U.S. historical initial jobless claims. Is it different with the coronavirus crisis? A Fractional Integration analysis

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ABSTRACT

This research paper makes an empirical analysis based on long memory to understand the historical behavior of initial unemployment claims (ICSA) in the United States (U.S.) during all the recession periods and epidemic diseases such as Severe Acute Respiratory Syndrome (SARS), Middle East Respiratory Syndrome (MERS) and COVID-19 since 1967 applying statistical methods based on long range dependence and fractional differentiation. Using unit root/stationarity tests (ADF, PP and KPSS) we discover that the original time series is stationary I(0) and the subsamples are non-stationary I(1). Finally, to analyze the original time series as well as the several periods corresponding to the recessions that occurred in U.S. and the three epidemic diseases, we use AIC and BIC criterion to fit the best ARFIMA model. We conclude that the results display long memory with a degree of integration strictly below 1 (d < 1) for the COVID-19 episode and for the rest of the subsamples, except for the original time series and the 2nd subsample. Thus we can conclude that the impacts will be transient and with long lasting effects of shocks and expecting to disappear on their own in long term. Finally, we use a methodology proposed by Bai and Perron to estimate structural breaks not being necessary to know the time of the breaks in advance. The results are similar to those obtained previously.

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1. Introduction

Humanity has always lived with microorganisms around it. Some of these microorganisms, controlled and monitored by the health authorities, can cause diseases more or less harmful to health. Following the argue done by Potter (2001) who says that in the past 300 years 10 pandemics are identified. Also, the researcher not reject the hypothesis about other pandemics appear or new medical disasters. This is because Potter (2001) states that these pandemics follow a recurrent but not regular periodic pattern.

Kilbourne (2005) states that in the 20th century the world was hit by the Spanish influenza in 1918 that was the most severe killing at least 40 million people worldwide and 675.000 in the U.S. (Brainerd and Siegler, 2002), the Asian influenza in 1957 and the Hong Kong influenza in 1968. In more recent years we have suffered from other major diseases such as SARS and HIV/AIDS (Jonung and Roeger, 2006)

The last virus to appear is the one called SARS-CoV-2, of the Coronaviridae family, and which causes the COVID-19 disease. According to Hui et al. (2020) and World Health Organization (WHO)[1], this infectious disease was identified in Wuhan City, China, in December 2019.

Since then, there has been an unprecedented major public health crisis, and not only because of the emergence of a new pathogen affecting humans, but also because health authorities have failed to respond to its spread and expansion.

Many virus containments measures (see Lee et al. 2020; Chen et al. 2020; among others) have been carried out around the world, causing significant economic consequences (see Keogh-Brown et al. 2010). According to OECD (2020), the virus will cause a negative supply shock to the world economy, by forcing factories to shut down and disrupting

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[1] https://www.who.int/news-room/q-a-detail/q-a-coronaviruses

global supply chains. If we compare it with the SARS crisis, Beutels et al. (2009) carried out a research study for the case of Beijing, using time series of daily and monthly SARS cases and deaths and volume of public train, airplane and cargo transport, tourism, household consumption patterns and gross domestic product growth, where they concluded that much of this consumption was merely postponed. However, the irrecoverable losses related to the tourism was about USD 1.4billion, or 300 times the cost of treatment for SARS cases in Beijing.

Another important mechanism by which a disease has an adverse impact on the long-term growth of the economy is the destruction of human capital. Following the statement done by Barro and Sala-I-Martin (1995), the stock of knowledge embodied in the population is determinant for the long-term growth.

Labor productivity is also affected due to the movement limitation of labor across regions within a country as well as across countries where it is most productive (see for example the analysis of Haacker 2002).

Although various studies have been attempted on the impact of pandemics on macroeconomic variables (in terms of loss of growth and production), there is little consensus in the literature, since the results depend fundamentally on the models used and the availability of data (see Bell and Lewis, 2004).

Focusing on unemployment, in the literature there are several unemployment theories like NAIRU (Friedman 1968 and Phelps 1967, 1968), hysteresis models (see Blanchard and Summers 1986, 1987 and Barro 1988) and structuralist models (Phelps 1994, Pissarides 1990, Blanchard 1999, Phelps 1999, Nickell 1998 y Nickell el al. 2000) that have been statistically analyzed in the literature following the standard unit root tests like Blanchard and Summers (1986) and Alogoskoufis and Manning (1988). Other researchers such as Gordon (1989), Lopez et al. (1996) and Wilkinson (1997) analyzed the statistical

properties of the hysteresis hypothesis. Others like Mitchell (1993), Bianchi and Zoega (1998) and Papell et al. (2000) studied these properties allowing structural breaks. Amable and Mayhew (2011), Fosten and Ghoshray (2011), Holl and Kunst (2011), King and Morley (2007), Srinivasan and Mitra (2012), among others reported mixed evidence in the more recent literature.

Unit root tests have very low power if the data is fractionally integrated (see Diebold and Rudebush, 1991; Hassler and Wolters, 1994; Lee and Schmidt, 1996), for this reason, and following the research done by Tschernig and Zimmermann (1992), Crato and Rothman (1996), Gil-Alana (2001, 2002), Caporale and Gil- Alana (2007, 2008), Lahiani and Scaillet (2009) among others, our goal is to do a statistical analysis using a fractional integrated (ARFIMA) model from the point of view of supply effects, related to the loss in hours worked. To be more precisely, we examine the time series properties of the weekly initial jobless claims in U.S. over the period January 1, 1967 to March 21, 2020. The contribution of the paper is to analyze the seven periods of recession since 1967, including the Severe Acute Respiratory Syndrome (SARS), Middle East Respiratory Syndrome (MERS) and COVID-19 crisis. For this purpose, we use methodologies based on the concepts of long-run dependence and long memory using fractional integration techniques. Using these techniques, we can determine if the effect of the shocks is going to be transitory or permanent, and this is important for policy makers and for the implementation of policy measures.

The rest of the paper is structured as follows. Section 2 presents the methodology applied in the paper. Section 3 describes the data and Section 5 presents the main empirical results, while Section 6 concludes the paper.

2. Methods

2.1. Unit roots methods

There exist many different ways of testing for unit-roots. The most common ones are those of Fuller (1976) and Dickey and Fuller (1979), the ADF tests. They are asymptotically optimal when the data are stationary. However, in the unit root case there are many other tests available that have greater power. Phillips (1987) and Phillips and Perron (1988) consider tests that employ a non-parametric estimate of the spectral density of u_t at the zero frequency, for example, a weighted autocovariance estimate. On the other hand, to test a null hypothesis that an observable time series is stationary around a deterministic trend (i.e. trend-stationary) against the alternative of a unit root, we use the methodology carried out by Kwiatkowski et al. (1992).

2.2. ARFIMA (p, d, q) model

To carry out this research based on also fractional integration analysis, we employ long memory methods where the number of differences required to render a series I(0) stationary is fractional.

Following a mathematical notation, given a time series $x_t, where\ t = 1, 2, ...$ is said to follow an integrated of order d process (and denoted as $x_t \approx I(d)$) if

$$(1 - L)^d x_t = u_t, \quad t = 1, 2, ..., \quad (1)$$

Where d can be any real value, L is the lag-operator ($Lx_t = x_{t-1}$) and u_t is I(0), defined as a covariance stationary process with a spectral density function that is positive and finite at the zero frequency. Thus, u_t may display some type of time dependence of the weak form, i.e., the type of an Autoregressive Moving Average (ARMA) form such that, for example, if u_t is ARMA (p, q), x t is said to be ARFIMA (p, d, q).

Depending on the value of the parameter d, several specifications based on (1) can be observed.

The process would be short memory or I(0) when $d = 0$ in (1). This occur because $x_t = u_t$. The high degree of association between observations which are far distant in time receive the name of long memory process and occur when $d > 0$. Within this last assumption, the process is still covariance stationary if $d < 0.5$ because the autocorrelations decay hyperbolically fast.

The reading that we can do on the results obtained from the fractional d is as follows: we consider a process of reversion which means that the shocks disappear in the long run when d is smaller than 1. In contrast to the above, the shocks are expected to be permanent when $d \geq 1$.

Although there are several procedures to estimate the degree of long- memory and fractional integration (see Geweke & Porter-Hudak, 1983; Phillips, 1999, 2007; Sowell, 1992). We base our results on the maximum likelihood procedure (see Sowell, 1992) and we use Akaike information criterion (AIC, Akaike, 1973) and Bayesian information criterion (BIC; Akaike, 1979) to select the right ARFIMA model.

2.3. Structural breaks

Finally, we have followed the methodology proposed by Bai and Perron (1998, 2003) that permit the modeler to endogenously estimate structural breaks and it is not necessary to know the time of the breaks in advance.

Using this methodology, we assume that $t = 1, 2, 3, \dots T$, m unknown breaks and the partitioned time series for $m + 1$.

Some of the coefficients contained in ρ matrix are invariable across all partitions. Others represent the estimated coefficient for each partition 1 to $m+1$ and are located in a series of ϕ matrices. The following equation shows this:

$$(Y - X\rho - \overline{D}\phi)'\,(Y - X\rho - \overline{D}\phi) = \sum_{i=1\,t=T}^{m+1} \sum_{i-1+1}^{T_i}(y_t - x_t'\rho - d_t'\phi_i)^2 \qquad (1)$$

Least square is the method used to calculate the coefficients in ρ and ϕ, that are the parameters and matrices, respectively, used to minimize the number of square errors. Where the sum of squared residuals is calculated first across all time points in a given segment 1 to $m+1$. Also, $S_t(T_1, T_2, \ldots, T_m)$ represent the sum of squared residuals in m −partition and $(T_1, T_2, \ldots, T_m)$ are specific to the break dates.

3. Data

In this paper we used seasonally adjusted weekly initial claims in U.S. over the period January 1, 1967 to June 4, 2020. The data were obtained from the Federal Reserve Bank of St. Louis[2] and it is shown in figure 1.

To consider the several U.S. recessions we have taken into account the dates provided from Federal Reserve Bank of St. Louis[3].

Also, we have considered the others disease outbreaks like Severe Acute Respiratory Syndrome (SARS) that according to WHO, began in November 2002 and ended in May 2004[4], Middle East Respiratory Syndrome (MERS) began in September 2012 and it is actually activated, and finally we analyze the COVID-19. To consider the coronavirus crisis (10th recession period), we have taken the start date indicated by Hui et al. (2020) and World Health Organization (WHO) up to the current available data.

The dates that we have used for our analysis are collected in the following table:

Table 1: U.S. Recessions		
1st period	December 1969	November 1970
2nd period	November 1973	March 1975
3rd period	January 1980	July 1980
4th period	July 1981	November 1982
5th period	July 1990	March 1991
6th period	March 2001	November 2001
7th period	December 2007	June 2009
Source: Federal Reserve Bank of St. Louis (https://fredhelp.stlouisfed.org/fred/data/understanding-the-data/recession-bars/)		
Pandemic, epidemic diseases		
8th period	November 2002	May 2004
9th period	September 2012	August 2020
10th period	December 2019	August 2020
Source: World Health Organization		
Structural breaks using Bai and Perron (1998, 2003)		
1st structural break	January 18, 1975	
2nd structural break	October 29, 1983	
3rd structural break	July 19, 2008	
4th structural break	October 29, 2011	
5th structural break	December 9, 2017	

Also, we have also represented in Figure 1 the time series that includes each of these periods in recession and structural breaks.
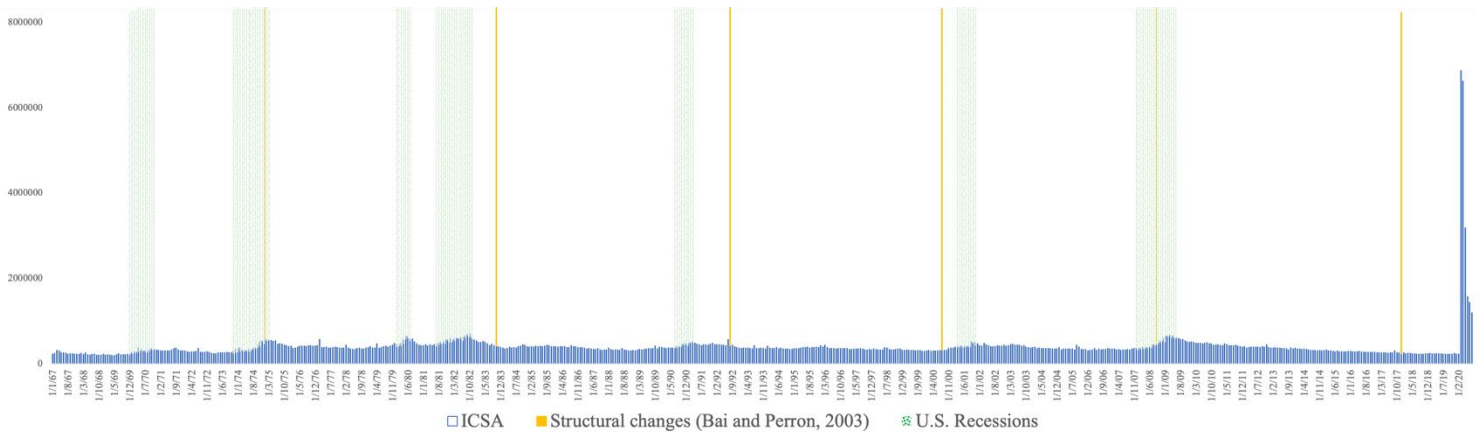
Figure 1. Seasonally adjusted weekly initial claims in U.S. over the period January 1, 1967 to April 4, 2020. (including U.S. Recession periods and Structural Changes according to Bai and Perron (2003) methodology.

4. Results

We start the analysis by performing the three standard unit root tests outlined in Section 3. We select the Augmented Dickey-Fuller test (ADF), the Phillips Perron test (PP) and the Kwiatkowski-Phillips-Schmidt-Shin test (KPSS) to examine the statistical properties of the original series of weekly initial jobless claims in U.S. and to obtain robust results. Table 1 displays the results, which suggest that the original data are stationary I(0). The subsamples analyzed in this paper are non-stationary I(1) except the subsample related to MERS pandemic that is stationary I(0).

	ADF			PP		KPSS	
	(i)	(ii)	(iii)	(ii)	(iii)	(ii)	(iii)
Weekly Initial Jobless Claims in U.S. (ICSA)							
Original Data	-9.649	-17.41	-17.537	-10.711	-10.798	0.489119	0.208989
U.S. Recessions							
1st period	0.6682	-2.1386	-2.849	-2.3543	-3.0899	0.9054	0.1421
2nd period	1.6875	-0.1008	-1.9283	-0.2943	-0.2943	1.6708	0.4072
3rd period	0.9027	-1.2256	-0.8547	-1.307	-1.137	0.9061	0.1536
4th period	0.8687	-1.7233	-2.7205	-1.5984	-4.8178	1.7167	0.1206
5th period	1.817	-0.8598	-2.9942	-0.8979	-3.3645	1.0167	0.0771
6th period	0.6092	-1.3839	-2.9097	-1.2609	-2.6522	0.7153	0.1375
7th period	1.4095	-0.8612	-1.9777	-0.7466	-2.2193	2.0585	0.2331
Pandemic, epidemic diseases							
8th period	-0.7024	-1.2748	-3.0866	-1.2024	-3.2173	1.6783	0.3668
9th period	-4.2247	-16.7232	-18.5172	4.1882	4.618	0.176	0.1738
10th period	-1.8222	-2.7509	-2.7238	-1.8683	-1.7552	0.242	0.1614
Structural breaks using Bai and Perron (1998, 2003)							
1st structural break	1.3426	0.402	-0.7363	0.5046	-1.0609	2.9807	0.3475
2nd structural break	-0.875	-2.4773	-2.9779	-2.6598	-3.2258	2.4732	0.7175
3rd structural break	-0.6336	-5.164	-5.2057	-4.9012	-4.9603	1.062	0.3863

4th structural break	-0.3232	-1.1853	-2.9725	-1.2803	-3.3254	2.1071	0.3099
5th structural break	-1.1917	-2.0509	-7.9014	-1.7223	-9.2197	5.3117	0.5835

Table 2. Unit roots tests. (i) Refers to the model with no deterministic components; (ii) with an intercept, and (iii) with a linear time trend. I reflect t-statistic with test critical value at 5%.

Once we have analyzed the original data and the subsamples, we have verified that we must not use the first differences so that our data is stationary I (0) for the original data, for the time series related to MERS pandemic (9th period) and for the 3rd structural break. For the rest, we must use first differences. Due to the low power of the unit root methods under fractional alternatives[5] presented in table 2, now we are going to use an ARFIMA (p, d, q) model to study the persistence of the original series as the subsamples corresponding to the different periods of recession experienced in the US since 1967. Also, using the methodology proposed by Bai and Perron (1998, 2003) we have identified unknown break periods from a specified number of observations, T and m possible breaks that have been analyzed using the ARFIMA model, that we have identified in Table 1.

To select the right ARFIMA model, we present a methodology based on information criteria such as Akaike information criterion (AIC; Akaike, 1973) and Bayesian information criterion (BIC; Akaike, 1979). Using these criteria for each time series, we show in the following table the correct model that we have chosen:

Information Criteria			
Data analyzed	Model Selected	AIC	BIC
Original time series	ARFIMA (1, d, 2)	63009,4	63039,1
1st period	ARFIMA (2, d, 1)	1011,44	1023,04
2nd period	ARFIMA (2, d, 2)	1489,55	1505,58
3rd period	ARFIMA (2, d, 1)	603,585	611,789

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[5] See Diebold and Rudebusch (1991), Hassler and Wolters (1994) and Lee and Schmidt (1996)

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4th period	ARFIMA (0, d, 1)	1490,86	1500,02
5th period	ARFIMA (0, d, 2)	722,535	730,723
6th period	ARFIMA (2, d, 1)	764,654	774,48
7th period	ARFIMA (1, d, 2)	1629,73	1644,17
8th period	ARFIMA (2, d, 2)	1564,29	1581,14
9th period	ARFIMA (0, d, 1)	10135,9	10152,1
10th period	ARFIMA (0, d, 0)	985,84	990,59
Structural breaks using Bai and Perron (2003)			
1st structural break	ARFIMA (0, d, 0)	8256,53	8268,64
2nd structural break	ARFIMA (2, d, 2)	9187,58	9216,47
3rd structural break	ARFIMA (1, d, 0)	24836,1	24856,8
4th structural break	ARFIMA (2, d, 2)	3348,44	3370,43
5th structural break	ARFIMA (2, d, 2)	5980,36	6006,71

Table 3. Akaike information criterion (AIC) and Bayesian information criterion to choose the right ARFIMA model

Table 3 shows the results of AIC and BIC information criterion and the different parameterizations of the ARFIMA (p, d, q) model that we have chosen. The configurations that we have made of the ARFIMA model have been "(0, d, 0)", "(1, d, 0)", "(2, d, 0)", "(0, d, 1)", "(0, d, 2)", "(1, d, 1)", "(1, d, 2)", "(2, d, 1)", "(2, d, 2)".

Once the various configurations were calculated for ARFIMA models and following the selection criteria mentioned above, we are left with those value that have been greater in the AIC and BIC. These models are collected in the table 3.

Taking into consideration that the AR and MA terms capture short-term influences over the ARFIMA (0, d, 0) baseline model and according to the selection criterion explained above, we can observe that for each time series we have several configurations.

Long memory test on seasonally adjusted weekly initial claims in U.S.						
Data analyzed	Sample size (weeks)	Model Selected	d	Std. Error	Interval	I(d)
Original time series	2798	ARFIMA (2, d, 0)	1,06212	0,0169529	[-0.01, 0.04]	I(0)
1st period	52	ARFIMA (2, d, 1)	0,5411632	0,6232175	[-0.68, 1.36]	I(0), I(1)
2nd period	74	ARFIMA (2, d, 2)	1,1106023	0,2756084	[-0.14, 0.76]	I(0)
3rd period	30	ARFIMA (2, d, 1)	0,427549	0,614085	[-0.74, 1,27]	I(0), I(1)
4th period	74	ARFIMA (0, d, 1)	0,663221	0,298764	[-0,29, 0.69]	I(0)
5th period	39	ARFIMA (0, d, 2)	0,095406	0,319374	[-0.49, 0.55]	I(0)
6th period	39	ARFIMA (2, d, 1)	0,237487	0,868447	[-1.22, 1.63]	I(0), I(1)
7th period	83	ARFIMA (1, d, 2)	0,9834455	0,3569314	[-0.23, 0.93]	I(0)
8th period	83	ARFIMA (2, d, 2)	0,9196082	0,3224903	[-0.23, 0.82]	I(0)
9th period	397	ARFIMA (0, d, 1)	0,502221	0,0021881	[-0.00, 0.00]	I(0)
10th period	37	ARFIMA (0, d, 0)	0,690702	0,165045	[-0.15, 0.38]	I(0)
Structural breaks using Bai and Perron (2003)						
1st structural break	420	ARFIMA (0, d, 0)	0,7378417	0,0353695	[-0.03, 0.08]	I(0)
2nd structural break	549	ARFIMA (2, d, 2)	1,0482130	0,1296148	[-0.07, 0.35]	I(0)
3rd structural break	1291	ARFIMA (1, d, 0)	0,6822554	0,0273752	[-0.02, 0.06]	I(0)
4th structural break	172	ARFIMA (2, d, 2)	1,2973907	0,1903681	[-0.06, 0,56]	I(0)
5th structural break	320	ARFIMA (2, d, 2)	0,62906	0,175784	[-0.18, 0.40]	I(0)

Table 4. Results of long memory tests.

Table 4 display the fractional parameter d and the AR and MA terms obtained using Sowell's (1992) maximum likelihood estimator of various ARFIMA (p, d, q) specifications with all combinations of (p, q) with p, q ≤ 2, for seasonally adjusted weekly

initial claims in U.S. and for each recession subperiods in U.S. localized by Federal Reserve Bank of St. Louis, including coronavirus crisis that started in December 2019. Assuming the explanation done in the Methodology where the process would be short memory or I(0) when $d = 0$. So, we consider a mean reversion process (the shocks disappear in the long run) when $d < 1$. On the opposite side, the shock is expected to be permanent when $d \geq 1$. So, we can see that for the subperiods 1st, 3rd, 4th,5th,6th ,7th, 9th and 10th, where this last one period corresponds to COVID19 episode, the value of $d < 1$ implying transitory shocks through with long lasting effects and a low persistence. Mean reversion ($d < 1$) implies transitory shocks and thus, in the event of an exogenous shock if the series is $I(d, d < 1)$ the series will return to its original time trend in the future. For the case of the 3rd, 5th and 6th subperiod, the parameter d is lower than 0.5 meaning that the time series analyzed is covariance stationary. We observe mean reversion for these periods where the shock is transitory, and the recovery will take place in a short period of time.

The original time series and the 2nd period the fractional parameter presents a result $d \geq 1$, concluding that in these periods are not mean reversion and the shock is expected to be permanent (e.g. lasting forever), causing a change in trend. So, it requires strong measures by the authorities to recover the original trends.

In the case of the subperiods of the structural breaks that we get using the methodology proposed by Bai and Perron (1998, 2003), we can observe that the parameter d is lower than 1 in the 1st, 3rd and 5th structural break periods. Also, for the 2nd and 4th period $d > 1$, but according to the confidence interval we cannot reject the hypothesis of I(0) in each of the structural changes found.

To conclude and observing the confidence intervals, the I(0) hypothesis cannot be rejected in all subsamples assuming that the effect of a shock disappear in the short term.

In the case of the 1st, 3rd and 6th periods we cannot reject the hypothesis of I(1), where the effect of shock persists indefinitely, due to the confidence intervals are very wide (clearly due to the small sample sizes in some of the periods examined).

5. Conclusions

In this paper we have examined eleven time series corresponding to the original time series which is seasonally adjusted weekly initial claims in U.S. and the eight sub-periods corresponding to each one of the recessions located in time by the Federal Reserve Bank of St. Louis. Also, we have considered the others disease outbreaks like Severe Acute Respiratory Syndrome (SARS) that according to WHO, began in November 2002 and ended in May 2004, Middle East Respiratory Syndrome (MERS) began in September 2012 and it is actually activated, and finally we analyze the COVID-19 that start in December 2019.

Our first focus has been to analyze the statistical properties of these time series using unit roots and fractional integration methods to understand the behavior of the unemployment in the U.S.

We have started to perform several unit root methods, ADF, PP, KPSS. The results suggest that the original time series is stationary I(0) and the subperiods are nonstationary I(1).

On the other hand, we have also estimated the differencing parameter d in terms of fractional model using ARFIMA (p, d, q). To select the right model, we have combine all the possible cases ["(0, d, 0)", "(1, d, 0)", "(2, d, 0)", "(0, d, 1)", "(0, d, 2)", "(1, d, 1)", "(1, d, 2)", "(2, d, 1)", "(2, d, 2)"] to find the best selection criteria following the models proposed by Akaike (1973) and Akaike (1979), which are AIC and BIC respectively.

Once we have selected the specific ARFIMA model, which as we see for the time series and the respective sub-periods are different, we obtain that for the subperiods 1st, 3rd, 4th,5th,6th ,7th, 9th and 10th the value of $d < 1$ implying transitory shocks through with long lasting effects. For the case of the 3rd, 5th and 6th subperiod, the parameter d is lower than 0.5 meaning that the time series analyzed is covariance stationary. We observe mean reversion for these periods where the shock is transitory, and the recovery will take place in a short period of time.

The original time series and the 2nd period the fractional parameter presents a result $d \geq 1$, concluding that in these periods are not mean reversion and the shock is expected to be permanent (e.g. lasting forever), causing a change in trend. So, it requires strong measures by the authorities to recover the original trends.

In the case of the subperiods of the structural breaks that we get using the methodology proposed by Bai and Perron (1998, 2003), we can observe that the parameter d is lower than 1 in the 1st, 3rd and 5th structural break periods. Also, for the 2nd and 4th period $d > 1$, but according to the confidence interval we cannot reject the hypothesis of I(0) in each of the structural changes found.

To conclude and observing the confidence intervals, the I(0) hypothesis cannot be rejected in all subsamples assuming that the effect of a shock disappear in the short term. In the case of the 1st, 3rd and 6th periods we cannot reject the hypothesis of I(1), where the effect of shock persists indefinitely, due to the confidence intervals are very wide (clearly due to the small sample sizes in some of the periods examined).

The results presented in this research paper may help to a better understanding of the dynamics of unemployment by policy makers and economic analysts during and after the coronavirus crisis, comparing previous economic and financial crises with the case of the last sub-periods corresponding to a pandemic.

Declarations section:

1. Availability of data and materials

Not applicable

2. Competing interest

Not applicable

3. Funding

Not applicable

4. Authors' contribution

The author read and approved the final manuscript.

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