Unemployment dynamics in Italy: a counterfactual analysis at Covid time

Illya Bakurov, Fabrizio Culotta

1. Introduction

The experience of the Covid pandemic has revealed the importance of statistical monitoring systems. When the phenomenon of interest is evolving, information about past and future dynamics becomes fundamental to assess both effects and future trajectories. This is true especially during the recovery and post-recovery phases.

The various measures undertaken in each country to contain the spread of the virus moved towards the reduction of physical interaction and, a fortiori, gathering of people. The underlying uncertainty, in the Knightian sense, forced governments of almost all countries to impose harsh remedies. The freedom of movement has been suspended for a while. Undoubtedly, the onset of Covid was an unprecedented and unexpected shock for the world population and, thus, for the whole economy. In this, Italy can be considered a case of study.

Focusing on labour markets, from one side, a substantial drop in unemployment has been observed in Italy during the year 2020 (Fig. 1). The conditions of active search and (immediate) availability to work, whose simultaneous fulfilment identifies an unemployed individual, were not met. Accordingly, a consequent rise in inactivity occurred. From the other side, the Italian government introduced a ban on dismissal operating throughout the year 2020. The goal was to preserve the employment level avoiding firms to fire workers massively. In doing so, the level of employment was forced not to drop. Overall, this was the extraordinary regime under which the observed dynamics of unemployment evolved in Italy during the year 2020.

The aim of this work is to compare the observed dynamics of unemployment during the year 2020 in Italy with a counterfactual outcome to assess the (broad) impact of Covid in Italy in terms of unemployed individuals. In doing so, counterfactual outcomes are generated by Seasonal ARIMA models (SARIMA). Results are presented for the whole population of unemployed individuals and disaggregated by socioeconomic dimension as gender, age, education.

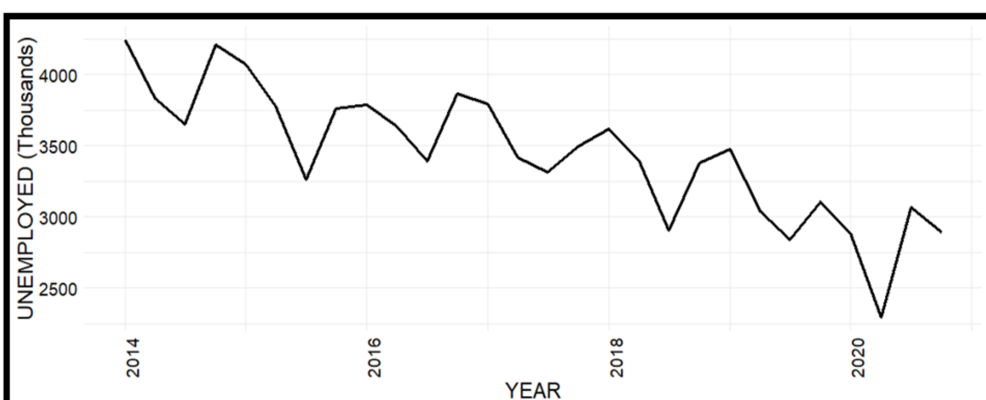

Figure 1: Unemployed individuals (thousands) in Italy over the years 2014-2020 quarters. Source: Italian Labour Force Survey.

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2. Data and Methods

This work adopts data from the Italian Labour Force Survey (Rilevazione sulle Forze di Lavoro, hereafter ILFS, for the years 2014-2020 at quarterly frequency focusing on working age population, i.e. aged 15-64 years, is considered. Raw (not smoothed) data covering the period 2014-2019 are used to train SARIMA models to forecast the four quarters of year 2020 (see Hyndman and Athanasopoulos, 2018, as a reference book). It is implicitly assumed that the first quarter of 2020 is the first period affecting unemployment dynamics, that is training data are not affected by the treatment. Estimated projections are then compared with observed values. The causal impact of Covid will be then defined as the difference between what is observed during the 2020 quarters (under the influence of Covid measures) and what would have been observed (in the absence of Covid measures). This empirical exercise is performed not only for the total population but also for eleven socioeconomic groups: two by gender (males and females), five by age (15-24, 25-34, 35-44, 45-54, 55-64), four by educational level (primary, lower and upper secondary, tertiary). The analysis is performed in *R* with help of the package *fpp2* (Hyndman et al., 2020).

Diagnostics analyses are also performed and available upon requests. In particular, trend-cycle decompositions visually suggest that each series exhibits strong seasonality which however is stable in variance over time. The visual inspection suggests that both seasonal and first differencing could take place. Therefore, we run a sequence of Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test (Kwiatkowski et al., 1992) for the null hypothesis of stationarity in the data, and we look for the evidence of rejection. Results from KPSS tests confirm that both seasonal and first differencing should take place. Model orders are selected by inspecting PACF and ACF. The winner model has been selected based on common information criteria AIC and BIC. Estimated models are reported below (Table 1).

Profile	ARIMA $(p,d,q)(P,D,Q)_m$	Drift
Total	ARIMA $(0,0,0)(0,1,1)_4$	Included
Female	ARIMA $(0,0,0)(0,1,1)_4$	Included
Male	ARIMA $(0,0,0)(0,1,1)_4$	Included
Aged 15-24	ARIMA $(0,0,0)(0,1,1)_4$	Included
Aged 25-34	ARIMA $(0,0,0)(0,1,1)_4$	Included
Aged 35-44	ARIMA $(0,0,0)(0,1,1)_4$	Included
Aged 45-54	ARIMA $(2,1,0)(0,1,1)_4$	Excluded
Aged 55-64	ARIMA $(0,0,1)(0,1,0)_4$	Included
Primary	ARIMA $(0,0,0)(0,1,0)_4$	Included
Lower Secondary	ARIMA $(0,0,0)(0,1,1)_4$	Included
Upper Secondary	ARIMA $(0,0,0)(0,1,1)_4$	Included
Tertiary	ARIMA $(6,0,0)(0,1,1)_4$	Included

Table 1: Estimated Seasonal ARIMA (SARIMA) models.
Drift refers to the time-invariant intercept component.

The resulting error components are distributed as white noise. Results from Ljung-Box suggest accepting null hypothesis of serially uncorrelated errors. Accordingly, we use such model specifications to produce the counterfactual trajectories for the 2020 quarters.

3. Results

Results are reported in figures 2-5. For sake of graphical clarity, confidence intervals are provided only for the total profile (Fig. 2). For the other profiles, they are available upon requests.

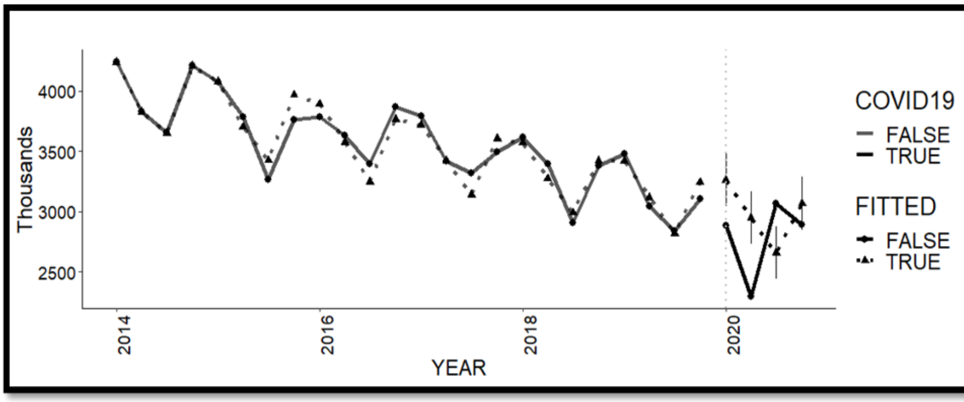

Figure 2: Total profile. Observed (FITTED=F) vs Forecast (FITTED=T) at Covid time (COVID19=T). Source: authors' own elaborations on ILFS data.

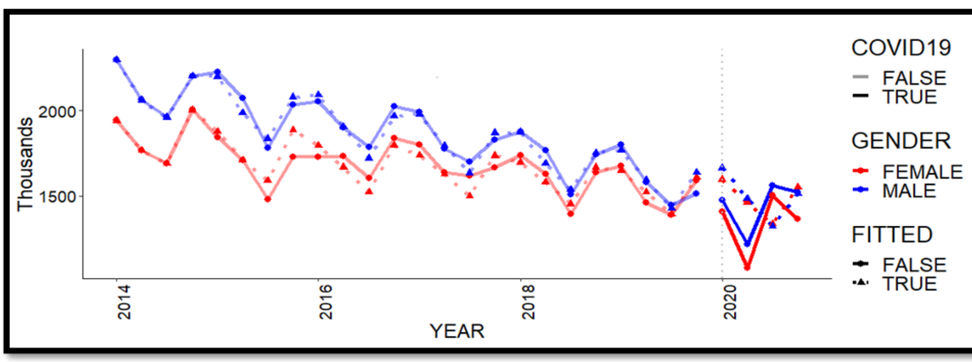

Figure 3: Gender Profiles. Observed (FITTED=F) vs Forecast (FITTED=T) at Covid time (COVID19=T). Source: authors' own elaborations on ILFS data.

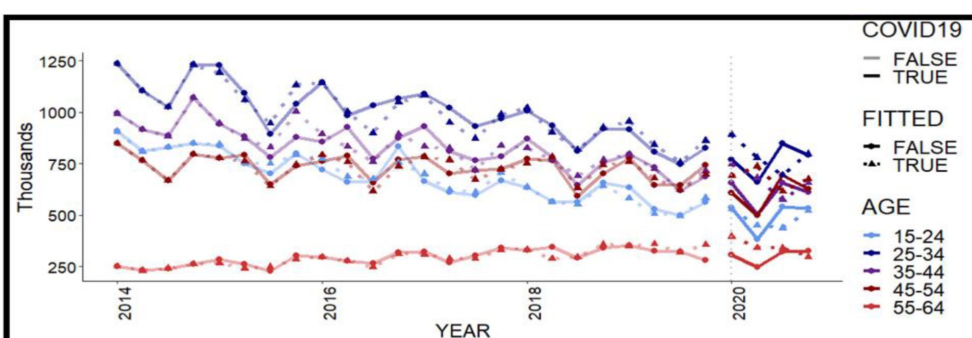

Figure 4: Age profiles. Observed (FITTED=F) vs Forecast (FITTED=T) at Covid time (COVID19=T). Source: authors' own elaborations on ILFS data.

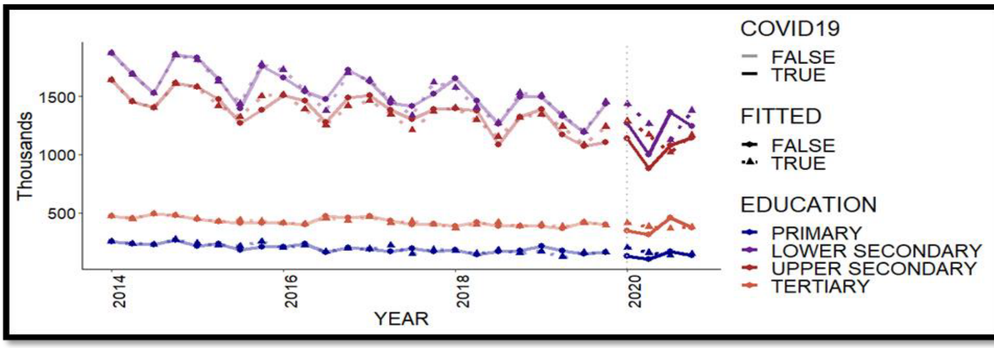

Figure 5: Education profiles. Observed (FITTED=F) vs Forecast (FITTED=T) at Covid time (COVID19=T). Source: authors' own elaborations on ILFS data.

All profiles depicted above share some general features. The difference between observed and forecast values, i.e. the impact of Covid on the number of unemployed, is negative during the first quarter of 2020. The difference is even larger (in absolute value) during the second quarter of 2020, where the impact of Covid in 2020 led a relevant drop in the number of unemployed. The difference is positive at the third quarter, coinciding with the summer season, and becomes negative during the fourth.

Results are also displayed in a tabular format (Table 2). The largest impact of Covid on unemployed workers corresponds to 2020-Q2 (-652000). This drop is concentrated among females (-385000, about 60% of the total drop). Across age classes, 45-54 reports the largest reduction (-237000, around 36%). Whereas unemployed with lower secondary education are the educational group (-295000, 45%). During the third quarter of 2020, the raise in unemployed occurred (410000). Of such a raise, men were the majority (242000, 60%). The age class 25-34 shows the largest share (153000, 37%). Similarly, the largest increase is observed for the upper secondary educational group (238, 58%). Overall quarters, it results that the drop in unemployment caused by Covid during the year 2020 regarded women more than men especially from the second quarter. Among the age groups, Covid had an impact especially on unemployed individuals aged 45-54. Across educational levels, following this logic, individuals without a tertiary education were affected the most.

4. Conclusions

This work studies the impact of Covid pandemic, and related measures, on the number of unemployed workers during the 2020 quarters in Italy. Observed and counterfactual outcomes are compared to identify the causal impact of the onset of Covid since the first quarter of 2020.

In doing so, counterfactual outcomes are produced by means of SARIMA models applied to different socioeconomic groups in the population of unemployed. The causal impact is then measured as difference between observed and forecast values. Results confirms that the drop in unemployment caused by Covid was heterogenous, i.e. not homogenously distributed in the population. Females, individuals aged 45-54 and those with secondary educational levels were those groups associated with the highest drop.

In general, the counterfactual analysis is used as a tool to identify causal mechanism. In the case of this work, the (macro-)econometric model is also offered as a (simple) policy statistical tool. It can be used to identify future patterns and to reason on possible thresholds or rebounds. It can offer an informative, yet statistical, support to face important decisions under uncertainty. Possibly, it can reveal insights for future planning.

PROFILE	Source	2020-Q1	2020-Q2	2020-Q3	2020-Q4
Total	Observed	2883	2295	3067	2891
	Forecast	3261	2947	2657	3065
	Covid Impact	***-378***	***-652***	***410***	***-174***
Female	Observed	1407	1078	1504	1366
	Forecast	1597	1463	1337	1551
	Covid Impact	***-190***	***-385***	***167***	***-185***
Male	Observed	1476	1217	1563	1525
	Forecast	1664	1484	1321	1514
	Covid Impact	***-188***	***-267***	***242***	***11***
Aged 15-24	Observed	539	381	543	532
	Forecast	529	450	437	524
	Covid Impact	***10***	***-69***	***106***	***8***
Aged 25-34	Observed	770	663	849	793
	Forecast	892	780	696	798
	Covid Impact	***-122***	***-117***	***153***	***-5***
Aged 35-44	Observed	658	502	658	613
	Forecast	748	682	576	657
	Covid Impact	***-90***	***-180***	***82***	***-44***
Aged 45-54	Observed	609	500	693	628
	Forecast	690	737	616	675
	Covid Impact	***-81***	***-237***	***77***	***-47***
Aged 55-64	Observed	307	249	324	325
	Forecast	396	341	340	298
	Covid Impact	***-89***	***-92***	***-16***	***27***
Primary Ed.	Observed	129	105	167	132
	Forecast	54	158	137	149
	Covid Impact	***75***	***-53***	***30***	***-17***
Lower Secondary Ed.	Observed	1136	877	1079	1142
	Forecast	1287	1172	1021	1167
	Covid Impact	***-151***	***-295***	***58***	***-25***
Upper Secondary Ed.	Observed	1271	999	1364	1243
	Forecast	1435	1265	1126	1378
	Covid Impact	***-164***	***-266***	***238***	***-135***
Tertiary Ed.	Observed	348	314	457	374
	Forecast	413	381	367	379
	Covid Impact	***-65***	***-67***	***90***	***-5***

Table 2: Counterfactual analysis on unemployment dynamics (thousands of individuals) in Italy at Covid time (2020 quarters). Covid impact is the difference between observed and forecast values. Source: authors' own elaborations on Italian Labour Force Survey data.

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