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Do Covid-19 mobility restrictions affect economic uncertainty in Italy? Evidence from a SVAR approach

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Abstract

The implications of Covid-19 are severe not only in terms of healthcare, but also from a socio-economic perspective. However, its impact on economic systems and the evaluation of related policy decisions are difficult to assess due to lack of related data. One possibility is to focus on the epidemic induced economic uncertainty: in this article we investigate the links between individual mobility limitations due to the pandemic outbreak and the resulting economic distrust in Italy, measured with an ad hoc Google Trend index. We propose an analysis based on Structural Vector Autoregressive models discovering a persistent surge in economic uncertainty as a response to Covid-19 and mobility shocks.

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1. Introduction

Economic uncertainty, i.e., the impossibility of predicting future economic events, can manifest as a consequence of shocks such as recessions, wars or pandemics, and its repercussions are severe: from a household perspective, uncertainty in future incomes leads to risk-aversion with a higher propensity for savings with respect to consumption; similar conclusions apply also at firm level for investment and hiring decisions. As a consequence, the output slows down and the downturn following the initial shock is amplified.

Leduc and Liu (2016), for instance, compare uncertainty shocks to aggregate demand ones since they both increase unemployment and reduce inflation. In line with this finding, Basu and Bundick (2017) document a negative co-movement of consumption, investment, hours worked and output as a response to an adverse uncertainty shock. Bloom (2009) considers instead the impact on firms which, with heightened uncertainty, postpone their investment and hiring decisions, leading to an output loss. Other contributions move in similar direction, such as Caggiano et al. (2014), who investigate the unemployment dynamics subsequent to uncertainty rise, or Moore (2017), who builds an economic uncertainty index for Australia highlighting the reduction in investment and employment growth due to uncertainty spikes.[1] Uncertainty, however, affects financial market volatility too, whose interaction with the real economy makes the resulting implication even more severe: as pointed out among the others by Liu and Zhang (2015); Ludvigson et al. (2015); Carriero et al. (2018), uncertainty about financial market is an additional source of output fluctuation. Finally, uncertainty poses several challenges to policy makers: Fernández-Villaverde et al. (2015) consider the cost of uncertainty in terms of fiscal policy volatility shocks documenting negative and sizable effects for the economic output; Aastveit et al. (2017); Caggiano et al. (2017) investigate the role of uncertainty in monetary policy in terms of reduced effectiveness which is even more exacerbated in the case of Zero Lower Bound; moreover, Bayer et al. (2019) emphasize the wealth redistribution and welfare effects of economic policies under income uncertainty.

Starting from this premise, Covid-19 outbreak is surely a major driver for economic uncertainty and finding a way to correctly capture the phenomenon is arduous. If on the one hand mobility reduction policies are effective to prevent the spread of the pandemic (Chernozhukov et al., 2021), on the other hand they will most likely induce a slowdown in economic activity (Chen et al., 2020). The impossibility of determining the persistence of the crisis eventually causes a worry for the economic stability and an increasing social pressure, leading to a spike in uncertainty. Caggiano et al. (2020), for instance, using the VIX index as a proxy for pandemic-induced uncertainty, predict a cumulative economic output loss in terms of world industrial production of 14% in one year.

Measuring economic uncertainty is challenging given its unobservability. Suggested approaches are to use as proxies financial volatility indexes (e.g., the VIX), *ad hoc* measures such as the Economic Policy Uncertainty index (EPU) as proposed by Baker et al. (2016), or Google Trends-based indexes (GTIs) as stressed in Dzielinski (2012); Donadelli and Gerotto (2019). GTIs, in particular, are based on web searches which should reflect economic agents thoughts and worries (Castelnuovo and Tran, 2017): by retrieving the number of times some specific keywords have been searched, we can draw implications on how economic agents react to economic policy news. However, even if there is evi-

[1] For a detailed literature review see Castelnuovo et al. (2017).

dence that such indicators well capture different aspects of economic uncertainty, it is still unclear how Covid-19 related mobility policies *directly* affect uncertainty. In this work we aim precisely to investigate whether recent limitations in individual mobility foster economic distrust.

In particular, we perform the analysis with Italian data: the country has been characterized by high contagions from the very beginning, and has almost immediately adopted strict mobility restrictions. The state of emergency was declared by Italian institutions on 31^{st} January 2020, much earlier than the official global health emergency statement by the World Health Organization (11^{th} of March). In February, eleven municipalities in northern Italy were placed under quarantine; on 9^{th} March, the quarantine was extended to all Italy; after two weeks, the Government disposed the closure of all non-essential businesses and industries, together with the human movement restriction between and within Regions. Starting from May, the imposed restrictions were gradually eased, till November, when new mobility policies were introduced to counter a new spread of contagions. However, the policy has changed with the beginning of the "second wave", moving from National to Regional regulation.

We propose a Structural Vector Autoregressive (SVAR) approach to analyze the dynamics of Covid-19, mobility policies and perceived economic uncertainty. We will use the Covid-19 Replication index, the Google Mobility index for housing permanence as indicator of mobility restrictions, and finally a GTI to proxy economic uncertainty, showing how the last one is significantly affected by Covid-19 and mobility shocks.

The major contribution of this paper is to provide a comprehensive picture of the dynamic interdependence of these three variables. Since it is so far difficult to evaluate the impact of the pandemics on the real economy, we believe it is crucial to focus on the uncertainty counterpart, which reacts quickly. Moreover, we use high frequency and rather innovative data, in particular, proposing a new index to measure economic uncertainty for the Italian case and on daily basis.

The structure of the article is the following. Section 2 describes the data. Section 3 includes a description of the SVAR model and the related findings. In Section 4, we report further analyses to investigate the robustness of the results. Finally, Section 5 concludes.

2. Dataset

This section provides a comprehensive description of the used data, with particular emphasis on the definition of the variables: *(i)* the R index, R_t *(ii)* the Google housing permanence index, $housing_t$ *(iii)* a GTI for economic uncertainty, GTU_t; they represent, respectively, a quantification of the Covid-19 epidemic trend of infections, a measure of mobility restrictive policies and an index reflecting economic worry. The dataset refers to Italy during the first pandemic wave, i.e. from 2^{nd} March to 2^{nd} November 2020. The choice of the time span is based on two fundamental matters: from the one hand, the beginning coincides with the Covid-19 data availability from public sources, and from the other, we have decided to focus on the "first wave" of contagions with the idea of capturing more directly the economic effects of the pandemic when it was largely unknown and not direct countermeasures were available (vaccines or drugs). We restrict the analysis to 2^{nd} November 2020, since thereafter the "second wave" has officially begun and the related mobility policy has changed.

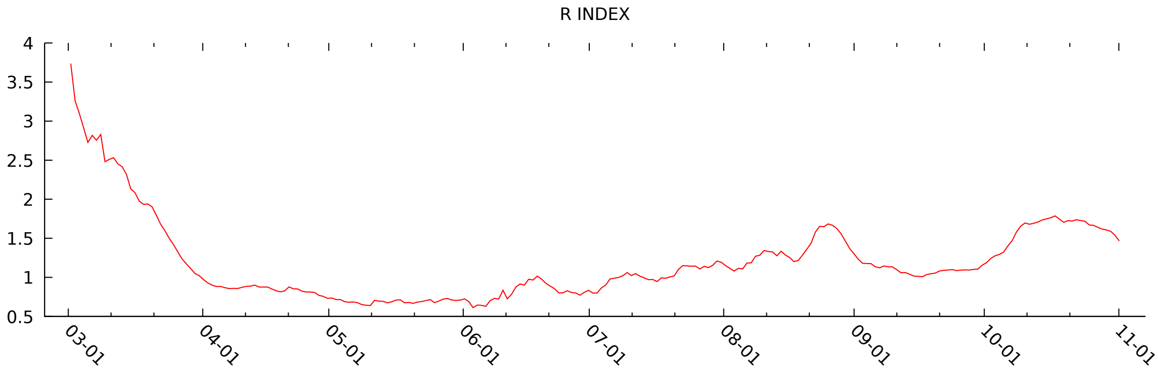

Figure 1: R_t series, daily data

2.1 The R index

A simple and direct indicator of Covid-19 spread is surely the series of daily contagions, however this measure is highly sensitive on how the disease is detected i.e., the number of nasopharyngeal swabs tested. As a consequence, it can easily underestimate the real magnitude of the phenomenon if not adjusted.

To correctly quantify the precise epidemic-related scenario, we therefore employ the so-called R index, defined as the reproduction number of the epidemic through time, given the incidence time series and the serial interval distribution (Cori et al., 2013). In other words, it estimates the expected number of cases generated by a single infected individual in a not immunized population.

We compute[2] the R_t starting from the "new infected" (nuovi positivi) series from Italian Protezione Civile daily data.[3] The serial interval distribution is assumed as a Gamma with parameters of shape $\alpha = 1.87$ and rate $\beta = 0.28$, as estimated for Lombardy Region (Cereda et al., 2020) and suggested by the Italian National Health Institute.[4] The series is reported in Figure 1.

2.2 Google mobility index

During Covid-19 emergency, Google has made mobility data coming from Google Maps publicly disposable: the 2020 Google Global Mobility Report[5] provides aggregated and anonymous information related to the variation of visits or length of stay at places of different categories, with respect to a benchmark defined via the daily median computed from the 3^{rd} January to the 6^{th} February 2020. Place categories are "Retail and recreation", "Grocery and Pharmacy", "Parks", "Transit stations", "Workplaces" and "Residential". Whereas the last one is expressed as percentage change of permanence duration with respect to the baseline, all the other ones are instead computed as percentage changes of visits number. For the mobility restrictions dynamics, in particular, we define our variable $housing_t$ as the "Residential" series: since it manifests a quite evident seasonal pattern, we employ a structural model *à la Harvey (1990)* as a filter. Figure 2 reports in

[2]"EpiEstim" R package, `https://cran.r-project.org/web/packages/EpiEstim/index.html`.

[3]`https://github.com/pcm-dpc/COVID-19`.

[4]Istituto Superiore della Sanità:
`https://www.iss.it/coronavirus/-/asset_publisher/1SRKHcCJJQ7E/content/faq-sul-calcolo-del-rt`.

[5]`https://www.google.com/covid19/mobility/`.

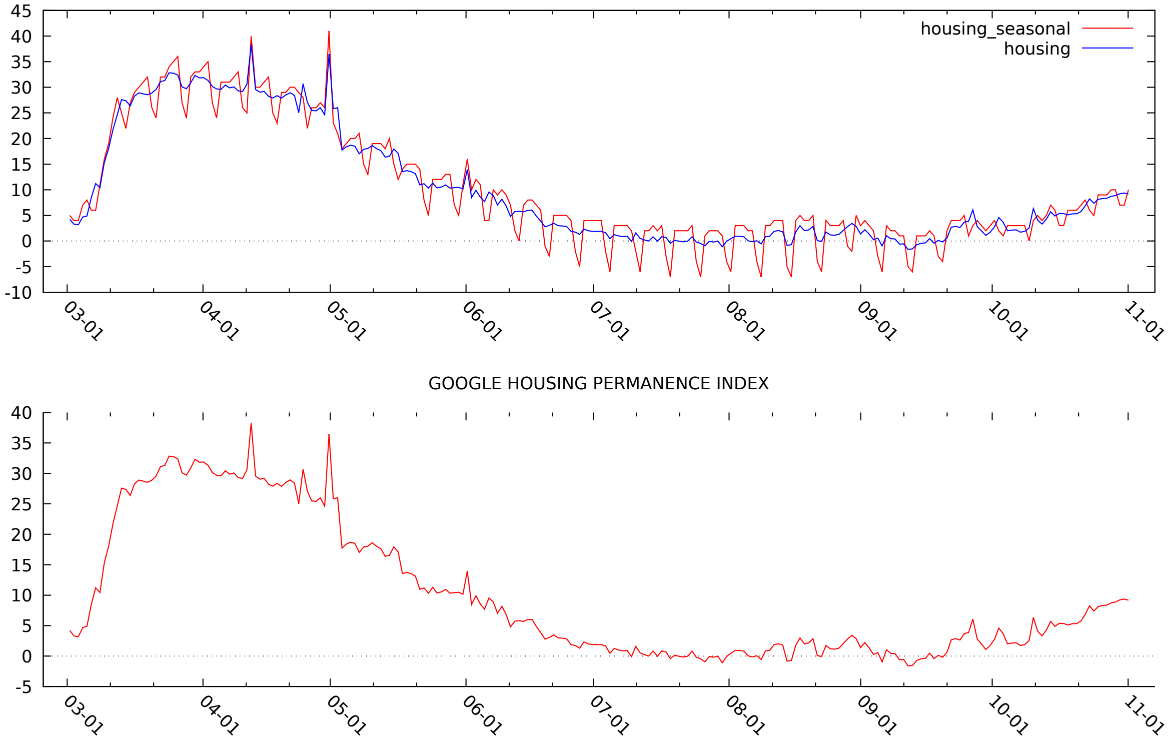

Figure 2: Original and structural model filtered series for $housing_t$

the top panel both the original series (denoted as $housing\_seasonal_t$) and the seasonal-adjusted $housing_t$, whereas the bottom panel depicts only the seasonal-adjusted one for the seek of clarity.

Notice that the variable is associated with high values when mobility policies are more restrictive and with lower ones when such measures are relaxed.

2.3 Uncertainty index

We exploit Google Trends to download search volumes data for the keywords reported in Table I, which should reflect the level of economic-related worry from the individual perspective. Our GTU_t variable is obtained as the first principal component of the key-

Table I: Keywords used for GTU_t construction

Keyword	Description
Cassa Integrazione	Wages Guarantee Fund by the Italian legislation
Caritas	Catholic volunteering and charity confederation
Bollette	Bills
Disoccupazione	Unemployment
Aiuti economici	Economic aid

words volume searches time series. The series exhibits a pronounced seasonal pattern as it can be grasped from Figure 3; for this reason the same procedure based on structural model filtering is here applied too.

From the filtered series (bottom panel of Figure 3) we observe a surge in economic uncertainty in the first weeks of the sample, followed by a slow but persistent decline.

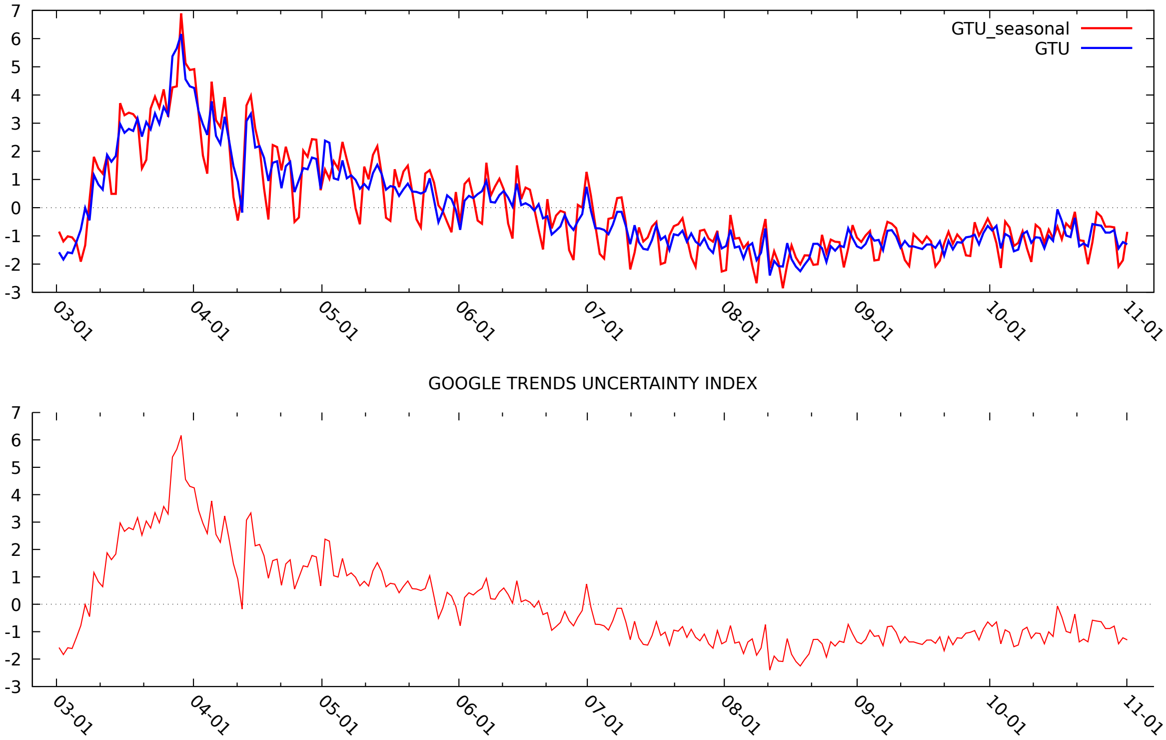

Figure 3: Original and structural model filtered series for GTU_t

2.4 Preliminary analysis

In this section, we discuss the properties of the series we outlined above. At first, we run the Augmented Dickey Fuller (ADF) unit root test (Dickey and Fuller, 1979) on the three series.

Table II: Augmented Dickey-Fuller Tests

Variable	Lags	Test statistic τ	p-value
R_t	15	-2.5064	0.1139
$housing_t$	20	-3.3745	0.0119
GTU_t	9	-1.5815	0.4921

Note: Lags determined by AIC (max=21). The deterministic component only includes a constant.

Table II collects the results of the ADF tests showing that the null hypothesis, under which the series are $\sim I(1)$, is rejected only for the variable $housing_t$. At this point, a cointegration analysis is performed to detect any possible long-run relationship among the three variables. For almost all the specifications, the Johansen's Cointegration test (Johansen, 1988) detects a full rank cointegration matrix, suggesting the stationarity of the system. A detailed list of the results is reported in Table III in Appendix A.

In line with these findings, we believe that the results of the ADF tests could be misleading if we take into account the nature of the problem we are analyzing. Firstly, it is reasonable to assume that the behavior of the three series in the initial period of the sample is due to few extreme shocks, given by the sudden pandemic outbreak, rather than reflecting permanent fluctuations due to a unit root. Moreover, it is well known that unit root tests exhibit low power when the persistence of a time series is strong (DeJong et al., 1992). We will thus treat the series as stationary. [6]

3. Empirical Analysis

This section firstly introduces the Vector Autoregressive (VAR) model and the related identification scheme for structural shocks. Then, we show the main results from the baseline model. In order to provide a wider set of results, we report the Granger-causality analysis in Appendix B.

3.1 Methodology

The empirical analysis is based on the estimation of the reduced form VAR model of order 3, VAR(3), in Equation (1) for the variables collected in the vector $\mathbf{y}_t = \{R_t, housing_t, GTU_t\}$:

$$\mathbf{y}_t = \mu + \sum_{k=1}^{3} \mathbf{\Psi}_k \mathbf{y}_{t-k} + \mathbf{e}_t, \quad t = 1, \dots, T, \tag{1}$$

where μ denotes an intercept, $\mathbf{\Psi}_k$ represents a 3×3 matrix collecting coefficients and $\mathbf{e}_t$ is the idiosyncratic component.

Starting from the reduced form residuals $\mathbf{e}_t$, the identification of the structural shocks $\mathbf{u_t}$ is achieved by means of "short-run" restrictions in $\mathbf{B}$ given by a Cholesky scheme, so that $\mathbf{e}_t = \mathbf{Bu_t}$ as in Equation (2),

$$\mathbf{e}_t \equiv \begin{pmatrix} e_t^R \\ e_t^{housing} \\ e_t^{GTU} \end{pmatrix} = \begin{bmatrix} b_{11} & 0 & 0 \\ b_{21} & b_{22} & 0 \\ b_{31} & b_{32} & b_{33} \end{bmatrix} \begin{pmatrix} u_t^{covid} \\ u_t^{policy} \\ u_t^{distrust} \end{pmatrix}. \tag{2}$$

The first structural shock, u_t^{covid}, identifies an exogenous epidemic-related perturbation; the second one, u_t^{policy}, corresponds to a shock coming from the policy maker decisions about mobility restrictions; finally, $u_t^{distrust}$ captures shocks related to the disbelief concerning the economic environment.

Clearly, the ordering of the variables reflects our beliefs on the scheme listing the series from the "most exogenous" to the "most endogenous" ones. This identification strategy imposes restrictions such that the shocks in R_t are instantaneously affected by exogenous "covid" ones only, whereas $housing_t$ is assumed to respond also to contemporaneous "policy" shocks. Moreover, our measure of "economic uncertainty" is affected by covid-related and policy shocks, further to "distrust" ones, resulting fully endogenous in our system.

All the model parameters are estimated by Ordinary Least Squares (OLS). The order of the VAR model is determined following the Akaike Information Criterion. Confidence

[6] Note that the VAR model would be a valid inferential tool when some variables in the model are integrated of order $I(1)$, see Toda and Yamamoto (1995).

intervals (C.I.) for structural shocks are derived by residual bootstrap with 1999 replications.

3.2 Baseline results

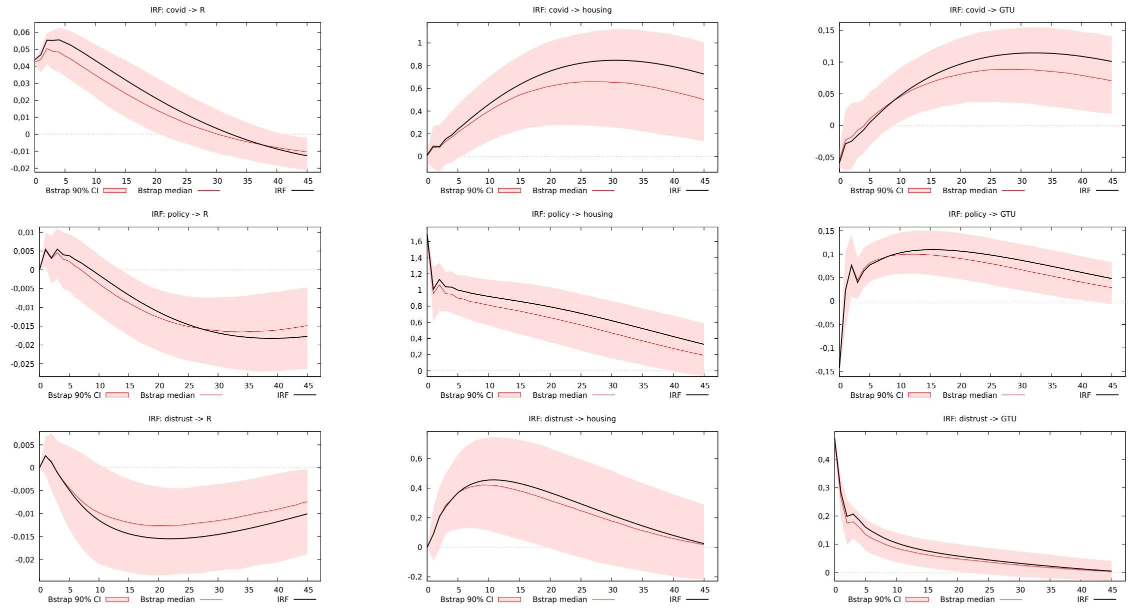

Figure 4: S-IRF, VAR(3). Shaded area: 90% C.I.

Figure 4 shows the impact of the three structural shocks (by rows) on the R, mobility and uncertainty indexes by means of the Impulse Response Functions (IRFs). The "covid" shock persistently affects the R_t over a month and induces a remarkable and consistent restriction in mobility through time; at the same time, there is rise in economic uncertainty.

The effect of mobility-related policy starts to produce a sizable and significant restrain effect on the R index in two weeks. Differently, mobility restrictions lead to an increment in economic uncertainty in a few days and the effect propagates for 40 days.

"Distrust" shocks negatively and remarkably affect the R_t in a few days and the impact slowly mitigates in time. The effect on $housing_t$ is instead positive and it declines to zero in a month.

Figure 5 shows that covid- and mobility-specific shocks explain more than 40% of the variability in GTU_t in 30 days and about the 50% in 45 days.

Our results suggest that both Covid-19 contagions and the related mobility restrictions largely affect economic uncertainty. Bad news related to Covid-19 spread and mobility restrictions produce negative expectations about the economic scenario with a consequent rise in uncertainty. Of course this effect is not instantaneous but it takes a few days to show up. Agents can only observe the outcome of the disease in terms of infected, health care services demand and deaths, which is subsequent to contagions. Also, the delay of mobility effect is smaller since only a minimal time occurs from announcement to implementation of the policy.

Additionally, as a response to a "distrust" shock, we observe a reduction on R_t and a rise on $housing_t$: these may be explained again through the expectations channel that produces worry about the future economic situation, thus reducing expected income,

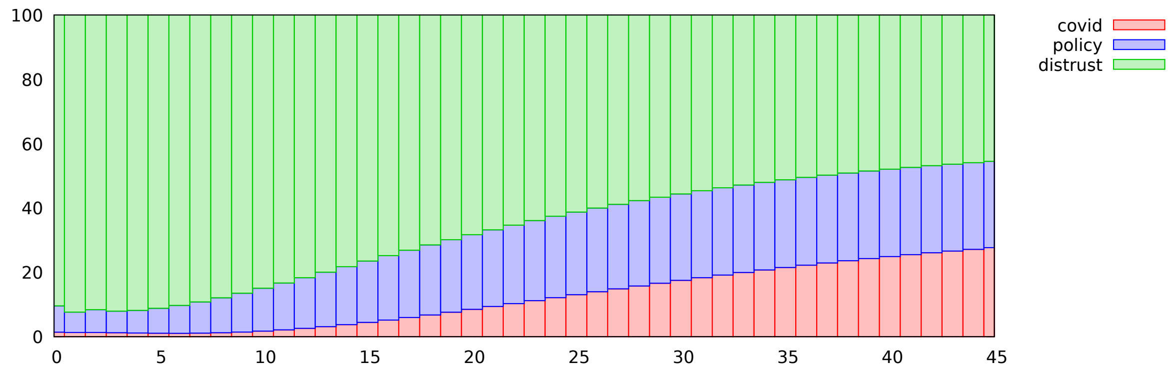

Figure 5: Forecast Error Variance Decomposition for GTU_t

inducing precautionary savings and lowering consumption-related mobility. Interestingly, the shock is absorbed in a few time, suggesting that individual reaction to news is only momentary.

4. Robustness Analysis

With the purpose of extending the validity of our results, we propose two additional investigations. The first one concerns the use of different mobility proxies, whereas the second one consists in a different methodological approach, following Local Linear Projections as proposed byJordà (2005).

4.1 Mobility measures

Although we have focused on the "Residential" Google series, for robustness analysis we repeat the empirical exercise exploiting two other mobility measures, specifically two indexes constructed as the first principal components of *(i)* the other variables in the Google Mobility Report, and of *(ii)* three mobility series provided by Apple Mobility Trends,[7] respectively. The resulting series will be denoted as $pca\_mob\_google_t$ and $pca\_mob\_apple_t$.

First, from the Google Mobility Report, we consider the variables corresponding to the mobility variation for the following place categories: "Retail and recreation", "Grocery and Pharmacy", "Parks", "Transit stations" and "Workplaces".

Further, 2020 Apple data come from Apple Maps and report information on car movements ("Driving" series), public transportation mobility ("Transit" series) and walking ("Walking" series). These are expressed as deviations from the reference value of January 13^{th} 2020.[8] Note that the above mobility indexes convey the opposite information of the $housing_t$ variable, since they express a direct measure of how much people move, rather than house permanence.

By substituting $housing_t$ variable with $pca\_mob\_google_t$ in equation (1), we get the IRFs reported in Figure 6, while Figure 7 reports the case for $pca\_mob\_apple_t$. The results are coherent with those of the baseline model. In both scenarios here considered, the R index positively responds to a shock in mobility, even though with different delay.

[7] `https://covid19.apple.com/mobility`.

[8] Apple missing data ($11 - 12^{th}$ May 2020) have been recovered by interpolation.

At the same time, an increase in mobility produces a temporary and negative effect on uncertainty, confirming that restrictions would exacerbate economic worry.

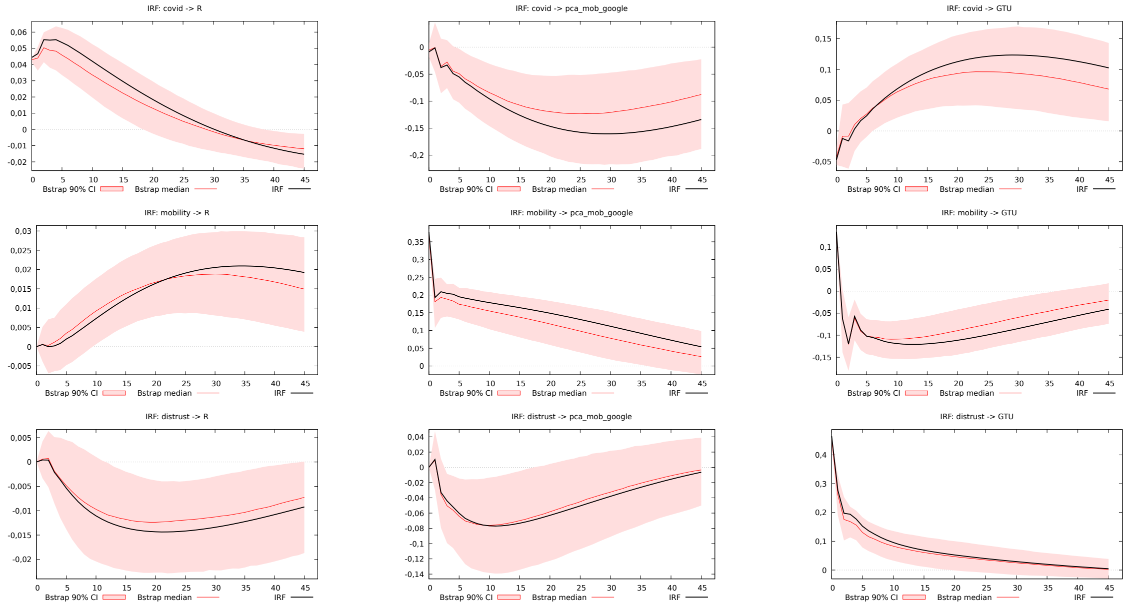

Figure 6: S-IRF, VAR(3), Google Mobility data. Shaded area: 90% C.I.

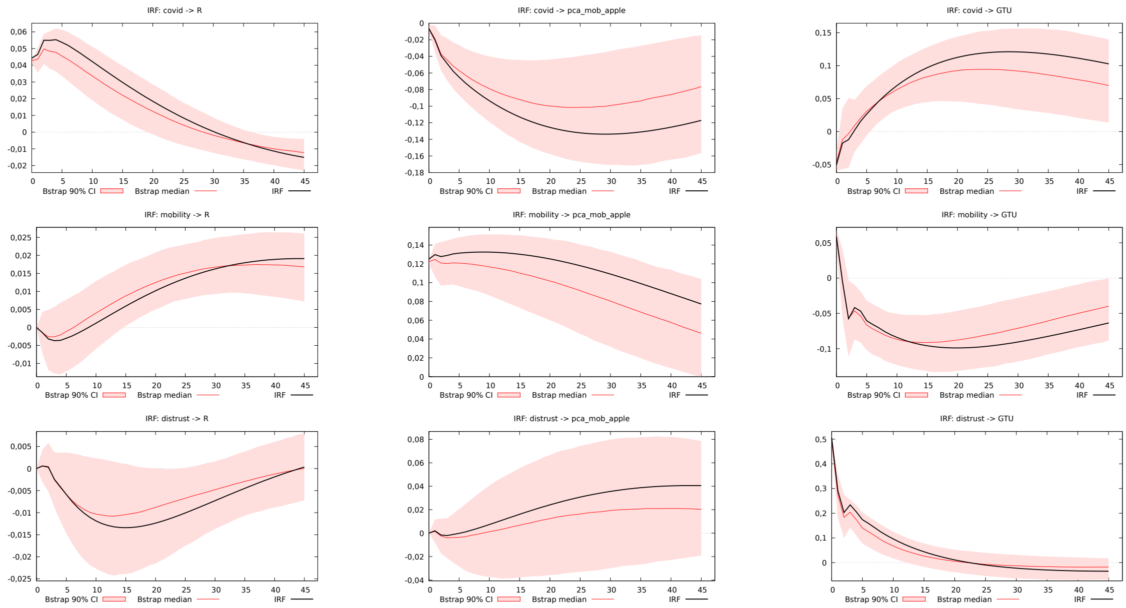

Figure 7: S-IRF, VAR(3), Apple mobility data. Shaded area: 90% C.I.

4.2 Local projections

Local linear projections (Jordà, 2005) offer the opportunity to estimate the IRFs without specifying the full multivariate model; in particular, they are robust to misspecification of the Data Generating Process and are easy to be implemented.

This technique relies on the direct estimation of impulse responses at each horizon with separate regressions. This way, it suffices to represent, via companion matrix, the reduced form VAR model from Equation (1) and to estimate the parameters for each IRF horizon $h = 1, \dots, H$, as

$$\mathcal{Y}_{(t+h)} = \mathcal{M}_h + \mathbf{C}^{(h)}\mathcal{Y}_{t-1} + \mathcal{E}_{t+h}, \quad h = 1, \dots, H, \tag{3}$$

where $\mathcal{Y}$, $\mathcal{M}_h$, $\mathbf{C}^{(h)}$ and $\mathcal{E}$ denote the companion form counterparts of the original reduced form VAR elements.

Figure 8 provides the resulting IRFs for the baseline model.

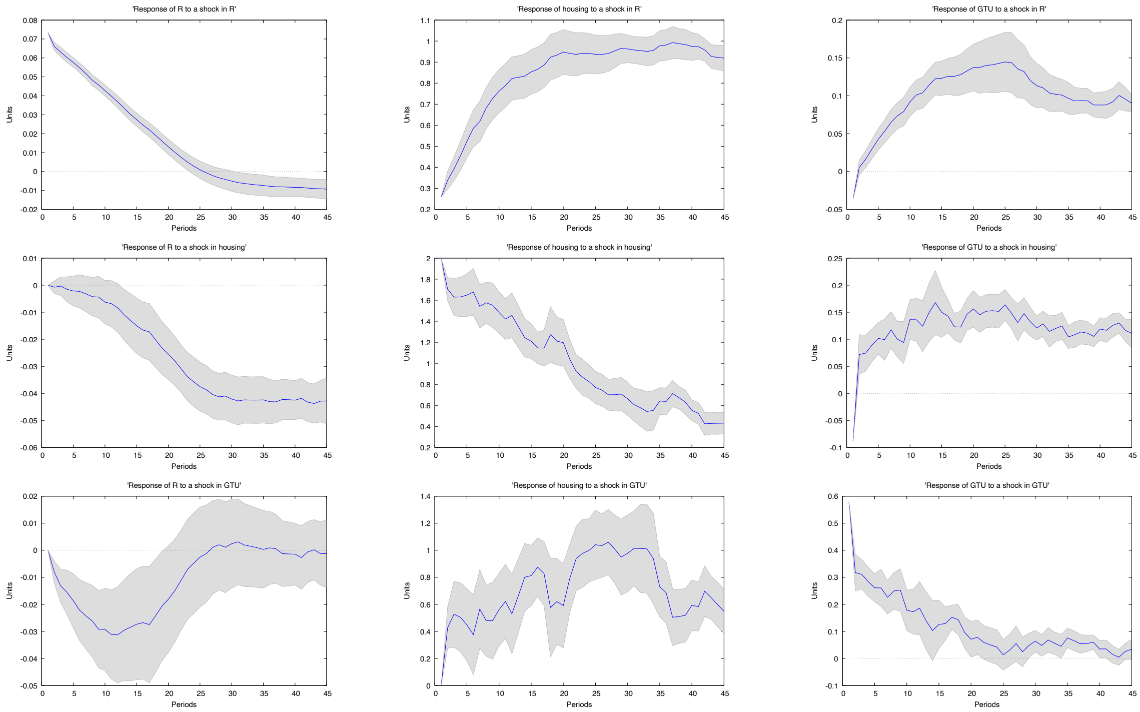

Figure 8: IRFs, Local Linear Projections, Baseline model. Shaded area: 90% C.I.

In general, the results are coherent with those of the VAR analysis. However, IRFs derived with Local Linear Projections are less smoothed and highlight even wider effects, with respect to VAR-based ones. Moreover, the IRF associated to a shock in economic uncertainty on $housing_t$ is characterized by a larger magnitude and the effect is persistent over the horizon of 45 days, while the effect on R_t goes to zero even more rapidly.

5. Final remarks

The article investigates the relation between Covid-19-induced contraction of mobility and economic uncertainty in Italy. By using a SVAR approach, our main findings are that both Covid-19 contagions and the related mobility restrictions positively affect economic uncertainty. Furthermore, Covid-19 and mobility shocks explain more than 40% of the economic uncertainty variability in 30 days and about the 50% in 45 days. These results are robust to the subsequent analyses we have implemented.

Given the rapid evolution of the pandemic and the lack of adequate data to directly measure the effects on the economic activity, it is interesting to study the cost of economic uncertainty during other disastrous events. Baker et al. (2020), for instance, perform an illustrative exercise to project the macroeconomic consequences of the pandemic, using natural disasters, revolutions and other similar scenarios to estimate the causal impact of such shocks on output growth, via the uncertainty channel. Within this framework, they predict that the output contraction due to Covid-19 will be due by more than a half to induced economic uncertainty. Similarly, Ludvigson et al. (2020) try to quantify the economic impact of disasters of recent US history and to extend the related findings to the current epidemic crisis; they conclude that, even in an unrealistic case of a Covid-19 shock persisting for only 5 months, US industrial production is likely to cumulatively drop by 20% and the service sector employment of nearly 39%. Clearly, analyzing the phenomenon is of extreme importance, and quantifying Covid-19-induced economic uncertainty is crucial to understand the future economic implications of this unexpected shock.

Specifically, as documented in Section 1, the economic uncertainty stemming from the Covid-19 pandemics and the related mobility restriction policy could have severe consequences for the economy, across three main channels: (i) from the macroeconomic perspective, the rise in precautionary savings opposed to reduction in consumption (Baker et al., 2020) causes a slowdown in GDP growth; (ii) from the microeconomic side, the negative effect is given by companies postponing decisions in terms of investment and employment; (iii) another effect is given by the financial factor, which makes the cost of debt rising when uncertainty is high. Overall, in addition, uncertainty may cause permanent changes in behavior of households and businesses.

Finally, there are some policy considerations which should be taken into account. As documented for instance in Bloom (2014), both fiscal and monetary policies become less effective in terms of economic output when there is a spike in uncertainty, whereas at the same time, unclear or hyperactive policies may cause further uncertainty, because they can generate panic overreactions. As a consequence, policy makers should become forward looking and embody directly the uncertainty factor in their response. If from the one hand mobility restriction policies such as lock-downs are necessary and somehow optimal in the medium term (Acemoglu et al., 2020; Alvarez et al., 2020; Eichenbaum et al., 2020), on the other their short run effects in terms of supply chain disruption or decrease in hours worked need to be mitigated considering also the related uncertainty. Expansionary fiscal and monetary policy should stabilize expectations and guarantee a flexible and prompt tool which rapidly adjusts to the pandemic evolution: for instance, monetary authorities, by cutting the nominal interest rates, can effectively limit uncertainty (and recession) effects. However, when the Zero Lower Bound is reached, the interaction with the fiscal policy (and maybe unconventional monetary policies) becomes crucial. As reported in Pekanov and Schiman (2020), a credible policy to contain uncertainty and pandemic effects should combine both the medical and the economic aspects of policy measures such as a lock-down. If monetary and fiscal policy can effectively act, the role of health policy should not be underestimated in fixing expectations.

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Appendix

A. Cointegration analysis

This appendix reports the results of the Johansen's Cointegration tests described in Section 2.4. The order of the VAR is 3 and is determined according to the Akaike Information Criterion. The Table reports estimated eigenvalues, the trace- and the λ-max test as well as the relative p-values. We consider all the possible specifications for the deterministic component as a robustness check.

Table III: Johansen's Cointegration Tests

Deterministic Component	Rank	Eigenvalue	Trace Test	p-value	λ-max Test	p-value
No Constant	0	0.1198	47.186	0.0000	31.006	0.0001
	1	0.0520	16.180	0.0100	12.987	0.0227
	2	0.0131	3.1937	0.0859	3.1937	0.0878
Restricted Constant	0	0.1735	79.459	0.0000	46.299	0.0000
	1	0.0852	33.160	0.0003	21.631	0.0042
	2	0.0463	11.529	0.0162	11.529	0.0163
Unrestricted Constant	0	0.1728	78.621	0.0000	46.093	0.0000
	1	0.0847	32.527	0.0000	21.503	0.0023
	2	0.0444	11.024	0.0009	11.024	0.0009
Restricted Trend	0	0.1979	90.670	0.0000	53.578	0.0000
	1	0.1010	37.092	0.0009	25.873	0.0035
	2	0.0451	11.219	0.0814	11.219	0.0811
Unrestricted Trend	0	0.1940	85.561	0.0000	52.414	0.0000
	1	0.1005	33.147	0.0001	25.738	0.0016
	2	0.0300	7.4088	0.0065	7.4088	0.0065

Note: the test is based on the VAR(3) model.

B. Granger-causality Analysis

Since the seminal paper proposed by Granger (1969), Granger-causality analysis has become a popular tool aimed at studying the relationships, in terms of predictive power, among time series in a VAR model. In this regard, Table IV reports the Granger-causality tests for the baseline VAR(3) model. Since the results are likely to be affected by the choice of the information set, and this is substantially an arbitrary choice, we also double the length of the VAR model and we run the same analysis including six lags of the variables in order to avoid an excessive parametrization.

Table IV: Granger-causality Analysis

Model: VAR(3)	Dependent variable		
Restrictions	R_t	$housing_t$	GTU_t
R_t	6404.3	10.357	0.3804
	(0.0000)	(0.000)	(0.7672)
$housing_t$	1.9077	486.07	9.2409
	(0.1290)	(0.0000)	(0.0000)
GTU_t	1.2708	2.1243	79.104
	(0.2851)	(0.0979)	(0.0000)
Model: VAR(6)	**Dependent variable**		
Restrictions	R_t	$housing_t$	GTU_t
R_t	1926.8	5.2554	1.1019
	(0.0000)	(0.000)	(0.3621)
$housing_t$	2.1065	219.34	4.0187
	(0.0536)	(0.0000)	(0.0008)
GTU_t	1.5340	1.0267	34.772
	(0.1681)	(0.4087)	(0.0000)

Note: F-tests of zero restrictions. The Table reports the test statistics and the p-values (in parenthesis).

Overall, the two model specifications provide similar results. The GTU_t series does not Granger-cause the other variables. This is in line with the theory: if we assume that the uncertainty is somehow a byproduct of the pandemic and the related policies, it would be counter-intuitive to think the past of an uncertainty measure can have some explanatory power in R_t and $housing_t$.

The R_t index Granger-causes $housing_t$ but not GTU_t. The first result is trivial: mobility restrictions are subsequent to the epidemic conditions. The second one suggests that, conditional on the past values of the mobility index, the past of R_t is not useful for predicting GTU_t. This effect could apparently seem not fully coherent with the empirical findings outlined in Section 3.2. Moreover, it is not sensitive to the number of lags in the VAR model.

Finally, $housing_t$ Granger-causes GTU_t. This result is coherent with the previous points and the theoretical setup. We can observe a weak statistical evidence about the Granger-causality from $housing_t$ to R_t, which only appears in the VAR(6) model.