MIDAS Annual Conference

Reopening California: Seeking Robust, Non-Dominated COVID-19 Exit Strategies

Pedro Nascimento de Lima, Robert Lempert, Raffaele Vardavas, Lawrence Baker, Jeanne Ringel, Carolyn Rutter, Jonathan Ozik

PARDEE RAND GRADUATE SCHOOL

Presentation Outline

1. **Introduction:** Policy question, prior work and approach
2. **Decision Framing:** Policy Levers, Model, Uncertainties & Outcomes
3. **Experimental Design:** Exploring strategies over a wide range of futures
4. **Results**
5. **Conclusions**

These are **preliminary results.** **As we test and refine our models, results will change.** We do however welcome you to refer to our published work:

Vardavas et al. *The Health and Economic Impacts of Nonpharmaceutical Interventions to Address COVID-19: A Decision Support Tool for State and Local Policymakers*, Santa Monica, Calif.: RAND Corporation, TL-A173-1, 2020. 2021: https://www.rand.org/pubs/tools/TLA173-1.html

Motivation and Policy Question:

How to manage NPIs in 2021 in a State like California?

California is going through a test of its reopening strategy.

How should the state manage their existing NPIs going forward, given:

1. The uncertainties surrounding multiple vaccines and their uptake
2. The costs of alternative stringency levels
3. The health/economic robustness tradeoffs implied by different policies
4. Existing inequities and the higher costs of NPIs for the most vulnerable.

Motivation and Policy Question:

How to manage NPIs in 2021 in California?

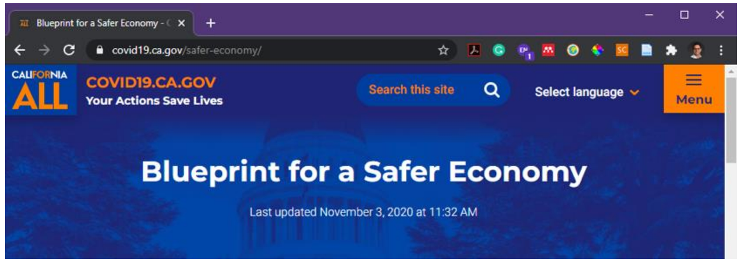
A. Reopening thresholds are defined at the county level

B. The plan is highly detailed and contains restrictions on capacity and detailed regulations on *how to reopen*

C. The plan does not contain justification for its thresholds, neither a statement about how the plan will change in the future

D. 40 million of people currently live under the widespread risk level

https://covid19.ca.gov/safer-economy/



County risk level	Adjusted case rate* 7-day average of daily COVID-19 cases per 100K with 7-day lag, adjusted for number of tests performed	Positivity rate** 7-day average of all COVID-19 tests performed that are positive	
		Entire county	Healthy equity quartile
WIDESPREAD Many non-essential indoor business operations are closed	More than 7.0 Daily new cases (per 100k)	More than 8.0% Positive tests	
SUBSTANTIAL Some non-essential indoor business operations are closed	4.0 – 7.0 Daily new cases (per 100k)	5.0 – 8.0% Positive tests	5.3 – 8.0% Positive tests
MODERATE Some indoor business operations are open with modifications	1.0 – 3.9 Daily new cases (per 100k)	2.0 – 4.9% Positive tests	2.2 – 5.2% Positive tests
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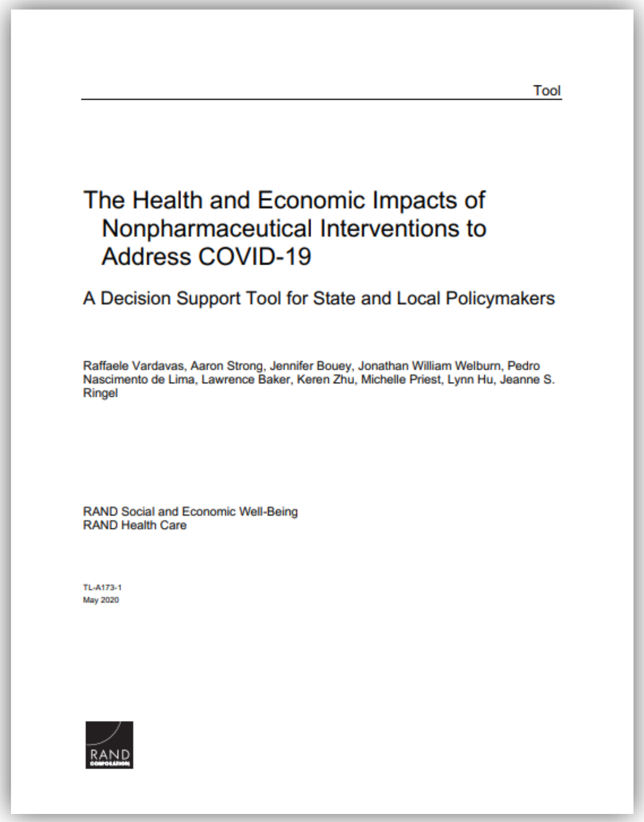
*Small counties (those with a population less than 106,000) may be subject to alternate case assessment measures for purposes of tier assignment.

**Health equity metric is not applied for small counties. The health equity metric is used to move to a less restrictive tier.

Prior Work:

The Health and Economic Impacts of Nonpharmaceutical Interventions to Address COVID-19



Tool

The Health and Economic Impacts of Nonpharmaceutical Interventions to Address COVID-19

A Decision Support Tool for State and Local Policymakers

Raffaele Vardavas, Aaron Strong, Jennifer Bouey, Jonathan William Welburn, Pedro Nascimento de Lima, Lawrence Baker, Keren Zhu, Michelle Priest, Lynn Hu, Jeanne S. Ringel

RAND Social and Economic Well-Being
RAND Health Care

TL-A173-1
May 2020

RAND CORPORATION

- https://www.rand.org/pubs/tools/TLA173-1.html

Prior Work:

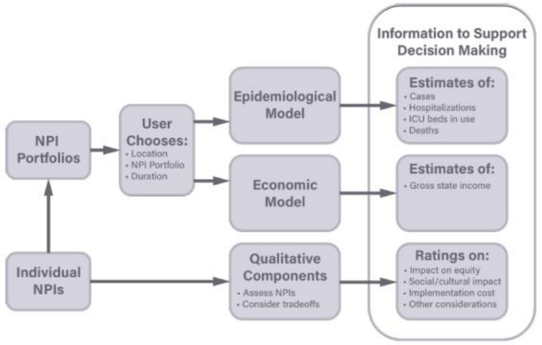
The Health and Economic Impacts of Nonpharmaceutical Interventions to Address COVID-19

We built two models to represent health and economic effects of Nonpharmaceutical interventions at the state level:

A. **Health Outcomes:**
   A. **Stratified ODE model** (similar to those used to evaluate vaccination policies). Uses pre-defined mixing matrices to specify how mixing changes; magnitude of transmission reduction is obtained by calibration.
   B. Outputs: Deaths, Cases, Days under specific NPI Portfolios levels.

B. **Economic Outcomes:**
   A. **Computable general equilibrium model**: Can estimate the spillover effects of shutting down specific industries. Has its own limitations as do all "comparative statics" models, but is valuable because it represents interconnected economic sectors.
   B. Key output: Income Loss, as a function of days under specific portfolios.

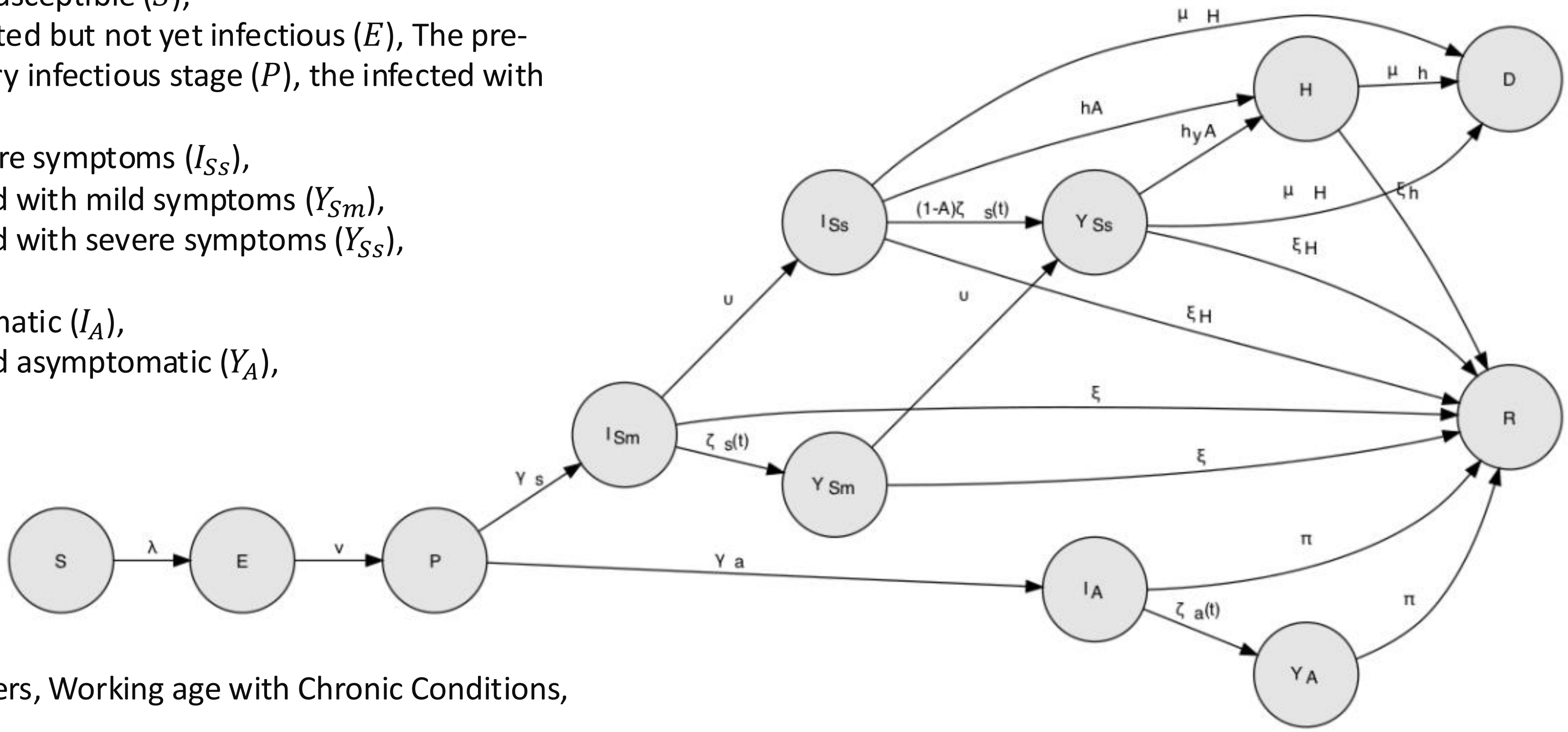
Figure 2.1. Components of the Decision Support Tool



Model Documentation: https://www.rand.org/pubs/tools/TLA173-1.html

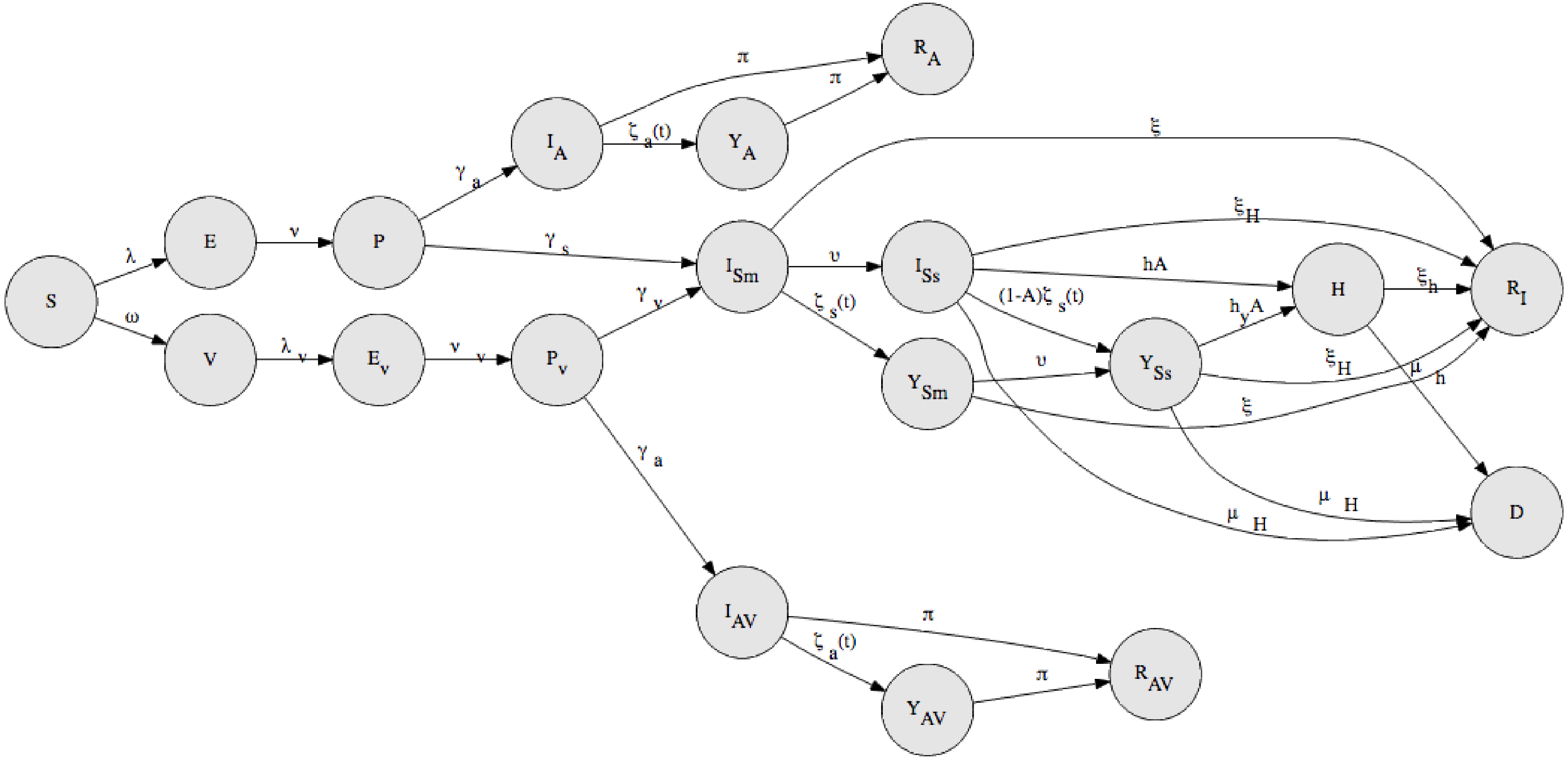
Disease Progression Model without Vaccination

- The noninfected and susceptible (S),
- The exposed and infected but not yet infectious (E), The pre-symptomatic or primary infectious stage (P), the infected with mild symptoms (I_{Sm}),
- The infected with severe symptoms (I_{Ss}),
- The diagnosed infected with mild symptoms (Y_{Sm}),
- The diagnosed infected with severe symptoms (Y_{Ss}),
- The hospitalized (H),
- The infected asymptomatic (I_A),
- The diagnosed infected asymptomatic (Y_A),
- The recovered (R), and
- those that died (D).



Strata: <19, HCEW, Workers, Working age with Chronic Conditions, 65+

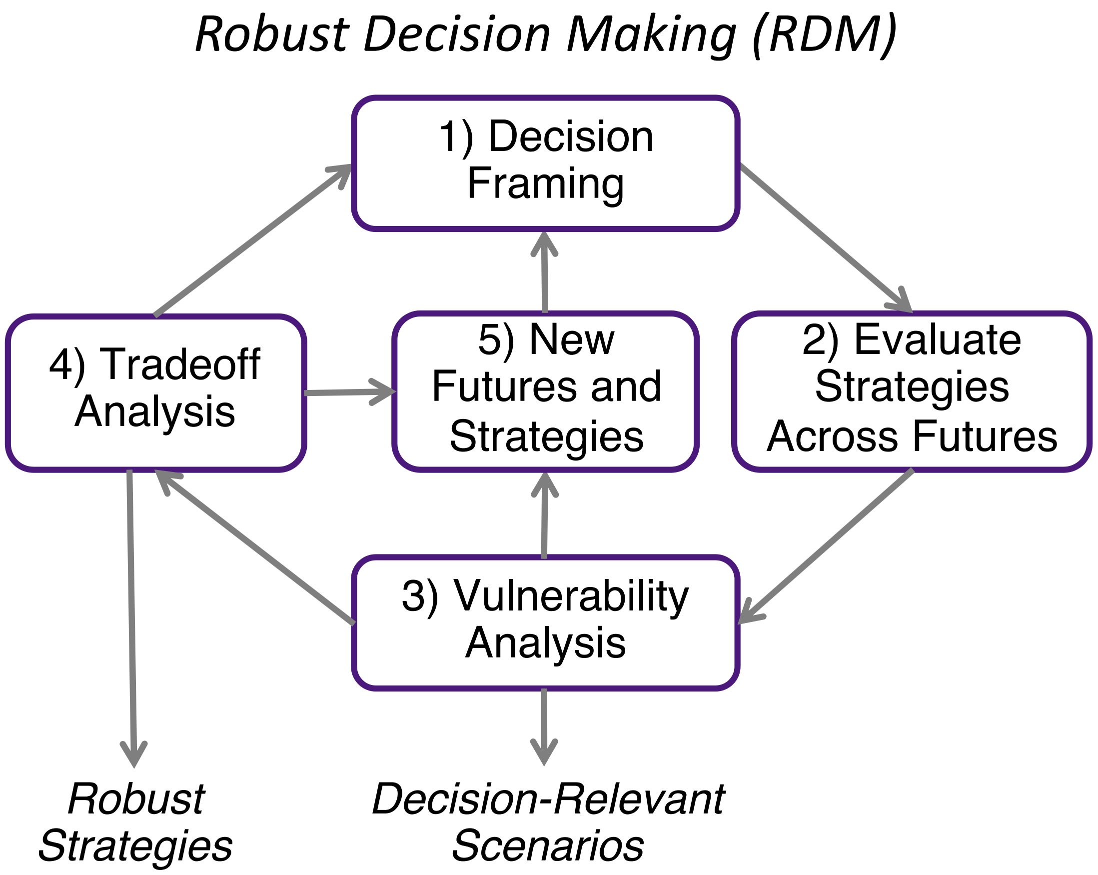
Disease Progression Model with Vaccination



Using the Robust Decision Making (RDM) approach to evaluate reopening strategies under uncertainty

1. RDM provides an ***iterative framework*** for evaluating policies while accounting for *deep uncertainty*
2. Uses *models* to **stress-test policies across wide range of futures**, reflecting uncertainties
3. *Quantitative* ***vulnerability analysis*** **identifies the assumptions that lead policies to be successful and unsuccessful**, and informs development of *adaptive strategies*
4. Tradeoff analysis helps balance across **multiple objectives** and identify *robust* strategies
5. RDM Is part of a family of **Decision making Under Deep Uncertainty (DMDU) methods**.

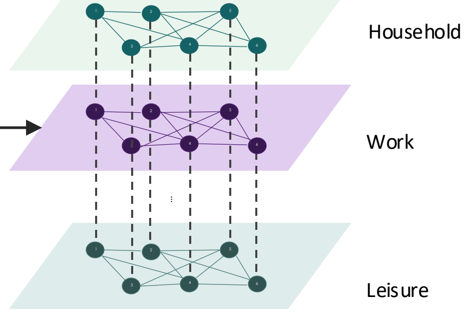
More information on RDM:
https://www.rand.org/methods/rdmlab.html



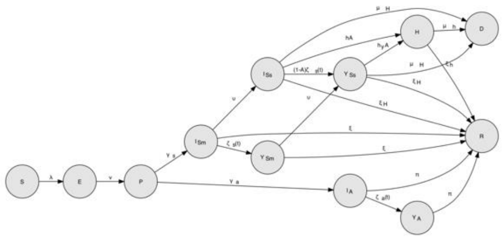
Decision Framing:

Representing the pandemic control loop

NPI-dependent mixing matrix



Disease Progression Model



Observed Prevalence

NPI Level ~
Prevalence * Level of Caution * 10^3

Level of Caution

Outputs

Deaths

Cases

Income Loss

Days of NPIs

Decision Framing:

Representing the pandemic control loop

New Strains

Behavioral Changes / resistance to NPIs

Multiple vaccines with uncertain transmission efficacies

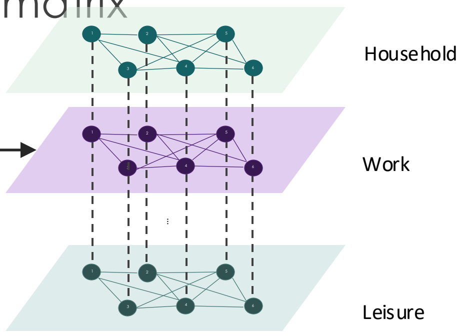
Future willingness to Vaccinate

Behavioral response to vaccination

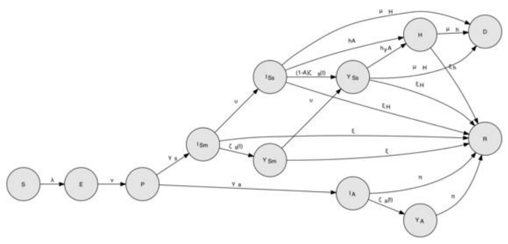
Seasonal Effects

…

NPI-dependent mixing matrix



Disease Progression Model



Observed Prevalence

NPI Level ~
Prevalence * Level of Caution * 10^3

Level of Caution

Outputs

Deaths

Cases

Income Loss

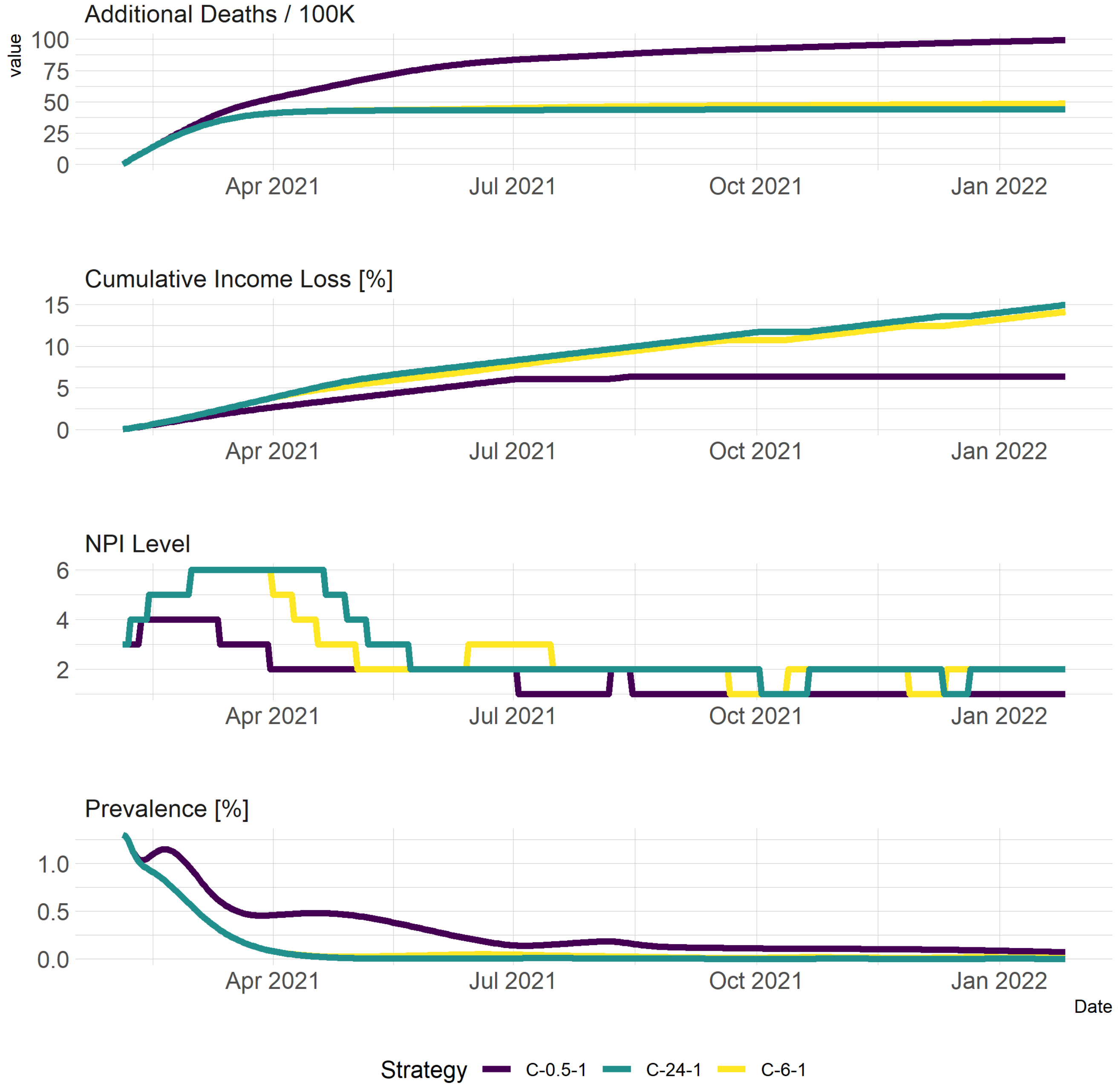
Days of NPIs

Representing NPIs dynamically

I. Each line represents a strategy with a **constant** "level of caution" (0.5, 6 and 24)

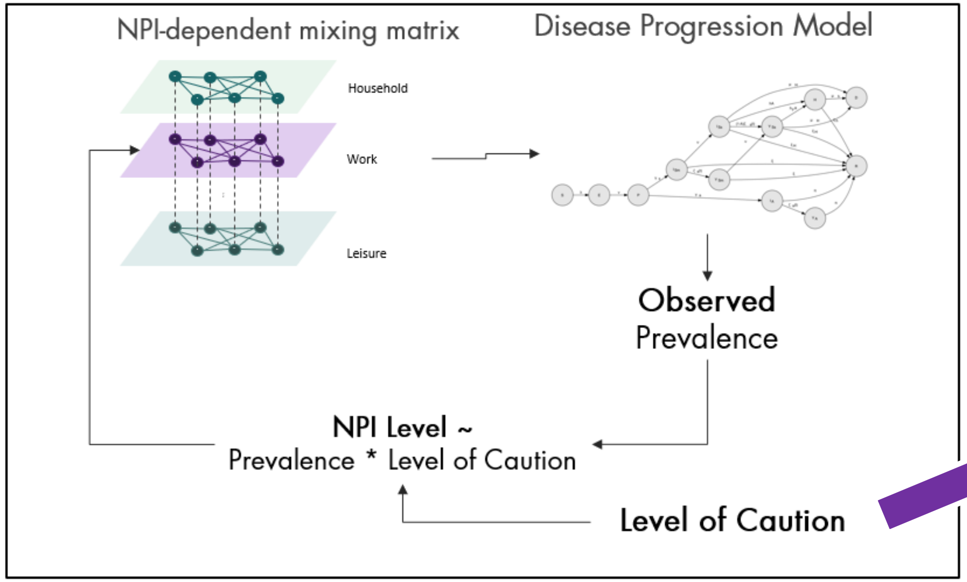
II. NPI Levels are endogenously defined by prevalence

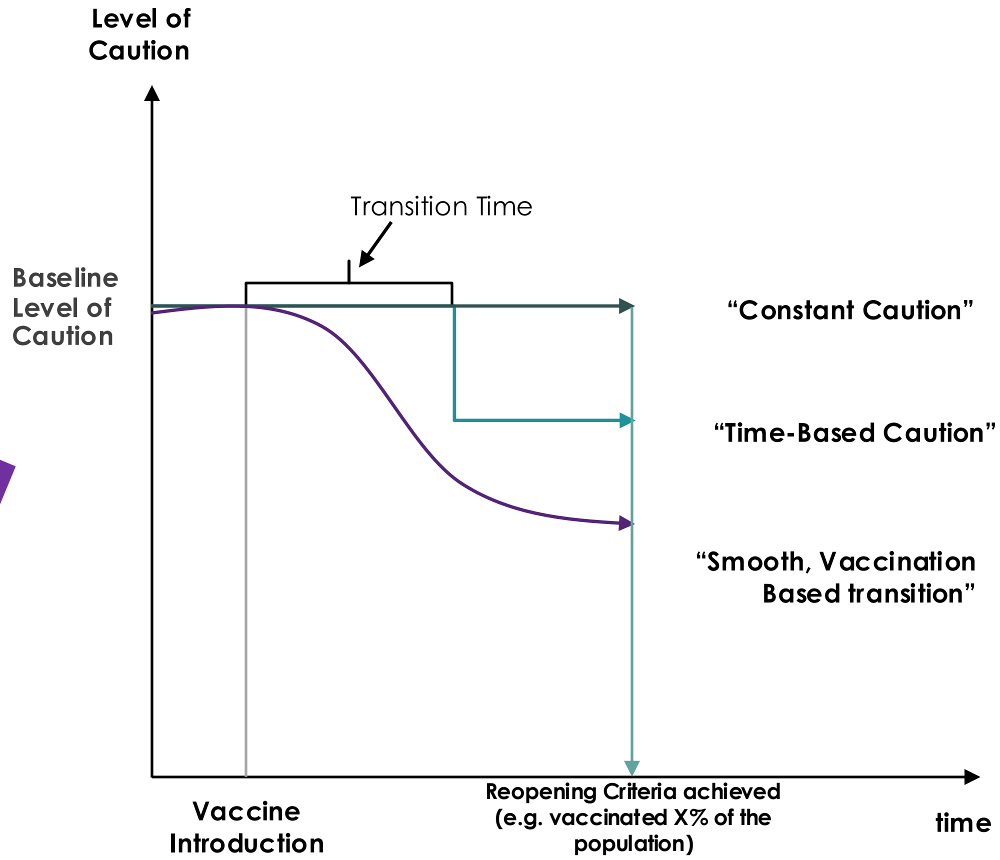
III. Income loss is proportional to the time spent under each NPI level.



Decision Framing:

Policy question: How to manage this level of caution over time?





Decision Framing:

Policy Levers and Strategies

We test three types of NPI Strategies:

1. **Constant Caution NPI Strategies:** Uses the same Level of caution throughout the simulation
   Baseline plan with Level of caution ~ 6
2. **Time-Based NPI Strategies:** Changes the Level of Caution at a given date – e.g. Spring or Fall.
   1. **Transition Date:** When will we transition a different level of caution?
   2. **New Level of Caution Multiplier:** When we transition, how cautious will we be, relative to our prior level of caution?
3. **Vaccination-Based NPI strategies:** Changes the Level of Caution as a function of vaccination.
   1. **Caution relaxation rate**: Controls how fast society relaxes NPIs as a function of vaccination (steepness of reverse S curve).
   2. **Adaptive caution midpoint**: Controls at which point the baseline level of caution is halved (position of the midpoint of the S curve).

All strategies start with a **Baseline Level of Caution:** The Prevalence level we need to see to intervene with NPIs

Decision Framing:

Alternative strategies are represented by how our “level of caution” is managed over time

The NPI level is defined as a function of known prevalence p_t with this controller function:

$$NPI_t^* = min(p_t * x_t * 10^3, 5) + 1$$

x_t , **our level of caution**, can be defined exogenously as a function of time or endogenously by the vaccination status rate with an inverse S curve:

$$x_t = x_b * \left(1 - \frac{1}{1 + e^{-k_c*(V^* - V_{mid})}}\right)$$

where V^* is the current vaccination coverage, V_{mid} is the vaccination coverage where the level of caution is halved and k_c is the rate at which the level of caution decreases.

Uncertainties

Each strategy is stress-tested in a set of State of the World (SOWs) defined by a combination of uncertainties

1. **Vaccine Efficacy to prevent transmission (10%-100%):** A parameter that controls to what extent vaccine efficacy is attributed to disease prevention or infection prevention.
2. **Behavioral Response to Vaccination (0%-25%)**: Will people mix more once they get vaccinated? We have a parameter that allows mixing to increase dynamically as more people get vaccinated.
3. **Willingness to Vaccinate (60% - 100%)**: A single parameter controls a uniform willingness to vaccinate parameter.
4. **Changes in transmissibility (-50% + 50%):** New strains are expected to change transmissibility to an uncertain degree. So is our level of mask wearing / voluntary social distancing in the future. We have a single parameter that controls changes in transmissibility as a deviation from the baseline value.
5. **Actual Vaccination Rate (-50% - 150%):** As we saw in the initial rollout we cannot take for granted that vaccination will follow pre-specified, often optimistic timelines.
6. Uncertainties not explored in the previous experimental design:
    1. Change in Mortality (-20% - 50%)
    2. Change in Vaccine Efficacy (-50% - 0%)

Approach Summary

Inputs Preparation and Normalization

- Obtain deaths and incidence timeseries from the COVID-19 Tracking API
- Construct a state-level NPI Timeseries compatible with the economic and the epidemiological models

Model Calibration – Simulate the Past

- Find **n** sets of parameters that explain past deaths timeseries.
- Use either an Latin Hypercube Sample of 35 model parameters or the IMABC algorithm.

Define future Experimental Design

- **Strategies**: Create **s** Strategies by obtaining a full factorial design of all policy levers**.**
- **Deep Uncertainties**: Obtain a new LHS sample with **u** lines for the additional uncertainties not included in model calibration (future vaccination rate, change in transmissibility, behavioral effect of vaccination, etc.)
- **Obtain full future experimental design** with **n * s * u** cases. Choose **n, s, and u** such that we stay under a computational budget. A **future state of the world (SOW) is defined as a combination of calibrated and "deeply uncertain" parameters**.

Evaluate Strategies across all futures

- Simulate all the **n * s * u** cases.

Compute Regret across strategies and futures for all outcomes of interest

- For each future state of the world and strategy, find the regret for each metric.
- For example, deaths regret $R_{s,f}$ of strategy s in future f is defined as $R_{s,f} = D_{s,f} - \min_x(D_{x,f}) \ \forall\, s, f$, that is the difference in the outcome between each strategy and the best strategy for that future.

Trace Robustness tradeoffs curve, find pareto-dominated strategies

- Use a percentile of the regret distribution conditional on the strategy to trace the resulting many-objective robustness tradeoffs curve. Use this curve to judge strategies.

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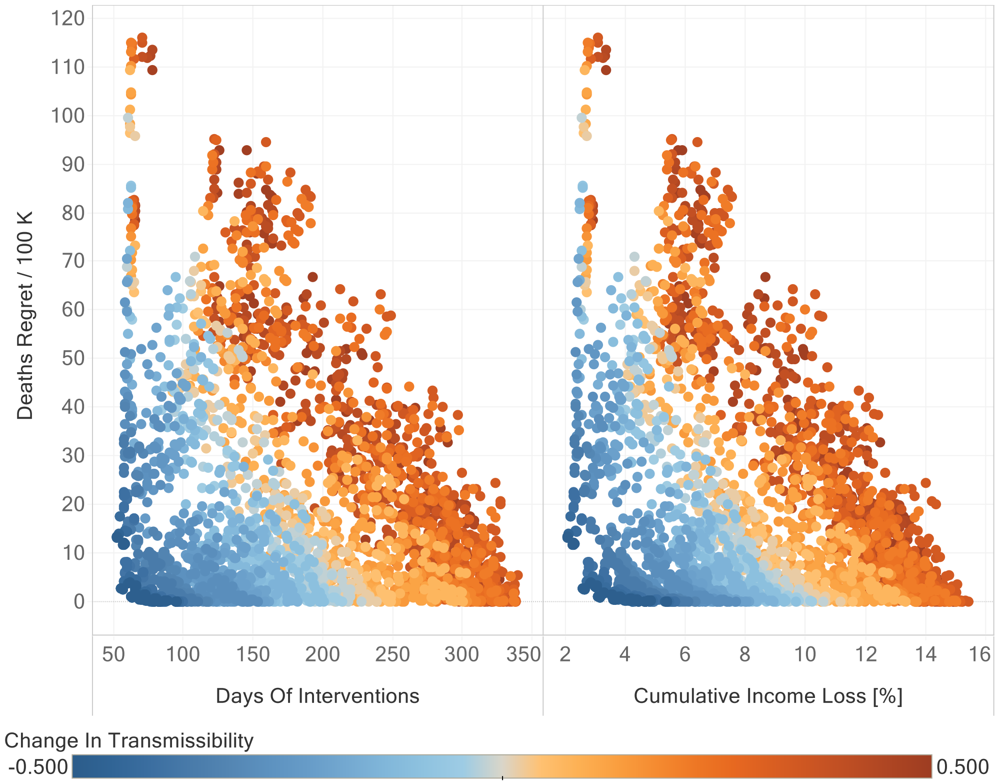
The Outcome Space



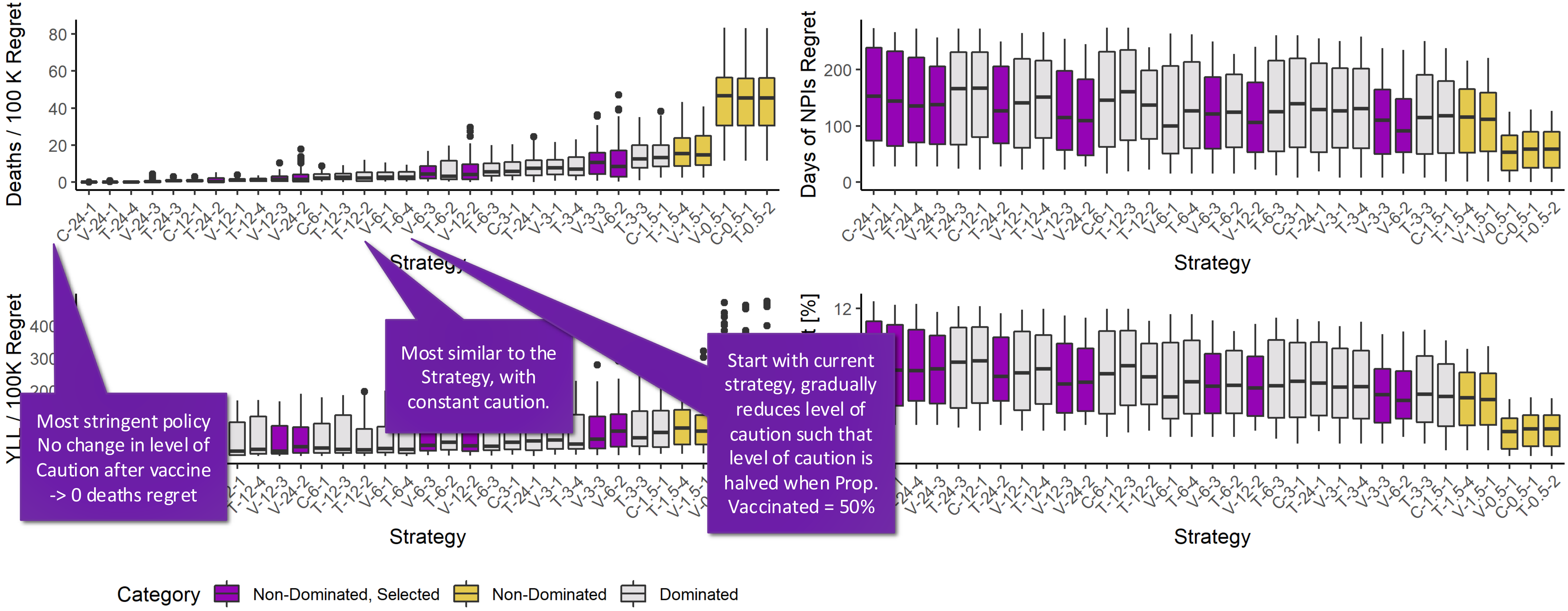
Each dot represents the performance of an strategy in one future. We stress-test 78 strategies across 20,000 futures

The most significant uncertainty driving results is, unsurprisingly, the change in transmissibility.

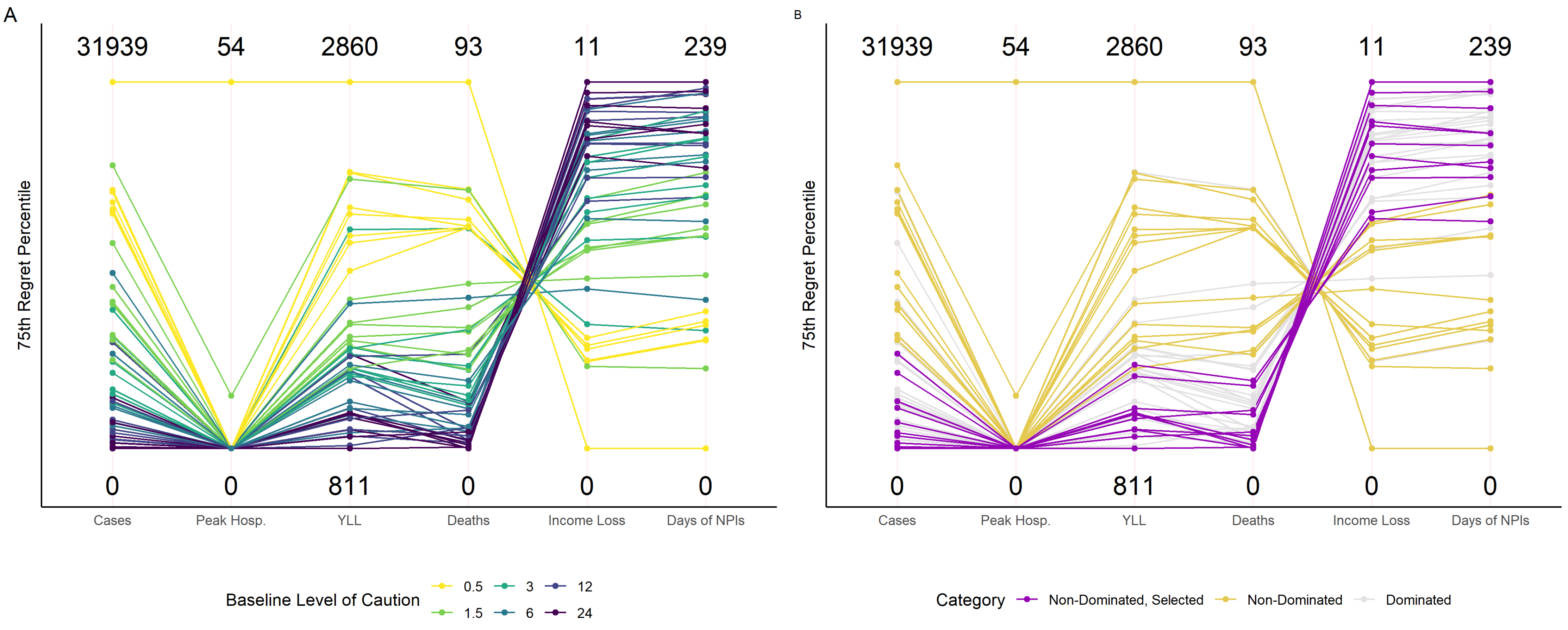
Robustness is measured with regret – the difference between the performance of each policy and the best policy, in each future state of the world.

This allows us to rank strategies by their **robustness** across all futures rather than by their **optimality** in a best-guess of the future.

Regret distributions by Strategy

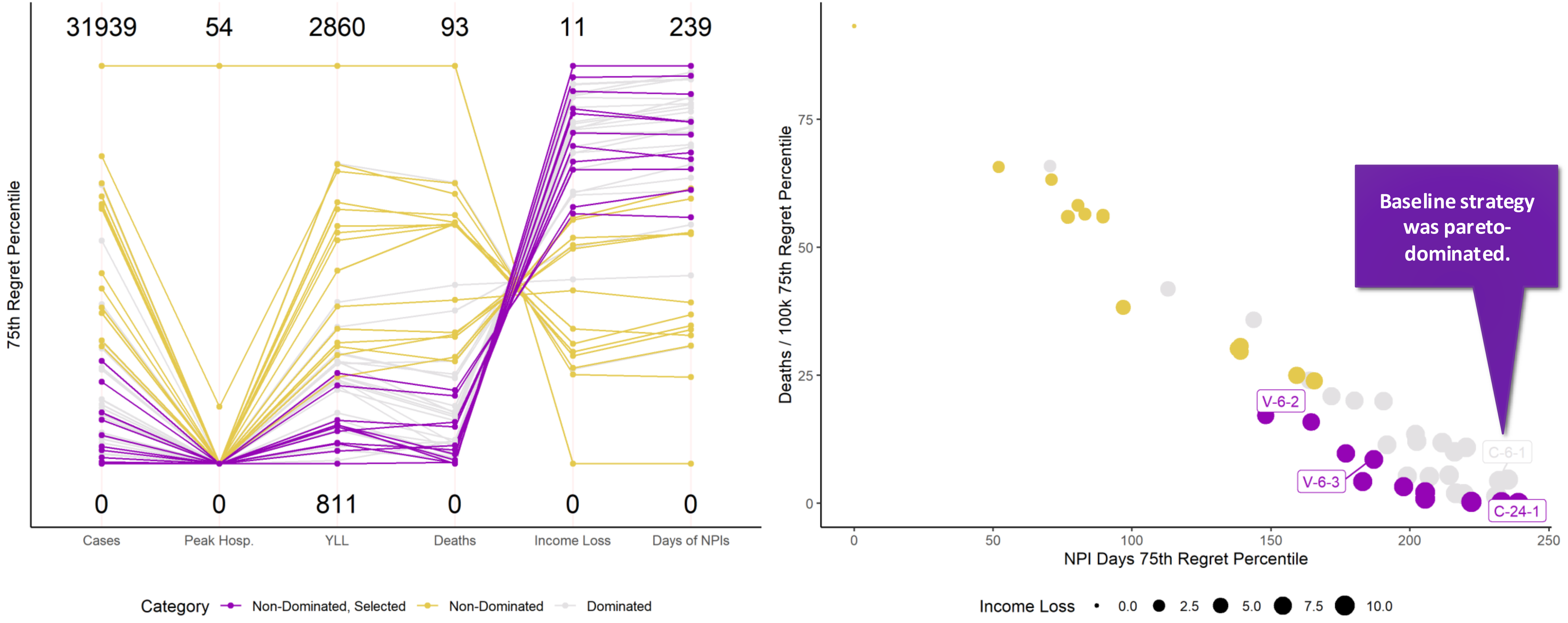


Health-Economic Robustness Tradeoffs



Health-Economic Robustness Tradeoffs

These results indicate that many strategies – including our baseline strategy - are dominated



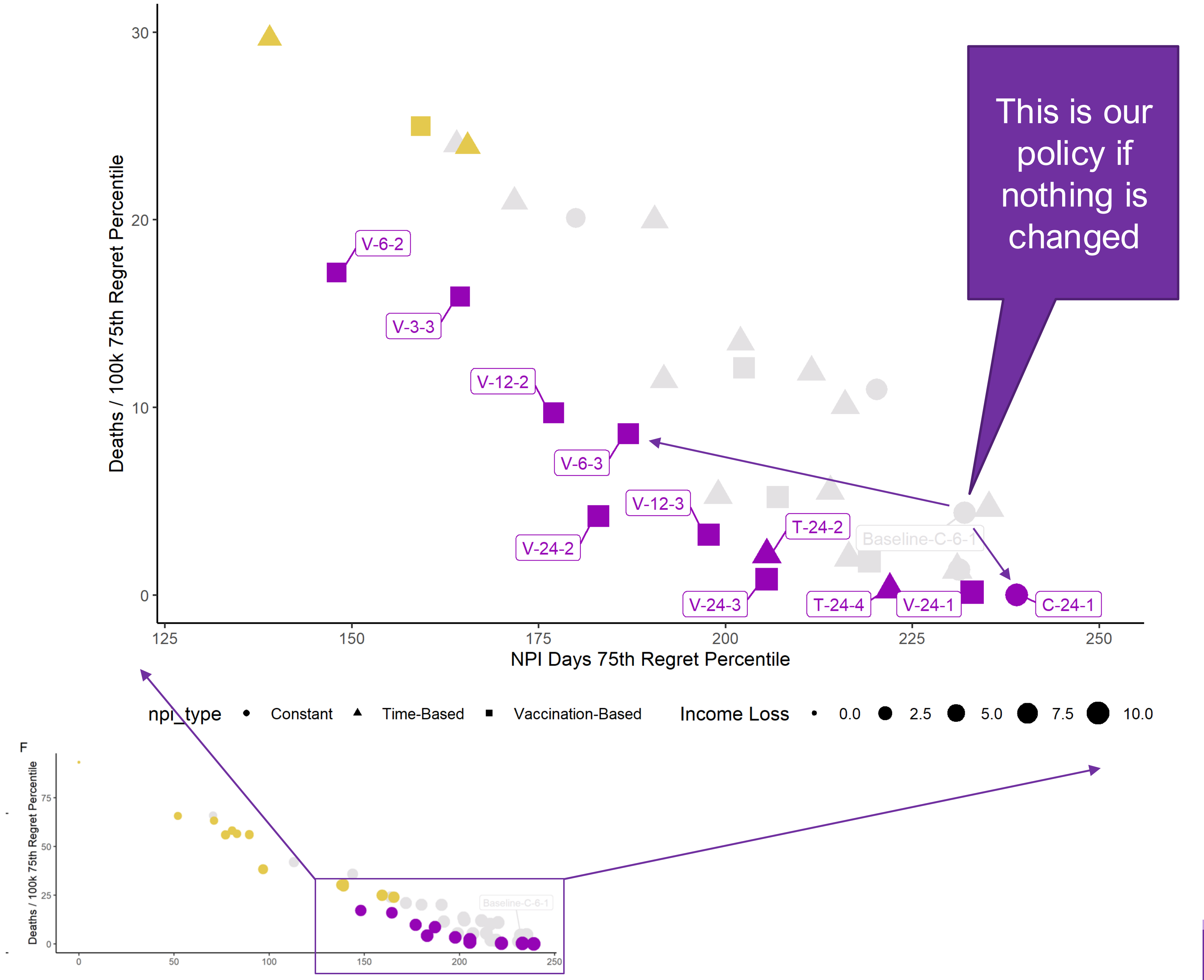
Vaccination-Based or Time-based policies resulted in better trade-offs

I. Vaccination-Based policies often are in the pareto front.

II. A few time-based policies also were in the pareto front

III. The only constant-caution policy in the pareto-front is the most-stringent, and the current policy was dominated.

IV. We stop the model in Feb 2022. If we ran the model for more time, these differences will likely increase.



Summary of Non-Dominated Strategies

The baseline Strategy was dominated. These are the non-dominated alternatives found in this experimental design.
These numbers are not predictions.

Category	Strategy	Initial Level Of Caution	Strategy Description	Percentile (75) of Cumulative Deaths Regret	Median Cumulative Deaths Regret	Percentile (75) of NPI Days Regret	Median NPI Days Regret	Percentile (75) of Cumulative Percent Income Loss Regret	Median Cumulative Percent Income Loss Regret
Dominated	C-6-1	6	Constant Caution	4.4	2.3	232.0	146.0	10.1	6.7
Non-Dominated, Selected	C-24-1	24	Constant Caution	0.0	0.0	239.0	153.0	11.0	7.5
	T-24-4	24	Reduces Level of Caution by 50% on 2021-09-26	0.3	0.1	222.0	135.5	10.3	6.9
	V-24-3	24	Reduces Level of caution by 1/2 when vacc. coverage is 0.5	0.8	0.3	205.5	138.0	9.8	7.1
	T-24-2	24	Reduces Level of Caution by 90% on 2021-09-26	2.2	0.4	205.5	127.0	9.7	6.5
	V-12-3	12	Reduces Level of caution by 1/2 when vacc. coverage is 0.5	3.2	1.5	197.8	115.0	9.1	5.9
	V-24-2	24	Reduces Level of caution by 1/2 when vacc. coverage is 0.4	4.2	1.6	183.0	109.0	8.7	6.0
	V-6-3	6	Reduces Level of caution by 1/2 when vacc. coverage is 0.5	8.6	4.5	187.0	121.5	8.3	5.7
	V-12-2	12	Reduces Level of caution by 1/2 when vacc. coverage is 0.4	9.7	4.2	177.0	106.0	8.1	5.5
	V-3-3	3	Reduces Level of caution by 1/2 when vacc. coverage is 0.5	15.9	10.5	164.5	110.0	7.1	5.0
	V-6-2	6	Reduces Level of caution by 1/2 when vacc. coverage is 0.4	17.2	8.4	148.0	91.0	6.9	4.5

Back to the Policy Question:

How to manage NPIs in 2021 in a State like California?

1. Society will need to **be cautious and consistent** in their reopening strategies to minimize COVID-19 deaths during vaccination rollout.
2. Reopening strategies based on **stringent reopening thresholds** unsurprisingly lead to robust health outcomes when stress-tested over a wide range of futures.
3. However, **fixed-threshold reopening strategies seem to be pareto-dominated** when one accounts for economic outcomes.
4. These results emphasize **the need for a structured approach for reopening,** and the **potential regrets of following dominated strategies.**
5. These regrets might seem small – but we must acknowledge **that they will be concentrated on the most vulnerable.**

Back to the Policy Question:

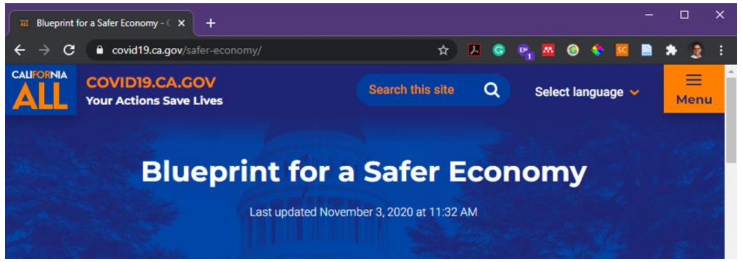
As always, implementation is the key

A. **The plan will have to change anyways** as vaccination progresses and COVID-19 becomes endemic – that is expected.

B. **Frequent changes to the reopening plan seem arbitrary and unscientific** when they are not backed up by analysis – but the absence of change is also undesirable: as we demonstrated, **fixed thresholds are pareto dominated**.

C. **The plan could be explicit** about when criteria will change based on progress in the vaccination rollout and the situation in the ground.

D. **Robustness analyses could support the reopening strategy while ensuring that it is robust against a wide range of emerging uncertainties**.



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**Health equity metric is not applied for small counties. The health equity metric is used to move to a less restrictive tier.

Limitations and potential extensions

1. This analysis did not presented all the steps in the RDM analysis – scenario discovery could still illuminate conditions under which one would switch between strategies.
2. Multiple vaccines are not represented explicitly – model parameters represent average efficacies
3. We don't model tradeoffs involved with two doses vs single-dose regimes
4. Given their structure, the economic models make strong assumptions about instantaneous economic recovery.
5. We don't address other long-term outcomes from alternative policies (lack of traditional education in the long-term, long-term COVID-19 health effects / lung damage).
6. Our model is deterministic, implying that eradicating COVID-19 is never achieved (unfortunately this is still reasonable assumption for US states given traveling and lack of cooperation among states; not a good assumption for an island or countries with tight border controls).
7. We consider no interactions among different geographic levels.
8. This analysis does not explicitly consider distributional concerns: "Who pays the price of NPIs and who benefits from them?". This matters and deserves more attention.

Thanks!

And thanks to the awesome people who contributed to this work

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