Impfstrategie

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Vaccination strategies against the novel Corona (COVID-19) virus - Why we should target the social hubs.

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1 Abstract

We currently have the choice which group of people to prioritize for vaccinations agains the Corona Virus. In the present analysis, we use recent demographic data and information about the severity of infections to compare three strategies of vaccination w.r.t. the exected number of severe cases (deaths or hospitalization): 1. Random vaccinatinations, 2. Vaccinating older people first, 3. Vaccinating spreader hubs first, i.e. people with many contacts We demonstrate that for any reasonable set of paramters that describe the current spreading in Germany, the third strategy performs almost 10x better than the second, which is only slightly better than the first. These results show that the current strategy targeted by the German government -vaccinating mainly the most at-risk population- is, simply put, wrong. Instead of prioritizing the elderly a priorization of the spreaders, such as social care, medical employees, teachers and other people with high numbers of expositions and contacts must be priorized.

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2 Introduction

2.1 Motivation: Reduce Hospitalizations

The target of an effective Vaccination strategy is to minimize the number of (new daily) intense-care (hospitalized) patients H_total(t) at any given time. In a mean-fiel approximation, this number is given by

$$H_{total}(t) = N * p_I(t) * p_H,$$

where - N is the number of individuals, - p_I is the probability that one person is infected at a given time t, and - p_H is the probability that an infected person will need intensive care.

For instance, for Germany with 83M inhabitants, an incidence of 200/100K for 7 days, and a percentage of 14% (see RKI1, but note that only the 20% patients were used where an inidcation was given about the severity of the health, presumably the number is lower), we get $H = 3320/day$

```
[95]: print("Mean Field daily hospitalization: ",int(83E6*200/100E3/7*0.14)," per␣
      ↪day")
```

```
Mean Field daily hospitalization:  3320  per day
```

2.2 Effect of time

It is important to note, that the given number is just a snapshot of a specific time, and the number is highly dependent on the incidence (assumed to be 200/100K inhabitants). More precisely, one typically assumes that the number of infected follows the equation

$$N * (p_I(t) - p_I(t - t_r)) = (p_T * N_C) * N * p_I(t - t_r),$$

i.e. each infected at a time t-t_r will recover until t, and infect his N_C contacts with a probability p_T each over the timescale of his infection (typically a timescale assumed to be about 12 days long). This leads to the exponential solution

$$p_I(t) = p_I(0) * exp(t/t_r * p_T * N_C))$$

In popular science this effect is captured as a meanfield by the infection rate/reproductive number $r = (p_T * N_C)$, indicating the numer of infections caused by an infected on average. For instance at , $r > 1$ (on average 1.0 - 1.6, depending on the severity of measure in place) means that $p_I(t)$ and thus the number of infected grows exponentially.

2.3 Effect of vaccinations

For the mean-field approach, vaccinations have 2 effects on the number of hospitalizations H_{total}(t): 1. Vaccinated people will not need to be hospitalized, i.e.

$$p_H = p_{H0} * (1 - p_v),$$

where p_H0 is the percentage of hospitalization without vaccinations and p_v is the percentage of the population vaccinated.

2. Infected people will infect less others, i.e.

$$p_T = p_{T0} * (1 - p_v),$$

where p_T0 is the percentage of infections among a persons contacts without vaccinations and p_v is again the percentage of the population vaccinated.

Putting it all together, leads to

$$H_{total}(t) = Np_I(0)*exp(t/t_r*(p_{T0}*(1-p_vt)*N_C))*p_{H0}*(1-p_vt) = H_0*e^{t/t_r*p_{T0}*(1-p_vt)*N_C}*(1-p_vt)$$

, where H_0 is the current level of hospitalization.

For completeness, we note that all these approximations hold true when the number of infected is much small than the overall population, i.e. $p_I << 1$. Otherwise, higher order corrections would be required, that take into account the reduction of contacts by already infected people.

[172]:
```
import math
import pandas as pd
import numpy as np
def H_tot(t,  pv, pT0 = 0.22, NC = 5):
    return np.exp( pT0 * NC * (1.- pv * t) * t )* (1.-pv * t)
```

3 Vaccination strategies

3.1 Strategy 1: Random vaccinations

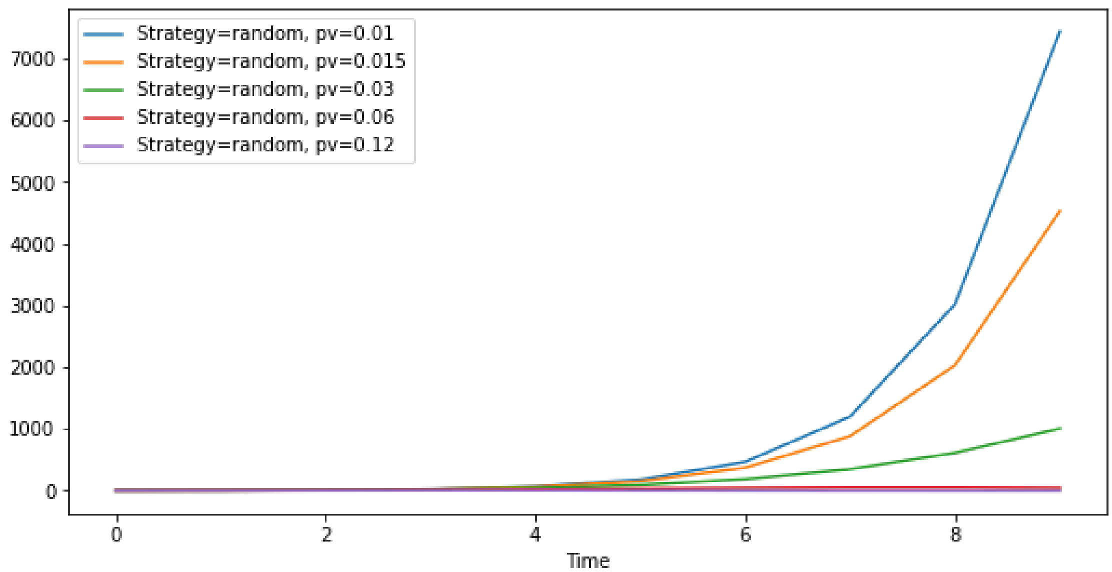
As a simple example let us understand the effect of random vaccinations,i.e. a random person is vaccinated For instance,if we assume that - per day 100.000 inhabitants are vaccinated conforming to optimistic estimates (~ 1.5% of the population per infection cycle), and we assume - a reproductive number of $r = p_{T0} * N_C = 0.22 * 5 = 1.1$ then we get

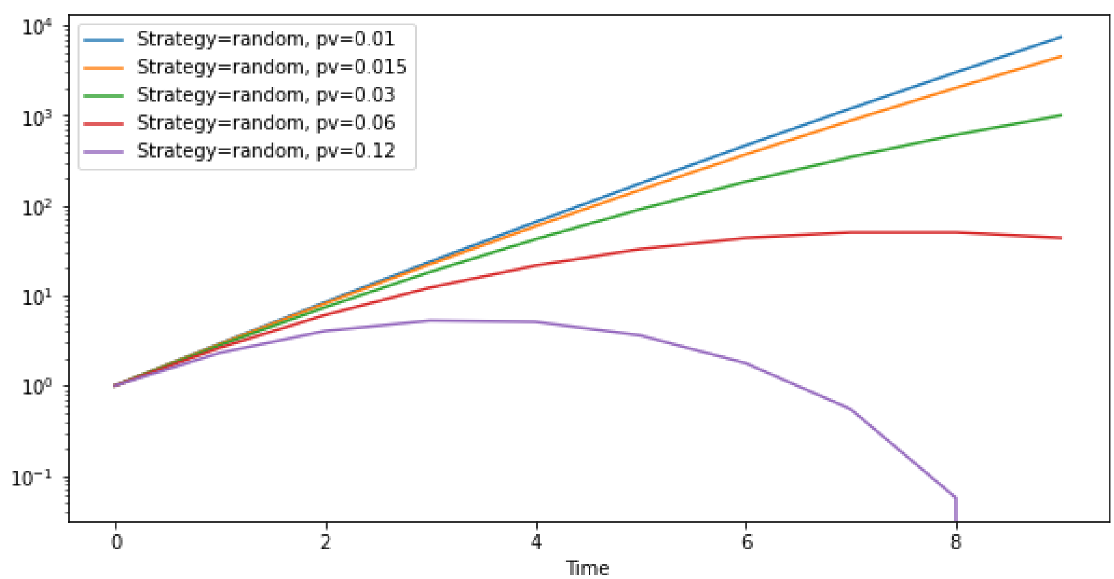
[207]:
```
simulation = pd.DataFrame([[x] for x in range(10)], columns = ["Time"])

for p_v in [0.01,0.015, 0.03, 0.06, 0.12]:
    simulation['Strategy=random, pv='+str(p_v)] = H_tot(simulation['Time'],p_v)
simulation.set_index('Time',inplace = True)
```

[210]:
```
to_plot = simulation.loc[:,[col for col in simulation.columns if "random" in␣
 ↪col]]
to_plot.plot(figsize = (10,5)),to_plot.plot(figsize = (10,5),logy=True)
print("Hospitalizations compared to today for random vaccinations")
```

```
Hospitalizations compared to today for random vaccinations
```





The graphs demonstrate that even with a reproductive number of 1.1, a vaccination strategy that covers only 1.5% of the population (100K/day) is insufficient and will lead to an exponential growth. Success of this strategy can be had with vaccination quotas $> 6\%$ (400K/day in Germany), and even then an increase in hospitalization of a factor of 100 is visible.

3.2 Strategy 2: Older people first (Risk based)

According to (RKI1) and targeted by protection programmes, hospitalization is much more likely for the elderly. Hence, as a second example, let us include that information into the vaccination strategy.

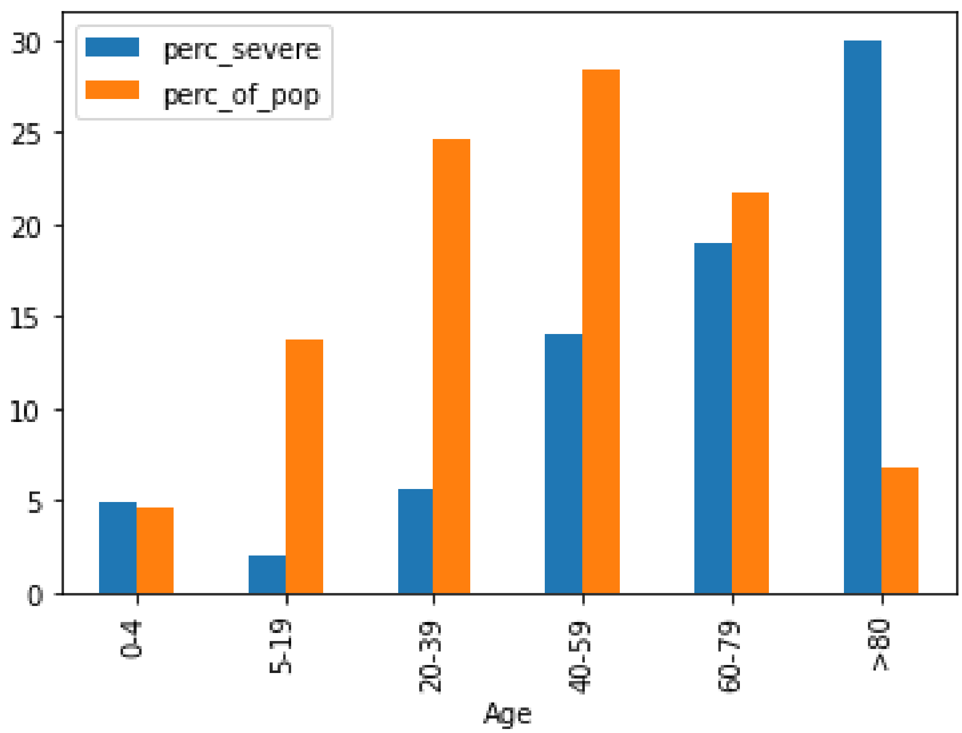
We include two types of information: - Based on the 2019 census (StatBA1), we include the age distribution among the 83 166 711 inhabitants in Germany. - Based on (RKI1), we include the percentage of severe cases of corona. Since the datasets delivers two values (for hospitalization and deaths) independently, i.e. a patient could be both hospitalized and died and would be counted twice, we use the maximum value, $perc_severe$, as a reference value for the likelihood of a corona case being a severe cases of corona in our analysis

[189]:
```
per_age = pd.DataFrame([elem.split(",") for elem in  """0-4,4.9,0;5-19,2,0;
↪20-39,5.6,0.1;40-59,14,0.7;60-79,19,9.6;>80,10,30""".split(";")], columns =␣
↪"Age,perc_hospital,perc_dead".split(",")).set_index("Age").astype(float)
per_age['perc_severe'] = per_age.max(axis = 1)
per_age['perc_of_pop'] = [18.4*0.25, 18.4*0.75,24.6, 28.4, 21.7,6.8] # FROM␣
↪StatBA1, values for 2019, splitting up the value for 1-20yrs evenly
per_age['cumperc_of_pop'] = per_age['perc_of_pop'][::-1].cumsum()[::-1].
↪shift(-1).fillna(0)
per_age[['perc_severe','perc_of_pop']].plot(kind='bar')
print("Severe among all infected:␣
↪",round((per_age['perc_severe']*per_age['perc_of_pop']).sum()/100,2),"%")
per_age
```

```
Severe among all infected:  12.02 %
```

[189]:

Age	perc_hospital	perc_dead	perc_severe	perc_of_pop	cumperc_of_pop
0-4	4.9	0.0	4.9	4.6	95.3
5-19	2.0	0.0	2.0	13.8	81.5
20-39	5.6	0.1	5.6	24.6	56.9
40-59	14.0	0.7	14.0	28.4	28.5
60-79	19.0	9.6	19.0	21.7	6.8
>80	10.0	30.0	30.0	6.8	0.0



If we assume that the oldest people are vaccinated first, then formulat for Hospitalization becomes

$$H_{total}(t) = H_0 e^{t/t_r * p_{T0}(1-p_v t)N_C} \sum_{age:\,a} p_a p_H(a)(1. - p_v(a)),$$

where - p_H(a) ist the hospitalization rate of the age range as it gets infected - p_v(a) is the percentage of vaccinations of that age range (p_v is still vaccinations of the - p_{a} is the demographic distribution of this age range among the population We not the the infection term is in front of the sum as we assume that the elderly do not have a particualt influence on the infection spreading. In other words, we assume that the elderly represent the society and do not have more or less contacts compared to others.

[235]:
```
def H_perAge(t, pv ,pT0 = 0.22, NC = 5):
    pv_total_perc = pv*t*100
    tmp = per_age
    tmp['pvage'] = ((pv_total_perc - tmp['cumperc_of_pop'])/tmp['perc_of_pop']).
 ↪clip(0,1)
    tmp['Hage'] = np.exp( pT0 * NC * (1.- pv * t) * t ) * tmp['perc_of_pop']/
 ↪100 * tmp['perc_severe']/100* (1.- tmp['pvage'])
    tmp['Hage'] *= 1./(per_age['perc_severe']*per_age['perc_of_pop']).
 ↪sum()*10000
    return tmp['Hage'].sum()
#sanity_check:
```

```
print("Deviation between no-vaccination cases for both strategies:␣
↪",(H_perAge(1,0.000) - H_tot(1,0.00))/(H_tot(1,0.00))*100,"%")
```

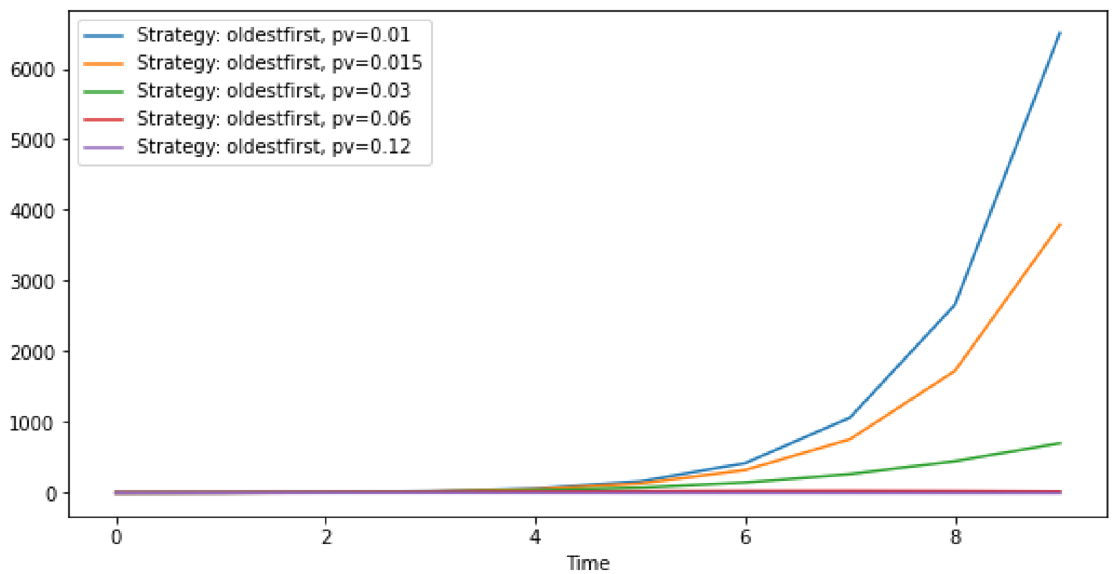
```
Deviation between no-vaccination cases for both strategies:
-1.478244565414142e-14 %
```

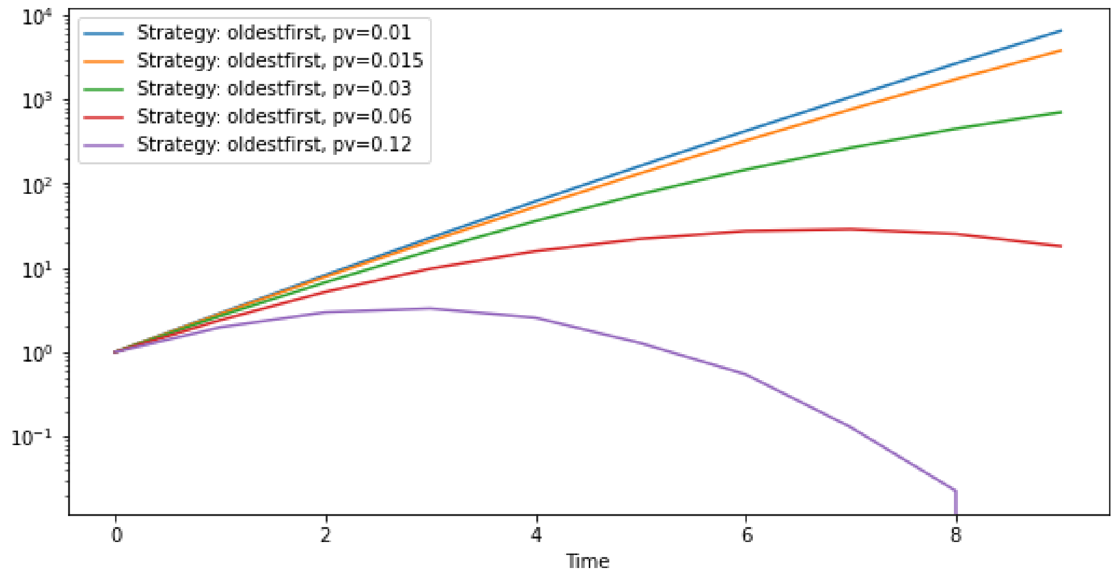
[236]:
```
# Do the simulations
for p_v in [0.01,0.015, 0.03, 0.06, 0.12]:
    simulation['Strategy: oldestfirst, pv='+str(p_v)] = [H_perAge(t,p_v) for t␣
↪in simulation.index.get_level_values('Time')]
```

[240]:
```
to_plot = simulation.loc[:,[col for col in simulation.columns if "oldestfirst"␣
↪in col]]
to_plot.plot(figsize = (10,5)),to_plot.plot(figsize = (10,5),logy=True)

#to_plot = simulation.loc[:,[col for col in simulation.columns if "0.03" in col␣
↪or "0.06" in col]]
#to_plot.plot(figsize = (10,5)),to_plot.plot(figsize = (10,5),logy=True)
print("Hospitalizations compared to today for over time for different␣
↪vaccination rates")
```

```
Hospitalizations compared to today for over time for different vaccination rates
```





We observe that -while much better- even with this strategy requries mich higher vaccination rates to avoid an overload of our health system

3.3 Strategy 3: Contact-Hubs first

The second factor affecting spreading are the contacts a person has, or rather the number of infections a person spreads by meeting non-vaccinated contacts. Hence, following the standard procedure, we will take a look at a strategy that targets the hubs of a social networks, i.e. the people with the most contacts, in that order.

While discussion around what are correct degree distributions in social networks are ongoing and the effect of social distancing measures may be hard to estimate, we use a power-law distribution as our base:

$$d(k) = k^{-l},$$

where - k is the number of contacts a node has in the social graph and - d is the relative number of these nodes in the population - l is a distribution-specific constant Furthermore, we note that in the mean-field the average of $\sum_k d(k)kp_{T0}$ results in the number, because it describes that a person in population d(k) has k contacts.

To relate these distributions to our original analysis, we note, that we can simply substitute $(1 - p_v t) * N_C$ by $\sum_k d(k)k(1-p_{v,k}(t))$, where $p_{v,k}$ is the vaccinated percentage of people with k contacts at time t.

To set the boundary condition problem, we furthermore note, that (assuming $l > 2$, since that we have a finite distribution) $(r =) \sum_k d(k)kp_{T0} = p_{T0}C_N \to l = \frac{2N_C-1}{N_C-1}$

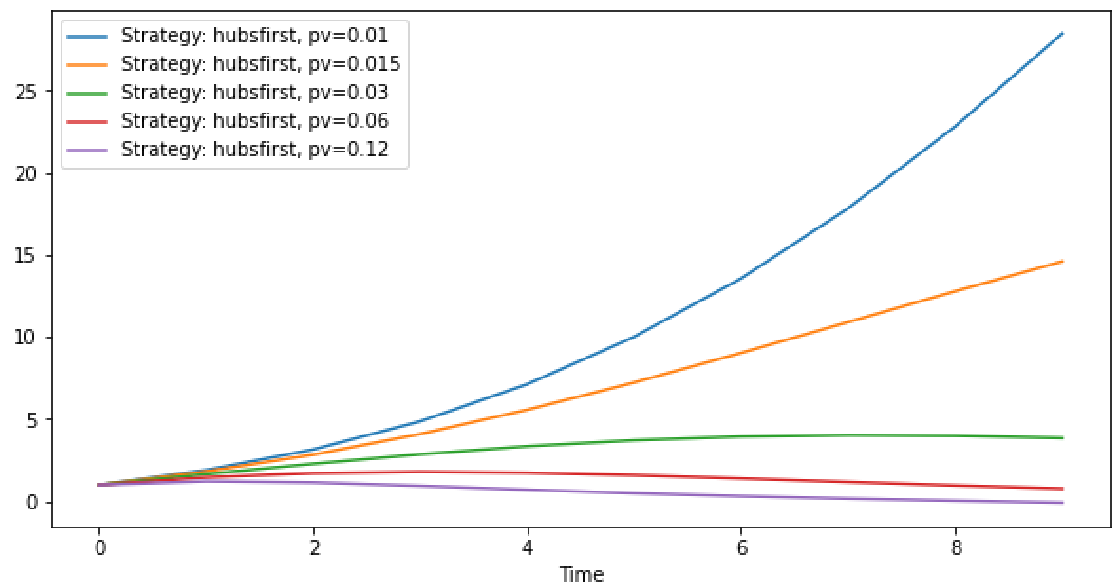
[280]:
```
def H_perContacts(t, pv ,pT0 = 0.22, NC = 5):
    if t== 0 or pv ==0:
        return np.exp( pT0 * NC * (1.-pv * t) * t ) * (1.-pv * t)
```

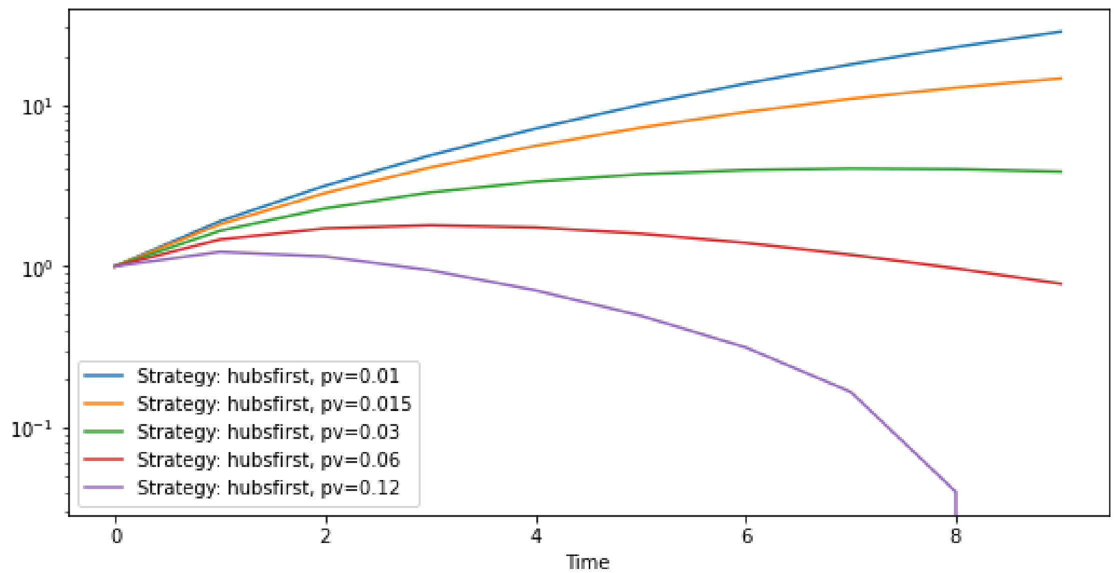
```
    l = (2*NC-1)/(NC-1)
    cutoff = (pv*t)**(-1./(l-1))
    def dkk_cutoff(cut):
        "INT_1..cut d(k)k dk"
        return (l-1)/(l-2) * (1-cut**(2-l))
    return np.exp( pT0 * dkk_cutoff(cutoff) * (1.-pv * t) * t ) * (1.-pv * t)
#Sanity check
#H_perContacts(1,0.0000000000000000000000000000001), H_tot(1,0.
 ↪0000000000000000000000000000001)
```

[281]:
```
# Do the simulations
for p_v in [0.01,0.015, 0.03, 0.06, 0.12]:
    simulation['Strategy: hubsfirst, pv='+str(p_v)] = [H_perContacts(t,p_v) for␣
 ↪t in simulation.index.get_level_values('Time')]
```

[282]:
```
to_plot = simulation.loc[:,[col for col in simulation.columns if "hubsfirst" in␣
 ↪col]]
to_plot.plot(figsize = (10,5)),to_plot.plot(figsize = (10,5),logy=True)
print("Hospitalizations compared to today for over time for different␣
 ↪vaccination rates")
```

```
Hospitalizations compared to today for over time for different vaccination rates
```

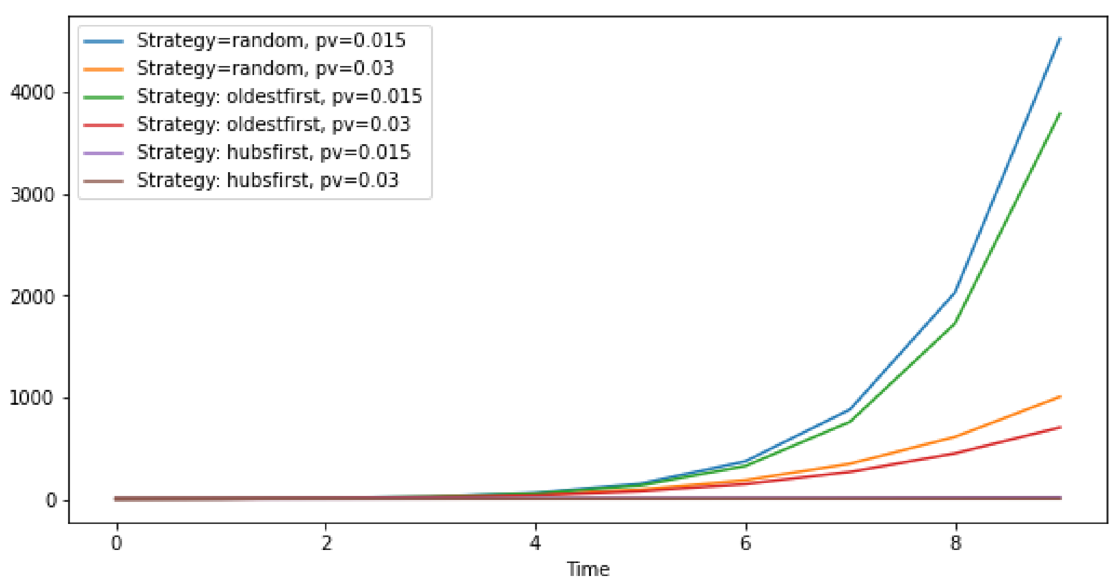


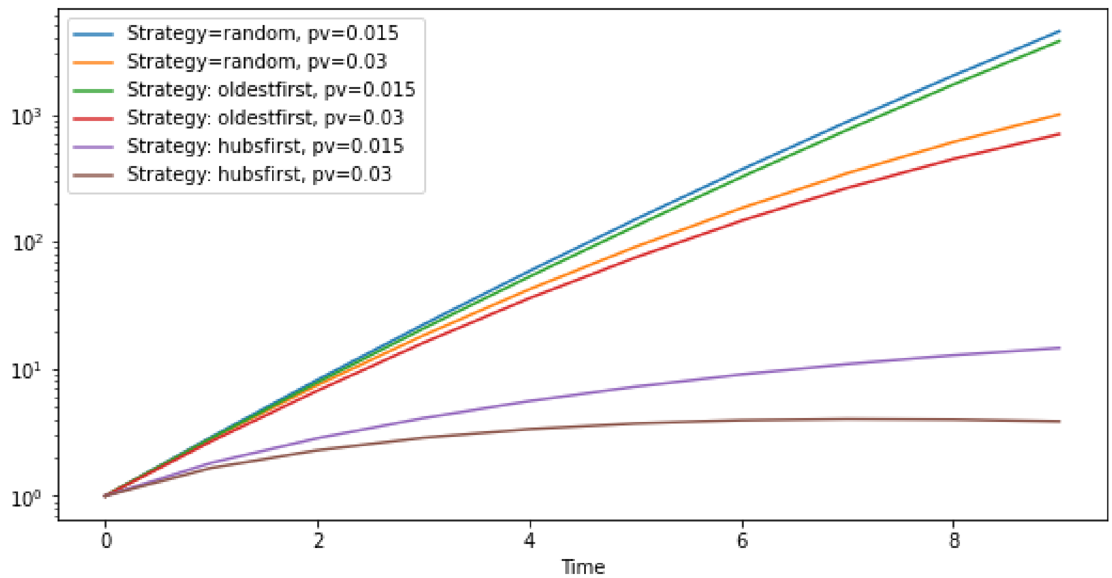


4 Summary & Comparison of strategies

[247]:
```
to_plot = simulation.loc[:,[col for col in simulation.columns if "0.015" in col␣
 ↪or "0.03" in col]]
to_plot.plot(figsize = (10,5)),to_plot.plot(figsize = (10,5),logy=True)
```

[247]: (<AxesSubplot:xlabel='Time'>, <AxesSubplot:xlabel='Time'>)





As becomes visible in the graphs above, the current strategy for vaccinations is far from optimal. Even when assuming that our vaccination capacity will be about double of what is currently expected (100K/day), the strategy of vaccinating old people first, will lead to an almost 10x higher number of intense cases (and deaths), than a targeted vaccination program for people with many contacts, such as teachers, nurses etc. Intuitively speaking, stopping the exponential spreading of Corona through vaccination of central spreaders overweighs largely over the linear effect that can be had by vaccinating people with pre-conditions.

5 Notes

5.1 Caveates

As all modelling, also the above results are based on simplified models. Nevertheless, they use use the main demographic data available at this time, including the current demography and the influence of the age on the severity of Corona-Cases, as well as reasonable estimates for other unknown facts, such as social contacts.

5.2 Mixing the strategies

In the discussion we only consider two extreme strategies, vaccinating people at risk and those with many contacts. While in our scenarios the latter is much better, one may expect the optimal strategy to be a mixture between the two. However, analyzing the limit effects of adding one vaccination to an at-risk patient compared to removing it from vaccinating people with many contacts only leads to a postive effect of the former in cases where rates of vaccination are much higher than what can reasonably be achieved.

[286]:

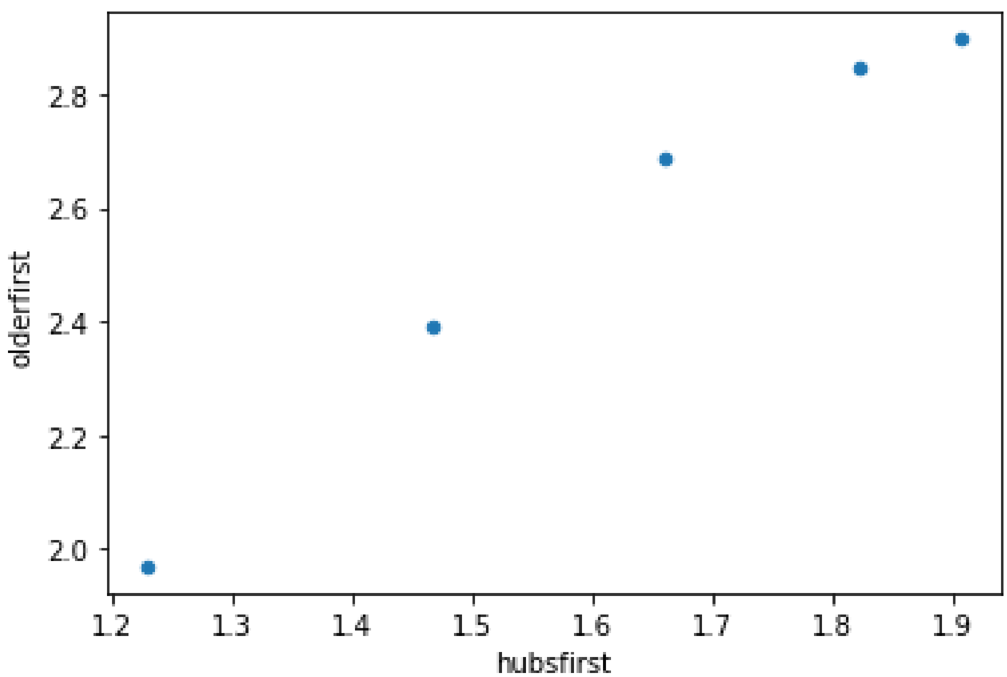
```
combined = pd.DataFrame(simulation.loc[1].values.reshape(3,5)[1:],columns=["pv␣
↪= "+str(pv) for pv in [0.01,0.015,0.03,0.06,0.12]]).rename({0:'olderfirst',␣
↪1:'hubsfirst' }).T
combined
```

[286]:

	olderfirst	hubsfirst
pv = 0.01	2.897130	1.906770
pv = 0.015	2.844357	1.823213
pv = 0.03	2.688974	1.660932
pv = 0.06	2.391080	1.466790
pv = 0.12	1.969357	1.229635

[288]:
```
combined.plot(kind = 'scatter', y='olderfirst',x='hubsfirst')
print("Incidences comparing the strategies against different rates of␣
↪vaccination")
```

```
Incidences comparing the strategies against different rates of vaccination
```



6 References:

- RKI1: https://www.rki.de/DE/Content/Gesundheitsmonitoring/Gesundheitsberichterstattung/GBEDownl
- StatBA1: https://www.destatis.de/DE/Themen/Gesellschaft-Umwelt/Bevoelkerung/Bevoelkerungsstand/Tabellen/liste-altersgruppen.html

```
[ ]:
```