Green mobility

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This note has nothing to do with bicycles, electric cars and other zero-emission vehicles. Its purpose is only to investigate the effects of the extensive use of the so-called “Green Pass”, i.e. the EU digital COVID certificate, by using Google mobility data (Google LLC, 2021).

Green Pass and Covid testing

In Italy, the first reference to the Green Pass dates back to Decree 52/2021 of April 2021, but its implementation was defined only in June 2021 by a government regulation.[1] Initially, its application was limited to restaurants, museums, cinemas and a few other activities; but since then it has been extended to hotels, universities, public transports, and many other places.

Since October 15, public and private employees, as well as self-employed persons, have had to possess a Green Pass, which enlarges and deepens the original scope of the regulation. Apart from a few exemptions, the new policy concerns almost 23 million citizens (Sole24Ore 11.10.2021) who, if they want to work, should either be fully vaccinated, recovered from COVID, or have been tested negative within the previous 72 hours. The Italian government has used it as an incentive – a mix of ‘stick’ and ‘carrot’ – to obtain the highest possible amount of vaccinated people, convince the remaining vaccine sceptics, and limit the externalities of those belonging to the variegated category of ‘anti-vaxxers’.

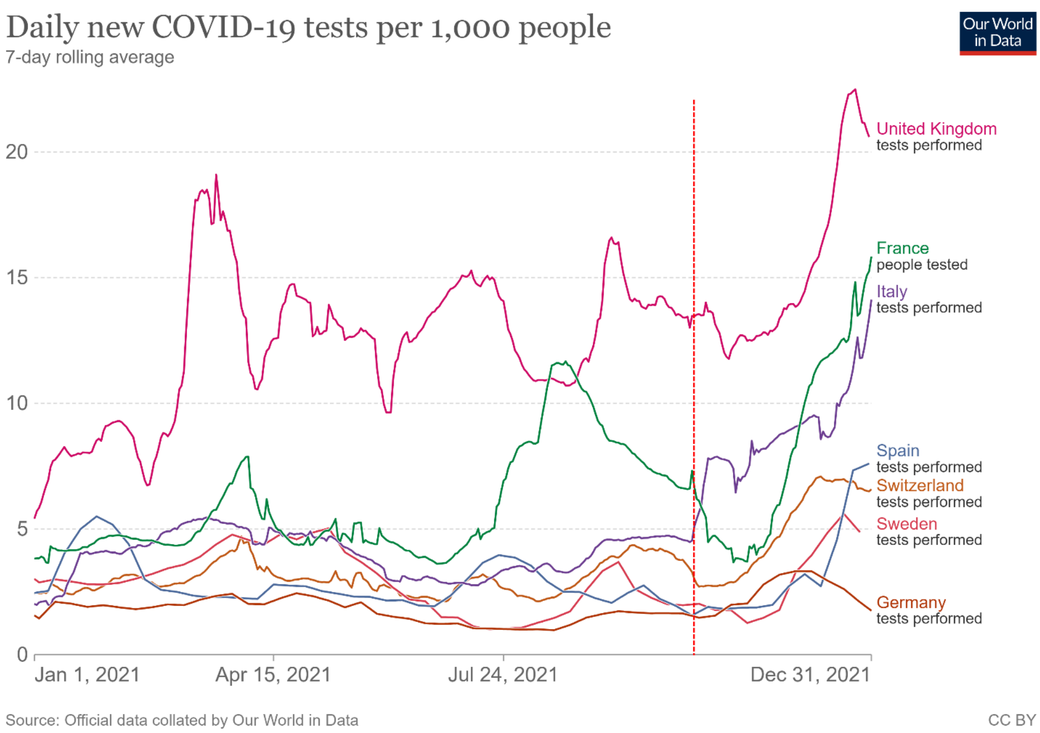

Figure 1. Covid-19 tests per population in some European countries

[1] Anticipating its implementation at the EU level, where it has been introduced as an instrument to make travel easier and safer.

The possibility to use PCR and rapid antigen tests has partially reduced the strictness of the measure, and provided an excuse for all those opposing vaccination. However, tests must be taken in a medical center or a pharmacy, so that the results can be officially registered on the national health system's digital platform and finally transferred to the Green Pass.

As shown by the violet line in Figure 1, the new policy produced in Italy a sudden jump in the incidence of tests corresponding to its implementation (vertical red dotted line), with absolute figures that doubled within a week, moving from approximately 250,000 tests per day, to a new plateau of 500,000. Thereafter, as in other countries, the numbers continued to increase due to deterioration of the epidemiological situation, and also in connection to the Christmas period, in which many people, due to travel restrictions or the desire not to transmit any disease to their (elderly) family members, decided to preventively test themselves.[2]

Day after day, the combination of all the above factors produced a visible increase in the number of those wanting a test in a pharmacy. The result was long queues of people waiting all day long to enter a pharmacy (Sole24Ore 27.12.2021). I shall investigate whether this presence close to pharmacies is captured by Google mobility data, which are able to estimate the numbers of visitors in different types of places by collecting aggregated, anonymized data from users who have turned on the "Location History" setting on their devices. These quantities are then compared to a benchmark period before the pandemic, in order to assess the increase or decrease in the number of visitors in different locations. Amongst these locations, Google has a special category for "Pharmacies and Groceries", considered to be "essential trips" for any citizen. If grocery stores are really essential visits, they should not have experienced any specific trend, if not those dependent on some particular season of the year. On the contrary, my expectation was that Italian pharmacies may have experienced a non-seasonal increase in the number of visitors which may have been due to the extension in the implementation of the Green Pass that started in mid-October 2021.

An empirical test

To test this expectation, I downloaded all the daily mobility data concerning each Italian province since the beginning of the pandemic. I then produced de-seasonalized data by subtracting the mobility trend around pharmacies and grocery stores from the corresponding value of the preceding year.[3] My dependent variable thus represented the mobility in each day compared to that in the same day of the year before, thereby cancelling any non-policy, time-specific trends in mobility, including those regarding grocery stores (and not pharmacies). Given that Google has provided these data publicly only since the second week of February 2020, on taking the first difference my dataset was automatically reduced to the period from 14 February 2021 to 31 December 2021.

My main independent variable was a dummy variable that took the value of 1 for each day after 12 October 2021, 72 hours before the mandatory exhibition of the Green Pass in workplaces, and 0 otherwise. I further

[2] Regarding the second alternative, most people simply decided to self-test themselves, with test kits that could have been bought elsewhere, and which therefore do not necessarily enter in these statistics.

[3] Since Google mobility data are already percentage changes compared to the median values in two weeks before the pandemic, the quantity is simply a difference between percentages. For example, if on December 1, 2020 a specific province had a decrease in mobility in a certain place of 20% compared to the benchmark period, and on December 1, 2021 that decrease, against the same benchmark, was 10%, the value will be a positive increase of 10%=-10% -(-20%).

included in the model a series of potentially confounding factors. The first related to anti-Covid measures restricting mobility such as the local color-coding system in place in Italy since November 2020 (Camera dei Deputati, 2021; Manica et al., 2021; Panarello and Tassinari, 2021): this is an ordinal variable taking the value of 1 for white areas, representing the benchmark category, 2 for yellow, 3 for orange, and 4 for red areas, those with the most rigid restrictions. All other things being equal, the stricter the policy, the less I expected to have mobility also in grocery stores and pharmacies. I further controlled for the differential mobility in residential areas, often with dynamics perfectly symmetrical to most other places categorized by Google. I then introduced a variable capturing the severity of the epidemiological situation, which, especially after the introduction of vaccines, was better represented by the incidence of Covid deaths. As explained at the end of the previous section, the worries connected to the new wave of the pandemic should have boosted the demand for tests, and thus should be positively associated with the mobility around pharmacies. More specifically, I used the smoothed values of the daily number of certified Covid deaths per million people provided by "Our World in Data" (Ritchie et al., 2020). Finally, I introduced weekly fixed effects to capture any remaining time trend in the data, and a categorical variable for the day of the week, to avoid the confounding effects of the reduced opening time of pharmacies during weekends. To control for the latter risk, I also ran a robustness test using a slightly different dependent variable, comparing mobility data to those 364 (and not 365) days earlier, in order to match the same day of the week in the preceding year.

The results of panel regressions

In Table 1, I have run a series of panel regressions with random (models 1, 3) and fixed effects (models 2,4), testing the impact of the extension of the Green Pass on mobility around pharmacies.

Models 1 and 2 use as dependent variable the change in mobility against the previous year, while models 3 and 4 incorporate the effects of different workdays by computing the change in mobility against 364 days earlier.[4] Each of the models reports a certain degree of intraclass correlation, as highlighted by the rho coefficient at the bottom of the table: a minimum of 7% (model 3) and a maximum of 27% (model 2) of the variance in the number of pharmacy visitors is due to differences among provinces. Most of the variation is thus longitudinal, and this helps explain why there are not many differences between models with random and fixed effects.

Focusing on the first two models, and starting with the control variables, the effects of the different policies/colors only partially reflect the expectations. Yellow regions have the same number of pharmacy visitors as white ones, while then registered is an increase in orange regions, and finally an even clearer decrease in red regions. A possible explanation, apart from some unusual interaction with the epidemiological control included in the model, is that the more severe conditions that characterize orange regions also require more frequent visits to pharmacies, whereas in red regions the mobility constraints prevail over all other factors. These effects are already discounted by the wider changes in mobility that are captured by the greater tendency to stay at home during the pandemic. In fact, as expected, the duration of the stay in residential areas is inversely associated with the trend in pharmacy visits.

[4] I kept the day-of-the-week categorical variable also in the latter models, since several pharmacies extended their opening hours, and started to accept reservations for tests on Sundays as well.

Table 1. The impact of the Green Pass on mobility around pharmacies

		(1)	(2)	(3)	(4)
Green Pass		1.43*	1.43*	2.45**	2.44**
		0.82	0.82	1.24	1.24
Policy	Yellow	0.22	0.22	-3.21***	-3.2***
		0.33	0.33	0.5	0.5
	Orange	2.25***	2.27***	-1.66**	-1.65**
		0.45	0.45	0.68	0.68
	Red	-3.96***	-3.93***	-10.01***	-9.96***
		0.56	0.56	0.84	0.84
Change resident mobility		-1.34***	-1.34***	-0.49***	-0.5***
		0.02	0.02	0.03	0.03
New deaths (per million)		2.76***	2.74***	13.94***	13.9***
		0.47	0.47	0.72	0.72
Day of week	Monday	40.04***	40.06***	1.93***	1.98***
		0.24	0.24	0.37	0.37
	Tuesday	14.35***	14.35***	3.17***	3.17***
		0.22	0.22	0.34	0.34
	Wednesday	14.40***	14.41***	-0.31	-0.31
		0.22	0.22	0.34	0.34
	Thursday	14.88***	14.88***	3.36***	3.37***
		0.22	0.22	0.34	0.34
	Friday	15.50***	15.5***	6.99***	7.00***
		0.22	0.22	0.34	0.34
	Saturday	0.39*	0.38*	-2.99***	-3.02***
		0.23	0.23	0.35	0.35
Week		✔	✔	✔	✔
Constant		-25.70***	-25.64***	-74.3***	-74.12***
		2.62	2.58	3.93	3.9
Effects		Random	Fixed	Random	Fixed
rho		0.16	0.27	0.07	0.13

***p≤0.01; **p≤0.05; ***p≤0.10

By contrast, as said, the seriousness of the epidemiological situation, measured by the incidence of certified Covid deaths, is positively related to those visits. Finally, comparing the magnitudes of the coefficients, most visits to pharmacies seem to happen on Monday, probably for those who fear that they have been infected during the weekend, or for those who need the Green Pass to start the working week. Nonetheless, each workday presents a systematic increase in visits compared to the baseline Sunday level. The only day of the week in which the increase is only weakly, and not strongly, significant, and in which the magnitude of the coefficient is clearly lower, is Saturday. In reality, some of these results could depend on the 1-year difference that produced the dependent variable, with Monday's mobility being computed against Sunday's mobility 365 days earlier, Saturday's against Friday's, and so forth. These concerns are better addressed in models 3 and 4. Finally, each model includes weekly fixed effects to capture any remaining time contingency.

Coming to the covariate of interest, both models with random and fixed effects show a significant impact of the introduction of the Green Pass. The coefficient is only weakly significant, and its magnitude reveals an increase, all other things being equal, of approximately 1.5% of visits, much lower than the visual perceptions due to the long queues close to pharmacies. However, considering the range of control variables used, and the inclusion of grocery stores in the same category of places, it is already a success to find a significant result.

In models 3 and 4, in which the dependent variable provides a better comparison between the same days of the week, the effect of the introduction of the Green Pass is larger and more significant. Moreover, this time the impact of anti-Covid policies is consistent with my original expectations, while the mobility in residential areas and the seriousness of the epidemiological situations preserve the anticipated effects already shown in models 1 and 2. Some predictable changes regard the effect of the different days of the week, keeping in mind that the coefficients represent the relative increase/decrease in mobility compared to the benchmark difference in mobility between Sundays at a one-year distance. All other things being equal, Mondays, Tuesdays, Thursdays and Fridays show some systematic increase in pharmacy visits compared to similar days in the preceding year, Wednesdays present a null effect, while Saturdays register some decrease compared to the difference in mobility between Sundays. This apparently odd result concerning Saturdays instead makes perfect sense, at least in the Green Pass period. If it is true that some pharmacies started to open on Sundays as well, the benchmark already includes a significant increase against the preceding year, which is not matched by a similar increase between Saturdays, on which they were probably already open in the previous year.

A comparative outlook

One possible criticism of the foregoing analysis is that, in spite of all the controls used, similar trends may have happened also elsewhere, without the mandatory requirement of the Green Pass to work. As can be easily seen in Figure 1, most countries experienced an increase in tests in the last part of the year, and countries like France and the United Kingdom had a number of tests per thousand people which was higher than in Italy, also admittedly without any sudden leap like the one experienced in the Italian case around the middle of October, in correspondence with the extended use of the Green Pass.

I thus collected mobility data at the national level also for 28 other European countries[5], and I applied a difference-in-differences model for panel data, which is one the most used techniques to infer causality (Cunningham, 2021). I thus had for each country 365 daily measures of mobility for the whole 2021 year (my dependent variable), which were matched with epidemiological (deaths per million people) and policy (stringency index) data (Hale et al., 2021). In so doing, I replicated a model whose structure was similar to the one used for the Italian case in the preceding section, including categorical variables for the week and day of the week.

[5] The complete list of countries is the following: Austria, Belgium, Bulgaria, Croatia, Czechia, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, Netherlands, Norway, Poland, Portugal, Romania, Slovakia, Slovenia, Spain, Sweden, Switzerland, United Kingdom.

Table 2. A difference-in-differences model comparatively estimating the impact of the Green Pass

Difference-in-differences regression Number of obs = **10,502**
Data type: Longitudinal

(Std. err. adjusted for **29** clusters in **ctrycode**)

Pharmacy	Coefficient	Robust std. err.	t	P>|t|	[95% conf. interval]	
ATET						
Greenpass (1 vs 0)	**4.622645**	**1.20789**	**3.83**	**0.001**	**2.148394**	**7.096897**

Note: ATET estimate adjusted for covariates, panel effects, and time effects.

Table 2 reports directly the output of the model in Stata. The average treatment effect on the treated (ATET) is positive and highly significant, reporting an increase of 4.6% in the number of visitors to pharmacies and grocery stores, giving some robustness to the previous results using only Italian data.

Similar results are obtained by applying interrupted time series (Linden, 2015) using daily as well as weekly data. In both cases, the methodology suggests the existence of a (weakly) significant 5% increase in pharmacy visitors in correspondence with the implementation of the Green Pass in workplaces and, after that leap upwards, a further increase whose slope is not systematically different from those of other countries.

Conclusion

This research note is mostly an exercise. Normatively, empirically, and politically speaking, it is not particularly interesting to know that a certain policy has systematically increased the number of citizens visiting pharmacies. To know this fact, one could have simply read the newspapers or taken a walk in the streets. Much more interesting is verifying once again the possibility offered to the social sciences by Google mobility data, even for registering tiny effects like ours and in spite of noisy data.

These data are being increasingly used by epidemiologists and social scientists, as any query in Scopus or Web of Science can easily demonstrate. For example, they have helped with the following: monitoring economic trends during the pandemic (Spelta and Pagnottoni, 2021); demonstrating that people engaged in outdoor recreational activities in parks or natural areas did not contribute to spreading the virus further (Venter et al., 2021); evaluating if “compliance with the mobility limitations has affected the number of infections and deaths over time” (Panarello and Tassinari, 2021); and, more in general, assessing the effectiveness of containment policies and predicting the evolution of the epidemiological situation (Gaeta et al., 2021; Godio et al., 2020). They are reliable data capable of opening new perspectives to the work of social scientists.

References

Camera dei Deputati (2021) Misure sull'emergenza coronavirus (COVID-19) - Quadro generale. Rome: Servizio Studi.

Cunningham, S. (2021) *Causal Inference. The mixtape.* New Haven: Yale University Press.

Gaeta, A., Loia, V. and Orciuoli, F. (2021) 'A method based on Graph Theory and Three Way Decisions to evaluate critical regions in epidemic diffusion:: An analysis of COVID-19 in Italy', *Applied Intelligence*. Epub ahead of print 20210115. DOI: 10.1007/s10489-020-02173-6. 1-17.

Godio, A., Pace, F. and Vergnano, A. (2020) 'SEIR Modeling of the Italian Epidemic of SARS-CoV-2 Using Computational Swarm Intelligence', *International Journal of Environmental Research and Public Health* 17(10).

Google LLC (2021) *Google COVID-19 Community Mobility Reports*. Available at: https://www.google.com/covid19/mobility/ (accessed 15 November 2021).

Hale, T., Angrist, N., Goldszmidt, R., et al. (2021) 'A global panel database of pandemic policies (Oxford COVID-19 Government Response Tracker)', *Nature Human Behaviour* 5(4): 529-538.

Linden, A. (2015) 'Conducting interrupted time-series analysis for single- and multiple-group comparisons', *The Stata Journal* 15(2): 480–500.

Manica, M., Guzzetta, G., Riccardo, F., et al. (2021) 'Impact of tiered restrictions on human activities and the epidemiology of the second wave of COVID-19 in Italy', *Nature Communication* 12(1): 4570.

Panarello, D. and Tassinari, G. (2021) 'One year of COVID-19 in Italy: are containment policies enough to shape the pandemic pattern?', *Socio-Economic Planning Sciences*. Epub ahead of print 20210703. DOI: 10.1016/j.seps.2021.101120. 101120.

Ritchie, H., Mathieu, E., Rodés-Guirao, L., et al. (2020) 'Coronavirus Pandemic (COVID-19)', *Our World in Data*.

Spelta, A. and Pagnottoni, P. (2021) 'Mobility-based real-time economic monitoring amid the COVID-19 pandemic', *Scientific Reports* 11(1): 13069.

Venter, Z.S., Sadilek, A., Stanton, C., et al. (2021) 'Mobility in Blue-Green Spaces Does Not Predict COVID-19 Transmission: A Global Analysis', *International Journal of Environmental Research and Public Health* 18(23).