



Supply-side or demand-side? Assessing the economic impact of pandemics and wars on G7 countries since the 1800s^{*}

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ABSTRACT

We investigate the impact of major wars and pandemics on supply and demand dynamics in G7 economies since the 1800s. Using a neoclassical synthesis framework, we decompose real GDP per capita into trend (supply) and cyclical (demand) components via univariate filters and unobserved-components models. Country-specific local projections reveal that catastrophic events primarily and persistently damage the supply side, with wars causing large, long-lasting losses in productive capacity. Demand-side effects are generally smaller and more short-lived. However, no uniform G7 response exists; effects vary considerably in direction, magnitude, and persistence across countries. These differences are amplified by how shocks are measured—binary indicators versus intensity-based metrics—highlighting the importance of shock severity. By disentangling channels and incorporating heterogeneity, our analysis underscores the need for tailored, country-specific stabilization and reconstruction policies.

1. Introduction

This paper addresses a central policy question: Do wars and pandemics primarily affect GDP per capita through transitory demand shocks or through persistent supply-side damage – and how do these effects vary across G7 countries and historical episodes? The distinction is critical. Demand-driven shocks call for counter-cyclical stabilization; long-term losses require rebuilding capital, restoring labor supply, and protecting productivity. Correctly identifying the dominant channel is therefore essential for choosing the right policy response and for gauging whether major crises leave permanent marks on economic potential.

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Recent global crises, namely the COVID-19 pandemic and the ongoing Russian-Ukrainian war, have starkly highlighted the critical importance of distinguishing between demand- and supply-side economic shocks. While both triggered widespread disruption and inflation, their mechanisms and primary impacts were fundamentally different. The pandemic initially caused a severe demand-side contraction. Lockdowns and uncertainty crippled consumer spending, investment, and service sectors like tourism. Concurrently, supply-side disruptions emerged from shuttered factories, logistical bottlenecks, and labour shortages. This combination, exemplified by the semiconductor shortage that halted auto production and drove up prices, created a complex economic environment. While massive fiscal stimulus helped sustain demand, it also seeded the inflationary pressures that surged with post-lockdown spending. In contrast, the war in Ukraine has acted primarily as a supply-side shock. Europe's reliance on Russian energy sent fuel costs soaring, forcing energy-intensive industries to scale back production. Simultaneously, the disruption to Ukraine's grain exports exacerbated global food insecurity and prices. Here, inflation was driven not by stimulus-fueled demand, but by spiraling production costs and severed trade routes. The long-term repercussions of these concurrent global shocks – including elevated public debt, shifts in labour force participation, and a realignment of global value chains – will reshape the economic landscape for years. Accurately diagnosing whether these shocks originate on the demand or supply side is essential for designing effective policies and strengthening long-term economic resilience.

Empirical studies on the economic impact of catastrophic events – such as pandemics and wars – have largely measured their effects through output indicators like GDP per capita (see, e.g., Donadelli et al., 2021; Bonam and Smādu, 2021; Novta and Pugacheva, 2021; Jordà et al., 2022; Stefański, 2022; Ma et al., 2023; Federle et al., 2024; Donadelli and Paradiso, 2026). While the widely used local projection method à la Jordà (2005) is intuitive, it does not by itself identify the channels through which these shocks affect the economy. In practice, exogenous shocks operate through both supply and demand: pandemics may shrink the labour force (constraining supply) while heightened uncertainty depresses consumption and investment (weakening demand); wars erode human and physical capital (weakening supply) and raise uncertainty, disrupting spending and investment. These events can also reshape innovation capacity and long-run expectations. Despite these complexities, existing works have struggled to separate supply-side from demand-side effects, largely because there is no universal standard for distinguishing demand-driven from supply-driven influences.

This paper fills this gap by providing a channel-based assessment of GDP per capita through a transparent decomposition into supply and demand components. Following the neoclassical-synthesis view – where short-run fluctuations are driven mainly by demand and long-run growth is determined by supply (e.g., De Vroey, 2016) – we implement this decomposition using univariate statistical filters and unobserved-components models. In this framework, the trend component – often referred to as potential output – reflects the supply side, determined by structural factors such as capital, labor, and technological progress, while the cyclical component, or output gap, captures deviations from the trend associated with periods of excess or slack demand (see, e.g., De Masi, 1997; Gottfries, 2013; ECB, 2013; Andersson et al., 2018).¹ Using annual data from the early 1800s onward—a period of mature capitalism—we decompose real GDP per capita for each G7 country into a trend (supply) and a cyclical (demand) component and estimate country-specific dynamic responses to war and pandemic shocks using local projections (Jordà, 2005). We measure shocks in two complementary ways: as binary indicators (equal to 1 in years when a war or pandemic occurs, and 0 otherwise) and as continuous intensity variables (deaths per 1000 population). This dual approach allows us to disentangle the effects of a shock's mere incidence from those driven by its severity.

Our findings establish a clear hierarchy: wars and pandemics primarily affect economies through persistent supply-side damage, while demand-side effects are smaller and more short-lived. However, there is no uniform “G7 response.” The direction, magnitude, and persistence of impacts vary substantially across countries. For instance, while wars generate persistently negative demand-side outcomes in nations like Canada and Italy, they can yield positive demand effects in Germany and the US. This heterogeneity extends to the supply side: trend output shows strongly positive long-run responses in Germany, Canada, and Japan, but remains depressed in France and the UK. This pronounced heterogeneity stems from differences in economic structures, policy responses, and shock exposure.

Notably, the way in which war or pandemic activity is measured – whether through simple a binary indicator or a continuous intensity/severity measure – has a substantial impact on the results and can, in some cases, even reverse the sign of the estimated coefficients. This sensitivity is particularly pronounced for demand-side estimates, whereas supply-side results, although not entirely unaffected, tend to remain more stable across specifications. These discrepancies underscore the risks associated with drawing overly uniform interpretations from the available evidence.

In sum, our channel-based analysis highlights key policy trade-offs. Short-run stabilization is essential when downturns are driven by demand shocks. However, when shocks cause persistent supply-side damage, recovery requires sustained rebuilding of capital, labor, and productivity. Correctly identifying the dominant channel is therefore crucial for designing effective policy responses.

The remainder of the paper is organized as follows. Section 2 reviews the related literature on the long-term macroeconomic effects of wars and pandemics. Section 3 motivates the supply–demand decomposition, provides theoretical and empirical justification for associating the trend component with supply-side factors and the cyclical component with demand-side factors, and discusses methods for extracting these components from long-span macroeconomic data. Section 4 outlines the empirical strategy. Section 5 describes the data and presents the main results by component (trend vs. cycle), shock type (wars vs. pandemics), measurement approach, and horizon. Section 6 concludes.

¹ Hereafter, the terms “demand component” and “excess/slack component” are used interchangeably to refer to the output gap, acknowledging that the demand side is defined relative to the supply-side trend.

2. Related literature

Recent years have seen growing interest in the long-term (secular) economic effects of catastrophic events such as pandemics and wars (Donadelli et al., 2021; Jordà et al., 2022; Stefański, 2022; Federle et al., 2024). This heightened attention is largely driven by the increasing availability and advancement of economic datasets spanning centuries.² A key methodological advance in this literature has been the widespread adoption of local projections (Jordà, 2005). Relative to traditional vector autoregressions (VARs), local projections offer greater robustness to misspecification and allow for more flexible and precise estimation of impulse responses, particularly over long horizons (Montiel Olea and Plagborg-Møller, 2021; Olea et al., 2024).

Macro-effects of pandemics. Donadelli et al. (2021) examine the impact of pandemics on English GDP per capita over five centuries (1500–2019). They find that pandemics are associated with positive effects on GDP per capita during the pre-industrial era (1500–1749), but exert negative effects under industrial capitalism (1750–1899) and financial capitalism (1900–2019). The authors argue that this divergence stems from the fundamentally different economic structures of the two periods. In pre-capitalist Malthusian economies, a declining labor force would have reduced competition among workers, producing short-term wage increases. These higher wages, they suggest, likely created additional incentives for producers to develop and adopt labor-saving technologies – a logical strategy for maintaining output in the face of rising labor costs.

Jordà et al. (2022) investigate the long-run macroeconomic effects of pandemics across key indicators such as real interest rates, GDP per capita, real wages, and public debt sustainability (captured by the gap between real interest rates and real GDP growth, $r - g$). Their analysis covers five European economies – England, Germany, Italy, the Netherlands, and Spain – using data extending back to the 14th century. They identify two particularly persistent effects: a prolonged decline in real interest rates and a significant, lasting increase in GDP per capita in England. Similarly, Stefański (2022) examine the long-term effects of pandemics, wars, and environmental disasters on GDP per capita across 33 countries from 1270 to 2016. They find a persistent positive impact of pandemics on GDP per capita. A robustness check across historical sub-periods shows that the effect is positive in the medieval era (pre-1500), negligible in the pre-modern period (1500–1815), and again positive in the modern industrial era (post-1815).

Macro-effects of wars. As a robustness exercise, Jordà et al. (2022) also examine the effects of wars on English GDP per capita, real wages, and public debt sustainability. Their results reveal a striking contrast with pandemic effects: while wars show negligible impacts on output and real wages, they significantly exacerbate public debt instability. The authors attribute this divergence to two key mechanisms: (1) wartime capital destruction, which erodes the economy's productive capacity and long-term growth potential, and (2) the dual fiscal pressures of war financing and postwar reconstruction, which collectively strain public debt dynamics. Stefański (2022) demonstrate that wars exert a persistent negative effect on GDP per capita across their sample of 33 countries. This finding aligns with Jordà et al. (2022)'s analysis of European economies, as both studies identify the destruction of productive capacity as the key mechanism through which conflicts undermine economic growth. The consensus emerging from these works suggests that wartime capital depletion – whether through physical infrastructure damage, human capital losses, or disrupted production networks – fundamentally weakens an economy's growth potential. More recently, Federle et al. (2024) make a significant advancement by considering both the direct and spillover effects of interstate wars from 1870 to 2022 on GDP and inflation for a sample of 60 countries. By distinguishing between the war-site economy (home) and other economies (foreign), they identify a substantial and long-lasting adverse effect on the home economy, with output declining by as much as 30% within five years and inflation surging by 15 percentage points (p.p.). Furthermore, spillover effects on neighboring economies are highly consequential, whereas distant economies can, in some instances, benefit from redirected trade flows and heightened military spending.

Our contribution. We open the black box of reduced-form estimates by *explicitly* separating the supply and demand channels through which catastrophic shocks affect output. The prevailing approach in the literature uses local projections to estimate the direct effect of pandemic and war shocks on GDP per capita, capturing aggregate movements but not the mechanisms underlying them. With the notable exception of Jordà et al. (2022), who isolate supply-side effects by tracing shocks into *potential* output through an unobserved-components framework, existing studies do not jointly identify demand- and supply-side responses.

Our contribution is twofold. First, we implement a transparent decomposition of GDP per capita into a long-run (trend, supply-side) and a short-run (cyclical, demand-side) component using a range of established univariate filters and unobserved-components models, so that identification of channels is embedded in the outcome measure itself rather than inferred indirectly. Second, we use local projections to estimate country-specific impulse responses of *each* component to pandemic and war shocks, thereby delivering channel-specific dynamics and allowing for different magnitudes and persistence across shocks, countries, and horizons. This design directly addresses the core identification problem of the literature: any exogenous disturbance can move both demand and supply, often with opposite signs and different persistence, so reduced-form effects on aggregate output alone are difficult to interpret.

To illustrate the necessity of our approach, consider the contrasting mechanisms of pandemics and wars. In a pandemic, a population decline concentrated among non-working cohorts can mechanically raise potential output per capita by increasing capital intensity: with $Y_t/Pop_t = (Y_t/L_t) \cdot \ell_t$ and $\ell_t \equiv L_t/Pop_t$, a fall in ℓ_t may be offset (or even overcompensated) if the surviving workforce

² Examples of these datasets include: the Maddison Project; the MacroFinance and MacroHistory Lab (Jordà-Schularick-Taylor Macrohistory Database); the Bank of England Research Dataset; MeasuringWorth; Schmeling (2020), Fouquet and Broadberry (2015), and the Long-term productivity database.

enjoys a higher capital-labour ratio, pushing up Y_t/L_t . Yet this potential supply-side gain can be outweighed by demand-side weakness if uncertainty leads households and firms to defer consumption and investment. In war, simultaneous destruction of labour and capital makes the net effect on potential output theoretically ambiguous. If labour losses exceed capital destruction ($\Delta L > \Delta K$), the capital-labour ratio K_t/L_t rises and can lift Y_t/L_t through $Y_t/Pop_t = (Y_t/L_t) \cdot \ell_t = f(K_t/L_t) \cdot \ell_t$; however, a concurrent fall in ℓ_t pushes the opposite way, leaving the overall effect on Y_t/Pop_t uncertain. Moreover, war-related uncertainty reduces demand as households and firms delay spending, which in turn intensifies existing supply disruptions. These examples show how mixing channels together can obscure the true propagation of shocks.

Building on Jordà et al. (2022), our study preserves their emphasis on supply shocks operating through the trend (potential output) component while explicitly quantifying the role of the demand channel via the cyclical component. Methodologically, we strengthen robustness by (i) employing multiple well-established decomposition techniques – ensuring results do not depend on any single filter or modeling choice – and (ii) estimating local projections separately for the trend (supply) and cycle (demand) components. This allows us to derive channel-specific impulse responses over a long historical sample for the G7 economies. Our approach provides a clearer link between shocks and policy responses. When inflation is driven by demand pressures, conventional stabilization policies remain appropriate. By contrast, when productive capacity is impaired, the policy focus should shift toward measures that rebuild supply potential and safeguard long-run growth.

3. Decomposing GDP variations into supply and demand components: Insights from theories and empirical strategies

This section outlines the theoretical basis and empirical methods used to distinguish demand-driven from supply-driven movements in output. The analysis builds on the standard view, rooted in the neoclassical synthesis, that short-run fluctuations in GDP are primarily shaped by aggregate-demand shocks, whereas long-run GDP dynamics reflect supply-side forces such as technology, capital accumulation, and labour-force growth. Within this framework, the cyclical component of GDP serves as a proxy for the demand channel, while the trend component captures the supply side.

In the following sections, we review the main methods used in the literature to separate observed GDP into its trend (potential output) and cyclical (output gap) components. These range from purely statistical filters to fully structural decompositions. This distinction is crucial when evaluating the economic impact of major shocks – such as pandemics, wars, financial crises or natural disasters – because it reveals whether their effects are primarily demand-driven (temporary deviations from potential output that tend to reverse over time) or supply-driven (permanent changes in the economy's productive capacity).

3.1. Trend-cycle interpretation of the neoclassical synthesis

The neoclassical synthesis offers a standard interpretation of how the economy operates over different time horizons: in the short run, output is largely driven by fluctuations in aggregate demand, and Keynesian mechanisms therefore dominate; in the long run, however, supply-side factors – technology, capital accumulation, and labour – take over, and classical or neoclassical forces determine potential output (Modigliani, 1944; Samuelson, 1948; Patinkin, 1956; De Vroey, 2016). This very distinction forms the intellectual foundation of the European Central Bank's Area-Wide Model (AWM), which was deliberately built on the principles of the neoclassical synthesis.³ In this view the economy can be written as

$$y_t = y_t^p + e_t, \quad (1)$$

where y_t is actual output, y_t^p is potential (or trend) output, and e_t is the cyclical component. The potential component y_t^p represents the level of production the economy can sustain when markets clear and factors are fully employed. It depends on supply-side determinants,

$$y_t^p = F(A_t, k_t, \ell_t^N), \quad (2)$$

with A_t denoting technology, k_t the capital stock, and ℓ_t^N the normal (or natural) level of labour input. This is the logic later made explicit by growth models and underlies policy discussions of “potential GNP” (Okun, 1962).

The cyclical component e_t in (1) collects mainly *demand-driven* deviations from trend. When prices and wages are sticky, shocks to government spending, monetary policy, credit conditions, or private expectations move aggregate demand; with quantities adjusting more than prices in the short run, actual output diverges from y_t^p . This is the mechanism the synthesis preserves from Keynes. A closely related supply-versus-demand separation underlies the well-known VAR identification in Blanchard and Quah (1989), where shocks with permanent effects on output are interpreted as supply disturbances and shocks with only transitory effects as demand disturbances. There are several ways to bring Eq. (1) to the data, as discussed below. In practice, researchers typically estimate the trend or potential output y_t^p using one of two broad approaches – statistical filters or fully structural methods – and then define the output gap e_t simply as the residual (i.e., $e_t = y_t - y_t^p$). Within the neoclassical-synthesis framework, this decomposition carries a clear economic interpretation: (i) y_t^p represents the supply-driven (long-run) component of GDP – the level of output the economy can sustain at full capacity, determined by technology, capital, and labour and (ii) e_t captures the demand-driven (short-run or cyclical) component – the temporary deviation of actual output from potential, driven by fluctuations in aggregate demand.

³ “The model is designed to have a long-run equilibrium consistent with *neo-classical* economic theory while the short-run dynamics are *largely demand-driven*.” (Fagan et al., 2005).

3.2. Model-based approaches

A common and theoretically grounded way to estimate potential output relies on an aggregate production function – most often the Cobb-Douglas form that lies at the heart of the Solow growth model (Artus, 1977; De Masi, 1997; Fisher et al., 1997; Proietti et al., 2007). The idea is straightforward: GDP is decomposed into contributions from three fundamental supply-side factors – capital, labour, and TFP – and the smooth, long-run trend of each factor is extracted. Potential output y_t^p is then constructed as the level of output that would prevail if these factors were at their trend levels and fully employed in production. More specifically, the trend components typically used are: (i) capital stock, i.e., the economy's accumulated physical assets that provide productive capacity; (ii) labour input, i.e., usually the working-age population or hours worked, adjusted for structural unemployment or the NAIRU (the rate consistent with stable inflation) and (iii) TFP, i.e., the efficiency with which capital and labour are combined, capturing technological progress and organizational improvements.

Potential output is then calculated by feeding these trend components into the production function. The output gap e_t is simply the difference (or percentage difference) between actual GDP and this estimated potential level, signaling whether the economy is running above capacity (overheating) or below capacity (slack). This production-function approach has a major advantage: it offers a structurally coherent way to separate lasting supply-side developments (e.g., slower capital accumulation, demographic shifts, or technological stagnation) from transitory demand-driven fluctuations. Its main practical drawback, however, is heavy reliance on high-quality, long-span data series for capital, labour, and TFP – data that are often scarce or imprecise, especially when analyses stretch back over many decades or centuries.

3.3. Empirical approaches

Most empirical studies to date have employed univariate and multivariate statistical techniques to estimate potential output and the output gap.

Univariate methods. Univariate frameworks use a single historical time series for the variable of interest. Broadly, two types of univariate methods can be distinguished:

- **Univariate Filters (HP, BK, CF, HA, BN):** We apply a set of standard univariate filters to separate real GDP into a smooth trend (potential output) and a cyclical component (output gap). These include the Hodrick-Prescott (HP) filter (Hodrick and Prescott, 1997; Ravn and Uhlig, 2002), the Baxter-King (BK) and Christiano-Fitzgerald (CF) band-pass filters (Baxter and King, 1999; Christiano and Fitzgerald, 2003), the Hamilton (HA) filter (Hamilton, 2018), and the Beveridge-Nelson (BN) decomposition (Beveridge and Nelson, 1981; Kamber et al., 2018).
- **Univariate Unobserved Components Models (UCM):** We estimate univariate unobserved components models that decompose GDP into trend and cyclical components within a state-space framework (Clark, 1987, 1989). By explicitly modeling the stochastic properties of the components, these UCMs provide a flexible and robust way to identify supply-side (trend) and demand-side (cycle) movements.
- **Trend-cycle decompositions with structural breaks (TC, HPb):** To account for potential changes in long-run growth regimes, we also consider decompositions that allow for structural breaks in the trend. Specifically, we use a trend-cycle (TC) decomposition with structural breaks following Mohr (2005), and a Hodrick-Prescott filter with structural breaks (HPb), which permits discrete shifts in the level or growth rate of potential output. These methods provide robustness checks on our baseline decompositions in the presence of structural change.

Multivariate methods. In contrast to univariate approaches, multivariate methods use multiple time series – such as GDP, inflation, employment, or other macroeconomic indicators – allowing for a more precise identification of supply- and demand-side components. By incorporating additional economic information, these methods provide richer and more nuanced insights. Their application, however, depends on reliable and consistent data across all series, which can be challenging for long historical periods. The main categories of multivariate approaches are as follows:

- **Multivariate Filters:** These methods extend univariate filters by incorporating information from multiple variables to enhance the separation of trend and cyclical components. See, for example, Laxton and Tetlow (1992), Murasawa (2015), and Azevedo (2011).
- **Multivariate Unobserved Component Models (MUCMs):** These models extend univariate UCMs by incorporating multiple series into a state-space framework. They allow for the simultaneous estimation of trends and cycles across variables while modeling their interdependencies. See, for example, Kuttner (1994) and Apel and Jansson (1999).
- **Sign-Restriction VAR Methods:** These methods impose theoretical sign restrictions on the responses of variables, such as GDP and inflation, in a structural VAR framework. Demand-side shocks are identified when GDP and inflation move in the same direction, while supply-side shocks are identified when they move in opposite directions (Della Chang et al., 2023; Shapiro, 2026).

In summary, multivariate empirical approaches – like the model-based methods discussed in Section 3.2 – face a key limitation in long-term (secular) studies: they require additional data beyond GDP, such as labor input, capital stock, or inflation, which are often unavailable or unreliable over extended periods. Consequently, statistical univariate methods, including filters and unobserved-component models, are generally preferred for long-term analyses due to their lower data requirements and suitability for limited historical datasets. Given the scarcity of macroeconomic data spanning 200 years – except for GDP per capita – and the difficulty of

obtaining reliable statistics on wars and pandemics prior to the 19th century, we adopt standard univariate approaches to extract the trend and cyclical components from each GDP per capita series. A deeper discussion in these empirical methodologies is provided in the next section (see [Section 4.1](#)).

4. Empirical strategy

This section details (i) the empirical methodology for estimating supply- and demand-side contributions to aggregate fluctuations – specifically, the degree of excess demand or slack in the economy ([Section 4.1](#)) – and (ii) the econometric approach adopted to quantify the impact of major wars and pandemics on these identified supply- and demand-side components ([Section 4.2](#)).

4.1. Estimating supply and demand components

Following the neoclassical framework laid out in [Section 3.1](#), we interpret the trend component of output as supply-driven and the cyclical component as demand-driven. We extract these components using a battery of univariate filters. This univariate approach is imposed by the scarcity of data: when constructing long-run series for all G7 countries from the 19th century onward, consistent macroeconomic indicators beyond real GDP per capita are generally not available. Rather than relying on a single method, we employ multiple filters – including the HP filter, the BN decomposition, other univariate filters, and techniques that explicitly account for structural breaks. There are three main reasons for this choice. First, the objects of interest (trend and cycle) are latent, making their identification inherently model-dependent, as no unique decomposition can be inferred from a single series. Second, different filters impose distinct identifying assumptions (e.g., smoothness penalties versus parametric stochastic cycles), exhibit varied frequency responses, and differ in sensitivity to end points and structural breaks. Triangulating across methods mitigates the risk that results are driven by any single specification. Third, consistency across methods serves as a straightforward robustness check: when multiple estimators yield similar patterns, confidence in the substantive finding increases, whereas discrepancies highlight model dependence and are addressed in our sensitivity analysis. To save space, details on methodology and implementation are provided in [Appendix A](#).

4.2. Local projection methodology

Having extracted the long-run trend (supply component, y_t^p) and the cyclical component (demand-driven excess or slack, c_t) using the univariate filters detailed in [Appendix A](#), we estimate the dynamic responses of these components to wars and pandemics via the local projection method of [Jordà \(2005\)](#). We consider two measures of catastrophic events: (i) a binary indicator equal to one in the year of the event and zero otherwise, and (ii) a continuous intensity measure defined as the number of deaths caused by the event per 1000 inhabitants.⁴

Binary indicator. The regression model for local projections follows the specification introduced by [Jordà \(2005\)](#) and extended by [Jordà et al. \(2022\)](#):

$$x_{t+h} - x_{t-1} = \alpha^h + \beta^h P_t + \gamma^h W_t + \sum_{l=1}^L (\theta_l^h P_{t-l} + \phi_l^h W_{t-l}) + \sum_{l=1}^L \rho_l^h x_{t-1-l} + e_{t+h}^h, \quad h = 0, 1, \dots, 30. \quad (3)$$

In this equation, x_t represents the variable of interest, which can be either the trend component y_t^p (potential output) or the cyclical component c_t (output gap or excess/slack demand). The term $x_{t+h} - x_{t-1}$ denotes the change in the variable of interest between time $t-1$ and horizon h . α^h is the intercept term at horizon h ; P_t and W_t are binary indicators for the occurrence of a pandemic or war in year t , respectively. β^h and γ^h measure the effects of pandemics and wars at horizon h , while e_{t+h}^h represents the error term. The coefficients β^h and γ^h capture the average treatment effects of pandemics and wars on potential output or the output gap over time. These effects are expressed as:

$$\begin{aligned} \mathbb{E}(x_{t+h} - x_{t-1} \mid P_t = 1; \Omega_t) - \mathbb{E}(x_{t+h} - x_{t-1} \mid P_t = 0; \Omega_t) &= \beta^h, \\ \mathbb{E}(x_{t+h} - x_{t-1} \mid W_t = 1; \Omega_t) - \mathbb{E}(x_{t+h} - x_{t-1} \mid W_t = 0; \Omega_t) &= \gamma^h, \end{aligned} \quad (4)$$

where Ω_t represents the information set available at time t . Put simply, these coefficients measure the short- and long-term impacts of pandemics and wars on the variable of interest (i.e., potential output or output gap).

⁴ More details on the construction of these indicators can be found in [Section 5.1](#).

Intensity indicator. When the pandemic and war indicators are expressed as intensity measures (for example, deaths per 1000 inhabitants on a per-capita basis), the model is modified to account for the magnitude of the events (see Jordà, 2023, for details):

$$x_{t+h} - x_{t-1} = \alpha^h + \beta^h s_{P,t} P_t + \gamma^h s_{W,t} W_t + \sum_{l=1}^L (\theta_l^h s_{P,t-l} P_{t-l} + \phi_l^h s_{W,t-l} W_{t-l}) + \sum_{l=1}^L \rho_l^h x_{t-1-l} + e_{t+h}^h, \quad h = 0, 1, \dots, 30, \quad (5)$$

where $s_{P,t}$ and $s_{W,t}$ represent the intensities of pandemics and wars, respectively, while other variables are as defined in Eq. (3). The effects of pandemics and wars under the intensity specification are defined as:

$$\begin{aligned} \mathbb{E}(x_{t+h} - x_{t-1} \mid P_t = 1 \cdot s_{P,t}; \Omega_t) - \mathbb{E}(x_{t+h} - x_{t-1} \mid P_t = 0; \Omega_t) &= \bar{s}_P \beta^h, \\ \mathbb{E}(x_{t+h} - x_{t-1} \mid W_t = 1 \cdot s_{W,t}; \Omega_t) - \mathbb{E}(x_{t+h} - x_{t-1} \mid W_t = 0; \Omega_t) &= \bar{s}_W \gamma^h, \end{aligned} \quad (6)$$

where $\bar{s}_P$ and $\bar{s}_W$ denote the average intensities of pandemics and wars, respectively. In empirical applications, when events are expressed as intensity measures, it is often more insightful to examine the dynamics of β^h and γ^h . These coefficients, in this context, represent the effects of pandemics and wars resulting in a 1% population reduction (see, for example, Stefański, 2022).⁵

Evaluating summary effects over short, medium, and long time frames. Estimating local projections delivers a full set of horizon-specific coefficients β^h and γ^h ($h = 0, \dots, 30$) that characterize the dynamic effects of wars and pandemics. Presenting every coefficient across all horizons and specifications would overwhelm the reader, as the baseline model alone produces over 200 point estimates. To enhance readability, we aggregate the responses into broader time windows and focus on the most salient short- and medium-term patterns. In the spirit of Ramey and Zubairy (2018), we summarize the effects using cumulative multipliers computed over fixed horizons (short-, medium-, and long-run differences). To do so, we define three successive, non-overlapping windows following each event at date t :

- Short run (Δx_t^S): change from one year before the event to ten years after ($x_{t+10} - x_{t-1}$)
- Medium run (Δx_t^M): additional change between 10 and 20 years post-event ($x_{t+20} - x_{t+10}$)
- Long run (Δx_t^L): incremental change between 20 and 30 years post-event ($x_{t+30} - x_{t+20}$).

These long-term differences provide a clear segmentation of the post-event trajectory into decade-long intervals, facilitating interpretation of the persistence and evolution of the effects. We then estimate local projections of the form:

$$\Delta x_t^K = \alpha^K + \beta^K P_t + \gamma^K W_t + \sum_{l=1}^L (\theta_l^K P_{t-l} + \phi_l^K W_{t-l}) + \sum_{l=1}^L \rho_l^K x_{t-1-l} + u_t^K, \quad K \in \{S, M, L\},$$

using the same set of controls and lag structure as in (3)–(5). As in the baseline specification, we compute HAC-robust standard errors to account for serial correlation induced by the overlapping horizons in calendar time.

Under the binary-event specification, the coefficients β^S and γ^S measure the average short-run effect of a pandemic or a war on the level of potential output (or the output gap) between $t-1$ and $t+10$. The medium- and long-run coefficients, β^M and β^L (pandemics) and γ^M and γ^L (wars), capture the incremental changes in the level of the variable between $t+10$ and $t+20$ and between $t+20$ and $t+30$, respectively. By construction,

$$x_{t+20} - x_{t-1} = (x_{t+10} - x_{t-1}) + (x_{t+20} - x_{t+10}) = \Delta x_t^S + \Delta x_t^M,$$

and similarly $x_{t+30} - x_{t-1} = \Delta x_t^S + \Delta x_t^M + \Delta x_t^L$. Under the maintained linear specification, the effect of an event on the long difference $x_{t+20} - x_{t-1}$ (or $x_{t+30} - x_{t-1}$) can therefore be decomposed into the sum of its effects on the constituent windows. This motivates the interpretation of

$$\text{Effect at 20 years} \approx \beta^S + \beta^M, \quad \text{Effect at 30 years} \approx \beta^S + \beta^M + \beta^L.$$

In finite samples, estimating each window in a separate regression rather than in a single long-difference regression may lead to small numerical differences, but the economic content of these linear combinations is that of cumulative effects on the level of the variable over 20- and 30-year horizons. Under the intensity specification in (5), the coefficients β^K and γ^K are interpreted in the same way, but scaled by the intensity of the event (for example, per one percentage point reduction in the population due to deaths).

By examining these non-overlapping windows, we can determine whether wars and pandemics produce lasting shifts in potential output or the output gap that persist beyond the initial decade, whether they trigger additional medium-run drift in years 10-20, and whether any further adjustment occurs in years 20-30. The approach is thus closely related to the cumulative-multiplier perspective

⁵ For each horizon h , we estimate (3) and (5) using observations indexed by $t \leq T - h$ for the regressors. Accordingly, the left-hand side x_{t+h} spans outcomes up to calendar date T , while shocks are always measured at time t and never beyond $T - h$. Post- $T - h$ shocks are excluded – avoiding look-ahead bias.

of Ramey and Zubairy (2018), while focusing directly on net level changes over policy-relevant horizons (short, medium, and long run).⁶

The cumulative impulse responses from Eqs. (3)–(5) measure, for each horizon h , the total deviation of x_{t+h} from its pre-event level. In contrast, the coefficients β^S , β^M , and β^L (and their counterparts for wars) decompose this cumulative effect into successive net changes across the short-, medium-, and long-run windows. This distinction is crucial: markedly different dynamic paths can produce identical cumulative effects at a given horizon. For instance, a sharp short-run drop followed by near-stability yields the same 30-year cumulative response as a modest initial decline followed by prolonged negative drift. Conversely, the window-specific coefficients may appear small even when the underlying impulse response exhibits large but offsetting movements within a decade-long window. These two sets of estimates are highly complementary. Cumulative impulse-response functions show the overall magnitude and persistence of the level shift at each horizon. The window-based coefficients, in contrast, identify when that persistent shift occurs - whether it materializes primarily in the short run (0-10 years), the medium run (10-20 years), or the long run (20-30 years).

5. Empirical analysis

5.1. Data description

Our analysis covers the G7 economies from 1800 to 2020 and combines long-run supply and demand series with indicators for pandemics and wars.

Supply-side vs. demand-side components. The supply and demand series are derived from GDP per capita using the univariate empirical approaches described in Section 4.1. GDP per capita data are sourced from Gapminder v31 and expressed in constant 2017 international dollars for comparability across time and countries. Fig. 1 shows the trend (supply-side) component, while Fig. 2 displays the cyclical (demand-side) component, both obtained using various filtering methods. Differences across methods are negligible for the trend component but more pronounced for the cyclical component, highlighting the sensitivity of demand-side estimates to the choice of filter. Appendix D presents the first principal component of the cycle and trend, extracted from the eight estimated indicators. This synthetic measure of demand and supply will be used in our policy analysis. The country-specific evolution of these synthetic indicators is shown in Figs. D.1 (Canada), D.2 (France), D.3 (Germany), D.4 (Italy), D.5 (Japan), D.6 (UK), and D.7 (US).

Pandemic indicators. We construct novel indicators of pandemic activity using a multi-source, robustness-oriented methodology. Our strategy proceeds in two steps. First, we use the AI chatbot ChatGPT v5 to identify, for each country, the main epidemic and pandemic events. Second, we systematically cross-check and refine this list by consulting bibliographic and historical sources (via Google Search and Wikipedia) in order to reconstruct, for each episode, the most accurate available estimate of country-specific deaths. Although the empirical series used for estimation cover 1800–2020, we extend the dataset through 2024 to ensure continuity and to better compute the figures for COVID-19. To ensure robustness and maintain comparability with existing empirical studies, we then construct two distinct indicators:

1. A binary indicator reflecting the presence or absence of a pandemic in a given year.
2. An intensity indicator quantifying pandemic severity as the number of deaths per 1000 population, using historical population data from Gapminder (v8).⁷

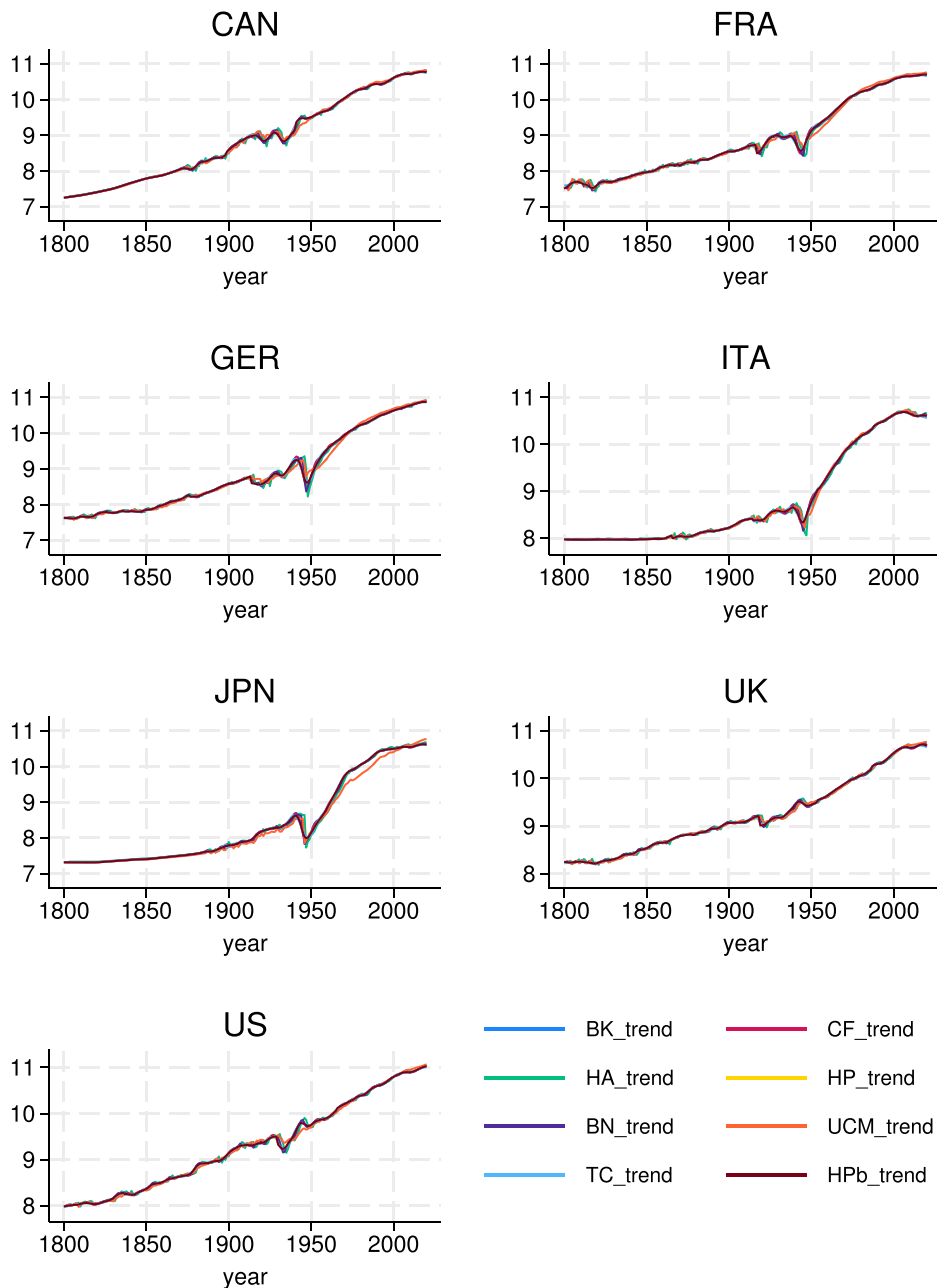
Fig. B.1 depicts our newly constructed indicators of pandemic activity, providing an immediate visual overview of the occurrence of such events over the past two centuries.

War indicators. Our baseline war series is drawn from Project Mars (Lyal, 2020), which codes *conventional* wars and campaigns worldwide from 1800 through 2011 that generate at least 500 battlefield fatalities (KIA) over the full duration of hostilities. Multi-front wars are split into separate campaigns (e.g., WWII theaters). Only soldier KIA are counted; deaths from disease and civilian casualties are excluded.⁸

⁶ There are two related but distinct notions of “cumulative effect” in the literature. Ramey and Zubairy (2018) construct cumulative multipliers by summing the responses of the numerator and the denominator over time, so that the cumulative effect up to horizon H is proportional to the area under the impulse response function, $\sum_{h=0}^H x_{t+h}$. By contrast, our window-based measures are defined as long differences in the level of the variable, e.g. $x_{t+10} - x_{t-1}$, and thus capture the net change between the beginning and the end of each horizon. As a result, short-, medium-, and long-run effects in our framework are informative about whether the level of potential output or the output gap is durably higher or lower after a catastrophic event, while potentially offsetting fluctuations within each window (e.g. an initial drop followed by a rebound) may largely cancel out in these long differences.

⁷ Additional details on the pandemic data reconstruction strategy and the construction of the two indicators are provided in Appendix B.

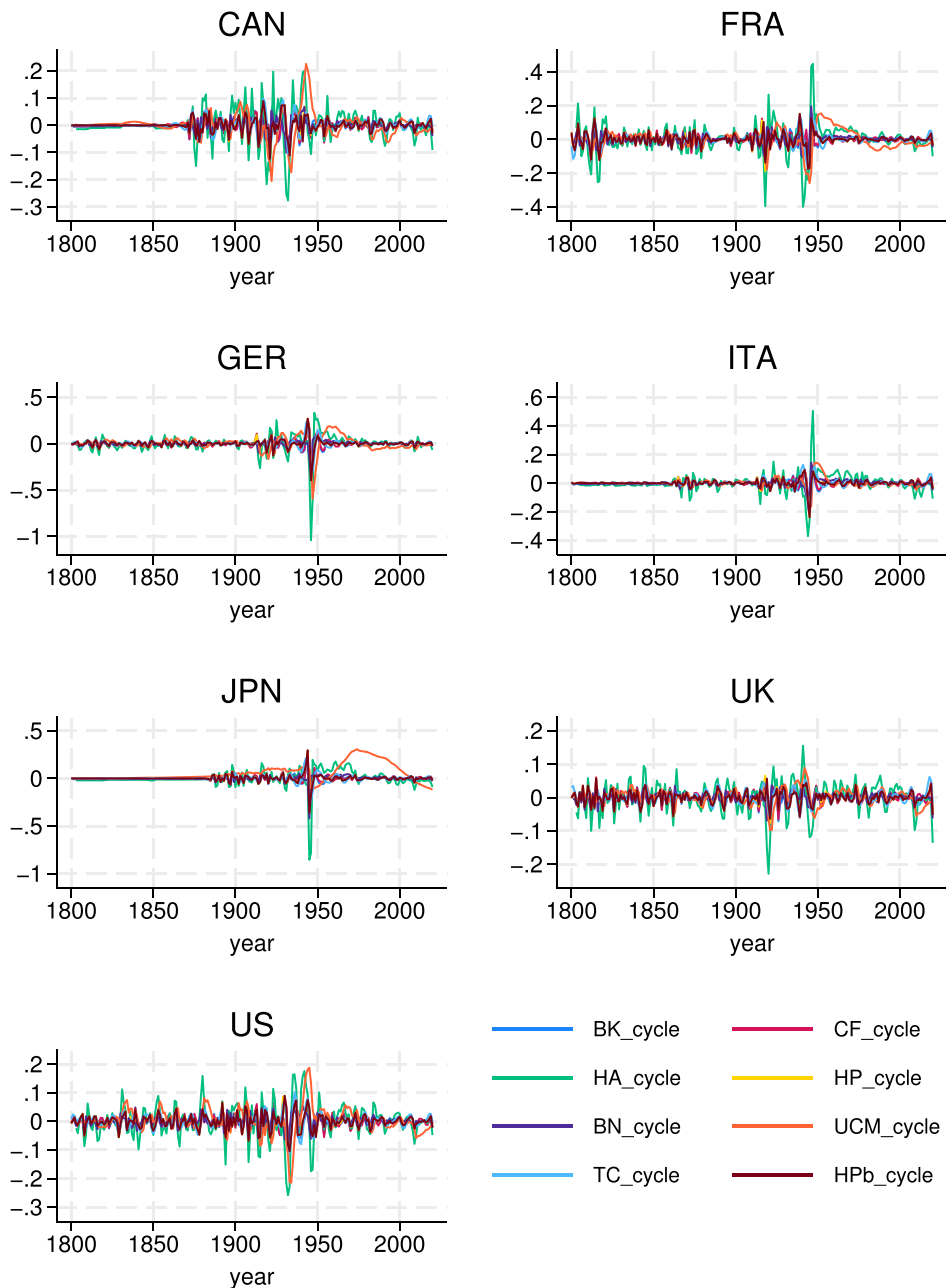
⁸ One of the referees, whom we thank, noted that the mortality threshold used for wars differs from the one used for pandemics. In Appendix C we show that a strict one-to-one correspondence between the two thresholds holds only in special cases; moreover, any specific thresholding rule (event totals, annual deaths, or per-capita rates) entails trade-offs and potential classification errors. Our preferred response is to exploit all available information: we work at the most granular level feasible (campaign-by-year for wars; event-level or year-attributed for pandemics) and report per-capita intensities alongside indicator variables. Since the core estimates hinge on continuous intensities, results are not driven by arbitrary cutoffs.



Note: **BK**: Baxter-King filter; **CF**: Christiano-Fitzgerald filter; **HA**: Hamilton filter; **HP**: Hodrick–Prescott filter; **BN**: Beveridge-Nelson decomposition; **UCM**: Univariate UCM with Random Trend; **TC**: trend/cycle decomposition with structural breaks (Mohr, 2005); **HPb**: HP decomposition with structural breaks.

Fig. 1. The Trend (Supply-Side) Component in G7 GDPs.

For this paper we restrict the source to the G7 subset (as belligerents and/or on their territory) and then post-process the campaign records to fit our annual, country-region panel. Specifically: (i) when a campaign spans multiple calendar years, we distribute its total KIA uniformly across the years in the campaign window; and (ii) when a campaign covers more than one world region, we proportionally allocate its KIA across the affected regions. Campaigns below the 500-KIA threshold are excluded, and – where useful – we aggregate included campaigns to form “macro-war” totals for a given conflict. Given that our analysis extends to 2020, we supplement the dataset with updated casualty figures retrieved from Wikipedia to maintain continuity and ensure completeness.



Note: **BK**: Baxter-King filter; **CF**: Christiano-Fitzgerald filter; **HA**: Hamilton filter; **HP**: Hodrick–Prescott filter; **BN**: Beveridge–Nelson decomposition; **UCM**: Univariate UCM with Random Trend; **TC**: trend/cycle decomposition with structural breaks (Mohr, 2005); **HPb**: HP decomposition with structural breaks.

Fig. 2. The Cyclical (Demand-Side) Component in G7 GDPs.

To systematically quantify the impact of wars, as we do for pandemics, we construct two distinct measures: (i) a binary indicator capturing the presence or absence of war in a given year, and (ii) an intensity indicator reflecting the severity of conflict based on casualty figures. These two indicators of war activity over the past two centuries are depicted in Fig. B.2.

5.2. Empirical findings

The empirical results in this section are obtained by estimating Eqs. (3) and (5) with $L = 5$ lags.⁹

In addition to the eight methods used to extract the country-level demand (cycle) and supply (trend) components (described in Appendix A), we also construct, for each country and for each component, an additional measure based on the first principal component of the eight indicators. This newly constructed synthetic indicator summarizes the information contained in all underlying indicators for each country and component.

Given the nine methods used to extract the demand (cycle) and supply (trend) components, the two components themselves, the two alternative shock indicators for each component (binary vs. intensity), and the seven countries in the G7 sample, the total number of estimated specifications is $9 \times 2 \times 2 \times 7 = 252$. Presenting full horizon-by-horizon responses for each specification would be extremely cumbersome — our baseline setup alone generates well over 200 coefficients — and would add limited insight. We therefore adopt the window-based approach described in Section 4.2 and summarize the dynamics using short-run, medium-run, and long-run measures. Statistical significance is assessed using HAC-robust standard errors and two-sided t -tests at the 68% confidence level. As discussed in Section 4.2, the window-based coefficients β^S , β^M , and β^L (and γ^S , γ^M , γ^L for wars) differ from conventional cumulative impulse responses derived from Eqs. (3) and (5). The window-based coefficients measure the net change in the variable between consecutive time segments (0–10, 10–20, and 20–30 years), whereas cumulative IRFs capture the total deviation from the pre-shock level at each horizon.

Given the sheer volume of results, summarizing the tables is inherently challenging. We therefore further condense the evidence by presenting the country-specific results in graphical form. For each country, and for every combination of component (cycle vs. trend) and shock type (wars vs. pandemics), we construct a dedicated panel that summarizes the key findings from Tables 1–14 (see Fig. 3).

We conclude by presenting the cumulative IRFs at the individual-country level, separately for the demand (cycle) and supply (trend) components, in response to war and pandemic shocks measured in intensity form (see Figs. 4–10). This provides a graphical representation of the continuous time evolution of the effects-expressed in terms of shock intensity-of wars and pandemics on country-level demand and supply.

5.2.1. Demand-side effects

Window-based local projections reveal that demand-side responses in the G7 are generally modest in magnitude and highly heterogeneous across countries. For wars, short-run effects vary with binary (on/off) indicators are typically small or mildly negative. When shocks are measured by intensity (battle-related deaths per 1000 population), responses are occasionally briefly positive but drop rather rapidly. Medium-run effects tend to be limited and, if anything, mildly expansionary, while long-run responses vary considerably across countries. Pandemic shocks, in contrast, trigger even weaker and statistically fragile demand responses. Short-run coefficients are usually near zero, and beyond the medium run, effects remain small and often slightly negative in several cases. Overall, the estimated profiles show no consistent pattern across countries or across the two measurement approaches (binary versus intensity-based). Demand responses to major wars and pandemics are highly heterogeneous and episode-specific.

Wars. Wars trigger sizable but highly heterogeneous cyclical effects across countries. In Canada, the demand response varies markedly depending on how the war shock is measured (Table 1, left panel). When wars are captured with a simple 0/1 dummy (i.e., treating all war episodes equally), the impact effect is mildly contractionary. However, once war intensity is accounted for the short- and medium-term response turns clearly expansionary, reflecting the fiscal stimulus and resource mobilization typical of a war economy. At longer horizons (beyond 20 years), both the binary and intensity-based indicators converge in showing a sustained decline in aggregate demand, consistent with postwar deleveraging, reconstruction fatigue, and the eventual unwinding of wartime stimulus. Germany exhibits a similar pattern of heterogeneous demand responses, though with some distinct features (Table 5, left panel). In the short run, a binary (0/1) war indicator produces moderately negative effects on aggregate demand, whereas intensity-weighted measures yield responses close to zero or mildly positive. Medium- and long-run effects are generally positive but not strongly significant, particularly at longer horizons. This suggests that — unlike in Canada — Germany's postwar demand dynamics are not systematically shaped by war shocks.

In both the UK and France, war shocks exert only modest influence on the short- and medium-run demand cycle, producing far weaker cyclical swings than those observed in Canada or Germany. In the UK, impulse responses remain small — generally confined to ± 1 -2 p.p. — throughout the short and medium horizons, with no consistent directional pattern. At very long horizons, however, intensity-weighted measures reveal persistently negative and often statistically significant effects on aggregate demand, consistent with the enduring fiscal scars and debt overhang left by major conflicts (Table 11, left panel). France displays a somewhat different

⁹ Estimation may suffer if the war and pandemic regressors are highly collinear. For each country we therefore compute (i) the ϕ coefficient (the Pearson correlation for two binary indicators) and (ii) the Jaccard index J (the share of years with both shocks among years with at least one shock, i.e. $J = n_{11}/(n_{11} + n_{10} + n_{01})$). As a rule of thumb, we regard $|\phi| < 0.10$ as negligible and $0.10 \leq |\phi| < 0.30$ as small; for Jaccard, $J < 0.25$ indicates low overlap. Country results are: US $|\phi| = 0.07$, $J = 0.12$; UK $|\phi| = 0.18$, $J = 0.07$; JPN $|\phi| = 0.05$, $J = 0.03$; FRA $|\phi| = 0.11$, $J = 0.17$; GER $|\phi| = 0.11$, $J = 0.15$; ITA $|\phi| = 0.04$, $J = 0.07$; CAN $|\phi| = 0.01$, $J = 0.03$. All values lie in the negligible-to-small range. Since our intensity variables (deaths per 1000 population) are nonzero only in years flagged by their respective indicators and positive overlap is rare, their correlation is likewise limited; problematic multicollinearity is therefore unlikely in our local projections.

Table 1
Canada: Demand-side effects of war and pandemic shocks.

	War			Pandemic		
	S (γ^S)	M (γ^M)	L (γ^L)	S (β^S)	M (β^M)	L (β^L)
BK_b	-1.64	4.49*	-2.45*	-1.16*	0.81	0.30
BK_i	1.93*	3.08*	-2.78*	-0.14*	0.25*	-0.04
BN_b	-1.56	0.92	-2.04*	-0.05	0.01	0.16
BN_i	3.76*	-0.11	-2.73*	-0.03	0.10	0.05
CF_b	-2.64*	4.85*	-2.57*	-0.50	0.31	0.35
CF_i	1.00*	2.90*	-2.41*	-0.18*	0.28*	-0.05
HA_b	-5.34	7.67*	-8.60*	-0.33	1.34	-3.52*
HA_i	3.99*	6.64*	-8.50*	-0.33*	0.65*	-0.70*
HP_b	-1.55	2.67*	-1.29*	-0.31	0.26	0.23
HP_i	3.93*	0.40	-1.17*	-0.07	0.22*	-0.09
UCM_b	-4.22*	1.64*	9.08*	-0.71	2.04*	-2.04*
UCM_i	-3.13*	-2.49*	13.65*	-0.14	0.40*	-0.56*
TC_b	-2.32*	4.35*	-3.03*	0.39	0.12	-0.56
TC_i	-0.65	3.83*	-2.40*	0.01	0.16	-0.31*
HPb_b	-3.61*	1.73*	0.05	-0.43	0.70	-0.28
HPb_i	3.92*	-0.05	-0.37	-0.08	0.21*	-0.08
$PC1_b$	-2.73*	3.67*	-2.30*	-0.40	0.72	-0.70
$PC1_i$	3.04*	1.74*	-2.08*	-0.09	0.26*	-0.17*

Notes: The results reported in this table are obtained from local projection regressions estimated with $L = 5$ lags. For each country and specification, we estimate three separate equations corresponding to short-, medium-, and long-run windows. The short-run coefficients (S) are based on regressions where the dependent variable is $\Delta x_t^S = x_{t+10} - x_{t-1}$, capturing the net change in the variable between the pre-event year and 10 years after the event. The medium-run coefficients (M) are obtained from $\Delta x_t^M = x_{t+20} - x_{t+10}$ and measure the additional change between 10 and 20 years after the event. The long-run coefficients (L) are obtained from $\Delta x_t^L = x_{t+30} - x_{t+20}$ and measure the additional change between 20 and 30 years after the event. Under this linear specification, the cumulative effect at 10, 20, and 30 years can be approximated by β^S , $\beta^S + \beta^M$, and $\beta^S + \beta^M + \beta^L$, respectively (and analogously for the war coefficients γ^S , γ^M , and γ^L). This window-based long-difference approach is in the spirit of Ramey and Zubairy (2018), who summarize dynamics by focusing on cumulative effects over fixed horizons rather than reporting each horizon-specific response. **BK**: Baxter-King filter; **CF**: Christiano-Fitzgerald filter; **HA**: Hamilton filter; **HP**: Hodrick-Prescott filter; **BN**: Beveridge-Nelson decomposition; **UCM**: Univariate UCM with Random Trend; **TC**: trend/cycle decomposition with structural breaks (Mohr, 2005); **HPb**: HP decomposition with structural breaks; **PC1**: First principal component of all above methods. The suffixes b and i indicate whether the war and pandemic indices are constructed as binary indicators or as intensity measures (mortality per 1000 population), respectively. Values marked with “*” indicate statistical significance at least at the 68% level. The number of observations in the window-based local projections varies with the cycle/trend decomposition and the horizon considered, ranging from 181 to 205 for the short run, from 171 to 195 for the medium run, and from 161 to 185 for the long run.

profile. Short-run responses are typically modestly negative across specifications. At medium horizons, effects are small in magnitude and turn slightly positive when wars are identified with a simple 0/1 dummy, but remain very small under intensity-based measures. Long-run responses are mixed in sign and, in most cases, statistically insignificant (Table 3, left panel). Overall, neither country experiences pronounced wartime or postwar demand booms or busts in the first several years following a war shock; any lasting consequences are either delayed, weak, or statistically indistinguishable from zero. Japan stands out with unambiguously contractionary short-run demand responses to war shocks, regardless of whether wars are measured with a binary (0/1) indicator or intensity-weighted metrics. At medium and longer horizons, however, the effects lose any systematic pattern: responses fluctuate in sign, remain small in magnitude, and are typically statistically insignificant (Table 9, left panel). This combination of a sharp initial downturn followed by near-random longer-term dynamics clearly differs from the demand-side responses observed in other advanced economies during or shortly after major conflicts. For the US, war shocks produce only modest cyclical fluctuations in aggregate demand (Table 13, left panel). Short-run responses are predominantly negative but small in magnitude. At medium horizons, the effects become weakly positive, and at long horizons several estimates – particularly those based on intensity-weighted measures – are positive and statistically significant. Thus, the US exhibits neither a pronounced wartime demand boom nor a sharp postwar contraction. Italy shows one of the starkest contrasts between the two war-shock identification strategies (Table 7, left panel). With a binary (0/1) indicator, the short-run demand response is contractionary and occasionally significant. In contrast, intensity-weighted measures – capturing the scale of mobilization and fiscal effort – produce clear short-run expansions consistent with wartime production stimulus. At medium horizons, responses become mixed across specifications. At longer horizons, intensity-based measures reveal a clearer pattern, with coefficients consistently negative and often significant, pointing to a persistent postwar drag on demand.

Pandemics. Overall, pandemic shocks appear to generate weaker cyclical effects than war shocks. In Canada, short-run coefficients are consistently small and predominantly negative across all pandemic activity measures, and they are rarely statistically significant. At medium horizons, the estimates shift uniformly to weakly positive values, likely reflecting temporary rebound or compensatory

Table 2

Canada: Supply side effects of war and pandemic shocks.

	War			Pandemic		
	S (γ^S)	M (γ^M)	L (γ^L)	S (β^S)	M (β^M)	L (β^L)
BK_b	-3.93	-9.77*	25.48*	-4.32*	-3.31*	-4.33*
BK_i	-6.57*	-18.01*	23.98*	-0.61*	-0.16	-1.05*
BN_b	-4.30	-4.52	22.72*	-4.34*	-1.17	-4.62*
BN_i	-5.81*	-14.74*	23.46*	-0.69*	-0.05	-1.24*
CF_b	-5.10	-10.60*	26.00*	-3.00*	-0.63	-5.27*
CF_i	-6.60*	-18.69*	24.50*	-0.55*	-0.21	-1.11*
HA_b	-1.03	-10.73*	28.93*	-3.98*	-2.44	-0.92
HA_i	-6.20	-22.60*	29.97*	-0.34*	-0.56*	-0.53*
HP_b	-5.96*	-6.98*	23.53*	-3.16*	-1.04	-5.20*
HP_i	-6.93*	-15.26*	21.71*	-0.60*	-0.16	-1.09*
UCM_b	0.24	-5.01	13.16*	-4.26*	-3.57*	-3.66*
UCM_i	-10.23*	-9.94*	12.38*	-0.61*	-0.46*	-0.95*
TC_b	-2.33	-11.43*	23.66*	-4.10*	-0.67	-4.93*
TC_i	-6.21*	-17.04*	22.79*	-0.69*	-0.15	-1.06*
HPb_b	-1.59	-11.55*	21.20*	-3.94*	-1.65	-4.43*
HPb_i	-6.62*	-15.98*	20.92*	-0.64*	-0.14	-1.10*
$PC1_b$	-4.79	-9.26*	22.51*	-5.34*	-3.59*	-3.64*
$PC1_i$	-7.26*	-17.03*	21.52*	-0.76*	-0.14	-1.02*

Notes: The results reported in this table are obtained from local projection regressions estimated with $L = 5$ lags. For each country and specification, we estimate three separate equations corresponding to short-, medium-, and long-run windows. The short-run coefficients (S) are based on regressions where the dependent variable is $\Delta x_t^S = x_{t+10} - x_{t-1}$, capturing the net change in the variable between the pre-event year and 10 years after the event. The medium-run coefficients (M) are obtained from $\Delta x_t^M = x_{t+20} - x_{t+10}$ and measure the additional change between 10 and 20 years after the event. The long-run coefficients (L) are obtained from $\Delta x_t^L = x_{t+30} - x_{t+20}$ and measure the additional change between 20 and 30 years after the event. Under this linear specification, the cumulative effect at 10, 20, and 30 years can be approximated by β^S , $\beta^S + \beta^M$, and $\beta^S + \beta^M + \beta^L$, respectively (and analogously for the war coefficients γ^S , γ^M , and γ^L). This window-based long-difference approach is in the spirit of Ramey and Zubairy (2018), who summarize dynamics by focusing on cumulative effects over fixed horizons rather than reporting each horizon-specific response. **BK:** Baxter-King filter; **CF:** Christiano-Fitzgerald filter; **HA:** Hamilton filter; **HP:** Hodrick-Prescott filter; **BN:** Beveridge-Nelson decomposition; **UCM:** Univariate UCM with Random Trend; **TC:** trend/cycle decomposition with structural breaks (Mohr, 2005); **HPb:** HP decomposition with structural breaks; **PC1:** First principal component of all above methods. The suffixes b and i indicate whether the war and pandemic indices are constructed as binary indicators or as intensity measures (mortality per 1000 population), respectively. Values marked with “*” indicate statistical significance at least at the 68% level. The number of observations in the window-based local projections varies with the cycle/trend decomposition and the horizon considered, ranging from 181 to 205 for the short run, from 171 to 195 for the medium run, and from 161 to 185 for the long run.

dynamics, though they remain only marginally significant. In the long run, the coefficients generally turn negative again and, as at other horizons, in few cases reach statistical significance (Table 1, right panel). In France, short- and medium-run coefficients are mostly positive but small and barely significant. In the long run, the response to a pandemic shock turns mostly negative, though rarely significant (Table 3, right panel). In Japan, short- and medium-run estimates are mixed in sign across specifications and rarely statistically significant. Only in the long run do estimates become mostly positive, with significance observed in slightly more cases (Table 9, right panel). In the UK, demand responses to a pandemic shock are generally positive at short horizons but not statistically significant. At medium and long horizons, they turn negative and are statistically significant in more specifications, though magnitudes remain modest, rarely exceeding 2 p.p. (Table 11, right panel). The US exhibits a closely comparable pattern: short-run effects are close to zero or mildly positive and typically insignificant, medium-run responses are more frequently negative, and long-run coefficients are predominantly negative. However, unlike the UK, these negative medium- and long-run effects are less frequently statistically significant across specifications and are, on average, even smaller in magnitude, never exceeding 1.5 p.p. in absolute value (Table 13, right panel). In Italy, pandemic shocks generally produce small and statistically weak effects at all horizons. Short- and medium-run pandemic-induced demand effects are mostly negative but not significant. In the long run, they turn mostly positive, though still modest in magnitude and rarely significant (Table 7, right panel).

5.2.2. Supply-side effects

Examining the effects of these catastrophic events on the trend component of output, local projections based on time-window identification indicate that supply-side responses to wars and pandemics are generally larger, more persistent, and more consistently signed than demand-side effects. In most cases, shocks produce pronounced short-run disruptions to trend output, followed by non-negligible medium- and long-run adjustments. The direction and persistence of these effects vary across countries and between war- and pandemic-type disturbances. Wars typically cause sharp initial contractions in the trend, sometimes followed by partial, reconstruction-driven recoveries. In contrast, pandemics tend to produce slower, often permanent downward shifts in potential output.

Table 3

France: Demand-side effects of war and pandemic shocks.

	War			Pandemic		
	S (γ^S)	M (γ^M)	L (γ^L)	S (β^S)	M (β^M)	L (β^L)
BK_b	-1.53*	0.21	0.44	0.27	-0.10	0.11
BK_i	-0.74	0.11	-1.04*	0.23	0.31	-0.63
BN_b	-0.08	0.32	0.50	1.41*	0.70	0.01
BN_i	-0.28	-0.50*	-0.17	-0.05	0.79*	-0.16
CF_b	-0.90	0.37	0.46	0.03	-0.12	0.37
CF_i	-0.45	0.12	-0.75*	-0.26	0.52	-0.29
HA_b	-0.44	-1.94	5.64*	4.34*	0.47	-2.72
HA_i	-0.18	-1.11*	-0.39	0.52	0.81	-1.87
HP_b	-1.98*	0.45	1.68*	1.52*	0.47	-0.48
HP_i	-0.84	-0.58*	-1.07*	0.84*	0.71	-0.67
UCM_b	-1.11	-2.26*	3.16*	0.40	-1.51	-1.36
UCM_i	0.74*	-1.33*	-1.33*	0.72	-1.35*	0.40
TC_b	-0.82*	0.65	1.62*	0.93*	0.20	-0.09
TC_i	-0.06	-0.84*	-0.51	0.96*	-0.22	-0.55*
HPb_b	-1.90*	0.37	1.58*	1.03*	0.45	-0.38
HPb_i	-0.81*	-0.60*	-1.05*	0.19	0.59	-0.54
$PC1_b$	-1.27*	-0.02	1.62*	1.43*	0.38	-0.20
$PC1_i$	-0.85	-0.55*	-0.79	0.65*	0.47	-0.81

Notes: The results reported in this table are obtained from local projection regressions estimated with $L = 5$ lags. For each country and specification, we estimate three separate equations corresponding to short-, medium-, and long-run windows. The short-run coefficients (S) are based on regressions where the dependent variable is $\Delta x_t^S = x_{t+10} - x_{t-1}$, capturing the net change in the variable between the pre-event year and 10 years after the event. The medium-run coefficients (M) are obtained from $\Delta x_t^M = x_{t+20} - x_{t+10}$ and measure the additional change between 10 and 20 years after the event. The long-run coefficients (L) are obtained from $\Delta x_t^L = x_{t+30} - x_{t+20}$ and measure the additional change between 20 and 30 years after the event. Under this linear specification, the cumulative effect at 10, 20, and 30 years can be approximated by β^S , $\beta^S + \beta^M$, and $\beta^S + \beta^M + \beta^L$, respectively (and analogously for the war coefficients γ^S , γ^M , and γ^L). This window-based long-difference approach is in the spirit of Ramey and Zubairy (2018), who summarize dynamics by focusing on cumulative effects over fixed horizons rather than reporting each horizon-specific response. **BK**: Baxter-King filter; **CF**: Christiano-Fitzgerald filter; **HA**: Hamilton filter; **HP**: Hodrick-Prescott filter; **BN**: Beveridge-Nelson decomposition; **UCM**: Univariate UCM with Random Trend; **TC**: trend/cycle decomposition with structural breaks (Mohr, 2005); **HPb**: HP decomposition with structural breaks; **PC1**: First principal component of all above methods. The suffixes b and i indicate whether the war and pandemic indices are constructed as binary indicators or as intensity measures (mortality per 1000 population), respectively. Values marked with “*” indicate statistical significance at least at the 68% level. The number of observations in the window-based local projections varies with the cycle/trend decomposition and the horizon considered, ranging from 181 to 205 for the short run, from 171 to 195 for the medium run, and from 161 to 185 for the long run.

Differences also arise across identification strategies (binary event indicators versus continuous intensity measures) and detrending filters, so the estimates should be interpreted as robust qualitative patterns rather than precise quantitative magnitudes.

Wars. War-related shocks strongly affect the economy's supply side exhibiting more consistent patterns across countries than the highly variable demand-side responses. In Canada, these shocks consistently reduce trend output at short- and medium-term horizons, with the medium-term effects larger and more statistically significant across different trend-cycle decompositions and war activity measures. In the long run, however, the effects reverse, becoming strongly positive and highly significant in nearly all specifications (Table 2, left panel). France shows a similar short-run pattern but a contrasting long-run trajectory. War shocks depress the trend in the short and medium run – often significantly, especially at medium horizons – while long-run effects remain strongly negative and frequently increase in magnitude, particularly when measured using war intensity indicators (Table 4, left panel). War-related effects on Germany's supply side are somewhat puzzling. Short-run trend effects are clearly negative and statistically significant, while medium-run coefficients are mostly positive and often significant. Both short- and medium-run effects are generally stronger when war activity is measured using a binary indicator. In the long run, most specifications show positive effects, though they are statistically significant and sizeable in only a few cases – again, primarily with the binary measure. The few negative long-run effects that appear are not significant (Table 6, left panel). In Italy, short-run effects of war shocks on trend GDP vary considerably depending on the filtering method and the war activity measure (Table 8, left panel). Sizeable and statistically significant positive short-run effects appear almost exclusively when using a binary (0/1) indicator of war involvement. Medium-run effects are more consistent across specifications, generally pointing to a positive supply-side impact, though significance is largely confined to the binary measure. In the long run, the sign and significance depend critically on the war measure: binary indicators tend to produce positive but rarely significant effects, whereas continuous measures of war intensity typically yield negative but also insignificant effects. Japan exhibits both large magnitude and a pronounced sign reversal in its trend GDP responses to war shocks. Short-run coefficients are very large, negative, and highly significant across nearly all filtering methods. In the medium and long run, however, coefficients turn strongly

Table 4
France: Supply-side effects of war and pandemic shocks.

	War			Pandemic		
	S (γ^S)	M (γ^M)	L (γ^L)	S (β^S)	M (β^M)	L (β^L)
BK_b	-0.15	-4.84*	-0.80	2.05	-4.43*	-7.39*
BK_i	1.01	-2.73*	-5.79*	0.57	-2.08*	-0.43
BN_b	-4.60*	-3.85*	-0.03	4.88*	-1.66	-11.78*
BN_i	-0.54	-1.97*	-5.60*	2.67*	-2.16*	-1.97*
CF_b	-0.65	-3.96*	-0.04	5.00*	-1.51	-10.91*
CF_i	1.44	-2.00*	-5.30*	1.21	-1.76*	-0.83
HA_b	-1.16	-1.57	-5.08*	1.87	-1.49	-9.44*
HA_i	-0.39	-1.43*	-5.35*	1.31	-1.97*	-0.30
HP_b	-2.39	-4.08*	-1.13	5.46*	-2.02	-10.55*
HP_i	0.72	-1.86*	-4.82*	1.61	-1.98*	-1.49
UCM_b	-3.90*	-2.83*	-2.79	2.99	-1.06	-10.89*
UCM_i	-1.15*	-0.19	-4.08*	2.54*	-1.54*	-2.18*
TC_b	-2.14	-4.15*	-1.49	6.18*	-1.18	-10.86*
TC_i	-1.01	-1.60*	-4.85*	2.32*	-1.13	-1.87*
HPb_b	-2.63	-3.93*	-0.74	6.25*	-1.73	-10.74*
HPb_i	-1.43	-1.82*	-4.74*	2.59*	-1.57*	-1.66*
$PC1_b$	-1.58	-4.56*	-1.42	2.47	-4.59*	-7.32*
$PC1_i$	-1.10*	-2.00*	-5.10*	1.01	-2.18*	-0.98

Notes: The results reported in this table are obtained from local projection regressions estimated with $L = 5$ lags. For each country and specification, we estimate three separate equations corresponding to short-, medium-, and long-run windows. The short-run coefficients (S) are based on regressions where the dependent variable is $\Delta x_t^S = x_{t+10} - x_{t-1}$, capturing the net change in the variable between the pre-event year and 10 years after the event. The medium-run coefficients (M) are obtained from $\Delta x_t^M = x_{t+20} - x_{t+10}$ and measure the additional change between 10 and 20 years after the event. The long-run coefficients (L) are obtained from $\Delta x_t^L = x_{t+30} - x_{t+20}$ and measure the additional change between 20 and 30 years after the event. Under this linear specification, the cumulative effect at 10, 20, and 30 years can be approximated by β^S , $\beta^S + \beta^M$, and $\beta^S + \beta^M + \beta^L$, respectively (and analogously for the war coefficients γ^S , γ^M , and γ^L). This window-based long-difference approach is in the spirit of Ramey and Zubairy (2018), who summarize dynamics by focusing on cumulative effects over fixed horizons rather than reporting each horizon-specific response. **BK:** Baxter-King filter; **CF:** Christiano-Fitzgerald filter; **HA:** Hamilton filter; **HP:** Hodrick-Prescott filter; **BN:** Beveridge-Nelson decomposition; **UCM:** Univariate UCM with Random Trend; **TC:** trend/cycle decomposition with structural breaks (Mohr, 2005); **HPb:** HP decomposition with structural breaks; **PC1:** First principal component of all above methods. The suffixes b and i indicate whether the war and pandemic indices are constructed as binary indicators or as intensity measures (mortality per 1000 population), respectively. Values marked with “*” indicate statistical significance at least at the 68% level. The number of observations in the window-based local projections varies with the cycle/trend decomposition and the horizon considered, ranging from 181 to 205 for the short run, from 171 to 195 for the medium run, and from 161 to 185 for the long run.

positive, with long-run effects highly significant, reflecting the classic post-war reconstruction pattern (Table 10, left panel). In the UK, short-run effects of war shocks on trend GDP are uniformly negative, sizable, and highly significant, ranging roughly from -3 to -7 p.p. Medium-run coefficients are mostly positive but small in magnitude, averaging just under 1 p.p., and generally not significant. In the long run, effects are highly sensitive to the war measure: they are negative and marginally significant with a binary (0/1) indicator, but positive and consistently significant when using continuous intensity-based measures (Table 12, left panel). For the US, trend GDP responses to war shocks are generally small and often positive at short and medium horizons. Robust statistical significance across specifications is observed exclusively for the medium-run positive effects. Long-run coefficients are predominantly positive but lack statistical significance in most cases. Negative long-run effects emerge only under specific trend extraction methods and exclusively when binary (0/1) war indicators are used (Table 14, left panel).

Pandemics. Overall, our findings show that pandemic-induced shocks produce statistically significant, persistent negative effects on the supply side of G7 economies.

In Canada, pandemic shocks consistently produce negative and statistically significant effects on the supply side across short-, medium-, and long-term horizons, regardless of the identification method. The impact is strongest in the short and long run and is more pronounced when using a binary (0/1) event indicator (Table 2, right panel). In France, the short-run impact of pandemic shocks on the supply-side trend is positive across all filters and pandemic-activity measures, strongest when using a binary (0/1) dummy. Statistical significance, however, occurs only in some specifications. At medium and long horizons, the coefficients turn negative, with long-run effects becoming both larger and statistically more significant (Table 4, right panel). Germany displays a complex response of its supply side to pandemic shocks. Short-run effects on the trend are consistently positive and often statistically significant. At medium horizons, results are mixed: coefficients are negative with a binary (0/1) proxy but positive with continuous, intensity-based measures. In the long run, however, effects are uniformly large, negative, and highly significant across all identification methods and filters (Table 6, right panel). In Italy, short-run supply-side responses to pandemic shocks are mixed, with significantly negative

Table 5
Germany: Demand-side effects of war and pandemic shocks.

	War			Pandemic		
	S (γ^S)	M (γ^M)	L (γ^L)	S (β^S)	M (β^M)	L (β^L)
BK_b	-5.55*	5.71*	2.19	1.90*	-1.71*	1.25
BK_i	0.14*	0.24*	0.10	1.32*	-0.37	0.05
BN_b	-2.38	2.00	-1.85*	0.99	-0.4	0.98
BN_i	0.06	-0.09*	-0.08*	0.87*	-0.19	0.81*
CF_b	-3.35*	4.31*	1.78	1.79*	-2.31*	1.42
CF_i	0.10	0.14	0.20*	1.49*	-0.84*	0.35
HA_b	-10.36*	10.07*	-5.66*	3.37*	-1.52	2.31
HA_i	0.30*	-0.12	-0.26*	3.99*	-0.58	1.44
HP_b	-3.40*	2.82	2.04	1.19*	-1.52*	0.49
HP_i	0.38*	0.01	0.16	2.18*	-0.85*	-0.50
UCM_b	-5.46*	9.05*	-3.58*	1.35	-2.04*	-5.20*
UCM_i	0.15	0.43*	-0.32*	2.14*	0.07	-6.25*
TC_b	-2.95*	3.00*	0.61	1.39*	-2.08*	0.02
TC_i	0.07	0.34	-0.10	0.89*	-0.83*	-0.84
HPb_b	-3.12*	2.64	2.03	0.77	-1.11*	0.37
HPb_i	0.41*	0.02	0.07	1.72*	-0.78*	-0.59*
$PC1_b$	-5.43*	5.04*	1.22	1.62*	-1.46*	0.71
$PC1_i$	0.31*	0.07	0.04	2.19*	-0.72*	-0.26

Notes: The results reported in this table are obtained from local projection regressions estimated with $L = 5$ lags. For each country and specification, we estimate three separate equations corresponding to short-, medium-, and long-run windows. The short-run coefficients (S) are based on regressions where the dependent variable is $\Delta x_t^S = x_{t+10} - x_{t-1}$, capturing the net change in the variable between the pre-event year and 10 years after the event. The medium-run coefficients (M) are obtained from $\Delta x_t^M = x_{t+20} - x_{t+10}$ and measure the additional change between 10 and 20 years after the event. The long-run coefficients (L) are obtained from $\Delta x_t^L = x_{t+30} - x_{t+20}$ and measure the additional change between 20 and 30 years after the event. Under this linear specification, the cumulative effect at 10, 20, and 30 years can be approximated by β^S , $\beta^S + \beta^M$, and $\beta^S + \beta^M + \beta^L$, respectively (and analogously for the war coefficients γ^S , γ^M , and γ^L). This window-based long-difference approach is in the spirit of Ramey and Zubairy (2018), who summarize dynamics by focusing on cumulative effects over fixed horizons rather than reporting each horizon-specific response. **BK:** Baxter-King filter; **CF:** Christiano-Fitzgerald filter; **HA:** Hamilton filter; **HP:** Hodrick-Prescott filter; **BN:** Beveridge-Nelson decomposition; **UCM:** Univariate UCM with Random Trend; **TC:** trend/cycle decomposition with structural breaks (Mohr, 2005); **HPb:** HP decomposition with structural breaks; **PC1:** First principal component of all above methods. The suffixes b and i indicate whether the war and pandemic indices are constructed as binary indicators or as intensity measures (mortality per 1000 population), respectively. Values marked with “*” indicate statistical significance at least at the 68% level. The number of observations in the window-based local projections varies with the cycle/trend decomposition and the horizon considered, ranging from 181 to 205 for the short run, from 171 to 195 for the medium run, and from 161 to 185 for the long run.

effects when pandemic severity is measured using continuous indicators. At medium and long horizons, the effects become consistently negative and statistically significant, reaching their largest magnitude and strongest significance in the long run (Table 8, right panel). In Japan, short-run supply-side responses to pandemic shocks depend heavily on the measure used. Binary indicators generally yield positive but insignificant effects, while intensity-based measures produce large, significant declines. Medium-run effects are mostly positive, though significant primarily with binary indicators. In the long run, consistent with other G7 economies, pandemic shocks cause severe and highly significant damage to Japan's supply side (Table 10, right panel). In the UK, short- and medium-run supply-side effects of pandemic shocks are generally positive. The short-run response is larger and more significant with intensity-based measures, while the medium-run response is more pronounced when using a binary (0/1) indicator. In the long run, consistent with other G7 economies, effects are uniformly large, negative (ranging from -1 to -7 p.p.), and highly significant (Table 12, right panel). The US presents a more ambiguous pattern. In the short run, binary indicators produce positive effects on the supply-side trend, while intensity-based measures generate negative, statistically significant declines. Medium-run effects are uniformly negative and larger in magnitude than short-run effects, but reach significance only with intensity-based measures. Unlike most other G7 countries, long-run pandemic shocks do not consistently depress the US supply side; instead, long-run coefficients (β^L) vary in sign depending on the specification and pandemic proxy (Table 14, right panel). The supply side of the U.S. economy appears thus to exhibit partial immunity to pandemic shocks over the long run, likely reflecting its strong capacity for innovation, adaptive production structures, and underlying structural resilience, which enable it to absorb disruptions and recover more effectively.

5.2.3. Empirical evidence summary

The regression results reported in Tables 1–14 generate a large number of coefficients, which makes it difficult to extract clear cross-country patterns by simply inspecting the tables. To improve readability, we construct the graphical summary in Fig. 3, which displays the dynamic responses of the demand and supply components to war- and pandemic-related shocks, separately for each country and for each type of event indicator (binary vs. intensity). Each panel in Fig. 3 corresponds to a given country-shock-component

Table 6
Germany: Supply-side effects of war and pandemic shocks.

	War			Pandemic		
	S (γ^S)	M (γ^M)	L (γ^L)	S (β^S)	M (β^M)	L (β^L)
BK_b	-16.36*	12.03*	0.14	6.39*	-3.50*	-16.64*
BK_i	-1.07*	0.96*	-0.01	2.69*	0.15	-9.71*
BN_b	-17.27*	11.76*	5.03	7.44*	-3.17	-13.77*
BN_i	-0.40	1.82*	0.77*	3.67*	2.37*	-9.33*
CF_b	-13.63*	10.92*	-0.82	6.34*	-2.11	-13.89*
CF_i	-1.09*	1.34*	0.01	1.52	1.43*	-8.87*
HA_b	-10.44*	4.66	8.79*	6.13*	-1.58	-15.81*
HA_i	-0.74	1.70*	0.85*	0.80	2.60*	-10.18*
HP_b	-14.66*	10.63*	-0.49	7.07*	-1.48	-12.93*
HP_i	-1.05*	1.26*	0.31*	1.88	2.40*	-8.33*
UCM_b	-9.17*	0.57	9.54*	4.31*	-0.52	-9.16*
UCM_i	-0.42	1.11*	1.25*	1.38	1.05	-3.49*
TC_b	-14.48*	11.19*	-0.65	6.64*	-2.78	-12.73*
TC_i	-1.07*	1.63*	0.21*	1.51	1.73*	-8.71*
HPb_b	-15.19*	10.46*	-0.44	6.89*	-2.54	-12.62*
HPb_i	-0.89*	1.45*	0.32*	1.76	2.07*	-8.53*
$PC1_b$	-18.40*	9.93*	2.21	6.41*	-3.21	-15.73*
$PC1_i$	-0.88*	1.35*	0.30*	1.99	2.37*	-10.09*

Notes: The results reported in this table are obtained from local projection regressions estimated with $L = 5$ lags. For each country and specification, we estimate three separate equations corresponding to short-, medium-, and long-run windows. The short-run coefficients (S) are based on regressions where the dependent variable is $\Delta x_t^S = x_{t+10} - x_{t-1}$, capturing the net change in the variable between the pre-event year and 10 years after the event. The medium-run coefficients (M) are obtained from $\Delta x_t^M = x_{t+20} - x_{t+10}$ and measure the additional change between 10 and 20 years after the event. The long-run coefficients (L) are obtained from $\Delta x_t^L = x_{t+30} - x_{t+20}$ and measure the additional change between 20 and 30 years after the event. Under this linear specification, the cumulative effect at 10, 20, and 30 years can be approximated by β^S , $\beta^S + \beta^M$, and $\beta^S + \beta^M + \beta^L$, respectively (and analogously for the war coefficients γ^S , γ^M , and γ^L). This window-based long-difference approach is in the spirit of Ramey and Zubairy (2018), who summarize dynamics by focusing on cumulative effects over fixed horizons rather than reporting each horizon-specific response. **BK:** Baxter-King filter; **CF:** Christiano-Fitzgerald filter; **HA:** Hamilton filter; **HP:** Hodrick-Prescott filter; **BN:** Beveridge-Nelson decomposition; **UCM:** Univariate UCM with Random Trend; **TC:** trend/cycle decomposition with structural breaks (Mohr, 2005); **HPb:** HP decomposition with structural breaks; **PC1:** First principal component of all above methods. The suffixes b and i indicate whether the war and pandemic indices are constructed as binary indicators or as intensity measures (mortality per 1000 population), respectively. Values marked with “*” indicate statistical significance at least at the 68% level. The number of observations in the window-based local projections varies with the cycle/trend decomposition and the horizon considered, ranging from 181 to 205 for the short run, from 171 to 195 for the medium run, and from 161 to 185 for the long run.

combination. On the vertical axis, the distance from zero captures the magnitude of the average coefficient. The intervals $[0, M_S]$, $[M_S, M_M]$, and $[M_M, M_L]$ correspond to average coefficients falling in the ranges 0–5, 5–10, and > 10 , respectively. Similarly, the intervals $[-M_S, 0]$, $[-M_M, -M_S]$, and $[-M_L, -M_M]$ represent the same magnitude ranges (0–5, 5–10, and > 10) but for negative coefficients. On the horizontal axis, the segments $0-T_S$, T_S-T_M , and T_M-T_L denote time horizons of 0–10, 10–20, and 20–30 years, respectively. Within each panel, circles report average coefficients when catastrophic shocks are measured using continuous intensity indicators, whereas squares correspond to averages obtained from binary (0/1) event-occurrence dummies. Filled markers denote that the average effect is statistically significant; empty markers indicate that it is not. The sign of the average effect is classified as positive (negative) if at least five of the nine underlying coefficients share the same sign. The plotted magnitude is the mean of the coefficients exhibiting the dominant sign. This average is considered statistically significant (and the marker is filled) only if at least five of the individual coefficients with the prevailing sign are themselves statistically significant at conventional levels.

A closer look at Fig. 3 shows that major catastrophic events – such as wars and pandemics – produce substantially stronger effects on the supply side than on the demand side, consistent with the impulse response evidence in Section 5.2.4. The figures also reveal considerable cross-country heterogeneity in both the sign and magnitude of the effects, with demand-side responses exhibiting particularly pronounced dispersion. No consistent pattern emerges across shock types (wars versus pandemics) or macroeconomic components (demand versus supply), underscoring the highly country-specific nature of large historical shocks.

5.2.4. IRFs (1st PC).

Figs. (4)–(10) present local-projection response paths of the first principal component (PC1) of cycles and trends to war and pandemic intensity shocks. PC1 is constructed from the eight cycle and eight trend series obtained using the eight trend-cycle decomposition methods described in Section 3.3. Following the interpretation framework of Section 4.2, the impulse response functions (IRFs) trace the dynamic deviations of the synthetic cycle and trend (PC1) from their respective baselines; shaded areas denote one- and two-standard-error confidence bands. Consistent with the earlier window-based estimates, the IRFs provide strong corroborating

Table 7

Italy: Demand-side effects of war and pandemic shocks.

	War			Pandemic		
	S (γ^S)	M (γ^M)	L (γ^L)	S (β^S)	M (β^M)	L (β^L)
BK_b	-2.74*	1.51	-0.11	-0.03	-0.80*	0.74
BK_i	0.26	0.60*	-2.43*	-0.64*	-0.21	0.13
BN_b	0.66	-0.06	-0.35	0.63*	-0.21	-0.40
BN_i	0.50	-0.20*	-0.10	-0.96*	0.14	-0.14
CF_b	-1.47	0.46	-0.12	-0.09	-0.80*	0.82
CF_i	0.39	0.50*	-2.27*	-0.48*	0.10	-0.11
HA_b	0.96	-0.44	1.04	0.58	-0.73	-2.35*
HA_i	-0.14	0.27	-1.96	-3.12*	1.37*	-1.09
HP_b	-2.63*	0.69	0.20	0.25	-0.34	0.25
HP_i	0.13	-0.40*	-2.22*	-0.57*	0.39	-0.23
UCM_b	0.69	-1.64	-0.06	-0.75*	-0.03	0.67
UCM_i	1.30*	-1.73*	-1.72*	-1.55*	0.75*	1.46*
TC_b	-1.28	-0.46	1.80*	0.12	-0.25	0.58
TC_i	-0.37	-0.31	-1.97*	-0.07	0.13	0.15
HPb_b	-2.48*	0.94	0.11	0.37	-0.54	0.07
HPb_i	0.17	-0.34*	-2.26*	-0.60*	0.42	-0.19
$PC1_b$	-1.58	0.48	0.35	0.35	-0.48	0.23
$PC1_i$	0.21	-0.02	-2.00*	-0.71*	0.28	-0.19

Notes: The results reported in this table are obtained from local projection regressions estimated with $L = 5$ lags. For each country and specification, we estimate three separate equations corresponding to short-, medium-, and long-run windows. The short-run coefficients (S) are based on regressions where the dependent variable is $\Delta x_t^S = x_{t+10} - x_{t-1}$, capturing the net change in the variable between the pre-event year and 10 years after the event. The medium-run coefficients (M) are obtained from $\Delta x_t^M = x_{t+20} - x_{t+10}$ and measure the additional change between 10 and 20 years after the event. The long-run coefficients (L) are obtained from $\Delta x_t^L = x_{t+30} - x_{t+20}$ and measure the additional change between 20 and 30 years after the event. Under this linear specification, the cumulative effect at 10, 20, and 30 years can be approximated by β^S , $\beta^S + \beta^M$, and $\beta^S + \beta^M + \beta^L$, respectively (and analogously for the war coefficients γ^S , γ^M , and γ^L). This window-based long-difference approach is in the spirit of [Ramey and Zubairy \(2018\)](#), who summarize dynamics by focusing on cumulative effects over fixed horizons rather than reporting each horizon-specific response. **BK**: Baxter-King filter; **CF**: Christiano-Fitzgerald filter; **HA**: Hamilton filter; **HP**: Hodrick-Prescott filter; **BN**: Beveridge-Nelson decomposition; **UCM**: Univariate UCM with Random Trend; **TC**: trend/cycle decomposition with structural breaks ([Mohr, 2005](#)); **HPb**: HP decomposition with structural breaks; **PC1**: First principal component of all above methods. The suffixes b and i indicate whether the war and pandemic indices are constructed as binary indicators or as intensity measures (mortality per 1000 population), respectively. Values marked with “*” indicate statistical significance at least at the 68% level. The number of observations in the window-based local projections varies with the cycle/trend decomposition and the horizon considered, ranging from 181 to 205 for the short run, from 171 to 195 for the medium run, and from 161 to 185 for the long run.

evidence. Demand-side effects are generally modest, short-lived, and highly heterogeneous across countries. In contrast, supply-side responses are substantially larger and markedly more persistent. Although their magnitudes also vary across countries, cross-country heterogeneity is particularly pronounced in the timing of statistically significant effects.

Canada. [Fig. 4a](#) shows the response of the synthetic cyclical indicator (cycle PC1) to a war shock. Overall, Canada's cycle exhibits pronounced positive swings and milder, less frequent negative ones over the horizon considered, suggesting that war shocks generate sizable but temporary disturbances in the Canadian economic cycle. [Fig. 4b](#) instead reports the response to a pandemic shock. The estimated impulse responses are generally not statistically significant at any horizon. Taken together, these findings indicate that, unlike war shocks, pandemic shocks do not generate statistically significant movements in Canada's economic cycle. On the supply side, the trend component (trend PC1) declines sharply and persistently following a war shock, reaching a trough of roughly -25 p.p. after 15 – 20 years ([Fig. 4c](#)). It also drifts downward – albeit more gradually – after pandemic shocks ([Fig. 4d](#)). This pattern – a transitory war-induced boom in the cyclical component alongside sizable, long-lasting trend losses from both wars and pandemics – closely mirrors the window-based PC1 estimates for Canada reported in [Tables 1-2](#). A visual summary of these results is provided in [Figs. \(3a\)–\(3d\)](#).

France. In France, cyclical responses are small and short-lived. War shocks drive the cyclical PC1 only marginally into negative territory (0 to approximately -2 p.p.), while pandemic shocks produce brief positive deviations of similar magnitude (0 to roughly +2 p.p.); neither effect persists ([Figs. \(5a\)–\(5b\)](#)). Trend responses are markedly larger and more long-lasting, especially for war shocks. In fact, war shocks induce a sharp and highly persistent decline in the trend PC1 ([Fig. 5c](#)), whereas pandemic shocks generate smaller negative drifts that emerge only at longer horizons ([Fig. 5d](#)). The above evidence, i.e., weak and transitory demand-side (cyclical) effects alongside strong and predominantly adverse supply-side (trend) effects, matches the window-based PC1 estimates for France in [Tables 3-4](#) and are in line with the summary estimates depicted in [Figs. \(3e\)–\(3h\)](#).

Table 8

Italy: Supply-side effects of war and pandemic shocks.

	War			Pandemic		
	S (γ^S)	M (γ^M)	L (γ^L)	S (β^S)	M (β^M)	L (β^L)
BK_b	-4.42	10.85*	2.96	-0.30	-4.06*	-8.97*
BK_i	1.99	-0.06	-4.64*	-5.05*	-4.24*	-2.57*
BN_b	-11.63*	10.76*	3.04	0.88	-1.23	-13.80*
BN_i	0.35	0.89	-4.60	-4.07*	-4.46*	-3.38*
CF_b	-3.63	13.17*	4.19	2.80	0.42	-12.54*
CF_i	3.42	1.75	-3.28	-5.53*	-4.95*	-3.51*
HA_b	-12.37*	10.82*	1.44	2.57	-0.31	-11.66*
HA_i	-0.30	0.12	-3.89	0.48	-5.05*	-1.44
HP_b	-3.53	12.67*	4.19	1.43	-0.55	-12.82*
HP_i	1.93	1.67	-2.70	-7.14*	-5.94*	-3.65*
UCM_b	-14.09*	13.41*	4.45	1.14	-0.57	-13.87*
UCM_i	-2.01	3.48	-4.12	-0.49	-4.70*	-3.34*
TC_b	-5.47*	12.35*	3.24	0.21	-0.45	-13.76*
TC_i	2.08	2.02	-2.74	-7.66*	-6.32*	-4.93*
HPb_b	-5.53*	11.68*	3.73	0.27	-0.68	-13.48*
HPb_i	1.29	1.33	-2.75	-7.11*	-6.04*	-4.03*
$PC1_b$	-8.14*	10.68*	2.19	-2.42	-5.27*	-9.41*
$PC1_i$	0.85	0.64	-4.32	-6.13*	-5.33*	-3.12*

Notes: The results reported in this table are obtained from local projection regressions estimated with $L = 5$ lags. For each country and specification, we estimate three separate equations corresponding to short-, medium, and long-run windows. The short-run coefficients (S) are based on regressions where the dependent variable is $\Delta x_t^S = x_{t+10} - x_{t-1}$, capturing the net change in the variable between the pre-event year and 10 years after the event. The medium-run coefficients (M) are obtained from $\Delta x_t^M = x_{t+20} - x_{t+10}$ and measure the additional change between 10 and 20 years after the event. The long-run coefficients (L) are obtained from $\Delta x_t^L = x_{t+30} - x_{t+20}$ and measure the additional change between 20 and 30 years after the event. Under this linear specification, the cumulative effect at 10, 20, and 30 years can be approximated by β^S , $\beta^S + \beta^M$, and $\beta^S + \beta^M + \beta^L$, respectively (and analogously for the war coefficients γ^S , γ^M , and γ^L). This window-based long-difference approach is in the spirit of Ramey and Zubairy (2018), who summarize dynamics by focusing on cumulative effects over fixed horizons rather than reporting each horizon-specific response. **BK**: Baxter-King filter; **CF**: Christiano-Fitzgerald filter; **HA**: Hamilton filter; **HP**: Hodrick-Prescott filter; **BN**: Beveridge-Nelson decomposition; **UCM**: Univariate UCM with Random Trend; **TC**: trend/cycle decomposition with structural breaks (Mohr, 2005); **HPb**: HP decomposition with structural breaks; **PC1**: First principal component of all above methods. The suffixes b and i indicate whether the war and pandemic indices are constructed as binary indicators or as intensity measures (mortality per 1000 population), respectively. Values marked with “*” indicate statistical significance at least at the 68% level. The number of observations in the window-based local projections varies with the cycle/trend decomposition and the horizon considered, ranging from 181 to 205 for the short run, from 171 to 195 for the medium run, and from 161 to 185 for the long run.

Germany. Germany's response paths reveal a stark war-pandemic asymmetry. War shocks generate a small, hump-shaped cyclical response, with positive deviations of the cyclical PC1 concentrated around the middle of the horizon (Fig. 6a). The trend PC1 falls on impact but gradually recovers, returning to – and eventually slightly exceeding – its pre-shock level after roughly 20 years (Fig. 6c). By contrast, pandemic shocks produce a temporary early increase in the cyclical PC1, which vanishes within a few years (Fig. 6b). The trend PC1, however, suffers persistent losses that widen and remain significant at long horizons (Fig. 6d). Thus, demand-side (cyclical) effects are small and transitory under both shocks, whereas supply-side (trend) effects are large and permanent only for pandemics—a pattern that fully matches the German window-based estimates in Tables 5–6 and is visually summarized in Figs. (3i)–(3l).

Italy. For Italy, neither wars nor pandemics significantly affect the cyclical PC1. War-related cyclical responses remain close to zero, while pandemic-related responses are only mildly negative (around -0.5 p.p.) and dissipate quickly Figs. (7a)–(7b). Trend responses, by contrast, provide clearer evidence of structural damage. War shocks trigger a brief initial dip, followed by mixed and largely insignificant movements in the medium and long run (Fig. 7c). Pandemic shocks, however, generate increasingly negative trend deviations that emerge from the medium horizon onward and persist over time (Fig. 7d). These findings closely mirror the Italian window-based estimates reported in Tables 7–8: demand-side (cyclical) effects are negligible, whereas pandemics produce substantial and persistent supply-side (trend) losses – a pattern visually summarized in Figs. (3m)–(3p).

Japan. In Japan, the cyclical component of the economy responds quite differently to war and pandemic shocks. War shocks generate a pronounced negative, hump-shaped cyclical pattern, with the cycle remaining below zero for a substantial portion of the forecast horizon (Fig. 8a). By contrast, pandemic shocks produce a largely neutral cyclical response, with fluctuations oscillating around zero and showing no persistent or statistically meaningful deviations (Fig. 8b). This contrast suggests that geopolitical conflicts exert more disruptive and persistent effects on Japan's economic cycle, whereas pandemic shocks appear to have comparatively limited cyclical consequences. For the trend component, war shocks cause a sharp, statistically significant decline in Japan's long-term growth, remaining deeply negative for about a decade before gradually recovering, though never fully reaching its pre-shock

Table 9

Japan: Demand-side effects of war and pandemic shocks.

	War			Pandemic		
	S (γ^S)	M (γ^M)	L (γ^L)	S (β^S)	M (β^M)	L (β^L)
BK_b	-6.18*	-1.01	4.36*	0.12	-0.54	1.36
BK_i	-3.09*	0.89*	-0.62*	-0.00	-0.29	0.98*
BN_b	-2.72	-1.00	2.14*	-0.87*	1.10*	-0.03
BN_i	-2.87*	-0.17	-0.20	-0.06	0.22	0.24
CF_b	-4.10*	-1.33	2.58*	0.01	-0.97	1.71
CF_i	-2.16*	0.84*	-0.99*	0.45*	-0.65*	0.99*
HA_b	-0.78	-5.62*	6.87*	-0.52	3.33*	-2.11
HA_i	-5.57*	-0.65	-0.37	-0.79*	1.77*	-0.29
HP_b	-5.44*	-1.53	4.16*	-0.48	-0.66	0.66
HP_i	-3.01*	1.61*	-0.55	0.04	-0.50	0.67*
UCM_b	-6.72*	2.92*	8.23*	1.53	0.48	-1.57
UCM_i	-0.20	2.86*	1.69*	-0.22*	-0.08	-0.85*
TC_b	-2.60*	1.12	1.45	0.34	-1.49*	1.31*
TC_i	-1.33*	1.26*	0.26	-0.27	-0.50	1.04*
HPb_b	-5.53*	-1.49	4.04*	-0.41	-0.69	0.61
HPb_i	-3.03*	1.63*	-0.56	0.05	-0.47	0.63*
$PC1_b$	-4.86*	-1.37	3.71*	-0.39	-0.16	0.66
$PC1_i$	-2.72*	0.89*	-0.67*	0.01	-0.18	0.62*

Notes: The results reported in this table are obtained from local projection regressions estimated with $L = 5$ lags. For each country and specification, we estimate three separate equations corresponding to short-, medium-, and long-run windows. The short-run coefficients (S) are based on regressions where the dependent variable is $\Delta x_t^S = x_{t+10} - x_{t-1}$, capturing the net change in the variable between the pre-event year and 10 years after the event. The medium-run coefficients (M) are obtained from $\Delta x_t^M = x_{t+20} - x_{t+10}$ and measure the additional change between 10 and 20 years after the event. The long-run coefficients (L) are obtained from $\Delta x_t^L = x_{t+30} - x_{t+20}$ and measure the additional change between 20 and 30 years after the event. Under this linear specification, the cumulative effect at 10, 20, and 30 years can be approximated by β^S , $\beta^S + \beta^M$, and $\beta^S + \beta^M + \beta^L$, respectively (and analogously for the war coefficients γ^S , γ^M , and γ^L). This window-based long-difference approach is in the spirit of Ramey and Zubairy (2018), who summarize dynamics by focusing on cumulative effects over fixed horizons rather than reporting each horizon-specific response. **BK**: Baxter-King filter; **CF**: Christiano-Fitzgerald filter; **HA**: Hamilton filter; **HP**: Hodrick-Prescott filter; **BN**: Beveridge-Nelson decomposition; **UCM**: Univariate UCM with Random Trend; **TC**: trend/cycle decomposition with structural breaks (Mohr, 2005); **HPb**: HP decomposition with structural breaks; **PC1**: First principal component of all above methods. The suffixes b and i indicate whether the war and pandemic indices are constructed as binary indicators or as intensity measures (mortality per 1000 population), respectively. Values marked with “*” indicate statistical significance at least at the 68% level. The number of observations in the window-based local projections varies with the cycle/trend decomposition and the horizon considered, ranging from 181 to 205 for the short run, from 171 to 195 for the medium run, and from 161 to 185 for the long run.

level by the 30-year horizon (Fig. 8c). Pandemic shocks produce smaller initial losses, but these deepen over the medium run, yielding persistent negative deviations at longer horizons (Fig. 8d). In short, wars create a clear “collapse-then-recovery” pattern, whereas pandemics generate smaller but more enduring trend deterioration. These dynamics align with Japan’s window-based PC1 estimates (Tables 9–10) and are visually summarized in Figs. (3q)–(3t), which highlight the sharp war-induced collapse versus the persistent pandemic-induced trend drag.

United Kingdom. For the UK, neither war nor pandemic shocks produce a clear or systematic response in the cyclical component. Following war shocks, the cycle fluctuates around zero throughout the forecast horizon, showing both statistically significant positive and negative deviations at various points, but without a dominant or persistent pattern (Fig. 9a). After pandemic shocks, the cycle declines sharply within the first three years and then oscillates in mildly negative territory, stabilizing between 0 and -2 p.p. until the end of the horizon; these deviations, however, generally remain statistically insignificant (Fig. 9b). Overall, the UK’s business cycle appears remarkably resilient to both types of catastrophic shocks, exhibiting primarily temporary, non-persistent fluctuations rather than deep or prolonged downturns. As in other G7 economies, the UK’s trend responses to catastrophic shocks are stronger and more statistically significant than its cyclical responses, and they vary notably by shock type. War shocks trigger a sharp short-run decline in the trend component, with most of the adjustment occurring within the first decade. Beyond this period, changes are modest, leaving the trend persistently below its pre-shock level (Fig. 9c). By contrast, pandemic shocks generate slightly positive trend responses that persist for roughly two decades before gradually fading, with the trend returning to near zero by the end of the third decade (Fig. 9d). These IRFs are consistent with the window-based PC1 estimates for the UK reported in Tables 11–12, which show that higher pandemic intensity is associated with positive short- and medium-term trend effects but negative long-term outcomes (see also summary estimates in Figs. (3u)–(3x)).

United States. For the US, neither war nor pandemic intensity shocks exert a significant impact on the demand-driven cyclical component of the economy. For both types of catastrophic events, the IRFs of the cyclical PC1 remain tightly clustered around zero

Table 10

Japan: Supply-side effects of war and pandemic shocks.

	War			Pandemic		
	S (γ^S)	M (γ^M)	L (γ^L)	S (β^S)	M (β^M)	L (β^L)
BK_b	-26.84*	1.48	21.43*	2.61	6.76*	-5.07
BK_i	-12.12*	2.42	7.57*	-1.42*	0.39	-4.35*
BN_b	-27.40*	6.51	24.90*	5.79	5.02*	-3.18
BN_i	-4.82*	11.18*	8.56*	-1.40*	-0.24	-3.72*
CF_b	-24.34*	7.03	24.22*	3.57	7.30*	-5.16
CF_i	-11.65*	4.87*	8.67*	-1.43*	1.07*	-4.27*
HA_b	-27.22*	12.03*	20.15*	6.98	3.58	-0.95
HA_i	-0.78	12.80*	9.09*	0.77	-0.99	-3.27
HP_b	-24.35*	6.47	22.92*	3.61	6.59*	-4.29
HP_i	-12.87*	1.24	5.96*	-1.60*	0.35	-4.05*
UCM_b	-18.10*	6.24	15.60*	5.12*	3.28	-2.07
UCM_i	-0.59	9.94*	6.80*	-0.77*	-0.12	-3.25*
TC_b	-25.55*	3.59	23.56*	3.40	6.87*	-4.98
TC_i	-9.96*	5.48*	8.01*	-0.74*	0.76	-4.61*
HPb_b	-23.73*	5.91	23.19*	3.73	6.51*	-4.29
HPb_i	-13.07*	0.88	5.94*	-1.63*	0.05	-4.22*
$PC1_b$	-25.58*	5.29	22.15*	4.00	6.23*	-4.77
$PC1_i$	-11.30*	3.83*	6.91*	-1.73*	-0.15	-4.21*

Notes: The results reported in this table are obtained from local projection regressions estimated with $L = 5$ lags. For each country and specification, we estimate three separate equations corresponding to short-, medium-, and long-run windows. The short-run coefficients (S) are based on regressions where the dependent variable is $\Delta x_t^S = x_{t+10} - x_{t-1}$, capturing the net change in the variable between the pre-event year and 10 years after the event. The medium-run coefficients (M) are obtained from $\Delta x_t^M = x_{t+20} - x_{t+10}$ and measure the additional change between 10 and 20 years after the event. The long-run coefficients (L) are obtained from $\Delta x_t^L = x_{t+30} - x_{t+20}$ and measure the additional change between 20 and 30 years after the event. Under this linear specification, the cumulative effect at 10, 20, and 30 years can be approximated by β^S , $\beta^S + \beta^M$, and $\beta^S + \beta^M + \beta^L$, respectively (and analogously for the war coefficients γ^S , γ^M , and γ^L). This window-based long-difference approach is in the spirit of Ramey and Zubairy (2018), who summarize dynamics by focusing on cumulative effects over fixed horizons rather than reporting each horizon-specific response. **BK**: Baxter-King filter; **CF**: Christiano-Fitzgerald filter; **HA**: Hamilton filter; **HP**: Hodrick-Prescott filter; **BN**: Beveridge-Nelson decomposition; **UCM**: Univariate UCM with Random Trend; **TC**: trend/cycle decomposition with structural breaks (Mohr, 2005); **HPb**: HP decomposition with structural breaks; **PC1**: First principal component of all above methods. The suffixes b and i indicate whether the war and pandemic indices are constructed as binary indicators or as intensity measures (mortality per 1000 population), respectively. Values marked with “*” indicate statistical significance at least at the 68% level. The number of observations in the window-based local projections varies with the cycle/trend decomposition and the horizon considered, ranging from 181 to 205 for the short run, from 171 to 195 for the medium run, and from 161 to 185 for the long run.

across all horizons (Figs. (10a)–(10b)). This pattern fully aligns with the small and predominantly insignificant window-based cyclical coefficients reported in Table 13. The trend responses are far easier to interpret and statistically more robust. Following a war shock, trend PC1 initially turns negative at short and medium horizons but becomes positive at longer horizons (Fig. 10c). This trajectory closely mirrors the negative short-run and positive medium- and long-run window estimates for trend PC1 in Table 14. In contrast, pandemic shocks produce broadly negative trend responses that persist across most of the horizon, with only a partial and incomplete recovery by year 30 (Fig. 10d). These results are consistent with the negative short- and medium-run coefficients and only weakly offsetting long-run effects documented in Table 14. The overall impact of war and pandemic shocks on the demand and supply sides of the US economy is concisely summarized in Figs. (3y)–(3ab).

5.2.5. Understanding heterogeneity in results

Sources of Heterogeneity in the Findings. Our novel empirical findings reveal two main sources of heterogeneity in how catastrophic shocks affect economic cycles and trends across the G7:

1. Shock measurement approach: Responses often differ substantially depending on whether shocks are identified using binary indicators (occurrence of an event) or continuous intensity-based measures (capturing the severity of wars or pandemics). Intensity-based specifications typically yield sharper, more persistent, and statistically more robust effects, particularly on trend growth.
2. Cross-country structural differences: Even when using the same identification strategy, the magnitude, sign, and persistence of responses vary considerably across countries, reflecting differences in economic structure, institutional resilience, demographic vulnerability, fiscal capacity, and historical exposure to such events.

These two dimensions – methodological and country-specific – jointly account for most of the observed variation in the estimated impacts of wars and pandemics.

Table 11

UK: Demand-side effects of war and pandemic shocks.

	War			Pandemic		
	S (γ^S)	M (γ^M)	L (γ^L)	S (β^S)	M (β^M)	L (β^L)
BK_b	-0.30	-0.31	-0.20	0.66*	-0.37	0.01
BK_i	-0.15	1.12*	-1.66*	0.40	-1.05*	-1.22*
BN_b	-0.31	0.37	-0.73*	0.18	0.07	-1.29*
BN_i	0.43	0.56*	-1.72*	-0.67*	-0.32	-0.75
CF_b	0.15	-0.63*	0.00	0.80*	-0.83*	0.29
CF_i	0.41	0.58	-1.16*	0.46	-0.93*	-1.32*
HA_b	0.41	-0.80	-1.00	0.87	-0.14	-2.78*
HA_i	1.56*	1.17*	-5.07*	0.13	-0.44	-3.48*
HP_b	-0.22	-0.56*	0.10	0.12	-0.46	-0.10
HP_i	1.40*	0.22	-1.06*	-0.13	-0.86*	-1.45*
UCM_b	-0.71*	0.31	-0.09	-0.32	0.57	-1.55*
UCM_i	-0.72*	1.13*	0.54	0.04	0.47	-1.57*
TC_b	-0.02	-0.61*	0.26	0.05	-0.82*	0.49
TC_i	0.52*	0.52	-1.04*	-0.18	-1.05*	-0.31
HPb_b	0.06	-0.89*	0.39	0.53*	-0.84*	0.57
HPb_i	0.57	0.48	-0.95*	0.37	-0.95*	-0.82
$PC1_b$	-0.21	-0.59*	-0.0	0.11	-0.40	-0.37
$PC1_i$	0.21	0.93*	-1.76*	-0.29	-0.70	-1.26*

Notes: The results reported in this table are obtained from local projection regressions estimated with $L = 5$ lags. For each country and specification, we estimate three separate equations corresponding to short-, medium-, and long-run windows. The short-run coefficients (S) are based on regressions where the dependent variable is $\Delta x_t^S = x_{t+10} - x_{t-1}$, capturing the net change in the variable between the pre-event year and 10 years after the event. The medium-run coefficients (M) are obtained from $\Delta x_t^M = x_{t+20} - x_{t+10}$ and measure the additional change between 10 and 20 years after the event. The long-run coefficients (L) are obtained from $\Delta x_t^L = x_{t+30} - x_{t+20}$ and measure the additional change between 20 and 30 years after the event. Under this linear specification, the cumulative effect at 10, 20, and 30 years can be approximated by β^S , $\beta^S + \beta^M$, and $\beta^S + \beta^M + \beta^L$, respectively (and analogously for the war coefficients γ^S , γ^M , and γ^L). This window-based long-difference approach is in the spirit of Ramey and Zubairy (2018), who summarize dynamics by focusing on cumulative effects over fixed horizons rather than reporting each horizon-specific response. **BK**: Baxter-King filter; **CF**: Christiano-Fitzgerald filter; **HA**: Hamilton filter; **HP**: Hodrick-Prescott filter; **BN**: Beveridge-Nelson decomposition; **UCM**: Univariate UCM with Random Trend; **TC**: trend/cycle decomposition with structural breaks (Mohr, 2005); **HPb**: HP decomposition with structural breaks; **PC1**: First principal component of all above methods. The suffixes b and i indicate whether the war and pandemic indices are constructed as binary indicators or as intensity measures (mortality per 1000 population), respectively. Values marked with “*” indicate statistical significance at least at the 68% level. The number of observations in the window-based local projections varies with the cycle/trend decomposition and the horizon considered, ranging from 181 to 205 for the short run, from 171 to 195 for the medium run, and from 161 to 185 for the long run.

Sensitivity of Results to Shock Measurement. A key source of heterogeneity stems from how shocks are measured: binary (on/off) indicators versus continuous intensity-based measures. This choice significantly influences the timing, magnitude, and sometimes even the sign of estimated responses. Intensity measures, which better capture episode severity, often reveal larger, more persistent, or qualitatively different effects – particularly on the demand-driven cyclical component – than binary indicators.

For example, on the cyclical side: (i) in Canada and Germany, war shocks measured by intensity produce short-run expansions, whereas the same shocks coded as binary generate short-run contractions (Figs. 3a and 3i); (ii) in Japan, war-intensity shocks instead induce clear short-run contractions (Fig. 3q). On the trend side, the two approaches generally yield more consistent patterns, though notable differences remain. For instance, the long-run effect of pandemics on trend growth differs sharply in both magnitude and dynamic profile between Italy and the US when using intensity-based rather than binary measures (Fig. 3p vs. 3ab).

These discrepancies are unsurprising given the distinct information each measure conveys. Binary indicators treat all episodes equally, averaging over events that can produce opposing macroeconomic responses. Intensity measures, by contrast, emphasize severe episodes and capture non-linear, within-event dynamics, such as gradually accumulating casualties. Collapsing variation into a single onset, binary measures can understate, delay, or distort impulse-response effects.

Drivers of Cross-Country Heterogeneity. The cross-country heterogeneity we observe likely reflects structural and institutional differences. Variation across the G7 plausibly stems from differences in: (i) exposure and intensity (mortality, battle severity, mobilization and occupation, capital destruction); (ii) economic structure and openness (sectoral composition, energy dependence, integration in global value chains); (iii) policy mix and state capacity (speed and scale of fiscal and monetary support, conscription and procurement, containment mandates, social insurance); (iv) public-health infrastructure; (v) demographics and urbanization; and (vi) initial macro-financial conditions and the state of the business cycle at shock onset. While our estimates cannot isolate the contribution of each factor – doing so would require detailed micro-institutional data beyond the scope of this paper – they underscore that the macroeconomic effects of wars and pandemics do not follow a “one-size-fits-all” pattern.

Table 12

UK: Supply-side effects of war and pandemic shocks.

	War			Pandemic		
	S (γ^S)	M (γ^M)	L (γ^L)	S (β^S)	M (β^M)	L (β^L)
<i>BK_b</i>	-3.36*	0.93	-2.19*	0.61	2.20*	-4.98*
<i>BK_i</i>	-6.22*	-0.29	2.82*	3.15*	0.99	-3.53*
<i>BN_b</i>	-3.69*	0.08	-1.24	1.52	2.89*	-4.78*
<i>BN_i</i>	-4.62*	0.82	3.98*	4.16*	0.15	-4.25*
<i>CF_b</i>	-3.64*	1.24	-1.89*	1.90*	3.69*	-6.41*
<i>CF_i</i>	-6.50*	0.07	3.48*	2.86*	-0.02	-4.15*
<i>HA_b</i>	-4.33*	1.42	-0.63	1.18	3.33*	-3.18*
<i>HA_i</i>	-5.15*	-0.09	7.30*	3.48*	0.60	-1.05
<i>HP_b</i>	-3.43*	0.98	-2.01*	1.73*	3.48*	-5.83*
<i>HP_i</i>	-5.51*	0.78	2.89*	3.04*	0.23	-4.07*
<i>UCM_b</i>	-2.99*	-0.75	-0.19	0.75	2.01*	-1.51*
<i>UCM_i</i>	-4.26*	-1.17*	5.22*	4.13*	0.12	-1.68*
<i>TC_b</i>	-3.98*	1.09	-2.49*	1.53	3.72*	-6.72*
<i>TC_i</i>	-5.18*	0.97	2.89*	2.98*	0.74	-4.32*
<i>HPb_b</i>	-4.06*	1.09	-2.53*	1.09	3.69*	-6.81*
<i>HPb_i</i>	-4.30*	1.16*	2.95*	2.62*	0.60	-4.01*
<i>PC1_b</i>	-3.46*	0.61	-2.00*	0.17	1.88*	-4.73*
<i>PC1_i</i>	-5.51*	0.26	3.24*	3.09*	1.11	-3.65*

Notes: The results reported in this table are obtained from local projection regressions estimated with $L = 5$ lags. For each country and specification, we estimate three separate equations corresponding to short-, medium-, and long-run windows. The short-run coefficients (S) are based on regressions where the dependent variable is $\Delta x_t^S = x_{t+10} - x_{t-1}$, capturing the net change in the variable between the pre-event year and 10 years after the event. The medium-run coefficients (M) are obtained from $\Delta x_t^M = x_{t+20} - x_{t+10}$ and measure the additional change between 10 and 20 years after the event. The long-run coefficients (L) are obtained from $\Delta x_t^L = x_{t+30} - x_{t+20}$ and measure the additional change between 20 and 30 years after the event. Under this linear specification, the cumulative effect at 10, 20, and 30 years can be approximated by β^S , $\beta^S + \beta^M$, and $\beta^S + \beta^M + \beta^L$, respectively (and analogously for the war coefficients γ^S , γ^M , and γ^L). This window-based long-difference approach is in the spirit of [Ramey and Zubairy \(2018\)](#), who summarize dynamics by focusing on cumulative effects over fixed horizons rather than reporting each horizon-specific response. **BK**: Baxter-King filter; **CF**: Christiano-Fitzgerald filter; **HA**: Hamilton filter; **HP**: Hodrick-Prescott filter; **BN**: Beveridge-Nelson decomposition; **UCM**: Univariate UCM with Random Trend; **TC**: trend/cycle decomposition with structural breaks ([Mohr, 2005](#)); **HPb**: HP decomposition with structural breaks; **PC1**: First principal component of all above methods. The suffixes b and i indicate whether the war and pandemic indices are constructed as binary indicators or as intensity measures (mortality per 1000 population), respectively. Values marked with “*” indicate statistical significance at least at the 68% level. The number of observations in the window-based local projections varies with the cycle/trend decomposition and the horizon considered, ranging from 181 to 205 for the short run, from 171 to 195 for the medium run, and from 161 to 185 for the long run.

The pronounced heterogeneity in both the sign and magnitude of responses has important implications for empirical design. Pooling countries under a common treatment effect, as often done in historical macro panels, can mask offsetting country-specific responses and yield averages that are unrepresentative of any single economy. Consistent with [Stefanski \(2022\)](#), who shows that pandemics' long-run effects on GDP per capita differ sharply across regions – positive in Northern Europe but weak or negative in the South – our results underscore that the size and persistence of demand- and supply-side responses to major historical shocks depend critically on country-specific structures, institutions, historical experiences, and the method used to identify shocks.

Table 13

US: Demand-side effects of war and pandemic shocks.

	War			Pandemic		
	S (γ^S)	M (γ^M)	L (γ^L)	S (β^S)	M (β^M)	L (β^L)
<i>BK_b</i>	-0.14	0.41	1.19*	0.30	-1.02*	-0.06
<i>BK_i</i>	0.88	0.31	4.14*	-0.05	-0.28	0.19
<i>BN_b</i>	-1.17*	0.31	-0.24	0.25	-0.27	-0.13
<i>BN_i</i>	-0.50	-1.30	1.97*	0.45	0.01	0.30
<i>CF_b</i>	-0.53	0.45	1.02*	0.43	-1.34*	-0.42
<i>CF_i</i>	0.44	0.12	4.32*	-0.16	-0.14	-0.14
<i>HA_b</i>	-1.56	-0.67	-0.01	1.66	-1.24	-0.17
<i>HA_i</i>	-3.64*	4.48*	-3.16	0.53	0.34	0.37
<i>HP_b</i>	0.30	0.29	0.45	0.23	-1.13*	-0.68*
<i>HP_i</i>	1.99*	0.07	3.05*	0.33	-0.75*	-0.31
<i>UCM_b</i>	-0.54	1.52	-1.66*	-1.09	-0.51	-0.14
<i>UCM_i</i>	-4.40*	7.85*	-5.64*	-1.30*	0.21	0.25
<i>TC_b</i>	-0.67*	0.79	-0.09	0.90*	-1.11*	-0.12
<i>TC_i</i>	0.34	1.92*	-0.69	0.21	-0.64*	-0.64*
<i>HPb_b</i>	0.25	0.65	0.87	-0.08	-0.76	-0.67*
<i>HPb_i</i>	2.80*	0.19	2.69*	-0.13	-0.31	-0.26
<i>PC1_b</i>	-0.38	0.34	0.65	0.40	-0.84*	-0.68
<i>PC1_i</i>	0.35	0.78	2.00*	0.26	-0.33	-0.20

Notes: The results reported in this table are obtained from local projection regressions estimated with $L = 5$ lags. For each country and specification, we estimate three separate equations corresponding to short-, medium-, and long-run windows. The short-run coefficients (S) are based on regressions where the dependent variable is $\Delta x_t^S = x_{t+10} - x_{t-1}$, capturing the net change in the variable between the pre-event year and 10 years after the event. The medium-run coefficients (M) are obtained from $\Delta x_t^M = x_{t+20} - x_{t+10}$ and measure the additional change between 10 and 20 years after the event. The long-run coefficients (L) are obtained from $\Delta x_t^L = x_{t+30} - x_{t+20}$ and measure the additional change between 20 and 30 years after the event. Under this linear specification, the cumulative effect at 10, 20, and 30 years can be approximated by β^S , $\beta^S + \beta^M$, and $\beta^S + \beta^M + \beta^L$, respectively (and analogously for the war coefficients γ^S , γ^M , and γ^L). This window-based long-difference approach is in the spirit of Ramey and Zubairy (2018), who summarize dynamics by focusing on cumulative effects over fixed horizons rather than reporting each horizon-specific response. **BK**: Baxter-King filter; **CF**: Christiano-Fitzgerald filter; **HA**: Hamilton filter; **HP**: Hodrick-Prescott filter; **BN**: Beveridge-Nelson decomposition; **UCM**: Univariate UCM with Random Trend; **TC**: trend/cycle decomposition with structural breaks (Mohr, 2005); **HPb**: HP decomposition with structural breaks; **PC1**: First principal component of all above methods. The suffixes b and i indicate whether the war and pandemic indices are constructed as binary indicators or as intensity measures (mortality per 1000 population), respectively. Values marked with “*” indicate statistical significance at least at the 68% level. The number of observations in the window-based local projections varies with the cycle/trend decomposition and the horizon considered, ranging from 181 to 205 for the short run, from 171 to 195 for the medium run, and from 161 to 185 for the long run.

Table 14

US: Supply-side effects of war and pandemic shocks.

	War			Pandemic		
	S (γ^S)	M (γ^M)	L (γ^L)	S (β^S)	M (β^M)	L (β^L)
<i>BK_b</i>	2.06	1.10	0.56	0.29	-2.17	2.55*
<i>BK_i</i>	2.12	2.77	1.41	-1.66*	-2.99*	0.78
<i>BN_b</i>	2.54*	3.05*	-0.39*	2.26	-2.51	-1.61
<i>BN_i</i>	-1.65	8.55*	1.88	-0.40	-4.70*	1.75*
<i>CF_b</i>	1.61	2.36	-1.74	1.34	-1.17	-2.02
<i>CF_i</i>	2.36	2.43	3.01	-1.28*	-3.02*	1.39*
<i>HA_b</i>	2.41	4.29*	-0.74	1.90	-1.47	-1.41
<i>HA_i</i>	3.41	3.83*	6.85*	-0.03	-4.67*	1.59*
<i>HP_b</i>	1.83	2.78*	-1.11	1.76	-1.43	-1.13
<i>HP_i</i>	-1.43	4.71	2.51	-0.91	-3.41*	2.03*
<i>UCM_b</i>	3.82*	1.15	1.44	0.78	-1.77	-1.63
<i>UCM_i</i>	3.27*	3.50*	3.81*	-1.66*	-4.12*	0.01
<i>TC_b</i>	2.07	2.53*	-1.32	1.40	-1.48	-1.61
<i>TC_i</i>	0.14	5.20*	3.37	-1.27*	-3.33*	1.91*
<i>HPb_b</i>	1.79	2.69*	-1.95	1.84	-1.71	-1.28
<i>HPb_i</i>	-2.21	5.97*	1.76	-0.74	-3.70*	1.86*
<i>PC1_b</i>	1.49	1.48	0.66	0.53	-2.45	3.88*
<i>PC1_i</i>	-2.11	4.65	1.12	-1.25*	-3.83*	1.76*

Notes: The results reported in this table are obtained from local projection regressions estimated with $L = 5$ lags. For each country and specification, we estimate three separate equations corresponding to short-, medium-, and long-run windows. The short-run coefficients (S) are based on regressions where the dependent variable is $\Delta x_t^S = x_{t+10} - x_{t-1}$, capturing the net change in the variable between the pre-event year and 10 years after the event. The medium-run coefficients (M) are obtained from $\Delta x_t^M = x_{t+20} - x_{t+10}$ and measure the additional change between 10 and 20 years after the event. The long-run coefficients (L) are obtained from $\Delta x_t^L = x_{t+30} - x_{t+20}$ and measure the additional change between 20 and 30 years after the event. Under this linear specification, the cumulative effect at 10, 20, and 30 years can be approximated by β^S , $\beta^S + \beta^M$, and $\beta^S + \beta^M + \beta^L$, respectively (and analogously for the war coefficients γ^S , γ^M , and γ^L). This window-based long-difference approach is in the spirit of Ramey and Zubairy (2018), who summarize dynamics by focusing on cumulative effects over fixed horizons rather than reporting each horizon-specific response. **BK**: Baxter-King filter; **CF**: Christiano-Fitzgerald filter; **HA**: Hamilton filter; **HP**: Hodrick-Prescott filter; **BN**: Beveridge-Nelson decomposition; **UCM**: Univariate UCM with Random Trend; **TC**: trend/cycle decomposition with structural breaks (Mohr, 2005); **HPb**: HP decomposition with structural breaks; **PC1**: First principal component of all above methods. The suffixes b and i indicate whether the war and pandemic indices are constructed as binary indicators or as intensity measures (mortality per 1000 population), respectively. Values marked with “*” indicate statistical significance at least at the 68% level. The number of observations in the window-based local projections varies with the cycle/trend decomposition and the horizon considered, ranging from 181 to 205 for the short run, from 171 to 195 for the medium run, and from 161 to 185 for the long run.

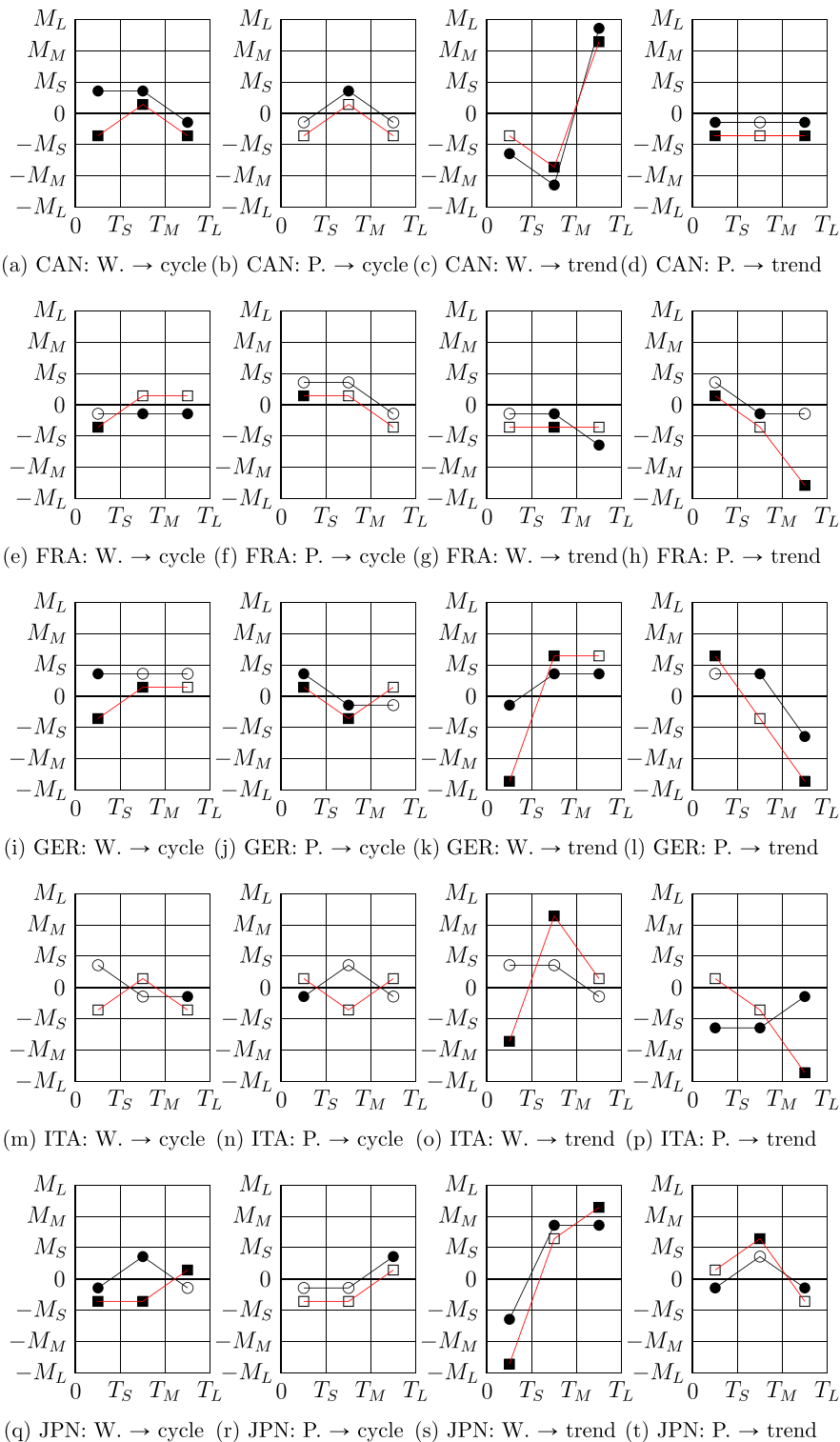
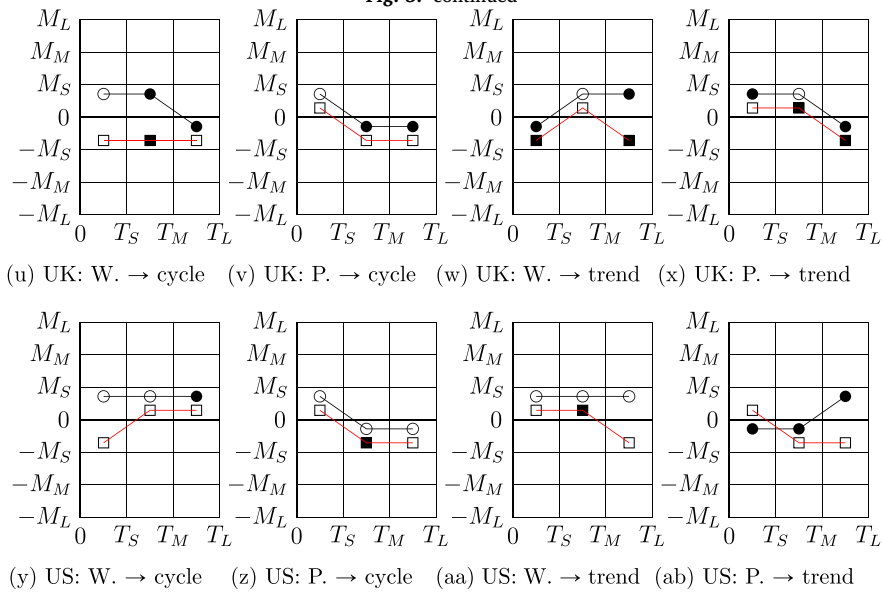
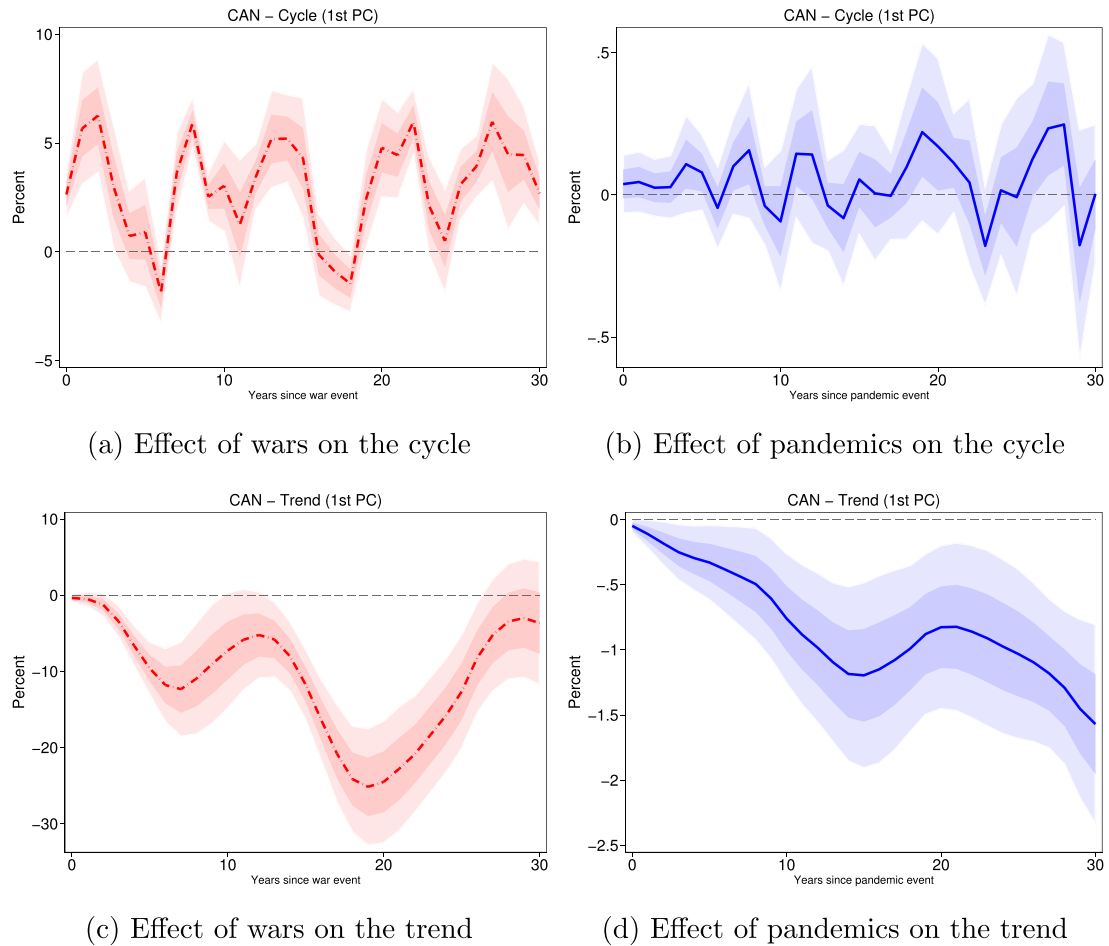


Fig. 3. Synthesis of Tables (1)-(14): GDP Component Response Paths to Wars and Pandemics.

Fig. 3. continued

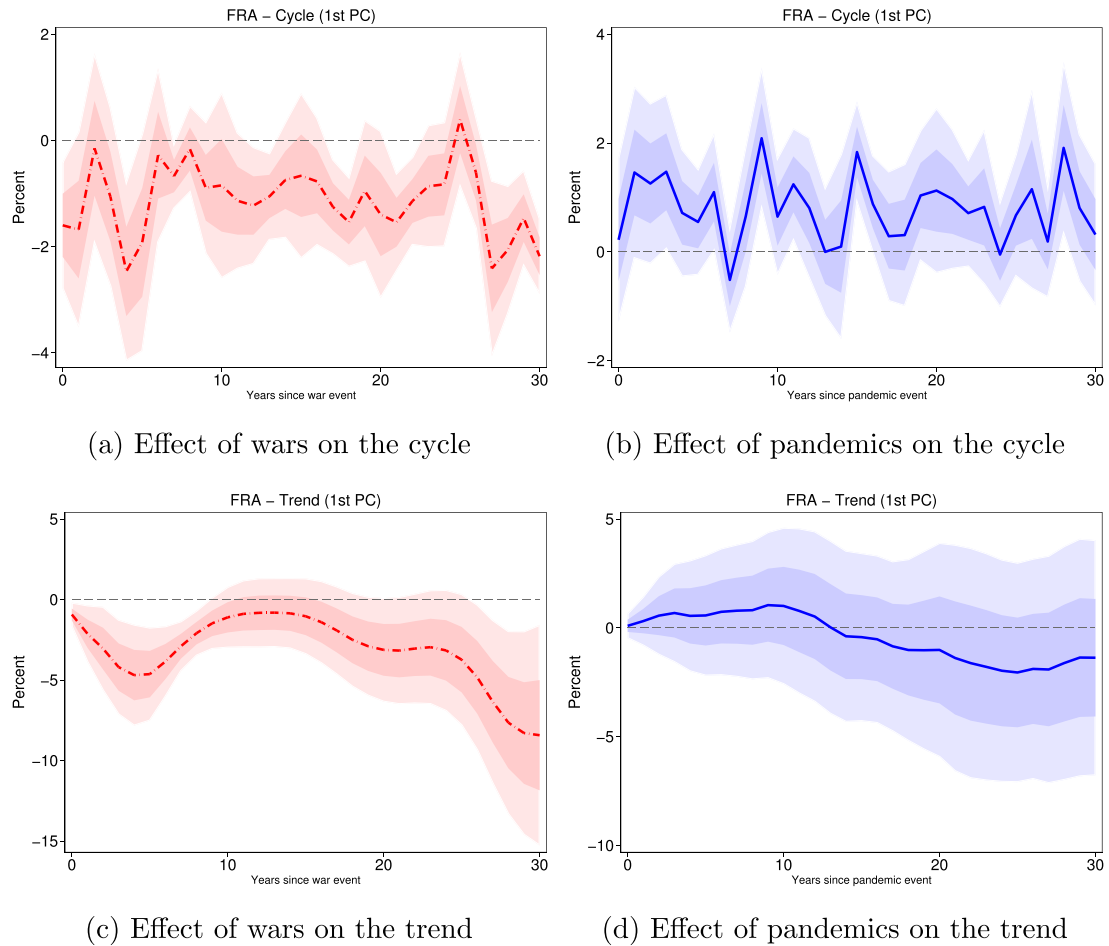


Notes: This figure summarizes the country-level results reported in Tables (1)–(14). “W. (P.) → cycle (trend)” denotes the effect of wars (pandemics) on the cycle (trend) component. On the vertical axis, the segments $0-M_S$, M_S-M_M , and M_M-M_L indicate coefficient magnitudes in the ranges 0–5, 5–10, and greater than 10, respectively. Similarly, the segments $-M_S-0$, $-M_M--M_S$, and $-M_L--M_M$ indicate coefficient magnitudes in the ranges $-5-0$, $-10--5$, and less than -10 , respectively. On the horizontal axis, the segments $0-T_S$, T_S-T_M , and T_M-T_L represent time horizons of 0–10, 10–20, and 20–30 years. Circles indicate coefficient values for events measured in terms of intensity, whereas squares indicate coefficient values for events measured as binary indicators. Filled markers denote statistically significant coefficients, while empty markers denote coefficients that are not statistically significant. Each point in the graphs reports the average coefficient. The sign of the effect is classified as positive (negative) if at least 5 out of 9 coefficients share that sign. The magnitude category is based on the average of the coefficients with the prevailing sign, and this average is treated as statistically significant only if at least 5 coefficients with that prevailing sign are statistically significant.



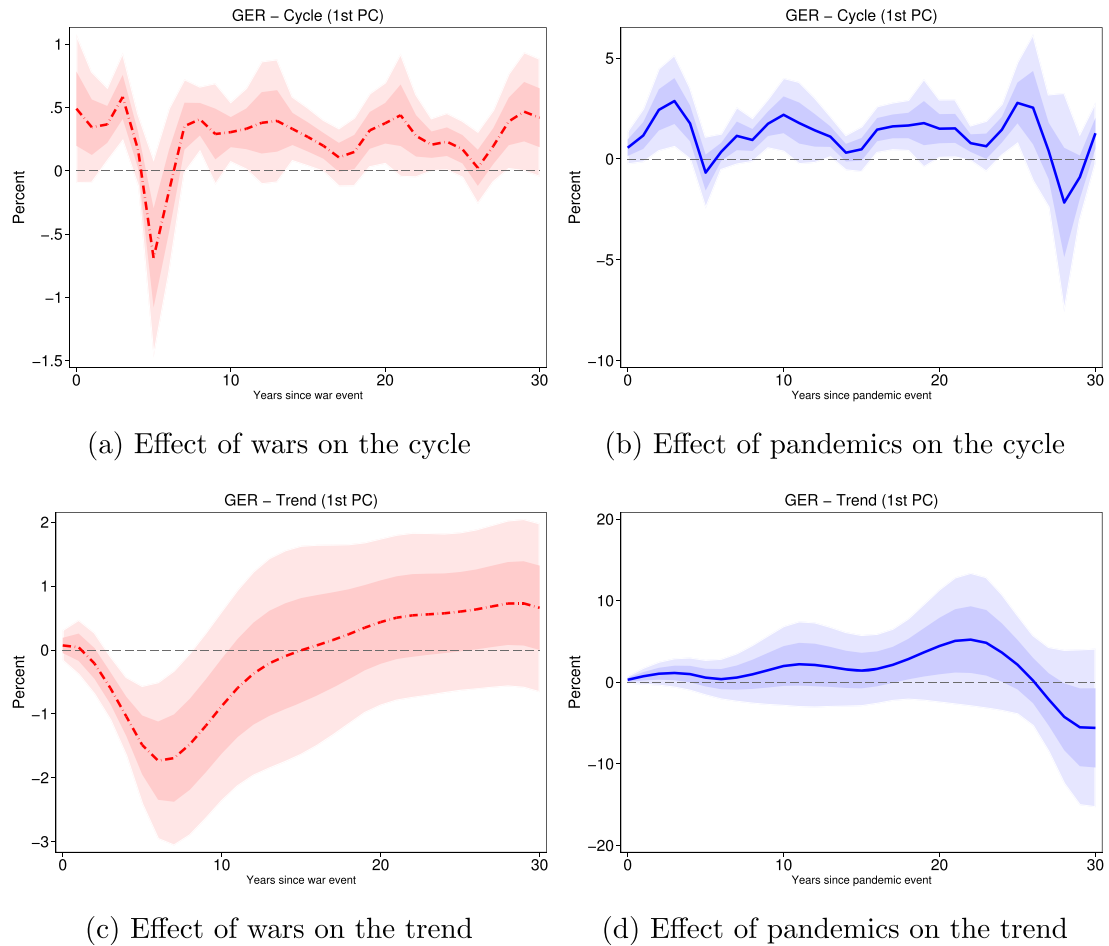
Notes: The trend and cycle components are constructed as the scores of the first principal component extracted from the eight alternative trend–cycle decompositions. The war and pandemic indices are measured in terms of mortality intensity (deaths per 1,000 population). Shaded areas denote 1- and 2-standard-error bands around the local-projection impulse response estimates. The number of observations in the local-projection regressions varies with the time horizon $h = 1, \dots, 30$ and ranges between 161 and 191.

Fig. 4. Response to pandemics and wars of the trend and cycle components for CAN.



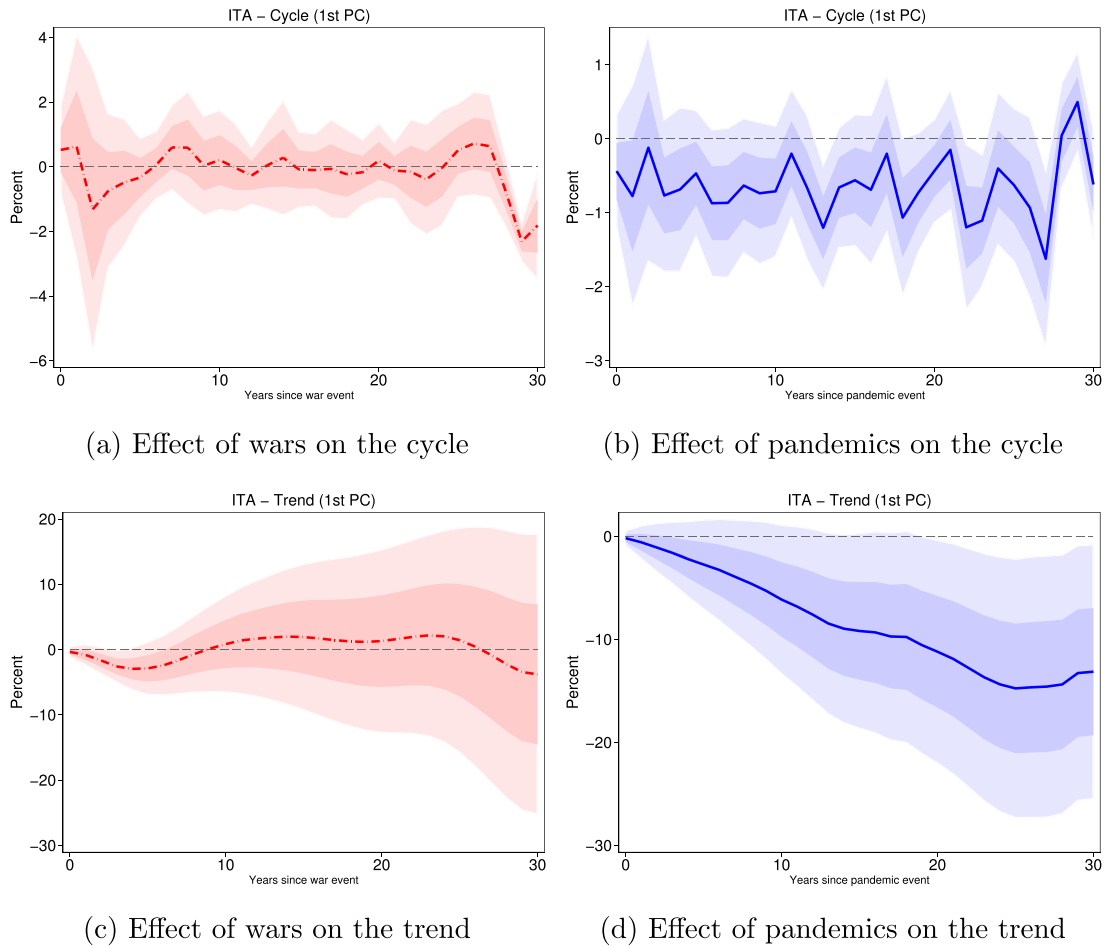
Notes: The trend and cycle components are constructed as the scores of the first principal component extracted from the eight alternative trend-cycle decompositions. The war and pandemic indices are measured in terms of mortality intensity (deaths per 1,000 population). Shaded areas denote 1- and 2-standard-error bands around the local-projection impulse response estimates. The number of observations in the local-projection regressions varies with the time horizon $h = 1, \dots, 30$ and ranges between 161 and 191.

Fig. 5. Response to pandemics and wars of the trend and cycle components for FRA.



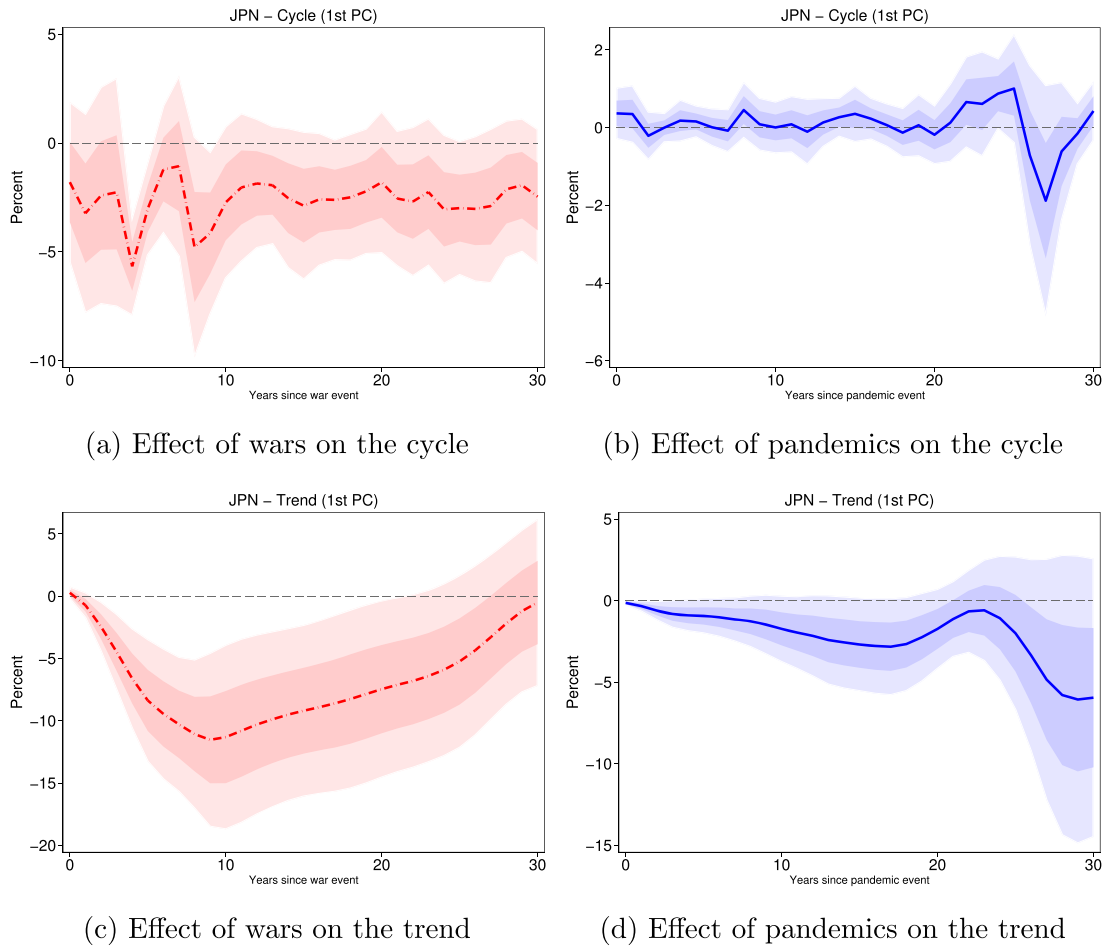
Notes: The trend and cycle components are constructed as the scores of the first principal component extracted from the eight alternative trend–cycle decompositions. The war and pandemic indices are measured in terms of mortality intensity (deaths per 1,000 population). Shaded areas denote 1- and 2-standard-error bands around the local-projection impulse response estimates. The number of observations in the local-projection regressions varies with the time horizon $h = 1, \dots, 30$ and ranges between 161 and 191.

Fig. 6. Response to pandemics and wars of the trend and cycle components for GER.



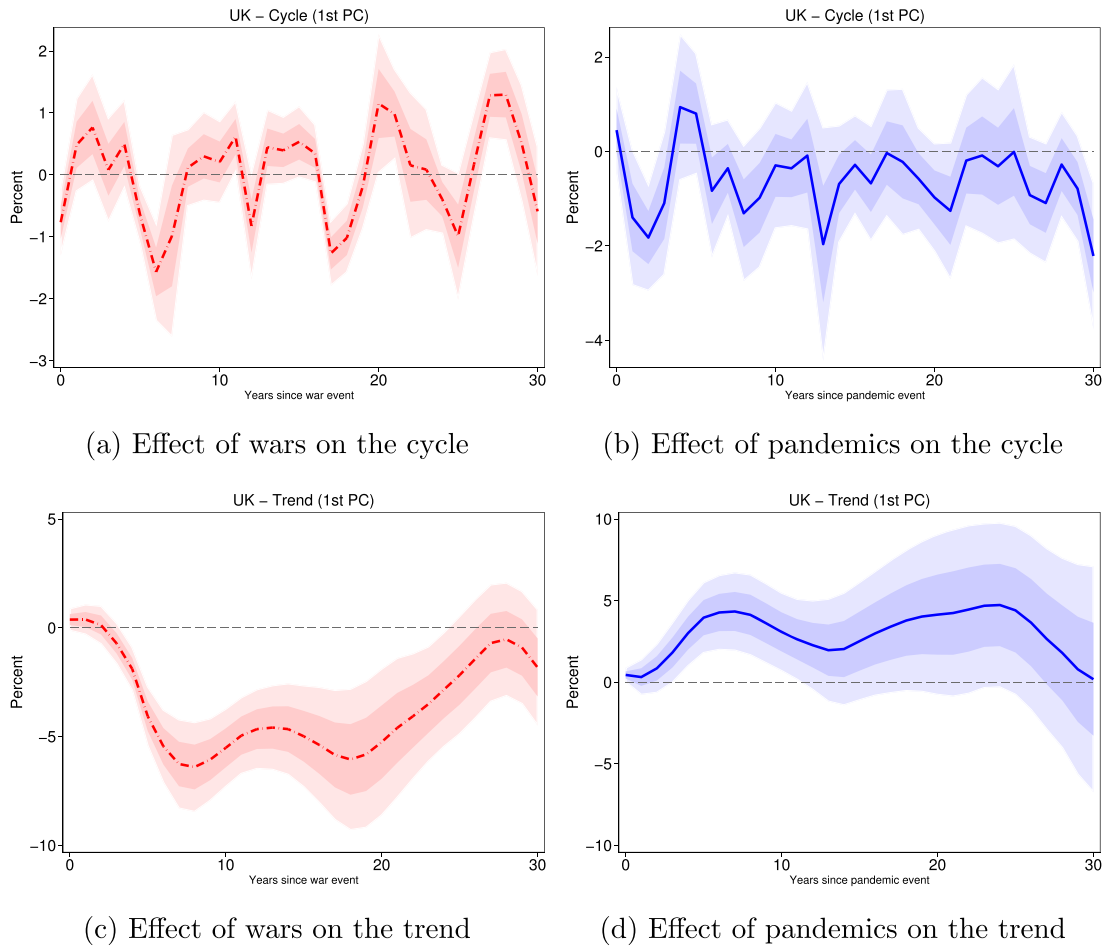
Notes: The trend and cycle components are constructed as the scores of the first principal component extracted from the eight alternative trend–cycle decompositions. The war and pandemic indices are measured in terms of mortality intensity (deaths per 1,000 population). Shaded areas denote 1- and 2-standard-error bands around the local-projection impulse response estimates. The number of observations in the local-projection regressions varies with the time horizon $h = 1, \dots, 30$ and ranges between 161 and 191.

Fig. 7. Response to pandemics and wars of the trend and cycle components for ITA.



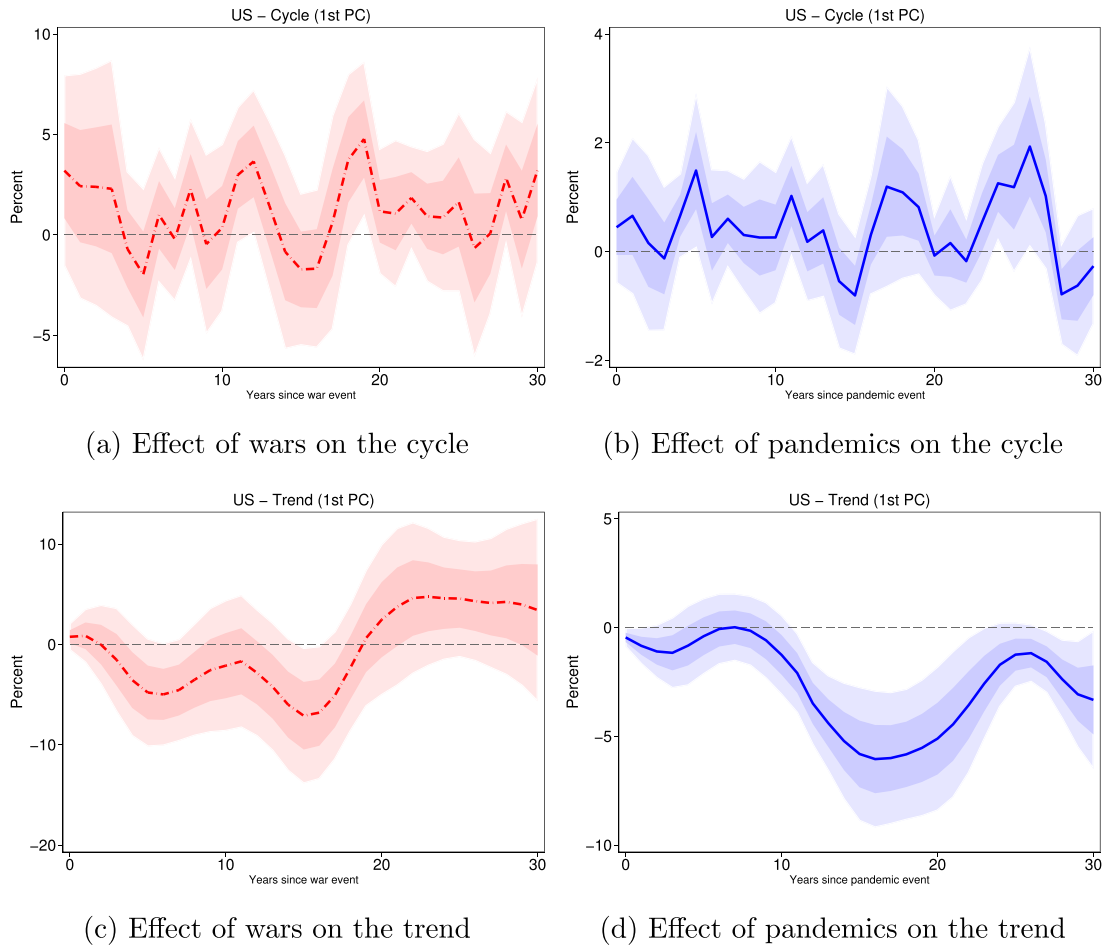
Notes: The trend and cycle components are constructed as the scores of the first principal component extracted from the eight alternative trend–cycle decompositions. The war and pandemic indices are measured in terms of mortality intensity (deaths per 1,000 population). Shaded areas denote 1- and 2-standard-error bands around the local-projection impulse response estimates. The number of observations in the local-projection regressions varies with the time horizon $h = 1, \dots, 30$ and ranges between 161 and 191.

Fig. 8. Response to pandemics and wars of the trend and cycle components for JPN.



Notes: The trend and cycle components are constructed as the scores of the first principal component extracted from the eight alternative trend–cycle decompositions. The war and pandemic indices are measured in terms of mortality intensity (deaths per 1,000 population). Shaded areas denote 1- and 2-standard-error bands around the local-projection impulse response estimates. The number of observations in the local-projection regressions varies with the time horizon $h = 1, \dots, 30$ and ranges between 161 and 191.

Fig. 9. Response to pandemics and wars of the trend and cycle components for UK.



Notes: The trend and cycle components are constructed as the scores of the first principal component extracted from the eight alternative trend–cycle decompositions. The war and pandemic indices are measured in terms of mortality intensity (deaths per 1,000 population). Shaded areas denote 1- and 2-standard-error bands around the local-projection impulse response estimates. The number of observations in the local-projection regressions varies with the time horizon $h = 1, \dots, 30$ and ranges between 161 and 191.

Fig. 10. Response to pandemics and wars of the trend and cycle components for US.

6. Concluding remarks

This paper investigates how wars and pandemics affect the demand- and supply-side drivers of output in the G7 economies. Within a neoclassical-synthesis framework – where short-run fluctuations are primarily demand-driven and long-run growth supply-determined – we decompose real GDP per capita into a cyclical (demand) component and a trend (supply) component using a broad set of filtering techniques and unobserved-components models. We then estimate country-specific local-projection impulse responses of each component to war and pandemic shocks, identified both as binary (on/off) indicators and as continuous intensity measures (e.g., deaths per thousand inhabitants). This dual approach allows us to track the timing, magnitude, and persistence of shocks while keeping demand-side and supply-side responses conceptually and empirically distinct.

Our results indicate that, on average, catastrophic events trigger only weak and short-lived cyclical (demand-side) responses, whereas supply-side responses are larger and more persistent. More importantly, both sets of responses – especially on the demand side – exhibit pronounced cross-country heterogeneity: there is no uniform “G7 response” to wars and pandemics. The direction, timing, and persistence of demand- and supply-side responses vary sharply across countries, reflecting differences in exposure and intensity, economic structure and openness, policy capacity, public-health infrastructure, demographics, and initial macro-financial conditions. In France and Italy, catastrophic shocks produce large, persistent declines in potential output. In Germany and Japan, war-related trend losses are front-loaded and partly offset by reconstruction, while severe pandemics drive most long-run supply-

side damage. Canada, the UK, and the US typically experience smaller or more reversible trend effects, though intense wars and high-mortality pandemics can still leave lasting consequences.

This heterogeneity has important implications for empirical design. Panel-data approaches that impose a common treatment effect, or allow only limited cross-country variation, risk averaging over widely divergent experiences. As our results show, such averages can obscure offsetting responses and yield estimates unrepresentative of any single economy. Ignoring dynamic and cross-sectional heterogeneity can therefore produce biased or misleading conclusions about the long-run effects of wars and pandemics. Reliable inference on the macroeconomic consequences of rare but severe shocks requires accounting for country-specific dynamics, carefully measuring shocks, and explicitly separating demand and supply channels.

From a policy perspective, our results underscore the need for tailored responses to large catastrophic events. Because demand effects are generally short-lived, timely fiscal and monetary interventions can stabilize spending around the onset of wars and pandemics. The main challenge, however, lies on the supply side: rebuilding and protecting productive capacity. After wars, this requires accelerating physical infrastructure reconstruction, restoring and upgrading human capital, and repairing disrupted production networks. Following pandemics, it calls for sustained investment in healthcare systems, public-health infrastructure, and innovation – including digitalization and new work modes – alongside policies that facilitate sectoral reallocation and labor-market adjustment. More broadly, our findings highlight the importance of strengthening supply-side resilience through structural reforms, education and R&D investment, and robust safety nets, so that future shocks generate smaller and less persistent losses in potential output.

Data availability

Data will be made available on request.

Declaration of competing interest

All authors with no competing interests to declare should select the option:

I have nothing to declare.

This declaration confirms that none of the authors have any financial, personal, or professional conflicts of interest that could inappropriately influence the work reported in this manuscript.

Appendix A. Empirical methods for estimating supply and demand components

In this section, we provide a brief overview of the various univariate approaches used in the paper to identify the trend component (interpreted as supply) and the cyclical component (interpreted as the output gap, reflecting excess or slack demand).

HP filter. The HP filter estimates the potential component of output (y_t^p) by minimizing the following loss function:

$$\min_{\{y_t^p\}_{t=1}^T} \sum_{t=1}^T (y_t - y_t^p)^2 + \lambda \sum_{t=2}^{T-1} (y_{t+1}^p - 2y_t^p + y_{t-1}^p)^2, \quad (\text{A.1})$$

where λ is the smoothing parameter. Following [Ravn and Uhlig \(2002\)](#), who studied business cycles in major Western economies using annual data, we set $\lambda = 6.25$. This value is widely adopted by scholars estimating potential output and business cycles over secular horizons (see, for example, [Antonakakis and Badinger, 2014](#); [Ritschl et al., 2016](#)).¹⁰ The cyclical component, or output gap, is calculated as the deviation of the observed series from its trend (i.e., $y_t - y_t^p$).

BN decomposition: The [Kamber et al. \(2018\)](#) extension. The Beveridge-Nelson (BN) decomposition expresses an integrated time series of order one, $I(1)$, as the sum of a permanent component (trend) and a transitory (cyclical) component. The trend component (τ_t) represents the deviation of the long-horizon conditional forecast of y_t from its deterministic drift (μ). Formally:

$$\tau_t = \lim_{j \rightarrow \infty} E_t[y_{t+j}] - j \cdot E[\Delta y], \quad \text{where} \quad \mu = E(\Delta y_t). \quad (\text{A.2})$$

The cyclical component, $c_t = y_t - \tau_t$, is interpreted as the output gap, capturing deviations of the process from its long-horizon forecast.

The BN decomposition begins by fitting an autoregressive moving-average (ARMA) model to Δy_t . For example, when using an AR(1) model, the steps are as follows:

1. Fit an AR(1) model to Δy_t :

$$\Delta y_t = \alpha + \phi \Delta y_{t-1} + e_t, \quad (\text{A.3})$$

where α is a constant, ϕ is the autoregressive coefficient, and $e_t \sim \text{iid}(0, \sigma_e^2)$ is the error term.

¹⁰ $\lambda = 100$ would yield an excessively smooth trend that might obscure relevant cyclical fluctuations. For our purposes, therefore, since we need to use both components (trend and cycle), we consider it more appropriate to set $\lambda = 6.25$, in line with the literature conducting secular studies as mentioned in the text.

2. Estimate the deterministic drift as the unconditional mean of the process:

$$\mu = \frac{\alpha}{1 - \phi}. \quad (\text{A.4})$$

3. Compute the BN trend process:

$$\tau_t = y_t + \frac{\phi}{1 - \phi} \Delta y_t - \frac{\phi}{1 - \phi} \mu. \quad (\text{A.5})$$

4. Derive the BN cycle component as a residual:

$$c_t = y_t - \tau_t. \quad (\text{A.6})$$

Kamber et al. (2018) extend this approach by explicitly modeling the signal-to-noise ratio (SNR) to address the so-called "pile-up problem." When ϕ is small, Δy_t lacks persistence, leading to a cycle component that is insufficiently persistent compared to the expected behavior of the true output gap. The pile-up problem arises when the variance of one component (typically the cyclical component) is estimated to be near zero, resulting in biased estimates of the trend and cycle.

The signal-to-noise ratio is defined as:

$$\delta = \frac{\sigma_{\Delta\tau}^2}{\sigma_e^2} = \psi(1)^2, \quad (\text{A.7})$$

where $\sigma_{\Delta\tau}^2$ is the variance of trend shocks, σ_e^2 is the variance of forecast errors, and $\psi(1)$ is the "long-run multiplier" capturing the permanent effect of a forecast error on the long-horizon expectation of y_t .

For a general AR(p) model:

$$\Delta y_t = c + \sum_{j=1}^p \phi_j \Delta y_{t-j} + \epsilon_t, \quad (\text{A.8})$$

where c is a constant, $\phi_1, \phi_2, \dots, \phi_p$ are the autoregressive coefficients, and $\epsilon_t \sim \text{iid}(0, \sigma_e^2)$ is the error term.

For an AR(p) model, the long-run multiplier $\psi(1)$ is:

$$\psi(1) = \frac{1}{1 - \phi(1)}, \quad \text{where} \quad \phi(1) = \phi_1 + \phi_2 + \dots + \phi_p. \quad (\text{A.9})$$

Thus, the signal-to-noise ratio becomes:

$$\delta = \frac{1}{(1 - \phi(1))^2}. \quad (\text{A.10})$$

Solving for $\phi(1)$:

$$\phi(1) = 1 - \frac{1}{\sqrt{\delta}}. \quad (\text{A.11})$$

The key innovation in Kamber et al. (2018) is to fix a specific value for the signal-to-noise ratio, say $\delta = \bar{\delta}$, and impose this restriction when estimating the AR model. Specifically, the AR coefficients are constrained such that their sum equals $\bar{\phi}(1) = 1 - \frac{1}{\sqrt{\bar{\delta}}}$.

This ensures that the BN decomposition is derived under a pre-specified signal-to-noise ratio.

To implement this, Eq. (A.8) can be rewritten as:

$$\Delta y_t = c + \rho \Delta y_{t-1} + \sum_{j=1}^{p-1} \phi_j^* \Delta^2 y_{t-j} + \epsilon_t, \quad (\text{A.12})$$

where $\rho = \phi_1 + \phi_2 + \dots + \phi_p$ and $\phi_j^* = -(\phi_{j+1} + \phi_{j+2} + \dots + \phi_p)$. Imposing the restriction $\rho = \bar{\rho} = \bar{\phi}(1)$ reduces the regression equation to:

$$\Delta \tilde{y}_t = \Delta y_t - \bar{\rho} \Delta y_{t-1} = c + \sum_{j=1}^{p-1} \phi_j^* \Delta^2 y_{t-j} + \epsilon_t. \quad (\text{A.13})$$

In this formulation, the regressand becomes $\Delta \tilde{y}_t = \Delta y_t - \bar{\rho} \Delta y_{t-1}$, ensuring that the signal-to-noise ratio is explicitly controlled during estimation.

In the case of annual data, the number of lags p in an autoregressive model AR(p) is generally set to 3. Kamber et al. (2018) used an AR(12) model for quarterly data, so it is appropriate to use AR(3) for annual data. The parameter $\bar{\delta}$, which represents the signal-to-noise ratio, is fixed at 0.25. This value was proposed by Kamber et al. (2018) to balance the amplitude of the business cycle and the goodness of fit of the model. Imposing $\bar{\delta} = 0.25$ implies that trend shocks account for 25% of the forecast error variance, leaving the remaining 75% attributed to cyclical shocks.

BK filter. The Baxter-King (BK) filter, as proposed by [Baxter and King \(1999\)](#), is a band-pass filter that separates a time series y_t into its trend (y_t^p) and cyclical (c_t) components. This approach aims to isolate the cyclical component, which represents stationary fluctuations driven by stochastic cycles within a specific frequency range. Mathematically, the BK filter approximates an ideal band-pass filter using a finite symmetric moving average (SMA) of order q , where the cyclical component is estimated as:

$$c_t = \sum_{j=-q}^q b_j y_{t-j}. \quad (\text{A.14})$$

Here, the weights b_j are chosen to approximate the ideal filter's gain function, which passes cycles within the desired frequency range and attenuates those outside it. The coefficients satisfy the symmetry condition $b_j = b_{-j}$ and are adjusted to ensure they sum to zero, thereby removing both deterministic and stochastic trends. The range of cycles is defined in terms of their periods (p_l and p_h), where p_l is the minimum period, and p_h is the maximum period. The corresponding frequencies are given by:

$$\omega_l = \frac{2\pi}{p_h}, \quad \omega_h = \frac{2\pi}{p_l}. \quad (\text{A.15})$$

To compute c_t , the BK filter applies the following truncated weights:

$$\hat{b}_j = b_j - \bar{b}, \quad (\text{A.16})$$

where $\bar{b}$ is the average of the ideal weights truncated at $\pm q$, ensuring that the coefficients sum to zero. The trend component y_t^p is then obtained as:

$$y_t^p = y_t - c_t. \quad (\text{A.17})$$

In practice, the filter parameters q , p_l , and p_h are chosen based on the data frequency and the specific cycles of interest. For example, for annual data, $p_l = 2$ and $p_h = 8$ are typical settings, corresponding to business cycles lasting 2 to 8 years.

HA filter. The HA filter ([Hamilton, 2018](#)) offers a regression-based approach to decompose a time series into trend and cyclical components. Unlike the HP filter, the HA filter avoids issues such as spurious dynamics, ad hoc smoothing parameters, and end-of-sample biases. Specifically, the trend is obtained by projecting the future values of a time series (y_t) onto its lagged observations, while the cyclical component is defined as the forecast error. The model assumes that for a forecast horizon h , the trend component y_t^p corresponds to $\mathbb{E}[y_{t+h} \mid y_t, y_{t-1}, y_{t-2}, y_{t-3}]$ and is obtained from the following regression model:

$$y_{t+h} = \beta_0 + \beta_1 y_t + \beta_2 y_{t-1} + \beta_3 y_{t-2} + \beta_4 y_{t-3} + v_{t+h}, \quad (\text{A.18})$$

where $\beta_0, \beta_1, \beta_2, \beta_3, \beta_4$ are coefficients estimated via OLS, and v_{t+h} represents the cyclical component or forecast error. In practice, the estimation process solves the following minimization problem:

$$\min_{\beta_0, \beta_1, \beta_2, \beta_3, \beta_4} \sum_{t=4}^{T-h} (y_{t+h} - \beta_0 - \beta_1 y_t - \beta_2 y_{t-1} - \beta_3 y_{t-2} - \beta_4 y_{t-3})^2. \quad (\text{A.19})$$

The trend component y_t^p is then the predicted value from the regression, and the cyclical component is derived as: $v_{t+h} = y_{t+h} - y_t^p$. For annual data, as considered in this study, a forecast horizon $h = 2$ is typically recommended to capture medium-term business cycle dynamics while minimizing distortions caused by long-term fluctuations ([Hamilton, 2018](#)).

Univariate UCM with random trend. Following the framework introduced by [Clark \(1987\)](#), the univariate Unobserved Components Model (UCM) decomposes a time series into two distinct components: a stochastic trend and a stationary cyclical component. In the random trend model, the observed series, y_t , is expressed as:

$$y_t = y_t^p + c_t, \quad (\text{A.20})$$

where y_t^p represents the underlying trend and c_t denotes the cyclical component. The trend evolves according to the random trend specification:

$$y_t^p = y_{t-1}^p + \beta_{t-1}, \quad (\text{A.21})$$

$$\beta_t = \beta_{t-1} + \xi_t, \quad (\text{A.22})$$

with ξ_t being a white noise process capturing innovations in the slope. Unlike a simple random walk, this formulation allows the growth rate (slope) β_t to vary stochastically over time. The cyclical component, c_t , is modeled as a stationary autoregressive process of order 2 (AR(2)):

$$\phi(L)c_t = v_t, \quad (\text{A.23})$$

where $\phi(L) = 1 - \phi_1 L - \phi_2 L^2$ is a polynomial in the lag operator L , and v_t is a white noise process. A key assumption in this framework is the independence between the innovations in the trend (ξ_t) and those in the cycle (v_t). This decomposition provides a flexible representation of the observed series, distinguishing long-term structural movements from short-term cyclical fluctuations. Model parameters are typically estimated via maximum likelihood using the Kalman filter, ensuring an optimal extraction of the latent components from the data.

Trend-cycle decomposition with structural breaks (HP and TC). We extract both the HP and TC cycles using the structural break correction proposed by [Mohr \(2005\)](#).¹¹ Let y_t be observed output (annual, no seasonality) and write

$$y_t = \tau_t + c_t,$$

where τ_t is a smooth trend and c_t is a cyclical component.

Break identification (level shifts only). We first date structural breaks as intercept shifts using the Bai–Perron methodology ([Bai and Perron, 1998, 2003](#)), keeping the slope common across regimes:

$$y_t = \alpha_j + \beta t + u_t, \quad t \in (\mathcal{T}_{j-1}, \mathcal{T}_j], \quad j = 1, \dots, m+1.¹²$$

Let D be the $T \times m$ matrix of step dummies constructed from the estimated break dates ($D_{k,t} = 1$ if $t > \mathcal{T}_k$, 0 otherwise). For a chosen difference order d (with annual data we set $d = 2$), define

$$U = \nabla^d D, \quad W = U(U'U)^{-1}U',$$

and the *break-corrected* trend roughness matrix

$$T_d = \nabla^{d'}(I - W)\nabla^d.$$

HP cycle with breaks. The HP trend with structural breaks solves

$$\hat{\tau}^{\text{HP}} = \arg \min_{\tau} \|y - \tau\|^2 + \lambda_{\text{HP}} \|(I - W)\nabla^2 \tau\|^2,$$

with $\lambda_{\text{HP}} = 6.25$ for annual data. Define the standard HP roughness matrix $R_2 \equiv \nabla^{2'}\nabla^2$ and the break-corrected one $T_2 \equiv \nabla^{2'}(I - W)\nabla^2$. Then the closed form is

$$\hat{\tau}^{\text{HP}} = (I + \lambda_{\text{HP}} T_2)^{-1} y, \quad \hat{c}^{\text{HP}} = y - \hat{\tau}^{\text{HP}},$$

i.e., the standard HP replaces R_2 with T_2 to purge spurious smoothing around the (estimated) level shifts.

Trend-cycle with breaks (TC). The TC filter augments the trend penalty with a stochastic cycle penalty. Define the second-order stochastic cycle ([Harvey, 1989; Harvey and Trimbur, 2003](#)) via

$$\alpha(L)c_t = \beta(L)\varepsilon_t, \quad \varepsilon_t \sim \text{iid}(0, \sigma^2),$$

with

$$\alpha(L) = 1 - 2\rho \cos(\mu)L + \rho^2 L^2, \quad \beta(L) = 1 - \rho \cos(\mu)L,$$

where $\mu = 2\pi/L^*$ determines the target business cycle period L^* (in years) and $\rho \in (0, 1)$ controls persistence. (The generalization to cycle order $c \geq 1$ is immediate by replacing α, β with α^c, β^c .) Let A and B be the convolution matrices associated with $\alpha(L)$ and $\beta(L)$, and define

$$C = A'(BB')^{-1}A.$$

Introduce the one-component smoothing matrices

$$M_T = (I + \lambda_T T_d)^{-1}, \quad M_C = (I + \lambda_C C)^{-1},$$

where $\lambda_T = \lambda_C = 1$ following [Mohr \(2005\)](#). The simultaneous two-component TC extraction is then

$$\hat{\tau}^{\text{TC}} = (I - M_T M_C)^{-1} M_T (I - M_C) y, \quad \hat{c}^{\text{TC}} = (I - M_C M_T)^{-1} M_C (I - M_T) y.$$

Letting $\lambda_C \rightarrow \infty$ (so $M_C \rightarrow 0$) collapses the TC filter to the HP-with-breaks case, yielding $\hat{\tau}^{\text{TC}} \rightarrow M_T y = \hat{\tau}^{\text{HP}}$ and $\hat{c}^{\text{TC}} \rightarrow y - \hat{\tau}^{\text{HP}}$.

Practical choices (annual data). We set $d = 2$ for the trend penalty, take $L^* \in [6, 10]$ years and ρ close to 1 (e.g., 0.95–0.98) for a persistent but stationary cycle, and compute both $\hat{c}^{\text{HP}}$ and $\hat{c}^{\text{TC}}$ using the *same* break correction W so that level shifts are treated consistently across methods. For $d = 1$, the drift is estimated once (common across regimes) and breaks remain pure level shifts.

Appendix B. Pandemic data: Construction and sources

In this appendix, we describe the strategy used to construct the pandemic dataset and present the corresponding list and details of the main epidemics and pandemics that affected the G7 countries in our sample. We focus on events that are estimated to have caused at least 10,000 deaths in a given country over their period of spread, within our data-collection window from 1800 to 2024. The death counts reported for each event are estimates and, as documented in the country-specific notes below, the degree of uncertainty increases as we move back in time. For completeness, the rightmost column of each table reports year-by-year information drawn from historical sources, highlighting the years of highest mortality along with other relevant details.

¹¹ We thank one of the anonymous referees for recommending this robust methodology to account for structural breaks in the identification of cyclical and trend components.

¹² Using the Bayesian Information Criterion (BIC) to identify structural breaks over the period 1800–2020 (with a maximum of 5 breaks), we obtain the following break dates by country: 1899, 1941, 1974 for Canada; 1833, 1866, 1915, 1955, 1988 for Italy; 1837, 1877, 1914, 1961 for Germany; 1833, 1870, 1917, 1964 for France; 1833, 1866, 1899, 1966 for Japan; 1833, 1878, 1919, 1954, 1987 for the UK; 1837, 1930, 1966 for the US.

The country lists were constructed using a two-step procedure similar to that employed by [Cao et al. \(2025\)](#). First, we queried an artificial-intelligence (AI) system (ChatGPT v5) to identify, for each country of the G7 group, the major epidemics and pandemics occurring between 1800 and 2024 that are estimated to have caused at least 10,000 deaths at the country level over the duration of the event. To limit potential response bias, we repeated this query 30 times in fresh, independent chat sessions. Second, we reviewed in detail the events that appeared in at least 20 of these runs, consulting dedicated Wikipedia pages and conducting targeted Google searches. The main references are listed, country by country, in the paragraphs that follow. Several reconstructions—especially for earlier events—remain subject to substantial uncertainty; as a result, newly uncovered sources may yield more reliable estimates in the future.

US. Main sources: [Rosenberg \(1987\)](#); [Pyle \(1969\)](#); [Ellis \(1992\)](#); [Baker \(1968\)](#); [Keating \(1879\)](#); [Taubenberger and Morens \(2006\)](#); [Glezen \(1996\)](#); [Simonsen et al. \(1998\)](#); [Shrestha et al. \(2011\)](#); Centers for Disease Control and Prevention (1918 Flu Pandemic, 1957–1958 Pandemic, 1968 Pandemic, HIV and H1N1 Pandemic); National Center for Health Statistics Reports (for different years). For the US, cholera mortality in the 1832, 1849–1850, and 1866 waves is documented mainly at the city or regional level in historical sources. Consequently, any national totals are reasonable aggregations reconstructed from city/area tallies (e.g., [Rosenberg, 1987](#); [Pyle, 1969](#)), and should be interpreted with appropriate caution and uncertainty.

Unites States			
Epidemic/Pandemic	Period	Deaths (USA)	Details (by year/wave)
Cholera (1st)	1832-33	20-30K +	1832 majority; 1833 decline
Cholera (2nd)	1849-50	30-50K	1849 peak; 1850 residual
Cholera (3rd)	1866	20-50K	Mainly in 1866
Yellow Fever	1878	13-20K	Summer-autumn 1878 peak
Spanish Flu	1918-20	~675K	1918 (~500K), 1919 (~150K)
Asian Flu	1957-58	~70K	1957 (~25-30K), 1958 (~40K)
Hong Kong Flu	1968-70	34-100K	1968-69 main wave
HIV/AIDS	1981-24	>700K	Peak 80s-90s; ↓ since 2000s
H1N1 (Swine)	2009	12-18K	Two waves: spring/autumn
COVID-19	2020-24	~1.1M	2020 (350K), 2021 (475K), 2022 (250K)

UK. Main sources: [Underwood \(1948\)](#); [Ministry of Health \(1960\)](#); [Roden \(1969\)](#); [Miller et al. \(1971\)](#); [Hunter and Young \(1971\)](#); [Mooney \(1997\)](#); [Millar et al. \(2020\)](#); [Krylova and Earn \(2020\)](#); [Berche \(2022\)](#); Her Majesty's Stationery Office (HMSO) (Cholera epidemics; 1918–19 Flu Pandemic, 1957–1958 Pandemic); Office for National Statistics (HIV/AIDS); Our World in Data (COVID-19). Most nineteenth-century cholera data were recorded at the city or local sanitary authority level and published in Registrar-General returns or Board of Health inquiries.¹³ Because no single UK-wide annual series exists, the national totals in our table are careful, good-faith reconstructions obtained by aggregating England & Wales returns with documented figures for Scotland (and, where relevant, Ireland) from the cited sources.

UK			
Epidemic/Pandemic	Period	Deaths (UK)	Details (by year/wave)
Cholera (1st)	1831-32	~32K	Late 1831 start, 1832 peak
Cholera (2nd)	1848-49	~53K	1849 peak
Cholera (3rd)	1853-54	~23K	1854 peak
Cholera (4th)	1866	~14K	Almost entirely in 1866
Smallpox	1870-72	40-45K	1871-72 peak
Russian Flu	1889-92	25-30K	Late 1889-early 1890 most lethal
Spanish Flu	1918-20	220-250K	1918 (~150K), 1919 (~50-60K)
Asian Flu	1957-58	~30-35K	1957 (1st wave), 1958 (2nd wave)
Hong Kong Flu	1968-70	~25-30K +	1968-69 and 1969-70 waves
HIV/AIDS	1981-24	25-35K +	Peak 1990s; ↓ since 2000s
COVID-19	2020-24	>200K	2020 (~75K), 2021 (~60-70K), 2022 (~30-40K)

Japan. Main sources: [Saito \(1996\)](#), [Ogasawara and Inoue \(2018\)](#), [Kikuchi \(1978\)](#), [Miyamae \(2024\)](#), [Chandra \(2013\)](#), [Ohmi and Marui \(2011\)](#), [Viboud et al. \(2005\)](#), [Johnston \(2019\)](#); additional data from Our World in Data and the Japanese Ministry of Health, Labour and Welfare (for COVID-19 statistics). For 1858-1876, no continuous national mortality series exists; figures are therefore order-of-magnitude reconstructions aggregated from city/domain and prefectural reports. From 1877 onward, we use official Home-Ministry statistics.¹⁴ We do not use the global “1st/2nd cholera pandemic” labels here, because Japan’s major cholera waves do not

¹³ See [Underwood \(1948\)](#), [Davenport et al. \(2019\)](#) and contemporaneous HMSO reports.

¹⁴ See [Johnston \(2014\)](#); see also National Diet Library notes on the 1879 epidemic ([Library \(2023\)](#)).

align with the classic global numbering of other Western economies. Instead, we list Japan-specific national waves by year (1858, 1862, 1867, 1879, 1882, 1886, 1890, 1895).

Japan			
Epidemic/Pandemic	Period	Deaths (JPN)	Details (by year/wave)
Cholera	1858	~100K	Mostly concentrated in 1858
Cholera	1862	~200K	Single devastating epidemic
Cholera	1867	~80K	Mostly concentrated in 1867
Cholera	1879	~100K	Official Home Ministry total
Cholera	1882	~34K	Official Home Ministry total
Cholera	1886	~100K	Official Home Ministry total
Cholera	1890	~35K	Official Home Ministry total
Cholera	1895	~40K	Official Home Ministry total
Russian Flu	1889-92	50-90K	1890 main peak
Spanish Flu	1918-20	250-400K	1918-19 lethal waves, 1920 residual
Asian Flu	1957-58	10-20K	1957 (1st wave), 1958 (2nd wave)
Hong Kong Flu	1968-70	10-20K +	Two main waves (68-69 and 69-70)
COVID-19	2020-24	80-90K +	2020 (~2-3K), 2021 (~15K), 2022 (sharp rise)

France. Main sources: [Unknown \(1865\)](#), [Vacher \(1868\)](#), [Rolleston \(1933\)](#), [Bourdelaïs and Raulot \(1987\)](#), [Smallman-Raynor and Cliff \(2002\)](#), [Viboud et al. \(2005\)](#), [Ansart et al. \(2009a\)](#), [Meslé \(2010\)](#), [Vagneron \(2020\)](#), [Viboud et al. \(2016\)](#); Our World in Data (COVID-19). The totals shown for the 1866 cholera wave and for nineteenth-century influenza episodes prior to the late-1890s statistical consolidation are not taken from a single, continuous national series. They are careful reconstructions obtained by aggregating departmental returns and large-city mortality reports published at the time (e.g., in the *Journal de la Société de Statistique de Paris*), complemented by later scholarly syntheses; ranges reflect the uncertainty inherent in these aggregates.¹⁵

France			
Epidemic/Pandemic	Period	Deaths (FRA)	Details (by year/wave)
Cholera (1st)	1832	~100K	Concentrated in 1832
Cholera (2nd)	1849	~100K	Spring-autumn 1849 peak
Cholera (3rd)	1853-54	~140-150K	1853 (70-80K), 1854 (60-70K)
Cholera (4th)	1866	~70-90K	Summer-autumn 1866
Smallpox	1870-72	>100K	1871-72 post-war peak
Russian Flu	1889-92	50-90K	Late 1889-early 1890 first wave
Spanish Flu	1918-20	200-400K	1918 (~150K), 1919 (50-60K), 1920 (20-30K)
Asian Flu	1957-58	20-30K	1957 (1st wave), 1958 (2nd wave)
Hong Kong Flu	1968-70	~25-30K	Two waves (1968-69, 1969-70)
HIV/AIDS	1981-24	>40-50K +	Peak 1990s; ↓ since 2000s
COVID-19	2020-24	~165-170K +	2020 (~64K), 2021 (~63K), 2022 (~38K)

Germany. Main sources: [Brauser \(1854, 1862\)](#), [Müller \(1867\)](#), [Hirsch \(1883\)](#), [Rosenberg \(1966\)](#), [Evans \(2005\)](#), [Kappner \(2025\)](#), [Buchholz et al. \(2016\)](#), [Förtsch and Rösel \(2021\)](#); Robert Koch-Institut (for HIV/AIDS); Statistisches Bundesamt (Destatis; for COVID-19); Our World in Data (COVID-19). For nineteenth-century cholera there is no single, continuous national series covering all German

¹⁵ See [Vacher \(1868\)](#), [Unknown \(1865\)](#) for departmental cholera tabulations around 1866; for nineteenth-century influenza before comprehensive national tabulation, see statistical/synthetic discussions such as [Vagneron \(2020\)](#).

states; totals are careful reconstructions obtained by aggregating Prussian provincial returns Brauser (1862) and municipal reports, complemented by city monographs (e.g., Müller, 1867).

Germany			
Epidemic/Pandemic	Period	Deaths (GER)	Details (by year/wave)
Cholera (1st)	1831-32	>100K	1832 peak
Cholera (2nd)	1848-49	50-60K +	1849 most lethal phase
Cholera (3rd)	1853-54	10-80K	Estimate for this wave
Cholera (4th)	1866	10-80K	Estimate for this wave
Cholera (5th)	1892	>10K	Hamburg ~8.6K
Smallpox	1870-73	>100K	1871-72 peak
Russian Flu	1889-92	50-100K	Late 1889/early 1890 peak
Spanish Flu	1918-20	200-400K	1918 most lethal wave
Asian Flu	1957-58	20-40K	1957 (1st wave), 1958 (2nd)
Hong Kong Flu	1968-70	25-40K	Two main waves (68-69, 69-70)
HIV/AIDS	1981-24	25-35K +	Peak 1990s; ↓ since 2000s
COVID-19	2020-24	~170K +	2020 (~35K), 2021 (~70K), 2022 (~40K)

Italy. Main sources: *Direzione di Statistica* (1870), *Direzione Generale di Statistica* (1893, 1894), *Istituto Centrale di Statistica* (1958), *Viboud et al.* (2016), *Snowden* (1995), *Tognotti* (2000), *Viboud et al.* (2005), *Ansart et al.* (2009b), *Alfani* (2014), *Fornasin et al.* (2018), *Francesco et al.* (2022); *Istituto Superiore di Sanità* (COVID-19); *Our World in Data* (COVID-19). For the 1889-92 influenza, national totals are uncertain: cause-of-death registers record about 12,000 deaths coded as “influenza” in 1890, whereas excess-mortality approaches indicate substantially higher burdens. A conservative, good-faith 30-50 thousand bracket for the overall episode is therefore reasonable.

Italy			
Epidemic/Pandemic	Period	Deaths (ITA)	Details (by year/wave)
Cholera (1st)	1835-37	100K-150K	1836-37: peak
Cholera (2nd)	1854-55	>100K	1854: main wave
Cholera (3rd)	1865-67	~113K	1866-67: violent phase
Cholera (4th)	1884-85	40K-55K	1884: Naples; 1885: tail
Russian Flu	1889-92	30K-50K +	1889-90: peak
Spanish Flu	1918-20	375K-600K	1918: worst wave
Asian Flu	1957-58	15K-25K	1957/58: two waves
Hong Kong Flu	1968-70	~25K	1968-69 & 1969-70
HIV/AIDS	1981-24	>40K	Peak 1990s; ↓ since 2000s
COVID-19	2020-24	~190K +	2020:75K, 2021:63K, 2022:40K

Canada. Main sources: *Bilson* (1974, 1977, 1980), *Quigley* (1994), *Harris* (1994), *Strathdee et al.* (1996), *Boyd* (1999), *Rijn* (2006), *Jenkins* (2007), *Zhang et al.* (2010), *Tuite et al.* (2011), *Bilson* (2015), *Fowler* (2018); Government of Canada (for calculating deaths of typhus epidemic in 1847, Spanish Flu), Statistics Canada (HIV/AIDS, COVID-19). For nineteenth-century cholera and the 1847 typhus crisis, no single national series exists; the country totals reported here are reconstructed by aggregating city- and province-level returns and, where necessary, inferred to order-of-magnitude from documented local tallies.

Canada			
Epidemic/Pandemic	Period	Deaths (CAN)	Details (by year/wave)
Cholera (1st)	1832-34	~15K-20K	1832:8-9K; 1833:thousands; 1834:4-5K
Cholera (other waves)	1849, 1854, 1866	>10K per wave	Repeated impact on Provinces
Typhus (Irish)	1847	~20K +	Summer-fall 1847 (Irish immigrants)
Smallpox (BC)	1862-63	>20K	Victoria → interior (mostly Indigenous)
Spanish Flu	1918-20	~50K	1918: worst wave; 1919-20: resid.
HIV/AIDS	1981-24	25K-30K +	Peak 1990s; ↓ since 2000s
COVID-19	2020-24	~54K	2020:15K, 2021:14K, 2022:16K, 2023:7-8K

We conclude this section by noting that, for all G7 countries except Japan, HIV/AIDS mortality exceeds our threshold. Accordingly, in Fig. B.1 Japan is the only country that does not display a continuous bar at value 1 for the binary pandemic indicator from the 1980s onward.

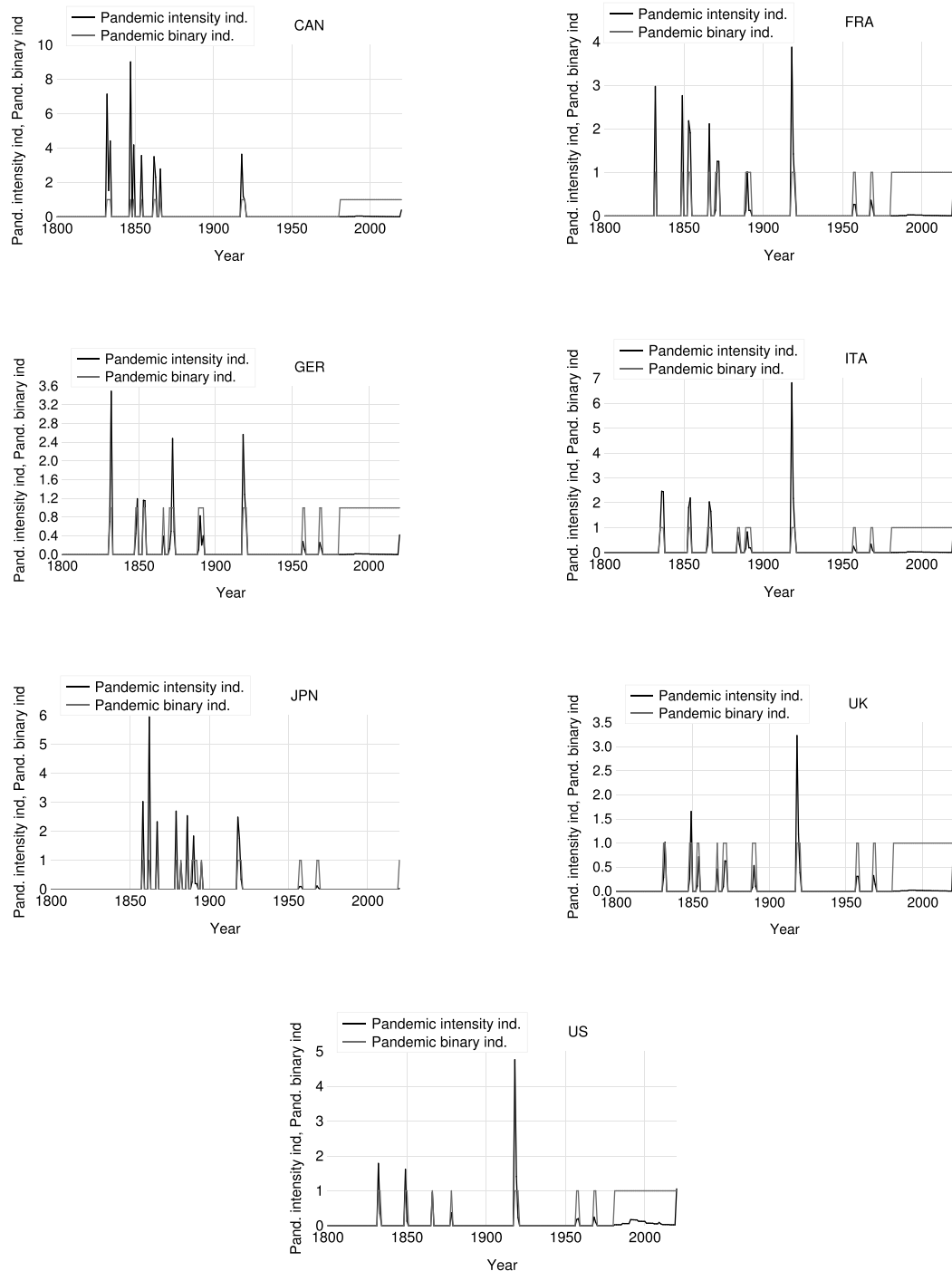


Fig. B.1. Pandemic Indicators for G7 countries.

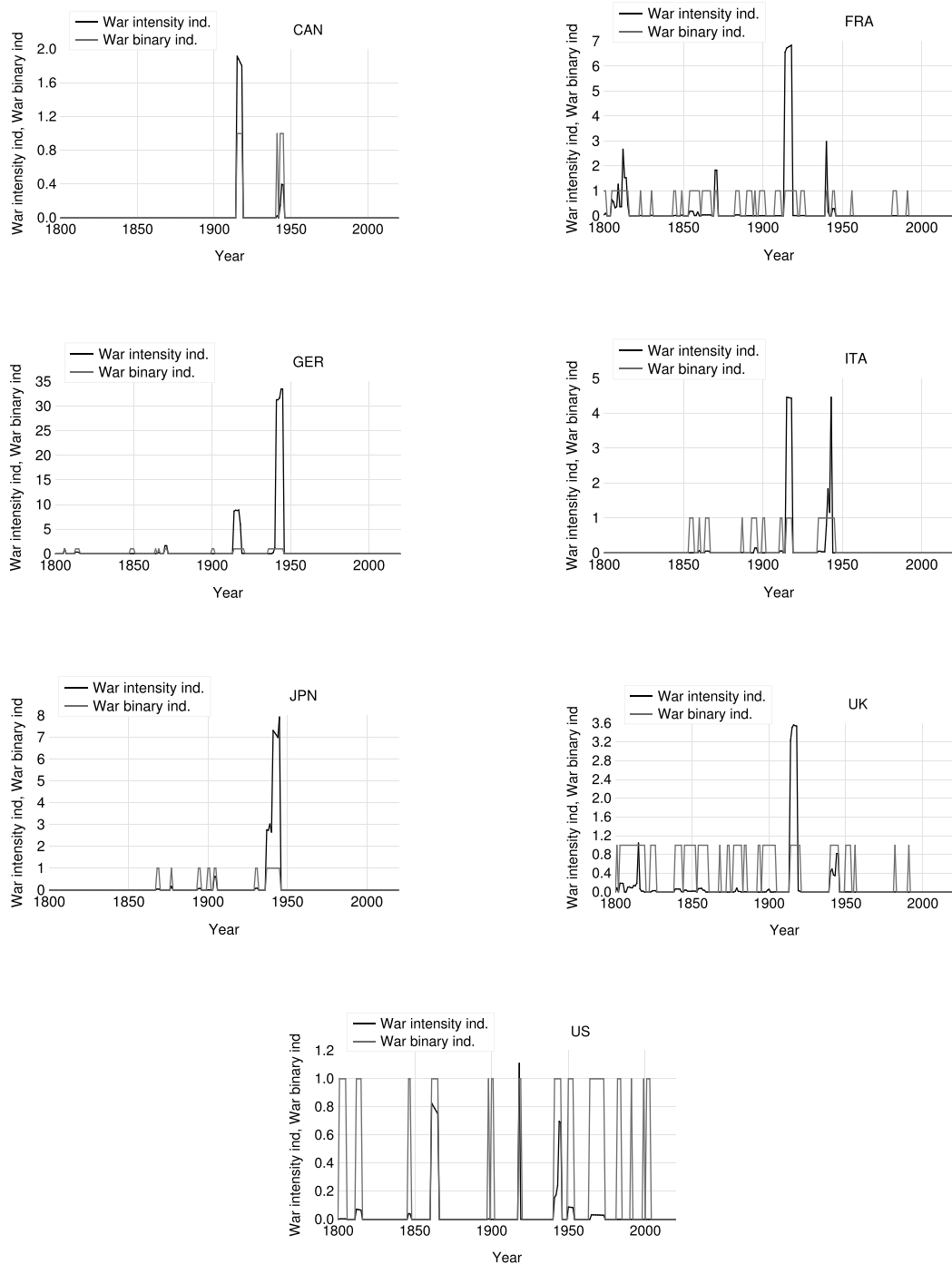


Fig. B.2. War Indicators for G7 countries.

Appendix C. The limits of comparing pandemic and war mortality

A direct comparison between pandemic and war deaths is generally unreliable when pandemics are measured by total deaths per event (spanning multiple years), while wars are measured in terms of annual deaths.

Suppose we set thresholds of A deaths per pandemic (measured as the total over the event's duration) and B deaths per year for wars. Let a pandemic event P have a total of D_P deaths occurring over L_P years. The pandemic dummy is defined at the event level as

$$\mathbf{1}\{P \text{ counts}\} = \mathbf{1}\{D_P \geq A\}.$$

Let $d_{W,t}$ denote *annual* battle deaths in year t of a war. The war dummy is defined at the year level as

$$\mathbf{1}\{W \text{ counts in year } t\} = \mathbf{1}\{d_{W,t} \geq B\}.$$

To make the two rules “comparable,” one would need the *per-year* pandemic intensity to be at least as large as the war-year cutoff:

$$\frac{D_P}{L_P} \geq B \iff L_P \leq \frac{D_P}{B}.$$

For the proposed case $D_P = A$, this implies *equivalence only if* $L_P \leq A/B$. If the pandemic lasts longer (e.g., $L_P > A/B$), then $D_P/L_P < B$: the event qualifies as a “pandemic” under the A rule but falls below the war-year benchmark B . Conversely, short pandemics (e.g., $L_P < A/B$) far exceed B on an annual basis. Hence any fixed per-year threshold B cannot, in general, be matched to a fixed event-total threshold A .

Because the two indicators operate at different measurement levels (event total vs. annual intensity), the suggested mapping holds only in the special case $L_P \approx A/B$. In practice, it will produce mismatches (false negatives for long, moderate-intensity events; false positives for brief, intense events) unless the two metrics are harmonized to the same level (event-to-event or year-to-year, e.g., per capita per year). That is, one should use a common threshold defined on the same metric and apply it consistently to both hazards (e.g., event-total deaths for wars and pandemics; or annual deaths; or per-capita deaths per year), rather than mixing event-level and year-level criteria.

Problems in using the same metric. Imposing a single, common metric for both hazards is appealing but problematic, because wars and pandemics differ in timing, aggregation, and how losses are recorded.

Event-total deaths. Setting a common threshold on event totals (e.g., “include any event with at least A deaths overall”) can be misleading for wars. A conflict may exceed A only because it is very long, while most intermediate years have near-zero casualties and negligible macro impact. For instance, 10,000 deaths concentrated in one year are not equivalent to 10,000 deaths spread thinly over twenty years (500 per year). By contrast, pandemics typically have limited duration or come in discrete waves; nineteenth-century cholera in Japan, for example, comprised distinct national waves rather than one continuous event (see Appendix B).

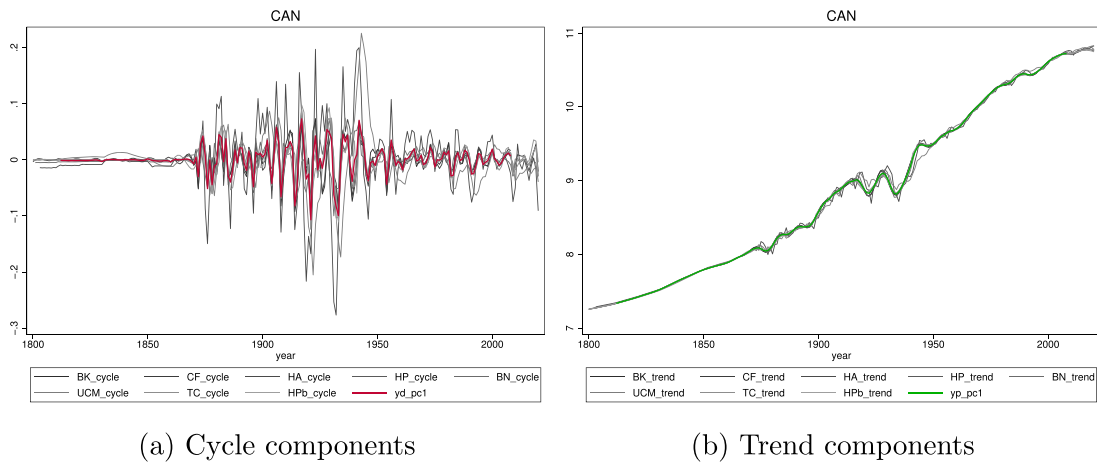
Annual deaths. Using an annual threshold (e.g., “include year t if deaths $\geq B$ in that year”) flips the bias. It may exclude multi-year wars whose yearly casualties fall just below B but whose cumulative toll is large (false negatives), while overweighting short, intense campaigns that briefly exceed B (false positives). For pandemics, a strict year cut can fragment a single episode into multiple on/off years and understate the event-level burden.

Per-capita deaths per year. Per-capita annual thresholds may help comparability across countries and over time, but do not eliminate timing asymmetries. They can penalize small-population countries (where modest counts imply high rates) and understate the macro salience of large countries. Moreover, coverage differs: wartime data often capture battle KIA only, whereas pandemic data reflect total disease mortality or excess deaths.

Implication. There is no single, dominance-proof metric or threshold. Even when applying the same metric symmetrically (event totals, annual deaths, or per-capita per year), the issues above persist because wars and pandemics are structured differently.

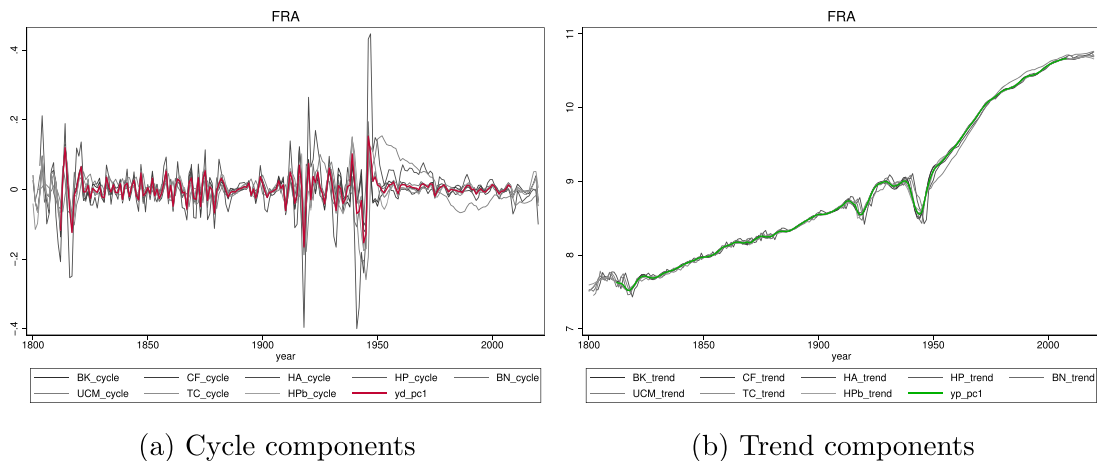
Practical recommendation. Leverage the most granular information available: (i) for wars, use campaign-by-year deaths; (ii) for pandemics, use event totals (or year-attributed deaths when available). Thresholds may differ by hazard, but final analyses should rely on intensity measures—preferably per-capita-reported alongside indicator dummies. This preserves detail (e.g., year-by-year war intensity), reduces sensitivity to arbitrary cutoffs, and improves cross-hazard comparability even if numeric thresholds are not perfectly aligned.

Appendix D. Cycle-trend decompositions: First principal component (graphs)



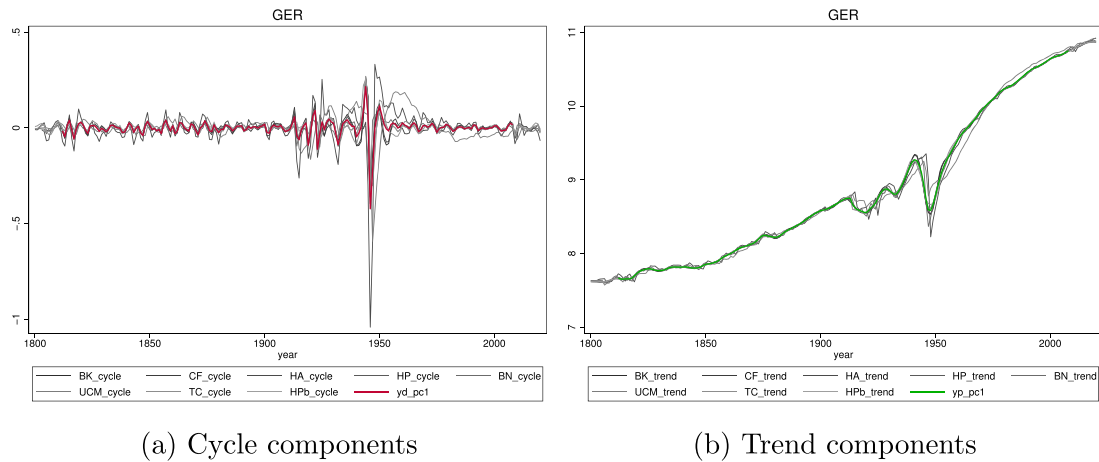
Notes: For both trend and cycle, we apply principal component analysis to the eight alternative decompositions and use the first-component scores as our **PC1** measures. **BK**: Baxter-King filter; **CF**: Christiano-Fitzgerald filter; **HA**: Hamilton filter; **HP**: Hodrick-Prescott filter; **BN**: Beveridge-Nelson decomposition; **UCM**: Univariate UCM with Random Trend; **TC**: trend/cycle decomposition with structural breaks (Mohr, 2005); **HPb**: HP decomposition with structural breaks.

Fig. D.1. Cycle/trend decompositions and the first principal component for CAN.



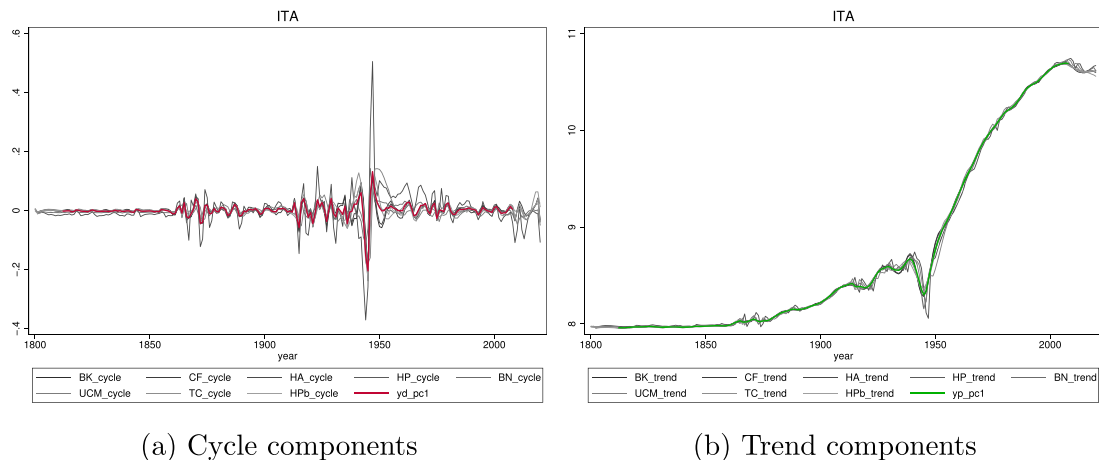
Notes: For both trend and cycle, we apply principal component analysis to the eight alternative decompositions and use the first-component scores as our **PC1** measures. **BK**: Baxter-King filter; **CF**: Christiano-Fitzgerald filter; **HA**: Hamilton filter; **HP**: Hodrick-Prescott filter; **BN**: Beveridge-Nelson decomposition; **UCM**: Univariate UCM with Random Trend; **TC**: trend/cycle decomposition with structural breaks (Mohr, 2005); **HPb**: HP decomposition with structural breaks.

Fig. D.2. Cycle/trend decompositions and the first principal component for FRA.



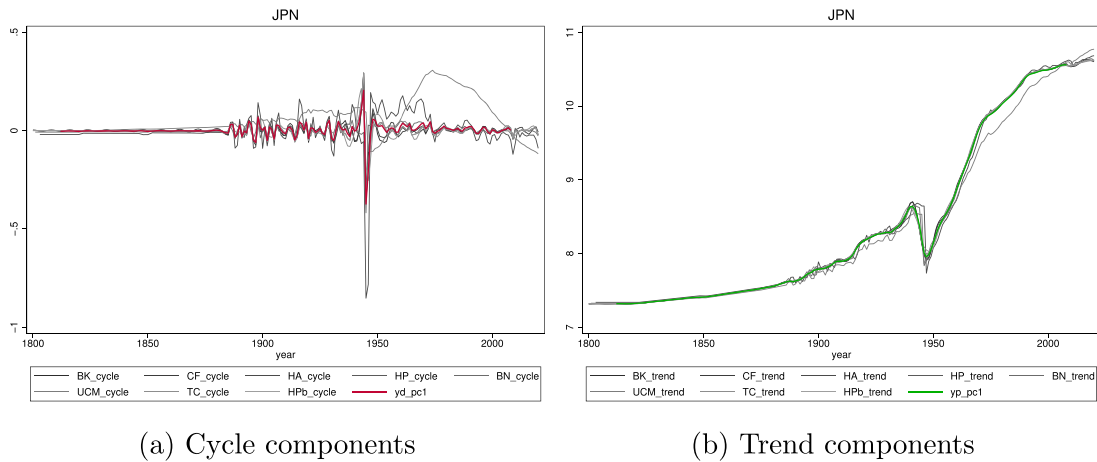
Notes: For both trend and cycle, we apply principal component analysis to the eight alternative decompositions and use the first-component scores as our **PC1** measures. **BK**: Baxter-King filter; **CF**: Christiano-Fitzgerald filter; **HA**: Hamilton filter; **HP**: Hodrick–Prescott filter; **BN**: Beveridge-Nelson decomposition; **UCM**: Univariate UCM with Random Trend; **TC**: trend/cycle decomposition with structural breaks (Mohr, 2005); **HPb**: HP decomposition with structural breaks.

Fig. D.3. Cycle/trend decompositions and the first principal component for GER.



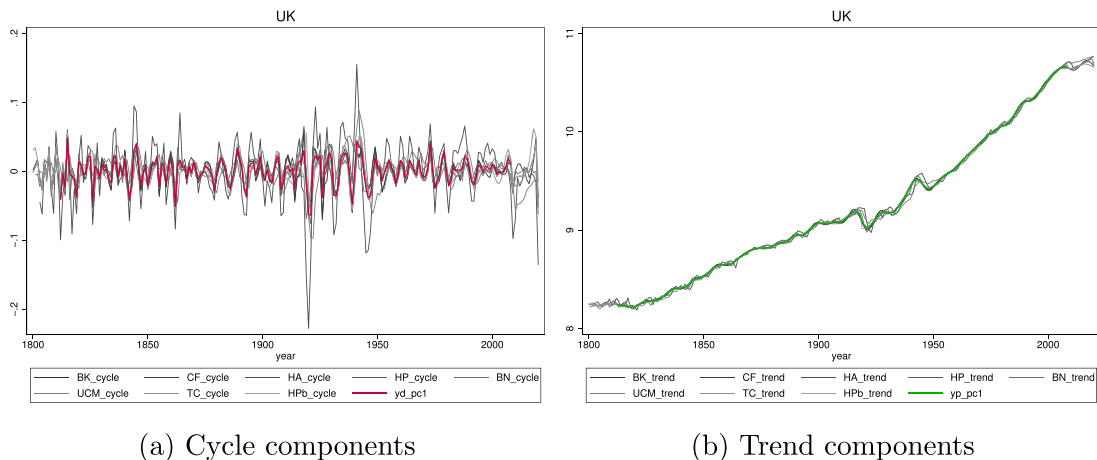
Notes: TFor both trend and cycle, we apply principal component analysis to the eight alternative decompositions and use the first-component scores as our **PC1** measures. **BK**: Baxter-King filter; **CF**: Christiano-Fitzgerald filter; **HA**: Hamilton filter; **HP**: Hodrick–Prescott filter; **BN**: Beveridge-Nelson decomposition; **UCM**: Univariate UCM with Random Trend; **TC**: trend/cycle decomposition with structural breaks (Mohr, 2005); **HPb**: HP decomposition with structural breaks.

Fig. D.4. Cycle/trend decompositions and the first principal component for ITA.



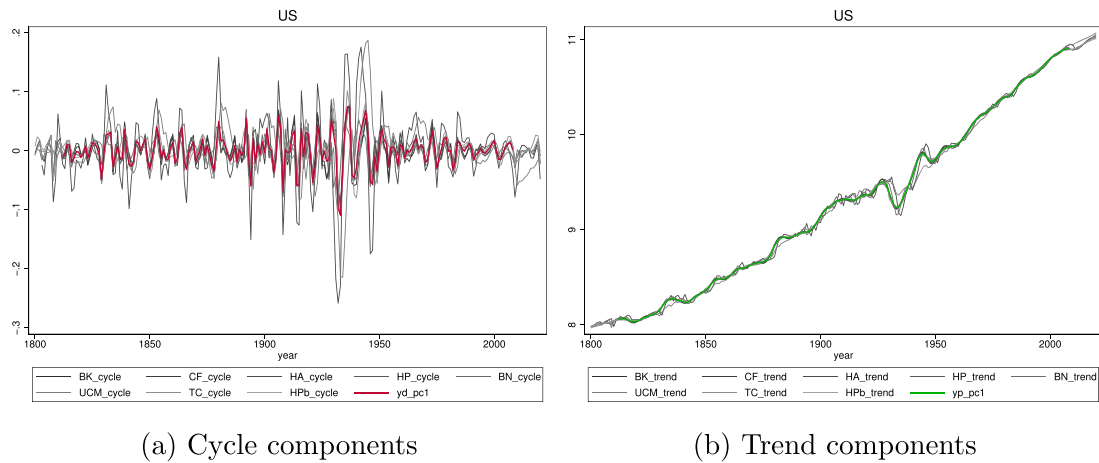
Notes: For both trend and cycle, we apply principal component analysis to the eight alternative decompositions and use the first-component scores as our **PC1** measures. **BK**: Baxter-King filter; **CF**: Christiano-Fitzgerald filter; **HA**: Hamilton filter; **HP**: Hodrick–Prescott filter; **BN**: Beveridge–Nelson decomposition; **UCM**: Univariate UCM with Random Trend; **TC**: trend/cycle decomposition with structural breaks (Mohr, 2005); **HPb**: HP decomposition with structural breaks.

Fig. D.5. Cycle/trend decompositions and the first principal component for JPN.



Notes: For both trend and cycle, we apply principal component analysis to the eight alternative decompositions and use the first-component scores as our **PC1** measures. **BK**: Baxter-King filter; **CF**: Christiano-Fitzgerald filter; **HA**: Hamilton filter; **HP**: Hodrick–Prescott filter; **BN**: Beveridge–Nelson decomposition; **UCM**: Univariate UCM with Random Trend; **TC**: trend/cycle decomposition with structural breaks (Mohr, 2005); **HPb**: HP decomposition with structural breaks.

Fig. D.6. Cycle/trend decompositions and the first principal component for UK.



Notes: For both trend and cycle, we apply principal component analysis to the eight alternative decompositions and use the first-component scores as our **PC1** measures. **BK**: Baxter-King filter; **CF**: Christiano-Fitzgerald filter; **HA**: Hamilton filter; **HP**: Hodrick–Prescott filter; **BN**: Beveridge–Nelson decomposition; **UCM**: Univariate UCM with Random Trend; **TC**: trend/cycle decomposition with structural breaks (Mohr, 2005); **HPb**: HP decomposition with structural breaks.

Fig. D.7. Cycle/trend decompositions and the first principal component for US.

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