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Research Paper

Identifying the impact of the business cycle on drug-related harms in European countries

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ABSTRACT

Background: The evidence resulting from the analysis of the association between economic fluctuations and their impact on the substance use is mixed and inconclusive. Effects can be pro-cyclical (drug-related harms are predicted to rise when economic conditions improve), counter-cyclical (drug-related harms are predicted to rise in bad economic times) or unrelated to business cycle conditions as different transmission mechanisms could operate simultaneously.
Methods: The main aim of this study is to assess, from a macroeconomic perspective, the impact of economic cycles on illegal drug-related harms in European countries over the 2000-2020 period. To this end, the regime-dependent relationship between drug-related harm, proxied by unemployment, and the business cycle, proxied by overdose deaths will be identified. Applying a *time dynamic linear* analysis, within the framework of *threshold panel data* models, structural-breaks will also be tested.
Results: The relationship between economic cycles (proxied by unemployment) and drug-related harms (proxied by overdose deaths) is negative, and therefore found to be pro-cyclical. One percentage point in the country unemployment rate is predicted to reduce the overdose death rate by a statistically significant percentage of 2.42. A counter-cyclical component was identified during the 2008 economic recession. The threshold model captures two effects: when unemployment rates are lower than the estimated thresholds, ranging from 3.92% to 4.12%, drug-related harms and unemployment have a pro-cyclical relationship. However, when unemployment rates are higher than this threshold, this relationship becomes counter-cyclical.
Conclusions: The relationship between economic cycles and drug-related harms is pro-cyclical. However, in situations of economic downturns, a counter-cyclical effect is detected, as identified during the 2008 economic recession.

Introduction

There is a considerable body of literature that analyzes the association between economic fluctuations and their impact on health (Catalano et al., 2011; Falagas et al., 2009; Stuckler et al., 2009; Stuckler et al., 2015). Nevertheless, the evidence resulting from this research is mixed and inconclusive. On the one hand, the consequent reduction in disposable income during periods of economic downturn, would lead to a potential deterioration in health outcomes (Marmot et al., 2008; Marmot & Bell, 2009). This situation seems to be more likely in countries with weaker social coverage. On the other hand, individuals may adopt healthier lifestyles, for example, by reducing their consumption of tobacco or alcohol. At aggregate level, there could also be an improvement in environmental conditions (Gertham & Rhum, 2006; Ruhm, 2005; Tapia-Granados & Ionides, 2008; Suhrcke & Stuckler, 2012). Even assuming that past recessions may have had some health benefits for certain population groups, there is evidence suggesting that economic downturns tend to have a greater negative effect on more vulnerable groups, like drug users, than on the overall population (Thomson et al., 2015).

It is well known that mental health is determined by socioeconomic and environmental factors and it is sensitive to economic changes (Thomson et al., 2018; Frasquilho et al., 2015; Guerra & Eboreime, 2021; Silva et al., 2020). Poverty, financial problems, and social deprivation are major socioeconomic risk factors for mental health problems and disorders (Fryers et al., 2005; Laaksonen et al., 2007). Symptoms

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related to depression and anxiety at the individual level rise with economic constraints, and may be reflected in an increase in risk factors, such as smoking, alcohol consumption, and drug use (Catalano et al., 2011; Dávalos et al., 2012; Degenhardt et al., 2018; Suhrcke & Stuckler, 2012).

Increased suicide rates and drug/alcohol-related deaths observed among certain groups of young and middle-aged men, especially in high-income countries, highlight the importance of analzying mortality rates and the associated burden of diseases (Case & Deaton, 2015; Ward et al., 2019; Patton et al., 2009, Snipes et al., 2011). In the US, mortality rates have been extensively studied (Case & Deaton, 2015; Shiels et al., 2019). Between 2014 and 2017, the overall life expectancy at birth fell in this country, reversing a century-long trend of declining mortality rates (Case & Deaton, 2017). Early mortality rates were mostly linked to drug overdoses, primarily from opioids, alcohol use, and suicides. These trends have been reaching epidemic levels, as is the case of opioid use in the USA (Case & Deaton, 2015; Dasgupta et al., 2018; Ruhm, 2019). Nevertheless, understanding the causes of these trends is not a straightforward task. Some authors refer to supply factors (Ruhm, 2019; Hempstead & Yildirim, 2014; Alpert et al., 2018; Hughes et al., 2020), while others highlight the role of structural economic changes caused by economic recessions, which may lead to desperation (Case & Deaton, 2015; Case & Deaton, 2017; Betz & Jones, 2018; McLean, 2016; Monnat, 2018; Wagner et al., 2019).

The results of the analysis of the effects of economic recessions on the prevalence of substance use in the European are also mixed and inconclusive. Effects can be pro-cyclical if drug-related harms are predicted to rise in bad economic times (Ruhm, 2005; Ettner, 1997; Granados, 2005; Arkes, 2012; Dávalos et al., 2012; Xu, 2013); counter-cyclical (Compton et al., 2014; Colell et al., 2015; Currie & Tekin, 2015; Golden & Perreira, 2015); or unrelated to business cycle conditions (McInerney et al., 2013; Ruhm, 2015).

Economic conditions impact on drug use through different transmission mechanisms that operate simultaneously, with various intensities and possibly contradictory impacts. The magnitude of overall impact depends on, among other factors, the severity of the economic recession, dominant transmission mechanisms, and the intensity and direction of each underlying mechanism.

Main five main transmission mechanisms can be identified (Casal et al., 2023). With the *income effect* mechanism, a reduction in disposable income means that fewer goods are purchased. Therefore, drug use decreases if drugs are considered normal goods (Dom et al., 2016). Conversely, according to the *economic-stress effect*, in periods of economic hardship and declining income, an increased amount of drugs may be used to help manage additional stress and tackle mental health issues (Frasquilho et al., 2015; Lijffijt et al., 2014). The *opportunity cost effect* states that, in periods of economic downturn, individuals working fewer hours and enjoying more free time may be increasingly willing to spend more time using drugs (Ruhm, 2000). The *supply effect* mechanism suggests that changes in drug use can be related to drug market conditions. Through economic hardship, people may feel pressurized to earn money through illegal activities. As a result, there is an increase in drug production, trafficking, and availability, driving drug prices down by stimulating the purchase of drugs (Costa & De Grauwe, 2009; Bretteville-Jensen, 2011). Finally, the *substitution effect* suggests that users may be tempted to substitute expensive drugs for cheaper ones or/and to adopt riskier patterns of use, impacting on drug-related harms (Lakhdar & Bastianic, 2011).

A detailed empirical analysis is therefore required by type of drug, specific social-subpopulations, and user characteristics (for instance, age) (Casal et al., 2023; Dom et al., 2016; De Goeij et al., 2015; Nagelhout et al., 2017). Casal et al. (2023) systematically reviewed the scientific literature and ran a meta-analysis to assess the impact of economic recessions on the use of illicit drugs. They concluded that economic downturns have a larger impact on the people who use drugs more frequently, tending to increase its prevalence, especially among groups of high-risk users. Other studies link business cycles to illicit drug use, using specific macroeconomic indicators rather than analyzing only the time-trends for drug use (Chalmers & Ritter, 2011; Carpenter et al., 2017; Hollingsworth et al., 2017; Ayllón & Ferreira-Batista 2018; Martin & Vall, 2016; Palling & Val (2017).

The aim of this study is to assess from a macroeconomic perspective the impact of economic cycles on illegal drug-related harms, in European countries over the 2000 to 2020 period. This research addresses two main questions: (1) if there has been a change in drug-related harms during the periods of economic crisis in EU countries and (2) the extent to which these changes can be associated with economic risks factors. Our article contributes empirically and methodologically to the debate on the impact of the economic cycle on drug-related harms.

Methods

This study analyzes non-linear relationships between macroeconomic conditions (proxied by unemployment rates), and overdose deaths, thus allowing for thresholds to identify structural breaks. The effects of an economic crisis on drug-related harms may have a strong and persistent dynamic component over time as different impacts of recession exist in the short- and long-term. In this sense, the model includes time lags in order to capture this potential effect. The sample includes 30 European countries (27 EU Member States, along with Norway, Turkey, and the United Kingdom) over the 2000-2020 period

Data and descriptive statistics

We consider two main variables in our analysis:

1 Drug-related harm variable

Mortality associated with drug use is the most dramatic health harm systematically monitored (*EMCDDA,* 2017). In Europe, drug overdoses are the main cause of death among high-risk users, even if under-reporting is considered for certain countries and years. In this research, *overdose deaths* are used as a dependent variable, since they represent the most adverse consequence of drug use. Overdoses deaths, as defined by the EMCDDA, refer to the overdose deaths directly caused by illegal drugs and mortality among drug users.

In order to guarantee the consistency of the data collected, the EMCDDA has a European Drug-Related Deaths protocol (EMCDDA, 2010). It establishes harmonized criteria to collect data based on the information available in different mortality registries at the endpoint of the chain of certification/ascertainment procedures. The EMCDDA concept of drug-induced deaths (DRD) is defined within the DRD protocol as 'people who die directly due to use of illegal substances', although these often occur in combination with other substances such as alcohol or psychoactive medicines. In the very specific field of drug-related deaths, the data used in this analysis, is the only dataset which has consistently been subject to harmonization and improvement practices.

The source of overdose death data is the *EMCDDA Statistical Bulletin* (EMCDDA, 2022).

1 Business cycle variable

The unemployment rate is used as the indicator for the business cycle. Recent studies have addressed the effects of unemployment on the risk of suffering mental health disorders (Urbanos-Garrido & Lopez--Valcarcel, 2015; Kaspersen et al., 2016). Unemployment is also associated with a higher risk of premature death (Brenner et al., 2011; Bloemen et al., 2018; d'Errico et al., 2021; Vodopivec et al., 2021). Among the studies that use macroeconomic indicators to explain drug use and harms, the vast majority of the literature uses unemployment as as proxy for assessing economic recessions affecting households and individuals (Dávalos et al., 2012; Nagelhout et al., 2017; Carpenter et al., 2017; Hollingsworth et al., 2017; Ayllón & Ferreira-Batista, 2018; Martin & Vall, 2016; Palling & Vall, 2017; Bosque-Prous et al., 2015; Kaiser et al., 2017). Unemployment is commonly measured by unemployment rates: the number of persons who are not employed (aged 15 to 74) as a percentage of the total population.

The literature suggests that economic recessions impact more severely on youth unemployment than they do on overall unemployment (Tanveer et al., 2012; Liotti, 2020). Therefore, *youth unemployment*, defined as unemployed people aged 15 to 24 as a percentage of the total population, was also considered in estimations.

Labor market data were extracted from *Eurostat Labour Force Survey Satistics* (Eurostat, 2022).

Tables 1A and 1B provide the descriptive statistics for the set of variables used in the empirical analysis.

Fig. 1 shows the general trends in overdose deaths and unemployment rates between 2000 and 2020 for the countries included in the analysis. In 2003 and 2019, overdose deaths registered their lowest values, registering 1.45 deaths and 1.54 deaths per 100,000 inhabitants, respectively. Aggregated overdose deaths reached a maximum in 2009 and 2017 (2.09 deaths per 100,000 inhabitants and 2.1 deaths per 100,000 inhabitants, respectively). The figure does not reveal an obvious relationship between economic conditions and drug-related deaths. On the contrary, observed trends suggest that the models to be estimated are capable of dealing with nonlinearities. The effects of unemployment on overdose deaths could not be captured in the same period of time, and, for some subperiods, a recurrent lag between both variables is also observed. The use of distributed lag-models that allow for lags in order to capture possible adaptive expectations is well-known in the literature (see e.g. Grether (1977)). In this paper we allow for the possible existence of a lagged effect of the impact of macroeconomic conditions on overdose deaths.

A lag of approximately two years can be observed between the rise of unemployment (2008-2010) and the increase in the overdose rate. From 2010, the overdose death rate consolidated its upward trend. In the same way, a counter-cyclical effect is also observed during the economic recovery period (from 2014 to 2019). The unemployment rate took a downward turn during these years and the decline in the overall overdose rate started approximately two years after a fall in the unemployment rate. This preliminary descriptive analysis suggests that a dynamic panel threshold model could be developed to examine the relationship between the business cycle and drug-related harms.

Empirical strategy

Until now, the relationship between macroeconomic conditions and drug-related death has been analyzed in the context of traditional panel models (Hollingsworth et al., 2017; Powell et al., 2018, Ionides et al., 2013; Palling & Val, 2017; Ruhm, 2015). Nevertheless this study introduces *two* novelties in literature that focuses on macroeconomic conditions and drug death rates: *first,* we consider the possibility that drug-related harm variables may have a strong, persistent, and dynamic component in time, allowing for a lagged dependent variable and also endogenous covariates; *second*, we also consider that economic proxy variables can be used as a threshold variable to describe a structural break in the relationships between drug-related harms and the unemployment rates.

The theoretical argument to support the first dynamic behavior is due to the possible persistence in time of causes that affect, for example, drug death rates, including provision of health services or economic recessions, among others (Snowdon, 2022). For instance, when a person loses his/her job, it will take some time for that person to adjust to his/her new socioeconomic condition and to be fully exposed to this additional stress. Many new situations are not immediate either: being exposed to stress, swapping their drug-taking methods, or being exposed to potential overdose. Therefore, the following panel data model (in a

Table 1A
Data set description and descriptive statistics.

Variable	Description	Source	Period 2000-2020 for the 30 countries of the sample except Romania. Obs.	Mean	Std. Dev.	Min.	First quartile	Median	Third quartile	Max.	Period 2005-2014 for the 30 countries of the sample except Romania and the Czech Republic Obs	Mean	Std. Dev.	Min.	First quartile	Median	Third quartile	Max.
Overdose	Overdose deaths EMCDDA 'national definition' per 100 thousand inhabitants	*EMCDDA Statistical Bulletin 2021-Overdose Deaths*	560	1.92	1.84	0.04	0.61	1.29	2.55	12.83	288	1.92	1.91	0.04	0.58	1.21	2.71	12.83
Unemployment	Unemployed population from 15 to 74 years. Percentage of total population.	*EUROSTAT-Labour force survey*	600	5.34	2.66	1.3	3.5	4.75	6.20	17.3	290	5.60	2.71	1.8	3.7	5.1	6.2	17.3
Youth unemployment	Unemployed population from 15 to 24 years. Percentage of total population.	*EUROSTAT-Labour force survey*	599	7.68	3.21	1.7	5.5	7.00	9.3	21.0	289	8.14	3.26	2.3	5.9	7.3	9.8	21.0

Notes:
The 30 countries included in the sample are: Austria, Belgium, Bulgaria, Croatia, Cyprus, Czechia, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Latvia, Lithuania, Luxemburg, Malta, the Netherlands, Norway, Poland, Portugal, Romania, Slovakia, Slovenia, Spain, Sweden, Turkey, and the United Kingdom.

Table 1B
Descriptive statistic for the half-periods that are employed.

Variable	Period 2005-2009 for the 30 countries of the sample except Romania and the Czech Republic								Period 2010-2014 for the 30 countries of the sample except Romania and the Czech Republic							
	Obs.	Mean	Std. Dev.	Min.	First quartile	Median	Third quartile	Max.	Obs	Mean	Std. Dev.	Min.	First quartile	Median	Third quartile	Max.
Overdose	145	1.96	1.70	0.04	0.63	1.54	2.71	9.96	143	1.88	2.11	0.10	0.55	0.98	2.92	12.83
Unemployment	145	4.65	1.76	1.80	3.50	4.30	5.40	11.70	145	6.56	3.13	2.20	4.50	5.70	7.90	17.30
Youth unemployment	144	7.08	2.46	2.30	5.50	6.60	8.60	17.00	145	9.20	3.61	3.50	6.60	8.50	11.5	21.00
	Period 2000-2009 for the 30 countries of the sample except Romania								**Period 2010-2020 for the 30 countries of the sample except Romania**							
Variable	**Obs.**	**Mean**	**Std. Dev.**	**Min.**	**First quartile**	**Median**	**Third quartile**	**Max.**	**Obs**	**Mean**	**Std. Dev.**	**Min.**	**First quartile**	**Median**	**Third quartile**	**Max.**
Overdose	266	1.93	1.68	0.04	0.69	1.53	2.51	9.96	294	1.92	1.98	0.10	0.10	1.16	2.86	12.83
Unemployment	282	4.97	2.30	1.30	3.30	4.40	5.80	12.40	318	5.66	2.90	1.30	3.70	5.05	6.50	17.30
Youth unemployment	281	7.44	2.99	2.30	5.50	6.90	8.00	17.80	318	7.90	3.38	1.70	5.50	7.20	9.80	21.00

Notes:
[a]The 30 countries included in the sample are: Austria, Belgium, Bulgaria, Croatia, Cyprus, Czechia, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Latvia, Lithuania, Luxemburg, Malta, the Netherlands, Norway, Poland, Portugal, Romania, Slovakia, Slovenia, Spain, Sweden, Turkey, and the United Kingdom.

log-level specification as in Rhum (2000) and Powell et al. (2018)) where allow for one lag of the dependent variable (i.e., introducing dynamics) and fixed effects (capturing any country-specific factors that differ across countries, but these factors do not vary over time) can be considered:

$$lnY_{jt} = \beta_0 + \beta_1 lnY_{jt-1} + X_{jt}'\alpha_1 + \eta_j + \varepsilon_{jt} \tag{1}$$

In Eq. (1), Y_{jt} represents a dependent variable that captures drug use harm in country j for year t; X_{jt} is a vector of possibly time-varying endogenous covariates, including lagged covariates or dummies, in addition to the traditional business cycle model and country-level indicators for economic crisis in year t;. η_j represents country fixed effects. ε_{jt} is the error term.

For the statistical analysis, the STATA program, version 16 (Stata Corp., College Station, United States) was used. In order to check the robustness of the results, the unknown parameters $(\beta_0, \beta_1, \alpha_1')'$ are estimated through two different estimations methods: 1) the *Arellano and Bond* estimator (Arellano & Bond, 1991), abbreviated as AB estimator (STATA command: xtabond), and 2) through the Arellano and Bover (Arellano & Bover, 1995) / Blundell and Bond (Blundell & Bond, 1998) estimator, abbreviated as ABBB estimator (STATA command: xtdpdsys). *Standard t-tests* in (1) for the null hypothesis that $\beta_1 = 0$, were carried out in our empirical application to check for the presence of the lagged effects.

As for our second novelty in the literature, in (1), we allow for a threshold variable and a threshold parameter that divide the equation into two regimes. *Dynamic threshold panel data* models have been proposed in previous literature (Avom et al., 2022; Seo and Shin, 2016; Seo et al., 2019; Yu et al., 2021; Zhu et al., 2020) and, recently, they have started being employed in health models (Abdussalam et al., 2022; Gaies, 2022). This modeling strategy, to the best of our knowledge, has not previously been used in existing research determining the relationship between economic hardship and illegal drug-related harms.

Therefore, the general framework for a *dynamic threshold panel data* model, as proposed in Seo and Shin (2016), is given as:

$$lnY_{jt} = \beta_0 + \left(\beta_1 lnY_{jt-1} + X_{jt}'\alpha_1\right) 1U_{jt} < \gamma + \eta_j + \varepsilon_{jt} \ + \left(\beta_2 lnY_{jt-1} + X_{jt}'\alpha_2\right) 1U_{jt} \geq \gamma \tag{2}$$

for country j=1,…,N and year t=1,…, T. $1U_{jt} \geq \gamma$ in (2) is an indicator function that equals 1 when $U_{jt} \geq \gamma$ holds and 0, otherwise. We use U_{jt} (unemployment rates) as the threshold variable to capture macroeconomic conditions and γ is the threshold parameter. The unknown parameters $(\beta_0, \beta_1, \beta_2, \alpha_1', \alpha_{1S}', \alpha_2', \alpha_{2S}', \gamma)'$ in (2) are estimated through the estimator developed in Seo et al. (2019) and Seo and Shin (2016). The results when estimating Eq. (1) using data from 2000 to 2020 are robust when reducing the sample size from 2005-2014. Standard t-tests for the null hypotheses that $\beta_1 = 0$ and $\beta_2 = 0$ in (2) are carried out in our empirical application to check that we need the presence of a dynamic model.

In order to estimate Eqs. (1) and (2), although the EMCDDA sample contains 30 countries, Romania was the only country that was not included, as its data were registered at sub-national level and the number of deaths was under-reported (Costa et al., 2011). In Eq. (1), since the AB and ABBB estimators allow for missing data, we use data for the entire 2000-2020 period (Arellano & Bond, 1991; Arellano & Bover, 1995; Blundell & Bond, 1998). Nevertheless, one drawback of Eq. (2) is that the Seo et al. (2019) estimator requires a panel without missing data. Since our dataset contains many missing values, as can be seen in Table 1, a restriction was imposed to limit the analysis to those years with data available for all countries. Consequently, in Eq. (2) the sample was restricted to the 2005-2014 period, the largest available sample data obtained for 28 countries without missing data. The Czech Republic was also removed due to lack of data for this period.

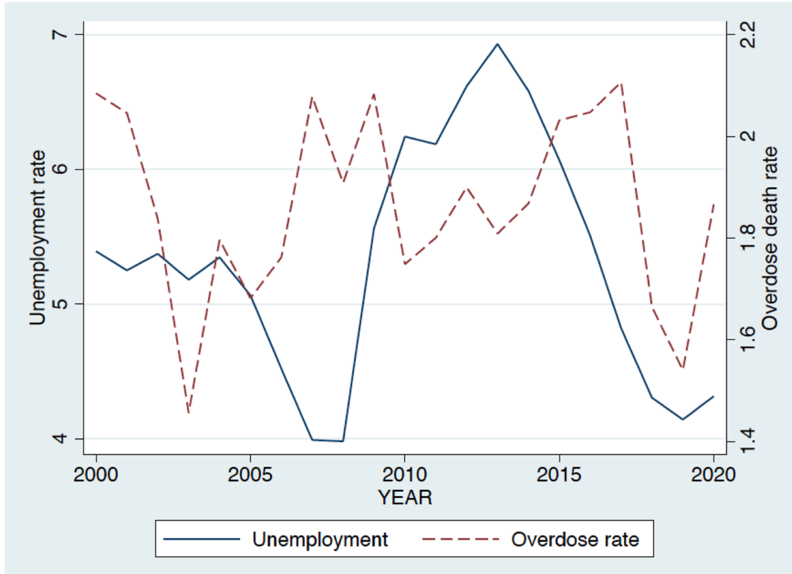

Fig. 1. Annual rate of unemployment and drug overdose deaths (2000-2020)
Source: Own's elaboration using data from EMCDDA and Eurostat. The countries included in the analyzed sample are: Austria, Belgium, Bulgaria, Croatia, Cyprus, Czechia, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Latvia, Lithuania, Luxemburg, Malta, the Netherlands, Norway, Poland, Portugal, Romania, Slovakia, Slovenia, Spain, Sweden, Turkey, and the United Kingdom.

With a sample longer than the 2005-2014 period, estimating Eq. (2) would involve removing a very large number of countries. Therefore, to prevent this loss of cross-section data, we decided to estimate Eq. (2) over this ten-year period. Nevertheless, we argue that his ten-year period is suitable for checking the existence of a structural break, since, during those years, European countries faced periods of economic expansion, recession (such as the global financial crisis), and recovery. Given the drawback of the different sample sizes that were used in Eqs. (1) and (2), the results of these models were considered to check the robustness of our conclusions.

A dummy variable for the years 2007, 2008, and 2009 was included in the estimations to capture the effect of the global financial crisis. 2007 was set as the start of the financial shock, followed by the global financial crisis in 2008, and then the Great Recession, which came after (Costa et al., 2011; Jimborean & Kelber, 2017; Mongelli & Camba--Mendez, 2018; Somarriba et al., 2015). With the aim of capturing COVID-19's effects, a dummy variable for the year 2020 was also included in the specifications.

To test the model and check the robustness of the results, several specifications were implemented, ranging from (1) to (5) in Table 2. These specifications made it possible to introduce a first lag in the dependent variable (overdose deaths) and two lags in the unemployment rate, to test the effects of country's unemployment rate on drug overdose mortality rates in different time periods. The empirical analysis also made it possible to have higher lags in the dependent variable and in unemployment rates to test for the persistence of the effects in the following years, but these were not statistically significant.

Results

Table 2 reports the results from the models estimated on country-level data. As previously mentioned, the high proportion of missing data makes it difficult to find a unique model specification from which we can obtain trustworthy empirical estimates. To overcome this limitation, we follow a similar strategy to the one found in Hollingsworth et al. (2017) by providing estimates for a wide variety of models and different sample sizes, which are nested in (2).

The column of specification (1) in Table 2 shows the results with the unemployment variable as a macroeconomic proxy for the business cycle, an iteration effect of unemployment and a dummy variable during the years 2007, 2008 and 2009, and a dummy variable for the year 2020. According to the primary findings in column of specification (1), the relationship between unemployment and drug death rates is negative, reflecting a pro-cyclical effect between the variables. Given the coefficient of –0.0242 when employing the ABBB estimator, one percentage point in the country unemployment rate is predicted to reduce the overdose death rate by a statistically significant percentage of 2.42. Nevertheless, estimations also suggest that, in times of economic weakness, (represented by the iteration effect between unemployment and a dummy variable for the period 2007-2009), there is a positive component (a counter-cyclical effect) to be added into that relationship. However, the resulting effect, even in the crisis years, is still negative. As a case in point, see, in specification (1) with the ABBB estimator, how 0.0117–0.0242 = –0.0125 continues to produce a negative estimated relationship.

Therefore, we find that as the country unemployment rate increases by one percentage point, the drug death rate per 100 thousand inhabitants decreases by a percentage of 1.25 in the years 2007, 2008 and 2009. This supports the assertion that drug mortality rates are pro-cyclical in Europe. The resulting coefficient for the variable reflecting the effects of COVID-19 is found to be non-significant with robust standard errors adjusted for clustering on the cross-section unit –however when using the wild cluster bootstrap the p-value is approximately 0.1-.

Specification (2) of Table 2 displays estimates with a two-year lag in the unemployment variable to the previous specification, checking for any persistent effects of the country unemployment rate on drug death rates after two years. In order to estimate the length of the effect, other lags in unemployment (different from two) were introduced in the specifications. We could not find statistically significant relationships. These results suggest that drug overdoses tend to increase two years after any increases in unemployment have been detected, confirming the lagged effect observed in Fig. 1.

Results obtained when the ABBB or the AB estimators in Table 2 for specifications (1) to (5) are shown to be robust throughout. The coefficients are similar, both in absolute values and in sign; and in most cases, they present common levels of significance.

The need for a dynamic model is shown in the first row of Table 2,

Table 2
The estimated effects of macroeconomic variables on drug-related overdose deaths.

Regressors	Eq. (1)[a]. 29 Countries. Period: 2000-2020										Eq. (2)[b]. 28 Countries. Period: 2005-2014			
	Parameter estimates by estimation method and specification (1)-(5)										Parameter estimates by regime and specification (4)-(5)			
	ABBB estimator					AB estimator					Lower regime	Upper regime	Lower regime	Upper regime
	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)	(4)		(5)	
First lag of log-overdose	0.7087***	0.7087***	0.7091***	0.7072***	0.7056***	0.5755***	0.5641***	0.5643***	0.5748***	0.5608***	-0.0226	-0.1250***	0.2116**	0.1171
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.678)	(0.000)	(0.046)	(0.297)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]				
Unemployment	-0.0242**	-0.0348***	-0.0347***	-0.0245**	-0.0342**	-0.0283**	-0.0399***	-0.0401***	-0.0286**	-0.0395***	-0.3623***	0.3071***	-0.5716**	0.4849**
	(0.035)	(0.004)	(0.003)	(0.033)	(0.004)	(0.018)	(0.002)	(0.001)	(0.017)	(0.002)	(0.001)	(0.009)	(0.011)	(0.035)
	[0.204]	[0.000]	[0.004]	[0.159]	[0.002]	[0.199]	[0.001]	[0.006]	[0.166]	[0.000]				
Second lag of Unemployment		0.0294**	0.0212**		0.0267**		0.0299***	0.0204**		0.0276***			-0.2203	0.2862
		(0.020)	(0.041)		(0.022)		(0.005)	(0.019)		(0.005)			(0.398)	(0.286)
		[0.000]	[0.002]		[0.000]		[0.001]	[0.001]		[0.001]				
Unemployment multiplied by dummy variable for years 2007, 2008 and 2009	0.0117*	0.0170**		0.0113*	0.0157**	0.0162**	0.0212**		0.0159**	0.0202**	-0.0325***	0.0705***	0.1068*	-0.0829
	(0.077)	(0.043)		(0.086)	(0.048)	(0.031)	(0.016)		(0.035)	(0.019)	(0.001)	(0.000)	(0.055)	(0.170)
	[0.053]	[0.005]		[0.066]	[0.011]	[0.046]	[0.005]		[0.059]	[0.010]				
Dummy variable for year 2020	0.0787	0.1110				0.0519	0.0846							
	(0.176)	(0.117)				(0.328)	(0.176)							
	[0.105]	[0.033]				[0.104]	[0.025]							
Constant	0.1813***	0.0699	0.1320	0.1865***	0.0874	0.2295**	0.1231	0.1963	0.2333***	0.1384	-0.9959**		-1.6130	
	(0.010)	(0.499)	(0.117)	(0.008)	(0.370)	(0.011)	(0.226)	(0.036)	(0.009)	(0.154)	(0.024)		(0.282)	
	[0.292]	[0.520]	[0.804]	[0.195]	[0.739]	[0.291]	[0.462]	[0.805]	[0.205]	[0.742]				
Threshold											4.1181*** (0.000)		3.9208*** (0.000)	

[a] Corresponding to the sample, where Romania is removed due to data being registered at sub-national level and the under-reporting number of deaths (EMCDDA, Statistical Bulletin (2022)). Estimated values and p-values in parentheses (*, **, *** indicate statistically significance at 10%, 5% and 1% respectively) are obtained using robust standard errors adjusted for clustering on the cross-section unit (STATA command: vce (robust)). p-values in brackets are obtained using wild cluster bootstrap (STATA command: boottest). The Arellano-Bond (1991) test for autocorrelation indicate that we cannot reject the null hypothesis of non-existence of serial correlation, implying that moment conditions are valid.

[b] Corresponding to the sample, where Romania is removed due to data being registered at sub-national level and the under-reporting number of deaths (EMCDDA, Statistical Bulletin (2022)). We also excluded The Czech Republic due to lack of data in 2005-2014 period. Estimated values and p-values in parentheses (*, **, *** indicate statistically significance at 10%, 5% and 1% respectively) are obtained with the estimator developed in Seo et al. (2019) and Seo and Shin (2016). The bootstrap p-value of Seo et al. (2019) rejects the null hypothesis of the linearity test in all specifications.

[c]P-values in parenthesis are obtained using robust standard errors adjusted for clustering on the cross-section unit. However, inference may be problematic since we have a small number of countries in our sample (see Cameron and Miller (2015) and MacKinnon, Nielsen and Webb (2023)). We therefore computed p-values in brackets using wild cluster bootstrap. We show that all our results are robust when using p-values in brackets or in parenthesis with the only exception of the statistical significance of the unemployment variable in specifications (1) and (4), where both p-values are in any case also lower than 0.2.

Notes:

according to the standard *t-tests* applied to the lagged components in Eq. (1) –for specifications (1)-(5)– and in Eq. (2), in at least one of the regimes. In Eq. (1), only one period with economic weakness was characterized, using the iteration effect of unemployment multiplied by dummy variable for years 2007, 2008 and 2009. The advantage of Eq. (2) over Eq. (1) is that it makes it possible to analyze the intensity and depth of economic weakness, depending on whether the unemployment rate is above or below the estimated threshold. Thus, it is possible to avoid needing to specify the crisis periods explicitly with dummies.

The estimates for Eq. (2) present new results depending on the level of unemployment: a) *Lower regime*, with unemployment rates lower than the estimated thresholds –in the range of 4.12% for specification (4) and 3.92% for specification (5)–; and b) *Upper regime*: if the unemployment rates exceed the estimated thresholds. The bootstrap test of linearity proposed in Seo et al. (2019) to test for the presence of the threshold effect in the panel provides evidence for rejecting the null hypothesis of linearity. Therefore, evidence is provided on the existence of the threshold part in the empirical application.

The empirical estimates in Eq. (2) allow us to extract highly relevant results that point to two different effects, depending on the level of unemployment registered in the set of countries. Thus, for unemployment rates lower than the estimated threshold specifications, the relationship between death rates and unemployment is always negative and the pro-cyclical effect remains. In contrast, in times of economic weakness, with unemployment rates larger than estimated thresholds, the relationship becomes positive in the upper regime (second row), supporting the existence of a counter-cyclical effect. This result is consistent with the results obtained in Eq. (1), since, in Eq. (2), when the empirical estimates from the upper regime are added to the lower one –0.3071-0.3623= -0.0552 for specification (4)–, a negative relationship is obtained.

Along the same lines, considering the fourth row in Table 2 in Eq. (2), the sum of the lower and upper regime estimates for specification (4) shows a positive term to add (0.0705–0.0325=0.038). This is consistent with the positive estimated results of the fourth row in Eq. (1). As a final remark, over the period of the 2008 economic recession, if we add the empirical estimates in the second and fourth row of Eq. (2) for specification (4) (0.3071-0.3623+0.0705-0.0325= -0.0172), then a negative estimated relationship is obtained. This result is thus consistent with the negative estimated relationship from Eq. (1) (0.0117–0.0242= –0,0125).

Table 3 presents variations from the main specification. Because young people make up the population group most negatively affected by job losses during economic recessions, youth unemployment rates were considered. This figure varies widely between European countries: the youth unemployment rate ranged from 6.0 % in the Netherlands to 33.6 % in Spain during the first quarter of 2009. Nevertheless, youth unemployment rates are significantly higher than the total unemployment rate in each country over the period (see Table 1).

Table 3 shows that results continue to be robust when youth unemployment rates, instead of total unemployment rates, are considered. The effects became insignificant if the youth unemployment variable with a lag of two years was considered when using standard errors adjusted for clustering on the cross-section unit, although they are statistically significant when using the wild cluster bootstrap. Depending on the levels of unemployment, Eq. (2) again confirms two differentiated regimes, as indicated by the estimated thresholds of 3.92% in the case of the overall unemployment rate, and 4.1% in the case of the youth unemployment rate. For youth unemployment levels below these rates, the estimated coefficient was found to be negative, confirming a pro-cyclical effect. For higher unemployment rates, a positive effect is found, indicating that an increase in unemployment levels leads to a rise in drug

Table 3
The estimated effects of unemployment on overdose drug-related deaths.

Regressors	*Eq. (1)*[a]. 29 Countries. Period: 2000-2020				*Eq. (2)*[b]. *28 Countries. Period: 2005-2014*			
	Parameter estimates by estimation method and specification (2)				Parameter estimates by regime and specification (5)			
	ABBB estimator		AB estimator		Lower regime	Upper regime	Lower regime	Upper regime
	v=unemployment	v=youth unemployment	v=unemployment	v= youth unemployment	v= unemployment		v= youth unemployment	
First lag of log-overdose	0.7087*** (0.000) [0.000]	0.7271*** (0.000) [0.000]	0.5641*** (0.000) [0.000]	0.5700*** (0.000) [0.000]	0.2116** (0.046)	0.1171 (0.297)	-0.6792 (0.385)	0.7141 (0.355)
v	-0.0348*** (0.004) [0.000]	-0.0223*** (0.009) [0.017]	-0.0399*** (0.002) [0.001]	-0.0270*** (0.002) [0.014]	-0.5716** (0.011)	0.4849** (0.035)	-2.5147* (0.083)	2.4594* (0.089)
Second lag of v	0.0294** (0.020) [0.000]	0.0134 (0.323) [0.003]	0.0299*** (0.005) [0.001]	0.0112 (0.292) [0.001]	-0.2203 (0.398)	0.2862 (0.286)	-0.0952 (0.795)	0.1223 (0.738)
v multiplied by dummy variable for years 2007, 2008 and 2009	0.0170** (0.043) [0.005]	0.0107* (0.076) [0.002]	0.0212** (0.016) [0.005]	0.0139** (0.011) [0.004]	0.1068* (0.055)	-0.0829 (0.170)	-0.4275*** (0.000)	0.4378*** (0.000)
Dummy variable for year 2020	0.1110 (0.117) [0.033]	0.1114 (0.117) [0.019]	0.0846 (0.176) [0.025]	0.0790 (0.206) [0.017]				
Constant	0.0699 (0.499) [0.520]	0.075 (0.341) [0.191]	0.1231 (0.226) [0.462]	0.1923 (0.101) [0.206]	-1.6130 (0.282)		-10.5997 (0.147)	
Threshold					3.9208*** (0.000)		4. 1000*** (0.000)	

[a] Corresponding to the sample, where Romania is removed due to data being registered at sub-national level and the under-reporting number of deaths (EMCDDA, Statistical Bulletin (2022)). Estimated values and p-values in parentheses (*, **, *** indicate statistically significance at 10%, 5% and 1% respectively) are obtained using robust standard errors adjusted for clustering on the cross-section unit (STATA command: vce(robust)). p-values in brackets are obtained using wild cluster bootstrap (STATA command: boottest). The Arellano-Bond (1991) test for autocorrelation indicate that we cannot reject the null hypothesis of non-existence of serial correlation, implying that moment conditions are valid.

[b] Corresponding to the sample, where Romania is removed due to data being registered at sub-national level and the under-reporting number of deaths (EMCDDA, Statistical Bulletin (2022)). We also excluded The Czech Republic due to lack of data in 2005-2014 period. Estimated values and p-values in parentheses (*, **, *** indicate statistically significance at 10%, 5% and 1% respectively) are obtained with the estimator developed in Seo et al. (2019) and Seo and Shin (2016). The bootstrap p-value of Seo et al. (2019) rejects the null hypothesis of the linearity test in all specifications.

Notes

overdose deaths, a counter-cyclical effect. The net effect is also pro-cyclical.

Finally, by comparing the results of Tables 2 and 3 we find that the estimated coefficients when taking youth unemployment are in general between four and five times higher than in the case of general unemployment. This result may suggest that the entire effect, in the general case, may be explained by the youth unemployment. However, when we use the the "non-youth" unemployment variable (defined as: unemployed population from 25 to 74 years. Percentage of total population from 25 to 74 years) we find out that the corresponding coefficient is also statistically significantly different from zero, supporting the fact that the entire effect is not only driven by the youth unemployment.

Discussion

This study analyzed the impact of economic crises on drug-related harms in 30 European countries over the 2000-2020 period. The severity of the crisis was measured through the worsening in labor market conditions. Unemployment rates were used to proxy fluctuations in the economic cycle, as these are the most generalized measure used in this field (Nagelhout et al., 2017; Hollingsworth et al., 2017; Martin & Vall, 2016; Kaiser et al., 2017). In comparison with other indicators, such as Gross Domestic Product (GDP) per capita, unemployment is closely associated with variations in health indicators. Therefore, it is assumed that the effect of GDP per capita on health is through their its impact on the unemployment rate (Brenner et al., 2011). As a sensitivity analysis, we employed GDP per capita growth rates instead of unemployment rates, but we did not find statistically significant relationships.

Standard panel data models show a pro-cyclical relationship between economic conditions and drug-related harms. Increases (decreases) in unemployment are associated with a decline (rise) in drug overdose mortality. In this sense, mechanisms, such as the *income* effect, seem to dominate other opposing mechanisms. This finding could be explained mainly by the fact that mental health problems tend to rise when economic conditions, such as high levels of unemployment, worsen (Hollingsworth et al., 2017; Durkheim, 2005). However, in situations of economic downturns, a counter-cyclical effect is detected, although the overall effect, even in the crisis years, remains negative. Youth unemployment`s effects on overdose deaths were also explored, obtaining the same type of relationship but with a stronger effect that the general unemployment.

Results´ precision is improved if the intensity of economic crisis and potential lags between the worsening in economic conditions and their effects on health outcomes are considered. In this sense, our study offers relevant and novel methodological insights by focusing on the relationship between unemployment and drug-related harms. Our use of *dynamic threshold panel* models enhances the understanding of whether the relationship between unemployment and overdose deaths depends on the intensity of recessions.

The results obtained by the *dynamic threshold panel* models show the existence of two different effects, depending on the level of unemployment reached by the countries. For unemployment rates below the estimated thresholds, the relationship between mortality rates and unemployment is negative (pro-cyclical). Conversely, in times of negative economic shocks, with unemployment rates above the estimated thresholds, the relationship becomes positive in the higher regime (counter-cyclical). The net effect is pro-cyclical, as we also find with *dynamic linear panel* models. The study provides, therefore, two main results: *first*, unemployment by itself has a robust association with drug-related harms in the set of countries analyzed, and *second*, this effect depends to a large extent on the severity of the economic crisis.

Another finding particularly worthy of attention is the possible persistent effects of economic crisis on drug-related harms. Changes in unemployment seem to have no significant impact on overdose deaths occurring in the same period (Brenner et al., 2011). However, if one considers the impact changes in unemployment have on overdose deaths after two years, this association is statistically significant. A two-year lag was also found by Brenner et al. (2011) in the impact of unemployment on heart disease mortality in European Union countries, over the 2000-2010 period. Furthermore, the inclusion of dummy variables to capture the specific years of the economic crisis supports the existence of structural breaks in the relationship between drug harms and both the global economic crisis and the COVID-19 pandemic.

To the best of the authors' knowledge, this is the first study that examines the potential non-linear effects of the economic cycle on drug-related harms, by making use of lagged-effects and thresholds. This empirical approach was recently applied to examine other relationships between the business cycle and health indicators. Gaies (2022) applied this methodology to examine the association between national health expenditures and economic growth in developing countries. The authors found that an improvement in human and physical capital seems to reinforce the positive effect of health spending on economic growth: the estimated thresholds were between 1.08 and 0.66 points for level of education and between 24.45% and 24.50% for the level of investment.

In the literature, few studies have addressed the effect of the economic cycle on drug-related adverse outcomes in Europe. More studies analyze the situation in the United States. For instance, Hollingsworth et al. (2017) analyzed the effects of the business cycle on drug-related harm, as measured by drug deaths in the US. The authors examined how deaths due to opioids analgesics and other drugs varied with fluctuations in economic conditions, measured using the unemployment rate. As the main result, the authors obtain a counter-cyclical macroeconomic effect: a one percentage point rise in the county unemployment rate is predicted to increase all drug fatalities by a statistically significant 0.36 per 100,000 (0.19 for opioid fatalities). If data are aggregated at the state level, the effects remain counter-cyclical.

Comparing these results with those obtained in the current study is a complex task since the types of drugs involved are different. While the current analysis of drug-related deaths focuses on an illegal drugs, overdoses by illicit opioids analgesics comprise the core of the mortality data used by Hollingsworth et al. (2017). Moreover, the researchers assume that the relationship between drug harm and unemployment is purely linear.

Considering that drug treatment is a consequence of drug-related harms, several studies have addressed the effects of the economic cycle on treatment admissions. Results cannot be directly compared to the ones found here. Admission to treatment depends mainly on the supply of treatment, which may tend to decrease during economic recessions due to public austerity measures. Therefore, the capacity of these services to absorb a rise in the demand during economic downturns might become an active restriction, which is difficult to capture with available data (MacLean et al., 2020).

Costa et al. (2011) used data for treatment demand in Europe, over the 2002-2007 period. These authors used fixed effect models to analyze how economic conditions affected the number of drug users entering treatment. As a main result, the authors find a pro-cyclical effect: when unemployment increases (declines) the number of drug clients seeking treatment declines (increases). Splitting the unemployment into cyclical and structural unemployment, the greater impact comes from the structural component of unemployment, not linked to the economic cycle. Maclean et al. (2020) used administrative data on substance abuse treatment between 1992 and 2015. Linear panel data models with fixed-effects find no statistically significant evidence that total admissions vary across the business cycle. By type of drug, they also find a pro-cyclical effect in heroin admissions and a counter-cyclical effect

Our results should be interpreted taking into account several limitations. As stated in the data description section, the most active limitation has been missing data. Moreover, data related to overdose deaths could be underestimated for certain years and countries, due to the limited availability of autopsies and differences in coding practices between countries. This last restriction should not affect results because this bias is constant over the sample period. It therefore does not introduces bias in estimators. Another limitation of the analysis concerns the level of data aggregation. To increase the number of observations, it would have been better to work with more disaggregated data. In this sense, disaggregated data at the regional level for drug-related harm variables were not available. It would also be desirable to analyze overdose deaths by drug type as it could affected the generalizability of the results obtained. However, the EMCDDA does not publish trend data by drug type and, consequently this study could not perform this analysis.

Notwithstanding these limitations, our findings provide relevant information for policy makers to address the adverse effects of drug-related harms in vulnerable groups, such as the unemployed, that emerge during recession periods. Monitoring critical thresholds in labor market variables is a relevant source of information for policy makers, who can then anticipate efforts for reinforcing drug harm reduction programs. This is especially the case when unemployment exceeds certain levels. In these circumstances, drug treatment interventions should be accompanied by specific employment measures. From the point of view of the economic evaluation of public policies, the results highlight the importance of evaluating the returns of investing in employment policies that minimize the social costs associated with drug-related harms.

Declarations and ethics

All co-authors have read and agreed with the contents of the manuscript and there is no conflict of interest to declare.

We certify that the submission is an original work and is not under review for any other publication.

The publication of the study research was not contingent on the sponsor's approval or censorship the manuscript.

Authors do not use AI and AI-assisted technologies in the writing process.

Ethics approval

The authors declare that the work reported herein did not require ethics approval because it did not involve animal or human participation.

CRediT authorship contribution statement

Bruno Casal: Writing – original draft, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Emma Iglesias:** Conceptualization, Formal analysis, Investigation, Methodology, Writing – original draft. **Berta Rivera:** Writing – original draft, Methodology, Investigation, Formal analysis, Conceptualization. **Luis Currais:** Writing – original draft, Investigation, Formal analysis, Conceptualization. **Claudia Costa Storti:** Supervision, Funding acquisition, Data curation, Conceptualization.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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