Humans Against Virus or Humans Against Humans:
A Game Theory Approach to the COVID-19 Pandemic

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Introduction

- An epidemic is a health shock that:
  - may induce consumers to reduce their activities to protect themselves.
  - prompt governments and policy-makers to implement restrictive measures to slowdown the spread of the virus.
- Both private and government responses produce an **economic-health trade-off**.
- Particularly, an epidemic like the Covid-19 features externalities and private information as key characteristics.
  - People make decisions in an environment of **strategic interaction**.
  - When they lack information about others' health, the containment of the epidemic is more complicated.
- Modeling such environment appropriately is essential to understand how information losses can affect the extent of externalities.
  - Privacy as a limitation on the collection and use of information.
  - Asymptomatic people.

Motivation

"All public health staff involved in case investigation and contact tracing activities with access to such information should sign a confidentiality statement acknowledging the legal requirements not to disclose COVID-19 information. Efforts to locate and communicate with clients and close contacts must be carried out in a manner that preserves the confidentiality and privacy of all involved. This includes never revealing the name of the client to a close contact unless permission has been given (preferably in writing), and not giving confidential information to third parties (e.g., roommates, neighbors, family members)."

Research Question

What is the cost of privacy and the role of incomplete information in determining the health-economic trade-off in a pandemic?

This Paper

- A framework to analyze and quantify the **role of information** and externalities in an epidemic and their economic consequences.
    - Game to model the strategic interactions of people in an epidemic.
    - Derive a macro-epidemioligical dynamic model in the spirit of Eichenbaum et al. (2020a)[1]
- With this set up
    - Analyze what happens under different **information environments**.
    - As a **case study**, apply the framework to the US in the Covid-19 epidemic and evaluate the welfare implications of changing peoples' information sets.
    - Evaluate some policy tools, how they interact with each other, and how they use and provide information to shape the health and economic outcomes during a pandemic.

[1] In fact, such model is a particular case of our framework.

Results

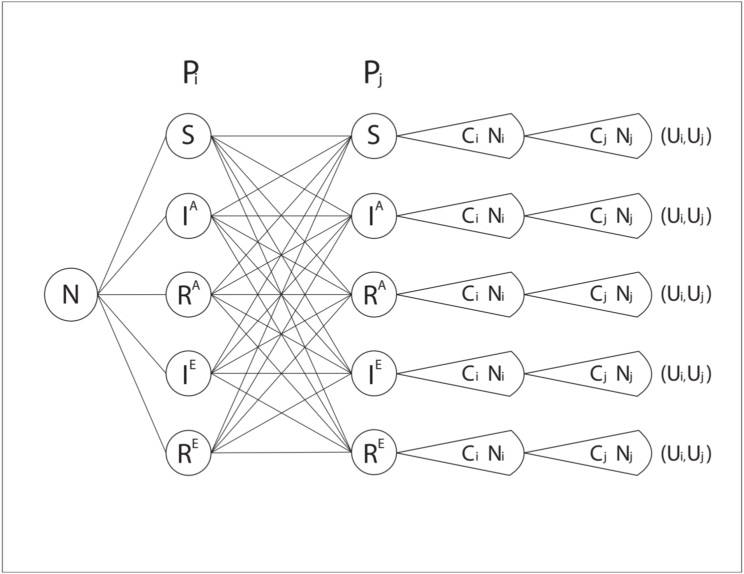
- We find that the greatest welfare losses are not due to the infection externality, but to the loss/lack of private and common information.
  - During the Covid-19 epidemic in the US costs of keeping health information **private** are between USD 5.9 trillion and USD 6.7 trillion.
- The policy tools most widely used to control the epidemic, Containment and Testing, alone yield low welfare gains.
  - Testing is a **double-edged-sword** (Information Assymetries).
  - Containments depend on **available information**: the scarcer information is, the more stringent and generalized they must be.
- The costs of keeping health information private are so large that actively disclosing information about people's health statuses can be a game-changer in the COVID-19 epidemic:
  - People can avoid risky interactions.
  - Challenge: Finding ways of making precise, private information available and usable.

Our Contribution and Related Literature

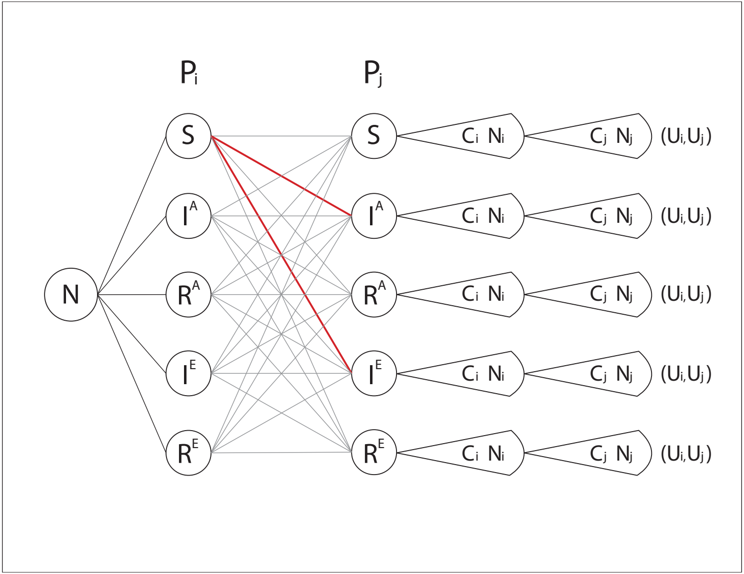
Our paper makes three contributions.

- First, a framework to analyze and quantify the **role of information** in an epidemic and its economic consequences, which adds to the existing literature found in:
  - Eichenbaum et al. (2020a), Acemoglu et al. (2020), Rowthorn and Toxvaerd (2020), Alvarez et al. (2020), Jones et al. (2020), Farboodi et al. (2020), and Garriga et al. (2020)
- Second, we measure the importance of **actively disclosing** disaggregated information about people's health status, as a powerful policy tool to reduce the economic health trade-off of the COVID-19. This contributes more closely to:
  - Argente et al. (2020), Eichenbaum et al. (2020b) and Berger et al. (2020).
- Third, we **microfound** how information affects economic and policy decisions in an epidemic, which allows for a more natural way of incorporating heterogenity and agents interaction in this macro-epidemic models.

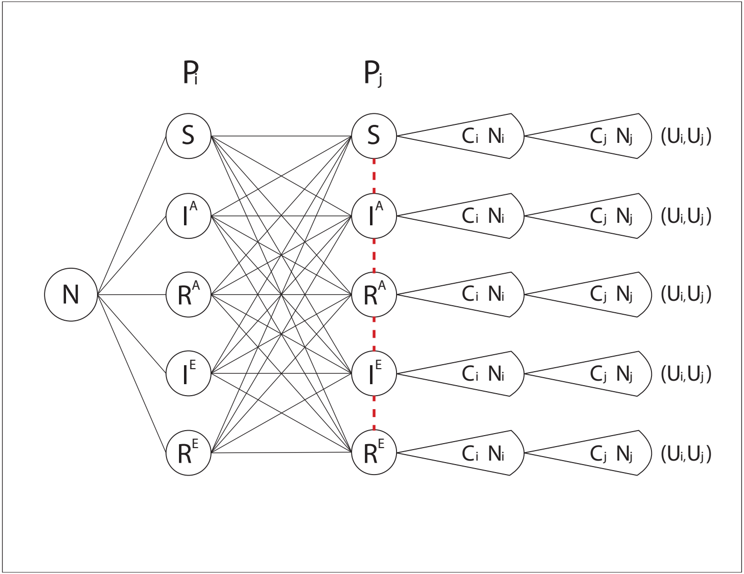
The Game



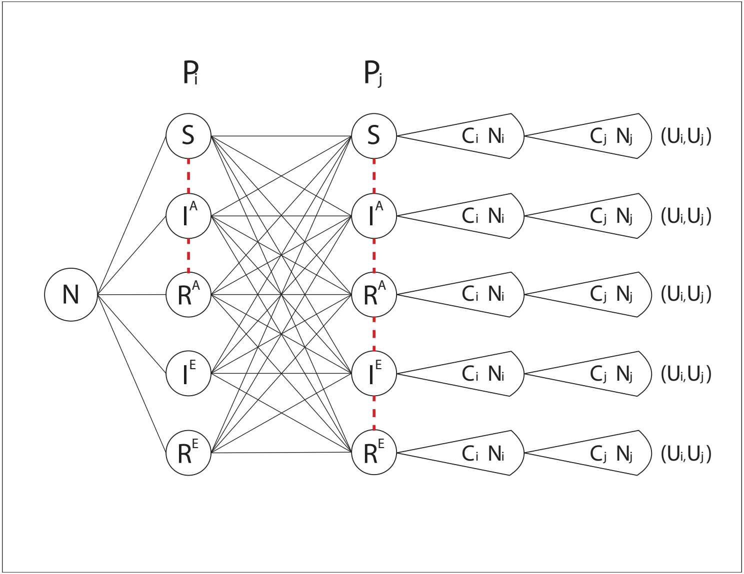
The Game: Complete Information



The Game: Partial Incomplete Information (PII)



The Game: Total Incomplete Information (TII)



Susceptible and Asymptomatic Player's Decisions in TII

Asymptomatic People

$$\max U_t^A = q_t^S U_t^{A,S} + q_t^{I^A} U_t^{A,I^A} + q_t^{R^A} U_t^{A,R^A}$$
$$s.t. (1+\mu_t) c_t^A = w_t n_t^A + \Gamma_t$$
$$\wedge \tau_t^{I^E} = \pi_1 c_t^A c_t^{I^E} + \pi_2 n_t^A n_t^{I^E} + \pi_3$$
$$\wedge \tau_t^{I^A} = \pi_1 c_t^A c_t^{I^A} + \pi_2 n_t^A n_t^{I^A} + \pi_3$$

With

$$U_t^{A,I^A} = u\left(c_t^A, n_t^A\right) + \beta\left[\left(1-\pi_r^A\right) U_{t+1}^{A,I^A} + \pi_r^A U_{t+1}^{A,R^A}\right]$$
$$U_t^{A,R^A} = u\left(c_t^A, n_t^A\right) + \beta U_{t+1}^{A,R^A}$$
$$U_t^{A,S} = u\left(c_t^A, n_t^A\right) + \beta\left[\left(1 - p_t^{I^E}\tau_t^{I^E} - p_t^{I^A}\tau_t^{I^A}\right) U_{t+1}^{A,S} + \left(p_t^{I^E}\tau_t^{I^E} + p_t^{I^A}\tau_t^{I^A}\right) U_{t+1}^{I}\right]$$

To deal with the uncertainty about her and others' type, Player i employs Harsanyi priors F and G.

- **Government**

$$\mu_t \left(c_t^A \left(S_t + I_t^A + R_t^A \right) + c_t^{I^E} I_t^E + c_t^{R^E} R_t^E \right) = \Gamma_t (S_t + I_t + R_t)$$

- **Equilibrium**

$$\left(S_t + I_t^A + R_t^A \right) c_t^A + I_t^E c_t^{I^E} + R_t^E c_t^{R^E} = AN_t$$

$$S_t n_t^A + I_t^A n_t^A + I^E \phi^I n_t^{I^E} + R_t n_t^R = N_t$$

Contagion Dynamics

Newly Infected:

$$T_t = \underbrace{\int_0^{S_t}\int_0^{I_t^A} \tau_t^{I^A} djdi}_{\text{Risky Interactions-Asymptomatic}} + \underbrace{\int_0^{S_t}\int_0^{I_t^E} \tau_t^{I^E} djdi}_{\text{Risky Interactions-Symptomatic}}$$

$$= \pi_1 c_t^A S_t c_t^I I_t + \pi_2 n_t^A S_t n_t^I I_t + \pi_3 S_t I_t$$

Infected Types:

$$I_{t+1}^A = I_t^A + \chi^A T_t - \pi_r^A I_t^A$$

$$I_{t+1}^E = I_t^E + \left(1 - \chi^A\right) T_t - (\pi_r^E + \pi_d) I_t^E$$

Population Dynamics I

Susceptible People

$$S_{t+1} = S_t - T_t$$

Total Infected People

$$I_{t+1} = I^A_{t+1} + I^E_{t+1}$$

Asymptomatic Recovered People

$$R^A_{t+1} = R^A_t + \pi^A_r I^A_t$$

Symptomatic Recovered People

$$R^E_{t+1} = R^E_t + \pi^E_r I^E_t$$

Deaths

$$D_{t+1} = D_t + \pi_d I^E_t$$

Total Population

$$P_{t+1} = P_t - \pi_d I^E_t$$

Calibration & Solution

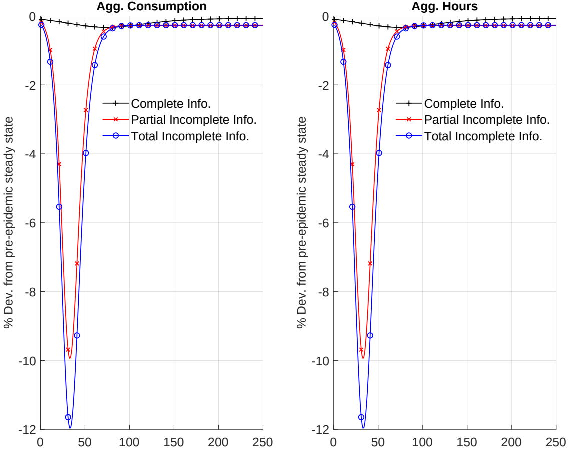
Parameter	**Value**
A	39.835
β	$0.96^{\frac{1}{52}}$
θ	0.0013
ϕ^{I}	0.8
π_1	$7.8408e^{-8}$
π_2	$1.2442e^{-4}$
π_3	0.3902
π_d	0.0032
π_R^A	0.3889
π_R^E	0.3857
χ^A	0.3993

$\rightarrow$ The model is solved using a numerical method, in which time iteration is mixed.

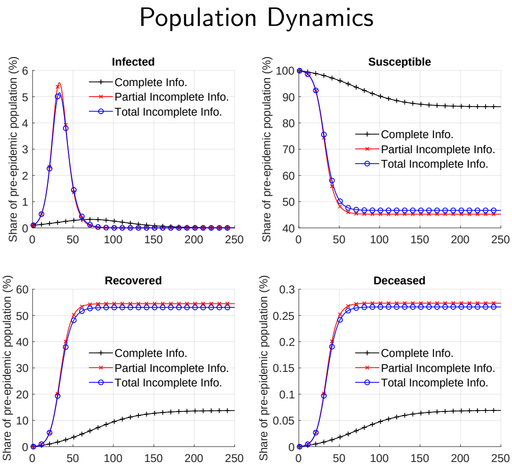
$\rightarrow$ Simulations have a 250 periods horizon of weekly periodicity.

Welfare Analysis

Economic Aggregates

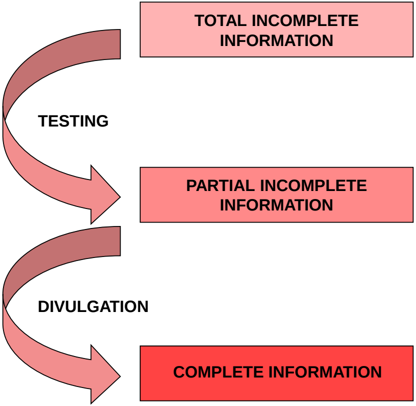


Welfare Analysis - Health and population variables



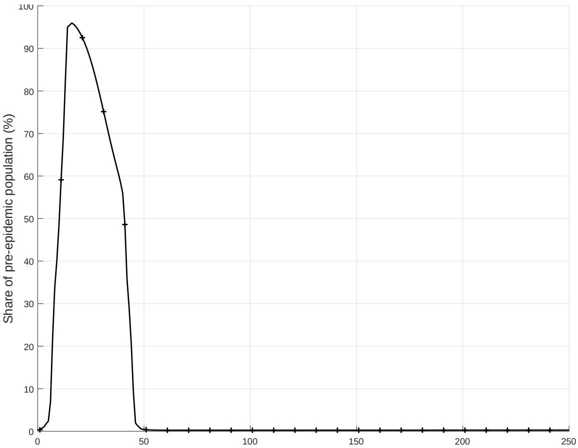
Policy Tools - Modified Model

The Policy Tools



Testing

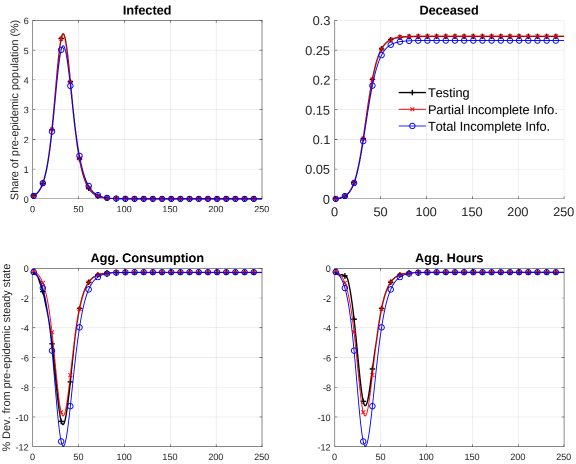
Optimal Tests



This path is consistent with a marginal cost for testing of $20 (CDC (2020)).

Testing

Testing:Economic-Epidemic Dynamics

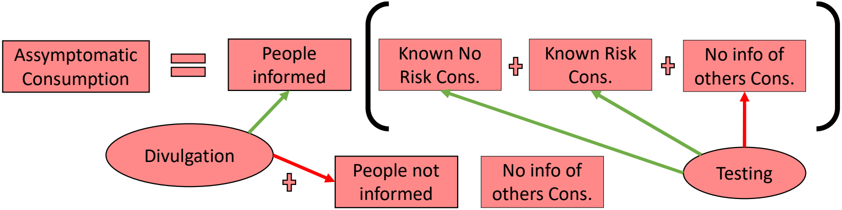


Active Disclosure (Divulgation)

- Divulgation makes information collected through testing publicly known.
- Argente et al. (2020) examined the effects of a policy along these lines in Seoul and found that people indeed modified their commuting patterns according to the information provided.
- You can think of disclosure in two ways:
  1. Putting a sign on people's faces
  2. Providing better, useful and usable information so that people make better decisions
- We favor the second interpretation, as the first one is a limit case:
  - For us, divulgation is a policy tool that **influences economic choices** by improving information that allows susceptible agents to better **assess contagion risk** in any interaction.
  - In the model we microfound these effects and look for ideal solutions.
  - In the real world, the more precise information is **given and used** the closer one gets to the "Putting a sign on people's faces" analogy.

Divulgation in the model

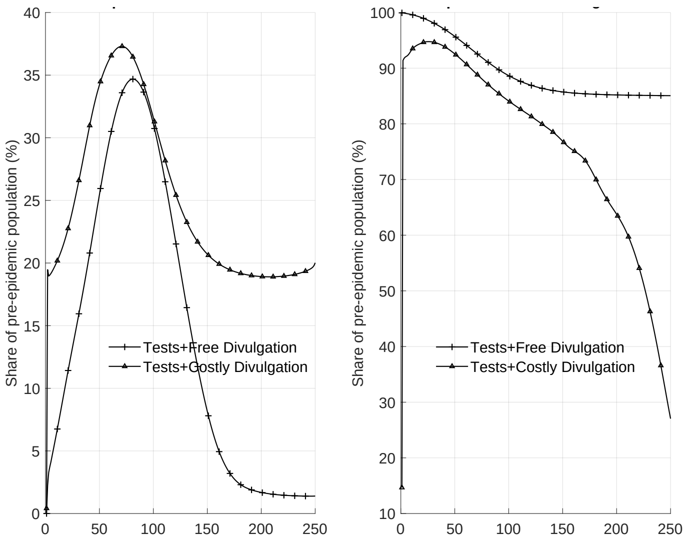
- The information disclosed is aimed at **Susceptibles**, who are split into 2 groups: the tested and the untested (don't know own type).
- The divulgation mechanism consists of giving the available information to a number of people from each group.
- In our model, divulgation is a tool that improves, in the **average interaction**, the information sets with which players choose their actions:



$$As_t c_t^A = \frac{Z_t^A}{P_t}\left[\left(S_t^X + R_t^X + R_t^E\right) c_t^{A^{NI}} + I_t^X c_t^{A^{I^A}} + I_t^E c_t^{A^{I^E}} + A_t^{NX} c_t^{A^U}\right] + \left(As_t - Z_t^A\right) c_t^{A^U}$$

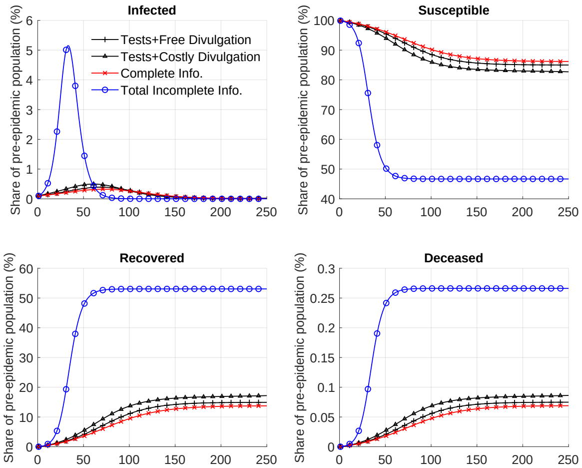
Optimal testing and divulgation

Optimal Information Policy



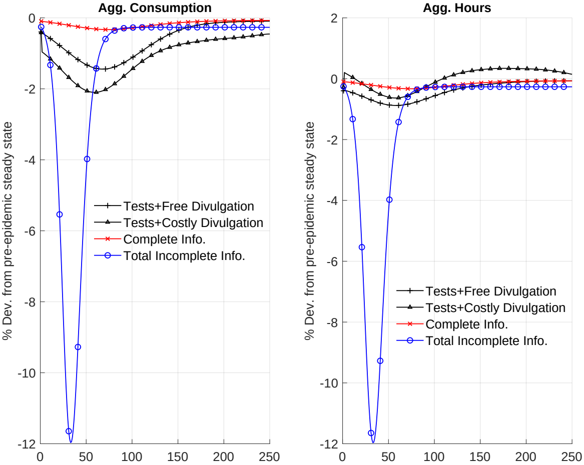
Divulgation improves health outcomes

Optimal Information Policy-Epidemic Dynamics



Divulgation and economic outcomes

Optimal Information Policy-Economic Outcomes



Welfare, economic and epidemiological results

	CI	PII	TII	Tests	Tests FD	Tests CD	Optimal Mix FD	Optimal Mix CD
Relative loss of Aggregate Welfare	0	-0.2005	-0.2314	-0.2079	-0.0334	-0.0705	-0.0287	-0.0655
Max Fall in Aggregate Consumption %	-0.33	-9.94	-11.96	-10.51	-1.44	-2.09	-1.31	-1.99
Cumulative Fall in Aggregate Consumption %	-0.17	-1.24	-1.54	-1.34	**-0.64**	**-1.12**	**-0.62**	**-1.08**
Max Fall in Aggregate Hours %	-0.33	-9.94	-11.96	-9.24	-0.87	-0.63	-0.72	-0.50
Peak Infection %	0.32	5.53	5.15	5.54	0.39	0.49	0.36	0.47
Final Deaths %	0.06	0.27	0.26	0.27	**0.07**	**0.08**	**0.07**	**0.08**
Final Recoveries%	13.74	54.49	53.05	54.43	14.92	17.19	14.39	16.85
Peak of General Conatinment%	-	-	-	-	-	-	0	0
Peak of Exhibit Containment %	-	-	-	-	-	-	78.15	63.51
Peak of Asymptomatic Containment %	-	-	-	-	-	-	66.72	56.88
Average % of Population Tested per Week	-	-	-	11.03	13.93	24.88	16.78	25.45
Max % of Population Tested per Week	-	-	-	95.96	34.68	42.26	35.18	38.00
Average % of Population Informed per Week	-	-	-	-	89.49	76.02	89.92	74.97
Max % of Population Informed per Week	-	-	-	-	99.93	94.76	99.93	94.00

Conclusions

- We developed an **analytical framework** that uses game theory to:
  1. Understand theoretically how information shapes epidemic dynamics
  2. Quantify the importance of information and externalities on health and economic outcomes
  3. Think about different policies and, given one, how much of the other you should do optimally.
- Applied to the COVID-19 epidemic in the US: loss of information generates sizable and most of the losses.
- **Containment** and **Testing** alone are insufficient to significantly reduce the economy-health tradeoff.
- The game changer is disclosure as a policy: Privacy is important, but its costs are much too great in the presence of externalities and this paper is useful for the privacy debate.
- At least 2 challenges:
  1. Theory and framework: measure costs of disclosure
  2. Practice: how to get info to people in a cheap, usable way

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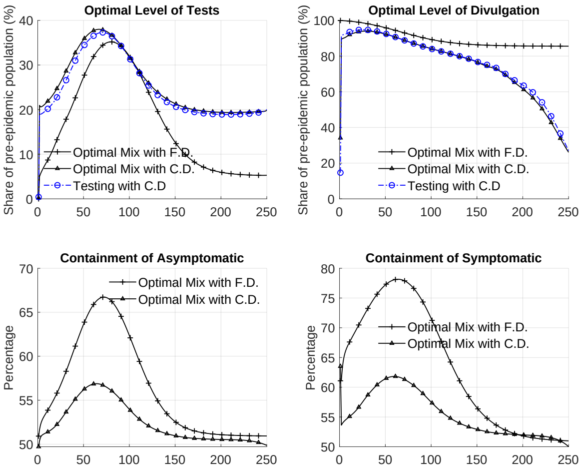
Welfare, economic and epidemiological results

	CI	PII	TII	CI GC	CI CC	PII GC	PII CC	TII GC
Relative loss of Aggregate Welfare	0	-0.2005	-0.2314	0	0.0003	-0.1741	-0.164	-0.1955
Max Fall in Aggregate Consumption %	-0.33	-9.94	-11.96	-0.33	-0.33	-28.53	-7.02	-30.78
Cumulative Fall in Aggregate Consumption %	-0.17	-1.24	-1.54	-0.17	-0.17	-4.97	-1.14	-5.88
Max Fall in Aggregate Hours %	-0.33	-9.94	-11.96	-0.33	-0.33	-28.53	-7.02	-30.78
Peak Infection %	0.32	5.53	5.15	0.32	0.32	3.37	3.58	3.11
Final Deaths %	0.06	0.27	0.26	0.06	0.06	0.22	0.23	0.21
Final Recoveries %	13.74	54.49	53.05	13.74	13.69	43.89	46.58	42.12
Peak of General Containment %	-	-	-	0	-	73.05	-	82.34
Peak of Exhibit Containment %	-	-	-	-	7.89	-	199.98	-
Peak of Asymptomatic Containment %	-	-	-	-	6.28	-	194.58	-

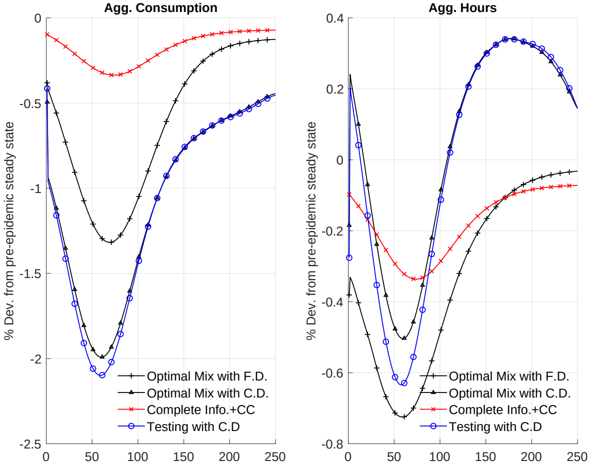
Optimal Mix

The Optimal Mix



Optimal Mix

The Optimal Mix



Optimal Mix

The Optimal Mix