THE ECONOMIC CONSEQUENCES OF DIFFERENT ATTITUDES OF A POLICY MAKER: A COMBINED EPIDEMIOLOGICAL-ECONOMETRIC STUDY

Marzio De Corato (944459)

Giulia Hadjiandrea (941780)

ABSTRACT

Within a standard compartmental model for the description of the dynamic of an epidemics (Susceptible-Infectious-Recovered-Dead), we considered a policy-maker (PM) that imposes stochastically different types of lock-downs. The probability that tune this stochastic process reflects his/her different attitude to face an epidemics (e.g. *laissez-faire* vs very strict). In order to simulate not only an epidemiological scenario but also an economic one we estimated , via a Difference-in-Difference regression, the impact of national lock-downs applied during the first wave of COVID19 in Italy from March 2020 to June 2020, on two microeconomic sectors: sales and on subsidies (*Cassa Integrazione*). We found that, by modifying with continuity the PM attitude to impose the lock-down a phase transition (as defined for a physical system) is obtained. The comparison of these two scenarios and their impact provide provide a bird's-eye view on the socio-economic consequences of the PM attitude

"It was then that, in a moment, I saw what I must have been harboring in my hidden thoughts for a considerable time. On the one hand, Trantor possessed an extraordinarily complex social system, being a populous world made up of eight hundred smaller worlds. It was in itself a system complex enough to make psychohistory meaningful and yet it was simple enough, compared to the Empire as a whole, to make psychohistory perhaps practical"
I.Asimov, Prelude to foundation

CONTENTS

1 INTRODUCTION

The recent pandemic due to the spread of SARS-CoV-2 virus, opened a highly debated issue about what it would be the best approach of the policy maker to face the epidemic. Differently from the past pandemics and in particular of the XX century (e.g. Spanish Flu, Asiatic Flu and Hong-Kong Flu), for this pandemic a very large amount of data are easily accessible. As a consequence not only the modelling of the virus diffusion but also the effect on socio-economic texture for different countries can be investigated with a finer resolution. Among the different scientific challenges that can come up in this context, an interesting one involves socio-economic effects of the attitude of the policy-maker (PM) to block the circulation of people (lock-down) in order to reduce the contagion rate (more formally the reproduction number, as described in Supporting Information). Indeed the policy maker can adopt, at a first approximation, a linear combination between these two extreme approaches: forcing all people to stay at home or to *laissez-faire*. In the first extreme, the spread of virus is, of course, stopped but, on the other side, the toll for such approach is that not only the economic activity (and so the income of people/firms) but also that the furniture of the primary goods are stopped. On the other side, if no lock-down measures are taken by the PM the toll to be paid will not only be the high number of deaths but also the economic damage produced by the very high number of deaths [1, 2]. In practice the PM can adopt intermediate approaches that shut down activities that contribute much more to diffusion with respect to other (for this purpose a very fine analysis was provided by Li et al. in [3] and by Brauner et al. in [4]). As consequence the lock-down efficacy, within certain limits, can be tuned. In the literature different scholars [5, 6] challenged the issue of finding the optimal lock-down policy for minimizing the economic impact as well as the deaths. In particular for the model in Ref. [5] it is assumed that the policy-maker knows perfectly the consequences of his/her choices and that he/she can act without delay to impose the optimal choice; finally it is assumed that the PM can impose a continuous factor for the lock-down while for different countries such factor seems to be much more discrete. It can be argued that most of these drawbacks of this last formidable research, are entangled with the fact that a deterministic approach was considered for the activation of the lock-downs by the policy maker. On this basis we would propose here an alternative way to model the decision of the policy maker that is based on a stochastic model instead of on a deterministic one. Furthermore, differently with respect to the previous researches that focused basically on macroeconomic impact, here we estimated and put in the model the impact of the different lock-downs at microeconomic level:

in particular, by means of difference in difference, we evaluated the effect of the different levels of lock-down on different sales sector as well as on subsidies (*Cassa Integrazione Ordinaria*) in Italy. Thus, the final output of the model will be not only the cumulative deaths, but also the economic damage for each selling sector. Moreover here we also considered that there is not only an economic cost for each death as done by [5] but there is also average cost for each infected person (referring to Italian data), because a consistent part of them may be recovered or even should take the intensive therapy. As we will show by varying with continuity the probabilistic parameter by which the PM impose the lock-down, a discontinuity in the SIRD model and in the days of the lock-down was obtained. Such behaviour belongs to a class of phenomena that, in physical sciences, is called a phase transition. For each phase we will discuss the result of the simulation and then we will compare them in order to get a general insight.

2   MODEL AND METHODS

The model of the present study is composed by an epidemiological part that shapes the diffusion of the virus and then its output is used by the economic model to quantify the damage. Thus we will discuss the epidemiological part and then the economic one

2.1   Epidemiological model

Among the very large number of compartmental model available in the literature [7] we considered, as the simulator of the epidemic diffusion the simplest one: the Susceptible-Infectious-Recovered-Dead (SIRD). Our choice is motivated by the fact that this relative simple model provides the gross features of an epidemic [8, 9] with a relative small number of parameters [1]). The SIRD model,first proposed by

---

1 One in principle can consider a SIRD model,in which the parameters that are time-dependent, as done by Ferrari et al. in Ref. [10] for the description of Italian situation. On the other side it is possible to increase the complexity of the model with other compartments as done in the following paper [11] by Giordano et al. Note that in this last case the resolution of 9 differential equation is required (accompanied by the estimation of a large number of parameters)

Kermack and McKendrick in 1927 [12], is given by the following set of differential equations[7]:

$$\frac{dS(t)}{dt} = -\frac{\beta I(t)S(t)}{N}$$
$$\frac{dI(t)}{dt} = \frac{\beta I(t)S(t)}{N} - \gamma I(t) - \mu I(t)$$
$$\frac{dR(t)}{dt} = \gamma I(t)$$
$$\frac{dD(t)}{dt} = \mu I(t)$$

(1)

where S is the number of people that are still susceptible, I the number of people that are infected and R people that are recovered while D are people that are death. N denotes the total population, that for the timing of this paper, it will be considered fixed [2]. On the other side β, γ and μ are the parameters that shape the probability by which one individual in the model moves from a compartment to another: in particular β is the probability to be infected, γ the probability to recover and μ the probability to die (basically the lethality defined as the probability to die conditionally to be ill). Usually epidemiologist are interested in the ratio:

$$R_0 = \frac{\beta}{\gamma + \mu}$$

(2)

known as the basic reproduction factor. This number is the average number of people that are infected by a single individual and describes if the epidemic is in a negative feedback ($R_0 < 1$), stationary ($R_0 = 1$), or in a positive feedback ($R_0 > 1$). As consequence if the epidemic is in a negative feedback will be dissipate, while if it is in positive feedback will grow. Note that in this simple model, since the parameters are not time dependent this factor is constant. As performed by Ferrari et al. [10], when time dependent parameters β and γ are taken in to account the reproduction factor R_0 become time depended: thus scholar rename it as R_t. For the present work, we limited to constant parameters: in particular we considered the parameter estimation for Lombardy provided by Neves and Guerrero in Ref [13]: β was set equal to 0.55 while γ equal to $\frac{1}{7}$. The μ was set in order to keep in to account the calculated lethality for Italy: 1 % [8] (see also the very fine analysis made by the Institute for International Political Studies (ISPI) [14])[3]. The overall population N was

---

2 Othervise, if longer horizontal timing is considered, it is necessary to consider also a source term for the births and a well term for the natural deaths. For further details see [7]

3 The authors are aware that this ratio is far from being homogeneus for the the different ages of population: however if this factor is taken into account, it requires the solution of a system of partial derivative equations. In this case the numerical calculations become much more complicated

set to 60M, in order to simulate Italian population. Within the daily temporal evolution of this model, that was obtained by numerically solving the differential equation above via the *DeSolve* package, we considered a trigger activated by the PM every 7 days: if the number of infected people normalized by the overall population is more than 1×10^{-7}, there is a probability that the PM impose laws that multiply the β factor by 0.7, if the normalized infected people are more than 10 the previous threshold he/she will impose with a certain probability restrictions that multiply β starting β factor by 0.25; finally, if the threshold is exceeded more than 50 times, the PM will impose with a certain probability restrictive measures that multiply β by 0.025. These attenuation parameters were adjusted taking in consideration results of Marziano et al. in Ref. [15]. Therefore such trigger make the R_0 parameter time dependent, although in to a discrete way. As we said the PM acts with a certain probability, more formally stochastically: each week a random number (from zero to one) is extracted: if this is higher than a certain threshold, the relative restrictive decision is taken, otherwise not. The threshold value captures the PM attitude to impose the lock-down: lower values model a careful PM, hight value a lazy one. In this way the model is able to simulate different scenarios for the different PM attitude: as we will see this can produce two very different results. At the end of the simulation, beside the values given by the standard SIRD model (recovered and deaths), the algorithm also provide the number of weeks in which each restriction was active: these values are then used for the economic model in order to evaluate the economic effect due to the restrictions and PM strategy. It is worth nothing that here as lock-down we considered only the national one that was applied in the first wave of the epidemics: from March 2020 to June 2020. This choice is motivated by the fact that modelling a unique system is more simpler with respect to modelling an ensemble of a communicating clusters that represent regions or provinces: therefore, if one is interested to model the second wave of pandemics such approach should be undertaken. Moreover in this latter case, as a further degree of complexity, the economic data described in the next subsection must be at regional or province level, and as far as the authors know, such data are not available. For these reasons here the modelling will be always referred to national data and national lock-downs, therefore the period after June when starting from October regional lock-down were imposed, will be not considered. Another point that is it is worth mentioning, is that in this model, on the contrary with respect to the SIS one, individual can not re-infect: concerning the COVID-19 the possibility of reinfection is still discussed among scholars [16, 17]. Basically to the know of author it is established that the immunity last at least 8 months [18] and very few cases of reinfection are reported.

Thus the immunity considered in the model, for an interval of one year seems almost a realistic approximation.

2.2 Economic model

The economic impact for each epidemiological scenario is shaped as follow: a first set of parameters, as the economic value of a death and of being infected by COVID-19, was taken directly from the reports/documentation of official sources; other parameters as the effect on selling for different areas and on the unemployment benefit (Cassa Integrazione Guadagni) were evaluated with empirical approaches from raw data. Concerning the first set, the number of deaths is multiplied by the maximum compensation value provided by the Court of Milan [19] for manslaughter (300k EUR). This choice is based on the idea that, if the PM acts improperly, can be incriminated for manslaughter (with the consent of parliament that has to validate the incrimination) and than, if judged guilty, charged by this amount for each death[4]. Beside this impact, there is also the cost associated to the medical care of each ill people, for this we considered the average value calculated by National Anti-Corruption Authority (ANAC) [20]: 28.180 kEUR [5]. Among the different sectors affected by the pandemic and the consequent lock-down, we focused on the selling for the following ATECO-2007 [21] categories [6]: Food, Clothing and furs, Footwear/leather and travel articles, Appliances/radios/televisions and tape recorders, Furniture/textile articles/furnishings for the home, Photo-optics/films/compact discs/ audio-video cassettes and musical instruments, Durable and non-durable Household kinds, Household tools and hardware, Games/toys/sports and camping articles. The choice to use sales as a parameter for the evaluation of the lock-down lies on the fact that with them is possible to capture not only the contraction for each sector but also the loss for the public treasury due to to the reduced incomes from the VAT[7]. Beside the selling we also considered the unemployment benefit for

---

4 In principle the judge also keep into account the age of the deaths: this in principle require an epidemiological model in which also the age of people is keep into account. In this case however a system of partial differential equation should be solved making the calculation and the computational cost incredibly high.

5 It is worth noting that, in principle, there is also another import health-care impact due to the fact that the ill people for COVID-19 saturate the health system thus making it unreachable for other diseases. This spillover translates in to more death and more ill people with respect to the baseline situation where there isn't an pandemic: however, by now, this effect is difficult to quantify and so we did not included in to the present model

6 In the rest part of the paper these categories will be referred as the part of the name labelled in blue.

7 For this purpose another sector that in principle can be also considered is the contraction of fuel selling, due to the reduced mobility, where in addition to the VAT

the following ATECO sectors: Manufacturing activities, Construction , Wholesale and retail trade/ repair of motor vehicles-motorcycles and personal and household goods. In this case, the choice to use also this parameter is based on the fact that this is the first aid provided by the government for the firms that were damaged the lock-down restrictions. For the empirical evaluation of the impact on selling and unemployment benefit we performed a multiple time Difference in Difference as presented in Refs. [22], [23] and [24]. The following regression was performed:

$$Y_{outcome} = \alpha + \beta_0 C + \sum_{i=1}^{3} \beta_i T_i + \sum_{i=1}^{3} \delta_i (C \cdot T_i) + \epsilon \qquad (3)$$

where Y is the selcted outcome, α the intercept, T_i a dummy variable for the lock-down timing i, C a dummy for the treated group and ϵ a error term. As control group for the sales, we considered the food ones since, in principle, people can be considered to use almost the same amount of food regardless with respect to the lock-down[8]. On the other side, for subsidies *Cassa integrazione*, we considered the Cassa Integrazione Straordinaria - Solidarità as the control group (note that this subsidy is different with respect Cassa Integrazione Solidarità that was dedicated to sectors not covered by Cassa Integrazione Ordinaria). This subsidy can be used by firms, damaged by the pandemics and by the lock-downs, in order to reduce their labour cost but at same time guaranteeing to the workers part of their original salary [9]. During the first months of the pandemic firms, following the rules stated by the Italian Government (Decreto Cura Italia [25]), firms that would reduce their labour cost, first forced the employees to use their holiday budget and than, after it was run out, they put the employees in to the Cassa Integrazione Ordinaria. Thus the Cassa Integrazione Straordinaria-Solidarietà can be considered as not treated by the first wave of the lock-down while the ordinary one the treated. The DID considered here has three different times for the national lock-down: for the sales we considered, as done for the epidemiological model, the months of March 2020 and May 2020 as medium lock-down, the month of April 2020 as high lock-down and

---

there is also a fixed taxation (accisa). Such calculation may be considered as a future outlook of this work

8 Although it is true that a slight increase of food sales during the lock-down is present in the plots in Fig. 1 2, it must be stressed the fact that, as proven numerically in the Supporting Info A, this change does not significantly affect the DID estimations

9 It is worth nothing that the *Cassa Integrazione Ordinaria* considered here is not the only one contribution that was provided by Italian Government: in fact there was also, for instance, the *Cassa Integrazione in Deroga* that was dedicated to the firms not covered by the *Ordinaria*. However in the present study we consider,for simplicity, only the sectors covered by Cassa Integrazione Ordinaria.

June 2020 as weak lock-down. On the other side concerning the subsidies, we considered as medium lock-down only May 2020: such choice was motivated by the fact that the effect of firms to use the subsidies for workers was slightly delayed basically due to the fact that firms forced their employees first to use their holiday and then the *Cassa Integrazione Ordinaria*: as consequence, because of this buffer effect, in the month of March there is no significant effect of this subsidies although there is a significant reduction of hours worked (see e.g. [26]). Performing the DID we estimated the coefficients for the effect of each intensity of lock-down on sales and subsidies, then we we rescaled them for a week. Finally we multiplied the number obtained from the previous calculation by the number of lock-down weeks, with the respective intensity, in each scenario simulated via the epidemiological model described before. As consequence we obtained, for each scenario, an economics simulation based on parameters obtained from an empirical evaluation.

3 DATA DESCRIPTION

The monthly sales data were retrieved from the National Institute of Statistics website [27]. In particular we considered the period starting from 2018 up to June 2020. The choice to not consider the months after June and in particular the last part of the year lies on the fact that in the latter lock-downs were imposed at regional level and not to national level [10] [11]. As discussed in Supporting Information, these data were not de-seasoned: thus we performed a de-seasoning via the *Forecast* R package [28] that uses a Hilbert-Huang transform [29] for the decomposition of a time series data. The decomposition results are reported in the Supporting Info E. Concerning subsidies we retried the data from the *Osservatorio Cassa integrazione guadagni e fondi di solidarietà* on the *Istituto nazionale della previdenza sociale* webpage [30]. It is worth nothing that here we considered only the authorized subsidies and not the asked one . Furthermore these data, differently with respect to the sales one were not affected by seasonality noise, and thus no de-seasoning was necessary. We checked also if any signifi-

---

10 With the only exception of Christmas holiday

11 In principle one may ask why the present analysis was not performed on regional cluster making it more flexible: unfortunately the economic data used here, as far as the author knows, were not available, at all for regional cluster. Moreover if regional cluster were considered it was necessary to model an ensemble of SIRD model that communicate each other with a defined rate (that change also with respect to the lock-down restriction). This make the model much more complicated. However if all the data that are necessary for performing the analysis will become available the author may consider, as an outlook, to extend the present analysis to regional clusters

cant effect on DID coefficient was obtained for sales and for subsidies by adding one and two year before 2018 (e.g. 2016 and 2017): no significant effect was found.

4 RESULTS AND DISCUSSION

As done for the section Model and methods we will divide the discussion of the results in the following way: first the outcomes of the economic model will be presented, then basing on this result, we will discuss the scenarios obtained with them via the epidemiological model. Finally we will discuss the overall results.

4.1 DID

For each sales category we run the regression reported in the Eq. 3 on de-seasoned data reported in Fig 1 and 2. The coefficients obtained are reported in Tab. 13 (the estimation of the other parameters is given in Supporting Information D). As one can point out from the plots, it is true that there is a pre-trend in the data before the event, however as proved numerically in the Supporting Info B, the slope of this pre-trend is almost two order of magnitude lesser with respect to the slope in the lock-down T_1 and T_2. As consequence this pre-trend, compared to the lock-down effect, can be considered negligible. In order to make a further control, a placebo test was performed by choosing timing before the pandemic of COVID19. As illustrated in the Supporting Info C, this test was successful. On the other side, concerning T_3 (low lock-down), only the effect for clothing and footwear can be considered significant, also by considering the pre-trend slope as discussed in the Supporting Information. Thus, concerning T_3, we considered not null, in the scenario simulations, only the clothing and footwear sectors. By inspecting the Tab. 13 we see that the most severe damage of lock-down hit the clothing, and the footwear. On the other side the Household kids and the Household tools seems lesser affected by the lock-down. The same DID regression was used for the subsidies, using as control group the extraordinary solidarity subsidies (cassa integrazione straordinaria solidarietà): the plot of the data and the DID coefficients are reported in Fig. 3 and in Tab 2. Also in this case the placebo tests were successfully performed. An interesting insight is also provided by the inspection of the extraordinary subsidies for renovation (*cassa integrazione ristrutturazione*): these subsidies, as compared to the solidarity ones, seems much more sensitive with respect to external shock in particular for trade sector.

4.2 Scenarios

Now that we have the parameters for the economic impact given by the lock-downs, we are ready to discuss the simulations that output the epidemiological and economic consequences of the attitude of PM. In Tab. 3 and 4 the outcomes of the epidemiological model are given, while the SIRD curves for the scenarios are provided in Fig. 6; on the other side the effect on selling and subsidies for both scenarios are given in Fig. 7 and 8. In order to assure the *ceteris pariubus* condition we used for both scenario the same set of random numbers. First, we see that where the PM is more reactive we have small different waves of epidemics, while if the PM is poorly reactive only one intense wave is present, indeed in the latter scenario the laziness of PM to apply the lock-down in the first weeks produce the full infection peak of the standard SIRD model: when the PM acts is too late, as shown in Fig. 6, since the pandemics has almost hit the large part of the population. This can be pointed out in Fig. 5 by noting that that the reproduction factor remains at its maximum level for large number of weeks after the beginning of the pandemic. This also explains why in the second half of the scenario the lock-downs are so week: the remaining part of the population is immune., an thus no further action is required. On the contrary in the first scenario the PM is able, using the lock-downs to transform the SIRD peak in to small waves (Fig. 6). As shown in Fig. 5 this result is basically obtained by keeping the reproduction factor in the value of medium lock-down value. These two theoretical model correspond, in practice, for the lazy PM to the one considered by the PMs that aimed to heard immunity, while, concerning the active-PM, to the PMs that would not saturate the saturate the health system and aimed to reduce the death at the minimum. It is interesting to point out that the change between the scenarios develops in a discontinuous way as showed in Fig. 18, as the reactivity of the PM is changed, we can consider this as a phase transition of a physical system (it is interesting to point out the closness with respect to the gold-standard diagram of Ising model [31, 32]). This explains our choice to consider only two scenarios: indeed we considered only a sample for each phase. It is worth nothing that a similar result, within a different epidemiological model, was obtained by Balcan and Vespignani in Ref. [33]. The explanation of this similar behaviour is that both model have a stochastic component, that as pointed out by Balcan and Vespignani, give the phase transition: indeed while in their model this was directly related to the contagion probability, here this is indirectly made stochastically by the decision of PM that modify the β parameter and so the transmission rate. Moving to the socio-economic outcome of the model used we see, from Tab. 3 and 4, that in the small wave scenario, the attitude of the PM largely reduce the overall number of

deaths and recovered (and so the cumulative cost for taking of patients) by a consistent use of the confinement. This has an immediate drawback on the economic data: as shown in Fig. 7 and 8, the loses for selling and the use of subsidies are widely large with respect to the one-wave scenario. In principle one can be attempted to find the PM attitude that minimize the overall cost (deaths, infected, selling and subsidies): in the authors view, this scenario is not realistic since, actually, the Italian (but also many other European) criminal law does not allow this option: although there is an economic cost for a life in terms of compensation, the actual criminal law does not consider an amount of money comparable to a money sum, on contrary it gives a value ex post not ex ante. For this reason here we considered the epidemiological consequences separated with respect to the economic ones. A more intriguing issue is come up when the economic cost is causally associated to an number indirect of deaths (for instance if people does not have the money for food or other first necessity goods), in this case the two factor (epidemiological and economic) can be, in principle, summed. We say in principle because the jurisprudence is here very reduced or totally missing since the pandemics are rare events. For the present study these indirect deaths are, by now, not easily to quantify and thus we did not considered this option.

5 CONCLUSIONS

We have obtained a model that combines the epidemiological aspects as well the economic ones within a stochastic approach. This was made possible by evaluating the effect of lock-downs, via a DID regression, on different sales sector as well on the subsidies dedicated to firms that would reduce the labour cost. Furthermore we show numerically that, within a stochastic approach, the PM attitude to impose the lock-downs is critical, as this attitude, within a *ceteris paribus* condition, decide the phase of the outcome scenario and thus the economic and social effects.

6 PICTURES AND TABLES

In all tables the following significance code will be used: *** for 0.001, ** for 0.01 and * for 0.05

(a) Clothing (blue)

(b) Footwear (green)

(c) Appliances (orange)

(d) Photo-optics (blue)

Figure 1: Selling data (I), with baseline of 2015, as provided by [27] de-seasoned via Forecast package [28] for the categories analysed in this paper compared with food (red) category. The timing for each lock-down is marked with a dashed line: red for high, orange medium and green for low. Note that despite there is a pre-trend this is negligible with respect to the slope of medium and high lock-down slopes

(a) Household kids (Orchid)

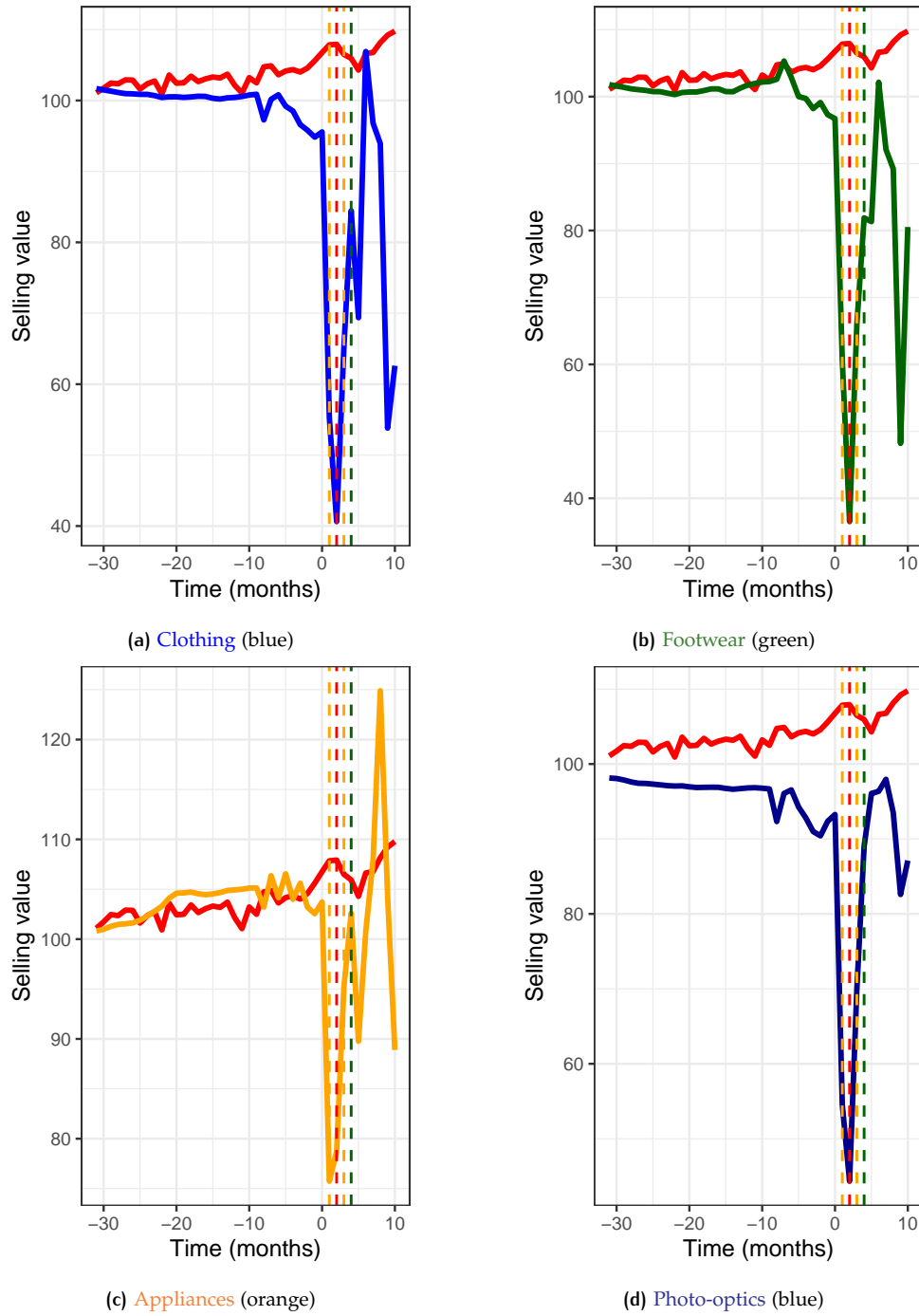**(b)** Household tools (Light green)

(c) Games (Thistle)

Figure 2: Selling data (II), with baseline of 2015, as provided by [27] de-seasoned via Forecast package [28] for the categories analysed in this paper compared with food (red) category. The timing for each lock-down is marked with a dashed line: red for high, orange medium and green for low. Note that despite there is a pre-trend this is negligible with respect to the slope of medium and high lock-down slopes
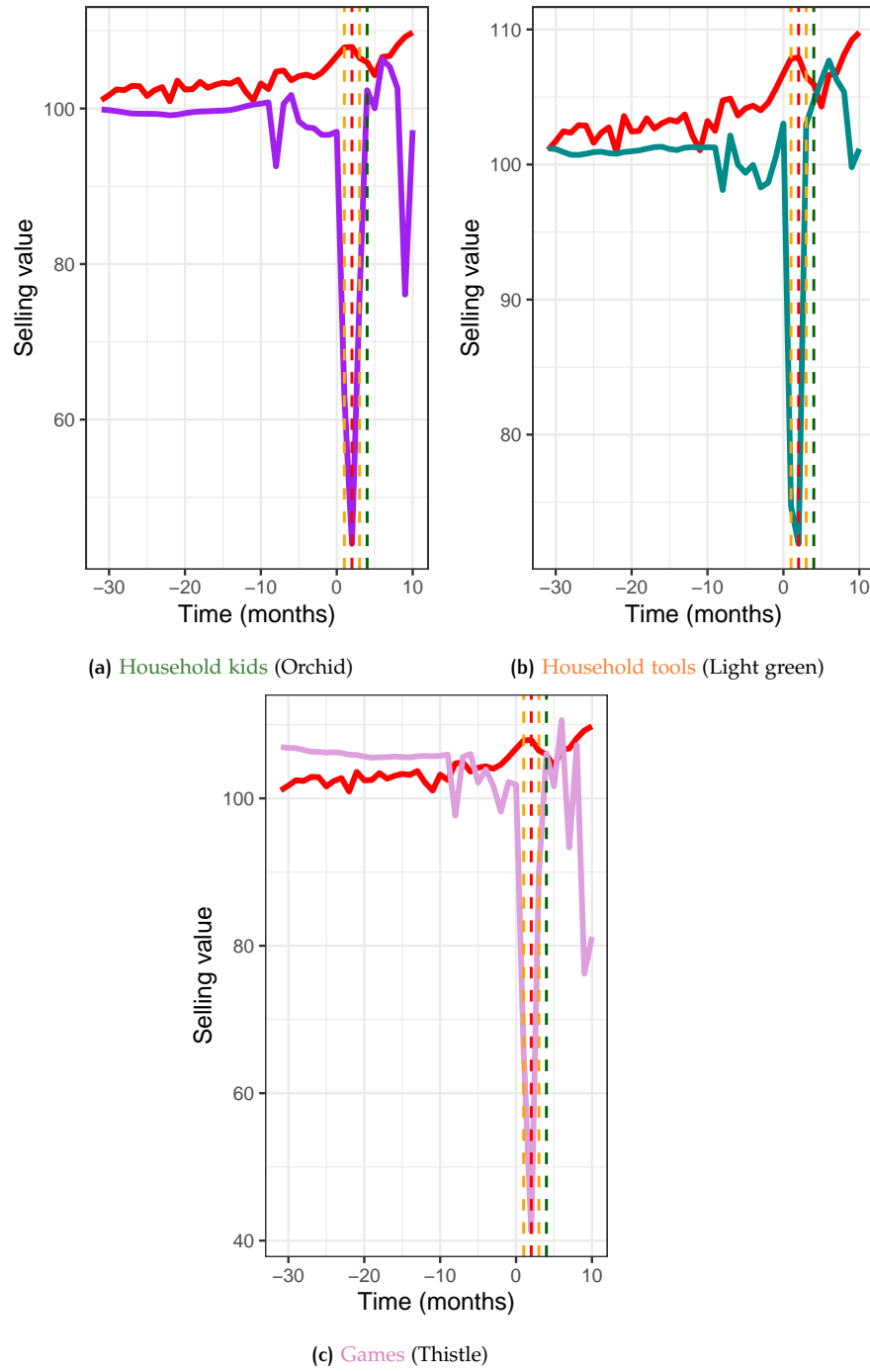
Table 1:

δ cofficients as obtained by the DID regression, for the selling data de-seasoned, according to equation 3 for the different lock-down timings. The values of the intercept (α), β_0 and β_i are provided in the Supporting Info.

	δ_1	σ_{δ_1}	t	δ_2	σ_{δ_2}	t	δ_3	σ_{δ_3}	t
Clothing	-40.16 ***	2.01	-19.99	-60.07 ***	2.77	-21.64	-16.45 ***	2.77	-5.92
Footwear	-38.70 ***	1.73	-22.35	-65.78 ***	2.39	-27.49	-20.62 ***	2.39	-8.62
Appliances	-20.32 ***	2.50	-8.11	-27.34 ***	3.45	-7.90	-3.68	3.45	1.06
Photo-optics	-34.14 ***	2.55	-13.38	-52.32 ***	3.52	-14.84	-7.86 *	3.52	-2.23
Household kids	-10.51 ***	1.50	-6.98	-18.99 ***	2.07	-9.13	-3.61	2.07	-1.74
Household tools	-13.02 ***	3.51	-3.70	-30.23 ***	4.85	-6.23	2.33	4.85	0.48
Games	-27.55 ***	3.47	-7.93	-64.31 ***	4.79	-13.40	0.26	4.79	0.05

(a) Subsidies paid for manufacture

(b) Subsidies paid for trade
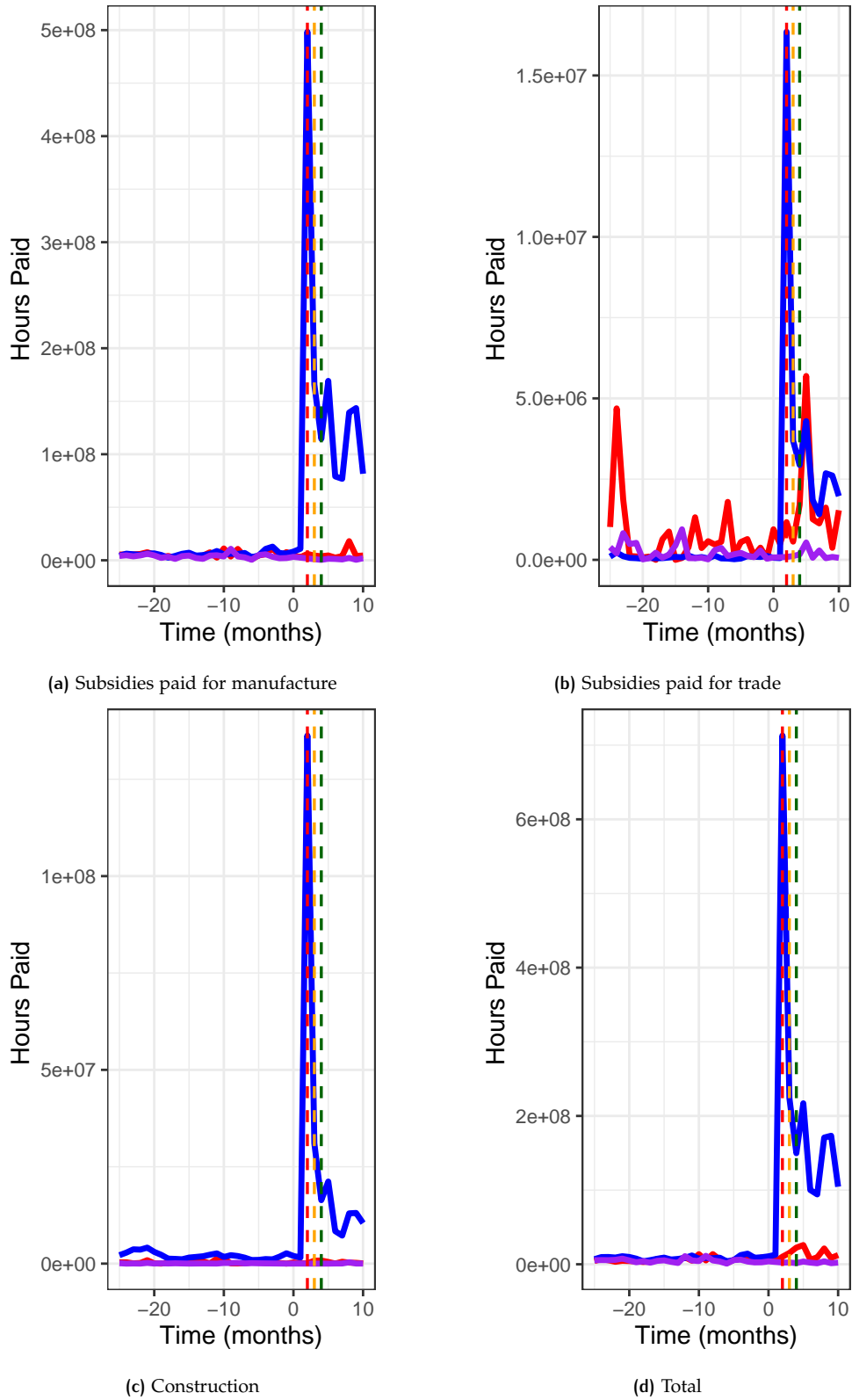
(c) Construction

(d) Total

Figure 3: Comparison between the ordinary subsides (blue) vs the extraordinary ones (renovation red and purple solidarity) for a selected set of sectors and the overall total. The dashed lines represent the different timing and intensity for the lock-down: red for high, orange medium and green for low.
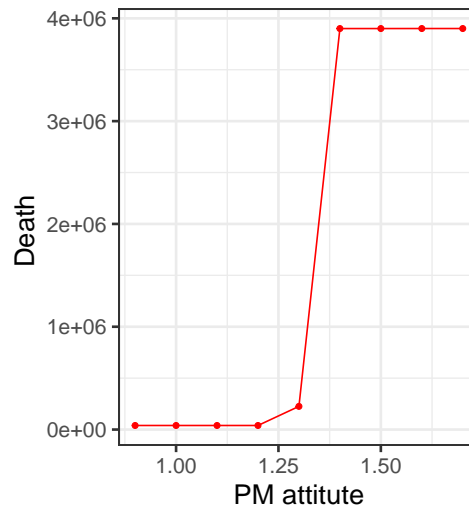
Figure 4: The number of deaths of SIRD scenario with stochasic lockdown
as obtained by chaing the PM attitute to active the lockdown (e.g.
by modifying the probability parameter by which the lock-down
is imposed). As the PM attitude is near 1.3 a sharp discontinuity is
present in the overall death: thus a different phase is obtained. It
is worth nothing the similarity of this plot with the gold-standard
one of phase transition: the Ising model (see [31] or [32] for a more
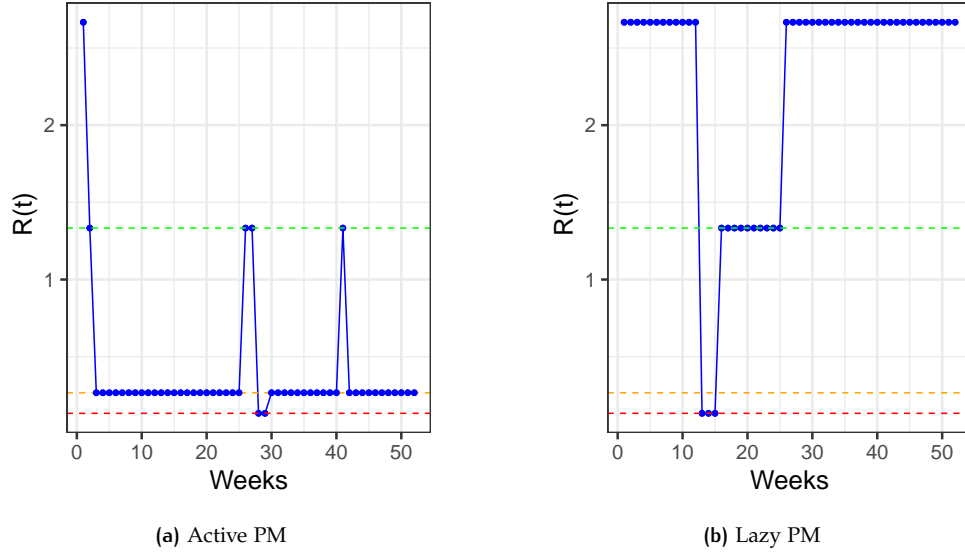deep analysis)

(a) Active PM

(b) Lazy PM

Figure 5: Comparison between the reproduction number (calculated as effective the $\frac{\beta}{\gamma+\mu}$ ratio when the lock-down is applied) for a highly reactive PM vs to the one of a poorly reactive one. It can be noted that while in the former the PM reactivity almost allows him/her to control this factor in to a stable medium lock-down, in the second one the reproduction number (and thus the epidemic) is almost out of control of the PM since it remains, for most of weeks at its maximum level. In particular in the second scenario, the laziness of PM to apply the lock-down in the first weeks produce the full infection peak of the standard SIRD model: when the PM act is too late since the pandemics has almost hit the large part of the population. This also explain why in the second half of the scenario the lock-downs are so week: the remaining part of the population is immune. On the contrary in the first scenario the PM is able, using the lockdown to transform the sharp SIRD peak in to small waves. Note that the levels of reproduction number are discrete, as marked by the dashed lines (green low, orange medium, red high) since the lock-down is the only way to change this number. On the contrary if a time dependent SIRD was considered as done by [10], a continuous form of R(t) would be obtained

Table 2:

δ cofficients, expressed in millions as obtained by the DID regression, for subsidies (controlling the extraordinary solidarity) according to equation 3 for the different lock-down timings. The values of the intercept (α), β_0 and β_i are provided in the Supporting Information D.

	δ_1	σ_{δ_1}	t	δ_2	σ_{δ_2}	t	δ_3	σ_{δ_3}	t
Total	706 ***	3	199.5	217 ***	3	61.48	144 ***	3	40.72
Manufacture	494 ***	3	158.56	162 ***	3	52	111 ***	3	35.7
Trade	16.4 ***	0.24	66.10	3.72 ***	0.24	15.00	2.92 ***	0.24	11.78
Construction	134 ***	0.87	153.10	29 ***	0.87	33.13	14 ***	0.87	16.41

Table 3: Comparison of epidemiological consequences for a reactive vs non-reactive PM with respect to the overcoming of the epidemiological thresholds. The values are reported as percentage with respect to the total population considered in the model (60 M)

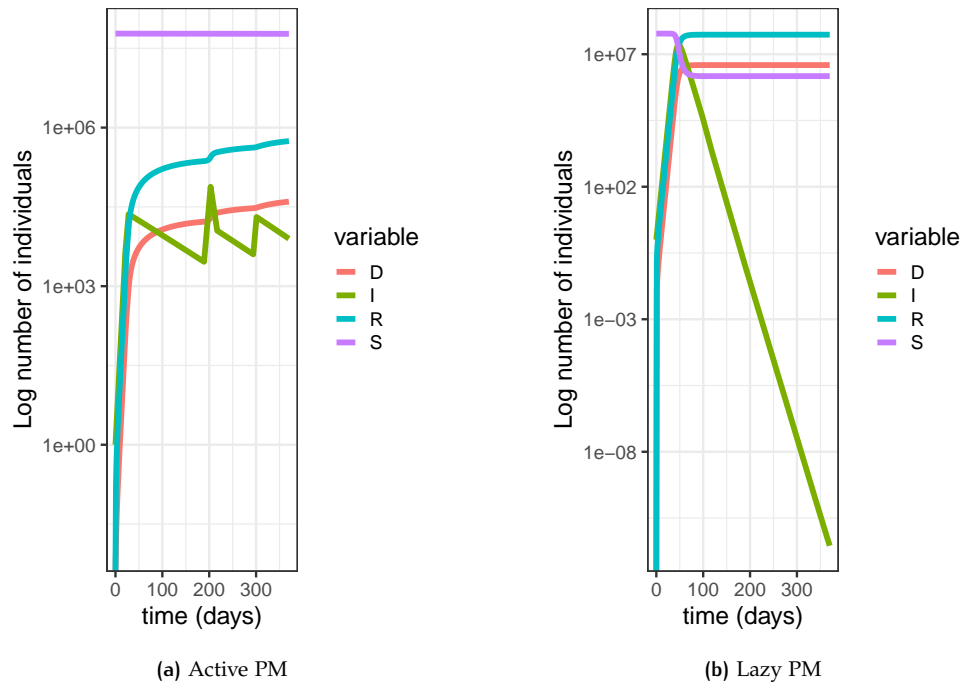|	Active	Lazy
Deaths	0,06	6,50
Infected	0,92	91,01

(a) Active PM   **(b)** Lazy PM

Figure 6: Comparison between the epidemiological scenarios obtained via a SIRD model (Susceptible-Infectious-Recovered-Dead) where the PM impose stochastically the different levels of the lock-down. In the left panel an active PM is considered: this is modelled by making more likeable that the PM impose the lock-down as the number of infected goes over the different thresholds. On the contrary, in the left panel a lazy PM that prefer the *laissez-faire* approach is considered: in this case, differently with respect to the previous scenario, the probability that the PM impose the lock-down is less likely.
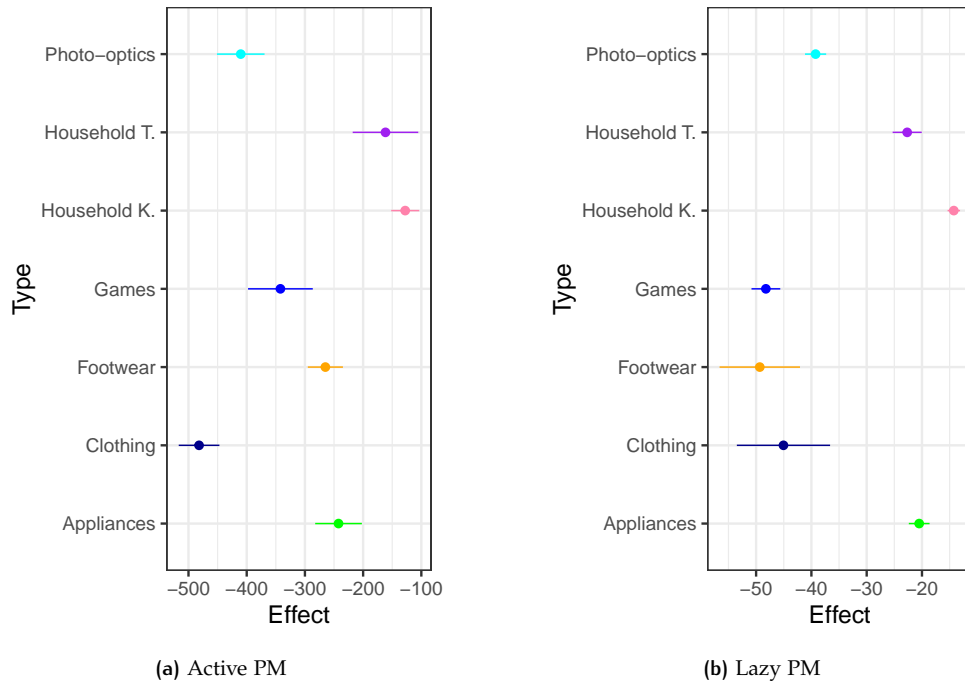
(a) Active PM   **(b)** Lazy PM

Figure 7: Comparison between the sales effects for the scenarios where an active vs lazy PM is considered. These effects were calculated by running a DID regression for the different national lock-down imposed during March-June 2020 and then multiplying the number of lock-down weeks, obtianed from the SIRD scenario ,with the coefficients obtained from the DID (divided by 4). The error bars were calculated by considering the error propagation

Table 4: Cost associated with deaths and infected people that need to be assisted in terms of 10^9 EUR. The value of life correspond to the maximum compensation according to Milan court [19], while the cost for infected people was taken from ANAC report [20]

	Active	Lazy
Deaths	11	1170
Infected	15	1538
Total	26	2708

(a) Active PM
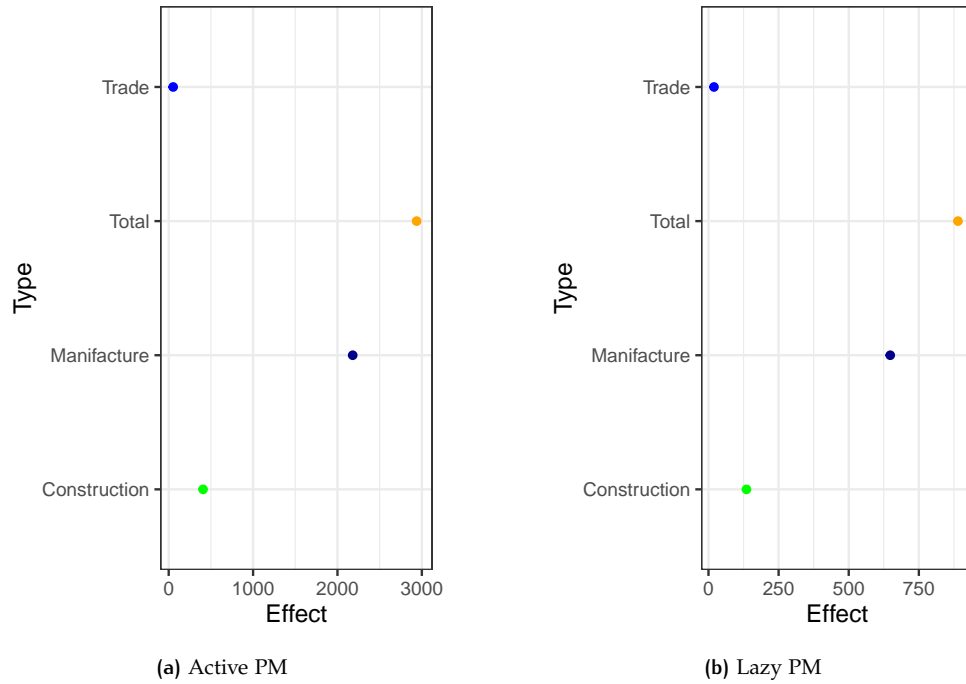
(b) Lazy PM

Figure 8: Comparison between the subsides effects for the scenarios where
an active vs lazy PM is considered. These effects were calculated
by running a DID regression for the different national lock-down
imposed during March-June 2020 and then multiplying the num-
ber of lock-down weeks, obtianed from the SIRD scenario ,with
the coefficients obtained from the DID (divided by 4). The error
bars, although are visible because are too reduced, were calculated
by considering the error propagation

REFERENCES

[1] Sergio Correia, Stephan Luck, and Emil Verner. Pandemics depress the economy, public health interventions do not: Evidence from the 1918 flu. *SSRN Electronic Journal*, 01 2020.

[2] Martin Karlsson, Therese Nilsson, and Stefan Pichler. The impact of the 1918 spanish flu epidemic on economic performance in sweden: An investigation into the consequences of an extraordinary mortality shock. *Journal of health economics*, 36:1–19, 2014.

[3] You Li, Harry Campbell, Durga Kulkarni, Alice Harpur, Madhurima Nundy, Xin Wang, Harish Nair, Usher Network for COVID, et al. The temporal association of introducing and lifting non-pharmaceutical interventions with the time-varying reproduction number (r) of sars-cov-2: a modelling study across 131 countries. *The Lancet Infectious Diseases*, 21(2):193–202, 2021.

[4] Jan M Brauner, Sören Mindermann, Mrinank Sharma, David Johnston, John Salvatier, Tomáš Gavenčiak, Anna B Stephenson, Gavin Leech, George Altman, Vladimir Mikulik, et al. Inferring the effectiveness of government interventions against covid-19. *Science*, 371(6531), 2021.

[5] KM Ariful Kabir and Jun Tanimoto. Evolutionary game theory modelling to represent the behavioural dynamics of economic shutdowns and shield immunity in the covid-19 pandemic. *Royal Society open science*, 7(9):201095, 2020.

[6] Robert Rowthorn and Jan Maciejowski. A cost–benefit analysis of the covid-19 disease. *Oxford Review of Economic Policy*, 36(Supplement_1):S38–S55, 2020.

[7] Emilia Vynnycky and Richard White. *An introduction to infectious disease modelling*. OUP oxford, 2010.

[8] Jesús Fernández-Villaverde and Charles I Jones. Estimating and simulating a sird model of covid-19 for many countries, states, and cities. Technical report, National Bureau of Economic Research, 2020.

[9] Marwan Al-Raeei. The forecasting of covid-19 with mortality using sird epidemic model for the united states, russia, china, and the syrian arab republic. *Aip Advances*, 10(6):065325, 2020.

[10] Luisa Ferrari, Giuseppe Gerardi, Giancarlo Manzi, Alessandra Micheletti, Federica Nicolussi, and Silvia Salini. Modelling provincial covid-19 epidemic data in italy using an adjusted time-dependent sird model. *arXiv preprint arXiv:2005.12170*, 2020.

[11] Giulia Giordano, Franco Blanchini, Raffaele Bruno, Patrizio Colaneri, Alessandro Di Filippo, Angela Di Matteo, and Marta Colaneri. Modelling the covid-19 epidemic and implementation of population-wide interventions in italy. *Nature medicine*, 26(6):855–860, 2020.

[12] William Ogilvy Kermack and Anderson G McKendrick. A contribution to the mathematical theory of epidemics. *Proceedings of the royal society of london. Series A, Containing papers of a mathematical and physical character*, 115(772):700–721, 1927.

[13] Armando GM Neves and Gustavo Guerrero. Predicting the evolution of the covid-19 epidemic with the a-sir model: Lombardy, italy and sao paulo state, brazil. *Physica D: Nonlinear Phenomena*, 413:132693, 2020.

[14] "https://www.ispionline.it/it/pubblicazione/coronavirus-la-letalita-italia-tra-apparenza-e-realta-25563".

[15] Valentina Marziano, Giorgio Guzzetta, Bruna Maria Rondinone, Fabio Boccuni, Flavia Riccardo, Antonino Bella, Piero Poletti, Filippo Trentini, Patrizio Pezzotti, Silvio Brusaferro, et al. Retrospective analysis of the italian exit strategy from covid-19 lockdown. *Proceedings of the National Academy of Sciences*, 118(4), 2021.

[16] Heidi Ledford. Covid-19 reinfection: three questions scientists are asking. *Nature*, 585:168–169, 2020.

[17] Akiko Iwasaki. What reinfections mean for covid-19. *The Lancet Infectious Diseases*, 21(1):3–5, 2021.

[18] Jennifer M Dan, Jose Mateus, Yu Kato, Kathryn M Hastie, Esther Dawen Yu, Caterina E Faliti, Alba Grifoni, Sydney I Ramirez, Sonya Haupt, April Frazier, et al. Immunological memory to sars-cov-2 assessed for up to 8 months after infection. *Science*, 2021.

[19] "https://www.tribunale.milano.it/files/news/TABELLE%20MILANO%20EDIZIONE%202018.pdf".

[20] "https://www.anticorruzione.it/portal/rest/jcr/repository/collaboration/Digital%20Assets/anacdocs/Attivita/Pubblicazioni/RapportiStudi/ContrattiPubblici/IndagineCovid19.fase2.13.08.20_.pdf".

[21] "https://www.codiceateco.it/".

[22] Mirko Draca, Stephen Machin, and Robert Witt. Panic on the streets of london: Police, crime, and the july 2005 terror attacks. *American Economic Review*, 101(5):2157–81, 2011.

[23] Guido W Imbens and Jeffrey M Wooldridge. Recent developments in the econometrics of program evaluation. *Journal of economic literature*, 47(1):5–86, 2009.

[24] Jeffrey M Wooldridge. Introductory econometrics: a modern approach (upper level economics titles). *Southwestern College Publishing, Nashville, T TN*, 2012.

[25] "https://www.gazzettaufficiale.it/eli/id/2020/03/17/20G00034/sg".

[26] "https://www.istat.it/it/archivio/253812".

[27] "https://www.istat.it".

[28] "https://cran.r-project.org/web/packages/forecast/index.html".

[29] Norden E Huang, Zheng Shen, Steven R Long, Manli C Wu, Hsing H Shih, Quanan Zheng, Nai-Chyuan Yen, Chi Chao Tung, and Henry H Liu. The empirical mode decomposition and the hilbert spectrum for nonlinear and non-stationary time series analysis. *Proceedings of the Royal Society of London. Series A: mathematical, physical and engineering sciences*, 454(1971):903–995, 1998.

[30] "https://www.inps.it/osservatoristatistici/5".

[31] "hhttps://www.ippp.dur.ac.uk/~krauss/Lectures/NumericalMethods/PhaseTransitions/Lecture/pt3.html".

[32] Valeriy A Ryabov. Phase transitions in the ising model. In *Principles of Statistical Physics and Numerical Modeling*, 2053-2563, pages 22–1 to 22–5. IOP Publishing, 2018.

[33] Duygu Balcan and Alessandro Vespignani. Phase transitions in contagion processes mediated by recurrent mobility patterns. *Nature physics*, 7(7):581–586, 2011.

[34] Philipp Schnabl. The international transmission of bank liquidity shocks: Evidence from an emerging market. *The Journal of Finance*, 67(3):897–932, 2012.

[35] "https://scholar.princeton.edu/sites/default/files/jmummolo/files/did_jm.pdf".

7 SUPPORTING INFORMATION

7.1 A – Food consumption during the lock–down

In order to check if any significant effect is obtained on the coefficients of Tab. 5 by the slight increase of food consumption during the lockdown, we considered an hypothetical scenario were this increase did not happened (e.g. the selling for March to June were identical to February): as one can point out by comparing the Tab. 5 with Tab, 13 no significant difference can be found. Thus since the real scenario where this increase happened (real one), and the scenario where this did not happened (hypothetical one) are indistinguishable, we can consider this increase negligible for the estimation of the DID δ coefficients

Table 5:

δ cofficients as obtained by the DID regression, for the selling data de-seasoned, according to equation 3 for the different lock-down timings where the food selling are modified in order to have, during the lockdown timings, the same constant value of February. Note that no significant difference can be found with respect to the coeffient obtained in Tab 13.

	δ_1	σ_{δ_1}	t	δ_2	σ_{δ_2}	t	δ_3	σ_{δ_3}	t
Clothing	-39.71 ***	2.00	-19.76	-59.34 ***	2.77	-21.37	-15.50 ***	2.77	-5.58
Footwear	-38.24 ***	1.73	-22.08	-65.05 ***	2.39	-27.18	-19.68 ***	2.39	-8.22
Appliances	-19.86 ***	2.50	-7.93	-26.61 ***	3.45	-7.69	-2.73	3.45	-0.79
Photo-optics	-33.68 ***	2.55	-13.21	-51.59 ***	3.52	-14.64	-6.91	3.52	-1.96
Household kids	-10.06 ***	1.50	-6.68	-18.26 ***	2.07	-8.75	-2.67	2.07	-1.28
Household tools	-12.57 ***	3.51	-3.57	-29.50 ***	4.85	-6.07	3.28	4.85	0.67
Games	-27.10 ***	3.47	-7.80	-63.58 ***	4.79	-13.24	1.21	4.79	0.25

Table 6: Clothing

	Value	σ
Δ Slope before T1	-0.33 ***	0.08
Δ_{T1}	-36.33 ***	2.15
Δ_{T2}	-56.23 ***	2.77
Δ_{T3}	-11.95 ***	2.86

Table 7: Footwear

	Value	σ
Δ Slope before T1	-0.18 *	0.08
Δ_{T1}	-38.70 ***	1.91
Δ_{T2}	-63.21 ***	2.47
Δ_{T3}	-17.61 ***	2.54

7.2 B – Pre-trend check

In order to perform a further assessment on the credibility of the DID coefficients obtained in Tab. 13 we make a comparison between the trends of the difference of food sales and the other sectors, before (Δ Slope before T_{T1}) and after the three lock-down at T_{T1}, T_{T2} and T_{T3}. As can be seen from the following tables (Tab. 6, 7, 8, 9, 10, 11 and 12) the lock-down Δ at T_{T1} and T_{T2} are much larger with respect to the pre-trend Δ before. Thus the DID coefficients obtained in Tab 13 can be considered credible. Concerning T_{T3}, as said in the main text, we considered significant only the values for Clothing and Footwear.

Table 8: Appliances

	Value	σ
Δ Slope before T1	-0.12	0. 07
Δ_{T1}	-19.21 ***	3.10
Δ_{T2}	-26.23 ***	4.00
Δ_{T3}	-2.37	4.12

Table 9: Photo-optics

	Value	σ
Δ Slope before T1	-0.40 ***	0.07
Δ_{T1}	-29.94 ***	2.73
Δ_{T2}	-48.11 ***	3.52
Δ_{T3}	-2.93	3.63

Table 10: Household kids

	Value	σ
Δ Slope before T1	-0.16 **	0.04
Δ_{T1}	-10.51 ***	1.55
Δ_{T2}	-19.00 ***	2.14
Δ_{T3}	-3.61	2.14

Table 11: Household tools

	Value	σ
Δ Slope before T1	-0.21 ***	0.05
Δ_{T1}	-13.02 ***	3.53
Δ_{T2}	-30.23 **	4.88
Δ_{T3}	2.33	4.88

Table 12: Games

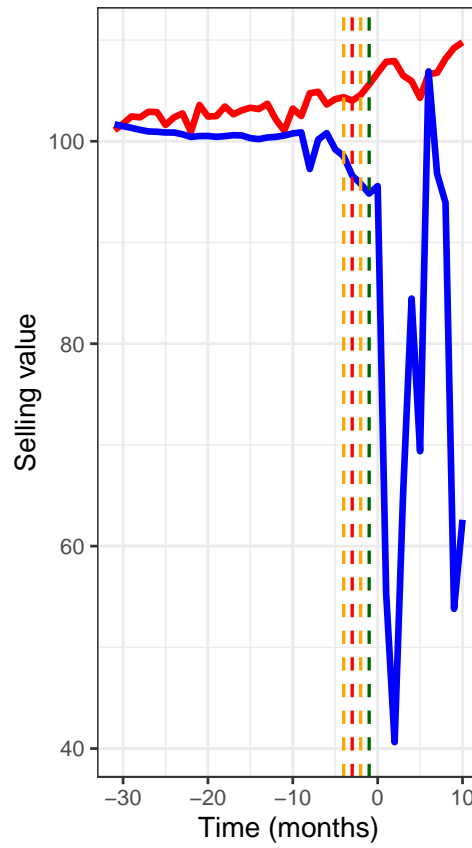|	Value	σ
Δ Slope before T1	-0.37 **	0.10
Δ_{T1}	-27.56 ***	3.63
Δ_{T2}	-64.31 ***	5.01
Δ_{T3}	0.27	5.01

Figure 9: Timing for placebo test for food vs clothing sales: T_4 is placed at $T = -4$ and $T = -2$, T_5 at $T = -3$ and T_6 at $T = -1$). For the other sales sector the placebo timing is identical

7.3 C – Placebo tests for DID

In order to assets the common trend the credibility of the DID co-efficient we performed a placebo test (as proposed e.g. by [34, 35]) by moving back the lock-down timings as illustrated in Fig. 9. As showed in Tab. 13 no significant effect was found for the placebo timing before the lock-down of March 2020-June 2020.

Table 13:

δ cofficients as obtained by the DID regression, for the selling data de-seasoned, according to equation 3 for a placebo timings as showed in Fig. 9

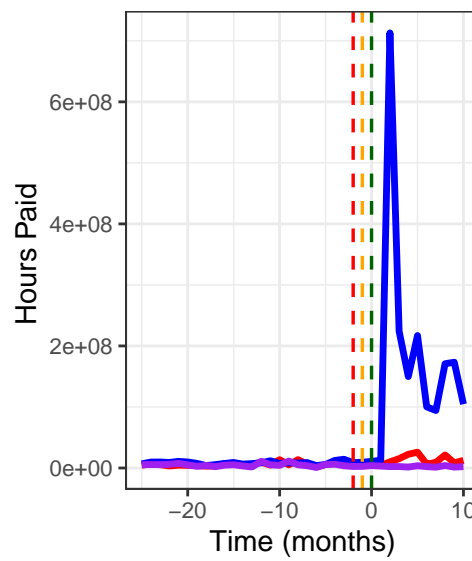|	δ_4	σ_{δ_4}	t	δ_5	σ_{δ_5}	t	δ_6	σ_{δ_6}	t
Clothing	4.87	17.47	0.28	3.94	12.65	0.31	0.70	17.48	0.04
Footwear	5.31	18.16	0.29	5.05	13.14	0.38	2.00	18. 16	0.11
Appliances	4.64	8.66	0.54	1.14	6.26	0.18	-0.81	8.66	-0.09
Photo-optics	1.71	15.18	0.11	0.84	10.99	0.07	0.70	15.18	0.11
Household kids	1.23	5.15	0.24	-0.07	3.72	-0.018	-0.86	5.15	-0.17
Household tools	0.26	8.78	0.03	-0.21	6.36	-0.03	0.14	8.79	0.97
Games	3.26	16.55	0.20	1.12	11.98	0.09	1.37	16.56	0.08

Figure 10: Timing for placebo test for the total subsidies paid (in hour) *Cassa integrazione Ordinaria* (blue) vs *Cassa integrazione Straordinaria Solidarietà* (purple) sales: T_4 is placed at $T = -2$, T_5 at $T = -1$ and T_6 at $T = 0$). For the other categories the placebo timing is identical

Table 14:

δ cofficients, expressed in millions as obtained by the DID regression, for subsidies (controlling the extraordinary solidarity) according to equation 3 for a placebo timings as showed in Fig. 10

	δ_4	σ_{δ_4}	t	δ_4	σ_{δ_4}	t	δ_5	σ_{δ_5}	t
Total	-36	144	-0.26	-36	144	-0.25	-36	144	-0.25
Manufacture	-26	101	-0.25	-26	101	-0.26	-26	101	-0.25
Trade	-0.88	3.2	-0.27	-0.60	3.2	-0.18	-0.70	3.2	-0.21
Construction	-6.7	26	-0.25	-5.8	26	-0.22	-6.5	26	-0.25

7.4   D – DID coefficients

Here we report the estimation of the other parameters, obtained in the DID regression for sales and subsidies, that were not put in to the main text

Table 15:

α, β_0 and β_1 obtained by the DID regression, for sales data de-seasoned, according to equation 3 for the different lock-down timings.

	α	σ_α	t	β_0	σ_{β_0}	t	β_1	σ_{β_1}	t
Clothing	102.88 ***	0.42	240.20	-3.66 ***	0.60	-6.05	1.47	1.96	0.75
Footwear	102.88 ***	0.37	278.66	-2.05 ***	0.52	-3.93	1.47	1.69	0.87
Appliances	102.88 ***	0.53	192.78	1.71 *	0.75	2.27	1.47	2.44	0.60
Photo-optics	102.88 ***	0.54	189.22	-7.69 ***	0.76	-10.00	1.47	2.49	0.59
Household kids	102.88 ***	0.32	320.61	-5.14 ***	0.45	-11.33	1.47	1.47	1.00
Household tools	102.88 ***	0.75	137.25	-2.21 *	1.06	-2.08	1.47	3.43	0.43
Games	102.88 ***	0.74	138.93	1.20	1.04	1.15	1.47	3.39	0.43

Table 16:

β_2 and β_3 obtained by the DID regression, for sales data de-seasoned, according to equation 3 for the different lock-down timings.

	β_2	σ_{β_2}	t	β_3	σ_{β_3}	t
Clothing	1.2012	1.4206	0.84	1.69	1.96	0.86
Footwear	1.20	1.22	0.98	1.69	1.69	1.00
Appliances	1.20	1.77	0.67	1.69	2.44	0.69
Photo-optics	1.20	1.80	0.66	1.69	2.49	0.68
Household kids	1.20	1.06	1.12	1.69	1.47	1.15
Household tools	1.20	2.48	0.48	1.69	3.43	0.49
Games	1.20	2.45	0.48	1.69	3.39	0.50

Table 17:

α, β_0 and β_1 obtained by the DID regression, for subsidies according to equation [3] for the different lock-down timings.

	α	σ_α	t	β_0	σ_{β_0}	t	β_1	σ_{β_1}	t
Total	4.75 ***	0.47	10.04	3.90 ***	0.66	5.84	-2.46	2.50	-0.98
Manufacture	3.72 ***	0.41	8.95	2.59 ***	0.59	4.40	-2.00	2.20	-0.91
Trade	0.23 ***	0.03	7.13	-0.16 **	0.05	-3.36	-0.15	0.17	-0.83
Construction	0.06	0.11	0.53	1.97 ***	0.16	11.91	-0.06	0.62	-0.095

Table 18:

β_2 and β_3 obtained by the DID regression, for subsidies according to equation 3 for the different lock-down timings.

	β_2	σ_{β_2}	t	β_3	σ_{β_3}	t
Total	-2.39	2.50	-0.95	-3.17	2.50	-1.26
Manufacture	-2.72	2.20	-1.23	-3.33	2.20	-1.50
Trade	-0.12	0.17	-0.68	-0.07	0.17	-0.39
Construction	-0.06	0.62	-0.096	0.06	0.62	0.10

7.5 E – De-seasoning

In this section of we report the results of the de-seasoning for raw sales data taken from ISTAT [27]. The first panel refer to the raw data (data) the third to the seasonal component that is perfectly periodical (seasonal), the forth one to the seasonal component that is not perfectly periodical (remainder) and the second one the trend extracted (trend). This decomposition was made by using an Hilbert-Huang transform as implemented in the [28] R package. The final trend in the second panel was obtained from by subtracting from the raw data the signal obtained in the third and forth panel. This approach of de-seasoning is known as additive.
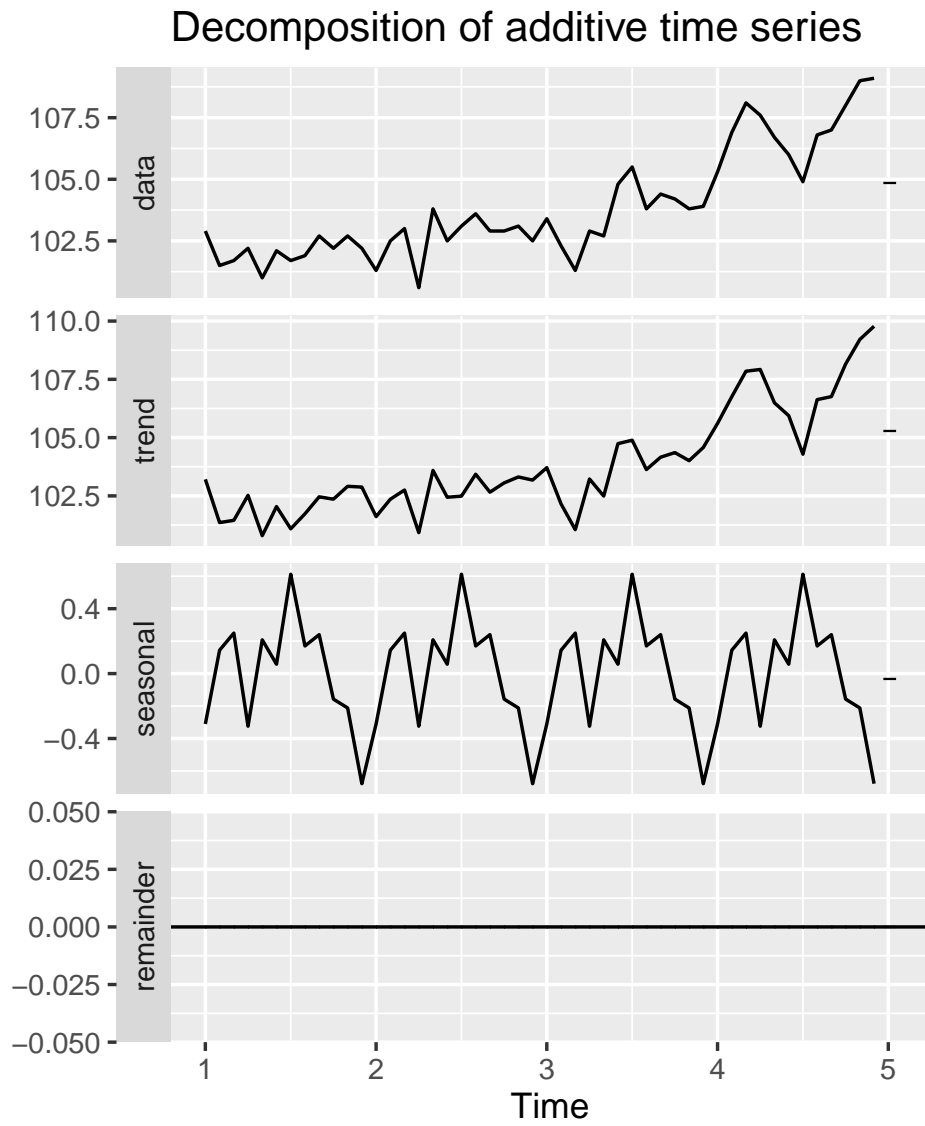
Figure 11: De-seasoning components for food sales
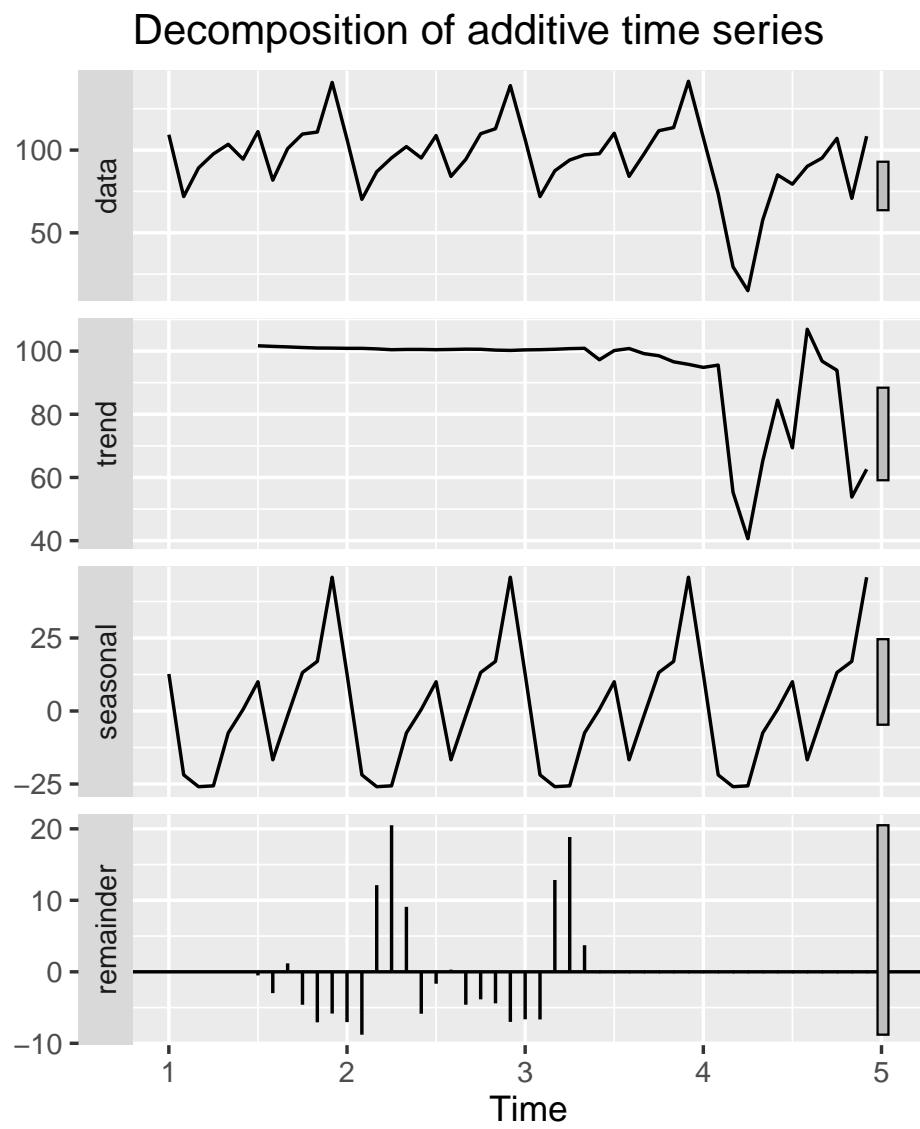
Figure 12: De-seasoning component for clothing sales
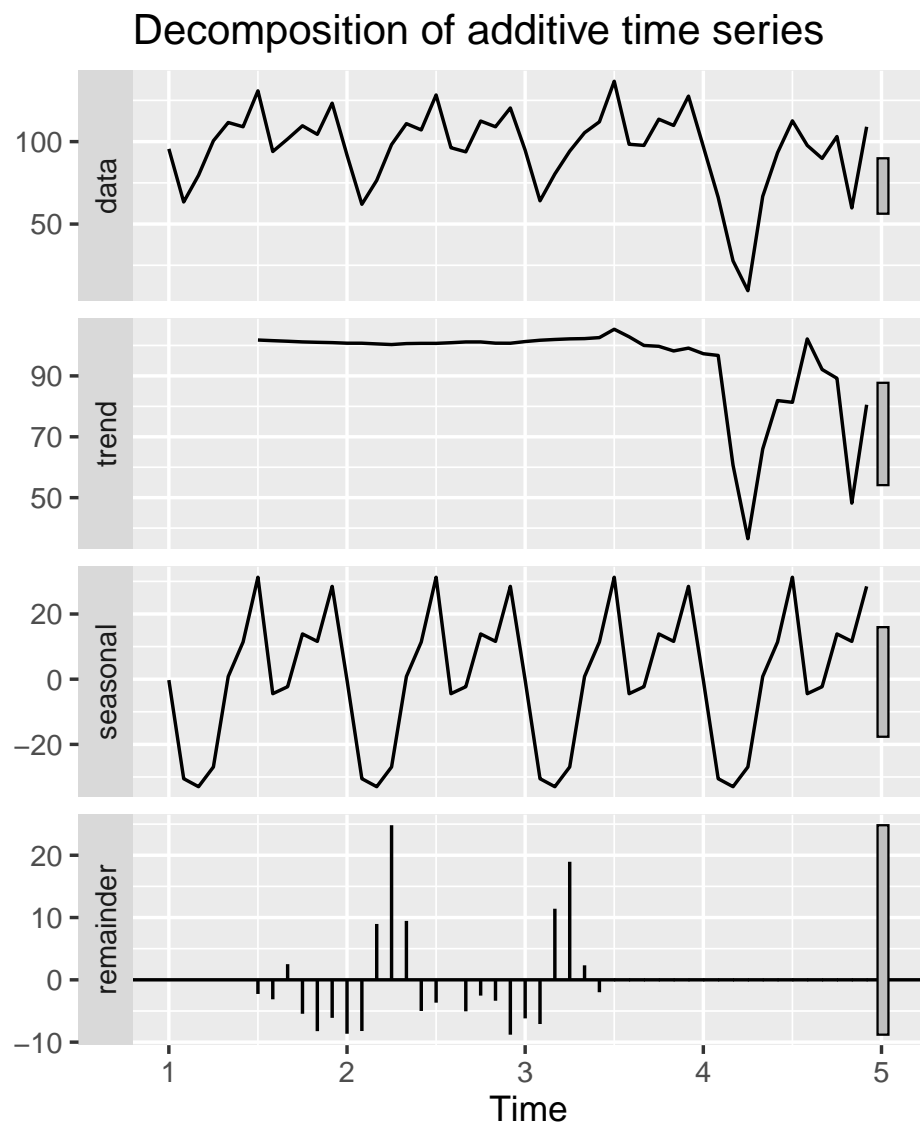
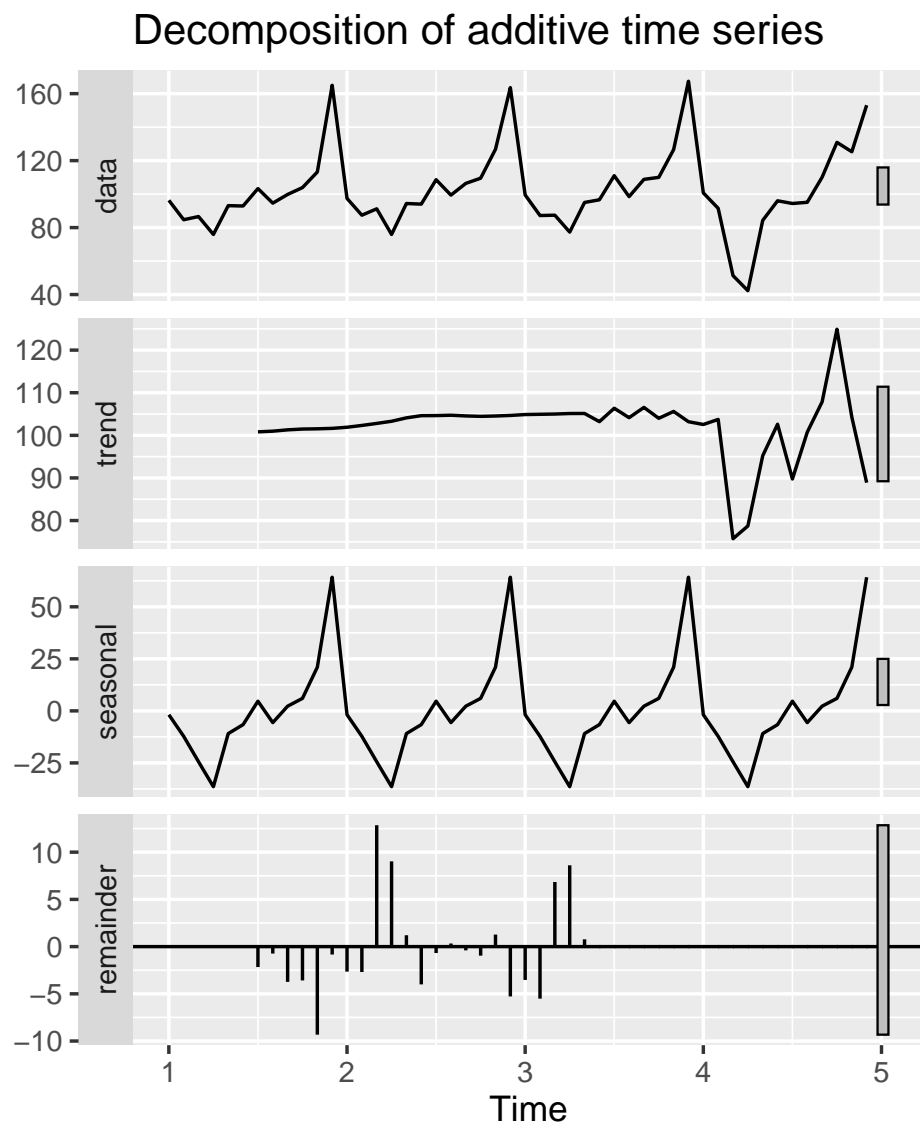**Figure 13:** De-seasoning components for footwear sales

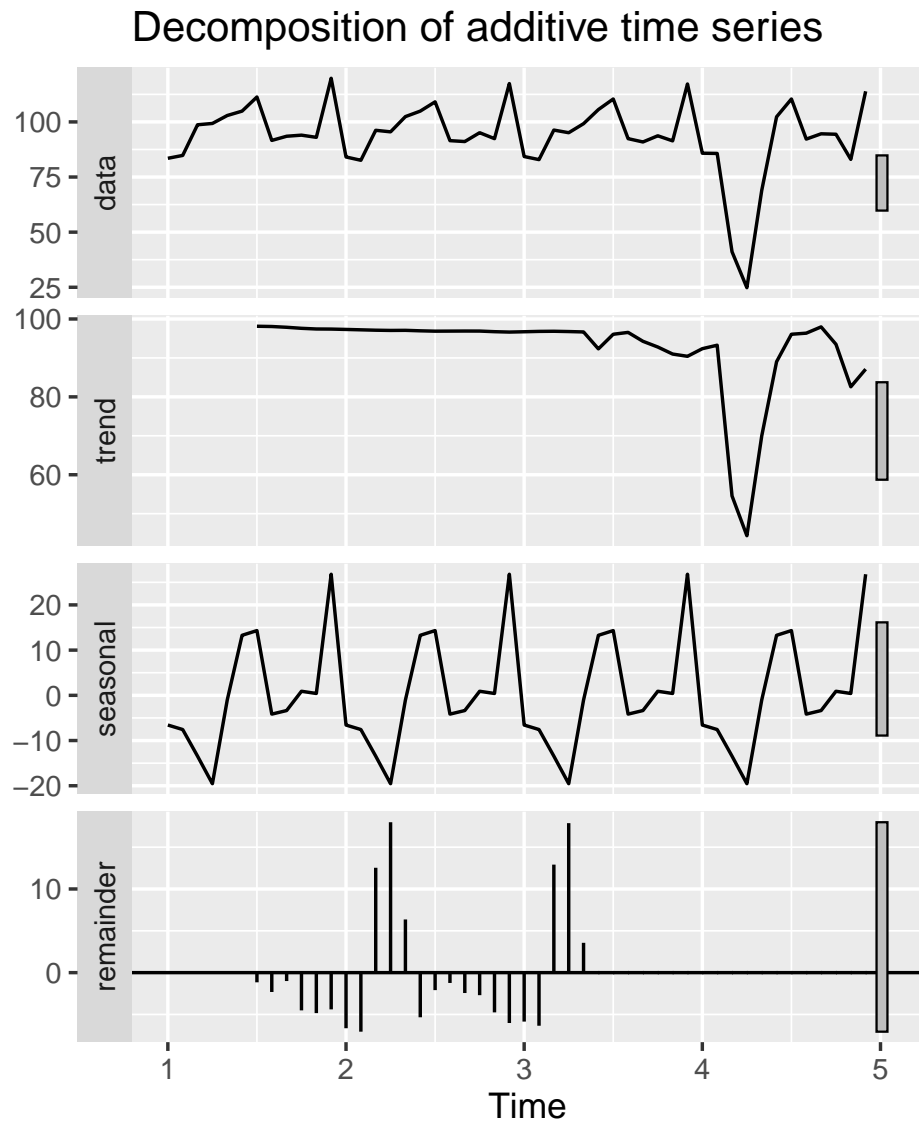**Figure 14:** De-seasoning components for appliances sales

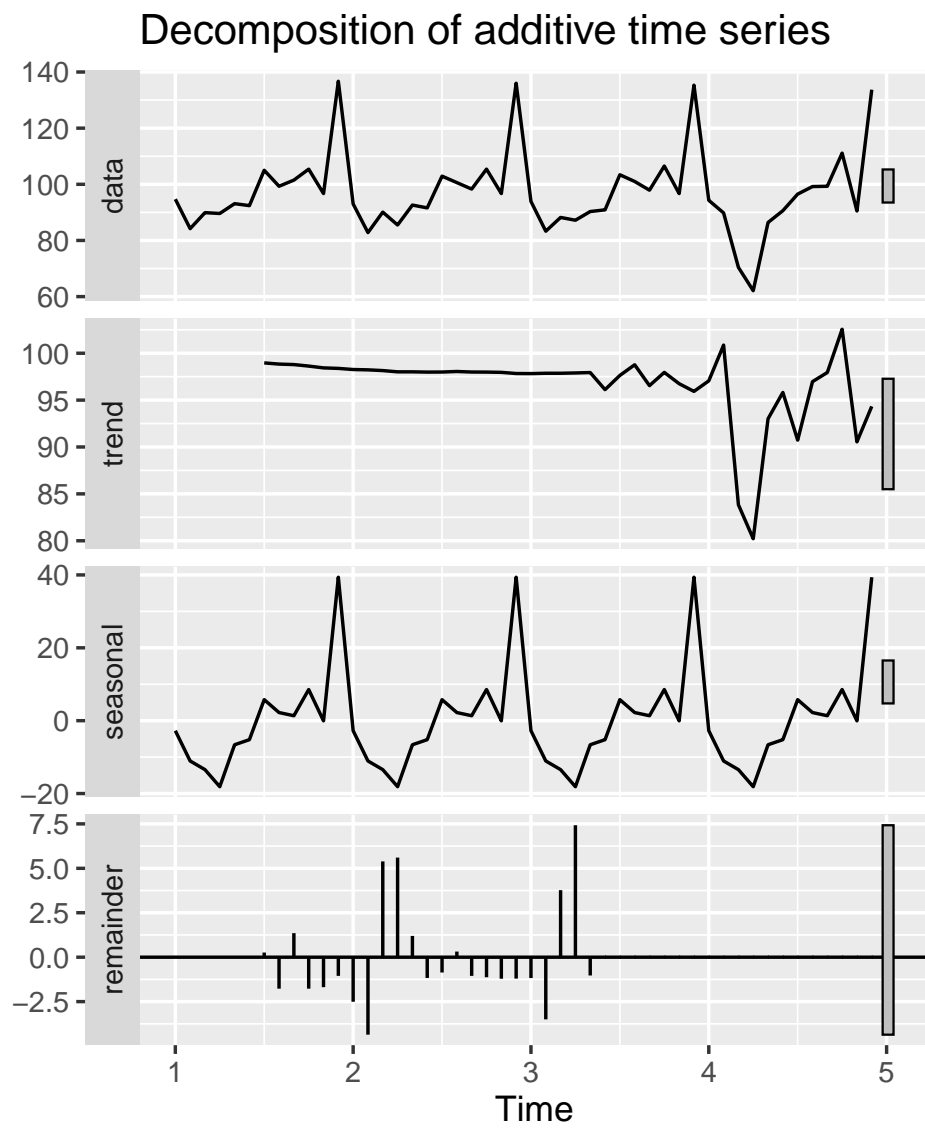**Figure 15:** De-seasoning components for photo-optics sales

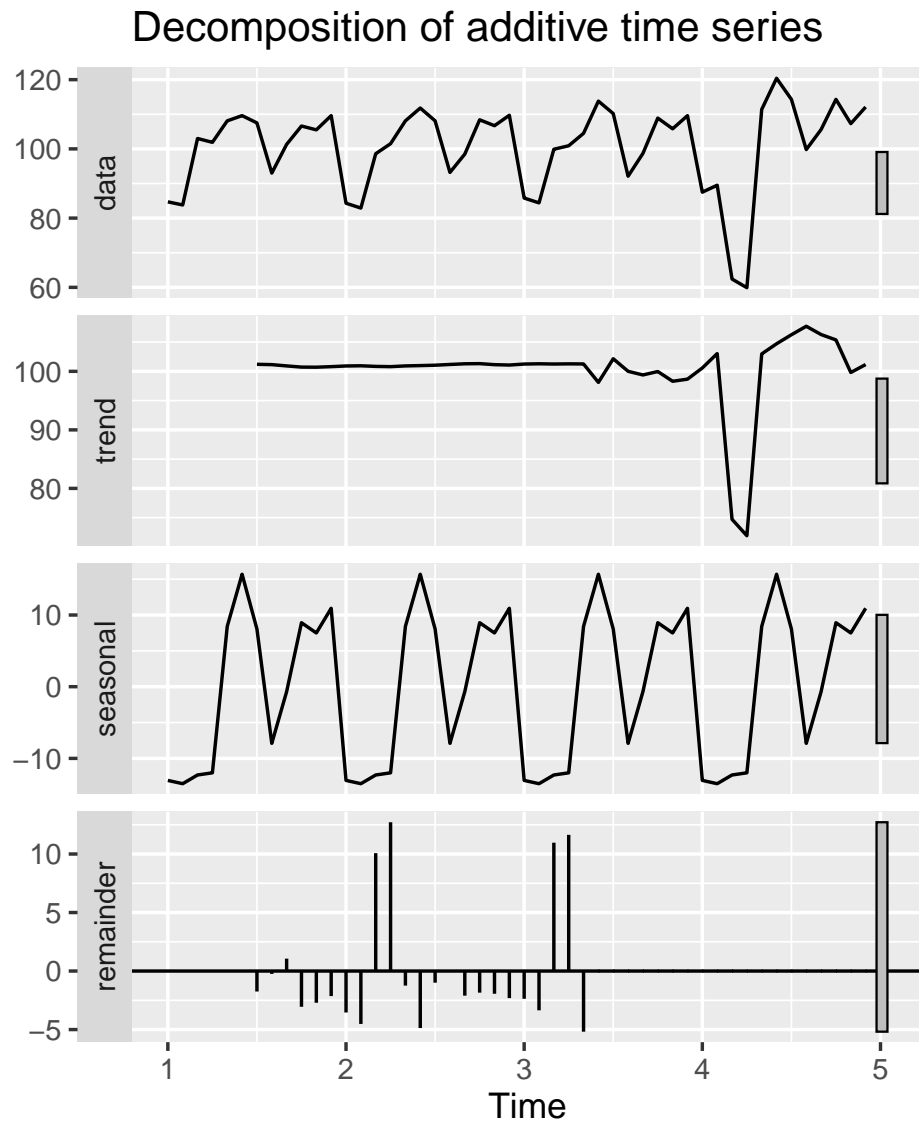**Figure 16:** de-seasoning components for household kids sales
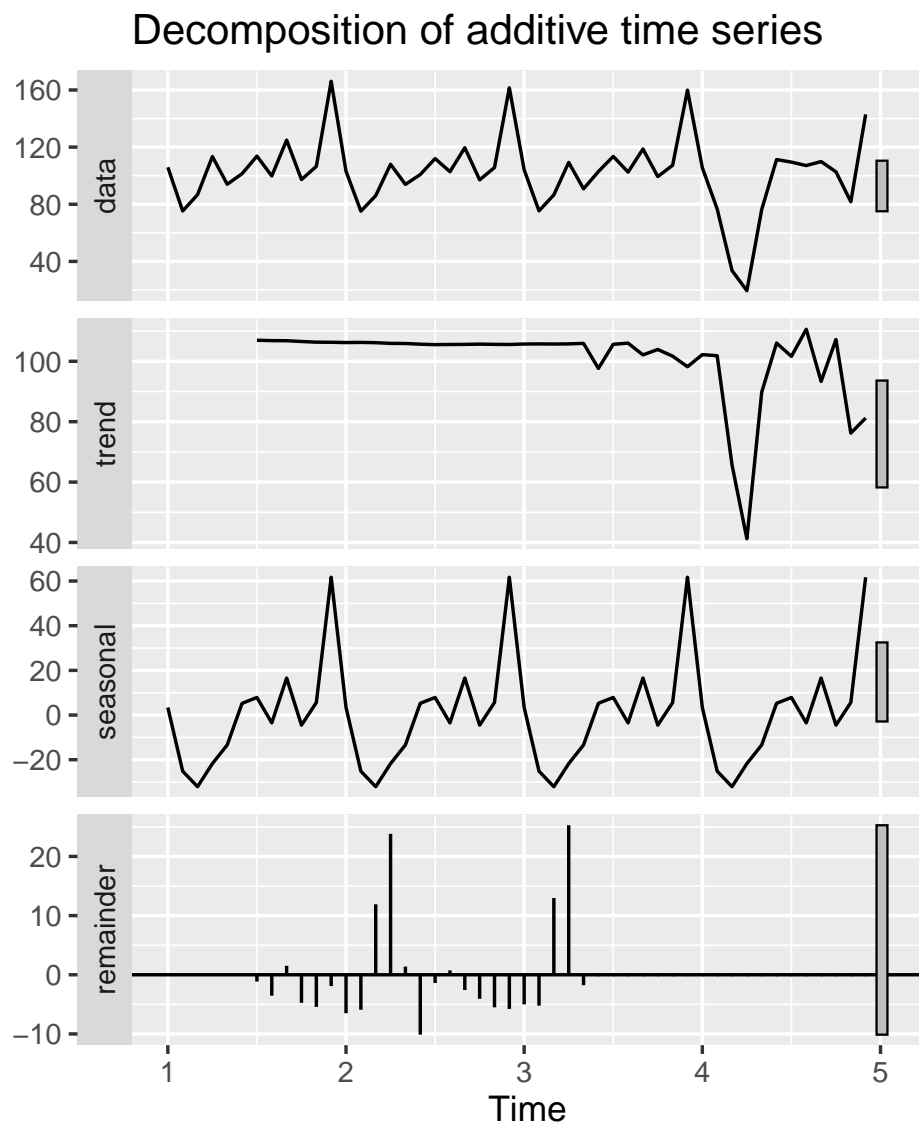
Figure 17: De-seasoning components for household tools sales

Figure 18: De-seasoning components for games sales