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Long-lasting economic effects of pandemics:
Evidence from the United Kingdom

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Abstract

This paper studies long economic series to assess the long-lasting effects of pandemics. We analyze if periods of time that cover pandemics have a change in trend and persistence in growth, and in level and persistence in unemployment. That is, we determine if economic events around the time of the pandemics have long-lasting effects. We find that there is an upward trend in the persistence level of growth across the centuries. In particular, shocks originated by pandemics in recent times seem to have permanent effect in growth. Moreover, our results show that the unemployment rate increases and it becomes more persistent after a pandemic. In this regard, our findings support the design and implementation of novel counter-cyclical policies to soften the shock of the pandemic.
Keywords: Long memory, persistence, structural change, pandemics, growth, and unemployment.

1. Introduction

The COVID-19 pandemic has already cost the life of hundreds of thousands of persons around the globe. Ferguson et al. (2020) highlight that COVID-19 can be positioned as one of the worst pandemic in the history. They estimate the death toll at 510,000 only in Britain. This incommensurable cost to human society is accompanied by an intense economic shock. As COVID-19 spreads through the globe, countries started to impose aggressive restrictions on economic activity, and social distancing as a way to slow the rate of infection. The early economic results following the start of the pandemic, and considering possible new waves of infections (see Prem

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et al. (2020), and Colbourn (2020), among others) point to a deep recession and the lost of millions of jobs. Moreover, even though some countries may start to relax some of the restrictions, the consensus is that overall economic activity will not rapidly return to levels achieved before the pandemic, see e.g. Guerrieri et al. (2020), and McKibbin and Fernando (2020).

Several studies have focused on the sort-term economic consequences of different outbreaks and pandemics, see e.g. Meltzer et al. (1999), Brainerd and Siegler (2003), and Karlsson et al. (2014). Until very recently, there has been an increase in interest of studying the medium, and long-term economic impacts of global pandemics, see Jordà et al. (2020), and Prados de la Escosura and Rodríguez-Caballero (2020). This paper adds to this line of research by using econometric techniques that, to the best of our knowledge, have not been explored before to study the possible long-lasting effects of epidemics in the economy.

Given the size of the economic shock, it is of the utmost importance to determine the possible long-lasting effects of the pandemic. Long memory is the statistical property that events in the past can be felt even after much time has passed. That is, events are more persistent than what standard models are capable of capturing. Establishing the long memory properties of an economic series helps in understanding the long-lasting effects of shocks. While the impact of shocks is transitory for stationary series, for nonstationary cases random shocks have permanent effects. In this regard, if an economic series has long memory properties, we can expect the effects of calamities to remain affecting the economy for the considerable future. Thus, the assessment of the level of persistence that pandemics have on the economy is of major interest in light of the current COVID-19 pandemic, also considering the possible .

If the effects of the pandemic are short memory, not showing a high level of persistence, we could expect a rapid recovery after the current crisis; that is, a V-shaped recovery. If, on the other hand, the effects of the pandemic are persistent, we could expect a slow U-shaped recovery. Thus, this paper gathers evidence from previous pandemics to determine their long memory properties with the aim of providing more information that could help in the recovery post-COVID-19.

Pandemics are random infrequent events. We require long datasets spanning several decades to properly study them. Thus, we focus on data from the United Kingdom (UK) given the existence of long series encompassing several centuries. The vast amount of data allows us to study the effect of previous pandemics both in terms of growth and unemployment.

This paper is organized as follows. The next section introduces the econometric tools used in the paper. In Section 3, we study the persistence levels in periods with outbreaks and epidemics in the UK. Finally, Section 4 presents some concluding remarks and policy recommendations.

2. Long memory and structural changes

In this section we present the econometric tools that we will use to assess the long-lasting effects of outbreaks and pandemics in the economy. We present the fractional difference operator, the most used procedure to model long memory in the econometric literature, and semiparametric methods for the estimation of the long memory parameter. Moreover, we present tests for structural change in levels and trends, and changes in persistence.

2.1. The fractional difference operator

The most common procedure to model long memory is the fractional difference operator of Granger and Joyeux (1980) and Hosking (1981). The authors proposed a model defined as:

$$x_t = (1 - L)^d \varepsilon_t, \tag{1}$$

where ε_t is a white noise process with variance σ^2, and $d \in (-1/2, 1/2)$. Following the standard binomial expansion, the fractional difference operator, $(1 - L)^d$, is decomposed to generate a series given by:

$$x_t = \sum_{k=0}^{\infty} \pi_k \varepsilon_{t-k}, \tag{2}$$

with coefficients $\pi_k = \Gamma(k + d)/[\Gamma(d)\Gamma(k + 1)]$ for $k \in \mathbb{N}$.

The properties of the fractional difference operator have been well documented in, among others, Beran et al. (2013).

Note the following implications of the parameter d:

- A process with $d = 0$ displays short memory, and implies that any shock that affects the series only has repercussions in the short-term and its impact will completely vanish in the long run.
- The process will display long memory for $0 < d < 1$, and implies that any shock that affects the series has long-lasting repercussions.
- The process will be stationary as long as $d < 0.5$.

- The process will revert to its mean as long as $d < 1$, but the speed to which it converges could be quite slow.
- Processes with $d > 1$ are such that past innovations have permanent effects.

Furthermore, let $f_X(\lambda)$ be the spectral density of a fractionally differenced process, then:

$$f_X(\lambda) = \frac{\sigma^2}{2\pi}\left|\sum_{k=0}^{\infty}\pi_k e^{-ik\lambda}\right|^2 = \frac{\sigma^2}{2\pi}\left|1 - e^{-i\lambda}\right|^{-2d} \sim \frac{\sigma^2}{2\pi}\lambda^{-2d} \quad \text{as} \quad \lambda \to 0, \tag{3}$$

where π_k are given in (2), see Beran et al. (2013).

Fractionally integrated models have been extensively used in empirical applications. For instance, Gil-Alana and Robinson (1997) analyze whether the macroeconomic variables involved in the original database of Nelson and Plosser (1982), GDP and unemployment among them, have long memory.

2.2. Semiparametric estimators of long memory

Tests for long memory in the frequency domain include the log-periodogram regression, see Geweke and Porter-Hudak (1983), and Robinson (1995); and the exact local Whittle approach of Shimotsu and Phillips (2005) that consistently estimate d beyond the unit root case. The idea is to evaluate the periodogram of the time series, an estimator of the spectral density, only in a vicinity of the origin, where the spectral density $f_X(\lambda)$ is driven only by the memory parameter d, see (3).

The log-periodogram regression [GPH, henceforth] is given by:

$$\log(I(\lambda_k)) = c - 2d\log(\lambda_k) + u_k, \quad k = 1, \cdots, m,$$

where $I(\lambda_k)$ is the periodogram of x_t, $\lambda_k = e^{ik2\pi/T}$ are the Fourier frequencies, c is a constant, u_k is the error term, and m is a bandwidth parameter that grows with the sample size. For our estimations, we use the mean-squared error optimal bandwidth of $T^{4/5}$, where T is the sample size, obtained by Hurvich et al. (1998).

On the other hand, the exact local Whittle estimator [ELW, henceforth] minimises the function:

$$R(d) = \log(G(d)) - \frac{2d}{m}\sum_{k=1}^{m}\log(\lambda_k), \quad G(d) = \frac{1}{m}\sum_{k=1}^{m} I_{\Delta^d}(\lambda_k),$$

where $I_{\Delta^d}(\lambda_k)$ is the periodogram of $(1-L)^d x_t$, and m is the bandwidth.

From (3), note that the log periodogram regression provides an estimate of the long memory parameter for fractionally differenced processes.

2.3. *Tests for change in persistence*

In recent years, several tests have been proposed to assess whether macroeconomic variables display changes in persistence within a specific period. Martins and Rodrigues (2014) propose a test capable of detecting changes in the order of integration of a fractionally integrated process. The authors propose a method based on recursive forward and reverse estimation of the Breitung and Hassler (2002) test. Furthermore, their method is capable of dealing with unknown date of change, trends, and serial correlation.

Let x_t be given as in (1), and let $\tau \in [\Lambda_l, \Lambda_u]$ with $1 < \Lambda_l < \Lambda_U < T$, and T the sample size. The test proceeds by recursively considering the auxiliary regression given by:

$$z_t = \phi(\tau) z^*_{t-1} + e_t, \quad t = 2, \cdots, [\tau T],$$

where $z_t = (1-L)^{-d} x_t$, and $z^*_{t-1} = \sum_{j=1}^{t-1} j^{-1} x_{t-j}$. Intuitively, the j coefficient helps in controlling for the hyperbolic decay. The statistic of the test is constructed by the supreme of the squares of the t-statistics associated to $\phi(\tau)$ as we recursively move τ, and the analogous t-statistic associated to the auxiliary regression in the time-reversed rest of the series.

2.4. *Tests for structural breaks*

The method proposed by Bai and Perron (1998, 2003) [BP, henceforth] deals with unknown multiple breaks, making the methodology suitable for a broad range of applications.

The general framework of BP analysis can be described by the following multiple linear regression model with b breaks, that is $b+1$ periods or regimes,

$$y_t = x_t \beta + z_t \delta_j + u_t, \quad t = T_{j-1} + 1, \cdots, T_j, \tag{4}$$

for $j = 1, \cdots, b+1$, where y_t is the dependent variable at time t, x_t and z_t are vectors of covariates with β and δ_j $(j = 1, \cdots, b+1)$ their corresponding vector of coefficients, and u_t is the usual disturbance at time t. Since the method treats the break point indices, $(T_1, \cdots, T_b)$, as unknown, the goal is the joint estimation of the unknown parameters together with the break points.

BP methodology employs a sequential F-test to infer the number of shifts on a time series. The idea is that the full sample is divided into subsamples. The null hypothesis is stability in the regression coefficients between subsamples, while the alternative considers that at least one of the parameters varies over time. The asymptotic critical values up to nine breaks are computed by Bai and Perron (1998) via simulations.

3. Evidence from the United Kingdom

In this section, we present the data used to assess the long-lasting effects of pandemics on the economy. We use data from the United Kingdom given the availability of large datasets spanning across several centuries. We then use these datasets to present the evidence of the effect that previous pandemics have had in growth and unemployment.

3.1. Data

We are interested in analyzing the effect that global pandemics and those of particular impact for the UK have had in the economy to get a preliminary assessment of the impact of the outbreak caused by the new coronavirus SARS-COV 2. We focus on two of the most important macroeconomic variables: i) annual real GDP per capita of the UK from 1270 to 2019, and ii) unemployment monthly rate of the UK from July, 1854 to December, 2016.

For the first variable, we use a standard strategy to construct the series. The Bank of England provides the series from 1870 to 2019 considering the current definition of The United Kingdom of Great Britain and Northern Ireland. A previous block of this series is obtained from 1700 to 1869 using the estimates from Campbell et al. (2015) for Great Britain. Finally, the oldest block of the series (1270-1699) is constructed using the same methodology for England.

For the second variable, we use the dataset from Thomas and Dimsdale (2017) which contains information for the UK for dozens of variables for several centuries. The dataset is available at the Bank of England data repository.

These large datasets allows us to study the long-run behaviour of both important economic variables, and the effect that major outbreaks and pandemics have had on their trends and persistence.

3.2. Real GDP per capita in the UK

Here we focus on the longer time series, real GDP per capita, to analyze the persistence of different regimes, whose periods cover some relevant outbreaks and pandemics in the history of the UK.

We consider a linear trend in the equation (4) as follows:

$$GDPpc_t = \beta_{0,j} + \beta_{1,j} t + u_t, \qquad (5)$$

for $t = T_{j-1}, \dots, T_j$, where $j = 1, \dots, b+1$ indicates the period, and t is the time index. In equation (5), $GDPpc$ is the real GDP per capita for the UK, while $\beta_{0,j}$, and $\beta_{1,j}$ are the intercept and the slope of each linear regression fitted in period j. Then, the underlying idea to define a period is that either of the parameters (β_0, and β_1) vary in two consecutive periods calibrated by a trimming parameter.

We work with the annual series of the real GDP per capita from 1270 to 2019 explained before. Figure 1 displays the respective time series, the breaks estimates by BP methodology, and their confidence intervals at 95% (also presented in Table 1).

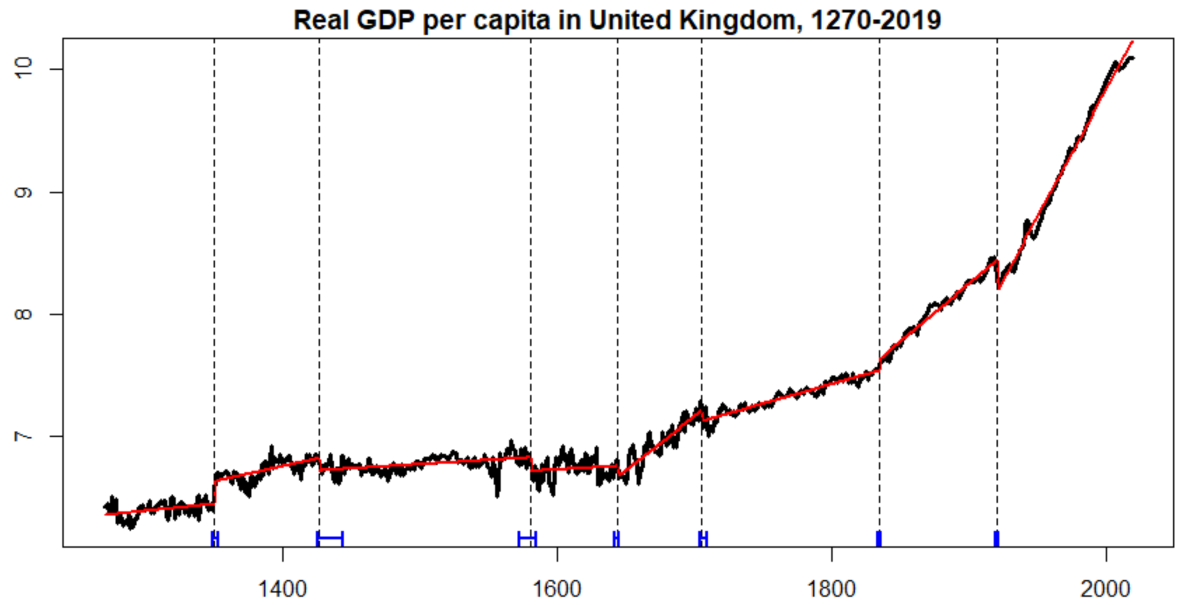

Figure 1: Real GDP per capita in the UK, 1270-2019 (in logs). Breaks are represented by the vertical black dashed lines, while their confidence intervals at 95% are displayed by blue small intervals in the bottom of the figure. BP methodology with a trimming parameter of $h = 0.08$ is executed.

Estimated date	1350	1426	1580	1644
Confidence interval	[1349-1353]	[1425-1444]	[1572-1584]	[1642-1645]
Estimated date cont.	1705	1834	1920	
Confidence interval cont.	[1704-1709]	[1833-1835]	[1919-1921]	

Table 1: Dates for structural changes detected by the BP methodology in yearly UK real GDP per capita. The confidence intervals are shown below each date.

As we can see in Figure 1, the BP methodology identifies eight periods over the last seven centuries in which GDP per capita of the United Kingdom undergoes structural changes in the aforementioned linear trend. To analyze the possible impact of COVID-19 in the GDP per capita, firstly, it is relevant to identify the main outbreaks and pandemics along these centuries. We consider only the deadliest episodes in the history of the UK in terms of total estimates of deaths. Table 2 shows the relevant outbreaks and pandemics in the specific period according to the sources consulted.

Period	Outbreaks or pandemics	Death toll in the UK
1270-1350	Black Death	$\approx$ 25% and 60% of total population
1351-1426	No relevant outbreaks	
1427-1580	Small London plagues	$\approx 40,000$
1581-1644	Small London plagues	$\approx 50,000$
1645-1705	Great plague of London	$> 100,000$
1706-1834	No relevant outbreaks	
1834-1920	Different cholera outbreaks,	$\approx 160,000$
	Great Pandemic of 1870-1875,	$\approx 80,000$
	and Russian flu	$> 100,000$
1921-2019	Spanish flu and remaining	$\approx 228,000$
	pandemics of the 20th century	

Table 2: Main outbreaks and pandemics in terms of death toll in the UK the respective period.
Source: https://en.wikipedia.org/wiki/List_of_epidemics and references therein.

As seen from Table 2, we can locate some outbreaks and pandemics in almost all periods defined. As documented by many historians, the most devastating pandemic has been the Black Death. Due to the lack of historical record in that time, it is extremely difficult to establish the death toll with a satisfactory degree of certainty. Even today, many historians still debate about it, although a general consensus estimate the death toll around 25-60% of the total population only in the UK. This pandemic was also relevant in terms of economic, social, and political change in Europe, and particularly in England, see Clark (2007, 2010), and Jordà et al. (2020). After the Black Death, outbreaks of plagues were frequent in England; there are some considered small plagues in the next three centuries. Other relevant pandemic in the UK was the Great Plague of London between 1870-1875, it is considered the last major epidemic of the bubonic plague to occur in England with an important number of deaths. With the increase in population, outbreaks and pandemics have been more devastating after the 18th century. The worst pandemic in terms of loss of human life is the Spanish flu originated alongside the First World War.

Considering the regimes defined in Table 2, we estimate the respective persistence level for each period by the GPH and ELW methods explained before. The analysis is also accompanied by the results of the MR test to assess if there exists a significant change in persistence between two consecutive periods. Table 3 presents the results.

Period	GPH est.	GPH s.e.	ELW est.	ELW s.e.	MR test			
					90%	95%	99%	Stat.
1270-1350	0.466	0.144	0.507	0.086				
1351-1426	0.597	0.147	0.583	0.087	5.324	6.440	8.878	3.122
1427-1580	0.498	0.102	0.494	0.066	5.294	6.519	9.426	2.107
1581-1644	0.589	0.161	0.606	0.093	5.288	6.497	9.335	5.155
1645-1705	0.865	0.166	0.867	0.094	5.340	6.411	8.654	5.318
1706-1834	0.877	0.112	0.813	0.071	5.331	6.495	9.139	5.653
1834-1920	1.084	0.138	1.080	0.083	5.248	6.460	9.305	11.116
1921-2019	1.041	0.129	1.186	0.079	5.690	7.022	10.853	7.846

Table 3: Long memory estimates and change of persistence tests for yearly real GDP per capita of UK. The table presents the estimates by both GPH and ELW methods together with their standard errors. Moreover, it presents the critical values for the MR test for the 90%, 95%, and 99% confidence levels, and the associated MR statistic for the test for change in persistence on either direction from the regime in the row above to the current row.

Table 3 reveals some interesting findings.

First, there seems to be an increasing trend in the level of persistence through the regimes considered. However, we note a slight increase in persistence from the period finalizing with the Black Death pandemic to the period after that is not maintained to the subsequent period (where no major outbreak or pandemic is reported). That is, the period after the Black Death pandemic seems to be more persistent than contiguous periods, pointing to the possible long-lasting effects of the pandemic on growth. Nonetheless, this increase in persistence does not appear to be statistically significant. The test for change in persistence does not reject the null of no change in persistence through the periods around the Black Death pandemic. One reason behind this result may be the short and imprecise data available before the pandemic.

Second, any shock before the 19th century has non-permanent effect on the series, indicating that shocks originated from respective outbreaks and epidemics were transitory even though potentially long-lasting. Moreover, we find that the small increase in persistence across the first five regimes are not statistically significant.

Third, shocks after the 19th century seem to have a permanent effect on the series, indicating that the most current outbreaks and epidemics have the longer-lasting effect on the GDP per capita. This could point to the fact that the world has become much more socially and economically connected in the last couple of centuries. Commerce and travel between countries is much more widespread and thus the effects of global pandemics on growth are compounded. It is interesting to remark that persistence has statistically changed at 5% (at least) in the last three regimes. This give us an idea that COVID-19 may present a change in the persistence of growth, which needs to be controlled by the policy makers.

These results highlight the relevance that the 21th century epidemics may have in the economy. It is too early to determine the persistence level that the effect of the COVID-19 pandemic has on growth. Nonetheless, if the upward trend on the level of persistence of the effects of pandemics in growth are maintained, we would expect the effects of the COVID-19 pandemic to be long-lasting.

As a robustness exercise, we analyze the yearly real GDP per capita for England from the Thomas and Dimsdale (2017) dataset. Results, available upon request, corroborate the upward increasing trend in persistence across the centuries and the slightly larger persistence after the Black Death pandemic. Moreover, we used other bandwidths for the long memory estimators obtaining qualitatively similar results.

One caveat of the above analysis is that the low sampling of the data makes it difficult to properly disentangle the impact of, for example, the Spanish flu pandemic in the economy of the United Kingdom. Periods with major pandemics are sometimes accompanied by episodes of turmoil as the First and Second World Wars, or the Great Depression. In this respect, in the next section we use a series sampled more frequently to explore a little deeper the role that epidemics may play in the economy.

3.3. Unemployment in the UK

In this section, we focus on the monthly UK inflation rate from July, 1854 to December, 2016. The more frequent sampling period allows us to better disentangle the economic effects that previous pandemics had in the economy.

To model structural change in unemployment, given that a linear trend is not observed, we consider a mean-shifting equation (4) as follows:

$$U_t = \beta_{0,j} + u_t, \tag{6}$$

for $t = T_{j-1}, \ldots, T_j$, where $j = 1, \ldots, b+1$ indicates the period, and t is time index. In equation (6), U_t is the unemployment rate for the UK, while $\beta_{0,j}$ are the intercept of each linear regression fitted in period j.

Figure 2 shows the monthly UK inflation rate from July, 1854 to December, 2016. Furthermore, the figure shows the structural changes detected by the BP methodology, and the mean for each regime. The dates for the structural changes are shown in Table 4.

The detected dates relate to major historical events, some of them already discussed for the real GDP per capita series, see Table 2. In particular, we are interested in the long memory properties of the period associated to the Great Pandemic of 1870-1875 and the Russian flu, and the period after the Spanish flu pandemic. The figure shows the higher level of unemployment during the period associated to the Great Pandemic of 1870-1875 and the Russian flu. Moreover, it shows a decrease in unemployment in the following period where no major pandemics are recorded, followed by a rapid increase in unemployment after the Spanish flu pandemic. In this regard, the effects of the Spanish flu pandemic on unemployment are much in line with preliminary estimates for the effects of COVID-19 on unemployment. To get a better understanding of the long-run effects of pandemics on unemployment, we first remove the mean for each regime and estimate the long memory parameters. Results from the long memory estimation are presented in Table 5.

Table 5 presents the long memory estimates for each regime by the GPH and ELW methods as before. Moreover, it presents the critical values for the MR test for the 90%, 95%, and 99% confidence levels. The last column presents the associated MR statistic for the test for change in persistence on either direction from the regime in the row above to the current row.

Note that unemployment has gone through several changes in the level of persistence across the regimes. Given the shorter span of the unemployment series, we can only analyze the effects of

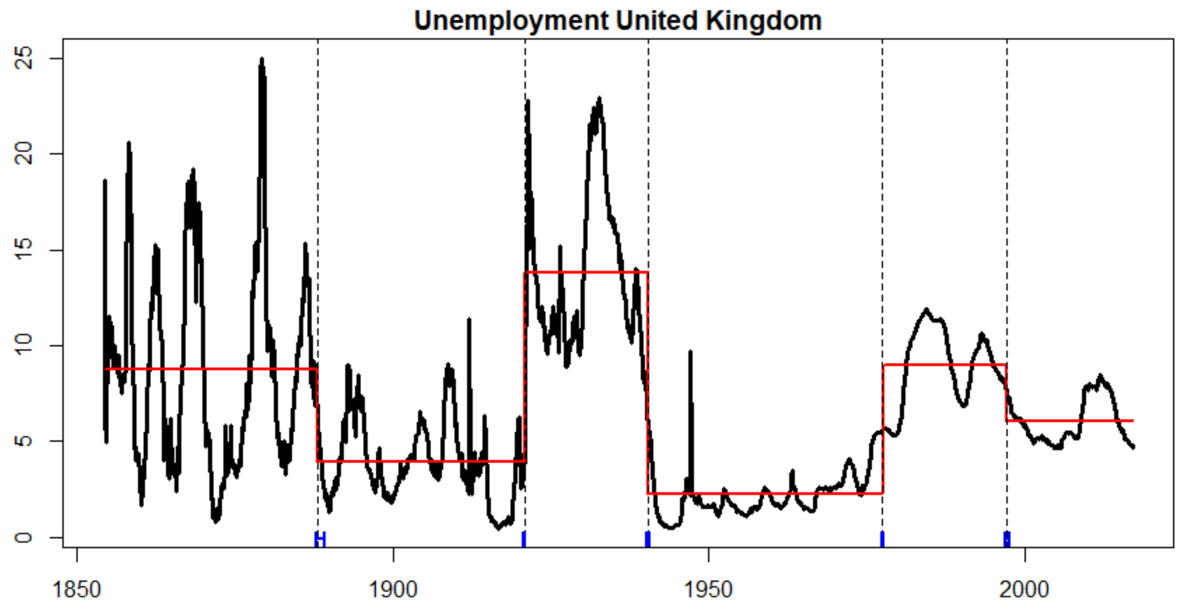

Figure 2: UK monthly unemployment rates. Breaks are represented by the vertical black dashed lines, while their confidence intervals at 95% are displayed by blue small intervals in the bottom of the figure. BP methodology with a trimming parameter of $h = 0.12$ is executed.

Estimated date	1888:2	1920:11	1940:5
Confidence interval	[1887:12-1889:04]	[1920:08-1920:12]	[1940:04-1940:07]
Estimated date cont.	1977:6	1996:12	
Confidence interval cont.	[1977:04-1977:07]	[1996:10-1997:06]	

Table 4: Dates for structural changes detected by the BP methodology in monthly UK unemployment rates. The confidence intervals are shown below each date.

the periods associated to the Great Pandemic of 1870-1875 and the Russian flu, and the Spanish flu.

The Great Pandemic of 1870-1875 and the Russian flu are contained in the first period detected. Note that the persistence level estimated in this period is quite high. The confidence intervals for the level of persistence for both estimators contain the $d > 1$ value that implies permanent effects on the economy. This contrasts with the level of persistence for the subsequent period where a persistence parameter of $d < 1$ is estimated. Furthermore, the MR test for change in persistence rejects the null of no change in persistence. This points to the catastrophic long-lasting effect of the pandemic in unemployment during the Great Pandemic of 1870-1875 and the

Period	GPH est.	GPH s.e.	ELW est.	ELW s.e.	MR test			
					90%	95%	99%	Stat.
1854:07-1888:02	0.963	0.065	1.137	0.045				
1888:03-1920:09	0.825	0.066	0.910	0.046	5.434	6.562	9.553	39.541
1920:10-1940:12	1.018	0.084	1.116	0.056	5.251	6.344	8.966	44.837
1941:01-1976:06	0.518	0.062	0.607	0.044	5.355	6.440	9.084	174.608
1976:07-1996:09	0.682	0.084	0.949	0.056	5.404	6.521	9.200	336.402
1996:10-2016:12	1.109	0.083	1.042	0.056	5.049	6.195	8.901	39.233

Table 5: Long memory estimates and change of persistence tests for monthly UK inflation. The table presents the estimates by both GPH and ELW methods together with their standard errors. Moreover, it presents the critical values for the MR test for the 90%, 95%, and 99% confidence levels, and the associated MR statistic for the test for change in persistence on either direction from the regime in the row above to the current row.

Russian flu.

Moreover, the long-lasting effects of the Spanish flu pandemic can be seen in the increase in persistence from the 1888:02-1920:09 regime to the 1920:09-1940:12 one. Both GPH and ELW estimates point to an increase in persistence from a value associated to a process that reverts to the mean, $0.5 < d < 1$, to a value associated to everlasting effects, $d > 1$. That is, the period associated to the Spanish flu pandemic seems to have the double effect of increasing the level of unemployment while making it much more persistent. Moreover, the change in persistence test rejects the null of no change in persistence on either direction at the 99% confidence level. These results may point to the fact that it was much more difficult for survivors to return to work after the end of the pandemic.

In the above discussion we have attributed the increase in unemployment level and persistence to the Spanish flu pandemic. Nonetheless, it could be argued that the First World War is the major historic event behind the results. To shed a light on whether major wars may be the main driver behind the increase in unemployment, it is enlightening to see the results from the 1940:12-1976:06 regime, which can be associated to the Second World War. The table shows a decrease in persistence from the regime associated to the Spanish Flu pandemic or First World War to the regime associated to the Second World War. Furthermore, the test for change of persistence strongly rejects the null of no change in persistence. Thus, there seems to be evidence that the period after Second World War was one of lower, less persistent, unemployment. Contrasting this result with the one associated to the Spanish flu pandemic or First World War suggests that the pandemic plays a significant role in the increased level and persistence of unemployment.

The results on unemployment are of particular interest in light of the current COVID-19 pandemic. As previously noted, governments across the globe decided to implement lockdowns to slow the speed of contagion. The restrictions have had a strong impact on several sectors of the economy like tourism that do not longer need their staff. The evidence found from previous pandemics suggest that, without policies specifically designed to avoid an increase in job losses, we should expect a higher level of unemployment that lasts for a long period.

As a robustness exercise, we analyze the yearly unemployment rate and consider different bandwidths and trimming parameters. The results from the robustness exercises, available upon request, are qualitatively similar to the main exercise presented.

4. Concluding remarks

We have analyzed long series from the United Kingdom to assess the effect that pandemics have on the economy. We studied the effects of pandemics both in growth, measured by real GDP per capita, and in unemployment.

For growth, our results indicate an overall trend upwards in the level of persistence across periods, with significant changes in persistence in the last three centuries. This indicates that, perhaps due to the increased connectivity between countries, contemporaneous outbreaks and pandemics may have longer-lasting effects on growth. We highlight the relevance of this finding due to the possible lasting effect that the current epidemic may have on growth in the UK and around the world.

In terms of unemployment, we find that the period associated to the Great Pandemic of 1870-1875 and the Russian flu shows a more persistent higher level of unemployment than in the subsequent period with no major pandemics. Moreover, after the Spanish flu pandemic and the First World War, unemployment suffered an increase in level and persistence. That is, unemployment increased and it became more rooted. This effect is not detected after the Second World War, which points to the relevance of the effect of the shock due to the Spanish flu pandemic.

Overall, the findings in this paper strengthen the case for economic policies aimed to soften the shock of the pandemic. Our results show that it is paramount to soften the impact on growth and avoid the loss of jobs if we want a V-shaped recovery after COVID-19.

In terms of growth, the high persistence of economic shocks supports the design and implementation of counter-cyclical policies. The high level of persistence in the series suggest that it is more costly to wait after the pandemic to introduce policies aimed to help in the recovery. In this regard, cash-transfers like the one implemented in the USA to sectors of the population more at risk could be implemented to reduce the effect of the pandemic on consumption and GDP.

In terms of unemployment, the increase in level and persistence of unemployment after the pandemic supports the design and implementation of policies that minimize or avoid that companies fire workers during the pandemic. Our results suggest that, once the number of unemployed increases, it is a long and arduous process to return to employment levels before the pandemic. This is in line with the notion that the longer people are out of the workforce, it gets more difficult to reintroduce them to the job market. In this regard, specific policies regarding unemployment could be implemented like the ones deployed in the United Kingdom, Australia, New Zealand, the Netherlands, Denmark, and in some other countries. For instance, the Danish government destined part of their budget to prevent layoffs within private companies facing financial pressures from COVID-19. Under the scheme, the state will cover 75% of the salaries of employees paid on a monthly basis who would otherwise have been fired, with companies paying the remaining amount. Thus, the idea is that once the pandemic recedes, people can go back to work faster, avoiding the looking for job and hiring period that could make unemployment more persistent.

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