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Estimating the Business Cycle of Ukraine Under the Conditions of Large External Compound Shocks

Abstract. Introduction. *Conventional business cycle estimation methods typically rely on the assumption that the shocks to an economy are normally distributed. However, global social and political instability can result in external shocks that are more severe than purely economic shocks, thus hampering the ability of these estimation methods to separate cyclical behavior from long-run dynamics. Since effective economic policy is dependent upon the ability to make accurate forecasts, an understanding of the properties of business cycle estimation methods in the presence of large shocks in the data is of first order importance.*

Purpose. *The purpose of this article was to compare the ability of various business cycle estimation methods — and in particular detrending filters — to account for large external compound shocks (i.e. those containing both economic and non-economic components) when extracting the cyclical component of the real GDP series of Ukraine. In view of Ukraine's policy of European integration, a secondary goal was to investigate the performance of various detrending filters in deriving a measure of business cycle co-movement of Ukraine vis-à-vis the EU that is robust to external compound shocks.*

Results. *Using an unobserved components model with external geopolitical shocks as a benchmark, it was found that the application of the boosted Hodrick-Prescott filter, the Christiano-Fitzgerald filter, and the Hamilton regression filter to the real GDP data of Ukraine produced cyclical components that exhibited spurious dynamics, particularly from 2020 and onward.*

Conclusions. *It was shown that no single business cycle estimation method performed the best in application to the real GDP series of Ukraine. While the unobserved components model relied on extensive researcher-specified assumptions and an ad hoc approach to identifying external compound shocks, the use of data filtering resulted in series that did not accurately reflect cyclical and trend dynamics in Ukraine toward the end of the sample. Thus, there is a practical need to develop new business cycle estimation models that would be able to account for the distorting influence of large external compound shocks.*

Keywords: *business cycles; external shocks, unobserved components model; detrending filters; business cycle co-movement; European integration.*

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Моделювання ділового циклу України в умовах великих зовнішніх неекономічних шоків

Стандартні методи моделювання ділових циклів типово ґрунтуються на припущені, що шоки в економічній системі є нормально розподіленими. Проте соціальна й політична нестабільність у світі може призвести до потрясіння таких систем зовнішніми шоками, що є набагато більш екстремальними, ніж суто економічні шоки. Це, своєю чергою, може призводити до неточної оцінки циклічної й довгострокової динаміки в рамках застосування цих методів.

У цій статті було проаналізовано здатність так званих фільтрів детрендингу ефективно вилучити циклічний компонент реального ВВП України в умовах зовнішніх компаудних шоків, тобто таких, що містять позаекономічну складову. З огляду на пріоритетність євроінтеграційного напряму політики України, було також розглянуто можливість застосування цих фільтрів для побудови міри синхронізації ділових циклів України та ЄС, що є стійкою до зовнішніх компаудних шоків.

За результатами дослідження було виявлено, що, у порівнянні з моделлю неспостережуваних компонентів, в якій зовнішні компаудні шоки можна врахувати безпосередньо, застосування фільтрів детрендингу — а зокрема посиленої версії фільтра Ходріка-Прескотта, фільтра Крістіано-Фіцджеральда і регресійного фільтра Гамільтона — призводило до, в тій чи іншій мірі, неточних оцінок ділового циклу України.

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З іншого боку, в результаті застосування моделі неспостережуваних компонентів було отримано таку оцінку ділового циклу України, що можна було узгодити з висновками описового підходу до аналізу економіки України. Попри це, модель неспостережуваних компонентів має суттєвий недолік, який полягає у тому, що її застосування ґрунтується на великій низці припущень і ad hoc підходу до визначення зовнішніх компаудних шоків. Отже, з точки зору розробки економічної політики, модель неспостережуваних компонентів складно застосовувати систематично.

З огляду на це, робиться загальний висновок, що, враховуючи сучасні економічні реалії в Україні й світі в цілому, набуває актуальності розробка нових підходів до моделювання ділових циклів, які б мали вбудовані механізми для врахування ефектів зовнішніх компаудних шоків.

Ключові слова*: ділові цикли; зовнішні шоки; модель неспостережуваних компонентів; детрендингові фільтри; синхронізація ділових циклів; євроінтеграція.*

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Formulation of the problem. Conventional business cycle estimation techniques are often grounded in the assumption that the shocks to the economic series of interest are independent and normally distributed. Under these assumptions, Utlaut and van Roye have shown that external shocks can have a significant impact on the business cycles of emerging economies [1]. However, there has recently been a rise in the number and severity of external compound shocks (i.e. those containing both economic and non-economic components) that are distinctly non-Gaussian; of note are the COVID-19 pandemic and the Russian invasion of Ukraine.

Some of the commonly used detrending filters — such as the Hodrick-Prescott filter — are well-known to suffer from an end-point bias that results in the observations at the end of the sample being given disproportionately large weight in determining the shape of the trend and cyclical components. In this respect, the 2022 situation in Ukraine presents a particularly challenging scenario for detrending filters.

Another problem relates to the duration of business cycles. Filters that were developed specifically to overcome the issue of end-point bias — such as the Hamilton regression filter — have been shown to have ambivalent properties in the frequency domain.

In contrast to the filters described above, the unobserved components model — given the right specification — has the advantage of being able to decompose level series into trend and cyclical components that are adjusted for the influence of external compound shocks. Nevertheless, the unobserved components model has the drawback of requiring the researcher to specify prior information about the behavior of the trend and cyclical components.

Since effective economic policy is largely dependent upon the ability of policymakers to assess the current state of event and make accurate forecasts, a comprehensive understanding of the performance of these business cycle estimation methods in the face of large external compound shocks is imperative. From the point of view of Ukraine's European integration policy, unbiased estimation of its business cycle and its co-movement vis-à-vis the EU is of particular relevance.

Analysis of recent research and publications. One of the first studies to analyze the various properties of detrending filters was done by Canova (1998), in which one of the notable findings was that the quantitative and qualitative features of detrended economic series were not robust to the choice of filter in the case of the US data [2]. Since then, the properties of newly developed detrending filters were generally investigated using the time and frequency domain methodology of Canova (1998) [2]. In this respect, one of the most comprehensives overviews with application to the macroeconomic series of the US was provided in Larsson and Vasi (2012) [3].

While the former studies focus on the US data, there has recently been a rising interest in analyzing the properties of detrending filters with application to other countries. In particular, Luvsannyam et al. (2019) find that the timing of recessions in the detrended real GDP series of Mongolia, as dated by the Harding-Pagan algorithm, is dependent upon the choice of filter [4]. Paramaguru (2021) reaches a similar conclusion with respect to the real GDP series of the United Kingdom. However, unlike Luvsannyam et al. (2019), Paramaguru (2021) finds that the Hodrick-Prescott filter produces cyclical series with more frequent recessions than the Hamilton regression filter [5, p. 12]. This suggests that the properties of detrending filters may in fact be country-dependent.

The properties of detrending filters with application to the nominal GDP series of Ukraine were recently investigated by Bhowik (2020) [6]. In this respect, the present study extends the findings of Bhowik (2020) [6] to the real GDP series of Ukraine, which covers a longer and more structurally heterogeneous period.

Formulation of research goals. The purpose of this study was to compare the ability of various detrending filters to account for external compound shocks when extracting the cyclical component of the real GDP series of Ukraine.

Outline of the main research material. Following the concept of *growth cycles*, business cycles are extracted from some level series y_t via its decomposition into a long-term trend τ_t and cyclical fluctuations c_t. In the present study, the following three commonly used detrending filters were considered: the unobserved components model, the boosted Hodrick-Prescott filter, the Christiano-Fitzgerald filter, and the Hamilton regression filter. To begin with, a brief overview of their theoretical properties is provided.

The boosted Hodrick-Prescott filter (bHP) is a machine-learning-enhanced version of the standard HP filter that was introduced by Phillips and Shi (2021) [7]. The bHP extracts the cyclical component of a series through repeated solving of the original HP optimization problem that fits a smooth trend to the level series. Mei et al. (2022) show that in simulations, the bHP filter performs well in a variety of settings, including series with stochastic trends and structural breaks [8].

The Christiano-Fitzgerald (CF) filter reformulates the cycle extraction problem in the frequency domain. In particular, the CF filter is an asymmetric approximation of the ideal band pass filter that preserves fluctuations at the *business cycle frequency* that, following Burns and Mitchell (1946), lasts from 6-32 quarters [9, 10]. Since the CF filter is asymmetric, its application does not involve the loss of observations at the beginning and the end of the sample.

The Hamilton regression (HR) filter is the most recently introduced filter that was developed by Hamilton (2018) to overcome the shortcomings of the standard HP filter. In order to separate the cyclical component of a series from the trend, Hamilton (2018) proposes to estimate a two-years-ahead forecast using a constant, the current value of the series and the three most recent lags. The cyclical component at time *t* is then defined as the difference between the forecast and the actual observed value of y_t [11]. Furthermore, Hodrick (2020) shows that in simulations, the HR filter outperforms the standard HP filter when the underlying data generating process is a random walk with drift; nevertheless, as the complexity of the underlying data generating process grows, the performance of the HR filter deteriorates [12, p. 24-25].

In order to assess the ability of the filters described above to handle external compound shocks, the cyclical and trend components extracted via their application were compared to the output of an unobserved components model in which these shocks were included as exogenous variables. In short, the specification of the unobserved components (UC) model used in this study decomposes a level series y_t as follows:

$$y_t = \tau_t + c_t + \beta \times shocks_t + \epsilon_t, \qquad (1)$$

where y_t, τ_t, and c_t are defined the same as before, $shocks_t$ is a dummy variable that takes the value of 1 at time *t* if a specific shock has occurred and 0 otherwise, and ϵ_t is a white noise error term. In this formulation, the estimated term $\beta \times shocks_t$ explicitly captures the effect of external compound shocks so that it is not absorbed by the cyclical component or the trend component. Due to the similarity of the UC model to the detrending filters, and for the sake of brevity, it is hereinafter referred to as the UC filter.

In the present application, three distinct large external compound shocks to the economy of Ukraine were identified: the 2014 Russian invasion of Ukraine, the COVID-19 pandemic, and the 2022 Russian invasion of Ukraine. Thus, three dummy variables for each of these crises enter equation (1) and respectively take the values of 1 from 2014Q1, 2020Q1, and 2022Q1 and onward, and 0 otherwise. This specification is intended to reflect the fact that these external compound shocks potentially induced long-term changes in the economy that are neither cyclical in nature nor reflect a change in the direction of the overall trend.

Other important modeling choices in equation (1) relate to the specification of the behavior of the trend component τ_t. Following Harvey and Jaeger (1993), τ_t was modeled as an integrated random walk, thus enforcing a smooth trend [13].

The data used in this study were the real GDP series of Ukraine, sourced from the World Bank's Global Economic Monitor database [14]. Moreover, data on real GDP for 2022Q4 was supplemented from a preliminary report by the Ministry of Economy of Ukraine [15]. The resulting series is quarterly and covers the period of 2001Q1–2022Q4. Before further analysis, a natural logarithmic transformation was applied to the level series. Data used for the construction of an index of business cycle co-movement of Ukraine vis-à-vis the EU considered later in this study were likewise sourced from the Global Economic Monitor database [14].

The properties of the detrending filters were first analyzed in the time domain. Following the non-parametric quarterly business cycle dating algorithm introduced by Harding and Pagan (2002), turning points and phases in filtered real GDP series were identified via the application of the following set of rules. First, peaks and troughs should alternate and be the local maxima and minima, respectively. Second, a complete business cycle should last no less than five quarters with a minimum expansion (and recession) phase length of two quarters [16, p. 368-369]. Moreover, as suggested by Engle (2007), a threshold rule that overrides the minimum phase length restriction on recessions in the event of a particularly steep but transient economic decline was applied; in particular, the proposed default value of a 10.4% decline with respect to the previous peak was used as the threshold [17]. As shown by Chang and Hwang (2015), the Harding-Pagan algorithm performs well in the case of US data and closely matches the quasi-official NBER business cycle chronology [18].

The evolution of the filtered real GDP series of Ukraine is presented in Fig. 1, with vertical shaded areas representing recessions according to the Harding-Pagan algorithm. For the purposes of comparison, the right side panels also present the unfiltered level series as a dashed line.

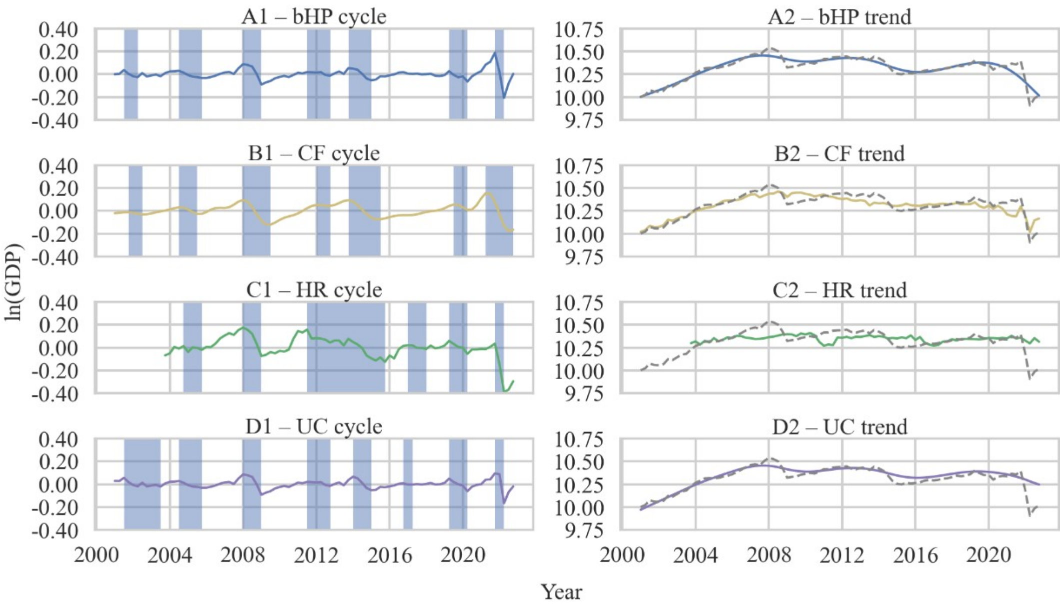

Figure 1 – **Level and filtered real GDP of Ukraine vs. recessions**

Source: compiled by the authors

Fig 1. reveals that while all four filters produce detrended series with recessions that match timing of major shocks, their end-of-sample properties differ. The standard HP filter is well-known to result in biased estimates of the detrended series in the presence of an incomplete cycle at the end of the sample. As elaborated by Alichi (2015), this occurs because the HP filter revises previous estimates as more data becomes available [19, p. 4]. In particular, the HP filter solves an optimization problem that both favors a smooth trend and penalizes deviations from it. Thus, if the sample ends on a major shock but does not include the recovery period, the optimum solution of the HP filter is to bend the trend line in the direction of the shock.

This bias can be clearly observed in panel 2A of Fig 1., which shows that the trend line of the real GDP series of Ukraine — as extracted by the bHP filter — started to display a relatively strong downward slope as early as the end of 2019. However, using a narrative approach, it is evident that the 2022 recession in Ukraine was the result of its reorientation to a war-time economy rather than the culmination of an earlier downward trend. Thus, it is found that the end-of-sample bias persists in the bHP filter and results in spurious cyclical dynamics from 2020 and onward.

The CF filter appears to induce a similar end-point bias in the estimated detrended series. As explained by Steehouwer and Lee (2011), the CF filter relies on the assumption that the underlying data generating process is a random walk, which is used to extrapolate the data beyond the end of the sample when deriving the filter weights [20, p. 5; p. 11]. In the event that the data generating process departs from this assumption, the CF filter may produce inaccurate end-of-sample estimates. Moreover, since the CF filter is asymmetric, it also induces a phase shift near the end of the sample; panel 1B of Fig 1. shows that the CF-detrended series enters into the 2022 recession earlier than the series produced by the other filters.

Unlike the HP and CF filters, the HR filter and the UC model do not produce spurious cyclical dynamics in the 2020–2022 period. However, they differ from the former two filters in terms of the amplitudes of the phases. For the purposes of numerical comparison, the mean duration of recessions and expansions, along with their amplitudes and cumulative movements, are presented in Table 1. Following the triangle approximation of Harding and Pagan (2002), the amplitude of the i^{th} phase is designated as Ai and calculated as the difference between two sequential turning points; duration of the i^{th} phase is designated as Di and is expressed in quarters. Cumulative movement is then calculated as 0.5(Di×Ai), which is an approximation of the cumulative losses (gains) during the i^{th} phase [16, p. 369-371].

Table 1. **Mean characteristics of cycles in detrended real GDP series of Ukraine**

Property	Recessions				Expansions			
	bHP	CF	HR	UC	bHP	CF	HR	UC
Duration	4.00	4.33	5.83	4.25	9.17	8.67	7.00	7.00
Amplitude	-0.13	-0.09	-0.19	-0.11	0.11	0.11	0.15	0.09
Cumulative Movement	-0.26	-0.30	-0.68	-0.24	0.53	0.52	0.59	0.33

Source: compiled by the authors

Strikingly, the HR filter produces detrended series with recessions that are — as measured by the cumulative movement statistics — two to three times more severe than in the case of the other filters. A repeat consideration of plots 1C and 2C of Fig. 1 reveals that the HR filters attributes almost the entirety of the 2022 recession to the cyclical component, which is at odds with the supposition that the observed recession is not cyclical in character. Conversely, expansions in the UC-detrended series are only approximately half as potent as those observed in the other detrended series.

In light of the above, it is not clear which filter produces the most accurate representation of the business cycle of Ukraine. Nevertheless, panels 1A and 1D of Fig. 1 show that the bHP filter — which has been shown to have excellent performance in simulations — and the UC model produce highly similar detrended series that only start to diverge toward the end of the sample; more formally, the Pearson correlation coefficient between the two series over the entire sample is 0.92. Given that the UC model in this study was specified as to explicitly handle external compound shocks, the UC-detrended series is thus deemed to be a reasonable benchmark when comparing filter performance.

Next, the properties of the filters were analyzed in the frequency domain. Periodogram estimates of the power spectral densities of the level and filtered real GDP series are presented in Fig. 2. Following Baxter and King (1999), it is generally accepted that a good business cycle filter should eliminate both low- and high-frequency fluctuations in the data series while preserving fluctuations at the business cycle frequency of 6 to 32 quarters [21, p. 10-11]. Fig. 2 reveals that while all four filters succeed at reducing the power at zero frequency, their performance with respect to intermediate- and high-frequency fluctuations varies. The bHP and UC filters appear to perform the best with respect to preserving fluctuations at the business cycle frequency, although they are less effective at eliminating high-frequency fluctuations than the CF filter. By contrast, the HR filter preserves some low frequency fluctuations and thus does not entirely remove long-term trends from the cyclical component.

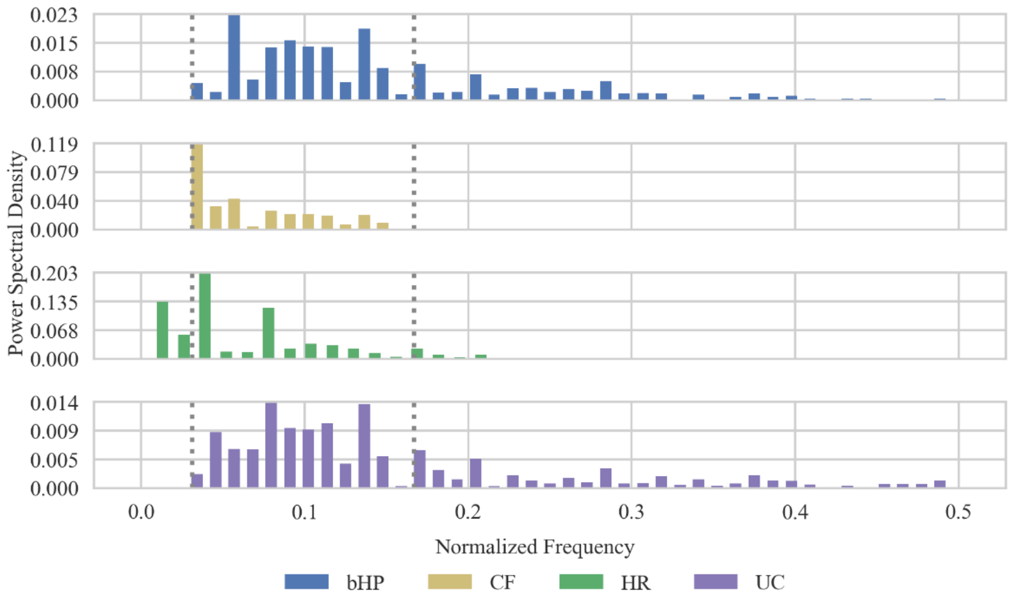

Figure 2 – **Power spectral density plot of detrended real GDP series of Ukraine**

The dashes vertical lines delimit the business cycle frequency range of one cycle per 6-32 quarters.
Source: compiled by the authors

Lastly, filter performance was considered in terms of its practical application. Estimates of cyclical components of real GDP series are frequently used when assessing the degree of business cycle co-movement among countries, which has implications for economic integration policy. Here, business cycle co-movement of Ukraine vis-à-vis the EU was computed as the cross-sectional mean of the negative Euclidean distance between the cyclical components of the real GDP series of Ukraine and 26 EU countries (not including Luxembourg); results are presented in Fig. 3.

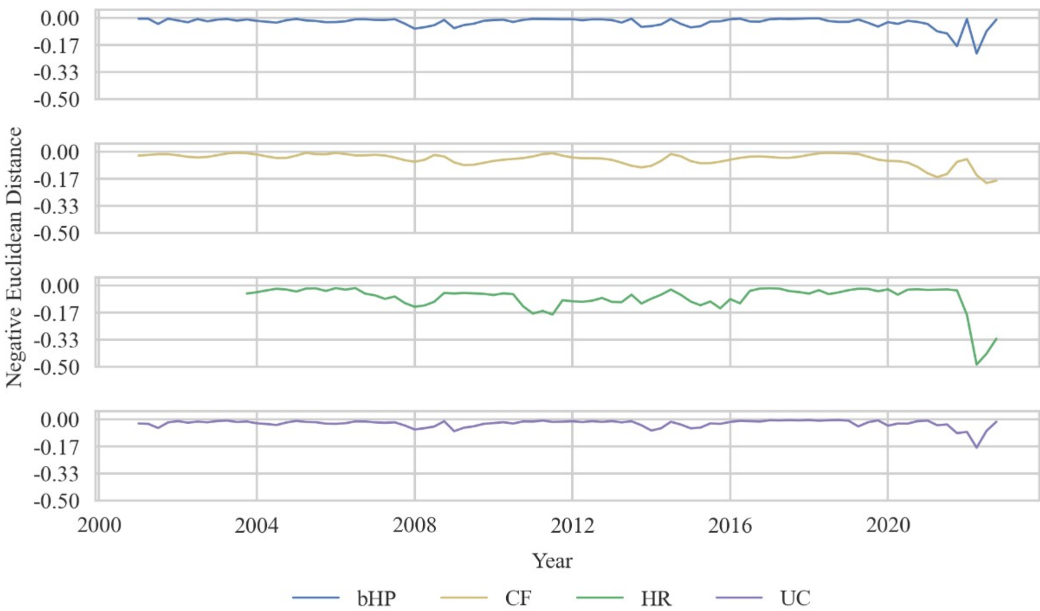

Figure 3 – **Co-movement of detrended real GDP series of Ukraine vis-à-vis the EU as estimated with different filters**

Source: compiled by the authors

Fig. 3 reveals that the application of different filters can lead to diverging conclusions regarding business cycle co-movement. In particular, the co-movement of the cyclical components of the real GDP series of Ukraine and EU countries — as estimated via the bHP and UC filters — rebounded to previous levels after an initial decline at the beginning of 2022. Conversely, the co-movement of the cyclical components estimated via the CF and HR filters remained low through the entirety of 2022. Notably, due to the fact that the UC filter avoids spurious cyclical dynamics from 2020 and onward, the evolution of the co-movement of the series detrended via its application is smoother than in the case of the bHP filter.

Thus, the differences in the time and frequency domain properties of the filters considered, as well as the resulting discrepancies in their practical application, suggest that their use should be context-sensitive. Overall, the UC filter appears to provide the most reasonable estimate of the business cycle of Ukraine in the face of external compound shocks, as evidenced by its favorable properties in the time and frequency domains. Nevertheless, its ad hoc specification and identification of external compound shocks casts doubt on whether it can be used in a systematic manner.

Conclusions. In this study, the ability of the bHP, CF, HR, and UC filters to handle external compound shocks was assessed with application to the real GDP series of Ukraine.

It was found that the bHP, CF, and HR filters — which implicitly separate a time series into trend and cyclical components — produced potentially biased series. In particular, the bHP and CF filters largely described the 2022 recession as the culmination of an earlier downward trend. Conversely, the HR filter attributed the 2022 recession almost entirely to a cyclical decline.

Following a narrative approach to the economy of Ukraine, neither version seems to be accurate. On the one hand, the real GDP of Ukraine was trending upward prior to the invasion by the Russian Federation. Thus, the 2022 recession appears to be more akin to a structural break than a change in the direction of the trend. On the other hand, the 2022 recession is also likely to have long-term consequences that will go beyond the length of a typical business cycle.

Conversely, the UC filter — through the explicit inclusion of dummy variables for external compound shocks — appeared to produce series with more reasonable dynamics. In particular, neither the cyclical nor the trend component displayed shifts in amplitude or direction that would go beyond what is expected of a severe but purely economic shock. Thus, the impact of the 2022 recession was mostly absorbed by the dummy variable for the Russian invasion of Ukraine. Moreover, the series produced by the UC filter performed favorably in both time and frequency domains.

In practical terms, the UC filter also outperformed the bHP and CF filters in producing a measure of business cycle co-movement of Ukraine vis-à-vis the EU that did not display a drop in co-movement prior to 2022 that, in the case of the latter two filters, was the result of end-point bias.

This illustrates that, in the face of the rise of global social and political instability, there is a need to develop models that would explicitly handle the distorting impact of large compound shocks, as conventional models are likely to produce estimates that are biased. In the case of Ukraine, it is shown in this study that — by constructing an ad hoc model that accounts for such shocks and cross-referencing its output with that of conventional models — it is possible to derive reasonable estimates of the business cycle of Ukraine even with 2022 data; such estimates are of particular interest for further development of Ukraine's European integration policy. Nevertheless, the ad hoc nature of some of the modeling choices are likely to make the model specification used in this study unsuitable for other applications.

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