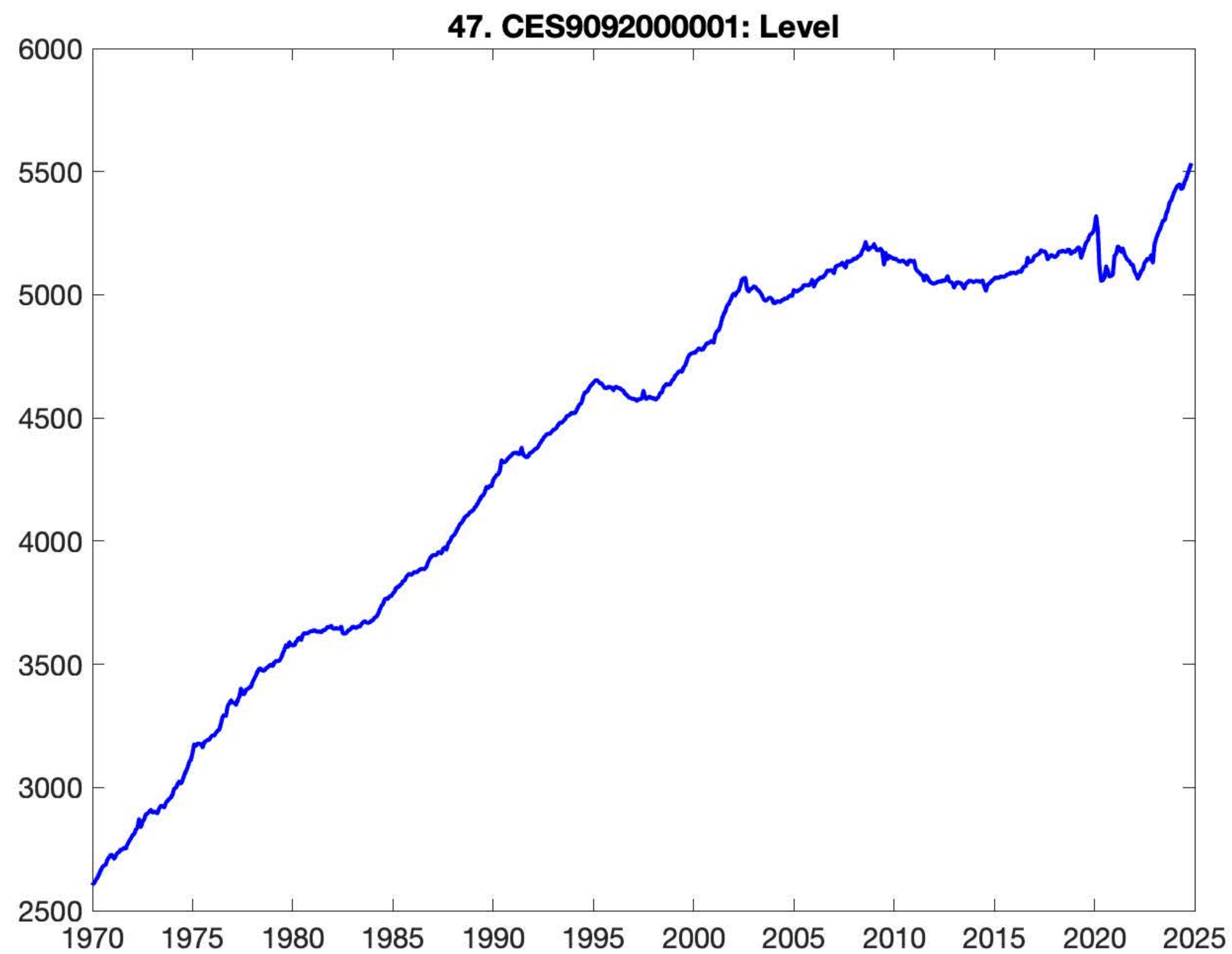
Decomposition: 2020m7 - 2024m9
10
8
6
4
2
0
-2
-4
2021m1
2022m1
2023m1
2024m1

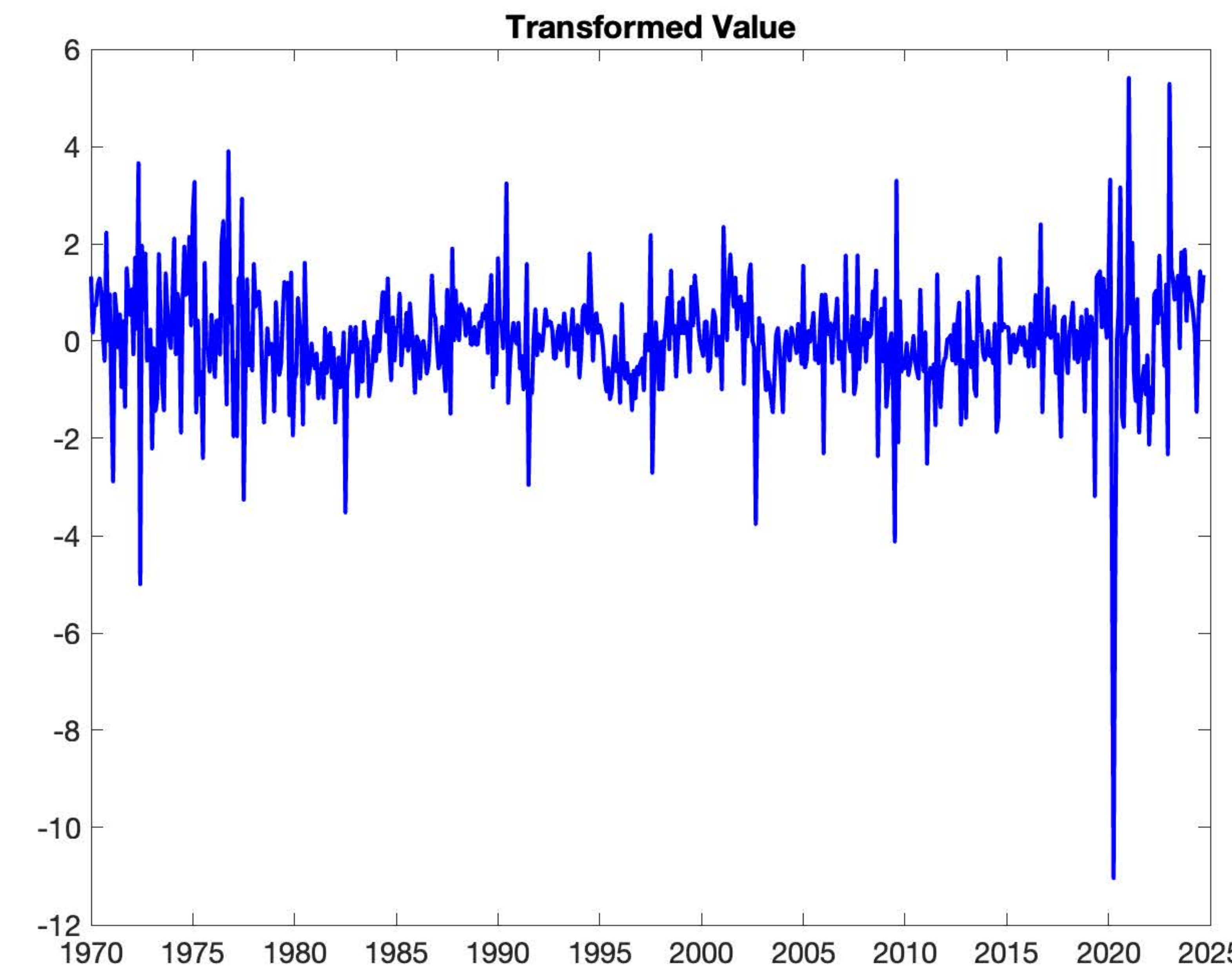

46. CES9091000001: Level

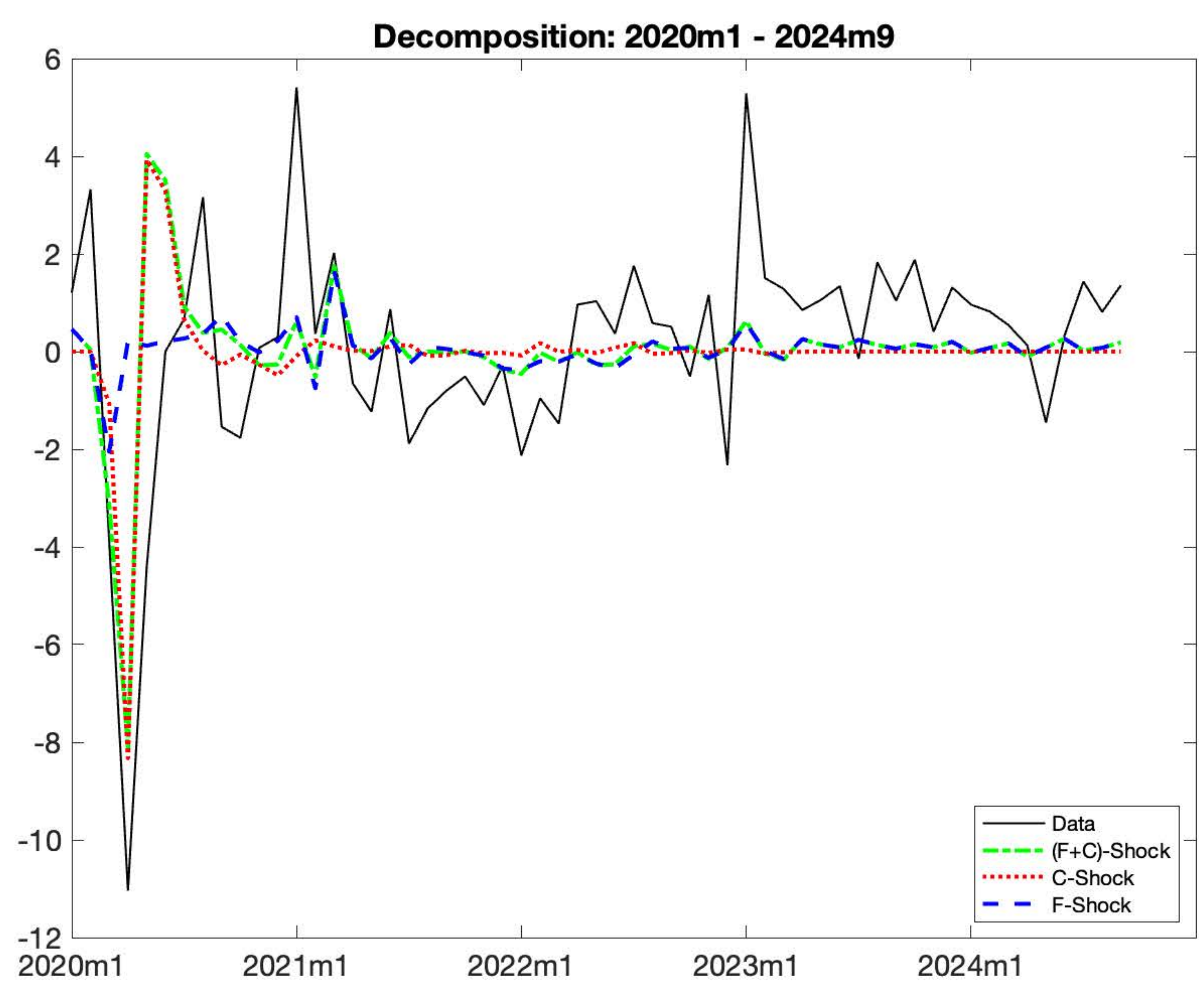

Transformed Value

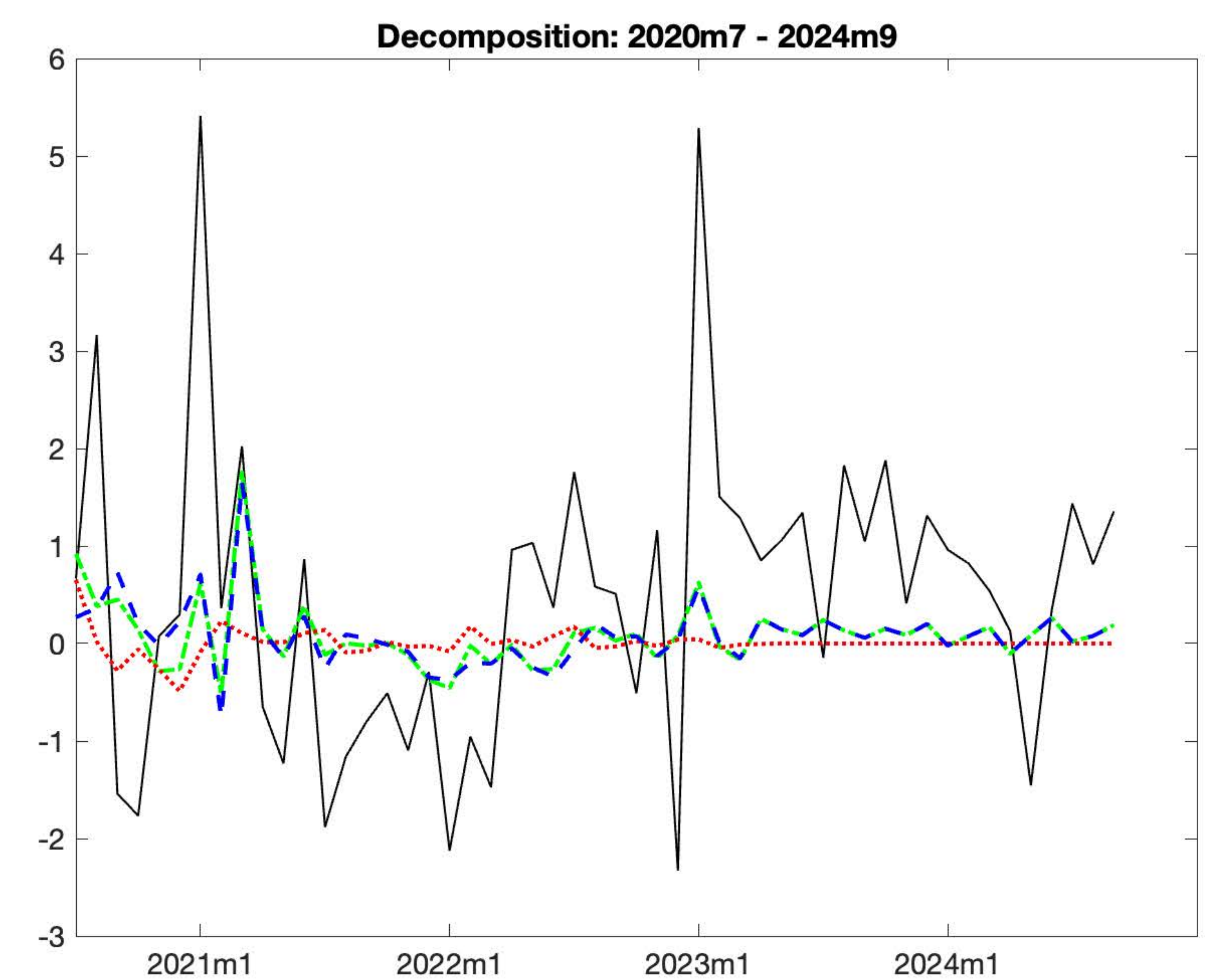

Decomposition: 2020m1 - 2024m9
Data
(F+C)-Shock
C-Shock
F-Shock

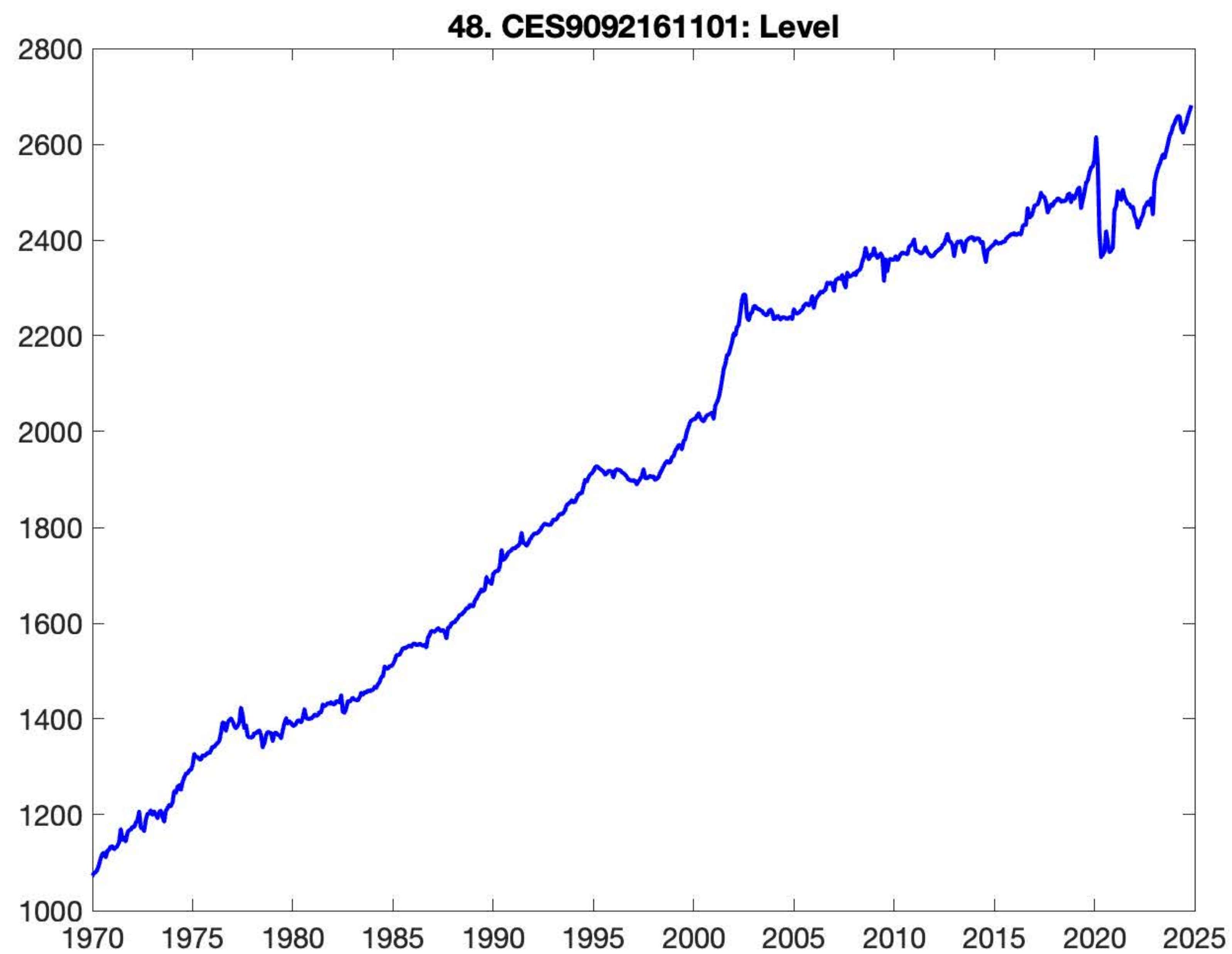

Decomposition: 2020m7 - 2024m9

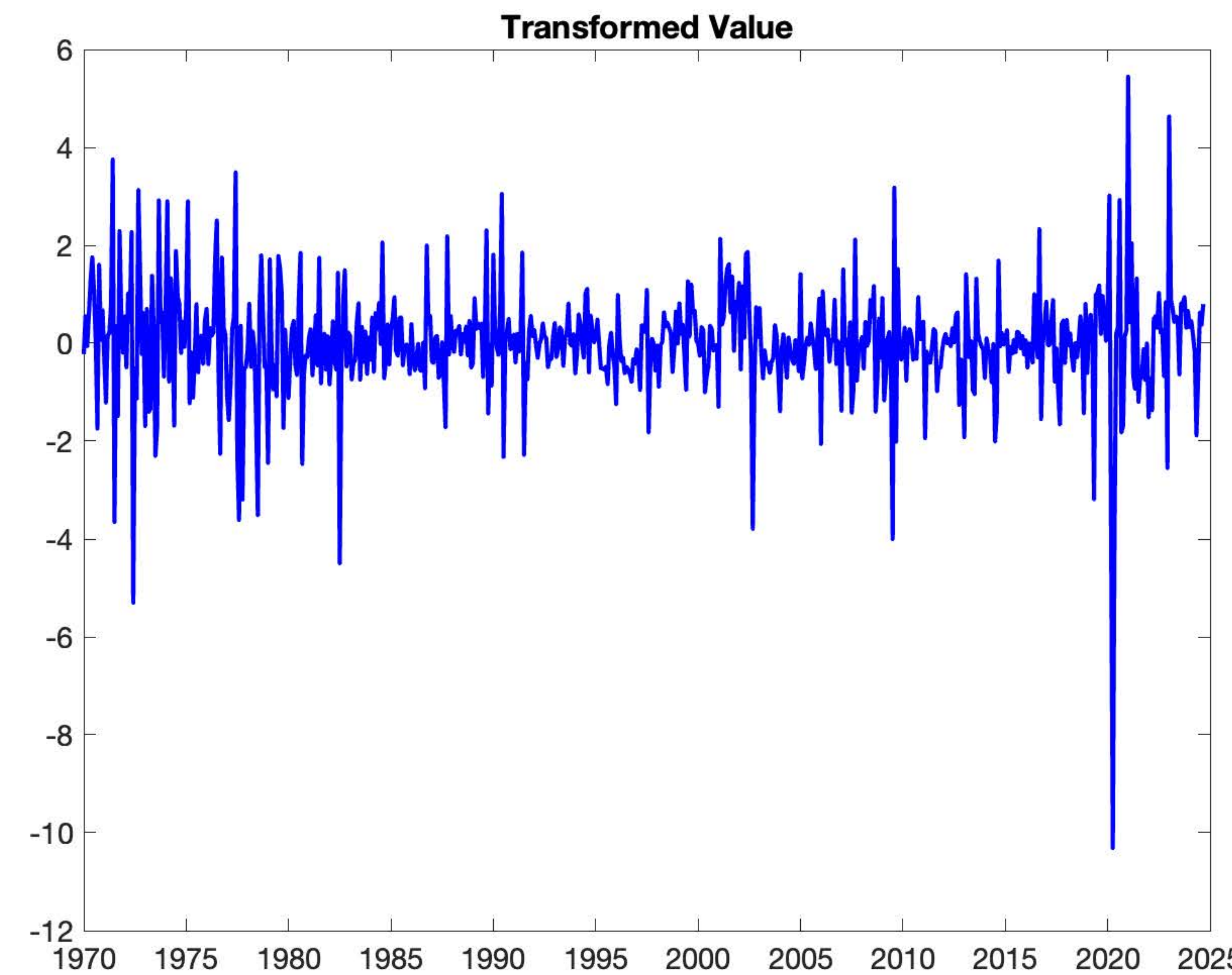

47. CES9092000001: Level

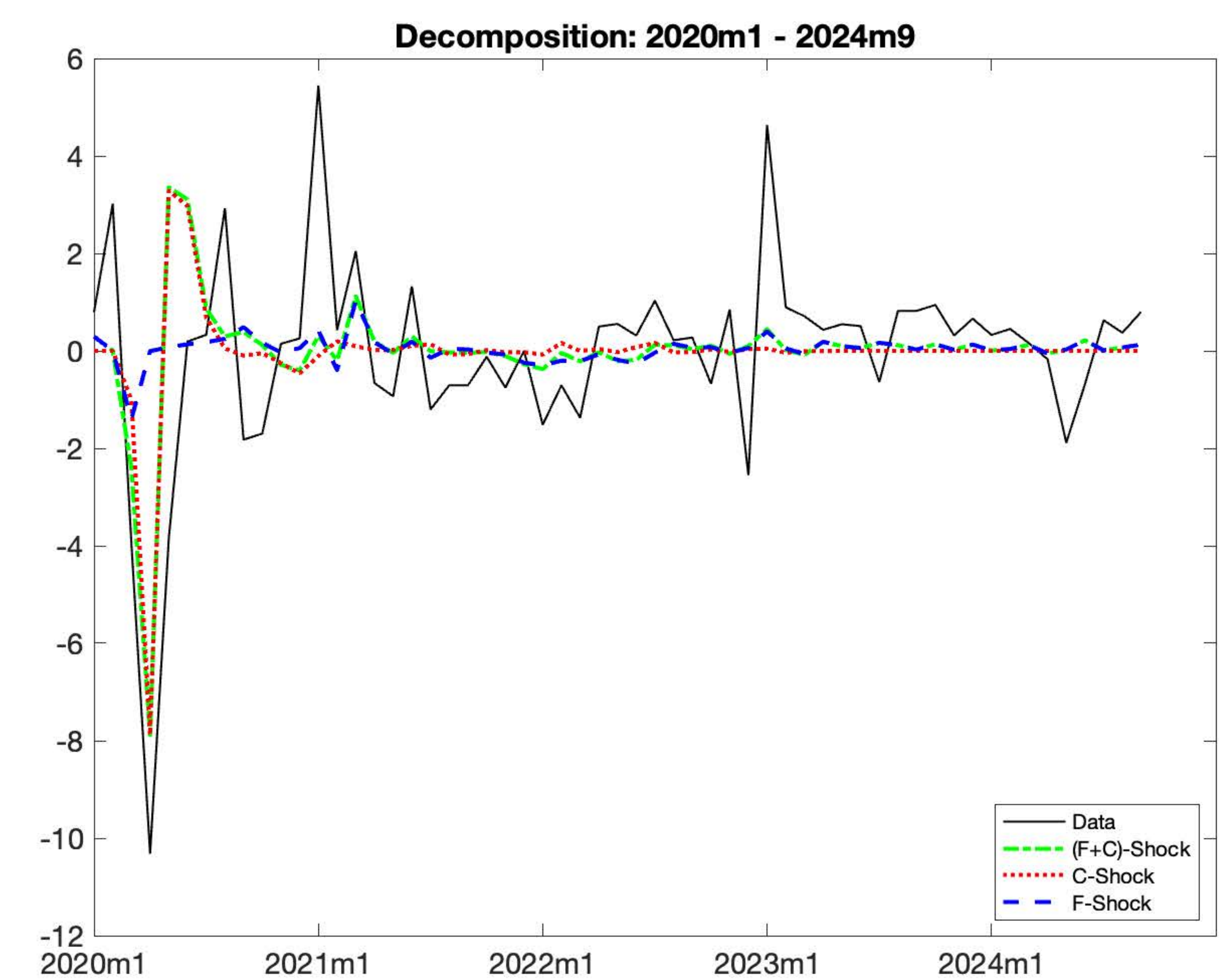

Transformed Value

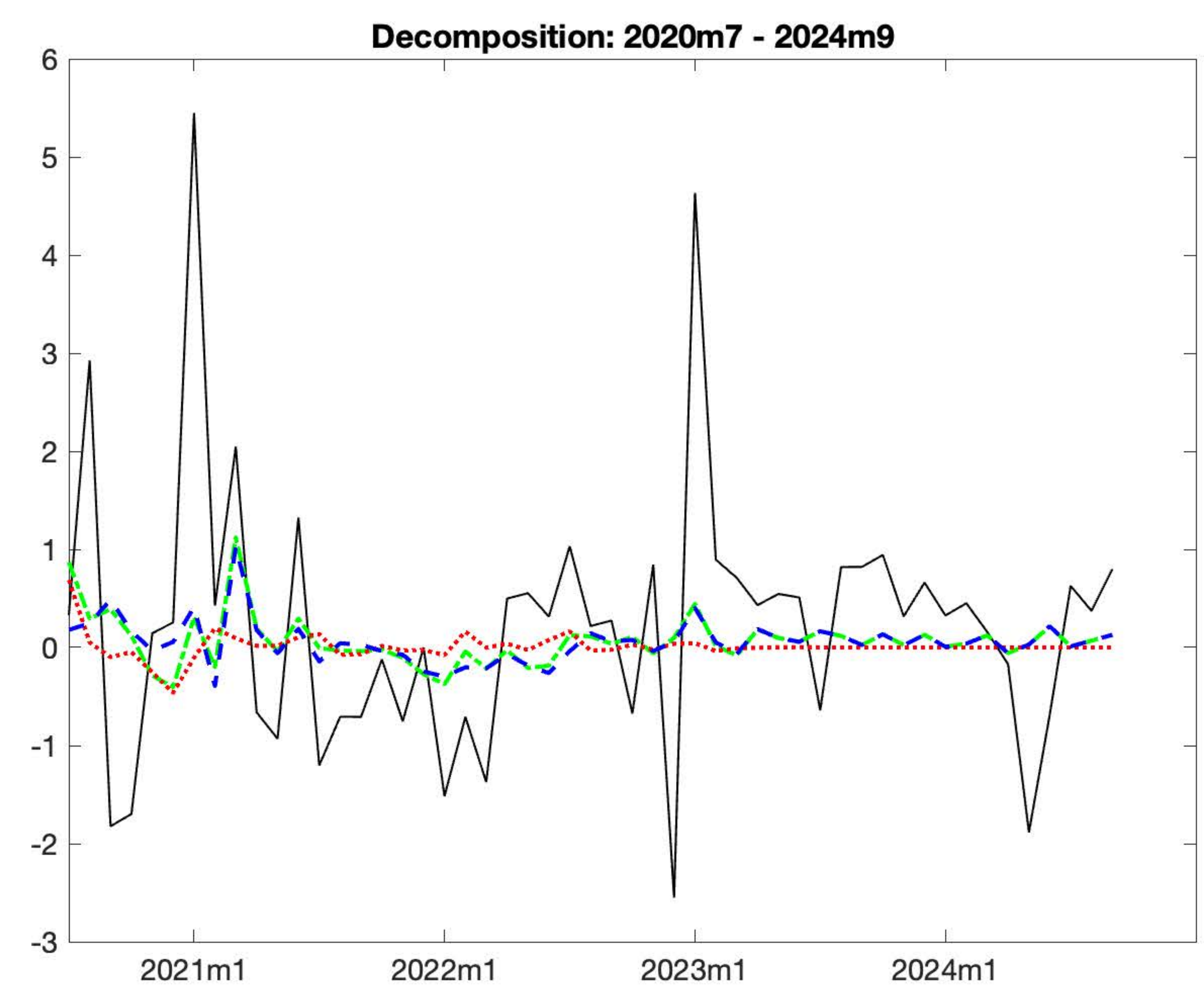

Decomposition: 2020m1 - 2024m9
Data
(F+C)-Shock
C-Shock
F-Shock

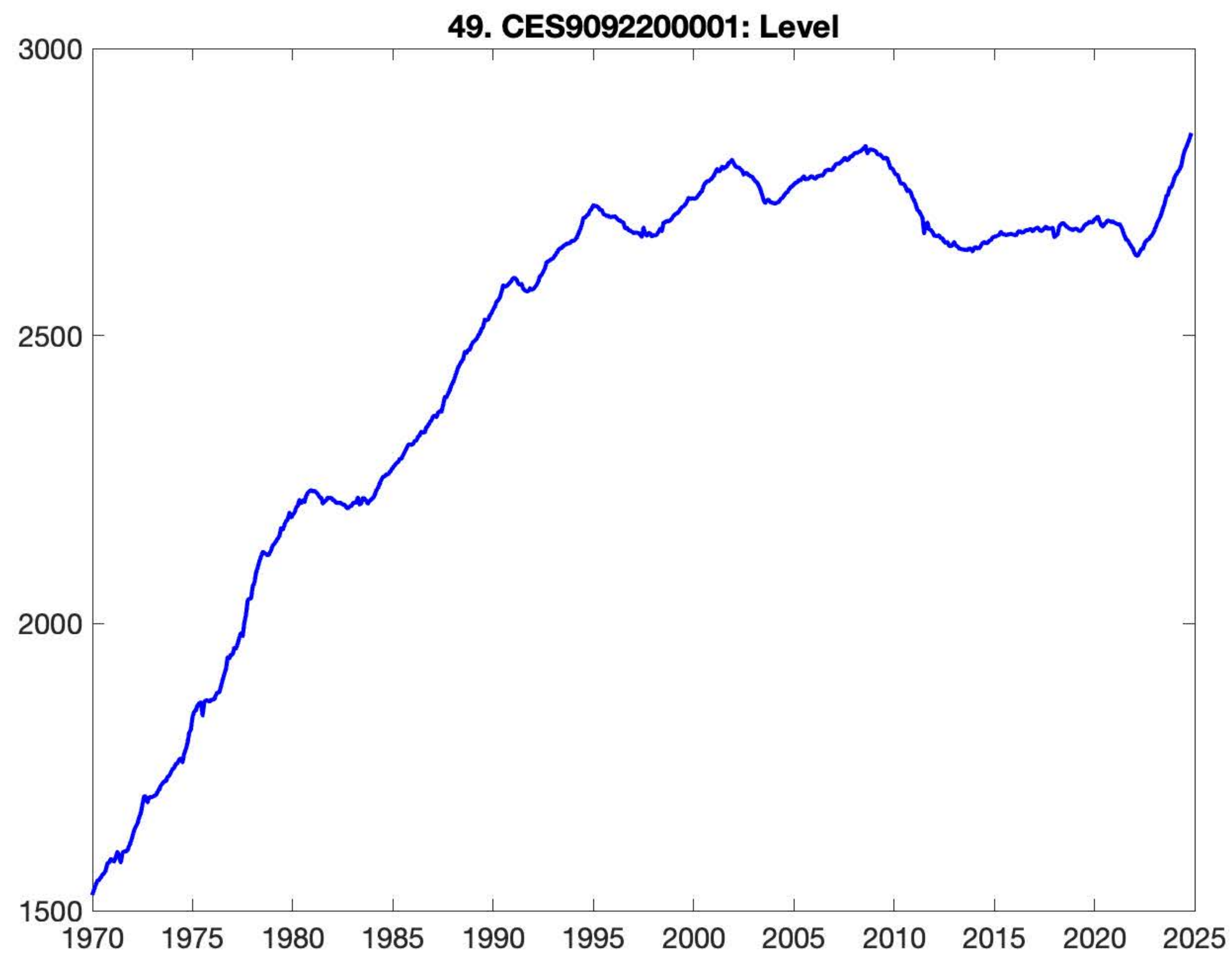

Decomposition: 2020m7 - 2024m9

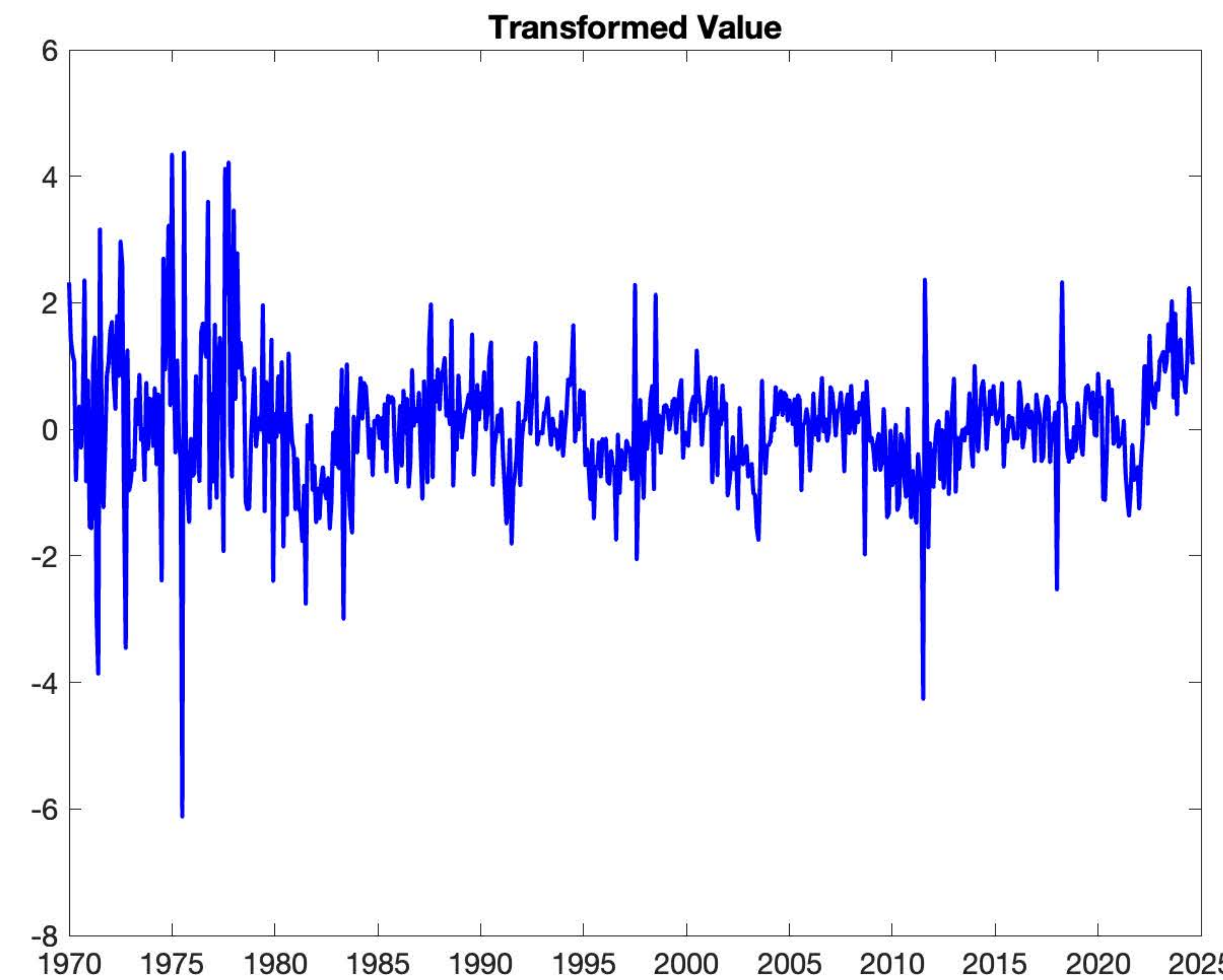

48. CES9092161101: Level
2800
2600
2400
2200
2000
1800
1600
1400
1200
1000
1970 1975 1980 1985 1990 1995 2000 2005 2010 2015 2020 2025

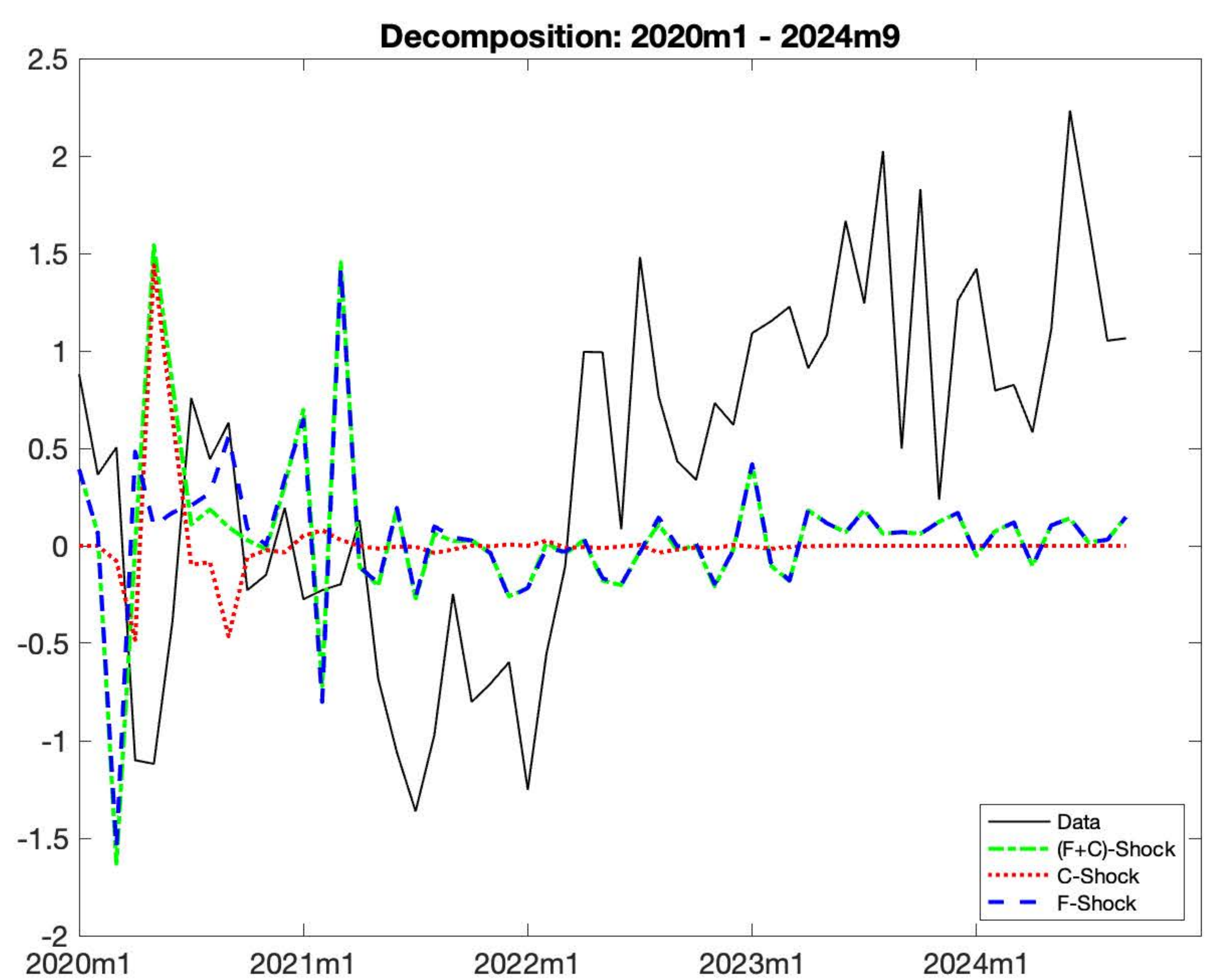

Transformed Value
6
4
2
0
-2
-4
-6
-8
-10
-12
1970 1975 1980 1985 1990 1995 2000 2005 2010 2015 2020 2025

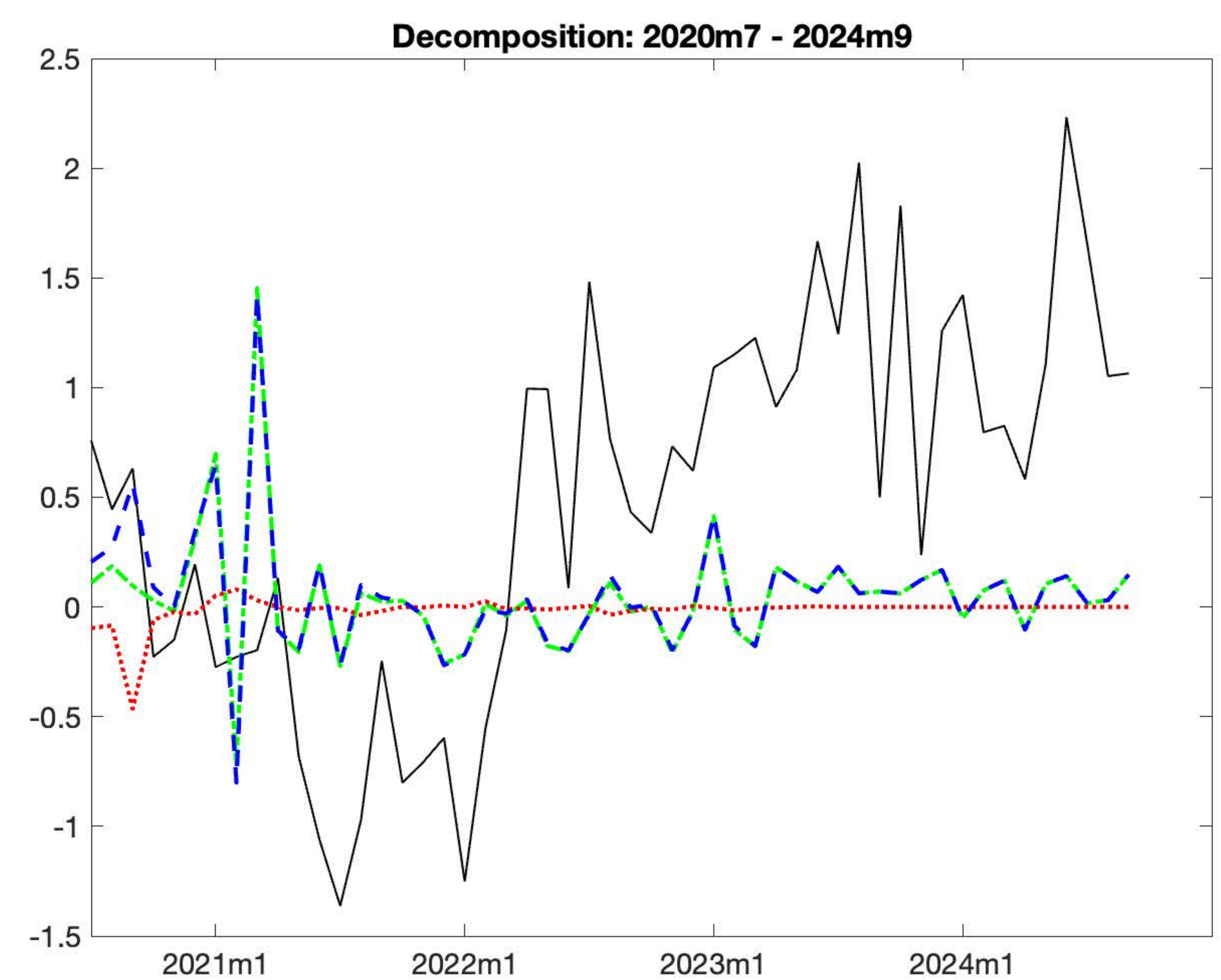

Decomposition: 2020m1 - 2024m9
6
4
2
0
-2
-4
-6
-8
-10
-12
2020m1 2021m1 2022m1 2023m1 2024m1
Data
(F+C)-Shock
C-Shock
F-Shock

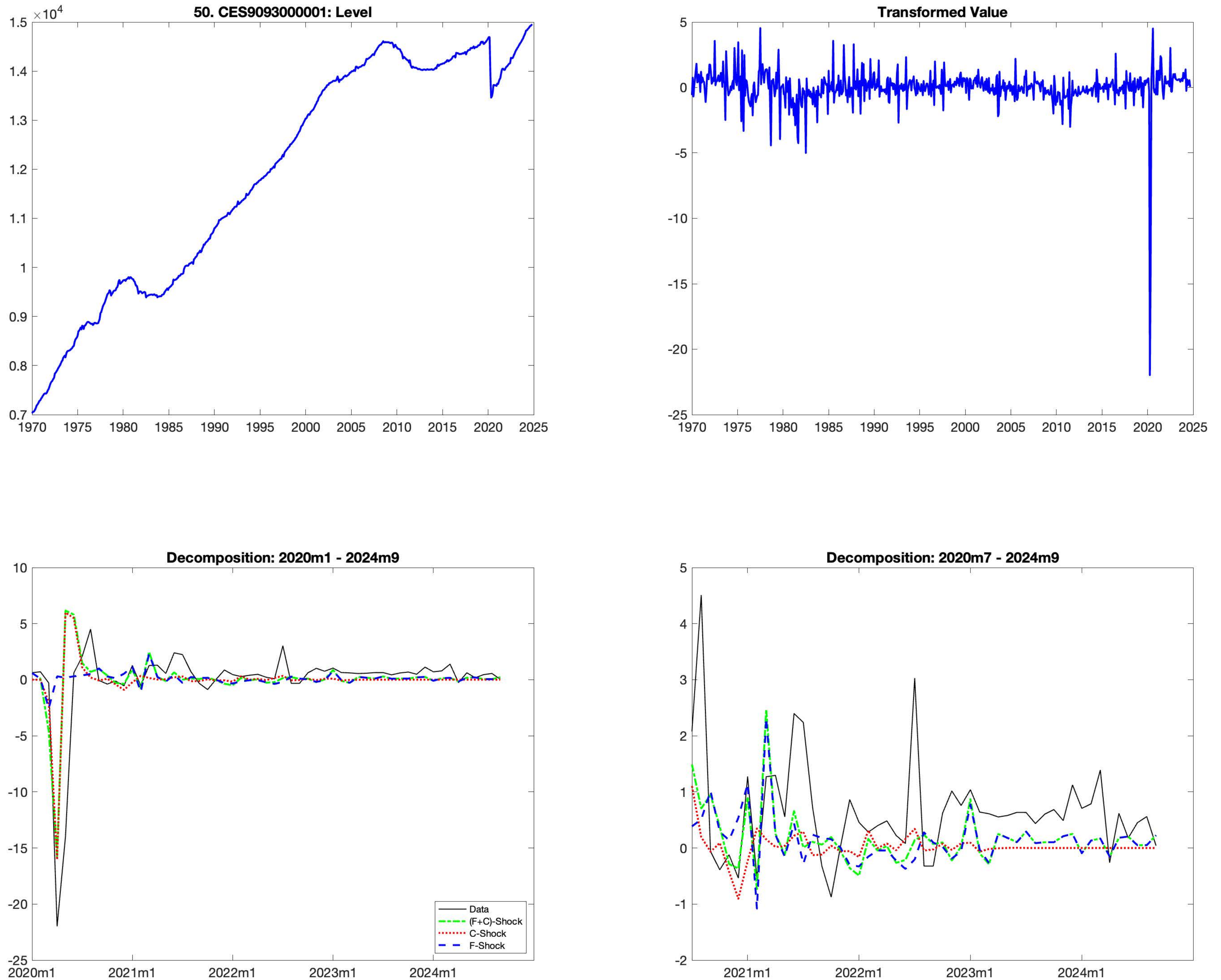

Decomposition: 2020m7 - 2024m9
6
5
4
3
2
1
0
-1
-2
-3
2021m1 2022m1 2023m1 2024m1


49. CES9092200001: Level
3000
2500
2000
1500
1970
1975
1980
1985
1990
1995
2000
2005
2010
2015
2020
2025

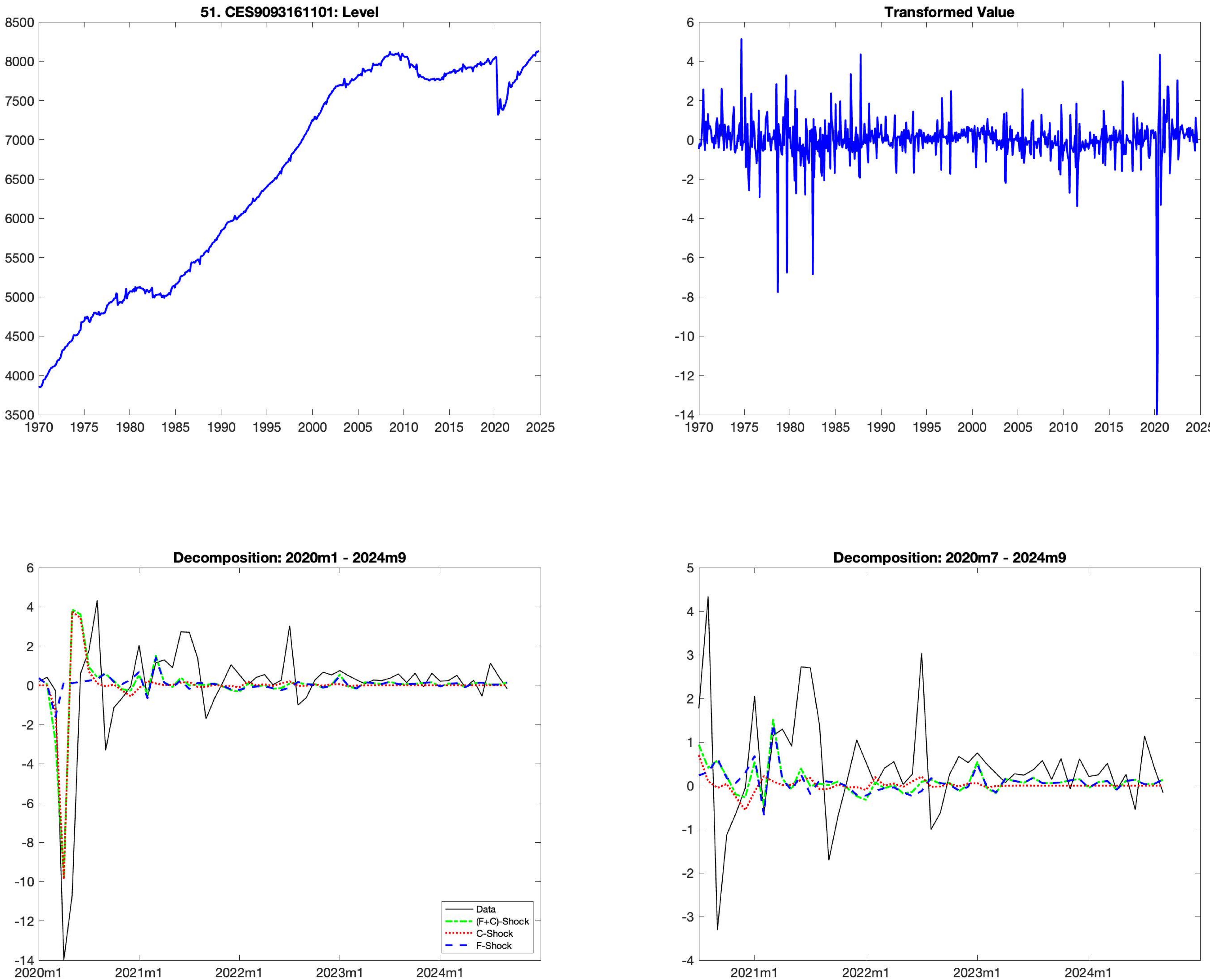

Transformed Value
6
4
2
0
-2
-4
-6
-8
1970
1975
1980
1985
1990
1995
2000
2005
2010
2015
2020
2025

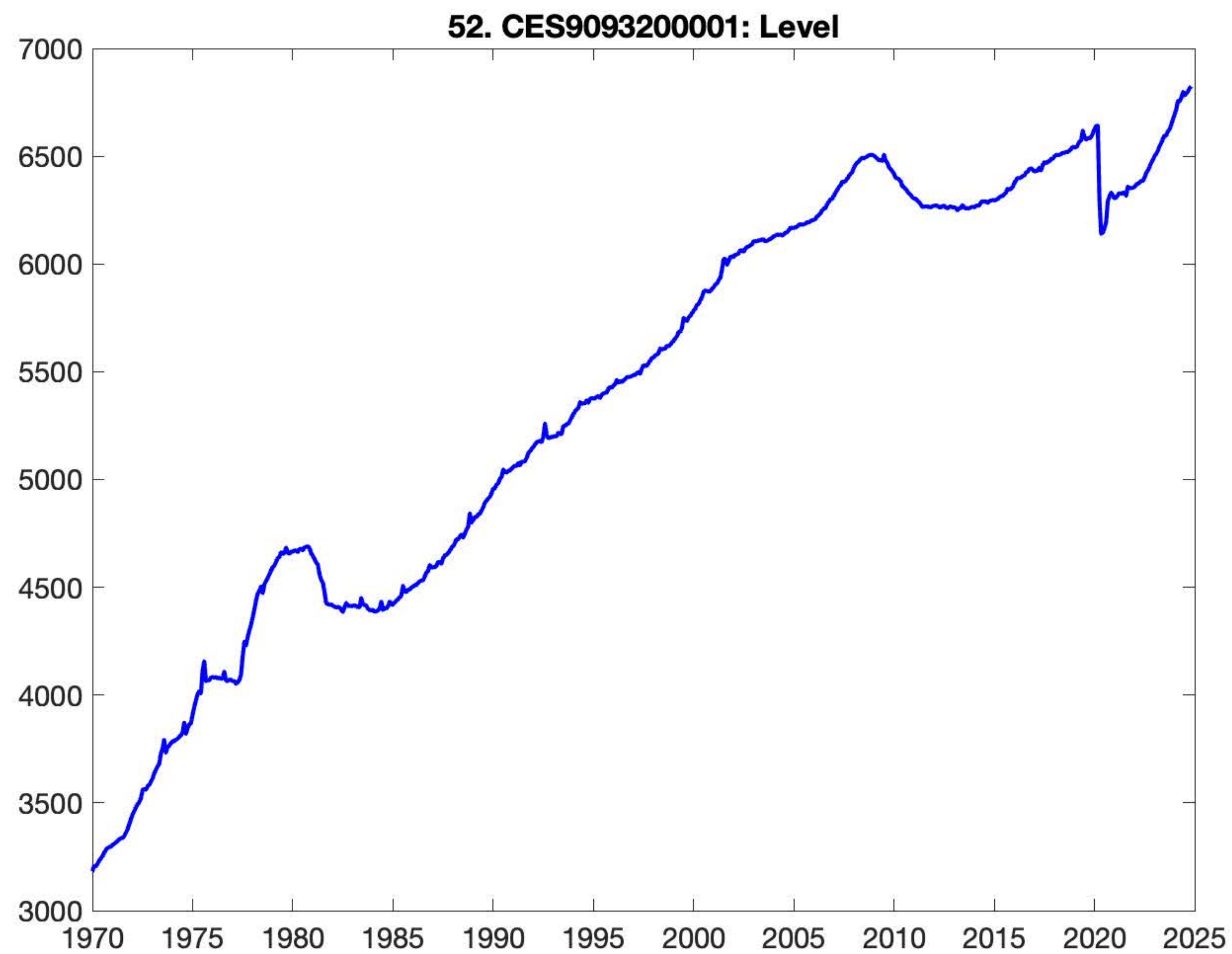

Decomposition: 2020m1 - 2024m9
2.5
2
1.5
1
0.5
0
-0.5
-1
-1.5
-2
2020m1
2021m1
2022m1
2023m1
2024m1
Data
(F+C)-Shock
C-Shock
F-Shock

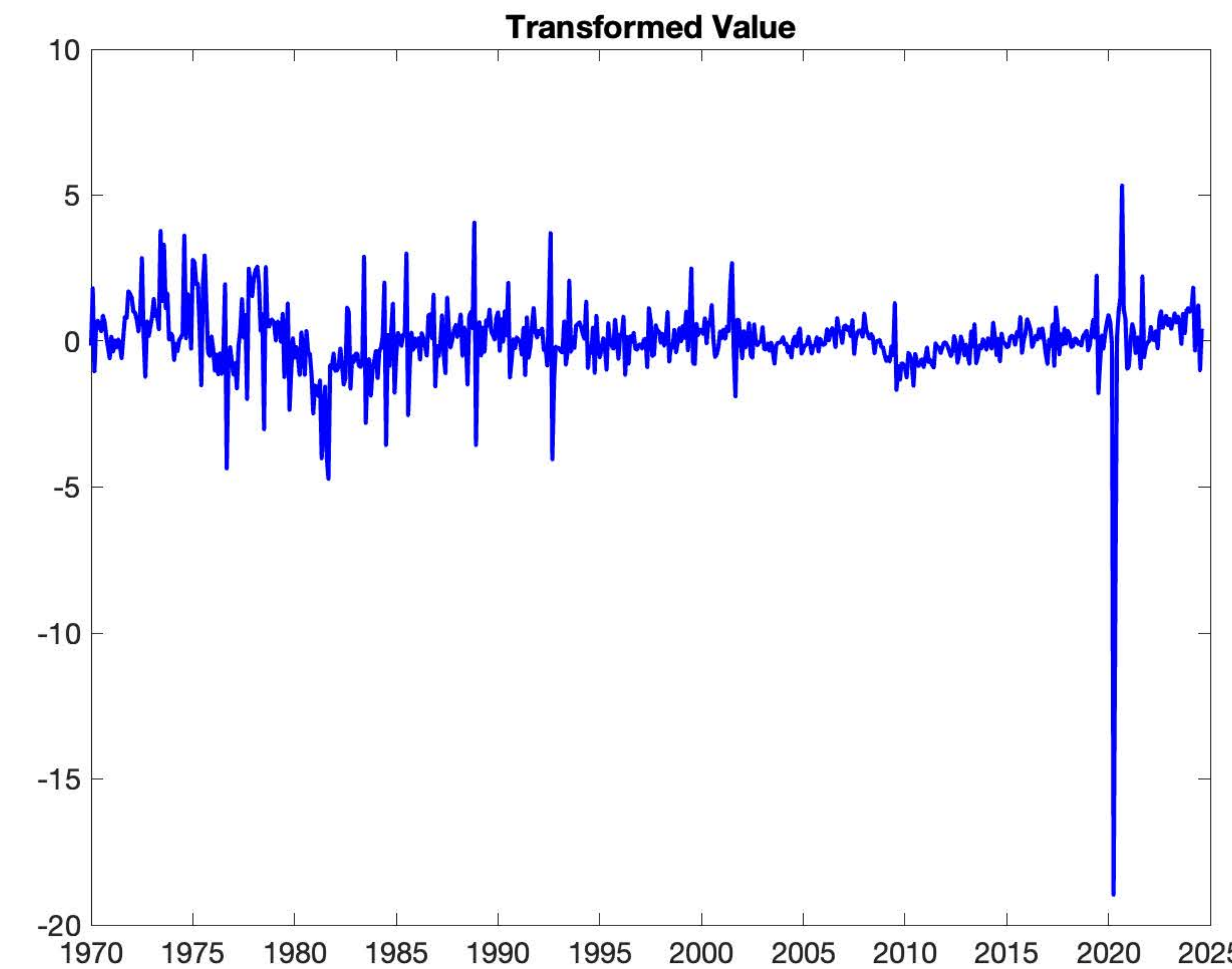

Decomposition: 2020m7 - 2024m9
2.5
2
1.5
1
0.5
0
-0.5
-1
-1.5
2021m1
2022m1
2023m1
2024m1

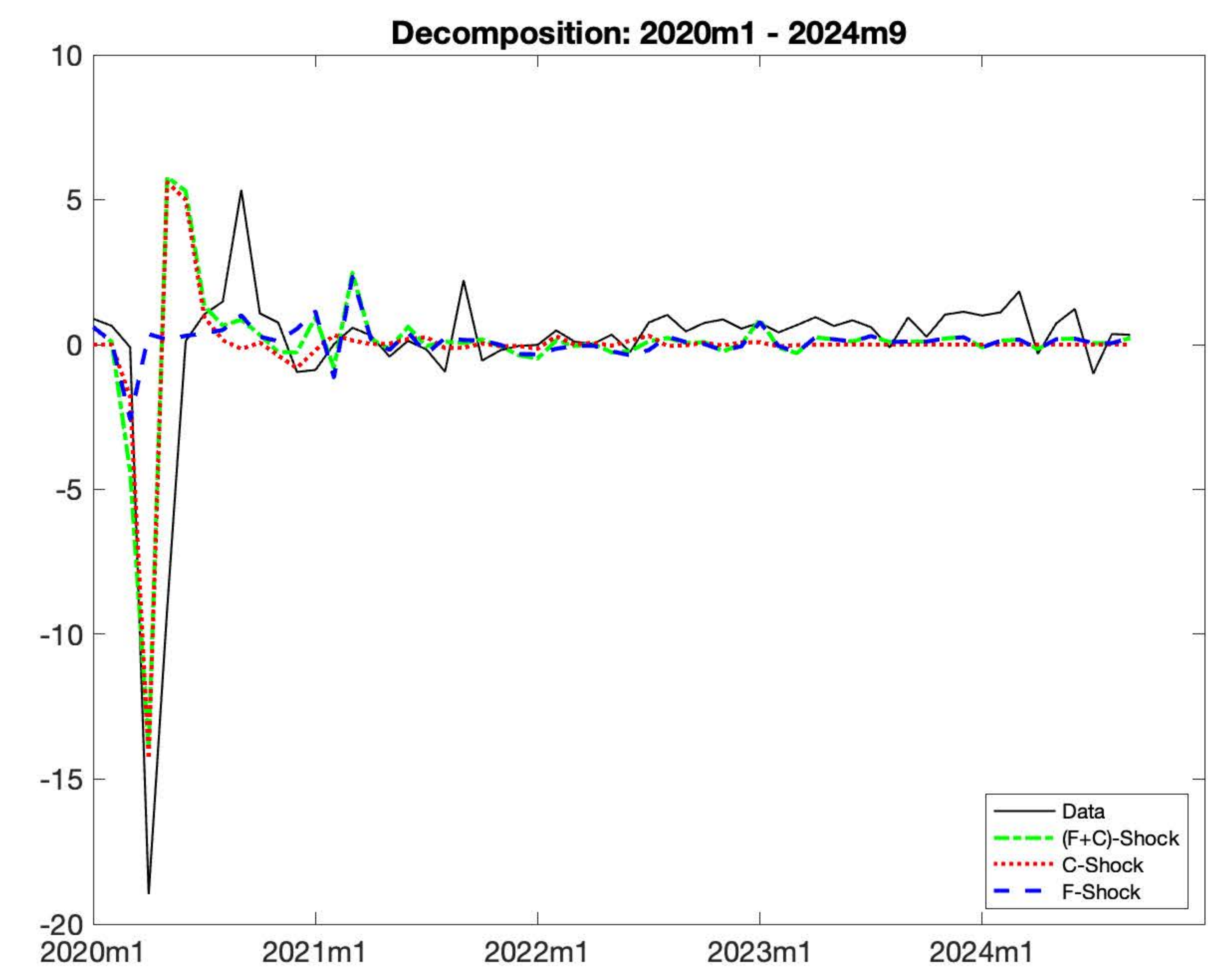


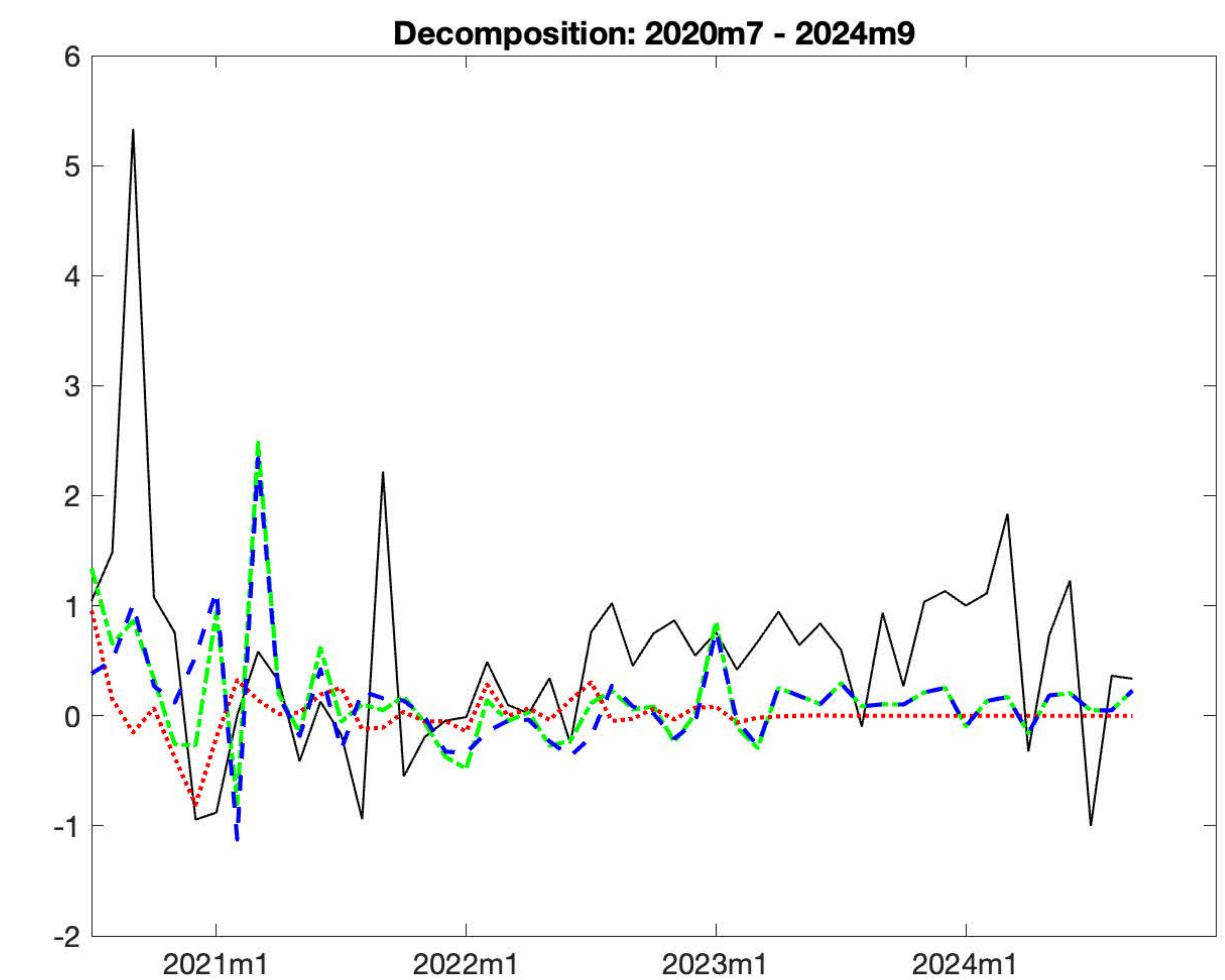
50. CES9093000001: Level
×10^4
1.5
1.4
1.3
1.2
1.1
1
0.9
0.8
0.7
1970
1975
1980
1985
1990
1995
2000
2005
2010
2015
2020
2025
Transformed Value
5
0
-5
-10
-15
-20
-25
Decomposition: 2020m1 - 2024m9
10
2020m1
2021m1
2022m1
2023m1
2024m1
Data
(F+C)-Shock
C-Shock
F-Shock
Decomposition: 2020m7 - 2024m9
4
3
2
1
-1
-2

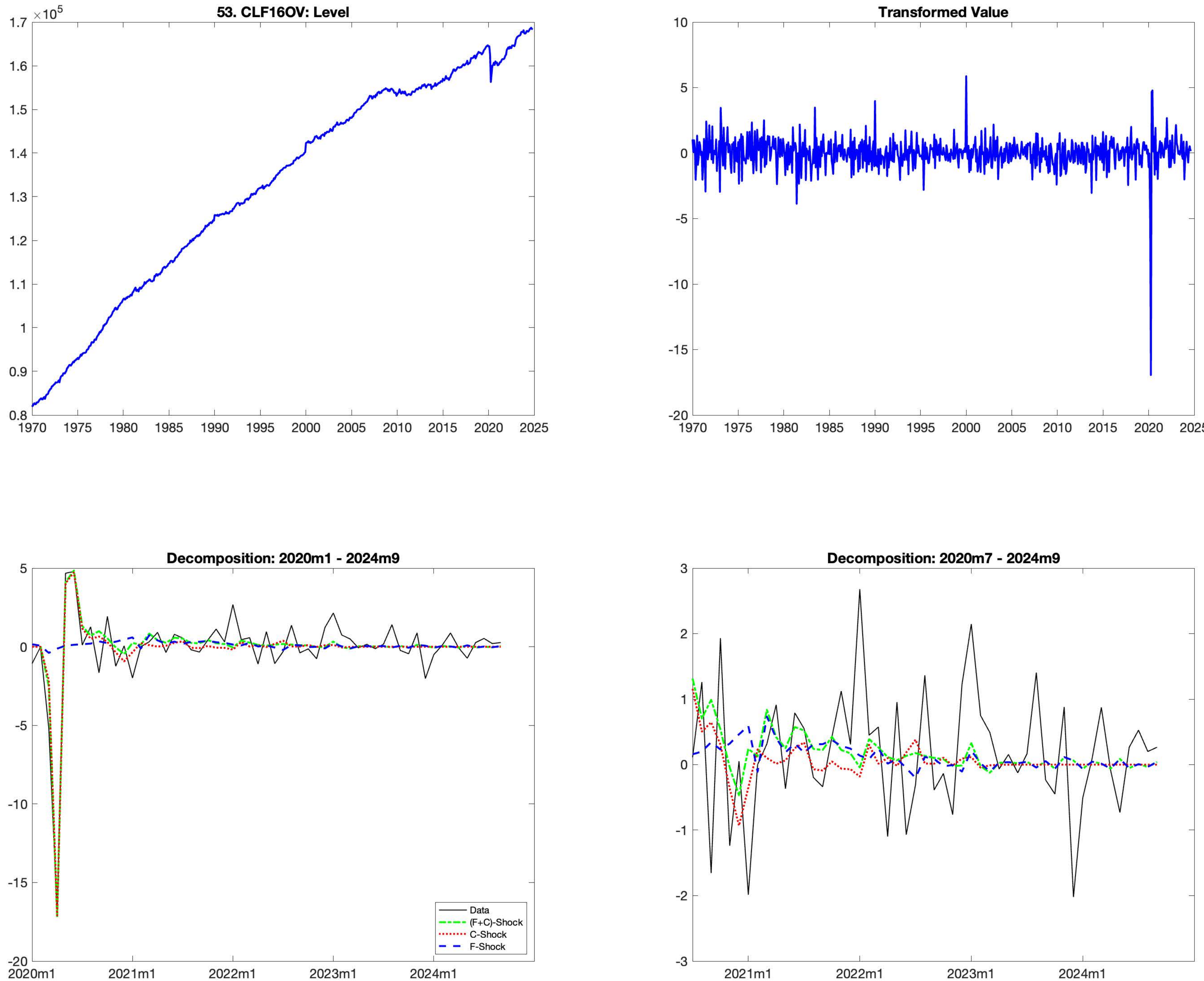

51. CES9093161101: Level
Transformed Value
Decomposition: 2020m1 - 2024m9
Data
(F+C)-Shock
C-Shock
F-Shock
Decomposition: 2020m7 - 2024m9

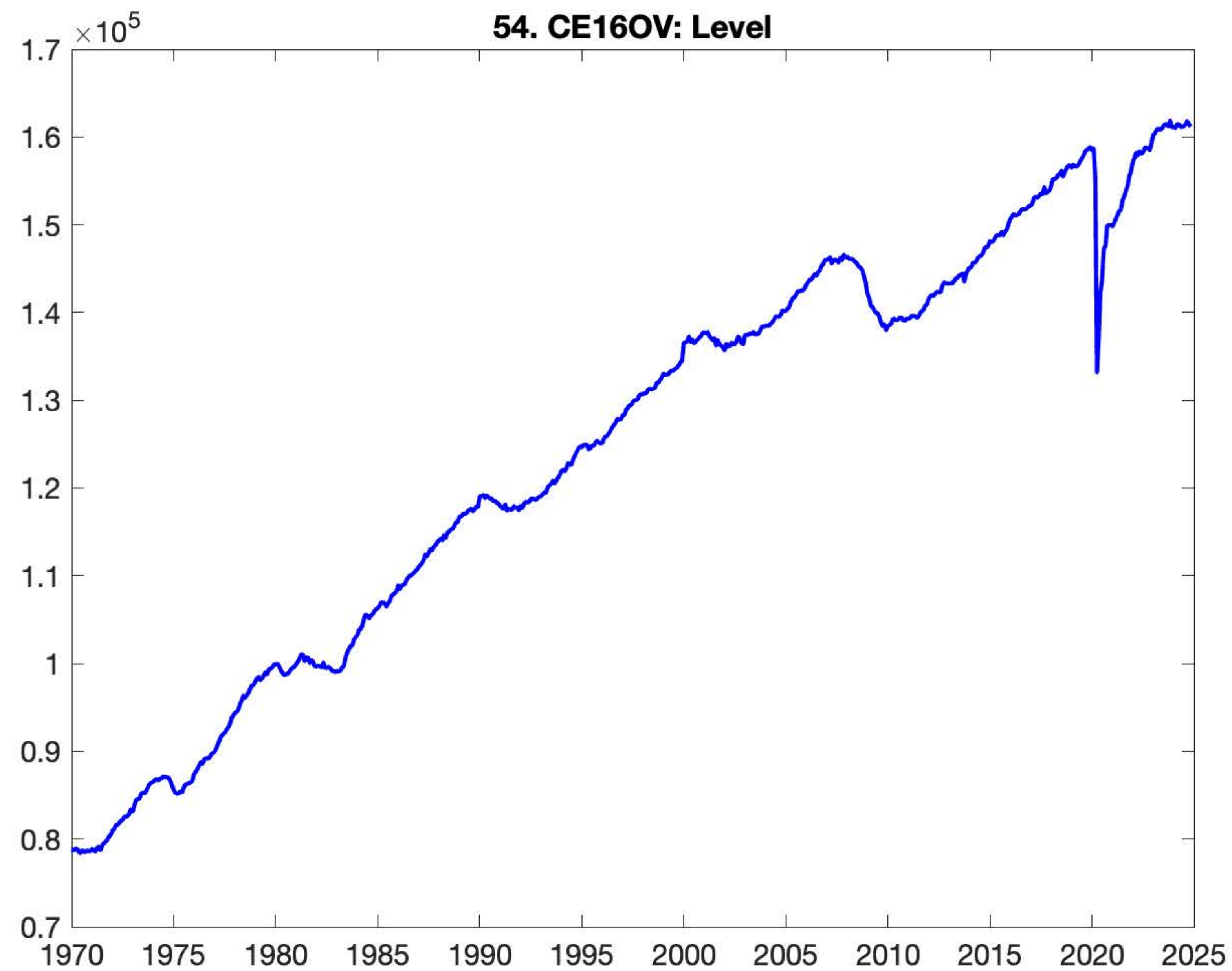

52. CES9093200001: Level
7000
6500
6000
5500
5000
4500
4000
3500
3000
1970
1975
1980
1985
1990
1995
2000
2005
2010
2015
2020
2025

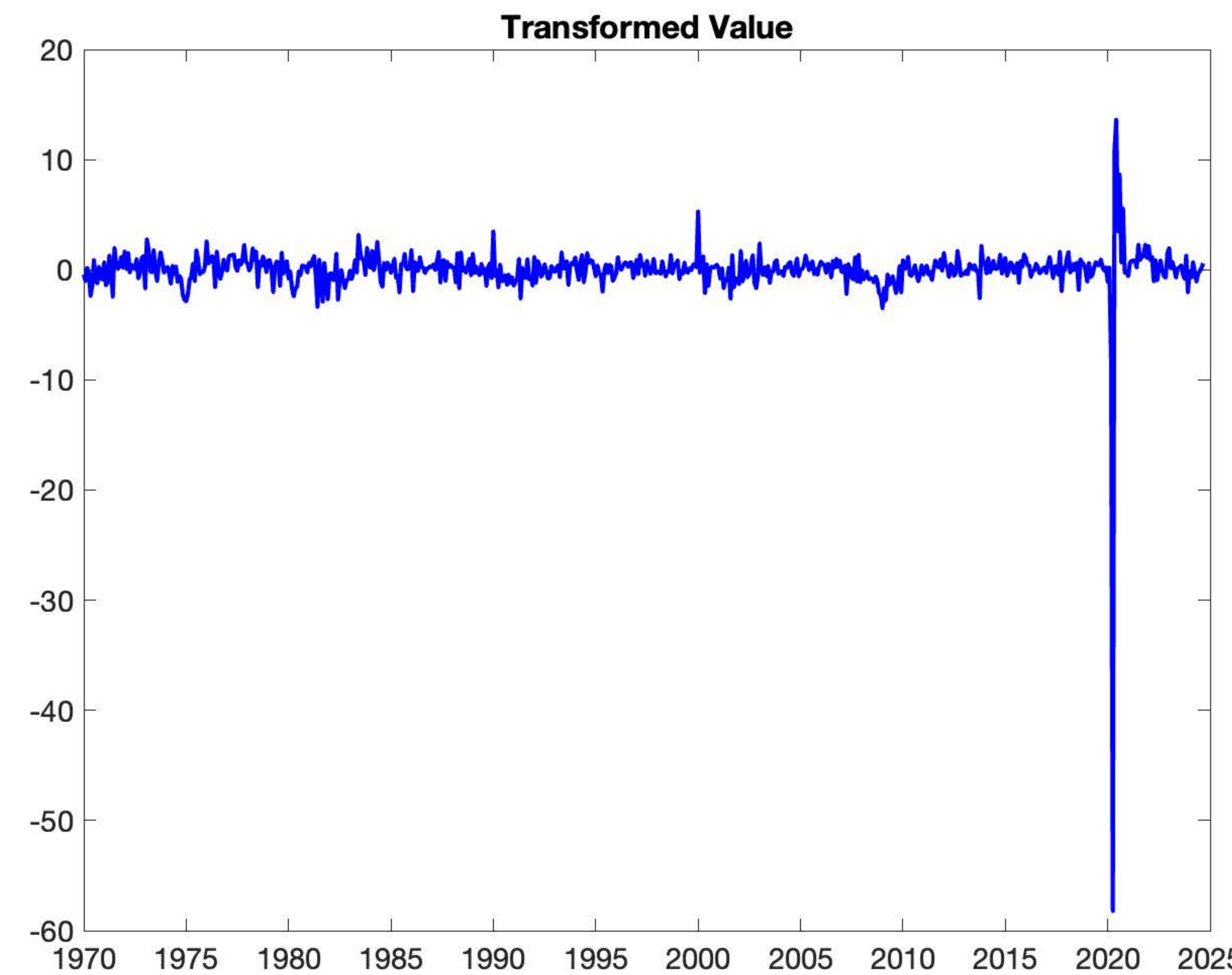

Transformed Value
10
5
0
-5
-10
-15
-20
1970
1975
1980
1985
1990
1995
2000
2005
2010
2015
2020
2025

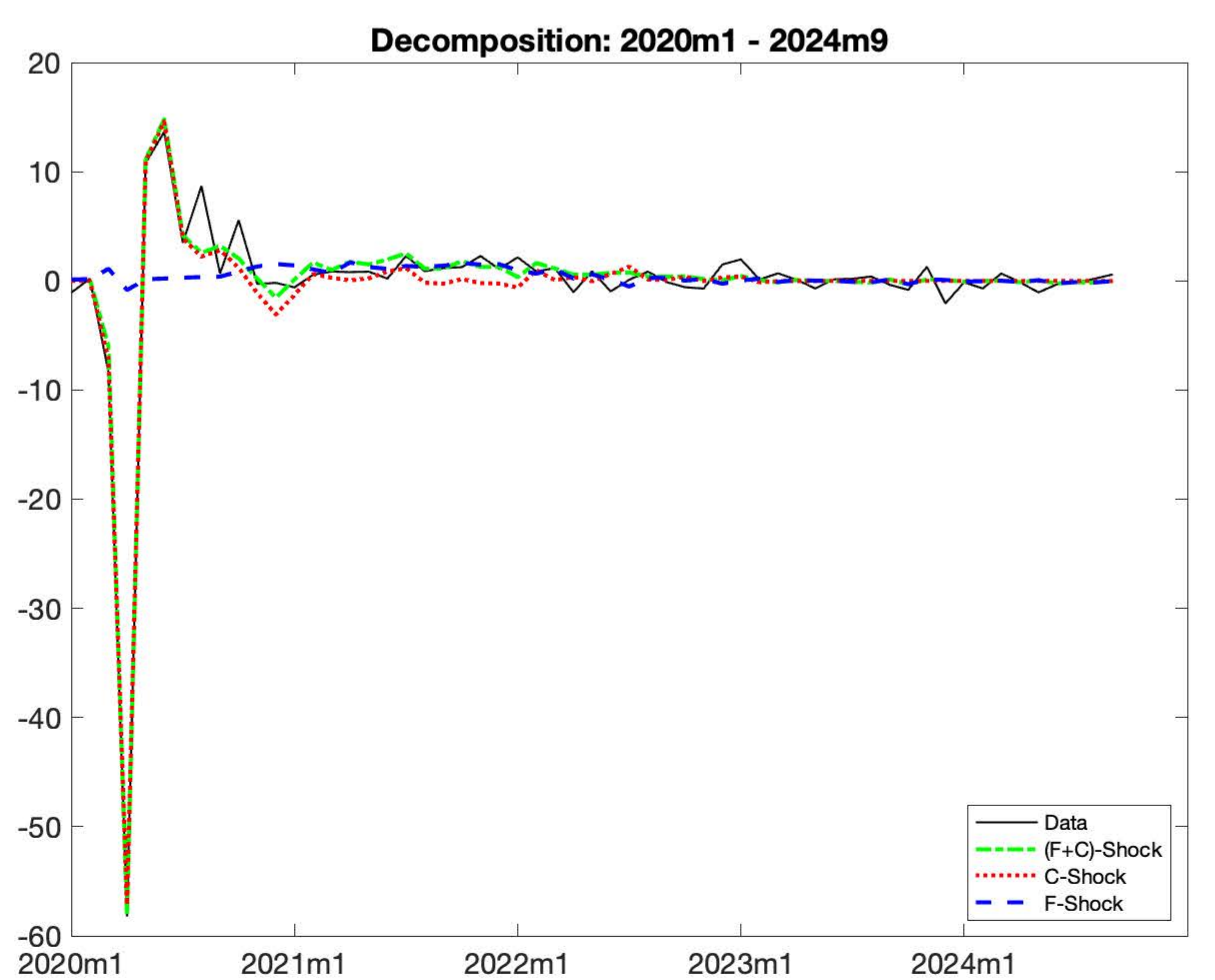

Decomposition: 2020m1 - 2024m9
10
5
0
-5
-10
-15
-20
2020m1
2021m1
2022m1
2023m1
2024m1
Data
(F+C)-Shock
C-Shock
F-Shock

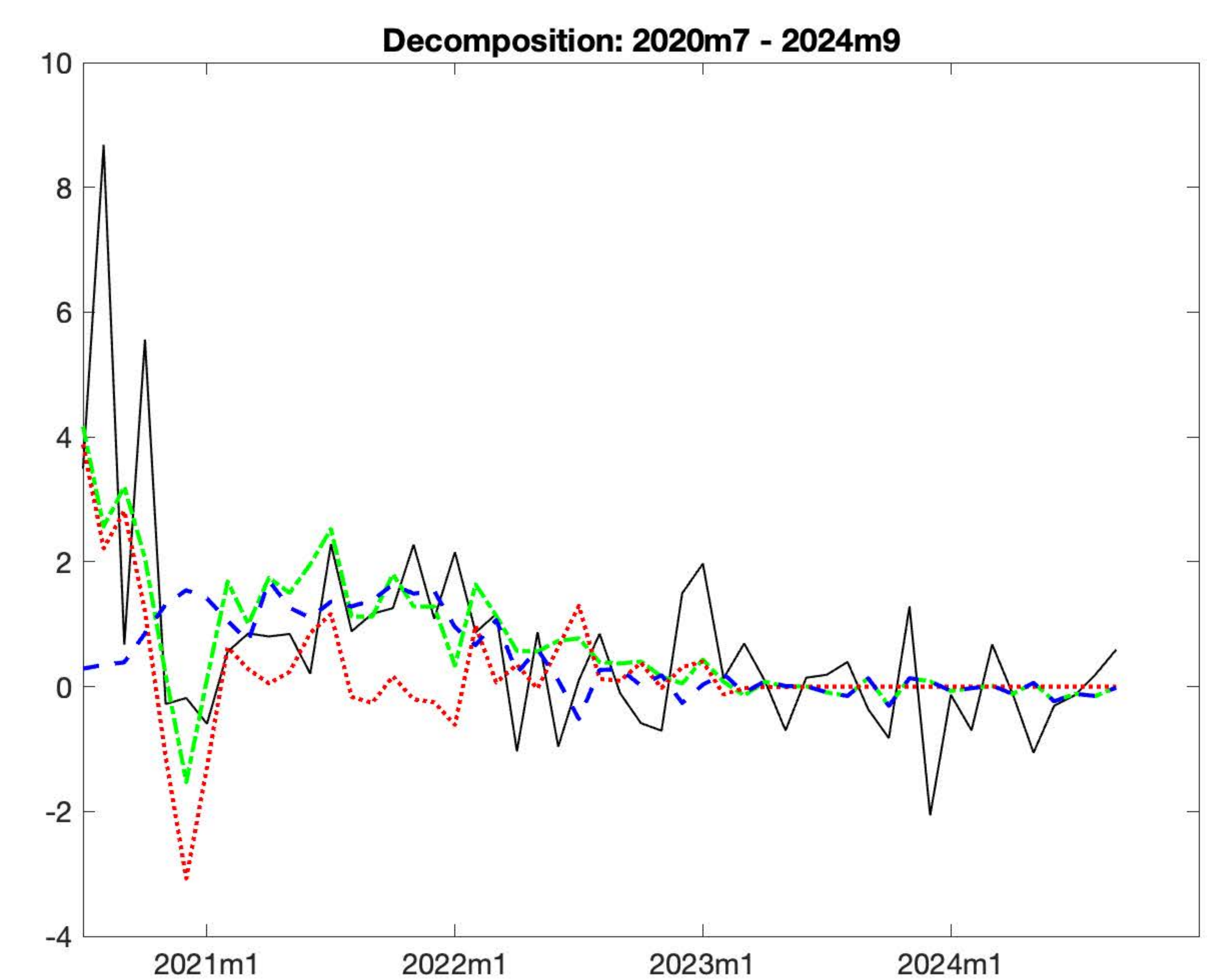

Decomposition: 2020m7 - 2024m9
6
5
4
3
2
1
0
-1
-2
2021m1
2022m1
2023m1
2024m1

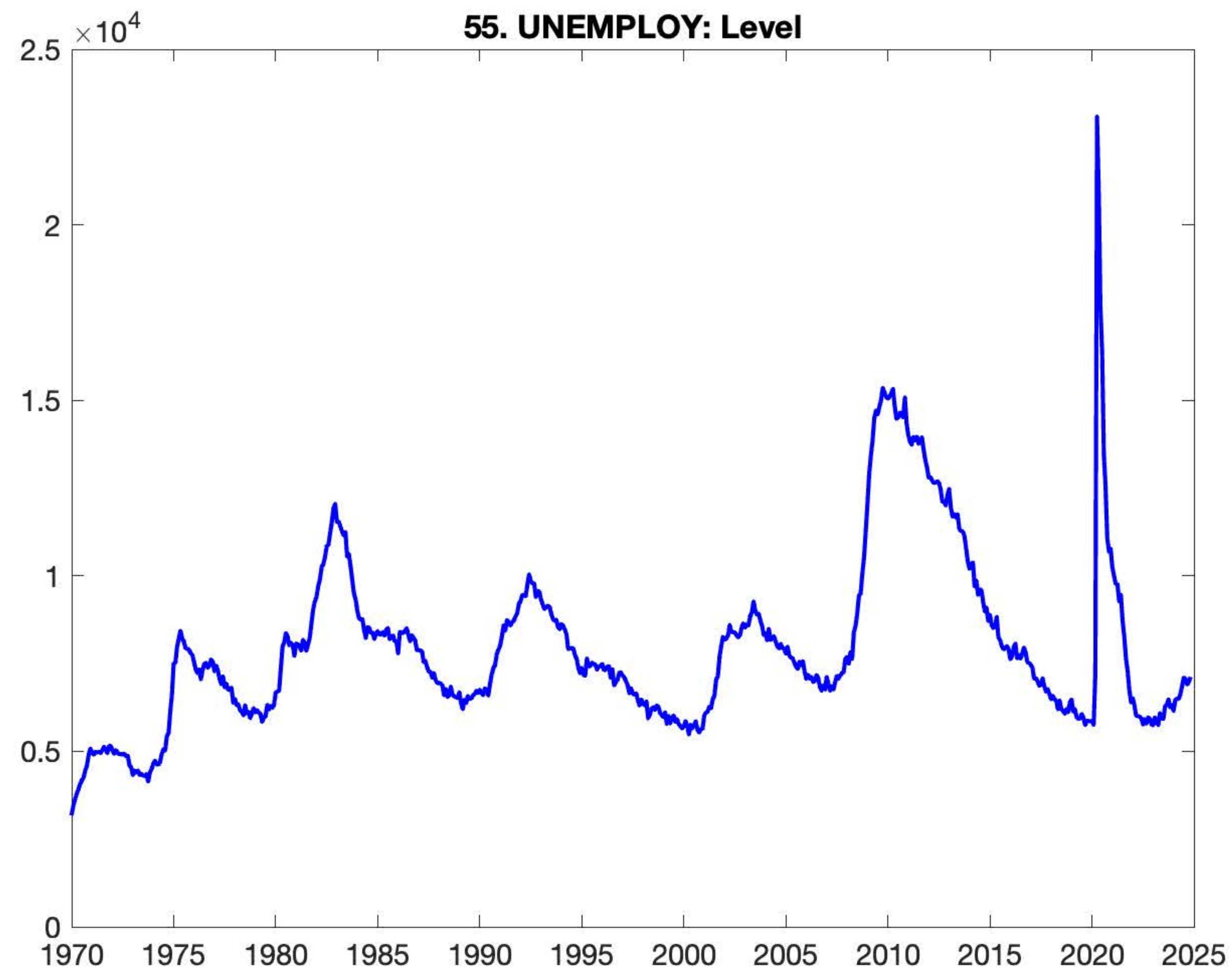

53. CLF16OV: Level
Transformed Value
Decomposition: 2020m1 - 2024m9
Data
(F+C)-Shock
C-Shock
F-Shock
Decomposition: 2020m7 - 2024m9

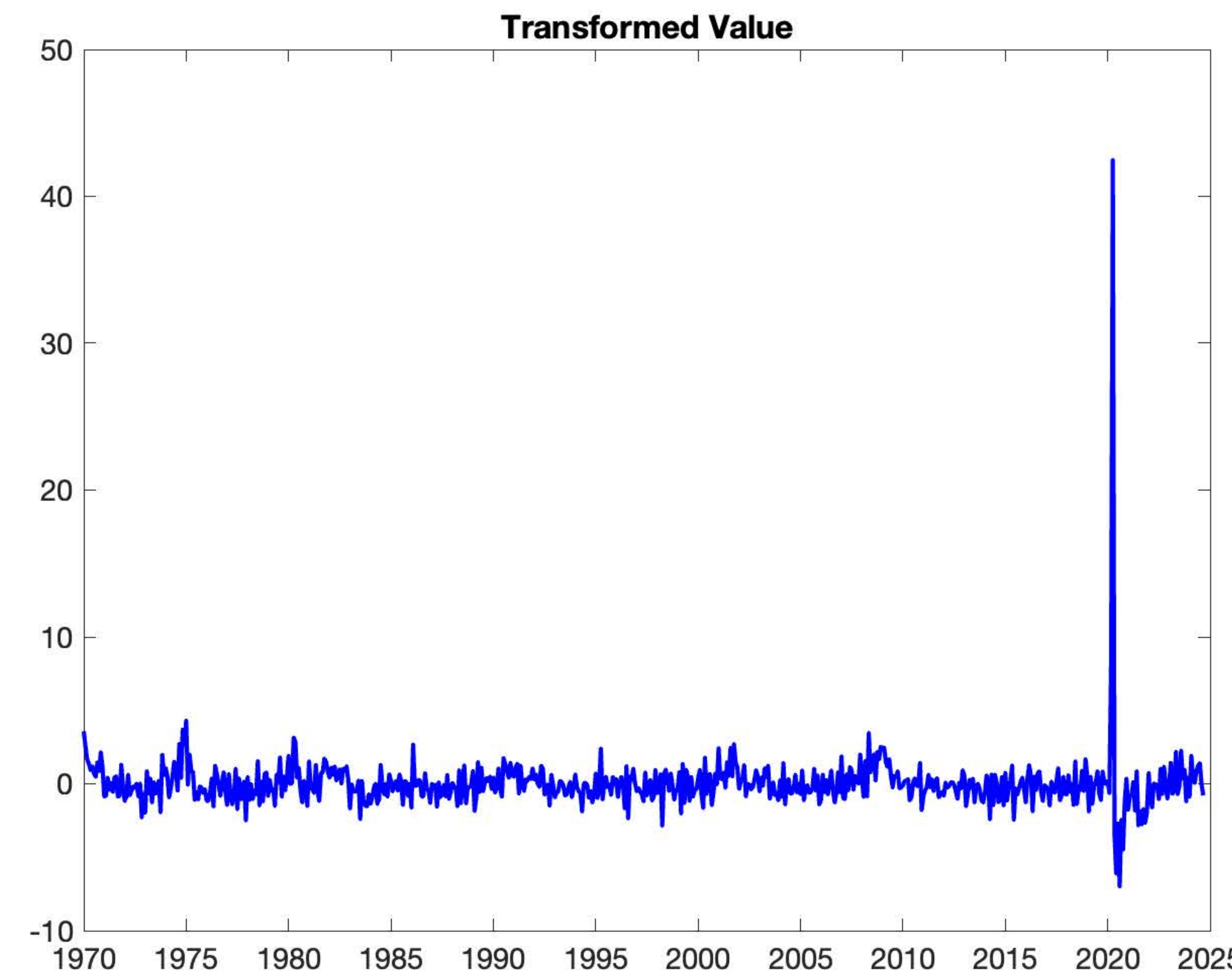

54. CE16OV: Level
×10^5
1.7
1.6
1.5
1.4
1.3
1.2
1.1
1
0.9
0.8
0.7
1970
1975
1980
1985
1990
1995
2000
2005
2010
2015
2020
2025

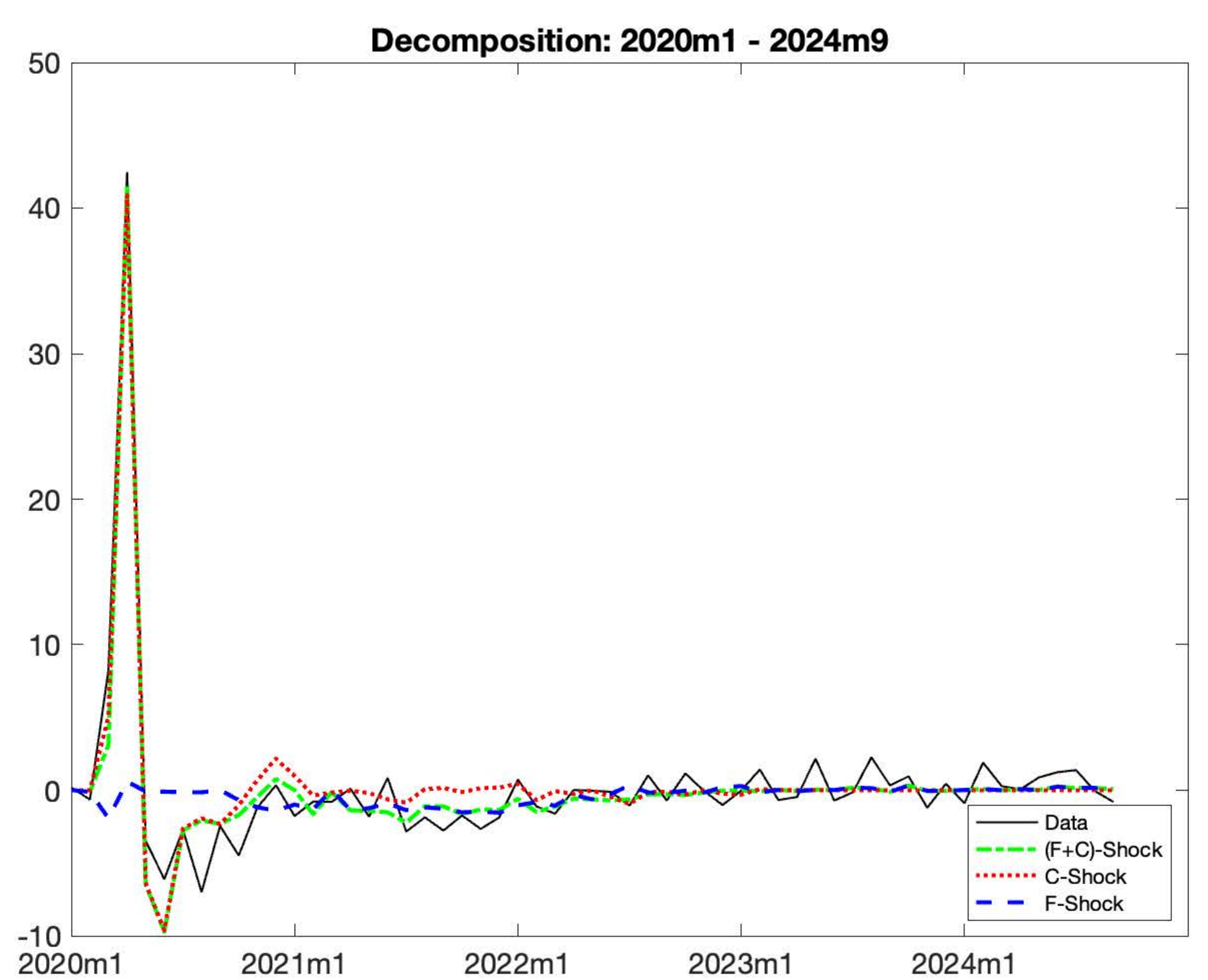

Transformed Value
20
10
0
-10
-20
-30
-40
-50
-60
1970
1975
1980
1985
1990
1995
2000
2005
2010
2015
2020
2025

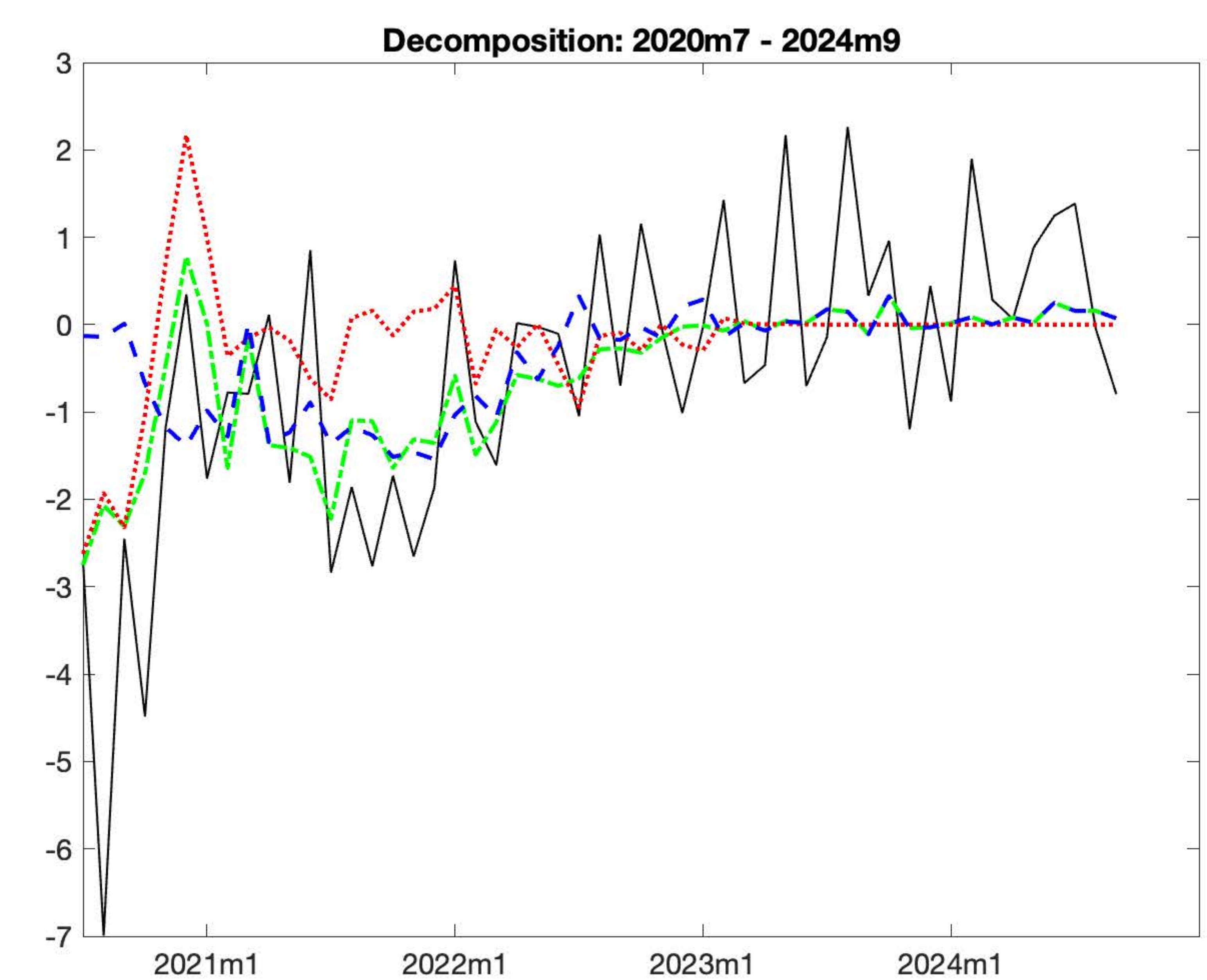

Decomposition: 2020m1 - 2024m9
20
10
0
-10
-20
-30
-40
-50
-60
2020m1
2021m1
2022m1
2023m1
2024m1
Data
(F+C)-Shock
C-Shock
F-Shock

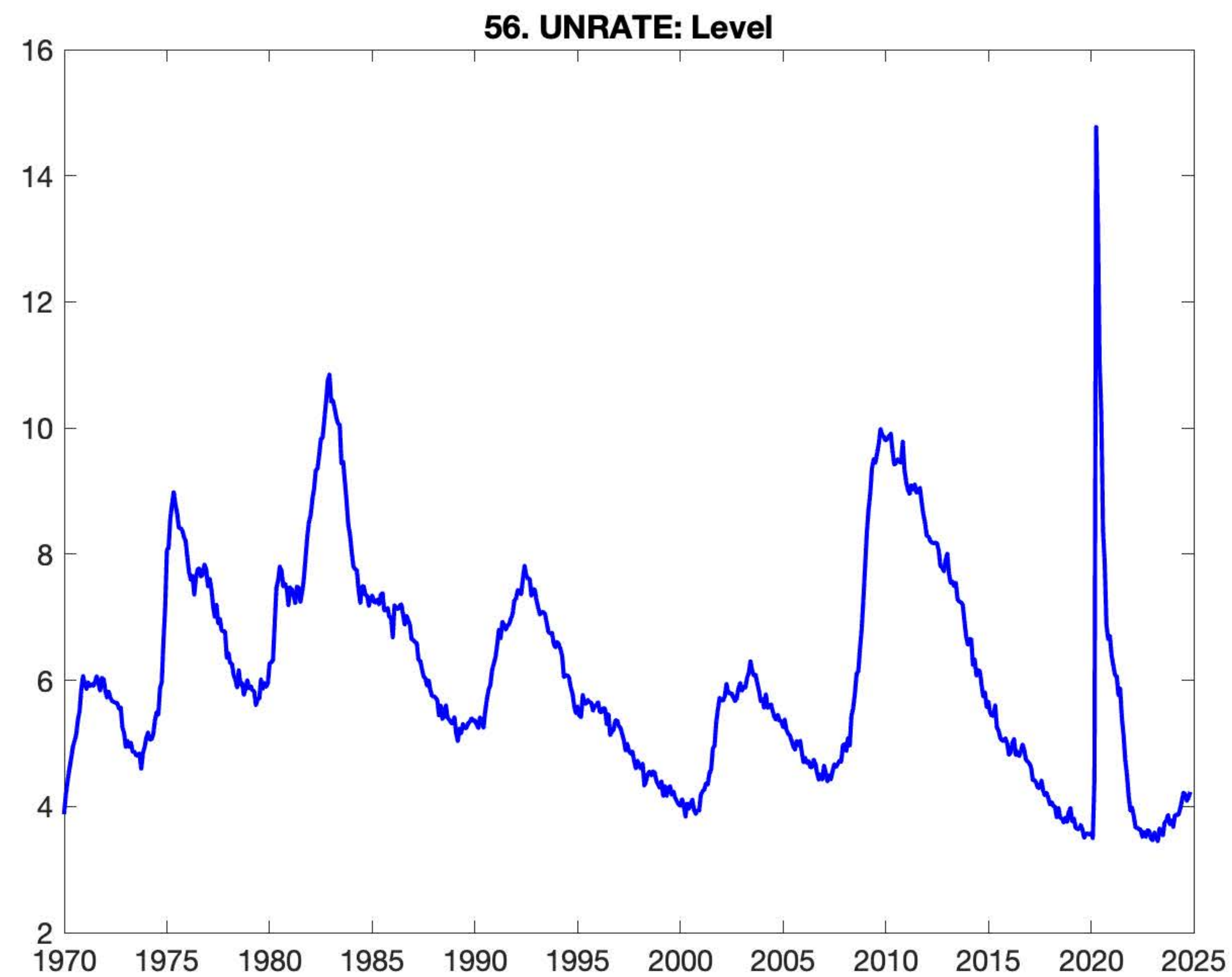

Decomposition: 2020m7 - 2024m9
10
8
6
4
2
0
-2
-4
2021m1
2022m1
2023m1
2024m1


55. UNEMPLOY: Level
×10^4

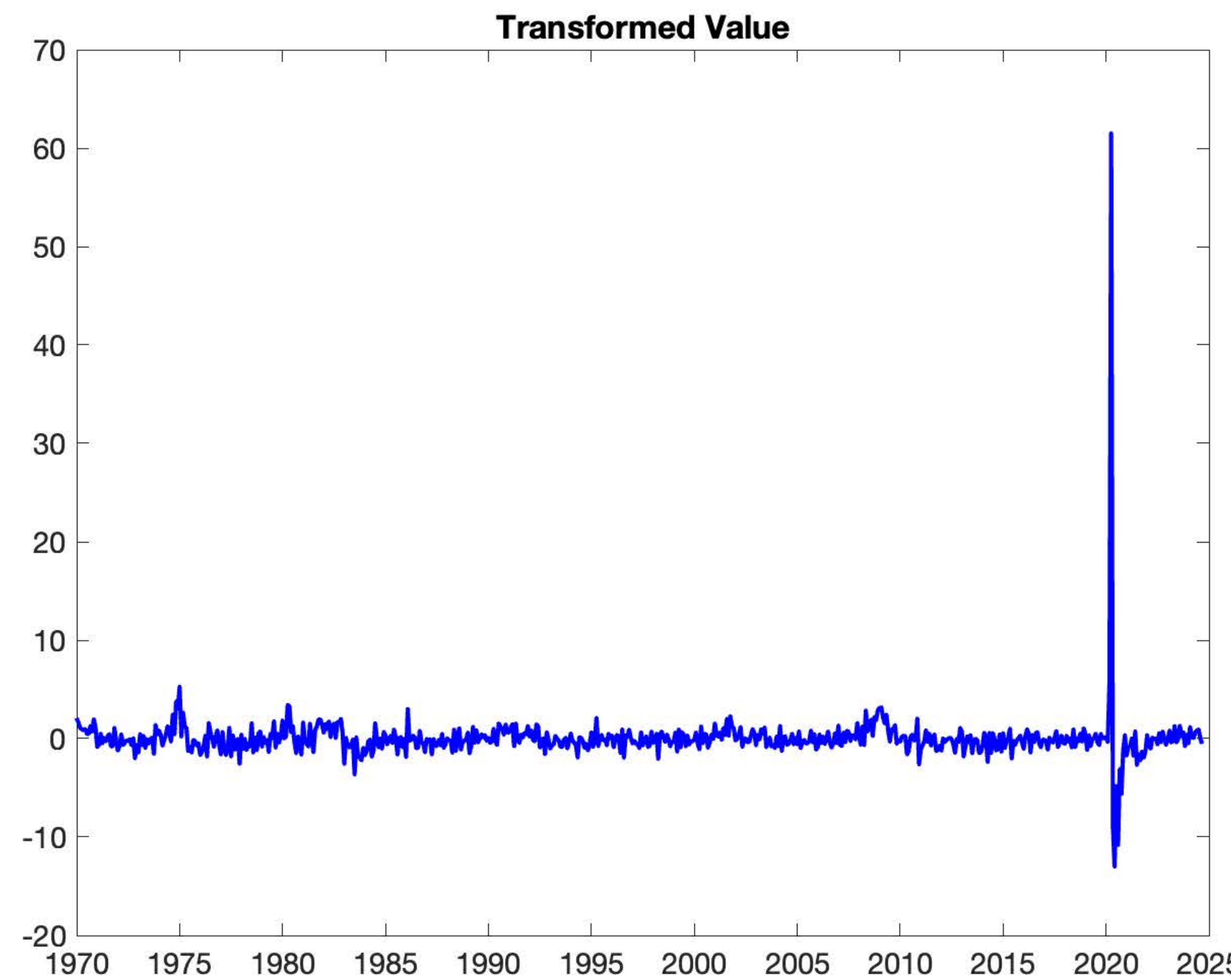

Transformed Value


Decomposition: 2020m1 - 2024m9
Data
(F+C)-Shock
C-Shock
F-Shock

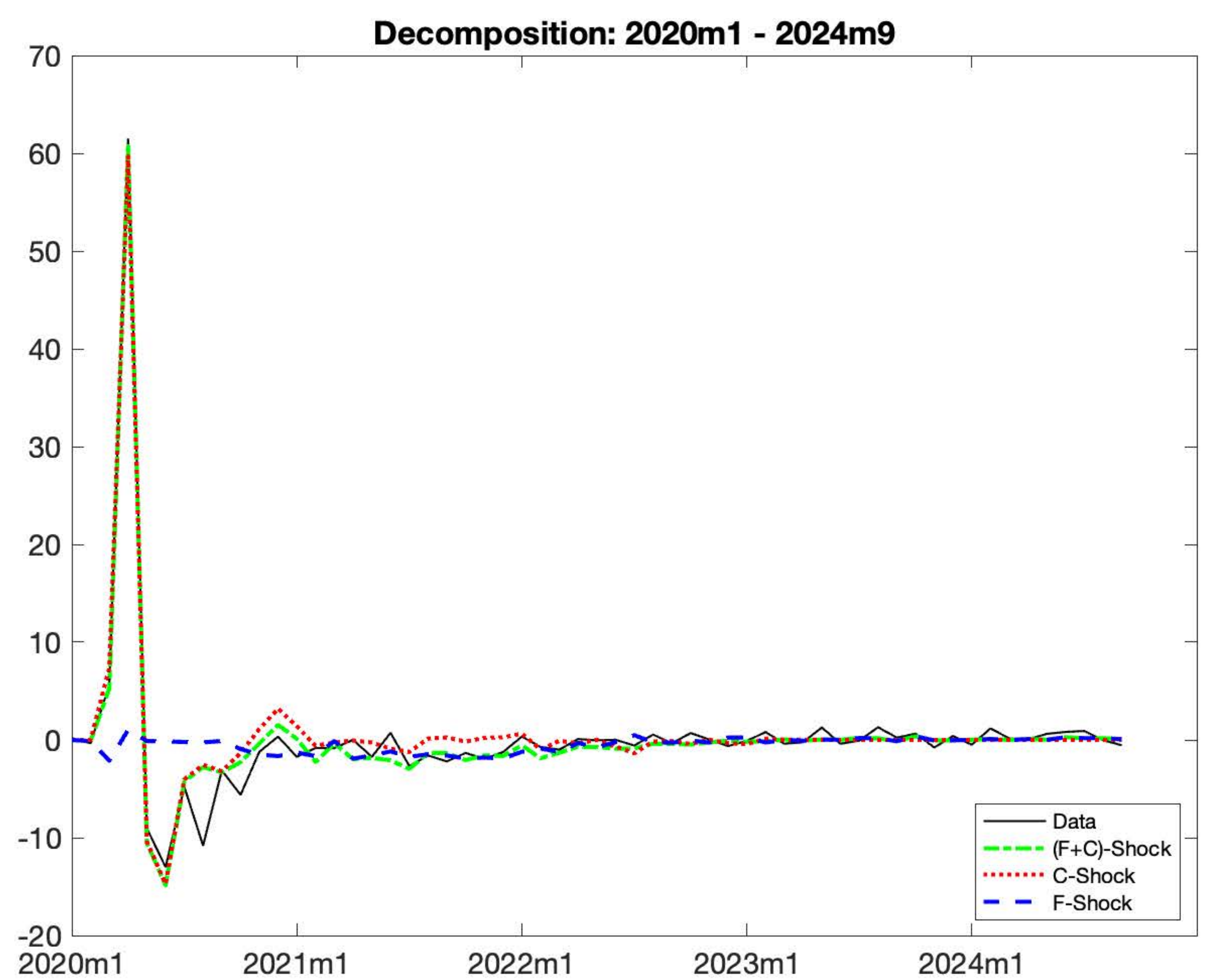

Decomposition: 2020m7 - 2024m9



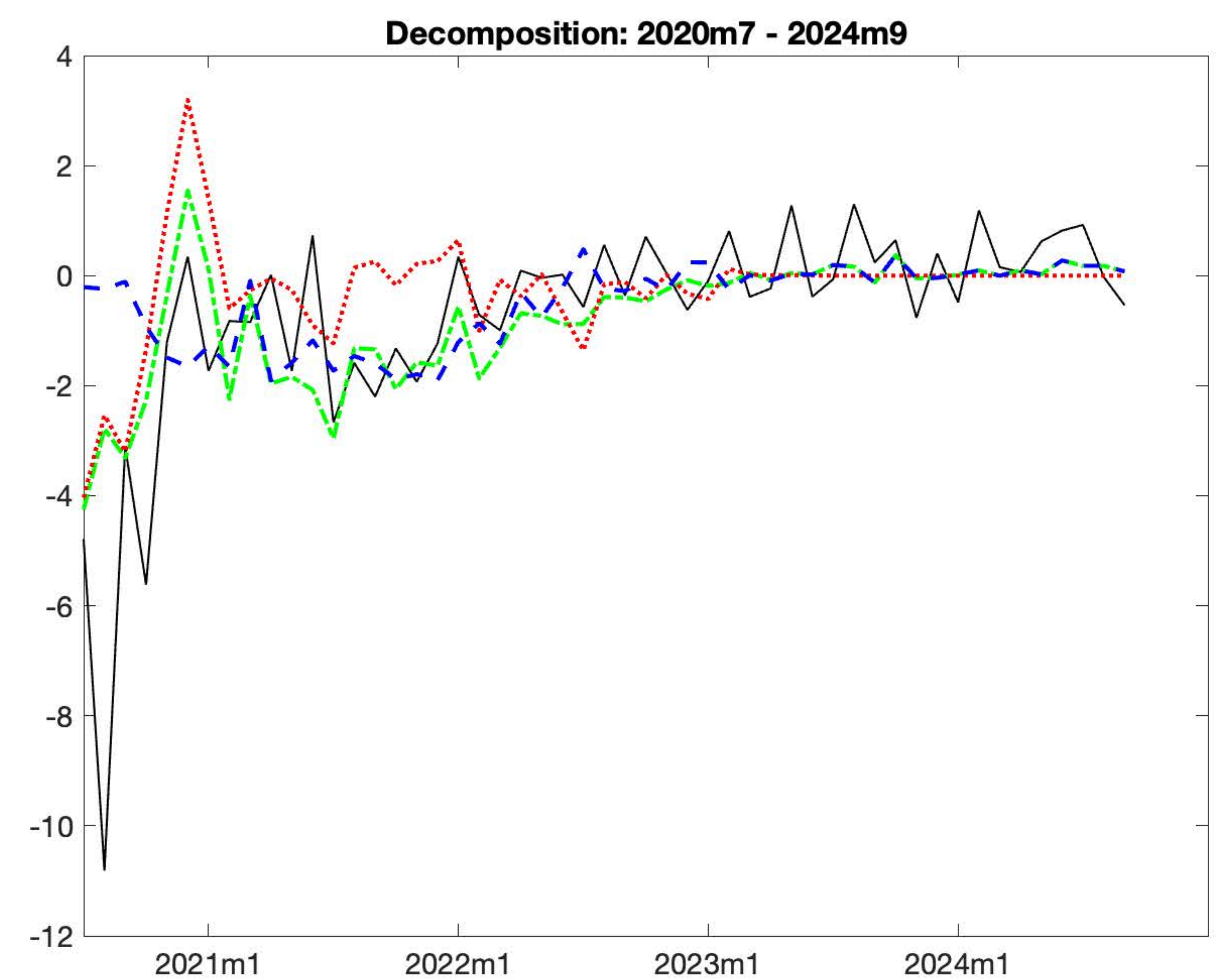
56. UNRATE: Level



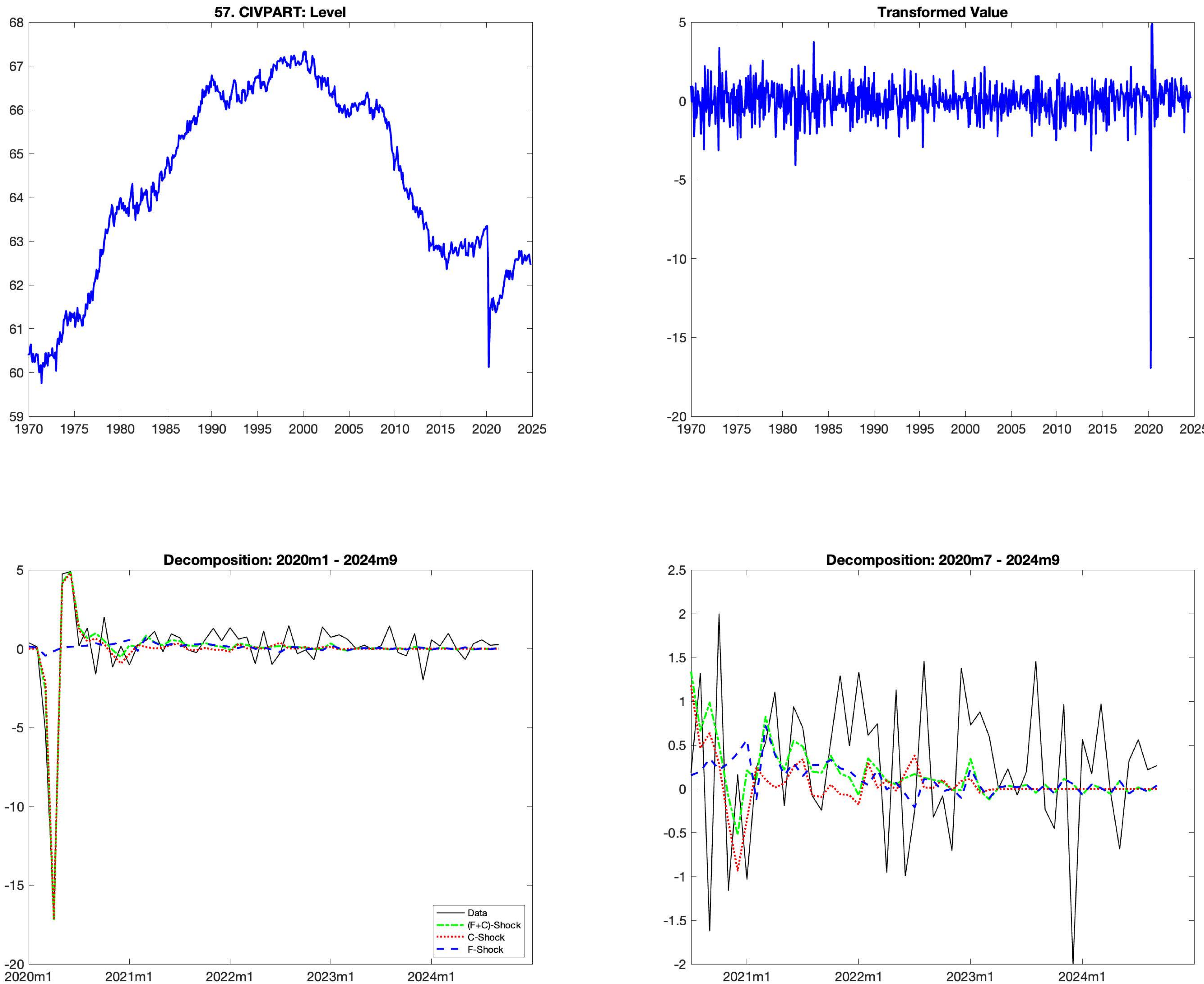
Transformed Value

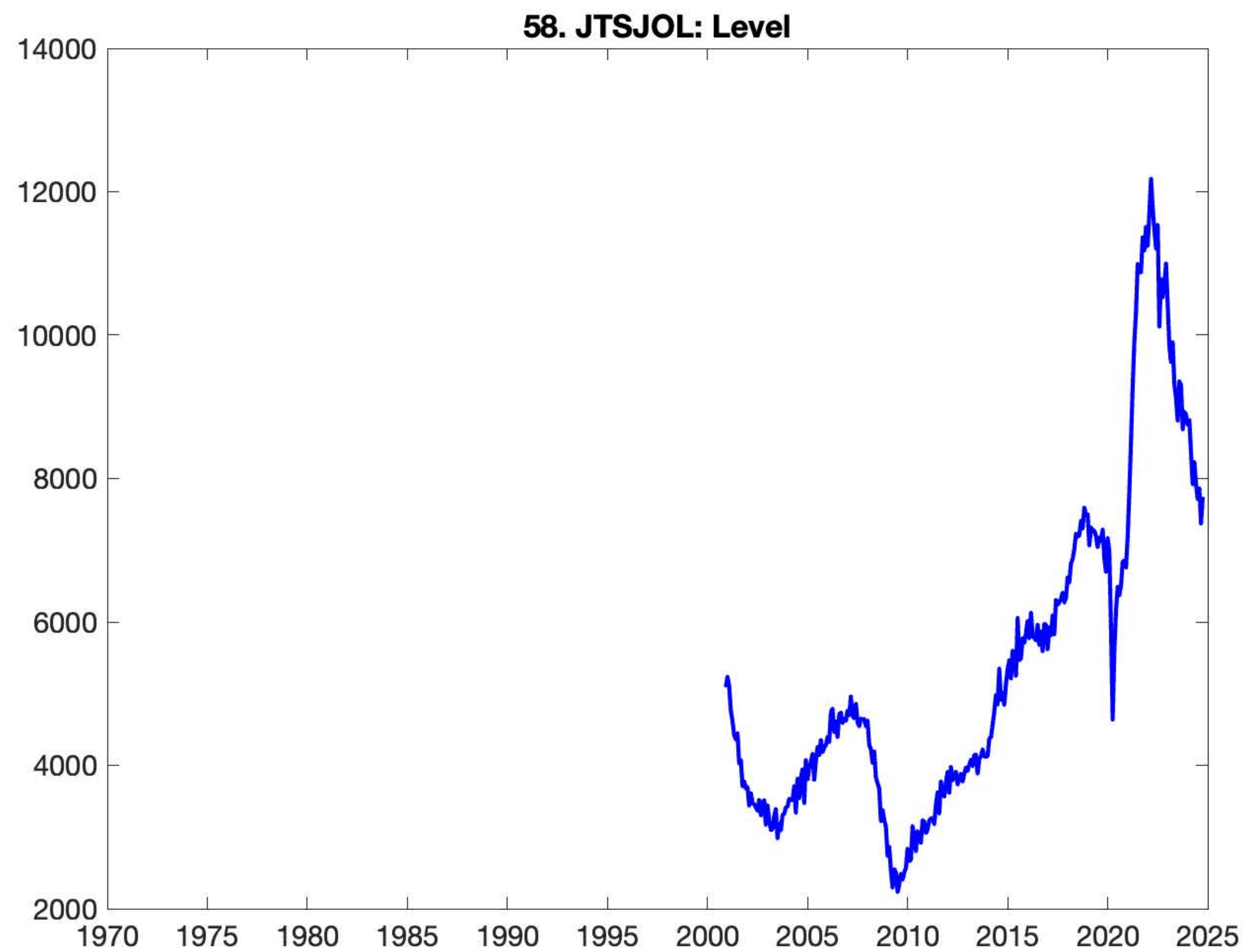


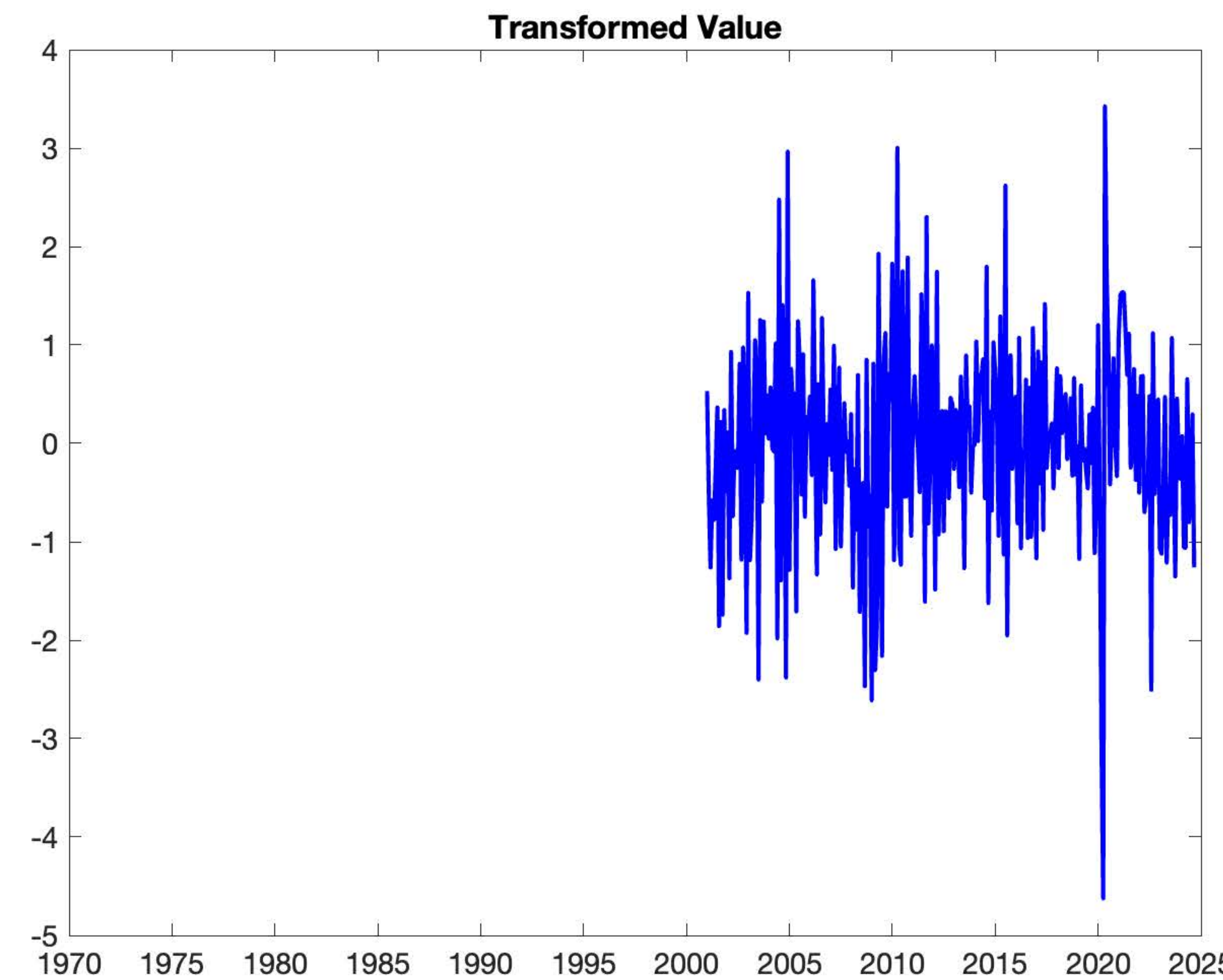
Decomposition: 2020m1 - 2024m9
Data
(F+C)-Shock
C-Shock
F-Shock

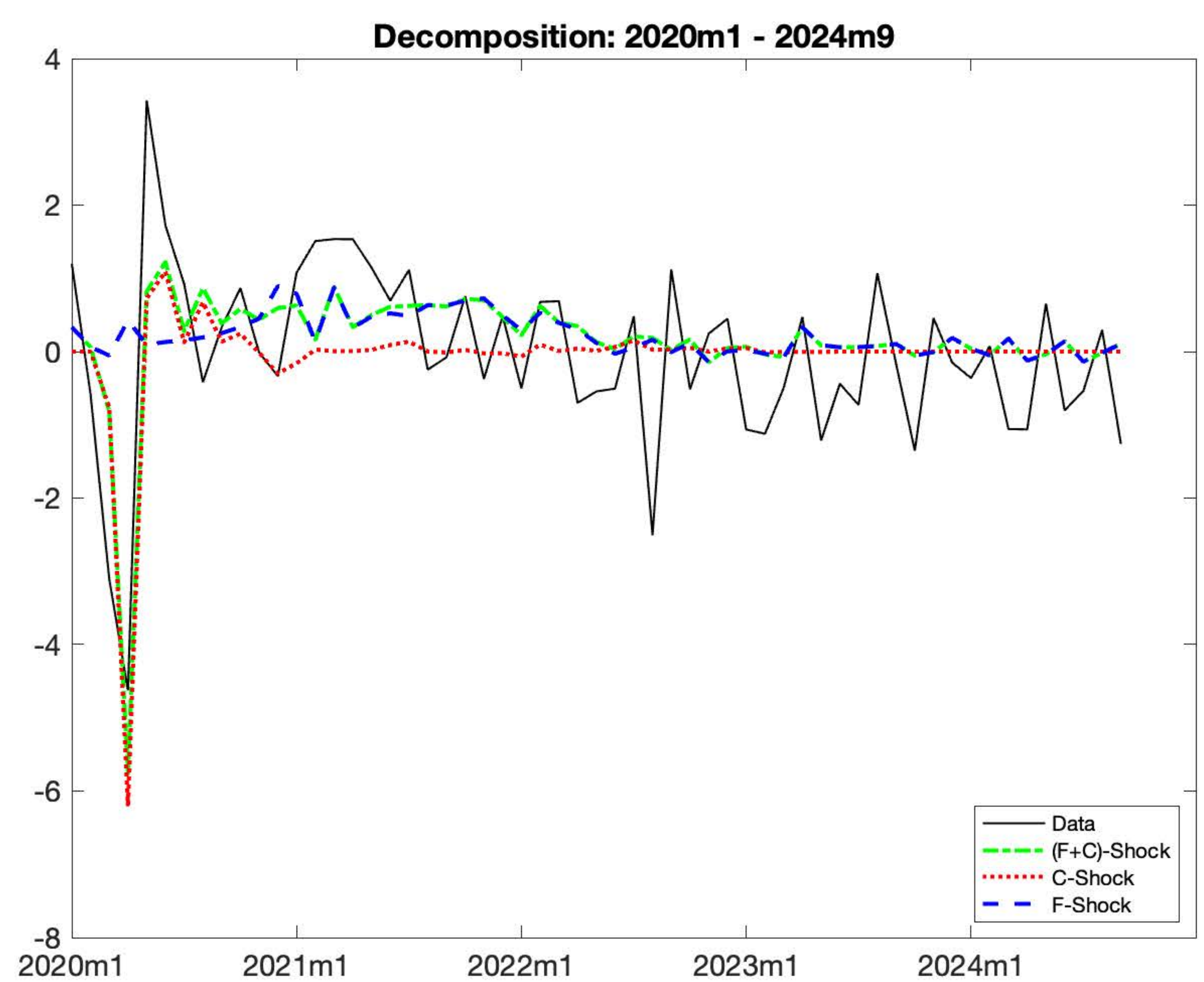


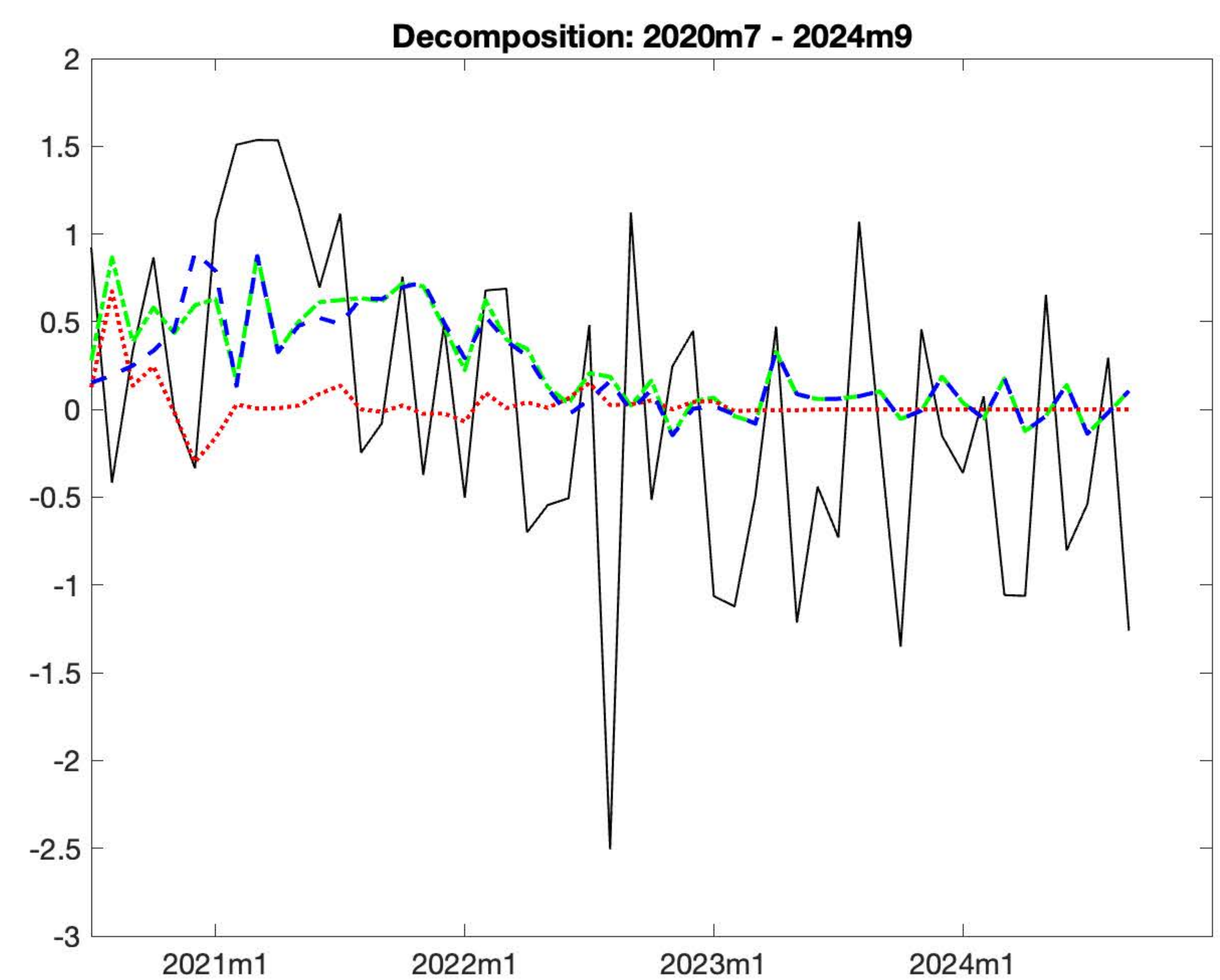
Decomposition: 2020m7 - 2024m9

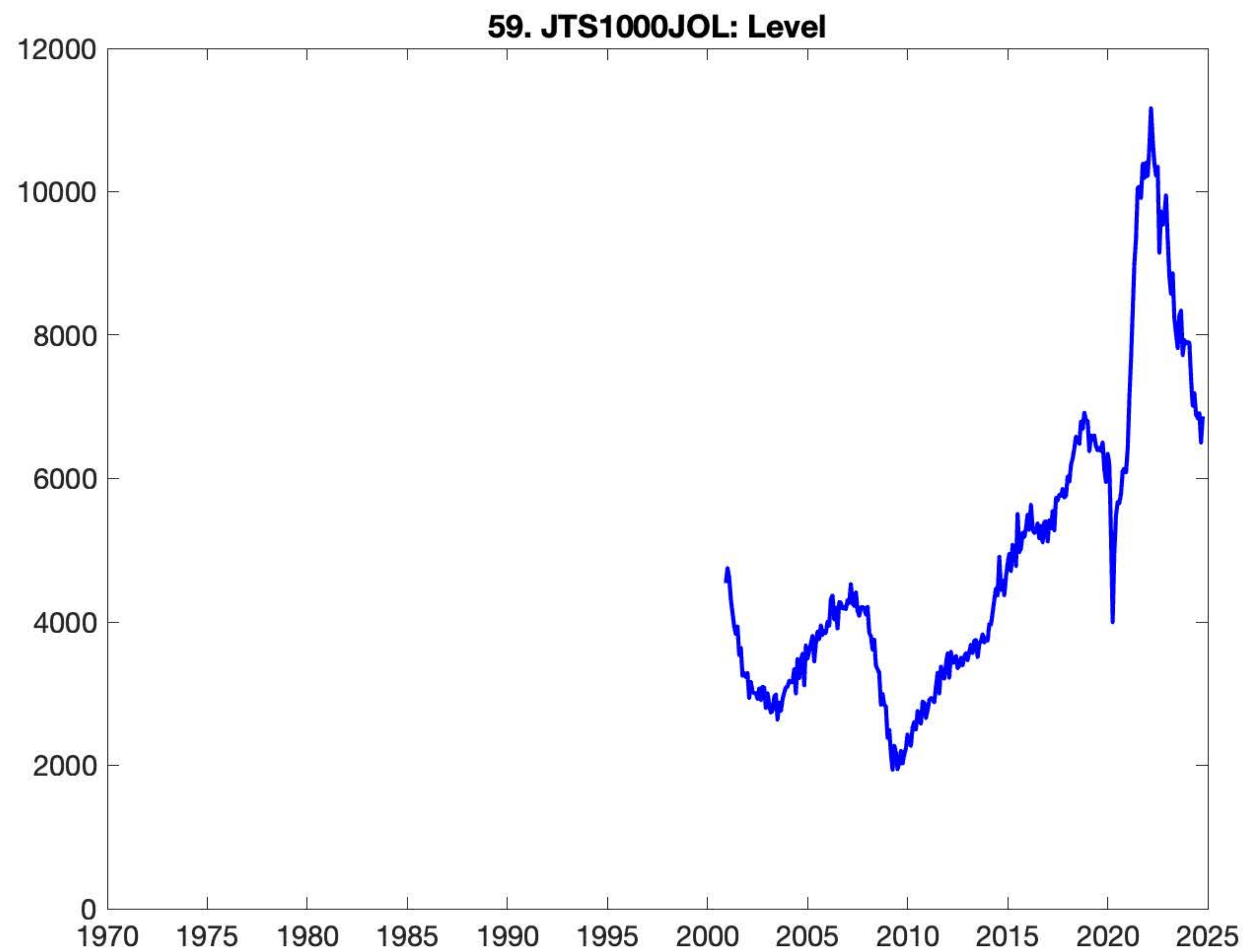

57. CIVPART: Level
Transformed Value
Decomposition: 2020m1 - 2024m9
Decomposition: 2020m7 - 2024m9
Data
(F+C)-Shock
C-Shock
F-Shock

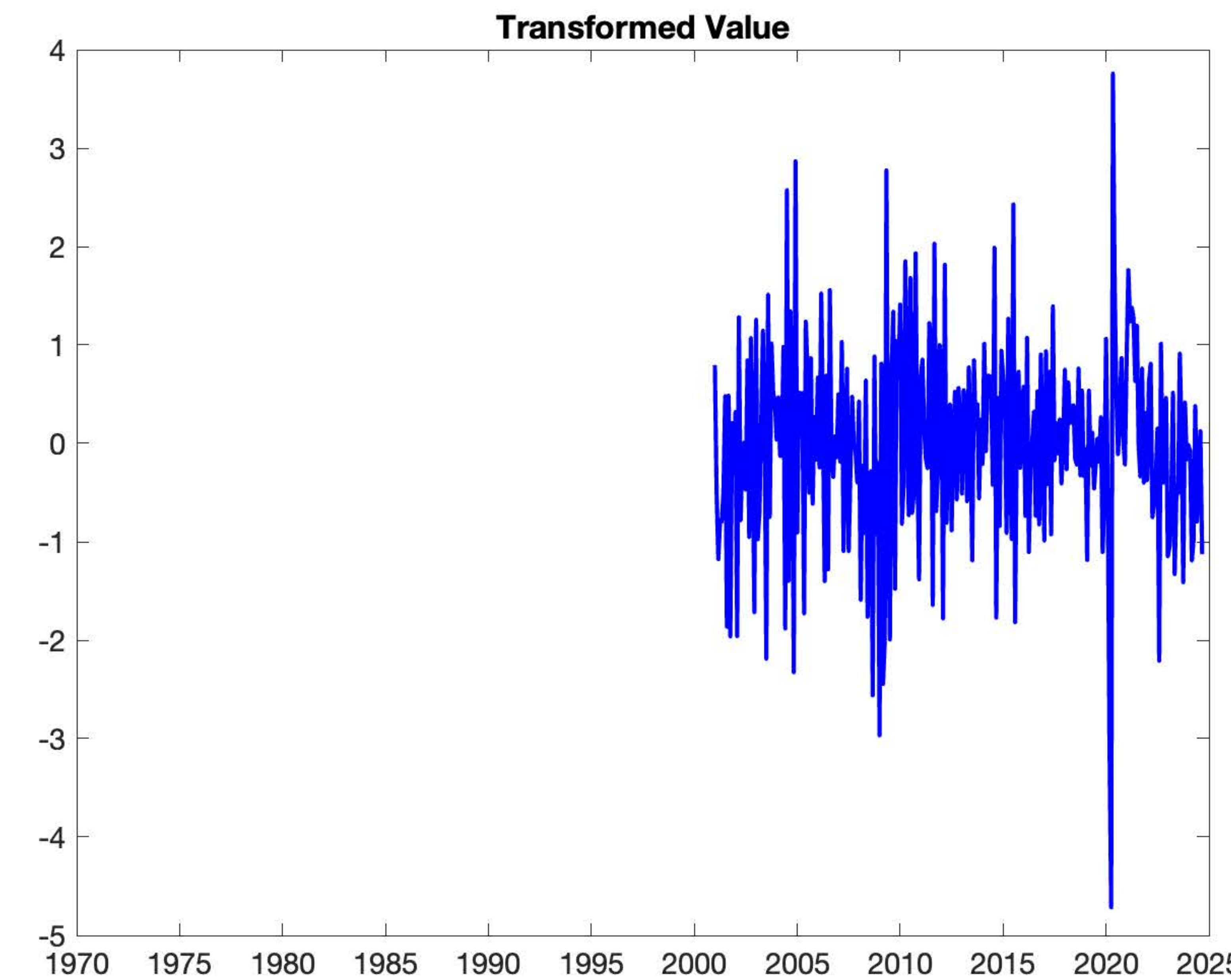

58. JTSJOL: Level
14000
12000
10000
8000
6000
4000
2000
1970
1975
1980
1985
1990
1995
2000
2005
2010
2015
2020
2025

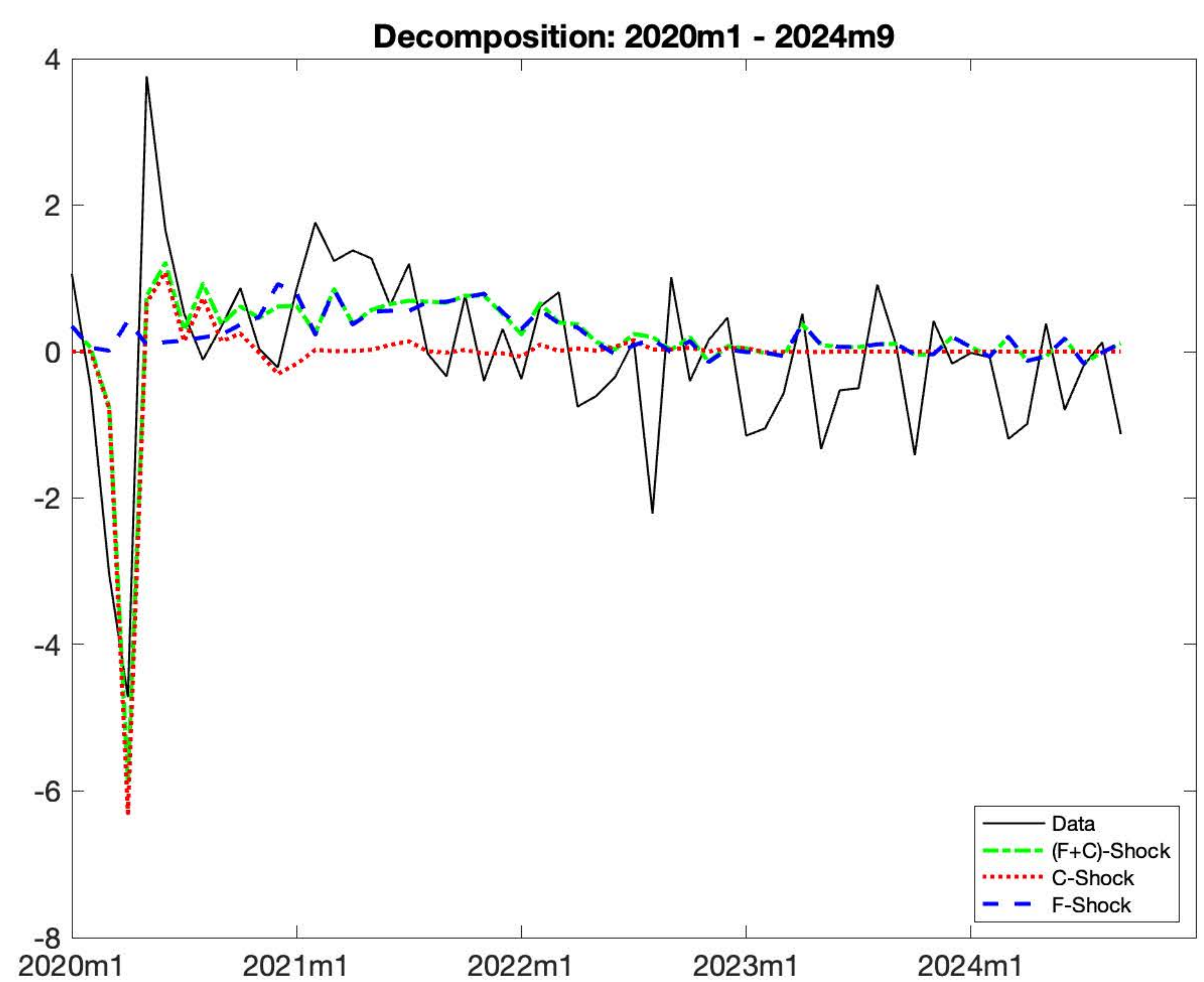

Transformed Value
4
3
2
1
0
-1
-2
-3
-4
-5
1970
1975
1980
1985
1990
1995
2000
2005
2010
2015
2020
2025

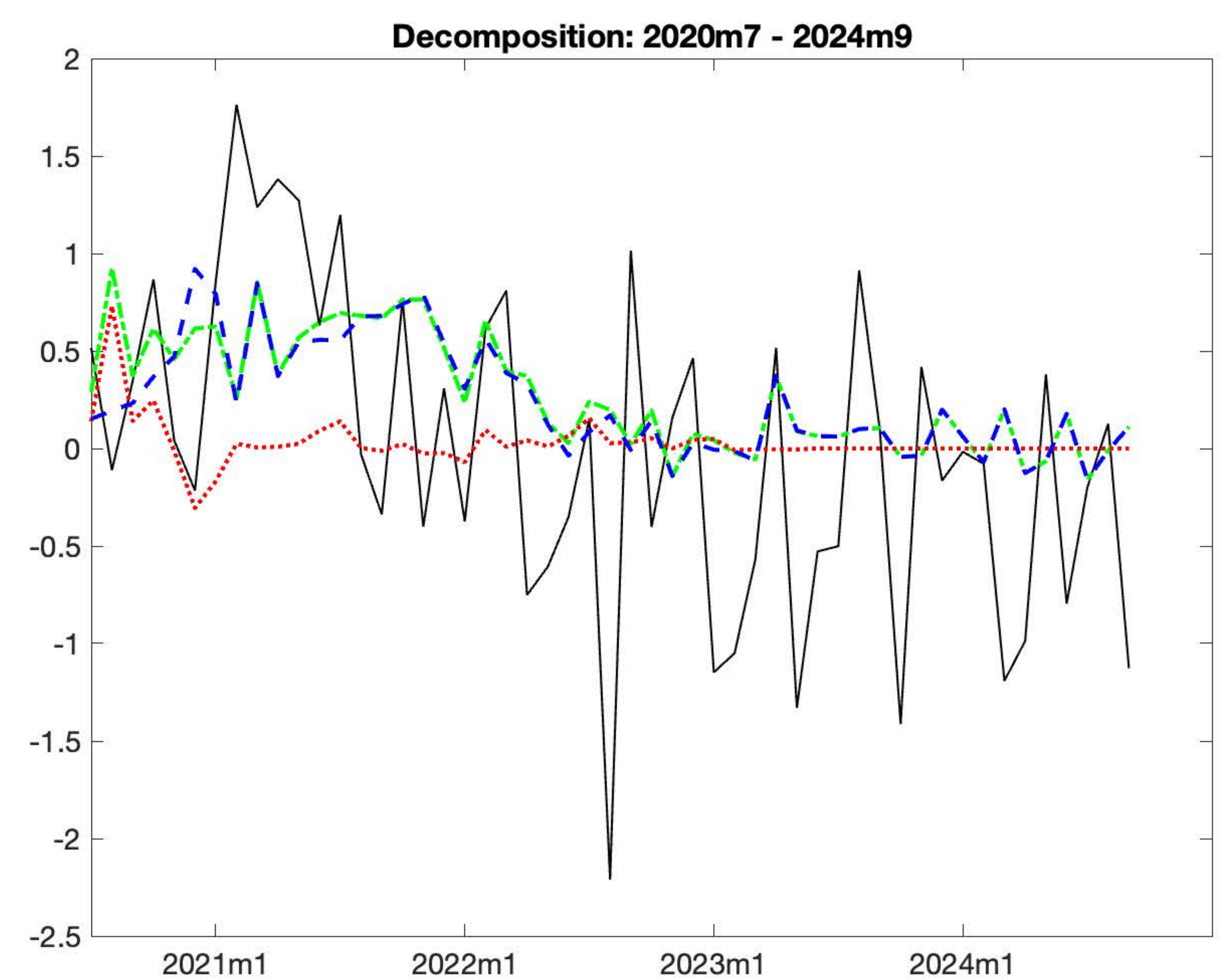

Decomposition: 2020m1 - 2024m9
4
2
0
-2
-4
-6
-8
2020m1
2021m1
2022m1
2023m1
2024m1
Data
(F+C)-Shock
C-Shock
F-Shock

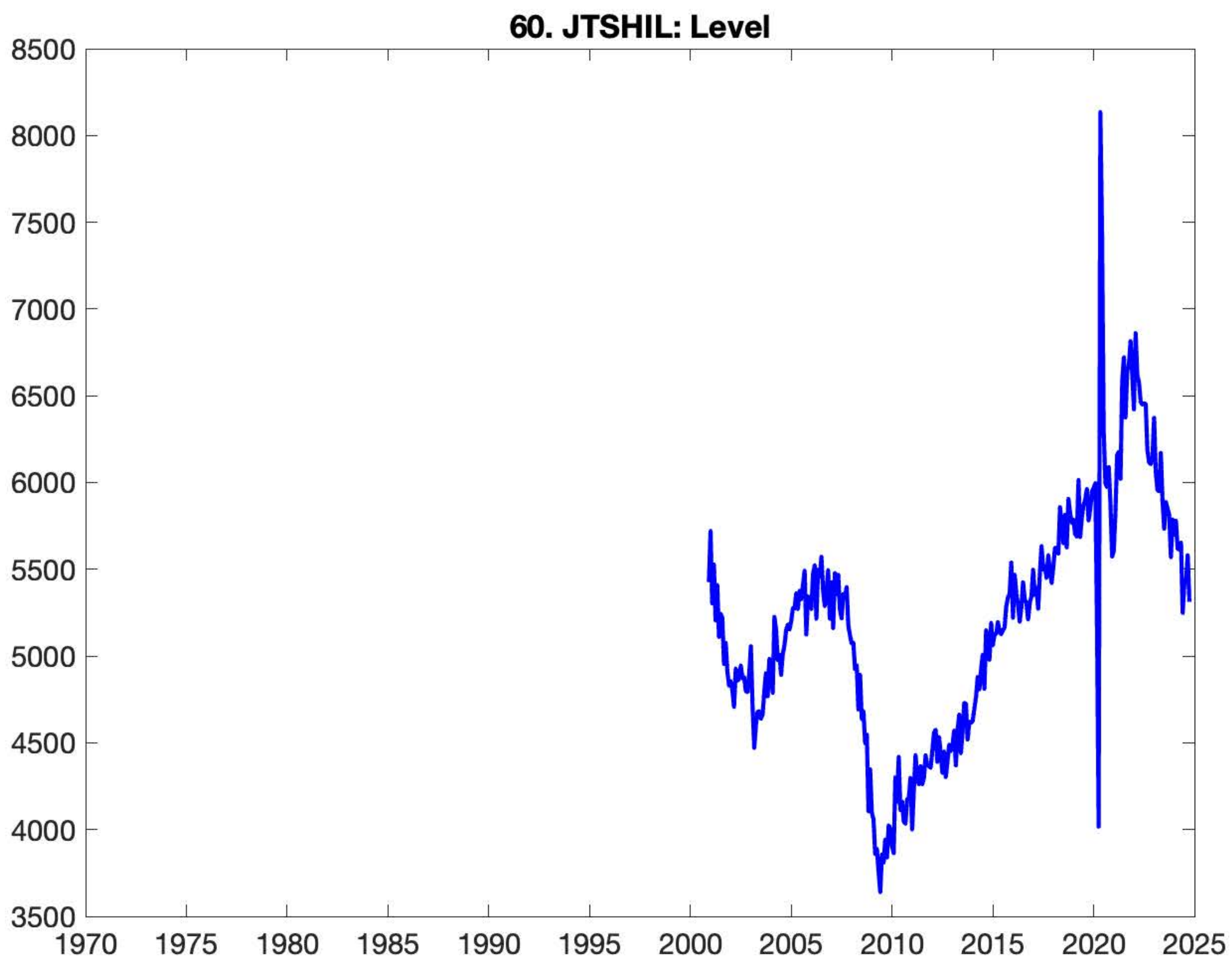

Decomposition: 2020m7 - 2024m9
2
1.5
1
0.5
0
-0.5
-1
-1.5
-2
-2.5
-3
2021m1
2022m1
2023m1
2024m1

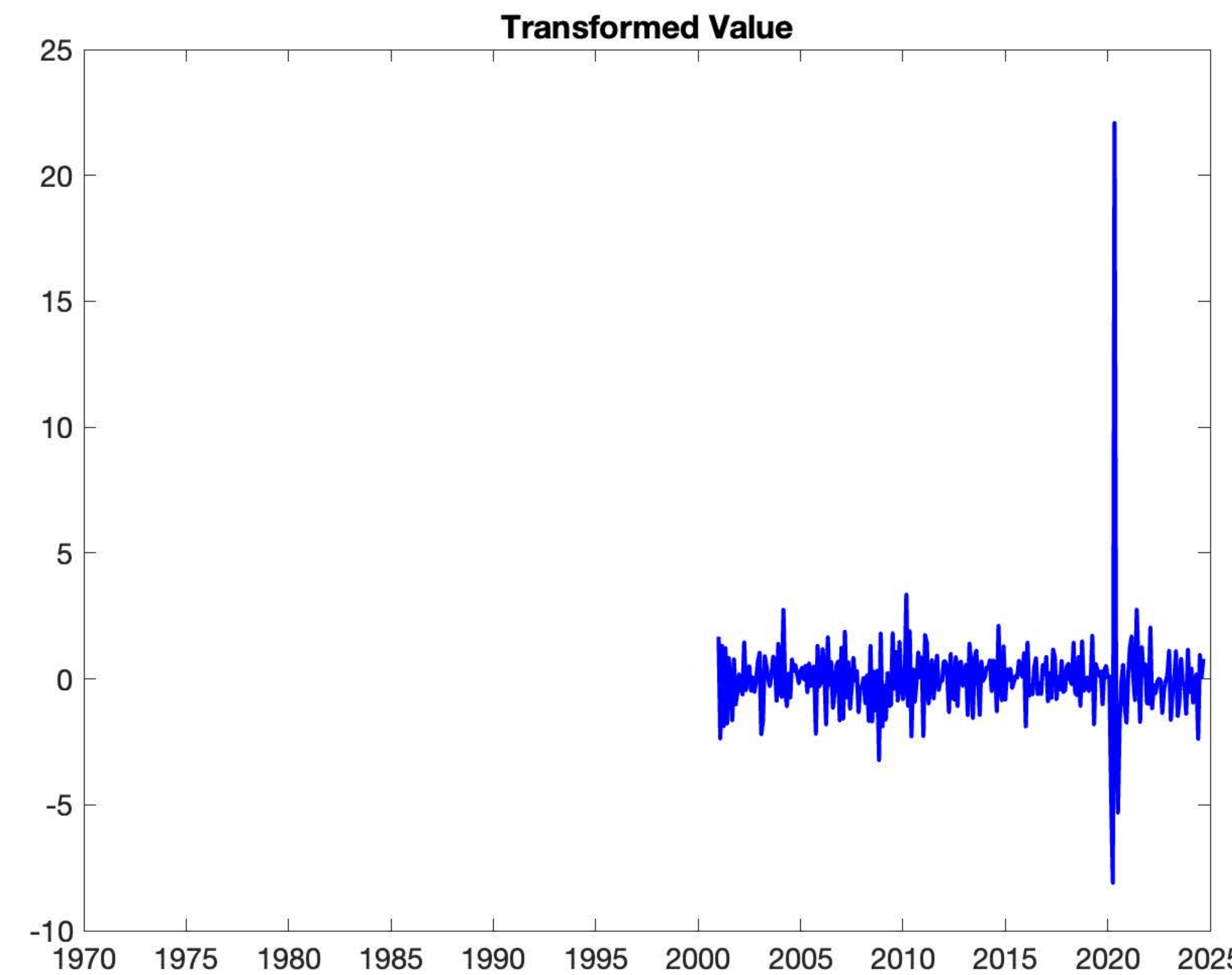

59. JTS1000JOL: Level

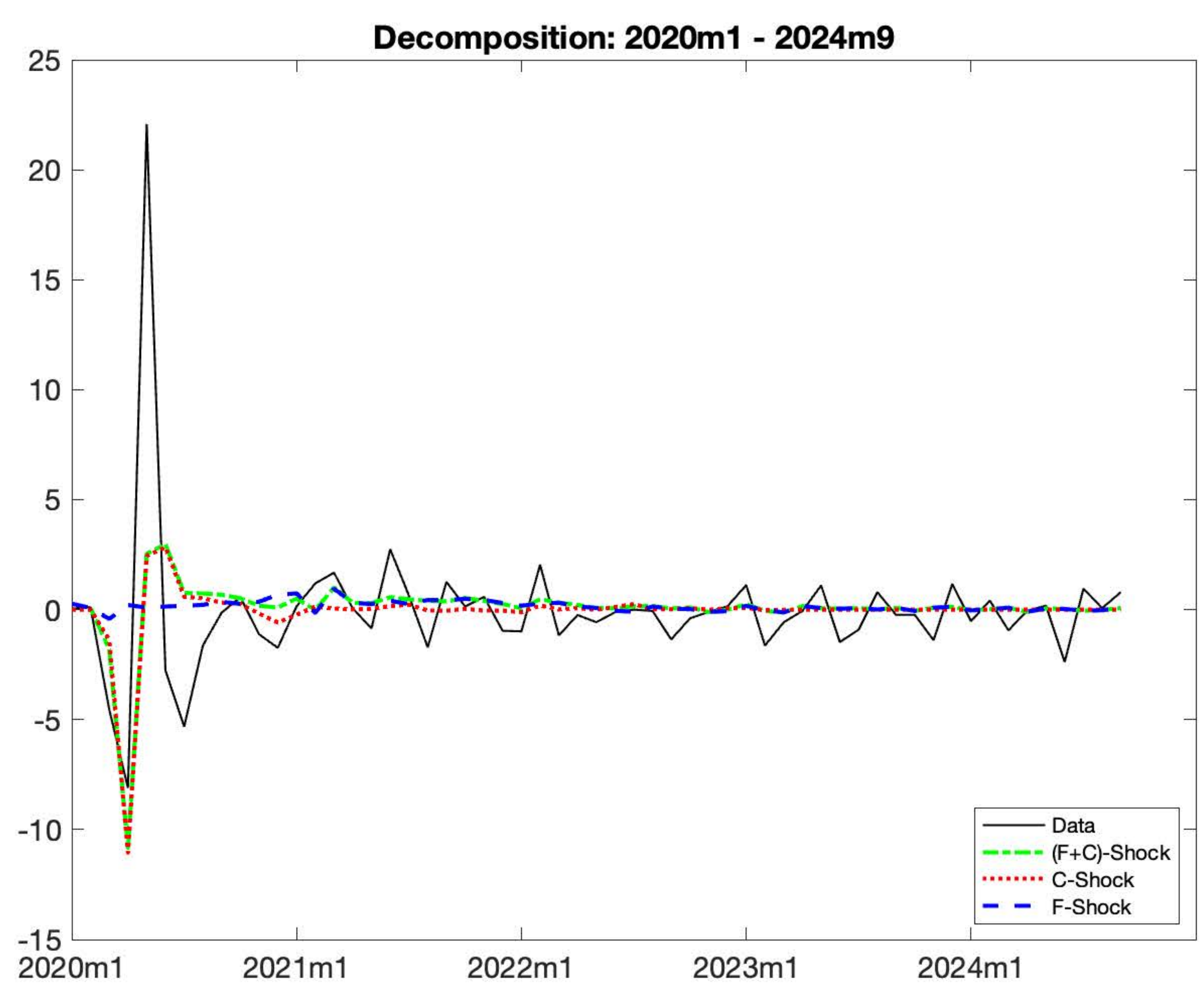

Transformed Value

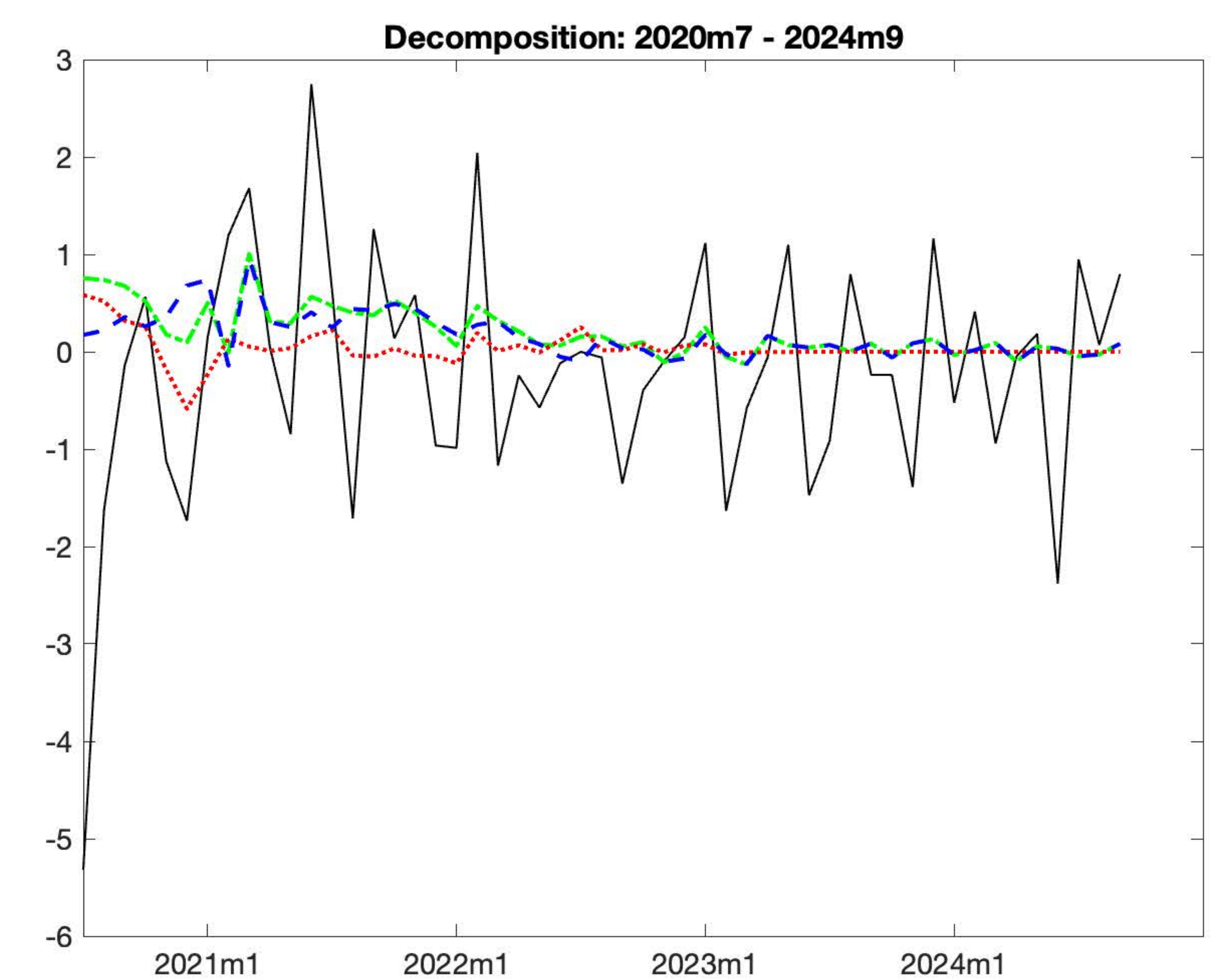

Decomposition: 2020m1 - 2024m9
Data
(F+C)-Shock
C-Shock
F-Shock

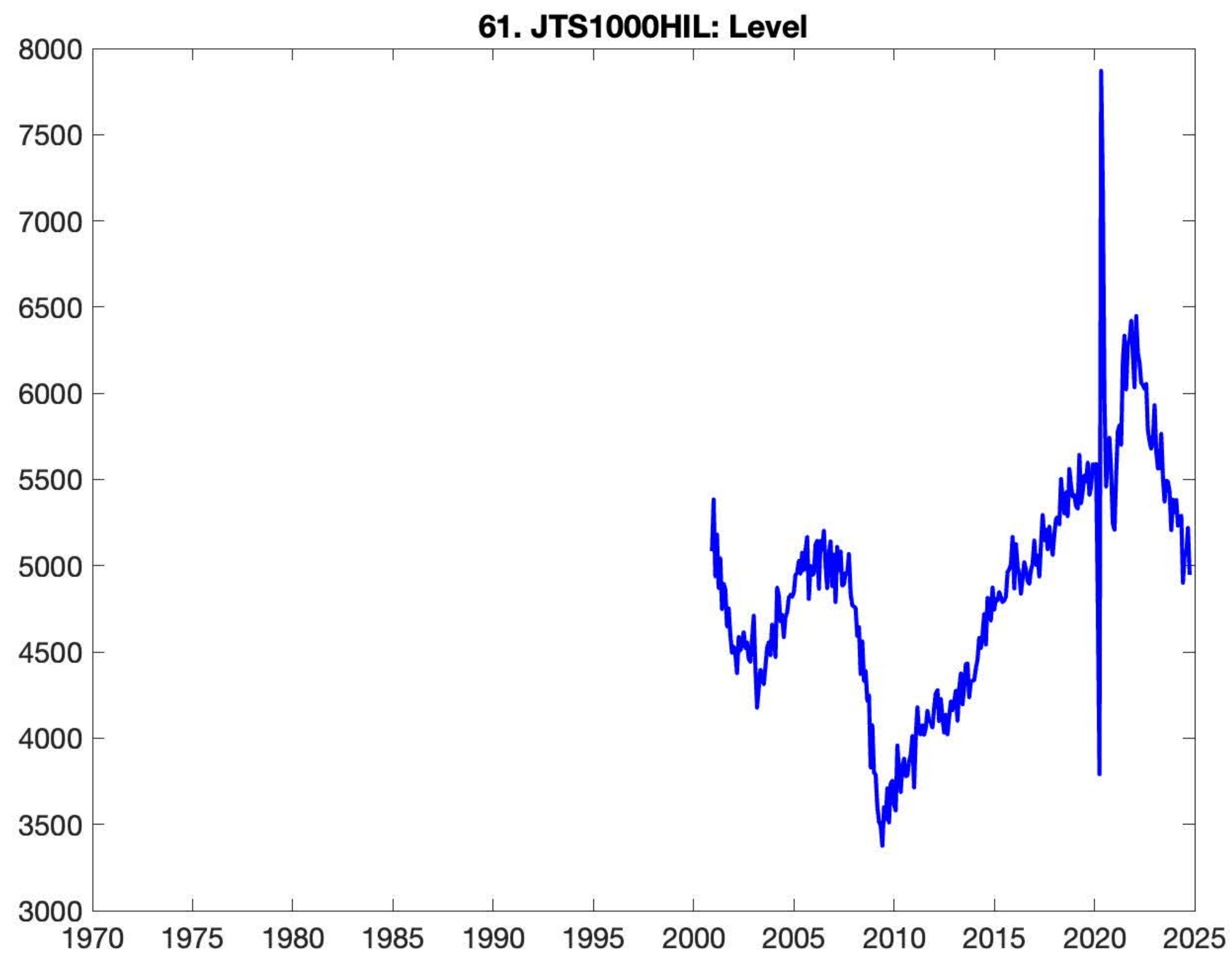

Decomposition: 2020m7 - 2024m9

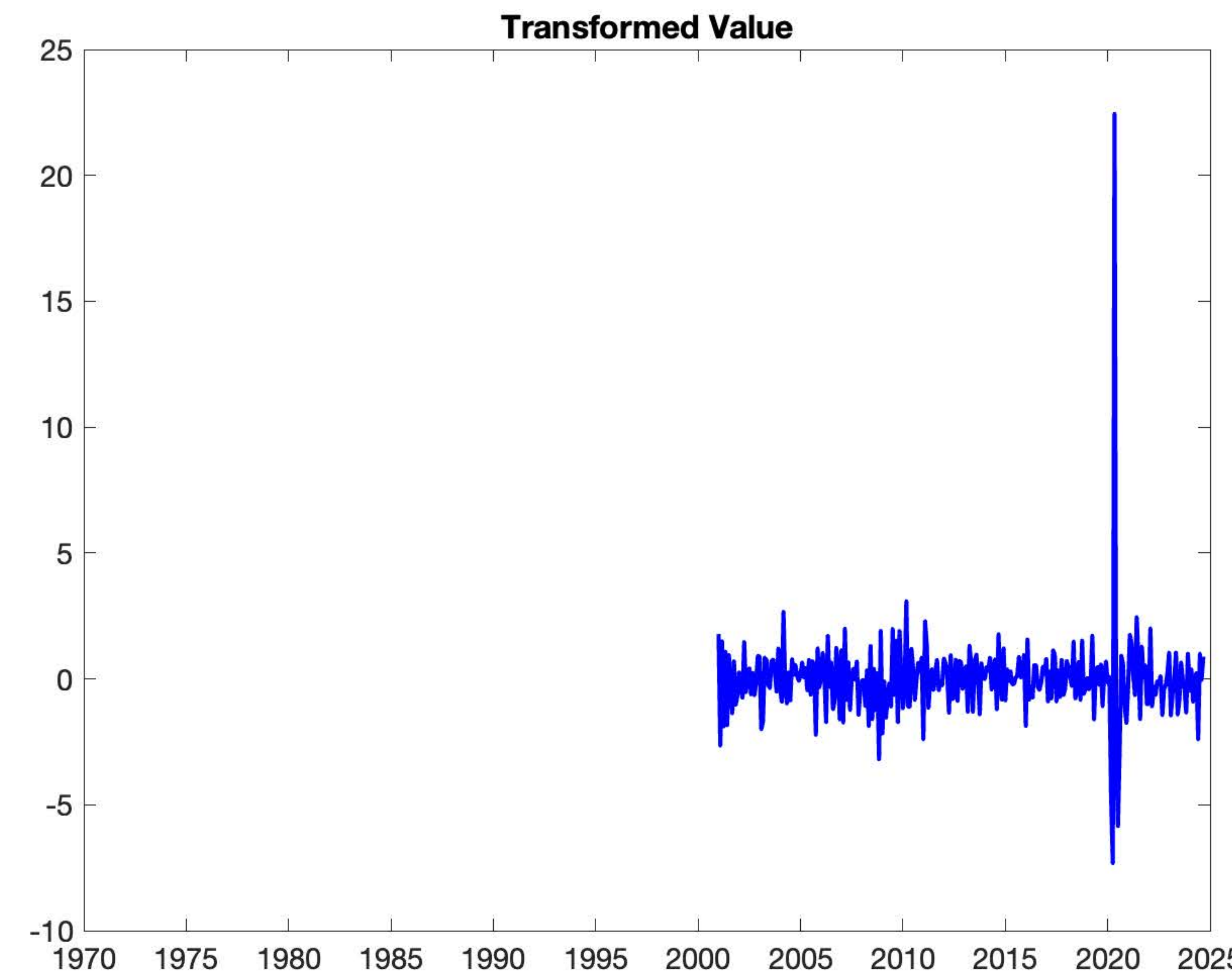

60. JTSHIL: Level

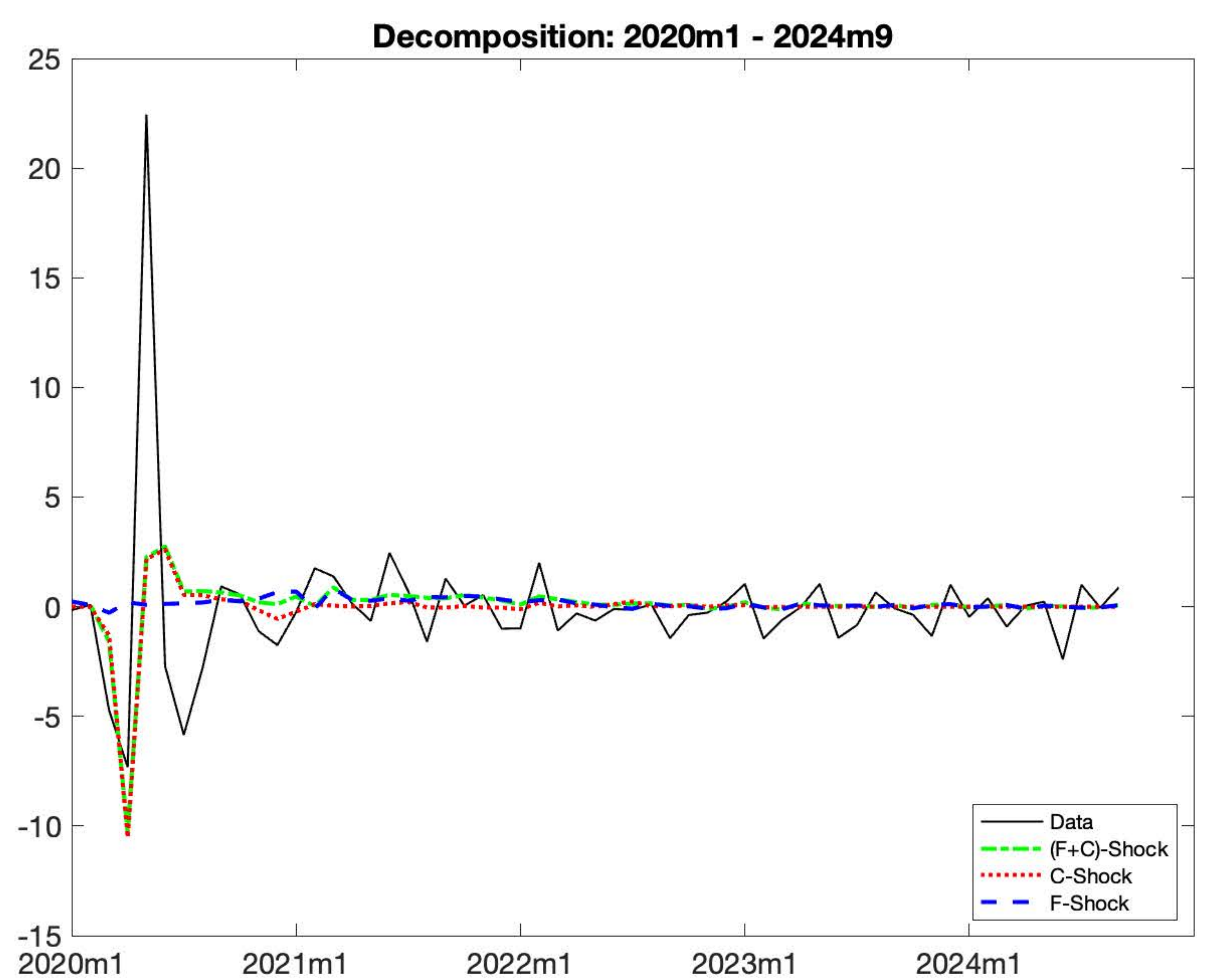

Transformed Value

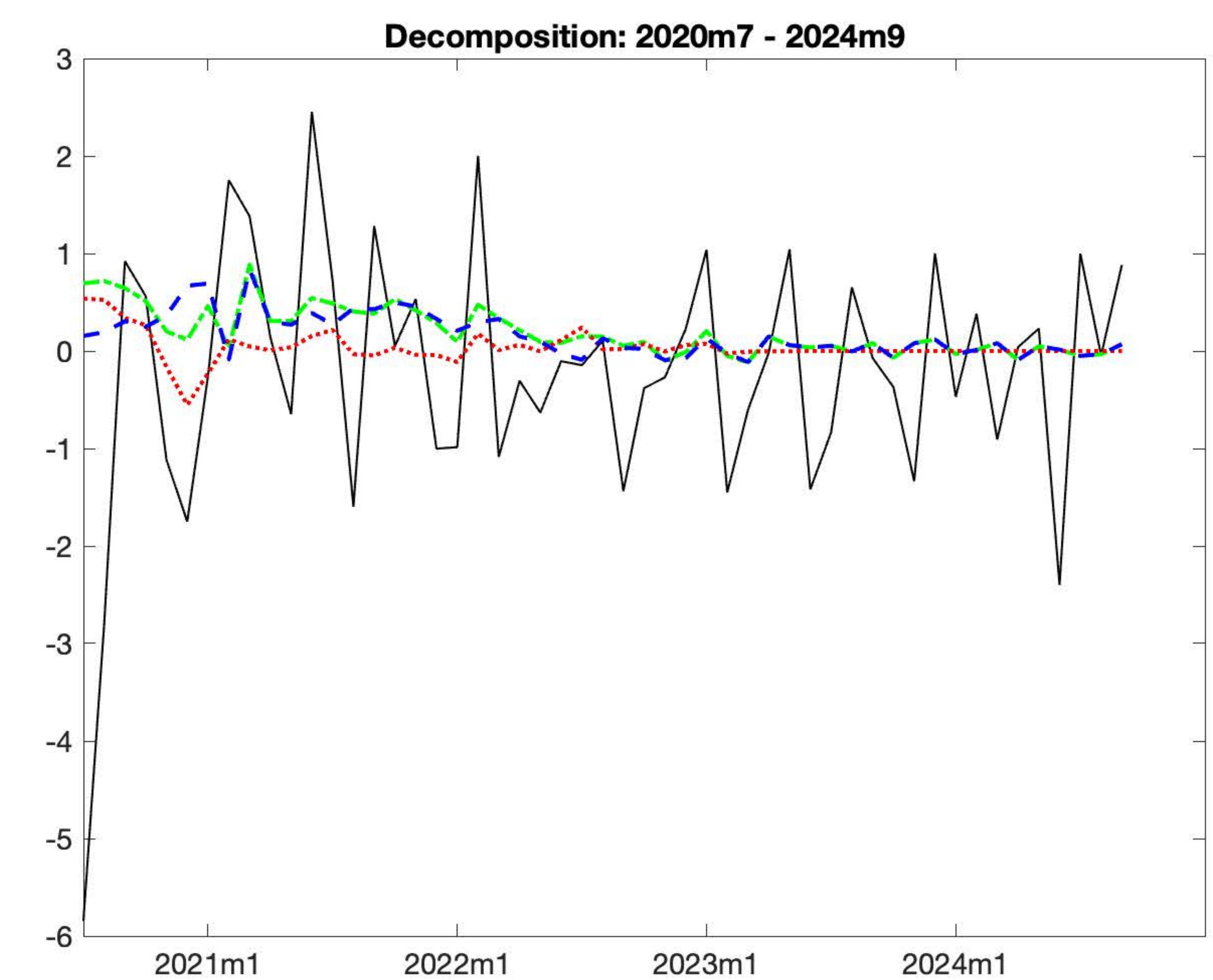

Decomposition: 2020m1 - 2024m9
Data
(F+C)-Shock
C-Shock
F-Shock

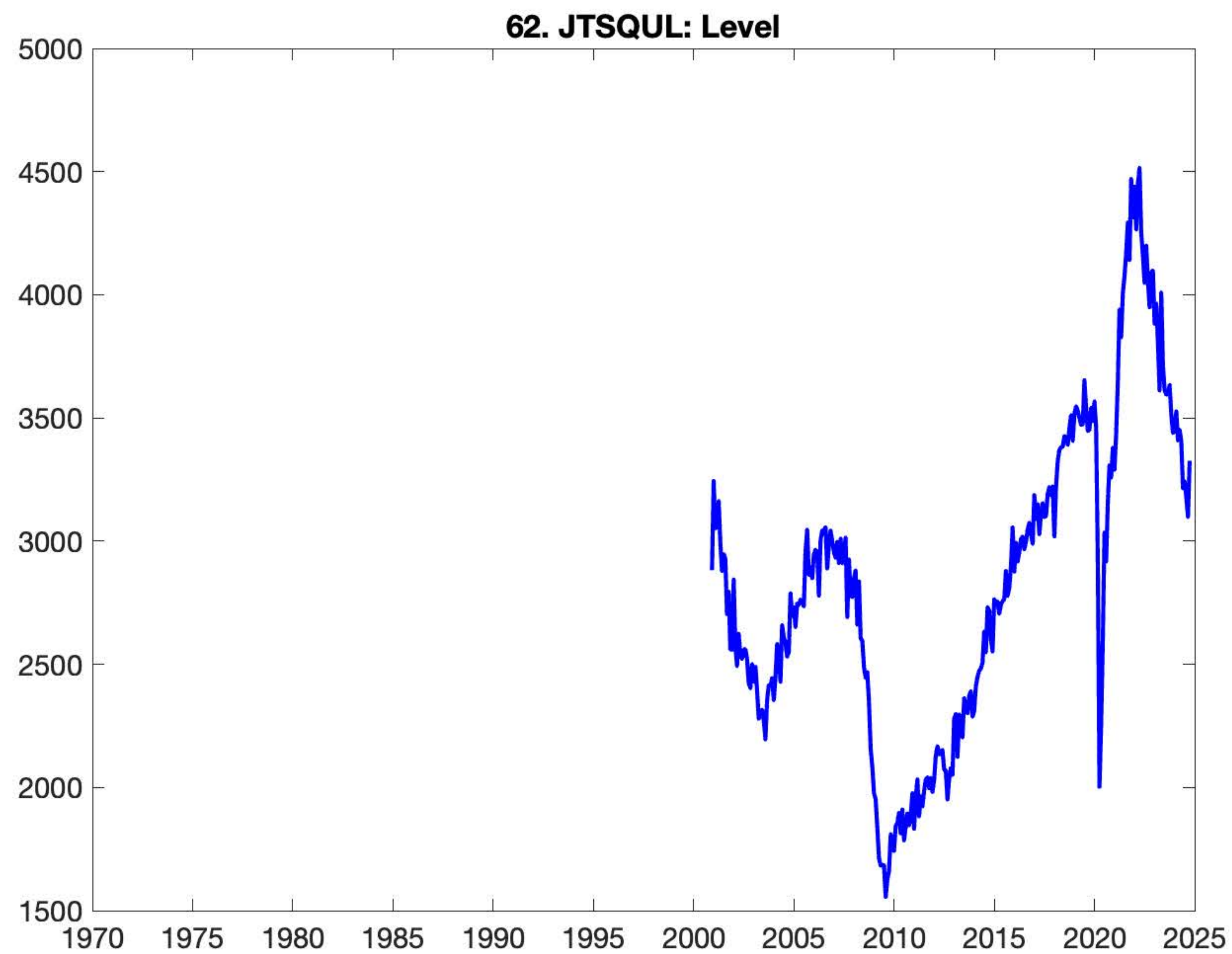

Decomposition: 2020m7 - 2024m9

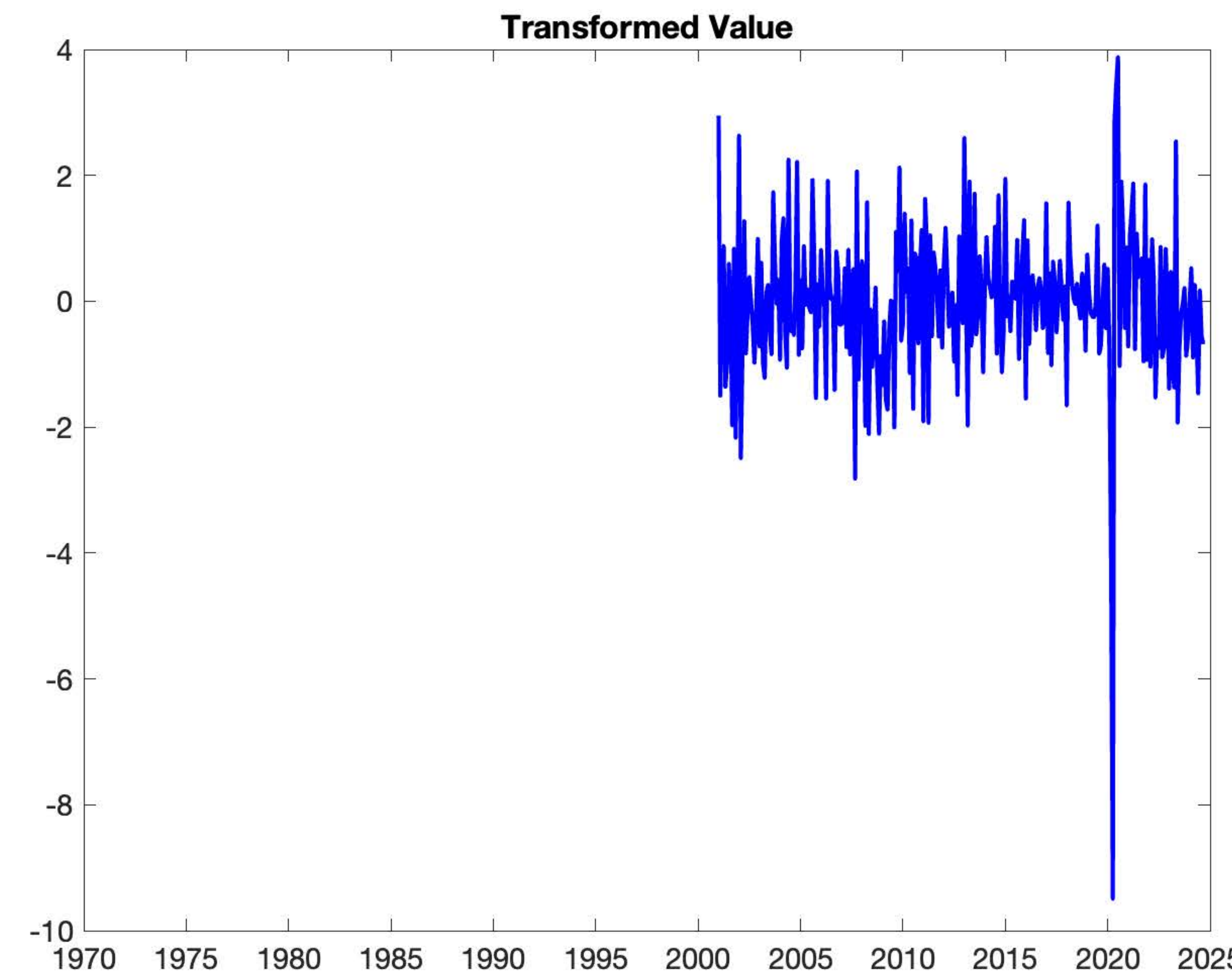

61. JTS1000HIL: Level
8000
7500
7000
6500
6000
5500
5000
4500
4000
3500
3000
1970
1975
1980
1985
1990
1995
2000
2005
2010
2015
2020
2025

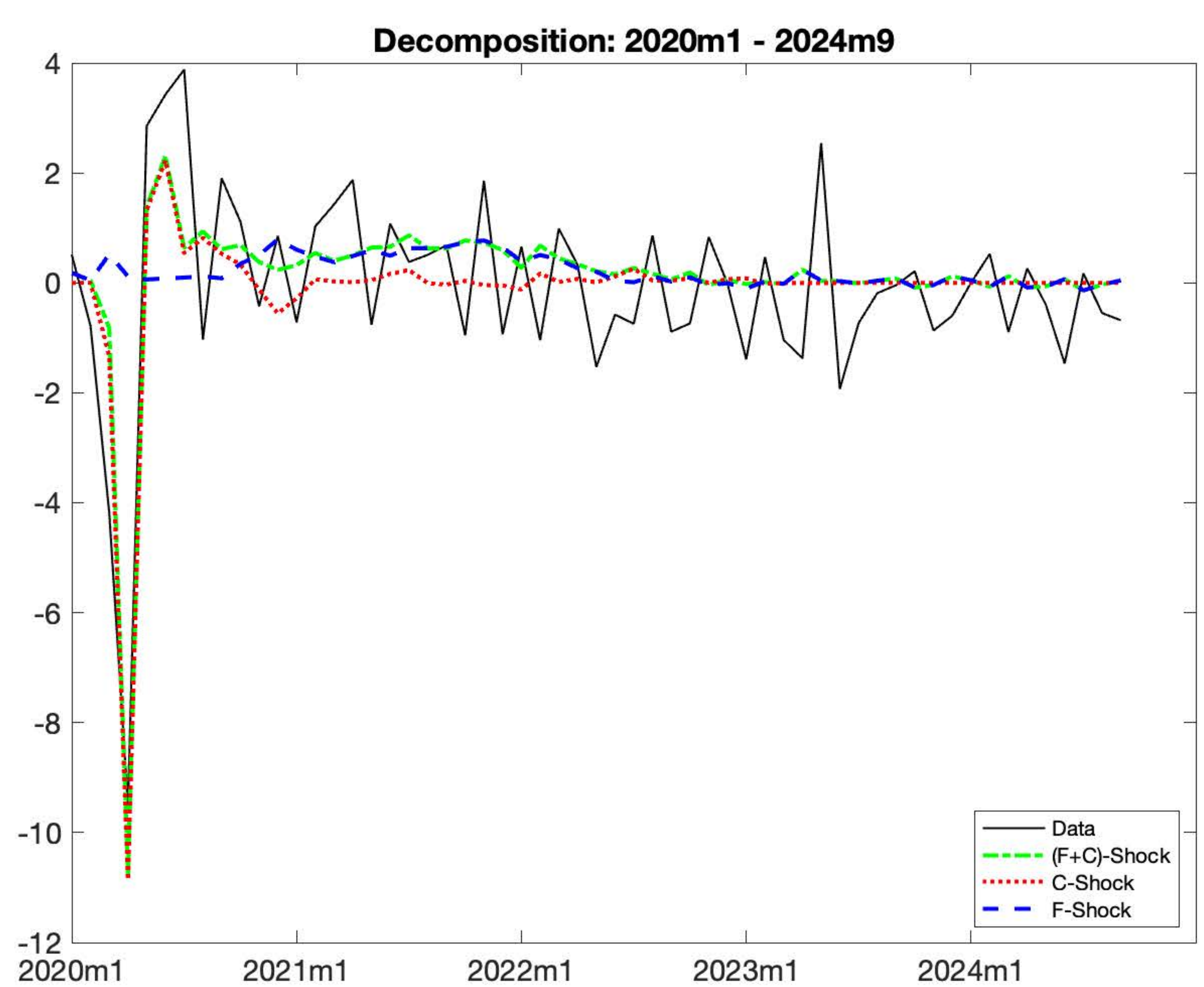

Transformed Value
25
20
15
10
5
0
-5
-10
1970
1975
1980
1985
1990
1995
2000
2005
2010
2015
2020
2025

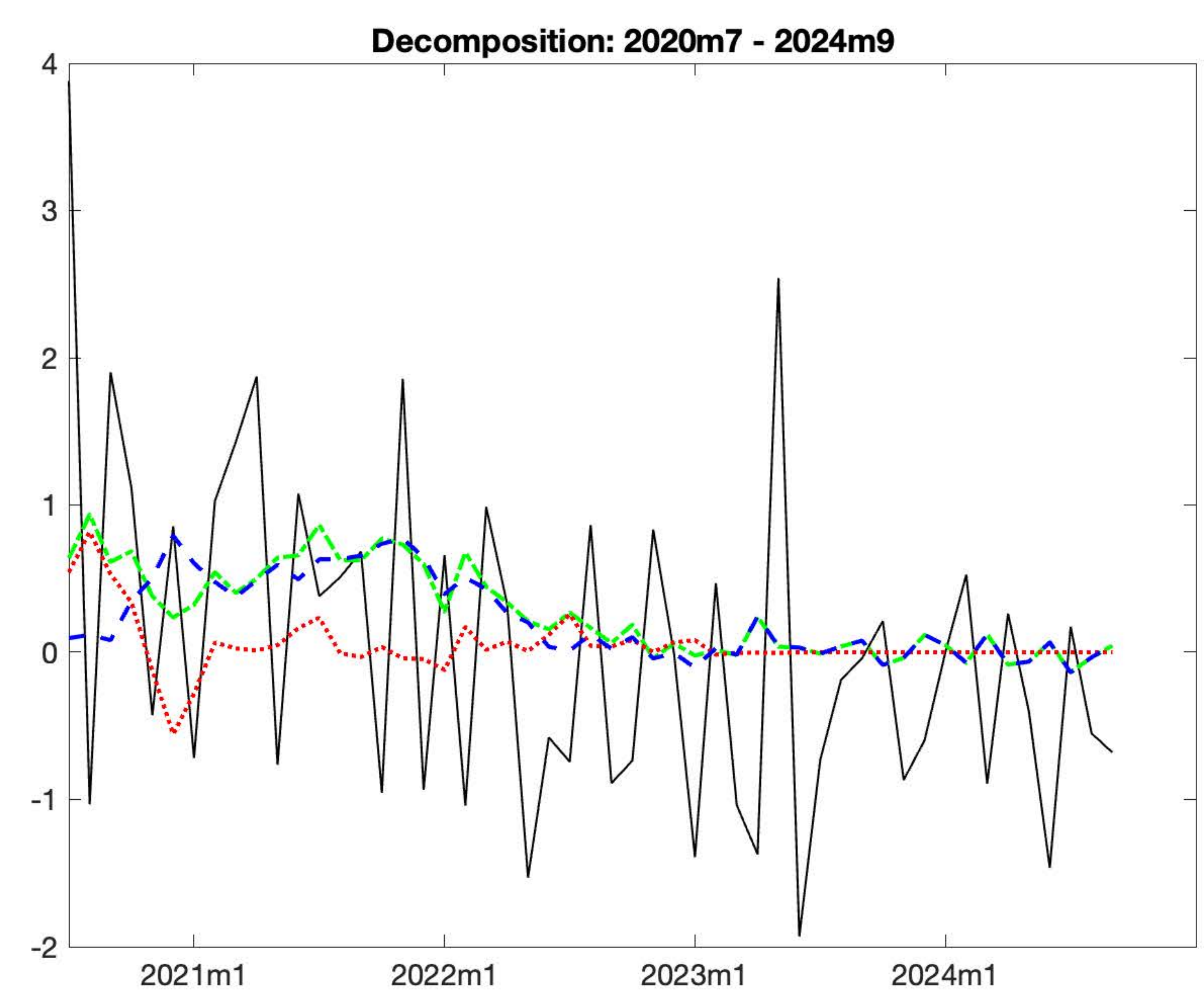

Decomposition: 2020m1 - 2024m9
25
20
15
10
5
0
-5
-10
-15
2020m1
2021m1
2022m1
2023m1
2024m1
Data
(F+C)-Shock
C-Shock
F-Shock

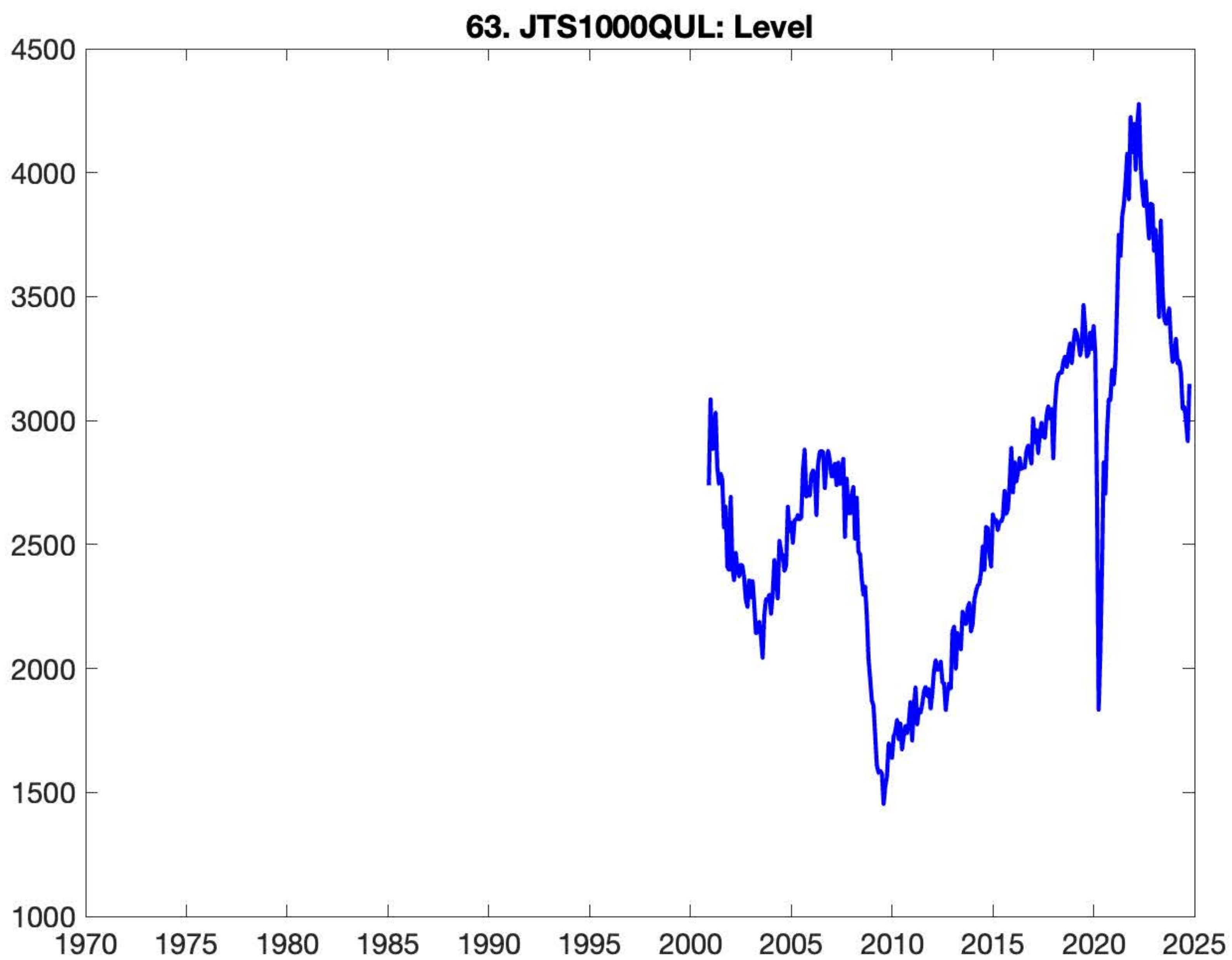

Decomposition: 2020m7 - 2024m9
3
2
1
0
-1
-2
-3
-4
-5
-6
2021m1
2022m1
2023m1
2024m1

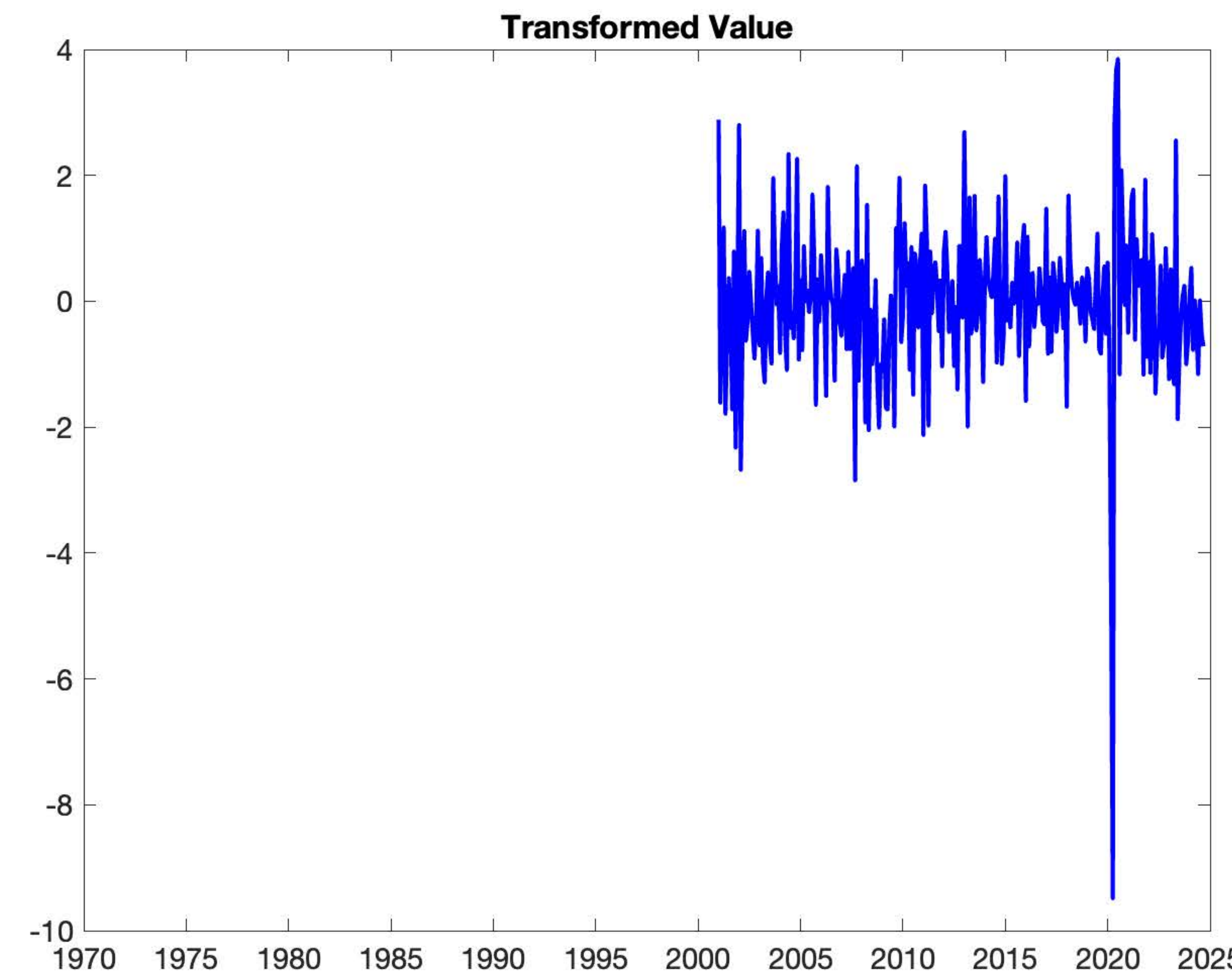

62. JTSQUL: Level
5000
4500
4000
3500
3000
2500
2000
1500
1970
1975
1980
1985
1990
1995
2000
2005
2010
2015
2020
2025

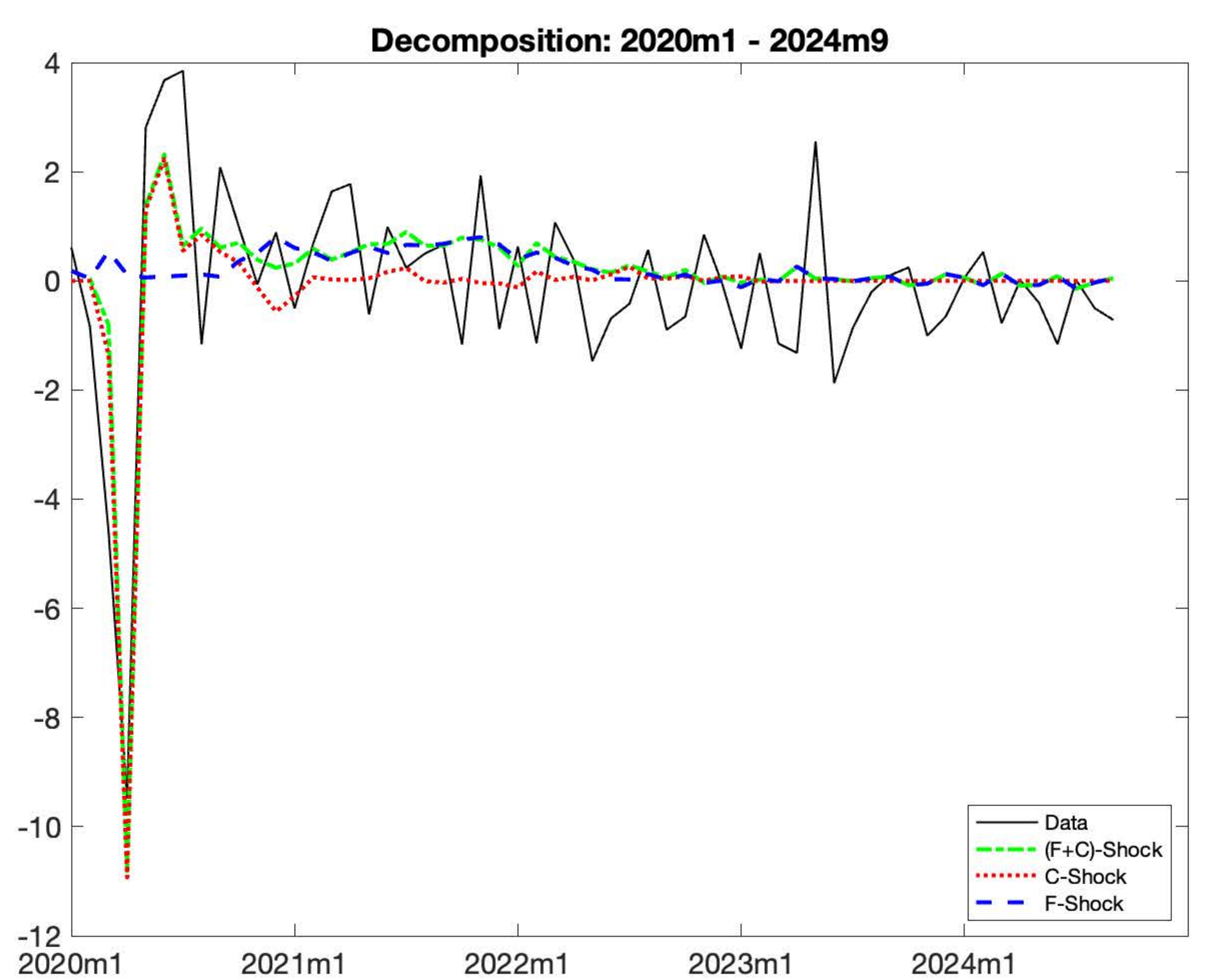

Transformed Value
4
2
0
-2
-4
-6
-8
-10
1970
1975
1980
1985
1990
1995
2000
2005
2010
2015
2020
2025

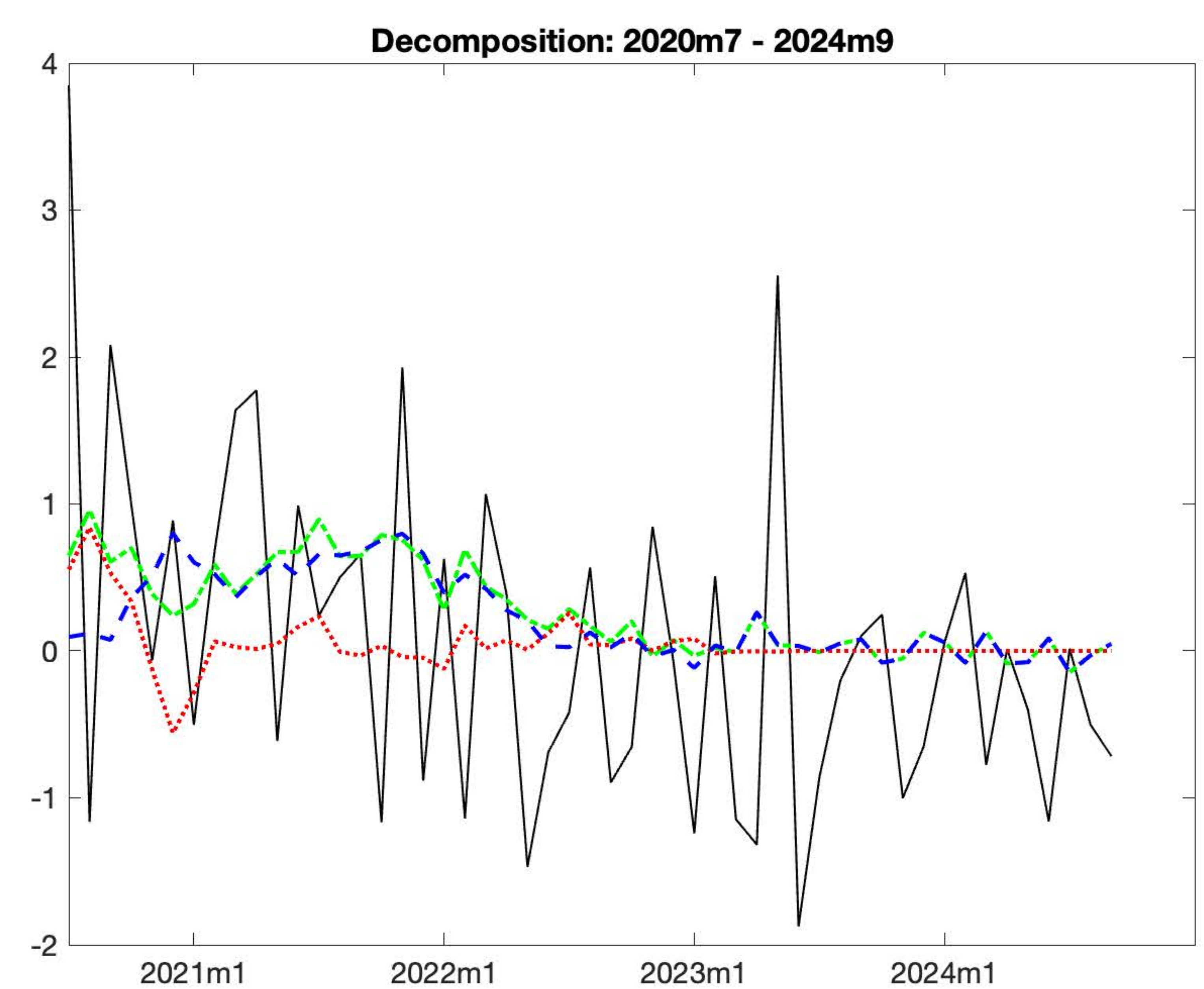

Decomposition: 2020m1 - 2024m9
4
2
0
-2
-4
-6
-8
-10
-12
2020m1
2021m1
2022m1
2023m1
2024m1
Data
(F+C)-Shock
C-Shock
F-Shock

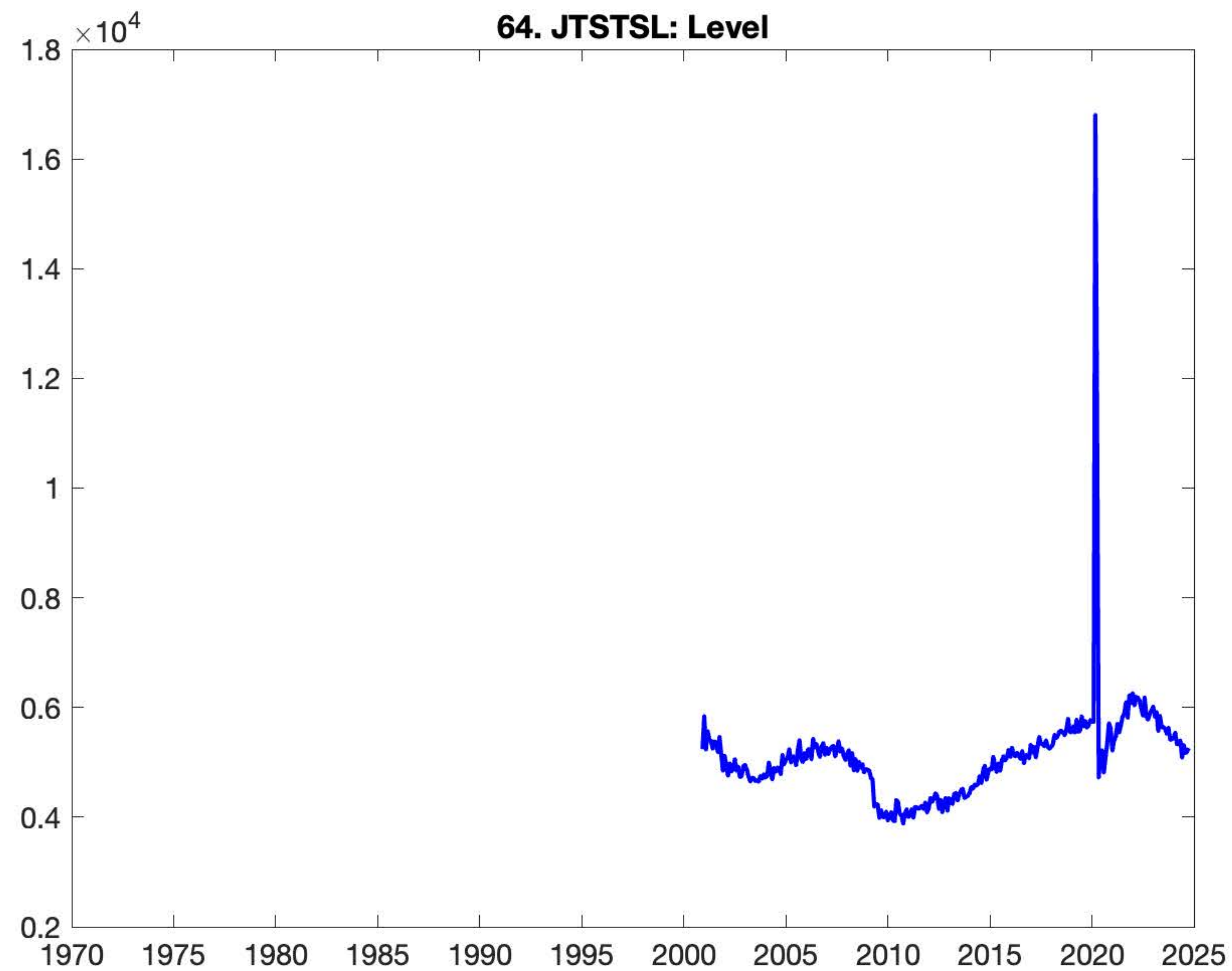

Decomposition: 2020m7 - 2024m9
4
3
2
1
0
-1
-2
2021m1
2022m1
2023m1
2024m1


63. JTS1000QUL: Level

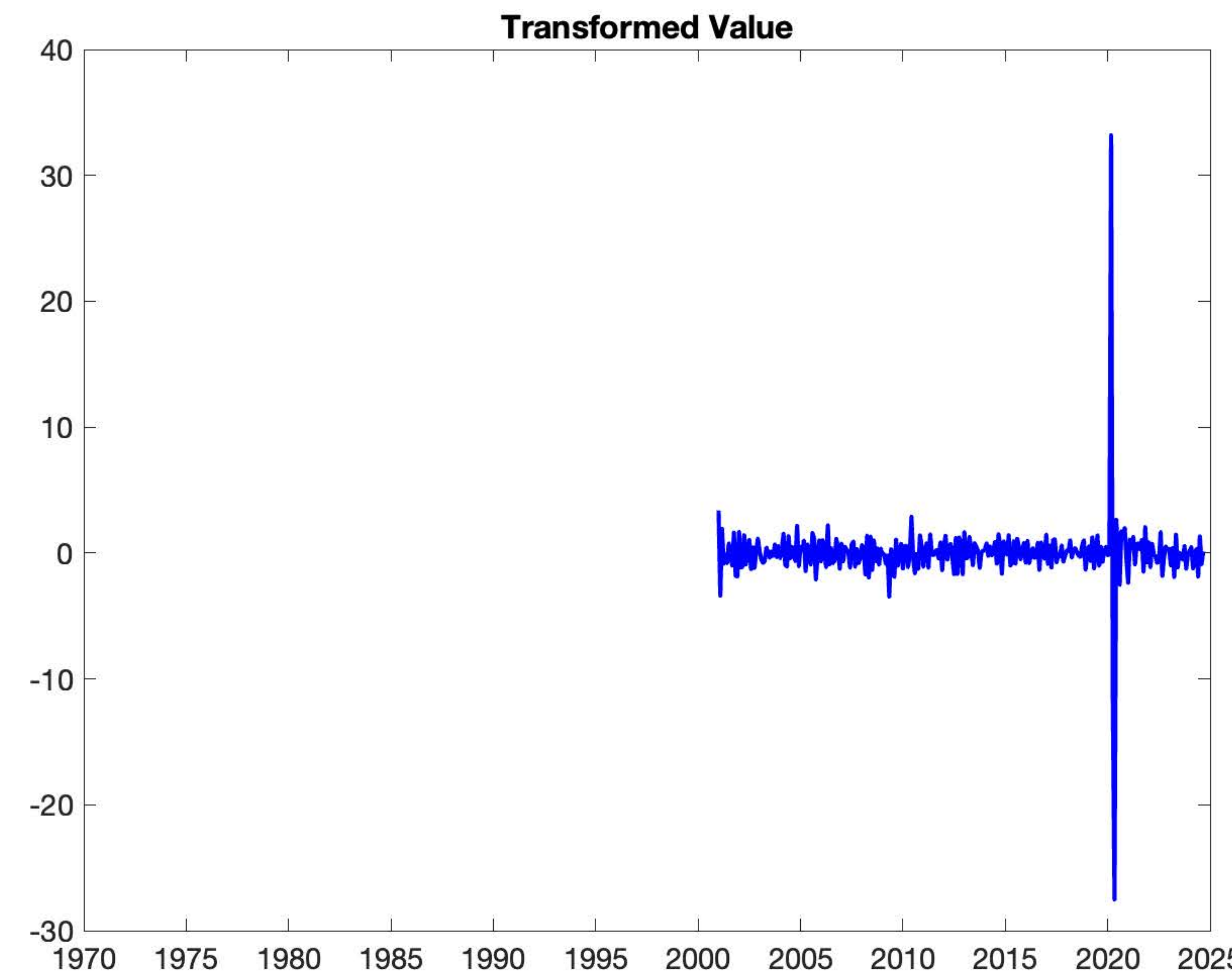

Transformed Value


Decomposition: 2020m1 - 2024m9
Data
(F+C)-Shock
C-Shock
F-Shock

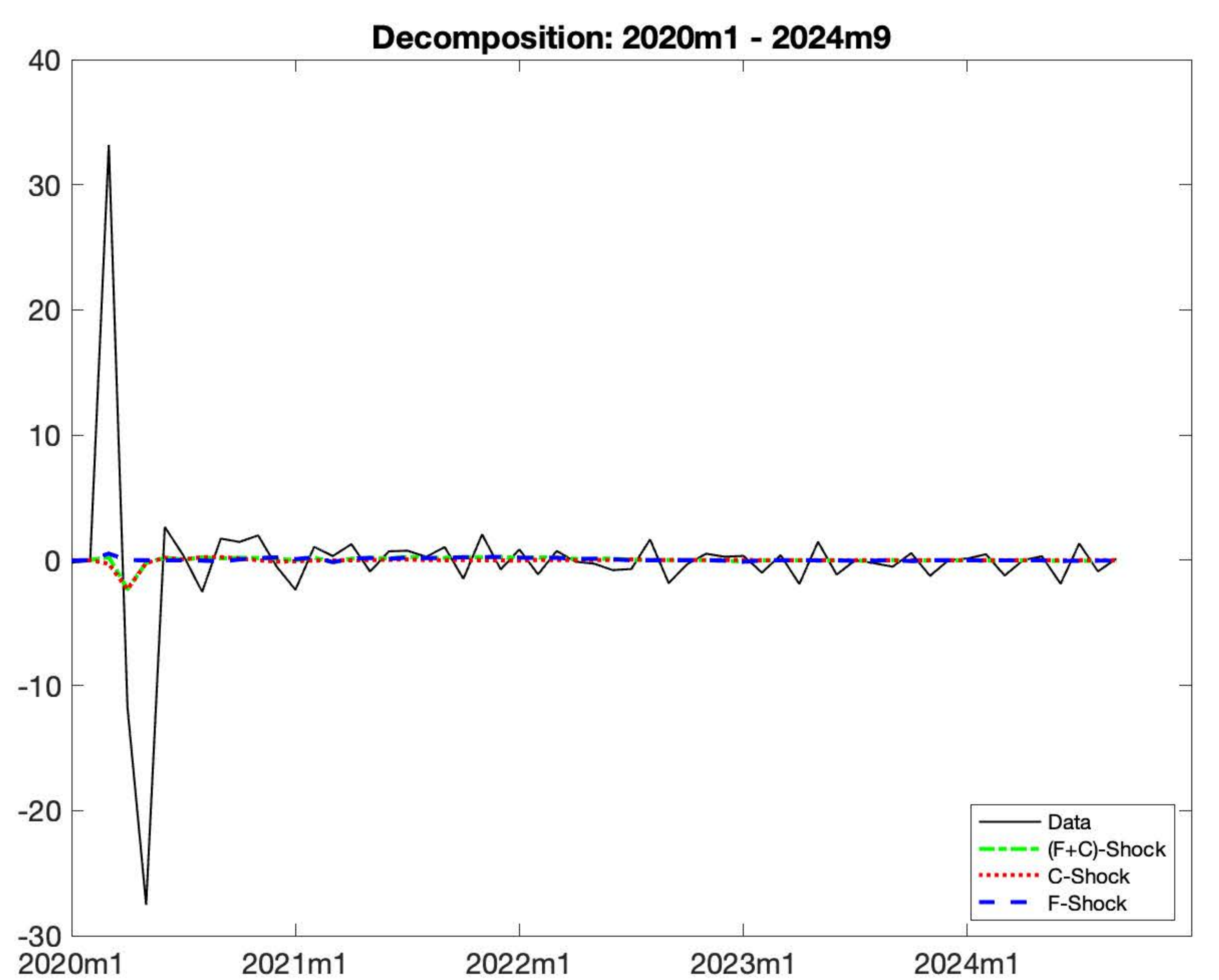

Decomposition: 2020m7 - 2024m9



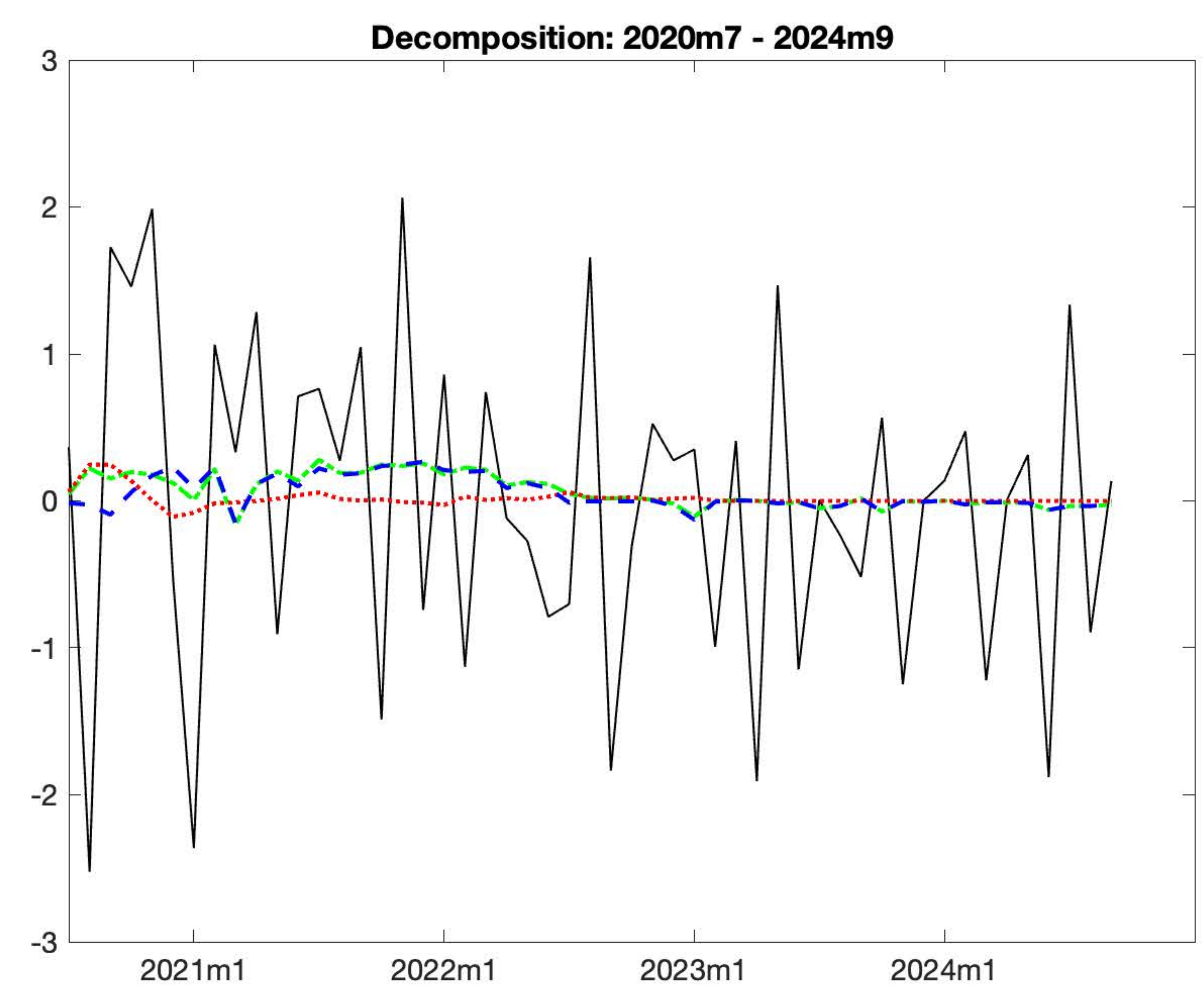
64. JTSTSL: Level
×10^4
1.8
1.6
1.4
1.2
1
0.8
0.6
0.4
0.2
1970 1975 1980 1985 1990 1995 2000 2005 2010 2015 2020 2025



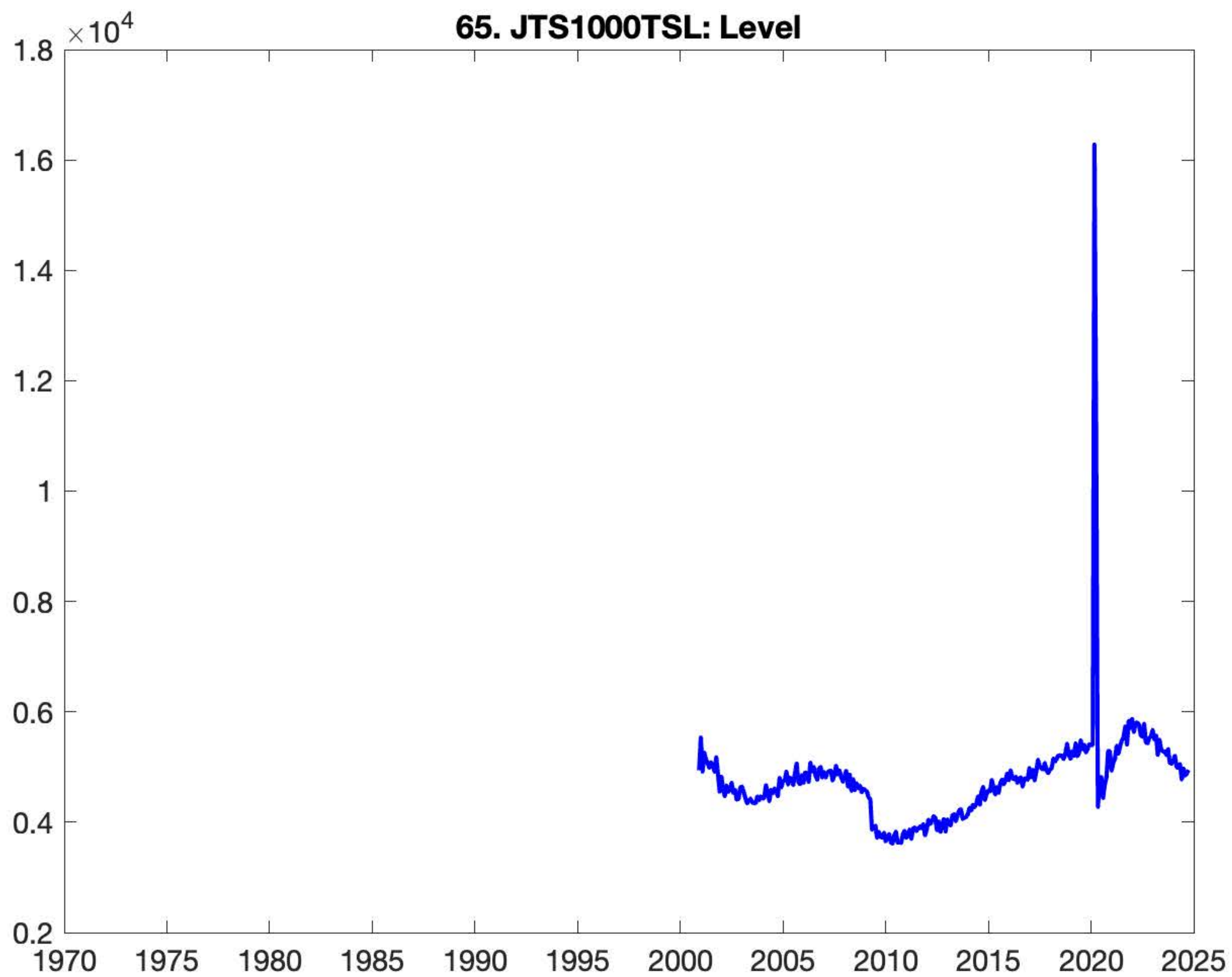
Transformed Value
40
30
20
10
0
-10
-20
-30
1970 1975 1980 1985 1990 1995 2000 2005 2010 2015 2020 2025

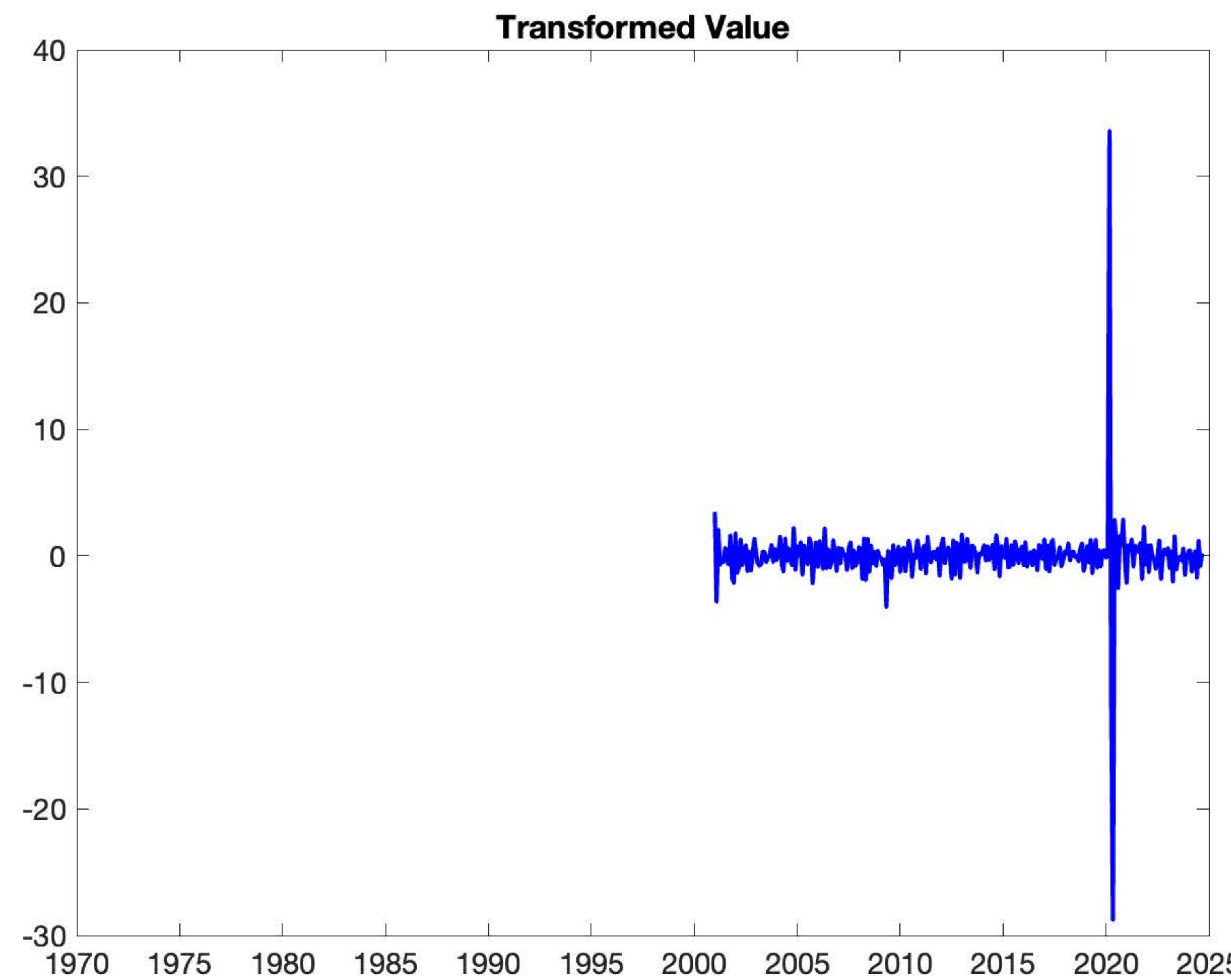


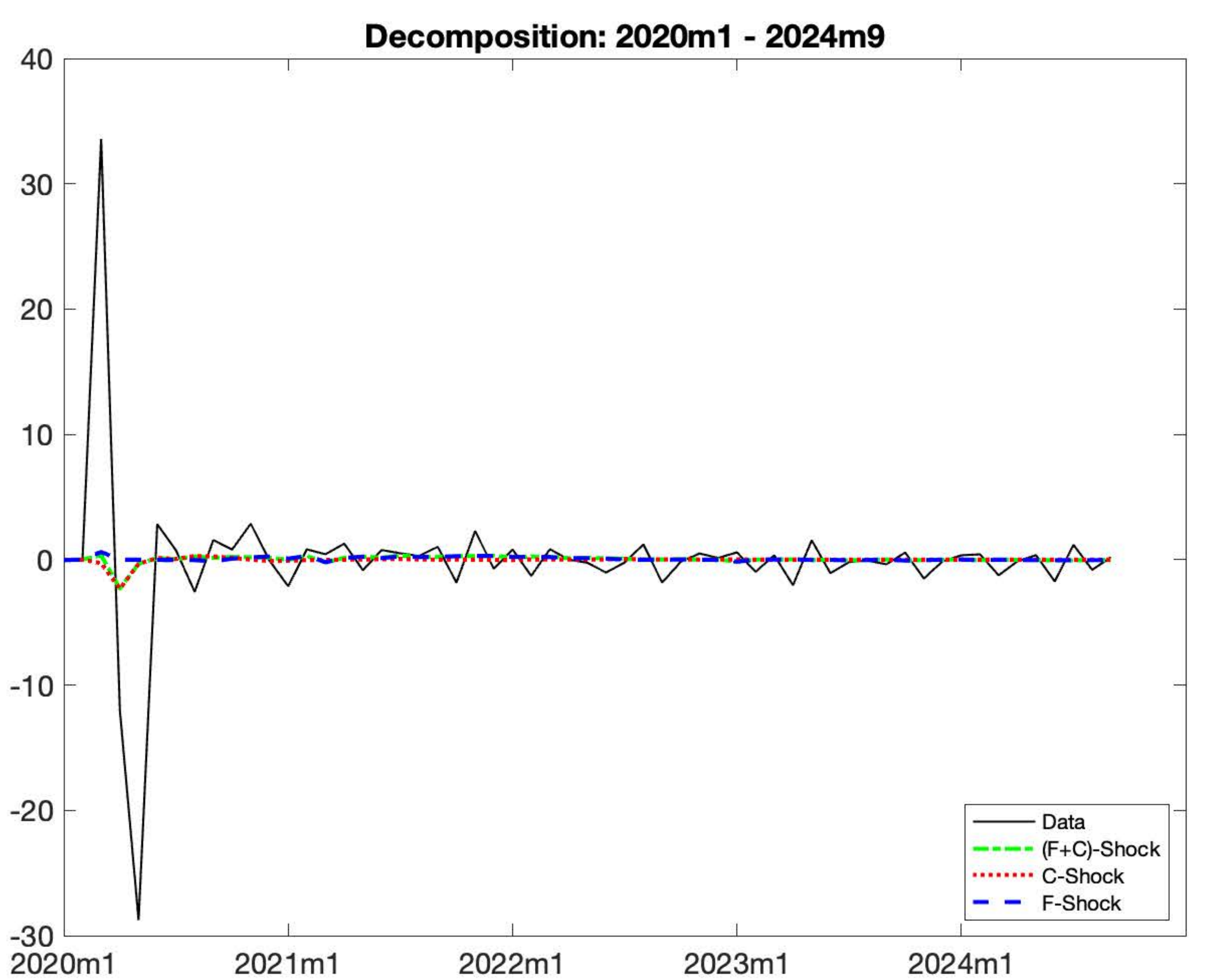
Decomposition: 2020m1 - 2024m9
40
30
20
10
0
-10
-20
-30
2020m1 2021m1 2022m1 2023m1 2024m1
Data
(F+C)-Shock
C-Shock
F-Shock

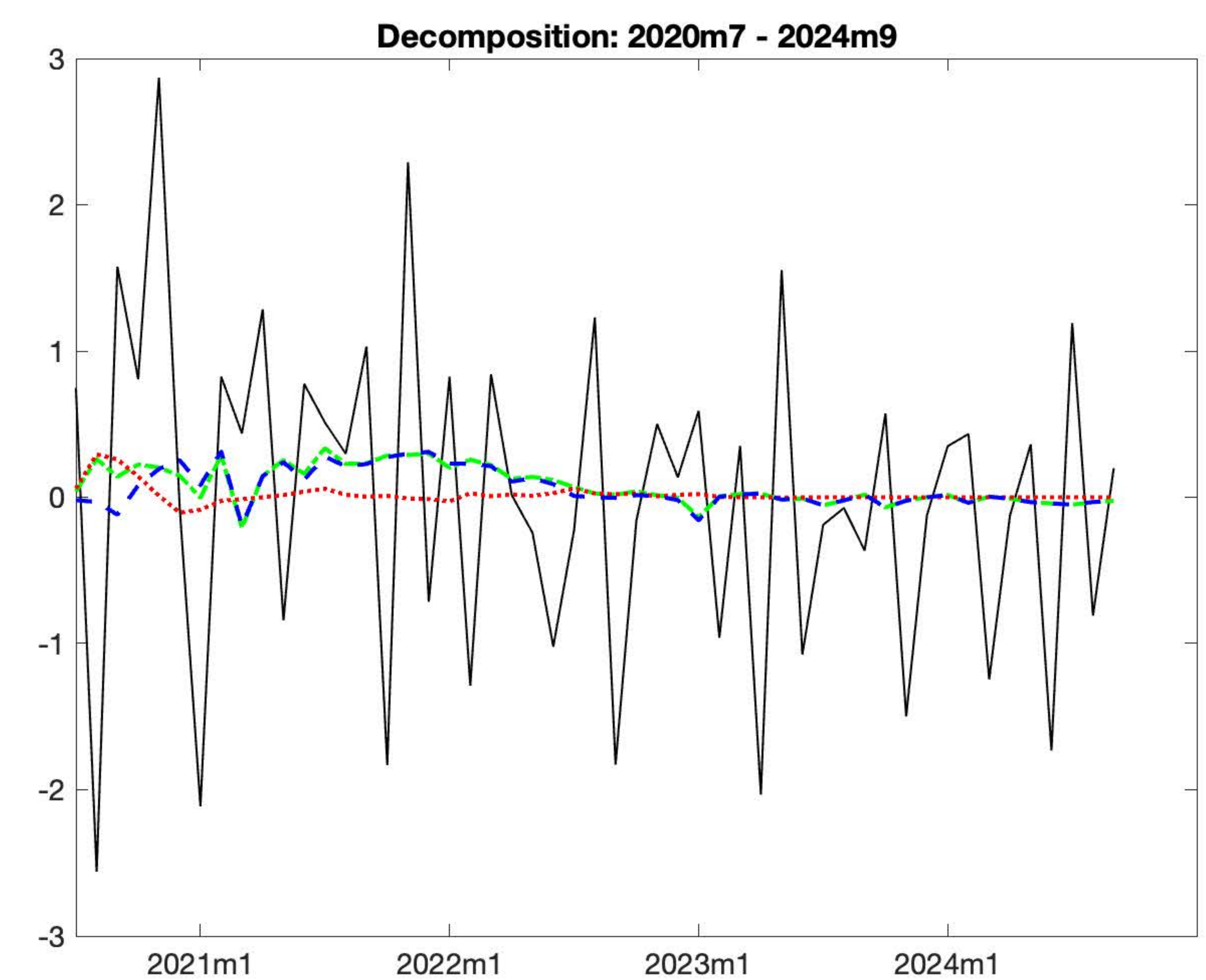


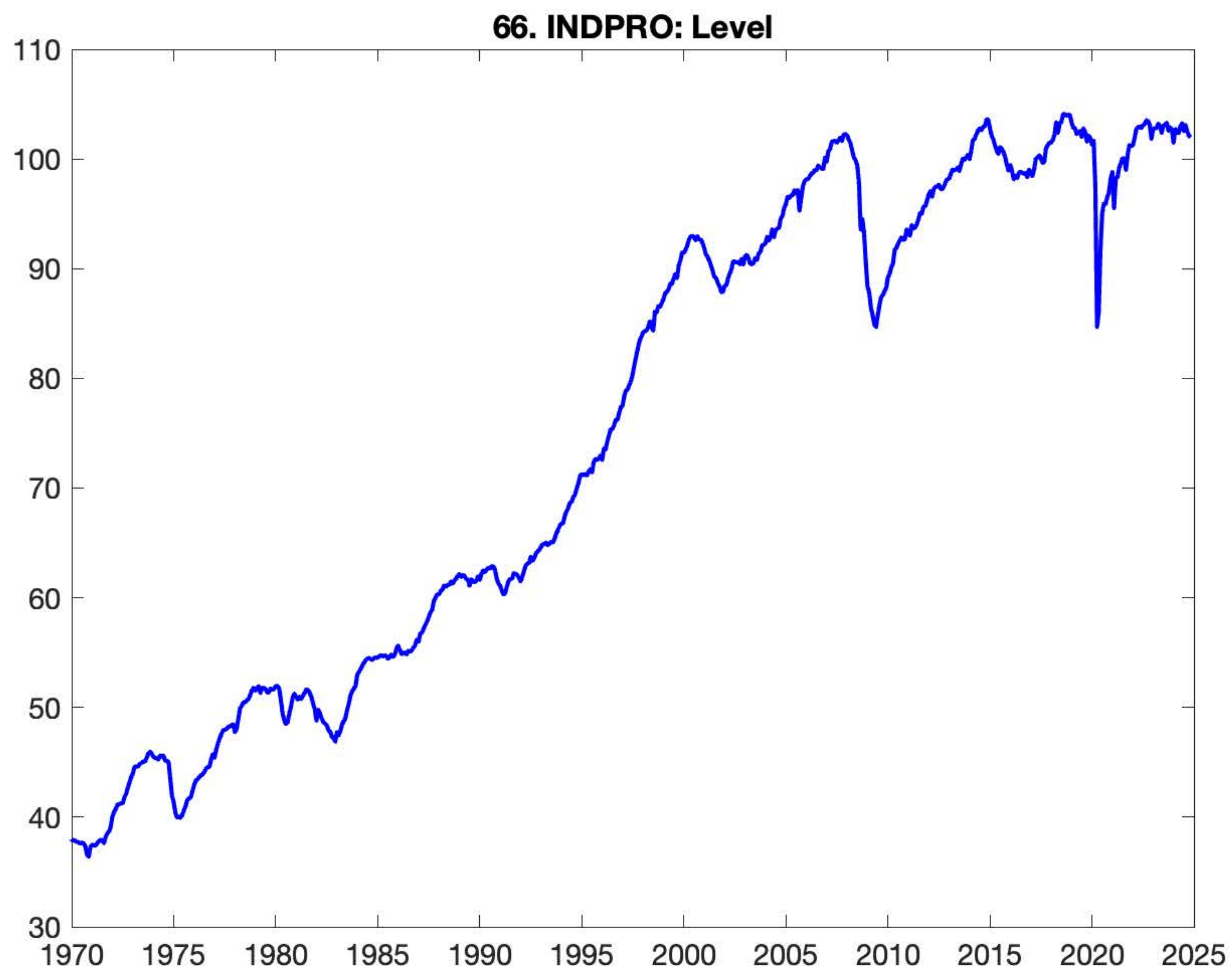
Decomposition: 2020m7 - 2024m9
3
2
1
0
-1
-2
-3
2021m1 2022m1 2023m1 2024m1

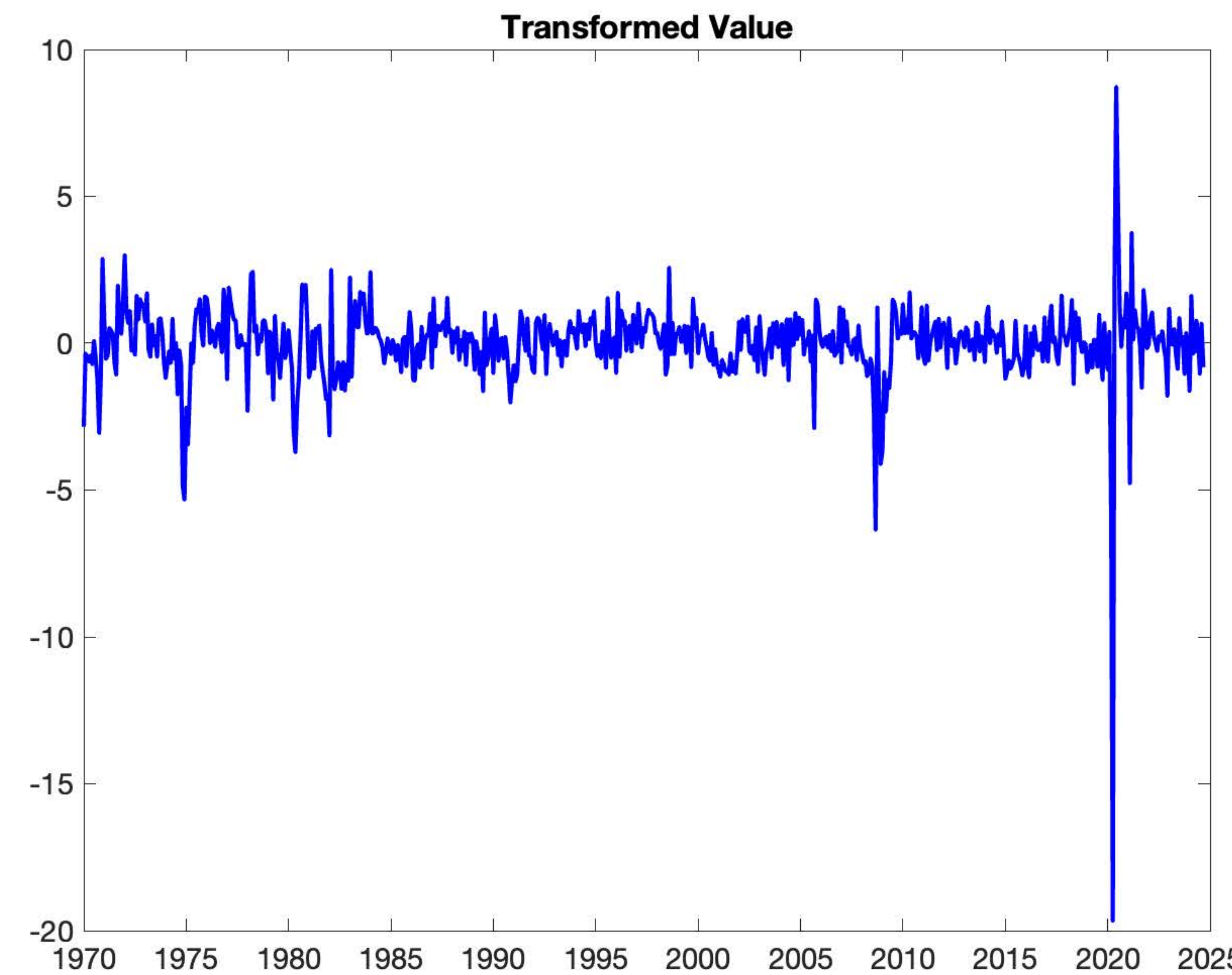

65. JTS1000TSL: Level
×10^4
1.8
1.6
1.4
1.2
1
0.8
0.6
0.4
0.2
1970
1975
1980
1985
1990
1995
2000
2005
2010
2015
2020
2025

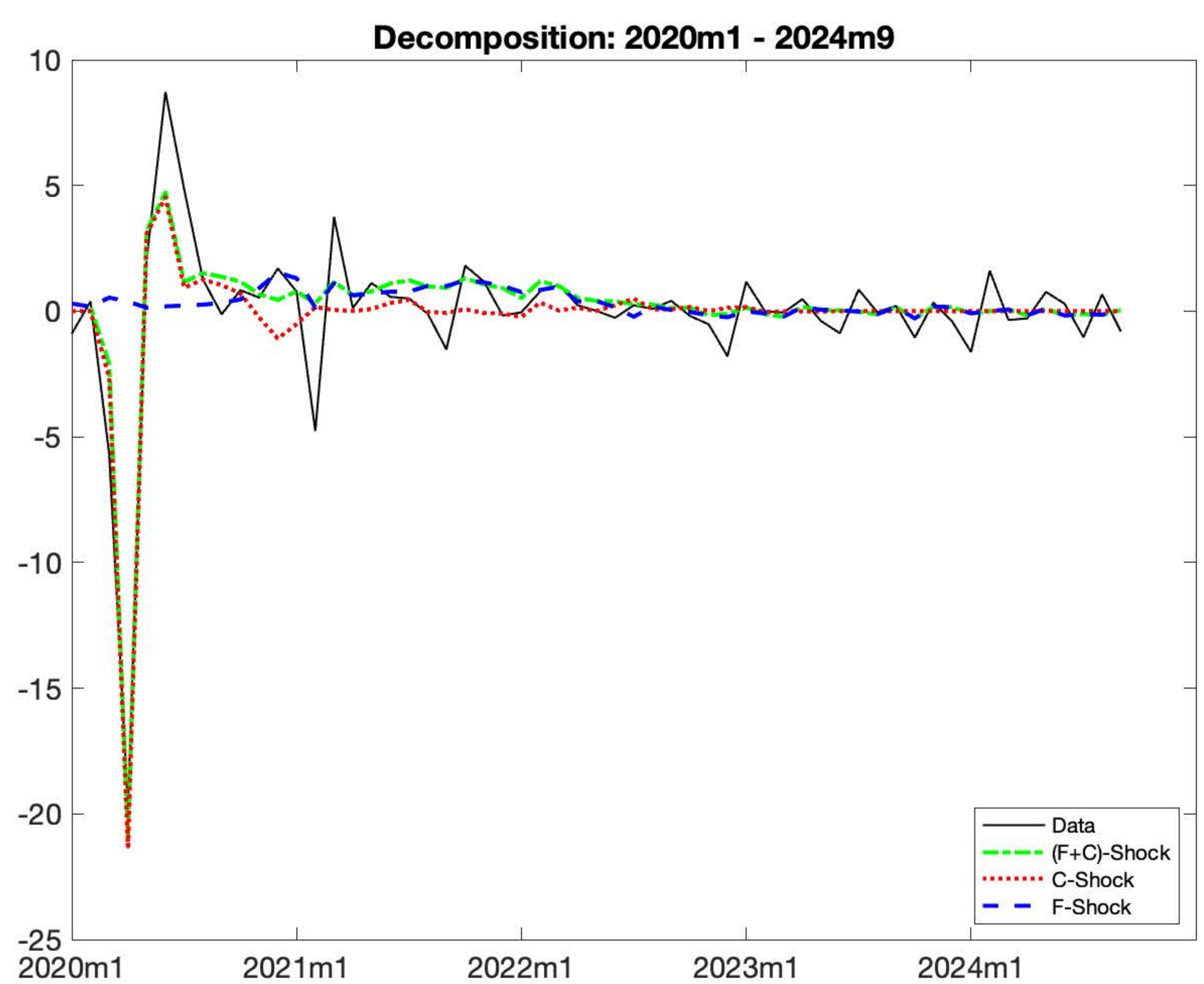

Transformed Value
40
30
20
10
0
-10
-20
-30
1970
1975
1980
1985
1990
1995
2000
2005
2010
2015
2020
2025

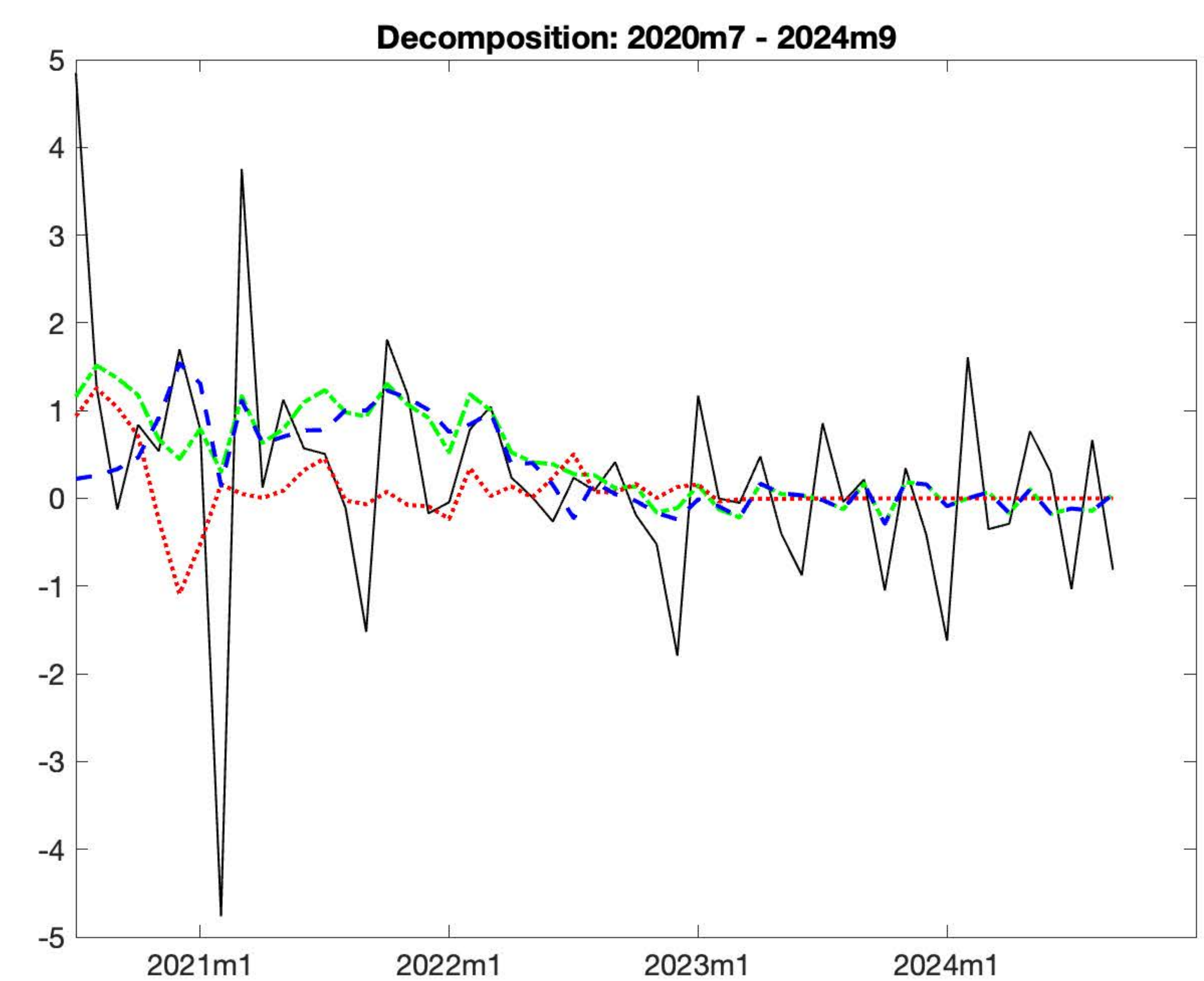

Decomposition: 2020m1 - 2024m9
40
30
20
10
0
-10
-20
-30
2020m1
2021m1
2022m1
2023m1
2024m1
Data
(F+C)-Shock
C-Shock
F-Shock

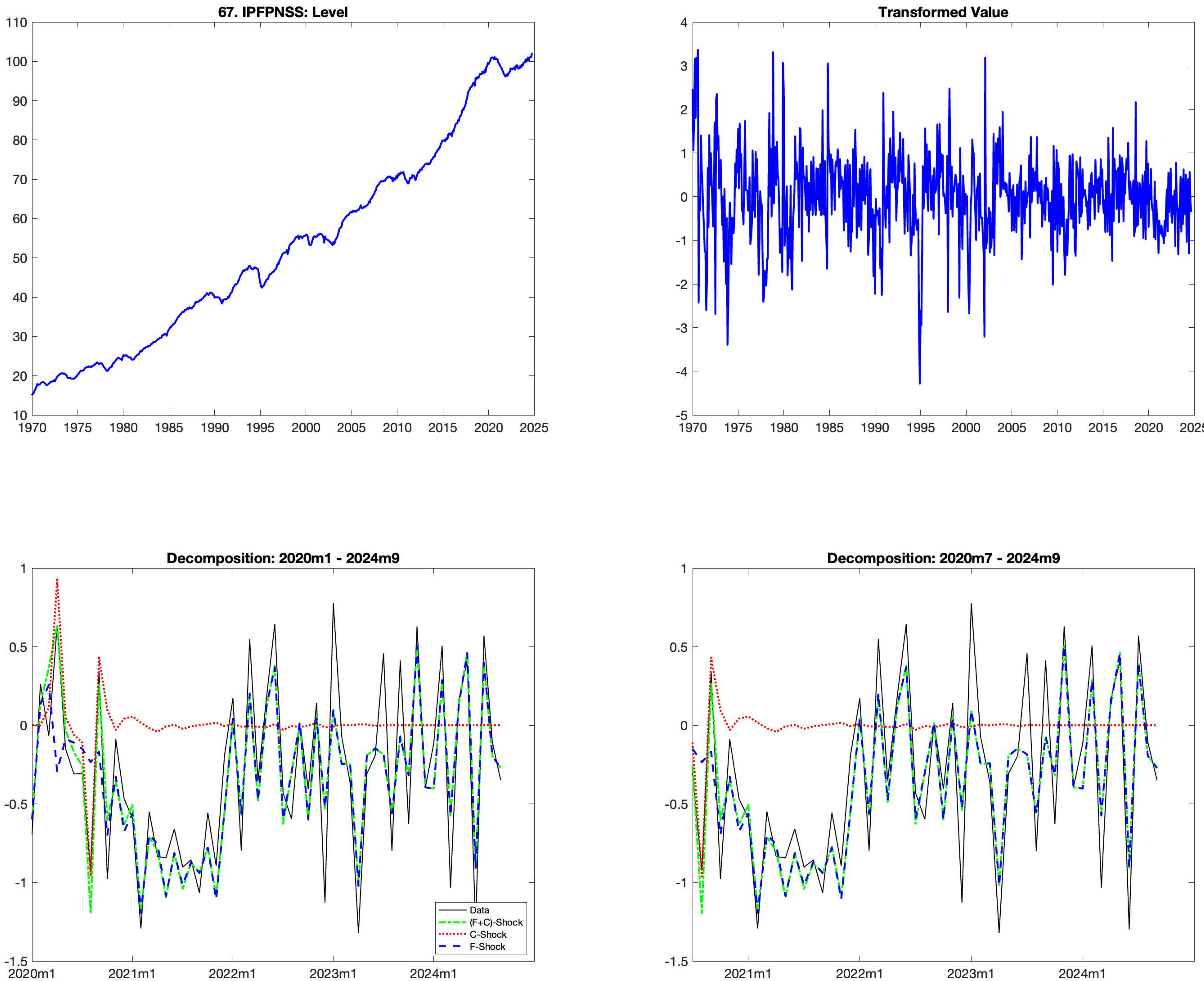

Decomposition: 2020m7 - 2024m9
3
2
1
0
-1
-2
-3
2021m1
2022m1
2023m1
2024m1


66. INDPRO: Level

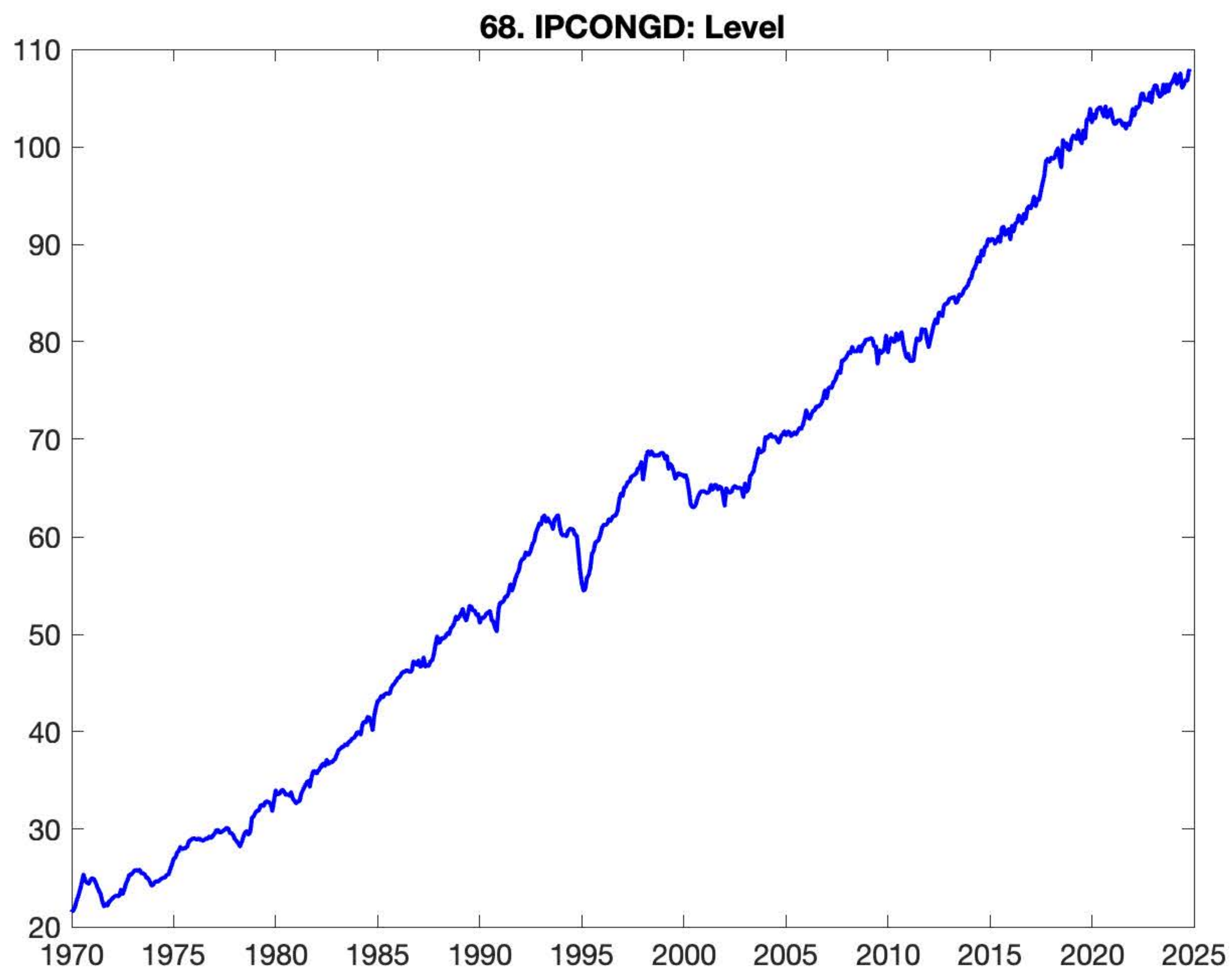

Transformed Value

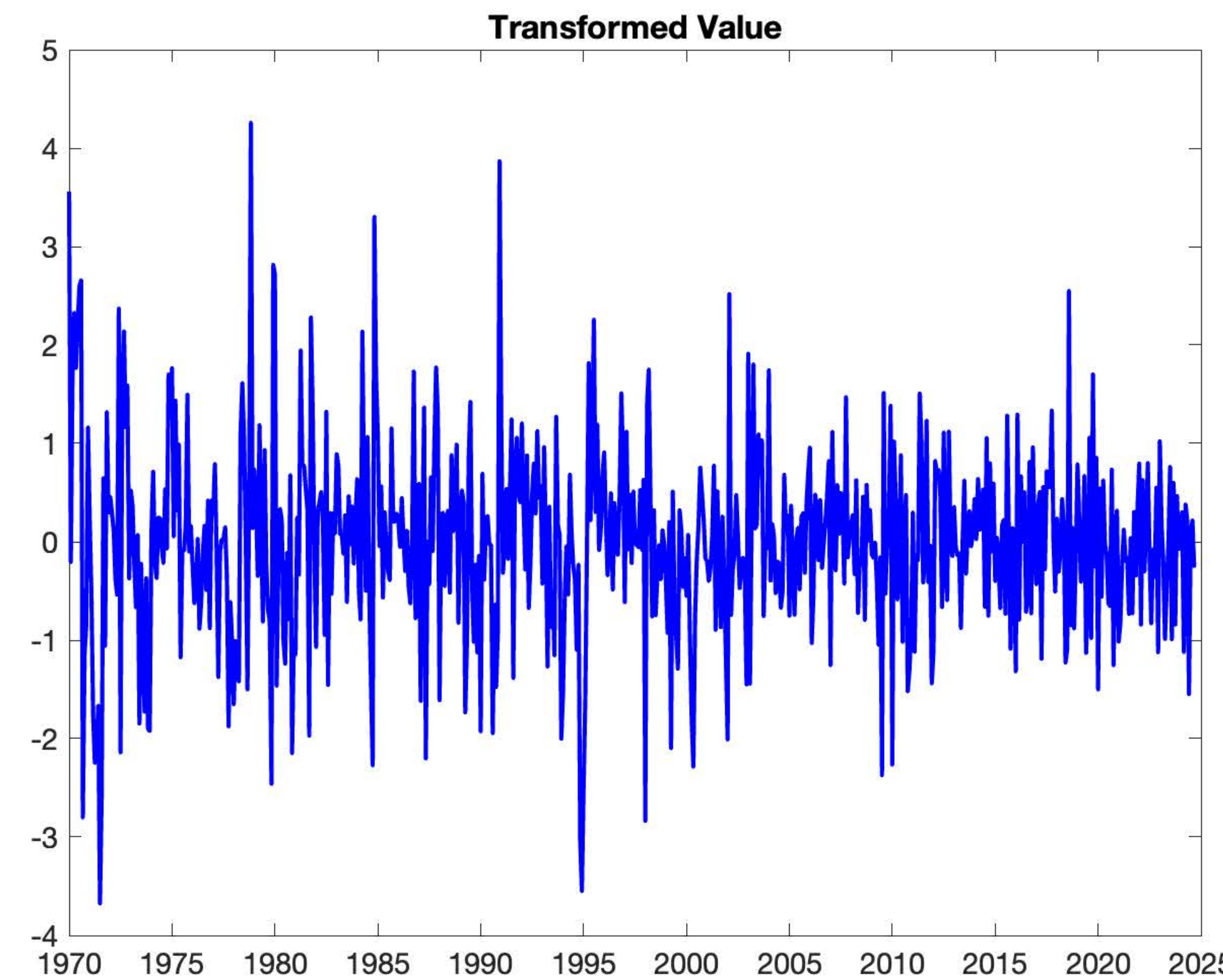

Decomposition: 2020m1 - 2024m9
Data
(F+C)-Shock
C-Shock
F-Shock

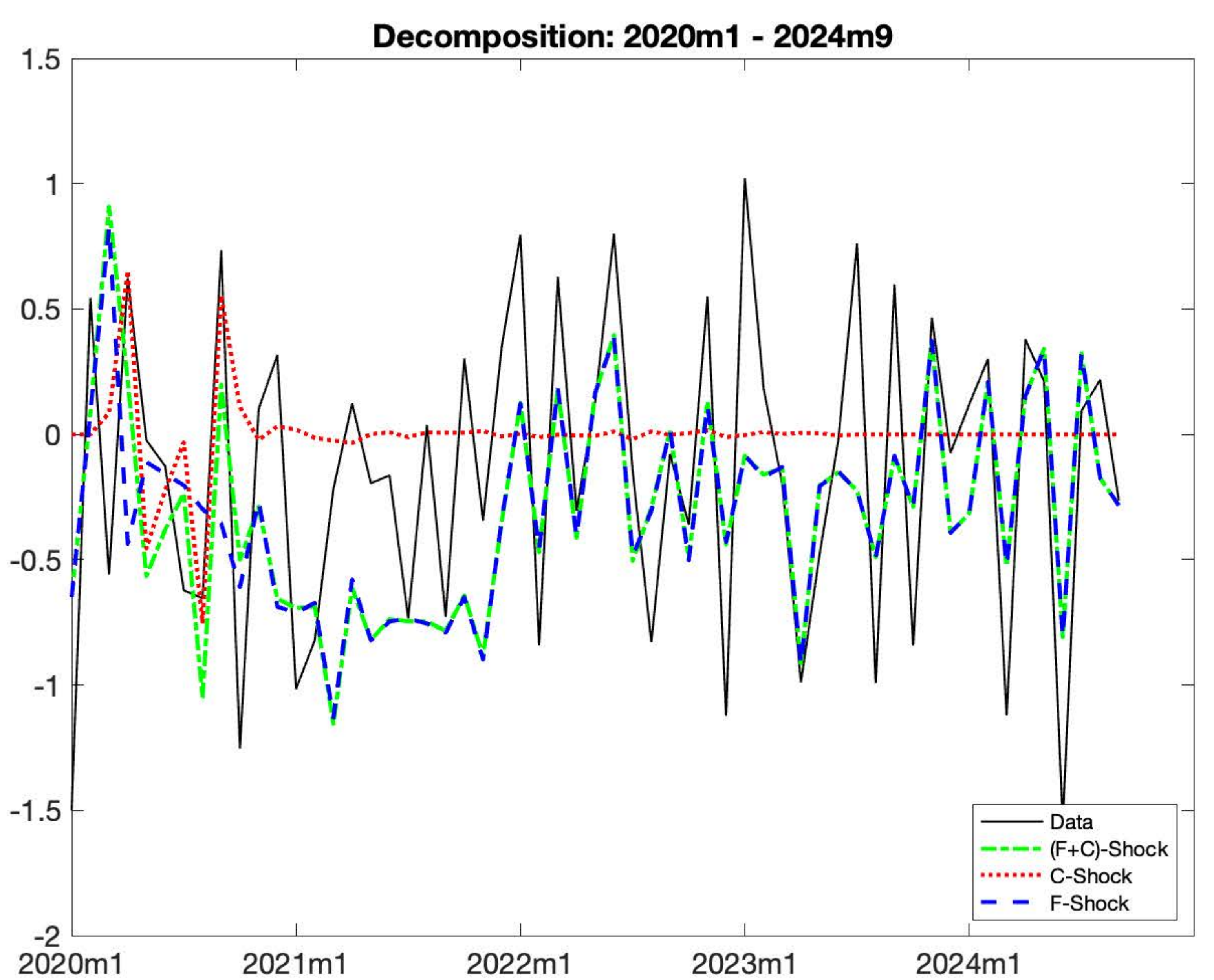

Decomposition: 2020m7 - 2024m9

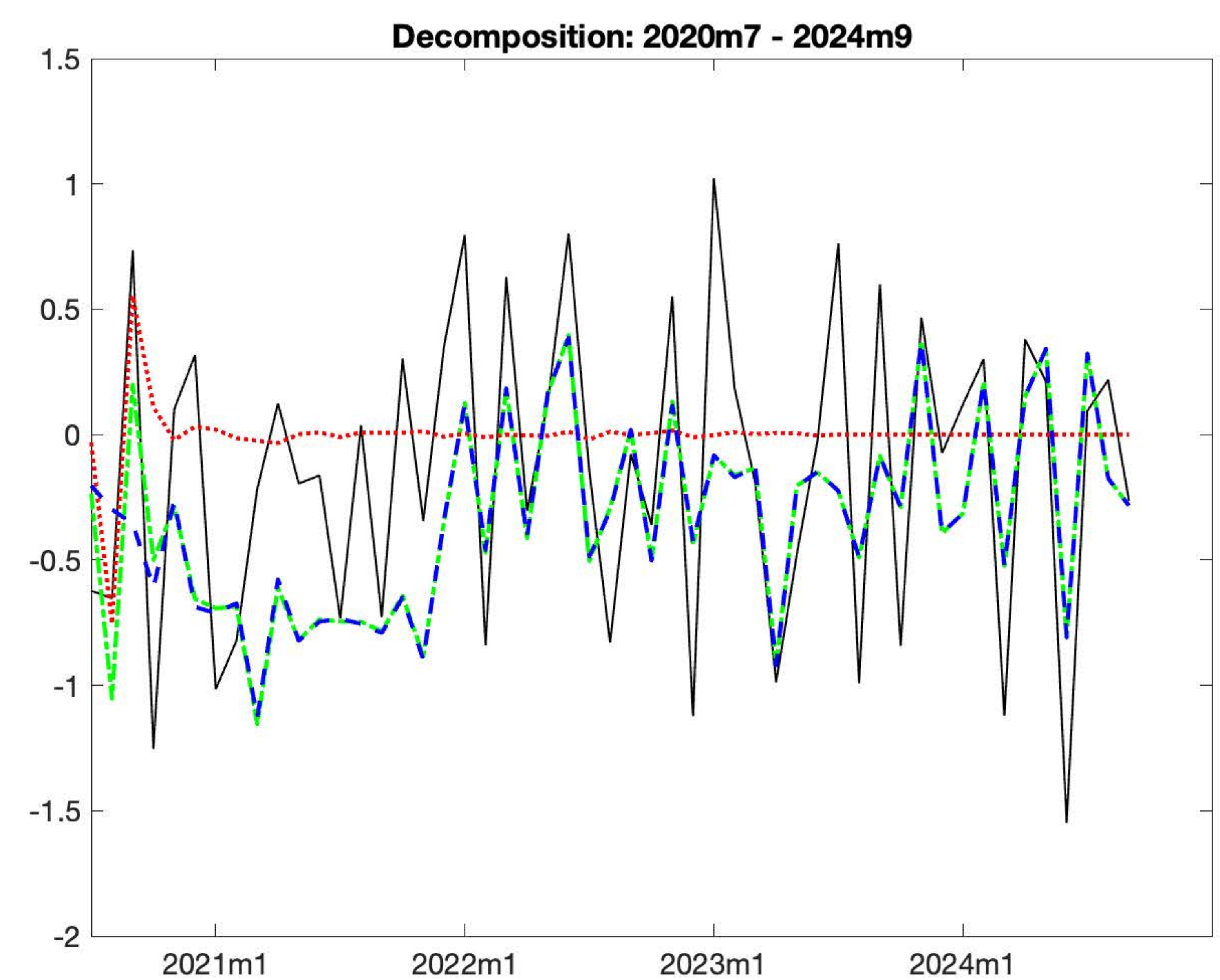


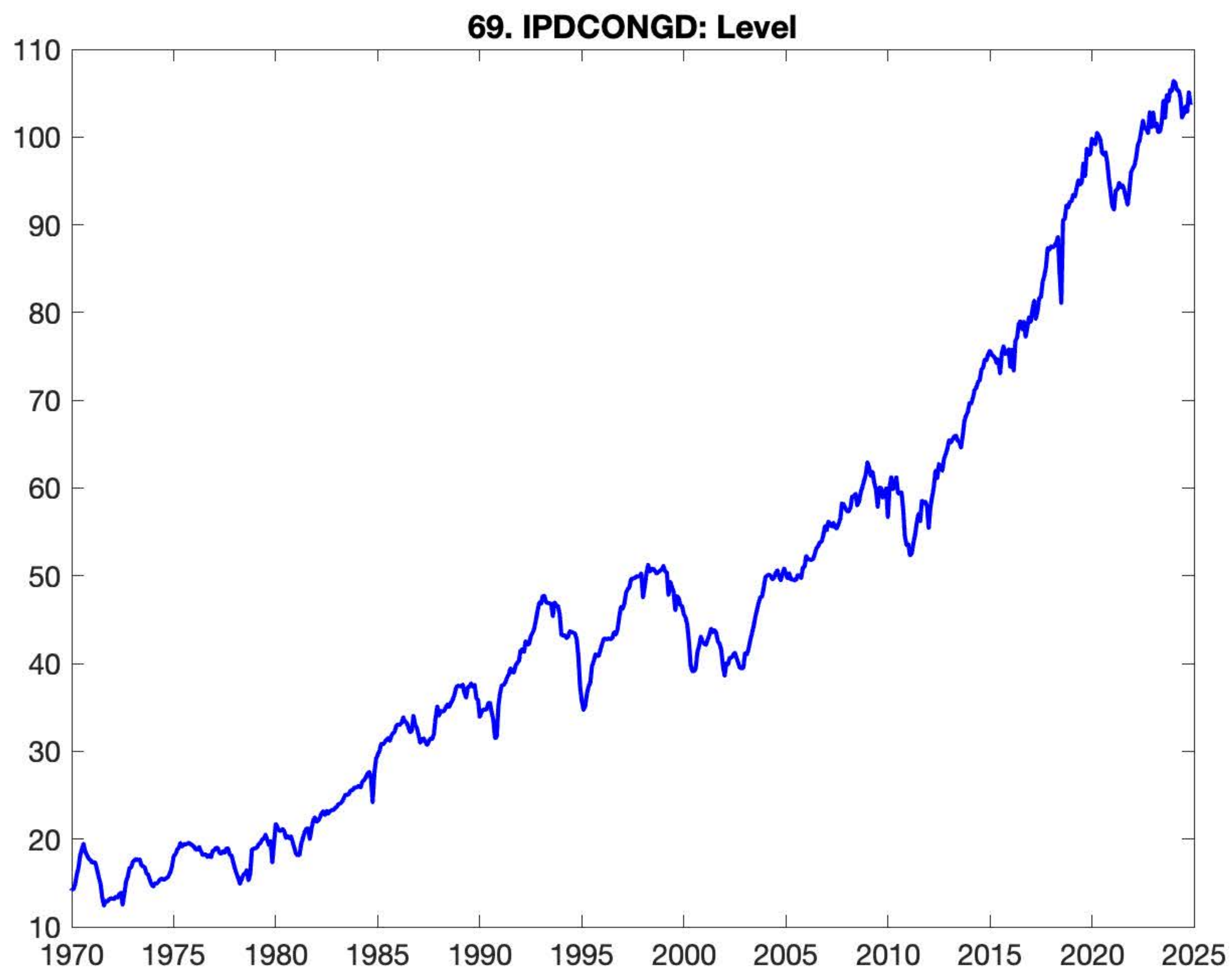
67. IPFPNSS: Level
Transformed Value
Decomposition: 2020m1 - 2024m9
Data
(F+C)-Shock
C-Shock
F-Shock
Decomposition: 2020m7 - 2024m9

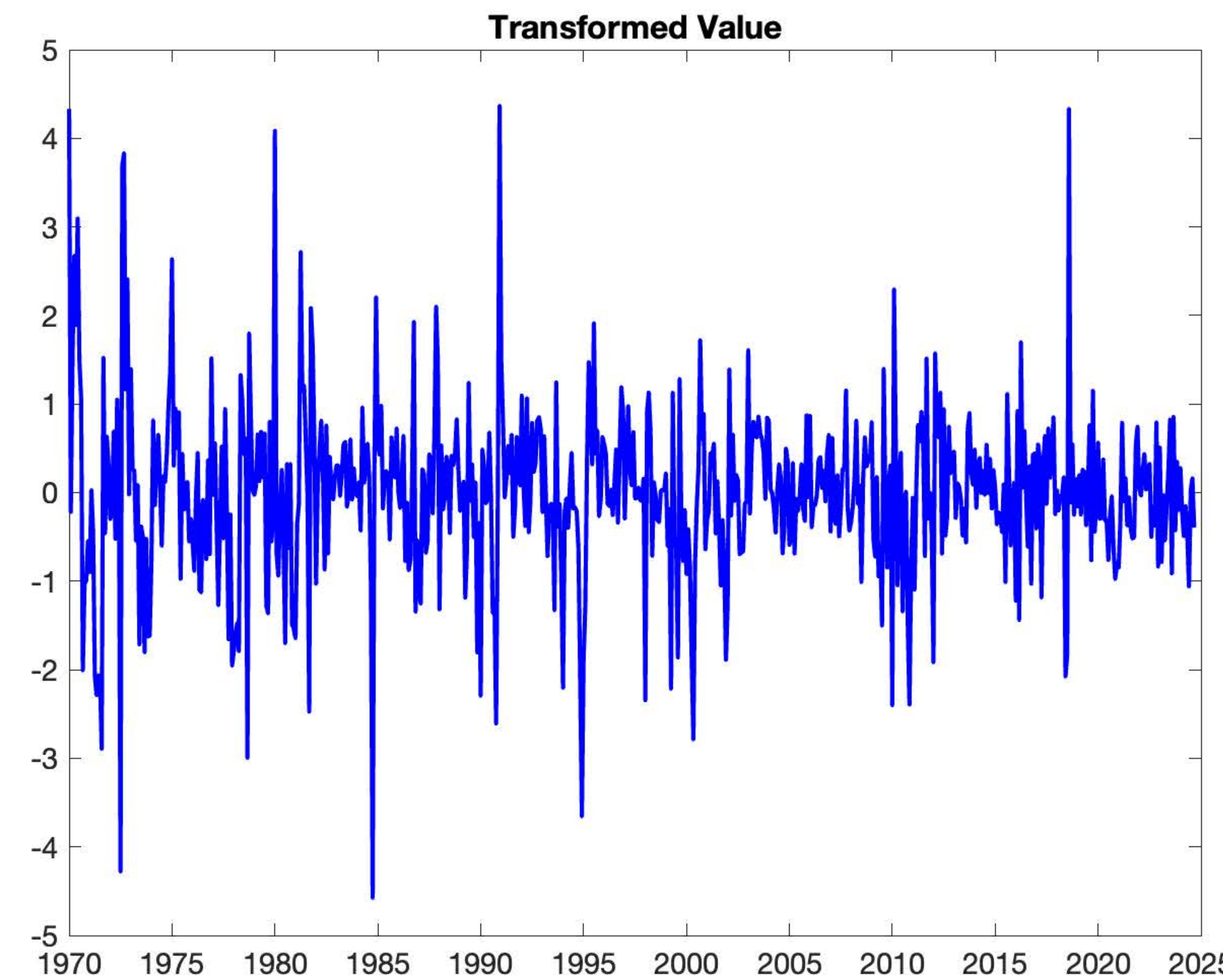

68. IPCONGD: Level
110
100
90
80
70
60
50
40
30
20
1970
1975
1980
1985
1990
1995
2000
2005
2010
2015
2020
2025

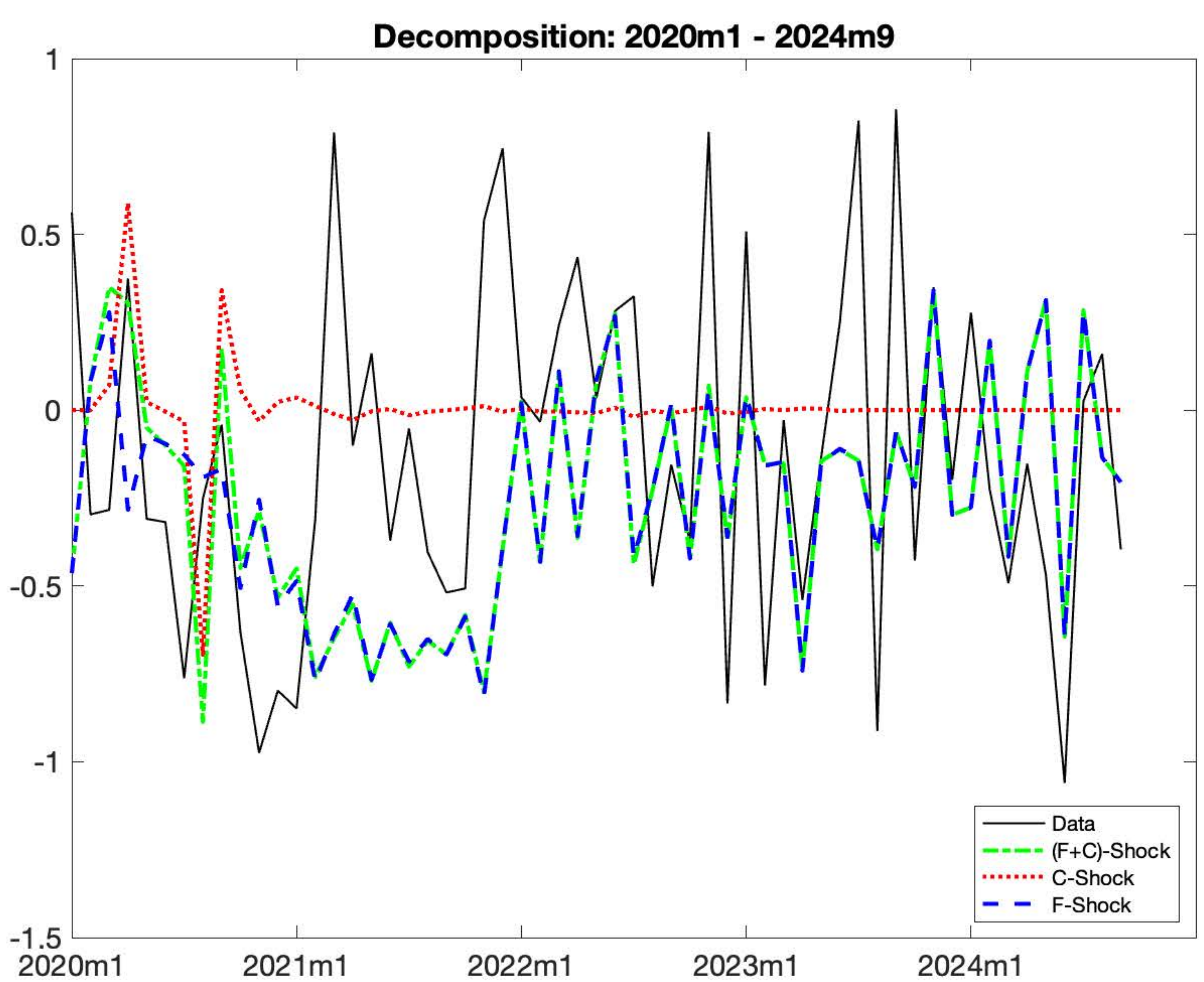

Transformed Value
5
4
3
2
1
0
-1
-2
-3
-4
1970
1975
1980
1985
1990
1995
2000
2005
2010
2015
2020
2025

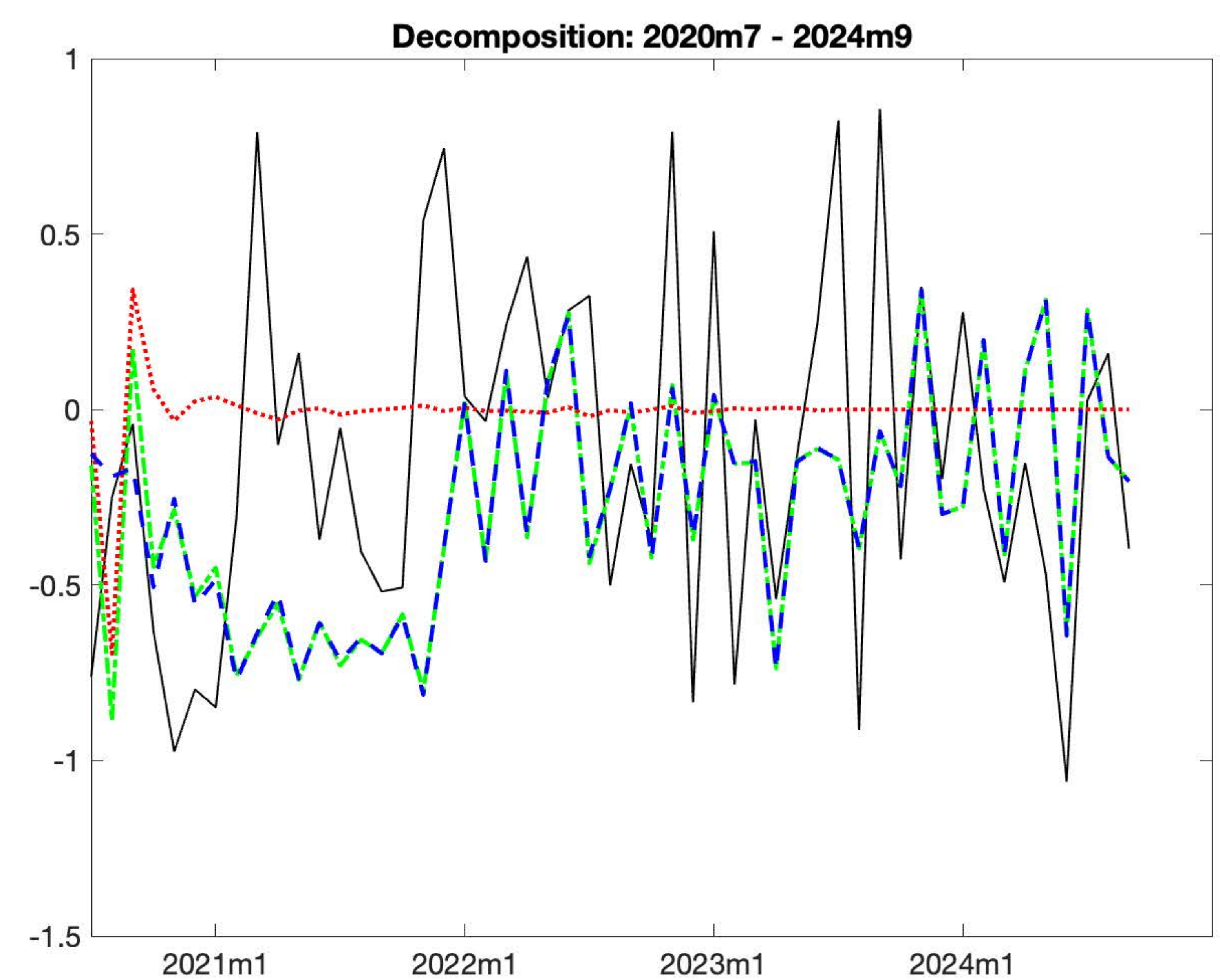

Decomposition: 2020m1 - 2024m9
1.5
1
0.5
0
-0.5
-1
-1.5
-2
2020m1
2021m1
2022m1
2023m1
2024m1
Data
(F+C)-Shock
C-Shock
F-Shock

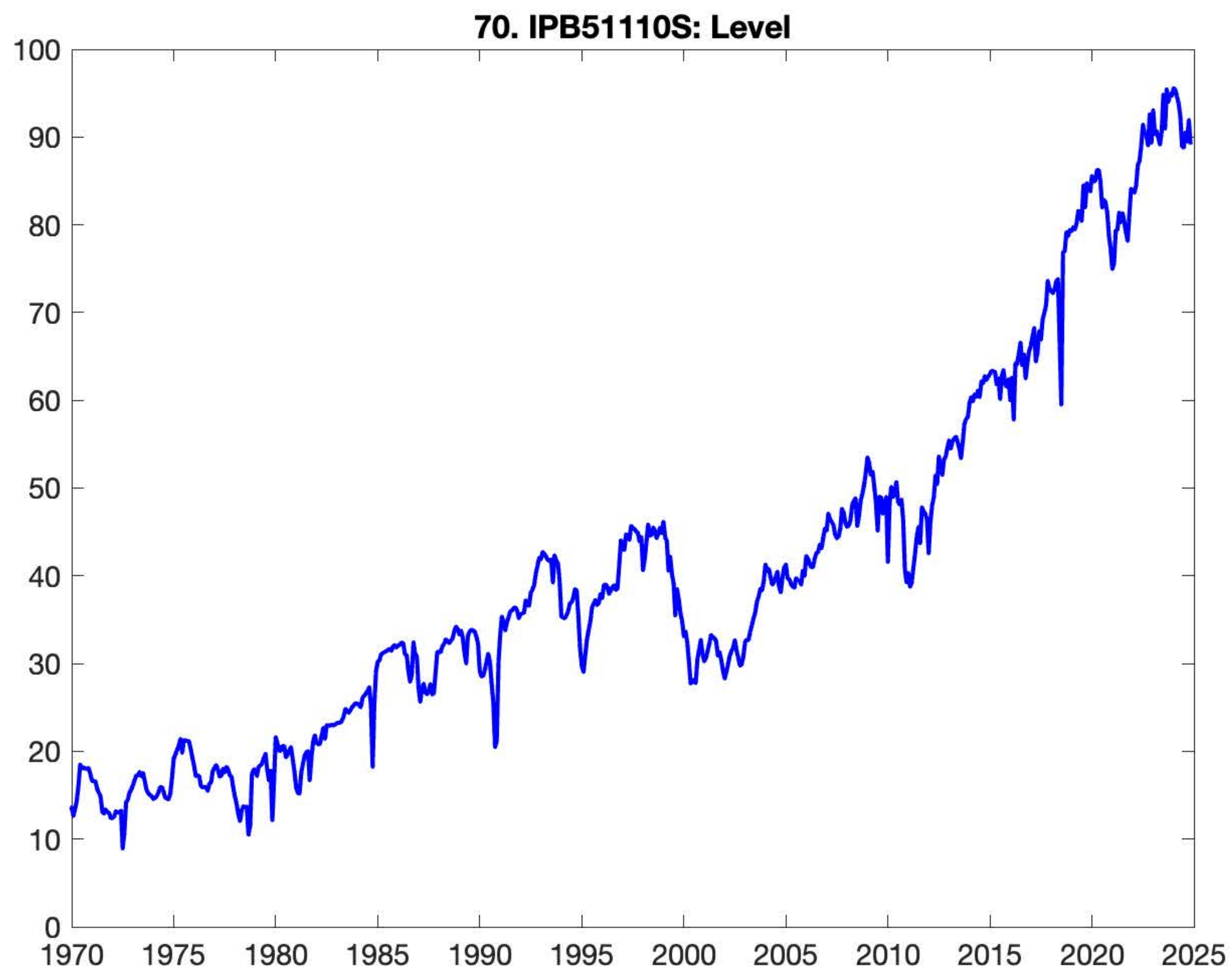

Decomposition: 2020m7 - 2024m9
1.5
1
0.5
0
-0.5
-1
-1.5
-2
2021m1
2022m1
2023m1
2024m1

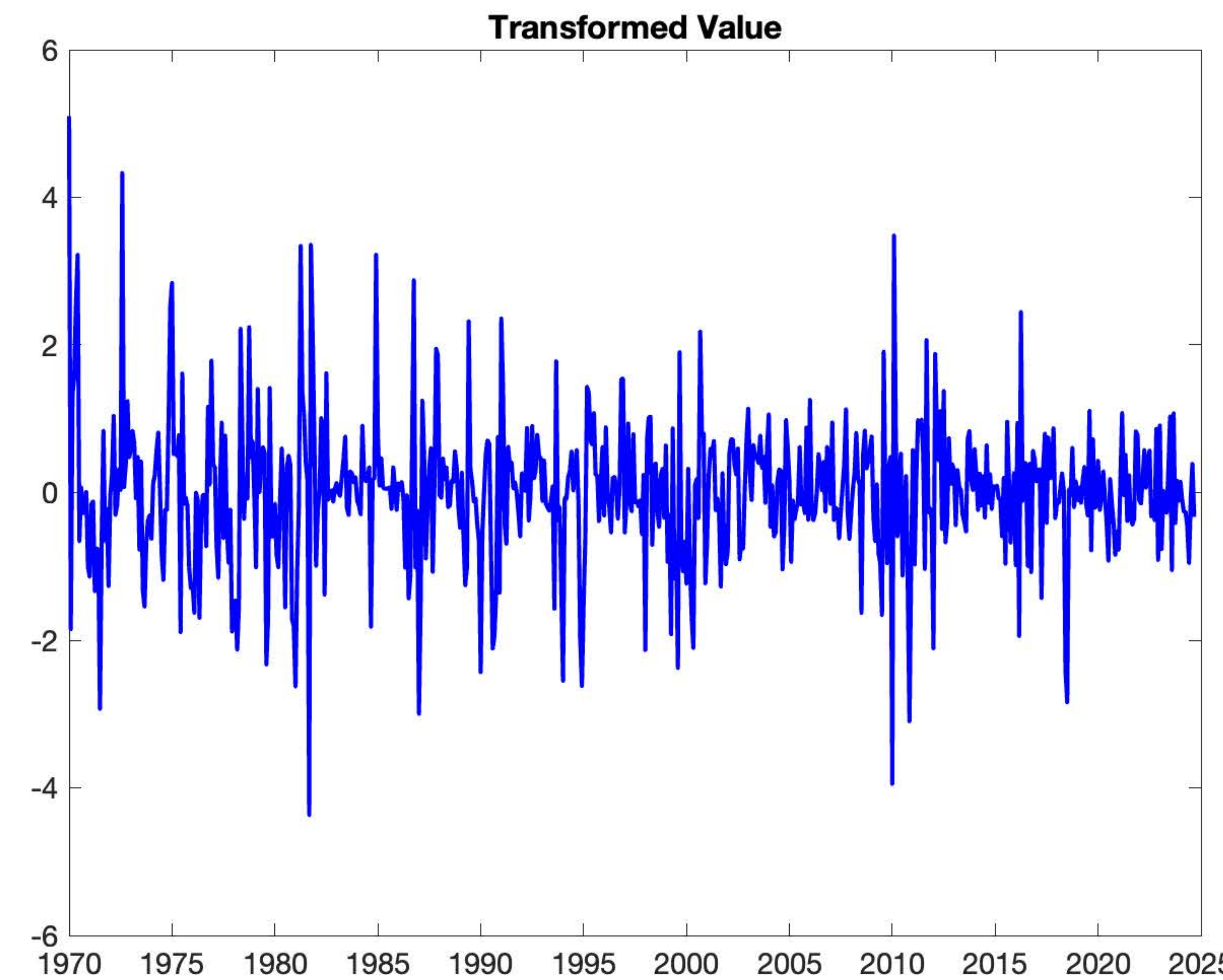

69. IPDCONGD: Level

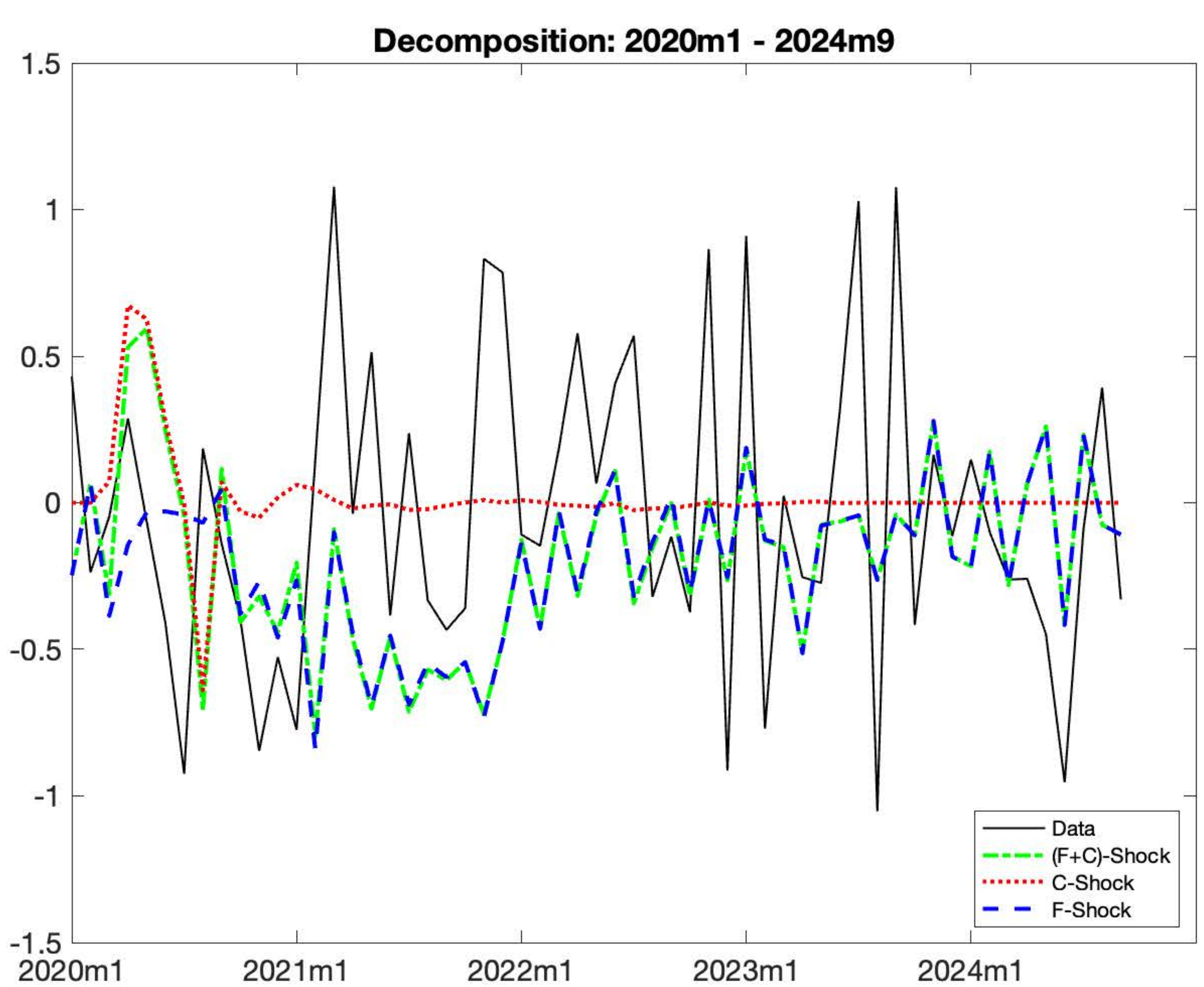

Transformed Value

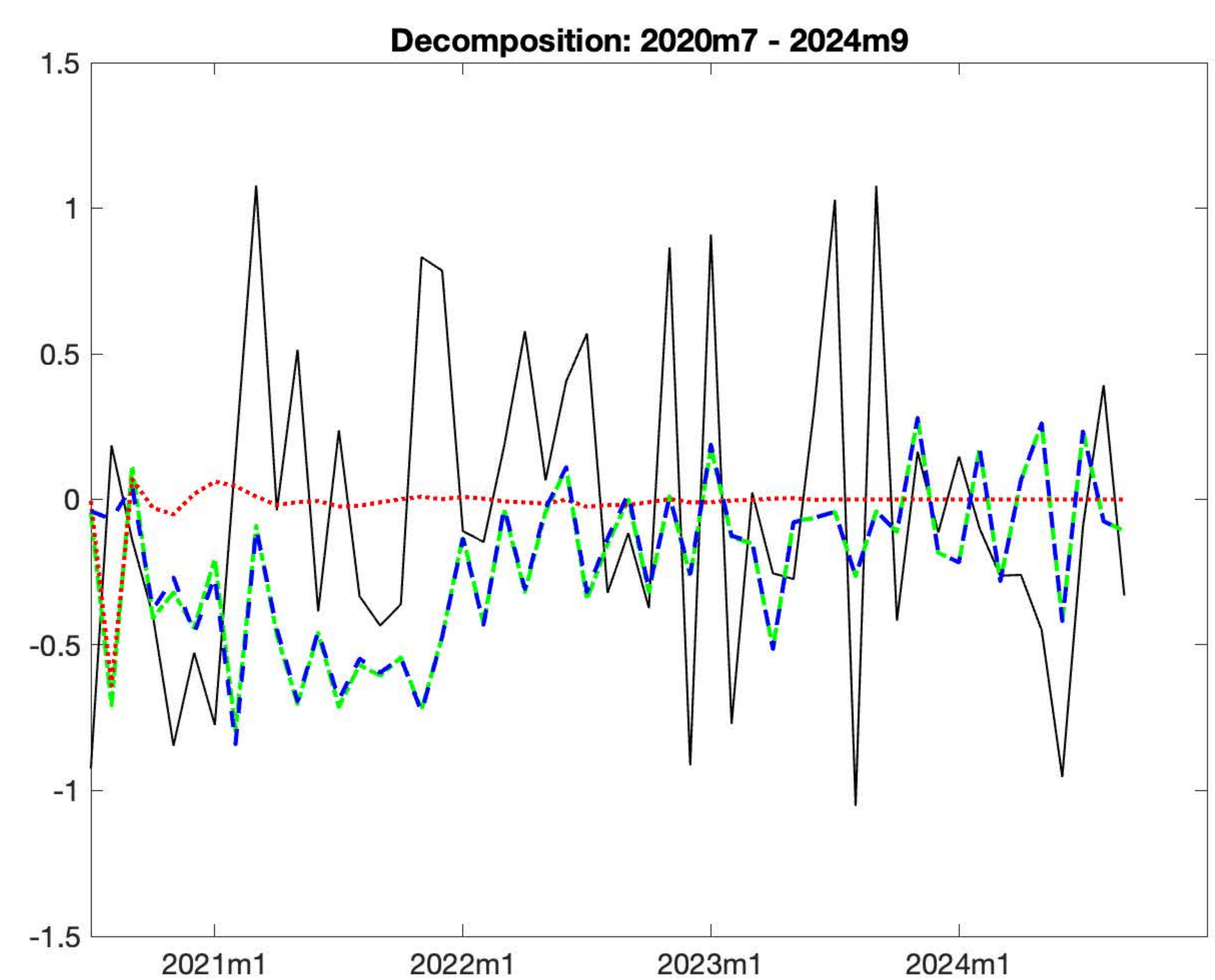

Decomposition: 2020m1 - 2024m9
Data
(F+C)-Shock
C-Shock
F-Shock

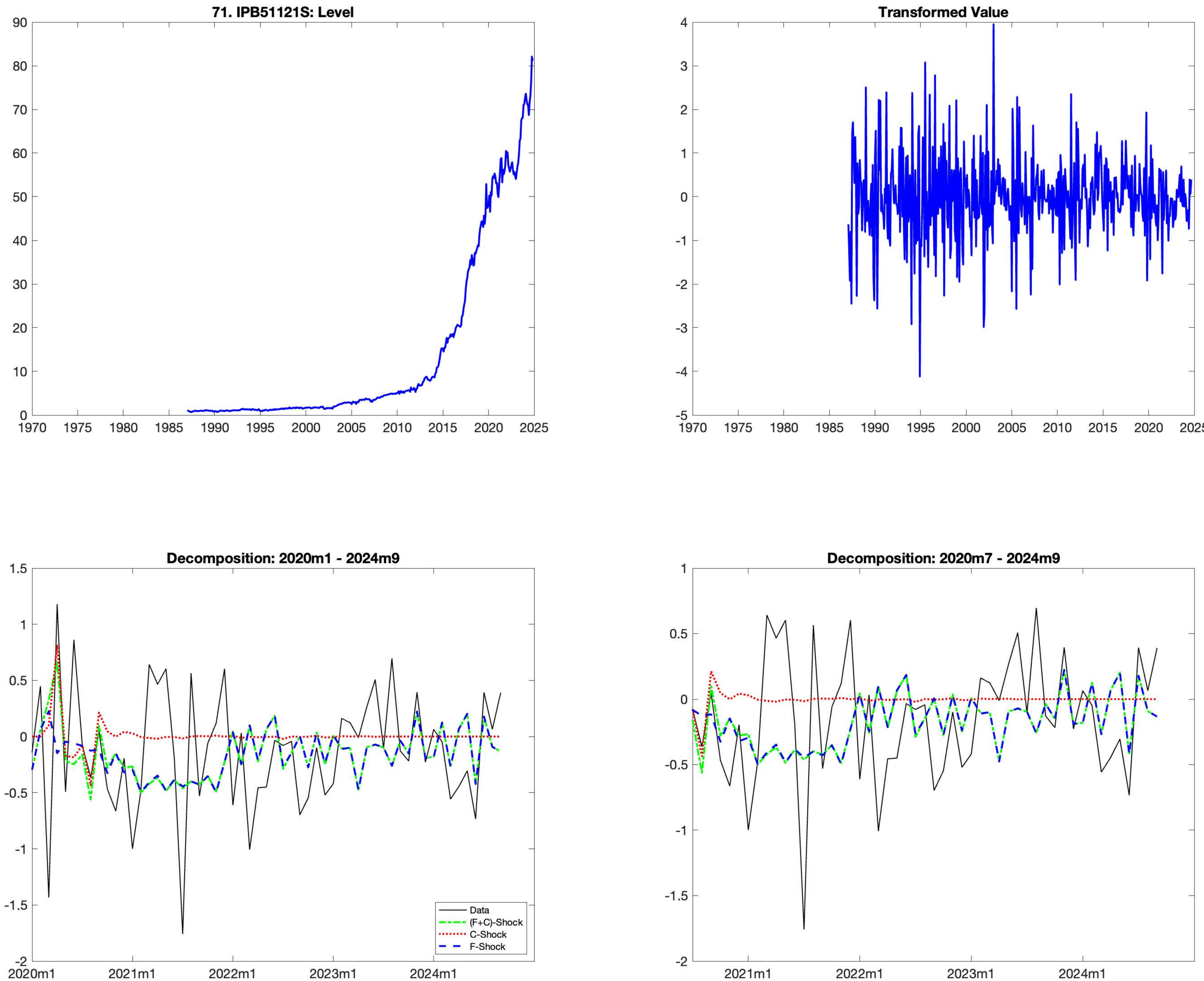

Decomposition: 2020m7 - 2024m9

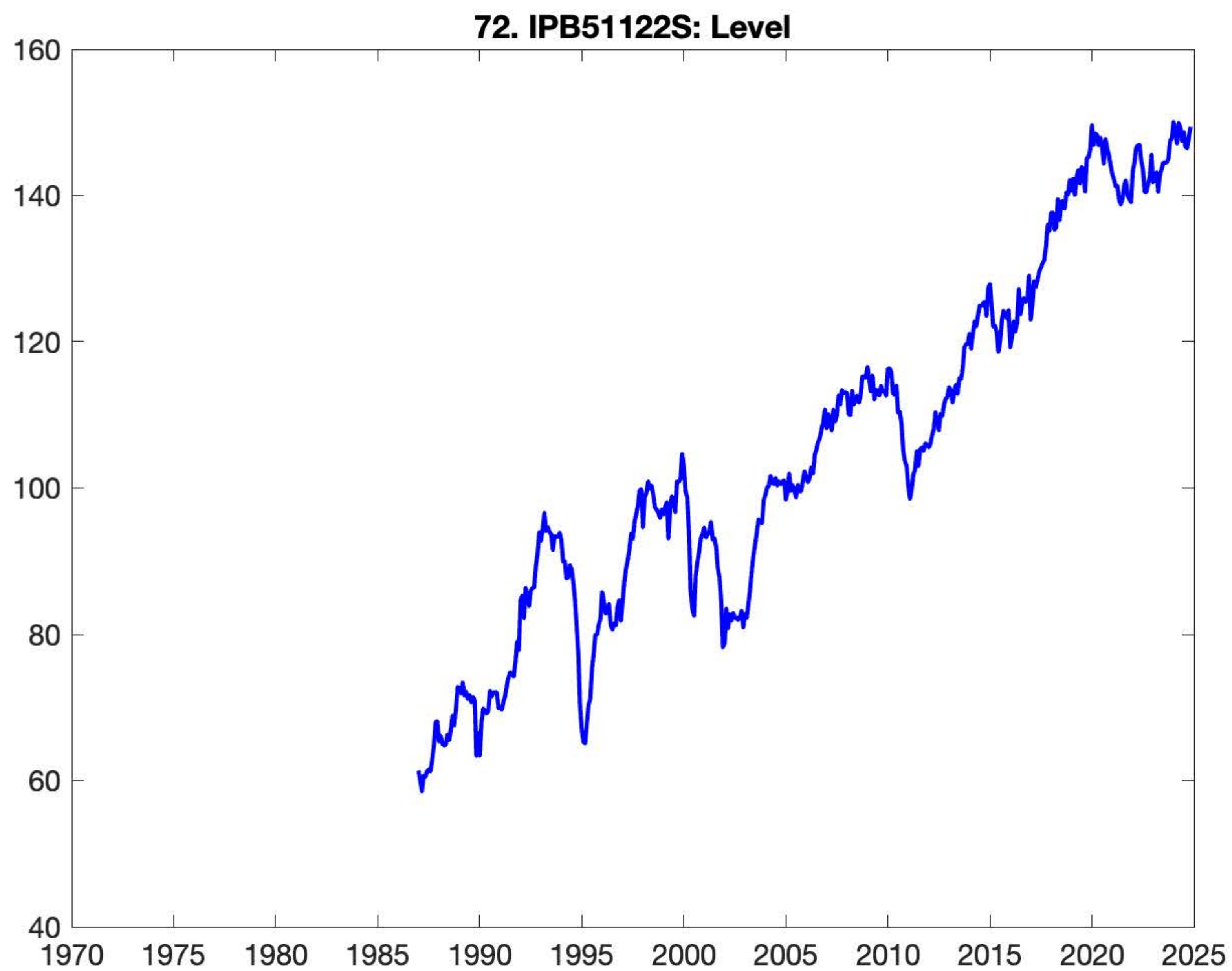

70. IPB51110S: Level
100
90
80
70
60
50
40
30
20
10
0
1970
1975
1980
1985
1990
1995
2000
2005
2010
2015
2020
2025

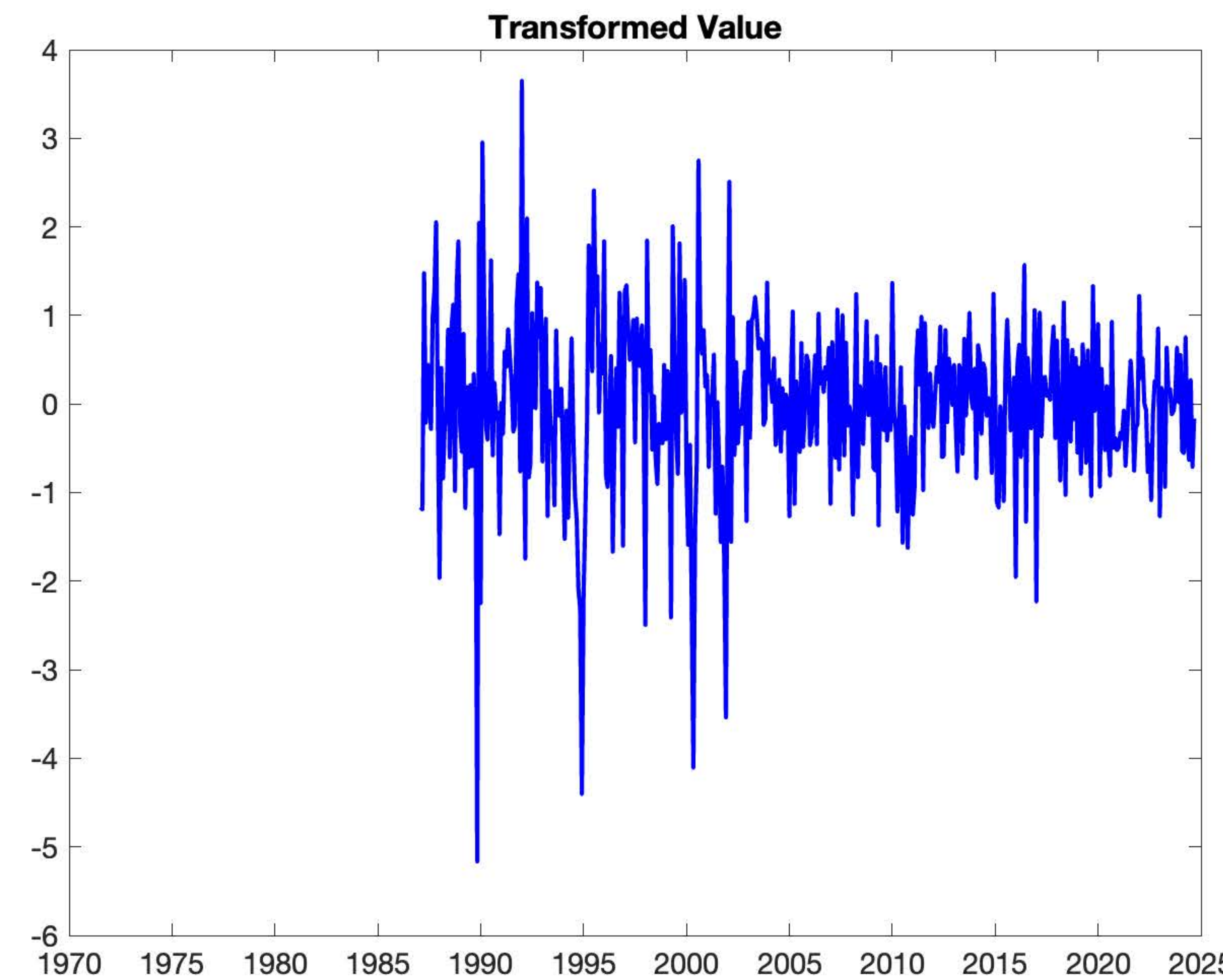

Transformed Value
6
4
2
0
-2
-4
-6
1970
1975
1980
1985
1990
1995
2000
2005
2010
2015
2020
2025

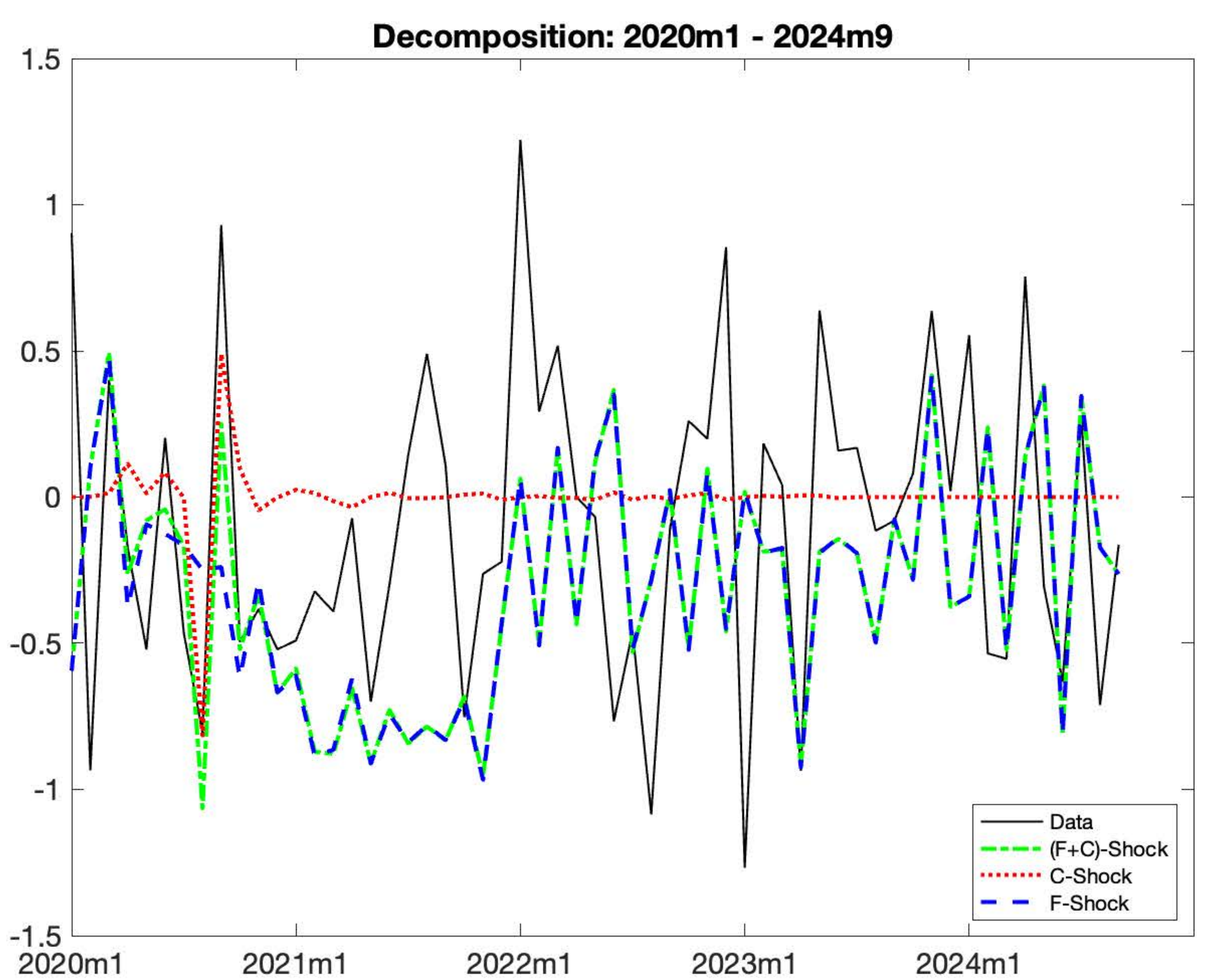

Decomposition: 2020m1 - 2024m9
1.5
1
0.5
0
-0.5
-1
-1.5
2020m1
2021m1
2022m1
2023m1
2024m1
Data
(F+C)-Shock
C-Shock
F-Shock

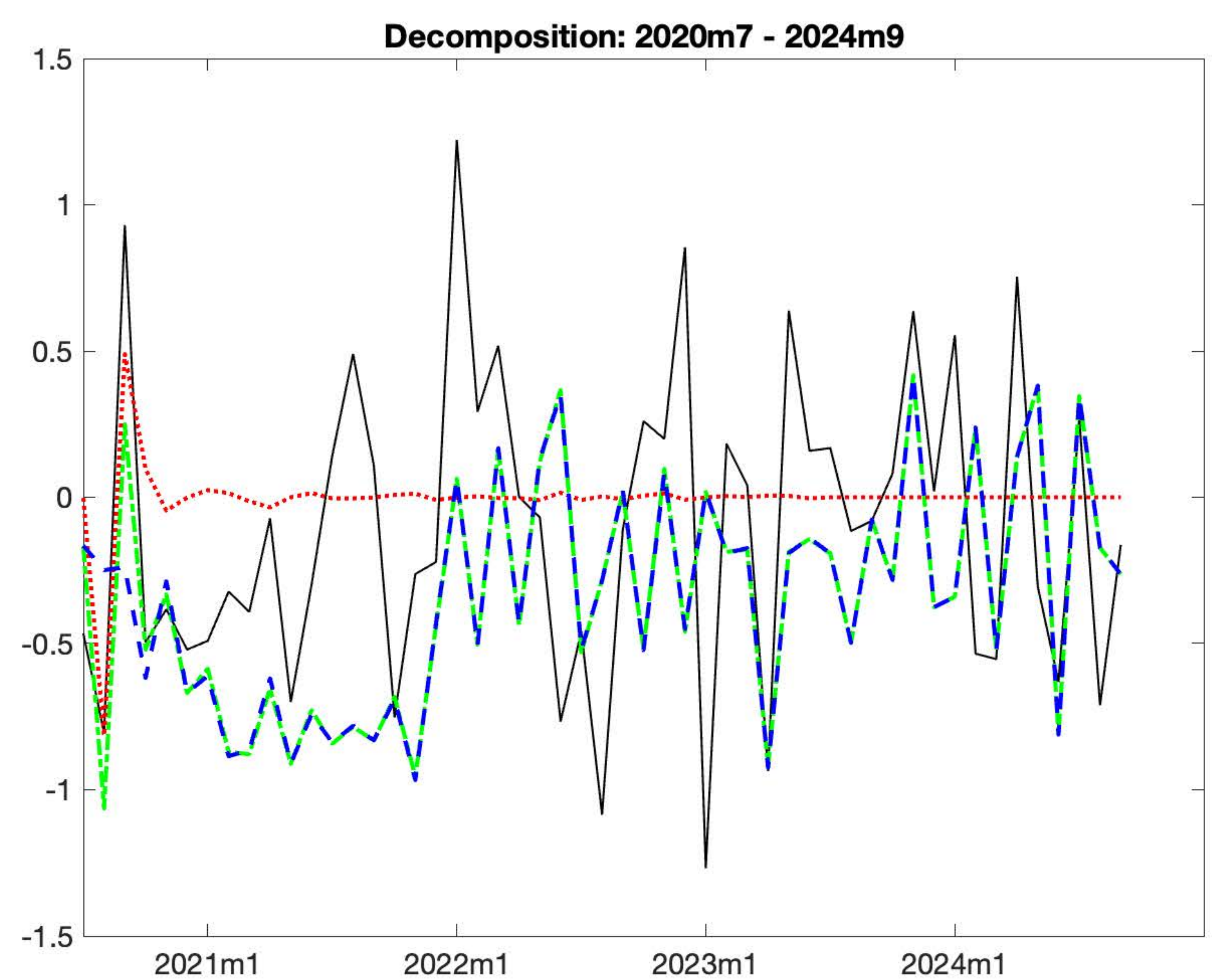

Decomposition: 2020m7 - 2024m9
1.5
1
0.5
0
-0.5
-1
-1.5
2021m1
2022m1
2023m1
2024m1

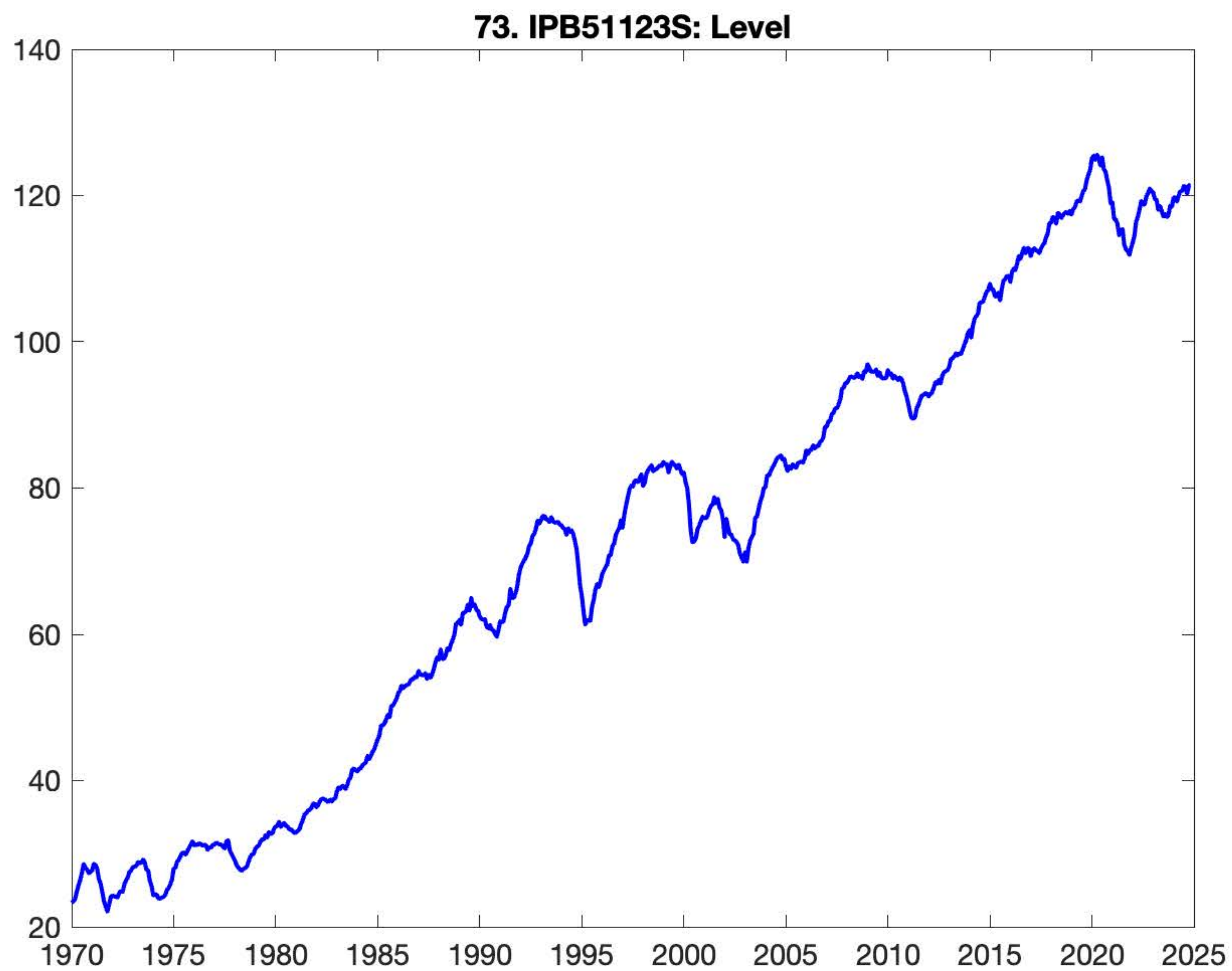

71. IPB51121S: Level
Transformed Value
Decomposition: 2020m1 - 2024m9
Decomposition: 2020m7 - 2024m9
Data
(F+C)-Shock
C-Shock
F-Shock
2020m1
2021m1
2022m1
2023m1
2024m1


72. IPB51122S: Level


Transformed Value


Decomposition: 2020m1 - 2024m9
Data
(F+C)-Shock
C-Shock
F-Shock


Decomposition: 2020m7 - 2024m9


73. IPB51123S: Level
140
120
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60
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1970
1975
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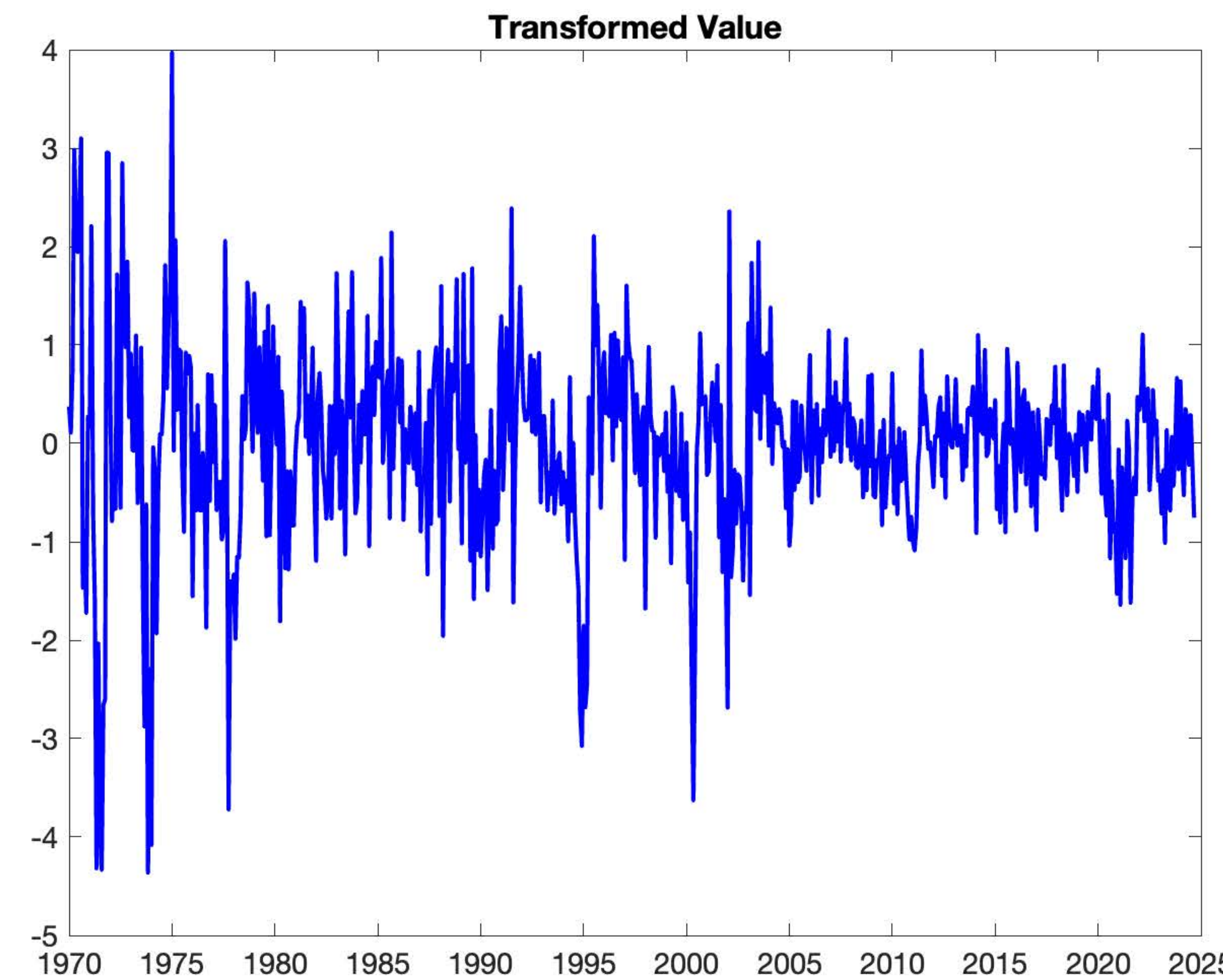
2015
2020
2025


Transformed Value
4
3
2
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0
-1
-2
-3
-4
-5
1970
1975
1980
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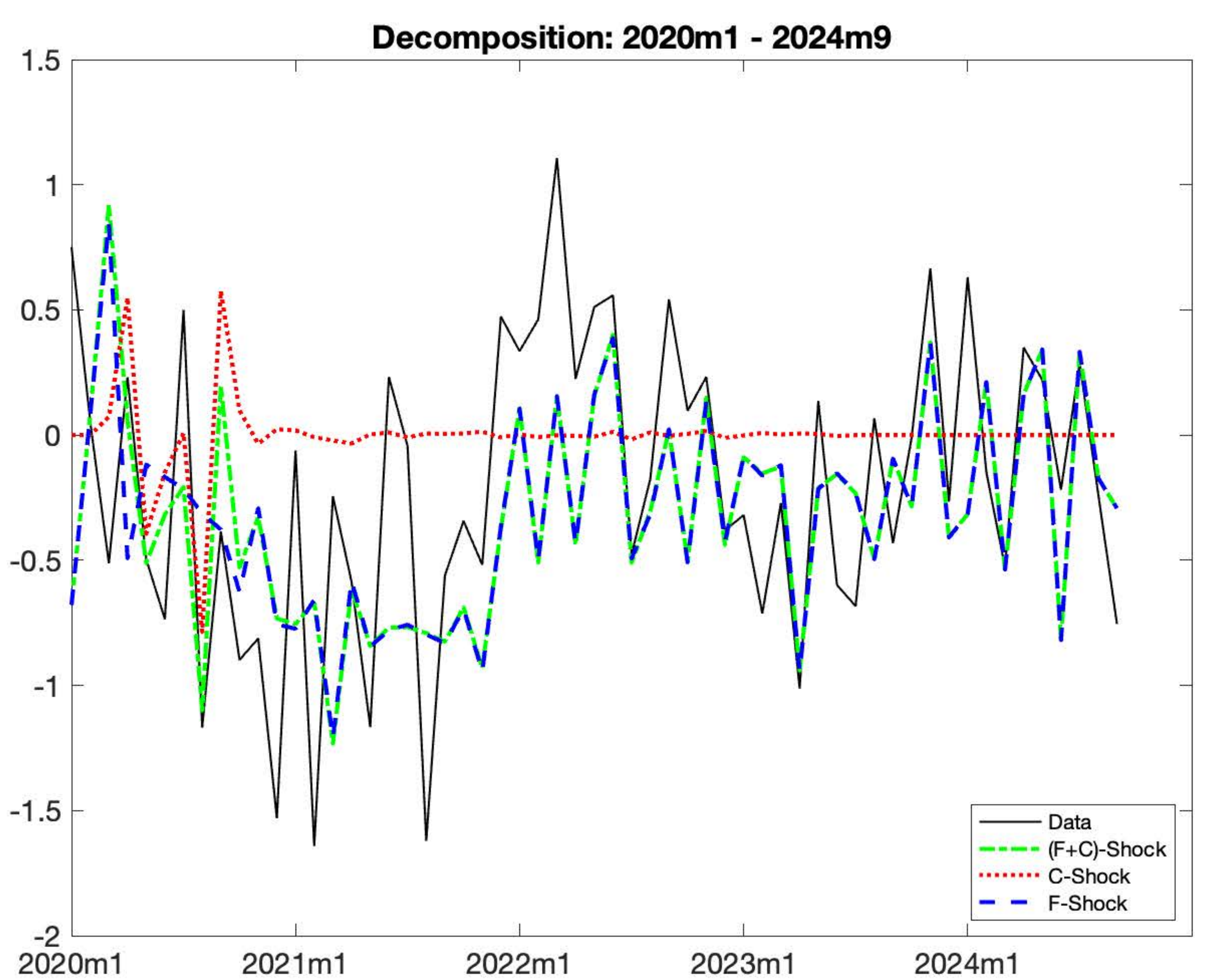
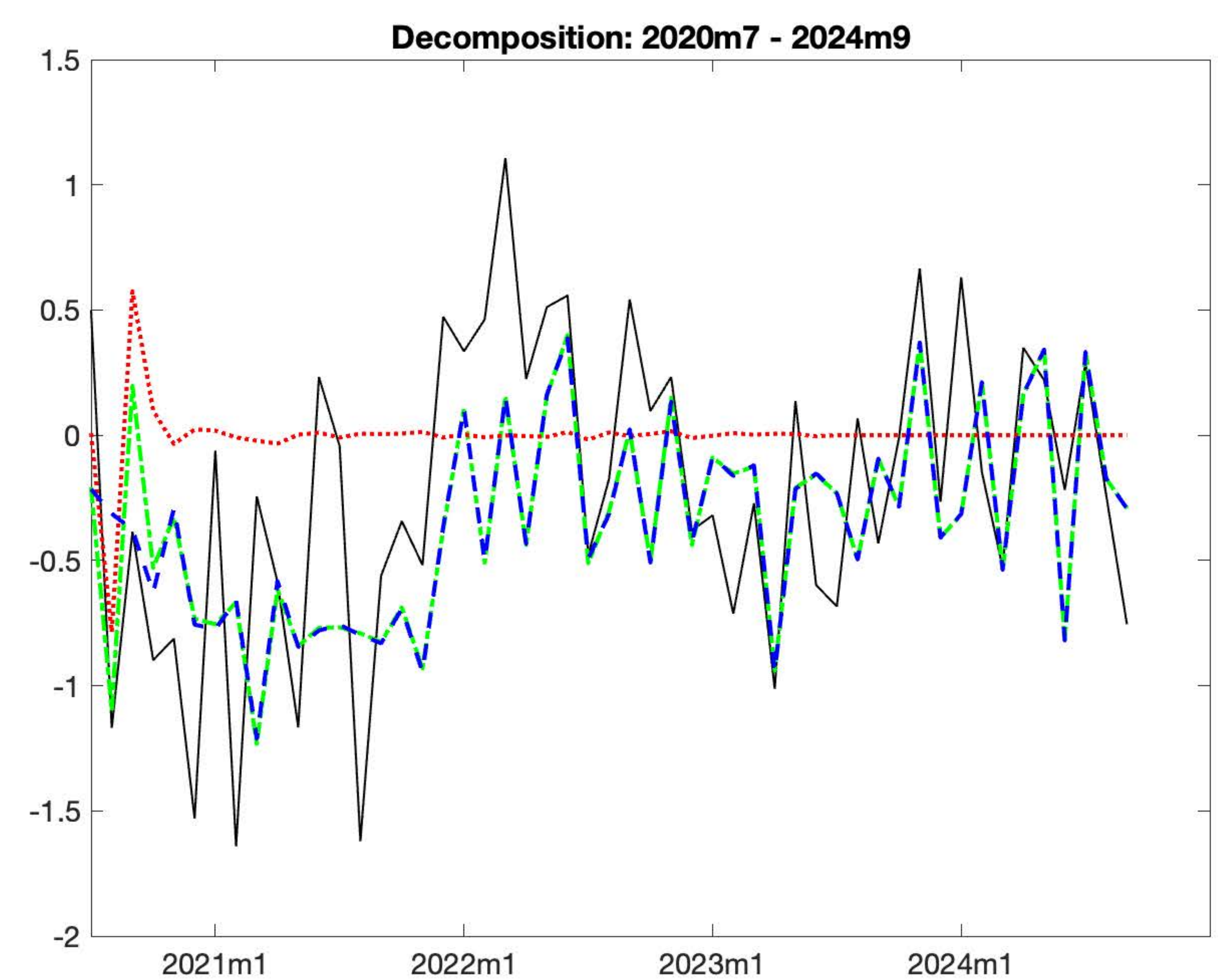
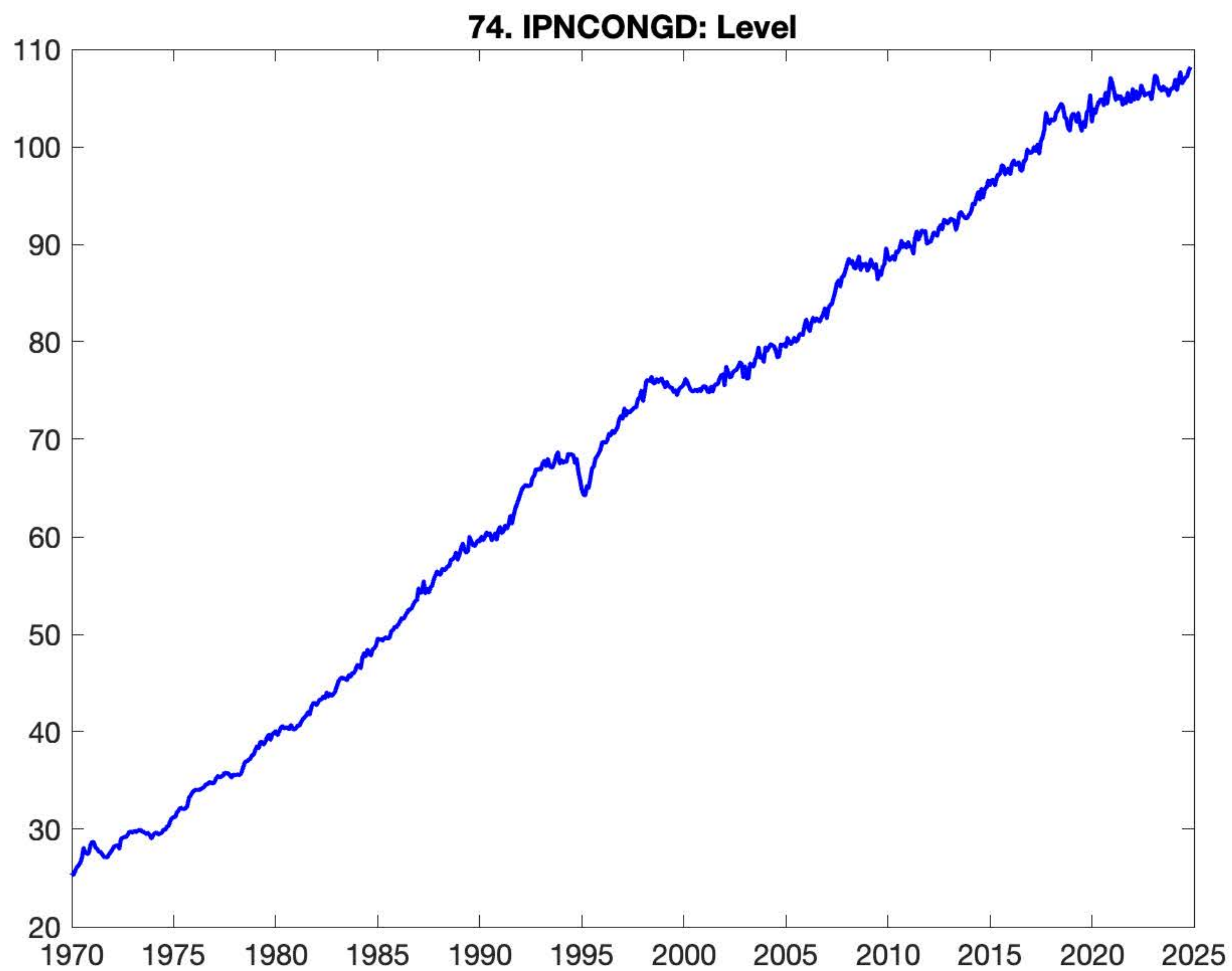
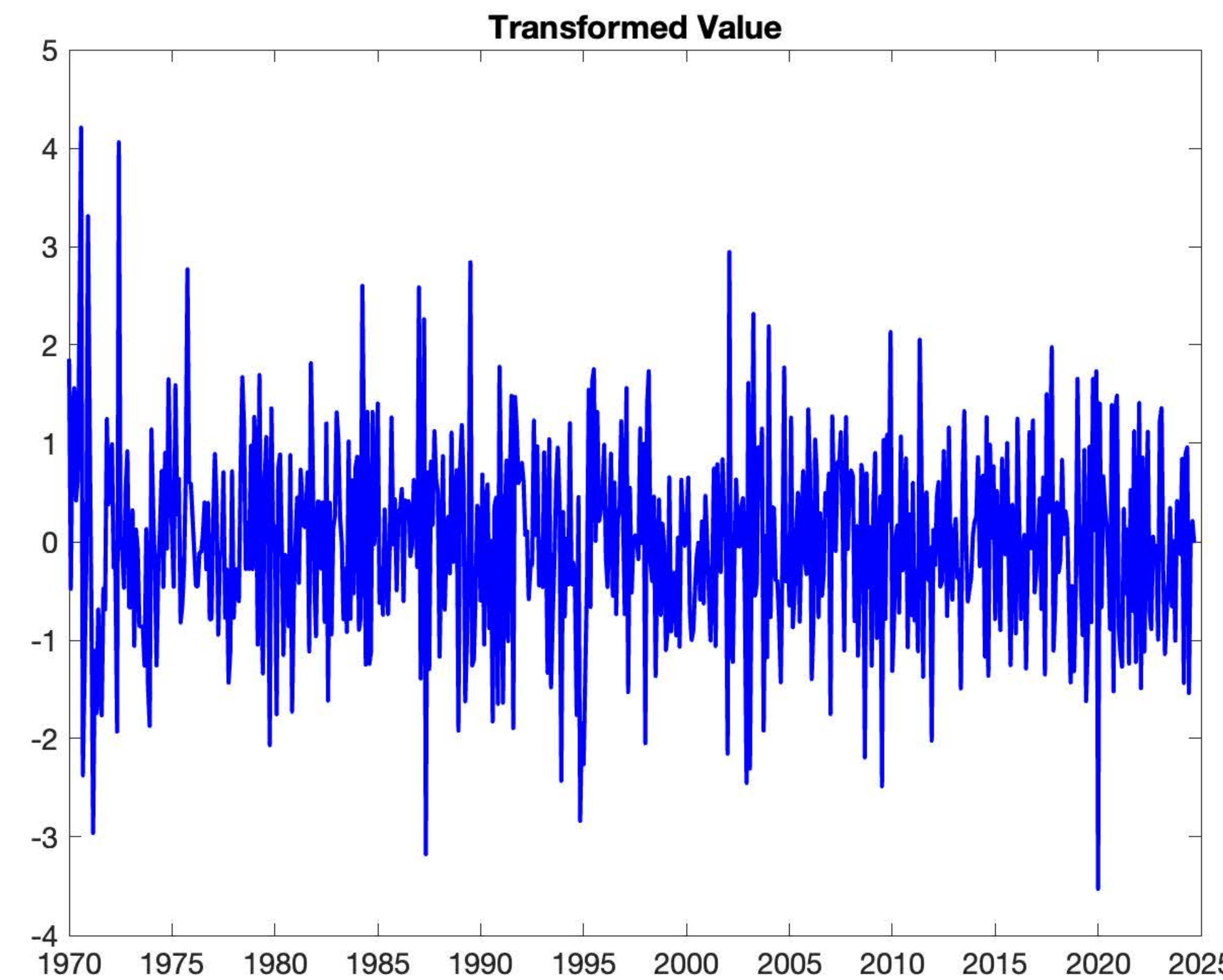
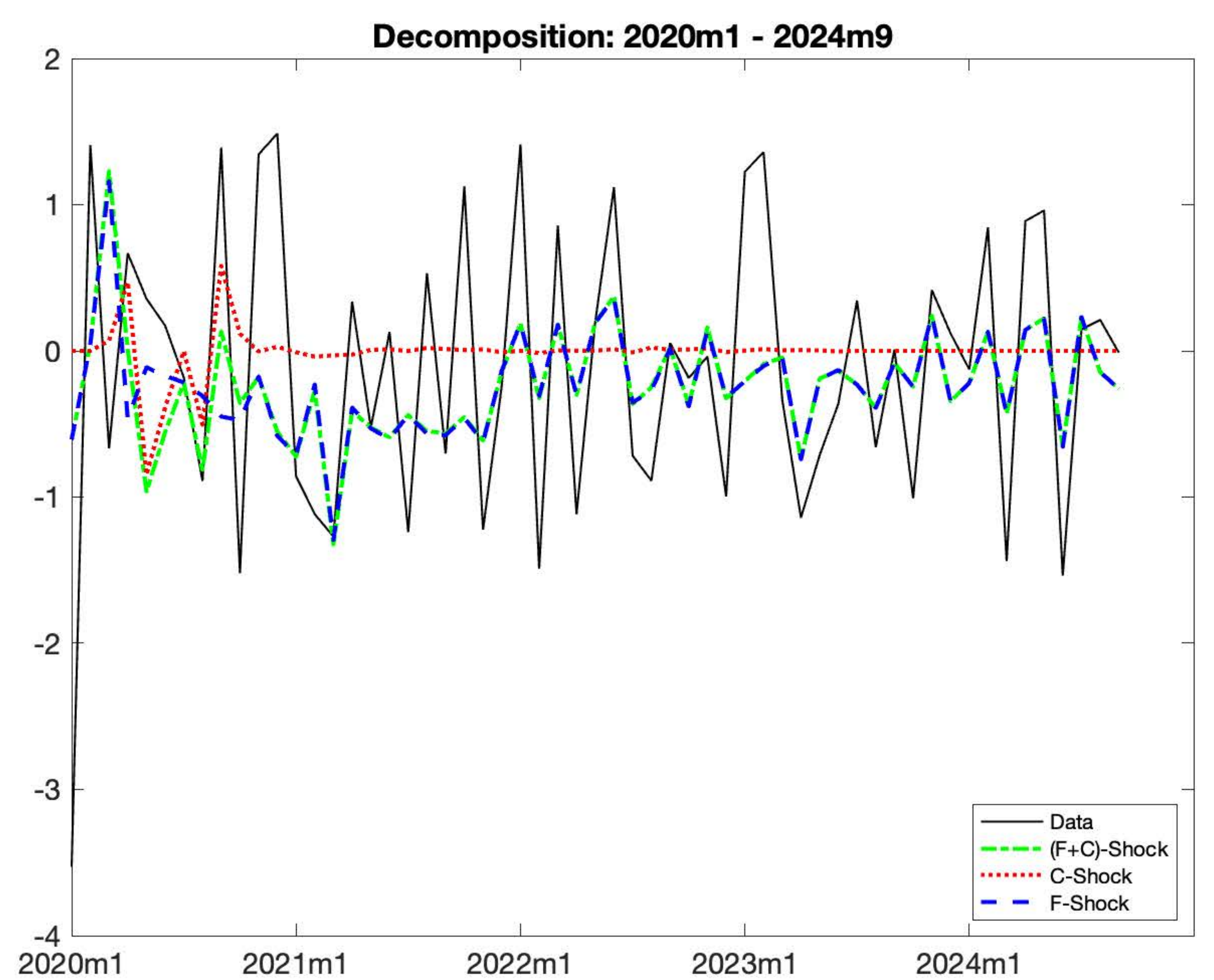
1990
1995
2000
2005
2010
2015
2020
2025

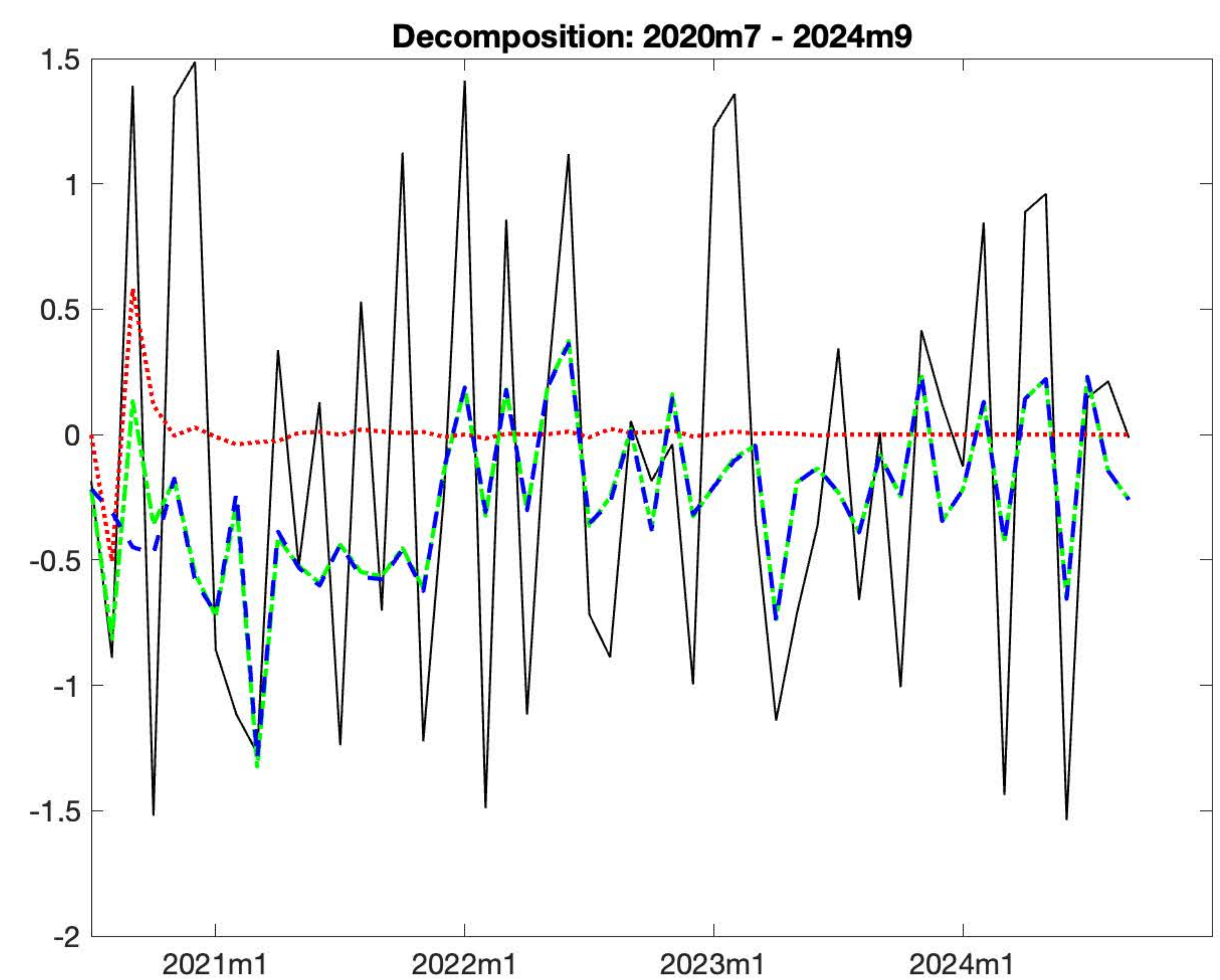

Decomposition: 2020m1 - 2024m9
1.5
1
0.5
0
-0.5
-1
-1.5
-2
2020m1
2021m1
2022m1
2023m1
2024m1
Data
(F+C)-Shock
C-Shock
F-Shock

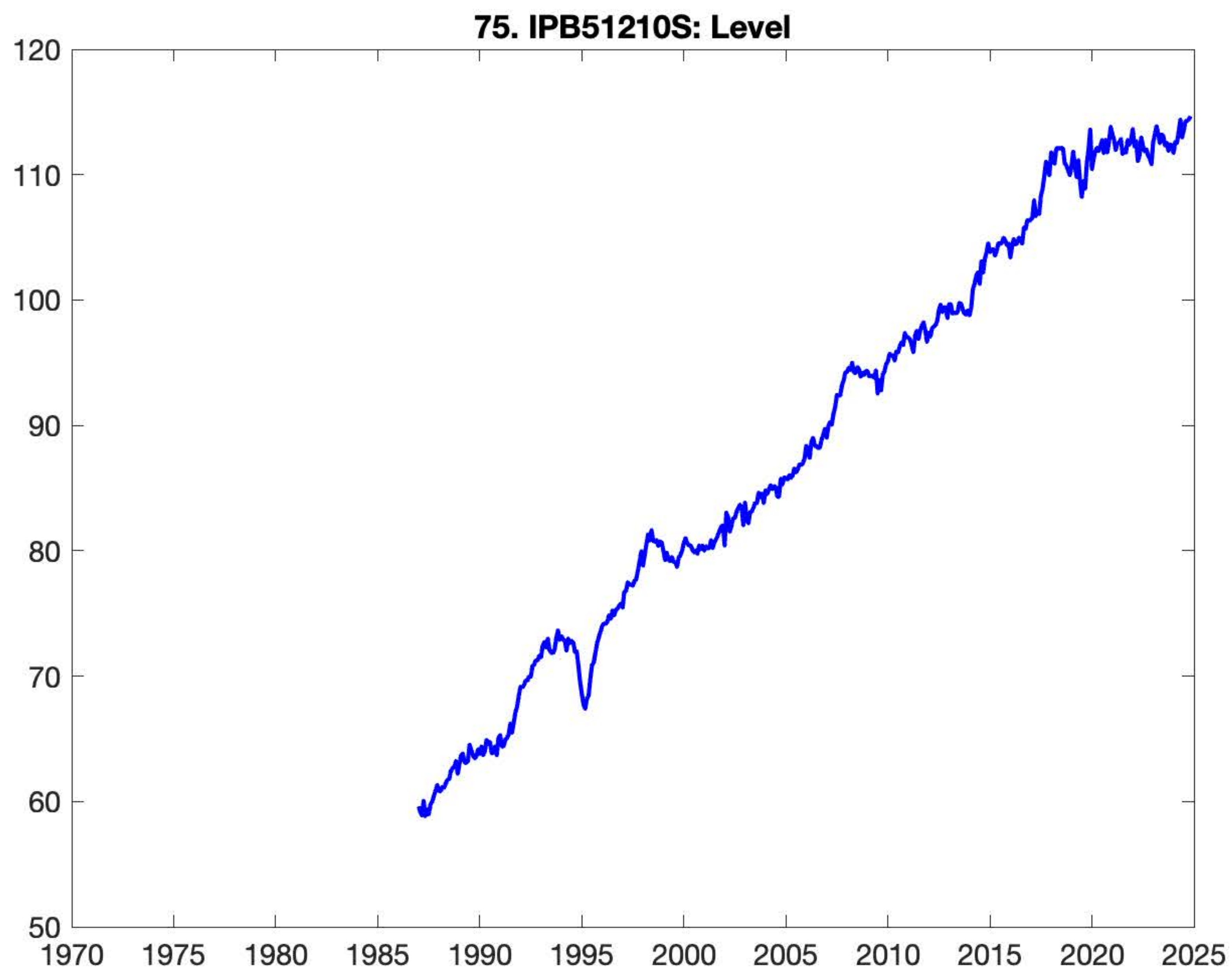

Decomposition: 2020m7 - 2024m9
1.5
1
0.5
0
-0.5
-1
-1.5
-2
2021m1
2022m1
2023m1
2024m1

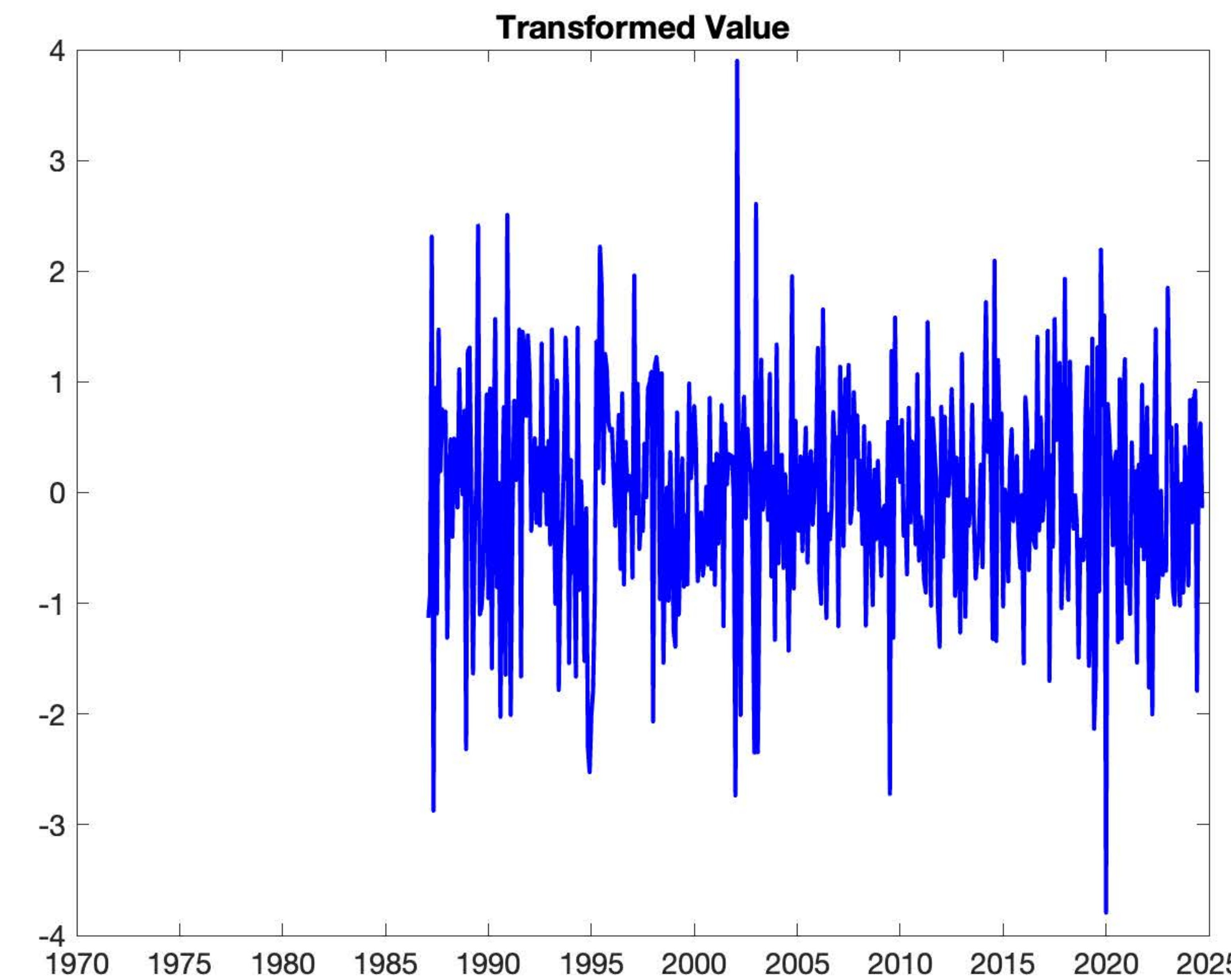

74. IPNCONGD: Level

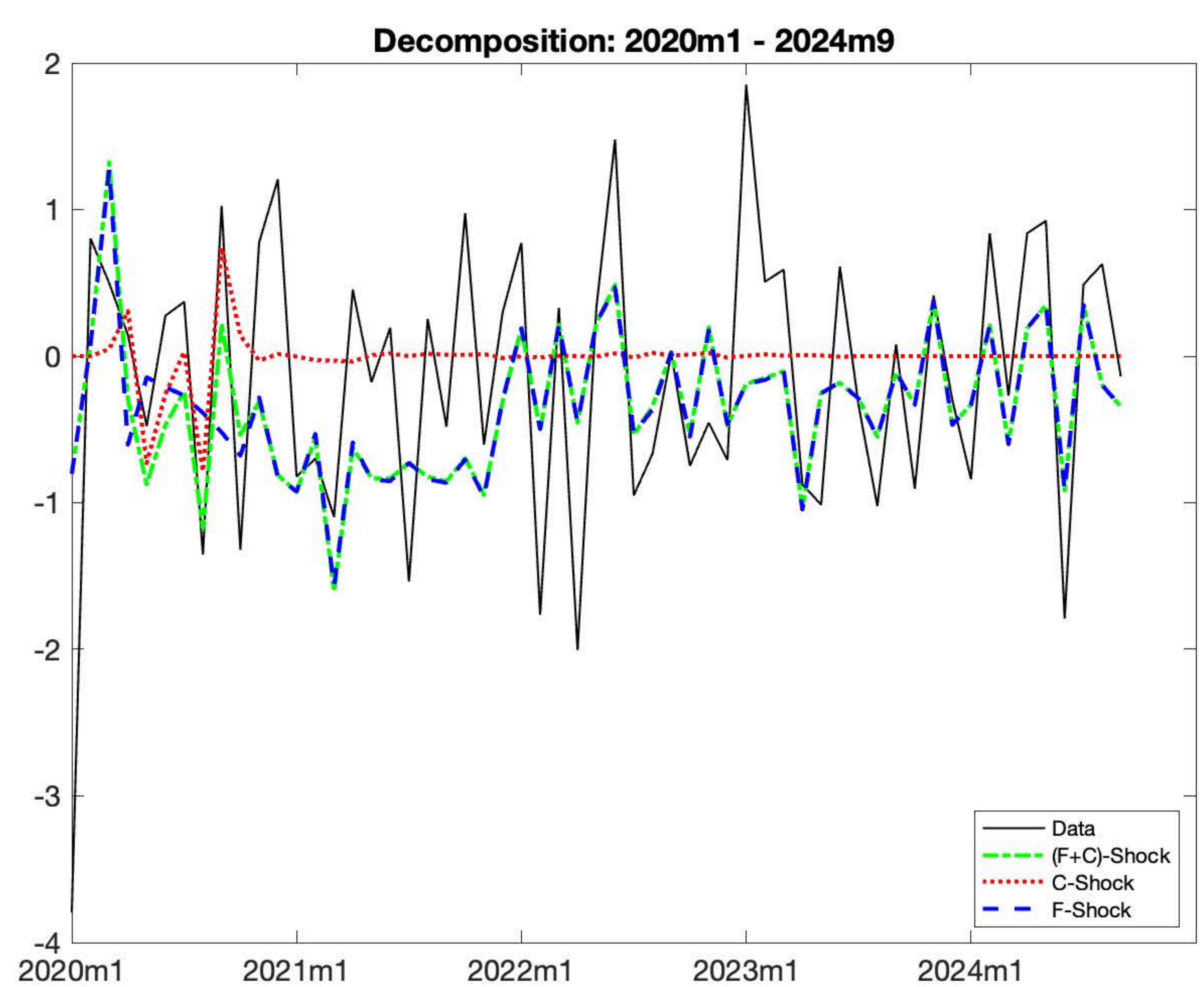

Transformed Value

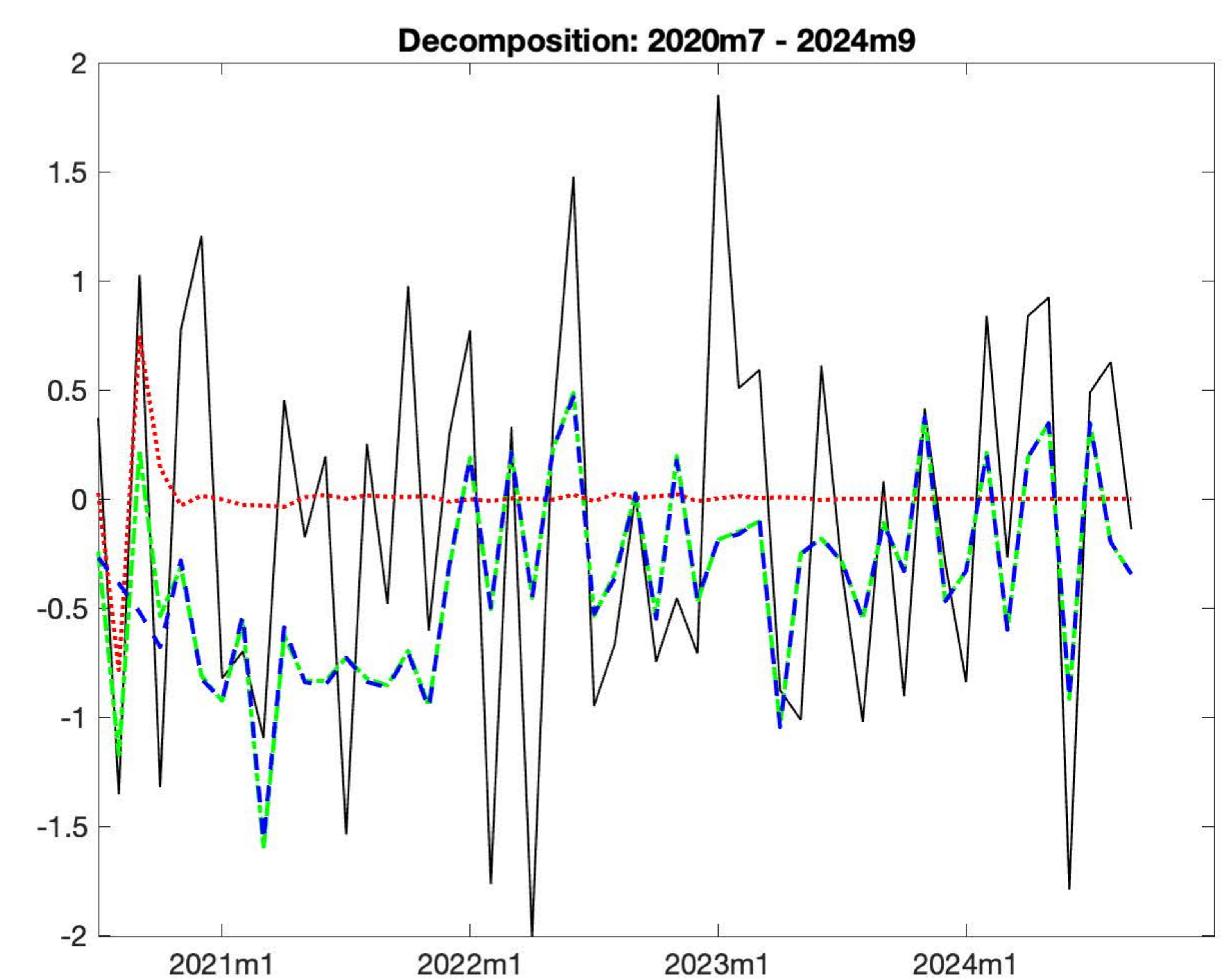

Decomposition: 2020m1 - 2024m9
Data
(F+C)-Shock
C-Shock
F-Shock

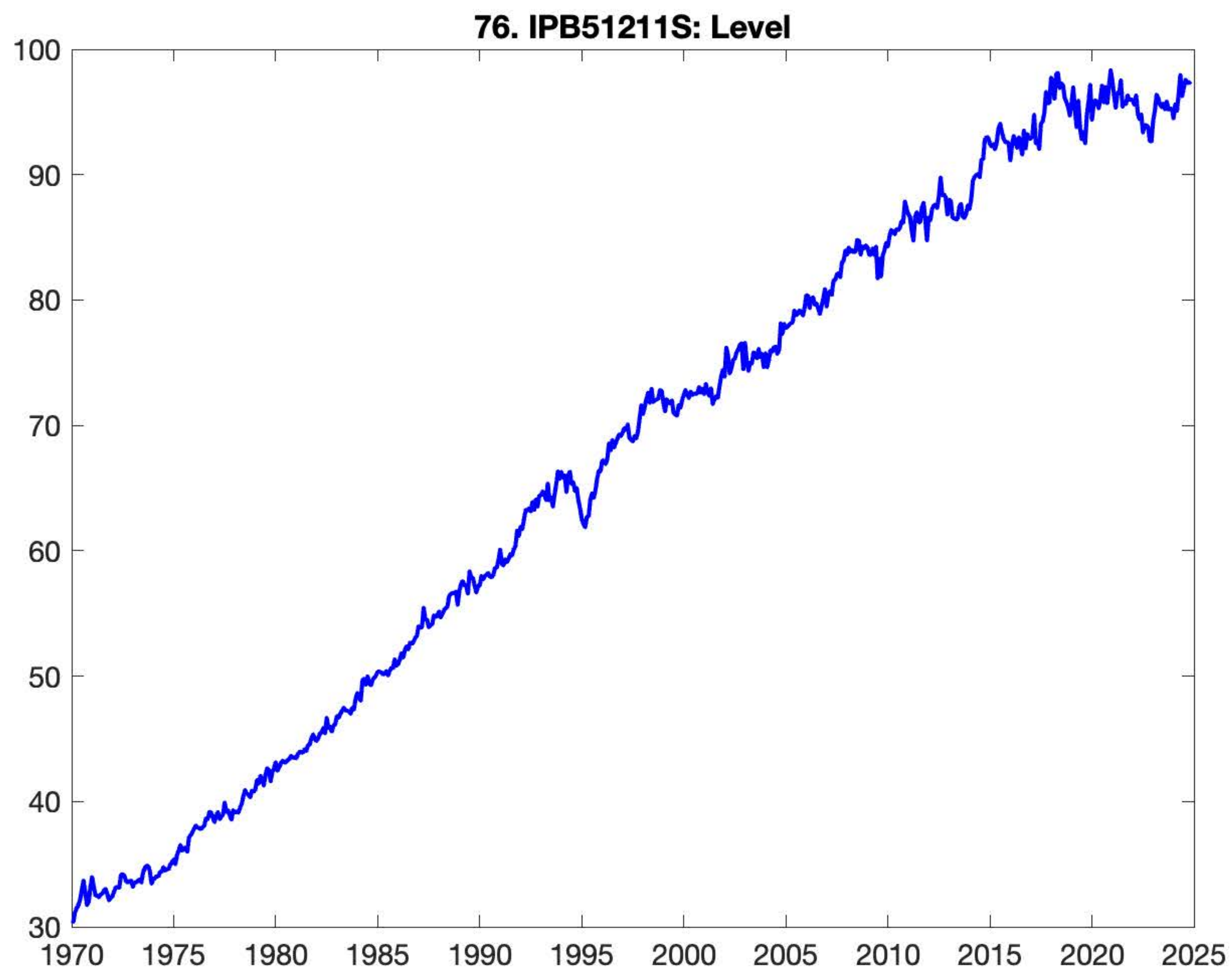

Decomposition: 2020m7 - 2024m9


75. IPB51210S: Level


Transformed Value


Decomposition: 2020m1 - 2024m9
Data
(F+C)-Shock
C-Shock
F-Shock


Decomposition: 2020m7 - 2024m9


76. IPB51211S: Level
100
90
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60
50
40
30
1970
1975
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2000
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2010
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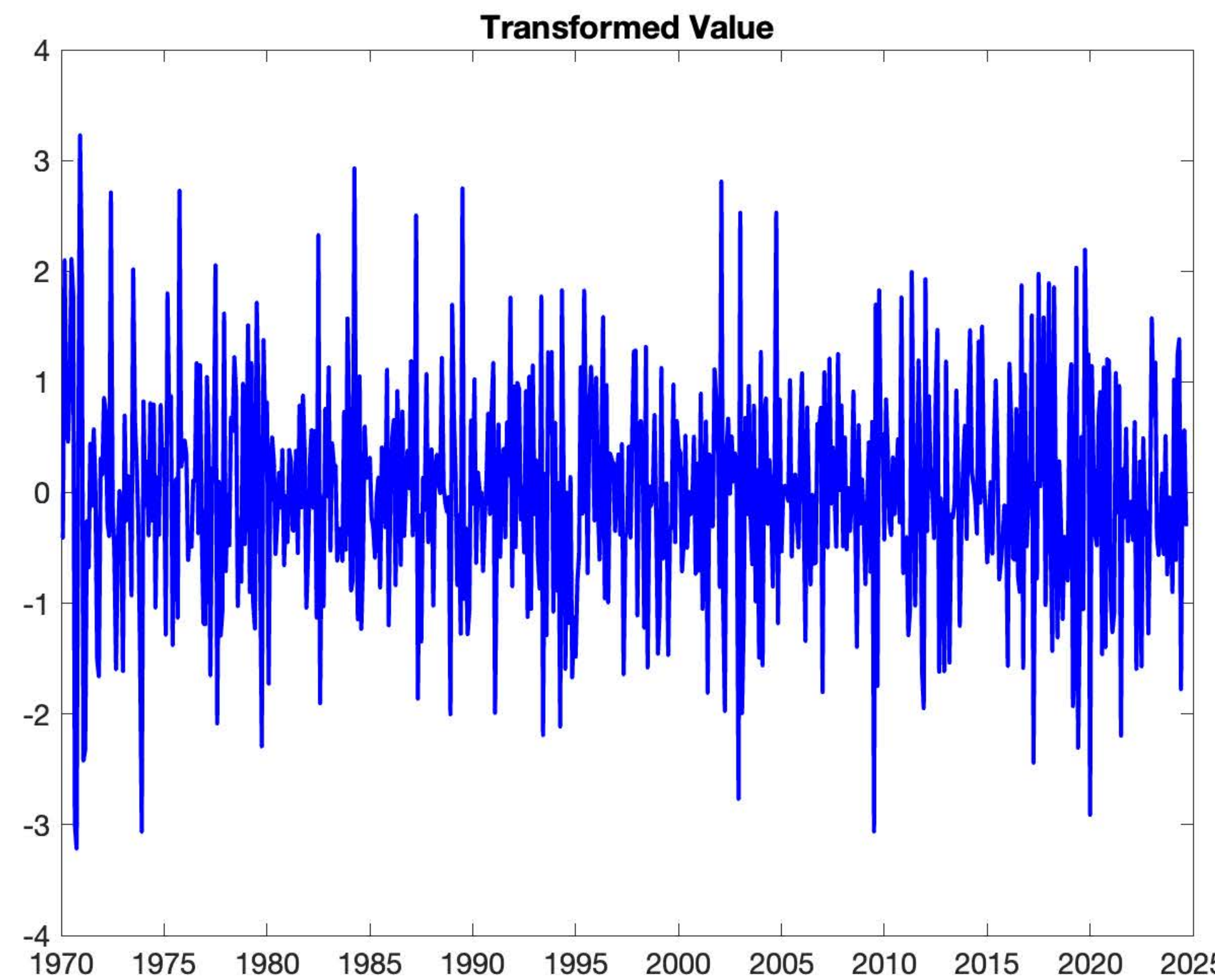
2020
2025


Transformed Value
4
3
2
1
0
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-2
-3
-4
1970
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1980
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1990
1995
2000
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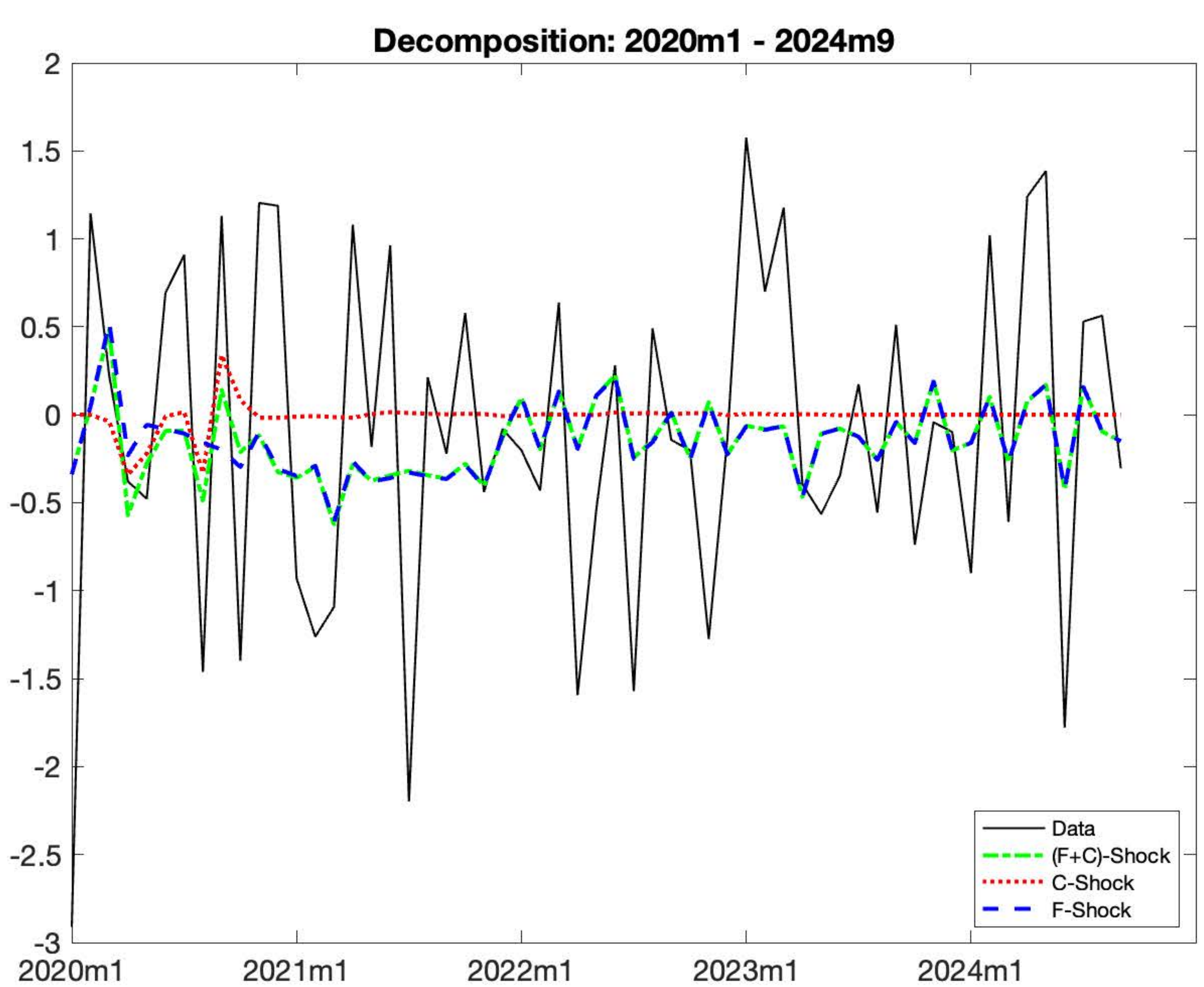
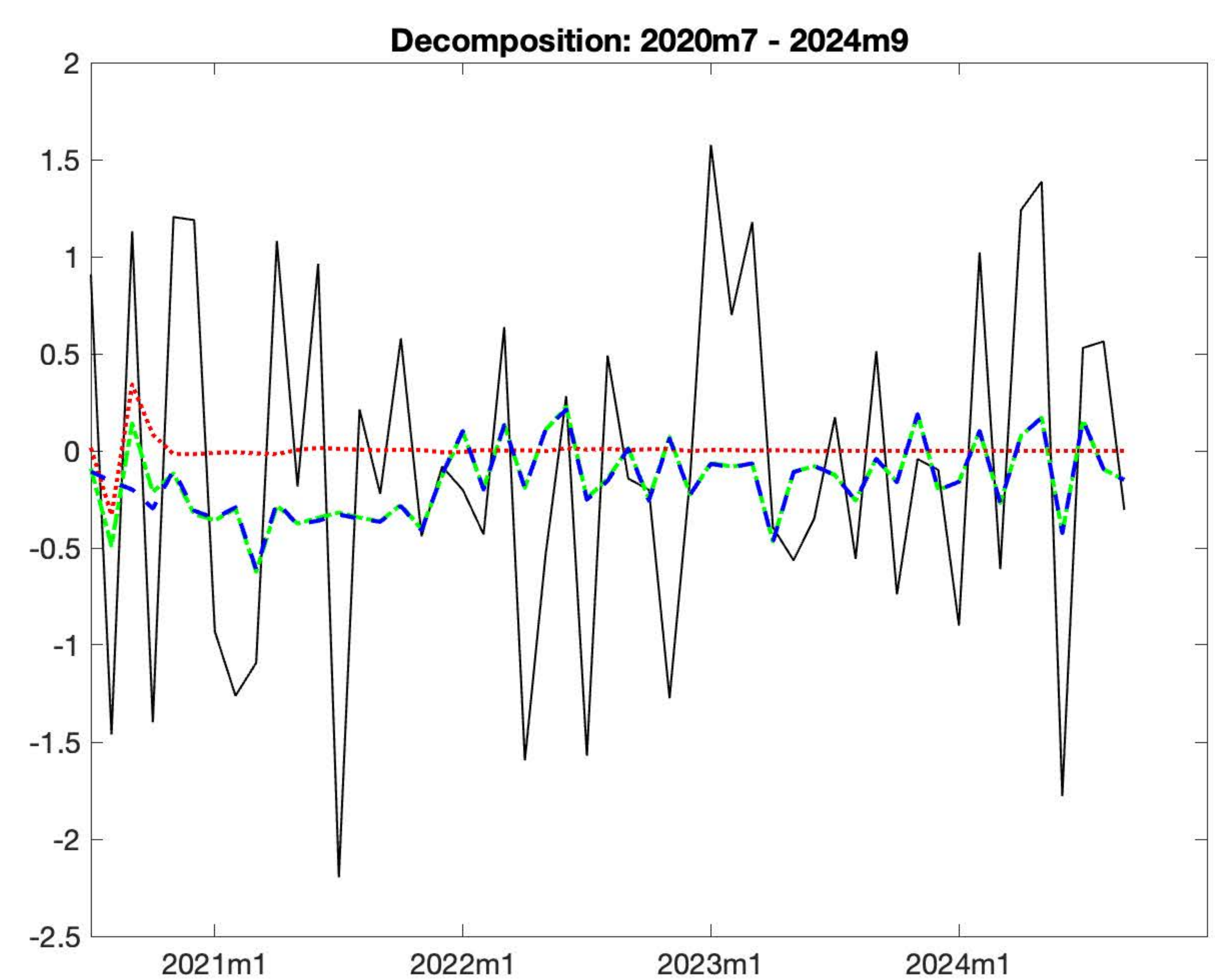
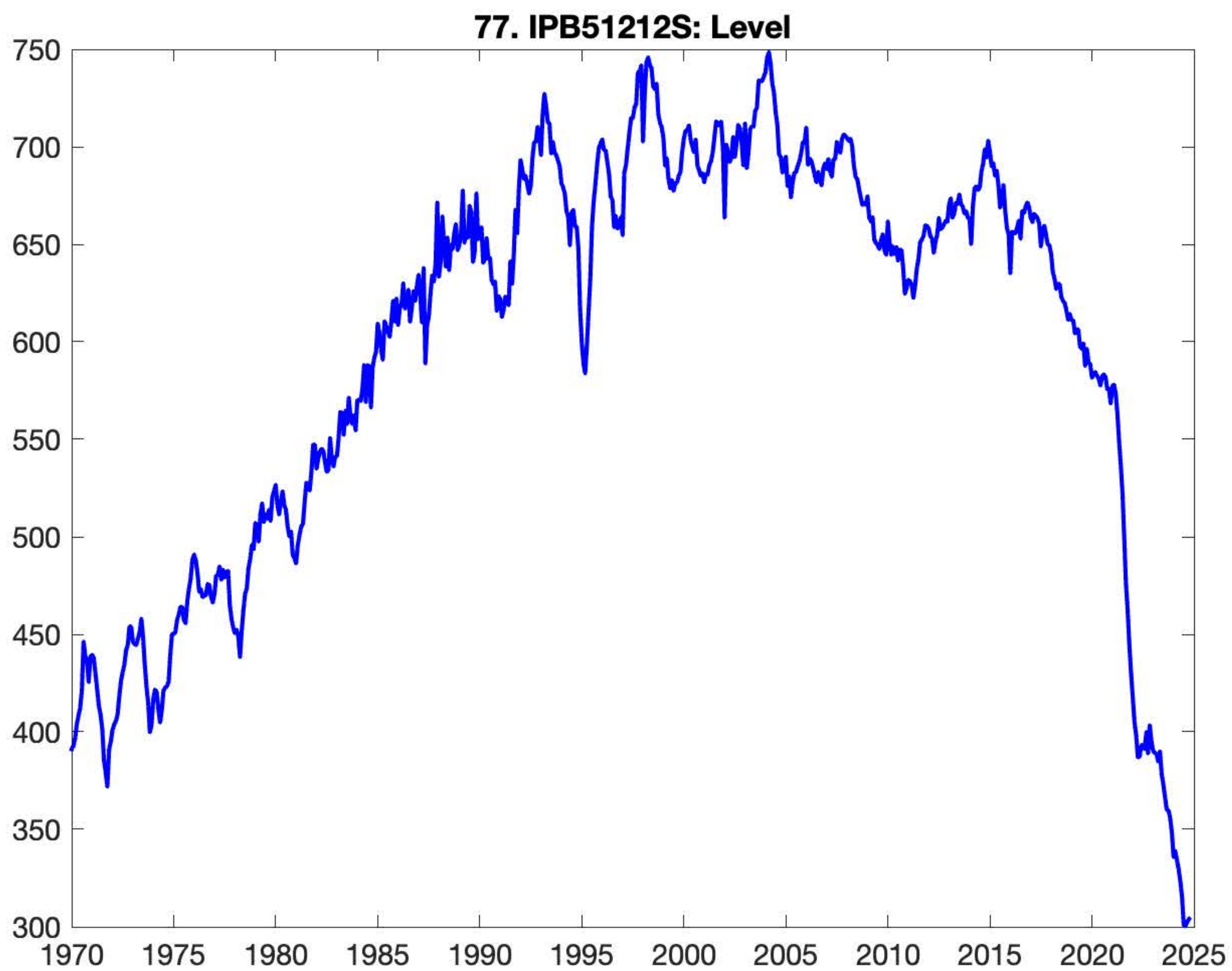
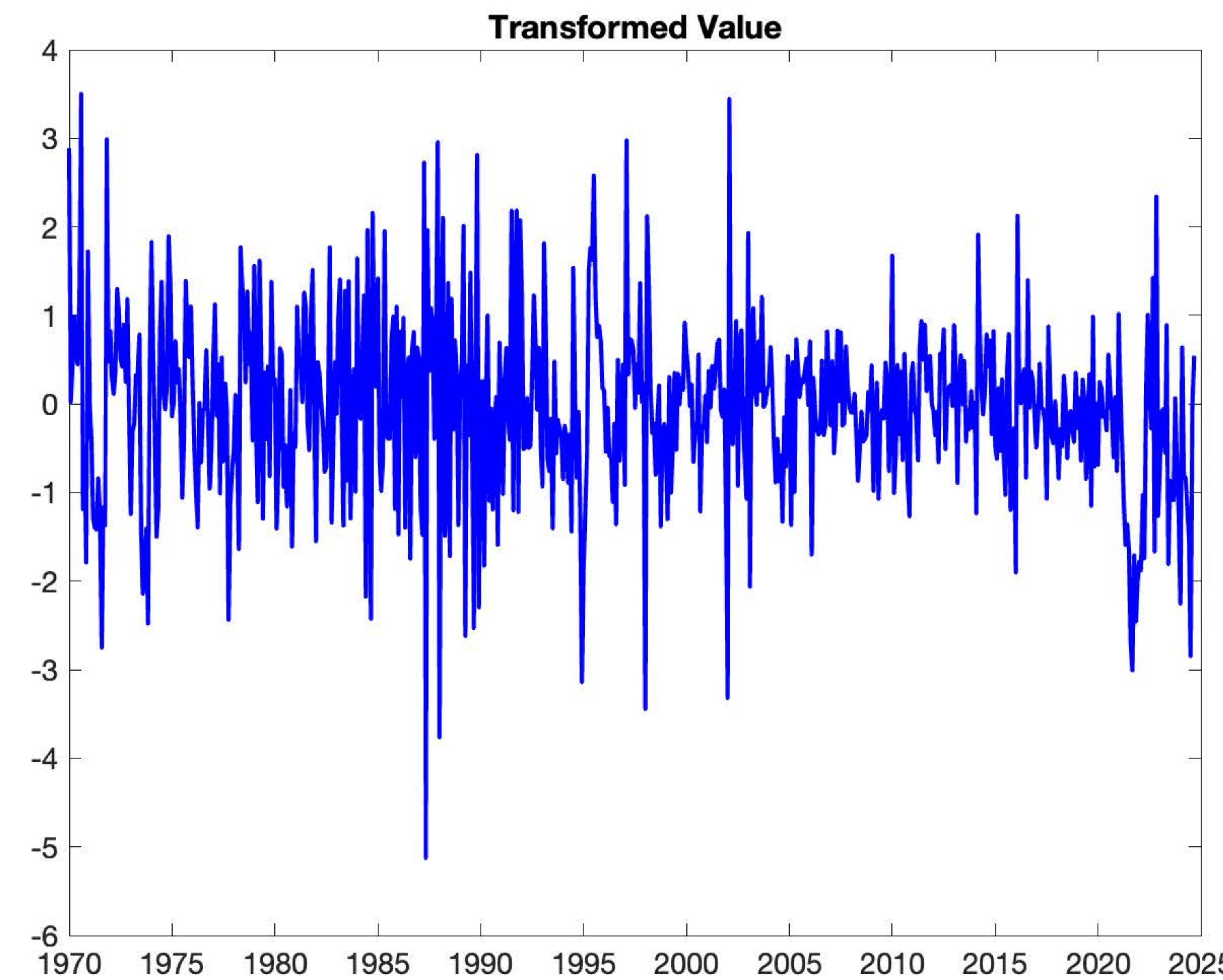
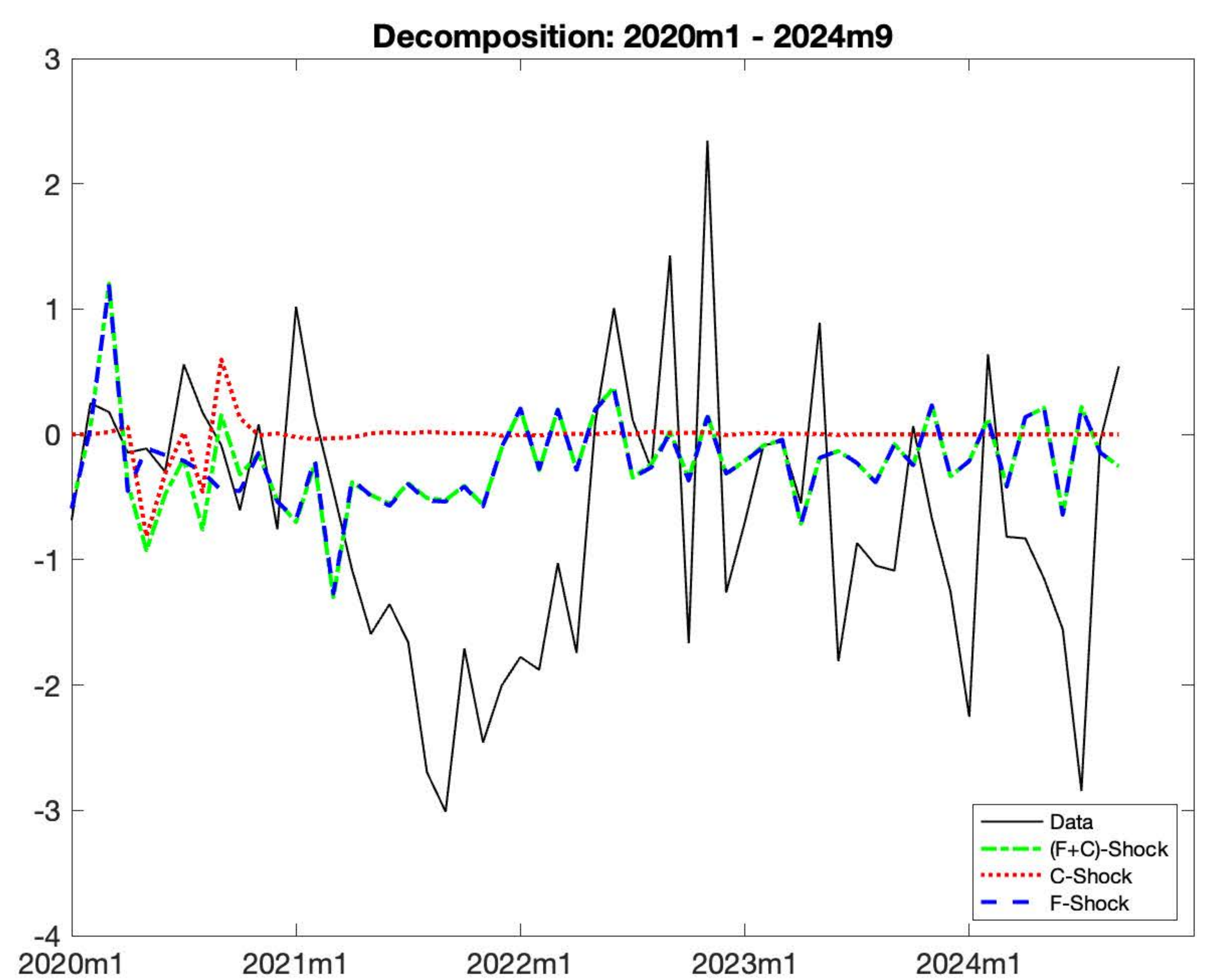
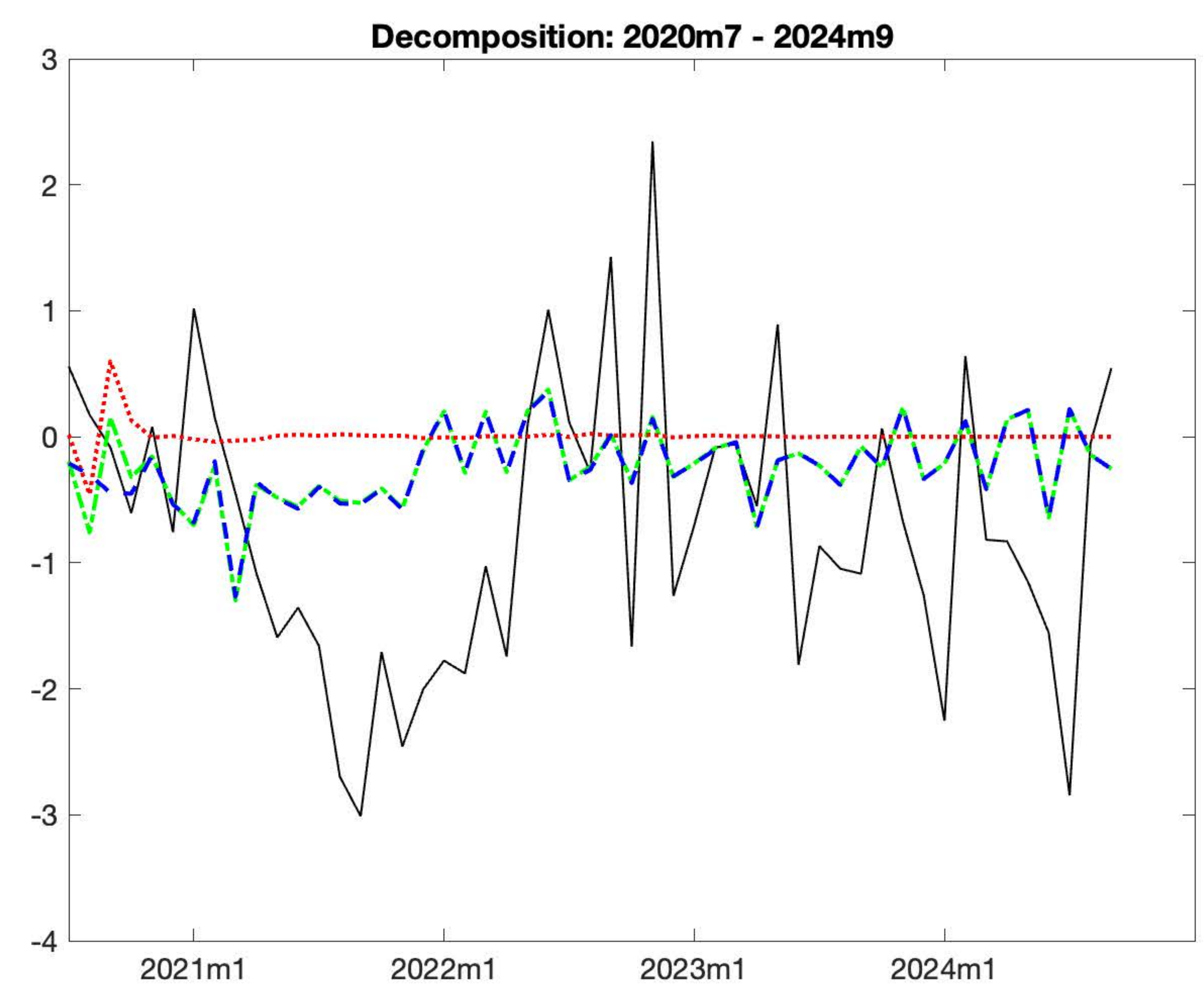
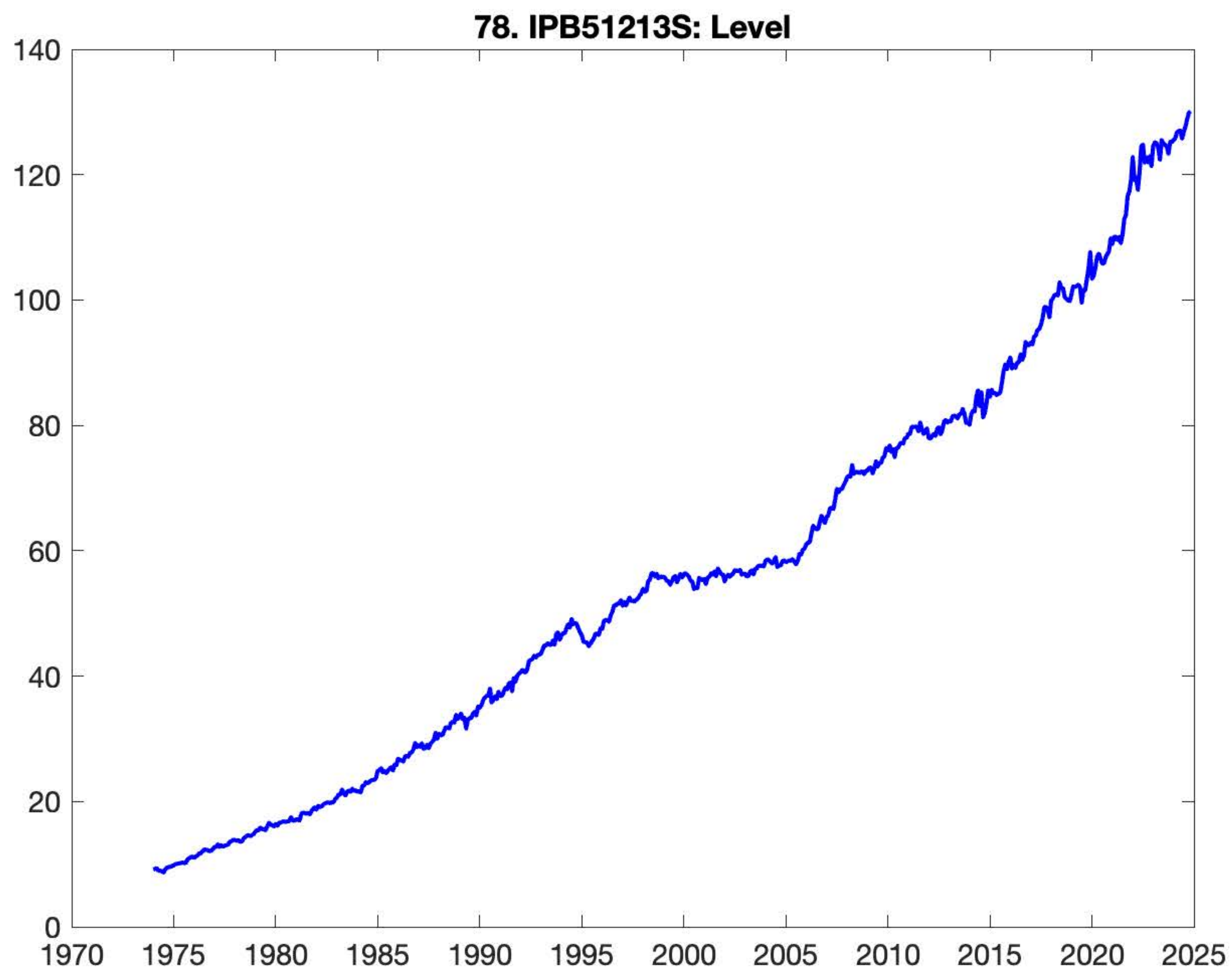
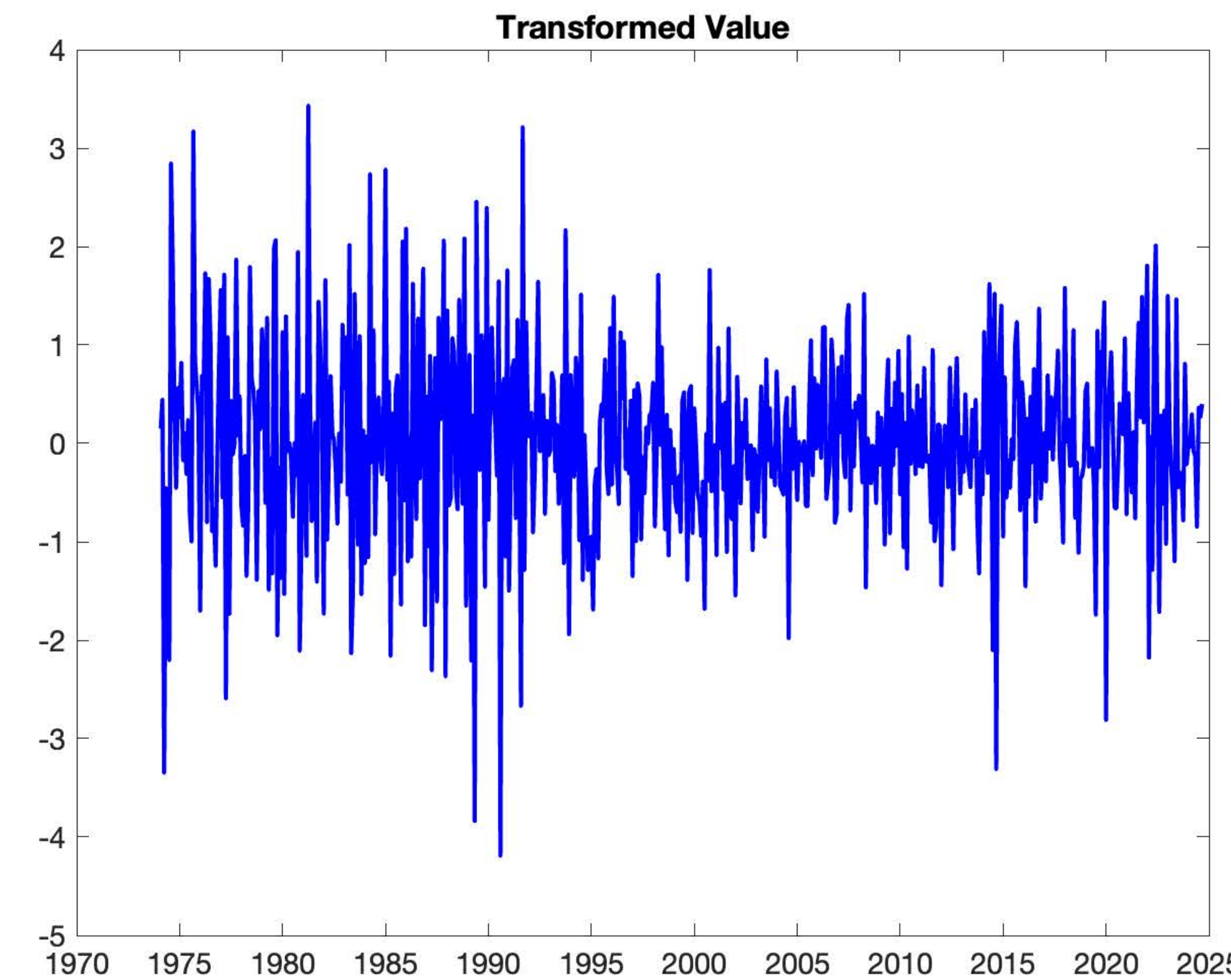
2010
2015
2020
2025

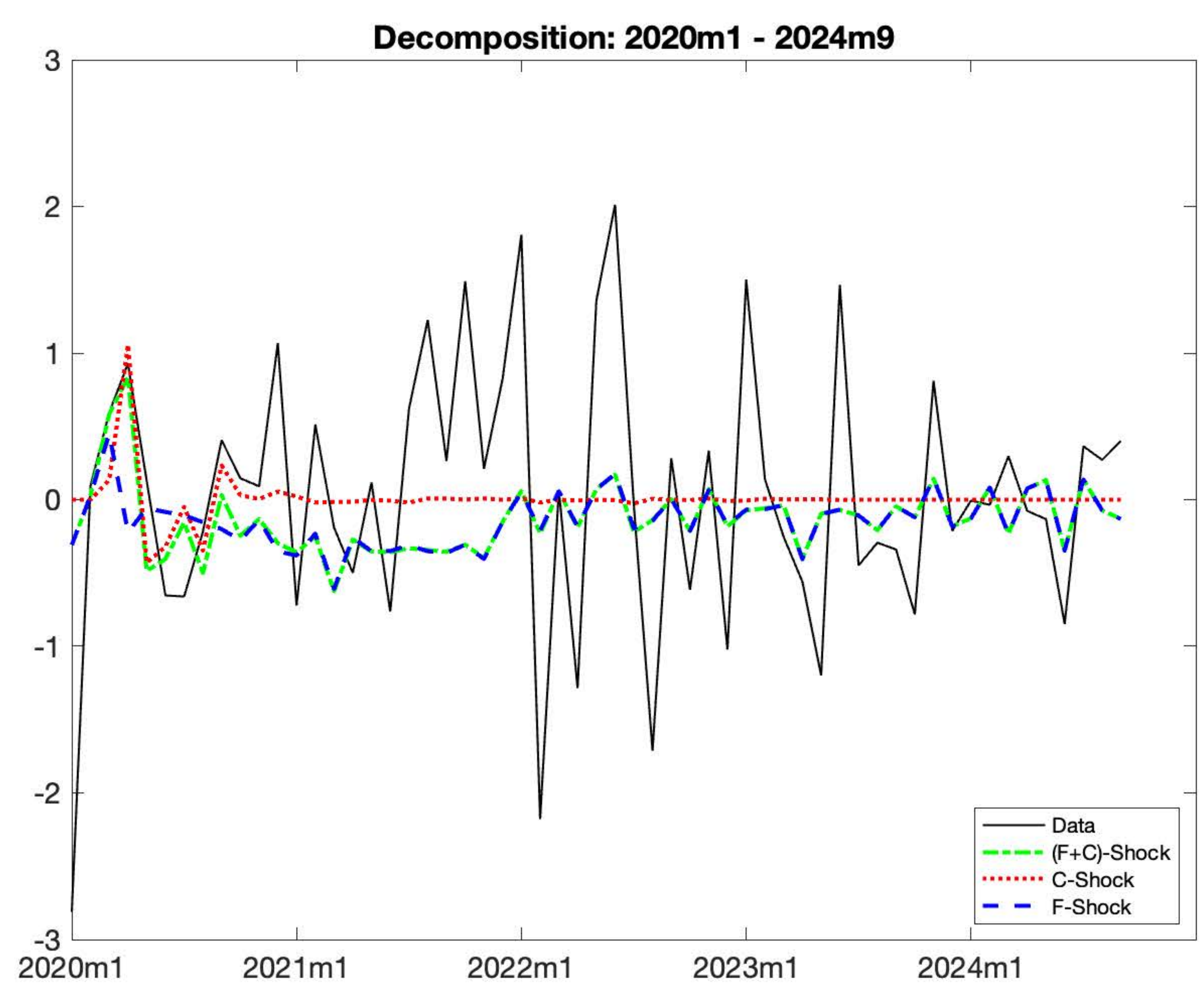

Decomposition: 2020m1 - 2024m9
2
1.5
1
0.5
0
-0.5
-1
-1.5
-2
-2.5
-3
2020m1
2021m1
2022m1
2023m1
2024m1
Data
(F+C)-Shock
C-Shock
F-Shock

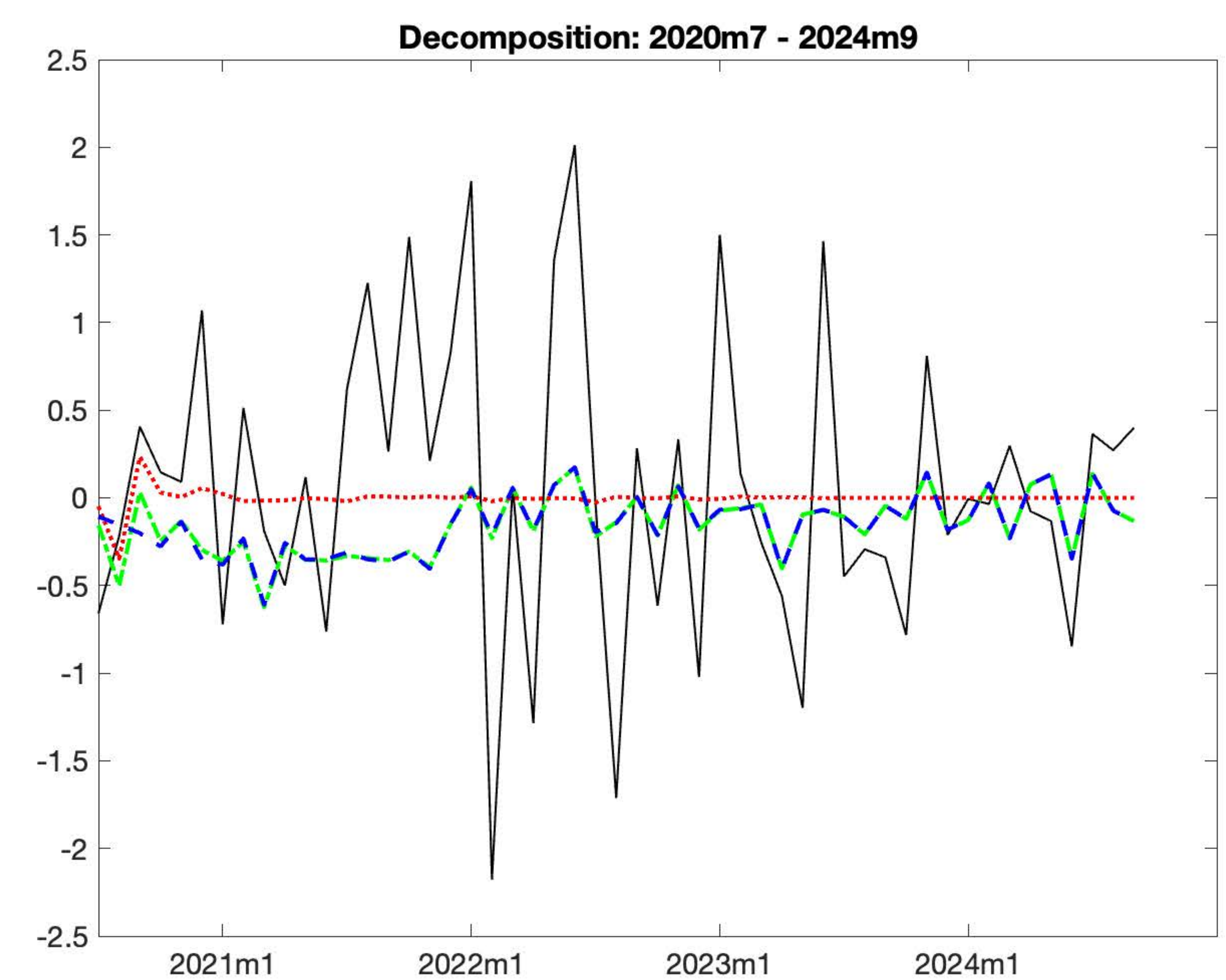

Decomposition: 2020m7 - 2024m9
2
1.5
1
0.5
0
-0.5
-1
-1.5
-2
-2.5
2021m1
2022m1
2023m1
2024m1

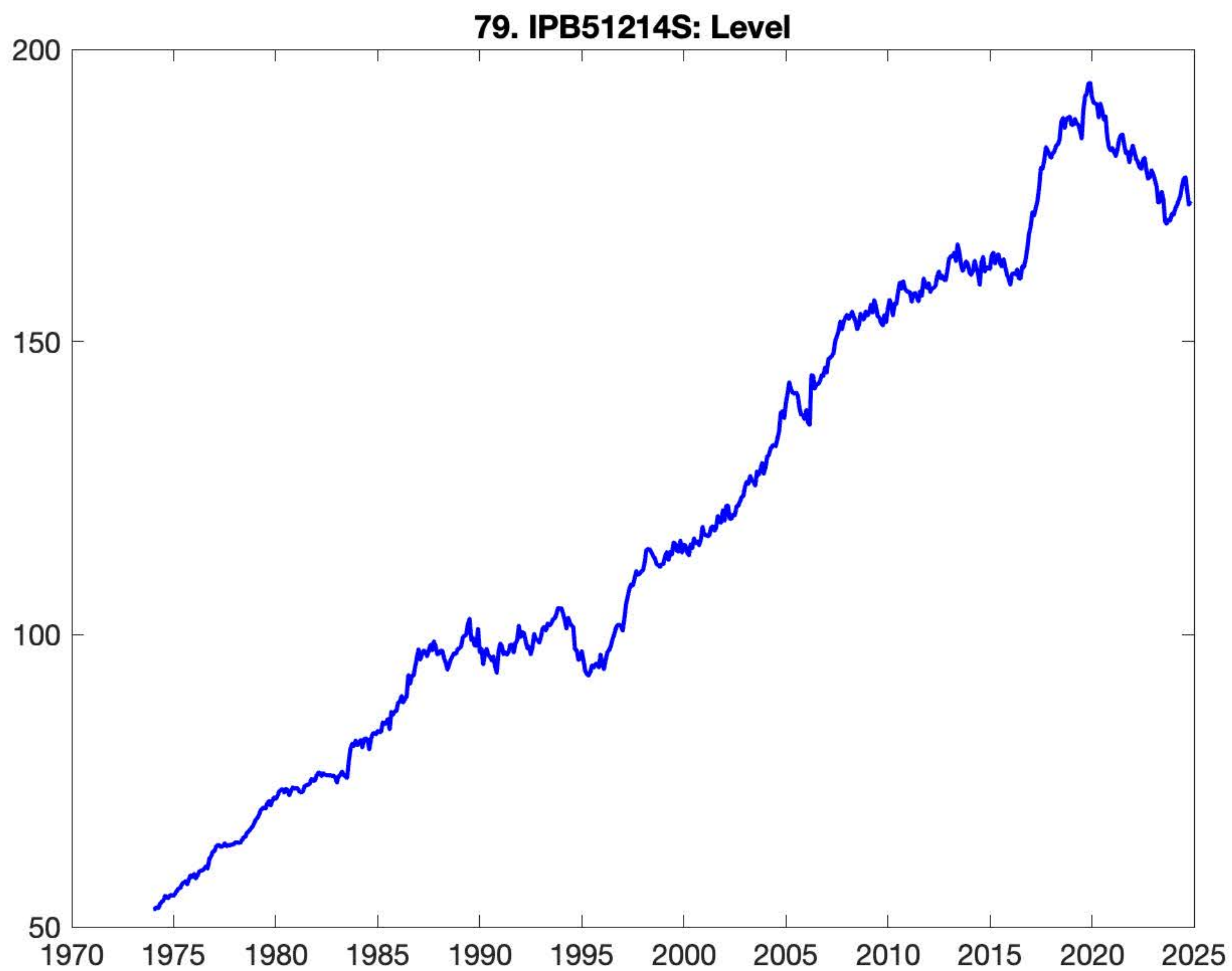

77. IPB51212S: Level

Transformed Value

Decomposition: 2020m1 - 2024m9
Data
(F+C)-Shock
C-Shock
F-Shock

Decomposition: 2020m7 - 2024m9

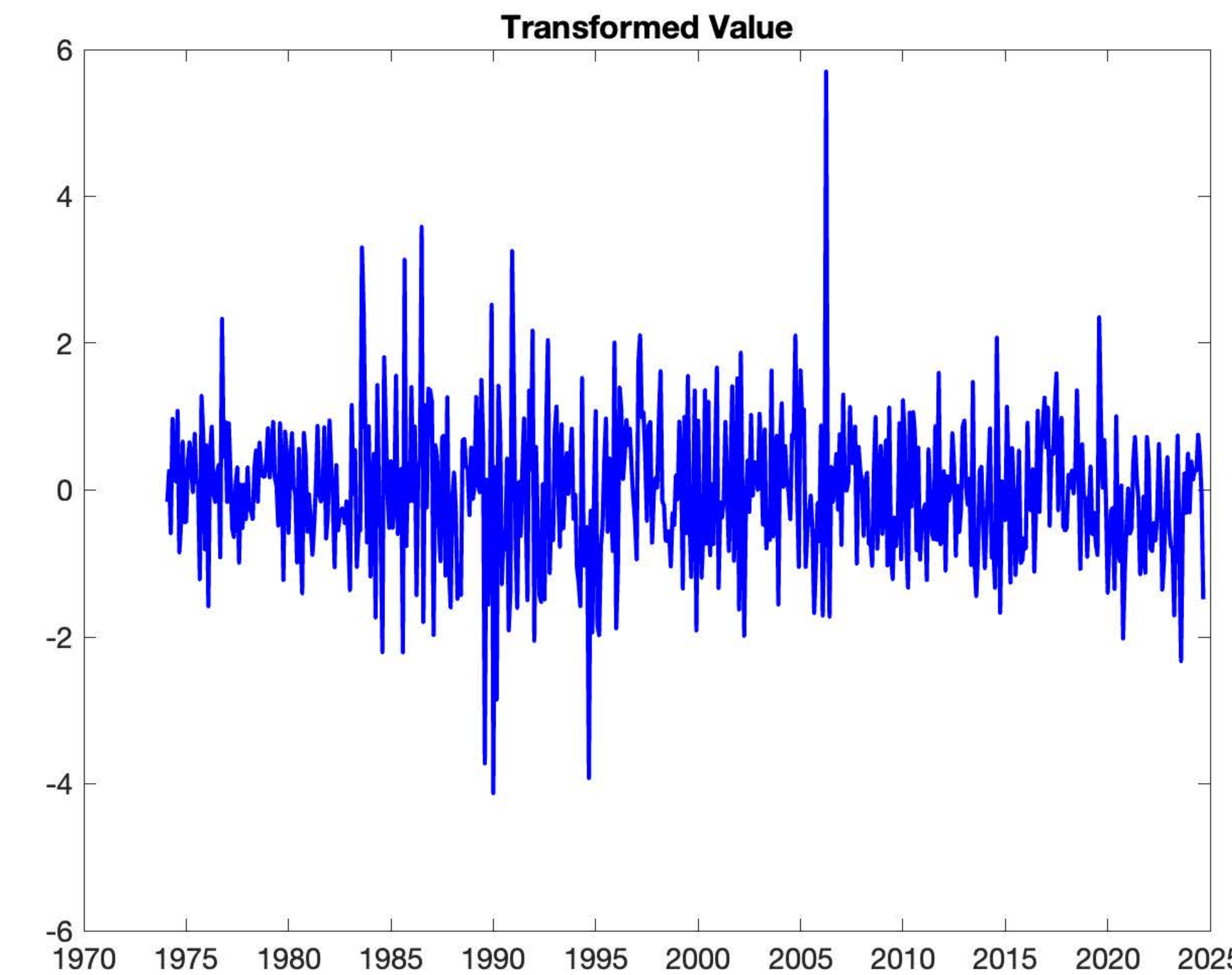

78. IPB51213S: Level

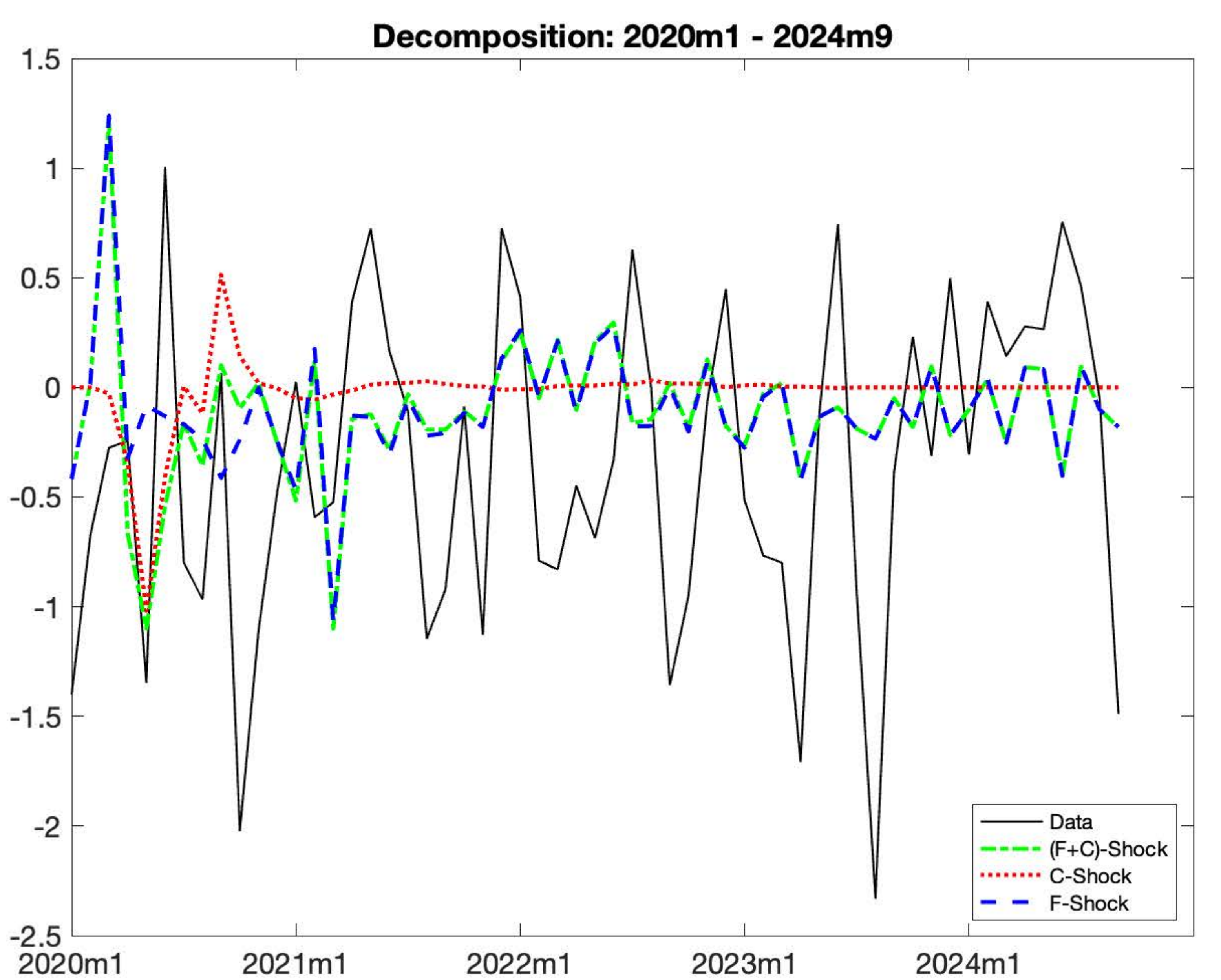

Transformed Value

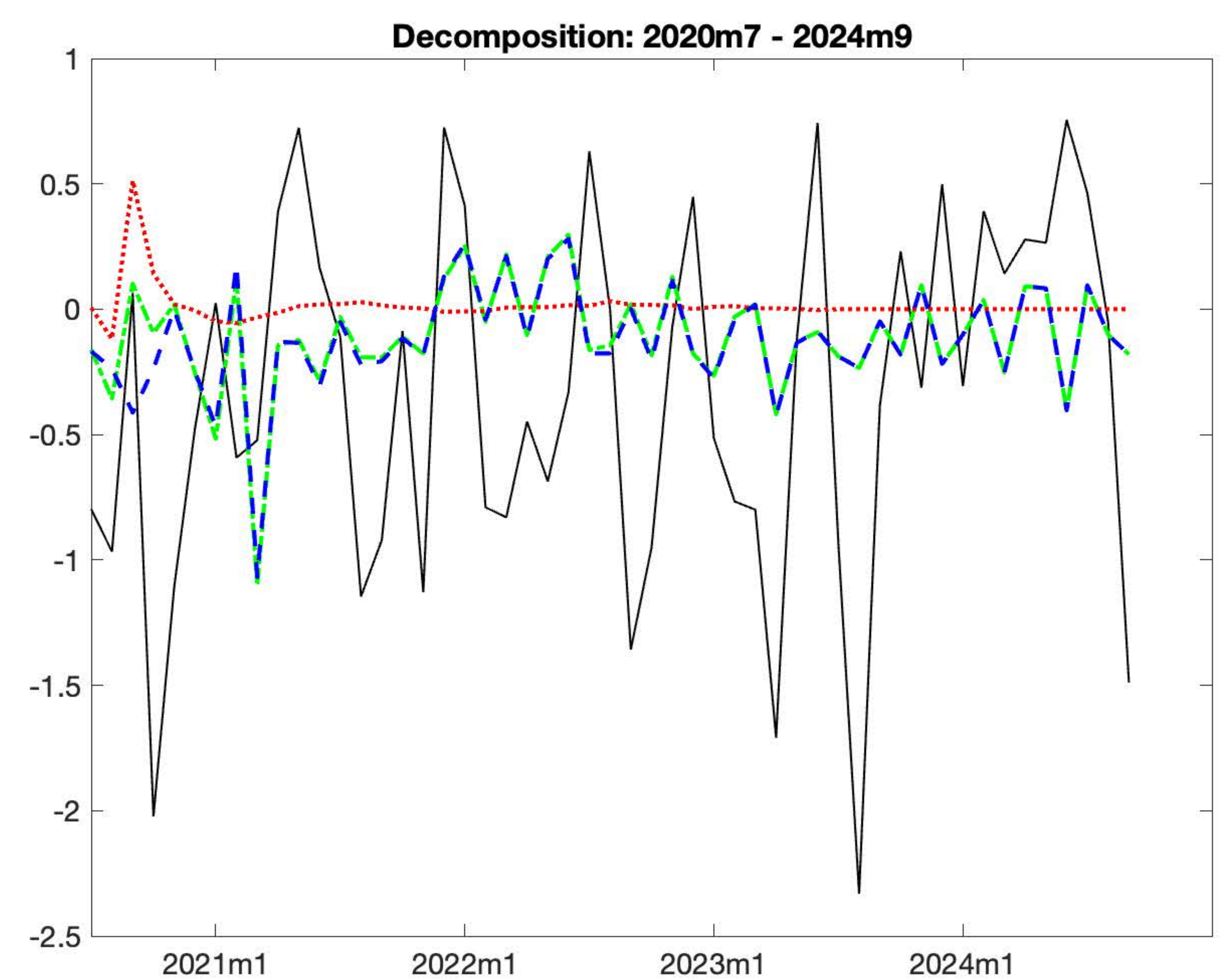

Decomposition: 2020m1 - 2024m9
Data
(F+C)-Shock
C-Shock
F-Shock

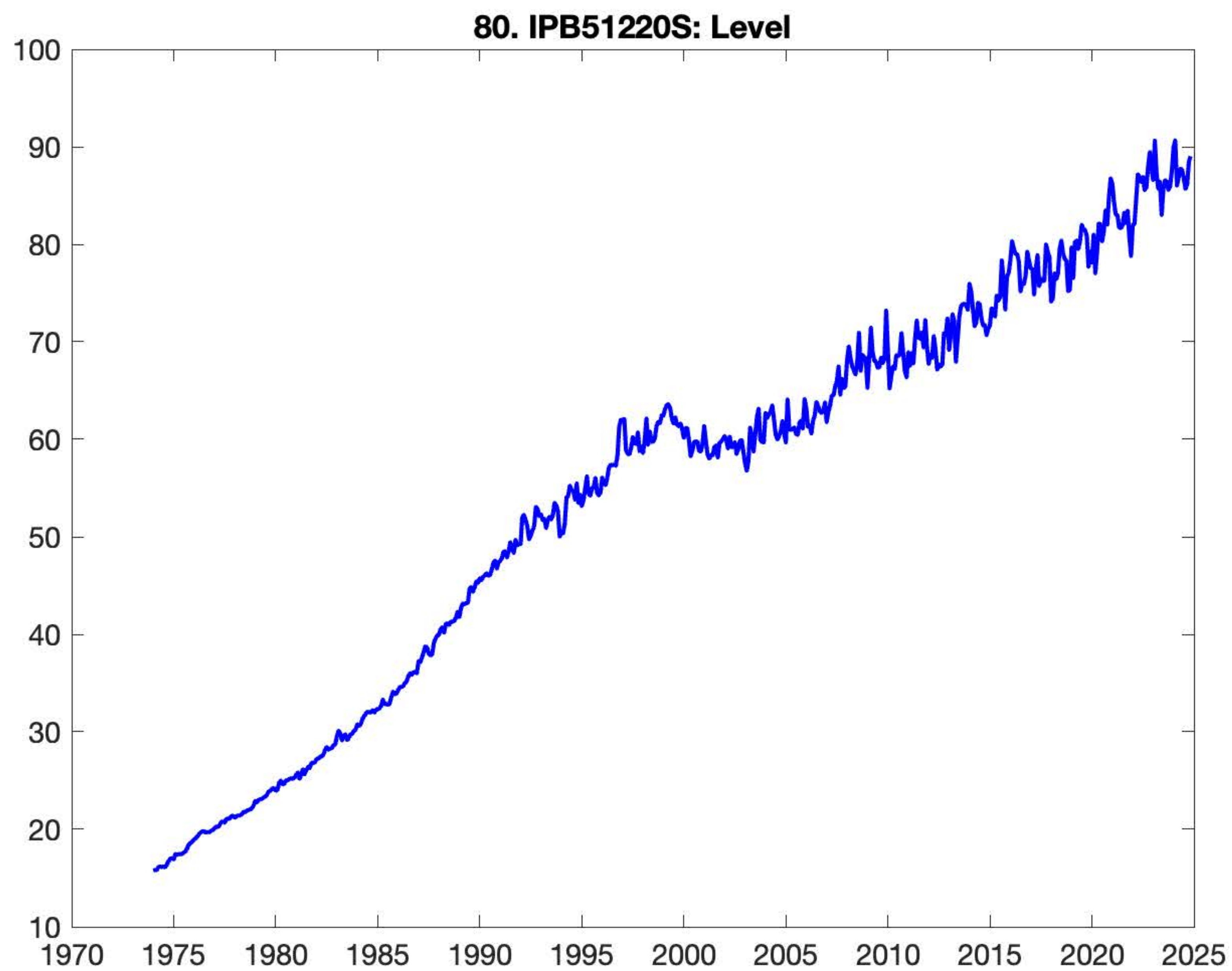

Decomposition: 2020m7 - 2024m9

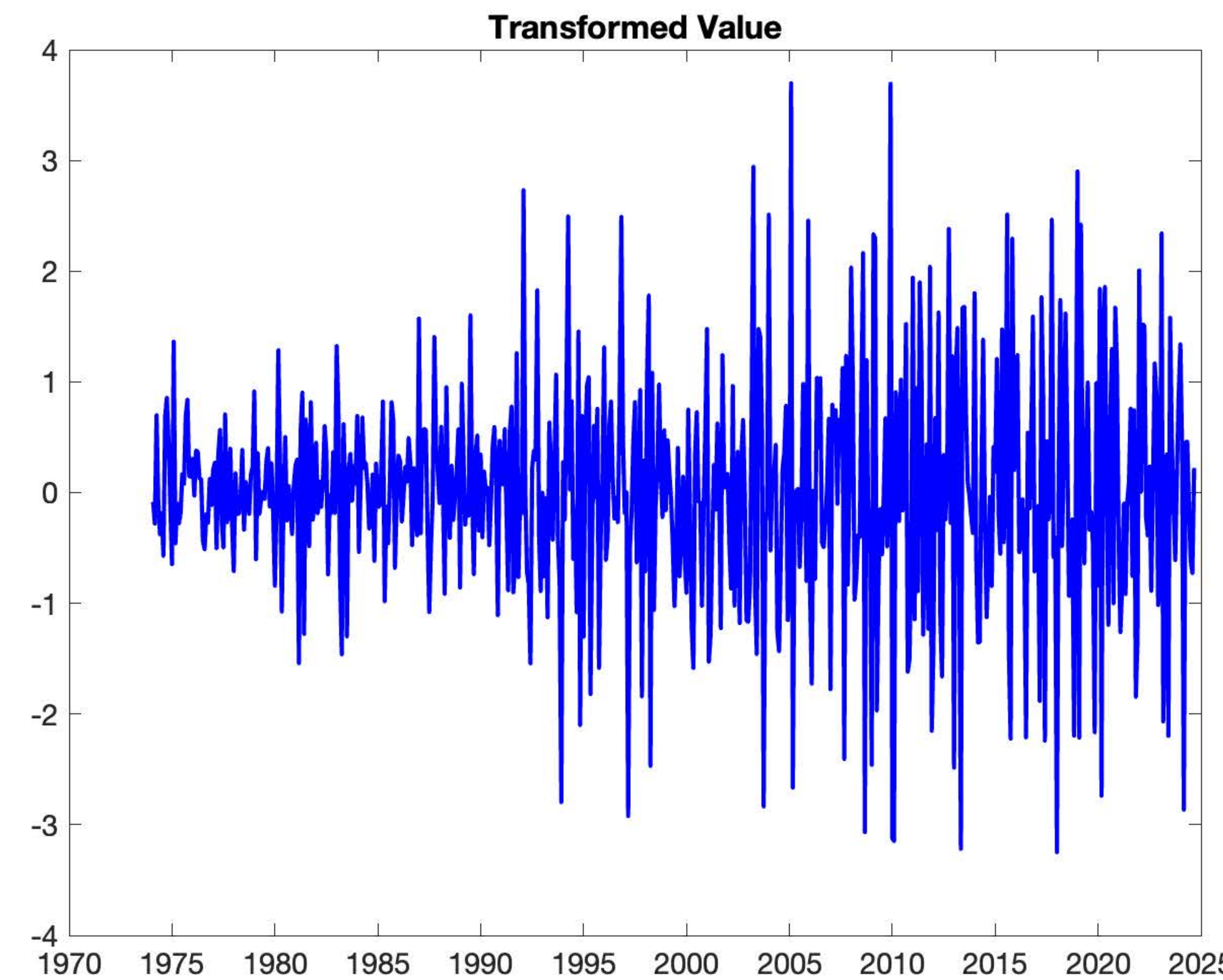

79. IPB51214S: Level
200
150
100
50
1970
1975
1980
1985
1990
1995
2000
2005
2010
2015
2020
2025

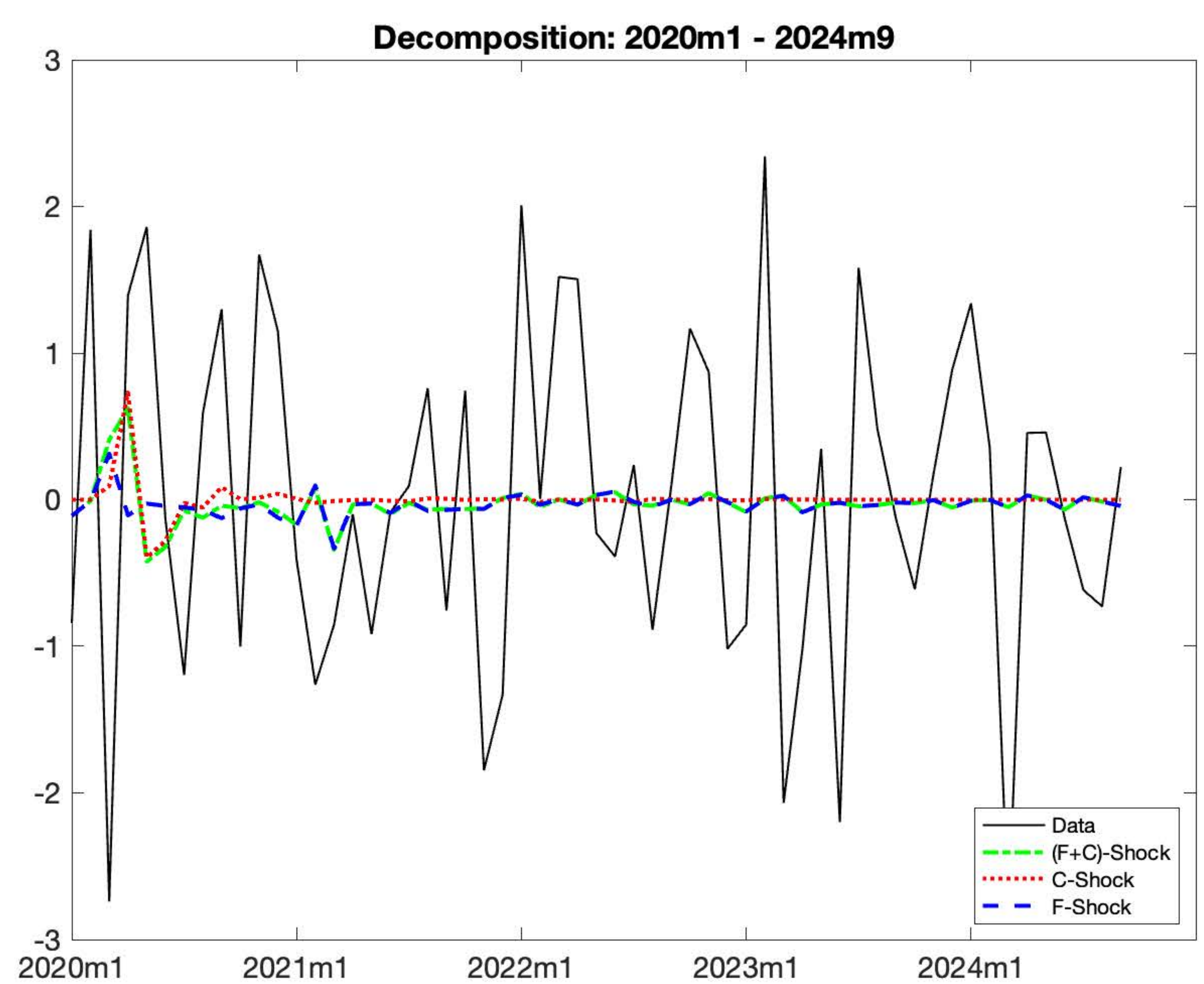

Transformed Value
6
4
2
0
-2
-4
-6
1970
1975
1980
1985
1990
1995
2000
2005
2010
2015
2020
2025

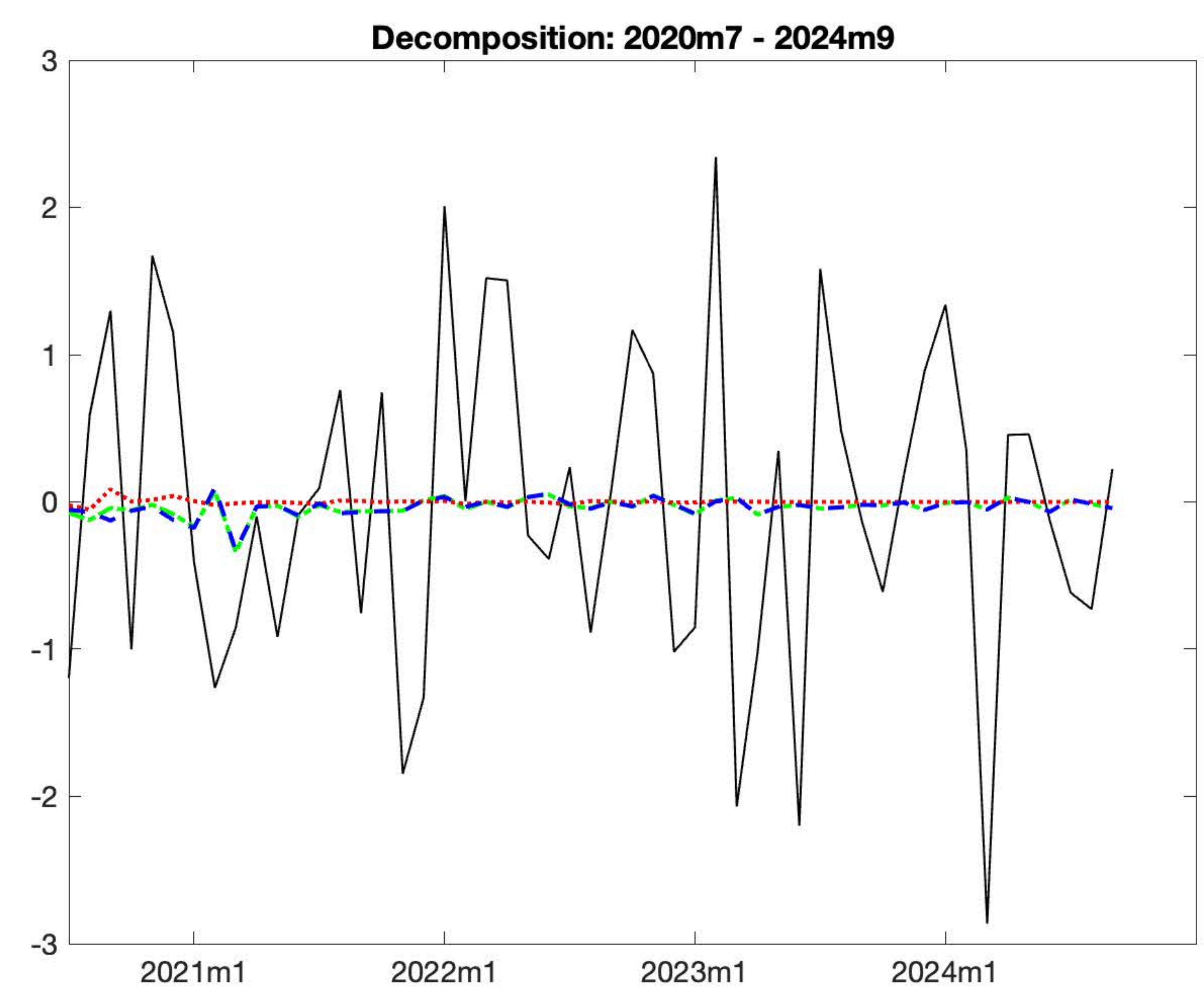

Decomposition: 2020m1 - 2024m9
1.5
1
0.5
0
-0.5
-1
-1.5
-2
-2.5
2020m1
2021m1
2022m1
2023m1
2024m1
Data
(F+C)-Shock
C-Shock
F-Shock

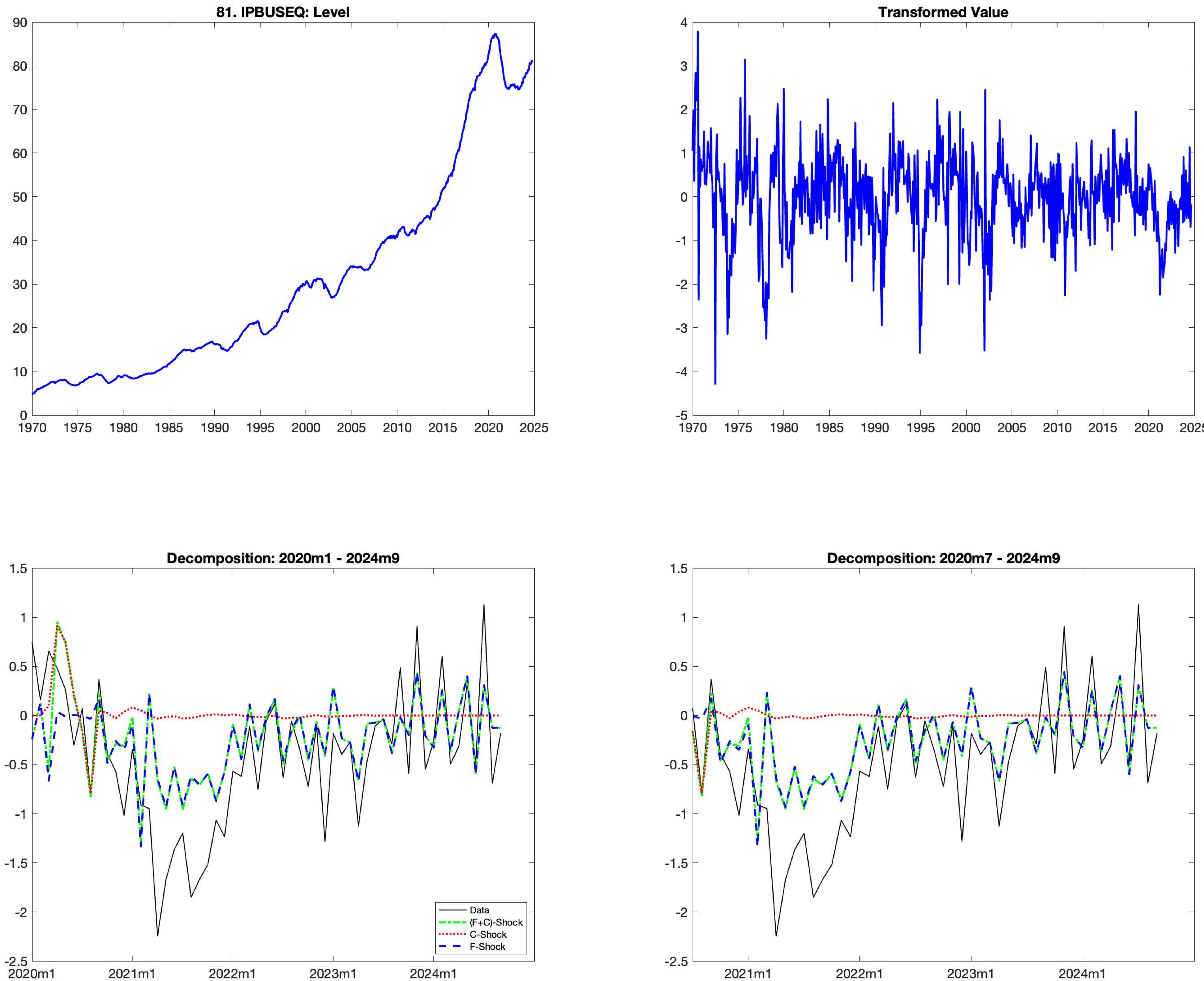

Decomposition: 2020m7 - 2024m9
1
0.5
0
-0.5
-1
-1.5
-2
-2.5
2021m1
2022m1
2023m1
2024m1


80. IPB51220S: Level


Transformed Value

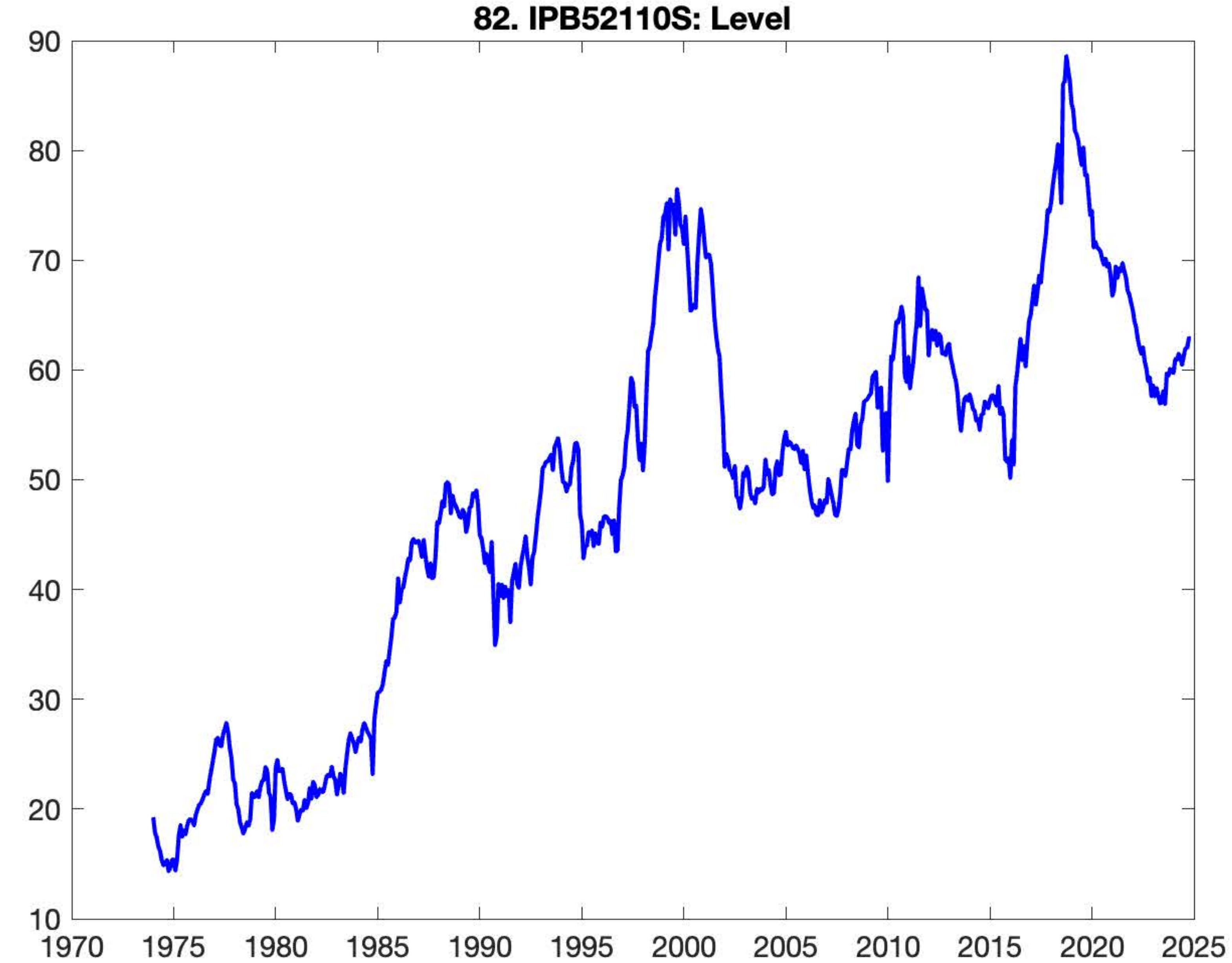

Decomposition: 2020m1 - 2024m9
Data
(F+C)-Shock
C-Shock
F-Shock


Decomposition: 2020m7 - 2024m9

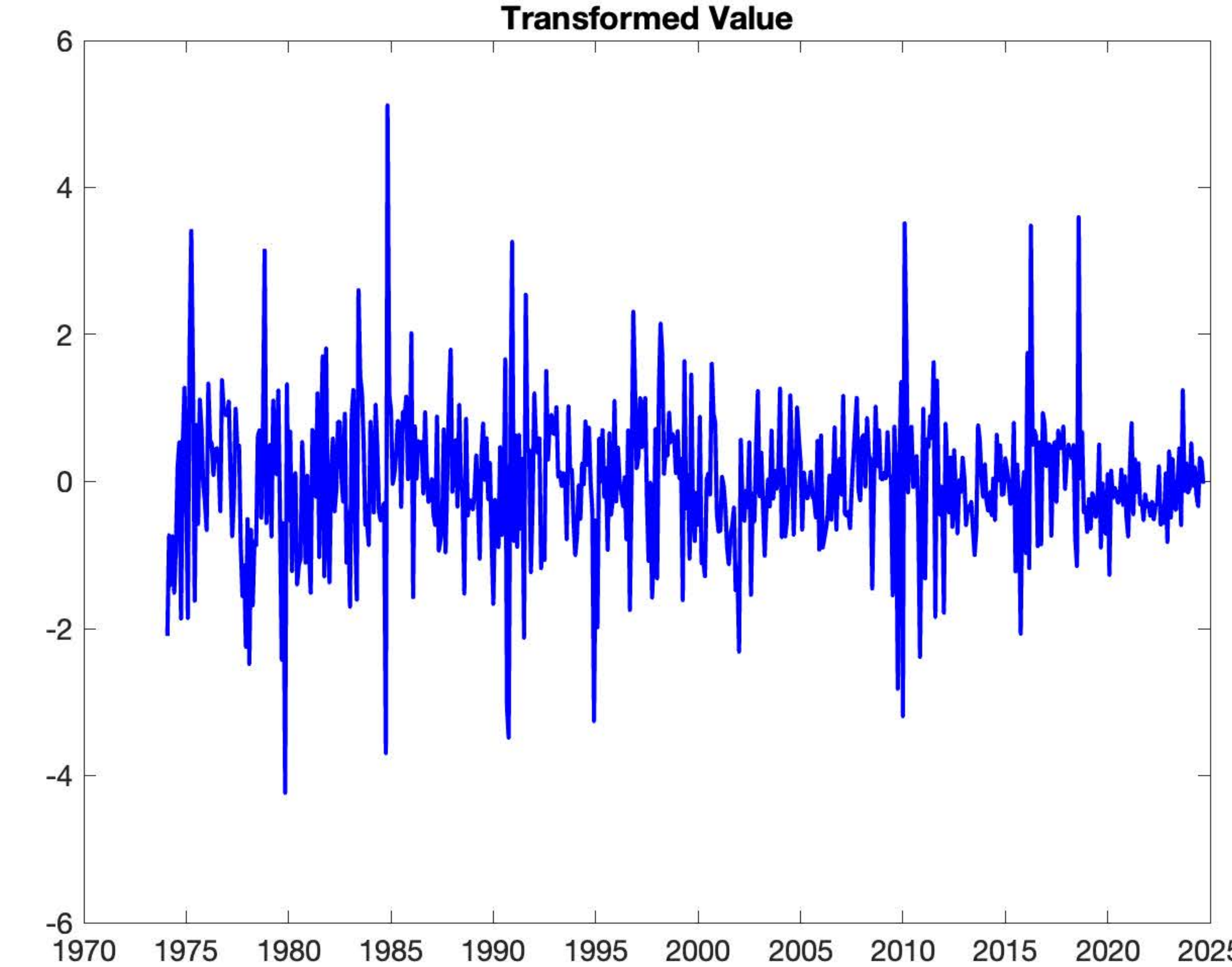


81. IPBUSEQ: Level
Transformed Value
Decomposition: 2020m1 - 2024m9
Decomposition: 2020m7 - 2024m9
Data
(F+C)-Shock
C-Shock
F-Shock

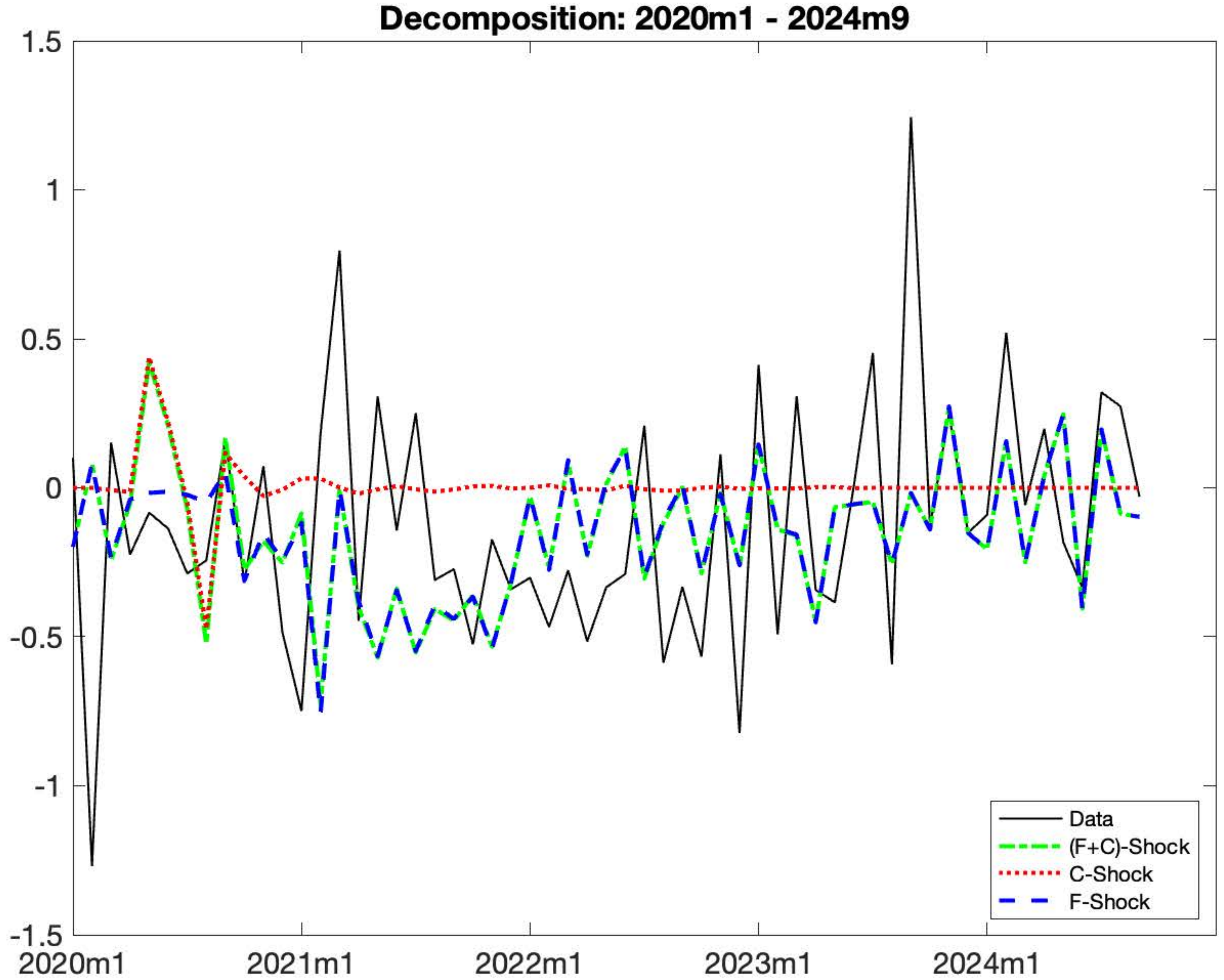
82. IPB52110S: Level



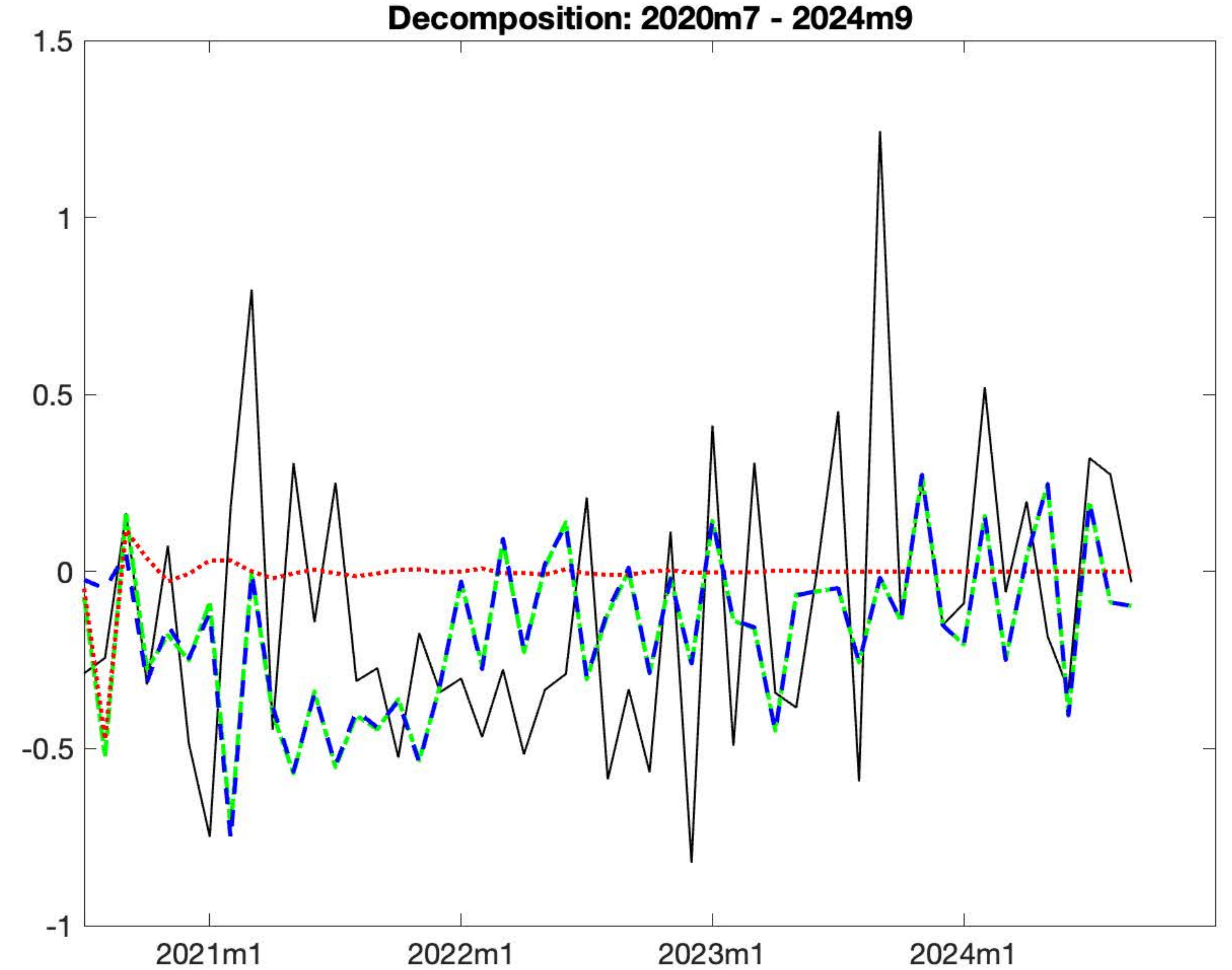
Transformed Value

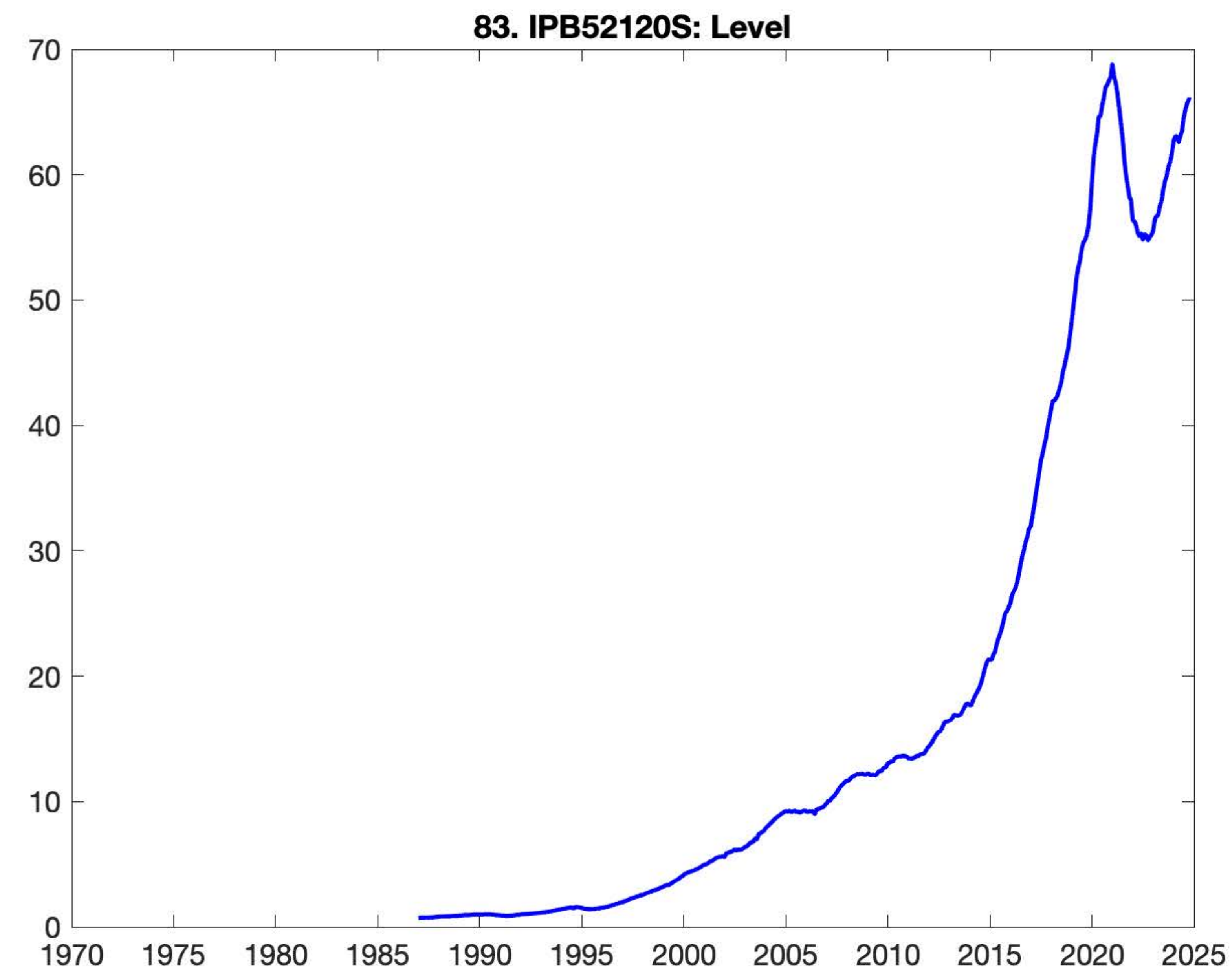


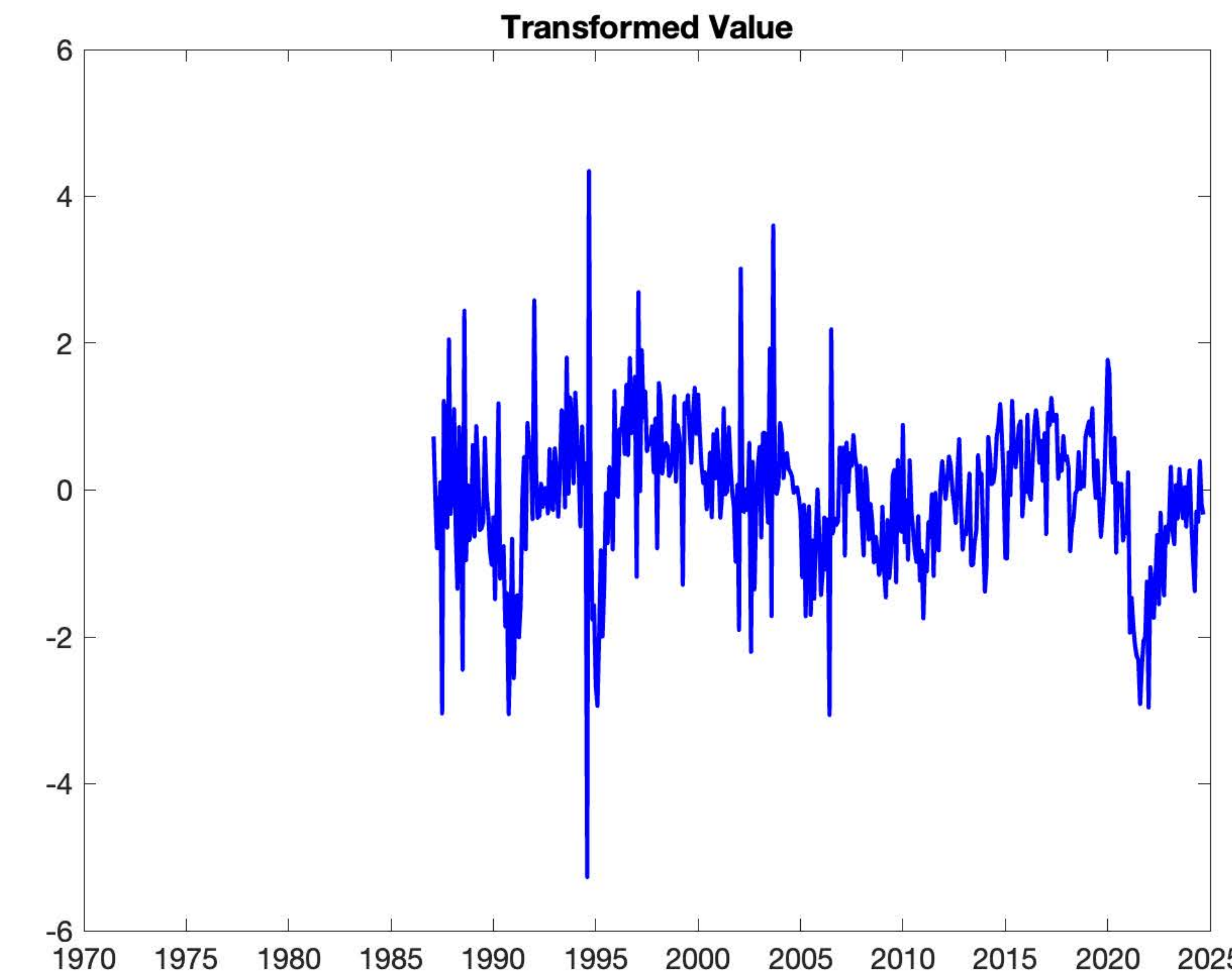
Decomposition: 2020m1 - 2024m9

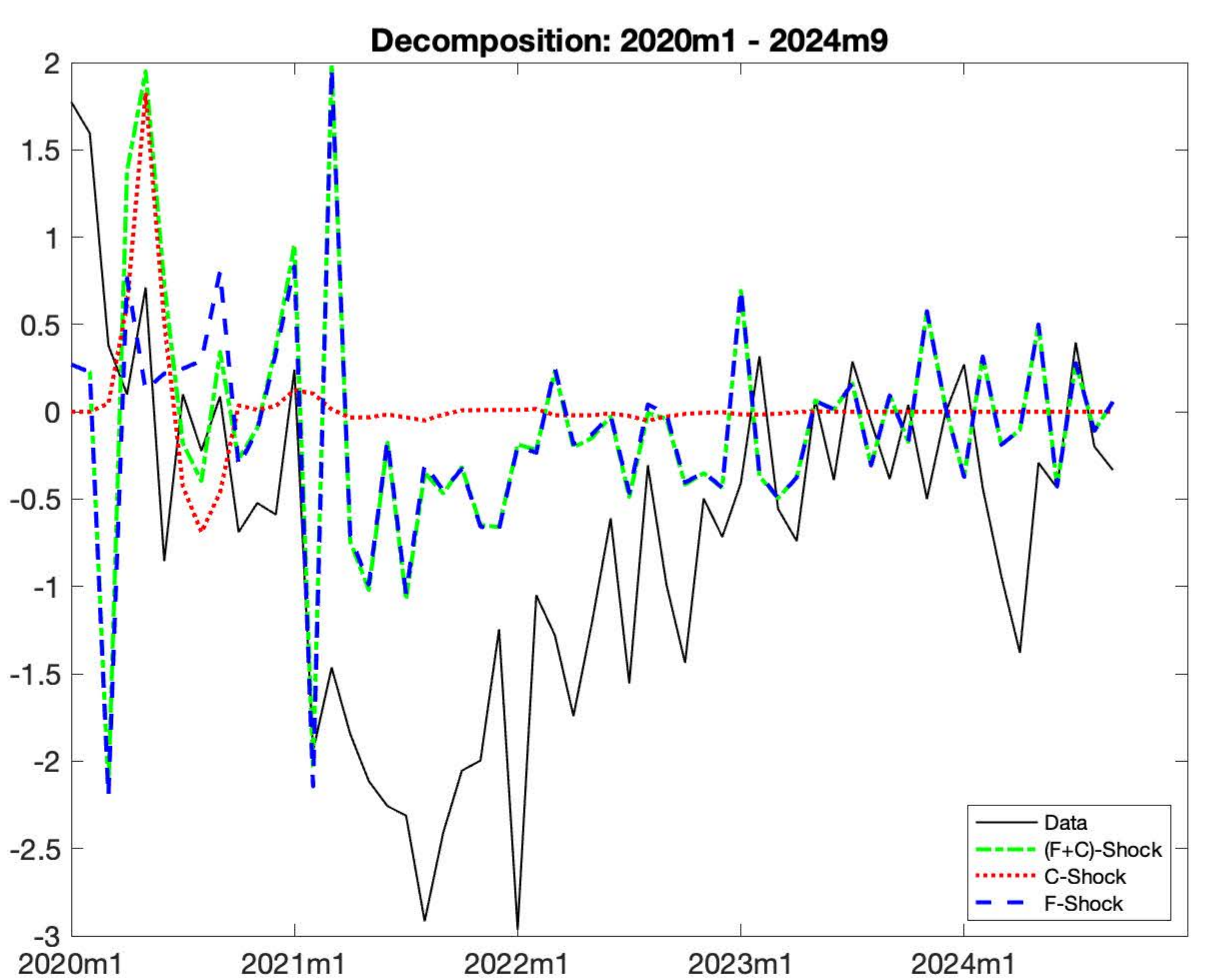


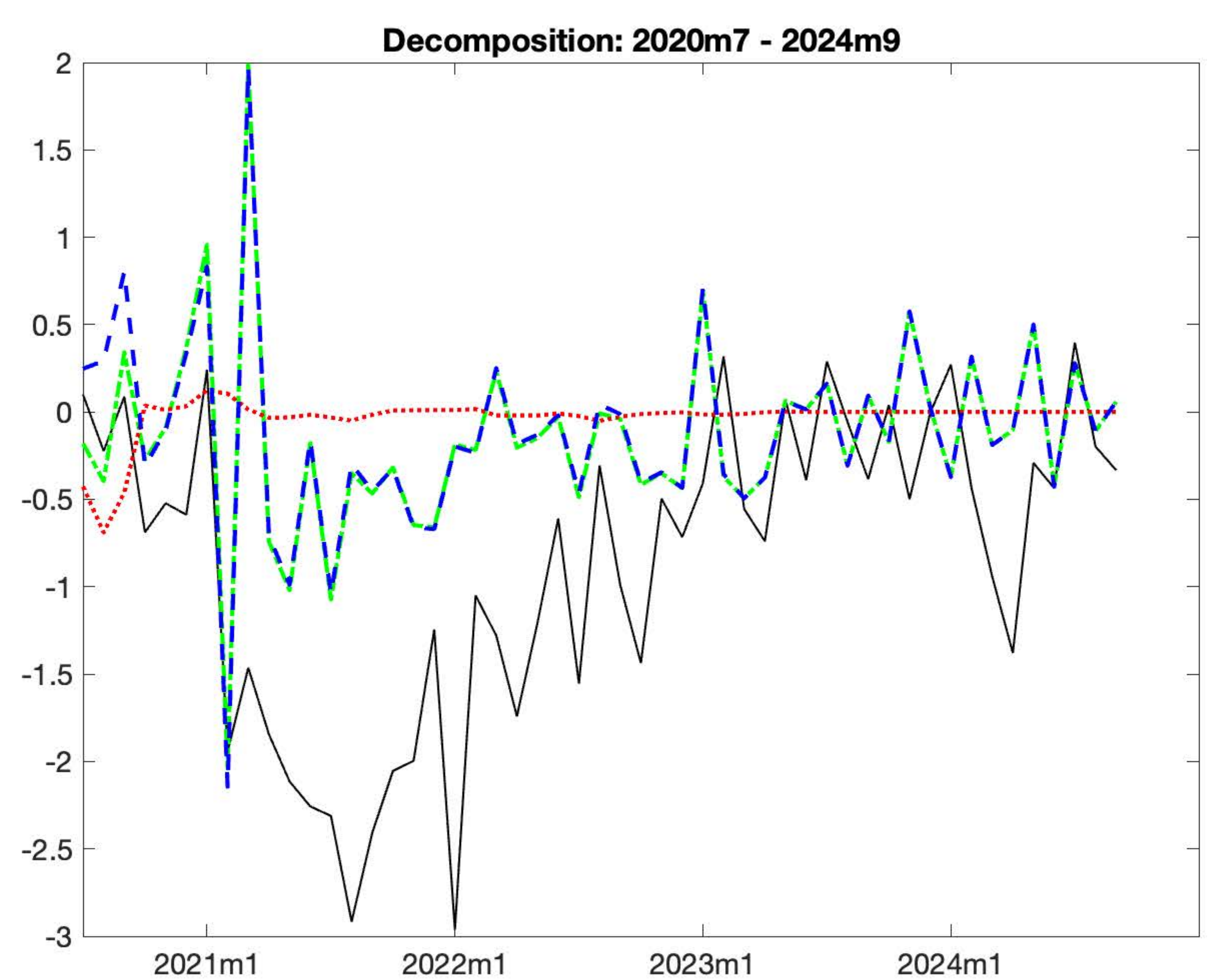
Decomposition: 2020m7 - 2024m9

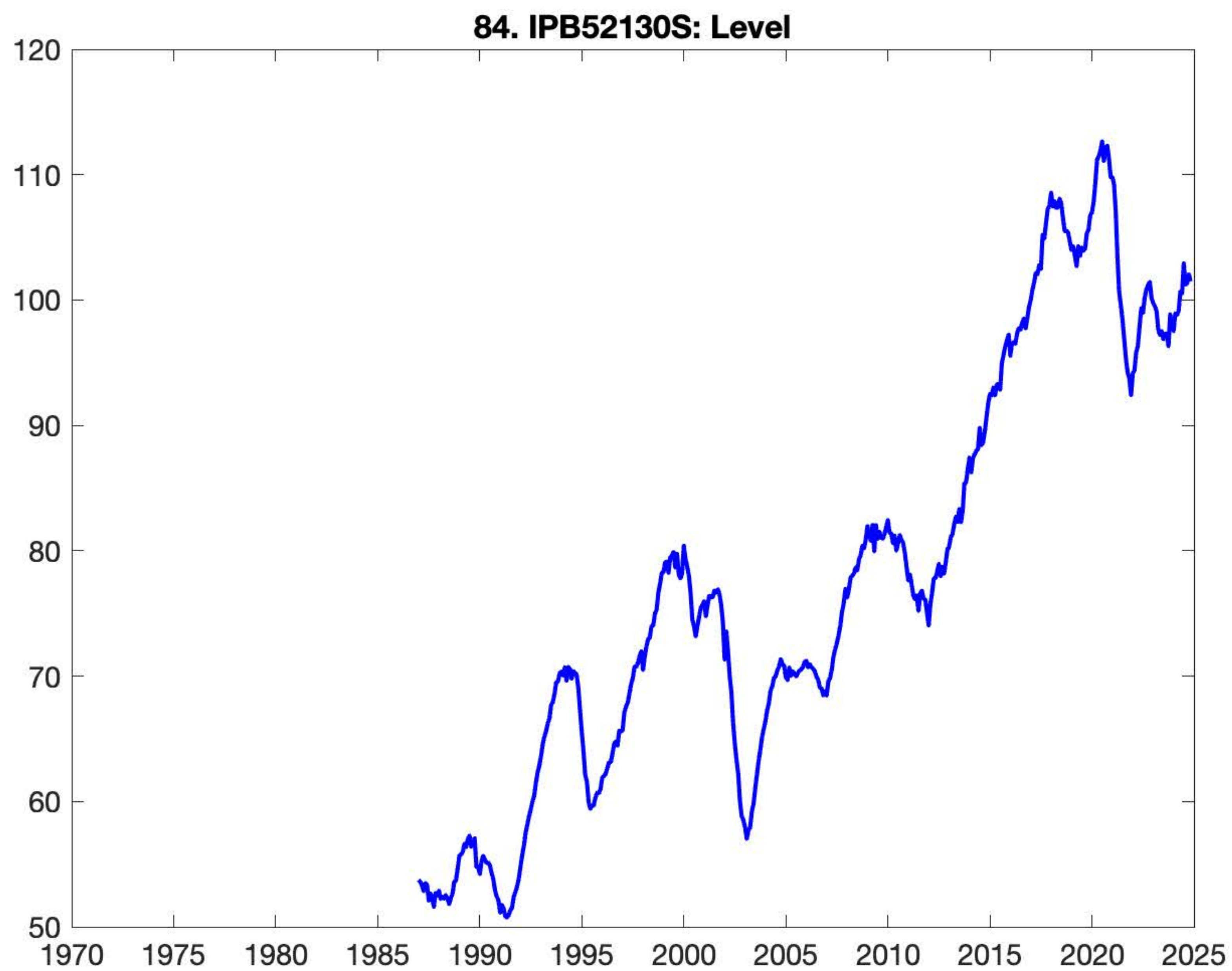



83. IPB52120S: Level


Transformed Value


Decomposition: 2020m1 - 2024m9
Data
(F+C)-Shock
C-Shock
F-Shock


Decomposition: 2020m7 - 2024m9


84. IPB52130S: Level
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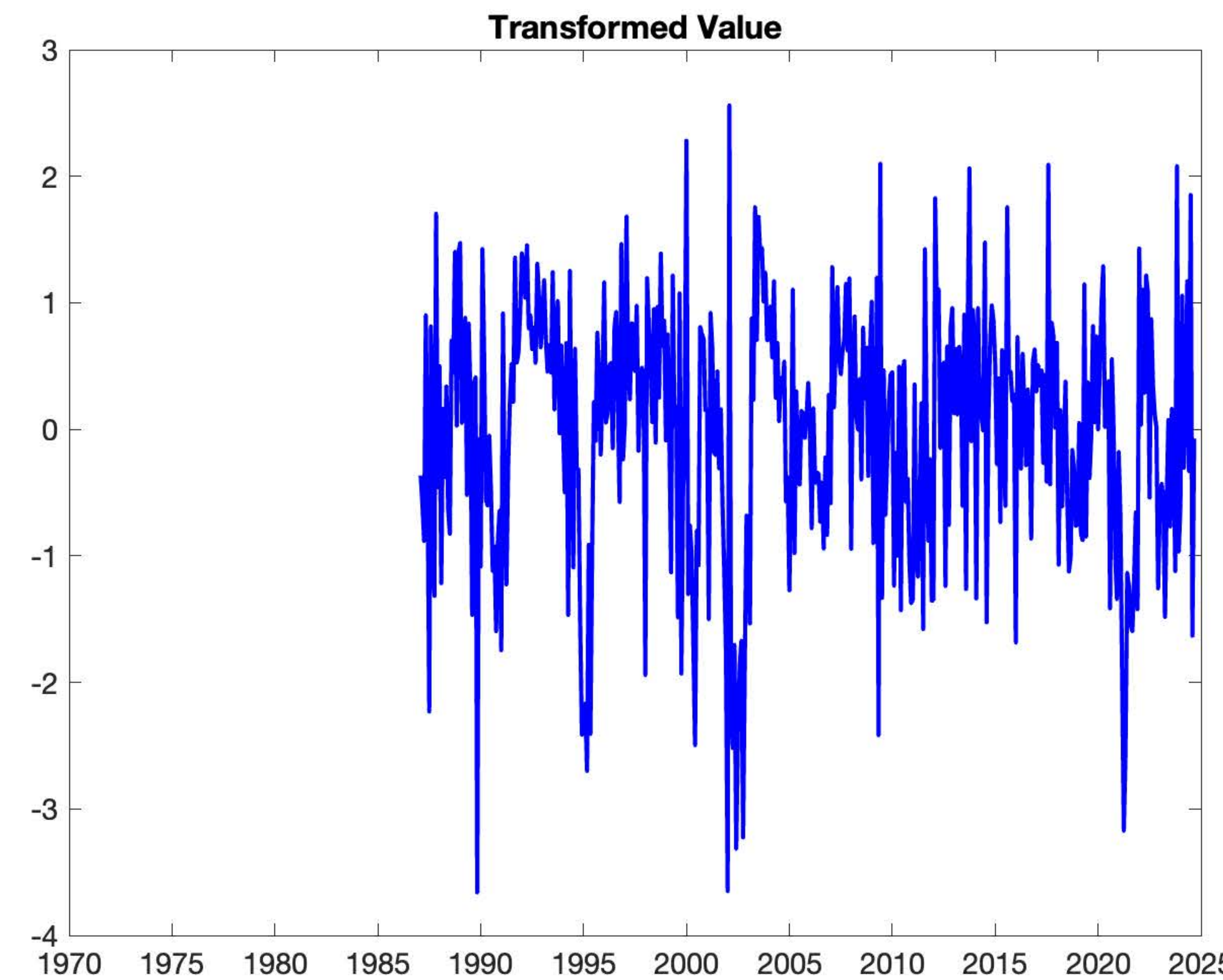
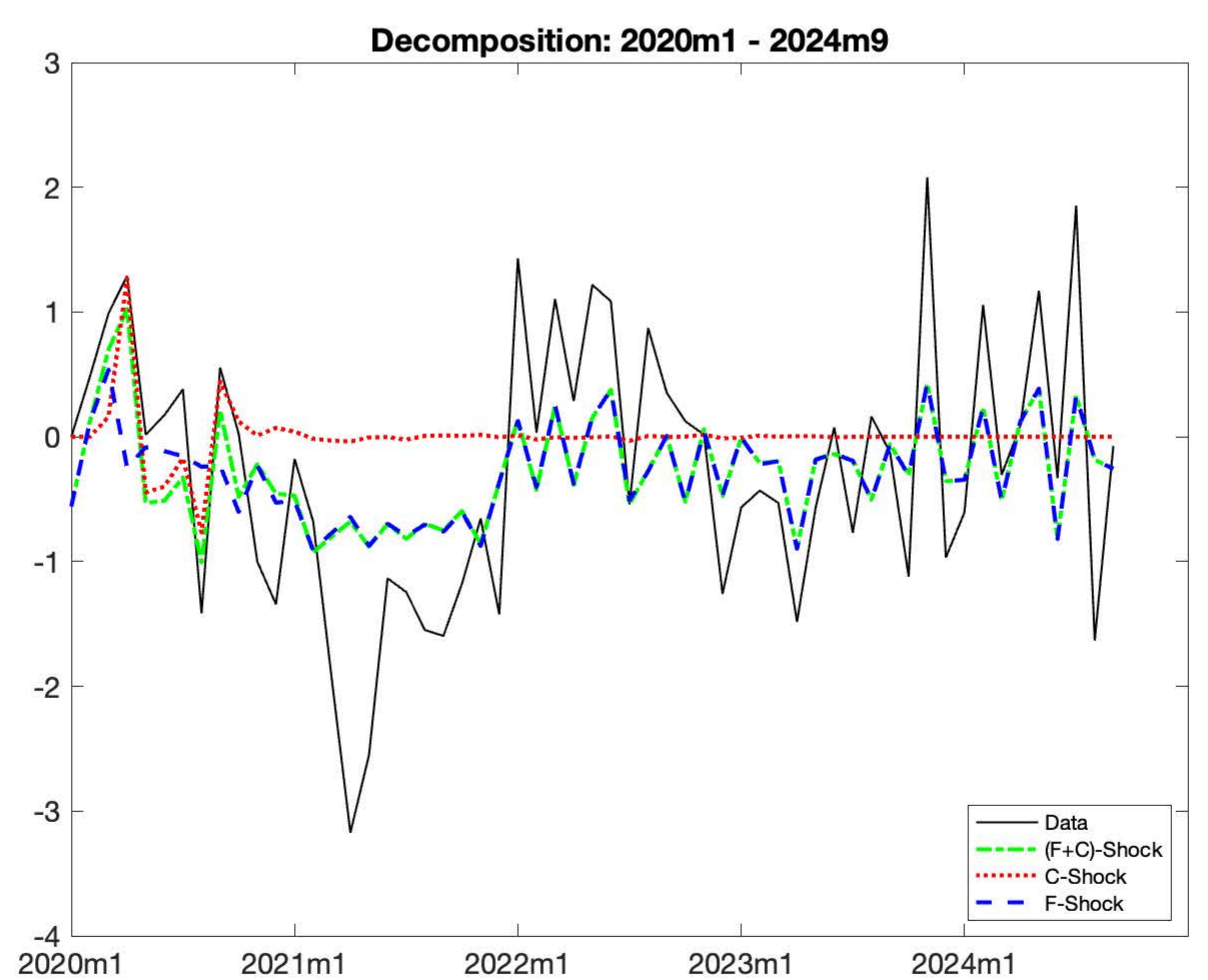
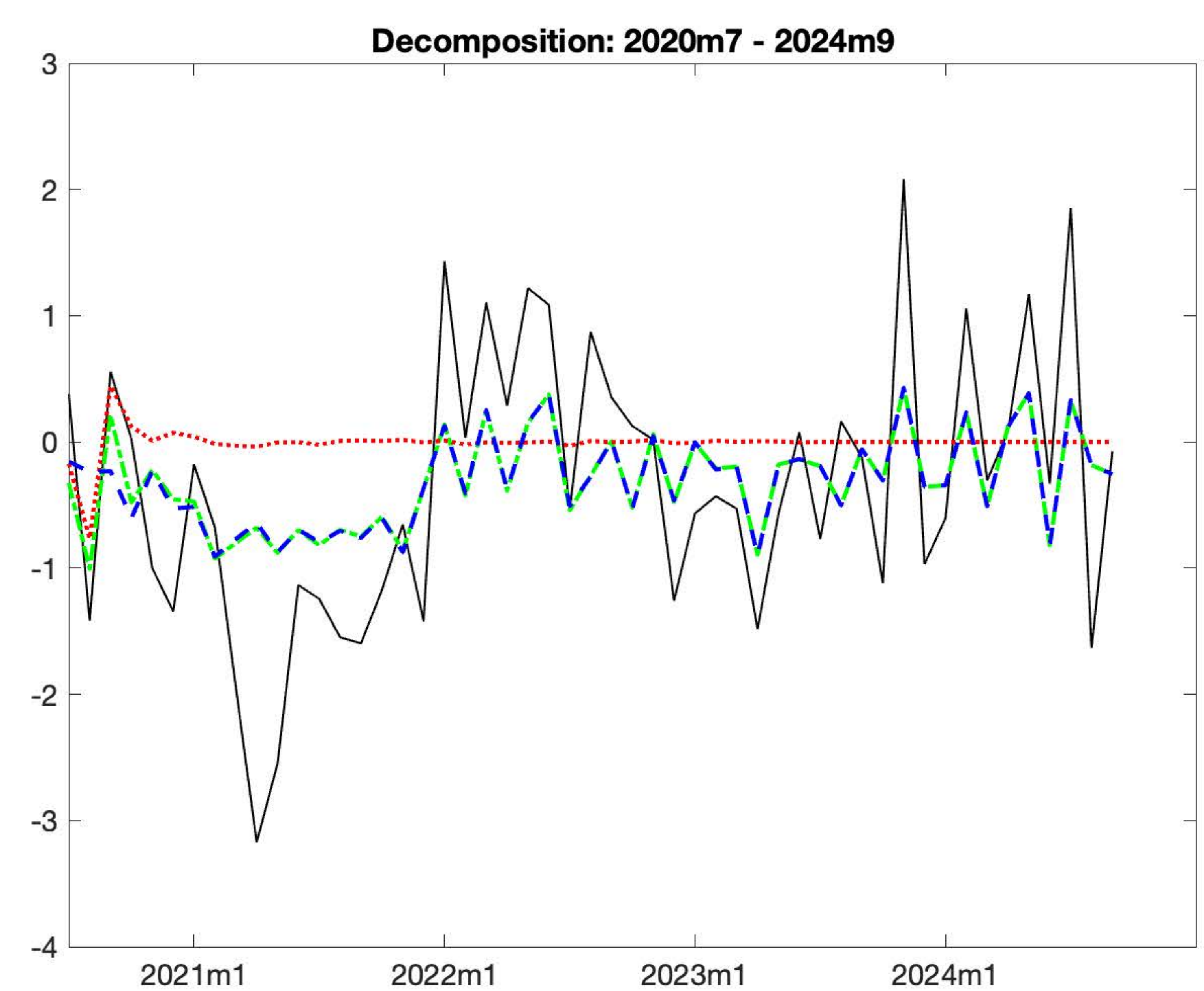
2025


Transformed Value
3
2
1
0
-1
-2
-3
-4
1970
1975
1980
1985
1990
1995
2000
2005
2010
2015
2020
2025


Decomposition: 2020m1 - 2024m9
3
2
1
0
-1
-2
-3
-4
2020m1
2021m1
2022m1
2023m1
2024m1
Data
(F+C)-Shock
C-Shock
F-Shock


Decomposition: 2020m7 - 2024m9
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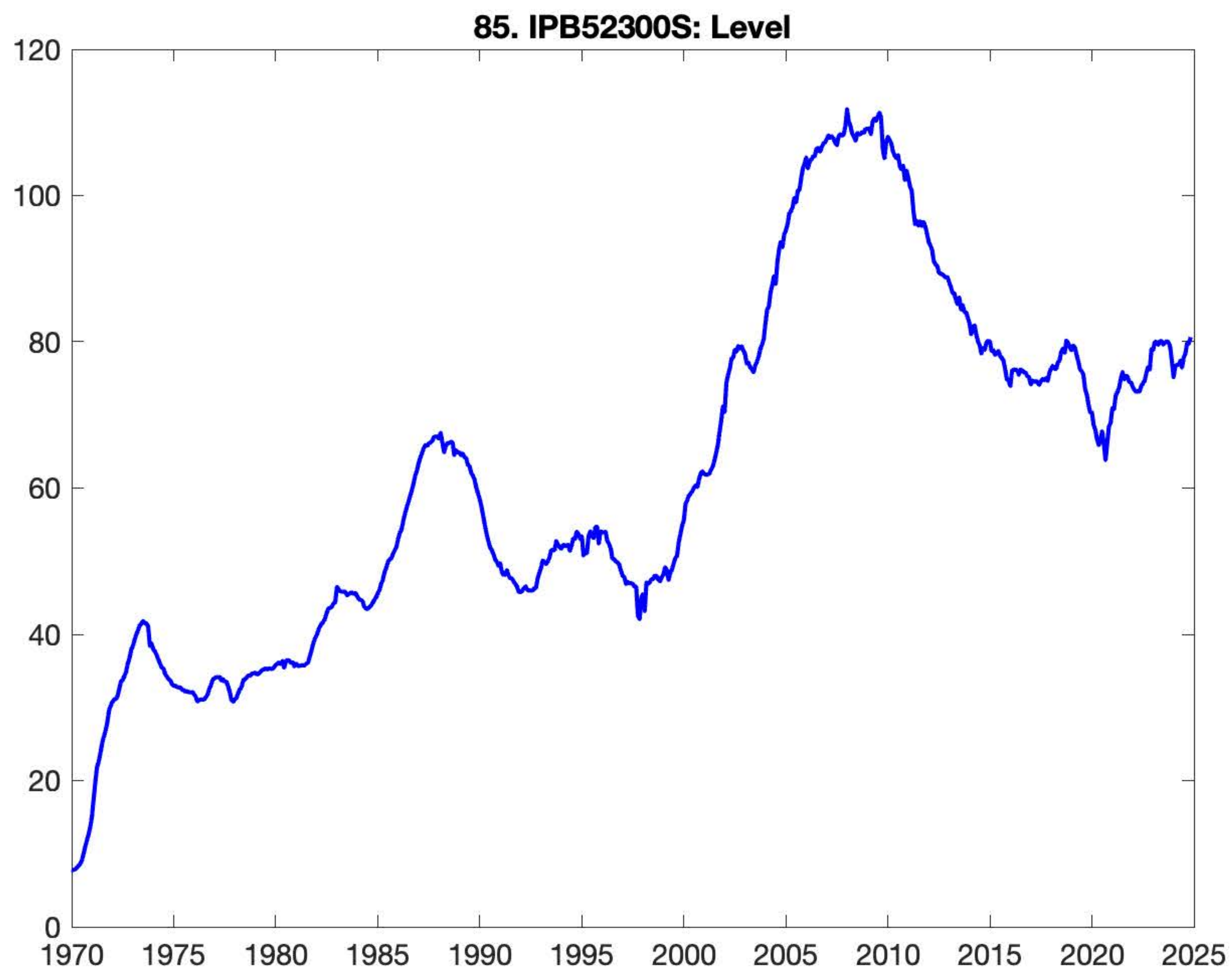
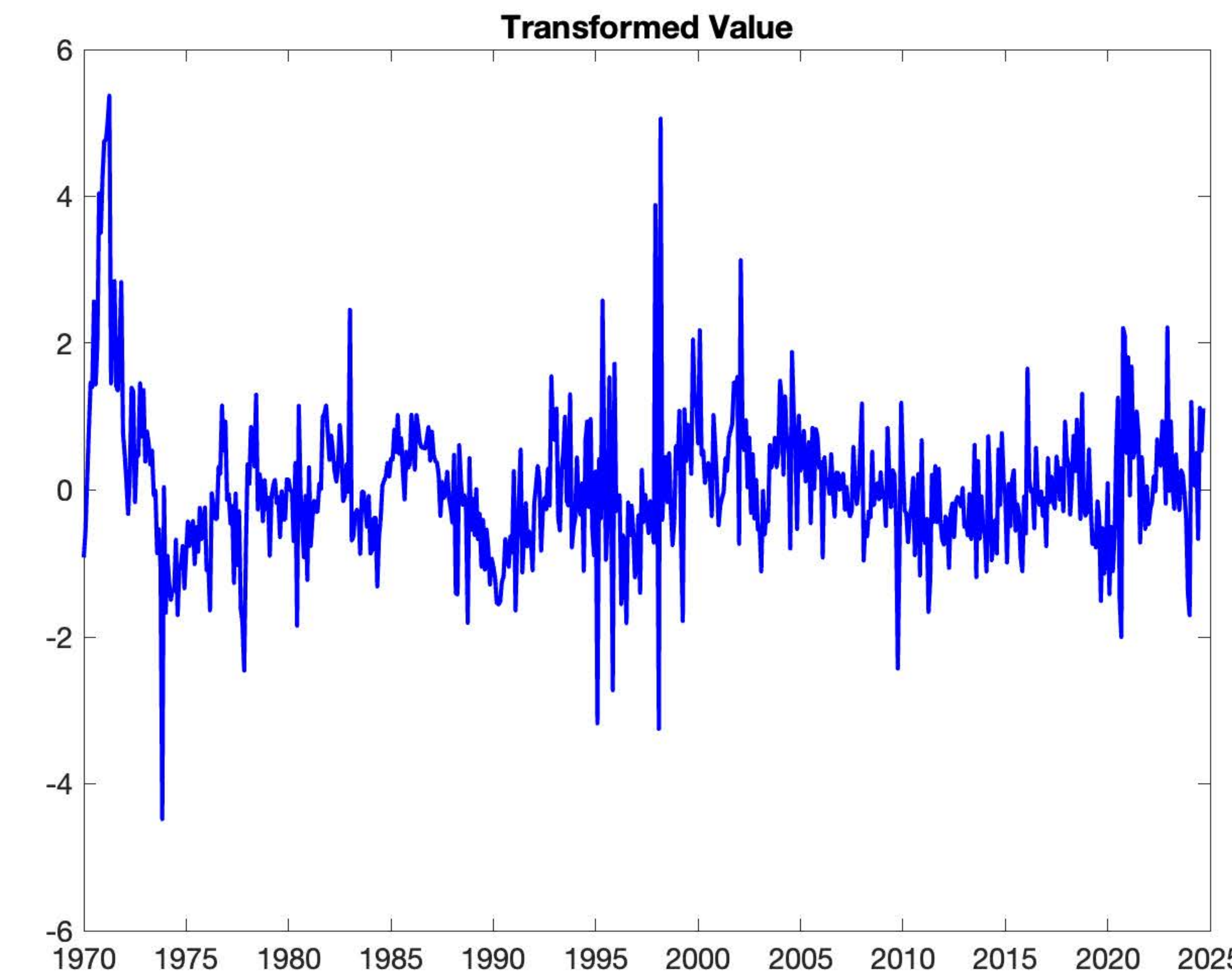
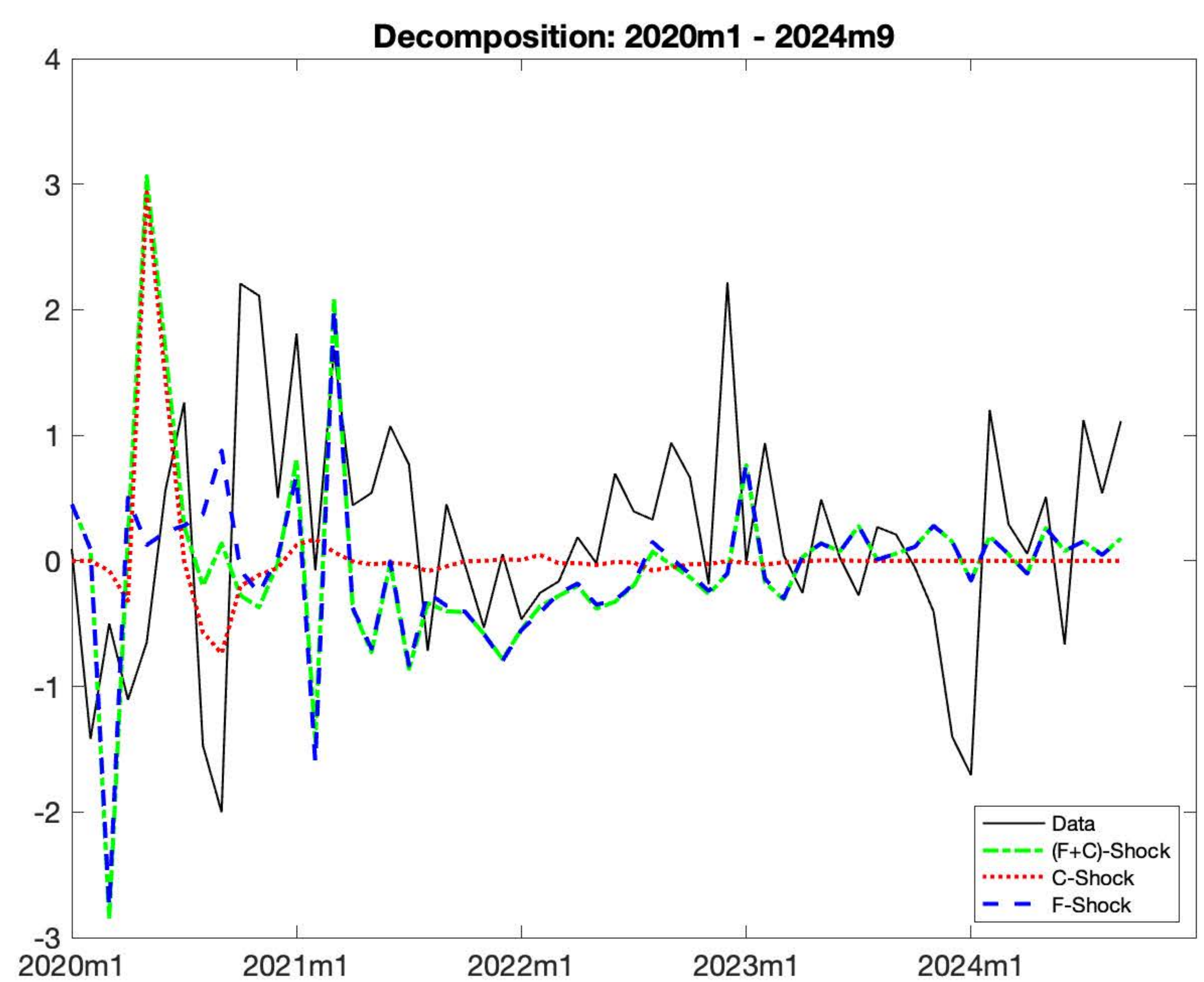
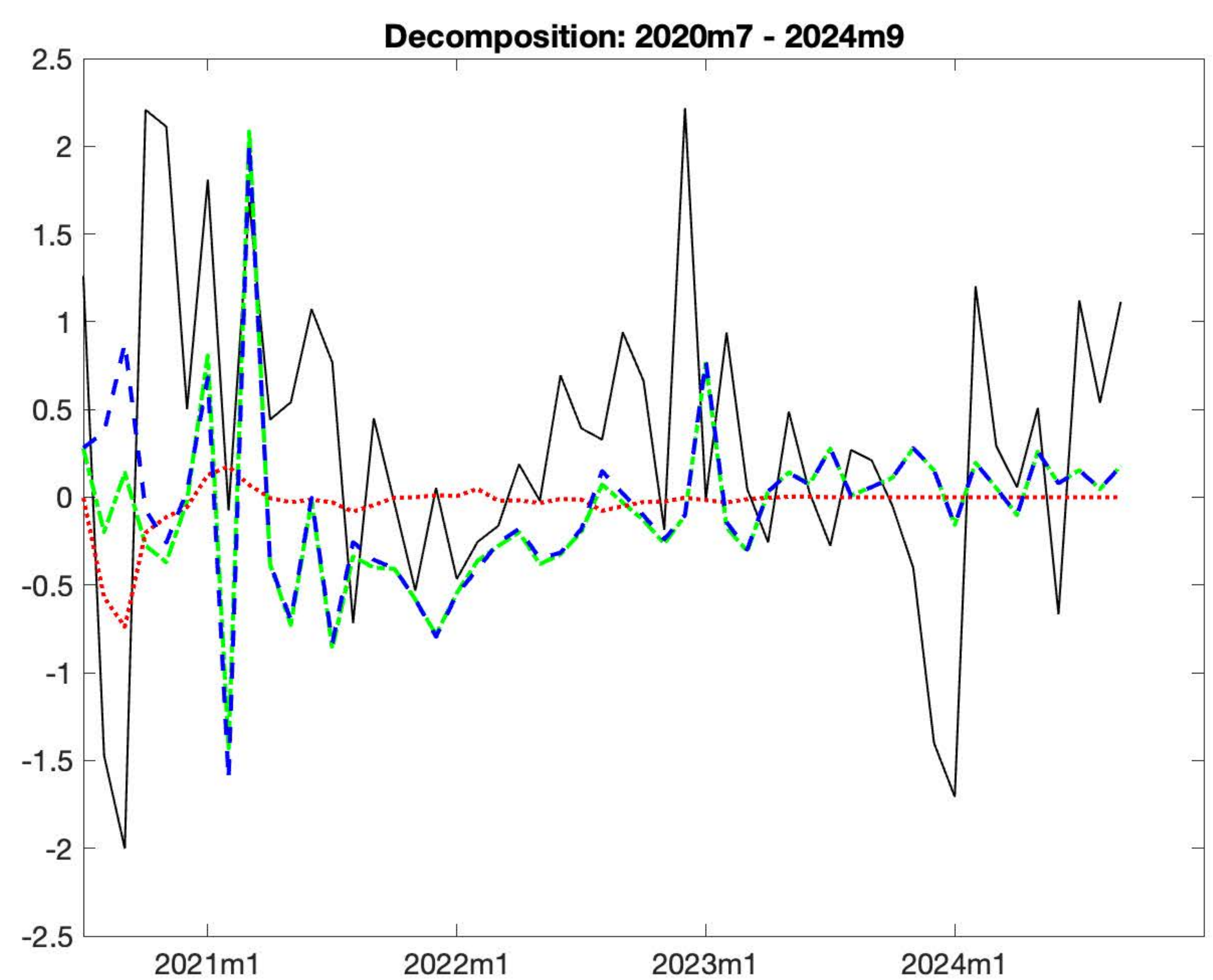
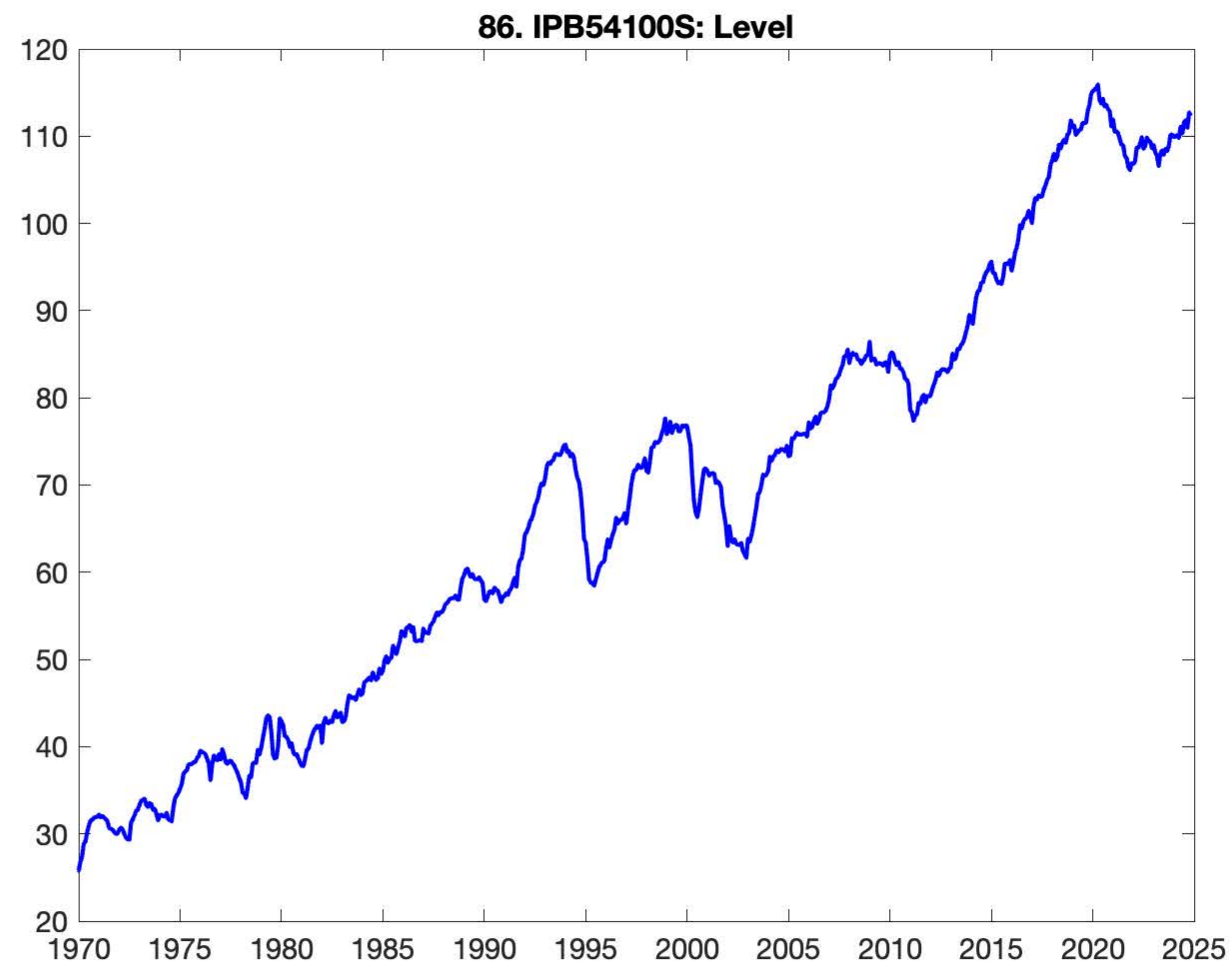
2
1
0
-1
-2
-3
-4
2021m1
2022m1
2023m1
2024m1


85. IPB52300S: Level


Transformed Value


Decomposition: 2020m1 - 2024m9
Data
(F+C)-Shock
C-Shock
F-Shock


Decomposition: 2020m7 - 2024m9


86. IPB54100S: Level
120
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1970
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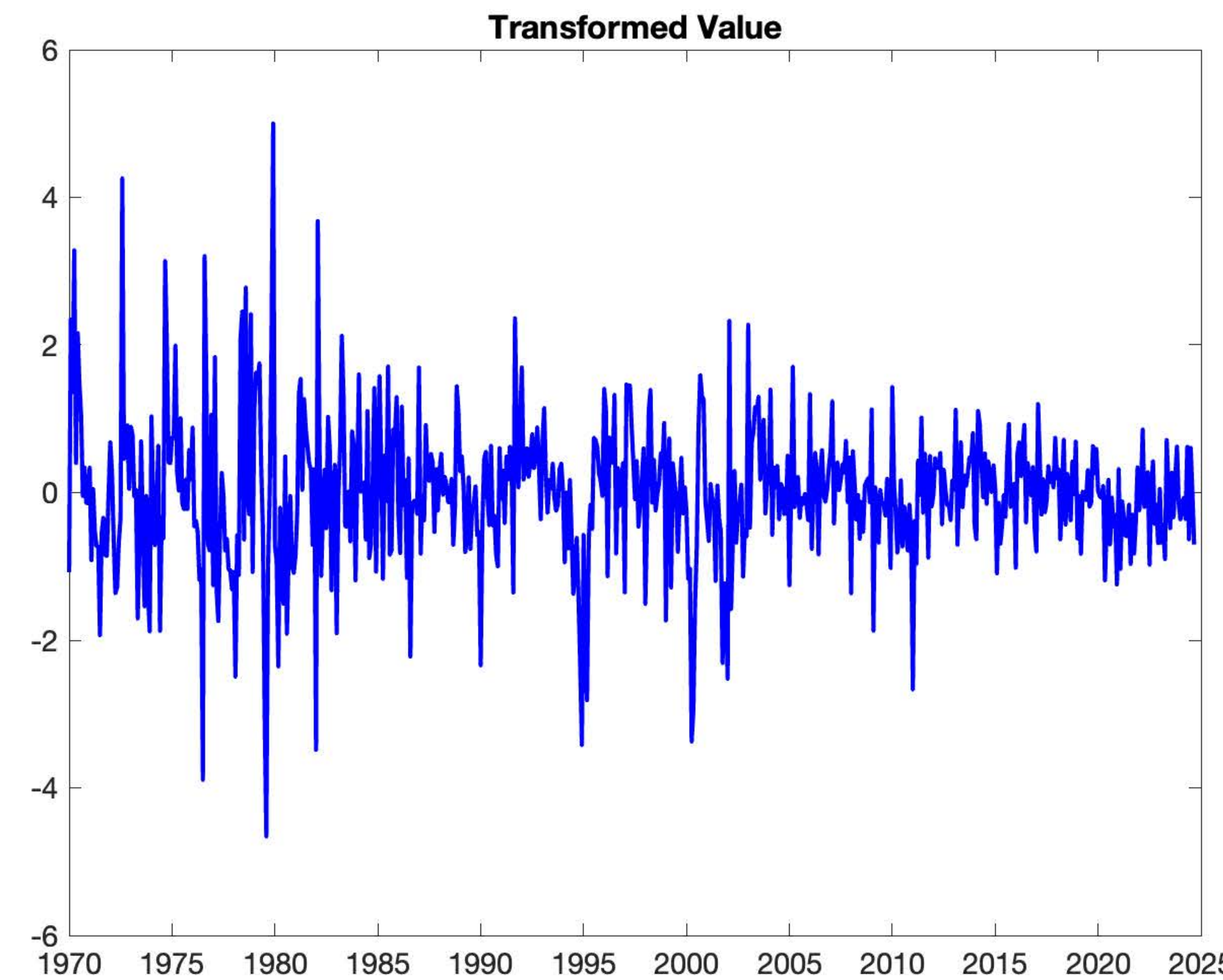
2015
2020
2025


Transformed Value
6
4
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-2
-4
-6
1970
1975
1980
1985
1990
1995
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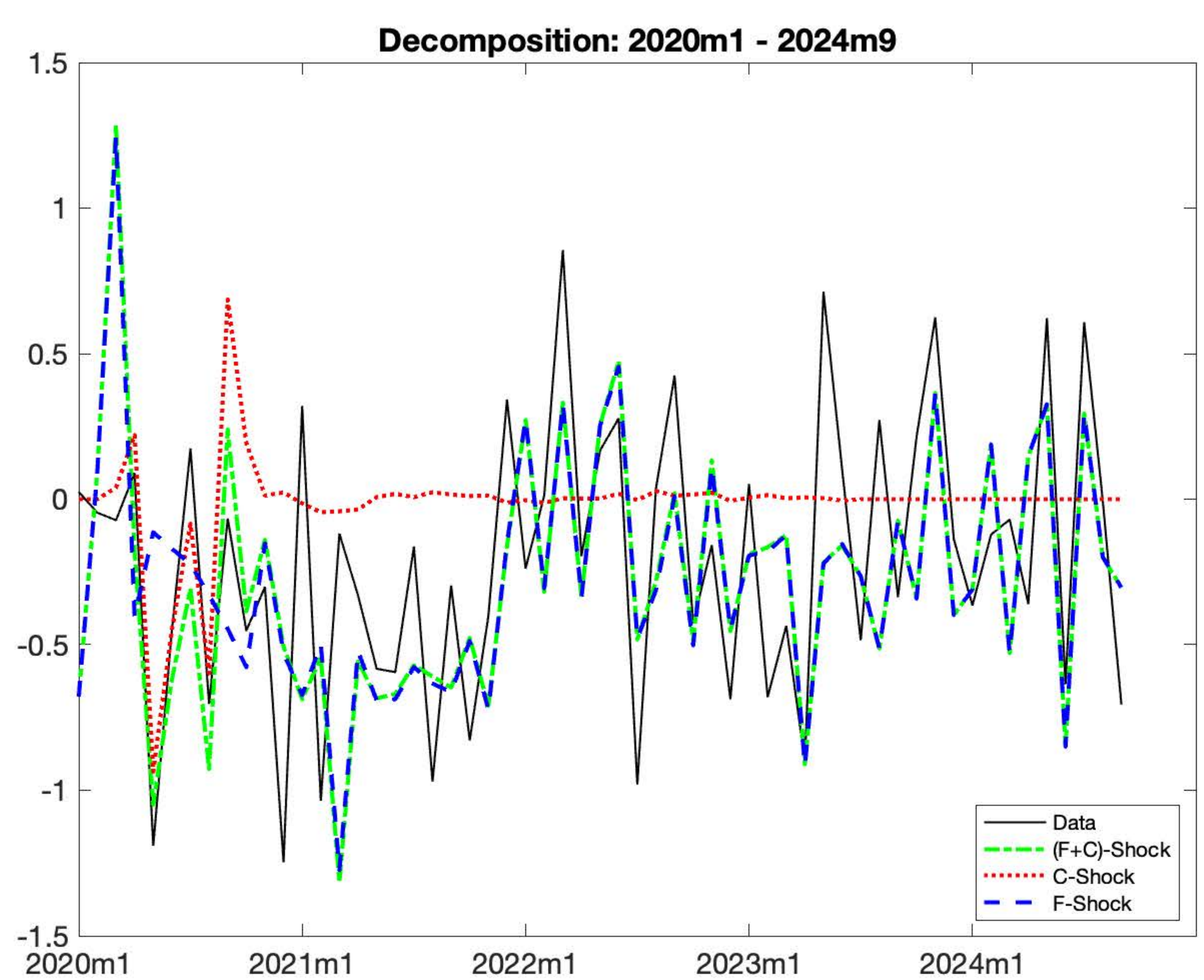
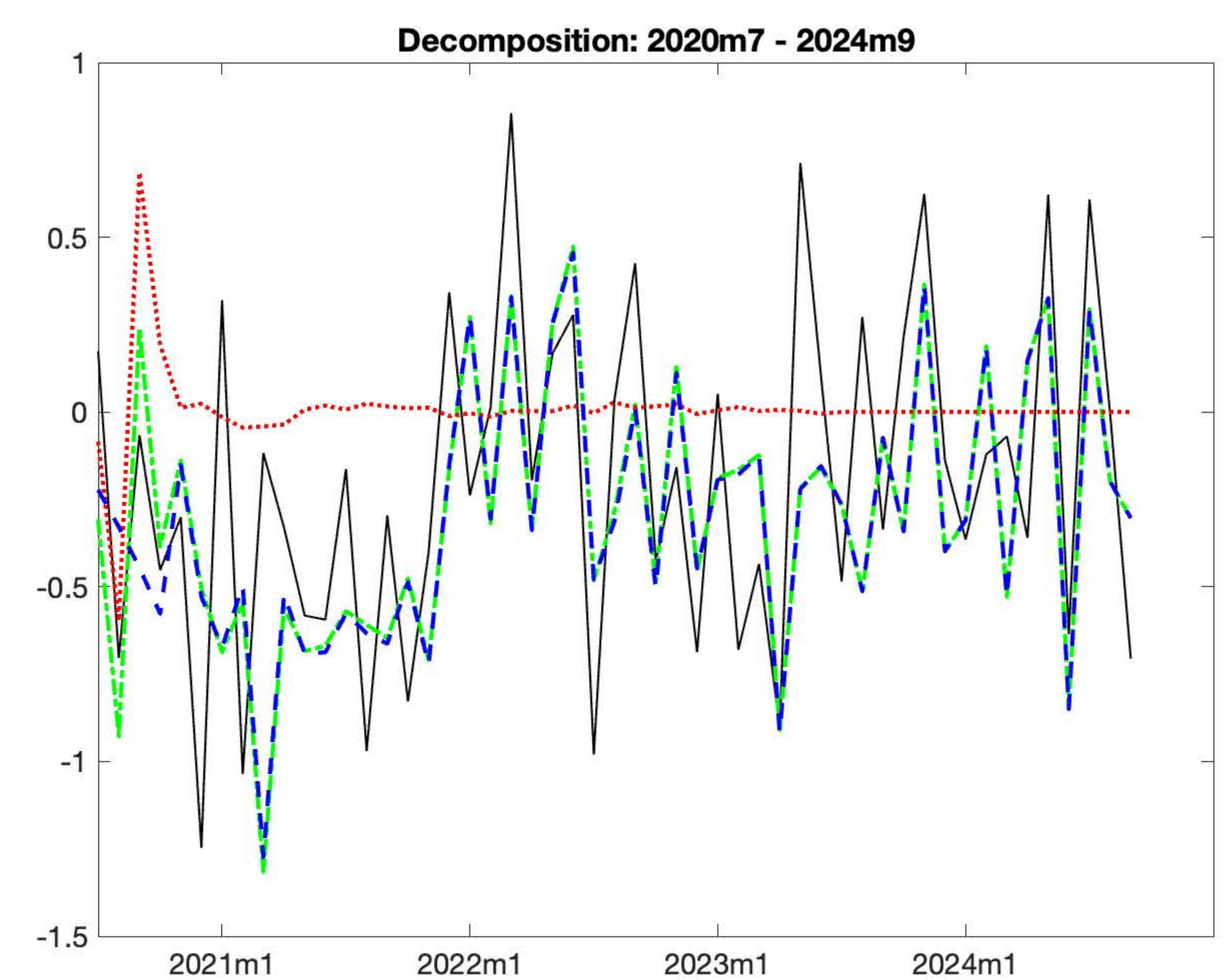
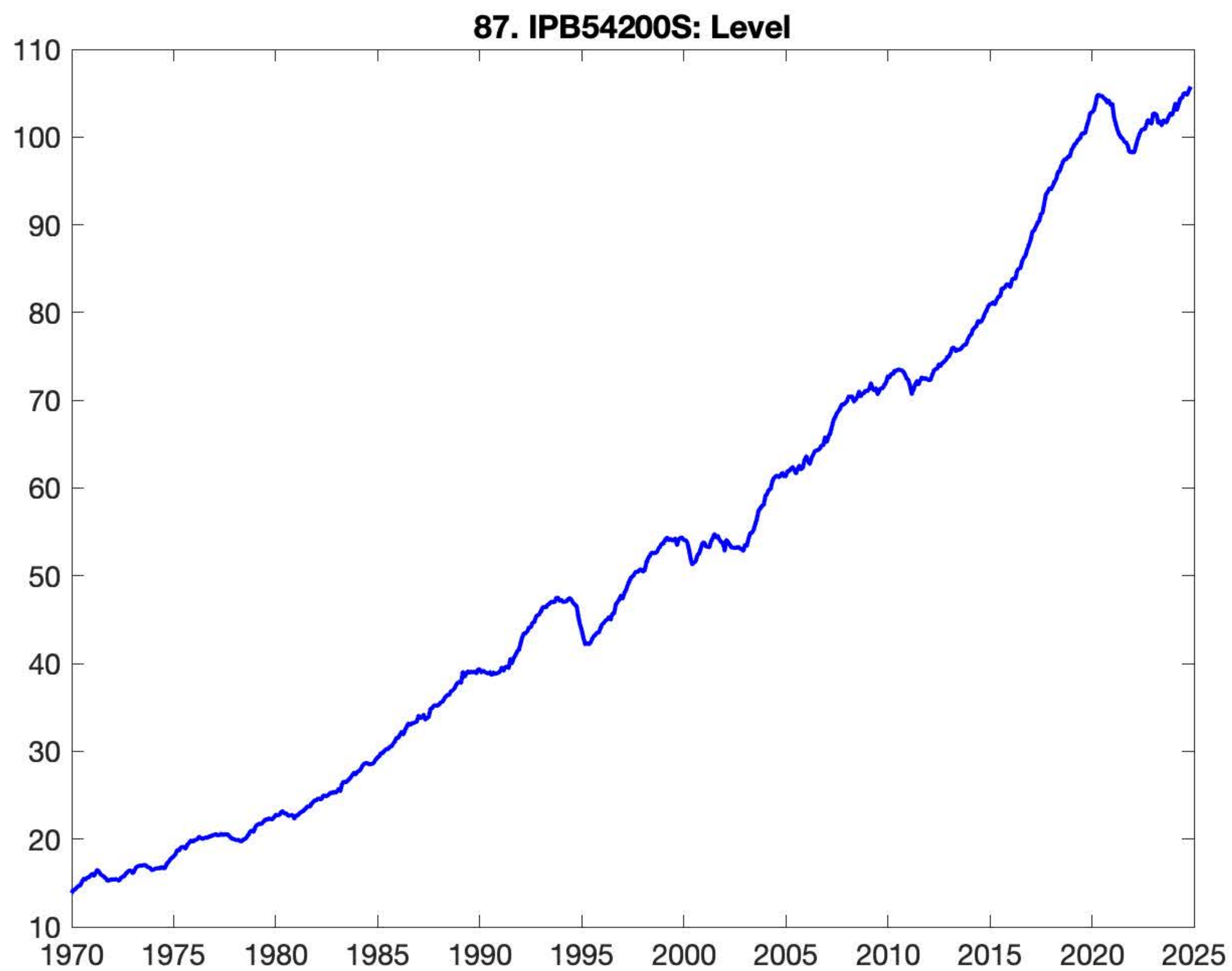
2005
2010
2015
2020
2025


Decomposition: 2020m1 - 2024m9
1.5
1
0.5
0
-0.5
-1
-1.5
2020m1
2021m1
2022m1
2023m1
2024m1
Data
(F+C)-Shock
C-Shock
F-Shock


Decomposition: 2020m7 - 2024m9
1
0.5
0
-0.5
-1
-1.5
2021m1
2022m1
2023m1
2024m1



87. IPB54200S: Level
110
100
90
80
70
60
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40
30
20
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1970
1975
1980
1985
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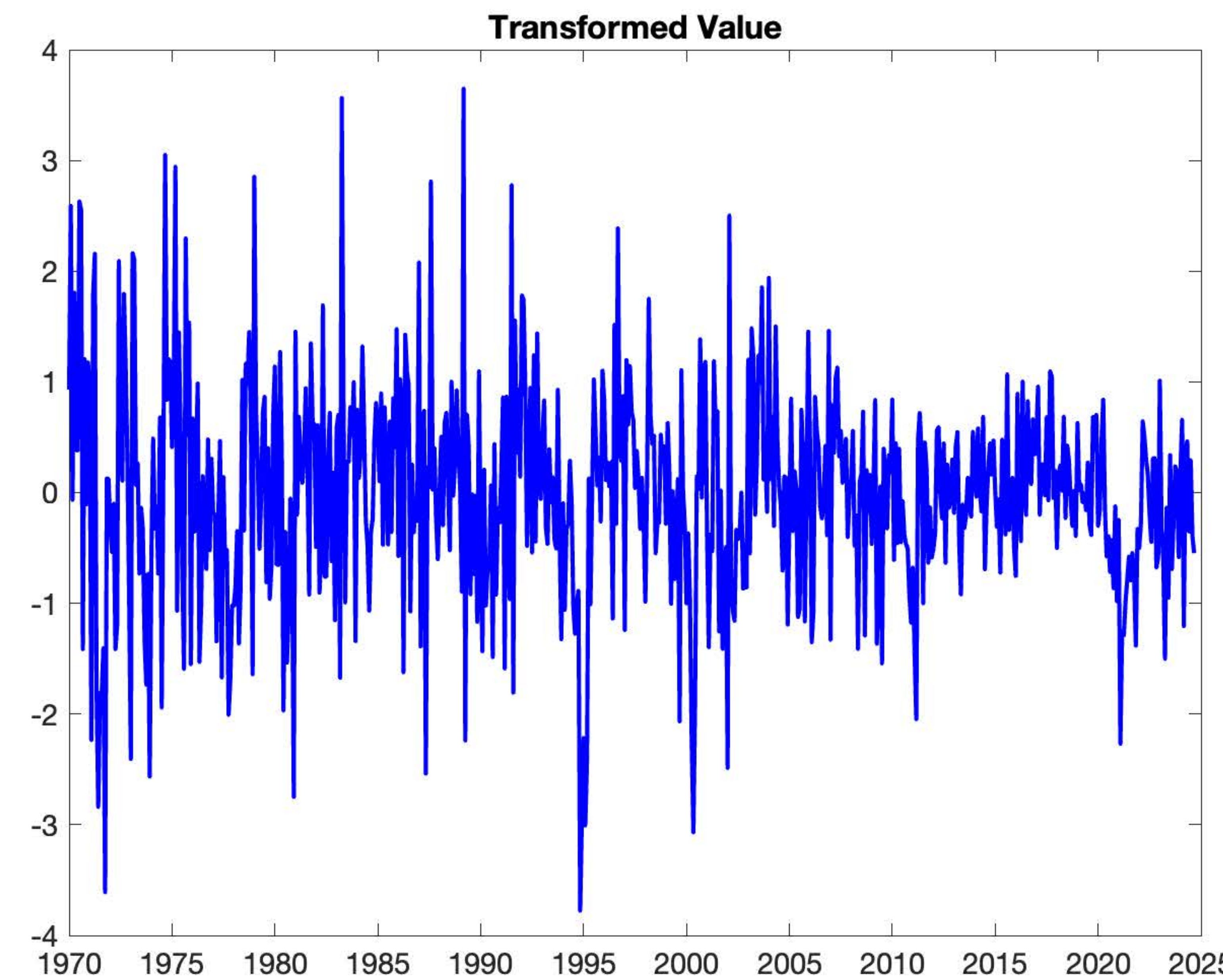
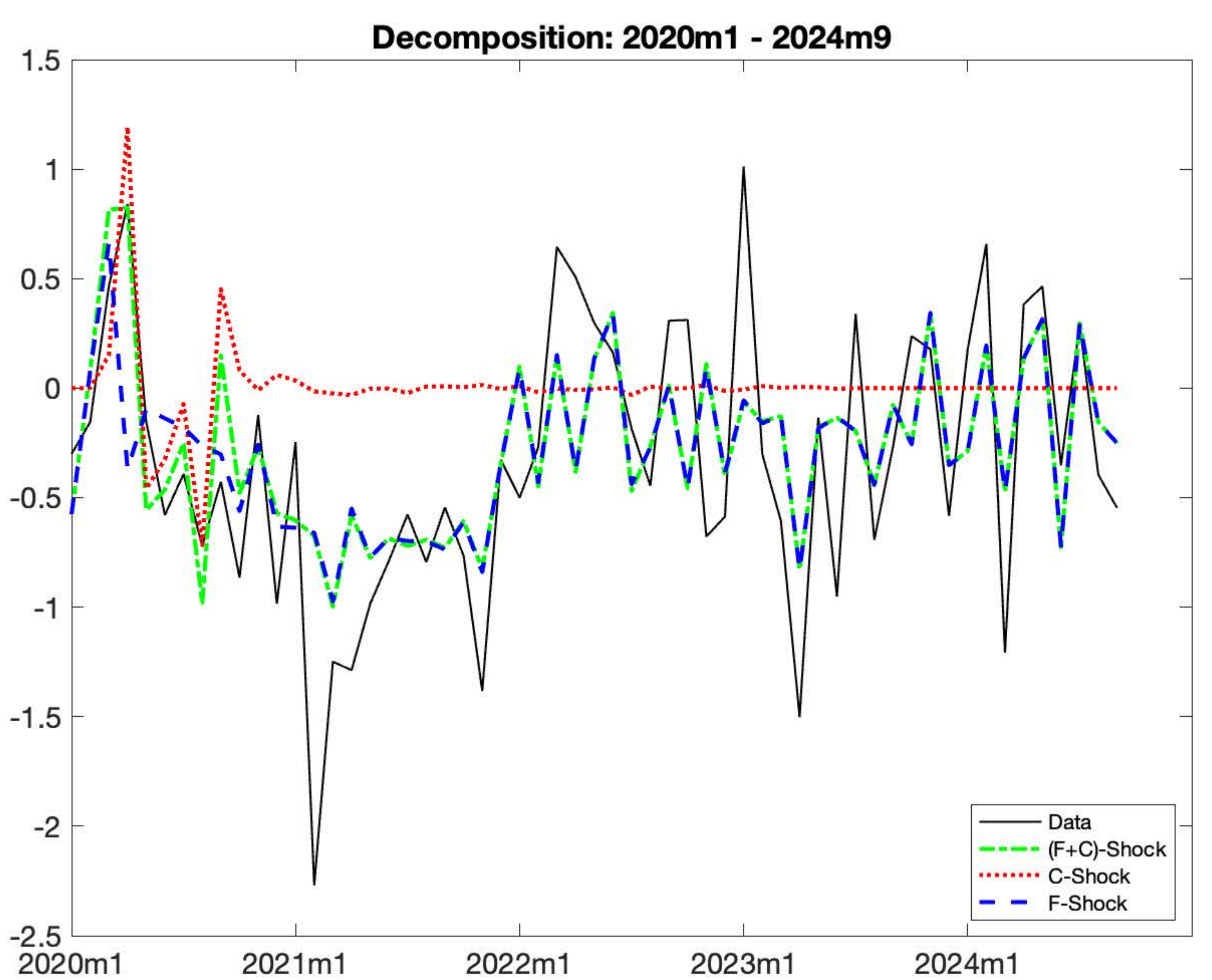
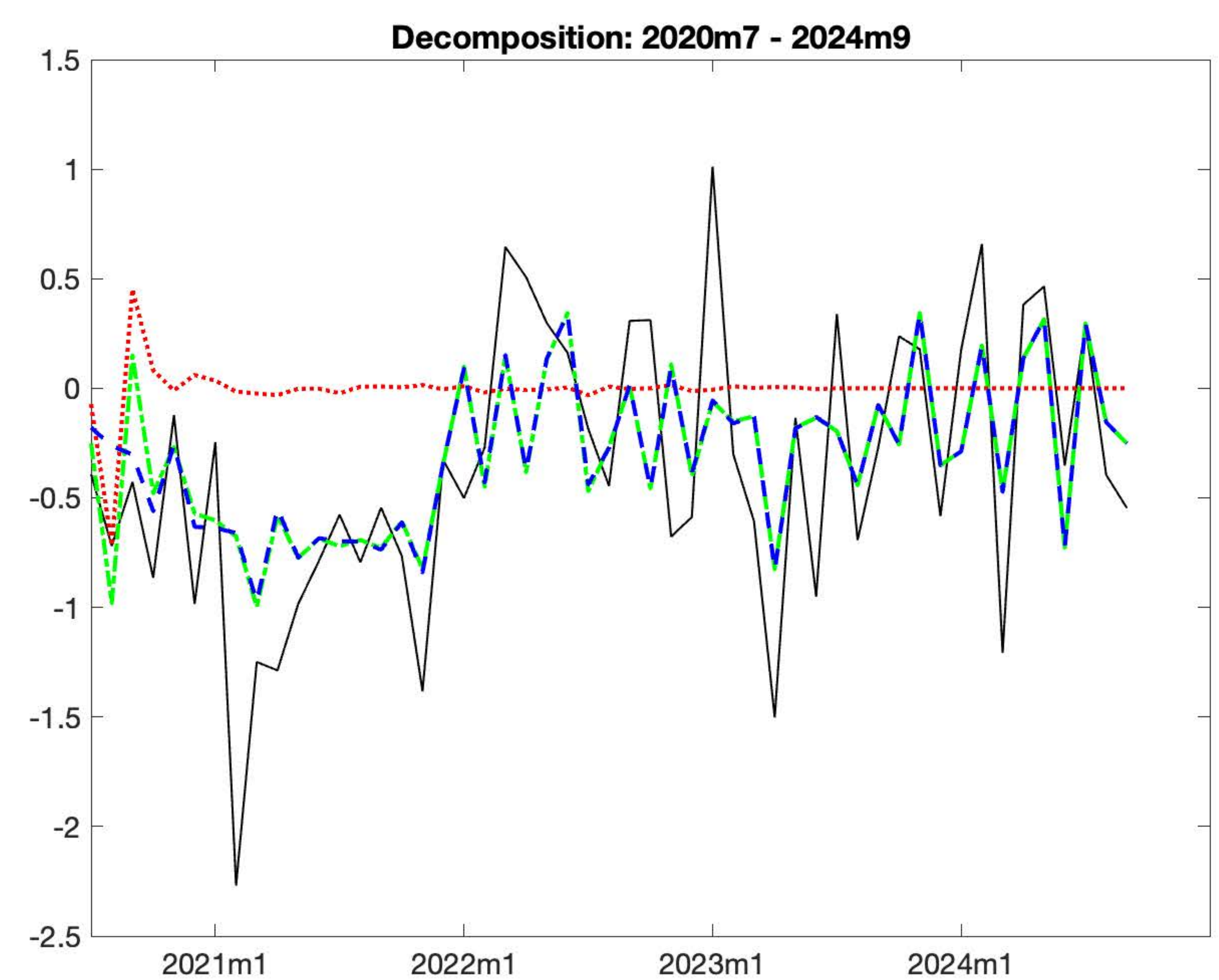
2010
2015
2020
2025



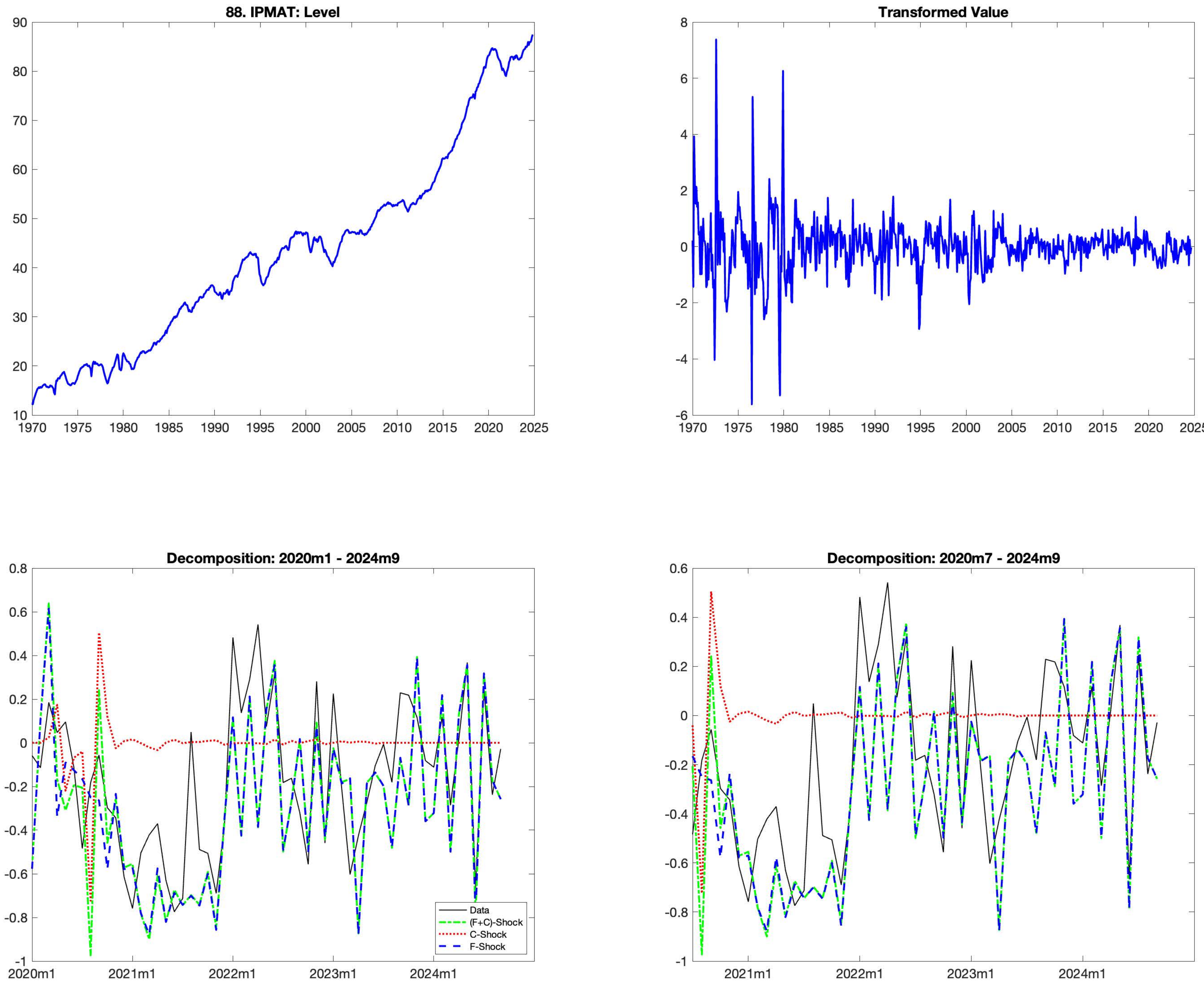
Transformed Value
4
3
2
1
0
-1
-2
-3
-4
1970
1975
1980
1985
1990
1995
2000
2005
2010
2015
2020
2025



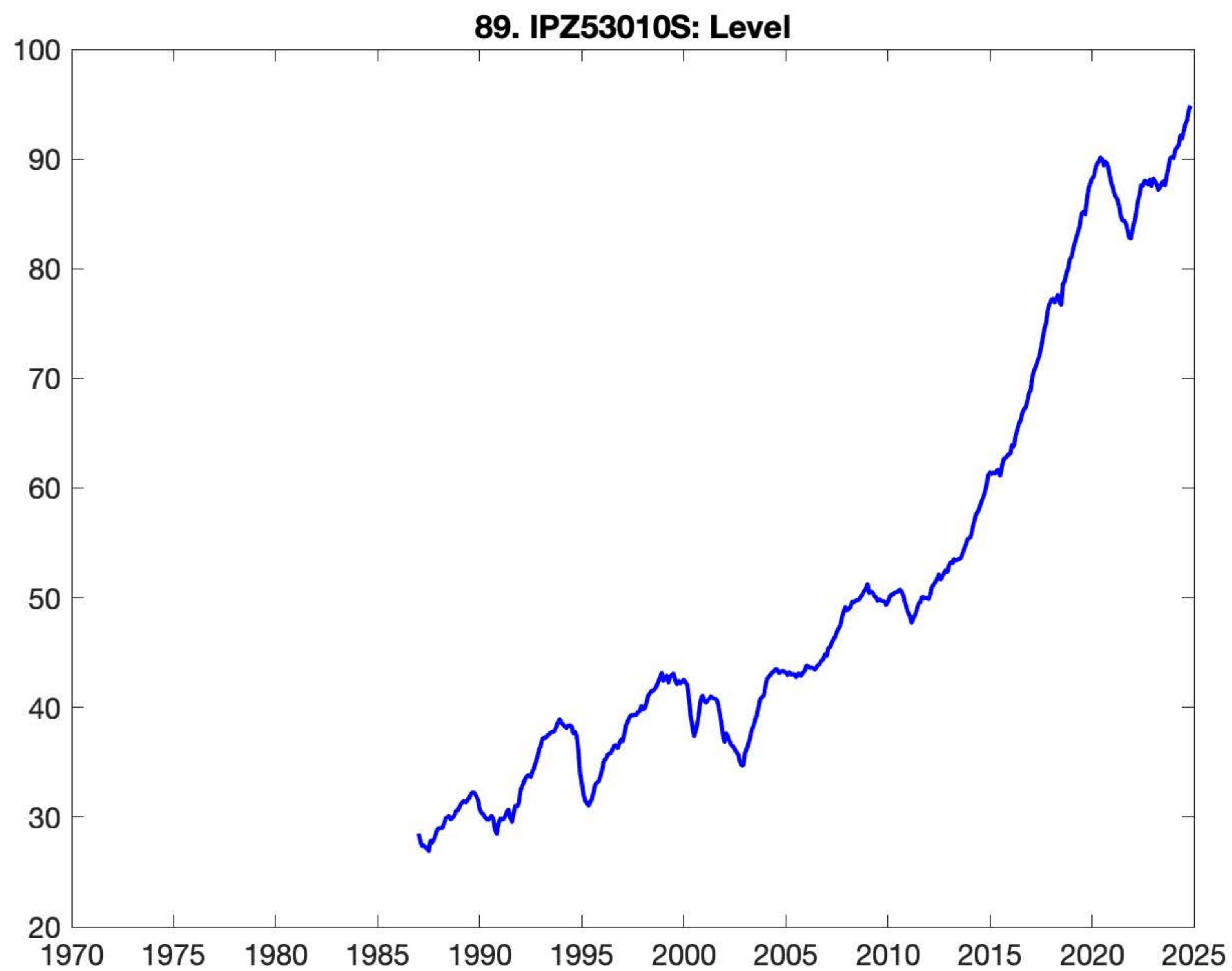
Decomposition: 2020m1 - 2024m9
1.5
1
0.5
0
-0.5
-1
-1.5
-2
-2.5
2020m1
2021m1
2022m1
2023m1
2024m1
Data
(F+C)-Shock
C-Shock
F-Shock

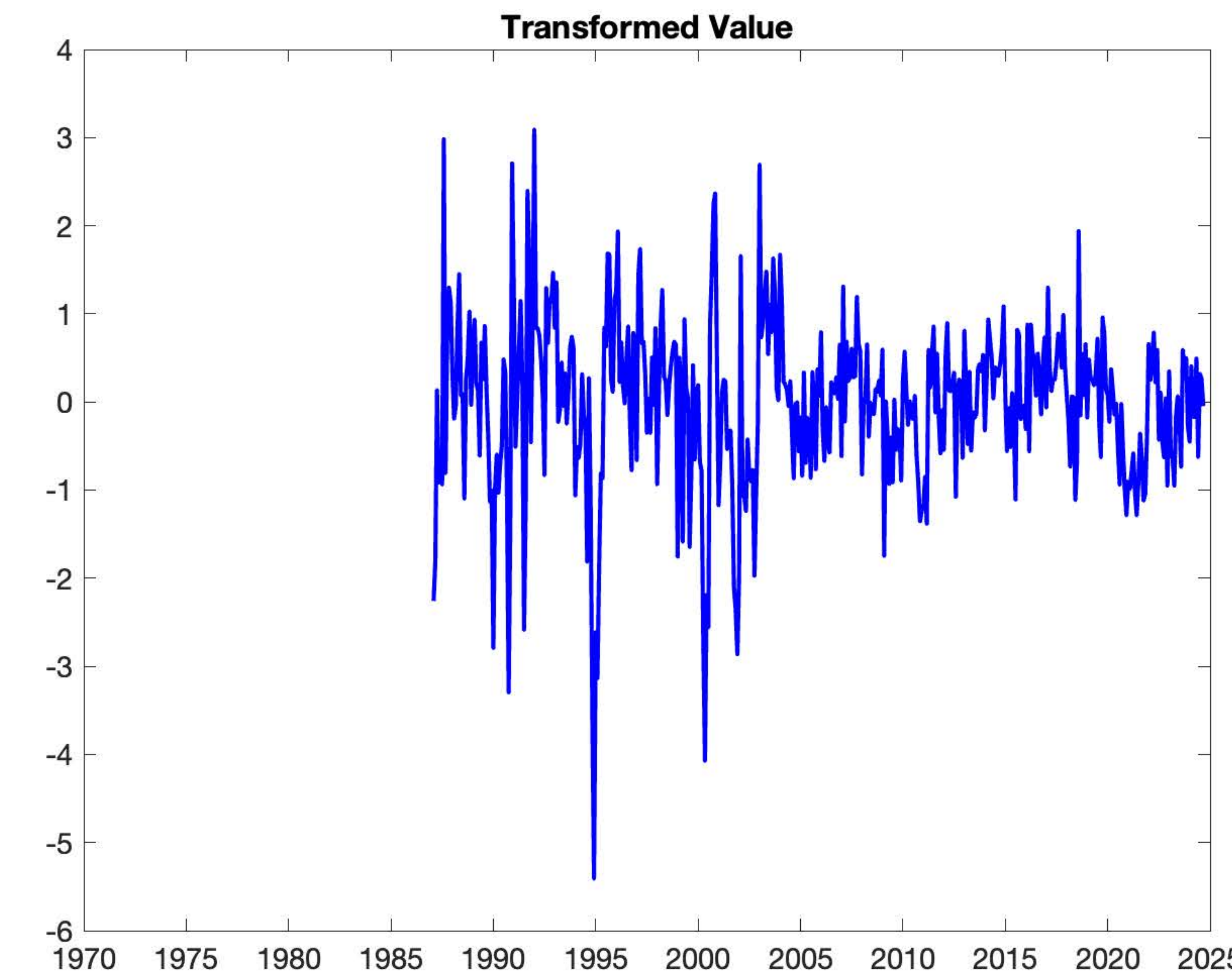


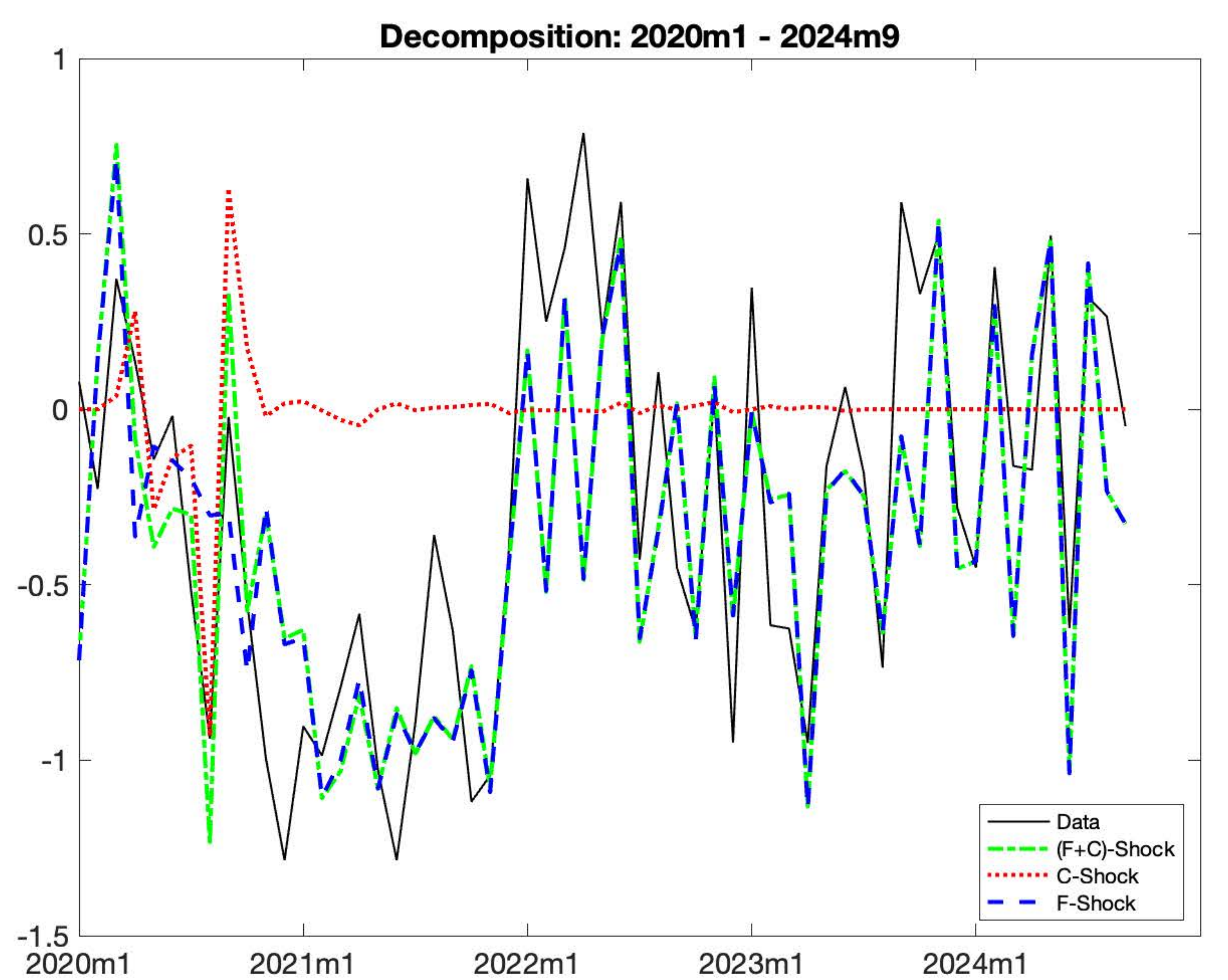
Decomposition: 2020m7 - 2024m9
1.5
1
0.5
0
-0.5
-1
-1.5
-2
-2.5
2021m1
2022m1
2023m1
2024m1

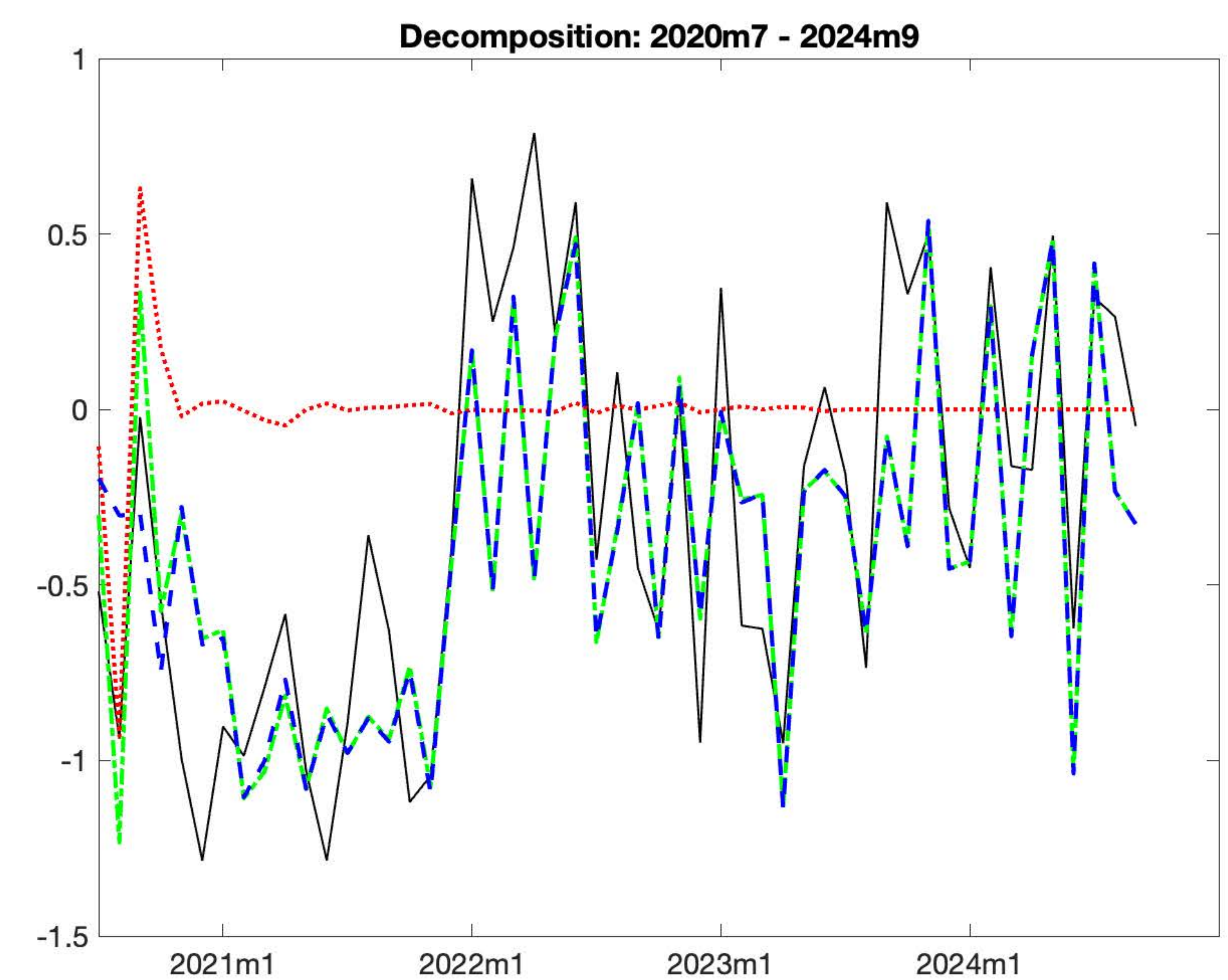


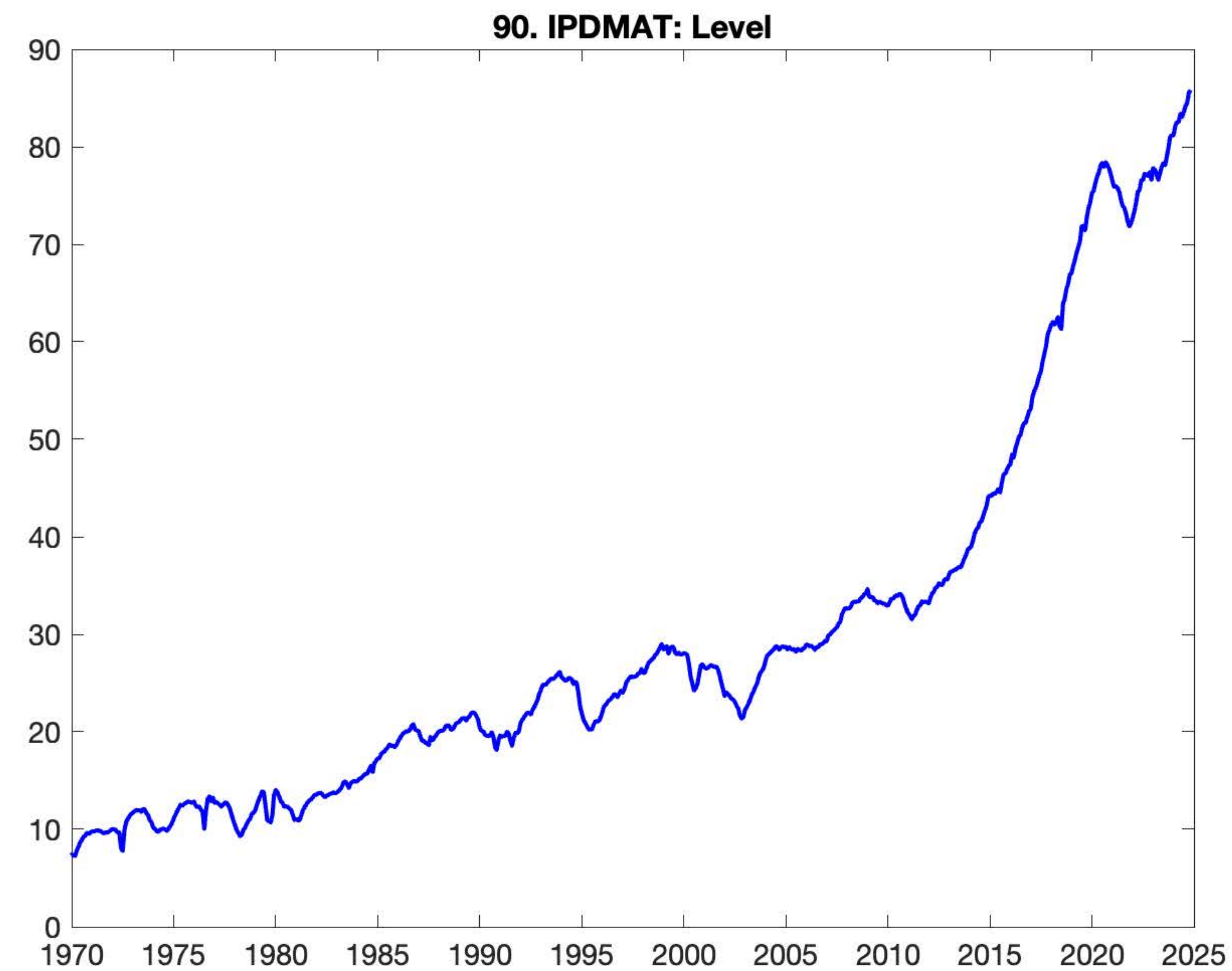
88. IPMAT: Level
Transformed Value
Decomposition: 2020m1 - 2024m9
Decomposition: 2020m7 - 2024m9
Data
(F+C)-Shock
C-Shock
F-Shock

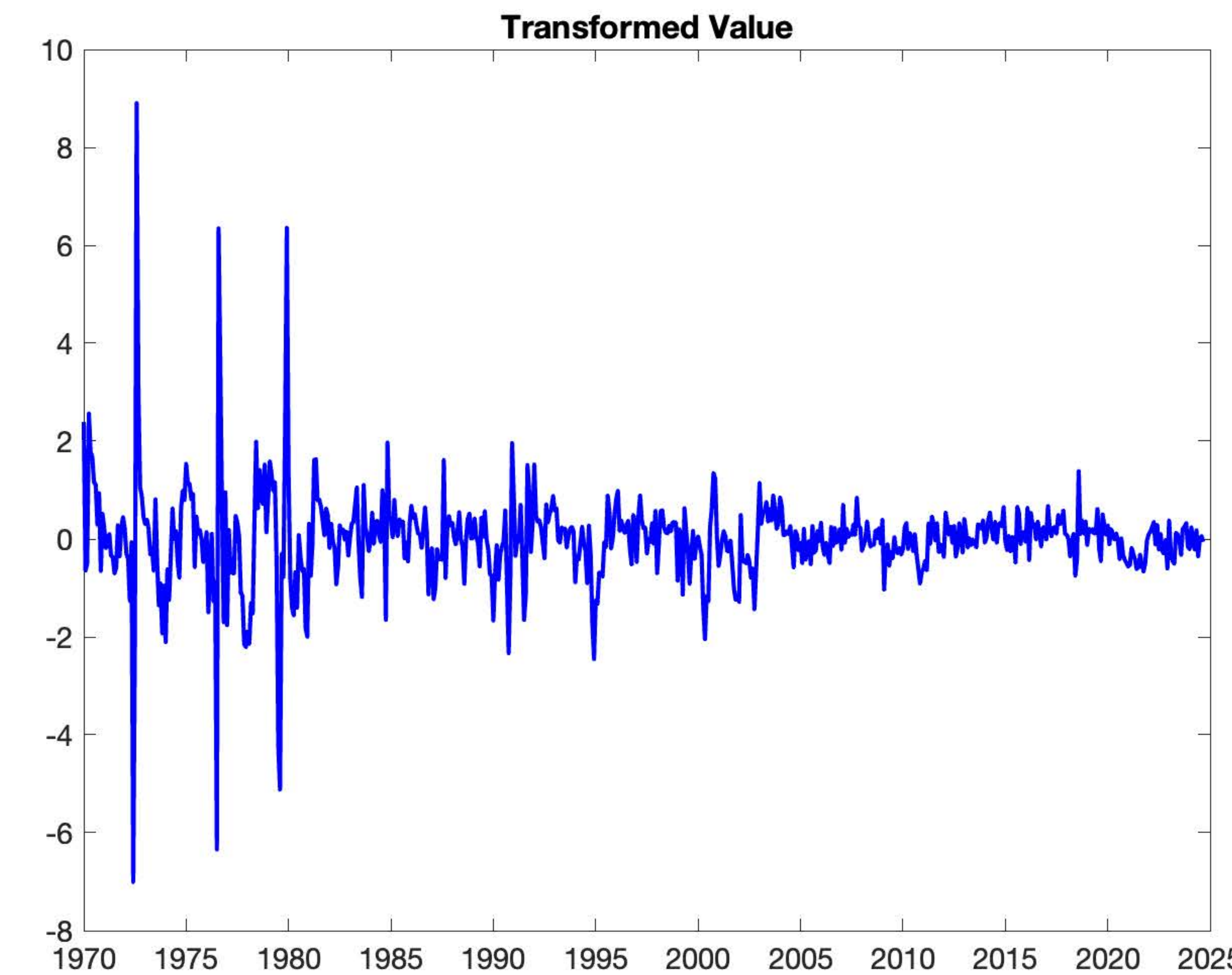

89. IPZ53010S: Level
100
90
80
70
60
50
40
30
20
1970
1975
1980
1985
1990
1995
2000
2005
2010
2015
2020
2025

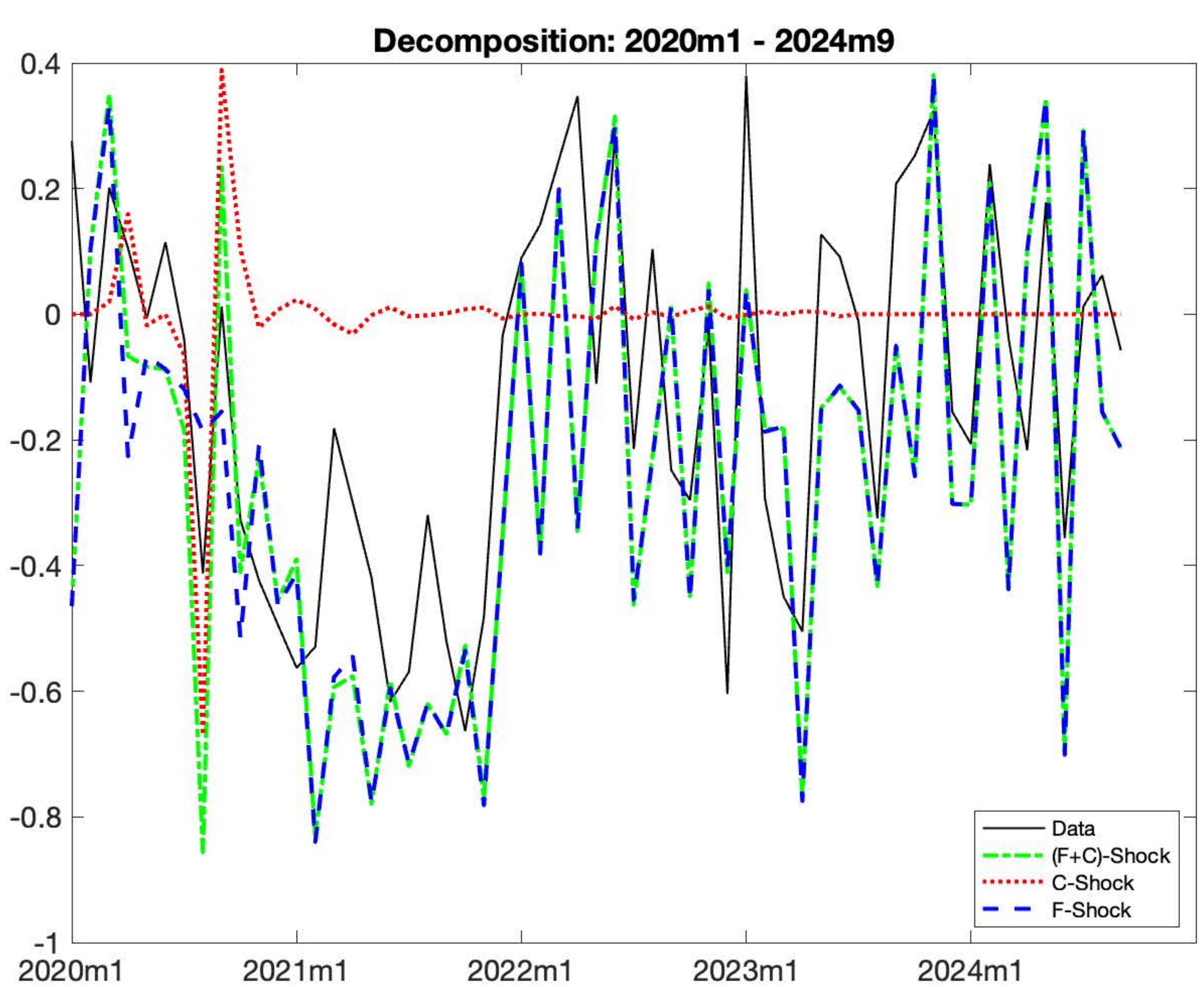

Transformed Value
4
3
2
1
0
-1
-2
-3
-4
-5
-6
1970
1975
1980
1985
1990
1995
2000
2005
2010
2015
2020
2025

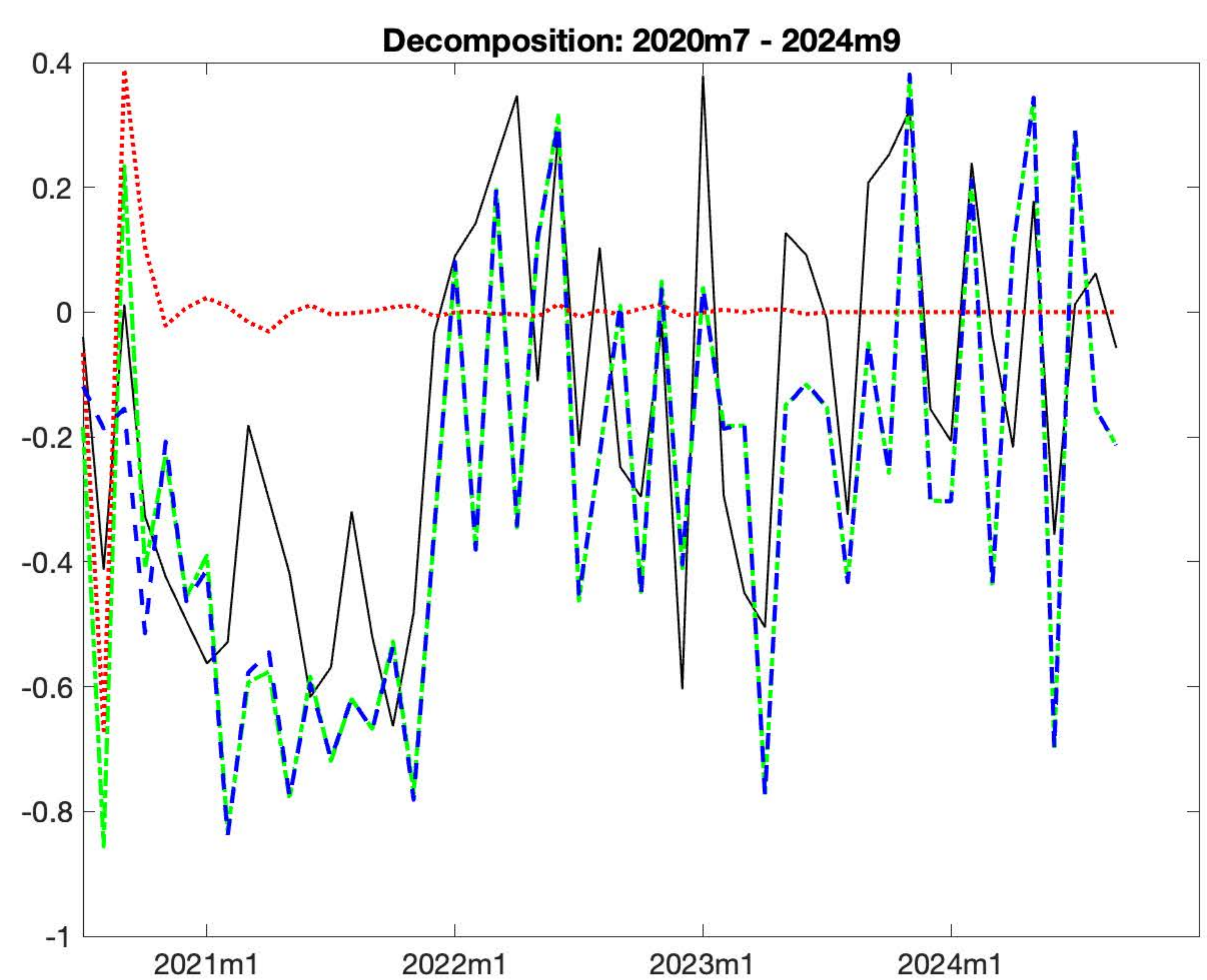

Decomposition: 2020m1 - 2024m9
1
0.5
0
-0.5
-1
-1.5
2020m1
2021m1
2022m1
2023m1
2024m1
Data
(F+C)-Shock
C-Shock
F-Shock

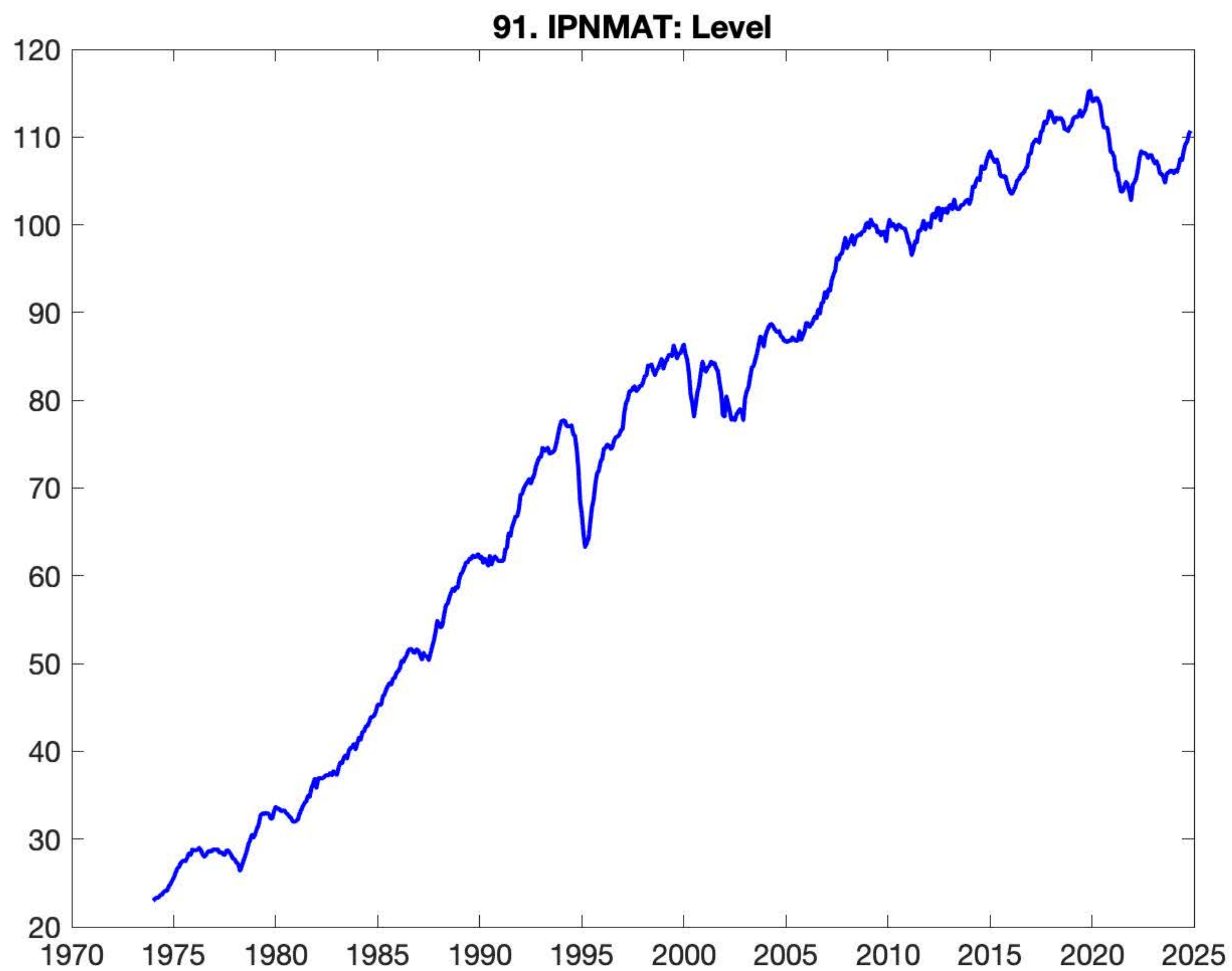

Decomposition: 2020m7 - 2024m9
1
0.5
0
-0.5
-1
-1.5
2021m1
2022m1
2023m1
2024m1

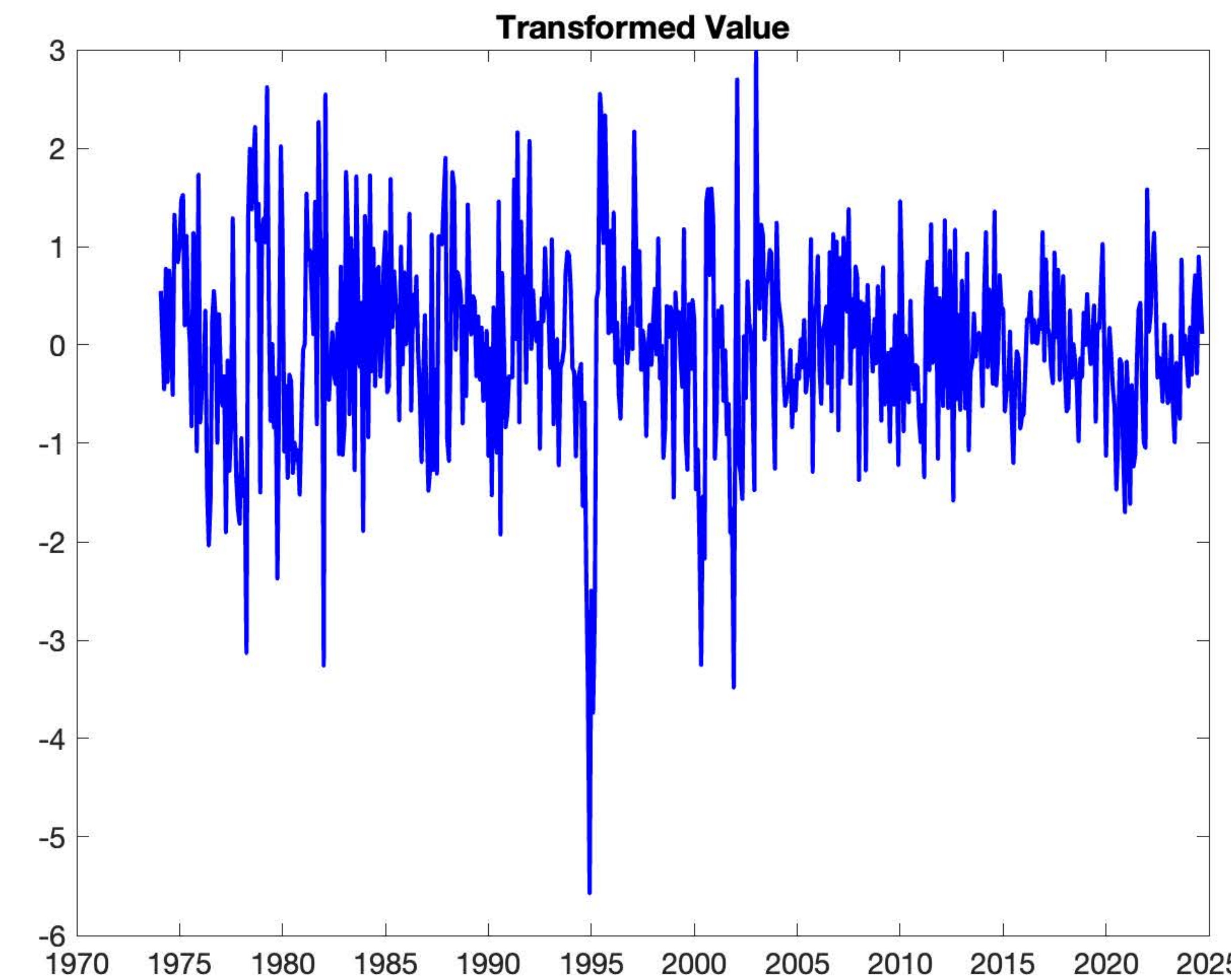

90. IPDMAT: Level
90
80
70
60
50
40
30
20
10
0
1970
1975
1980
1985
1990
1995
2000
2005
2010
2015
2020
2025

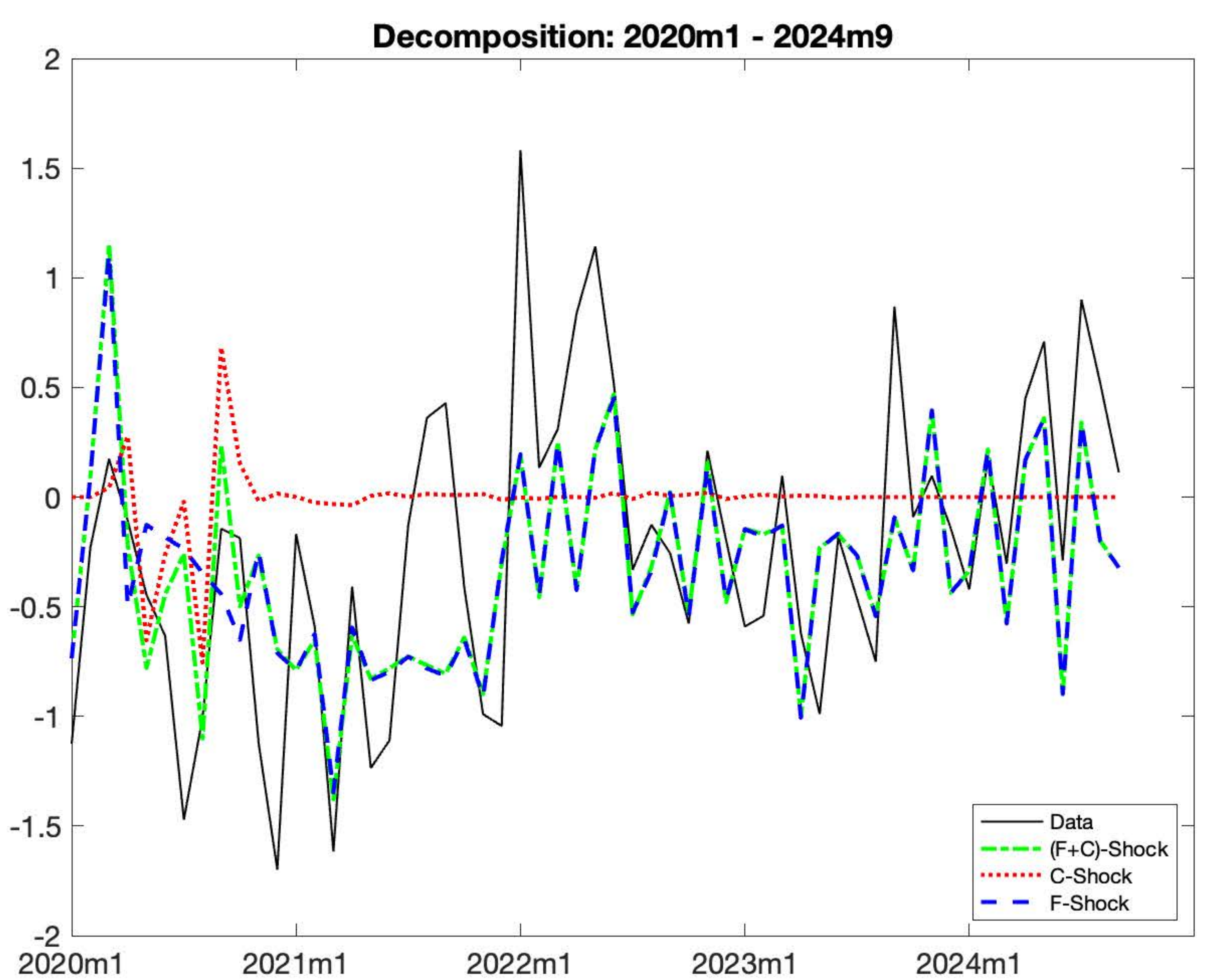

Transformed Value
10
8
6
4
2
0
-2
-4
-6
-8
1970
1975
1980
1985
1990
1995
2000
2005
2010
2015
2020
2025

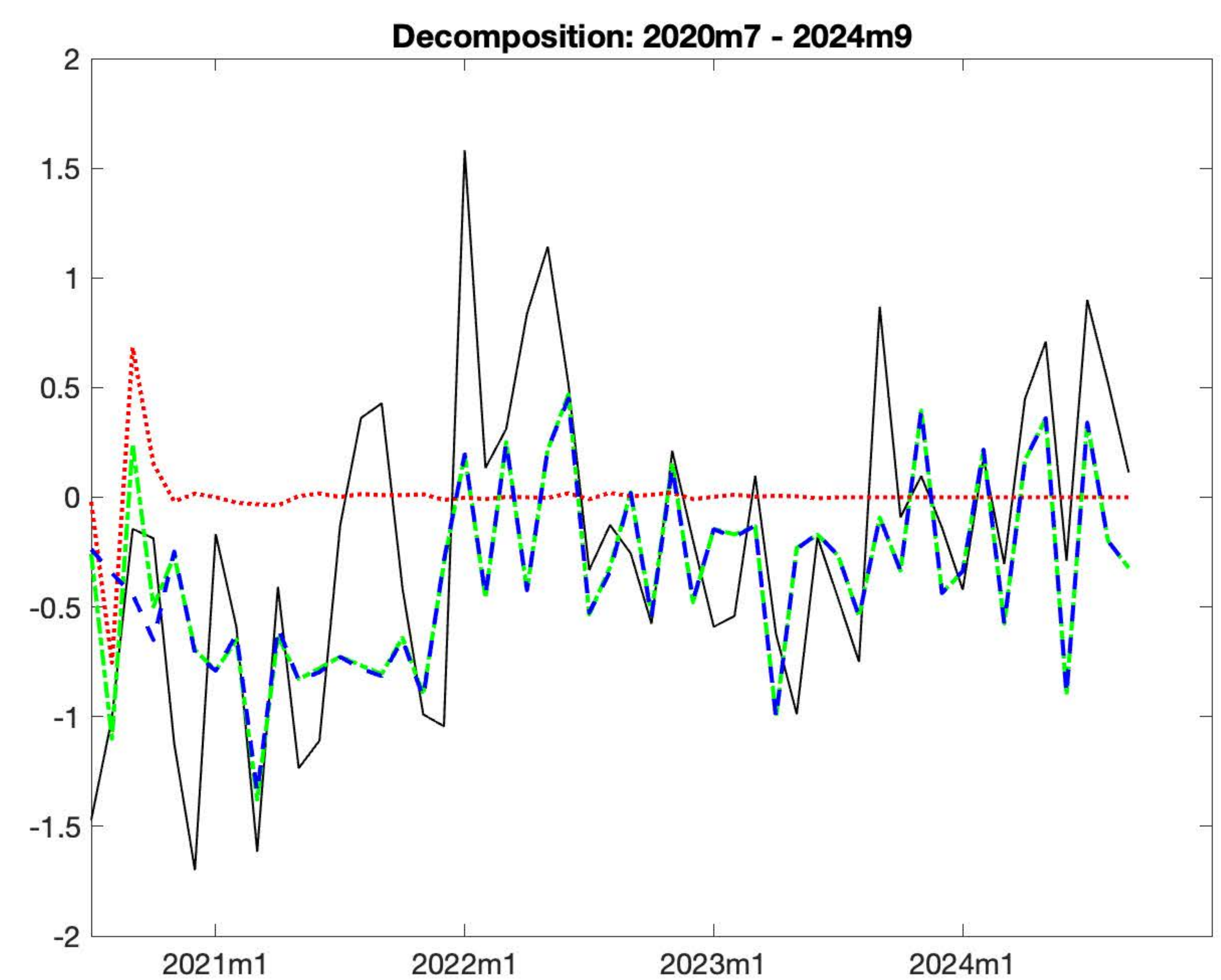

Decomposition: 2020m1 - 2024m9
0.4
0.2
0
-0.2
-0.4
-0.6
-0.8
-1
2020m1
2021m1
2022m1
2023m1
2024m1
Data
(F+C)-Shock
C-Shock
F-Shock

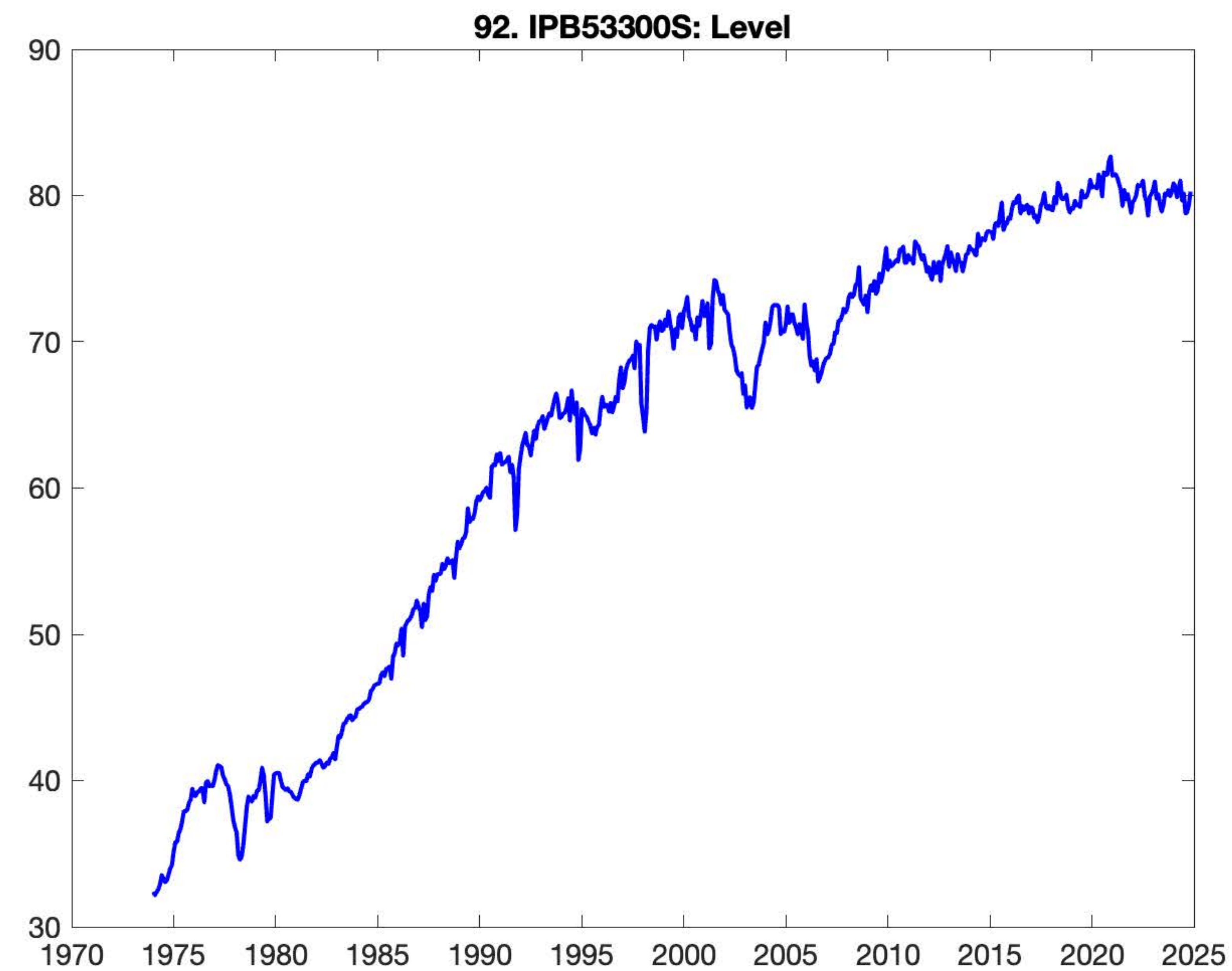

Decomposition: 2020m7 - 2024m9
0.4
0.2
0
-0.2
-0.4
-0.6
-0.8
-1
2021m1
2022m1
2023m1
2024m1

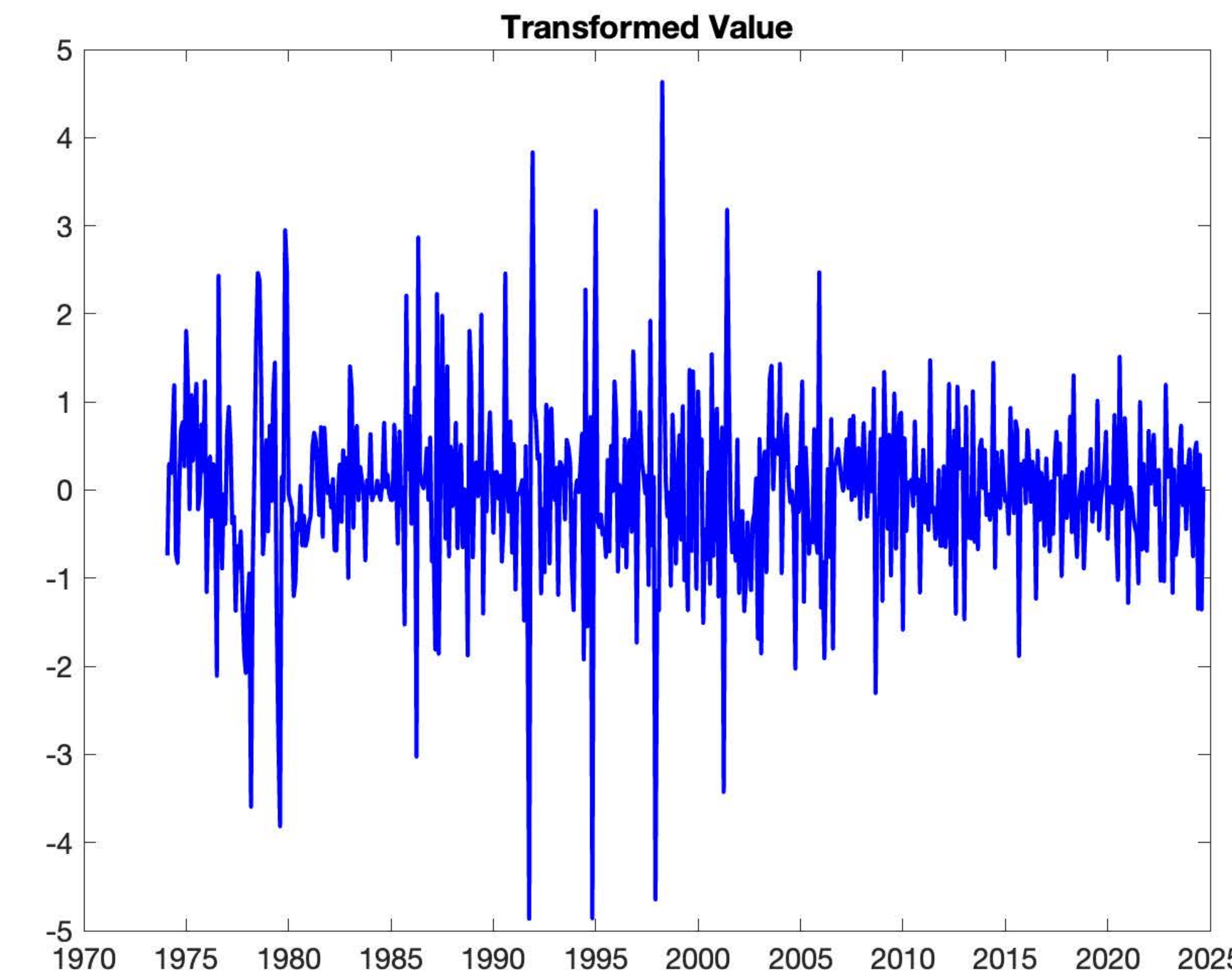

91. IPNMAT: Level
120
110
100
90
80
70
60
50
40
30
20
1970 1975 1980 1985 1990 1995 2000 2005 2010 2015 2020 2025

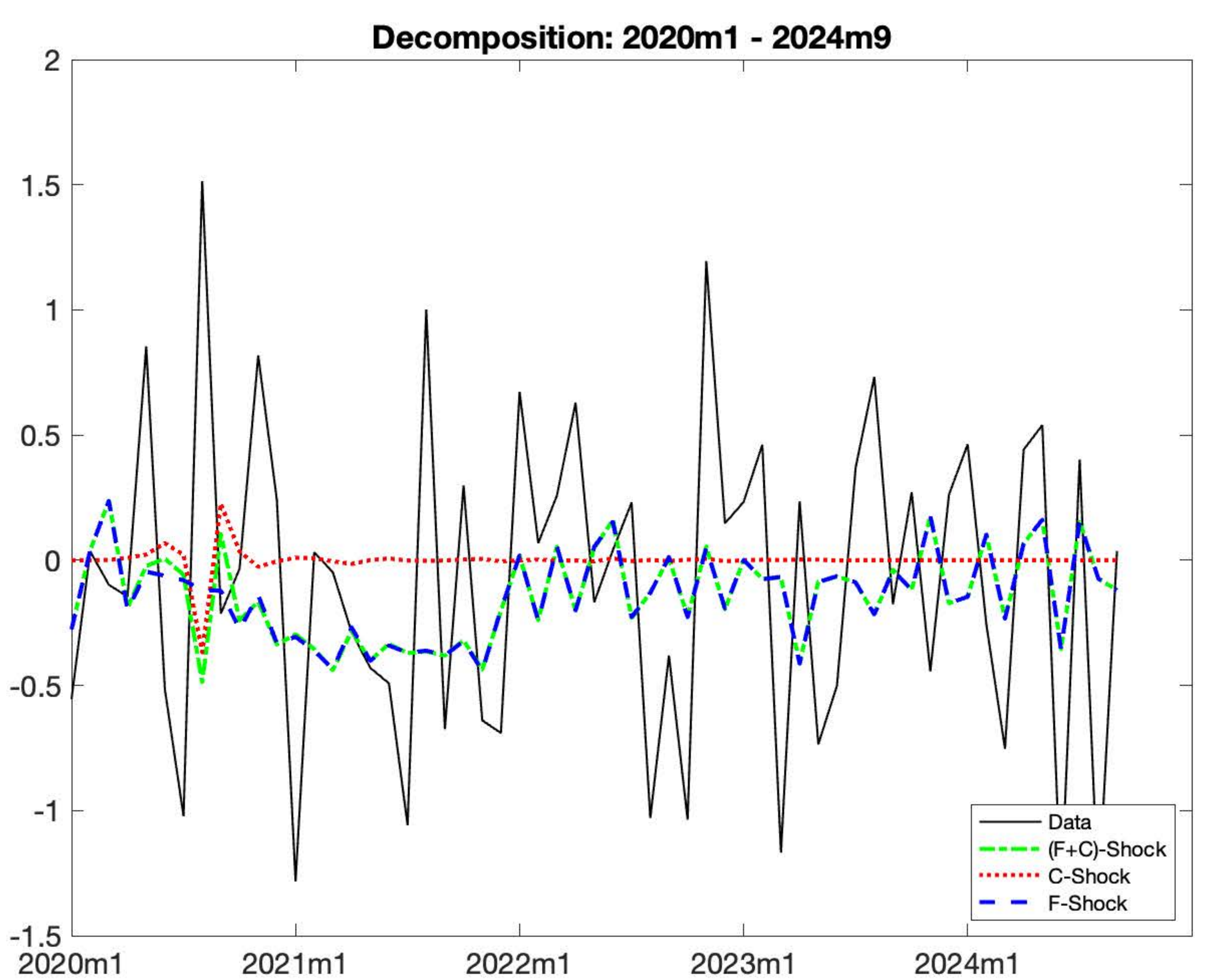

Transformed Value
3
2
1
0
-1
-2
-3
-4
-5
-6
1970 1975 1980 1985 1990 1995 2000 2005 2010 2015 2020 2025

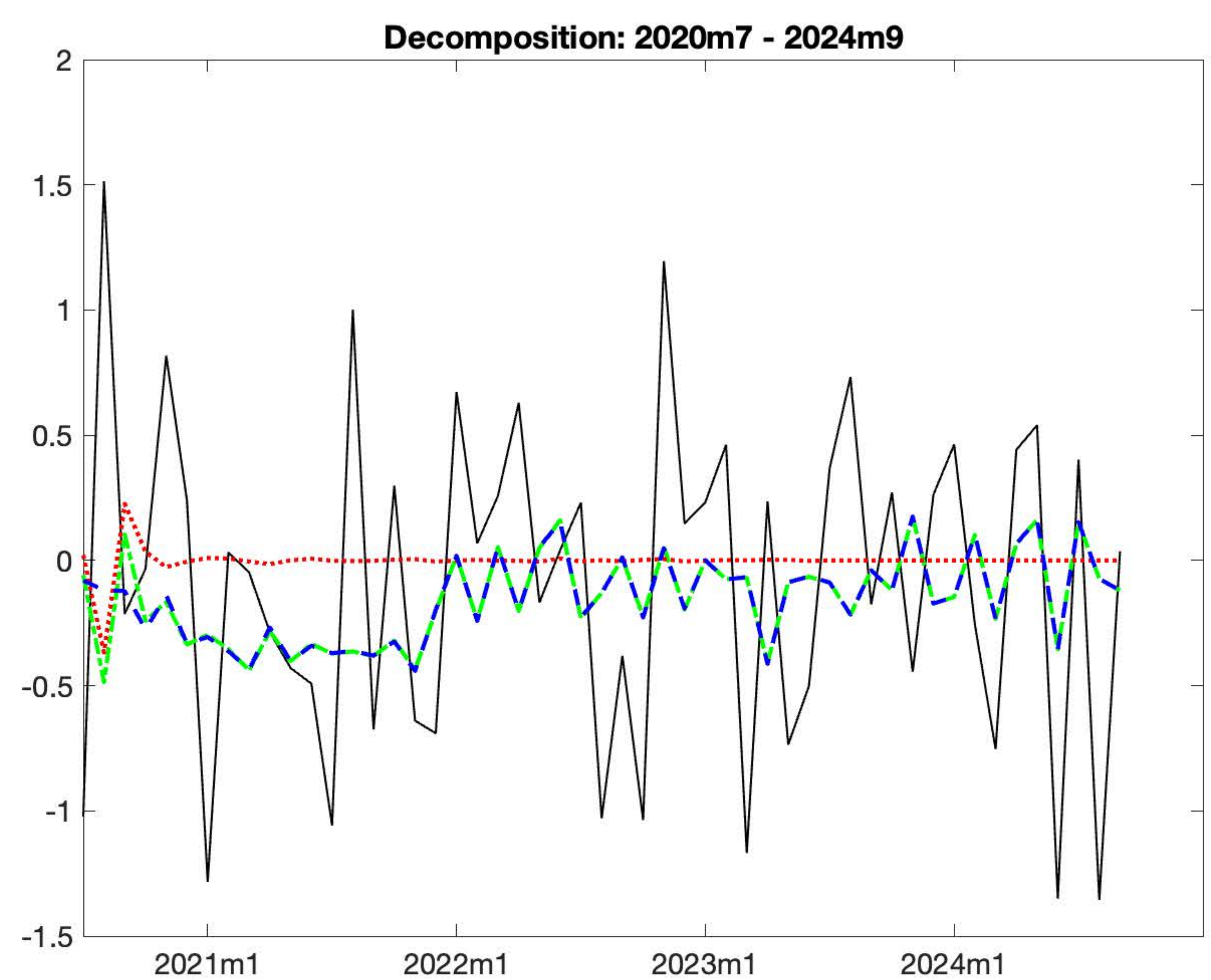

Decomposition: 2020m1 - 2024m9
2
1.5
1
0.5
0
-0.5
-1
-1.5
-2
2020m1 2021m1 2022m1 2023m1 2024m1
Data
(F+C)-Shock
C-Shock
F-Shock

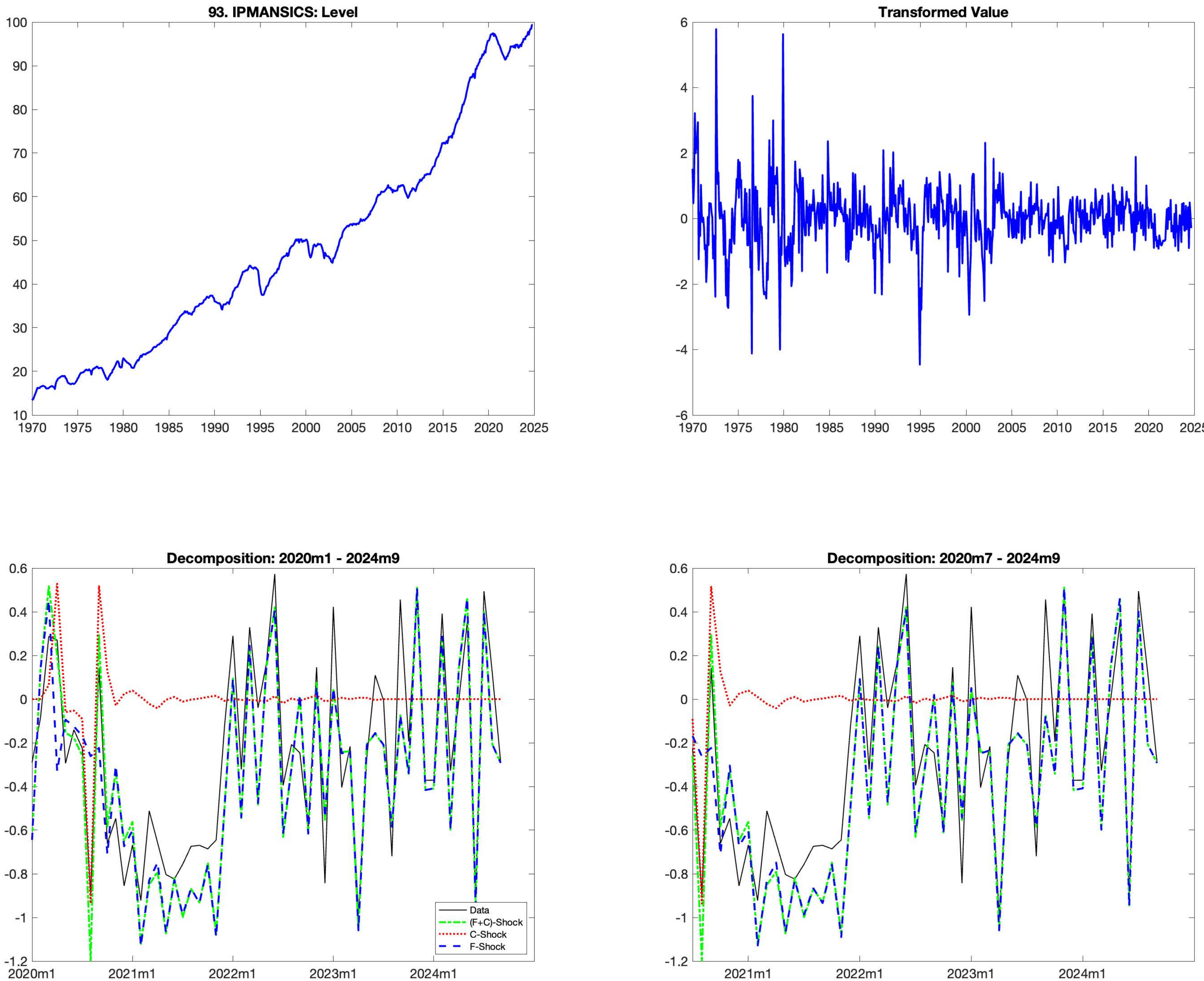

Decomposition: 2020m7 - 2024m9
2
1.5
1
0.5
0
-0.5
-1
-1.5
-2
2021m1 2022m1 2023m1 2024m1

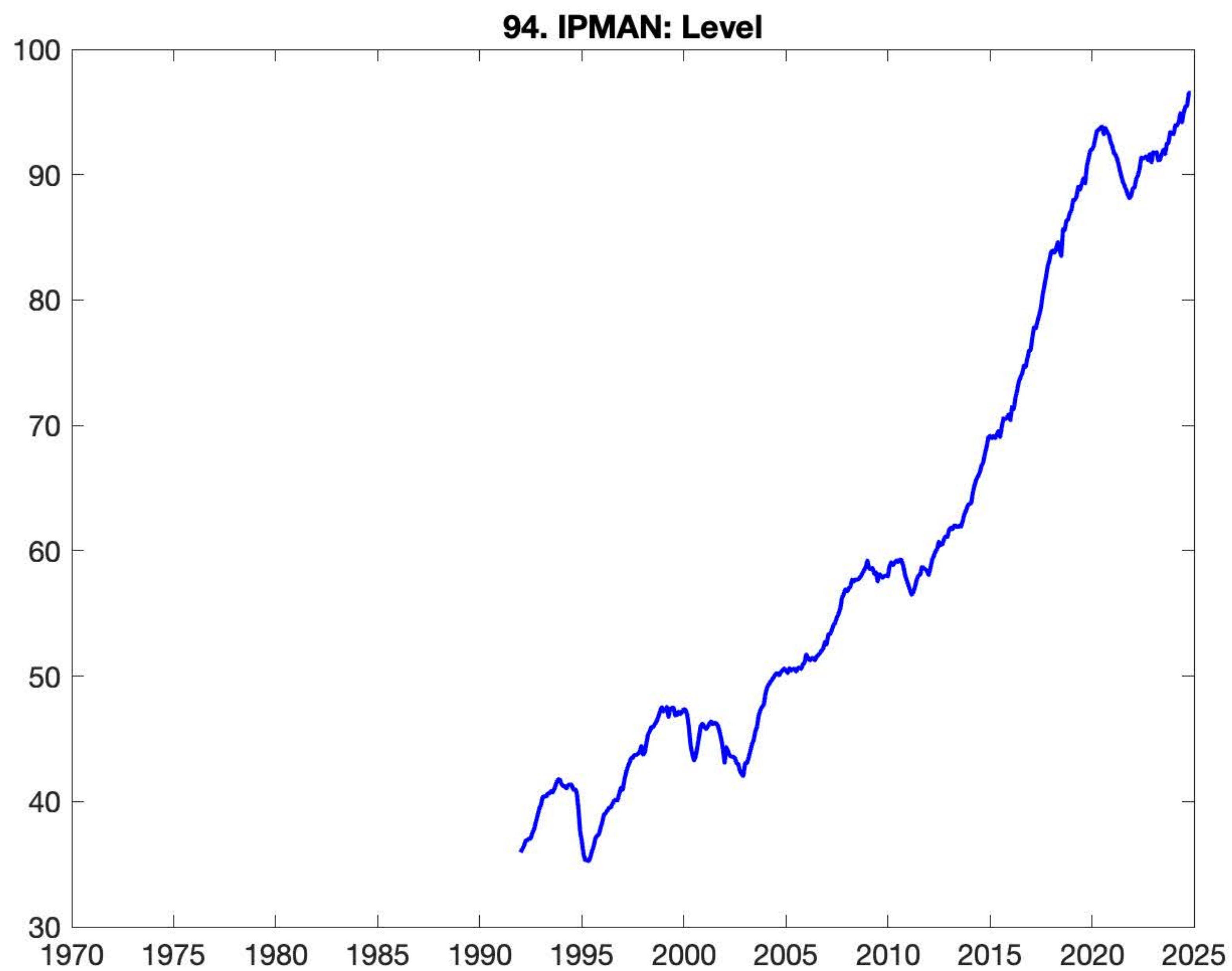

92. IPB53300S: Level
90
80
70
60
50
40
30
1970
1975
1980
1985
1990
1995
2000
2005
2010
2015
2020
2025

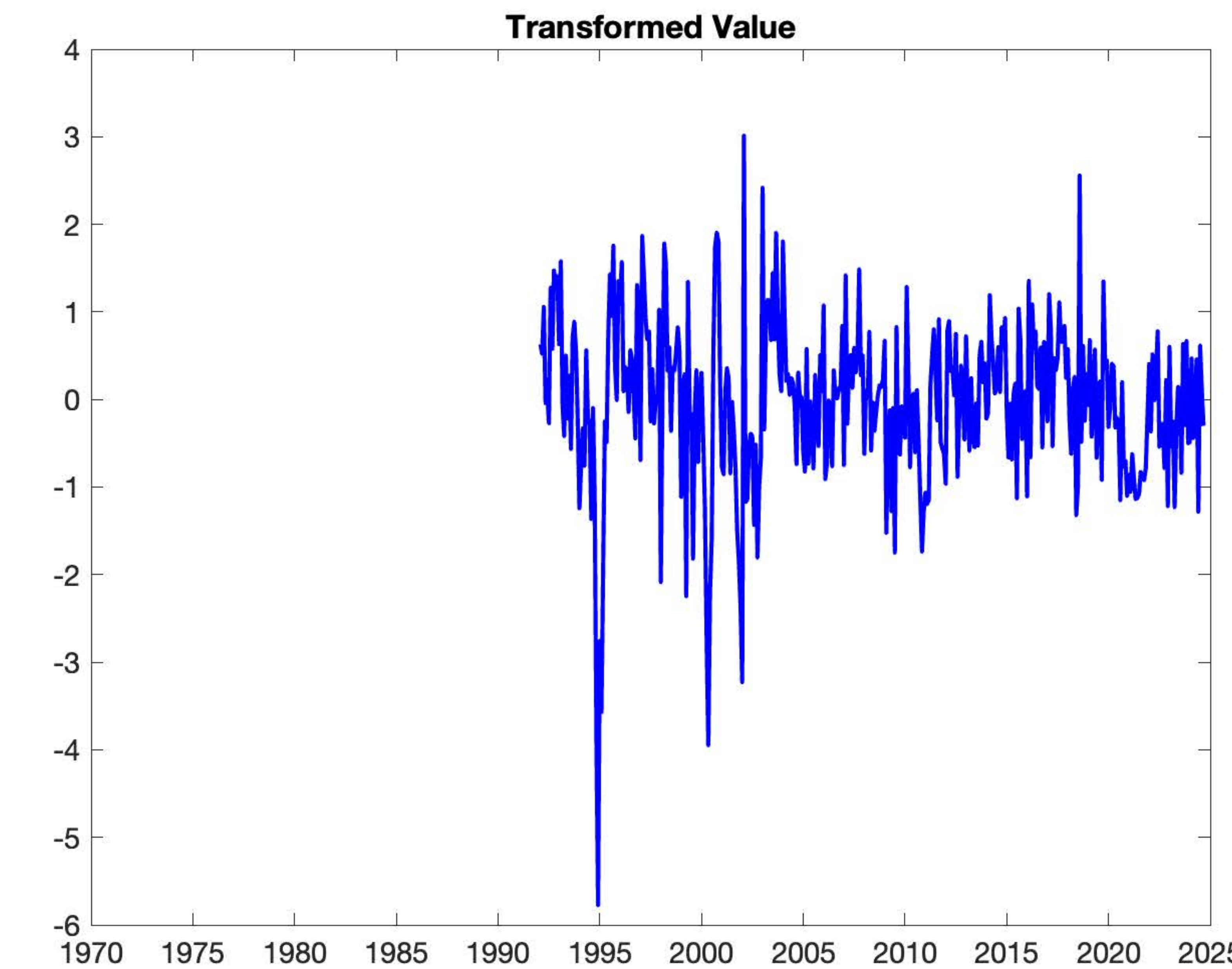

Transformed Value
5
4
3
2
1
0
-1
-2
-3
-4
-5
1970
1975
1980
1985
1990
1995
2000
2005
2010
2015
2020
2025

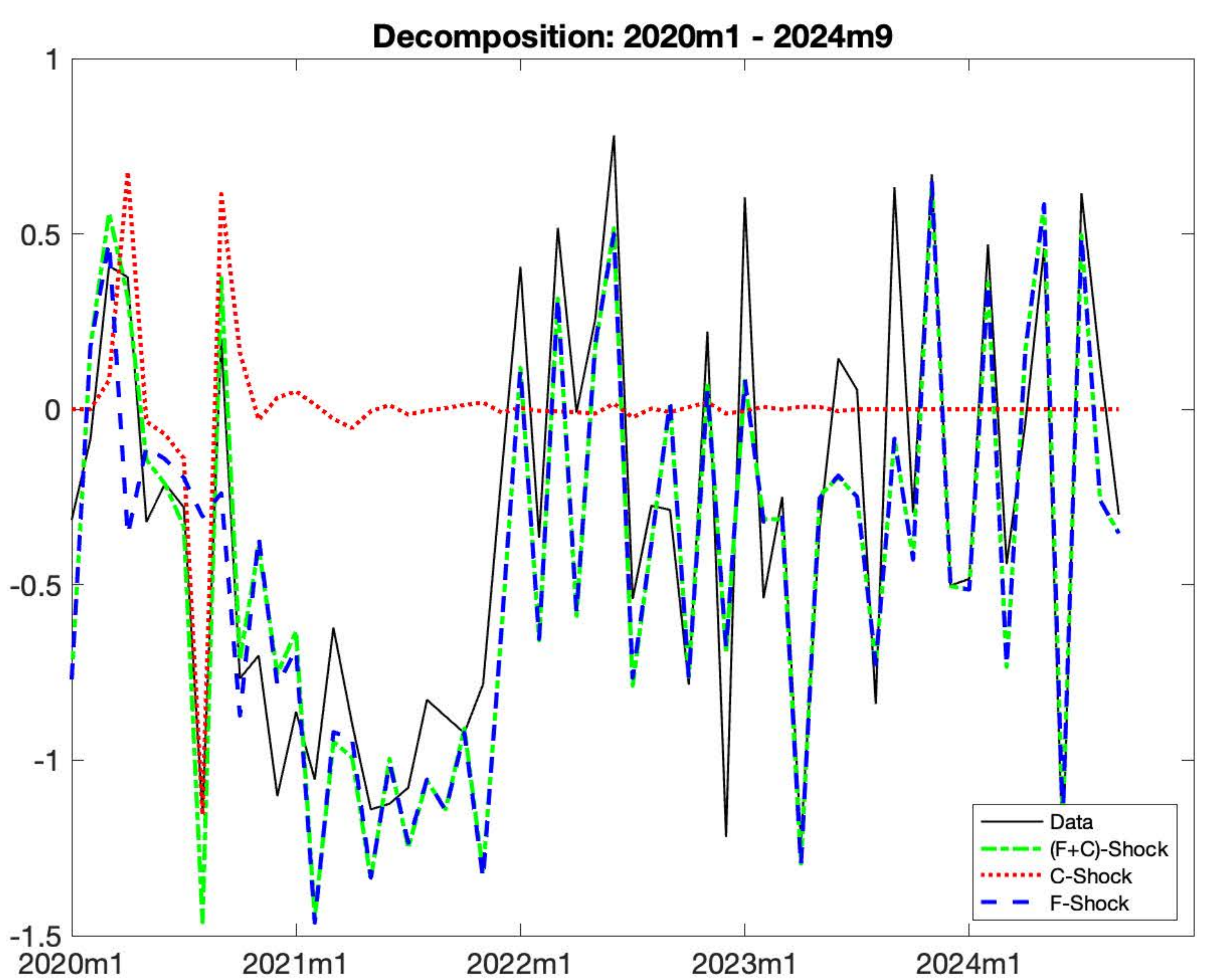

Decomposition: 2020m1 - 2024m9
2
1.5
1
0.5
0
-0.5
-1
-1.5
2020m1
2021m1
2022m1
2023m1
2024m1
Data
(F+C)-Shock
C-Shock
F-Shock

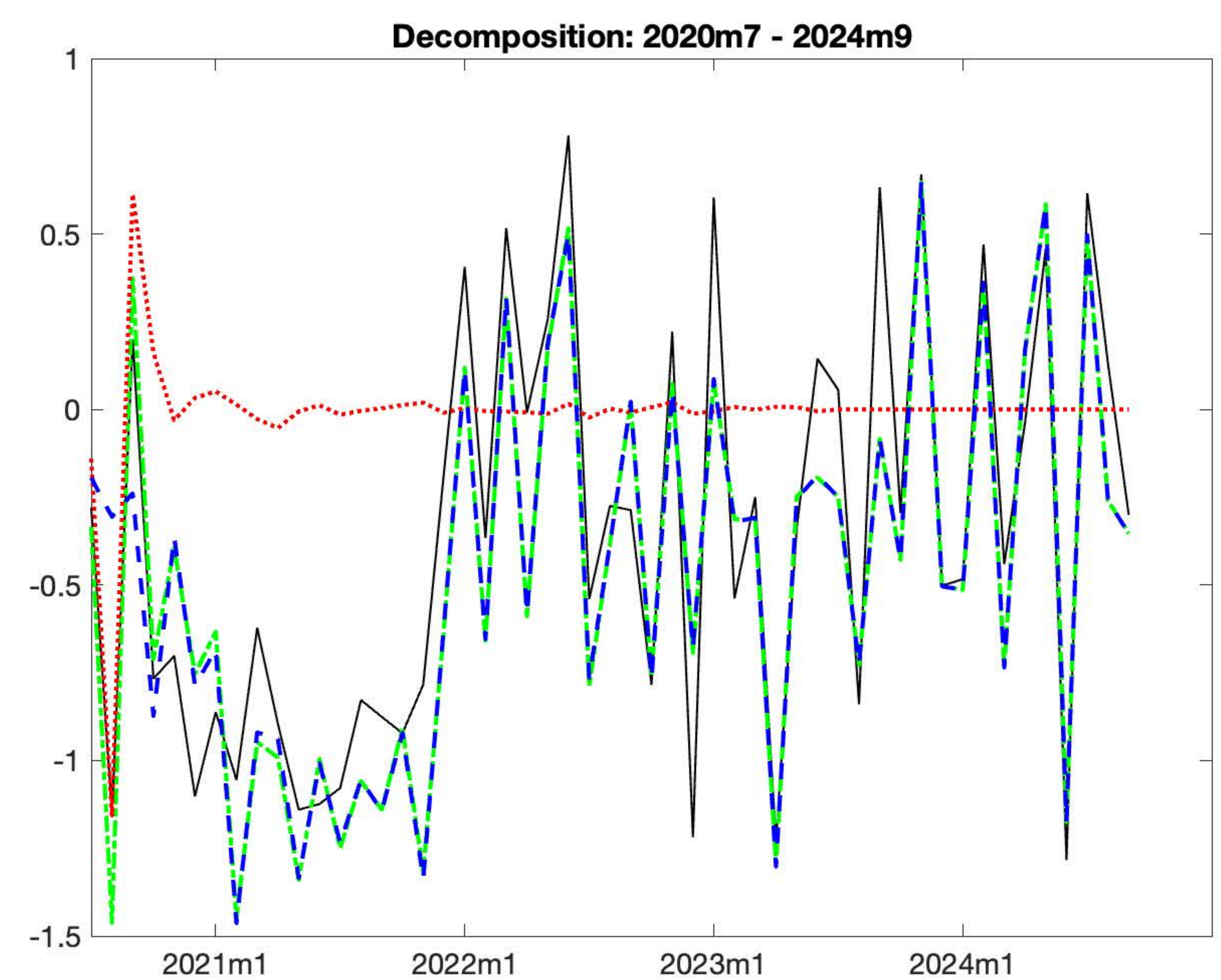

Decomposition: 2020m7 - 2024m9
2
1.5
1
0.5
0
-0.5
-1
-1.5
2021m1
2022m1
2023m1
2024m1

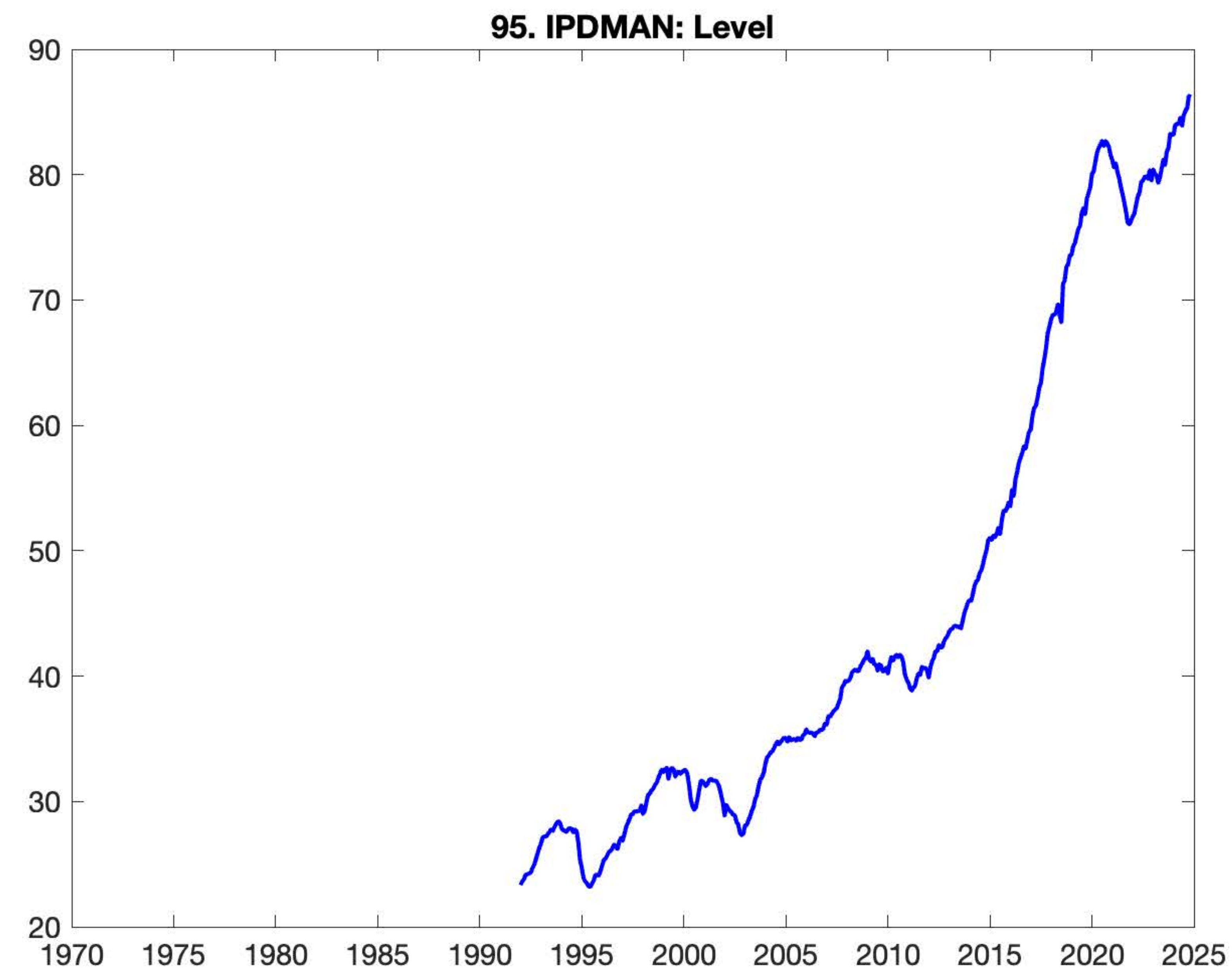

93. IPMANSICS: Level
Transformed Value
Decomposition: 2020m1 - 2024m9
Decomposition: 2020m7 - 2024m9
Data
(F+C)-Shock
C-Shock
F-Shock

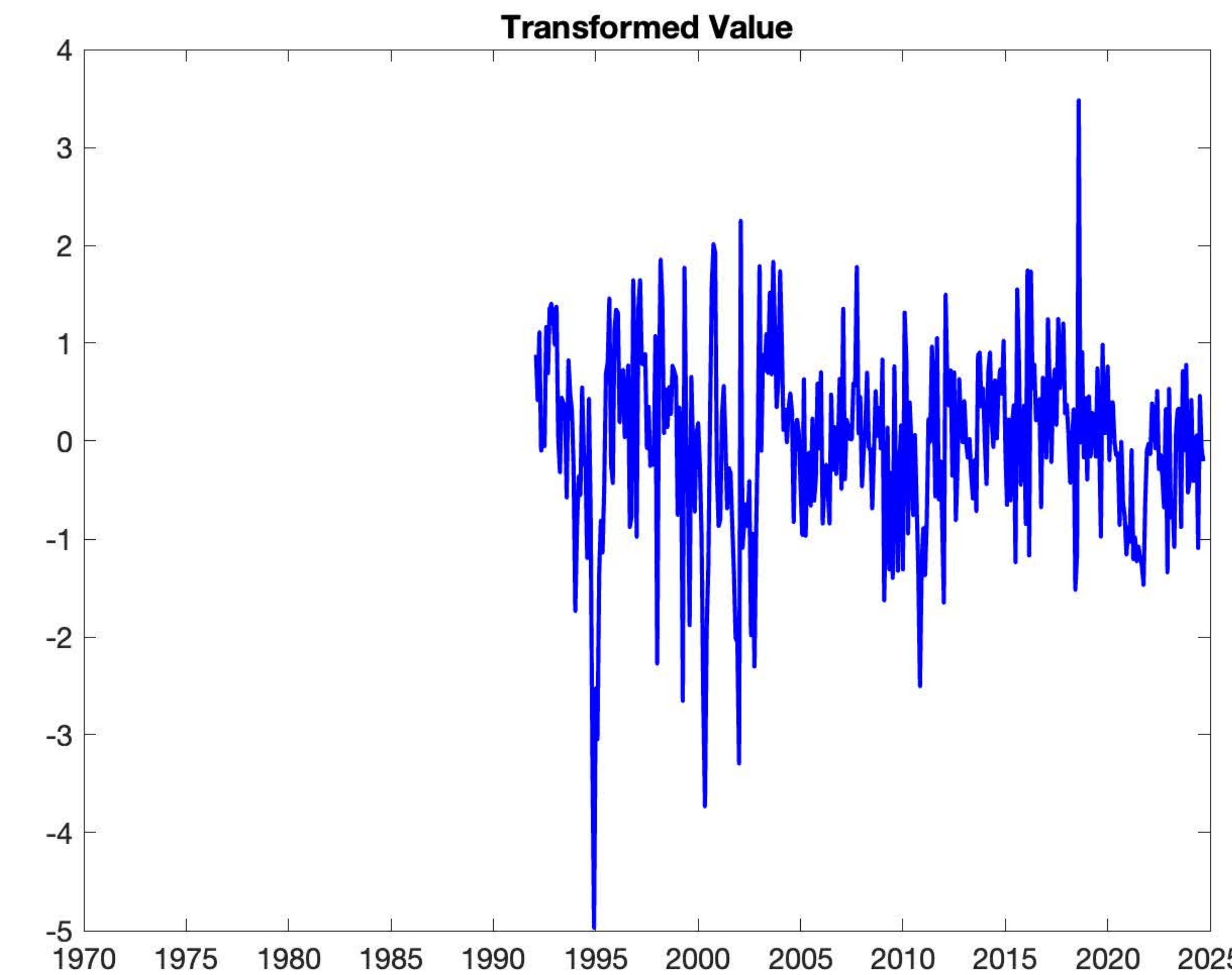

94. IPMAN: Level

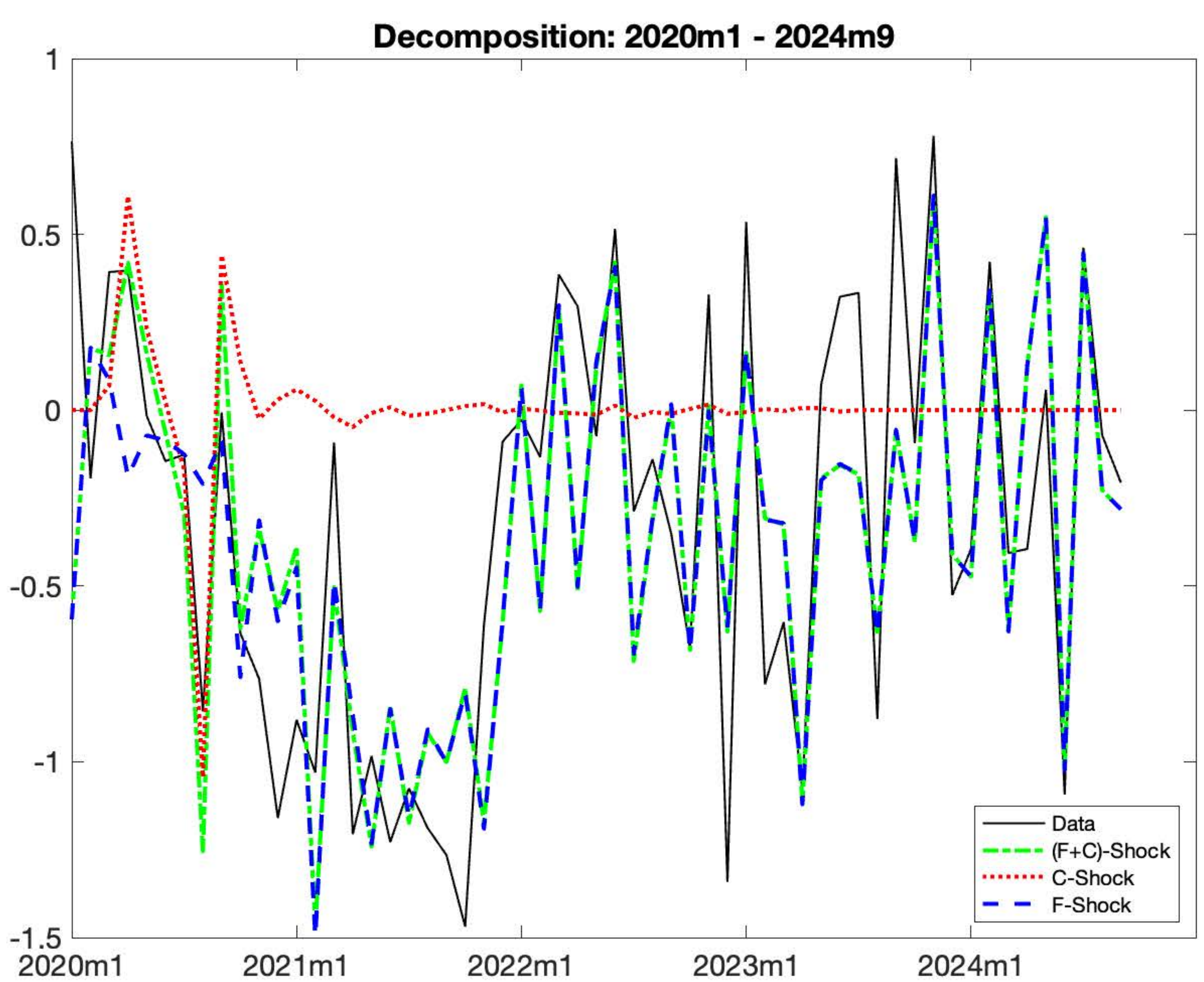

Transformed Value

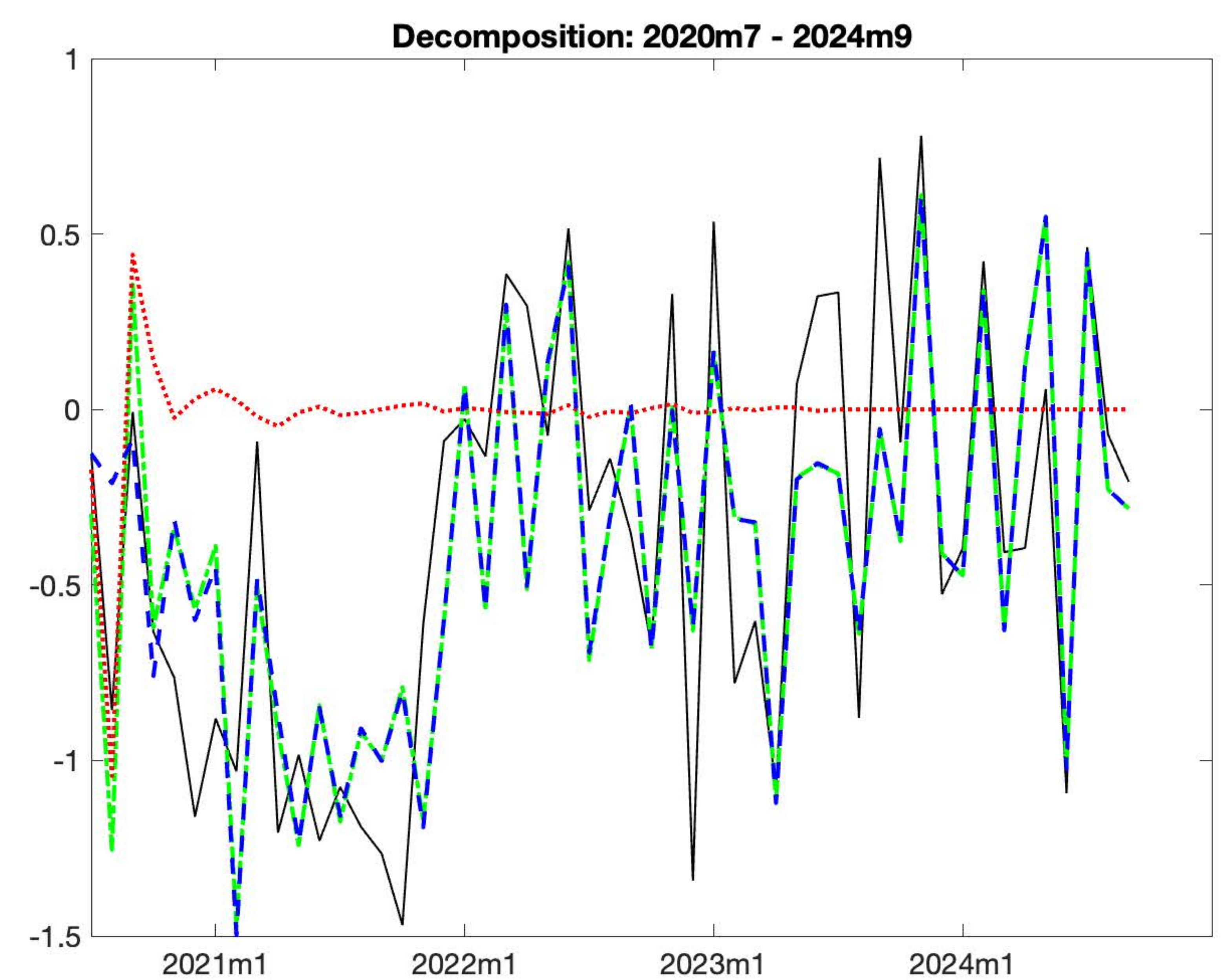

Decomposition: 2020m1 - 2024m9
Data
(F+C)-Shock
C-Shock
F-Shock

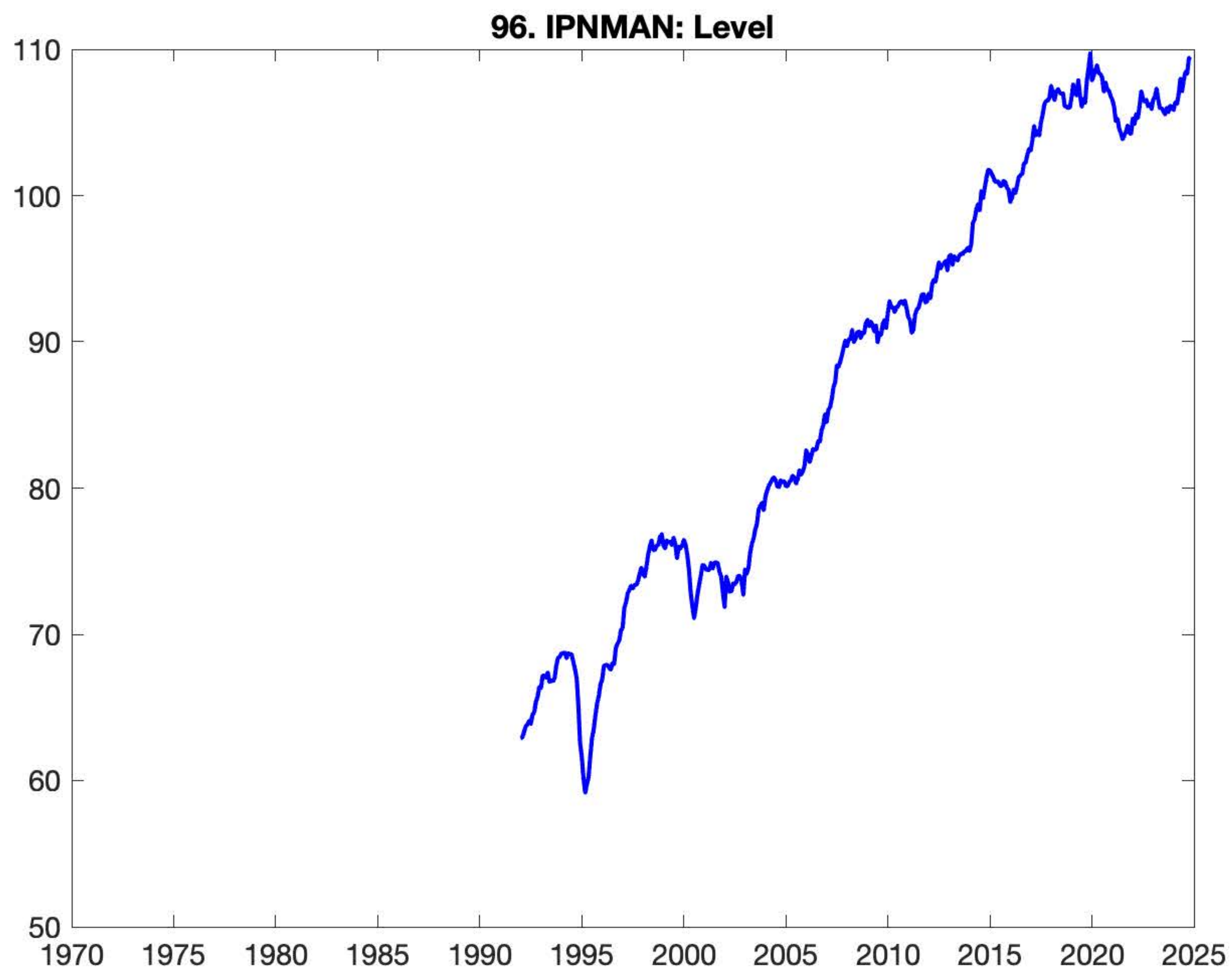

Decomposition: 2020m7 - 2024m9

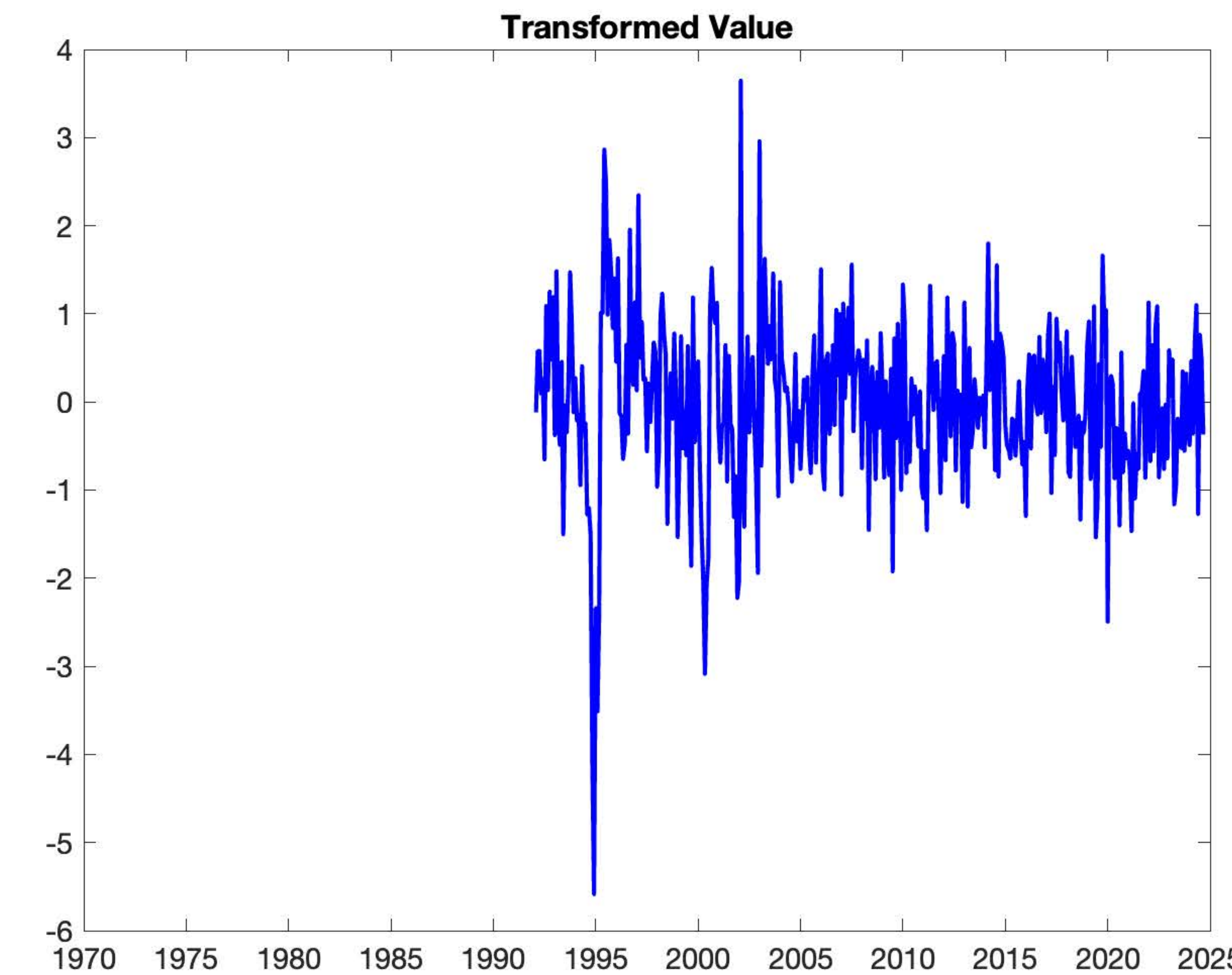

95. IPDMAN: Level

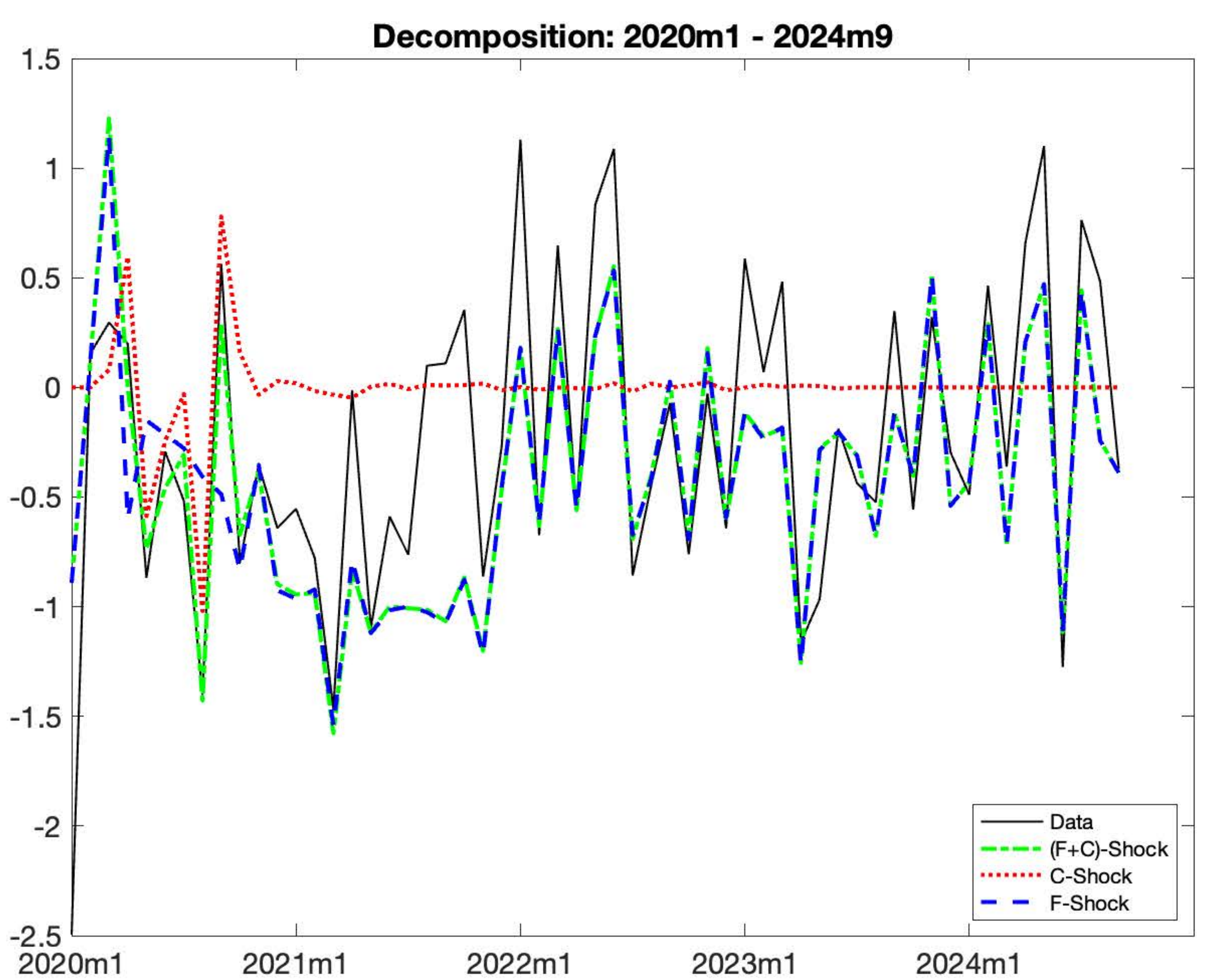

Transformed Value

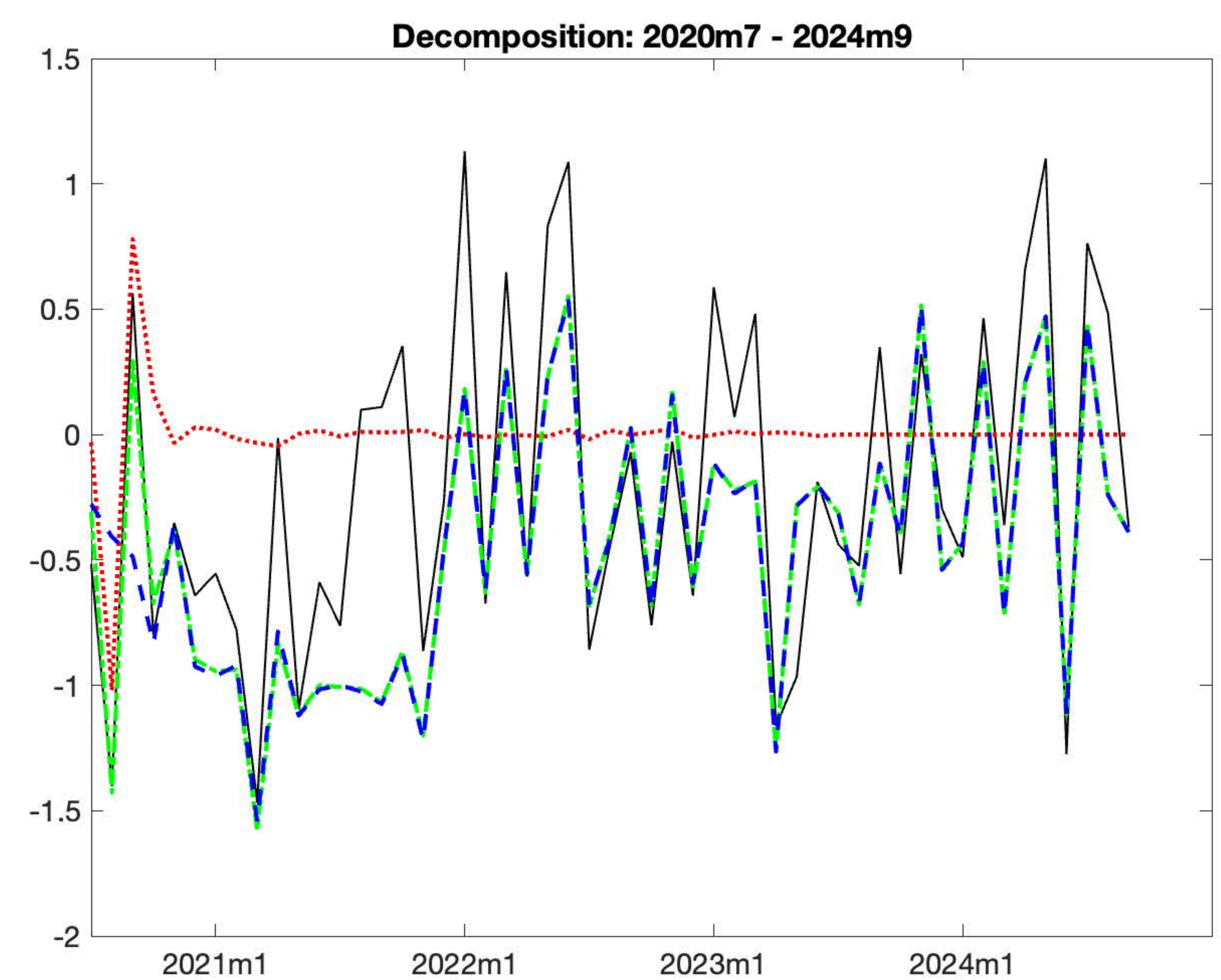

Decomposition: 2020m1 - 2024m9
Data
(F+C)-Shock
C-Shock
F-Shock

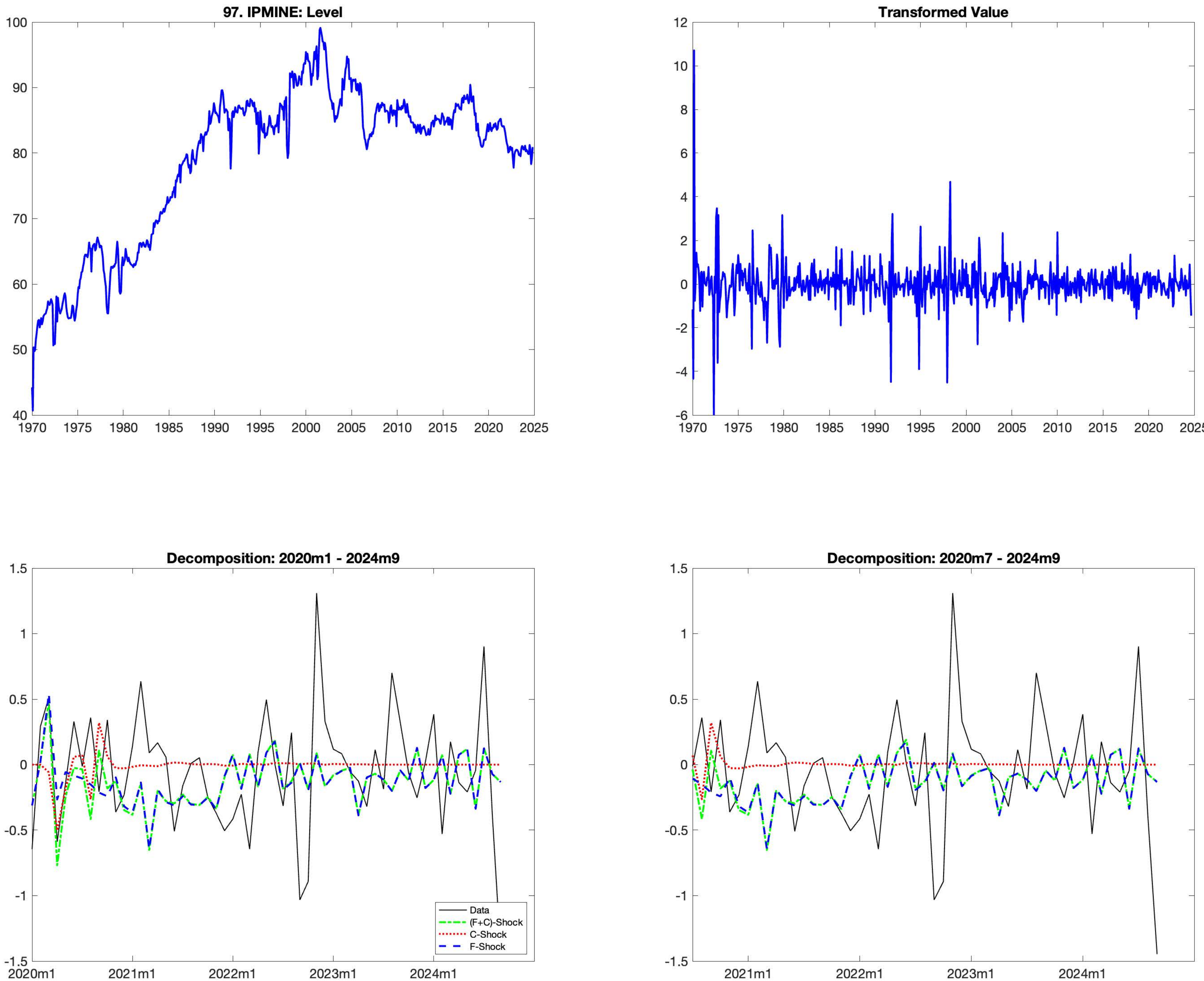

Decomposition: 2020m7 - 2024m9


96. IPNMAN: Level

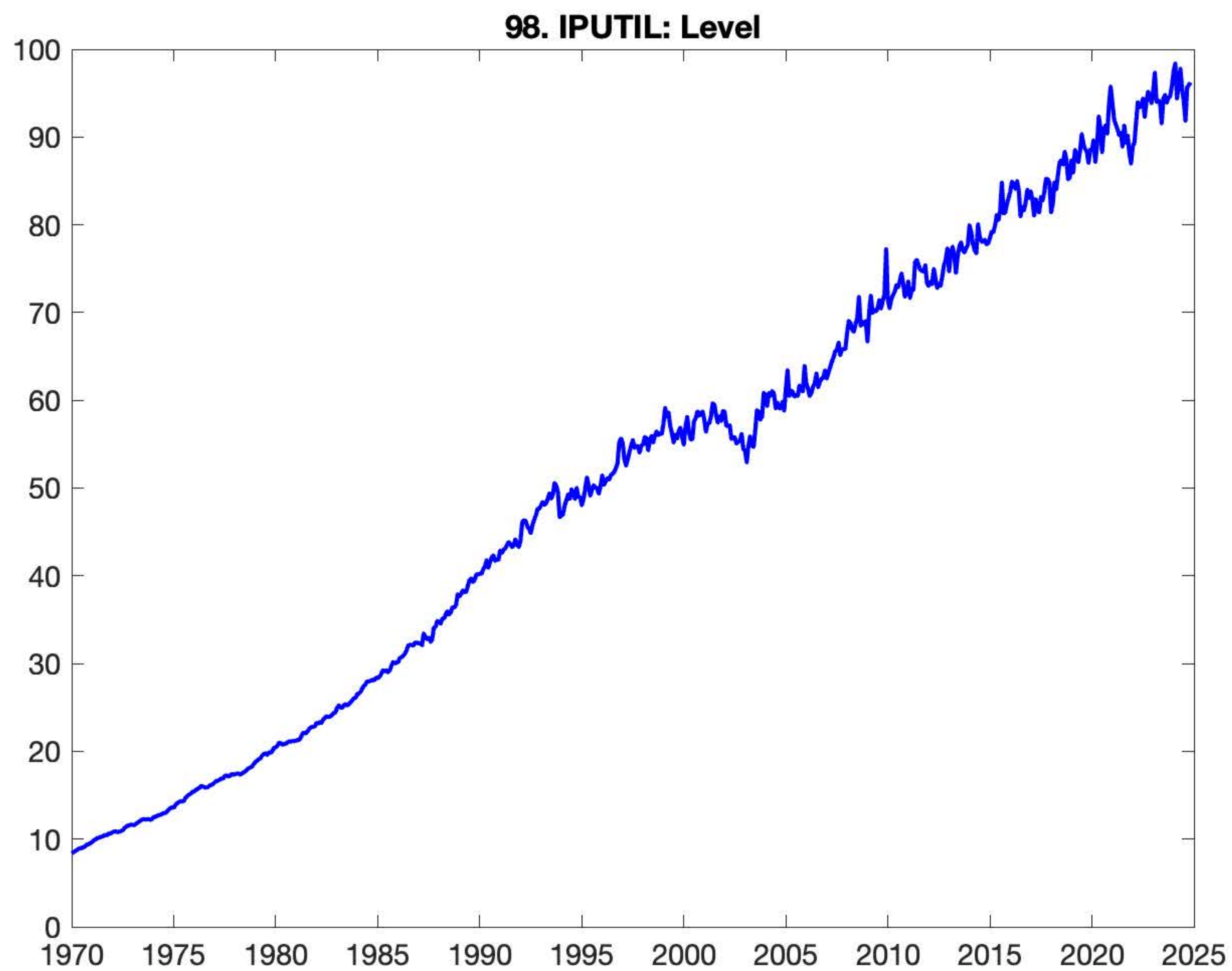

Transformed Value

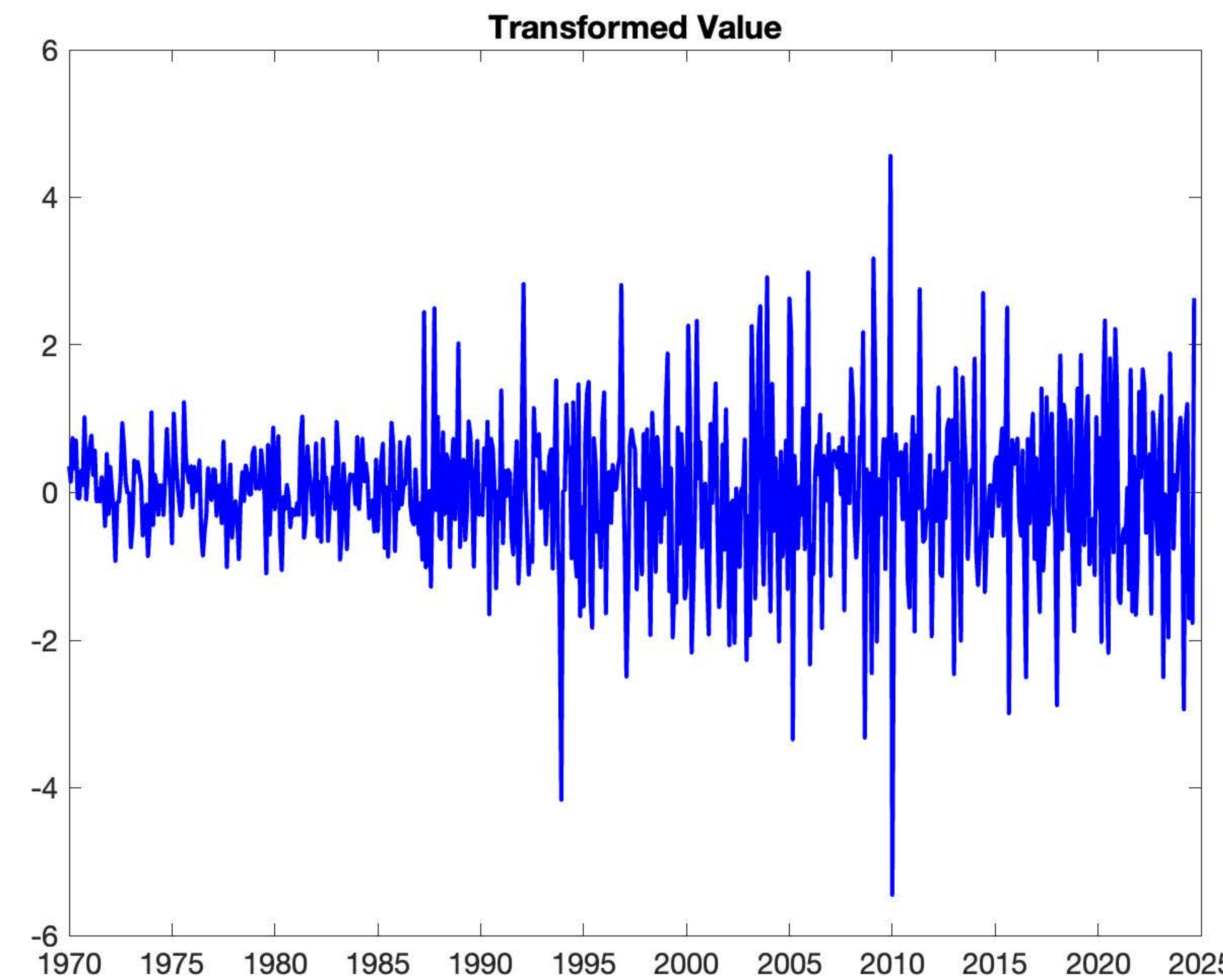

Decomposition: 2020m1 - 2024m9
Data
(F+C)-Shock
C-Shock
F-Shock

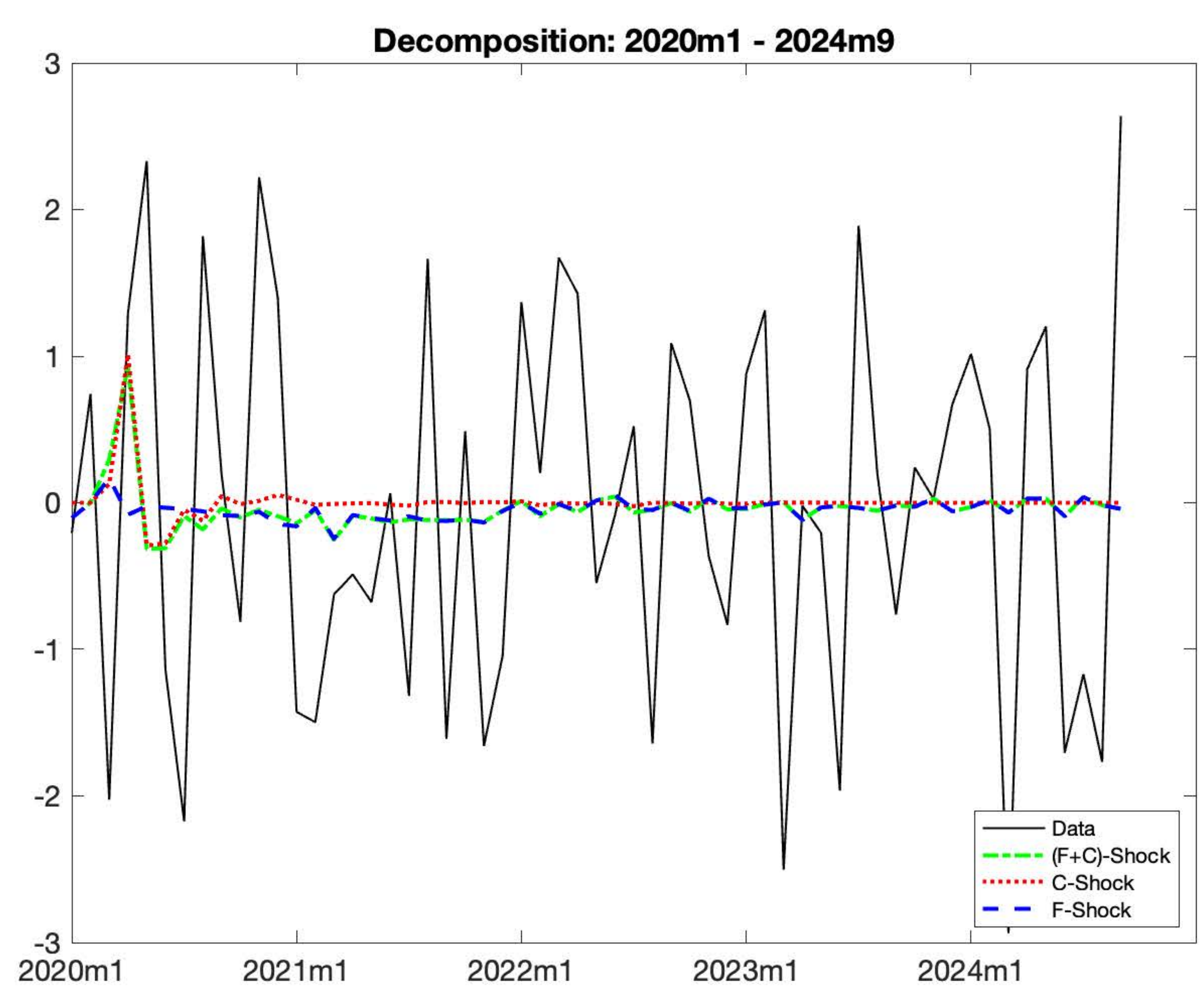

Decomposition: 2020m7 - 2024m9

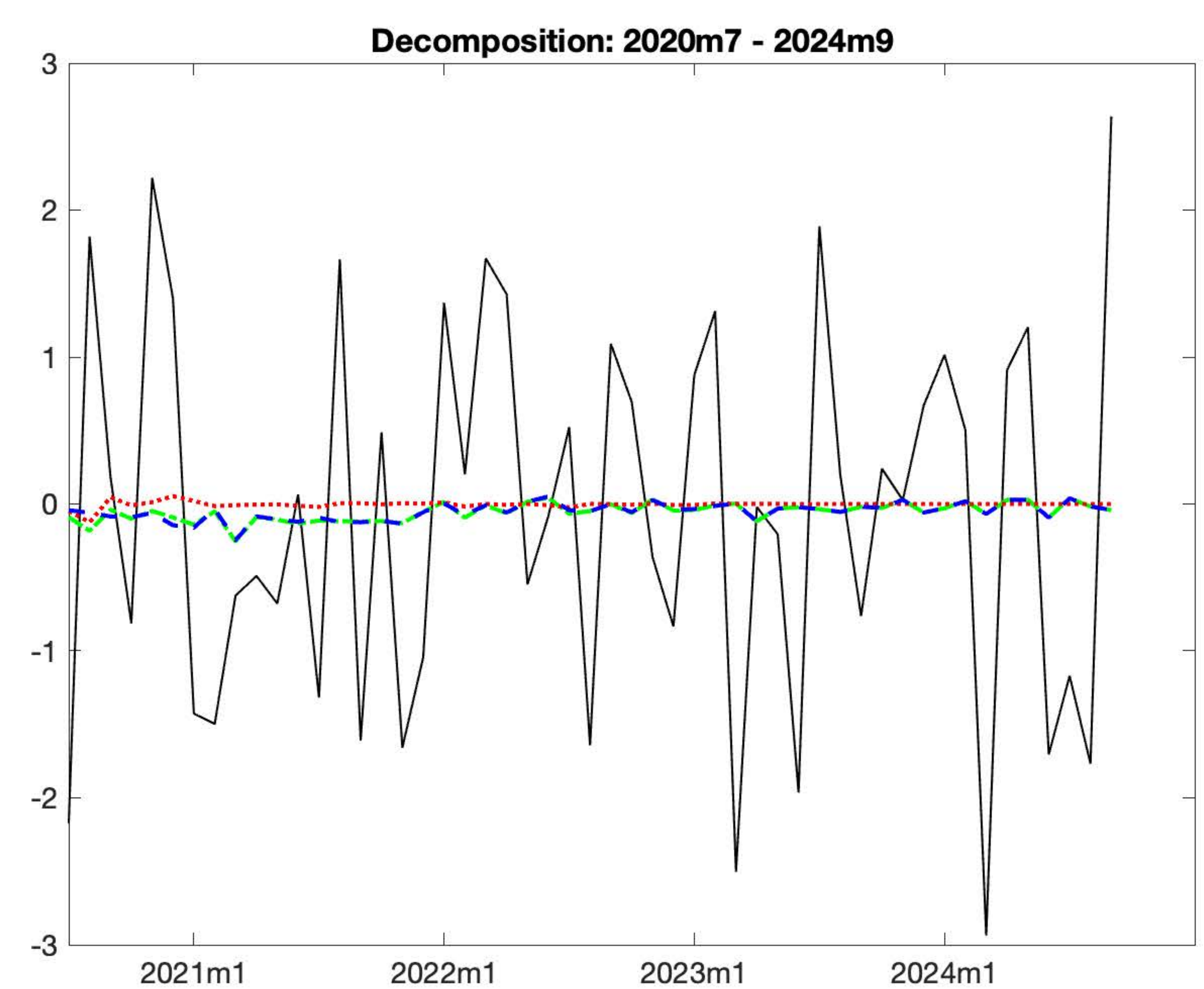


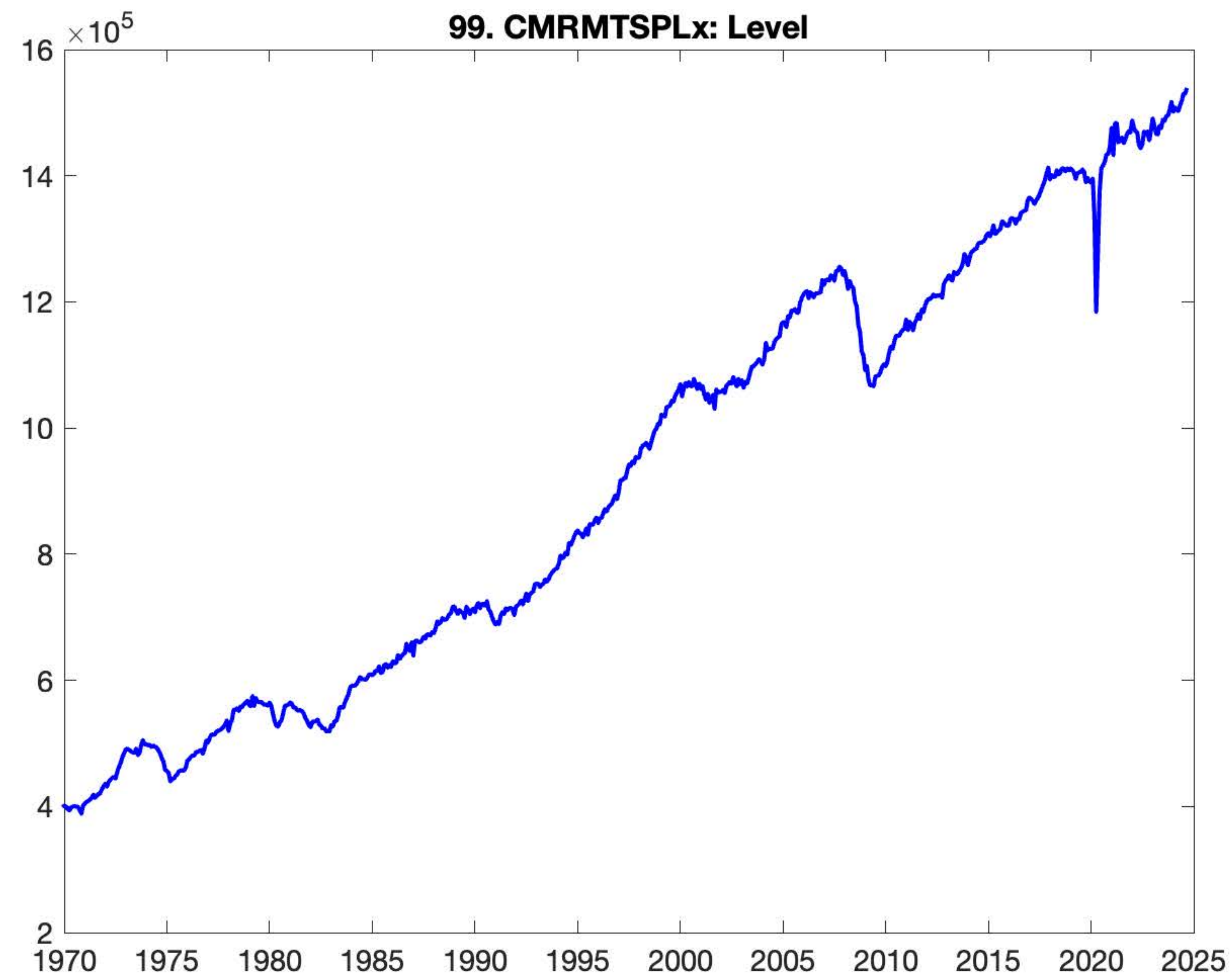
97. IPMINE: Level
Transformed Value
Decomposition: 2020m1 - 2024m9
Data
(F+C)-Shock
C-Shock
F-Shock
Decomposition: 2020m7 - 2024m9

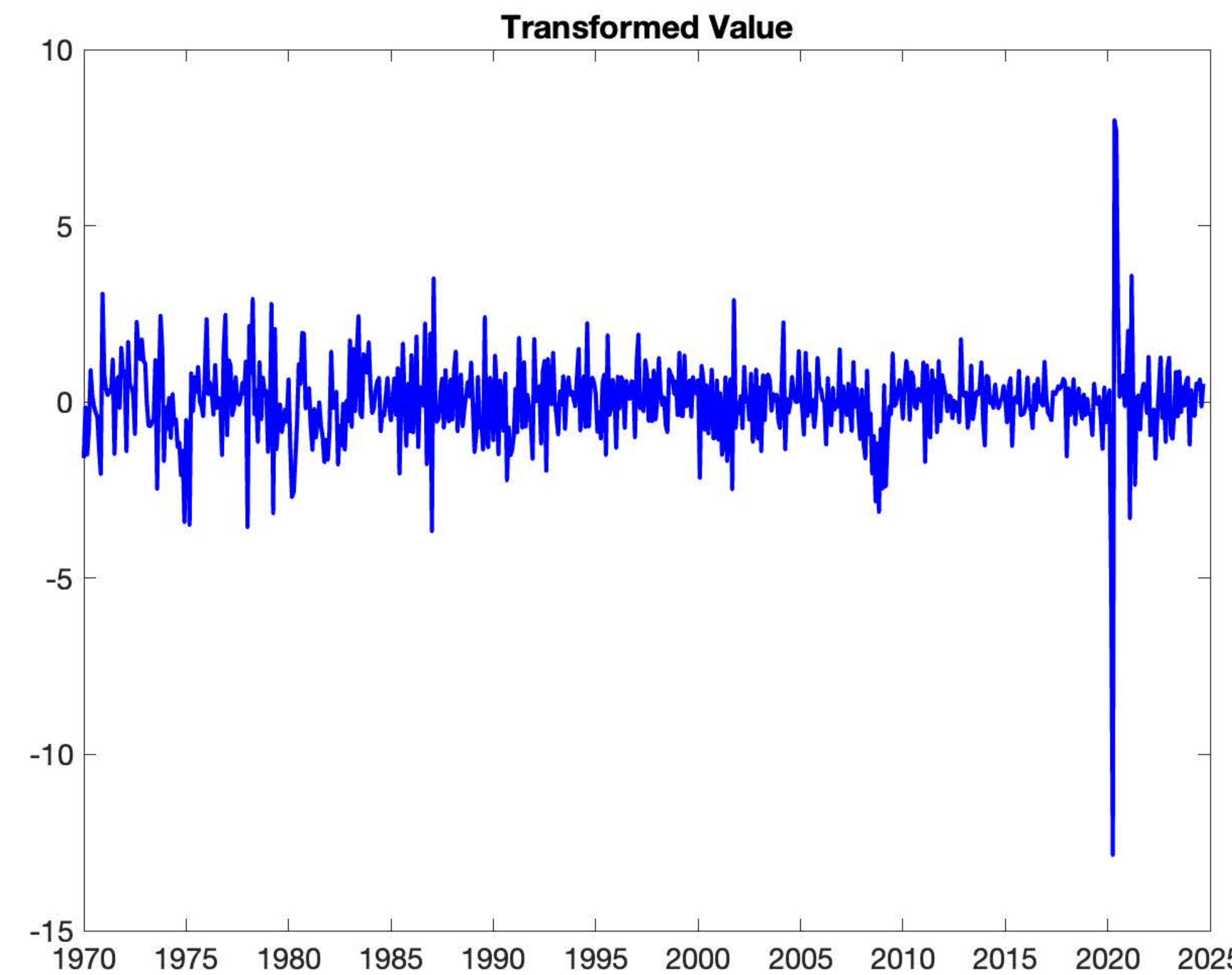

98. IPUTIL: Level
100
90
80
70
60
50
40
30
20
10
0
1970
1975
1980
1985
1990
1995
2000
2005
2010
2015
2020
2025

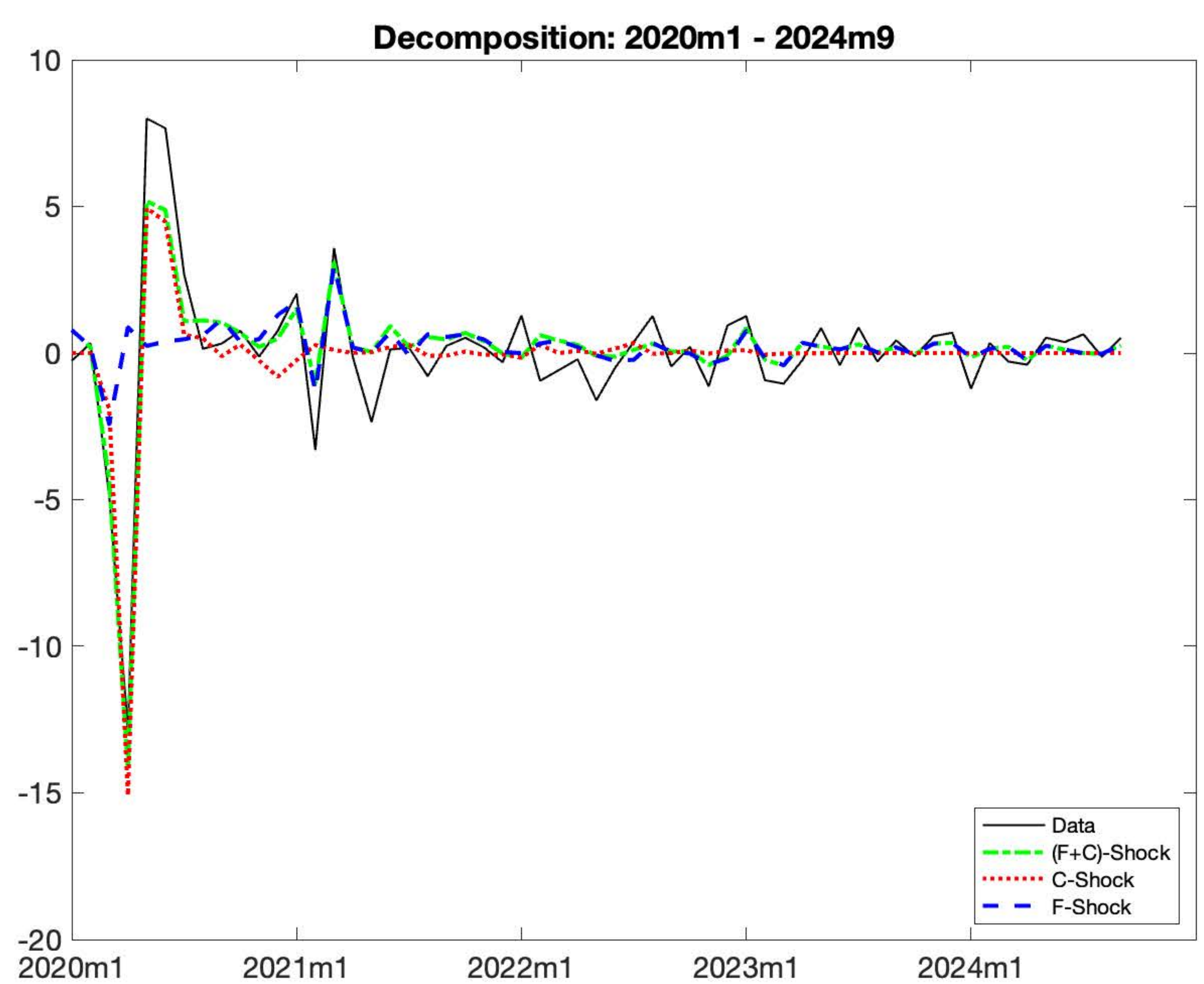

Transformed Value
6
4
2
0
-2
-4
-6
1970
1975
1980
1985
1990
1995
2000
2005
2010
2015
2020
2025

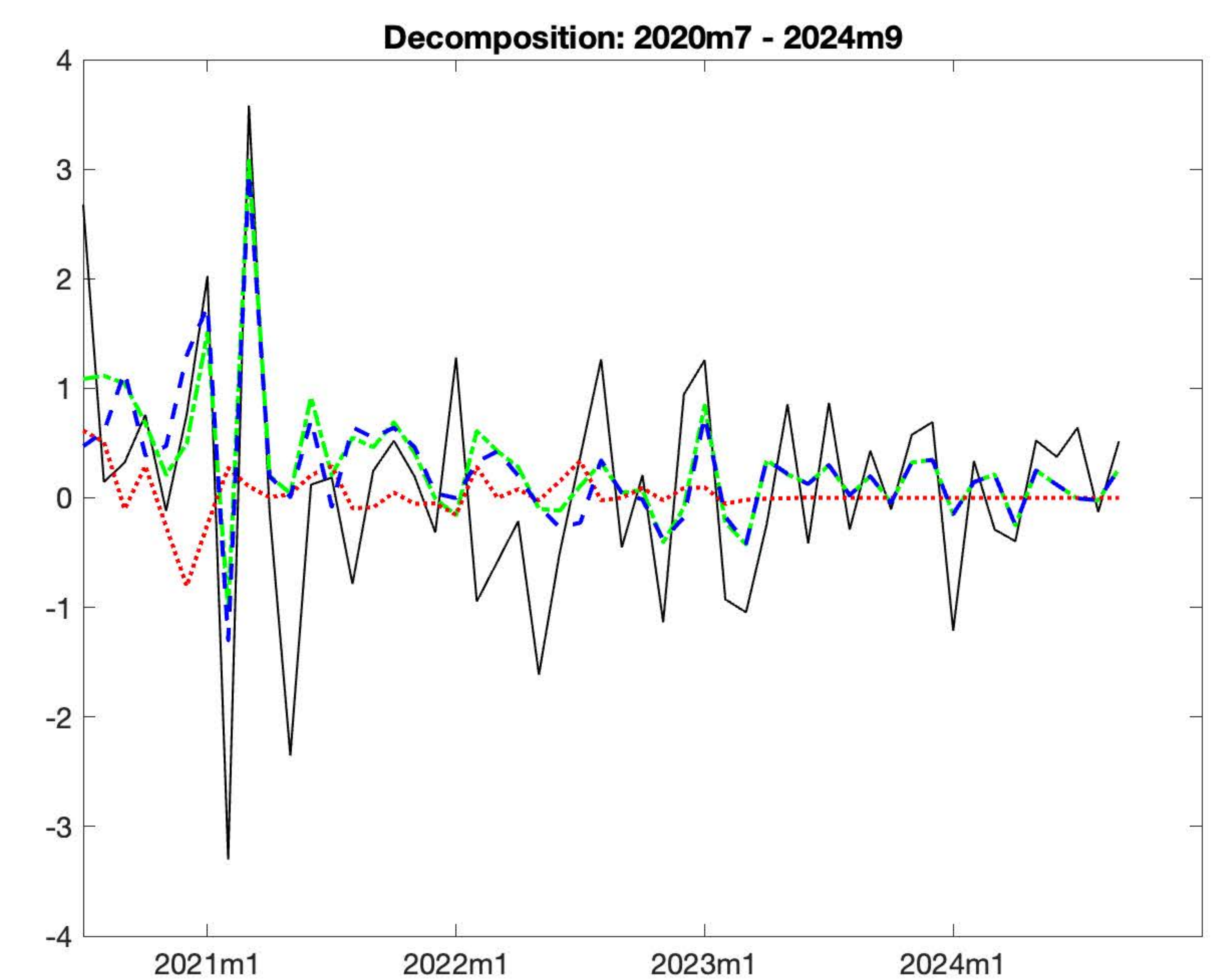

Decomposition: 2020m1 - 2024m9
3
2
1
0
-1
-2
-3
2020m1
2021m1
2022m1
2023m1
2024m1
Data
(F+C)-Shock
C-Shock
F-Shock

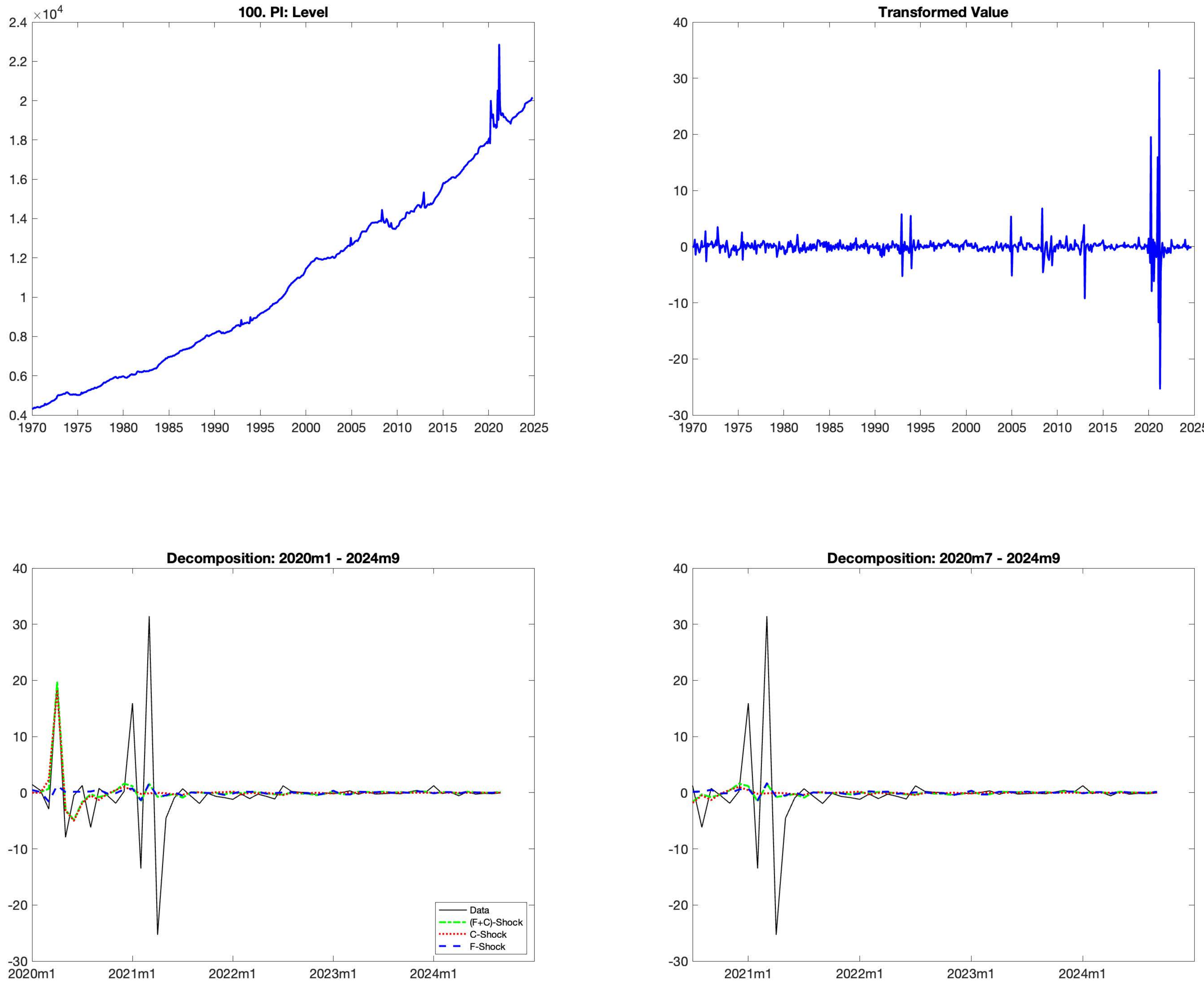

Decomposition: 2020m7 - 2024m9
3
2
1
0
-1
-2
-3
2021m1
2022m1
2023m1
2024m1

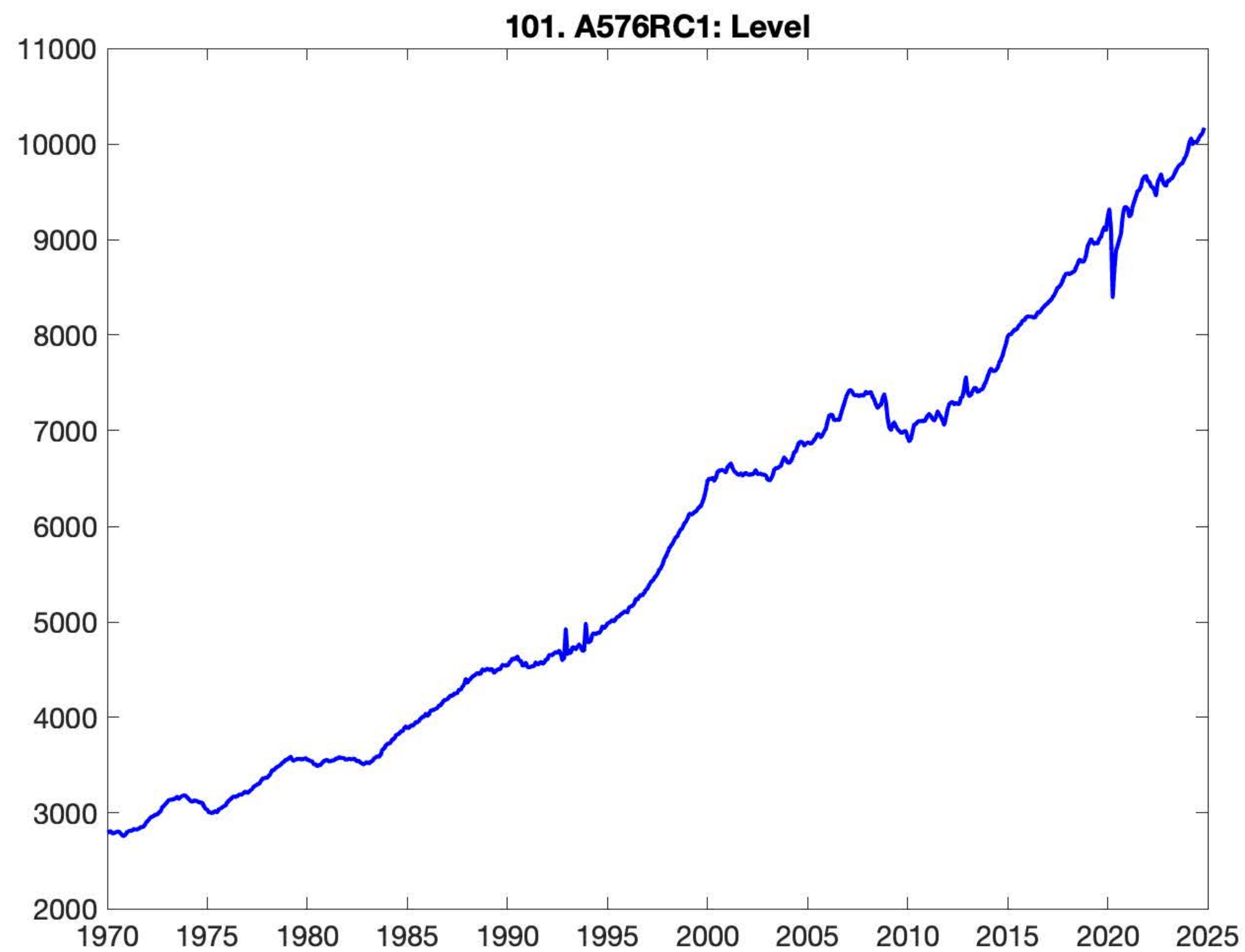

99. CMRMTSPLx: Level
×10^5
16
14
12
10
8
6
4
2
1970 1975 1980 1985 1990 1995 2000 2005 2010 2015 2020 2025

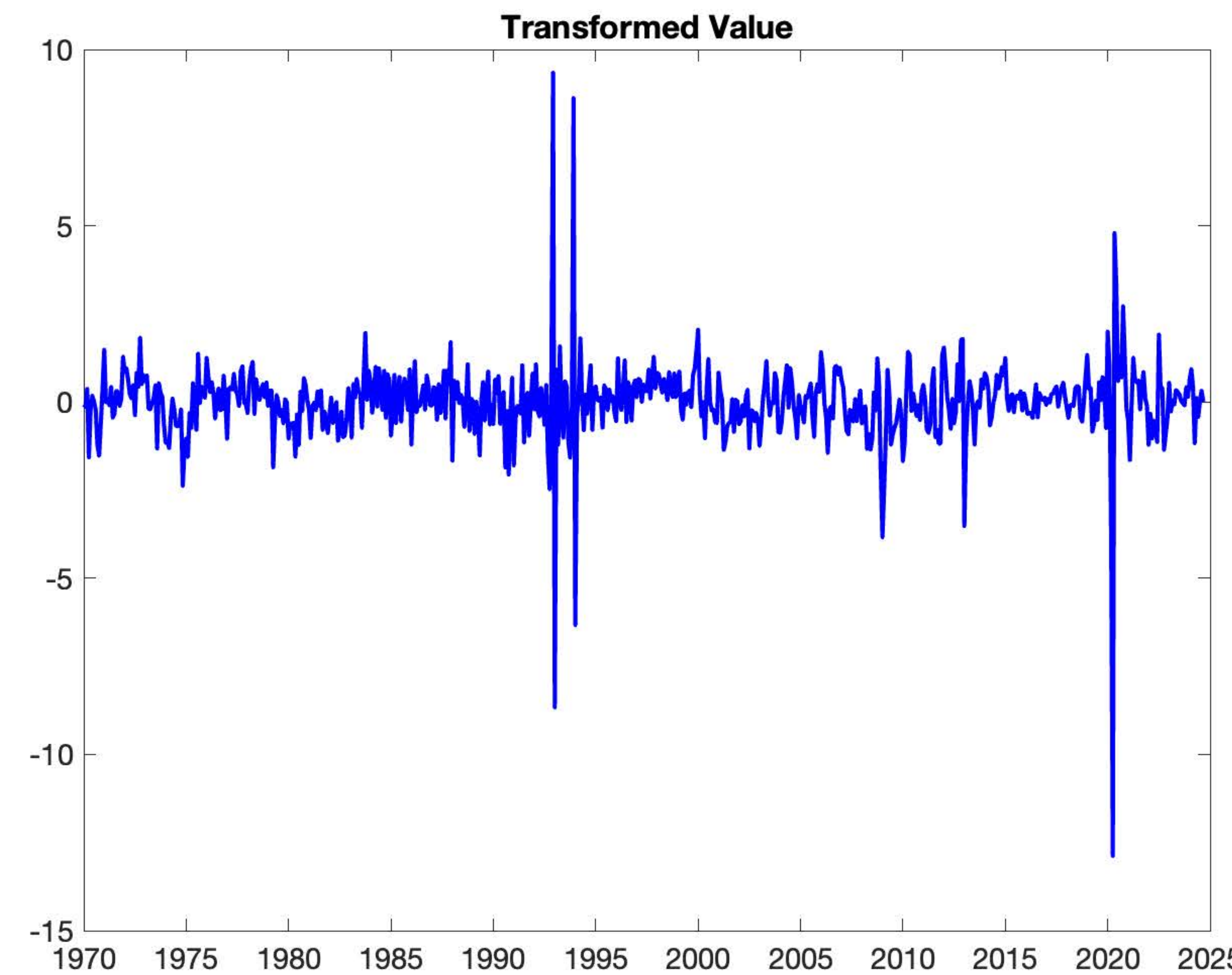

Transformed Value
10
5
0
-5
-10
-15
1970 1975 1980 1985 1990 1995 2000 2005 2010 2015 2020 2025

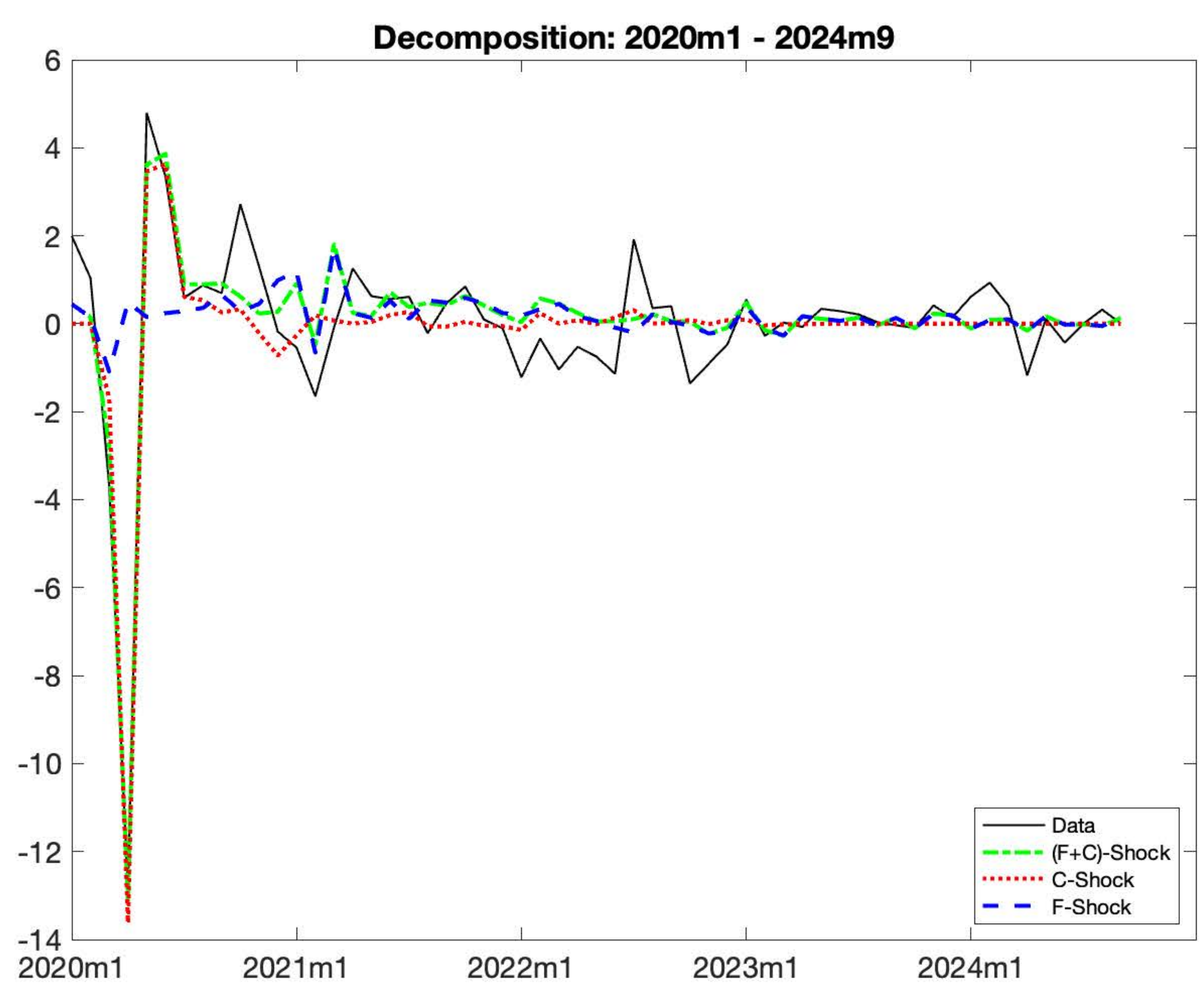

Decomposition: 2020m1 - 2024m9
10
5
0
-5
-10
-15
-20
2020m1 2021m1 2022m1 2023m1 2024m1
Data
(F+C)-Shock
C-Shock
F-Shock

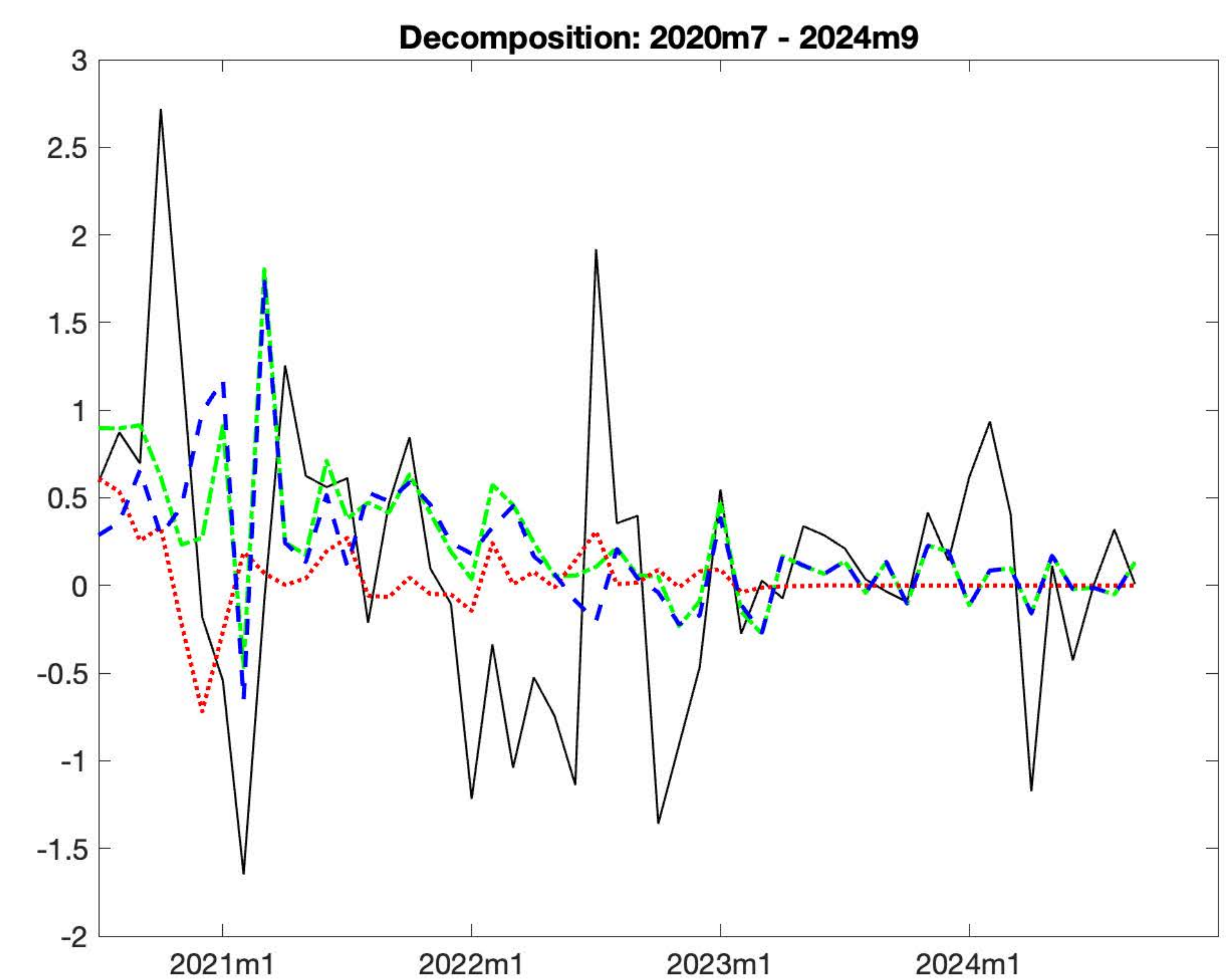

Decomposition: 2020m7 - 2024m9
4
3
2
1
0
-1
-2
-3
-4
2021m1 2022m1 2023m1 2024m1

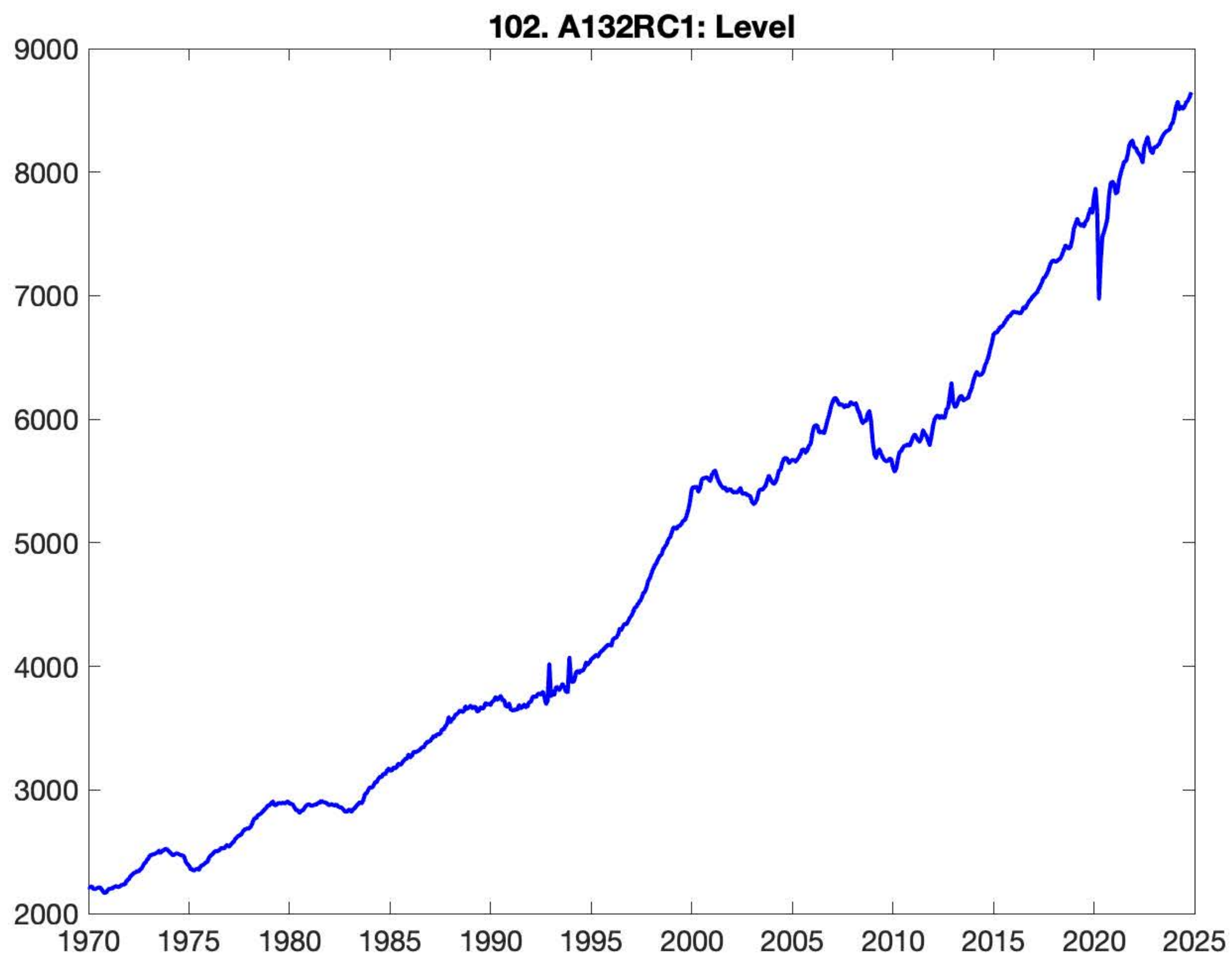

100. PI: Level
$\times 10^4$
Transformed Value
Decomposition: 2020m1 - 2024m9
Decomposition: 2020m7 - 2024m9
Data
(F+C)-Shock
C-Shock
F-Shock

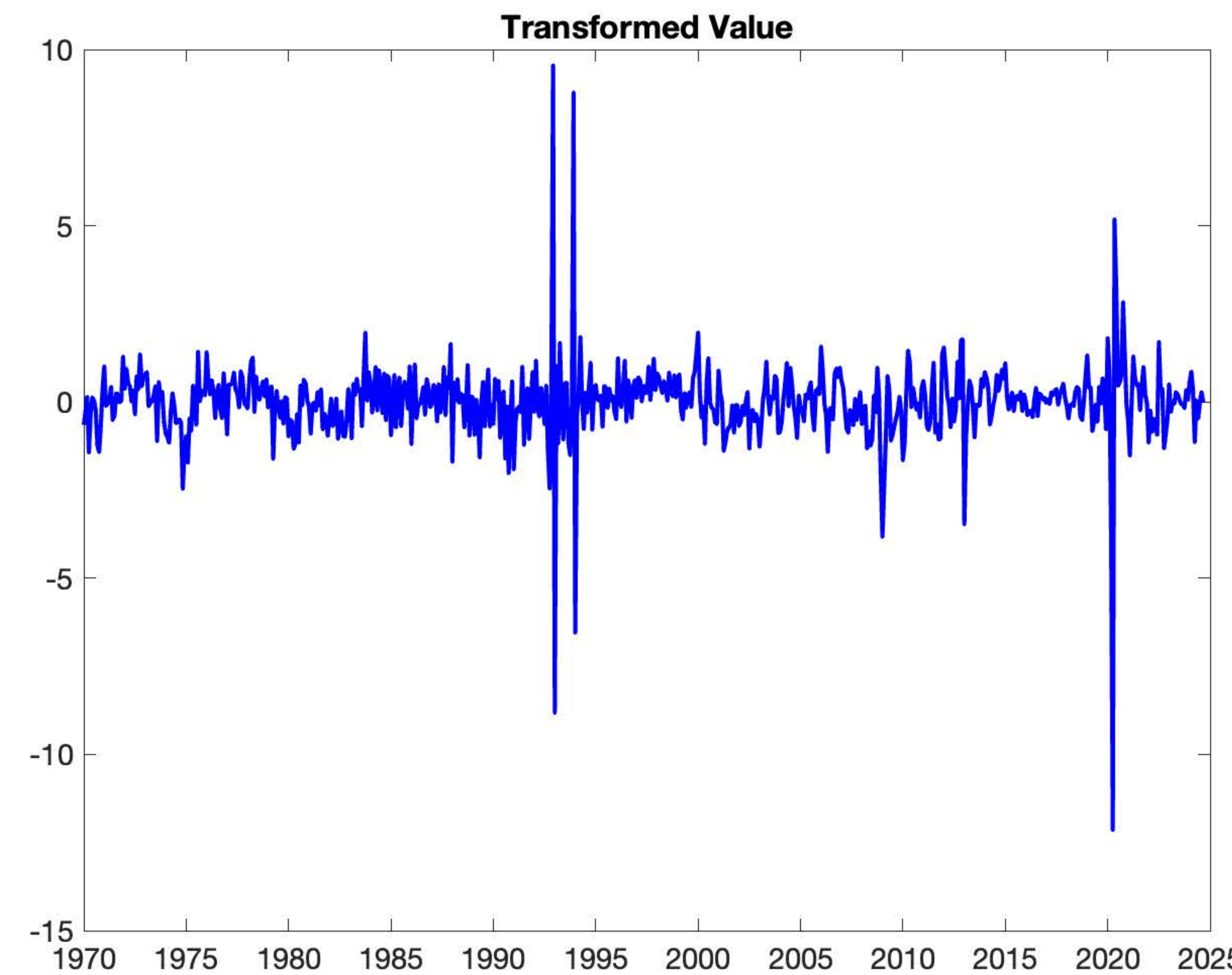

101. A576RC1: Level

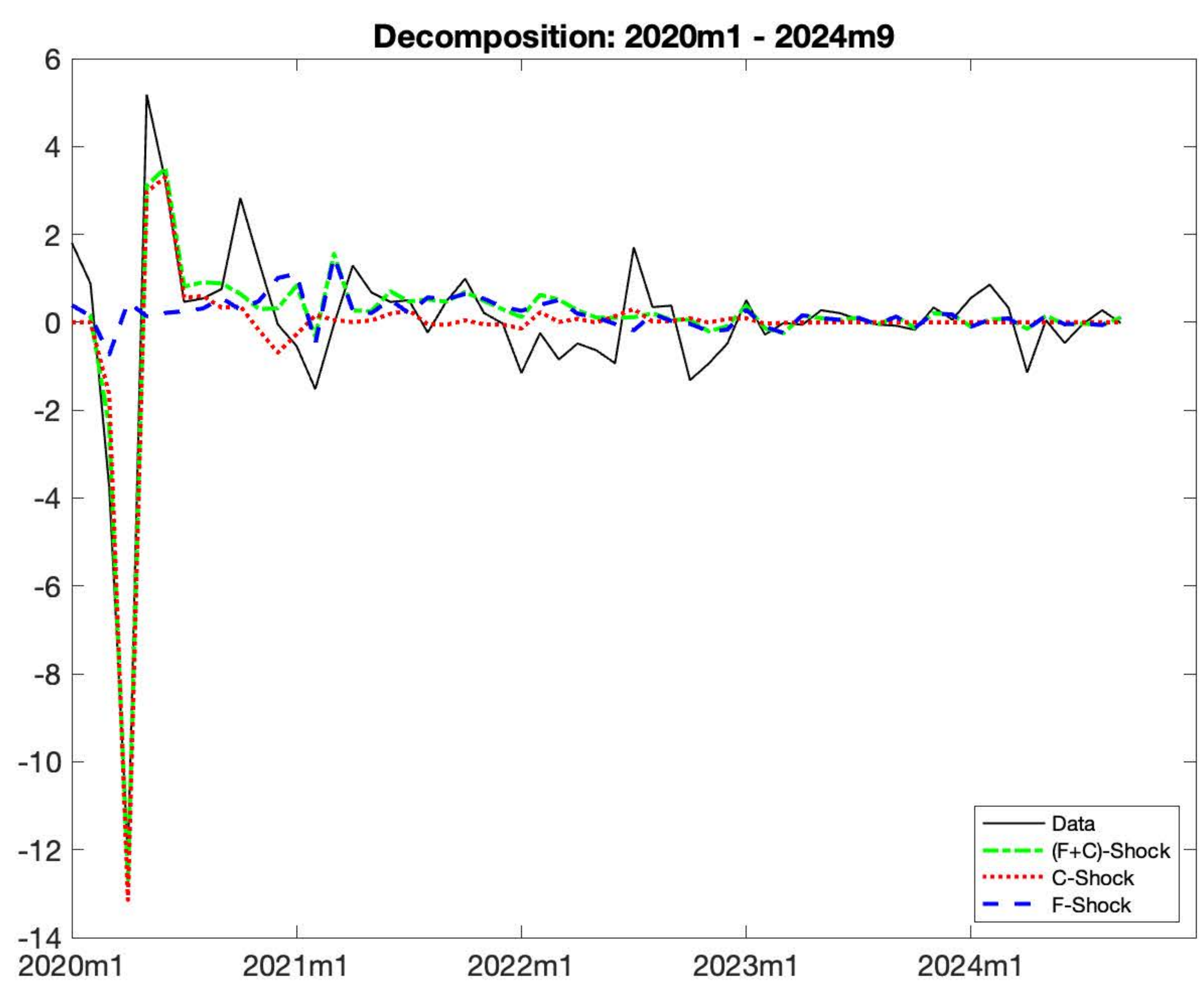

Transformed Value

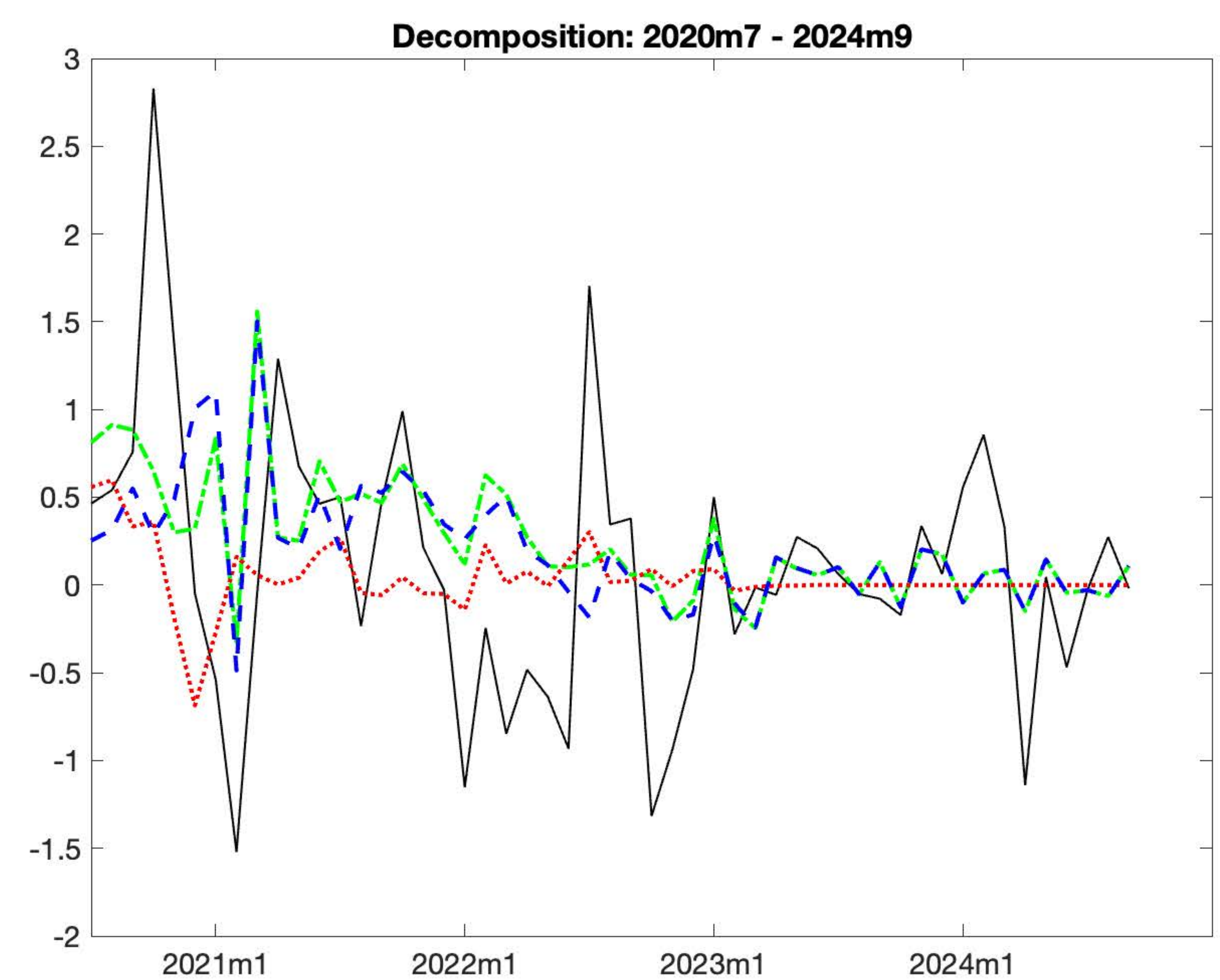

Decomposition: 2020m1 - 2024m9
Data
(F+C)-Shock
C-Shock
F-Shock

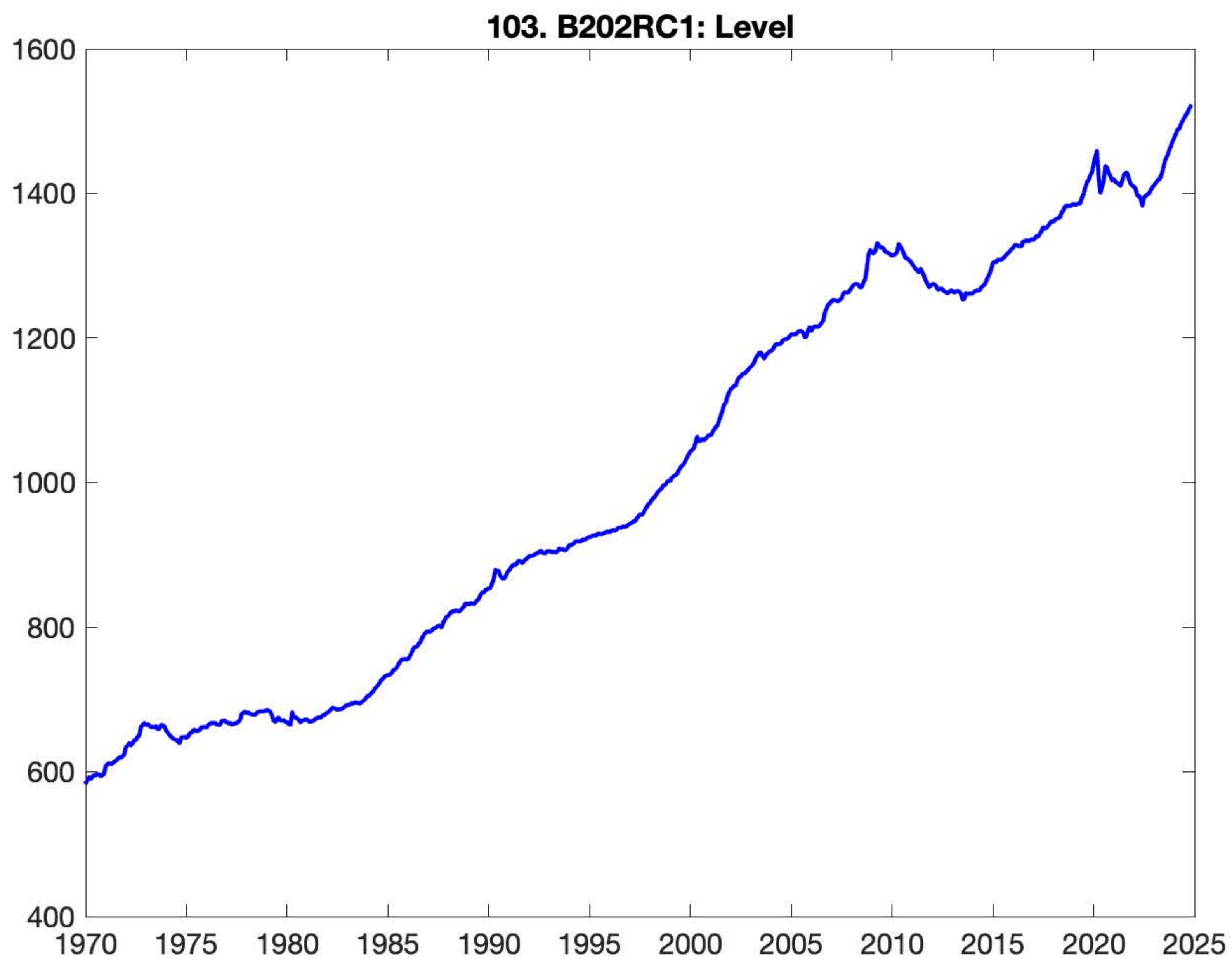

Decomposition: 2020m7 - 2024m9


102. A132RC1: Level
9000
8000
7000
6000
5000
4000
3000
2000
1970
1975
1980
1985
1990
1995
2000
2005
2010
2015
2020
2025

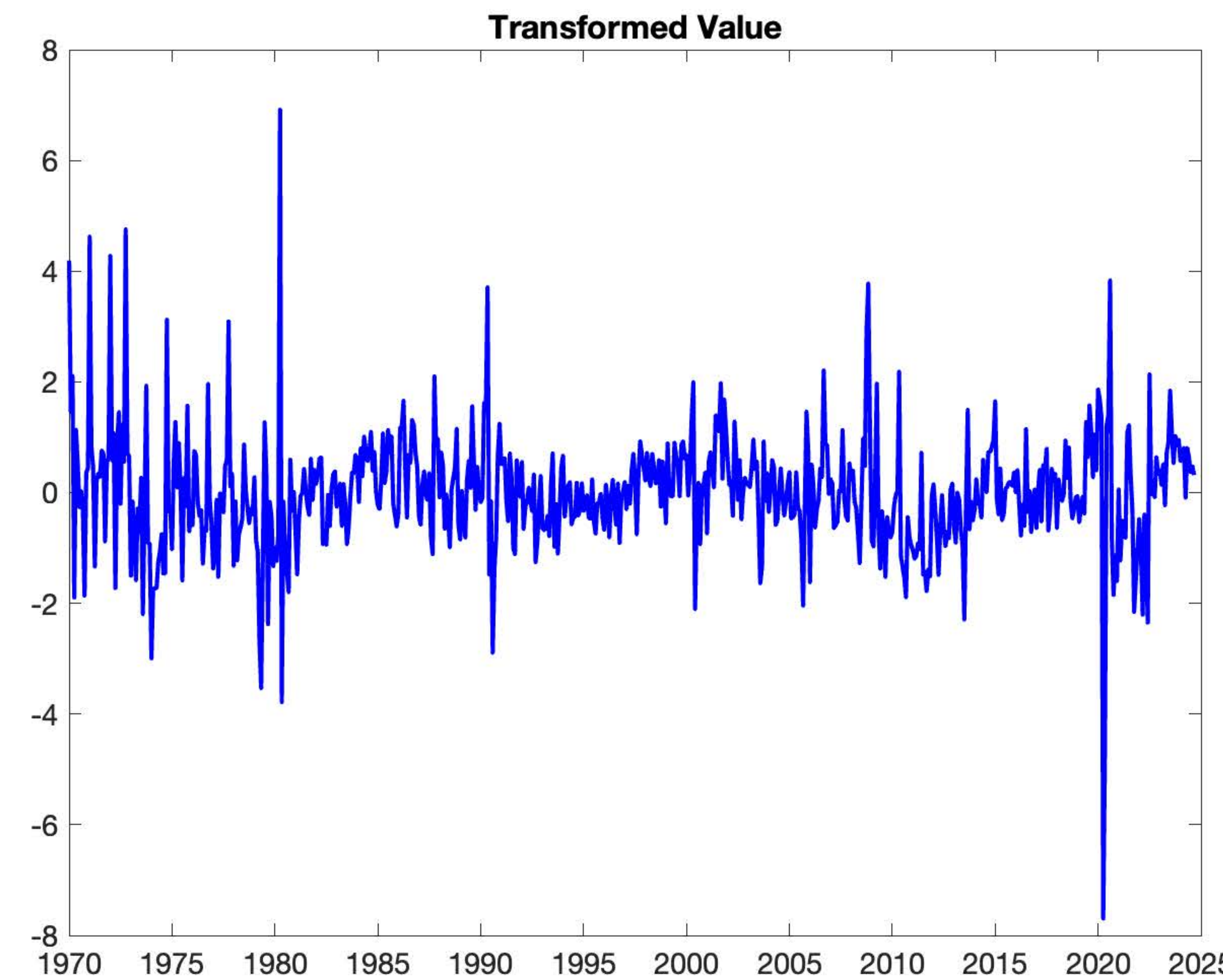

Transformed Value
10
5
0
-5
-10
-15
1970
1975
1980
1985
1990
1995
2000
2005
2010
2015
2020
2025


Decomposition: 2020m1 - 2024m9
6
4
2
0
-2
-4
-6
-8
-10
-12
-14
2020m1
2021m1
2022m1
2023m1
2024m1
Data
(F+C)-Shock
C-Shock
F-Shock

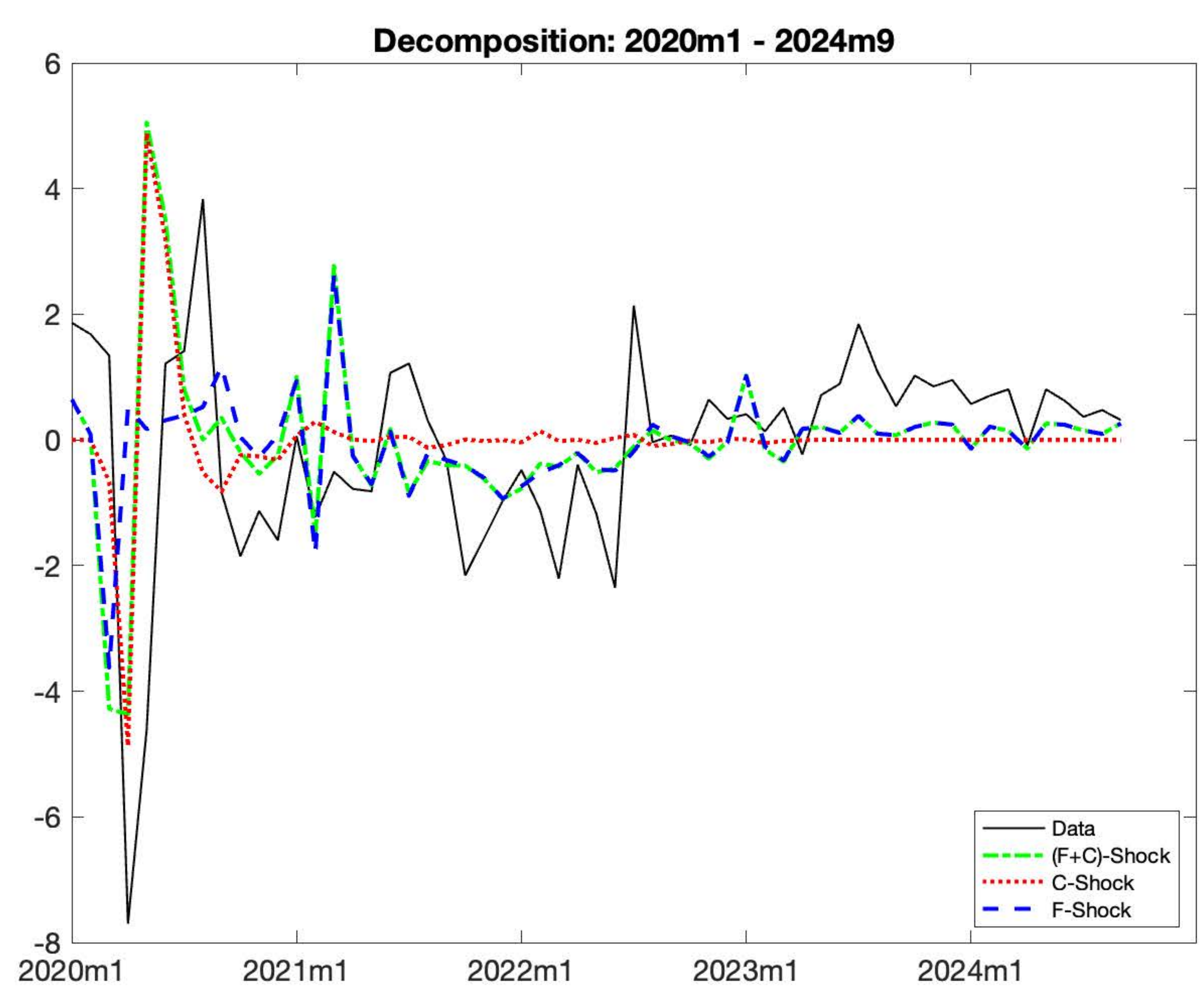

Decomposition: 2020m7 - 2024m9
3
2.5
2
1.5
1
0.5
0
-0.5
-1
-1.5
-2
2021m1
2022m1
2023m1
2024m1



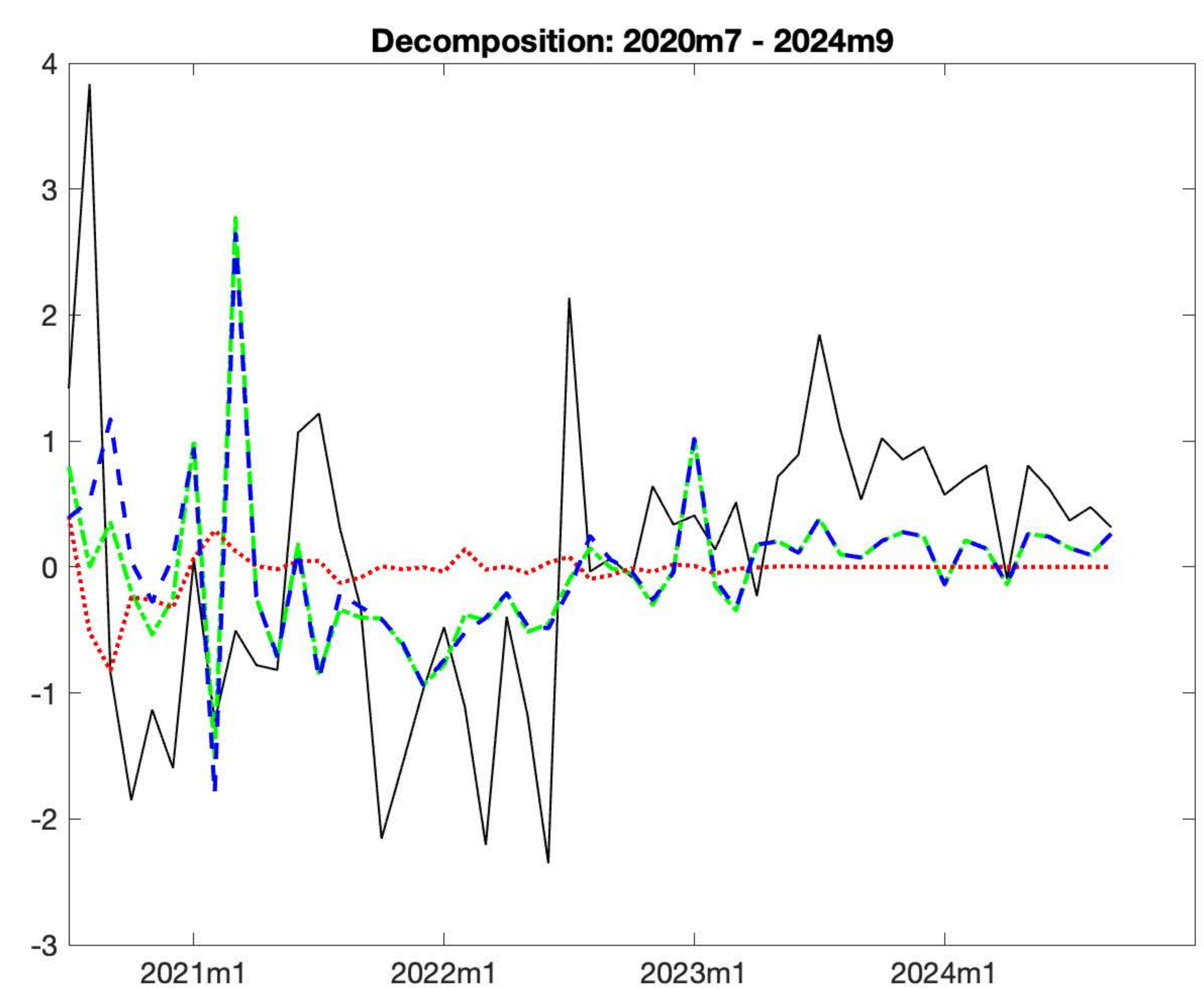
103. B202RC1: Level
1600
1400
1200
1000
800
600
400
1970
1975
1980
1985
1990
1995
2000
2005
2010
2015
2020
2025



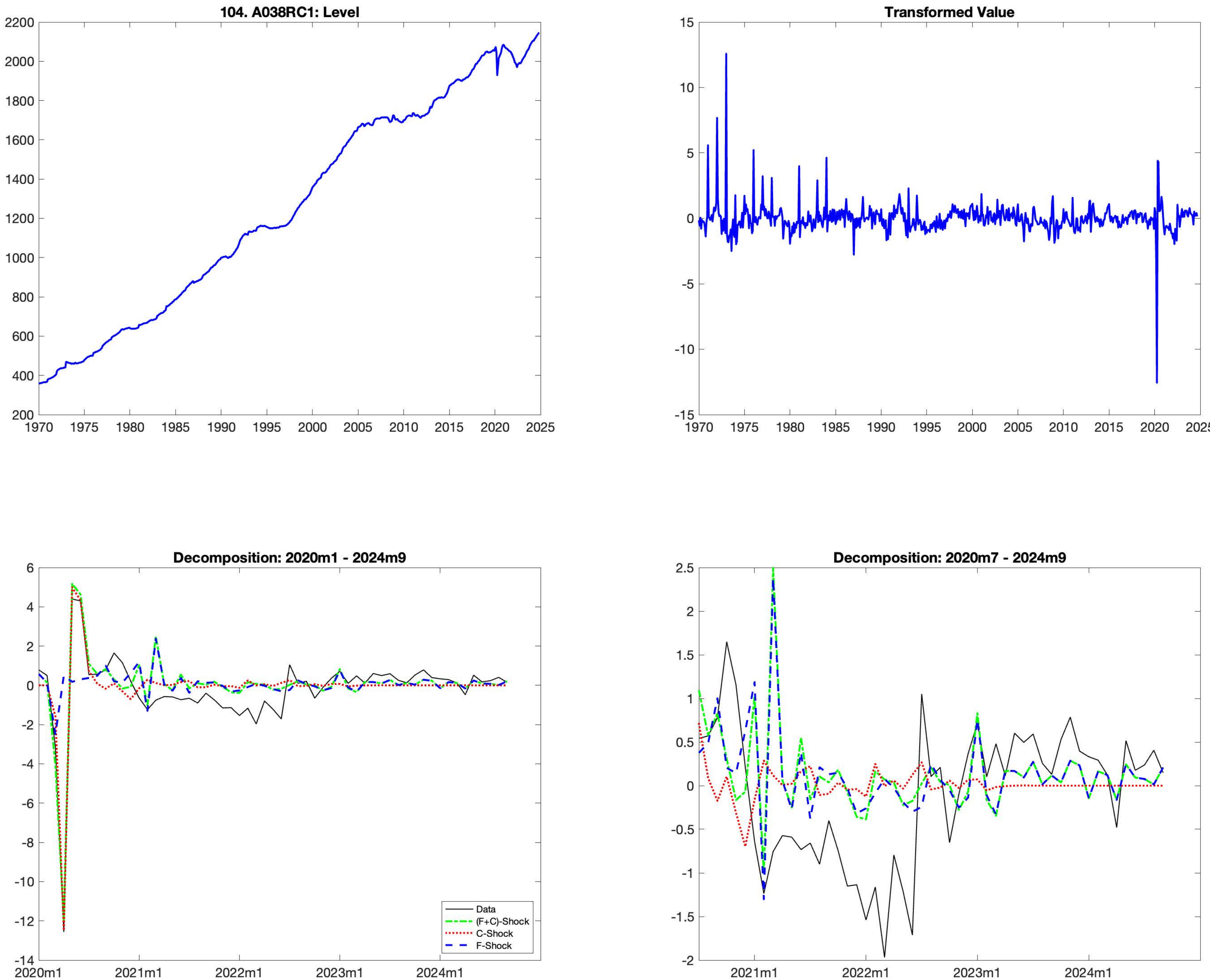
Transformed Value
8
6
4
2
0
-2
-4
-6
-8
1970
1975
1980
1985
1990
1995
2000
2005
2010
2015
2020
2025



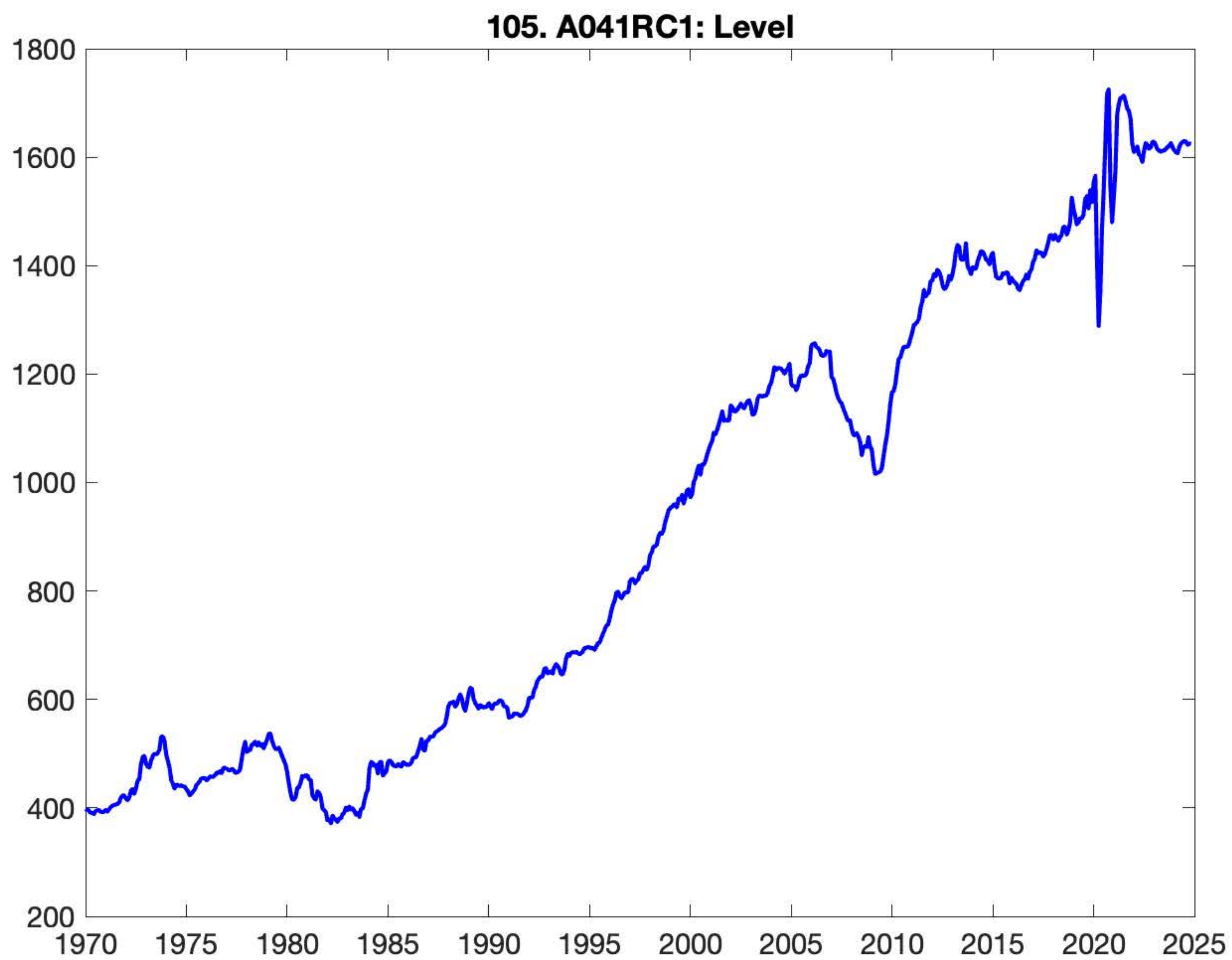
Decomposition: 2020m1 - 2024m9
6
4
2
0
-2
-4
-6
-8
2020m1
2021m1
2022m1
2023m1
2024m1
Data
(F+C)-Shock
C-Shock
F-Shock

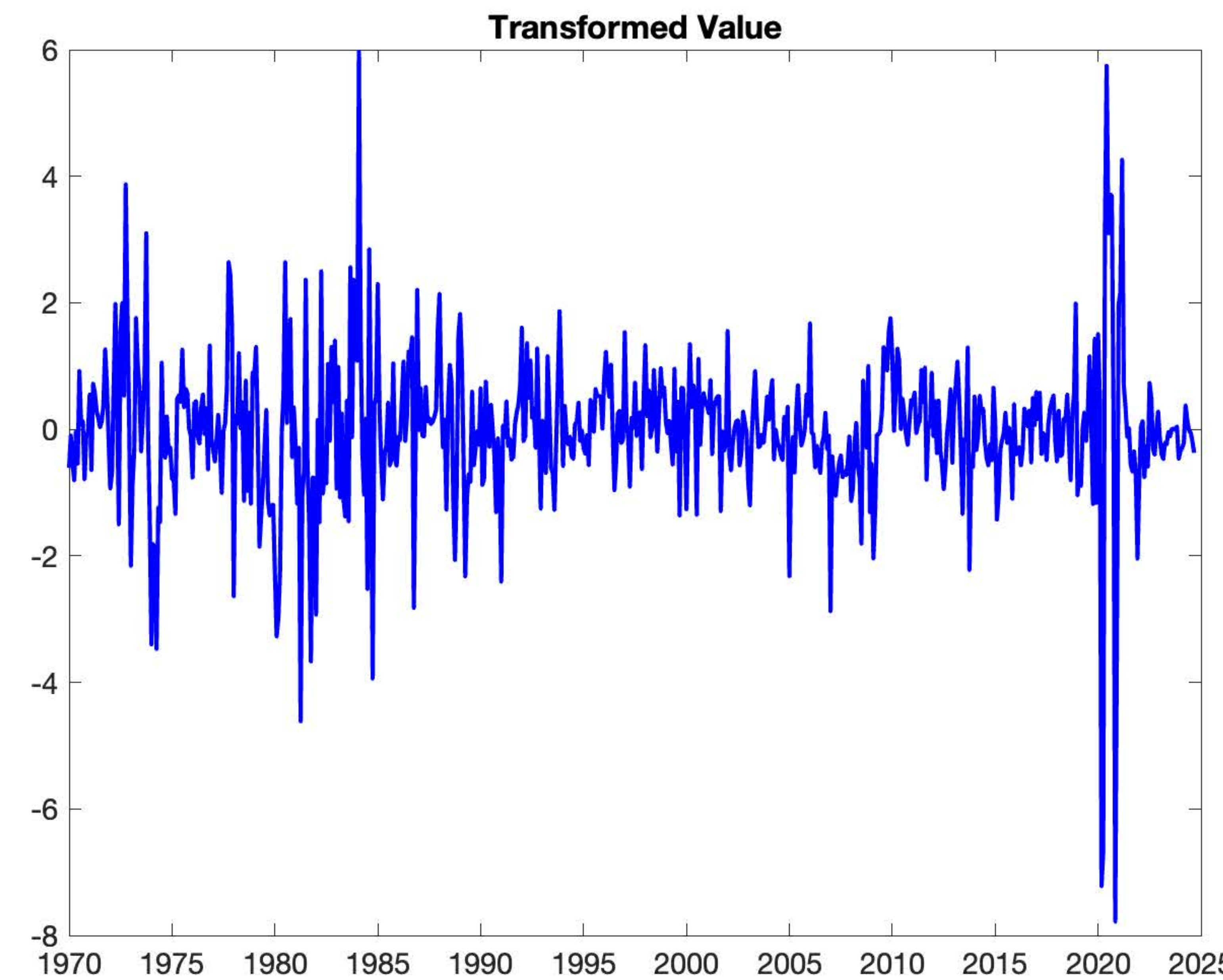


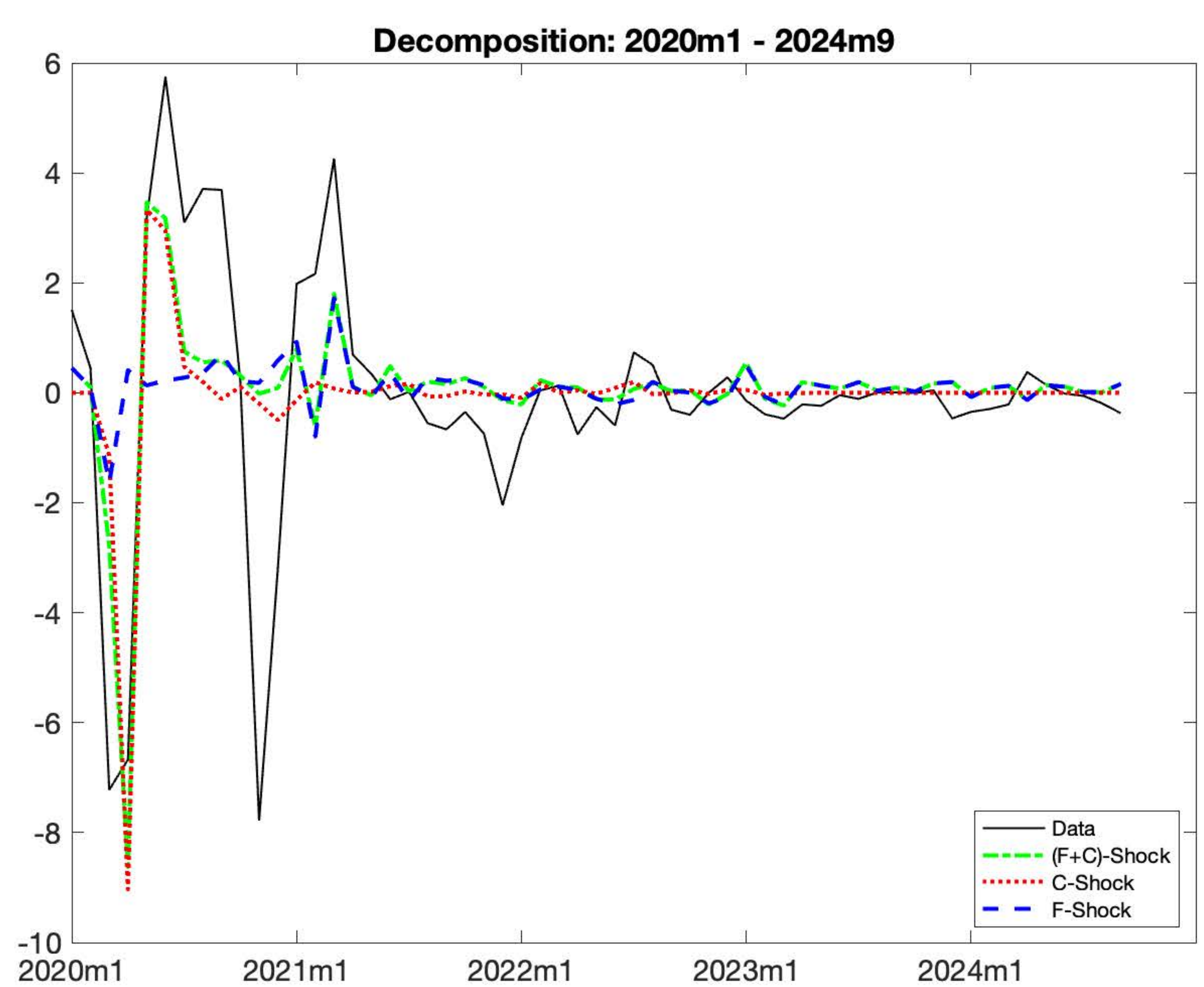
Decomposition: 2020m7 - 2024m9
4
3
2
1
0
-1
-2
-3
2021m1
2022m1
2023m1
2024m1

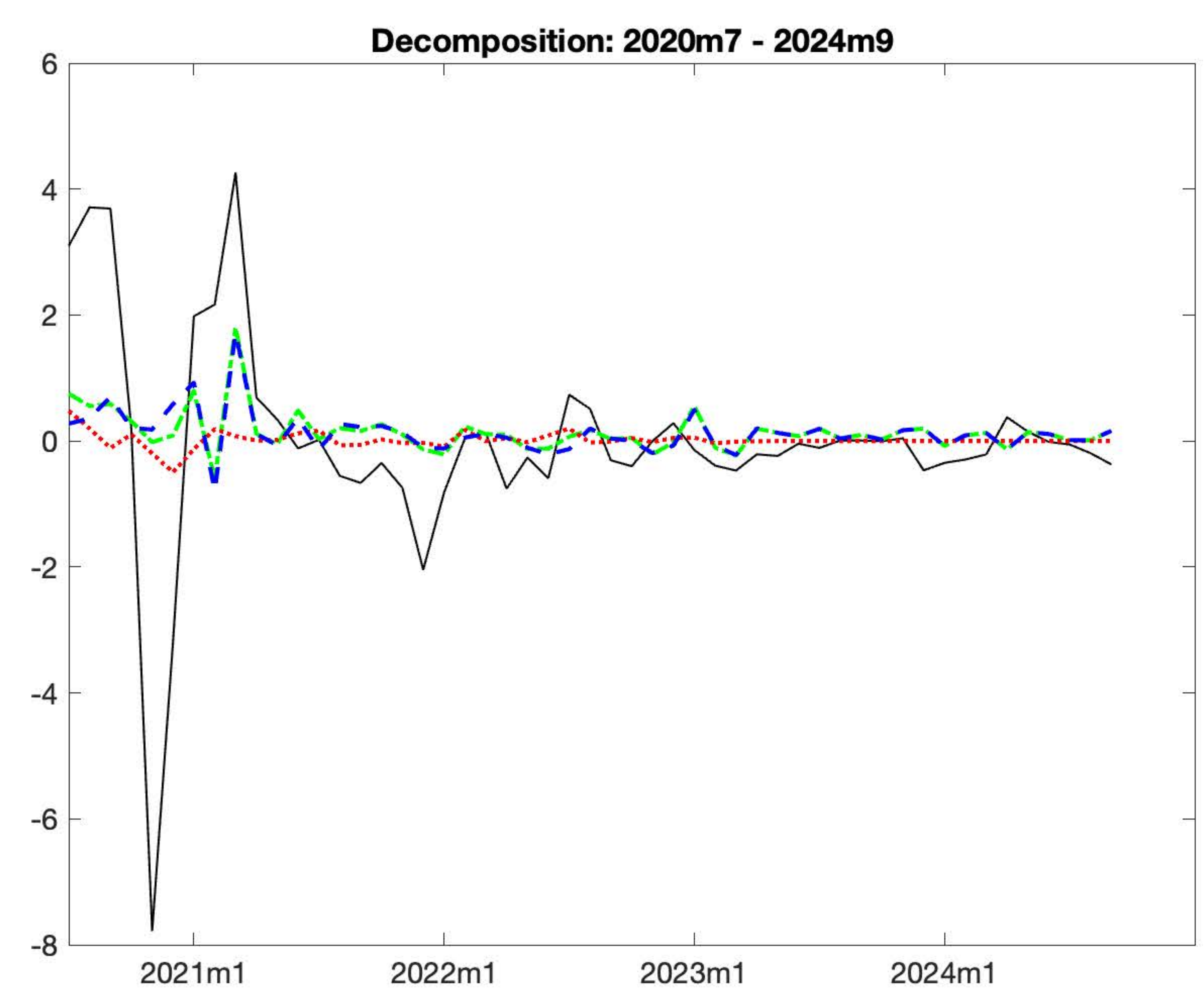


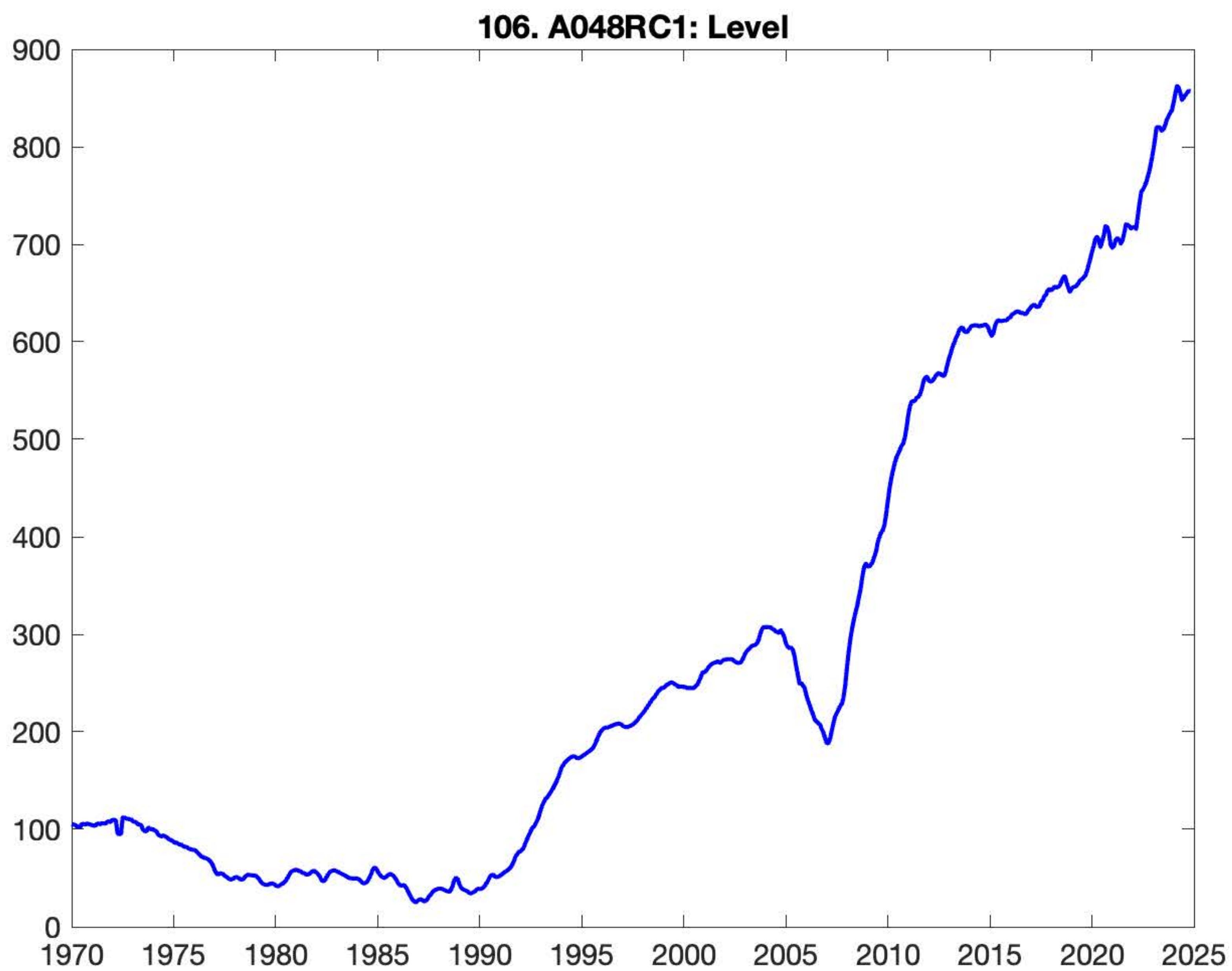
104. A038RC1: Level
Transformed Value
Decomposition: 2020m1 - 2024m9
Data
(F+C)-Shock
C-Shock
F-Shock
Decomposition: 2020m7 - 2024m9

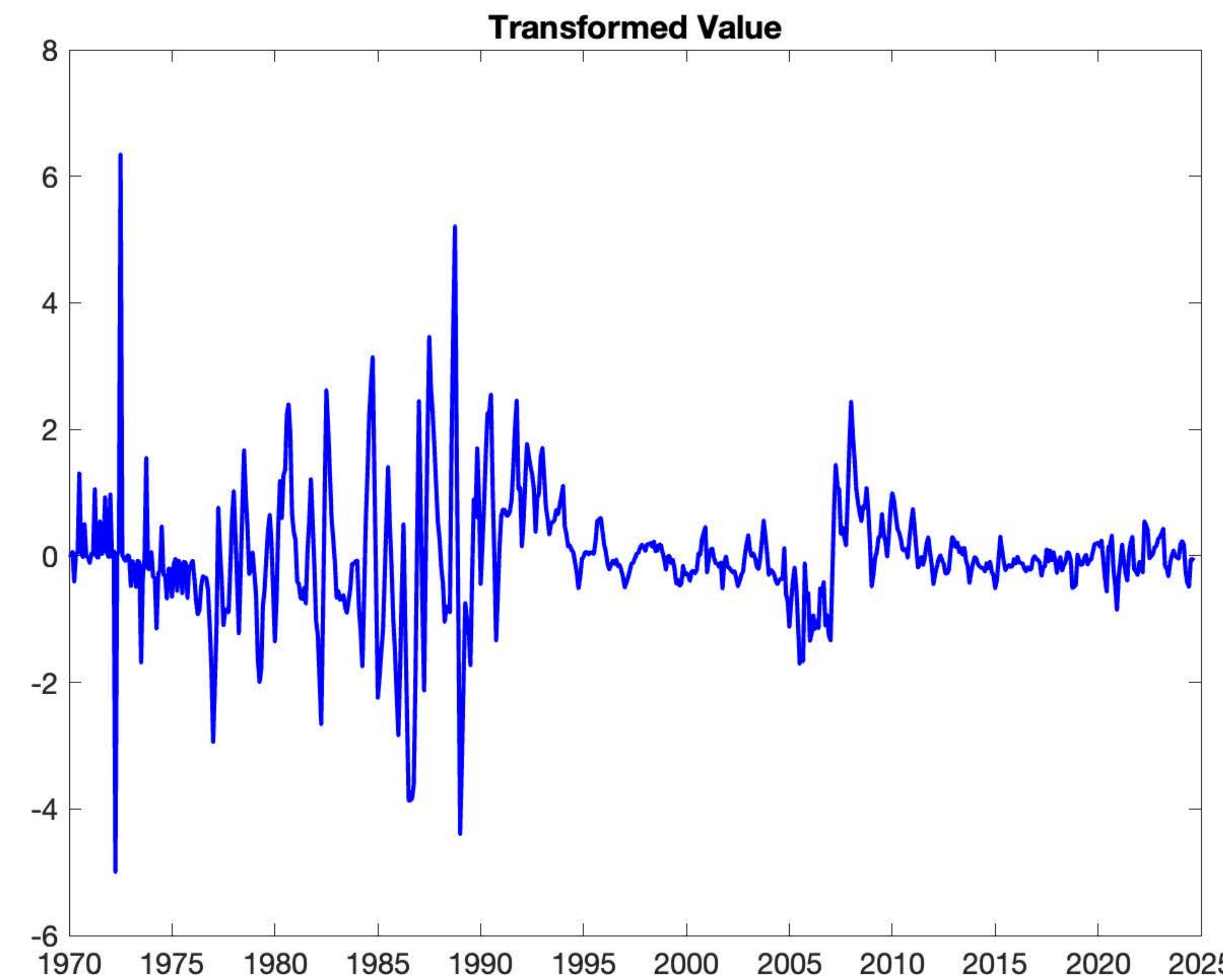

105. A041RC1: Level

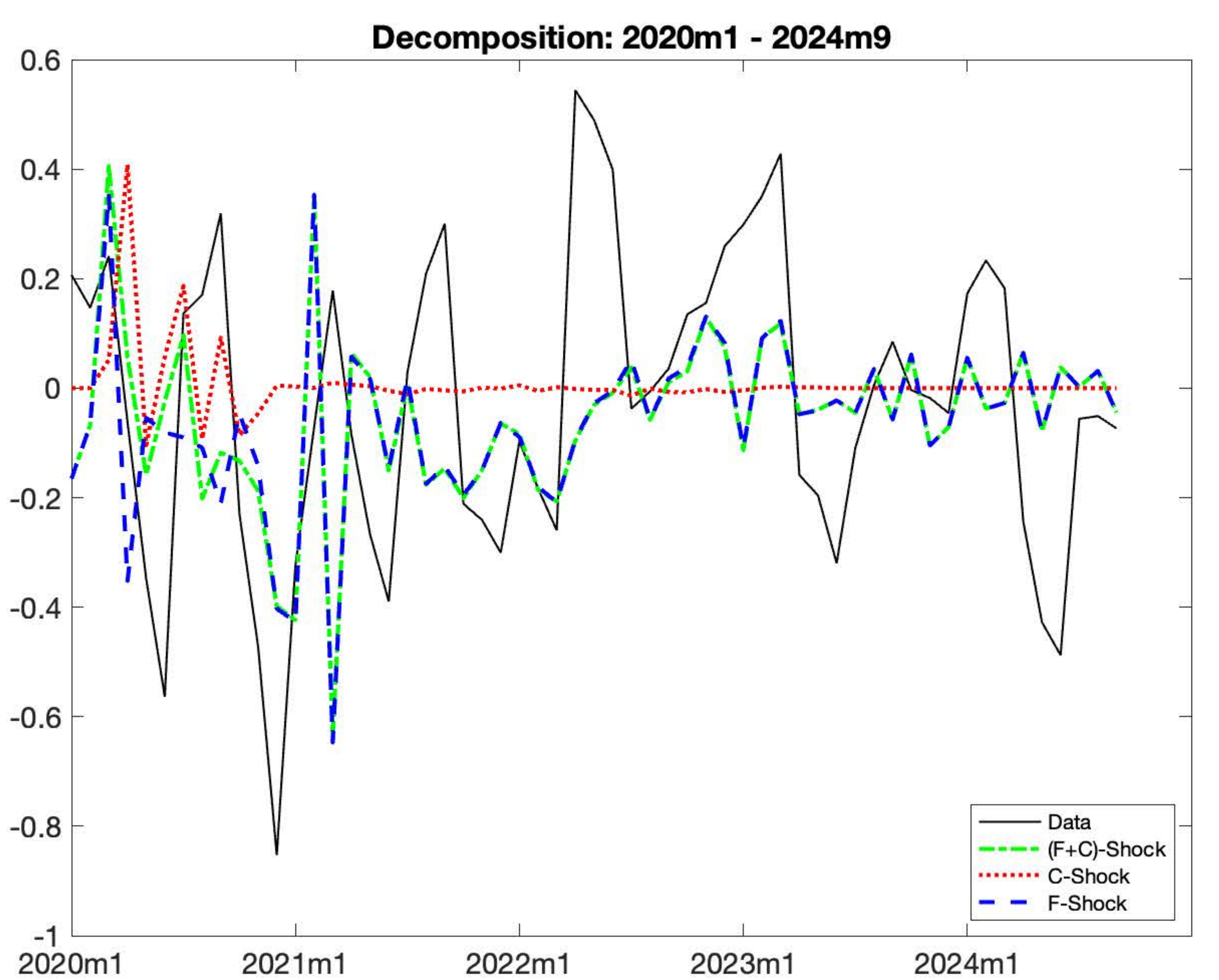

Transformed Value

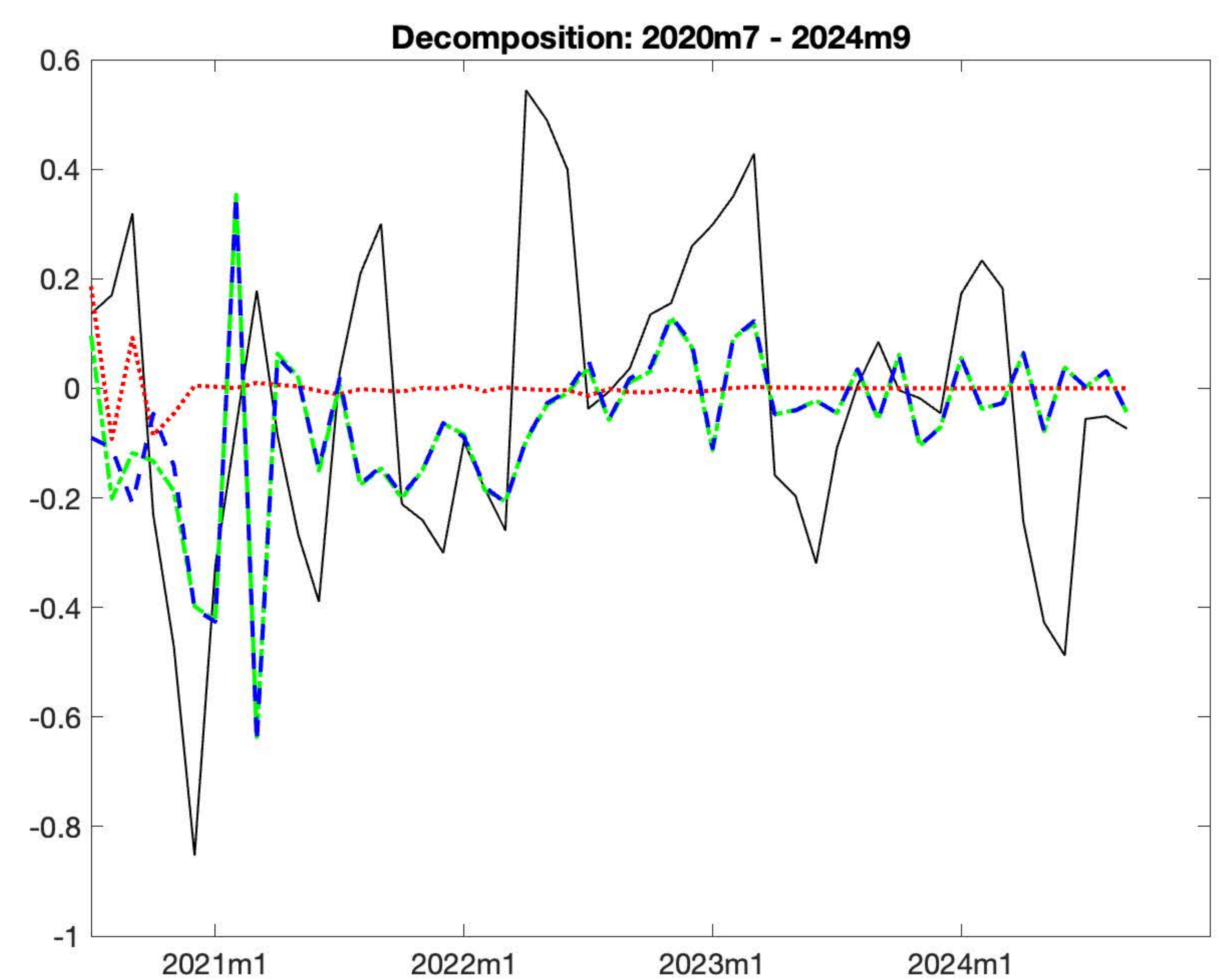

Decomposition: 2020m1 - 2024m9
Data
(F+C)-Shock
C-Shock
F-Shock

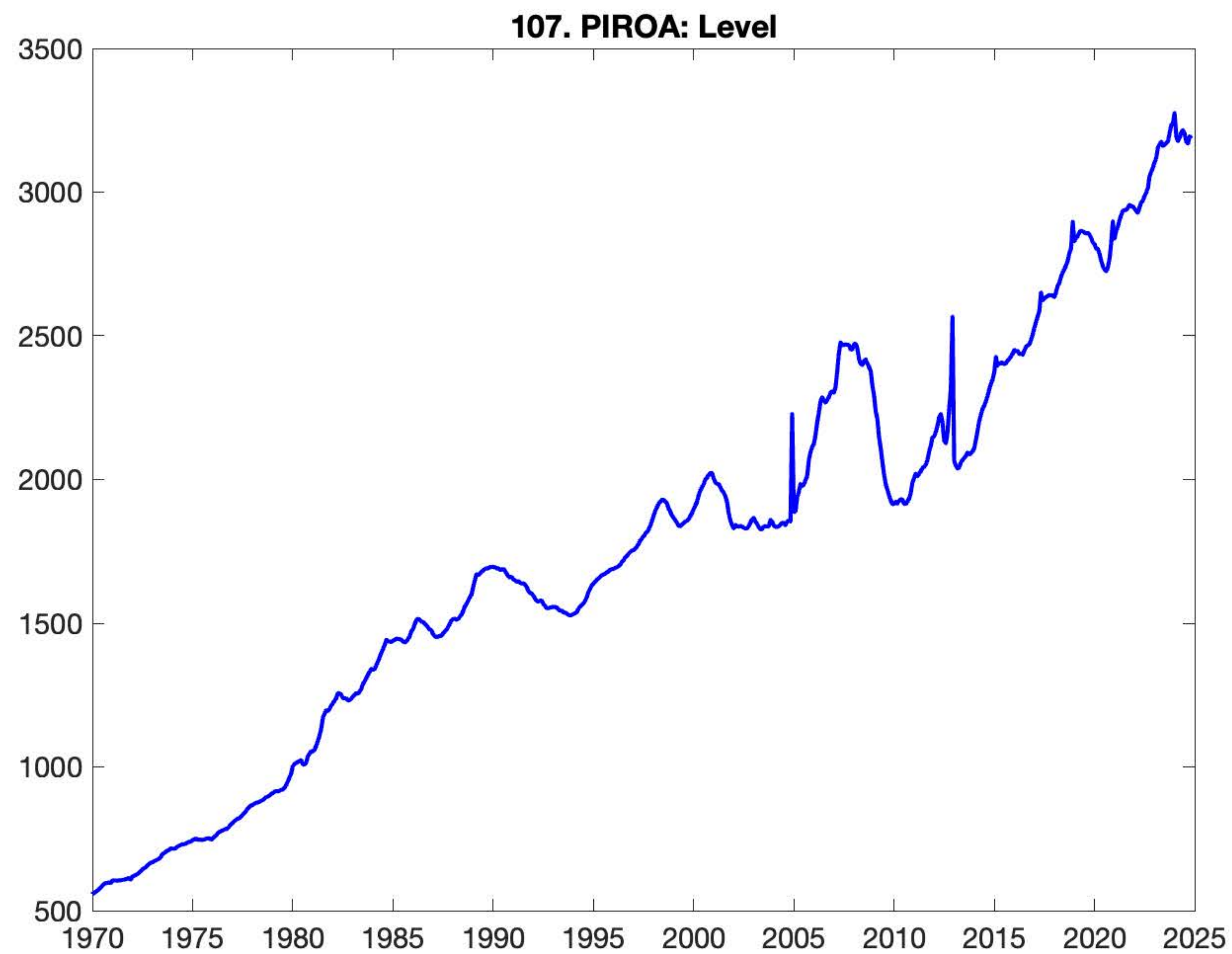

Decomposition: 2020m7 - 2024m9

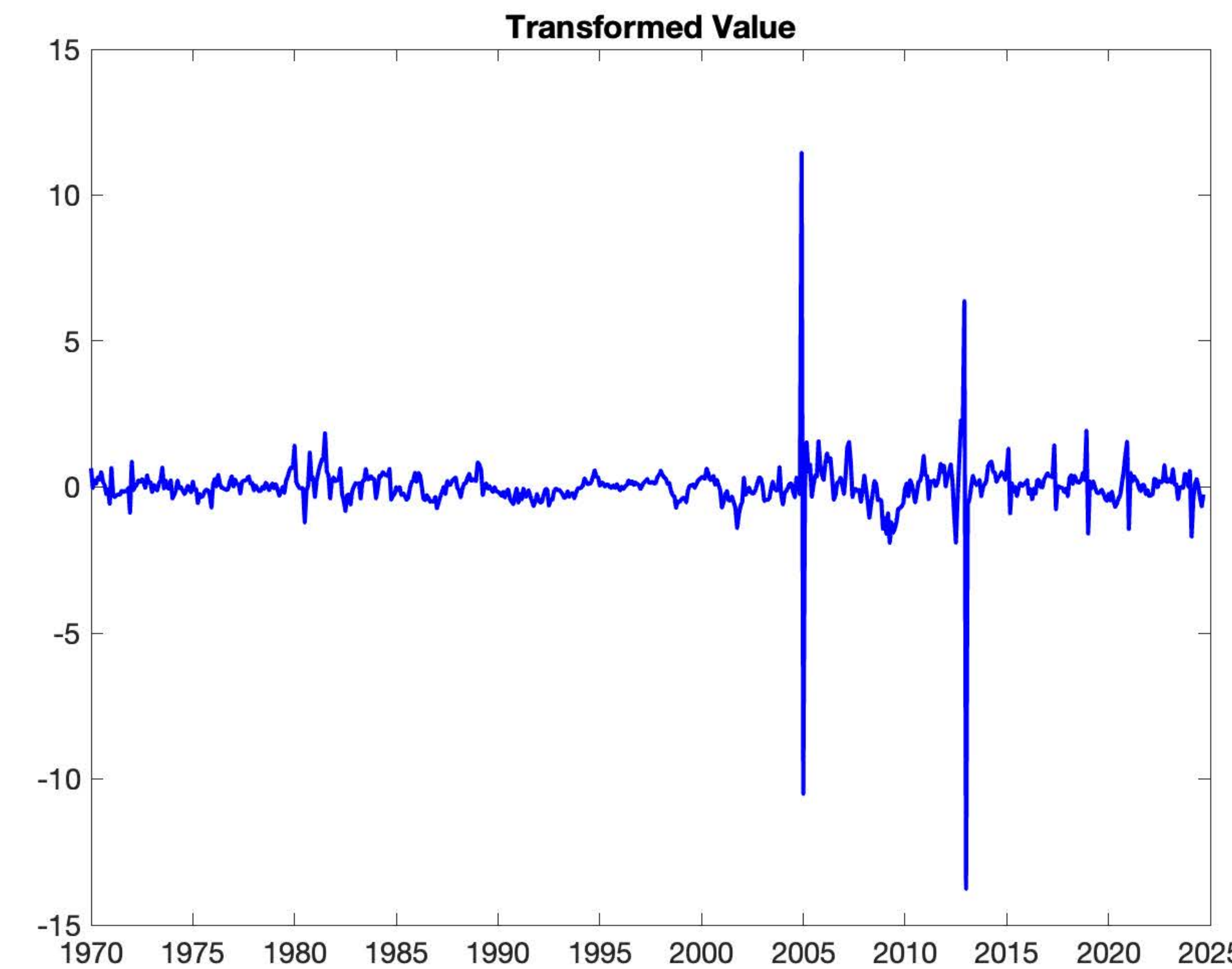

106. A048RC1: Level
900
800
700
600
500
400
300
200
100
0
1970
1975
1980
1985
1990
1995
2000
2005
2010
2015
2020
2025

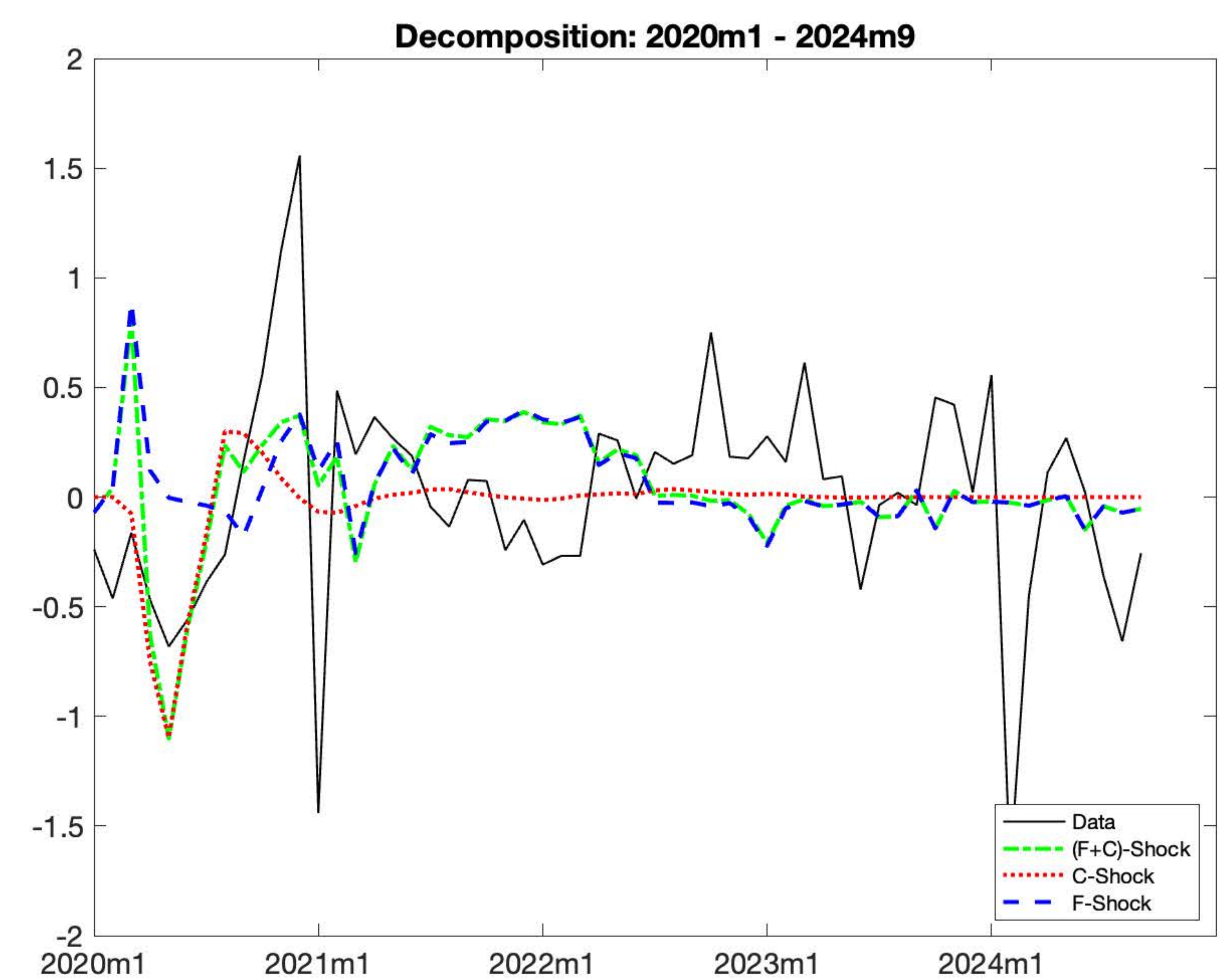

Transformed Value
8
6
4
2
0
-2
-4
-6
1970
1975
1980
1985
1990
1995
2000
2005
2010
2015
2020
2025

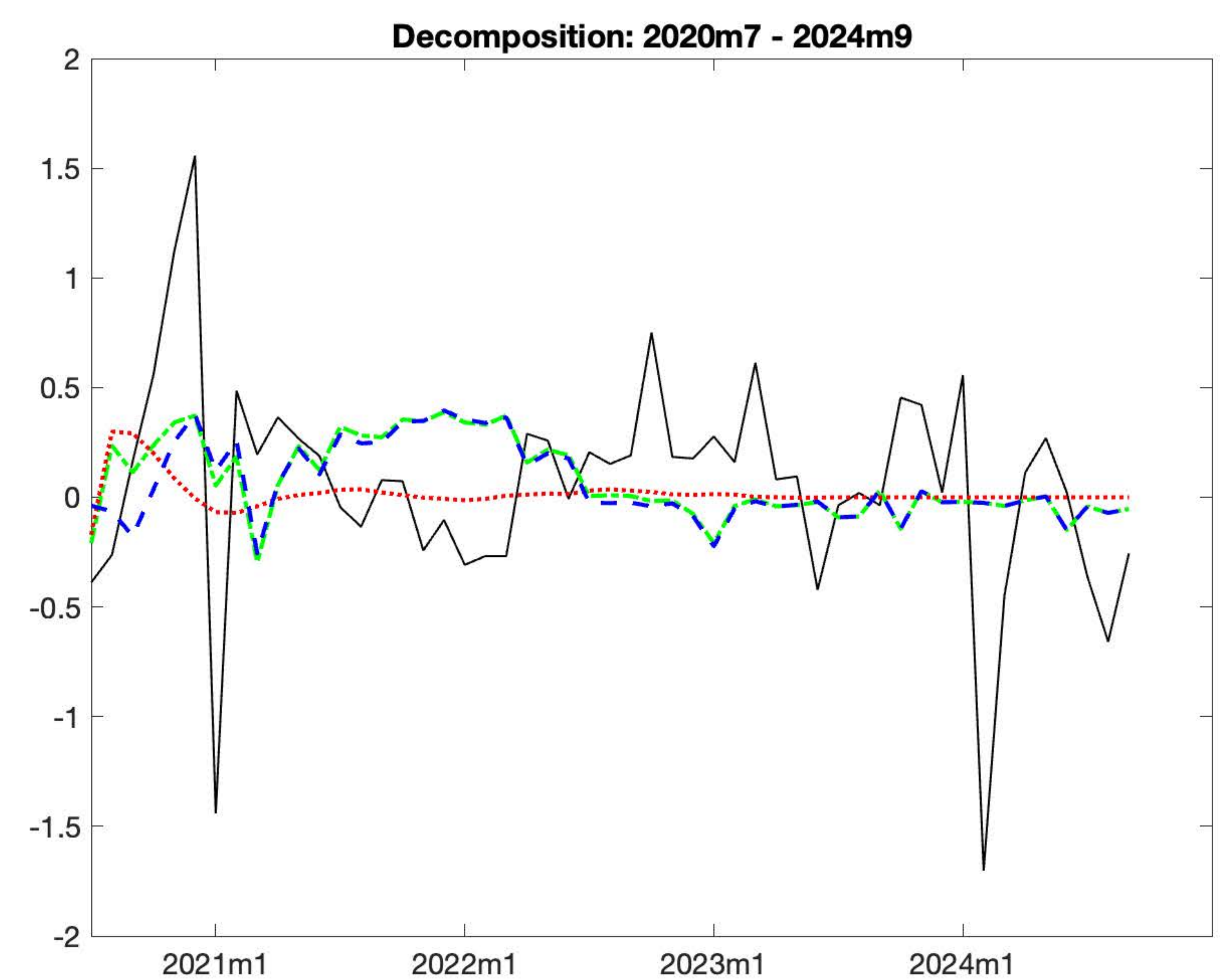

Decomposition: 2020m1 - 2024m9
0.6
0.4
0.2
0
-0.2
-0.4
-0.6
-0.8
-1
2020m1
2021m1
2022m1
2023m1
2024m1
Data
(F+C)-Shock
C-Shock
F-Shock

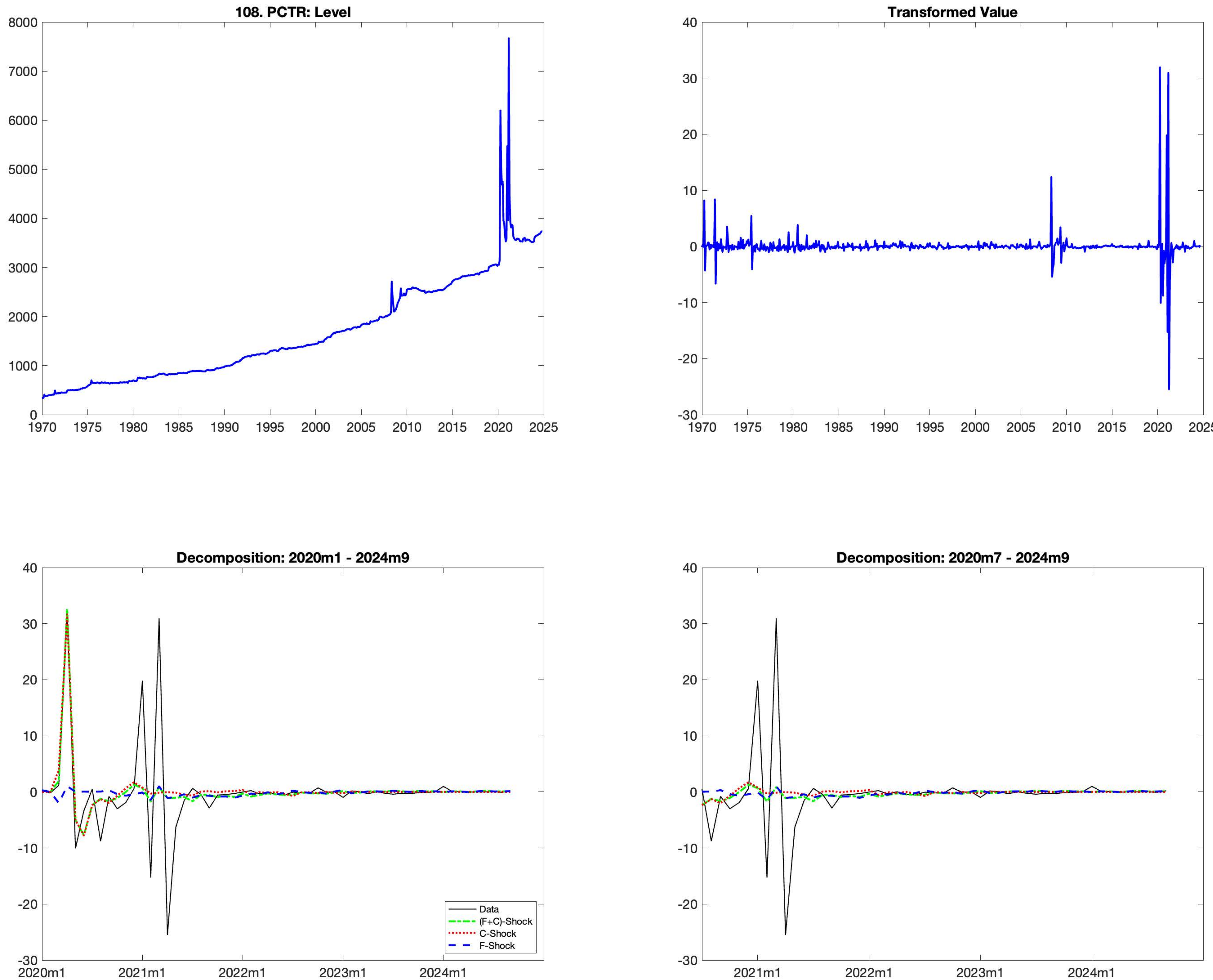

Decomposition: 2020m7 - 2024m9
0.6
0.4
0.2
0
-0.2
-0.4
-0.6
-0.8
-1
2021m1
2022m1
2023m1
2024m1

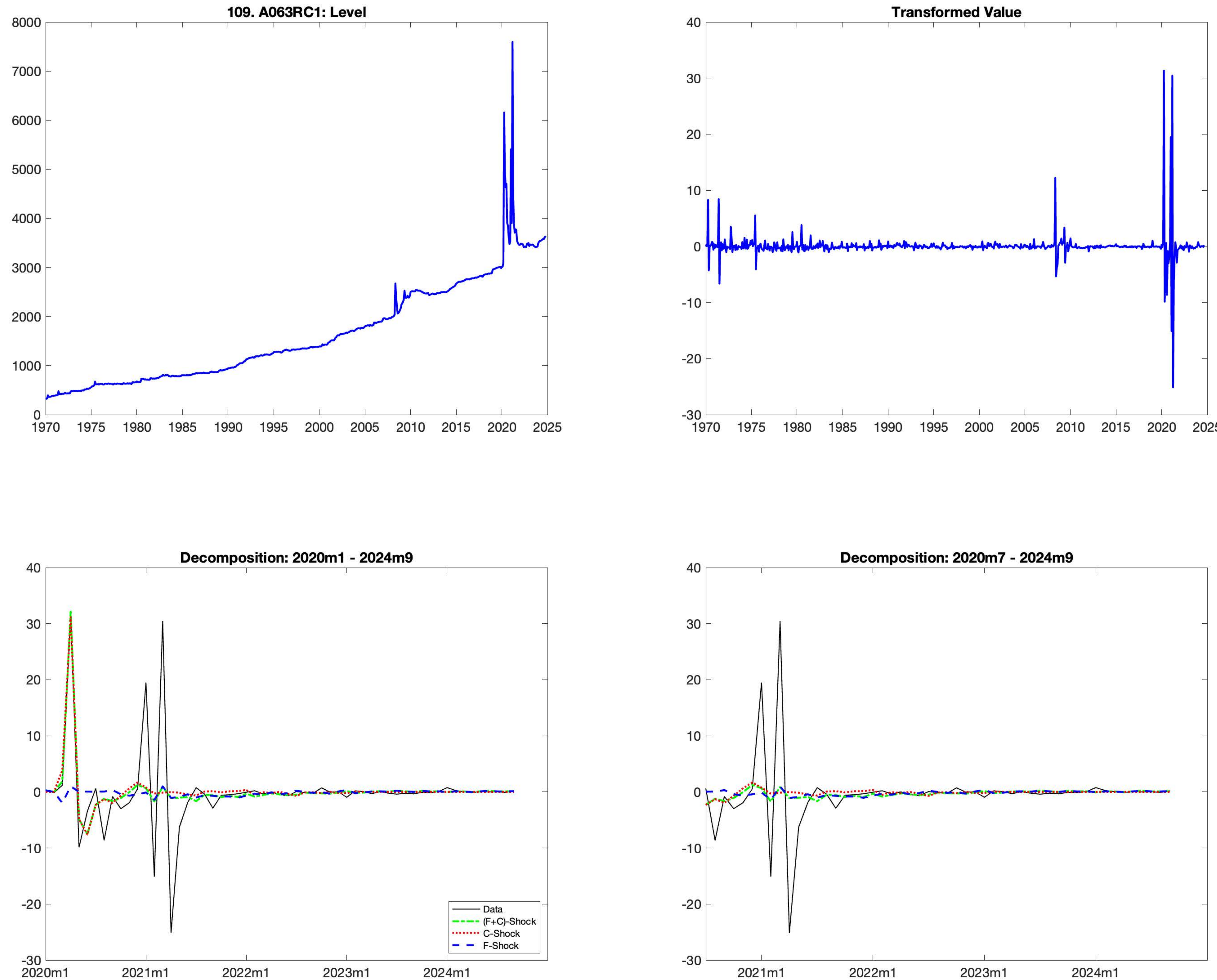

107. PIROA: Level


Transformed Value

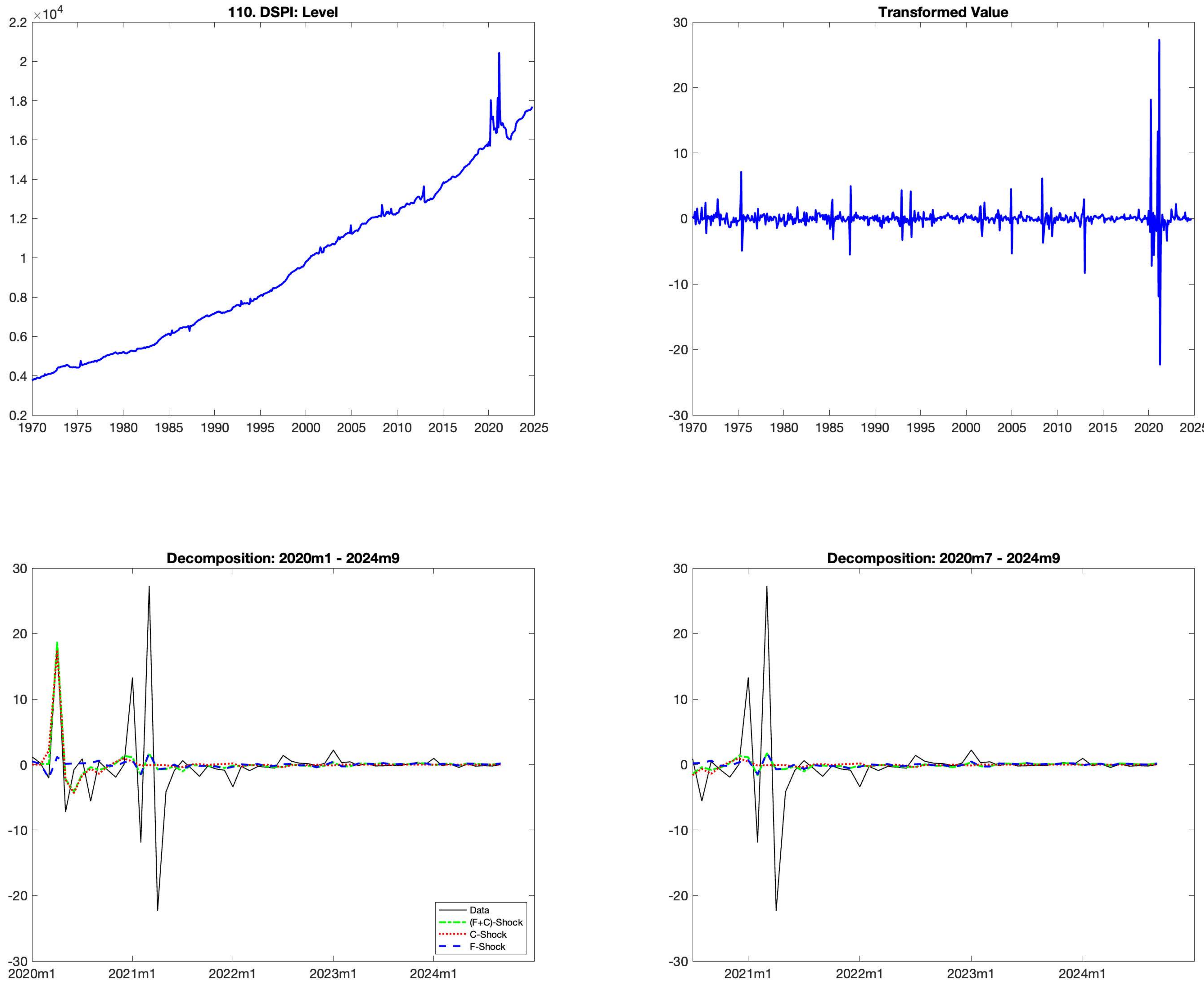

Decomposition: 2020m1 - 2024m9
Data
(F+C)-Shock
C-Shock
F-Shock


Decomposition: 2020m7 - 2024m9

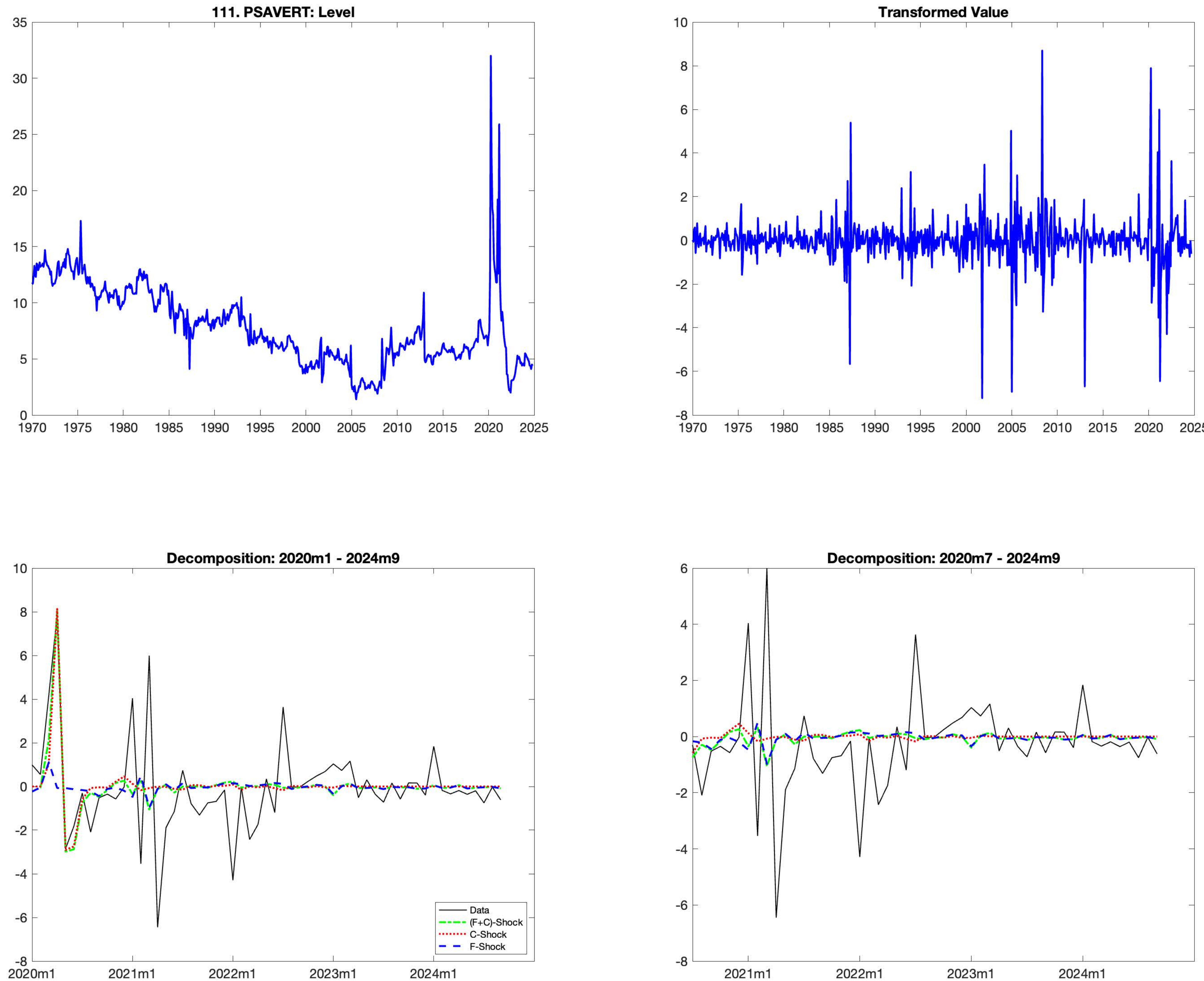

108. PCTR: Level
Transformed Value
Decomposition: 2020m1 - 2024m9
Decomposition: 2020m7 - 2024m9
Data
(F+C)-Shock
C-Shock
F-Shock

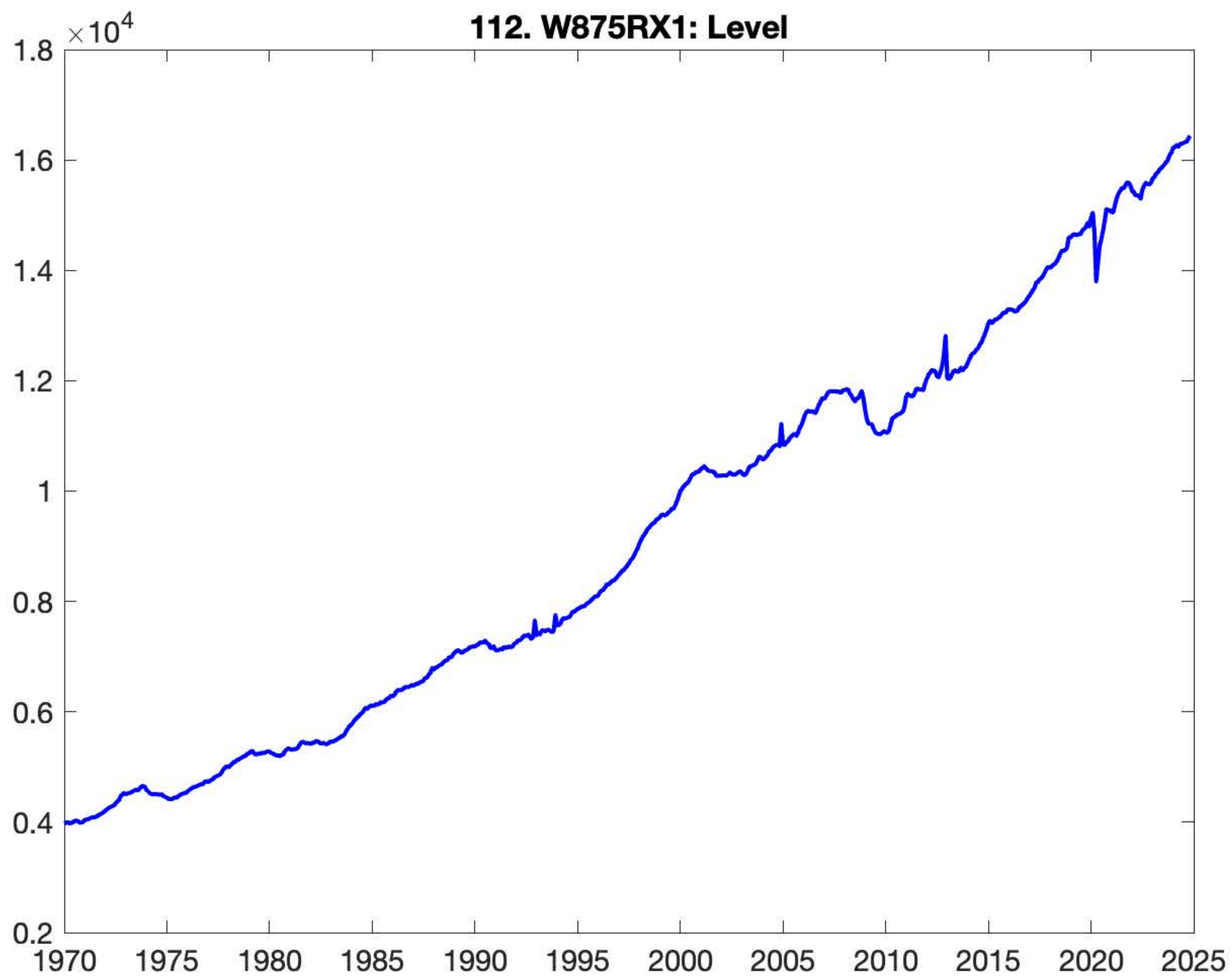


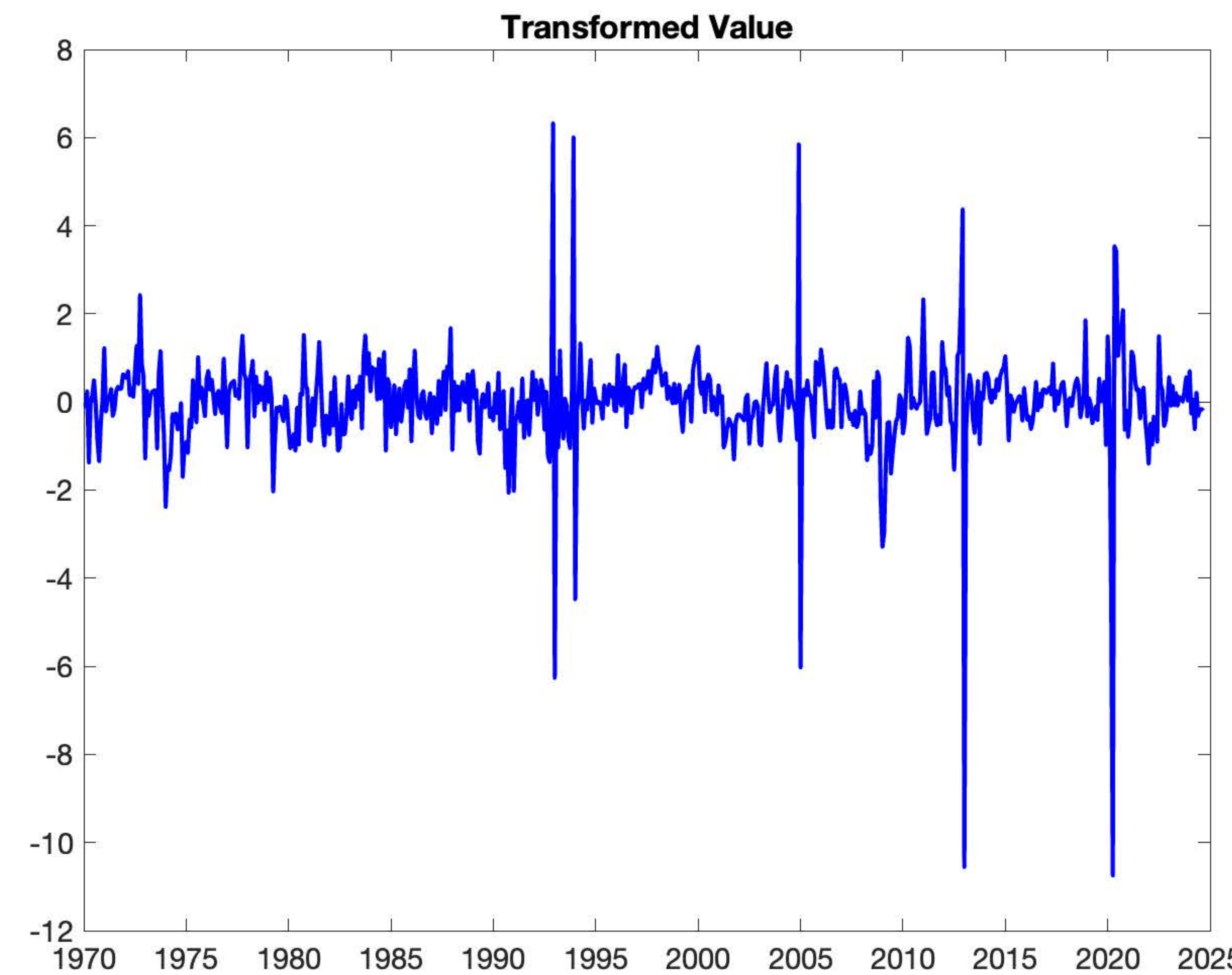
109. A063RC1: Level
Transformed Value
Decomposition: 2020m1 - 2024m9
Data
(F+C)-Shock
C-Shock
F-Shock
Decomposition: 2020m7 - 2024m9

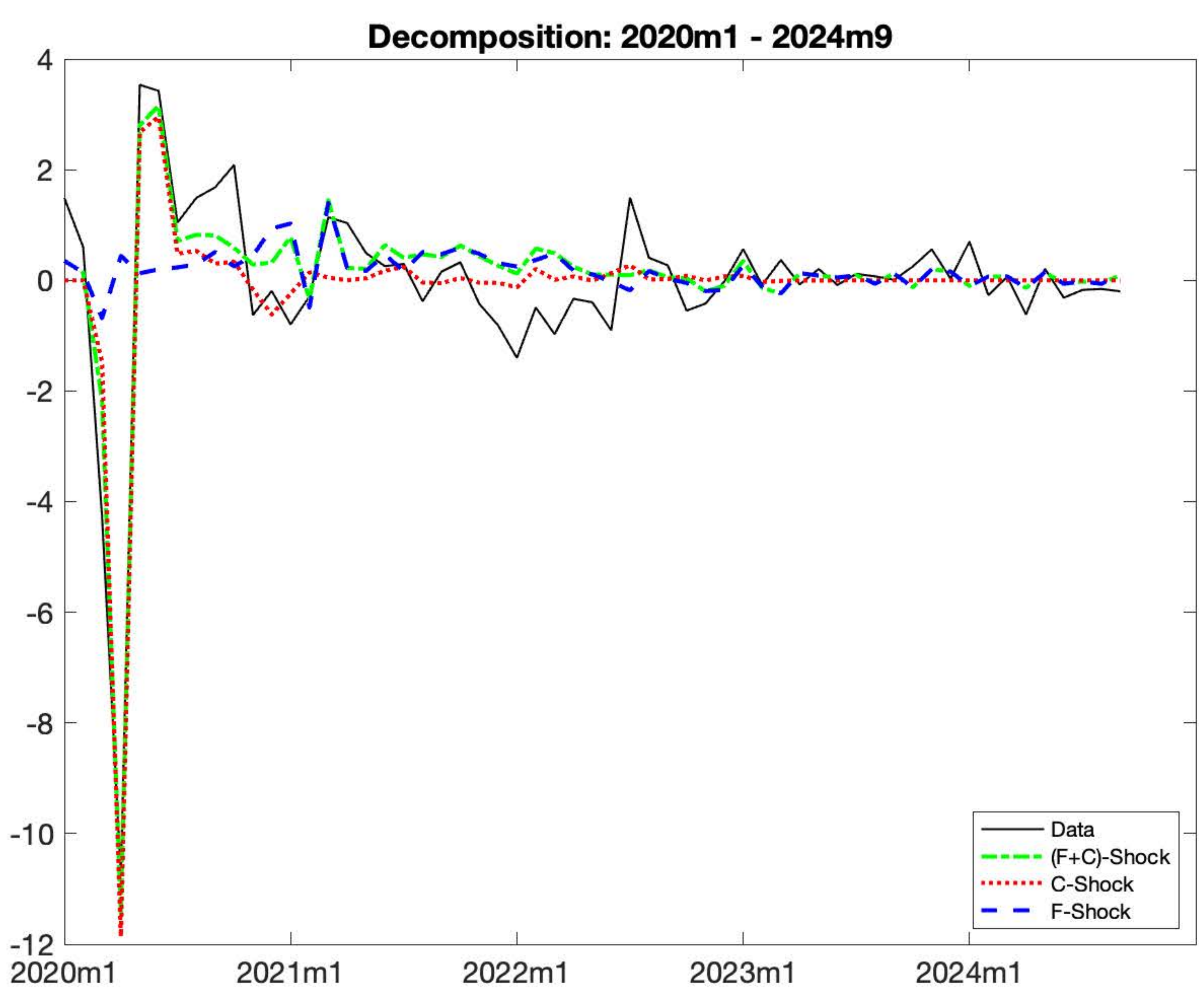


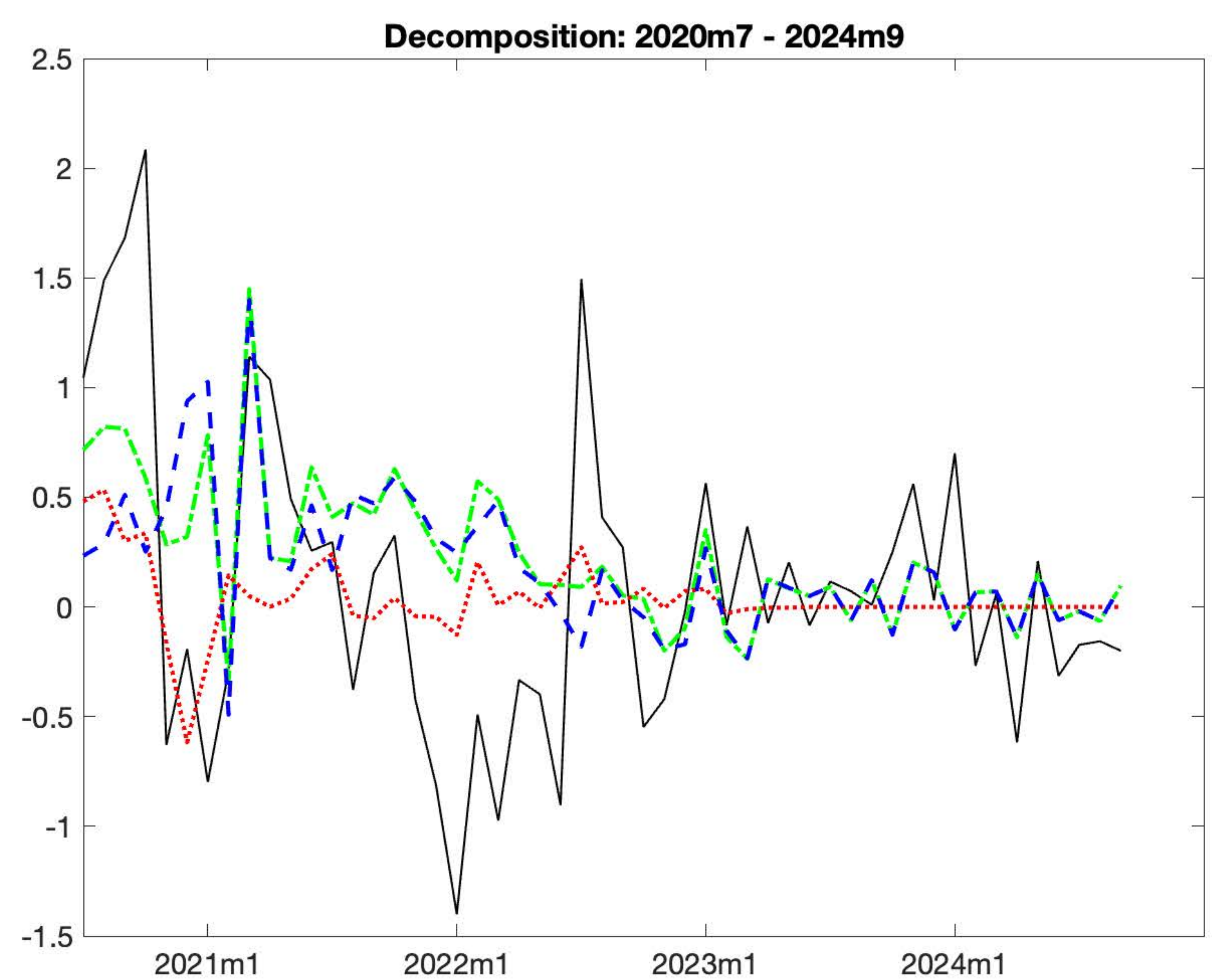
110. DSPI: Level
×10^4
Transformed Value
Decomposition: 2020m1 - 2024m9
Decomposition: 2020m7 - 2024m9
Data
(F+C)-Shock
C-Shock
F-Shock

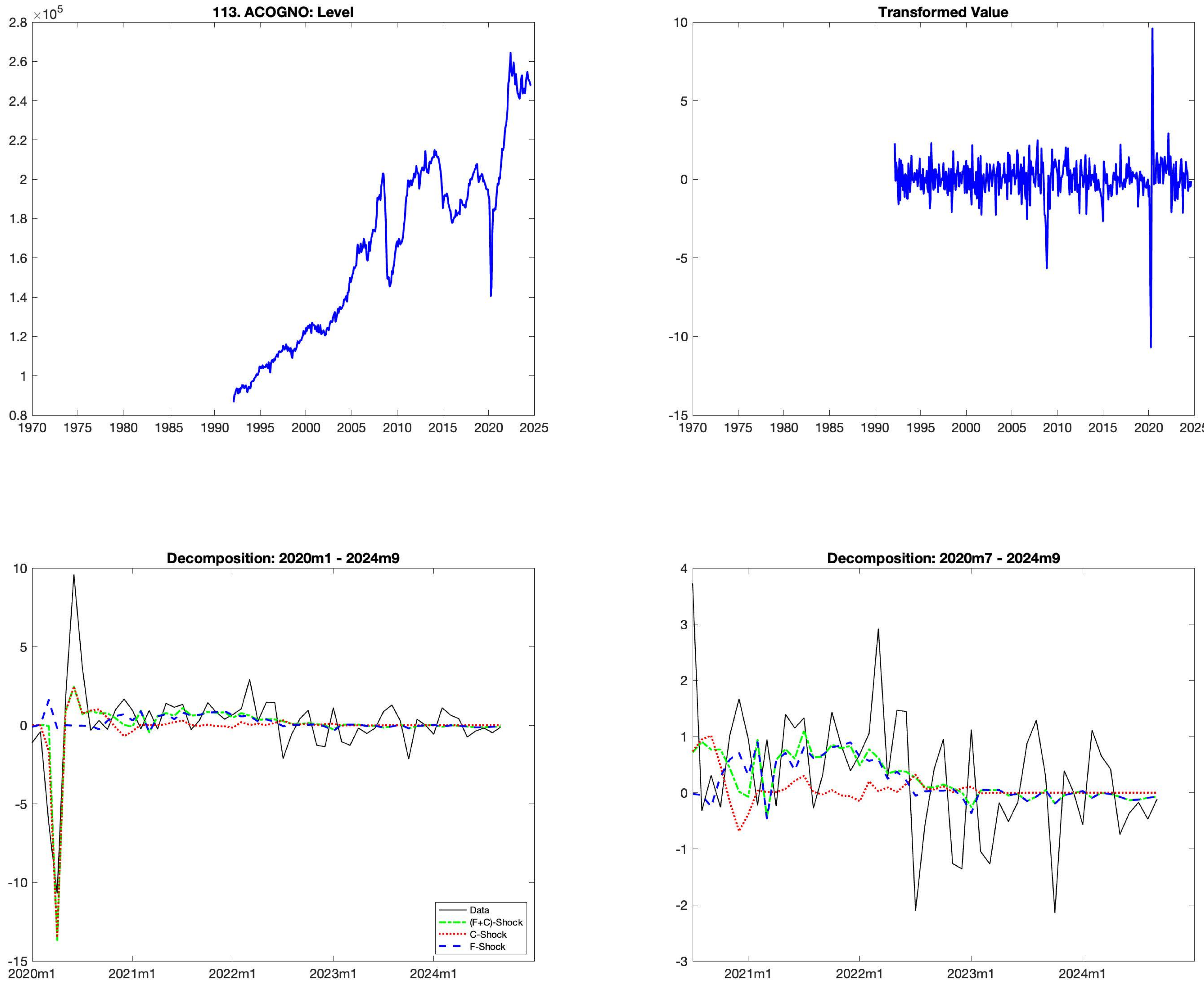

111. PSAVERT: Level
Transformed Value
Decomposition: 2020m1 - 2024m9
Data
(F+C)-Shock
C-Shock
F-Shock
Decomposition: 2020m7 - 2024m9


112. W875RX1: Level
×10^4
1.8
1.6
1.4
1.2
1
0.8
0.6
0.4
0.2
1970 1975 1980 1985 1990 1995 2000 2005 2010 2015 2020 2025

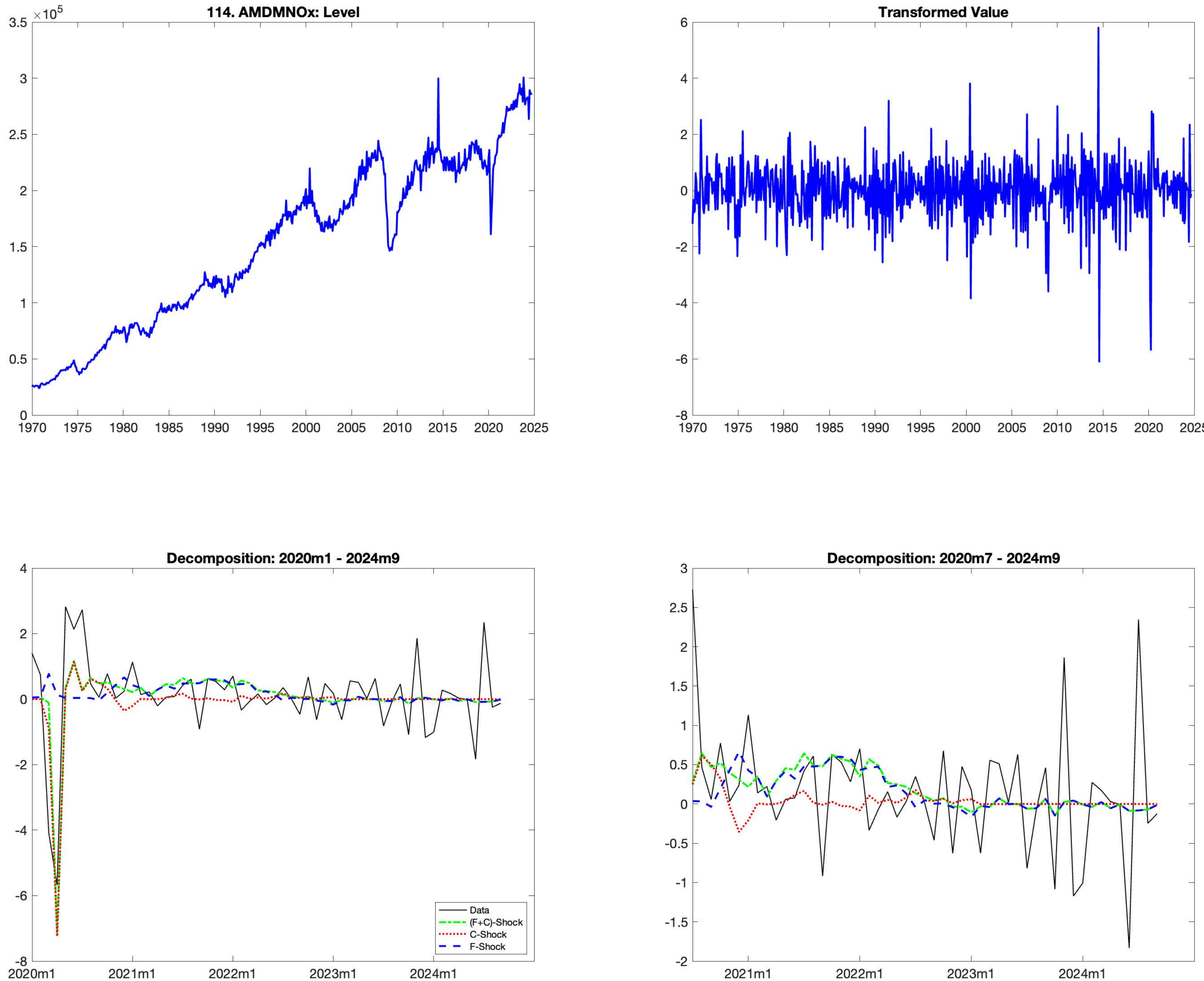

Transformed Value
8
6
4
2
0
-2
-4
-6
-8
-10
-12
1970 1975 1980 1985 1990 1995 2000 2005 2010 2015 2020 2025


Decomposition: 2020m1 - 2024m9
4
2
0
-2
-4
-6
-8
-10
-12
2020m1 2021m1 2022m1 2023m1 2024m1
Data
(F+C)-Shock
C-Shock
F-Shock

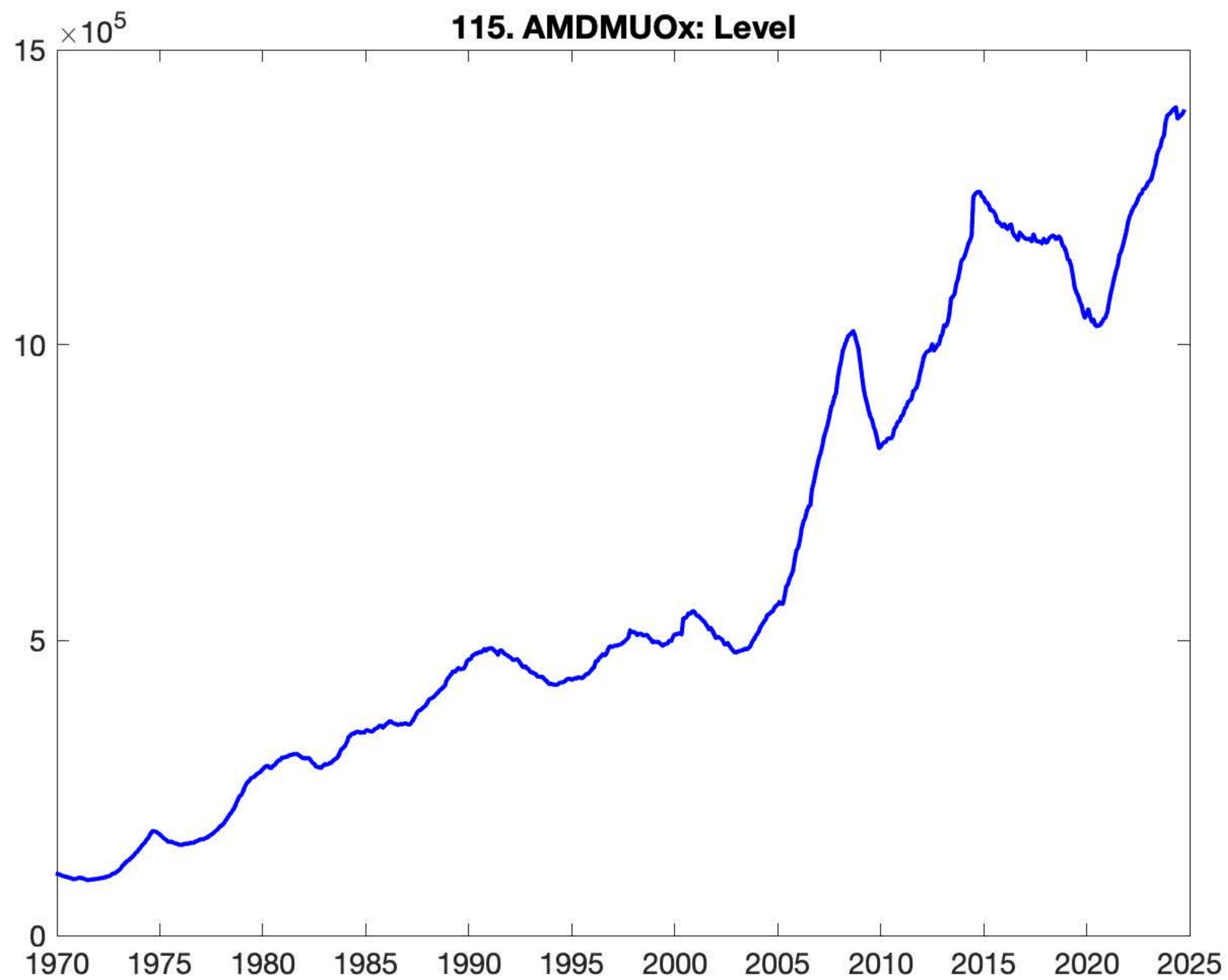

Decomposition: 2020m7 - 2024m9
2.5
2
1.5
1
0.5
0
-0.5
-1
-1.5
2021m1 2022m1 2023m1 2024m1

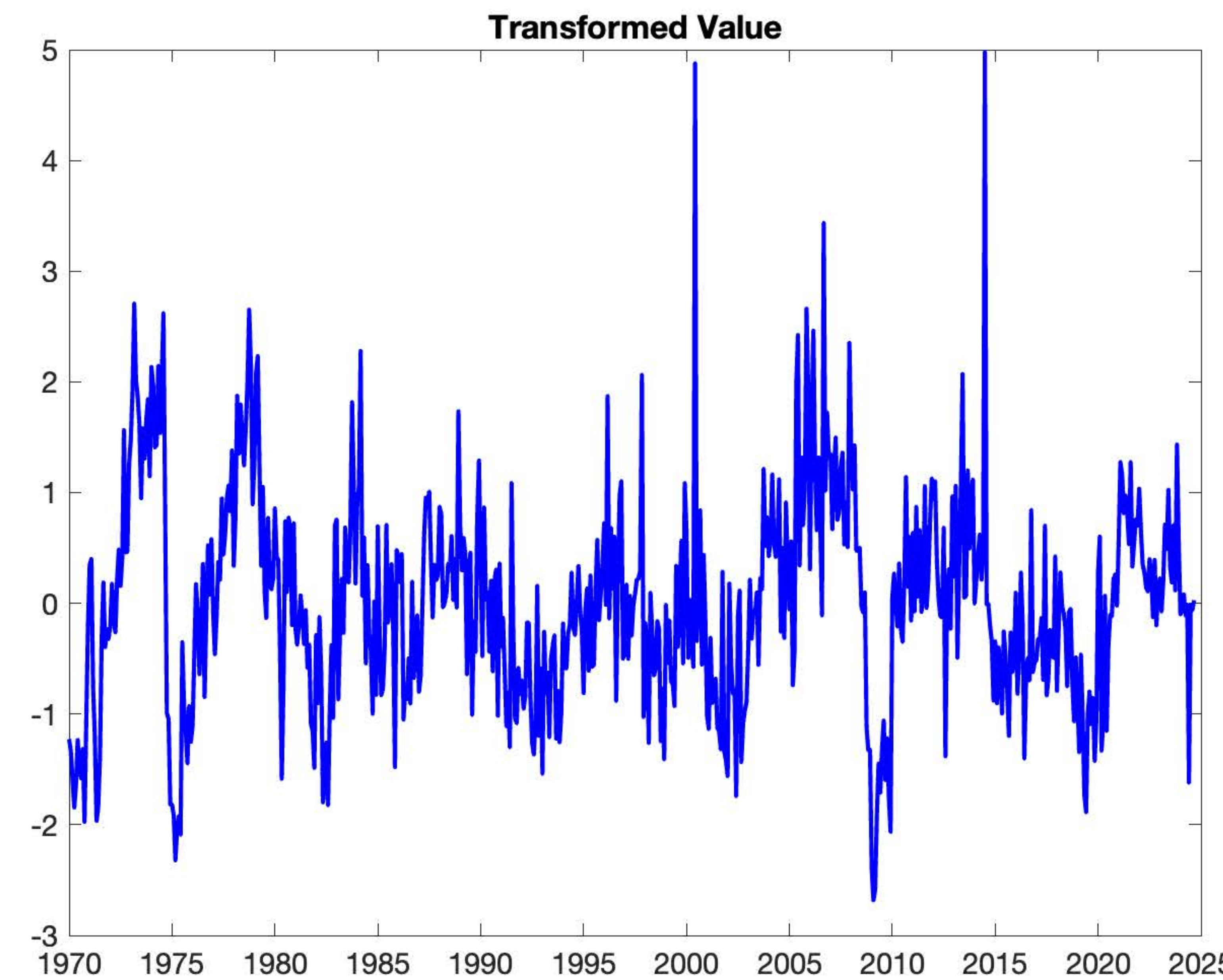


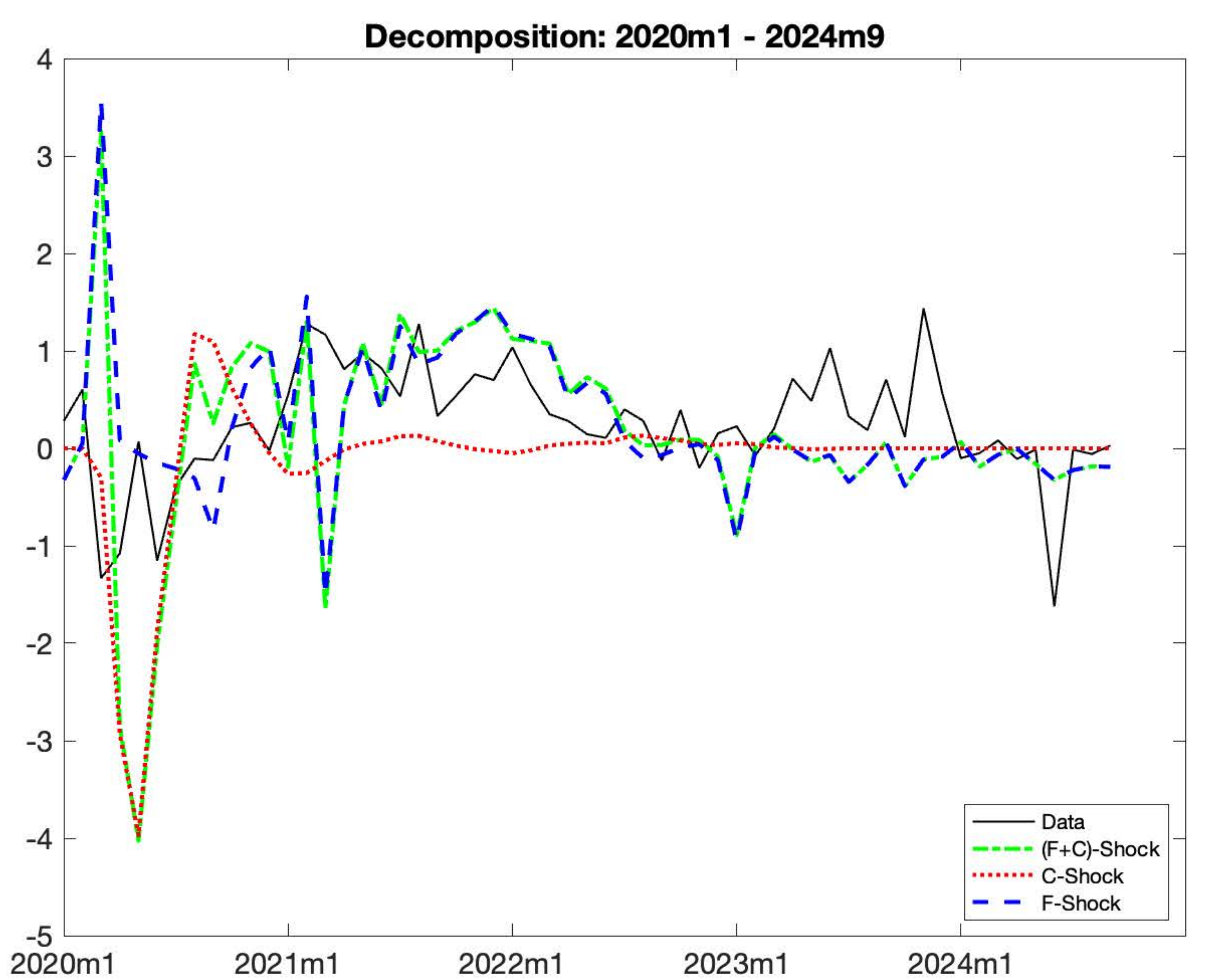
113. ACOGNO: Level
×10^5
Transformed Value
Decomposition: 2020m1 - 2024m9
Decomposition: 2020m7 - 2024m9
Data
(F+C)-Shock
C-Shock
F-Shock

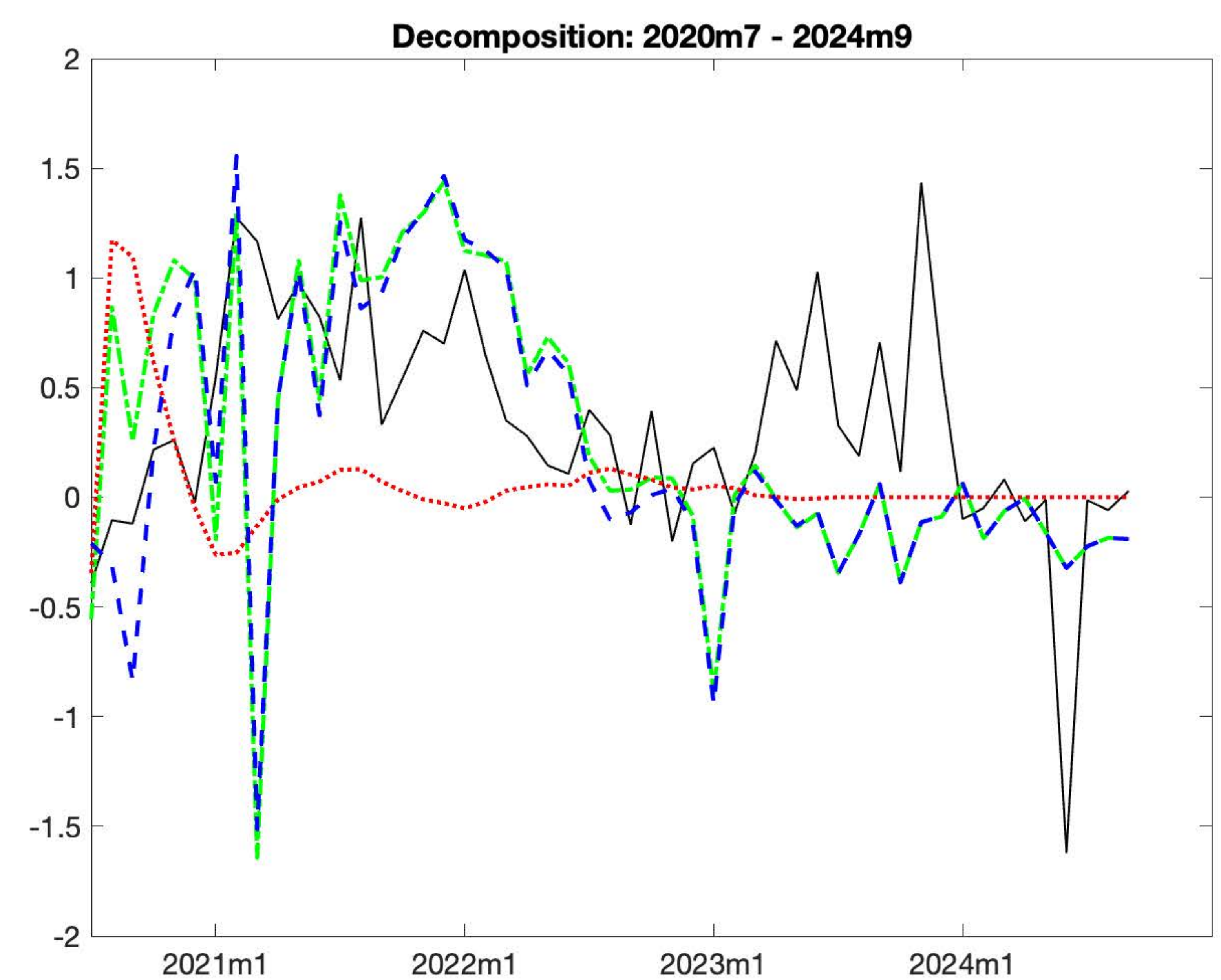


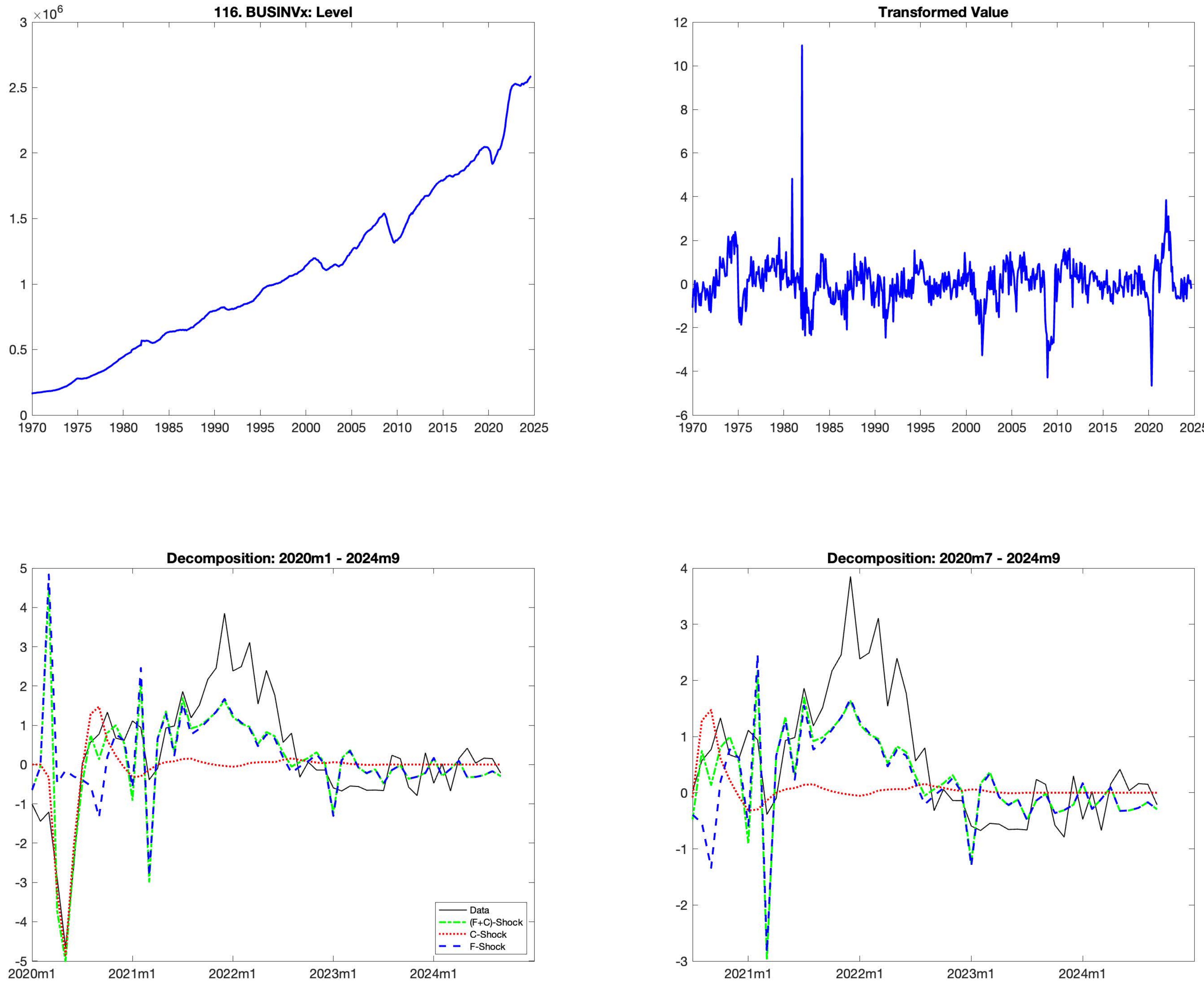
114. AMDMNOx: Level
Transformed Value
Decomposition: 2020m1 - 2024m9
Decomposition: 2020m7 - 2024m9
Data
(F+C)-Shock
C-Shock
F-Shock

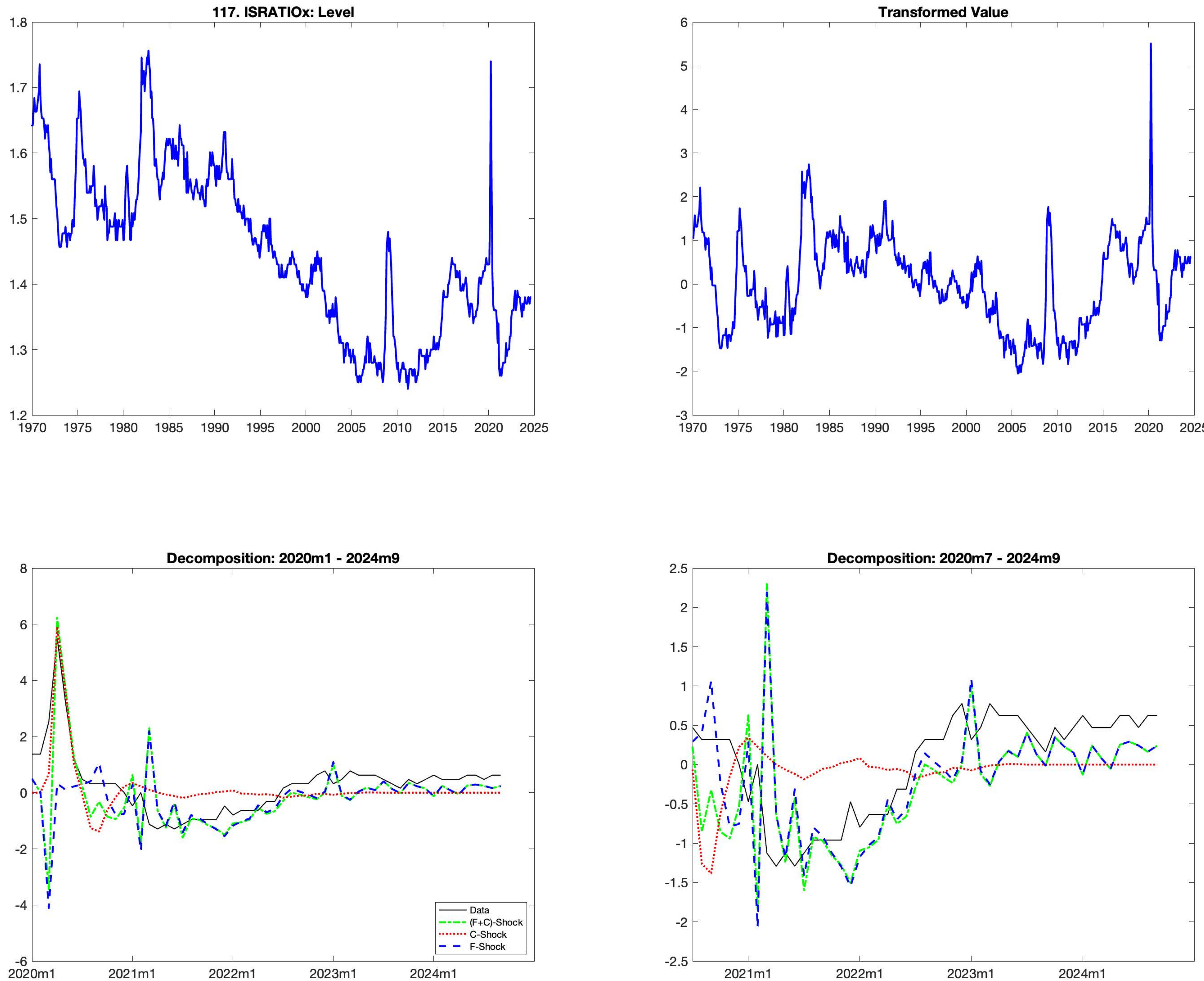

115. AMDMUOx: Level
×10^5
15
10
5
0
1970
1975
1980
1985
1990
1995
2000
2005
2010
2015
2020
2025

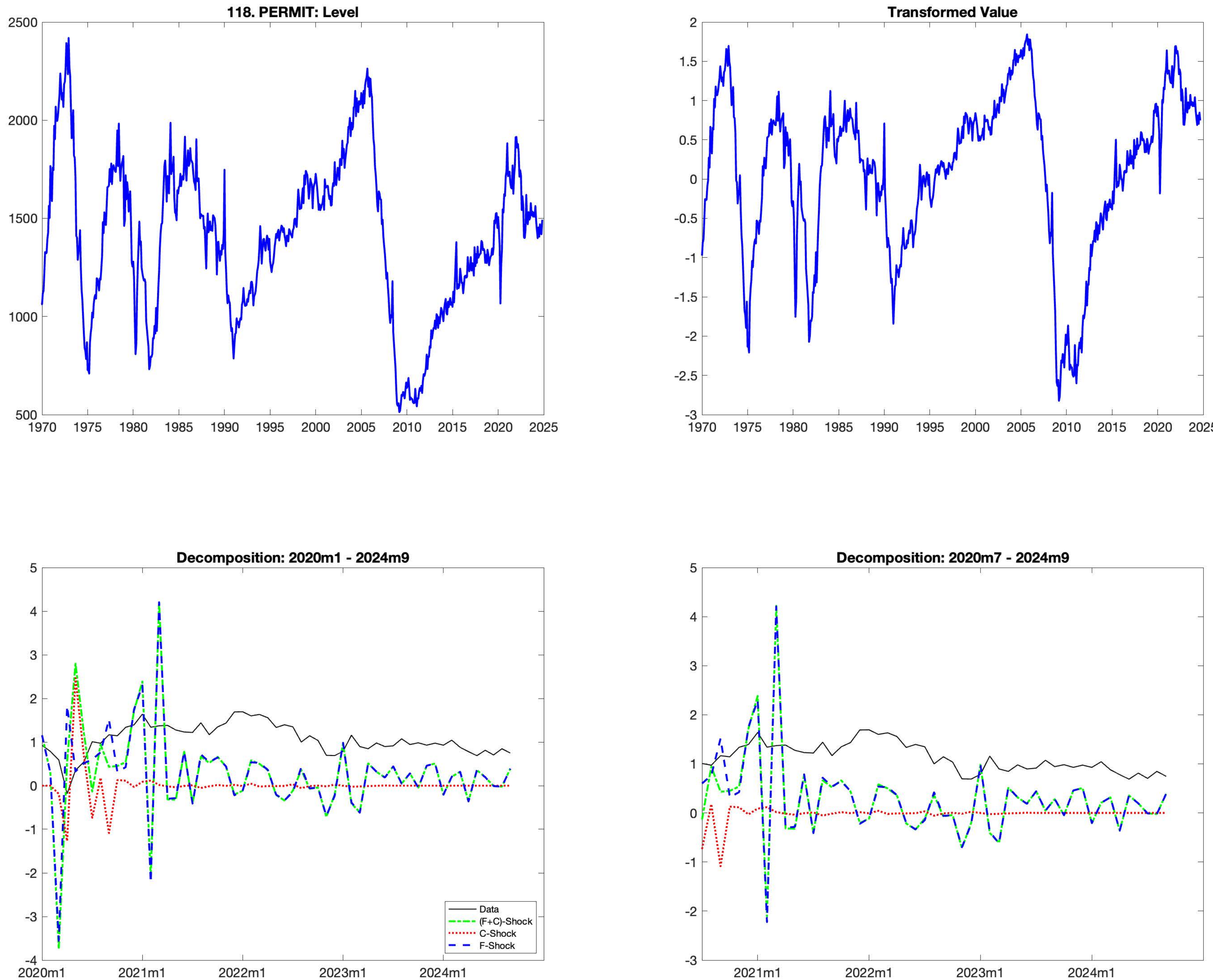

Transformed Value
5
4
3
2
1
0
-1
-2
-3
1970
1975
1980
1985
1990
1995
2000
2005
2010
2015
2020
2025

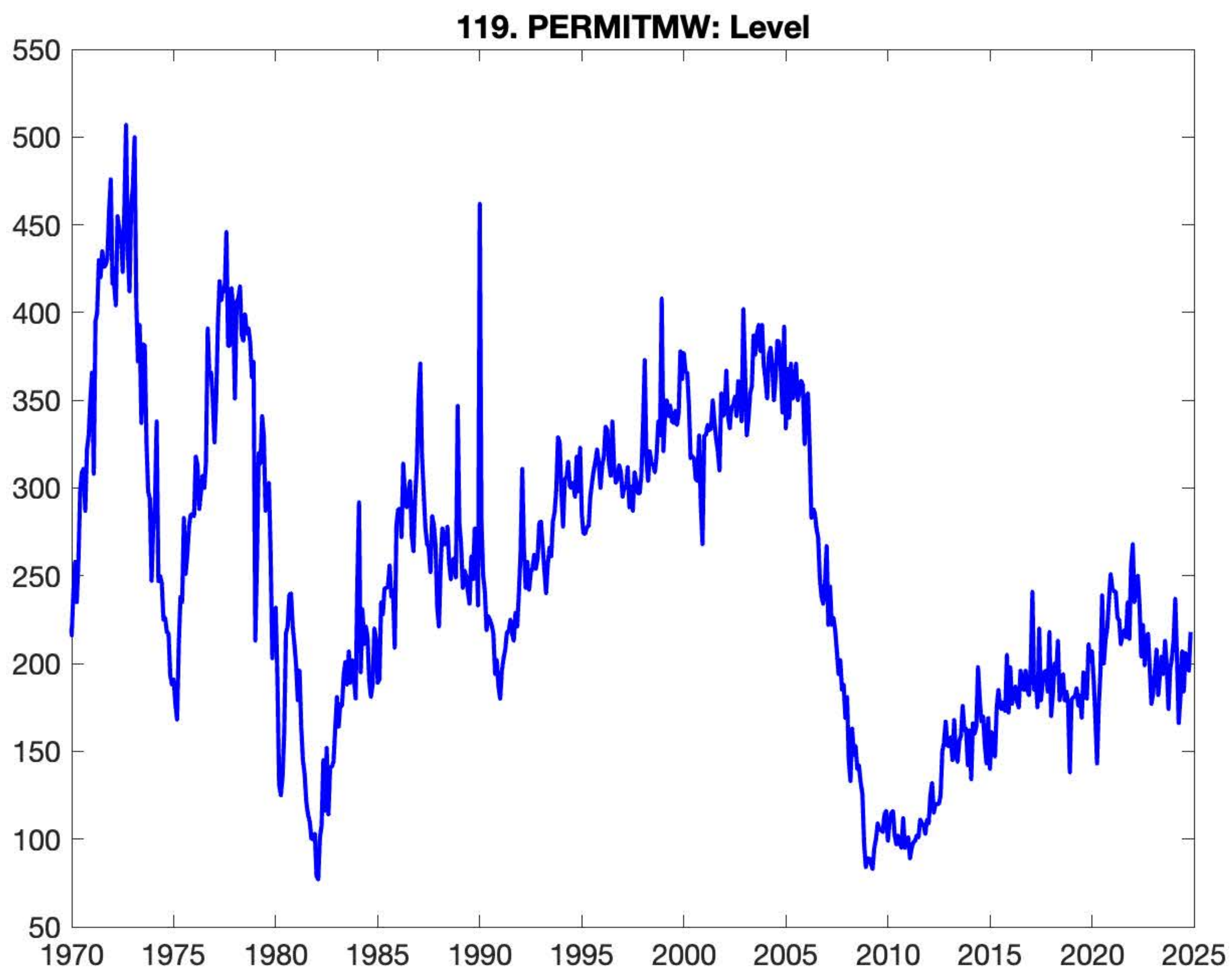

Decomposition: 2020m1 - 2024m9
4
3
2
1
0
-1
-2
-3
-4
-5
2020m1
2021m1
2022m1
2023m1
2024m1
Data
(F+C)-Shock
C-Shock
F-Shock

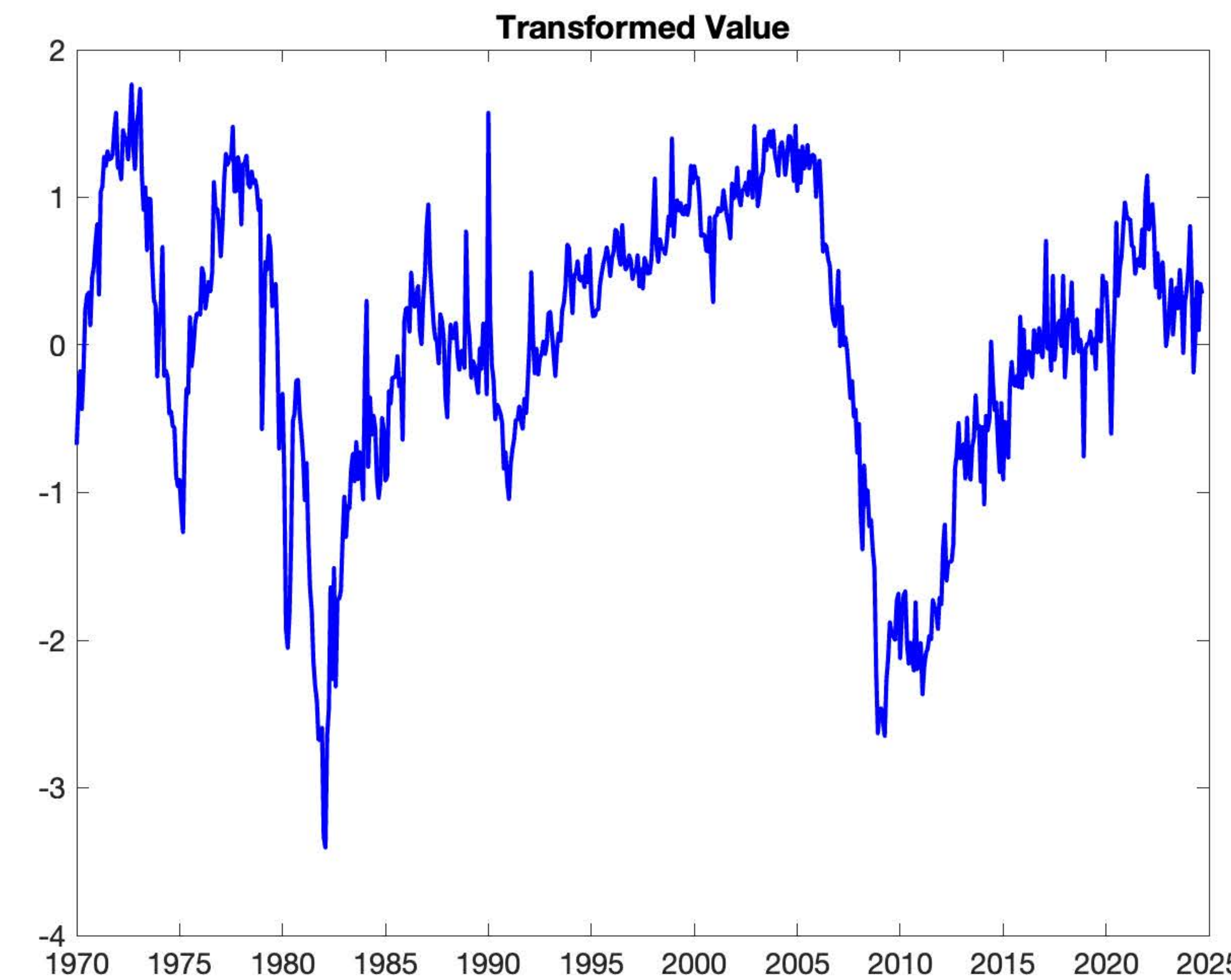

Decomposition: 2020m7 - 2024m9
2
1.5
1
0.5
0
-0.5
-1
-1.5
-2
2021m1
2022m1
2023m1
2024m1

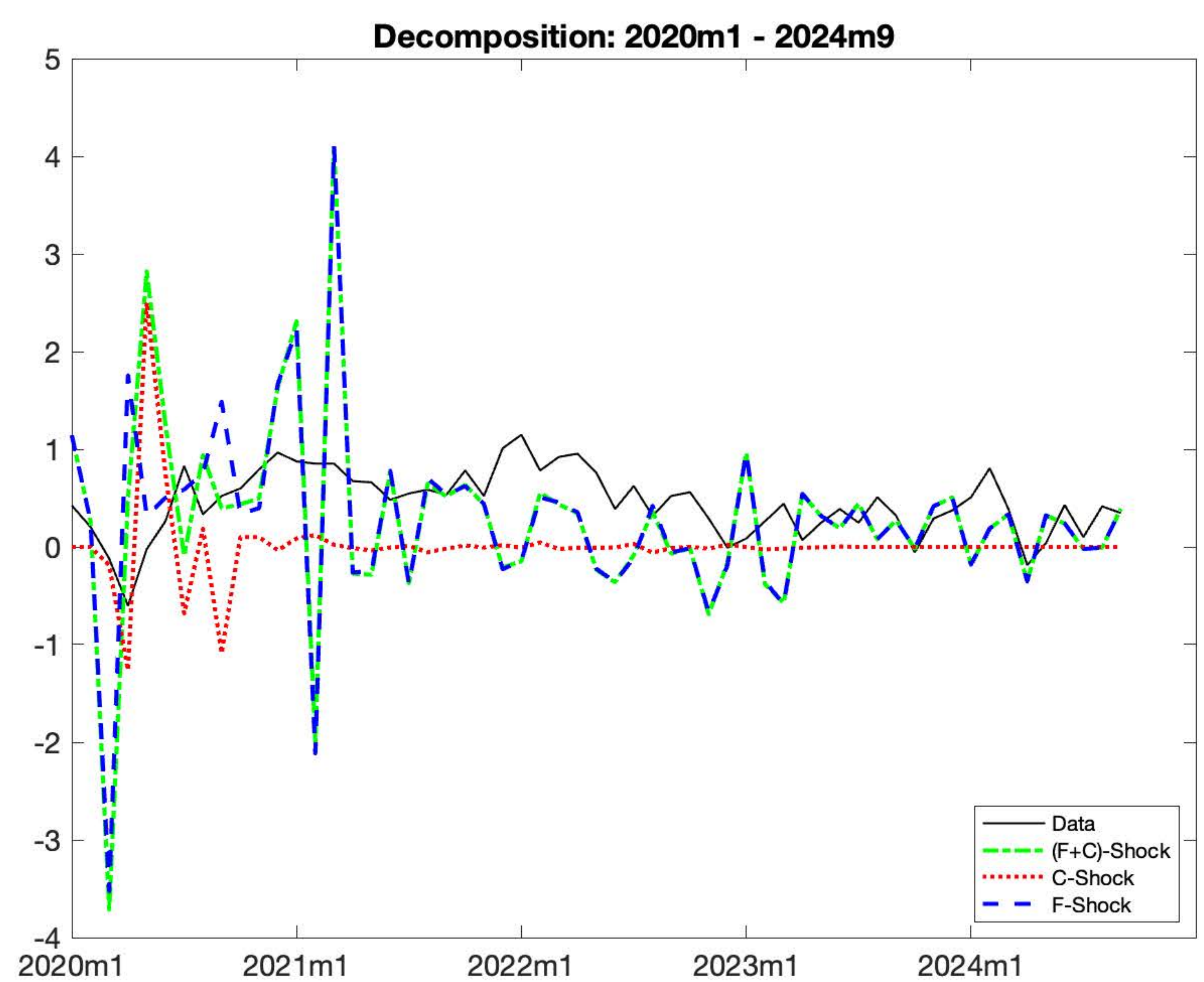

116. BUSINVx: Level
Transformed Value
Decomposition: 2020m1 - 2024m9
Decomposition: 2020m7 - 2024m9
Data
(F+C)-Shock
C-Shock
F-Shock

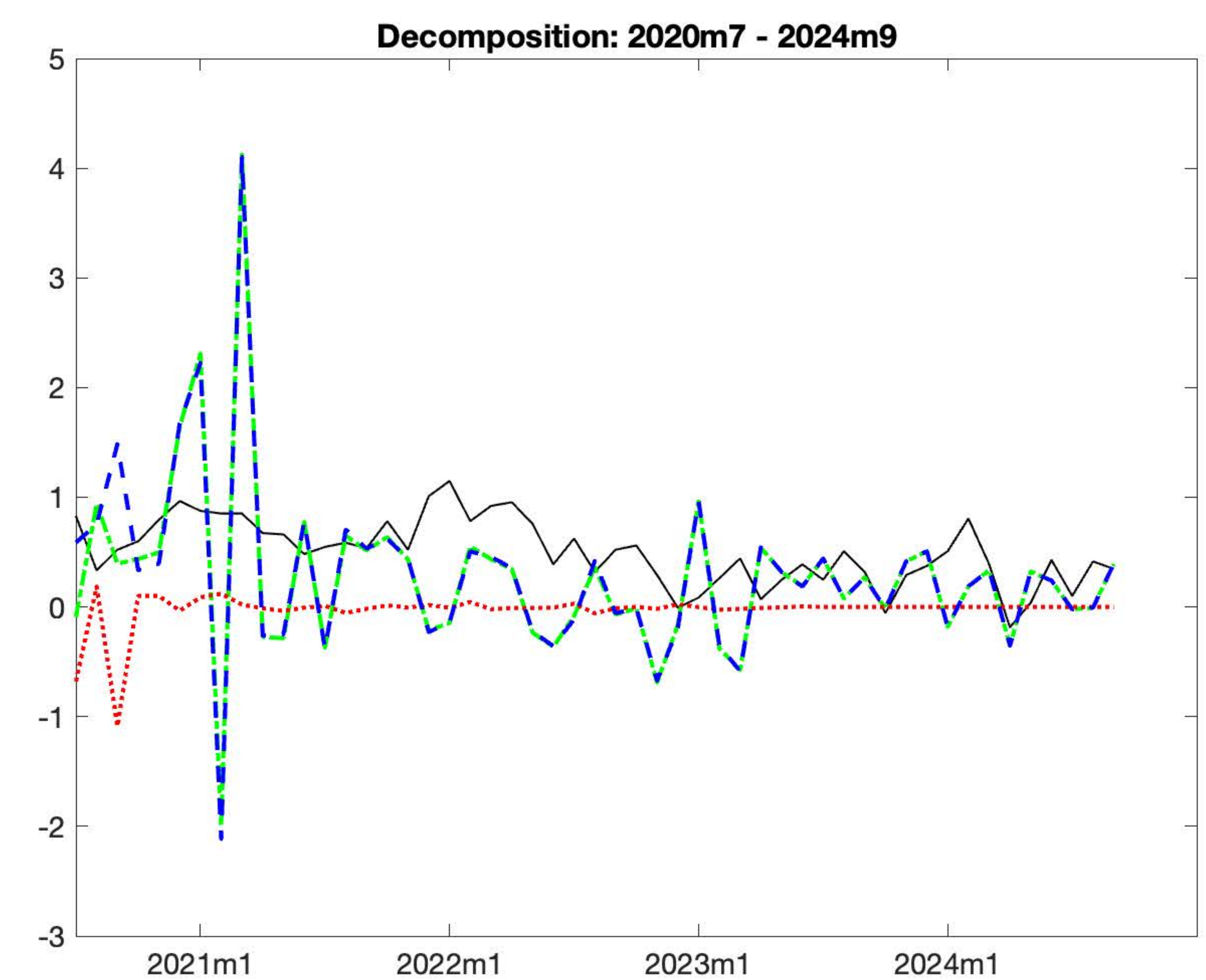

117. ISRATIOx: Level
Transformed Value
Decomposition: 2020m1 - 2024m9
Decomposition: 2020m7 - 2024m9
Data
(F+C)-Shock
C-Shock
F-Shock
2020m1
2021m1
2022m1
2023m1
2024m1

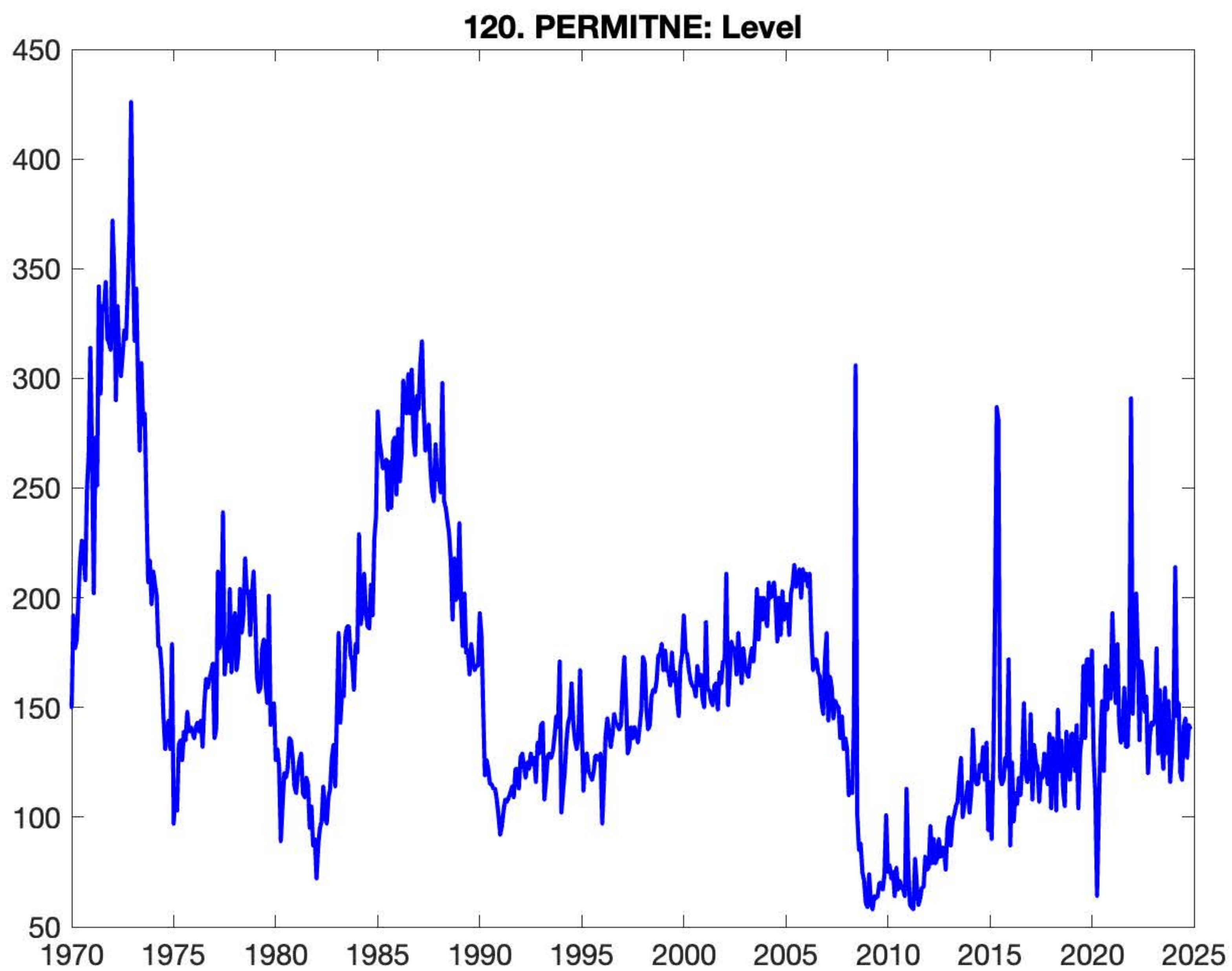

118. PERMIT: Level
Transformed Value
Decomposition: 2020m1 - 2024m9
Data
(F+C)-Shock
C-Shock
F-Shock
Decomposition: 2020m7 - 2024m9


119. PERMITMW: Level

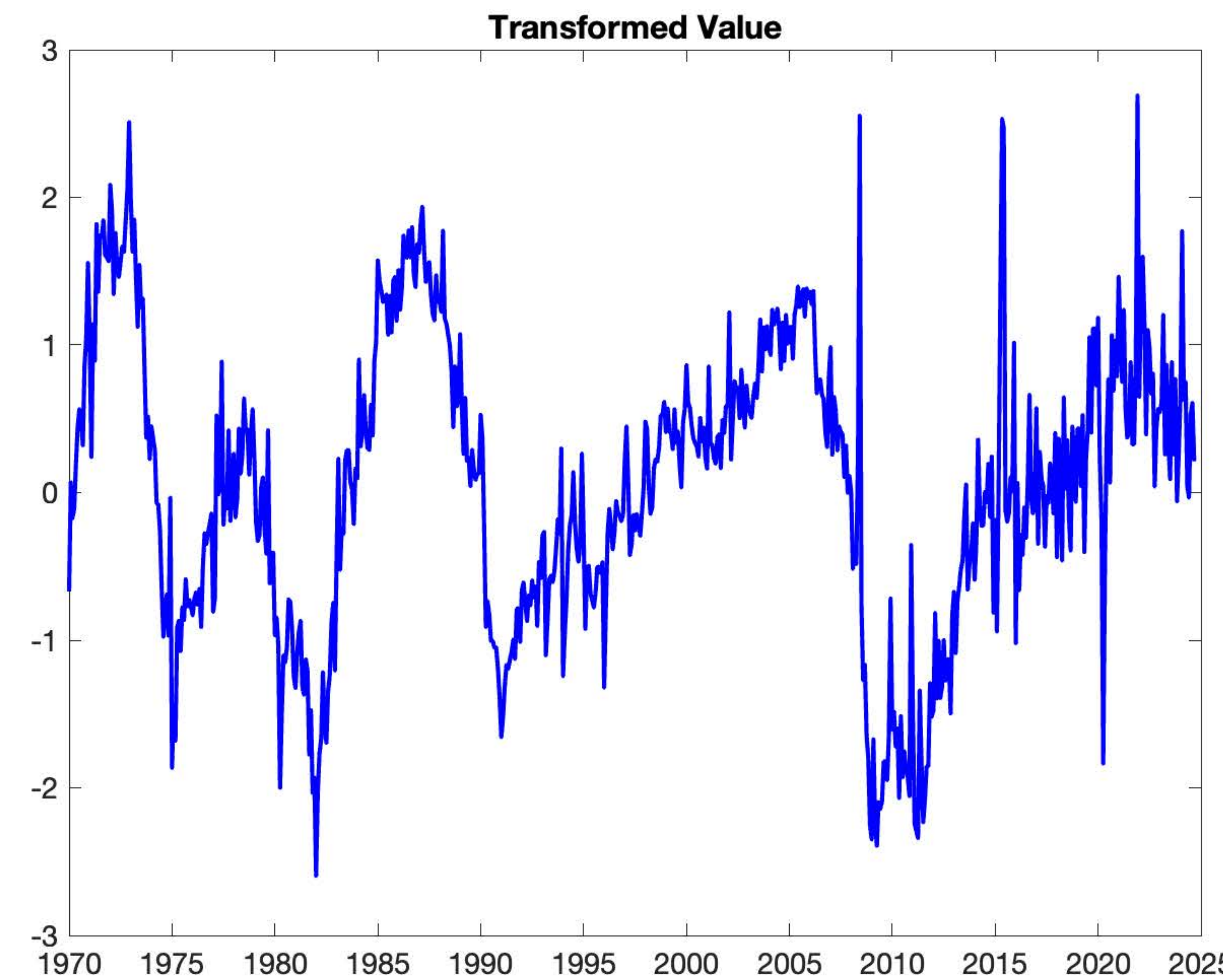

Transformed Value


Decomposition: 2020m1 - 2024m9
Data
(F+C)-Shock
C-Shock
F-Shock

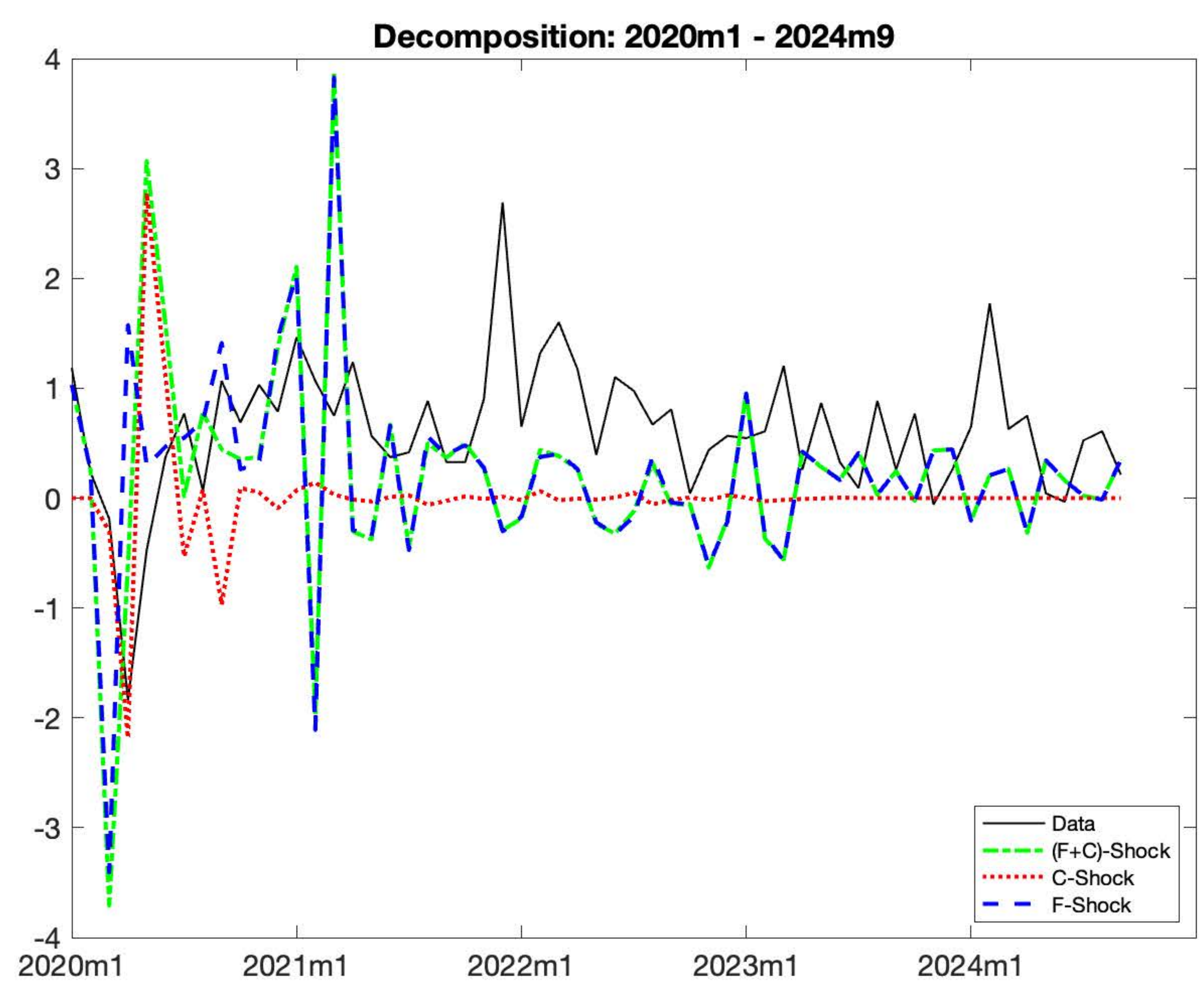

Decomposition: 2020m7 - 2024m9



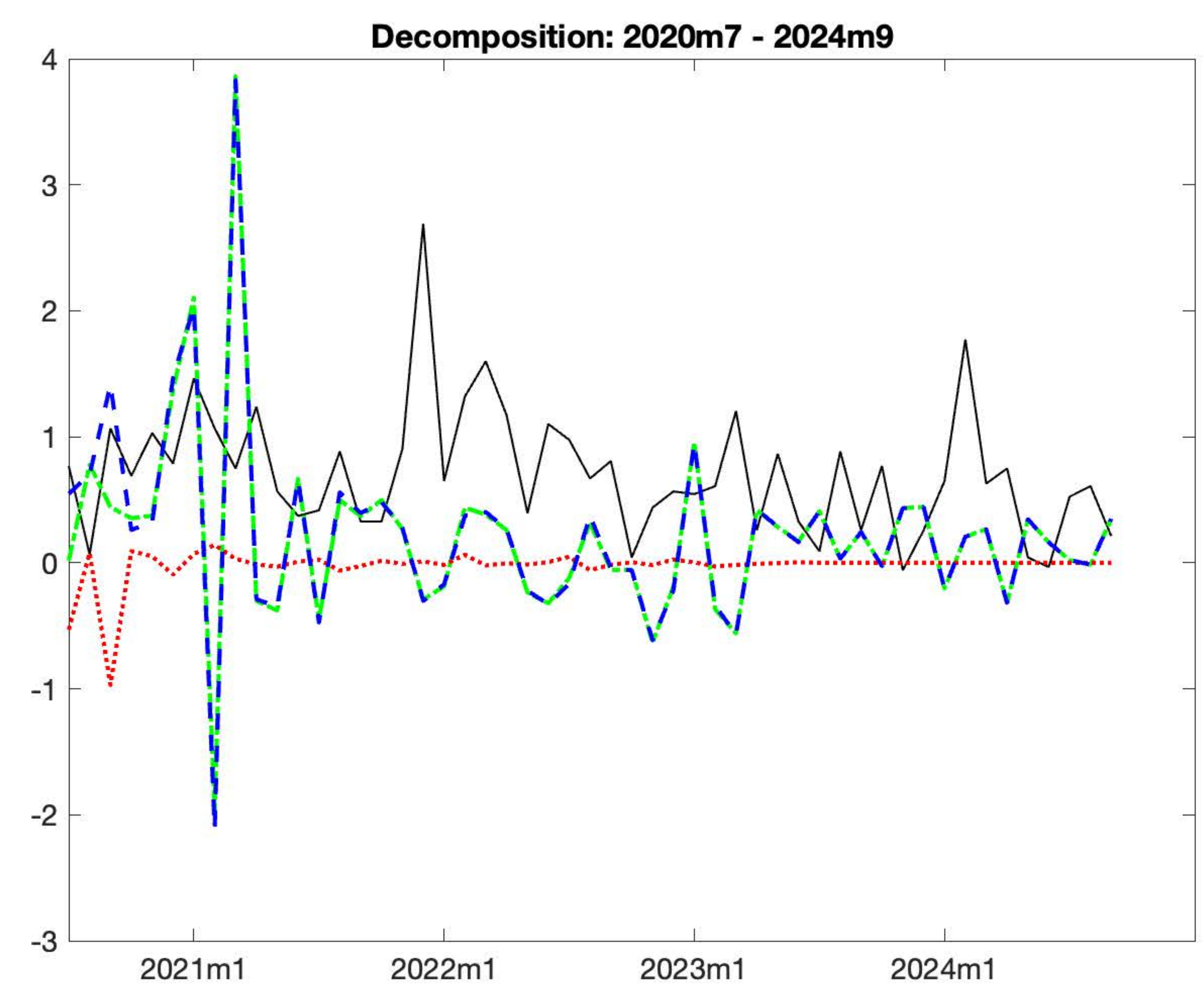
120. PERMITNE: Level
450
400
350
300
250
200
150
100
50
1970
1975
1980
1985
1990
1995
2000
2005
2010
2015
2020
2025



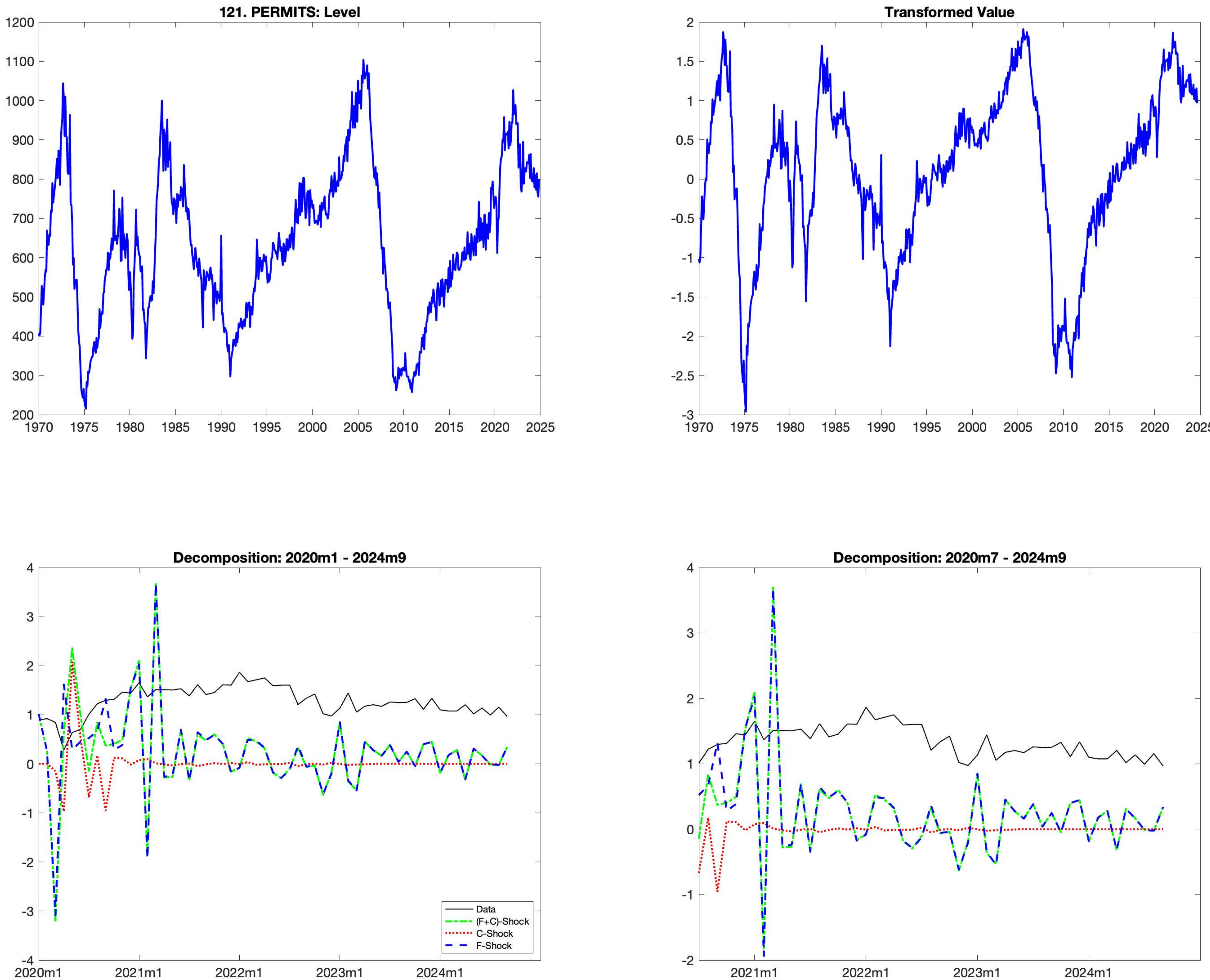
Transformed Value
3
2
1
0
-1
-2
-3
1970
1975
1980
1985
1990
1995
2000
2005
2010
2015
2020
2025

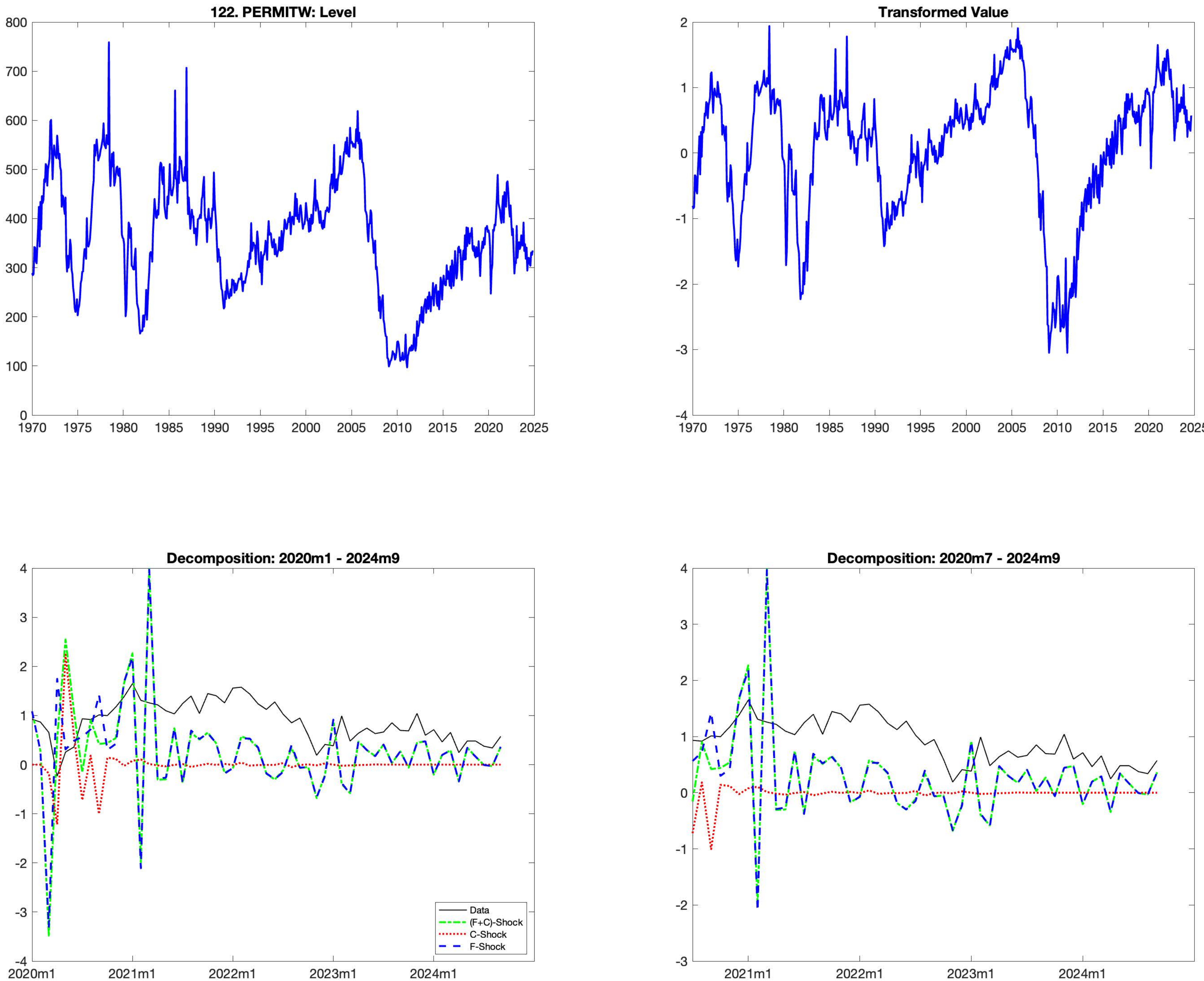


Decomposition: 2020m1 - 2024m9
4
3
2
1
0
-1
-2
-3
-4
2020m1
2021m1
2022m1
2023m1
2024m1
Data
(F+C)-Shock
C-Shock
F-Shock

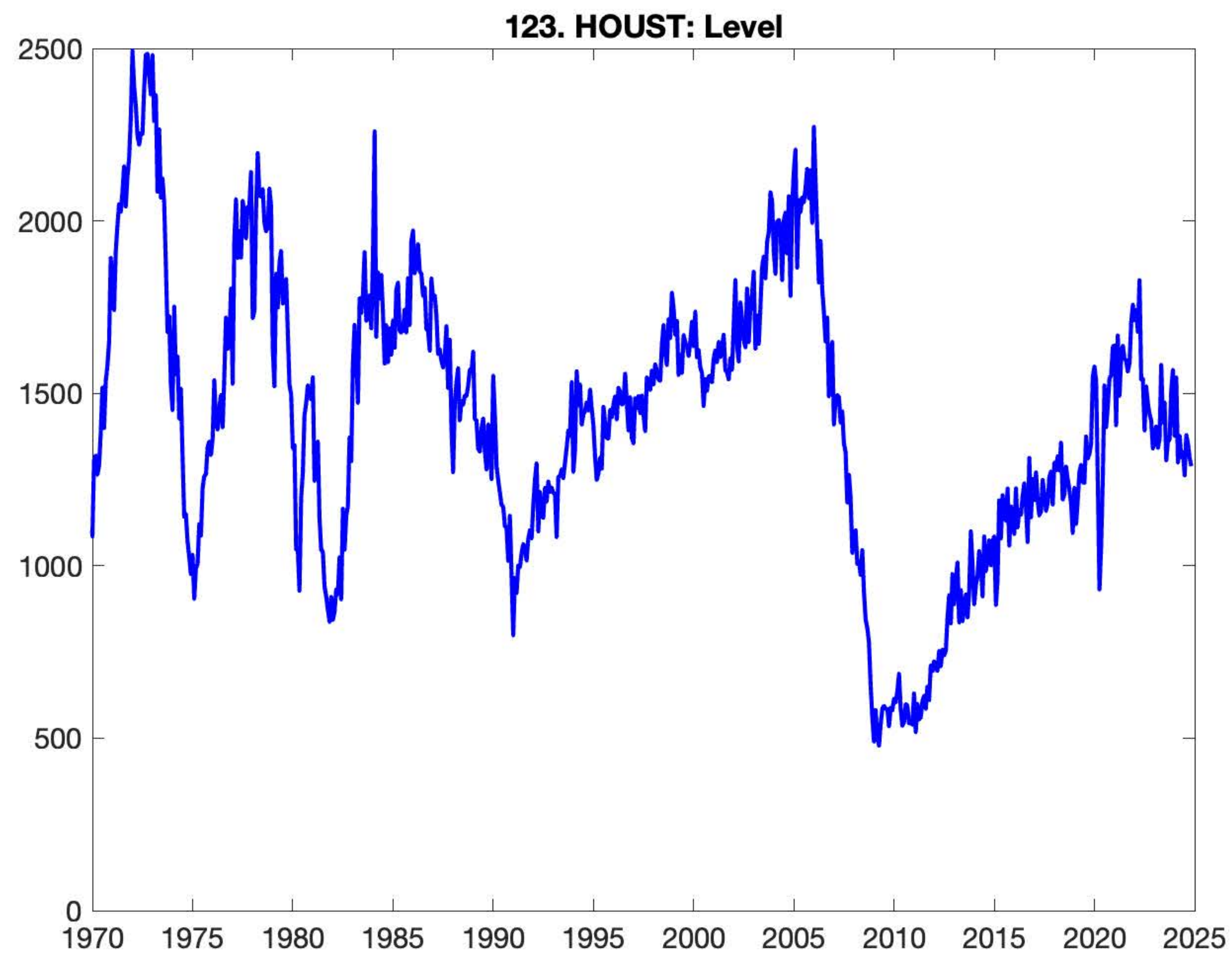


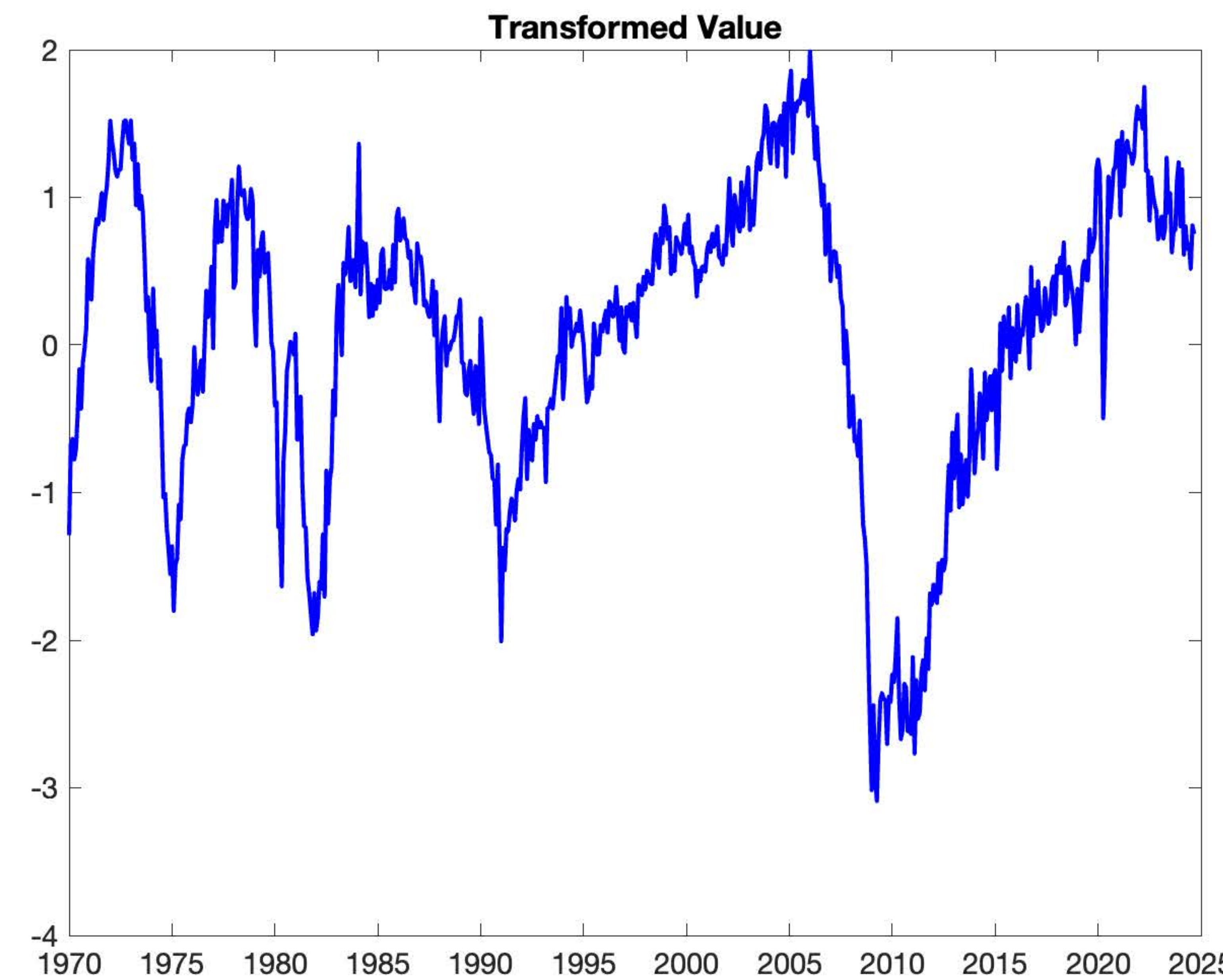
Decomposition: 2020m7 - 2024m9
4
3
2
1
0
-1
-2
-3
2021m1
2022m1
2023m1
2024m1

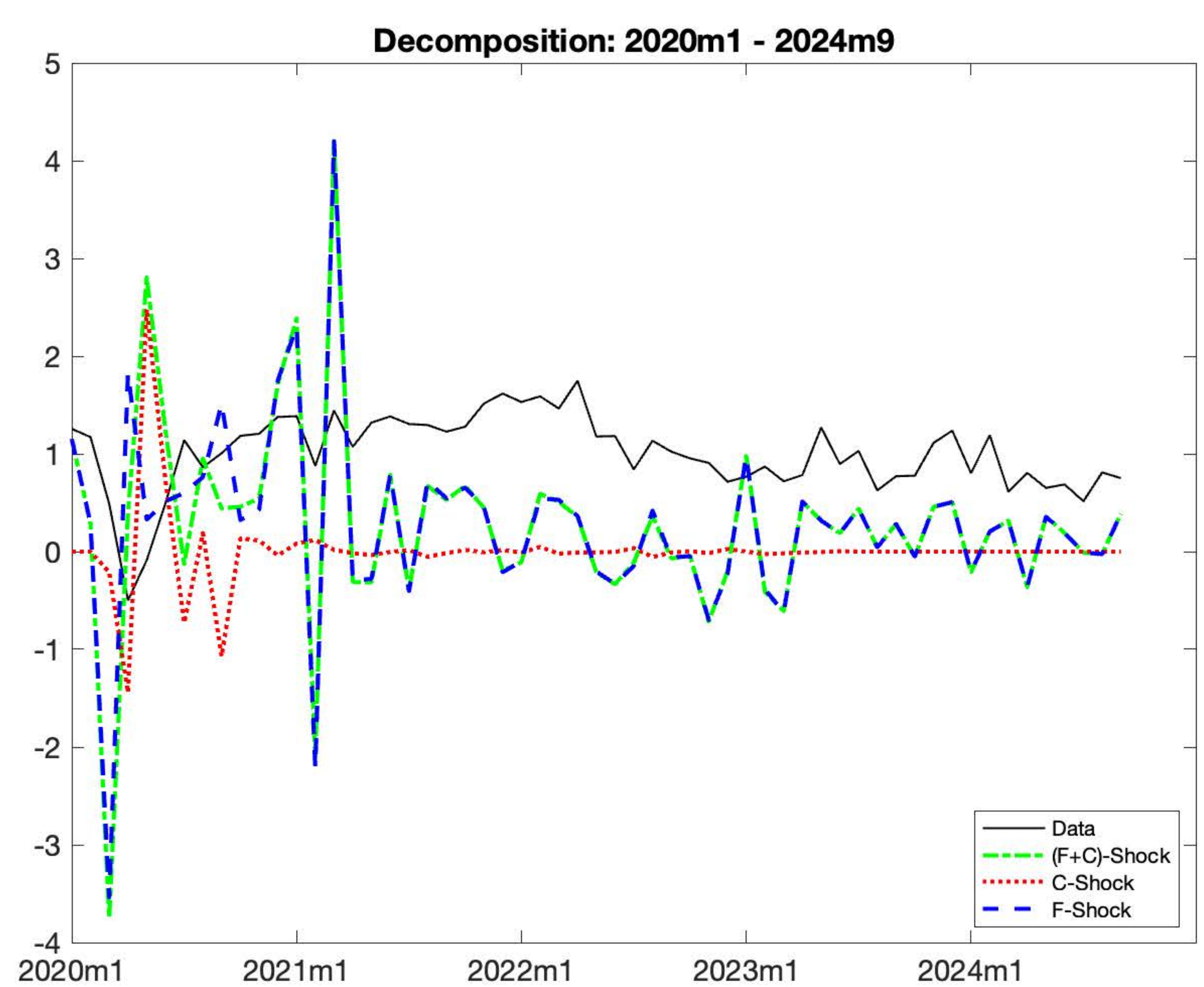

121. PERMITS: Level
Transformed Value
Decomposition: 2020m1 - 2024m9
Decomposition: 2020m7 - 2024m9
1970
1975
1980
1985
1990
1995
2000
2005
2010
2015
2020
2025
2020m1
2021m1
2022m1
2023m1
2024m1
Data
(F+C)-Shock
C-Shock
F-Shock

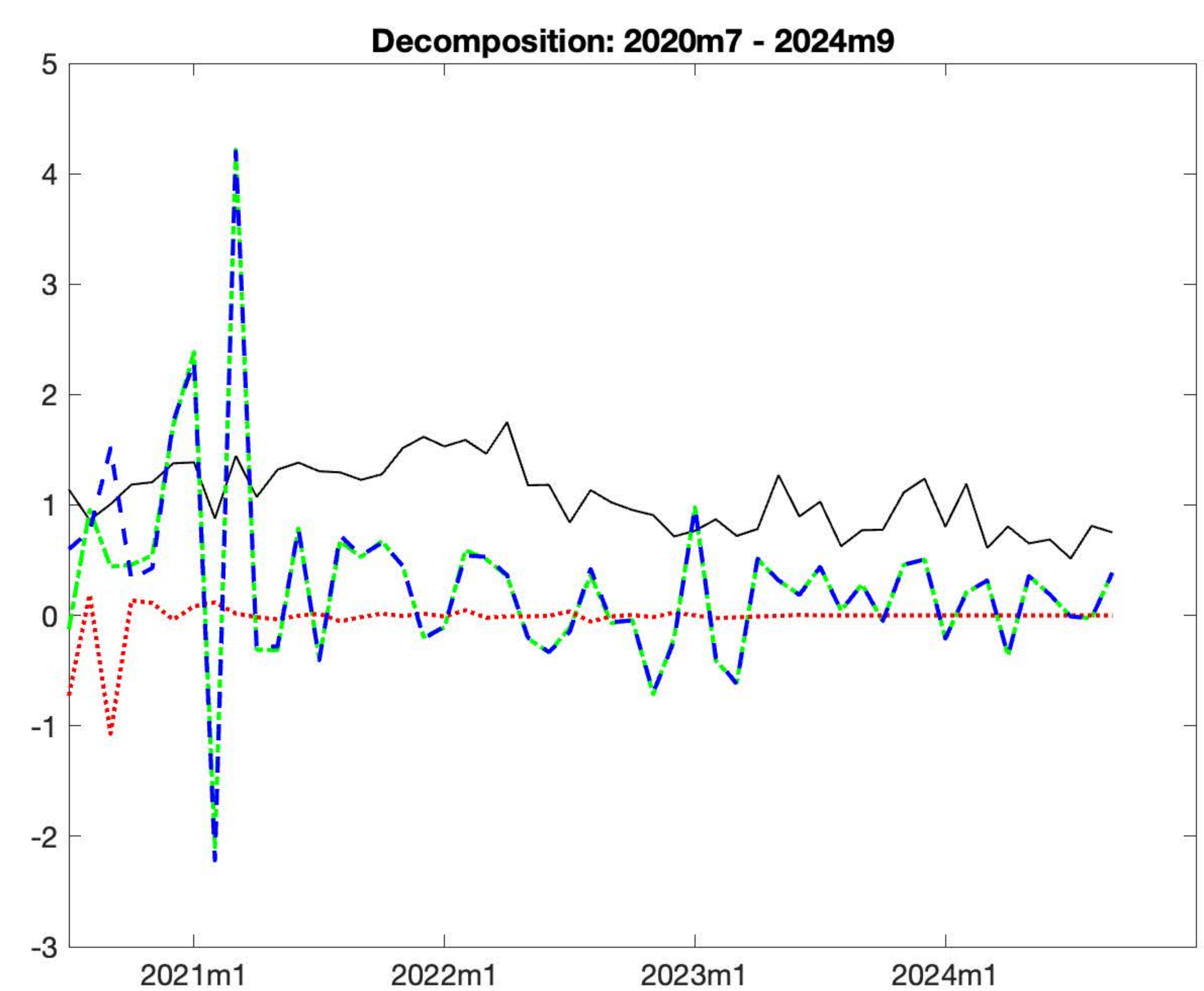


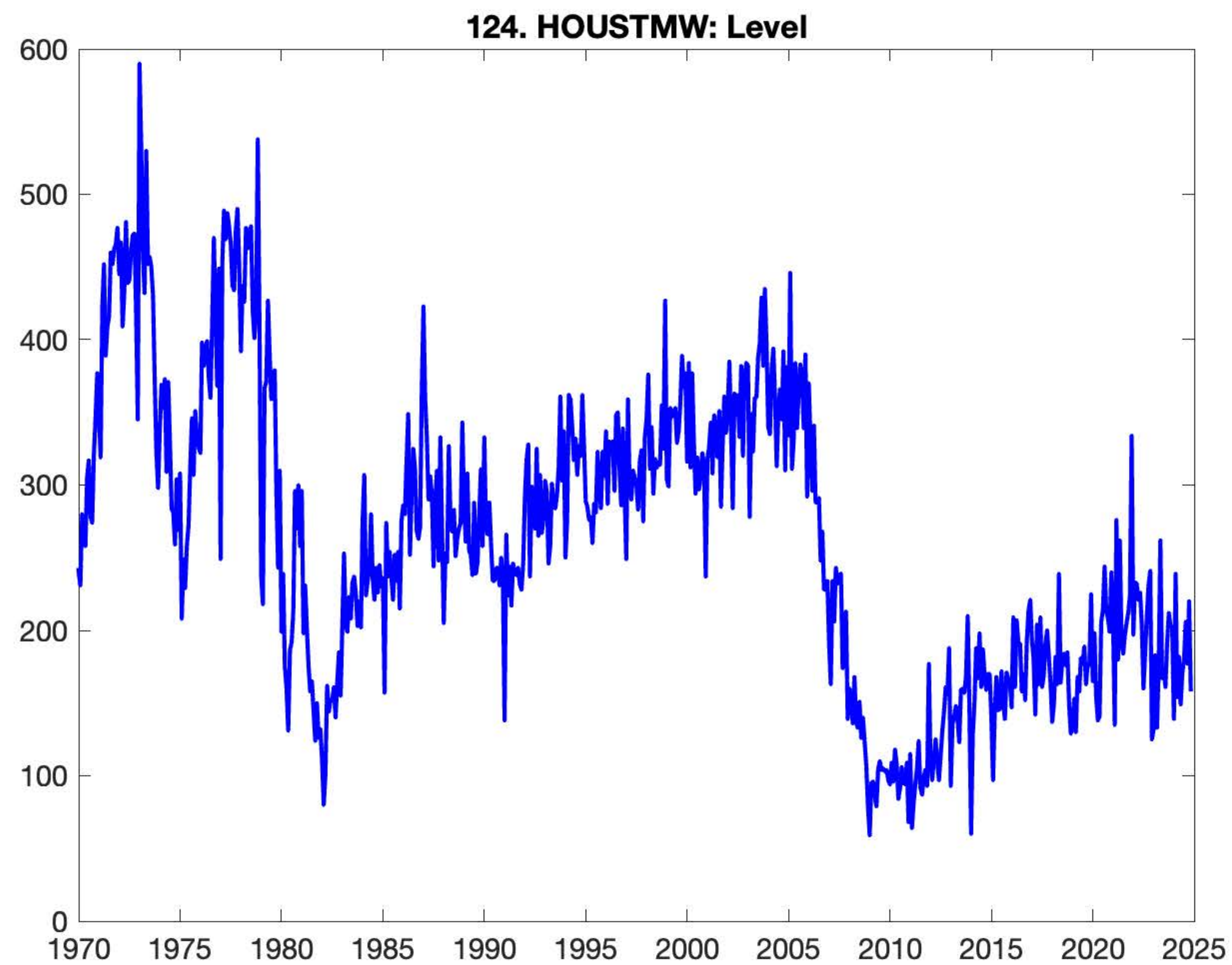
122. PERMITW: Level
Transformed Value
Decomposition: 2020m1 - 2024m9
Decomposition: 2020m7 - 2024m9
Data
(F+C)-Shock
C-Shock
F-Shock

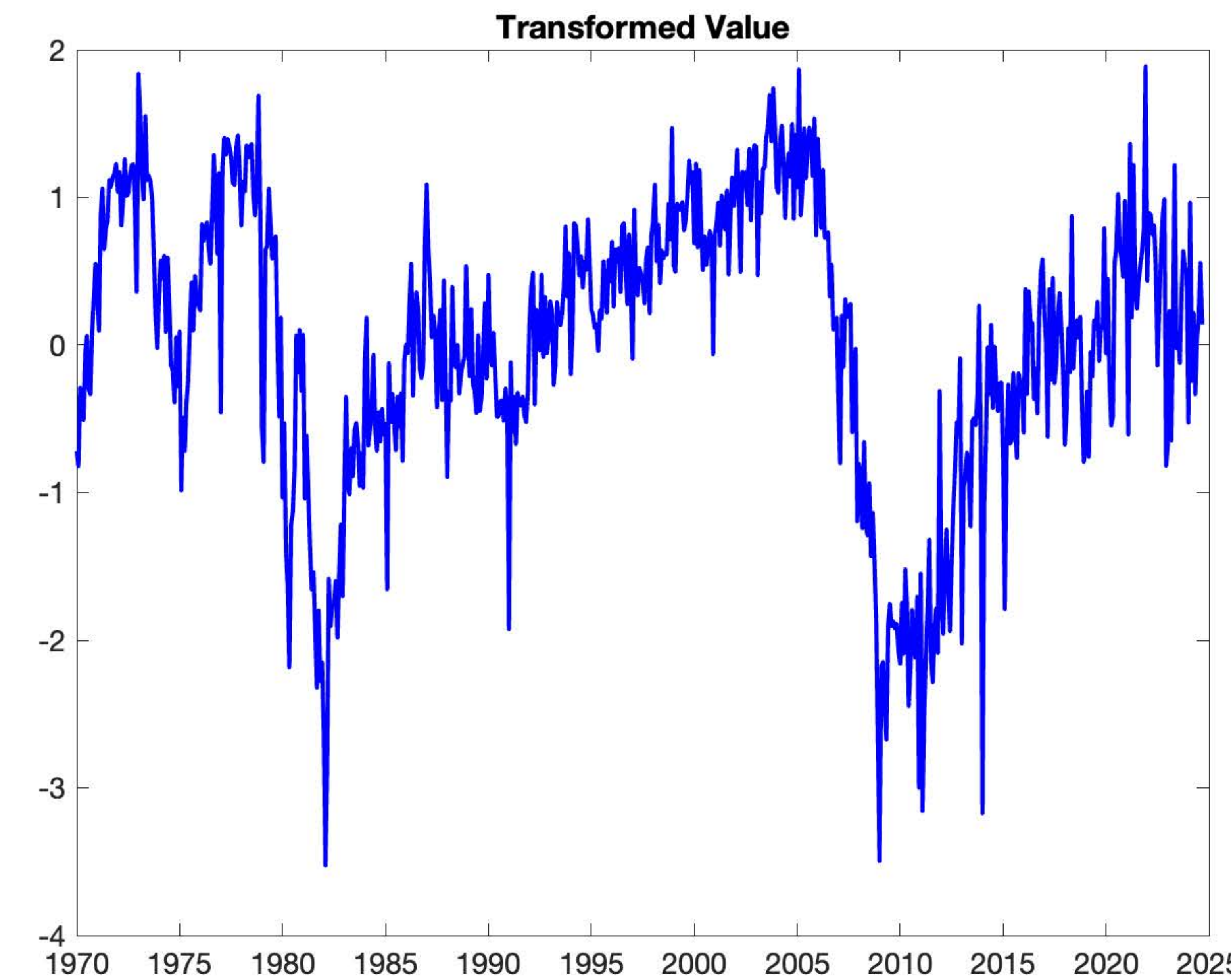

123. HOUST: Level
2500
2000
1500
1000
500
0
1970
1975
1980
1985
1990
1995
2000
2005
2010
2015
2020
2025

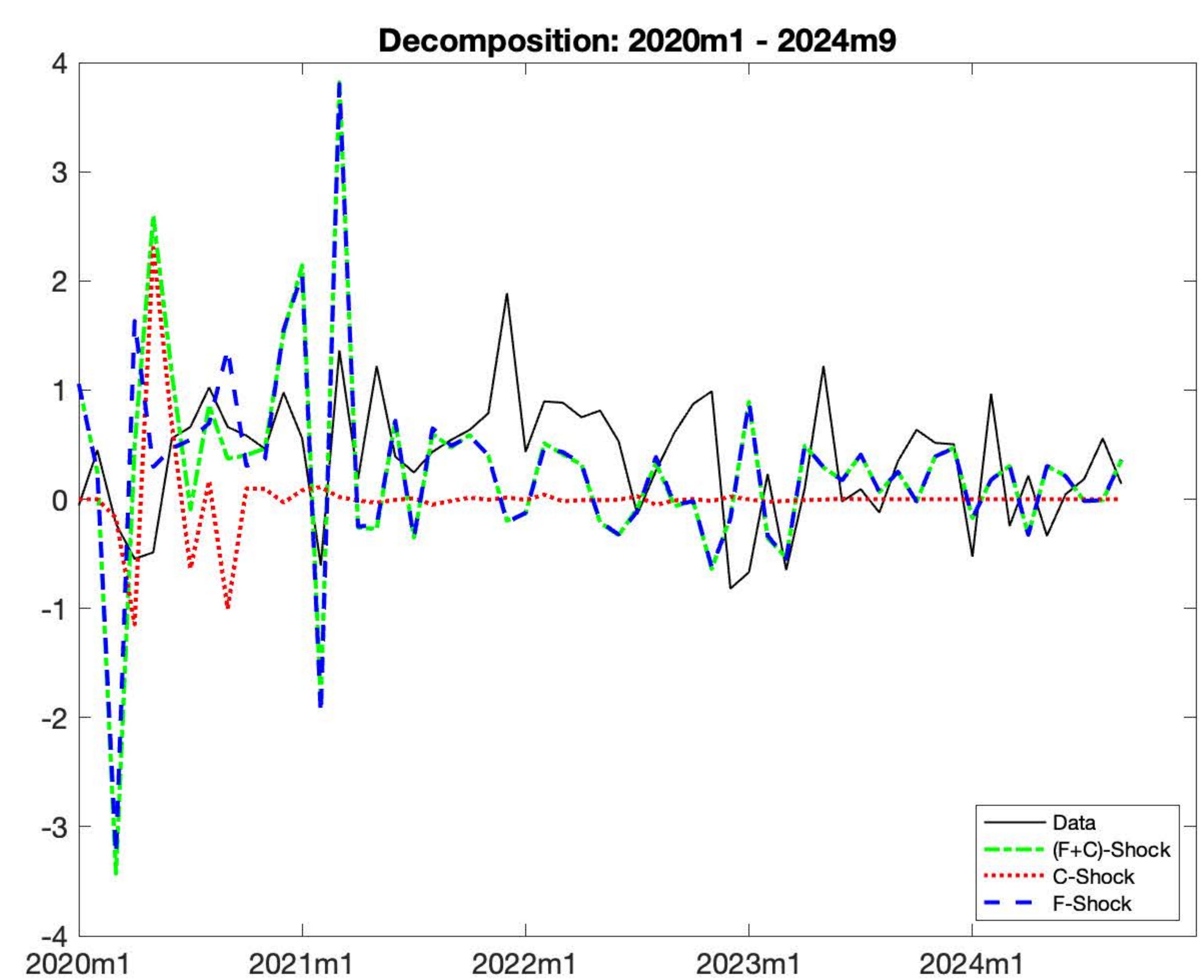

Transformed Value
2
1
0
-1
-2
-3
-4
1970
1975
1980
1985
1990
1995
2000
2005
2010
2015
2020
2025

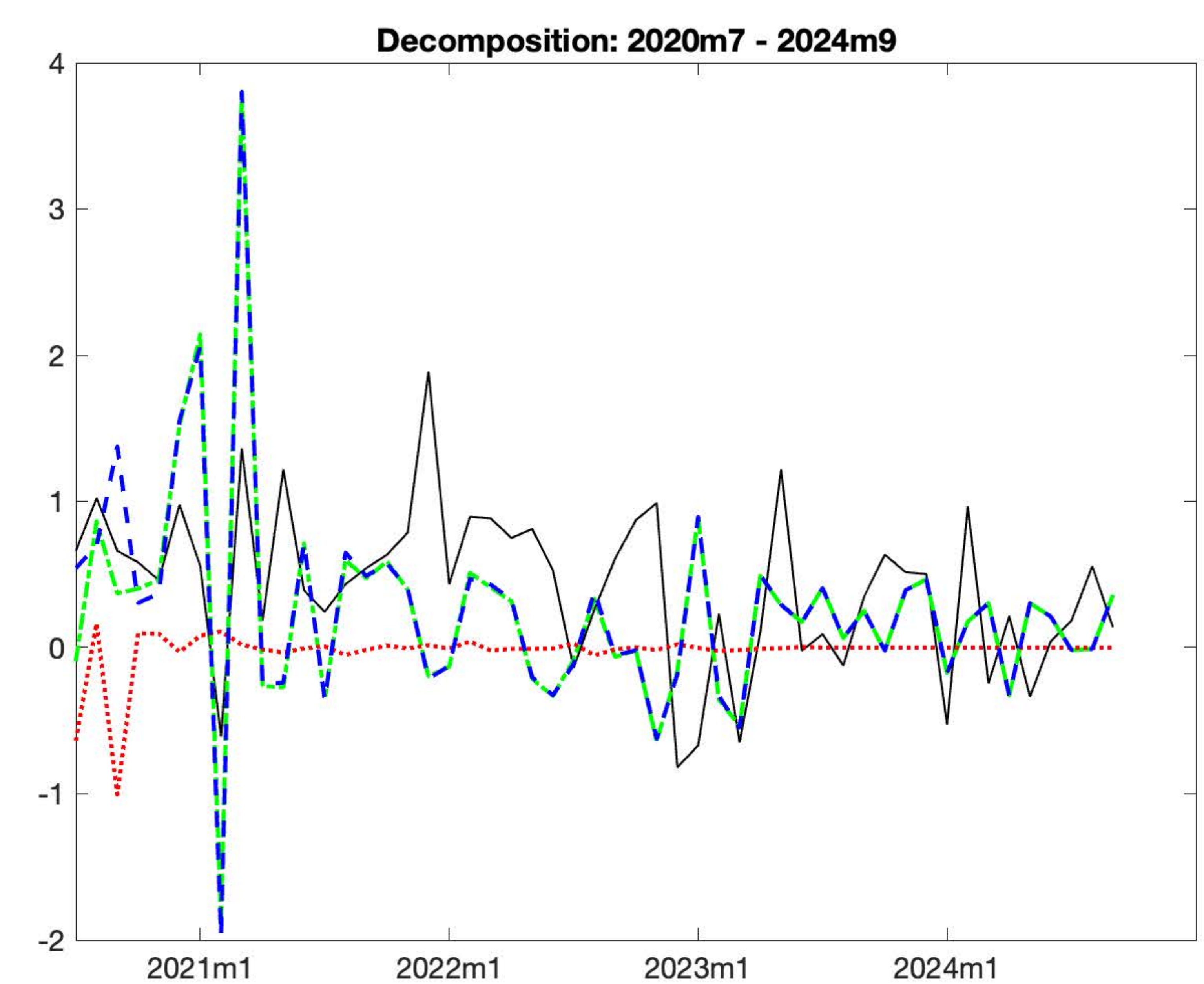

Decomposition: 2020m1 - 2024m9
5
4
3
2
1
0
-1
-2
-3
-4
2020m1
2021m1
2022m1
2023m1
2024m1
Data
(F+C)-Shock
C-Shock
F-Shock

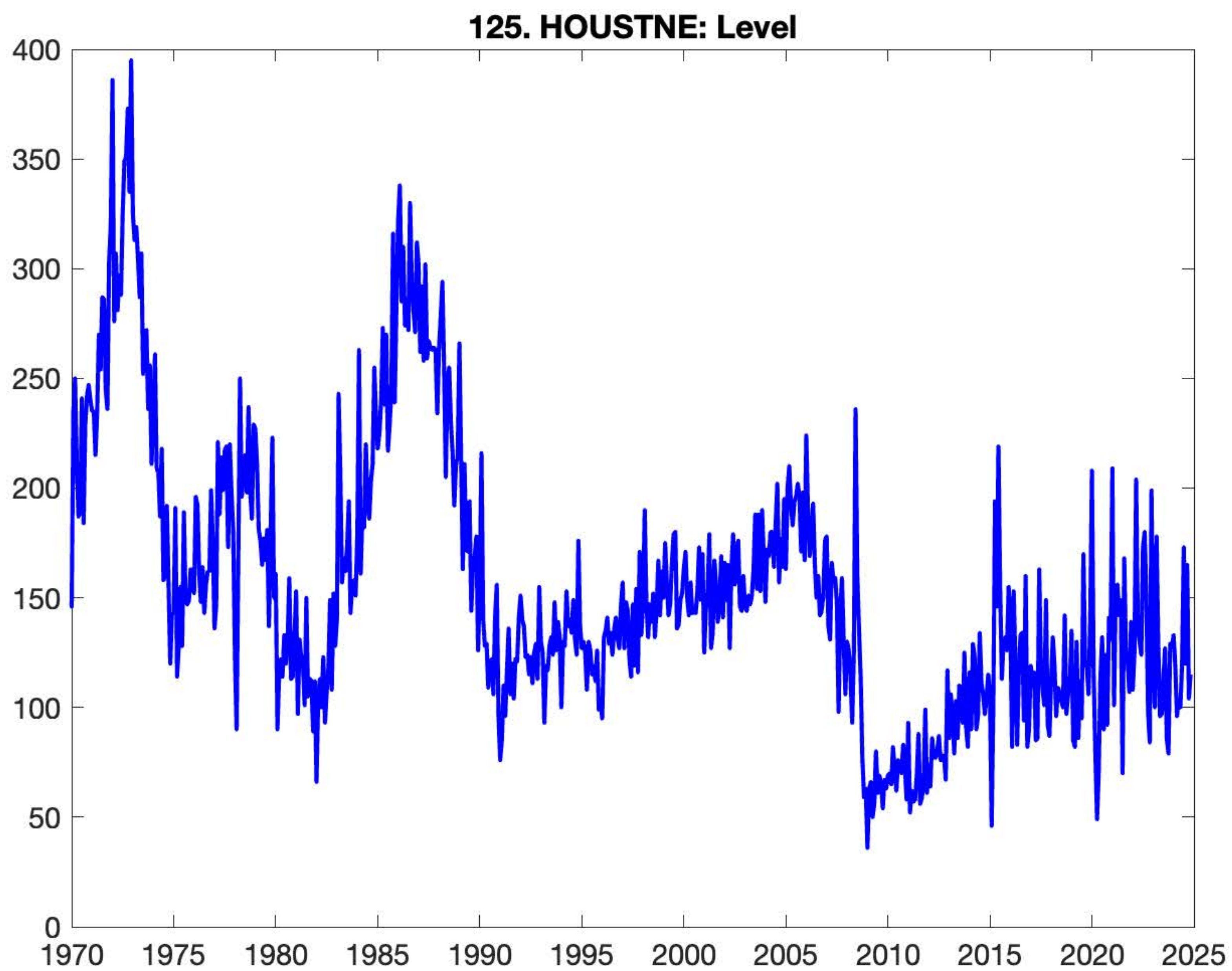

Decomposition: 2020m7 - 2024m9
5
4
3
2
1
0
-1
-2
-3
2021m1
2022m1
2023m1
2024m1

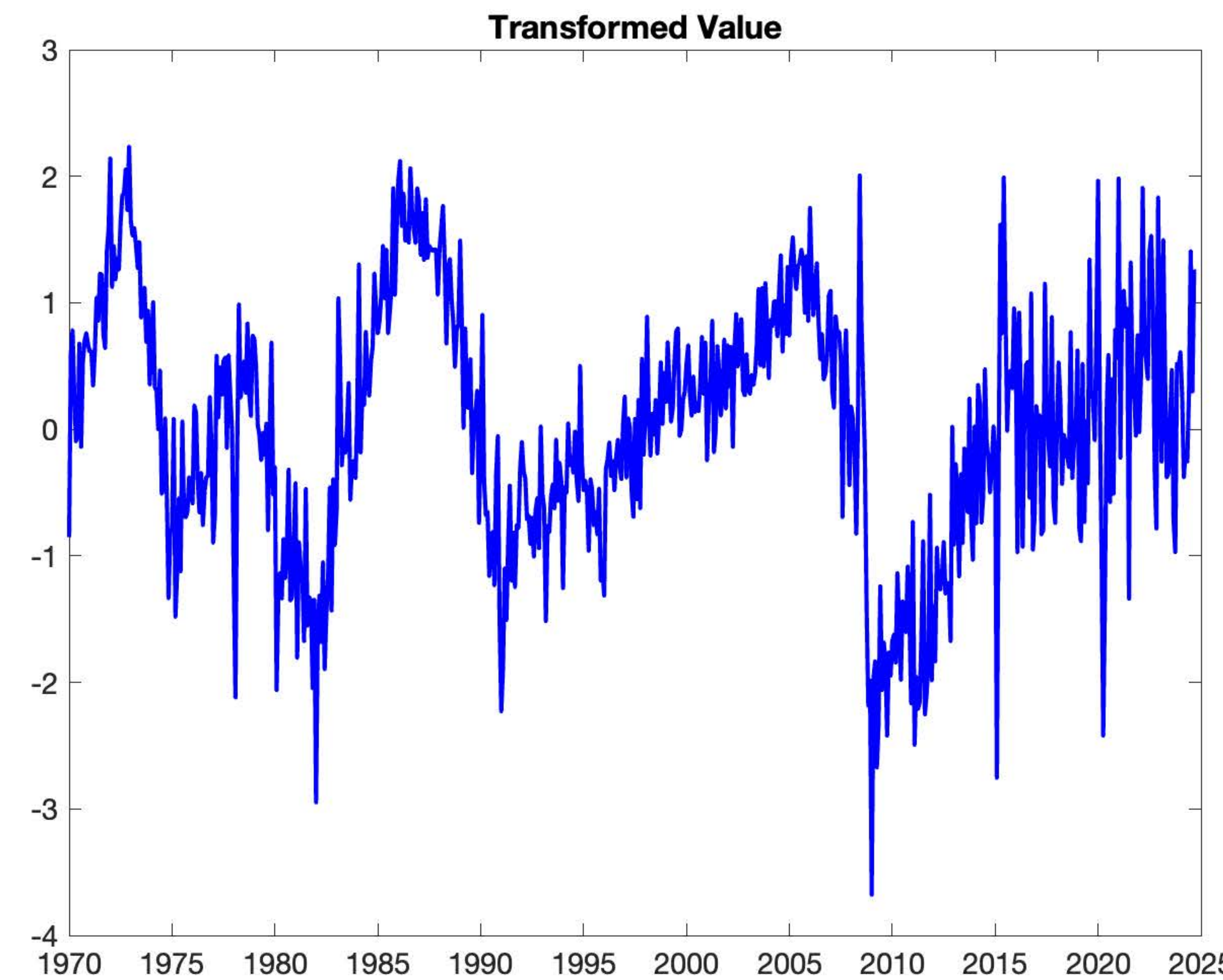

124. HOUSTMW: Level

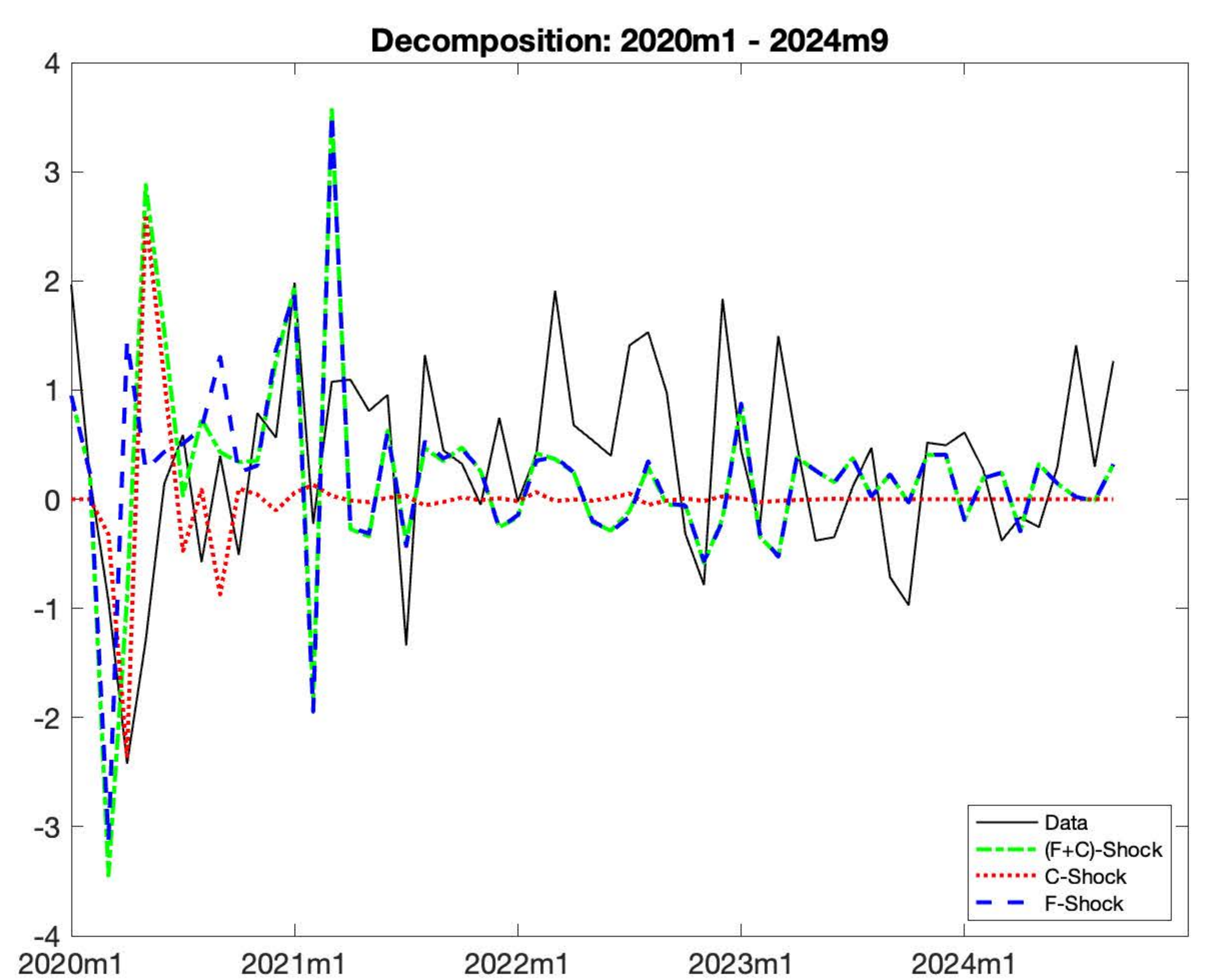

Transformed Value

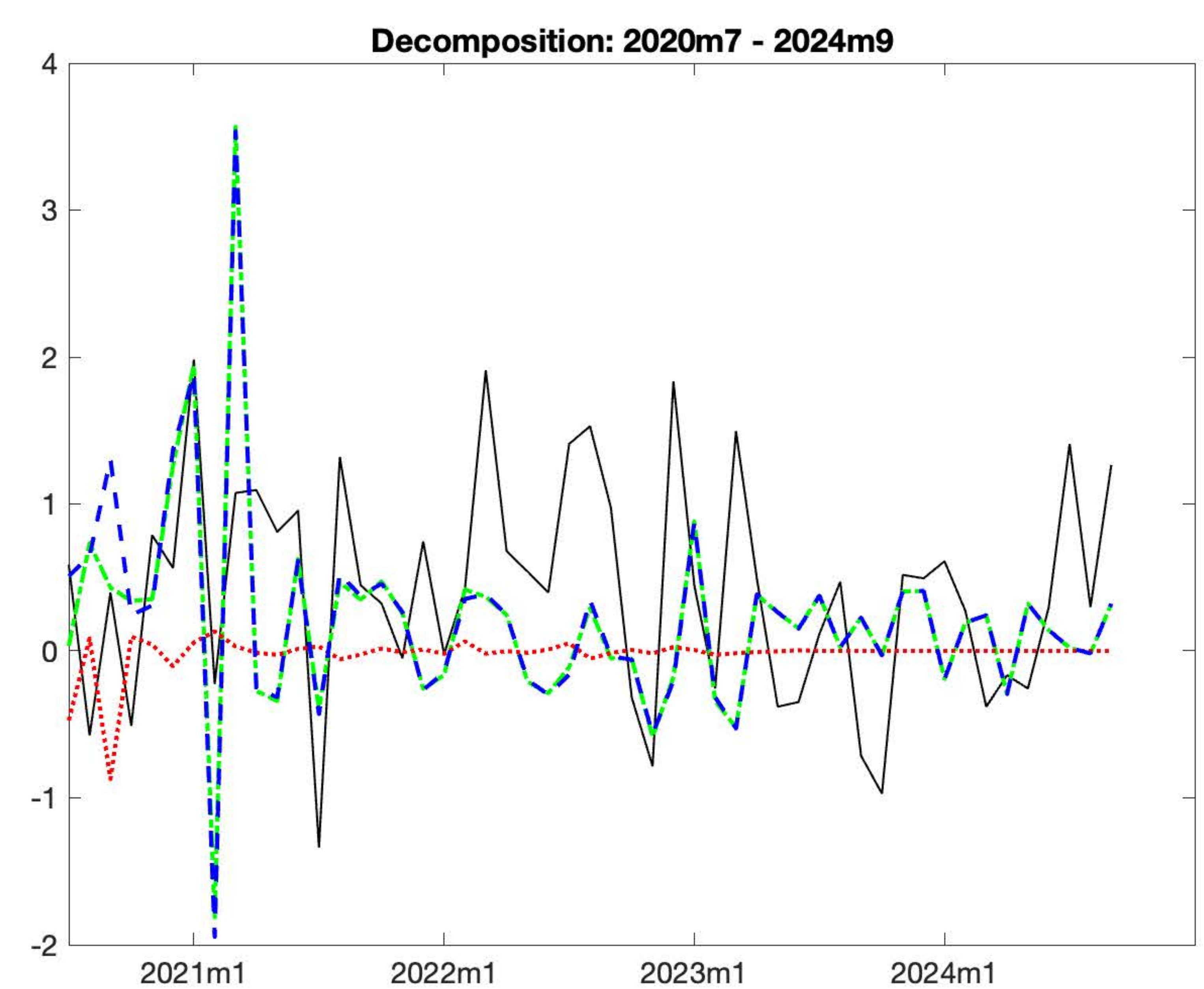

Decomposition: 2020m1 - 2024m9
Data
(F+C)-Shock
C-Shock
F-Shock

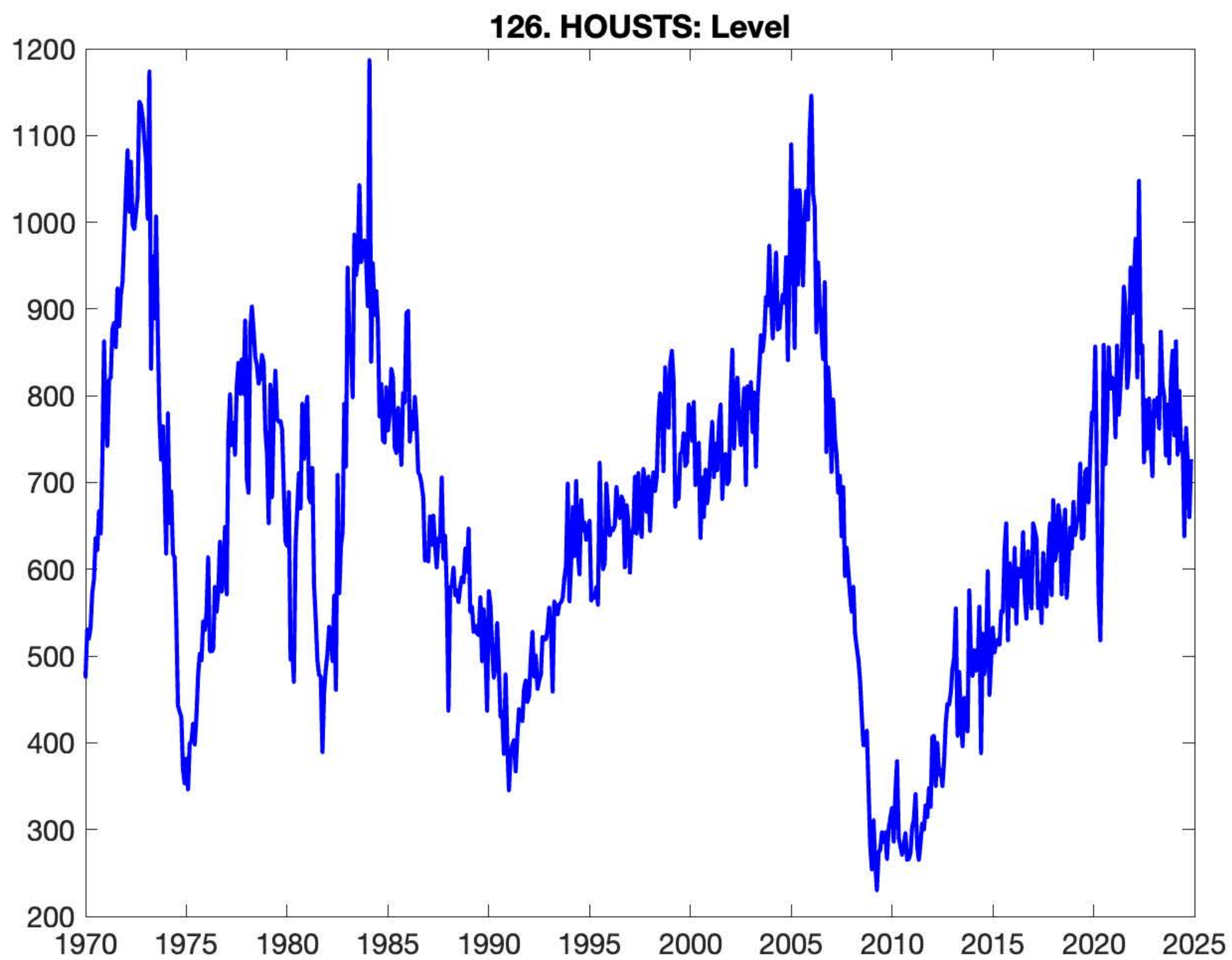

Decomposition: 2020m7 - 2024m9

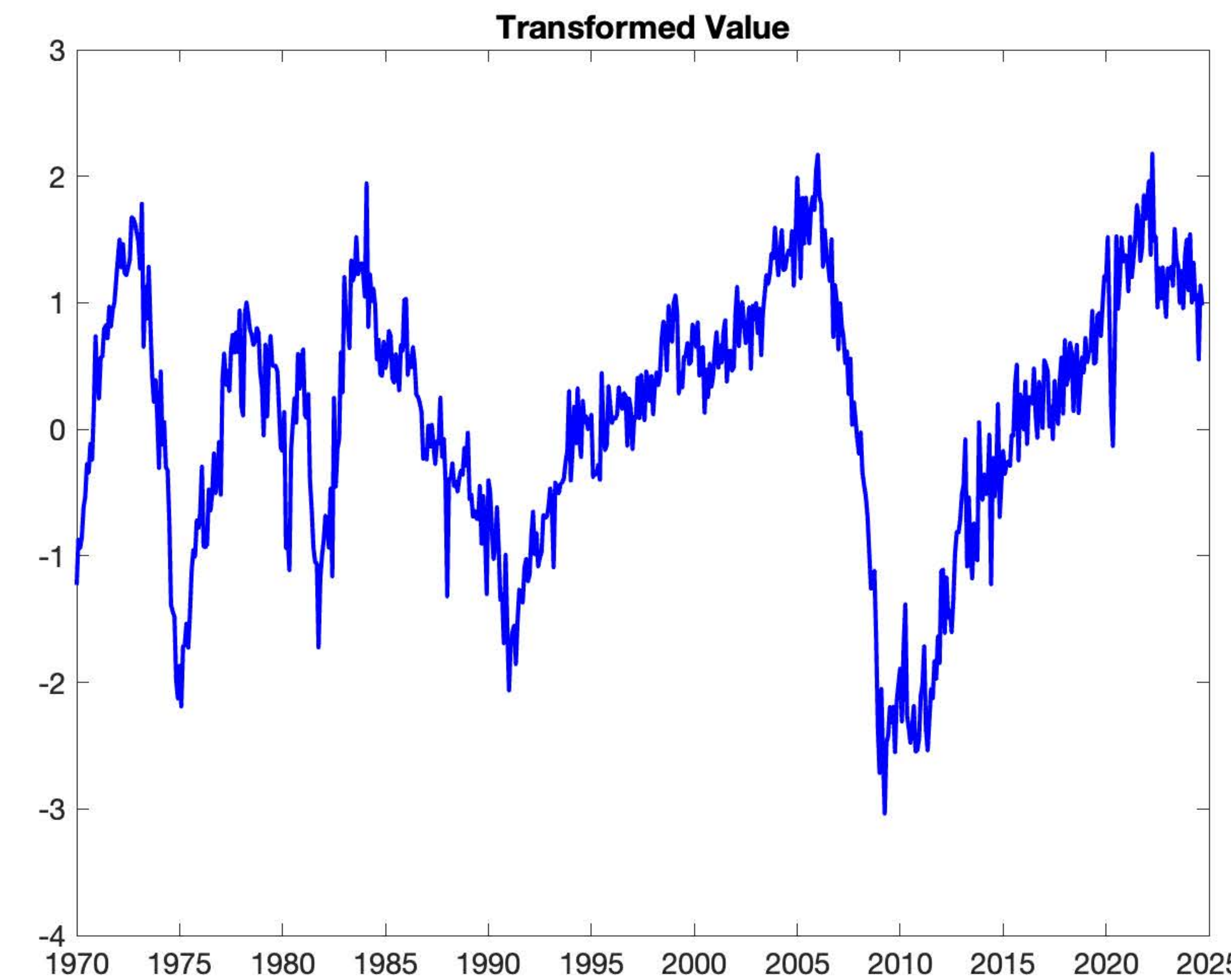

125. HOUSTNE: Level
400
350
300
250
200
150
100
50
0
1970
1975
1980
1985
1990
1995
2000
2005
2010
2015
2020
2025

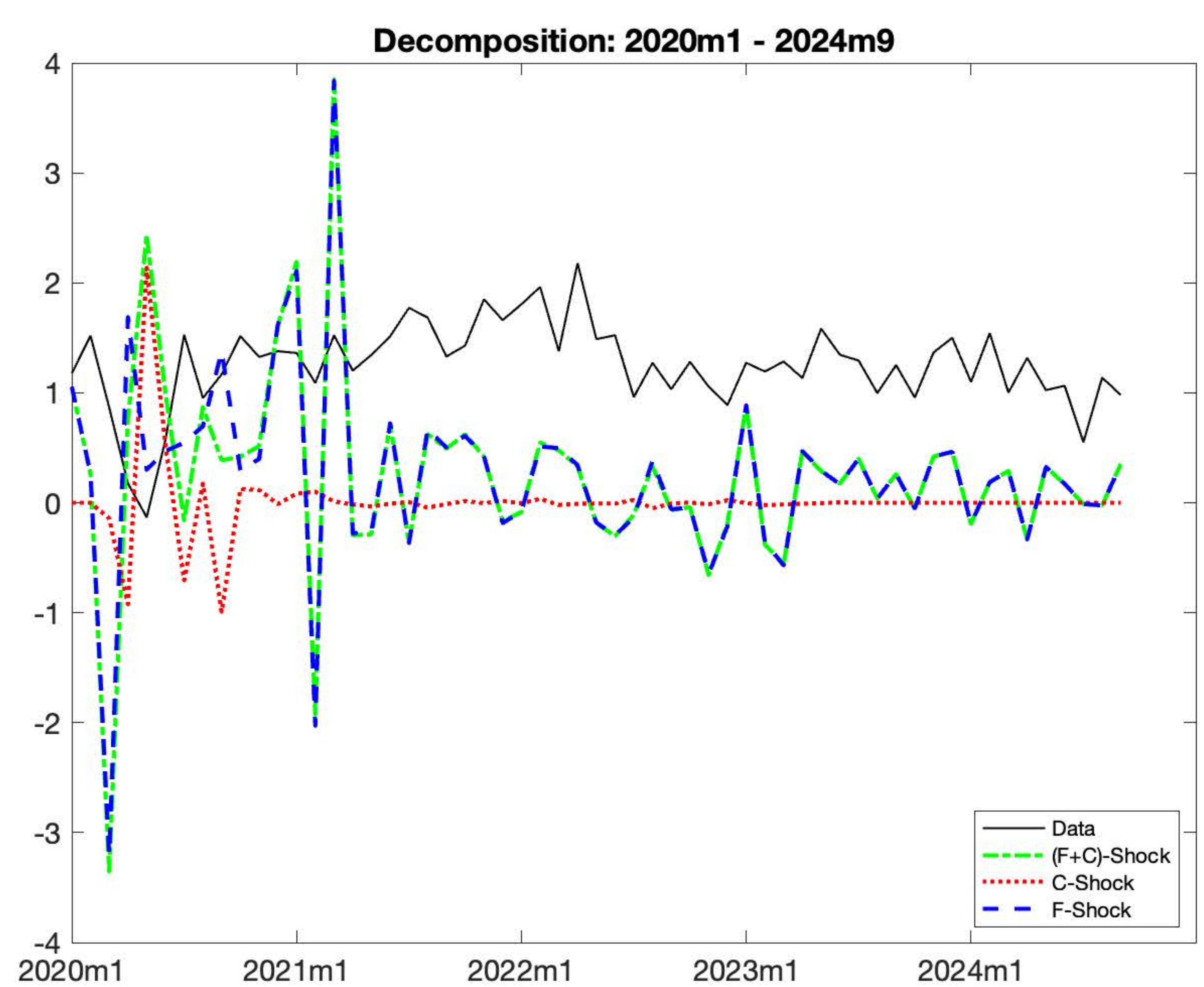

Transformed Value
3
2
1
0
-1
-2
-3
-4
1970
1975
1980
1985
1990
1995
2000
2005
2010
2015
2020
2025

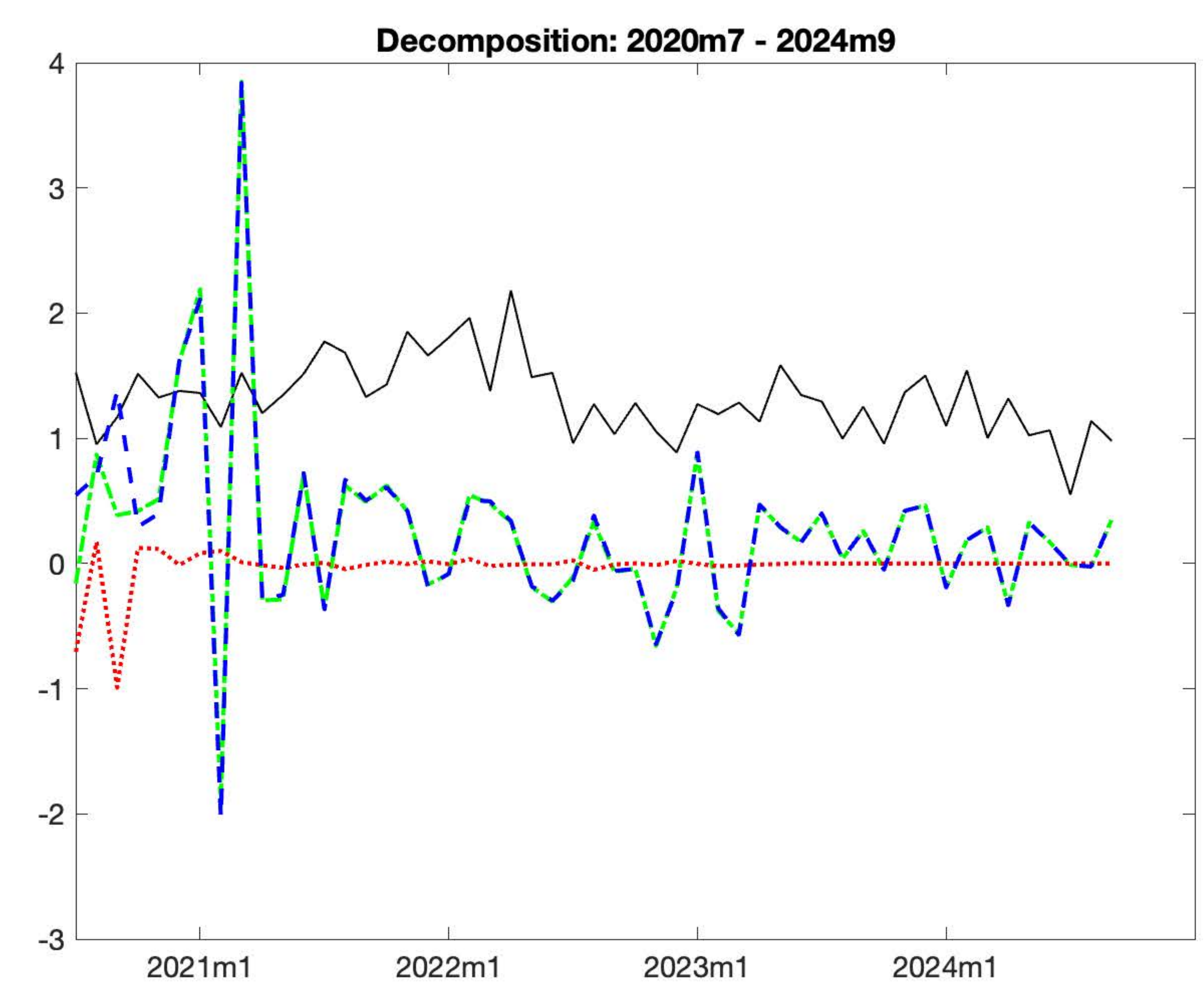

Decomposition: 2020m1 - 2024m9
4
3
2
1
0
-1
-2
-3
-4
2020m1
2021m1
2022m1
2023m1
2024m1
Data
(F+C)-Shock
C-Shock
F-Shock

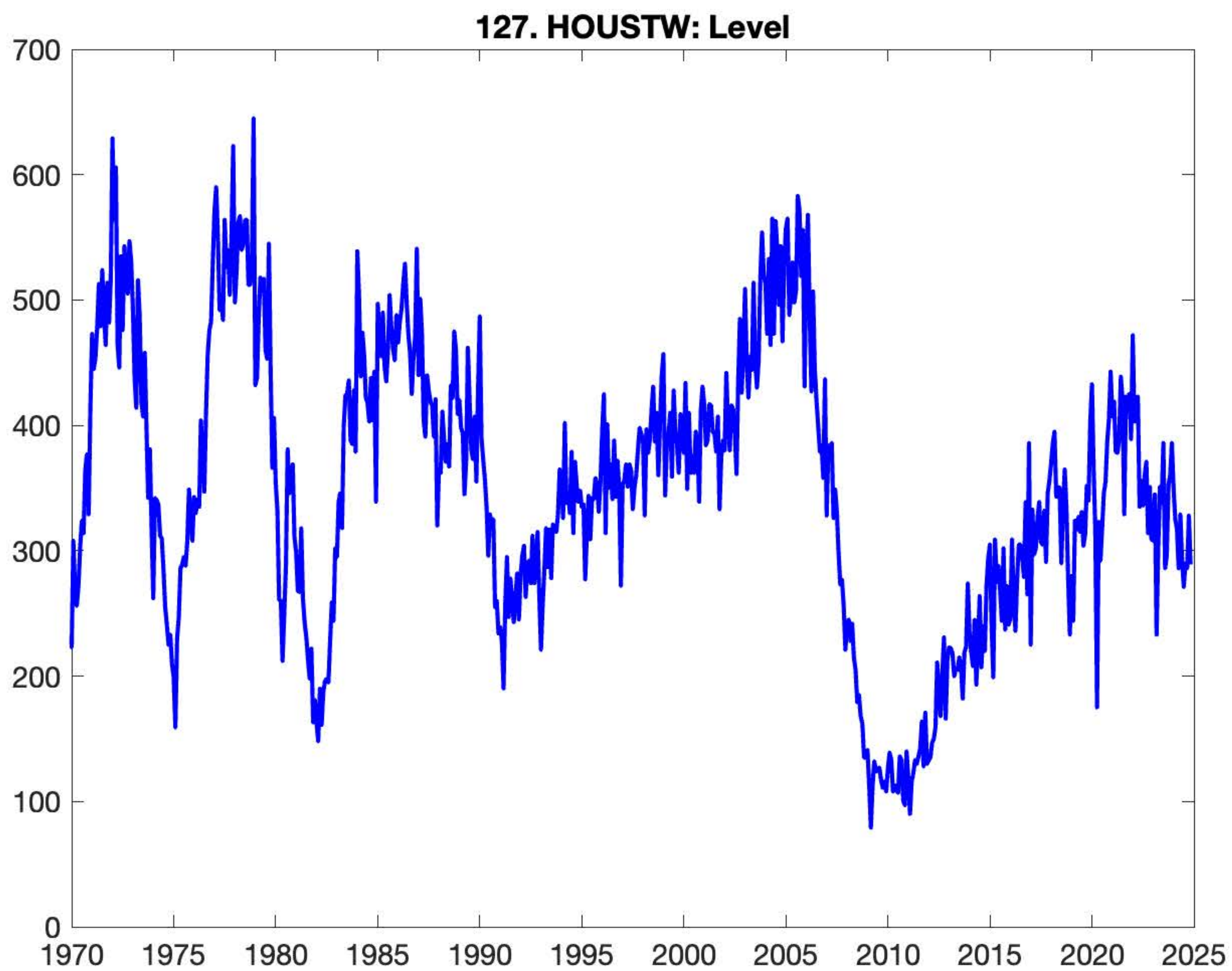

Decomposition: 2020m7 - 2024m9
4
3
2
1
0
-1
-2
2021m1
2022m1
2023m1
2024m1

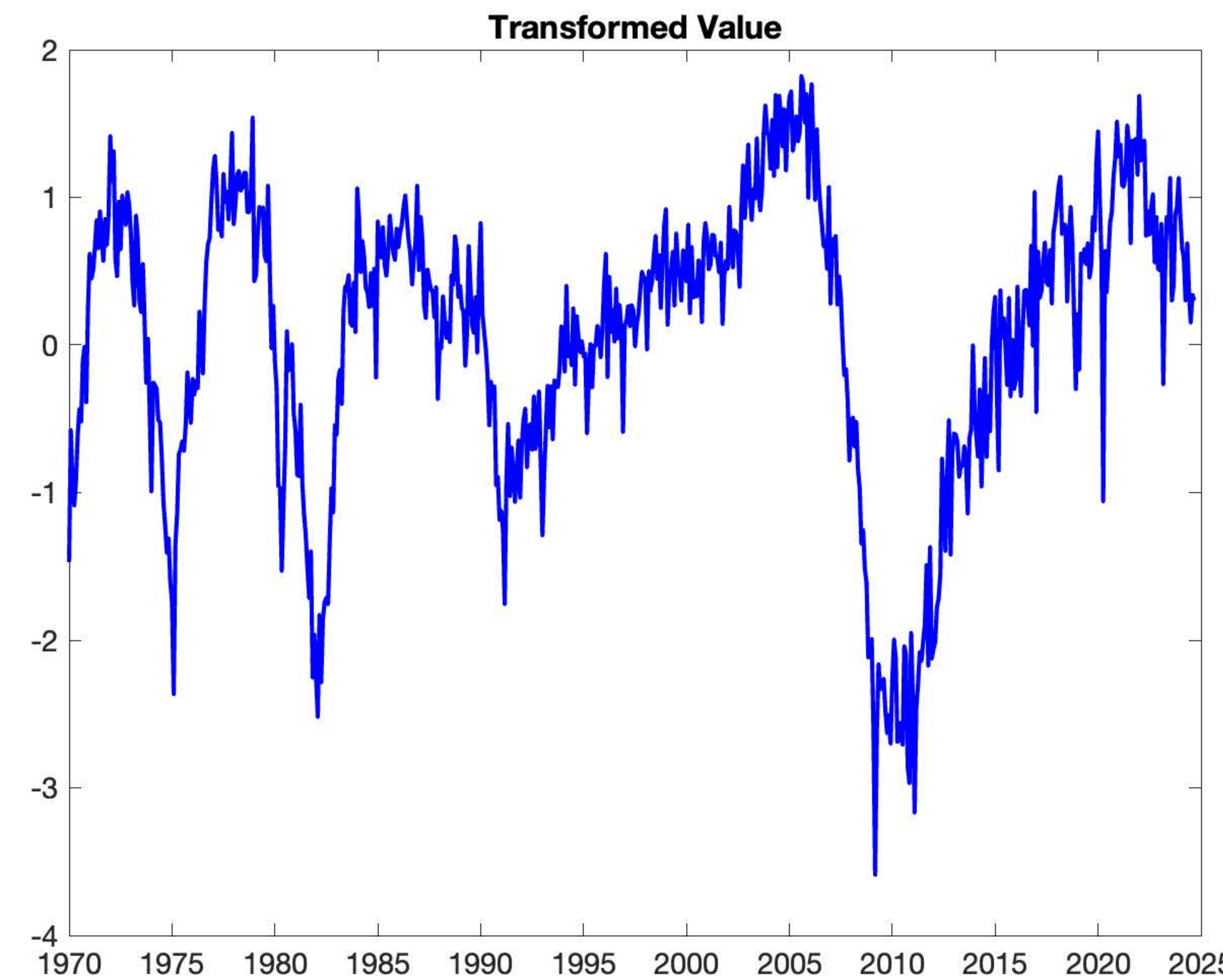

126. HOUSTS: Level

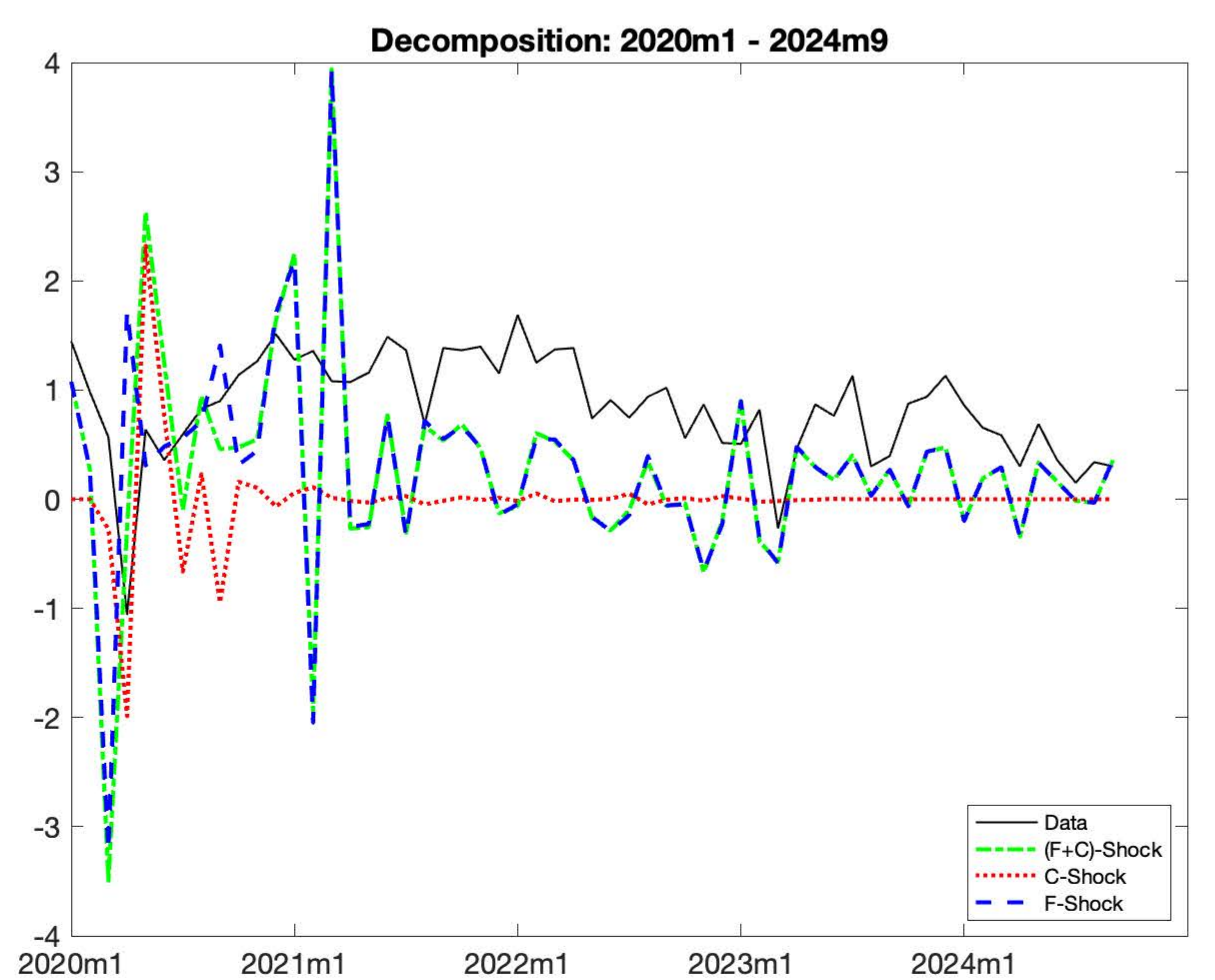

Transformed Value

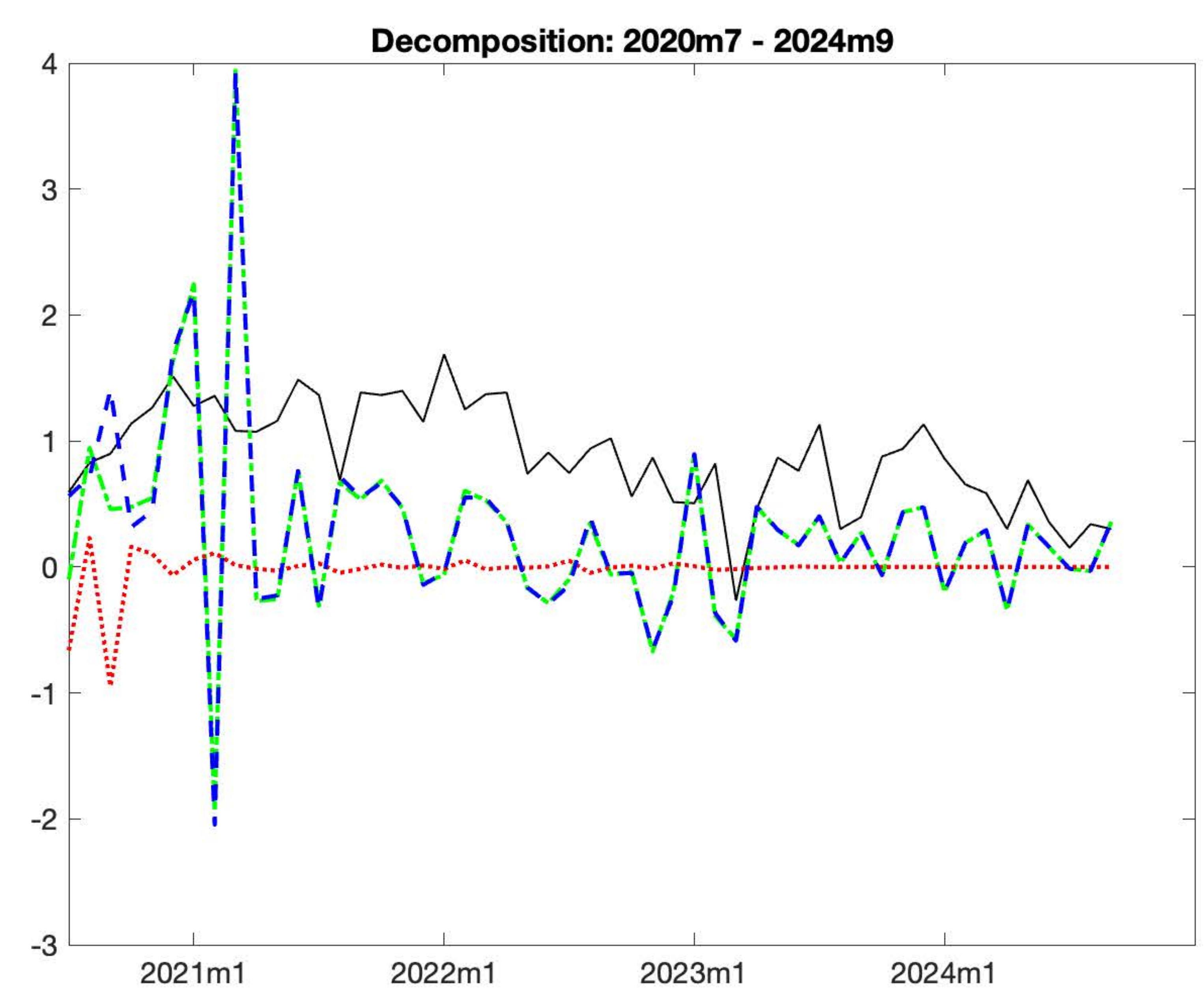

Decomposition: 2020m1 - 2024m9
Data
(F+C)-Shock
C-Shock
F-Shock

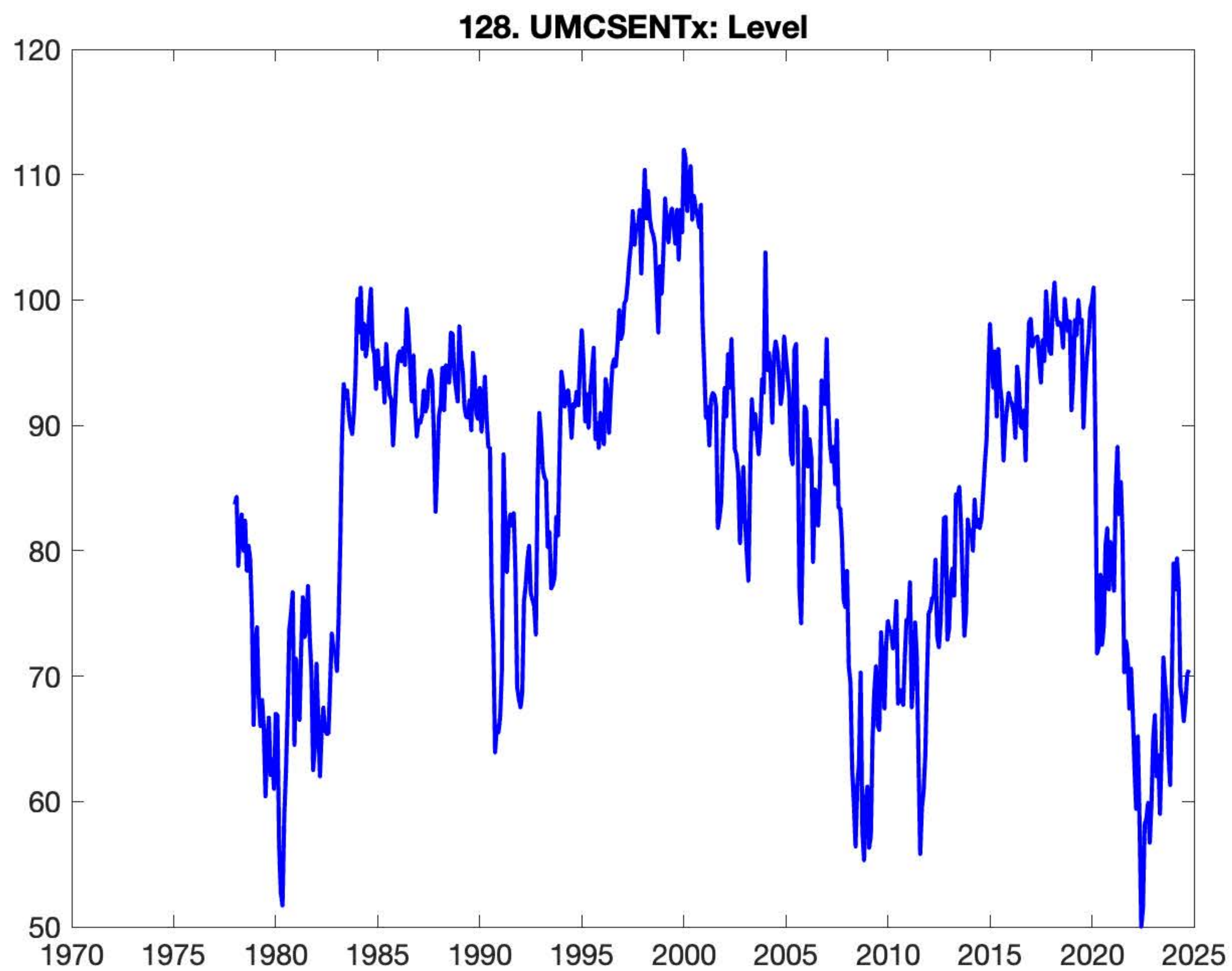

Decomposition: 2020m7 - 2024m9

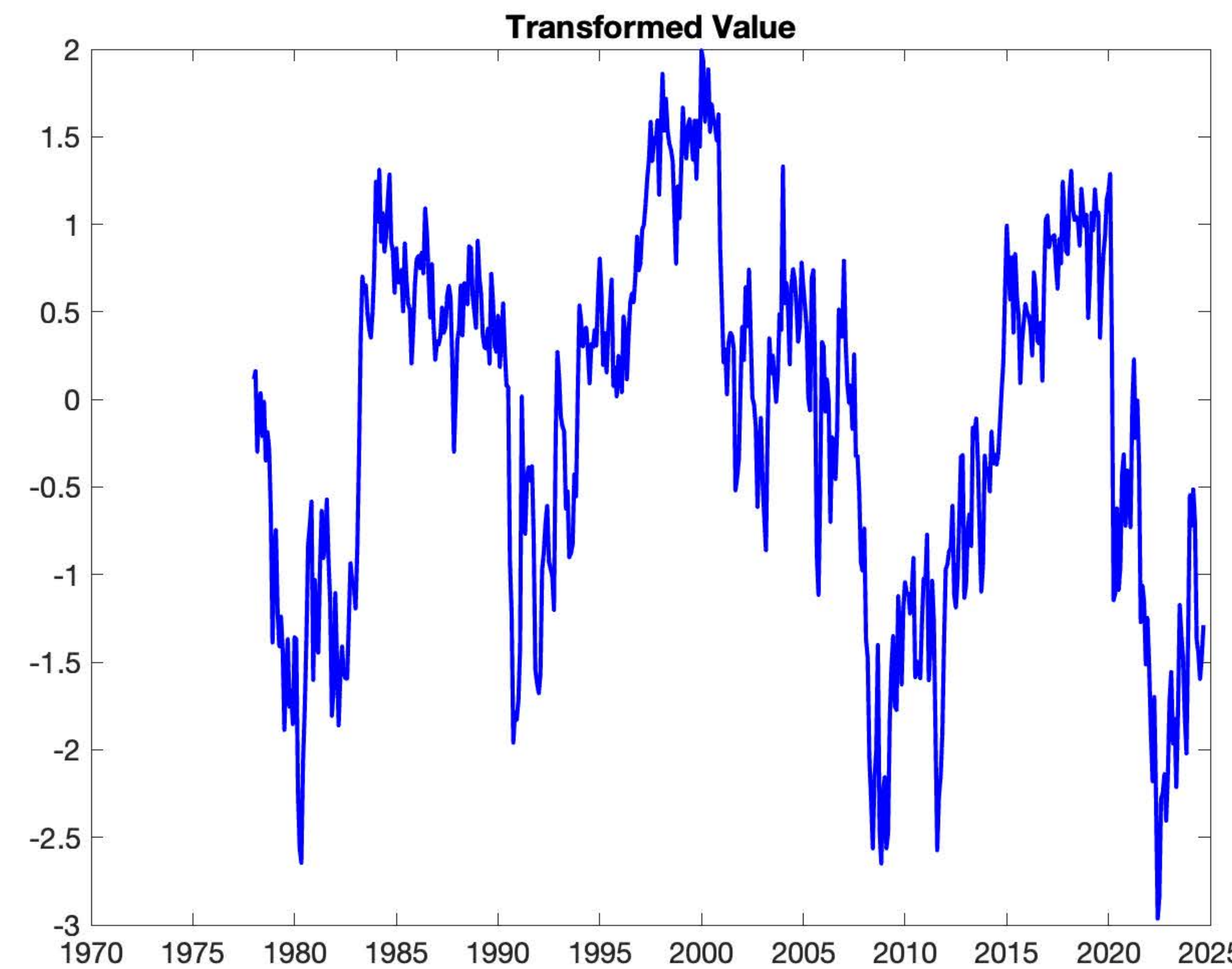

127. HOUSTW: Level

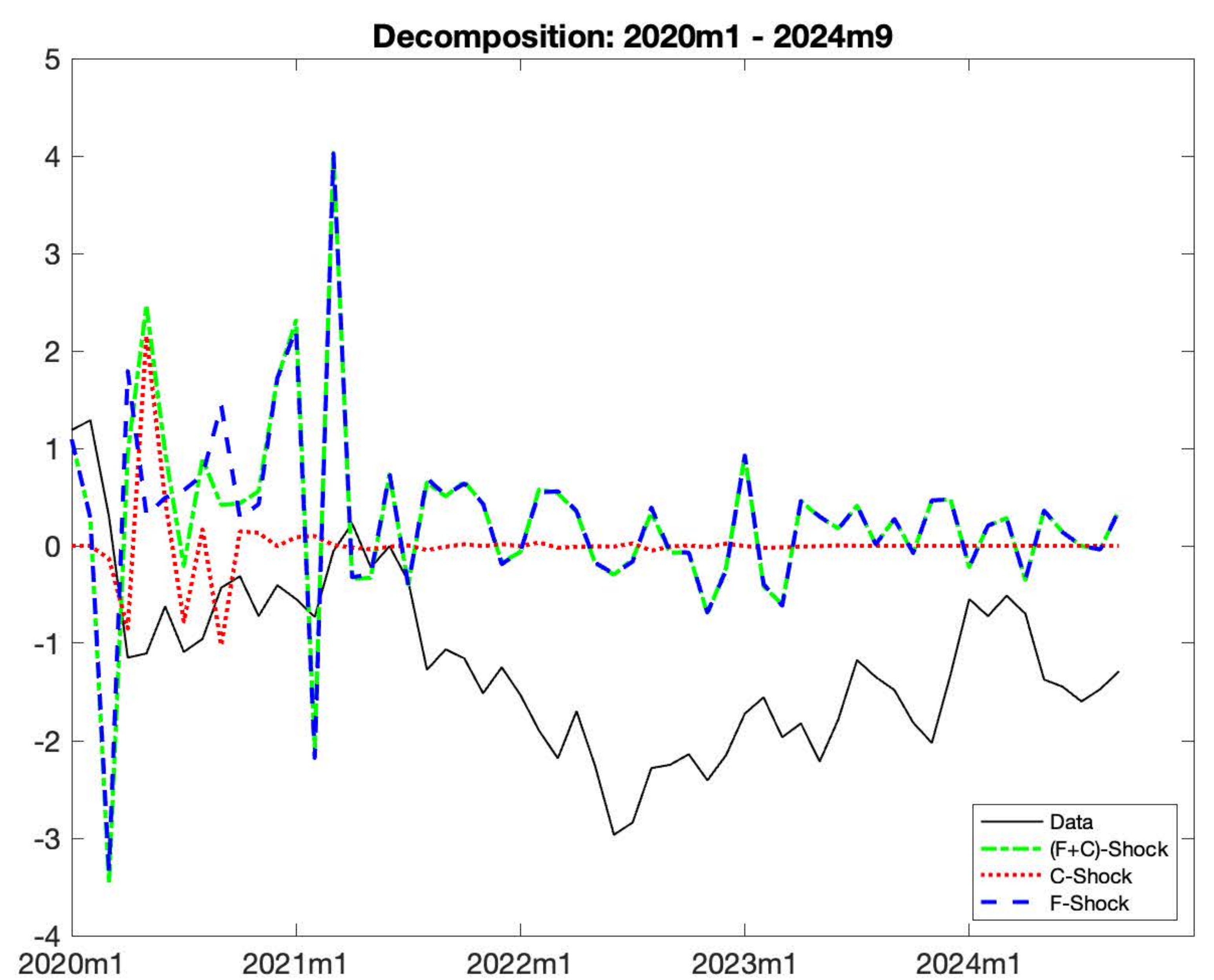

Transformed Value

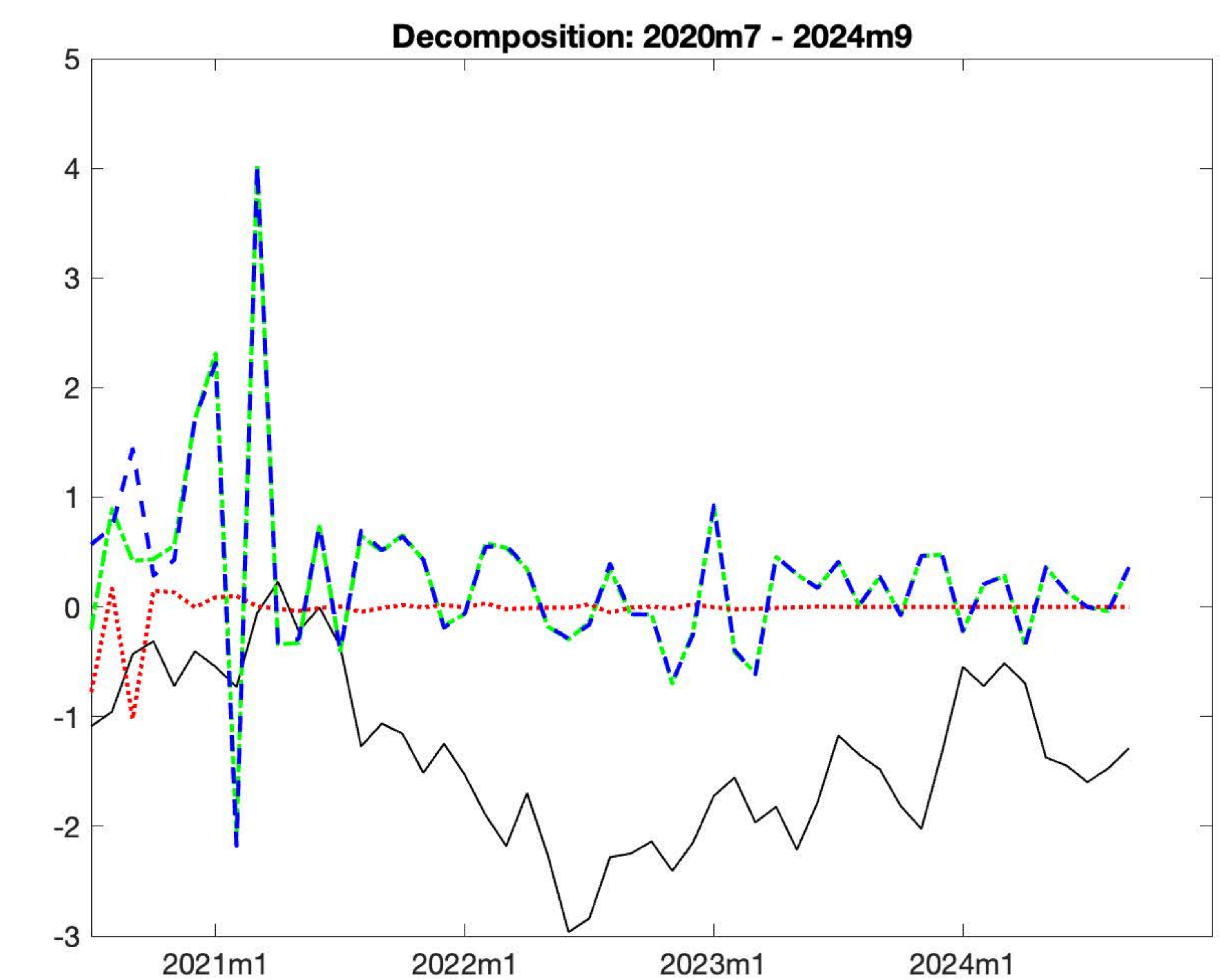

Decomposition: 2020m1 - 2024m9
Data
(F+C)-Shock
C-Shock
F-Shock


Decomposition: 2020m7 - 2024m9


128. UMCSENTx: Level
120
110
100
90
80
70
60
50
1970
1975
1980
1985
1990
1995
2000
2005
2010
2015
2020
2025


Transformed Value
2
1.5
1
0.5
0
-0.5
-1
-1.5
-2
-2.5
-3
1970
1975
1980
1985
1990
1995
2000
2005
2010
2015
2020
2025


Decomposition: 2020m1 - 2024m9
5
4
3
2
1
0
-1
-2
-3
-4
2020m1
2021m1
2022m1
2023m1
2024m1
Data
(F+C)-Shock
C-Shock
F-Shock


Decomposition: 2020m7 - 2024m9
5
4
3
2
1
0
-1
-2
-3
2021m1
2022m1
2023m1
2024m1